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RAMS
Reliability, Availability, Maintainability, and Safety

Reliability Management in subway sector

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Preface

This master thesis report has been submitted as a partial fulfilment of the requirements to the master degree (MSc) in Reliability, Availability, Maintainability and Safety (RAMS), in the Department of Mechanical and Industrial Engineering (MTP) at Norwegian University of Science and Technology (NTNU). This thesis has been written from October 2018 to March 2019.

This report is primarily prepared to study the reliability management in subway sector, focusing on understanding the current reliability management system and propose a new management proposal as an improvement to the current system.

The intended readers of this report should have practical knowledge in reliability analysis and some basic understanding of reliability management methods.

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Acknowledgement

I would like to thank my supervisor Yiliu Liu for his patient and helpful support. His professional view of RAMS helps me to find a path on the way of academic research. I would also like to thank my parents for their unselfish and unconditional support. They are the solid backup that allows me to put all my energy in academic study.

H.J

Summary

The main objective of this thesis is to study and understand the current reliability management system in the subway sector. Furthermore, based on the analysis results, the limitations of current system are discovered, and a new reliability management system that can overcome the limitations is brought up and tested in a real case.

Due to the complex supply chain of rolling stock, the reliability management is complex as well. Some preparation works are necessary. Firstly, existing reliability management systems are reviewed. The comparison with reliability management system in the subway sector provides a clearer overview of the whole process. Secondly, study of reliability management systems of other industries, such like electric power system, provide more experiences in reliability management as reference. Some of the factors affecting degradation of components in electric power systems are also critical in subway sector. Thirdly, new concepts and techniques are introduced. Internet of Things (IoT) provides a solution for hardware reliability improvement. Machine learning is a new concept and direction for better data analysis.

The study of reliability management system in the subway sector focuses on explanations of process. The reliability management follows the lifecycle of the product, dividing into two phases: design phase and service phase. After the analysis of current reliability management system, the limitations become clear. The management process is too long and lack short-term reliability follow-up and improvements.

Thus, the life-monitoring based RAM management system is proposed. It puts more emphasis on the reliability management on component level and make it the feedback loop shorter. The accuracy of failure diagnosis is improved and prognosis can be realized.

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1. Introduction

Subway plays an essential role in the development of big cites, especially those suburban areas. Subway can connect the economic circles in the city. "*With the growth of the population in large cities, ground transportation cannot meet the various needs, so the subway has become the most effective solution for relieving traffic pressure.*" (Zhang et al., 2011) Millions of people choose subway as their common traffic approach. As Sun (Sun and Guan, 2016) stated, 6.585 billion trips were made during a year in Shanghai, i.e., around 18.04 mil-lion trips per day, in which the Shanghai metro system accounts for approximately 43%. The reliability of the subways becomes critical to the daily work. The subway sector consists of many stakeholders, including customer, rolling stock, subsystem supplier, etc. The cooperation between the stakeholders is important to the reliability management. The subway manufacture also has a large supply chain, which contributes to the complexity of reliability management.

Although there are many international standards, such as EN50126 (CEN/TC, 1999), EN45545 (CEN/TC, 2013), that are used as guidance, the subway reliability management is facing many real-time problems and there is a delay for the reaction. This thesis focuses on analyzing the current reliability management system and attempting to provide an improvement solution for identifying the limitations and solving problems.

1.1 Background

In subway industry, the daily transportation task is large and demands high reliability. *"Since the first subway line was put into operation in October 1969, there are more than 20 cities owned their subway systems in China."* (Yin et al., 2017) In cosmopolis, like Shanghai, the transportation demand is extremely high. The investment in subway is enormous. For example, Xi'An government plans to build 4 new lines in 2019 and the total investment amounts to 100 billion RMB.

The earliest subway line of Shanghai was put into service 26 years ago. The related technologies develop fast, however the application in subway sector is always slow. Not only on the technology side, but also on the management side, subway sector is using the same management system developed long time ago without many developments. Nowadays, information technology develops fast and data analysis becomes a hot topic in all areas. It becomes a challenge but also an opportunity for railway industry.

1.2 Problem Description

The main challenge for subway daily service is in achieving high reliability and availability. Trains offline during service can cause large financial loss and damage to the brand image. The critical point is that it runs daily. If it fails, maybe with limited loss, the bad images caused in passengers' service experience are big problems. Some subway lines are driverless, which contributes to the demand for high reliability. Therefore, there is a continuous need to develop a reliable reliability management system. The current reliability management system has little difference from decades ago.

The challenging part is to find a solution that can adapt the current reliability management system to new theories, new trends and new technologies. One factor contributing to the challenge is that the supply chain consists of too many suppliers and stakeholders different from other industries. Hence, the reliability allocation becomes more complex. Compared to high speed railway in China, the quality and safety requirements for subway is less strict due to the limited speed and simpler external conditions.

1.3 Objectives

The aim of the thesis is to perform an analysis of the current reliability management system in subway sector and provide a new proposal for system improvement. The realization of the aim is accomplished by realizing the sub-objectives listed below.

I. Literature study of some reliability management models and new applicable methods.
   - To summarize some reliability management models.
   - To find some reliability example in other areas as reference.
   - To find some new applicable methods or solutions for the reliability management

II. Diagnosis and prognosis
   - Introduce the mathematical explanations of machine learning for diagnosis and prognosis

III. Review and discuss of the current reliability management in subway sector
   - Brief review of the current reliability management of subway sector

IV. Propose a new reliability management method
   - Try to implement the new method with real case and data

V. Discuss the results and scope of further research.

1.4 Scope and Limitations

An important aspect of the thesis is to review and understand the current reliability management system in subway sector. Based on the review, the direction to improvement will be clearer and then application of new methods can be possible.

Some limitations of the thesis are as followed.

- The review and analysis are done on the system level. Study of real project is not done.
- New reliability management solutions are not fully implemented or tested in real case.

1.6 Approach

The project begins with an overview of some reliability management models and theories. As comparison, some important points in reliability management of electricity sector is introduced. Study of machine learning and Internet of things is done for better understanding of their importance and its possible application in the reliability management of subway sector. Then the review and study of current reliability management system in subway sector is done in detail. The study is on system level and provides the overview of the structure of reliability management system. After the analysis, the limitations of the current reliability management system are analyzed. Some new reliability management methods are then proposed for improvement of the current system. Some of the methods are tested under limitations. The test can provide a overview of the feasibility of the methods. The schematic diagram of the adapted approaches is given in Figure 1.

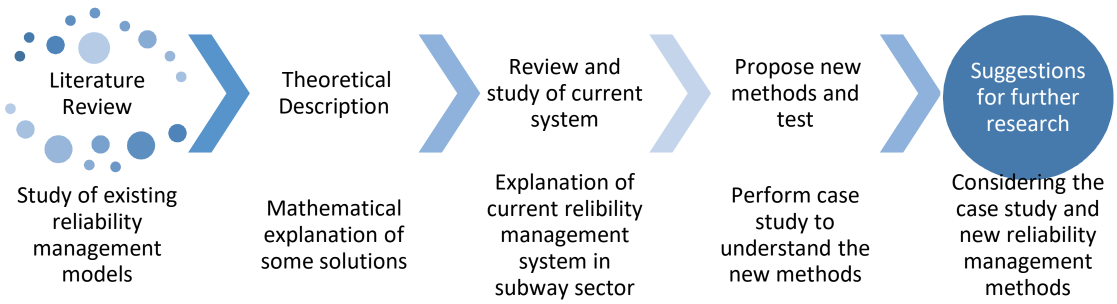


Figure 1. Adapted Approach

1.7 Structure

The remaining chapters of this report are organized as follows:

Chapter 2: Describes different reliability management systems and models. Introduce some new applicable methods of reliability management for improvement.

Chapter 3: Mathematical explanation of how some of the new methods work, which is the foundation of test and study in the work afterwards.

Chapter 4: Review and study the reliability management system in subway sector. Understand the system and analyze the limitations of the current system.

Chapter 5: Propose some new methods for better reliability management. Test some of the new methods with real case and data.

Chapter 6: An overall discussion is done based on the study of the current reliability management system and the test result of new methods.

2. Literature review

2.1 Reliability management models

For reliability management, determination of a product life cycle is important for bidding, design, manufacture, service and also warranty. Blischke (Blischke and Murthy, 2011) introduces product life cycle defined from two perspectives. The first definition is based on marketing consideration, and the second one from a production perspective.

For marketing perspective, the lifecycle is characterized in terms of the following four phases:

1. *Introduction phase (with low sales)*
2. *Growth phase (with rapid increase in sales)*
3. *Maturity phase (with near constant sales)*
4. *Decline phase (with decreasing sales)* (Blischke and Murthy, 2011)

For subway sector, the orders are mostly from the government. In China, the metro companies are mostly Sino-foreign joint venture. It means that the market is constant with little sale issue. Thus, the other definition of life cycle based on production perspective is more suitable for the metro industry.

