FAILURE ANALYSIS AND DIAGNOSTICS OF RAILWAY TURNOUTS

by

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I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

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M.S. Thesis – Computer Engineering
July 2009

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ABSTRACT

The importance of railway systems that include trains, metro, and tramway has been increasing in the world. It is now an obligation to improve reliability, availability, and safety of railway systems in order to accommodate increasing passenger and cargo transportation with higher train speeds, greater axle loads, and increased service frequency. Increasing reliability, availability and safety can be achieved by increasing the number of maintenance in the railway system. However, this will increase the operating and support cost. For example in England, 3.4 million pound is spent every year for maintenance of point machines in 1000 km of railways. Hence, it is now a great need to develop diagnostics methods that will help to identify the failures early enough. These failure diagnostics methods not only reduce the cost, but also increase the safety. In this thesis, failure identification methods in railway turnouts using time series analysis are studied.

Limited sensory data is collected from a healthy turnout system. Large numbers of data are simulated for healthy and faulty system using the limited real data. Simulated data in both healthy and faulty system are divided into two groups: training and testing. Noise is removed from the data using exponential smoothing algorithm. Self Organizing Map (SOM) and expert system are used for failure identification. Dynamic Time Warping and Euclidean Distance are employed for identification of similarity level between the real healthy system and signal under observation. Similarity level is used in expert system for failure identification.

Keywords: Failure Diagnostics, Expert Systems, Railway Turnouts, Time Series Analysis, Self Organizing Map, Euclidean Distance

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ÖZ

Tüm dünyada tren, metro ve tramvay sistemlerini içeren demiryollarına olan talebin gün geçtikçe arttığı görülmektedir. Bu artışa cevap verilebilmesi için demiryolları sistemlerinin güvenilirliği, hazır olma oranı ve yolcu emniyetinin arttırılması gerekmektedir. Bu ise demiryollarına uygulanan bakım sayısının arttırılmasıyla gerçekleştirilebilse de artan bakım sayısı maliyeti yükseltmektedir. Örneğin, İngiltere'de 1000 km'lik demiryolunda bulunan makas sistemlerinin bakımı için her sene 3,4 milyon sterlin harcanmaktadır. Bu yüzden bakım maliyetini en aza indiren erken hata teşhis metodlarının geliştirilmesi önem arz etmektedir. Bu metodlar oluşmakta olan hataları önceden haber vererek bakım maliyetini azaltmakta ve güvenliği arttırmaktadır. Bu tezde zaman serisi analiz yöntemleri kullanılarak demiryollarının en önemli bileşeni olan makas sistemlerinde arıza tespit metodları üzerine çalışılmıştır.

Bu çalışma kapsamında arızasız bir makas sisteminden çeşitli sensörler kullanılarak sınırlı miktarda veri toplanmıştır. Bu gerçek veriler simüle edilerek arızasız ve iki arıza türünde çok miktarda veri elde edilmiştir. Arızasız ve hatalı olarak simüle edilen veriler öğrenme ve test olmak üzere iki gruba ayrılmıştır. Bu veriler eksponansiyel düzleştirme algoritması kullanılarak gürültüden arındırılmıştır. Daha sonra uzman sistem ve Self Organizing Map (SOM) kullanılarak hata tespiti gerçekleştirilmiştir. Geliştirilen uzman sistemde arıza benzerlik seviyesi Dinamik Zaman Eğilimi (Dynamic Time Warping), ve Öklid Uzaklık (Euclidean Distance) metodları ile belirlenmiştir.

Anahtar Kelimeler: Arıza Teşhis, Uzman Sistemler, Demiryolu Makas Sistemleri, Zaman Serisi Analizi, Kendini Düzenleme Haritası, Öklid Uzaklık.

DEDICATION

Dedicated to my parents for their endless support and patience during the forming phase of this thesis.

The men who moves a mountain

begins with carrying away

small stones.

Confucius

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTON

1.1. 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 (Diego Jose P. T. et al, 2006). 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 Consortium, 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, which is considered as complex mechanisms and assembled from switches and crossing where the moving parts are often described as 'points' (F.P.Marquez et al, 2002). Points allow a rail vehicle to move from one set of rails to another and whole mechanical parts and their functions of railway turnout point machine are explained in detail, in at webiste www. seva.eng.ox.ac.uk/research_railway_points_machine. (see Figure-1.1).

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 (F.P.Marquez et al, 2002).

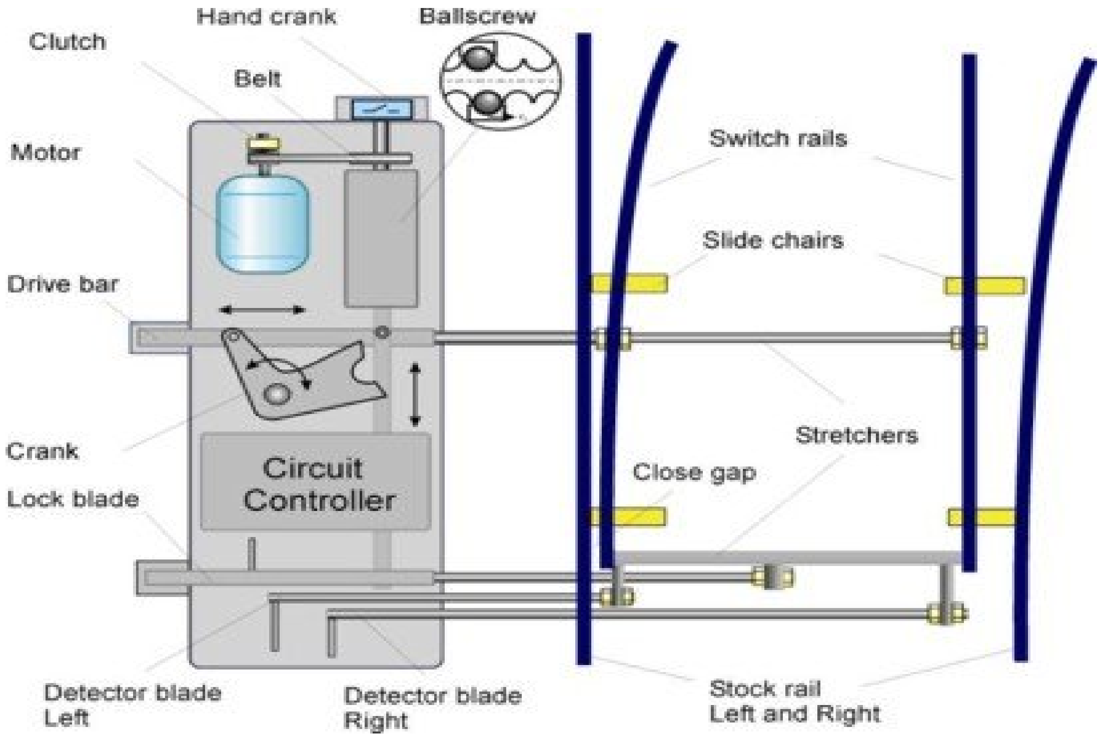

Figure 1.1 : General Diagram of Point Mechanism (Invensys, 2009)

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 (F.P.Marquez et al, 2006).

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.

1.1.1. 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-periodic;
- 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.

1.1.2. Failure 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 failures on point mechanism is done according to the seriousness of failures. 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 (Fig.1.2) (F.P.Marquez et al, 2006):

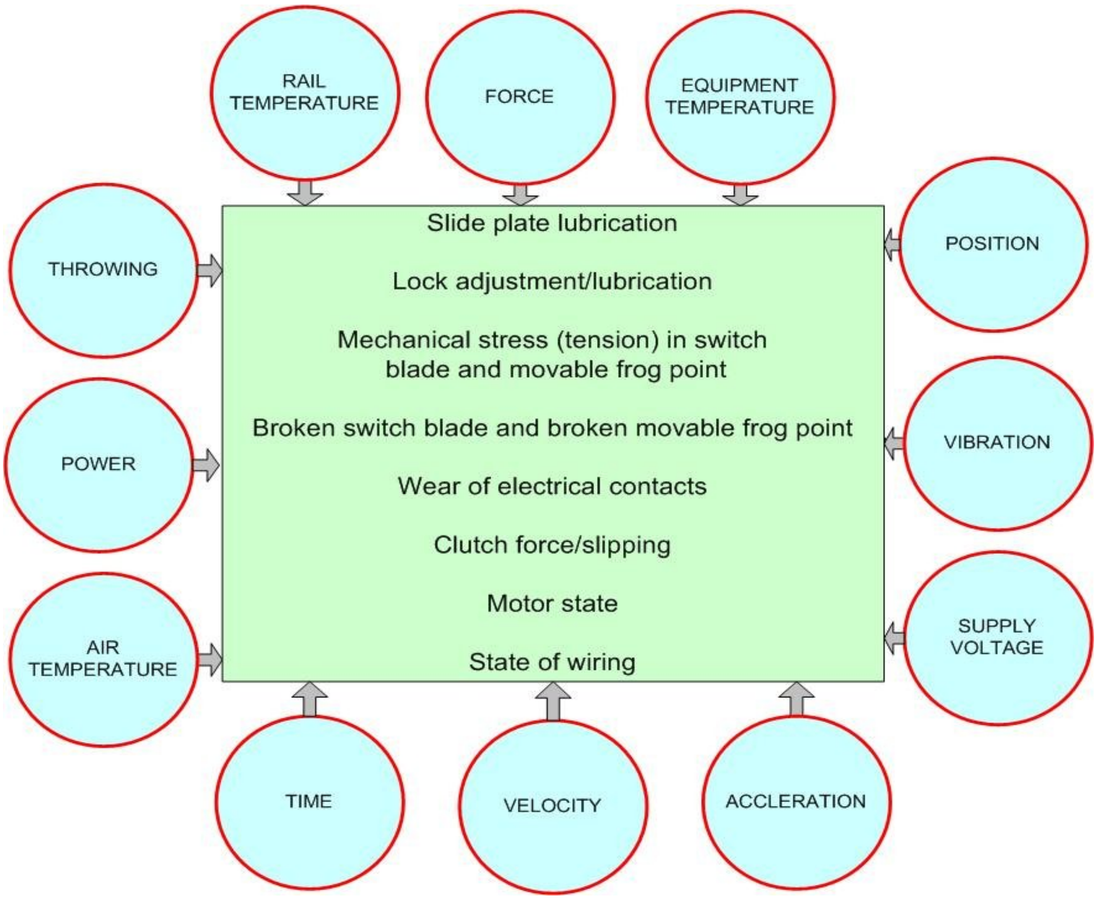

Figure 1.2 : Factors influencing fault levels in point mechanisms

Table 1-1 : Failures, failure modes.

	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	Microswitch 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

1.1.3. Potential Failures 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).

(i) Slide plate lubrication;

(ii) Poor lock adjustment and/or lubrication;

(iii) Mechanical stress (tension) in switch blade and movable frog point;

(iv) Broken switch blade and broken movable frog point

(v) Wear of electrical contacts;

(vi) Clutch force/slipping of clutch;

(vii) Motor state;

(viii) State of wiring;

(ix) Obstruction at bearer on normal side of points;

(x) Obstruction at bearer on reverse side of points;

(xi) Obstruction at toe on normal side of points;

(xii) Back drive overdriving at heel on normal side with dry slide chairs;

(xiii) Back drive slack end off at toe end;

(xiv) Back drive slack end off at toe end (LHS side drive basket slack end off);

(xv) Diode snubbing block disconnected;

(xvi) Dry slide chairs;

(xvii) Low tension on motor brush;

(xviii) Operational contact in original position;

(xix) Tight lock on reverse side;

(xx) Tight lock on reverse side (sand on all bearers on both sides).

(F.P.Marquez et al, 2006).

1.2. TRADITIONAL MAINTENANCE TECHNIQUES

Production capacity, cost and availability of industrial manufacturing are directly combined with the system, which is under proper maintenance. Breakdowns in industrial manufacturing systems can have significant impact on the profitability of a business. Expensive production equipment is idled, labor is no longer optimized, and the ratio of fixed costs to product output is negatively affected and other side effects. However, when equipment breakdowns occur the cost can go well beyond the period of repair. Those failures or problems are intolerable in manufacturing systems as well as in railway infrastructures. Rapid repair of down equipment is very critical issue to business succeed; because spending most of the time in maintenance tremendously decreases the capacity of the production system. Safety, reliability and availability can be considered as important issues of maintenance on complex systems (H. Saranga and J. Knezevic, 2001).

There are basically three types of proposed maintenance models for systems:

1) Improved maintenance (IM),

2) Corrective maintenance (CM),

3) Preventive maintenance (PM).

1) Main goal of *Improved maintenance (IM)* is to eliminate the need for maintenance, in design and production phase of a machines or equipment. However, producing perfect machinery which will not fail is nearly impossible; of course there may be a possibility to produce such machinery by installing complex systems and application of advanced electronics. But in many industries this expense is not affordable because of their prices.

