A PERFORMANCE BASED RELIABILITY ENGINEERING APPROACH FOR URBAN TRAINS IN MELBOURNE

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SUMMARY

The occurrence of functional failures in various sub-systems of an urban train system, such as the brake and traction systems, causes cancellation and delays in services, thus reducing service reliability. Frequent disruptions in the service results in operational and financial losses to the operator. Thus, there is an imperative for operators to reduce the functional failure frequency (denoted as FFF in this study) of the sub-systems through an effective maintenance regime for minimum disruption in the service.

Maintenance management systems based on reliability centred maintenance (RCM) have become commonly used for the maintenance planning of urban trains. There are three keys elements of RCM: the reliability analysis, the prioritisation of the maintenance strategies and the reliability measuring system. In RCM, the reliability analysis is used to identify the functionally critical sub-systems and the reasons for their criticality; maintenance strategies that are devised for the critical sub-systems are prioritised to achieve the maximum reduction in their FFF; and the effectiveness of these strategies is measured in terms of the key performance indicators (KPIs) for reliability. However, it is unclear how the third element (i.e. the data collected on the KPIs for both functional reliability and service reliability) is currently used in the other two elements of RCM. Furthermore, it is unknown how the influence of the latent variables (i.e. the operational constraints) on the operational performance of the sub-systems is incorporated.

The aim of this research is to investigate the RCM process used by the urban rail industry for the maintenance planning of trains, and to propose a new improved RCM process that achieves overall reliability by integrating the performance measures both for functional reliability and service reliability, and the influence of latent variables in the process. To achieve this broad aim, the research was divided into three key components, and a mixed-methods approach was adopted.

First, the conventional approach of reliability analysis for the operational performance characterisation of the sub-systems of the urban train system was assessed through a case study of the urban train service in Melbourne. In the conventional approach, the aim of the analysis of the KPIs data is to establish nine different operational characteristics of the sub-systems using Simple Descriptive Analysis (SDA). Thus, SDA was applied to the UTS Melbourne KPIs

data for six years. It was found that SDA could be used to summarise the KPIs data based on frequency counts. However, only four characteristics of the sub-systems could be established to a limited degree, and this approach did not consider the influence of the latent variables on the operational performance of the sub-systems. Given these limitations, the maintenance planning ultimately relies on a simple increase or decrease in the values of the KPIs of the sub-systems and thus does not establish whether each KPI has improved both individually and also in relation to each other. Hence, it was concluded that an improved approach for operational performance characterisation of the sub-systems is needed.

To develop an improved approach to reliability analysis, the conventional approach was first modified by preserving the conventional single criterion (i.e. FFF), and using an exploratory multivariate data analysis technique called Principal Component Analysis (PCA) instead of SDA. Using this new approach, the same UTS data was analysed in MATLAB. The application of the KPI for functional reliability using PCA established five characteristics of the sub-systems, and provided a clear insight into the effect of the latent variables. A comparison of PCA findings and SDA findings showed that PCA was a better technique for operational characterisation of the sub-systems. However, PCA cannot be applied for characterisation based on the multiple criteria that involve the KPIs for both functional reliability and service reliability.

Next, to further improve the conventional approach, multiple criteria were used, and a technique which is an extension of PCA called Multiple Factor Analysis (MFA) was applied. This approach applied the KPIs for functional reliability and service reliability in their cause-and-effect structure, and MFA was used to analyse the data set for FFF-and-number of services cancelled, and the data set for FFF-and-number of services delayed using RStudio. The application of the KPI for functional reliability together with the KPIs for service reliability using MFA established the remaining four characteristics that could not be obtained using PCA. The comparison of the results obtained based on the multiple criteria using MFA with the results obtained based on the single criterion using PCA showed that the critical sub-systems must be identified based on the multiple criteria. Based on these findings, a two-step process for characterisation of the sub-systems was devised to provide an improved framework for reliability analysis.

Finally, to ensure the incorporation of the KPIs both for functional reliability and service reliability in the selection of the maintenance strategy for each sub-system, a reliability performance-based model was developed that enables the overall reliability of the sub-system to be computed using a reliability index. This index explains the overall reliability of the sub-system based on the impact of a change in its FFF on the change in the number of services cancelled and the number of services delayed due to a proposed maintenance strategy considering the influence of the latent variables. This model was used to predict service reliability in two hypothetical maintenance scenarios and it was shown that it can be used to compare the performance of different maintenance strategies, thus providing valuable assistance in the maintenance planning of urban trains.

In this research, a better RCM process has been developed based on an improved approach for the reliability analysis used to characterise the operational performance of the urban train system, and a new maintenance model used to select the best maintenance strategies. This RCM process can be used to achieve more effective maintenance planning that in turn will ensure greater service reliability.

DECLARATION

I, Maryam Nawaz, declare that this thesis titled, `A Performance Based Reliability Engineering Approach for Urban Trains in Melbourne' and the work presented in it are my own. I confirm that:

- This thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief.
- This thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.
- The thesis is fewer than the maximum word limit in length, exclusive of tables, maps, bibliographies and appendices as approved by the Research Higher Degrees Committee.