From a production perspective, the product life cycle consists of six phases:

1. *Product concept (initial idea for the product)*
2. *Product evaluation (target characteristics pricing)*
3. *Research and development*
4. *Product design*
5. *Prototype development and testing*
6. *Manufacturing*
7. *Marketing*
8. *Postsale service* (Blischke and Murthy, 2011)

For subway sector, the eight points can be regarded as:

1. Subway project design
2. Project evaluation and bids

3. Technical liaison meetings
4. Design of systems and subsystems by suppliers
5. First equipment inspection
6. Manufacturing
7. No marketing
8. Commission and warranty

Based on the lifecycle, we can see several critical points. Firstly, the bidding requires supplier to provide technical description of our products. The invitations of bidding are sent from government to the rolling stock companies. Secondly, the technical liaison meetings determine technical solutions for most of the design, including reliability target. Thirdly, reliability targets need to be achieved within warranty period, which is normally two years.

We can see that the whole lifecycle focuses on meeting customers' requirements, which corresponds to the core principles of Total Quality Management (TQM) as introduced by Blischke (Blischke and Murthy, 2011):

1. *Focus on achieving customer satisfaction*
2. *Strive for continuous improvement*
3. *Involvement of the entire work force*

The customer driven quality requires a feedback cycle to continuously improve reliability performance. As shown in Figure 1 is an example introduced by Blischke (Blischke and Murthy, 2011).

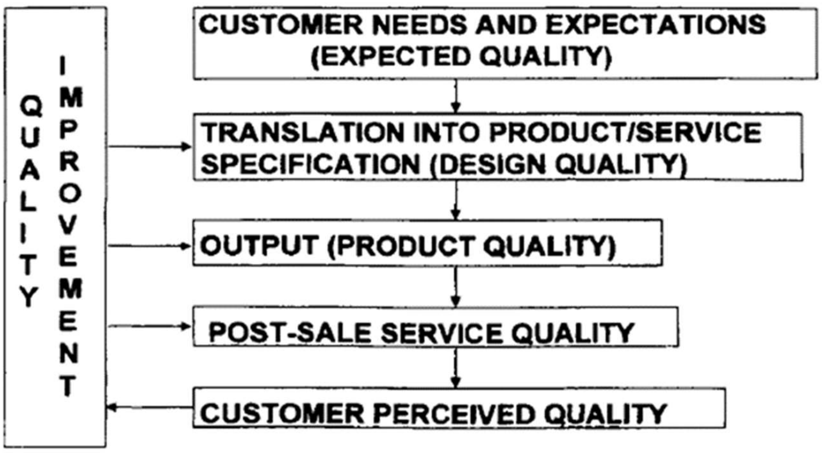


Figure 1. Quality Improvement Cycle

The quality improvement cycle corresponds to the lifecycle of subway product.

1. Customer needs and expectations are the RAMS requirements written in the bidding document and contract.
2. Translation of the requirements into product/service is the reliability allocation.
3. Output is the achieved RAMS targets proven by analysis documents.
4. Post-sale service quality is related to the reliability follow-up and return of experience.
5. Customer perceived quality is based on the site data and related to warranty. The reliability performance and daily service data can help with quality improvement.

However, the TQM cycle is rather simple. It can provide the basic principles for reliability management and an illustration for quality improvement loop. Eduardo (Calixto, 2016) introduces a more detailed reliability management process over enterprise phases, shown in Figure 2.

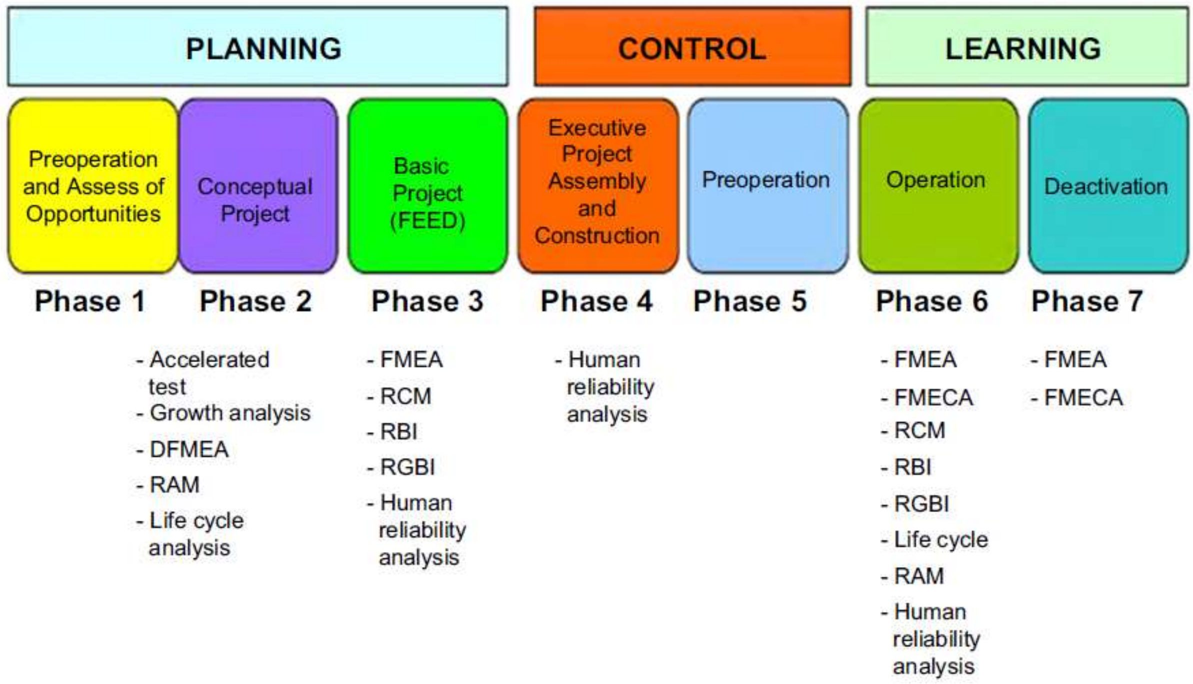
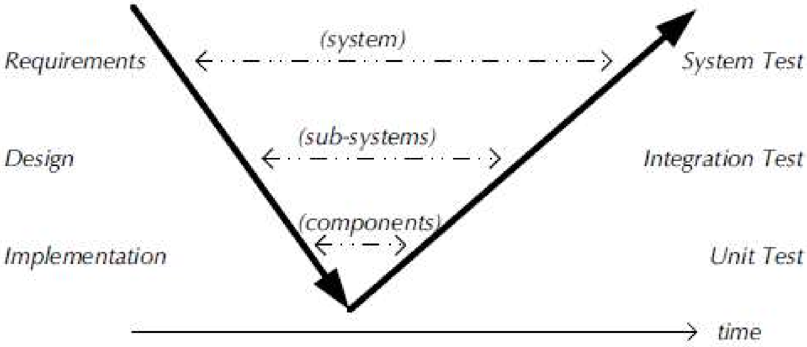


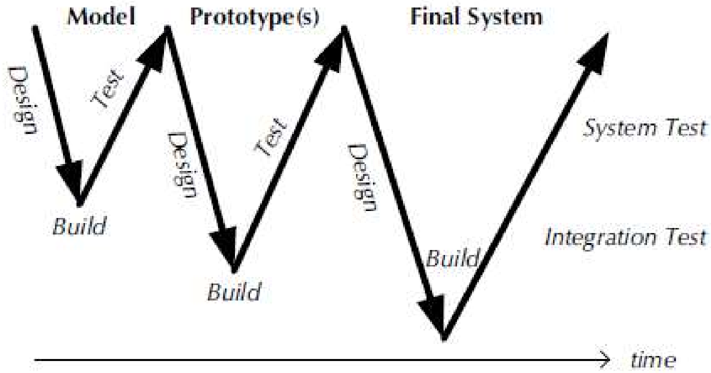
Figure 2. Reliability engineering applied over enterprise phases

The model above divides the reliability management process into three parts: Planning, Control, Learning. This model provides a good thinking of reliability analysis methods regarding different phases in management. However, the lifecycle of the product is not clearly presented and connected to the management of reliability.

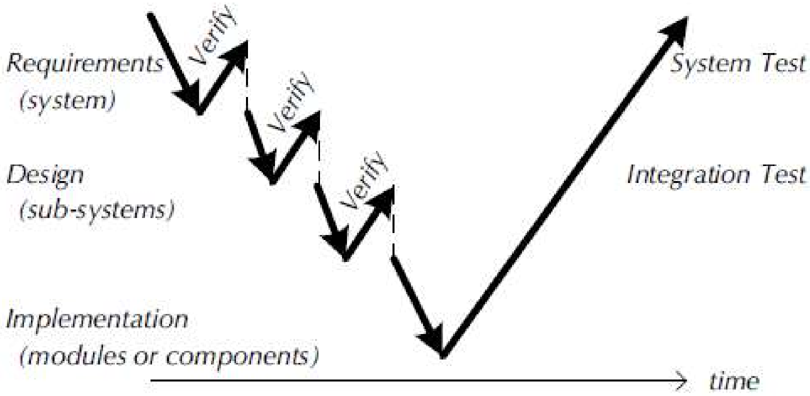
Haskins (Haskins and International Council on Systems, 2007) introduces several system process models, which are called V-model. The illustrations are shown in Figure 3.