2) *Corrective maintenance (CM)* is probably the most commonly used approach, but it is easy to see its limitations. When equipment fails, it often leads to downtime in production, and may cause tremendous loss in the assembly line. In most cases this is costly business, because failure of one component may stop the whole system and lead to catastrophic results. Also, if the equipment needs to be replaced, the cost of replacing it alone can be substantial. It is also important to consider health, safety and environment issues related to malfunctioning equipment.

3) *Preventive maintenance (PM)* model avoids failure of critical equipments before they occur. It is designed to preserve and restore equipment reliability by replacing worn components before they actually fail. Preventive maintenance activities include partial or complete overhauls at specified periods, oil changes, lubrication and so on. In addition, workers can record equipment deterioration so they know to replace or repair worn parts before they cause system failure. The ideal preventive maintenance program would prevent all equipment failure before it occurs. Time-based preventive maintenance, which

is the traditional approach for preventive maintenance, is the maintenance of the system in time intervals and its defined using statistical failure information of the system from the Database. This approach has an advantage and as well as disadvantage also. An advantage of preventive maintenance is, it decreases the down time of machines caused by failure modes, but disadvantage of preventive maintenance is, it increases the down time caused by maintenance. In time-based PM, whole system can be stopped because of maintenance to replace part of equipments, even if it's working properly. Replacement of parts is done according to predefined intervals.

And one of the more important points is how to schedule maintenance period. Deciding the maintenance period is not easy work. If one system is maintained more frequently, it will be too expensive, but if poor maintenance is applied to that same system, then it will result with a lot of numbers of failures before the scheduled time. As we see two above mentioned criteria's are not proportional to each other. The maintenance period should be scheduled in such way, that the corrective maintenance cost and the failure of system or equipment should be minimized and system availability and punctuality should be maximized. Fig.1.3 and 1.4 illustrates this concept. Minimum time can be chosen when scheduling maintenance period, but this also is not an optimum solution, this will lead again to costly business and replacement of unnecessary equipment which is working properly.

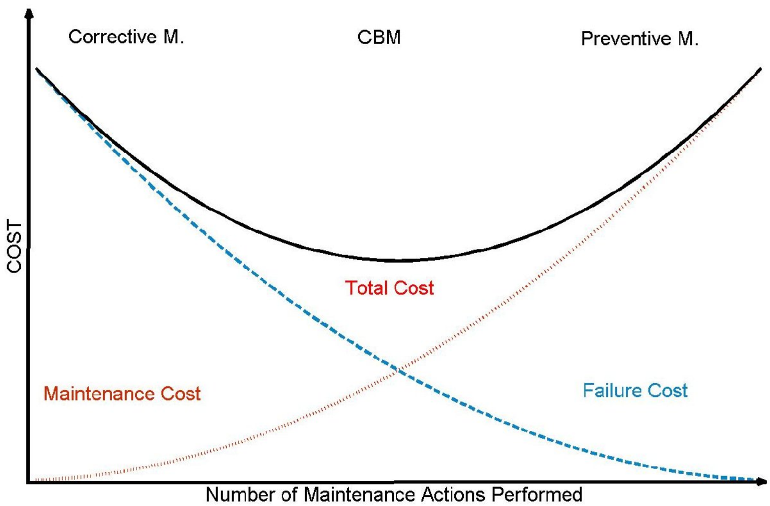

Figure 1.3 : Number of maintenance actions

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. Time-based preventive maintenance can be effective on non-critical machines, which have low priority of criticality; with less corrective maintenance. However, application of time-based preventive 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.

1.3. CONDITION BASED MAINTENANCE (CBM)

The goal of Condition Based Maintenance is to detect impending failures and perform preventative maintenance before a functional failure occurs. This approach does a monitoring over state of machines or equipments by performing analysis of real-time data acquired form different sensors to minimize failure and maintenance cost. 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 corrective maintenance is actually necessary. CBM uses real-time data to reduce down time of system. Ideally condition-based maintenance will allow the maintenance personnel to do only the right things, minimizing spare parts cost, system downtime and time spent on maintenance. Optimality of maintenance techniques are shown in Fig.1.6.

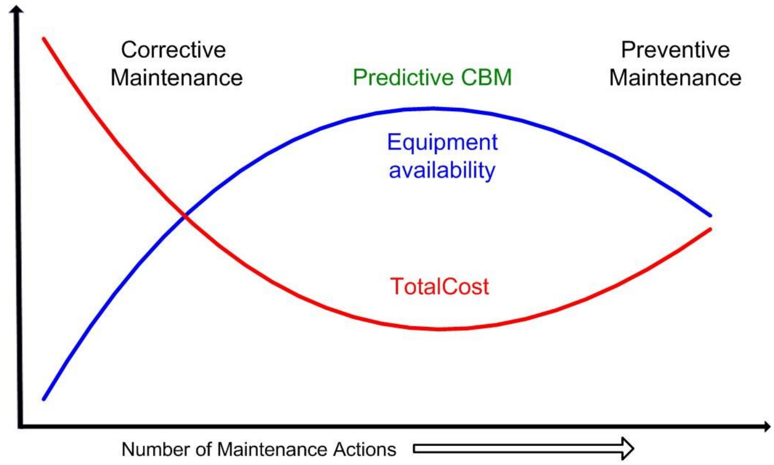

Figure 1.4 : Illustration of the concept of optimal maintenance with total cost and equipment availability

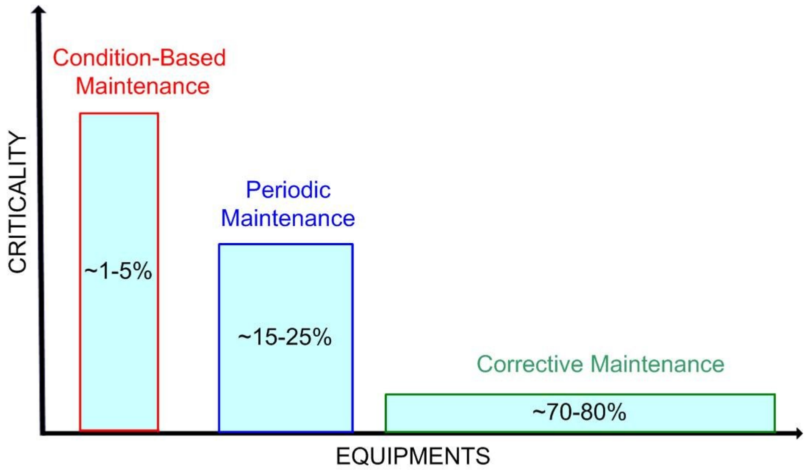

Figure 1.5 : Maintenance techniques and their usage with equipment criticality

1.3.1. Challenges of CBM

1) First and most important of all, installation of condition based maintenance is costly. It will require improved instrumentation or advanced electronics of your equipment. Often the cost of sufficient installation of instruments 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.

2) Secondly introducing CBM to the previous system will invoke a major change in how maintenance is performed, and potentially to the whole maintenance organization in a company. Organizational changes are in general difficult.

1.3.2. Benefits of CBM

The goal of Systems that adapt application of condition based maintenance model is to minimize corrective maintenance cost, strengthen system security and availability, and reduce severe failures (C.S.Byington and A.K. Garga, 2001).

Following subsections gives a brief explanation about corrective maintenance cost, system security and availability.

1.3.2.1 Maintenance Cost Reduction

Cost reduction can be analyzed in four categories (G. Allenby, 1990)
(Harbor Research Pervasive Internet Report, 2003).

1) *Machine downtime reduction:* maximizes production capacity, utilizes machinery, and optimizes system functionality. Jay Lee and Jun Ni, the Co-Directors of *National Science Foundation* (NSF) center of Intelligent Manufacturing System (IMS) state that $5 billion per year in equipment uptime improvement would be saved in US alone if CBM were implemented.
2) *Maintenance cost reduction:* is one of the goals of CBM and which helps to maximize the productivity of the system or equipment can be achieved by installation of CBM model to the system.
3) *Inventory reduction:* is possible by detecting failure time beforehand. Necessary equipments can be bought according to the needs, instead of

keeping them in stock for long periods. Useful in stock load optimization.

4) *Enhanced logistics and supply chain:* can be achieved if the overall health factor or working state of the system is known. Necessary equipment parts can be supplied from other companies if failures modes and causes of failures can be identified.

1.3.2.2.Availability and Safety

Reduction in production cost and profit maximization is one of the major points in industrial manufacturing, but sometimes safety and availability of system play an important role rather than cost reduction and profit minimization. For example, in Department of Defense, equipments must provide high safety and availability, in such systems installing cheapest equipments rather than advanced ones, will cause catastrophic results.

1.4. GENERAL PROCESS DIAGRAM OF CBM

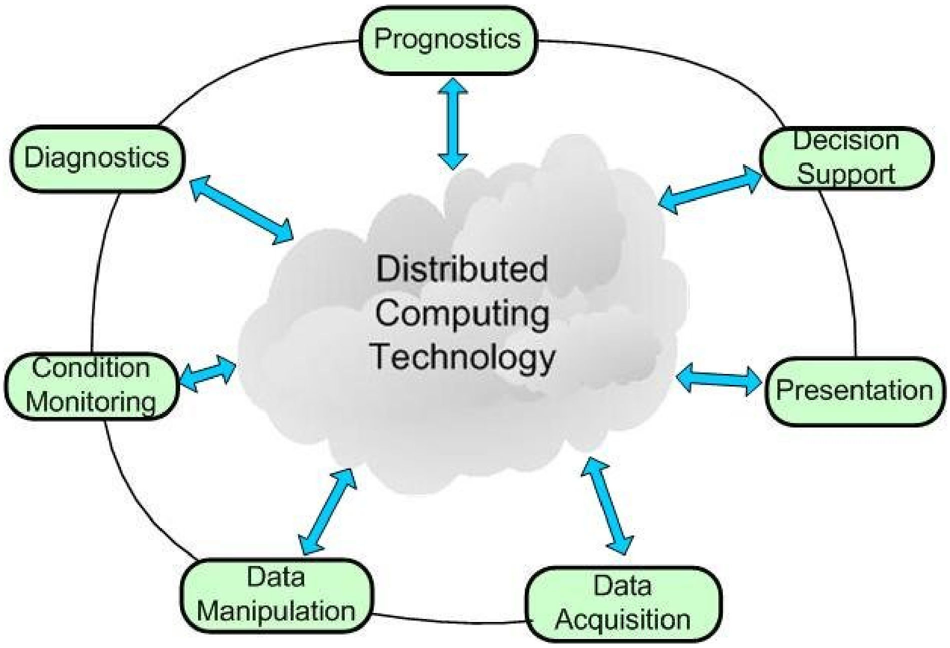

Figure 1.6 : General Process Scheme of CBM

1.4.1. Data Acquisition (DAQ/DAS)

This is the first stage of CBM data processing, which acquired real-data generation, takes place. Data acquisition is simply composed of acquired signal data to get useful information. These system components are especially different types of sensors, which converts acquired data to electrical readable signals, to be accessible by data acquisition equipment. Acquired unprocessed data is sent to signal processing unit for further operations.

Acquired row data's can be force, current, temperature, vibration signals of machines. A transducer is a device, usually electrical or elector-mechanical that converts one type of energy or physical attribute to another for various purposes including measurement or information transfer(for example current, pressure, force, sensors). Application of types of transducers is depends to the measurement purpose.

1.4.2. *Data Manipulation (Feature extraction)*

Different types of sensors are installed onto the machine or an equipment of a system to record the data about the health factor of the machine or the component. These sensors acquire digital signals that encoded from velocity, current, force, acceleration, strain, pressure, and vibration of equipments.

Acquired data from those sensors contains information about health state of the machine, but collected data might not show us the real health factor of equipment, in order to make collected data understandable we need to insert into feature extraction process.

Feature extraction includes simplifying the amount of resources required to describe a large set of data accurately. During analysis of complex data one of the major problems is the number of data involved. Analyzing a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training sample. Feature extraction is a general term for describing the data with sufficient accuracy.

1.4.3. *Condition Monitoring*

Condition monitoring is the process of monitoring the state or each action of system, in order to identify the incipient failures or abnormality of system. Sudden failures can be called as abrupt failures. Those abrupt failures are detected by monitoring techniques, which rely on statistical process control, such as charts and other detection techniques. Failure detection is done by comparing critical data with the predefined statistical limitations, which are set by statistical models.

1.4.4. Diagnostics

Diagnostics can be defined as the process of determining and identifying criticality of the failures (K. Maynard et al, 1999). There are two categories of failures; abrupt (sudden) failures and incipient failures. Abrupt failures happen in a very short period of time, so it's a bit difficult to track the failure data for future analysis.

But incipient data develop in long period of time, and their effects are easily seen in the features acquired. But the data collected to detect incipient failures are collected during working state of the machines in normal mode. Severity and criticality of the failure and its identification will show us health factor of machines.

1.4.5. Prognostics (Estimation of remaining usage life)

A prognostic is combined with diagnostics and it estimates the remaining useful life (RUL) of machinery by prediction of diagnosed failures. There are various types of algorithms that used in prognostics such as, artificial intelligence prediction, state-space tracking algorithms and higher-fidelity physics of failure algorithms.

It's the process of which evolves in time from the machine is first start till it fails.