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LIST OF ABBREVIATIONS

FFS	Functional Failures
FFF	Functional Failure Frequency
FMECA	Failure, Modes, Effects and Criticality Analysis
KPIs	Key Performance Indicators
MDBF	Mean Distance Between Failures
MFA	Multiple Factor Analysis
MMS	Maintenance Management System
OSR	Overall Sub-system Reliability
OSRI	Overall Sub-system Reliability Index
%OSRI	Percentage of Improvement in Overall Sub-system Reliability Index
PCA	Principal Component Analysis
RCM	Reliability Centred Maintenance
SDA	Simple Descriptive Analysis
SACI	Sub-system Average Cancellation Index
SADI	Sub-system Average Delays Index
UTS	Urban Trains Service

Chapter 1: INTRODUCTION

1.1 Introduction

Reliability centred maintenance (known as RCM) is a strategical and tactical level engineering process for the development of the maintenance plan for an asset that is used in many industries, including in urban train systems. In order to improve reliability, RCM identifies the functionally critical sub-systems of the system based on the criteria set to meet the strategical goals of the business. It also determines the reasons for the functional failures of the identified critical sub-systems to establish the basis for maintenance planning (Deakin, 1996, Rausand, 1998, Crespo Márquez, 2007).

This research explores how RCM ensures the achievement of strategical targets of service reliability of a fleet of urban trains subject to the maintenance plan. It aims to develop an understanding of the conventional process in use for this, and to find opportunities for improvements in this process.

This chapter introduces the background and motivation for this research, followed by the aims and objectives of the research. It also discusses the scope, limitations and contributions of this research. The chapter concludes by outlining the structure of this thesis.

1.2 Research Background and motivation

There is great commercial pressure on the operators of any urban train service to provide a reliable service to its users. On-time arrival of urban trains is an important measure of service reliability for passengers (Higgens A., Kozan E, 1998 cited in Treurnicht, 2012) and frequent disruptions in the service can discourage them from using the trains. Functional failures (FFs) in various sub-systems of the train system influence service reliability by bringing delays and cancellations in the service. These FFs can harm the company’s reputation and decrease its ridership. Any decrease in the number of passengers can make the operation of the service economically unviable. Hence, ensuring the delivery of reliable service to its users is a major concern for both owners and operators of an urban train system.

The operators make a great effort to prevent the occurrence of FFs through an effective maintenance regime. Various approaches for developing an effective and efficient maintenance plan have evolved including reliability centred maintenance (RCM) that has become a well-known method for maintenance planning in many industries including the rail industry. RCM offers a structured process to preserve the system's functional state by developing the maintenance strategies based on the findings of the reliability analysis (Rausand, 1998, Crespo Márquez, 2007). The reliability analysis identifies and investigates the functionally critical sub-systems. Its findings direct the process for the selection of the maintenance strategy that will offer the maximum reduction in the frequency of functional failures (FFF) in the critical sub-systems under given constraints. However, decreasing the FFF does not always ensure a reduction in their consequences (Treurnicht, 2012) which are the cancellations and delays in the case of urban trains.

To ensure not only the reduction in the FFF but also the reduction in their consequences, the maintenance planning must consider the KPIs for both functional and service reliability which are determined according to the perspectives of the main stakeholders (i.e. the users, owner and operator). FFF is used as a KPI for assessing functional reliability, and the number of delays and cancellations in service are used as KPIs for assessing service reliability. In RCM, although service reliability is observed against functional reliability, studies of reliability analysis do not show how all the data collected on the KPIs is manipulated for operational performance characterisation i.e. what information is extracted from the data and how the data is analysed. While it is claimed that considering all the KPIs in the process theoretically results in overall improvement in the reliability, in practice it is also possible that more frequent failures can cause less disruption in the service, while less frequent failures can bring more disruption (Bergström and Krüger, 2013). This is because of the influence of the latent variables of the dynamic operational environment of the urban rail system (Rezvanizaniani et al., 2009, Bergström and Krüger, 2013) . The latent variables govern the operational performance characteristics of any mode of public transport beyond the prescriptive procedures (Attah K. Boame (2004) and Daraio, C. and Simar, L. (2007) as cited in Georgiadis et al., 2020). However, the reliability analysis studies do not provide a clear understanding of how the influence of these latent variables is considered in the analysis in characterizing the operational performance. In addition, modelling has not been undertaken that integrates the KPIs both for functional reliability and service reliability and of the influence of the latent variables to prioritise different maintenance strategies in the maintenance planning.

To address these gaps in understanding, the RCM process of urban train systems needs to be investigated in detail. To examine current practice, a case study of a good urban train service needs to be undertaken. In this research, the urban train service (UTS) Melbourne was selected for the case study. The UTS successfully delivers 2200+ services on a daily basis and generates 233 million trips per annum (Lawson, 2017). The reliability performance has been constantly improved and the assigned targets have been achieved or surpassed (Victorian, 2016, Victorian-Auditor, 2016). The focus of this research is thus to examine the conventional practice using data from UTS Melbourne and to propose an improved process.

1.3 Aims and objectives

The research reported in this thesis focusses on the RCM based maintenance planning of the fleet of urban trains with a broad aim:

To investigate the RCM process used by the urban rail industry for trains, and to propose a new improved RCM process that achieves the overall reliability by integrating the performance measures for functional reliability and service reliability, and the influence of latent variables in the process.

To achieve the broad aim of this research, the following research objectives have been framed. These research objectives were developed in response to the major research gaps identified in the literature review presented in Chapter 2.