(a) Traditional V-model



(b) Multiple V-model (W-model)



(c) inc-V model with early and continuous verification

Figure 3. Traditional V, W and inc-V process models

Among the three types of V models, the traditional V model is frequently used in process management. V model clearly shows the relationship between time and different phases in the product lifecycle. The iterations in the different phases also corresponds to the real product design process.

The combination of V-model and reliability analysis methods allocating along the time scale can provide a thorough reliability management plan. The RAMS management is rather important. As Lundteigen et al. (Lundteigen et al., 2009) has introduced, the RAMS management can support:

1. Definition of RAMS requirements

2. Assessment and control of threats to RAMS
3. Planning and implementation of RAMS tasks
4. Achievement of compliance to RAMS requirements
5. On-going monitoring, during the life cycle, of compliance.

2.2 Reliability management in other industries

Reliability management of some other industries demanding high reliability can be studied as references. Here we focus on the experiences from the power industry, since it has many similarities with the subway in terms of reliability management.

Electric power system demands high reliability to satisfy the consumer requirements. The reliability has been a major concern in the power system operation, management and planning. Large blackout of the power system would cause nationwide damage to all industries and cause huge financial loss.

The power system consists of several electric components and the reliability of the components is the basis of the system reliability. The increase of the power system scale would result in the scale of the failures increasing by exponential rate. The reasons for the reliability variance with time are as followed (Liu, 2014):

1. *The aging of the system components,*
2. *The stochastic fluctuation of the load resulting in the electric parameters exceeding the constraints of the system operation and even causing the oscillation of the system*
3. *The increase of the load exceeding that of the system capacity*
4. *The false operation of the devices for the system control and protection*
5. *The aging of the computer software and hardware and the information and communication system*
6. *The gradual increase of the power grid scale making the short-circuit capacity, system reactance and the power angle bigger*
7. *The competition and non-coordination of the partners in the power market*
8. *The conflict between the local and the global optimization*

The main contributing points for power system faults can be reference of the subways. The problems affecting reliability of electric power system also exist in subway sector.

Aging and sudden change of working status are the two main problems affecting the reliability of electric power system, which is the same with subway trains. How to monitor the degradation of components and how to monitor the working status are the main issues. If the degradation and working status can be monitored, the failures are possible to be prevented in advance.

2.3 Fault monitoring and data collection

The monitoring of condition of railway point mechanisms is based on simple thresholding techniques. However, this kind of monitoring was not quite successful due to the large number of false alarms and non-detections. Some more recent researches introduce some better techniques for monitoring of train status.

Márquez (Márquez et al., 2010) introduces several techniques in his article for monitoring the status of the train, mainly divided into Electro-mechanical point mechanism, Electro-pneumatic point mechanism, Electro-hydraulic point mechanism.

Kim (Kim et al., 2017) analyzed some failure mechanism in railroad vehicle, which can also be used as reference on failure modes study. Cheng (Cheng et al., 2013) has done some failure mode analysis of metro doors using FMECA. Zhu (Zhu et al., 2016) has done analysis on failure modes of bogie of metro.

The techniques can be used for monitoring the train working status and degradation level of components. The mathematical solutions for will be introduced in chapter 3. Through the hardware, data collection is done.

Only monitoring is not enough for preventing the failures from happening. Data collection always comes with data analysis. *"Data analysis is the summarization and presentation of the data."* (Murthy et al., 2008) Currently, the data collected by sensors is stored in the train and can be accessed by engineers only during maintenance and test after daily service. Thus, the concept IoT (Internet of Things) is brought out.

The Internet of Things (IoT), also called the Internet of Everything or the Industrial Internet, is a new technology and hot topic all around the world. Connecting things and making the data transformation easier and faster are the main targets of IoT. In Subway sector, if connections are built between all sensors on all trains with the data base, the real-time status of the trains can be monitored and analyzed and the detection and reaction against abnormal situations will be possible during service.

The essential technologies for IoT are as followed (Lee and Lee, 2015):

1. Radio frequency identification (RFID)

Radio frequency identification allows automatic identification and data capture using radio waves, a tag, and a reader.

2. Wireless sensor networks (WSN)

Wireless sensor networks consist of spatially distributed autonomous sensor-equipped devices to monitor physical or environmental conditions and can cooperate with RFID systems to better track the status of things such as their location, temperature, and movements. (Li et al., 2015)

3. Middleware

Middleware is a software layer interposed between software applications to make it easier for software developers to perform communication and input/output.

4. Cloud computing

Clouding computing can provide analyzing support on demand using the shared database.

5. IoT applications

Nowadays, the analysis is normally based on the past experience and previous projects. In subway sector, the failure of components is not yet really predictable. The prediction is based on the lifetime analysis from test report. However, as Saarikko stated,(Saarikko et al., 2017)" *connected products have the potential to provide data on actual use and essentially replace guesswork with hard facts*".

2.4 Machine learning

Based on the application of IoT, the real-time data is accessible, which is diagnosis. The traditional approach for determining operation planning decisions, based on a single 'most likely' forecast along the considered lookahead horizon, is not appropriate anymore. Real-time reliability management essentially aims at ensuring that the system may survive any contingency within a list of credible contingencies.

"To take into account uncertainties in operation planning it is necessary to model in a suitable way the real-time reliability management strategy over many time steps and many lookahead scenarios, which implies a challenging computational burden." (Duchesne et al., 2017) To make this possible, machine learning is a rather good choice to build models for prognosis. As shown in Figure 4 is an illustration for methodology of machine learning for real-time reliability management.

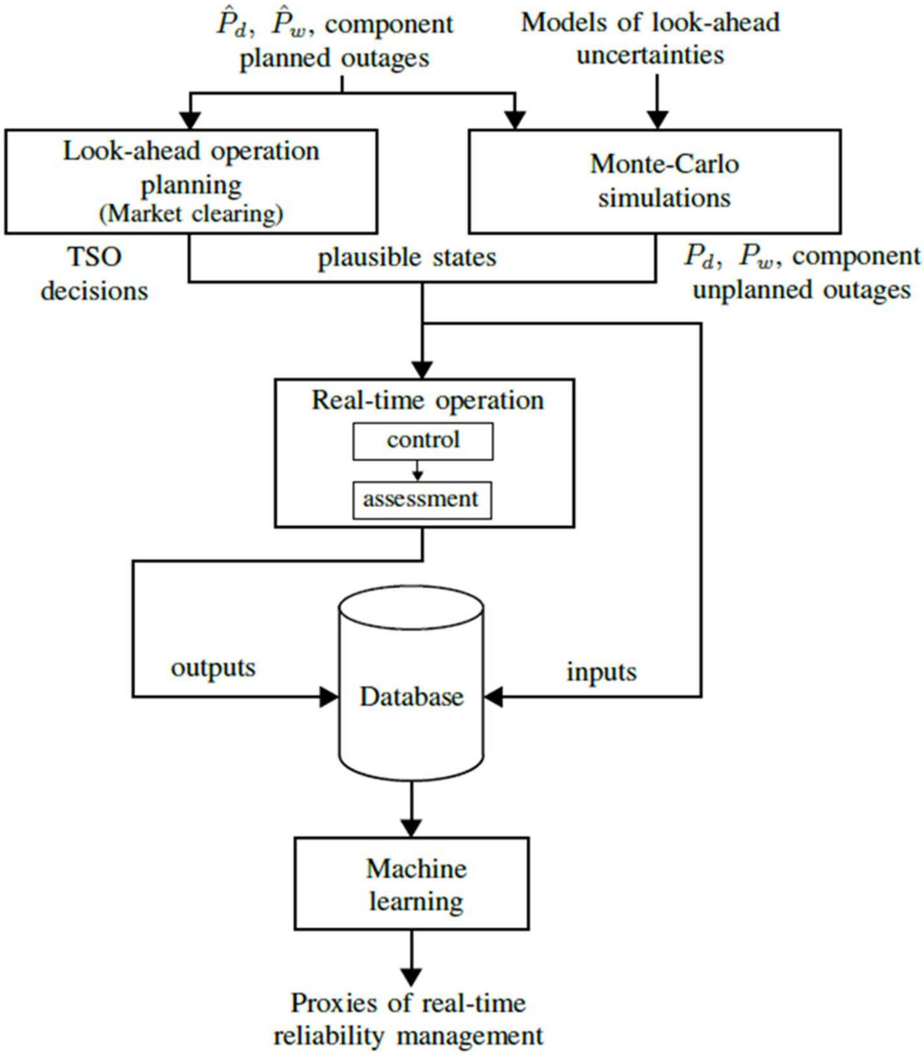


Figure 4. Methodology of machine learning for real-time reliability management

Machine learning is an efficient tool for data analysis. For this thesis, machine learning can be used for diagnosis and prognosis, which are the two most important process in the reliability management. Figure 4 introduces the flow chart for machine learning. In next chapter, some applications of machine learning in diagnosis and prognosis are introduced with mathematical descriptions.

3. Diagnosis and prognosis

This chapter focuses on introducing the mathematical explanations of application of machine learning in diagnosis and prognosis.

3.1 Diagnosis

Diagnosis is to detect failure when it happens based on the values sent back from sensors. The values may be temperatures or voltage values. The values present the working status or degradation level of the components.

Diagnosis methods can be divided into two main approaches: Statistical approach and Data based approach. Statistical approach is based on some built statistical models. Here are some typical statistical approaches.