1.4.6. Decision Support

This layer analyzes the data from previous layers and provides decision making to the user, which action to take in order to optimize the system that will lead to the cost reduction and maximization of system availability.

1.4.7. Presentation

Presentation layer includes not only the GUI that creates the interaction between system and maintenance staff but also tools that guide the maintenance staff on complex maintenance procedures. Augmented Reality Guided Maintenance is located in the presentation layer of CBM. This system guides the user through complex maintenance procedures by displaying virtual 2D-3D models, animations, and pointers on the Head Mounted Display (HMD). The maintainer has an opportunity of seeing the virtual images and animations of maintenance in this layer.

1.5. PROBLEM DEFINITION

In the future, railway systems must be improved to accommodate higher train speeds, greater axle loads, and increased service frequency, in terms of reliability, availability, maintenance and safety. Furthermore, passenger and crew safety is one of the most important requirements in railway industry. For example, on British Railways only, 852 people had been killed between 1989 and 1994 due to railway related faults (Kennedy A, 1997). In 1994 at least 36 people were killed and dozens injured when high-speed train derailed in northern Turkey (Aysen Atasir, 2004). Unidentified failure of railways has caused the accident. Any accident on railways though is of serious concern to society, which means new safety culture must be established and improved. Since its inception, the railway industry has searched for ways to improve the safety and the reliability of the railway subsystems.

Increasing the number of maintenance of railways in order to increase the safety is not a feasible solution. Reaching the expected safety levels may require excessive number of maintenance to be performed, which cause very high cost for the railway management. Thus, increasing the safety with minimum cost has crucial importance in railway systems.

Condition based maintenance aims to maintain the correct equipment at the right time based on using real-time data to prioritize and optimize maintenance resources. Observing the state of the system is known as condition monitoring. Such a system will determine the equipment's health, and act only when maintenance is actually necessary. Ideally condition-based maintenance will allow the maintenance personnel to do only the right things, minimizing spare parts cost, system downtime and time spent on maintenance.

A better and more cost-effective approach is reliable centered maintenance and remote condition monitoring. Using intelligent monitoring systems, it is possible to predict problems and enable quick recovery before component failure stops operation of the system. In this thesis, failure analysis and diagnostics of railway turnouts is studied. Identification of failure modes using the sensory data will be performed by using signal processing and time series analysis (TSA) model techniques**.**

In many other fields, a time series is a sequence of data points, measured typically at successive times, spaced at (often uniform) time intervals. The term time series analysis is used to distinguish a problem, firstly from more ordinary data analysis problems (where there is no natural ordering of the context of individual observations), and secondly from spatial data analysis where there is a context that observations (often) relate to geographical locations. 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. In my thesis, I have used throughput data in detection of failures by using Dynamic Time Warping algorithm of Time Series Analysis technique, after processing the real data from noise detection by using some filtering techniques, which is acquired from various sensors, current and force sensors, installed on Istanbul railway point.

The dynamic time warping (DTW) algorithm of TSA is able to find the optimal match between two data series, which is taken from some time observation. DTW is often used to determine time series similarity, classification, clustering and to find corresponding or related regions between two time series (Stan Salvador and Philip Chan, 2007). DTW is used for comparing discrete sequences of data (Corman, 1990), to sequence of continues data values (Sankoff, D., and Kruskall, 1983) and performs optimal match. Term ‘warping’ means, grabbing one of the time points from time dimension curve and moving it to its new location, and that warped time dimension is used in difference minimization of between two data series. The optimization process is performed using dynamic programming to find the warping that minimizes the area between the curves in time (Tim Oates et al, 1999)**.** An optimum solution can be reached by using DTW in one-dimensional problems such as time series, while the problem for two-dimensional “series” like images is NP-complete problem.

The purpose of the thesis is to improve established maintenance and intelligent monitoring system of railway turnouts under Condition Based Maintenance.

This thesis is a part of the project granted by TUBITAK with project number 108M275. The method developed in this thesis is applied to real data collected from railway systems in Istanbul. Like most mega cities in the world, Istanbul is also experiencing a great pressure from population growth and increase of traffic. Increase in traffic has also put a great pressure on transportation of Istanbul such as traffic jams and etc. We are used to hear traffic accidents in news, especially in traditional and religious holidays of Turkey. In this sense, developing and improving railway transportation with its high maintenance and intelligent monitoring systems may put the end to such disasters or at least minimize the accident rate. Establishing the intelligent monitoring systems on railway turnouts will reduce any railway faults.

CHAPTER 2

LITERATURE REVIEW

In (F.P.Marquez et al, 2007), methods described the development of a condition monitoring system based on pattern recognition for detecting and diagnosing point machine failures. Authors have presented a case study carried out on a type M63-point machine. The system was employed by $(RCM)^2$, based on principles of remote condition monitoring (RCM_1) (Stanley NF and Howard FH, 1978), and Reliability Centered Maintenance (RCM^2) (Diego Jose, 2006), (R.Consortium, 1998). It is shown that initially, when data is acquired from a point machine, it is difficult to detect faults because an acquired sensory datasets may have a possibility of being affected by an environment which means may include a noisy data. That is why; signals acquired from point machines via some sensors were filtered to reduce noise before comparison with non-faulty signal curves. They used voltage, force, current signals which were acquired from point machine.

An experiment that was carried out has two main sub-processes.
1) Reducing noise or noise filtration of raw signals
2) Comparison of filtered signals with fault-free dataset.

They proposed two type of filtering algorithms; Kalman (Kalman RE, 1960) and Effective filtering (smoothing). But before applying filtration algorithms, spectrum of the motor current was analyzed which was stated as Spectral Analysis.

Spectral Analysis

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 (G.Marquez et al, 2006), 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.

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 RE, 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 (G. Marquez, 2002), 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 RE, 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 (Diego, 2006), 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 (F.C. Robles et al, 2008) 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 (C.Roberts et al, 2000), 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 (Jesus 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.

In (H.Saranga and J, Knezevic, 2000) was studied methodology based on relevant condition predictor (RCP) for reliability prediction for systems under condition based maintenance.

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. In (Susan Lu et al, 2006), 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.

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), (Liao et al, 2005). 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. In (S.L.Ho et al, 2006) this paper authors introduced new condition monitoring approach which describes 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.

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

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 (W. Wang, 2000) paper 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 et al, 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 it's 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, 1990), (Mallet, 1986), (Feldman, 1988), (Sheiner and Beal, 1980, 1981, 983) and (Johnson, 1977)**.** 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.

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 (Frank et al, 1995) paper, 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.

Authors of (Diego et al, 2008) case study developed a forecasting system for vibration analysis based on bivariate vibration signals which was acquired from an 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.

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 et al, 1997) and generalized to the multivariate signal case by (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.

In system estimation Maximum Likelihood estimator was used. As a result of this experiment system passed all the tests systematically and instable parameters were detected, where a failure started to develop.

In (Tim Oates et al. 1999), authors tried to show a hybrid time series clustering algorithm that uses dynamic time warping and hidden Markov model. An experiment of clustering process is done over generated artificial dataset, was very successful. DTW produced initial clustering input data and the HMM revealed from those clusters the sequence that does not belong to them.

In (Tak-Chung Fu et al. 2001), discovery of patterns from time series is done by clustering approach. One of the most popular unsupervised learning methods is SOM-algorithm (T. Kohonen, 1995). SOM- is a special type of clustering algorithm (B. D. Ripley, 1996) which is used to reduce the multi-dimensional dataset into 2-dimensional dataset. And this algorithm was adopted for pattern discovery in temporal data sequences. Preparation of input data for SOM is done by segmentation of data sequences from time series using a continuous sliding window. Similar items then put into same cluster by SOM, which may subsequently be used to represent different structures of the data or temporal patterns. In compressing input pattern authors proposed perceptually important point (PIP) identification algorithm. Because of multi-resolutions of patterns the time needed for discovery process increased exponentially. That is why (PIP) algorithm was proposed before in reduction of pattern dimensions.

Clustering problems are common to many knowledge discovery and data mining tasks. In (T.Warren Liao, 2005) this paper authors surveyed and summarized previously done works which investigates the clustering of time series data in different algorithms. Clustering algorithms are presented basically, including their general-purpose which is commonly used in time series clustering studies. But here we will review only some of them, which will be used in this thesis in clustering time series dataset.

Self Organizing Map (SOM) is a type of artificial neural network which is trained using unsupervised learning method to reduce high-dimensional dataset into low-dimensional dataset (typically two-dimensional), discretized representation of the input space of the training samples, and called a map. Self-organizing maps are different than other artificial neural networks algorithms in the sense that they use a neighborhood function to preserve the topological properties of the input space.Which was invented by Finnish professor Teuvo Kohonen (T. Kohonen, 1995).

A self-organizing map consists of components called nodes or neurons. Each node has its own weight vector of the same dimension as the input data vectors and a position in the map space. The working procedure of SOM is placing a vector from data space onto the map is to find the node with the closest weight vector to the vector taken from data space and to assign the map coordinates of this node to our vector. İn the training process weights (*w*) of nodes or neurons are initialized randomly. Each training-iteration consists of three steps; the presentation of randomly choosen input vectors from input data, evaluation of network, and upadate of the weights of neurons. After pattern presentation, Euclidean distance between input vector and weight vector is calculated, to identify a neuron with smallest value,which is marked as *t.* The neuron with weight vector most similar to the input is called the best matching unit (BMU). The weights of the BMU and neurons close to it in the SOM lattice are adjusted towards the input vector. The magnitude of the change decreases with time and with distance from the BMU. The update formula for a neuron with weight vector Wv(t)

$$w_i(l+1) = \begin{cases} wi\ (l) + a(l)[x(l) - wi\ (l)] & \text{if } i \in N_t(l), \\ wi\ (l) & \text{if } i \notin N_t(l). \end{cases}$$

Both sizes of N_t and α decreases monotonically with iteration. During mapping, there will be one single *winning* neuron: the neuron whose weight vector lies closest to the input vector. This can be simply determined by calculating the Euclidean distance between input vector and weight vector. SOM does not work well with time series of unequal length due to the difficulty involved in defining the dimension of weight vectors.

In mathematics, the Euclidean distance or Euclidean metric is the "ordinary" distance between two points that one would measure easily with a ruler, which can be proven by repeated application of the Pythagorean theorem. By using this formula as distance, Euclidean space becomes a metric space .The Euclidean distance d*E* between two points *P=(p1,p2,..,pn)* and *Q=(q1,q2,...,qn)* is measured as:

$$\sqrt{(p_1 - q_1)^2 + (p_2 + q_2)^2 + ...(p_n + q_n)^2} = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2}.$$

And another distance measurement algorithm is root mean square distance. The root mean square distance (or average geometric distance) is simply:

drms = *dE/n*.

DTW algorithm is able to find the optimal alignment between two time series. It's often used to determine time series similarity, classification and to find corresponding regions between two time series. DTW has quadratic time $Q(N^2)$ and time complexity. In (Stan Salvador and Philip,2007) this paper authors introduces FastDTW, an approximation of DTW that has linear time and space complexity. It uses multilevel approach that recursively projects a solution from a coarse resolution and refines the projected solution. Linear time and space complexity was proven theoretically and empirically by FastDTW and analysis of the accuracy of DTW algorithm.

CHAPTER 3

METHODOLOGY PROCESS

3.1. DATA COLLECTION

Like most mega cities in the world, Istanbul is also experiencing a great pressure from population growth and increase of traffic. Increase in traffic has also put a great pressure on transportation of Istanbul such as traffic jams and etc. In this sense, developing and improving railway transportation with its high maintenance and intelligent monitoring systems may put the end to such disasters. The method developed in this thesis is applied to real data collected from railway systems in Istanbul. Raw time series dataset is acquired via some sensors which are installed on turnout points of Railway system in Istanbul. Each sensor listens and records time series data from turnout point machine which will be analyzed and used in failure identification. We have collected our raw signals by activating turnout point machine from normal to reverse and from reverse to normal movements. Sensors that we used in acquiring our time series dataset are explained in upcoming subsection in detail.

3.1.1. Force Sensor

Force and load sensors cover electrical sensing devices that are used to measure tension and compression forces. Tension cells are used for measurement of a straight-line force "pulling apart" along a single axis; typically annotated as positive force. Compression tension cells are used for measurement of a straight-line force "pushing together" along a single axis; typically annotated as negative force. In (Fig.3.1) illustrated force sensors installed on to point machine.

Figure 3.1: Stretcher force sensor

3.1.2. Proximity Sensor

A proximity sensor is a non-contact sensor able to detect the presence of nearby objects without any physical contact. A proximity sensor often emits an electromagnetic or electrostatic field, or a beam of electromagnetic radiation (infrared, for instance), and looks for changes in the field or return signal. In our work we have installed this proximity sensor (Fig.3.2) to measure distance between stock rail and switch rail of railway turnout systems.

Figure 3.2 : Proximity sensor

3.1.3. Linear Position Sensor

Linear position measuring sensor is installed on stretchers of point machine and measures linear position of switch rails. As you see in (Fig.3.3). Time series data is acquired from both normal to reverse and reverse to normal movements of point machine.