RO1 To investigate and find opportunities for improvement in the conventional approach of reliability analysis in the RCM process for the operational performance characterisation of a fleet of urban trains through a case study of the UTS Melbourne.

RO2 To develop an improved approach for the reliability analysis by:

(a) using an exploratory multivariate data analysis technique for better operational performance characterisation based on a single criterion considering the influence of the latent variables, and

(b) using an extension of this data analysis technique based on multiple criteria to integrate the KPIs for both functional reliability and service reliability.

RO3 To develop a model for prioritisation of the maintenance strategies based on their effectiveness at delivering overall improvement in the reliability of the sub-system or sub-systems.

In context of this thesis, the term “overall improvement in the reliability” refers to a level of reliability that is acceptable to all the main stakeholders. This improvement is established by striking a trade-off between the desired level of functional reliability and service reliability.

The research approach adopted in this research is outlined in Figure 1-1. It shows the three major research components with the research method used, the type of data inputs and the research objective for each component. The qualitative and quantitative data used in this research were obtained from UTS Melbourne. The selection of the analytical techniques for each research method used in each component is discussed in detail in the relevant chapters of the thesis.

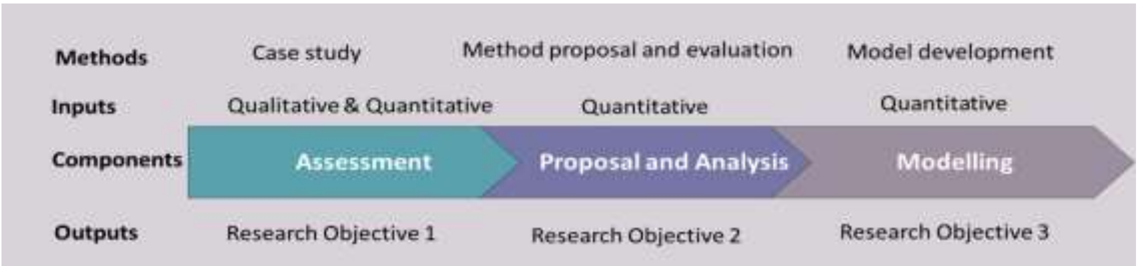


Figure 1-1: Research approach

1.4 Scope and limitations of the research

This study focuses on the key elements of reliability centred maintenance-based maintenance management system (RCM based MMS) of an urban train system that are the reliability analysis, prioritisation of the maintenance strategies and reliability measuring system. It is based on an investigation of the conventional process through a case study of RCM based MMS at UTS Melbourne. The conventional RCM process is investigated to understand how the KPIs are used for operational performance characterisation of the sub-systems in the reliability analysis and for prioritisation of the maintenance strategies, and to propose an improved process for overall improvement in the reliability of the urban trains. However, the proposed RCM process has a wider application as it can be incorporated into the maintenance management system for any urban train system when the particular requirements of that train system are taken into consideration.

The improved RCM process is proposed based on multivariate data analytical techniques using KPIs for both functional reliability and service reliability for characterising the operational performance. In addition, the process is extended by developing a model to provide a decision-making tool that enables the selection of maintenance strategies by evaluating the influence of the improved functional reliability on service reliability. To evaluate the model performance, relevant data from the UTS Melbourne are used. However, some assumptions are made where data are not available or cannot be reported because of confidentiality concerns. All assumptions are clearly stated in the relevant sections of the thesis chapters.

1.5 Contributions of this study

The key contributions of this research are:

(1) a detailed understanding of the reliability analysis in the RCM process currently used to characterise the operational performance of the urban train system in Melbourne

(2) an improved analytical approach for better characterisation of the operational performance of the urban train system that enables the influence of the latent variables to be considered

(3) an improved multiple criteria approach for managing the concerns of all the main stakeholders in the analysis

(4) a model for prioritising the maintenance strategies considering the impact of improved functional reliability on service reliability.

The improved analytical approach presented in this thesis will enable reliability analysts and decision makers to assess the historical trends of overall reliability in the data. It will aid in establishing realistic performance benchmarks for the fleet. In addition, the proposed model for the evaluation of the proposed maintenance strategies will aid in better cross fleet management between the maintenance and the operational departments. Finally, this model will enable the strategical goals of both functional reliability and service reliability to be achieved.

1.6 Thesis structure

The thesis has seven chapters including this introduction. The structure of the thesis is shown in Figure 1-2 which also highlights the original contributions to knowledge that are the outcomes achieved in each part of the research. The content of each chapter is outlined below.

Chapter 2 – Literature Review – this chapter first presents important definitions and concepts that provide essential background for the review. Maintenance types and strategies that are conventionally used for maintenance planning of the urban trains are outlined, and the key elements of RCM based MMS summarised. The development of the RCM process and its applications in the rail industry particularly for the urban train system, are reviewed. The key elements of RCM based MMS are then critically reviewed to investigate the criteria and the data analysis techniques that are used in practice in each element. Finally, the advanced multivariate data analysis techniques that are beginning to be employed for big data management in the urban rail industry are discussed. The chapter concludes by highlighting the research gaps that have been identified in the review.