3.1.1 Alarm bounds

Alarm bounds focuses on fault alarm, but the system maybe not faulty yet. This method is to set boundaries for fault detection. If the monitored parameter exceeds the normal range, the component is considered as failed.

For example, we monitor the working temperature of a component, which is sensitive to temperature like brake resistor, as the alarm for failure. The normal working temperature of this component is 35 degrees and we assume that the component is failed when the temperature is too low or too high. As shown in Figure 5, the density function of working temperature follows normal distribution.

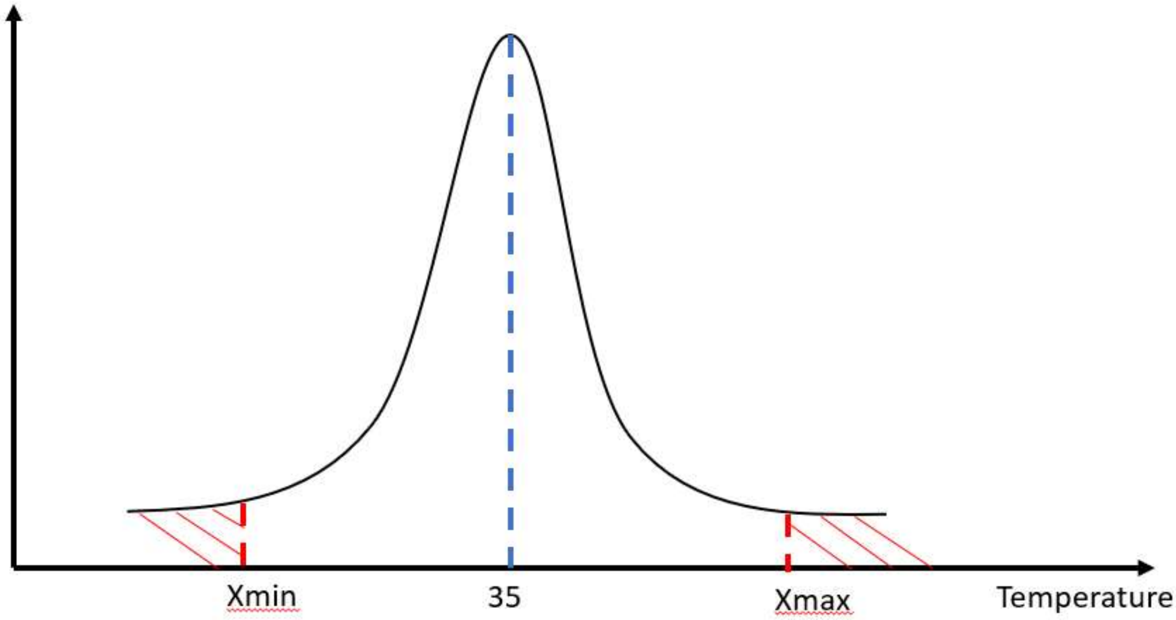


Figure 5. Alarm bounds

If the temperature of the component reaches the shaded range (Temperature smaller than Xmin degrees or larger than Xmax degrees), the fault alarm will be triggered. The boundaries are set based on expert experience or mechanical tests.

Alarm bound can be used for diagnosis of some component with simple failure mode related to a concrete measure. However, it can't be used for detection of degradation level. The output either faulty or normal. Another drawback is that this diagnosis method has false alarm. For the example above, the component may not fail when the temperature is larger than the set bound Xmax, but the alarm will still be triggered and component is considered failed.

3.1.2 Neyman Pearson test

Alarm bound is for diagnosis only knowing the probability density function of normal mode. If we know both the probability density function of normal mode and failure mode, Neyman Pearson test is a better and more reliable method.

Neyman Pearson test has three possible decisions: Faulty, Normal, No decision. For a component knowing the probability density function of both failure mode and normal mode following the normal distribution, we can draw a figure as shown in Figure 6.

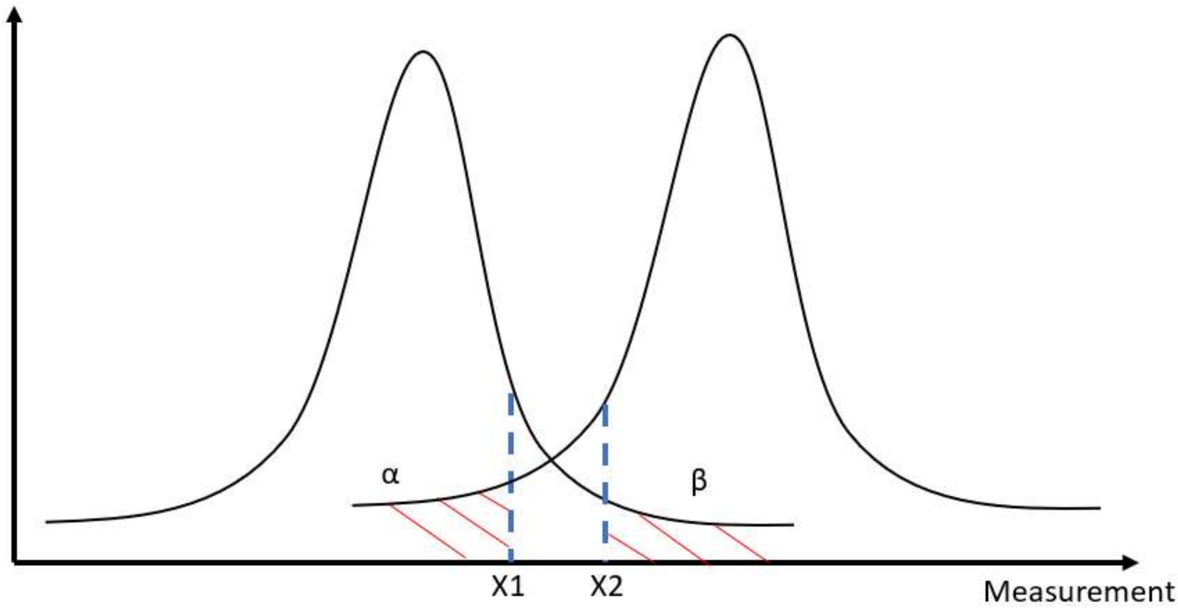


Figure 6. Neyman Pearson test

The left curve is the probability density function of normal working mode. The right curve is the probability density function of failure mode. X1 and X2 are the boundaries for decisions. If the measurement is smaller than X1, we assume that the component is normal. If bigger, then faulty. What is different from alarm bounds is that if the measurement is within range from X1 to X2, no decision is done, which means that we make no decision based on this measurement and wait for next measurement.

This method has two types of errors, false alarm and non-detection. If the real status of the component falls in α area, the component is failed. However, the decision is that component is normal. This kind of error is non-detection. If the real status of the component falls in β area, the component is normal with the decision of faulty. This kind of error is false alarm.

The measurement boundaries are set based on expert experience or test results. If X1 is set smaller, the non-detection rate will be smaller. If the X2 is set bigger, the false alarm rate will be smaller. However, these two ways will result in the increasing of non-decision area.

3.1.3 Data based approach

Data based approach is in the framework of machine learning. As we don’t know the probability density function of working mode or failure mode, one method is to estimate the two density functions and then apply statistical approach.

Parametric approach

Firstly, we choose a set of probability density functions, F. F={N(m,σ), Weibull(α,β),…}

Secondly, the data is divided into two parts.

1. (Xi,1), we learn the failure density function on this data set;
2. (Xj,0), we learn the working density function on this data set.

Thirdly, we choose one or more density function from F based on the histogram of the data set and optimize the parameters by maximizing the likelihood function, for example, Weibull distribution:

$$\alpha(X1) = \prod weibull(\alpha, \beta, X)$$

The higher is the value, the closer is the obtained function to real density function.

Non-parametric approach

There is also non-parametric approach for achieving probability density function. The method is based

$$g\varphi(x) = \frac{1}{n} \sum_{n}^{k=1} \varphi(x - x_k)$$

on the Kernel method. The probability density function can be obtained as followed:

The most commonly used kernel function is normal distribution N(0,σ). The value of σ needs to be optimized. "*An effective estimation of reliability function permits the appropriate application of several models of maintenance policies of components.*" (Alsina et al., 2018)

3.1.4 Summary

Diagnosis with the support of IoT is based on the measurements from sensors. Choosing appropriate diagnosis method can help with raising the accuracy of failure detection.

The statistical approaches for diagnosis can be separated into three main categories.

If we only know the probability density function of normal mode, alarm bounds is a good method.

If we know the probability density function of both normal mode and faulty mode, Neyman Pearson test and Bayes test are good choices.

If we know the probability density function of both normal mode and faulty mode and we decide with several observations, Wald test and Cusom test are appropriate test methods.

The choice of statistical diagnosis method is based on the understanding level of the component failure and working mode. With an adequate data base of component lifetime, the probability density function of component can be modelized on analysis.

Other than statistical approaches, data-based approach is another solution, which is in the framework of machine learning.

3.2 Prognosis

The objective of prognosis is to forecast the possible failure time of the components. *"One of the most common reasons for censoring is the fact of analyzing life test data before all units have failed."* (Meeker and Escobar, 1998) For a certain type of component, we have already observed and recorded the degradation measurements throughout the whole lifetime of all the failed ones. Based on this database, we use machine learning to estimate the failure date of a same component, which is still working.