Figure 3.3 : Linear position sensor

3.1.4. Motor Current Sensor

Current sensors (Fig.3.4) measure AC and/or DC current levels. They receive current inputs and provide outputs as analog voltage signals, analog current levels, switches, or audible signals. Motor current sensor records the current data of motor in both movements of point machine.

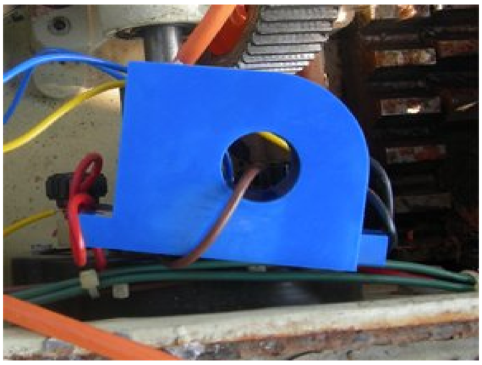

Figure 3.4 : Motor current sensor

3.1.5. Motor Voltage Sensor

Voltage sensors are used to measure voltage in electric circuits. Their main role is to condition (step down) the voltage to be measured to levels suitable for the measuring instrument. In our work we have installed it on to point machine as you see in (Fig.3.5) to record time series data.

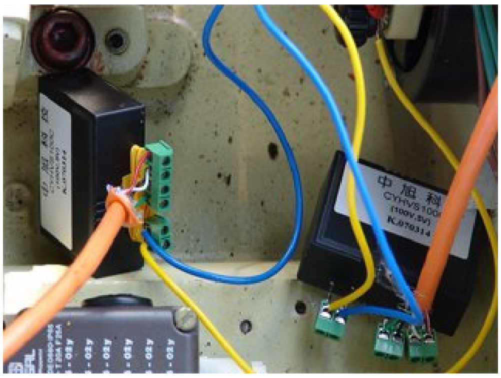

Figure 3.5 : Motor voltage sensor

3.2. MODELING STRUCTURE

Time series clustering requires a clustering algorithm to form clusters given a set of unlabeled input datasets and choice of clustering algorithm depends on purpose or the data type that we are going to cluster. But before performing clustering operation, samples to be used must be converted into other format, for example if our data set is non-uniformly sampled, or noisy, they must be converted into uniform samples or the noise must be filtered to be sure that our clustering algorithm clusters it accurately.

There are generally three different time series clustering approaches:

1) Raw-data-based

2) Feature-based

3) Model-based

Raw-data-based time series clustering approach works directly with raw samples without any conversion or filtration processes. But last two approaches first convert a raw time series data either into feature vector or a number or model parameters. But left branch (see Fig.3.6(c)) of model-based approach trains and uses model parameters for clustering without need for any other clustering algorithm.(Keogh et al, 2003). This is outlined in Fig.3.6 below.

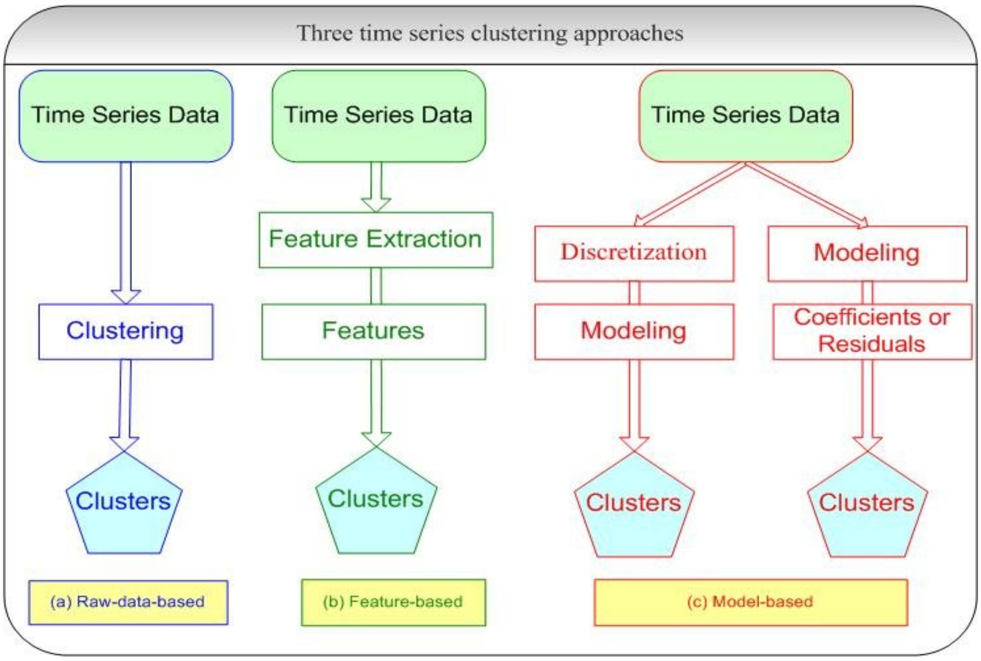

Figure 3.6 : Three time series clustering approaches. (Keogh et al, 2003).

In my thesis, I used model-based time series clustering algorithms in fault identification of railway point mechanism. Our developed modeling structure consists of three sub-models:

Pre-processing, time series analysis and expert system as shown in Fig.3.7.

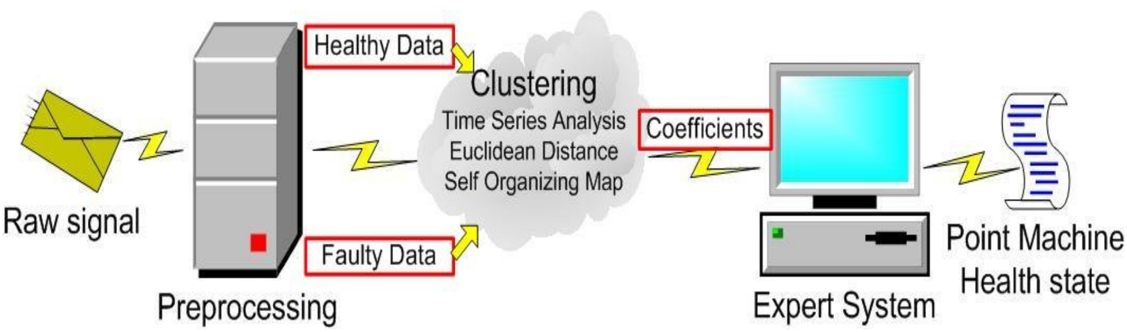

Figure 3.7 :Modeling Structure

3.2.1. Pre-processing

Railway point machine have two movements, normal to reverse and reverse to normal. We have installed different sensors (Fig.3.8) to point machine to acquire signals from both movement directions. Sensory data which is acquired via different sensors (Fig.3.7) must be filtered to reduce the noise before clustering is made. Because measurement data is affected by environment (humidity, temperature climate etc), friction force and vibration in the mechanical system, etc. The time series data collected during the point machine is working in normal or reverse direction is cleaned from noise in pre-processing. Several methods have been used in the literature such as Kalman Filter or exponential smoothing (Garcia Marquez et al, 2007)**,**(Felix Schmid et al,2002)**,** (Paul Weston et al, 2007). Noise reduction or filtration process is applied to time series dataset acquired form sensors is done to increase reliability of our failure detection model. We have employed moving average smoothing algorithm in our work. Noise reduction or filtration of our simulated time series data is shown in (Fig.3.9).

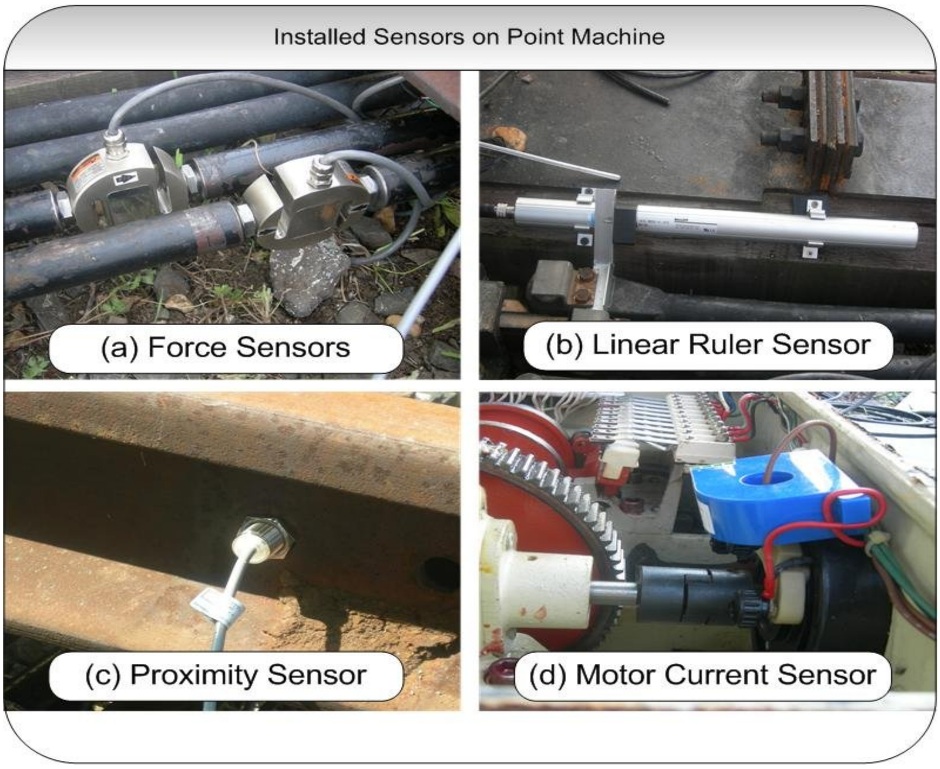

Figure 3.8 :Used Sensors in Data acquisition

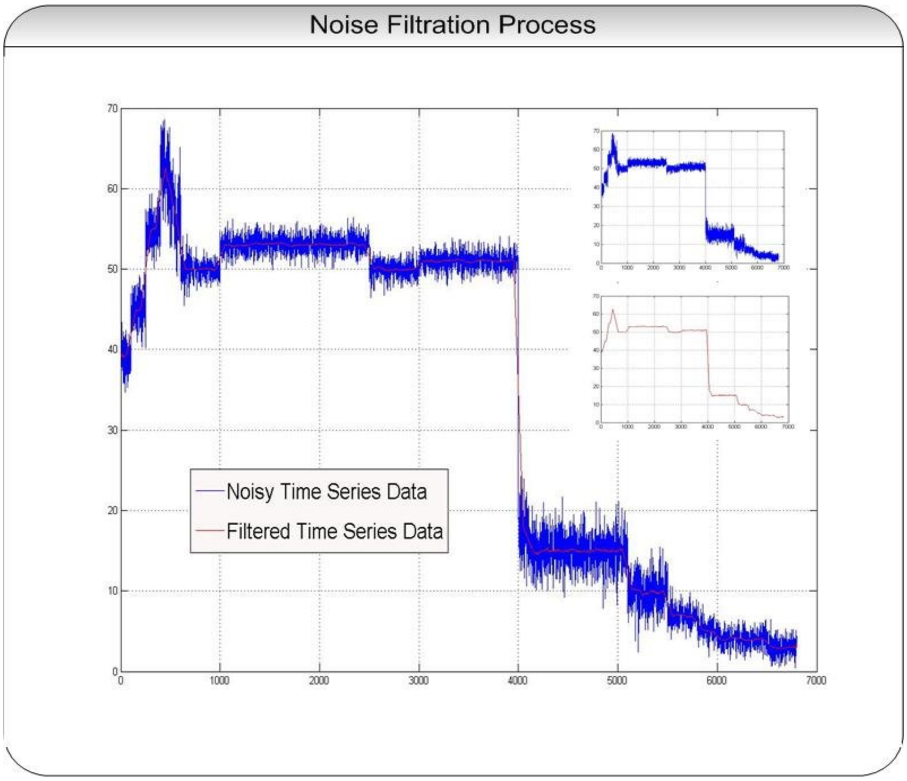

Figure 3.9 : Moving average smoothing applied to noisy time series data

3.2.2. Simple Moving Average Smoothing Technique

In statistics, weighted moving average is a technique that can be applied to time series data, either to produce smoothed data for presentation, or to make forecasts and also called rolling average, rolling mean or running average. A moving average is not a single number, but it is a set of numbers, each of which is the average of the corresponding subset of a larger set of data points. A moving average may also use unequal weights for each data value in the subset to emphasize particular values in the subset. A moving average is commonly used with time series data to smooth out short-term fluctuations and highlight longer-term trends or cycles. The time series data themselves are a sequence of observations. The observed data may be an essentially random process, or it may be an orderly, but noisy, process. It is often used in technical analysis of financial data, like stock prices, returns or trading volumes. It is also used in economics to examine gross domestic product, employment or other macroeconomic time series.