Chapter 3 – The conventional approach of reliability analysis for operational performance characterisation of an urban trains fleet - This chapter first explores the conventional approach for reliability analysis for operational performance characterisation of the sub-systems using information collected from the UTS Melbourne and the literature review. Next the chapter assesses the approach by analysing the KPIs data collected from the UTS Melbourne using simple descriptive analysis. Potential ways to improve the conventional reliability analysis approach are established.

Chapter 4 – Operational performance characterisation of an urban trains fleet based on a single conventional criterion by using principal component analysis - This chapter proposes an improved reliability analysis approach that uses the same single criterion, FFF, but a different data analysis technique, an exploratory multivariate data analysis technique called principle component analysis (PCA). This proposed approach aims to incorporate the influence of the latent variables into the analysis. The proposed approach is applied to analyse the same data from the UTS Melbourne to establish the operational performance characteristics, and the results are compared with those obtained using the conventional approach as reported in Chapter 3. It is found that PCA can be used for establishing five operational characteristics of the sub-systems considering the influence of the latent variables.

Chapter 5 – Operational performance characterisation of urban trains based on multi criteria by using multiple factor analysis - Based on the reliability approach presented in the previous chapter, this chapter proposes a reliability analysis approach that uses multiple criteria by integrating the KPIs for both functional reliability and service reliability, and applies a multiple factor data analysis technique, MFA, that is an extension of PCA. This approach aims to establish the operational characteristics that provides insight into the impact of functional reliability of the sub-systems on service reliability, thus integrating the KPIs in their cause-and-effect structure into the analysis. The results obtained using MFA analysis with multiple criteria are compared with PCA results with FFF, and it is found that the operational characterisation using multiple criteria is needed for identification of the sub-systems that are critical in relation to both functional reliability and service reliability.

Chapter 6 – Development of a simple model for reliability performance-based prioritisation of the maintenance strategies – In this chapter, a model is developed to prioritise the maintenance strategies by measuring the overall improvement in the reliability (i.e. improvement in functional reliability together with the improvement in service reliability) considering the influence of the latent variables. The model is validated by analysing the data collected from the UTS Melbourne. The chapter aims to provide a practical tool for comparing the different possible maintenance strategies by obtaining the value expected to be added to the overall reliability by the proposed strategies.

Chapter 7 – Conclusions and recommendations for future work – this chapter presents the key findings of the research and outlines valuable directions for the future work.