Based on the monitoring system, we can obtain a table recording degradation level and corresponding time as followed in Table 1.

		Operational mode varaibles			System condition			
Unit	Time	OP1	OP2	OP3	Sensor1	S2	…….	S21
1	t0	√			$x_1^1(t0)$	$x_1^2(t0)$		
.	.				…			
.	T1				$x_1^1(T1)$	…		
2	t0		√					
.	.							
.	T2							

Table 1. Sensor measurements records

Step 1 Reduce the dimension for the measures related to system condition. For example, in the table, there are 21 sensors measuring the system condition. However, 3 sensors are enough to determine the status. Principle component analysis is used for the reduction from 21 sensors to a reasonable number of measurements.

Step 2 Study of X_1^L and X_1^T

1. Group all the measures at failure date according to operation mode.
2. For each group, calculate the mean (Bayes center).

Step 3 Build the degradation indicator in X_0^L for any t before failure time.

D(tj)= Distance at time tj between the measure at time tj and the measure at the failure date.

After normalization, we can obtain the degradation curve of components. As shown in Figure 7, it is an example of the degradation curve of a component.

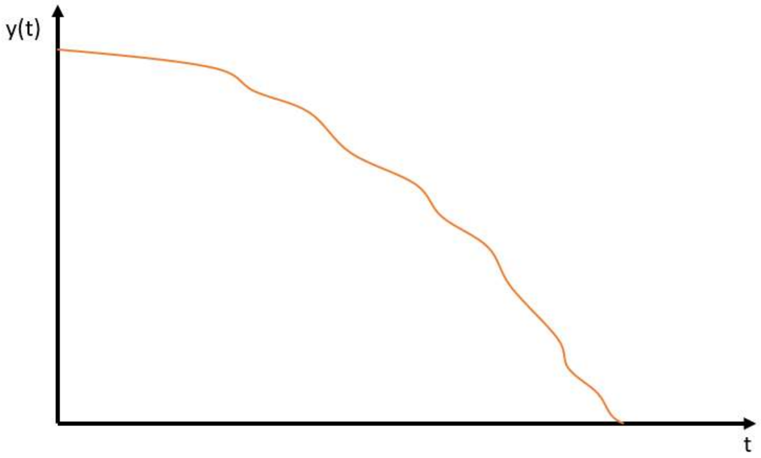


Figure 7. Degradation curve

Step4 Remaining Useful Lifetime (RUL) Estimation

We want to know at t_j, what is the RUL of unit *i*.

1. Calculate $y(t)$ for $t \in [0, t_j]$ for unit *i*
2. Plot $y(t)$ for unit *i* in the plot of all $y(t)$
3. Choose the "closest" path to estimate the RUL of unit *i*

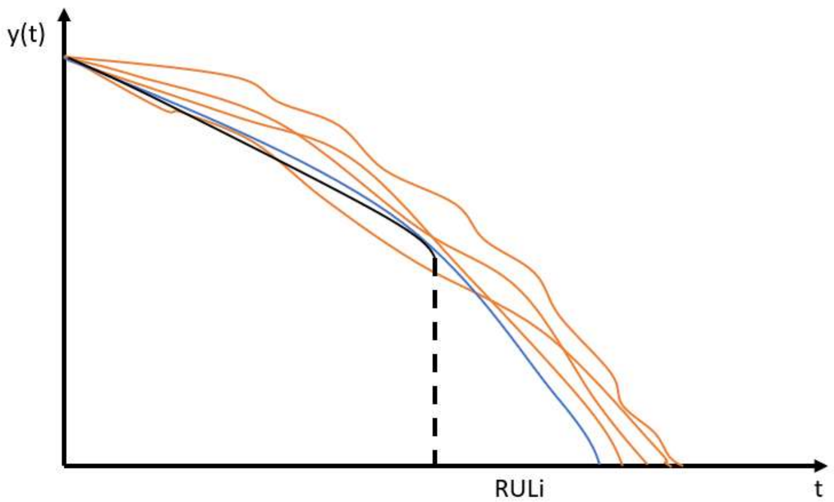


Figure 8. RUL estimation

The performance of the prognosis can be optimized by algorithm. For example, we can define better algorithm to determine how to choose the component with most similar degradation curve comparing to the studied serving component.

After the four steps, we can estimate the RUL of the studied component and schedule maintenance before its failure.

4. Subway sector reliability management

4.1 General process

In Alstom, there are two processes for product management. One is quality management process, which is DFQ (Development of Quality). The Alstom design review is an independent process paralleled with product quality development. It is for management of RAMS. These two processes making sure that the product can meet the requirements of customer needs and applicated standards and laws. The reliability management is within the scope of design reviews.

The reliability management are divided into two different parts, design phase and service phase. Design phase is the time period between when company wins the train contract and when the company delivers the products.

At the start-up phase of a project, the first step is to prepare a RAM plan. The content of a RAM plan is shown in Figure 9.

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Figure 9. RAM plan contents

RAM plan is an introduction and guidance file for the RAM management of product life cycle. It determines the RAM activities and the RAM targets for the product design, which is based on the agreement with customer and the contract.

1. Introduction

This section introduces the general scope of the RAM plan. The main contents are Objective of the plan, Document update process, who writes the plan and who validates it, product name and type.

2. References

This section introduces the applied standards and input files for RAM plan. In subway sector, the train manufacturer allocates the reliability targets to subsystems for reliability management.

3. Terminology

This section introduces the related vocabularies and abbreviations.

4. Description of train and sub-systems

This section introduces the general design of the train and the subsystems. The mission profile describes the main operating conditions of the train.

5. Organization and responsibilities

This section introduces the general organization of a rolling stock project, as showed in Figure 10.

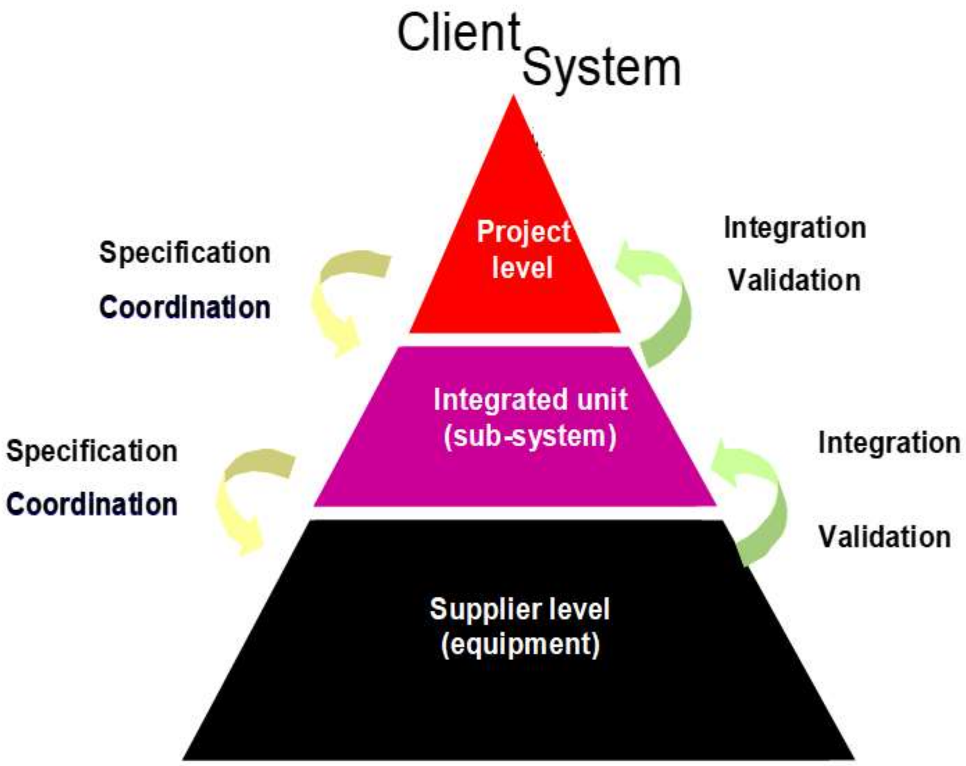

Figure 10. General organization

6. RAM management

This section consists of the detailed RAM management plan, which includes lifecycle determination, RAM requirements clarification, RAM analysis, list of RAM deliverables.

The purpose of RAM plan is to define and describe the process, activities, organization and deliverables related to Reliability, Availability, and Maintainability implemented by subway company for the dedicated project.

The RAM plan is produced in accordance with the general guidelines of EN 50126, "Railway Applications-The specification and demonstration of reliability, availability, maintainability and safety" and the RAMS management system within the company.

In the RAM management process, some activities and phases are determined.

4.1.1 Lifecycle

According to EN 50126 standard, the RAM activities are conducted along with the project development cycle (system, sub-system, hardware, and software). The lifecycle for project follows ALSTOM DFQ process.

The RAM and development cycles are closely linked, each one using the inputs from the other one. Several iterations are needed between the RAM and development cycles. Check points shall be defined to verify that the RAM requirements have been correctly considered in the development cycle.