Intuitively, the simplest way to smooth a time series is to calculate a simple, or unweighted, moving average. The smoothed statistic s_t is then just the mean of the last k observations:

$$s_t = \frac{1}{k}\sum_{n=0}^{k-1} x_{t-n} = \frac{x_t + x_{t-1} + x_{t-2} + \cdots + x_{t-k+1}}{k} = s_{t-1} + \frac{x_t - x_{t-k}}{k},$$

Where the choice of an integer $k > 1$ is arbitrary. A small value of k will have less of a smoothing effect and be more responsive to recent changes in the data, while a larger k will have a greater smoothing effect, and produce a more pronounced lag in the smoothed sequence.

3.2.3. Time Series Analysis and Clustering

After the noise is removed from the time series data, smoothed time series is compared with the control signal, which represents the normal behavior of the turnout system. The control signal has a special signature as illustrated in Fig.3.10. The time series data represents the sensory information collected during the process of turnout movement in the reverse or normal direction. The time series data follows a special signature due to the nature of movement. In Fig.3.11 and Fig.3.12 you can see real Force (Normal to Reverse) and Motor Current graphs, which was acquired in 4 movement of point machine, as time series dataset.

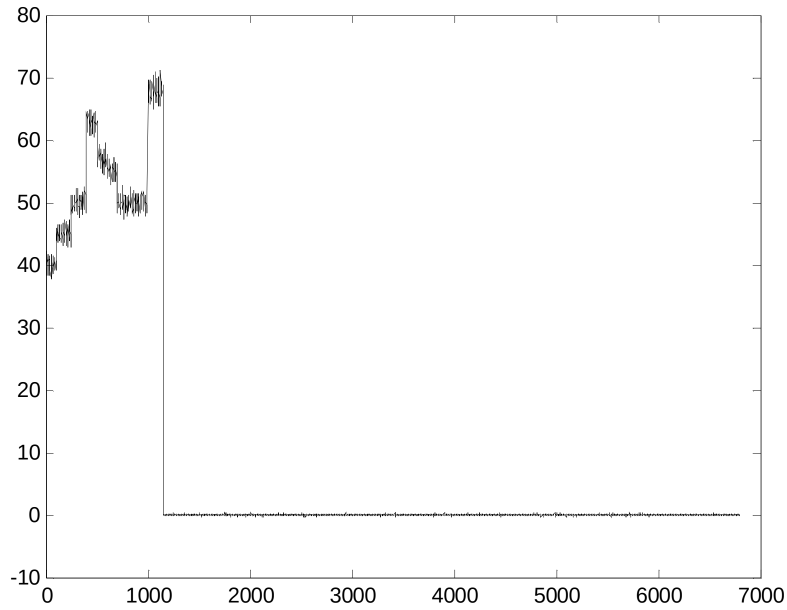

Figure 3.10 :Time series data for healthy turnout system

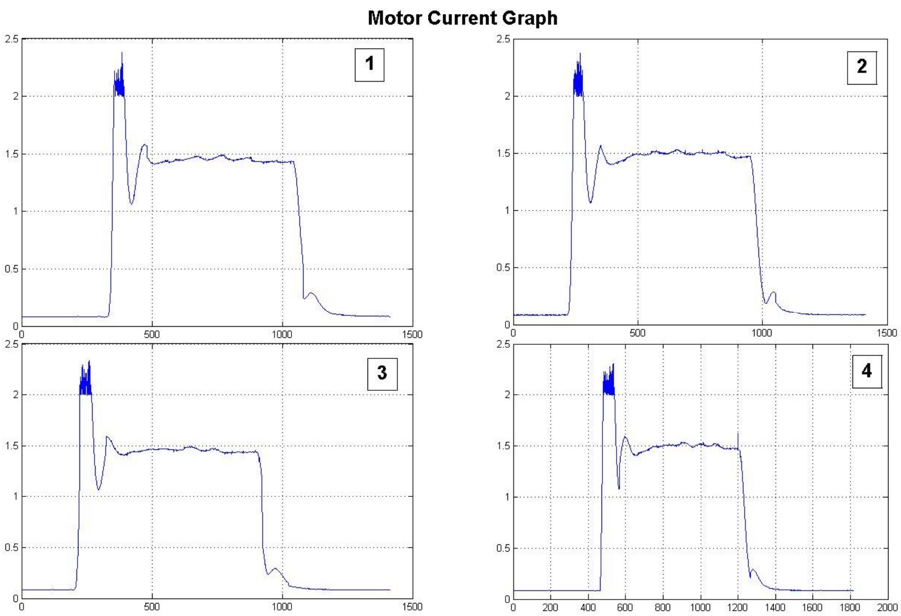

Figure 3.11 : Motor Current Graph of Railway Point Machine

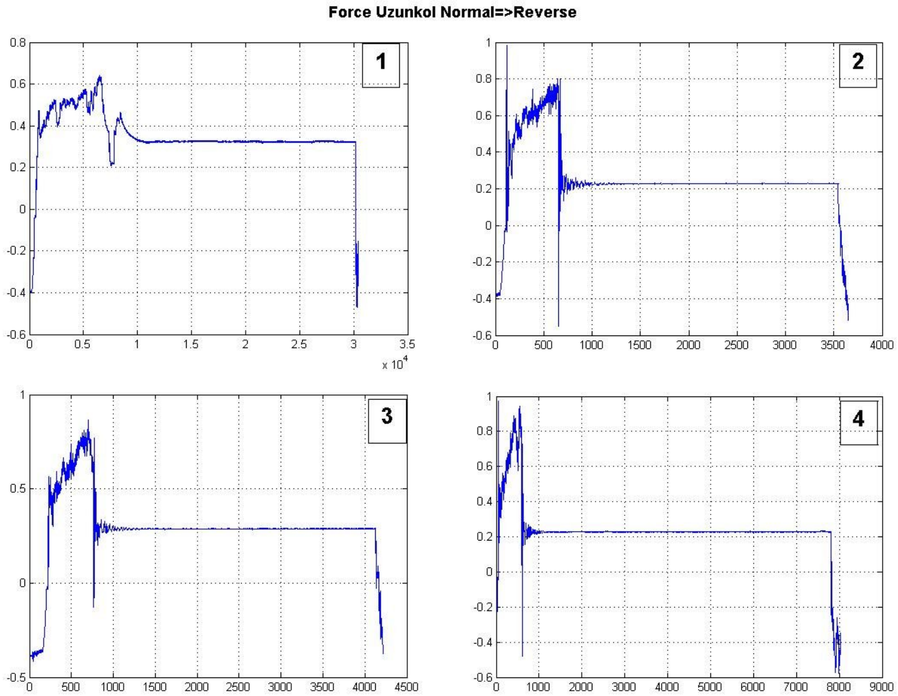

Figure 3.12 : Force Data Graph of point machine in(Normal to Reverse)

When a failure occurs, the time series data will move away from the normal signature. Thus, similarity between the observed time series and control signal gives us information about the health of the turnout system. Different failure modes affect the time series differently. A failure mode may affect the signature during the initial phase of the movement process, whereas another failure affects the signature in the middle or last phase of the movement. Hence, the time series data should be divided into several phases (Garcia Marquez et al, 2007), (C.Roberts et al.), (Shimonae T. et al, 1991**).** Similarity measure for each phase should be calculated differently. In other words, a similarity measure will be obtained for each phase for a given time series. Similarity calculation is performed using dynamic time warping algorithm. And besides DTW in clustering timer series data in my thesis, I used self organizing map (SOM) and Euclidean distance. And their performance results were compared and will be showed in experiment results.

Self Organizing Map (SOM) is a type of artificial neural network which is trained using unsupervised learning method to reduce high-dimensional dataset into low-dimensional dataset (typically two-dimensional), discredited representation of the input space of the training samples, and called a map. Self-organizing maps are different than other artificial neural networks algorithms in the sense that they use a neighborhood function to preserve the topological properties of the input space. This was invented by Finnish professor Teuvo Kohonen (T. Kohonen, 1960). The way SOMs go about reducing dimensions is by producing a map of usually 1 or 2 dimensions which plot the similarities of the data by grouping similar data items together. So SOMs accomplish two things, they reduce dimensions and display similarities. We have an input vector which is our sample to be clustered and weight vector which is assigned randomly to our neurons of network. In the training process we try to find closest weight vector to our input vector with minimum Euclidean distance. The neuron with weight vector most similar to the input is called the best matching unit (BMU). The weight with the shortest distance is the winner. If there is more than one with the same distance, then the winning weight is chosen randomly among the weights with the shortest distance.

Dynamic time warping (DTW) algorithm aims to find the optimal match between two time series. DTW is often used to determine time series similarity, classification, clustering and to find corresponding or related regions between two time series (Stan and Philip). Term ‘warping’ means, grabbing one of the time points from time dimension curve and moving it to its new location, and that warped time dimension is used in difference minimization of between two data series. The optimization process is performed using dynamic programming to find the warping that minimizes the area between the curves in time. For more information about dynamic time warping, readers are referred to (Keogh et al, 2003).

3.2.4. Discussion

Self organizing map is a method which maps high-dimensional data space into low-dimensional data space, and this clustering method tends to map similar data space to nearby neurons which means that SOM has a perfect visualization utility in comparison to other hierarchical clustering methods. When the time series is very long (high dimensional), some clustering algorithms can not cope with it. But by applying dimensionality reduction via SOM, we can cluster even long length time series very efficiently. However, clustering algorithms based on distance metric (Euclidean distance), can not handle time series with missing data or different lengths (dimensions), because of quadratic computational complexity (Selina Chu et al, 2002).

Even though Euclidean distance is one of the most widely used approaches, it can not be extremely robust distance measuring technique in clustering time series data, because it is too sensitive to small distortions in the time axes and may fail to produce an intuitive correct measure of similarity between two time series. Because of this problem a new technique Dynamic Time Warping was introduced which shifts X-axes in order to detect similarity of time series data with different phases. But DTW also displays weak performance on very large databases, because of quadratic time complexity. Two time series in same dimension but with different time axes is illustrated in Fig.3.13 (Ralph Niels, 2004)

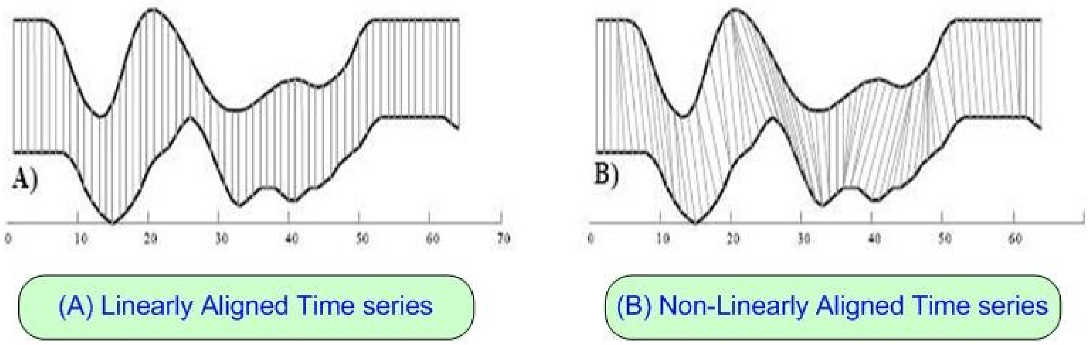

Figure 3.13 :Two time series having same shape, but different time axes.

As you see in Fig.3.13 both time series data have similar shape, but they are not aligned in the same time axes. Euclidean distance can calculate similarity measure of (A) easily but time series in (B) needs more intuitive distance measuring technique to be calculated correctly such as Dynamic Time Warping technique.

3.3. EXPERT SYSTEM

An expert system is a software or methodology which can be described as a system that simulates the specific problem solving behavior of human experts by analyzing different parameters of a system. In expert systems, problem solving is accomplished by applying specific knowledge rather than specific techniques. There are a lot of expert systems in which rule based and an inference engine cooperate to simulate the reasoning process that a human expert pursues in analyzing a specific problem and arriving at a conclusion. In these systems, in order to simulate the human reasoning process and come to reasonable result, a vast amount of knowledge needed to be stored in the knowledge base. Generally, the knowledge base of such an expert system consisted of a relatively large number of "if then" type of statements or clauses that were interrelated in a manner that, in theory at least, resembled the sequence of mental steps that were involved in the human reasoning process. To store such amount of knowledge, expert systems must have large storage capacities to handle large information accurately. In failure mode identification, several rules about the similarity measures of signals from different phases of the turnout movement are extracted.

Three different modes (i.e., two failure modes and healthy turnout) are modeled in my thesis. An example of rules for two-phased time series is given in the Table 3.1.

Table 3-1: Example of rules for failure mode identification

	RULE 1	RULE 2	RULE 3
Healthy	C1 > 0.6 & C2 > 0.8	C1 > 0.6 & C2 > 0.8	C1 > 0.6 & C2 > 0.8
Failure Mode 1	C1 > 0.6 & C2 > 0.8	C1 > 0.6 & C2 > 0.8	C1 > 0.6 & C2 > 0.8
Failure Mode 2	C1 > 0.6 & C2 > 0.8	C1 > 0.6 & C2 > 0.8	C1 > 0.6 & C2 > 0.8

3.3.1. Generated Simulation Formula

Two failure modes are simulated based on the previous study in (Paul Weston et al, 2007). Control signal, switched blocked 1 and switched blocked 2 are selected and simulated. Progression of a failure mode from healthy state is simulated by calculating the weighted average of corresponding healthy and faulty time series data as given in following formula. Healthy and faulty signals and progression of failure are displayed in Fig.3.14

$$x_{i,t} = \omega_i h_t + (1 - \omega_i) f_t$$

$x_{i,t}$: Value in time *t* for ω_i

ω_i : Weight value

h_t : Value in time *t* for healthy turnout

$f_{k,t}$: Value in time *t* for faulty turnout of failure mode *k*.