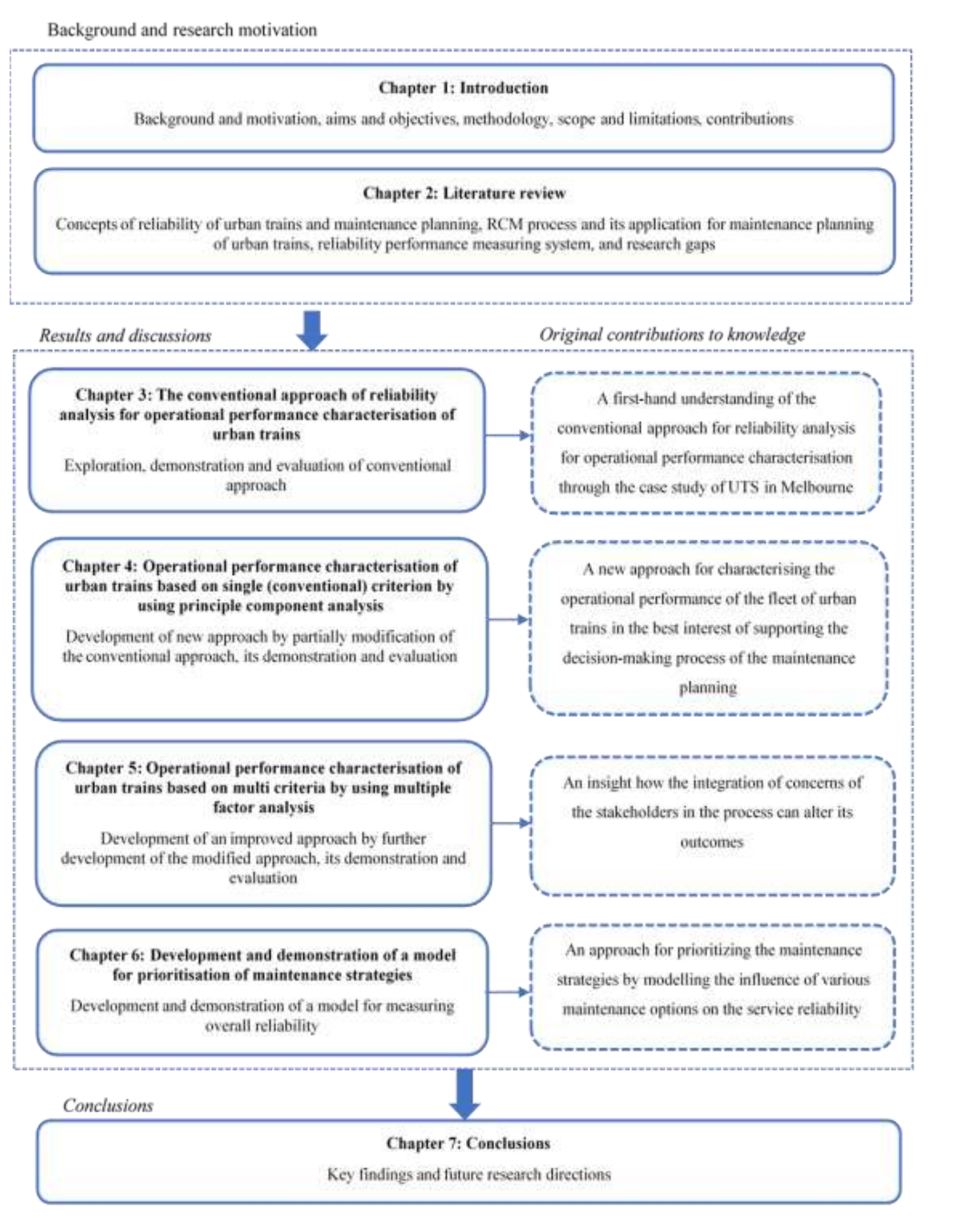


Figure 1-2: Thesis Structure and Research Contributions

Chapter 2: LITERATURE REVIEW

2.1 Introduction

Since the mid-1990s, reliability centred maintenance (RCM) has been widely used as the maintenance management system to improve the reliability of urban train systems. The aim of this review is to investigate the published research on the application of RCM-based maintenance planning for improving the operational performance of urban trains.

As for any maintenance management system, the three major elements of an RCM based maintenance management system are:

(1) reliability analysis (i.e. risk assessment)
(2) prioritisation of the maintenance strategies (i.e. evaluation of the maintenance strategies for selection)
(3) reliability measuring system (i.e. a set of key performance indicators for continuous monitoring of reliability-based operational performance)

Thus, in this chapter studies of these elements of the RCM based maintenance management system are critically reviewed. However, essential background of reliability and the maintenance management system of urban trains is first presented, and important terms and concepts are explained to establish the theoretical understanding required for the review. The chapter concludes by summarising the findings from the literature.

2.2 Basic definitions and the key concepts

2.2.1 Reliability, maintainability and availability

Reliability is defined as the probability of performing an intended function without any functional failure for a specific period under a given operating environment (MIL-STD-7217, 1981 as cited in Treurnicht, 2012); more precisely this is called functional reliability (Cota and Halloran, 2016, Kiran, 2017). In the case of urban trains, the intended function is to transport passengers (i.e. the users). However, random functional failures (FFs) occur in various sub-systems of the urban train system such as the brakes system, door system and traction system

(Teshome.M.M, 2012), thus taking the train out of operation and causing services to be cancelled and delayed.

The users measure service reliability in terms of on-time arrival of trains (Higgens and Kozan, 1998 as cited in Treurnicht, 2012). Since disruption in the service brings cost to the users (Transek, 2006 as cited in Bergström and Krüger, 2013), the frequent disruptions in the service negatively affect the relationship between the company and its users (McCredle, 2007). This results in financial losses to the company including the monetary penalties for the owner failing to provide services on time to its users. Hence, in ensuring the availability of the trains for operation, the operators pay great attention to improving functional reliability of the fleet through maintenance planning.

However, improving functional reliability of the urban train system through maintenance planning is not simple. Maintenance planning aims to achieve functional reliability of the sub-systems (Endrenyi et al., 2001) which can be measured in terms of mean distance between failures or of functional failure frequency (denoted as FFF) in a given period (Vaiciinas and Bureika, 2014). However, maintenance planning is constrained by the maintainability of the sub-systems which is measured in terms of ease, cost, safety and accuracy of performing the maintenance (Blanchard et al., 1995).

Maintenance planning is a process inclusive of all the technical, administrative and managerial actions that are taken during the life-cycle of each sub-system to retain or restore the sub-system to its functional state. By contrast the maintainability of the sub-system is a design parameter that refers to the ability of the sub-system to be maintained in a functional state (Blanchard et al., 1995, Crespo Márquez, 2007). These definitions make it clear that maintenance planning and maintainability are different terms. On the other hand, functional reliability and the maintainability are interrelated (Schenkelberg, 2021) since both depend on the inherit design characteristics of the sub-system (Kumar et al., 2000). Hence, functional reliability and maintainability jointly ensure the availability of the train for operation.

Within maintenance planning the selection of different levels of functional reliability and maintainability affects the availability of urban trains as shown in Table 2-1. As can be seen in the table, if the maintenance planning keeps functional reliability of the sub-system constant, even at a high value, it does not result in an increase in the availability of the train if the maintainability of the sub-system decreases. Since maintainability is associated with the time to re-instate the sub-system to its functional state (Kumar et al., 2000), a decrease in the maintainability involves an increase in the maintenance time that results in a decrease in the availability of the train. Similarly, keeping the maintainability of the sub-system constant, even if it involves much less time to restore the functional state of the sub-system, maintenance planning cannot increase the availability if functional reliability of the sub-system decreases. Hence, for the maintenance planning, the interaction between functional reliability and the maintainability determines the availability of the train for operation.

Table 2-1: Impact of functional reliability and maintainability on availability

Reliability	Maintainability	Availability
↔ Constant	↓ Decreases	↓ Decreases
↔ Constant	↑ Increases	↑ Increases
↑ Increases	↔ Constant	↑ Increases
↓ Decreases	↔ Constant	↓ Decreases

Source: Table from Chapter 6: Introduction to repairable systems from System Analysis Reference: Reliability, Availability and Optimization (Reliasoft Corporation, 2003) that shows the impact of interaction between functional reliability and the maintainability on the availability of a system.