As a part of ALSTOM DFQ process, RAM activities and requirements are included in the design process. Therefore, RAM design reviews shall be performed in line with this process to prepare the principal gate reviews of the project.

Figure 11 is the DFQ process of the whole project and Figure 12 shows the RAM management process throughout the DFQ process of the project. The RAM related activities are conducted at different phases of the project lifecycle to make sure the product reliability is under control. As shown in the figure, the RAM plan is necessary to pass SGR, specification gate review.

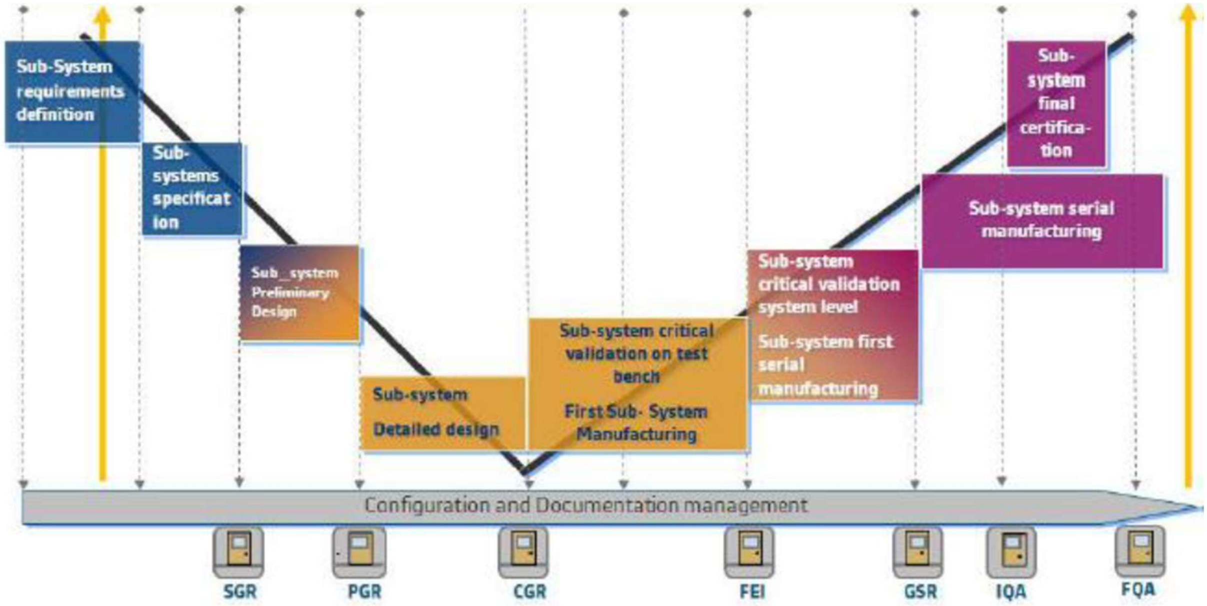

Figure 11. DFQ process

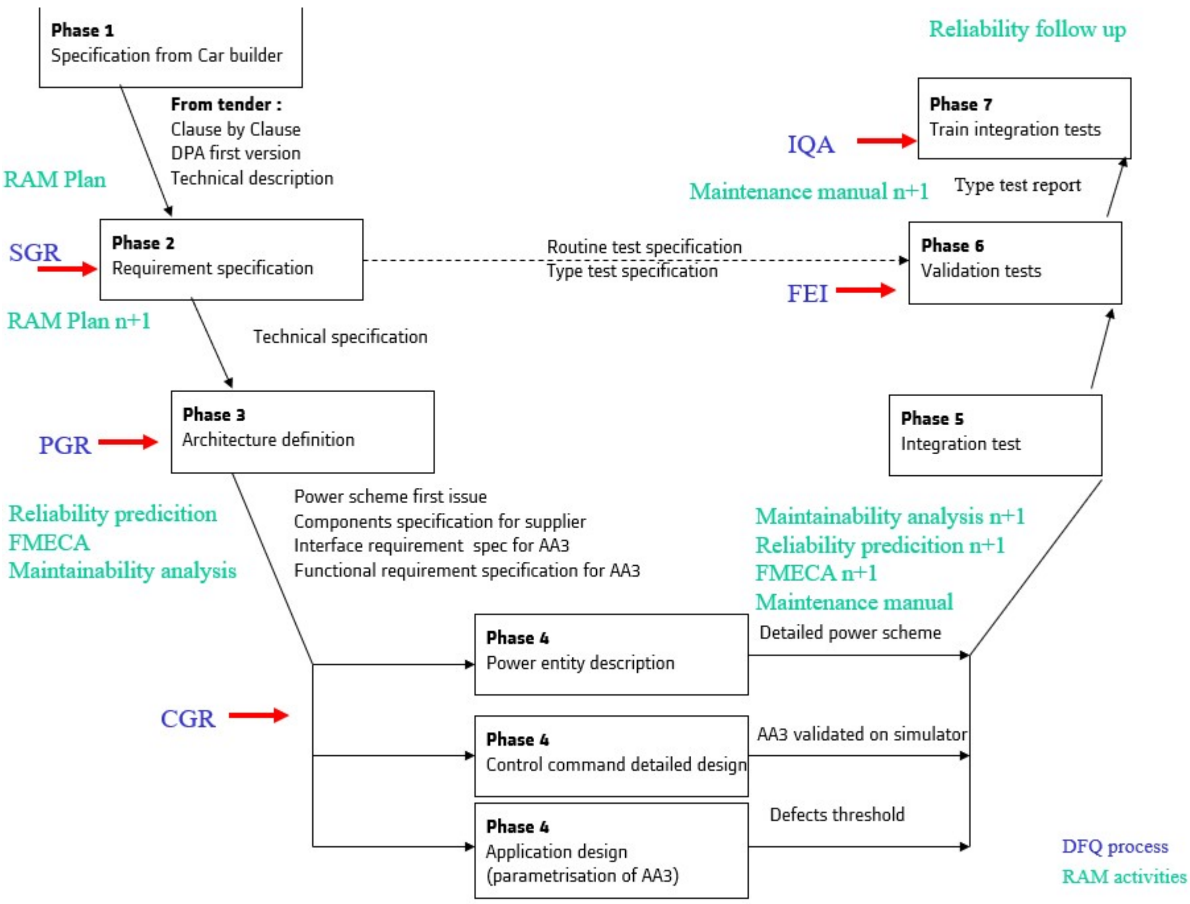

Figure 12. RAM management process

4.2 Design phase

In the design phase, there are many critical points in the process. As shown in Figure 12, the whole lifecycle of product RAM management is a V-cycle. The left part is the design phase.

4.2.1 Phase 1

Phase 1 is the reliability allocation on train level, which is to allocate the reliability target for subsystems and the suppliers. As shown in Table 2 is a template for the reliability allocation.

S. No.	**Subsystem**	**MDBSF (km)**
A.	Car body and gangway	
B.	Coupler and buffer unit	
C.	Car door (All)	
D.	Bogie and suspension device	
E.	Brake system (All)	
F.	Air-conditioning and ventilation	
G.	Auxiliary power supply system	
H.	Lighting equipment	
I.	Train control	
J.	Public address system and electronic map	
K.	Pantograph	
L.	Traction system	
M.	Finished vehicle control	

Table 2. Reliability allocation for subsystems

4.2.2 Phase 2

Phase 2 is the requirements specification phase. Specification gate review is the check point in the lifecycle to control this phase. There is a table of check points. The check points must be passed before the DFQ go to next phase. The main check points of SGR (Specification Gate Review) are as followed:

1. Train requirements (including RAMS) are allocated and agreed with internal and external sub-system specifications.
2. Train Architecture is defined.
3. All sub-system interfaces are defined and agreed. (mass, weight, volume, performance...)
4. Validation Plan is defined.
5. List of contractual documentation -including delivery schedule - is finalized and agreed with Customer.

4.2.3 Phase 3

Phase 3 is the phase for architecture definition. The check point in a lifecycle to control this phase is Preliminary Gate Review (PGR). The main check points are as followed:

1. Train specifications are completed and released
2. Architecture is frozen
3. Critical gaps or technical risks validation schedule is defined
4. All internal and external interfaces are frozen and consistent with system

The architecture is determined and frozen before passing preliminary gate review. Thus, after PGR, the reliability prediction analysis, maintainability analysis can be conducted.

In the reliability prediction analysis, the failure rates of all components are collected from suppliers and summarized for analysis, see Appendix A. The reliability prediction report consists of two parts, intrinsic reliability analysis and service reliability analysis.

The reliability prediction can be summarized by the following steps:

1. To detail the structure of the system down to the LRU (Line Replaceable Unit) level,
2. To determine the failure rate for each LRU,
3. To deduce the failure rate of the whole system and the corresponding MTBF.

The prediction is based on the LRU failure rates that are taken from the following reliability source:

1. In-service data from company records of the same equipment operating under similar conditions (Return of Experience, REX),

2. Generic data from recognized sources such as FIDES, MIL HDBK 217F or IEC 62380 for electronic components,
3. Supplier's data.

Intrinsic reliability analysis is based on the system breakdown structure. The result is the reliability of the whole product. Service reliability analysis is based on the fault tree analysis of failures affecting service. It considers the possible events affecting service, normally including traction subsystem, auxiliary subsystem, motors.