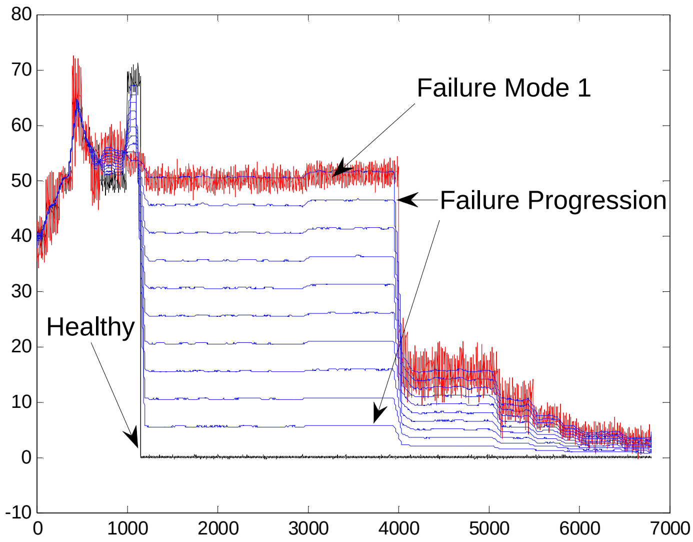

Figure 3.14: Time series representing healthy, faulty, and failure in progress states

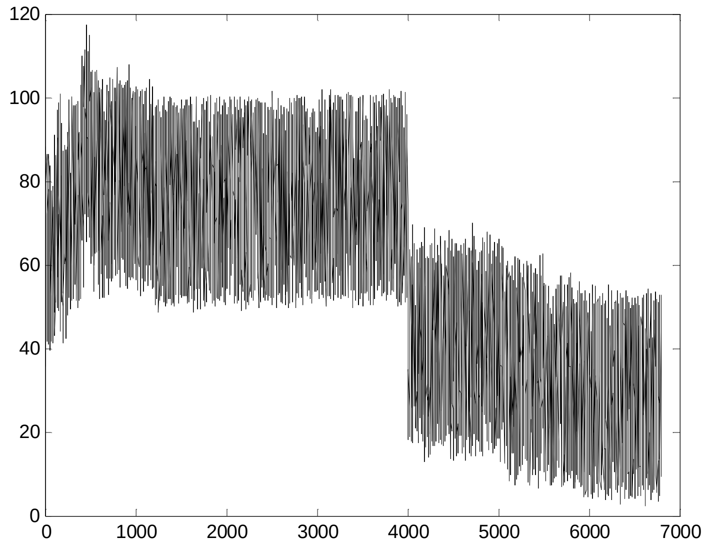

Figure 3.15: Noise added time series data to be used in failure mode identification.

Ten time series is obtained for each weight value from 0.1 to 0.9, except 0.5. When weight value is greater (less) than 0.5, the time series is assumed to represent healthy (faulty) turnout Thus, for each failure mode, 100 time series are obtained 200 time series for healthy turnout is obtained (100 for each failure mode, total of 100).

In this thesis I have simulated 100 time series datasets, by using above mentioned formula, for each corresponding failure modes (switch blockage 1, switch blockage 2) by using MATLAB program. In my thesis I used Self Organazing Map, Dynamic time Warping and Euclidean Distance clustering/classification techniques, to cluster/classify simulated failure modes. Those simulated time series data were put through DTW, Self organizing Map and Euclidean distance algorithms, which gives similarity coefficient of time series, and by using extracted rules for expert system, and simulated time series dataset were clustered/classified. Finally, results of this current work are presented in Experiment and Results chapter of my thesis, in detail

CHAPTER 4

EXPERIMENT & RESULTS

4.1. DATA COLLECTION

As we mentioned in former chapter, datasets to be used was collected via some sensors (Fig.3.1, Fig.3.2, Fig.3.3, Fig.3.4, and Fig.3.5) which was installed on turnout point machine in Istanbul. Each sensor listens and records time series data from turnout point machine which will be analyzed and used in failure identification. We have collected our raw signals by activating turnout point machine from normal to reverse and from reverse to normal movements. In this present chapter I have explained experiment results of my developed model, in detail.

4.1.1. Sensory time series data.

Sensory data which was acquired via different sensors is affected by environment (humidity, temperature climate etc), friction force and vibration in the mechanical system, etc. As you see in Fig.4.1, Fig.4.2, Fig.4.3, Fig.4.4 and Fig.4.5. Figures below illustrate the real time series data, collected from point machine of railway systems in Istanbul. Time series dataset were recorded during the process of point machine functioning. Plotted sensor figures below, show results of 25 (12 movements from normal to reverse, 13 movements from reverse to normal) movements done by turnout point machine.