In summary, this section has presented some basic definitions, highlighted the importance of functional reliability, and explained how functional reliability and the maintainability affect the availability of urban trains.

2.2.2 Reliability based operational performance measuring system and latent variables

With the growing need to report reliability based operational performance and the evolution of user-oriented maintenance planning, many key performance indicators (abbreviated as KPIs) have been developed over time to describe and to quantify the reliability of urban trains. The KPIs are selected for reporting and maintenance planning consistent with the perspectives of stakeholders, i.e. the users, owner and operator.

KPIs for reporting - the reliability of urban trains is reported to: (1) internal management, (2) governments, authorities, or franchisors and (3) users and the media (Karathodorou and

Condry, 2016). Since the aim of reporting is to regulate the on-time arrival of trains, the reliability is reported in terms of the KPIs that quantify the occurrence of FFs and their effect on on-time arrival of trains (Melo et al., 2011). An occurrence of FF in any sub-system of an urban train system prevents the train from its on-time arrival at the station and causes delays and cancellations that affect service reliability. Thus, FFF is used to report functional reliability, and the number of services cancelled and number of services delayed are used to report service reliability.

KPIs for maintenance planning - maintenance planning is carried out at three different levels of the organisational hierarchy - strategic, tactical and operational levels (Crespo Márquez, 2007). As each planning level has different objectives, different KPIs are used to quantify and describe the reliability of a fleet of urban trains at each level. For instance, at the strategic level, reliability is quantified in terms of functional failure frequency (i.e. FFF as defined earlier), while at the tactical level, mean distance between failures is usually used.

Mean distance between failures is a criterion for measuring the reliability of urban trains which is defined as the mean distance between mechanical failures (MDBF) of a car causing a delay of equal to or greater than five minutes (CoMet and Nova Group, 2006). It characterises the operational performance of the service where the higher the MDBF is, the more efficient the service. Since MDBF is the ratio of total travelled distance to the FFF and it is measured by considering a delay in service equal to or greater than five minutes, the total travelled distance for computation of MDBF is eventually measured in relation to the basic KPIs i.e. FFF, the number of services delayed and by extension the number of services cancelled. Thus, these three basic KPIs are used to quantify the reliability both for reporting and for maintenance planning (and even for operational planning). These KPIs are used collectively to describe the reliability based operational performance of urban trains. The measures that explain the performance of any system in the given operational environment, including the combined effect of deign characteristics, manufacturing quality, maintenance, organisational policy etc, are known as reliability based operational performance measures (Kumar et al., 2000), and the system in which this data is collected refers as reliability measuring system.

Many variables are combined together to form the operational environment of any system in which it operates (Kumar et al., 2000). Some of these variables are internal such as the asset condition, management policies and use of technology, while others are external such as the weather, passenger behaviour, signalling or the urban rail infrastructure system (Melo et al., 2011). The variables of the operational environment of any public transport mode affect its operational performance sometimes resulting in a failure to achieve the desired performance (Georgiadis et al., 2020), for instance, the degraded condition of track, which is an external variable that is beyond the control of the train's maintenance department, may cause a FF to occur in a wheel. In addition, the combined effect of operational environment variables determined the number of services cancelled and delayed due to the occurrence of a FF in any sub-system of a system of an urban train. For example, the occurrence of a FF in the door system of a train at the busiest station can halt the whole operation for hours. It was found in a study of the service reliability of the Taipei railway (Lane, 2018) that an initial three minutes delay in service are the consequent of FF in any sub-system of train. Other studies by (Melo et al., 2011) and (Alwadood et al., 2012) discuss how the variables that affect service reliability (in terms of delays) can cause the occurrence of FFs in trains.

Since the influence of these variables is not directly observable, they are called the latent variables (Shyrane, 2011). Thus, in order to improve the reliability of urban trains, it is important to identify the latent variables of the operational environment that influence the operational performance (Melo et al., 2011).

2.2.3 Maintenance types and strategies

With the increase in the complexity of the design and operational challenges of an urban train system, different maintenance types (also known as techniques) broadly categorised as corrective, preventive or predictive have evolved over many years. These maintenance types have been defined in International Standard IEC 60300-3-11 and its Australian version AS IEC 60300.3.11-2011 (Standards Australia Committee, 2011), and by a number of researchers (Duffuaa et al., 2000), (Kumar et al., 2000), (Moubray, 2001), (Crespo Márquez, 2007), (Wu, 2020) and (Upkeep Maintenance Management, 2021). Definitions from the mentioned standards and the authors have informed the following definitions that are used in this study. While these standards and authors defined the maintenance types for maintenance of an item, here they are defined for maintenance of a sub-system.

Corrective maintenance is a type of maintenance which is performed to restore the functional state of a sub-system after it has suffered a functional failure. It can be classified into two kinds of maintenance known as immediate maintenance (also known as unplanned corrective maintenance) and deferred maintenance (also known as planned run-to-failure).

Immediate maintenance involves the urgent and extensive repair of a sub-system that completely loses its functionality when an unplanned FF occurs, while deferred maintenance involves an urgent and extensive repair of the sub-system that is intentionally allowed to operate until it completely loses its functionality (i.e. when the FF is planned).