4.2.3 Phase 4

Phase 4 is to determine the detailed design of the main systems and software, such as programs in control units. The check point in lifecycle to control this phase is Critical Gate Review (CGR). The main check points are as followed:

1. Train (detailed) Design completed, frozen and released including 1st train applicable configuration,
2. All documentation for first train production released,
3. Validation Plan is frozen.

Phase 4 is the critical phase in the management lifecycle. In this phase, all the preparations for train manufacture should be done. The related RAMS documents are reliability prediction analysis, maintainability analysis, maintenance manual, etc.

4.2.4 Phase 5 & 6

Phase 5 integration tests and phase 6 validation tests are for validation and certification for the product. Both types of tests should be completed and passed before FEI (First Equipment Inspection).

4.2.5 Summary

As shown in Figure 11, the lifecycle and management process are divided into different phases and controlled by gate reviews. Gate reviews are conducted to make sure that the documentation, design, tests are done and under control. There are check lists for the gate reviews. A template of gate review check list is shown in Appendix B.

The check list consists of several parts regarding the responsibility. As shown in the template, the check point, due time, person in charge are clearly determined. All the open points in the gate review should be ok before entering next phase.

4.3 Service phase

The service phase starts from when the trains are delivered to customer to when the warranty expires. The main reliability activity in this phase is reliability follow-up and REX, return of experience.

4.3.1 Reliability follow-up

Reliability follow-up is based on the reports of warranty team. The onsite warranty team records the failures and components replacements. Appendix D is a template of the record table. Technical engineer and RAMS engineer analyze the failures and determine the root cause, random failure or quality issue, etc. RAMS engineer prepares the regular analysis report based on this.

The reliability follow-up analysis normally consists of project level, system level, component level. Project level is for analyzing the reliability of a certain project, for example, Shanghai metro line 3. If the reliability of a certain project shows obvious bad performance comparing to other project with same product, the problem solving may lead to management or other specific working conditions of the project.

The system level is for analyzing the reliability of different systems, such as traction subsystem and auxiliary subsystem. In subway sector, the reliability follow-up focuses on the main service affecting systems, which has quantitative reliability requirements in the contract.

The component level reliability analysis focuses on the components which frequently failed in the past certain time period. The root causes of this kind of frequent failure may be the quality problem of the supplier or consequence of other related failed system. The reliability analysis on component level plays a role of alarm in the train service phase.

4.3.2 Return of experience

Return of experience is based on the trouble shooting and root cause analysis of failures. For quality issue, supplier needs to provide an action plan. For design problem, a query for explanation and action plan will be sent to design department based on the cause. For some failures frequently happening spreading in different projects, the analysis result will be forward to all project leaders as alarm for preventive action.

Return of experience is the last step of quality and reliability improvement loop. It is by now mainly based on subjective judge of engineers.

4.4 Limitations

The current reliability management system shows good performance in the reliability improvements on the product level. The feedback loop returns experience of same products on various projects. However, there are still some limitations:

Firstly, the alarm takes long time to ring. The reliability management after train delivery lacks real-time monitoring and precaution based on data analysis. The reliability follow-up only consists of MTBF calculation. Only if the MTBF rises above contractual limit or a certain kind of component fails frequently in a short time period, an extra reliability analysis will be done to tract the root cause. This judgement is highly depending on the experience of the RAMS engineer.

Secondly, there is no lifetime or reliability prediction analysis for different components. The reliability analysis on component level is only taken at the design phase. The follow-up analysis on component level of lifetime or reliability is lacked.

Therefore, the improvement objective is to implement a new reliability management process or model that can conduct real-time reliability analysis for different components.

5. Life-monitoring based RAM management

5.1 Present system

A typical reliability management system of subway sector is discussed in chapter 4. The structure of the system is completed. The whole lifecycle of the products is covered. The system has been working for decades and still shows good stability and performance. For projects with long life time and relatively high fault tolerance, this system can fulfill the need of reliability monitoring.

However, the failure rates of the components are based on the working conditions of the labs. In real case, the working condition varies from line to line, city to city, even day to day. We can’t say a pantograph degrades the same in a snowing day and a sunny day, considering that some part of the trains is above ground, such as Shanghai Line 5. Even different driver habit may influence the lifetime of train. Some of the components are safety related. If a surge arrestor fails in a rainy summer day, we are then free from lightning protection. In Spring Festival’s Eve, Nangjing airport line was out of service due to failure of some relays. The root cause was related with snow and ice. Due to this failure, hundreds of passengers missed their planes. A real-time reliability monitoring system is needed.

Monitoring the working status of components is not enough for preventing the failures. How to use the data is another problem. Machine learning of data is a possible solution.

Therefore, the lifetime-monitoring based RAM management consists of two parts. First part is to implement IoT and build a monitoring system for all necessary components. Second part is data analysis of the collected data. The analysis targets are diagnosis and prognosis. As introduced in chapter three, machine learning can be used to for the data analysis. The accuracy of diagnosis and prognosis is based on the component status monitoring and database.

5.2 Status monitoring

Currently, the monitoring devices in the train are mainly two types: current and voltage monitoring, speed monitoring. Based on the logics in the software, failure of some relays and contactors can be detected by the current and voltage monitoring sensors. The motor status can be partly monitored by the speed sensor.

Generally, the monitoring of the status of temperature, humidity is missing. As the electric energy is huge, overheating is a frequent problem for trains. Short circuit, overload and many other problems may lead to overheating and overheating will lead to faster aging of components or immediate failure.

For some reliability related components, like capacitors, the performance is not monitored. For example, if the pre-charge contactor fails, the pre-charge module will not perform its function. When the pantograph is connected, the high voltage will directly connect to the main capacitors. The current monitoring system will only report the failure of the pre-charge contactor failure. The damage of capacitor will be neglect.

The monitoring of more reliability related components and parameters are needed. Only monitoring is not enough. The data connection between trains and the database is not built yet.

For now, the data collected by the sensors will be recorded in the train and maintenance engineers need to connect computers with the train to download the data. If the connection between train and database is built. The status of the train can be monitored and analyzed in real-time scale. The diagnosis of abnormal situation can be done faster and prognosis is possible to be done.

5.3 Lifetime monitoring and analysis

With the sufficient hardware support, the component real-time working status of a lot of projects can be monitored and stored. Here remains the problem of how to use it.

5.3.1 Lifetime record

The current replacement record is shown as in appendix D. The template is still missing some critical information for lifetime record. They are, but not limited to:

1. Part online date
2. Part degradation level record
3. Part maintenance date
4. Part failure date

The listed recordings are adequate for lifetime records and analysis. A proposed template is shown as below in Table 3.

Project	Component	Part number	Serial number	Online date	Failure date	Check date	Degradation level	Last retrofit date	Remark

Table 3. Degradation record sheet

In this template, the necessary information for drawing a lifetime degradation curve is recorded. The degradation level varies from different components. The criteria need to be determined individually. The determination of degradation level is not only important here, but also can be used for Markov chain analysis.

We try with an example of a subway project. Q-NEB is repeater relay. Its failure will affect service. In project Nanjing South 1, a lot of Q-NEB failed in the last 12 months. However, before 2018 limited number of Q-NEB was failed. It can be assumed that the failure of Q-NEB from this supplier in this time period is due to degradation. I transfer the data from commissioning and warranty team to the new template and it is shown in Table 4.

Project	Component	Part number	Serial number	Online date	Failure date	Check date	Degradation level
NJS1	Q-NEB	DTR0025731525	N.A	5/1/2014	4/9/2018		
NJS1	Q-NEB	DTR0025731525	N.A	5/1/2014	4/14/2018		
NJS1	Q-NEB	DTR0025731525	N.A	5/1/2014	6/18/2018		
NJS1	Q-NEB	DTR0025731525	N.A	5/1/2014	12/5/2018		
NJS1	Q-NEB	DTR0025731525	N.A	5/1/2014	12/6/2018		
NJS1	Q-NEB	DTR0025731525	N.A	5/1/2014	12/13/2018		
NJS1	Q-NEB	DTR0025731525	N.A	5/1/2014	1/6/2019		
NJS1	Q-NEB	DTR0025731525	N.A	5/1/2014	1/11/2019		

Table 4. Q-NEB records

The test date of this component is unclear. Normally a test will be done after everyday service. However, the test and check are general test of the service affecting functions. The test won't cover the degradation level of all components.

For a relay, the degradation is not linear. When it reaches the switching life, it will probably fail and can't continue service any more. For some components, the degradation is progressive and possible to monitor. For example, the degradation of capacitor can be monitored. The degradation level can be estimated based on the existing degradation model and monitored voltage and current value.

5.3.2 Life time analysis

With a proper system, it is possible to build a large data base. Adequate data could be used for building and updating the failure density function.

We try to analyze the Q-NEB relay with the above data and draw a curve as shown in Figure 13.