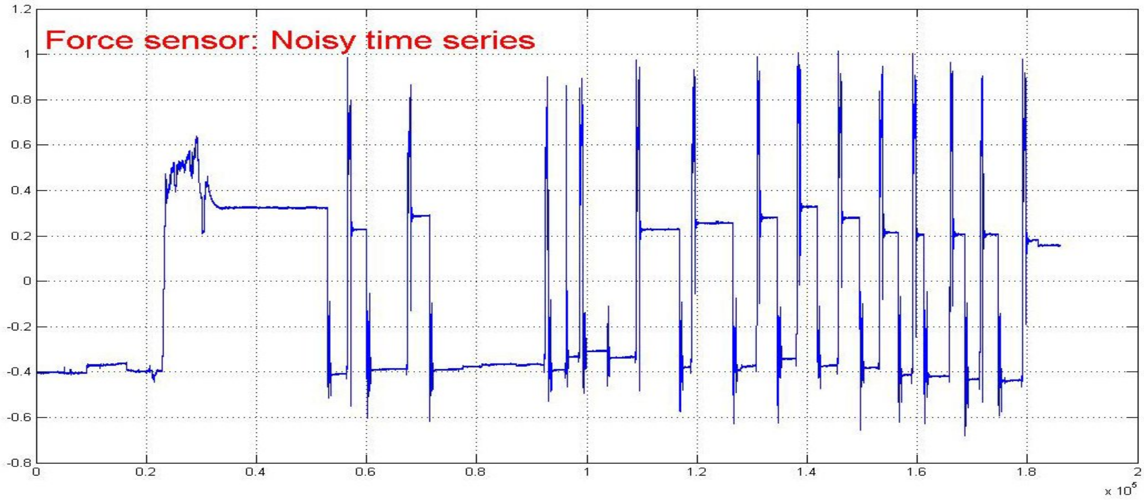

Figure 4.1 : Noisy time series collected by force sensor

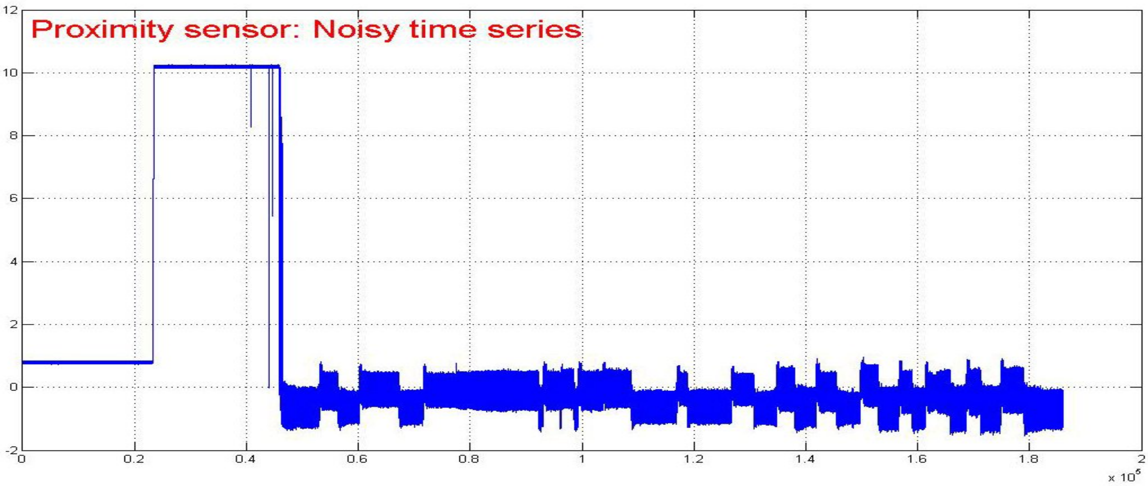

Figure 4.2 : Noisy time series collected by proximity sensor

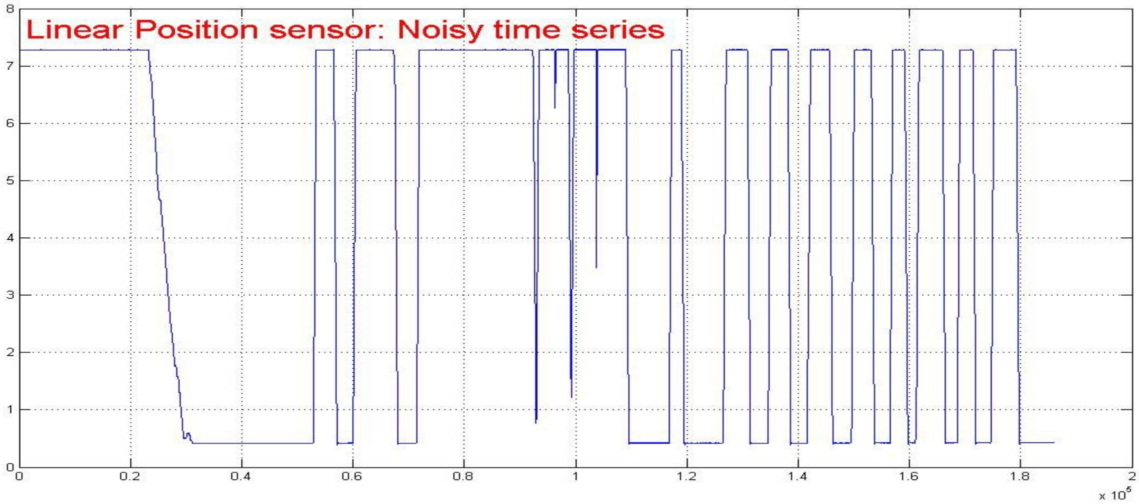

Figure 4.3 : Noisy time series collected by linear position sensor

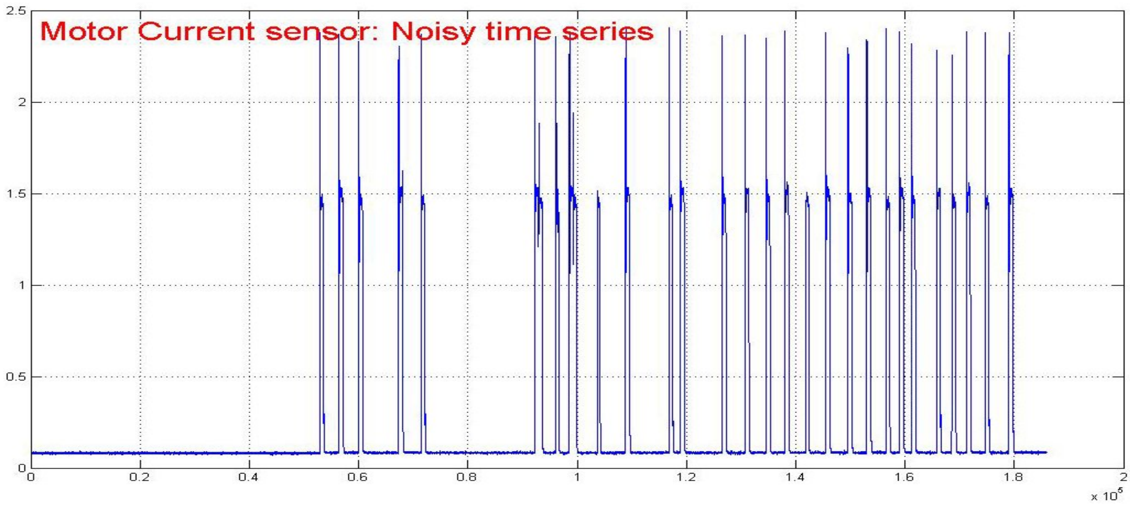

Figure 4.4 : Noisy time series collected by motor current sensor

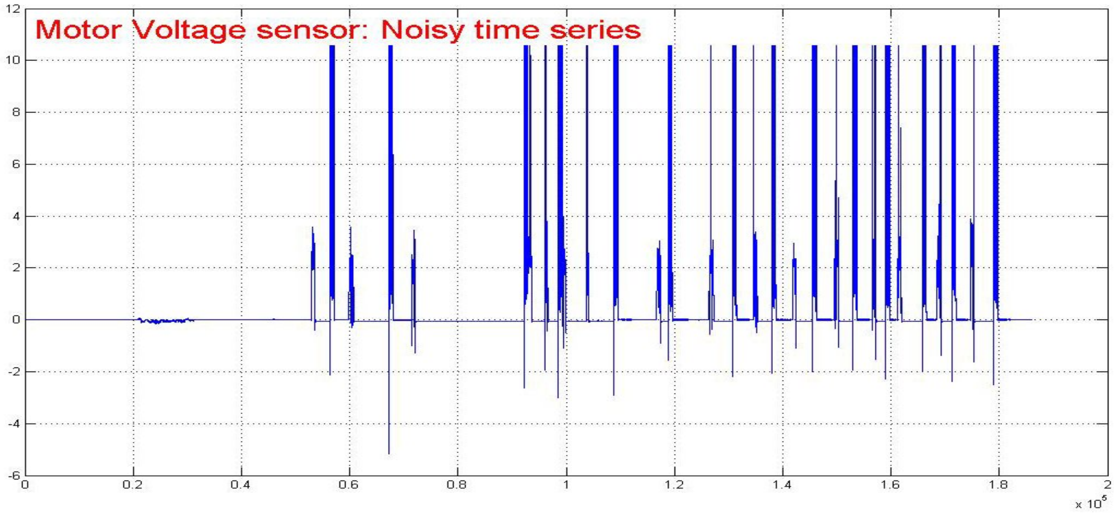

Figure 4.5 : Noisy time series collected by motor voltage sensor

4.1.2. Simulated Dataset

In my thesis I have used 3 types of signals in failure detection, control signal which was acquired from healthy point machine and switch blockage-1 switch blockage-2 which were simulated as faulty signals of point machine. Totally I have simulated 100 time series datasets, by using above mentioned formula, for each corresponding failure modes (switch blockage 1, switch blockage 2) by using MATLAB program. And in each progress the noise was added to simulated faulty signals. Fig.4.6, Fig.4.7 and Fig.4.8 illustrate control signal and simulated faulty signals.

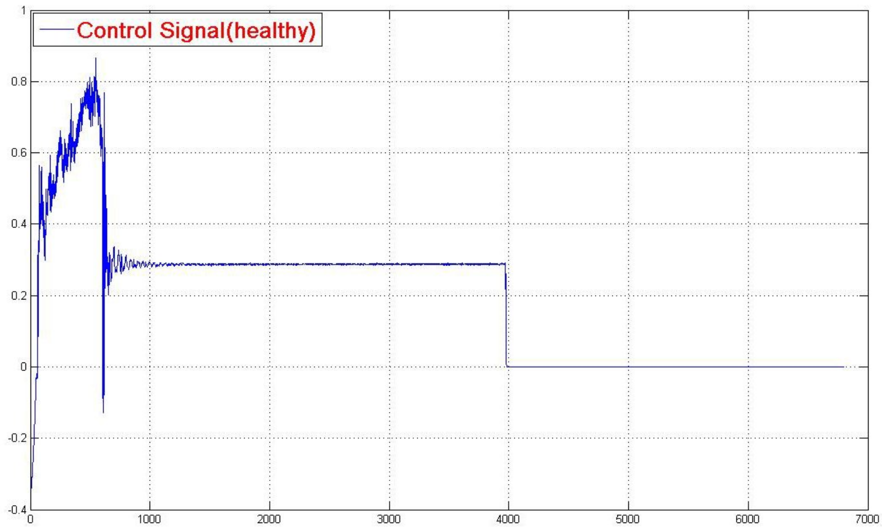

Figure 4.6 : Acquired real healthy force data

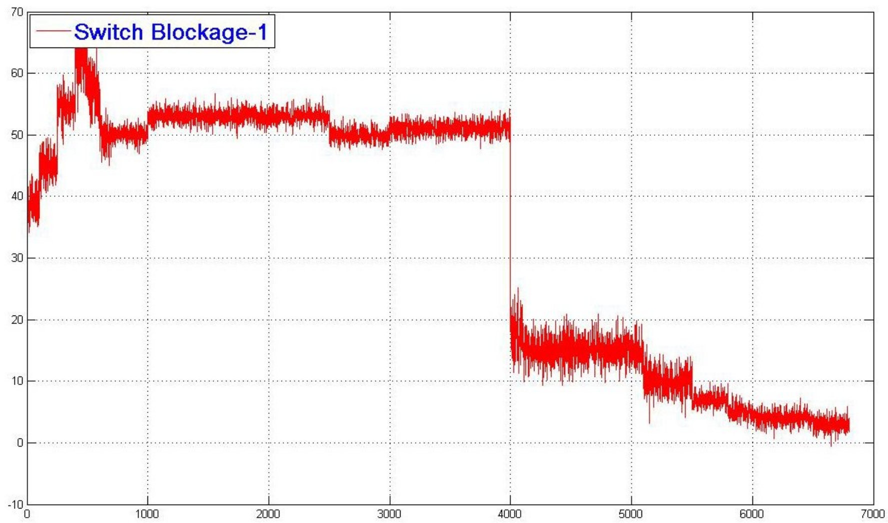

Figure 4.7 : Simulated failure mode 1 (switch blockage-1)

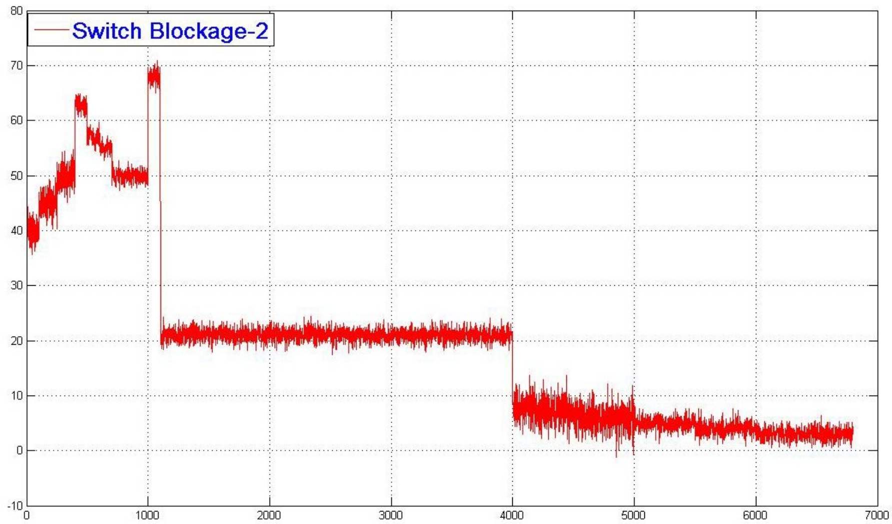

Figure 4.8 : Simulated failure mode 2 (switch blockage-2)

4.2. MODELING STRUCTURE

Before performing clustering operation, samples to be used must be filtered from noise, to be sure that our clustering algorithm clusters it accurately. Results of my developed model-based time series clustering algorithm is explained in upcoming subsections, in detail.

4.2.1. Preprocessing results

Sensory data which is acquired via different sensors must be filtered to reduce the noise before clustering is made. We have employed moving average smoothing algorithm in our work. Noise reduction or filtration is applied to Force data and to simulated time series data (switch blockage 1, switch blockage 2), which is shown in (Fig.4.9, Fig.4.10 and Fig.4.11).

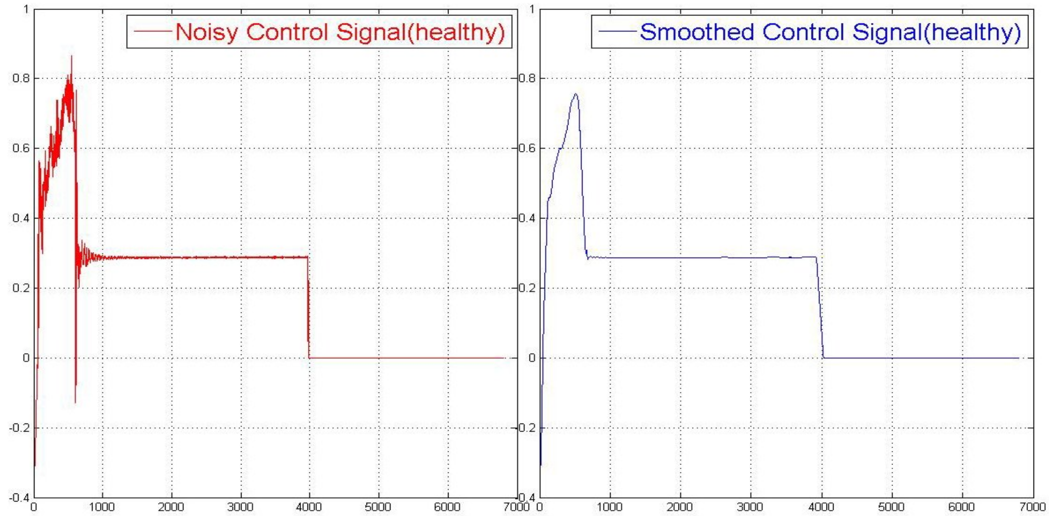

Figure 4.9 : Smoothed force data

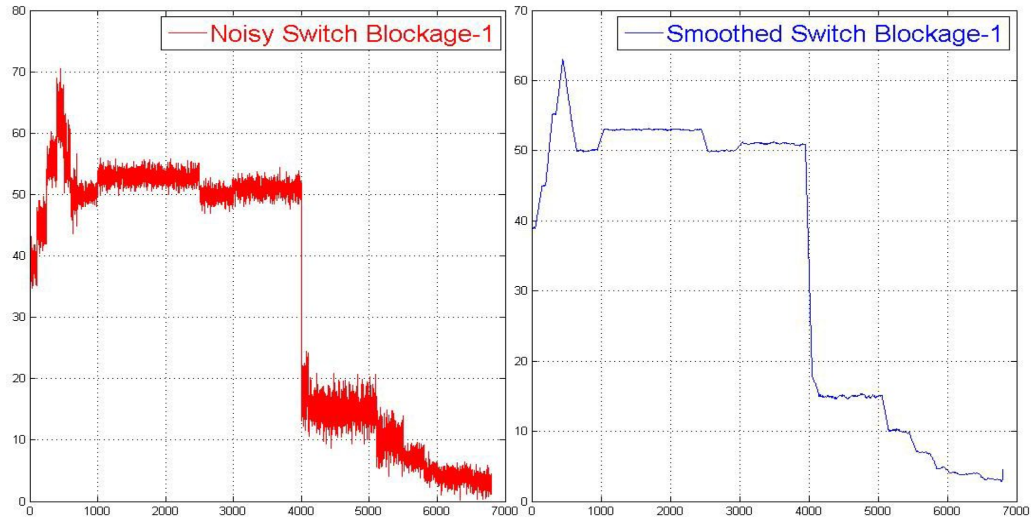

Figure 4.10 : Smoothed failure mode-1 (switch blockage-1)

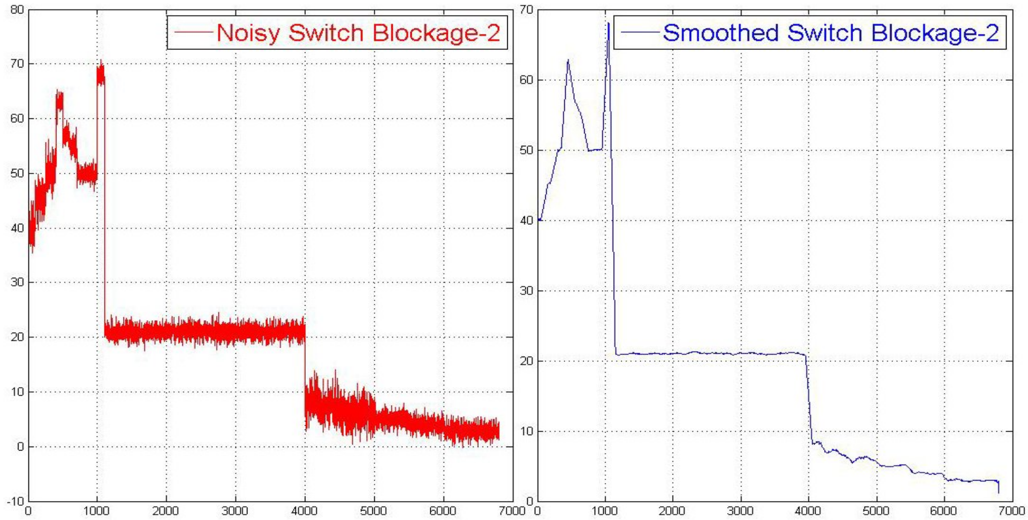

Figure 4.11 : Smoothed failure mode-2 (switch blockage-2)

4.2.2. Time series clustering

After the noise filtration from the time series data, smoothed time series is compared with the healthy control signal, which represents the normal behavior of the turnout system. Here our control signal is real force data which was acquired from force sensor. When a failure occurs, the time series data will move away from the normal signature. Thus, similarity between the observed time series and control signal gives us information about the health of the turnout system. Similarity calculation is performed using dynamic time warping algorithm, self organizing map (SOM) and Euclidean distance. And their performance results were compared and will be shown in proceeding tables.