Although run-to-failure maintenance makes the most of the maintenance process for railway assets (Kefalidou et al., 2018) including urban trains, it is not the best choice because it is costly and negatively impacts the service reliability (Umiliacchi et al., 2011).

Preventive maintenance is a type of planned maintenance performed to reduce the FFF of a sub-system and it is undertaken before the actual occurrence of an FF in the sub-system. It can be further classified as time-based, usage-based or condition-based preventive maintenance.

Preventive maintenance is time-based or periodic maintenance when it is planned to be performed at a fixed an interval of time throughout the year such as weekly, monthly, quarterly or yearly. Preventive maintenance is usage-based or performance-based maintenance when it is planned to be performed after specific measurement is reached such as a given number of KMs travelled or hours in operation. Finally, preventive maintenance is condition-based maintenance when there is a decline in its functional performance that is detected after monitoring of the actual condition of a sub-system.

Preventive maintenance is the most commonly used type of maintenance performed on urban trains. However, there are a number of limitations with this type of maintenance, including inadequate proactive maintenance, the recurrence of the problem, inappropriate maintenance activities, more frequent disruption in service and the relapse into corrective maintenance (Smith, 1993 as cited in Rezvanizaniani et al., 2008).

Predictive maintenance is an essentially condition-based maintenance, but it is performed following a prediction derived from the analysis of the data collected on certain parameters measuring the decline in the condition of the sub-system.

This maintenance type is highly desirable for maintenance of urban trains as it is the most proactive approach to prevent the FFs. However, it is still not very common as it involves integration of intelligent technologies for condition monitoring so it has not been explored much (Umiliacchi et al., 2011).

Each maintenance type has its advantages and disadvantages. Predictive maintenance results in greater improvement in functional reliability of a sub-system by incurring less maintenance cost than preventative maintenance, and preventive maintenance than reactive maintenance (Umiliacchi et al., 2011, Nappi, 2014). By contrast, initial cost for implementation of predictive maintenance is greater than that of preventive maintenance, which is in turn greater than that of reactive maintenance. Furthermore, the maintenance requirements for each sub-system are different and they also affect the safety and comfort of users differently, and thus more than one type of maintenance needs to be used to develop the whole maintenance plan. Hence, to achieve a cost-effective and well-balanced maintenance plan, a different maintenance strategy is developed for each sub-system by combining different maintenance types (Cheng and Tsao, 2010, Vaiciinas and Bureika, 2014).

Maintenance strategies are formulated from the maintenance objectives of the sub-systems that are consistent with the organisational strategical goals (Duffuaa et al., 2000, Moubray, 2001, Crespo Márquez, 2007). Maintenance strategies have been defined in a number of very similar ways as follows:

(1) a policy that explains which maintenance type is required to be performed on which component of the sub-system (Kumar et al., 2000).
(2) a set of rules that describes a sequence of steps for performing the planned maintenance of a sub-system (Sharma, 2012).
(3) a systematic process for detection, examination and execution of various maintenance decisions for repairing, replacing and inspecting different components of the sub-system (Kelly 1997 as cited in Velmurugan and Dhingra, 2015) .
(4) a method adopts by the management to achieve the accepted maintenance objectives i.e. assigned targets (the British and European Standard for maintenance management BS EN 13306:2017 as cited in Adams, 2019).

In this study, a maintenance strategy is taken to be a managerial policy for the maintenance of a sub-system that determines which maintenance type to use, when and how to use it and on which component of the sub-system.

In general, a maintenance strategy can be either corrective or proactive depending upon the maintenance type which contributes most in the formulation of this particular strategy. Common maintenance strategies that are listed in (Kumar et al., 2000) and (Jidayi, 2015) are classified into these two types and are outlined below.

Corrective maintenance strategies involve initiation of corrective maintenance activities after the occurrence of FF. A corrective maintenance strategy is usually considered for non-critical sub-systems with a knowledge of the resulting consequences of FF. It is classified as a failure-based maintenance strategy if the FF was not anticipated, and a run-to-failure-based maintenance strategy if FF was anticipated.

Proactive maintenance strategies involve implementation of preventive and predictive maintenance activities before the occurrence of FF. A proactive maintenance strategy is considered for critical sub-systems in which the occurrence of FF can result in poor consequences. It is classified as:

(1) a time-based maintenance strategy if it involves scheduling of preventive maintenance of the sub-system at a fixed interval such as x number of years or x number of run hours.

(2) an age-based maintenance strategy if it involves scheduling of preventive maintenance of the sub-system on reaching x age.

(3) a condition-based maintenance strategy if it involves scheduling of preventive maintenance or predictive maintenance based on the deterioration in the functional performance of the sub-system below the certain observable threshold.

(4) a design modification strategy if it involves redesign of the sub-system which is a part of the improvement maintenance strategy. It is applied only when the sub-system life cycle cost for maintenance and the downtime cost exceeds to the value of benefits i.e. availability of train for operation.

Each maintenance strategy has a number of advantages and disadvantages. For example, the selection of a short interval in time-based maintenance strategy may affect functional reliability of the sub-system negatively due to maintenance-induced FF (Rausand, 1998). Hence, in maintenance planning, different strategies are developed and evaluated in order to select the one that can achieve the assigned targets by satisfying most of the defined concerns.