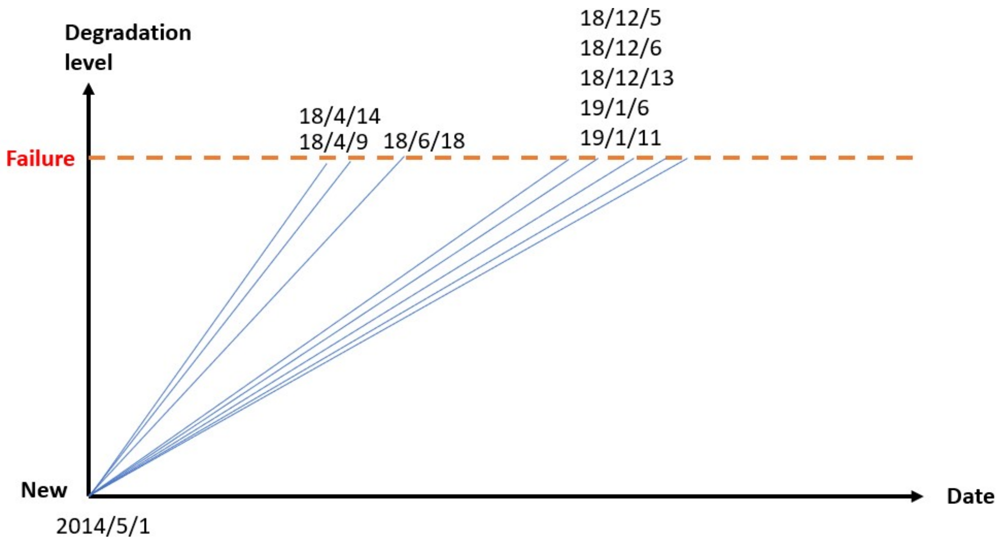

Figure 13. Q-NEB degradation curve

As no specific of reliability analysis for a single type of component is done before, we don't have the probability density function of neither working mode or failure mode. Thus, we try with data-based approach to obtain the density function. Due to the limited number of samples, non-parametric approach to get the probability density function is a better solution.

We still choose normal distribution as Kernel function. Firstly, transfer the failure date to lifetime.

Failure date	Lifetime (hours)
2018/4/9	34536
2018/4/14	34656
2018/6/18	36216
2018/12/5	40296
2018/12/6	40320
2018/12/13	40488
2019/1/6	41064
2019/1/11	41184

Table 5. Q-NEB lifetime

Based on the lifetime, we can obtain an approximated density function in Figure 14 by running the following codes in MATLAB. The method is non-parametric approach for obtaining the density function as introduced in chapter 3. The chosen kernel function is normal distribution. The method for getting density function varies from different components and the choice of kernel function is also optional for this method.

```
x = 20000:100:60000;

sigma = 3000;

y1 = normpdf(x, 34536, sigma);
```

```
y2 = normpdf(x, 34656, sigma);
y3 = normpdf(x, 36216, sigma);
y4 = normpdf(x, 40296, sigma);
y5 = normpdf(x, 40320, sigma);
y6 = normpdf(x, 40488, sigma);
y7 = normpdf(x, 41064, sigma);
y8 = normpdf(x, 41184, sigma);
y = y1+y2+y3+y4+y5+y6+y7+y8;
plot(x,y);
ymax=max(y);
id=find(y==ymax);
x(id);
grid on;
```

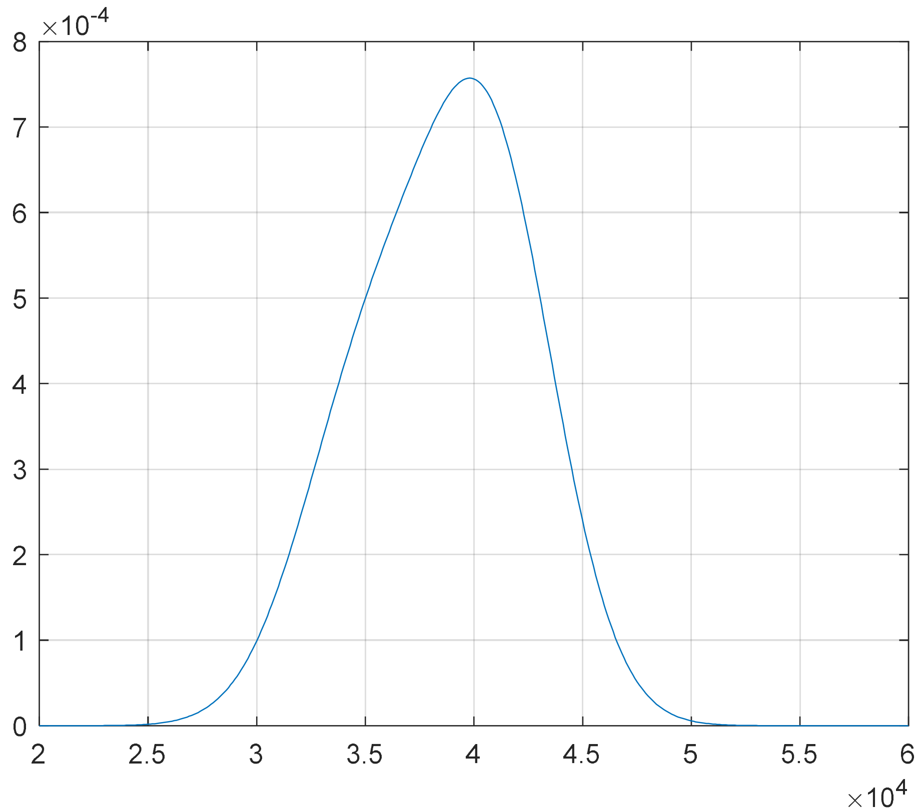

Figure 14. Probability density function of Q-NEB

As shown in the figure, we can assume that the lifetime of Q-NEB is the horizontal axis coordinates at the peak of the curve, which is 39800 hours. The value may get closer to the real value with more failure records. The density function may change if we change σ.

For prognosis, the degradation of individual component is assumed as linear, which may not be the real case. These are the improvements that can be done with a more adequate data base and better degradation monitoring.

7.Conclusion

In this chapter the accomplished work and the obtained results in the thesis are summarized. Later based on the findings, some recommendations are proposed for further work and research.

7.1 Summary and conclusions

As the city expands, the need for public transportation rises at the same time. Subway as a convenient and environment friendly transportation method plays an increasingly important role. The reliability requirements of subway are rather high due to the possible large financial and other loss of failure at commercial service. Literature review gives a brief image of some reliability management models and introduces some technologies that could help with the reliability management. After the analysis of the current reliability management system in subway sector, the limitations of the current system are clear. Based on the analysis, a new reliability management system, which is life-monitoring based RAM management, is proposed and tested with real data.

7.2 Recommendations

The primary objective of the thesis is to propose a new reliability management system or model for subway sector and the related stakeholders. For the realization of lifetime-monitoring based RAM management system, here are some recommendations:

1. Implement better monitoring system on the hardware level
2. Define detailed degradation levels for different components
3. Build a database for components degradation data records
4. Develop an auto failure alarm system based on the analysis of real-time data

Acronyms

TQM	Total Quality Management
IoT	Internet of Things
RUL	Remaining Useful Lifetime
DFQ	Development of Quality
SGR	Specification Gate Review
PGR	Preliminary Gate Review
LRU	Line Replaceable Unit
REX	Return of Experience
CGR	Critical Gate Review
FEI	First Equipment Inspection

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Appendix A Part of template for intrinsic failure rates

EQUIPMENTS DATA				
Item Description	**Name**	**Reference Number**	**Quantity/traction**	**FPMH**
Traction Cubicle	VVVF			
Input Stage				
Input current transducer	A-LCMD2			
Input Charging contactor Plate	LRU			
Filter voltage transducer	A-FVMD			
Line Inductor	L-FL			
Inverter Stage				
Power Module	Onix552			
Inverter capacitor fan	FAN1			
Inverter capacitor fan	FAN2			
Inverter capacitor fan	FAN3			
Phase current transducer	A-CMDR			
Phase current transducer	A-CMDS			
EMC Resistor	R-EMIK			
EMC Capacitor	C-EMIK			
Main Cooling				
Cooling Fan	FAN			
Inverter fan contactor	K-FAN1			
Long term rated rheofan contactor	K-FAN2			
Inverter fan thermal protection	Q-MCB1			
Long term rated rheo fan thermal protection	Q-MCB2			
DC/DC Converter	CM-DRIVE-SUPPLY			

Appendix B Part of gate review check list template

Id	Requirements	Deliverables	Maturity	Standard Template (Prisma Reference)	Responsible	KO	OK / NOT OK/NOT APP.	Evidence reference / link	Risk Description	Criticality	RAMP N°	Comments	Actions (in PSLI)	PIC (person in charge) for action in PSLI	Due Date (in PSLI)
1	**MANAGEMENT**														
1-1	**INTEGRATION**														
1-1	Project Management Plan is completed and approved	**Project Management Plan:** Fully completed PMP approved by Site Projects Director and Customer Director	Completed		Project Manager										

Appendix C Warranty team failure record template

Status	Type	FI No, NCR No, etc	Action date	NC Part sent out of depot	Project	Location	PIC	TRAIN No	Car No	Mileage (km)	Equipment	Event description	Agate Fault Log	Software version	Component Replaced	Part number	Old S/N	New S/N	Exchanged on	Source of Old part	Source of New Part	NC Part Receiver	Comment & Result