4.3. EXPERT SYSTEM

As I mentioned in former chapter I have modeled three different modes (i.e., two failure modes and healthy turnout) in my thesis. And here I have shown results of expert system with extracted rules and accuracy levels for used time series clustering algorithm.

4.3.1. Extracted rules and accuracy results for Dynamic time warping.

As I mentioned before an acquired time series data were put through dynamic time warping algorithm which gives similarity coefficient of time series and by using extracted rules for expert system, simulated time series dataset were clustered. Dynamic time warping is too sensitive algorithm to noisy data, because of that I had to check simulated time series with different noise levels several times to identify them correctly. Here I have shown results for dynamic time warping algorithm's extracted rules (see Table 4.2) and accuracy levels (see Table 4.1) of both trained and tested time series dataset.

Table 4-1 : Dynamic time warping algorithm accuracy results with different noises.

Weight	**Noise Level**	**Acc0(Healthy)**		**Acc1(Failure1)**		**Acc2(Failure2)**	
		Trained	Tested	Trained	Tested	Trained	Tested
0	1	100%	100%	100%	100%	100%	100%
0	1.25	100%	100%	100%	100%	100%	100%
0	1.50	100%	100%	80%	75%	80%	80%
0	1.75	100%	100%	73%	72%	70%	60%
0.1	1	100%	100%	100%	100%	100%	100%
0.1	1.25	100%	100%	100%	100%	100%	100%
0.1	1.50	100%	100%	78%	75%	77%	75%
0.2	1	100%	100%	88%	85%	86%	83%
0.2	1.50	100%	100%	75%	75%	75%	72%
0.3	1	100%	100%	86%	75%	82%	80%
0.3	1.50	100%	100%	73%	72%	73%	70%

Table 4-2 : Extracted rules for Dynamic time warping algorithm

Weight	**Noise level**	**Healthy**	**Failure mode1**	**Failure mode2**	
0	1	If (s<900)	If (s>1200)	Else(s>900 and s<1200)	
0	1.25	If (s<800)	Else(s<990 and s>800)	If (s>990)	
0	1.50	If (s<900)	Else(s>900 and s<1285)	If (s>1285)	
0	1.75	If (s<900)	Else(s>900 and s<1050)	If (s>1050)	
0.1	1	If (s<850)	If (s>1200)	Else(s>850 and s<1200)	
0.1	1.25	If (s<900)	Else(s>900 and s<1290)	If (1290)	**Rules**
0.1	1.50	If (s<890)	Else(s>890 and s<1250)	If (s>1250)	
0.2	1	If (s<900)	If (s>1040)	Else(s>900 and s<1040)	
0.2	1.50	If (s<900)	Else(s>900 and s<1258)	If (s>1258)	
0.3	1	If (s<940)	If (s>1025)	Else(s>940 and s<1025)	
0.3	1.50	If (s<1000)	Else(s>1000 and s<1040)	If (s>1040)	

4.3.2. Extracted rules and accuracy results for Euclidean distance.

In this subsection I showed results for Euclidean distance clustering algorithm with its extracted rules and accuracy levels. Noise levels that I had applied to simulated time series in simulation process of my model in this algorithm, is a bit higher than that I had used in dynamic time warping clustering, because it was not possible to cluster switch blockage-1 and switch blockage-2 failures from control signal with the noise levels that I had used in dynamic time warping clustering. But applying higher noise levels to time series data gave accurate clustering levels (see Table 4.4) with its extracted rules (see Table 4.3).

Table 4-3 : Extracted rules for Euclidean distance algorithm

Weight	Noise level	Healthy	Failure mode1	Failure mode2	
0	5	Else(s<24 and s>16)	If (s>24)	If (s<16)	
0	10	Else(s<26 and s>20)	If (s>26)	If (s<20)	
0	11	Else(s<26.5 and s>20)	If (s>26.5)	If (s<20)	
0	12	Else(s<26.6 and s>22)	If (s>26.6)	If (s<22)	
0.1	5	Else(s<24 and s>16)	If (s>24)	If (s<16)	
0.5	5	Else(s<25 and s>20)	If (s>25)	If (s<20)	**Rules**
0.1	10	Else(s<25.9 and s>22)	If (s>25.9)	If (s<22)	
0.2	10	Else(s<26 and s>20)	If (s>26)	If (s<20)	
0.1	11	Else(s<26.1 and s>20)	If (s>26.1)	If (s<20)	
0.2	11	Else(s<26.1 and s>20)	If (s>26.1)	If (s<20)	
0.1	12	Else(s<26.5 and s>23)	If (s>26.5)	If (s<23)	

Table 4-4 : Euclidean distance accuracy results with different noises.

Weight	**Noise Level**	**Acc0(Healthy)**		**Acc1(Failure1)**		**Acc2(Failure2)**	
		Trained	Tested	Trained	Tested	Trained	Tested
0	5	100%	100%	100%	100%	100%	100%
0	10	99%	100%	98%	94%	100%	100%
0	11	99%	98%	93%	92%	100%	100%
0	12	90%	87%	88%	92%	100%	100%
0.1	5	100%	100%	100%	100%	100%	100%
0.5	5	100%	100%	100%	100%	100%	100%
0.1	10	97%	93%	100%	100%	100%	100%
0.2	10	96%	93%	98%	95%	100%	100%
0.1	11	81%	78%	86%	82%	100%	100%
0.2	11	74%	75%	93%	97%	100%	100%
0.1	12	81%	83%	81%	82%	100%	100%

4.3.3. Accuracy results for Self organizing map algorithm.

In self organizing map we do not have any extracted rules because it is unsupervised learning technique. As I mentioned above I have simulated 100 time series data for each failure mode 1, failure mode 2 and healthy signal. In network construction for self organizing map I used 1 to 4 topology. I had tried also 1 to 3 topology for self organizing map network but SOM was able to identify time series as faulty and healthy signals not as failure mode 1 and failure mode 2 separately. Because of this problem I have constructed my network in 1 to 4 topology. Noise levels as you see in table below are a bit higher in comparison to Euclidean distance and Dynamic time warping algorithms. Because SOM could cluster simulated time series very accurately in low noise levels very efficiently, that is why I had applied higher noise levels to simulated time series data. Accuracy results of simulated time series for SOM is shown (Table 4.5) below.

Table 4-5 :Self organizing map accuracy results with different noises

Weight	Noise Level	Acc0(Healthy)		Acc1(Failure1)		Acc2(Failure2)	
		Trained	Tested	Trained	Tested	Trained	Tested
0	500	100%	100%	100%	100%	100%	100%
0	750	90%	82%	100%	100%	100%	100%
0	1000	75%	82%	100%	100%	98%	95%
0	1250	70%	65%	95%	100%	85%	92%
0.1	750	85%	80%	100%	100%	100%	100%
0.2	750	76%	77%	100%	100%	97%	97%
0.3	750	73%	72%	100%	100%	96%	95%
0.1	1000	75%	71%	96%	100%	93%	100%

4.3.4. Performance evaluation for Self Organizing Map, Dynamic Time Warping and Euclidian Distance.

So far, I have extracted rules and accuracy results for Self Organizing Map, Euclidean Distance and Dynamic Time Warping and shown in tables above. And results that I got from my expert system were shown in detail separately in different noise and weight values. But in this subsection I have tried to show performance evaluation of each clustering and classification algorithms'. In tables below, I tried to show performances of algorithms with weight values and without weight values in different noise levels. From those tables below, its easily seen that Self Organizing Map identifies healthy time series from failure mode-1 and failure mode-2, even in higher noise levels. After Self Organizing Map, Dynamic Time Warping classified time series data with a good performance. And finally Euclidean Distance could identify healthy time series from failure mode-1 and failure mode-2. In (Table1) it was shown only results for noisy time series without any weight values, in (Table2, Table3, Table4), noise was added to weighted healthy and failure modes and were shown in detail for each algorithm.

Table 4-6 : Unweighted noisy time series accuracy results of algorithms

Accuracy table of Self Organizing Map, Dynamic Time Warping and Euclidean Distance according to noise levels of healthy data when weight=0;												
Accuracy	100%=N			100%>N>=95%			95%>N>=85%			80%>N		
Failure modes	H	F1	F2	H	F1	F2	H	F1	F2	H	F1	F2
SOM	500	1000	750	---	1250	1000	750	---	1250	1250	---	---
DTW	1.75	1.25	1.25	---	---	---	---	---	---	---	1.75	1.75
ED	5	5	10	11	10	---	12	12	---	---	---	---

Table 4-7 : Noisy time series accuracy results with weight =0.1

Accuracy table of Self Organizing Map, Dynamic Time Warping and Euclidean Distance according to noise levels of healthy data when weight=0.1;												
Accuracy	100%=N			100%>N>=95%			95%>N>=85%			80%>N		
Failure modes	H	F1	F2	H	F1	F2	H	F1	F2	H	F1	F2
SOM	---	750	750	---	1000	1000	750	---	---	1000	---	---
DTW	1.50	1.25	1.25	---	---	---	---	---	---	---	1.50	1.50
ED	5	10	12	10	10	---	12	12	---	---	---	---

Table 4-8 : Noisy time series accuracy results with weight =0.2

Accuracy table of Self Organizing Map, Dynamic Time Warping and Euclidean Distance according to noise levels of healthy data when weight=0.2;												
Accuracy	100%=N			100%>N>=95%			95%>N>=85%			80%>N		
Failure modes	H	F1	F2	H	F1	F2	H	F1	F2	H	F1	F2
SOM	---	750	---	---	---	750	---	---	---	750	---	---
DTW	1.50	---	---	---	---	---	---	1	1	---	1.50	1.50
ED	---	---	11	10	11	---	---	---	---	11	---	---

Table 4-9 : Noisy time series accuracy results with weight =0.3

Accuracy table of Self Organizing Map, Dynamic Time Warping and Euclidean Distance according to noise levels of healthy data when weight=0.3;												
Accuracy	100%=N			100%>N>=95%			95%>N>=85%			80%>N		
Failure modes	H	F1	F2	H	F1	F2	H	F1	F2	H	F1	F2
SOM	---	750	---	---	---	750	---	---	---	750	---	---
DTW	1.50	---	---	---	---	---	---	1	1	---	1.50	1.50
ED	---	---	---	---	---	---	---	---	---	---	---	---

CONCLUSION

Railway turnouts are one of the most important components of railway infrastructure which take an important part in routing and controlling trains, metro and tramway direction exchanges. In increasing number of passengers, cargo transportation with higher train speeds, greater axle loads it's now compulsory to improve reliability, safety, availability and develop early identification systems for failure detection in turnout systems. Because point machines are special electro-mechanical equipments that cause frequent failures resulting in delays and increased maintenance costs. In early works, a lot of researchers developed new methods to detect failures of point machines. But in this work I have presented an expert system for identification of failure modes when the signal is not so clearly identifiable, in other words very noisy.

I have simulated 100 time series for each failure mode1, failure mode 2 and control signal. My control signal was derived from real force data which was acquired via force sensor from railway point machine, in Istanbul. Noisy time series were simulated by adding noise to the failure mode1, failure mode 2 and control signal, randomly by using most know MATLAB program. Sensory data which is acquired from railway point machines via different sensors must be filtered to reduce the noise before clustering is made. Because measurement data is affected by environment (humidity, temperature climate etc), friction force and vibration in the mechanical system, etc.

In this present thesis, I have developed a new model for failure detection of railway point machines. First of all, in pre-processing phase I have normalized my simulated data, because my simulated time series data must be in same shape with my control signal which is real force data. Then I have cleaned, normalized time series data, from noise by applying most known and most used moving average smoothing algorithm. One reason of employing average smoothing algorithm is to reduce computational time problem and second reason was to increase reliability of our failure detection model. Afterwards, smoothed time series data was clustered by employing one of the most used hierarchical clustering algorithm, self organizing map, distance metrics based dynamic time warping and Euclidean distance techniques. Coefficients of above mentioned algorithms were used in my failure diagnostics and analysis model and rules with their accuracy levels were reported in separate tables in Experiments and Results chapter of my thesis.

Finally, my expert system showed that Self organizing map could identify all failure modes from healthy signals very accurately, secondly Dynamic time warping and then Euclidean distance algorithm was successful in clustering time series, when we compare accuracy results of algorithms.

This thesis is a part of the project granted by TUBITAK with project number 108M275. The method developed in this thesis is applied to real data collected from railway systems in Istanbul. Like most mega cities in the world, Istanbul is also experiencing a great pressure from population growth and increase of traffic. Increase in traffic has also put a great pressure on transportation of Istanbul such as traffic jams and etc. In this sense, developing and improving railway transportation with its high maintenance and intelligent monitoring systems may put the end to such disasters or at least minimize the accident rate. Establishing the intelligent monitoring systems on railway turnouts will reduce any railway point machine failures.

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