In summary, this section has discussed the maintenance types and strategies that are commonly employed in the maintenance planning of urban trains.

2.2.4 Maintenance management systems

As for any asset-intensive industry, the development of a well-balanced maintenance plan is the key to improve key to improve the operational performance of an urban train system. A maintenance plan is considered to be very effective if the percentage ratio of preventive maintenance to corrective maintenance is 80/20 in its formulation (Åhrén, 2008, Mike Shekhtman as cited in Sigga Technologies, 2021), but such a high ratio is rarely achieved. Although various maintenance strategies from reactive to proactive in nature have been evolved, a selection and execution of an appropriate strategy within a limited time is quite challenging.

Given these issues, a centralised maintenance management system (MMS) has been developed to streamline the overall process of maintenance planning. A brief overview of a MMS and its development over a time is discussed by (Crespo Márquez, 2007) and it is outlined here. Crespo Márquez (2007) states that a comprehensive MMS aims to perform the following functions:

(1) it defines the maintenance objectives (i.e. what are assigned maintenance performance targets?)
(2) it determines the maintenance strategies (i.e. what is a managerial approach to achieve the assigned targets?)
(3) it devises an implementation plan including details about maintenance quality control and improvement procedures and methods (i.e. how is maintenance executed?)

However, over a time it has been realised that a well-designed MMS is needed of to deal with many concerns, data sources, strategies, techniques and tools. The MMS structured on an IT system, maintenance engineering process and the organisational values has been commenced to be installed. The MMS is characterised by the maintenance engineering process, while an IT system and the organisational values aid in the functioning of an engineering process in developing and executing the maintenance plan.

The two most common maintenance engineering processes are total productive maintenance (TPM) and reliability centred maintenance (RCM). TPM aims to improve the effectiveness of a system in terms of its availability for operation by eliminating various losses involved in the process, while RCM aims to improve the reliability of a system by preserving its functional state (Marten Jr, 2009, Prabhakar P and V. P, 2019). This means that the selection of a maintenance engineering process reflects the underlying philosophy for the MMS of the particular organisation.

Since RCM based MMS is widely used in the urban rail industry, it will be described in detail in the next section.

2.2.5 Reliability centred maintenance-based maintenance planning

RCM based maintenance planning provides a structured process for determining the maintenance needs of any physical asset in its operational context (Moubray, 2001). It is used to formulate a preventive maintenance plan for an asset in which it is assumed that the reliability of any asset relies on its inherent design characteristics and manufacturing quality (Rausand, 1998). The focus of RCM based maintenance planning is on preservation of a system's functions by prioritising the maintenance tasks based on the criticality of failure modes of the system (Nowlan and Heap (1978) as cited in Backlund, 1999). The purpose of the formulated maintenance plan is to maintain, restore or improve the operational performance of the system (Farooq and Vallabh, 2010). It is a continuous closed loop process which is used to develop or to review a maintenance plan on the basis of functional failure analysis of the sub-systems that have a substantial influence on the safety, operations and lifecycle cost of the system (Lachemot, 2013).

In the mid-to-late 70's, (Nowlan and Heap) established the concept of RCM for aviation (Moubray, 2001). Nowlan and Heap (1978) stated in their work that "In the traditional approach, a scheduled maintenance plan was developed based on the concept that all items of a complex system required to be overhauled at a "right time". Over the years, it was realised that many types of failures could not be prevented by this traditional approach. To resolve this issue, the designers started to design "failure-tolerant" airplanes by adding multiple engines, and by designing the damage-tolerant structures. This resulted in significant increase in design and maintenance cost of airplanes, but the failure rate of certain types of unreliable engines could not be improved by feasible options i.e. change in procedure or in frequency of scheduled overhauls. Thus, a task force was designed to develop an approach that can assist the aviation industry in developing an efficient preventive maintenance plan for airplanes."

This reliability engineering-based systematic process was first used by the aviation industry and after its successful application in aviation, it was adopted by various industries (Bulmer (1996) including the urban rail industry. In the early 1990s, London Underground began implementing RCM on its trains, signals, and tracks (Dallaway, 1996) and several projects in the European Union including RAIL, REMAIN and Norway railways used RCM based maintenance planning for railway infrastructure (Carretero et.al. 2003 cited in Rezvanizaniani et al., 2008). Today, while this maintenance approach is now used by railway companies all over the world, most focussed on applications of RCM for the maintenance of tracks and signals (Rezvanizaniani et al., 2008).

To develop a maintenance plan, RCM answers the following seven questions about the system's functionality as listed by (Moubray, 2001):

(1) What are the functions and the associated performance standards of the system under the given operating environment?
(2) In what ways does the system fail in performing the functions?
(3) What are the causes of each functional failure?
(4) What happens when each failure occurs?
(5) In what way does each failure matter?
(6) What can be done to predict or prevent each failure?
(7) What should be done if a suitable proactive task cannot be found?

The RCM based maintenance planning process is exhaustively explained in a number of studies including studies by (Nowlan and Heap, 1978) , (Rausand, 1998), (Moubray, 2001),(Crespo Márquez, 2007) ,(Rezvanizaniani et al., 2008), (Farooq and Vallabh, 2010), (Nordin, 2015) and (Emovon et al., 2016). The steps in the closed-loop process are shown in Figure 2-1.

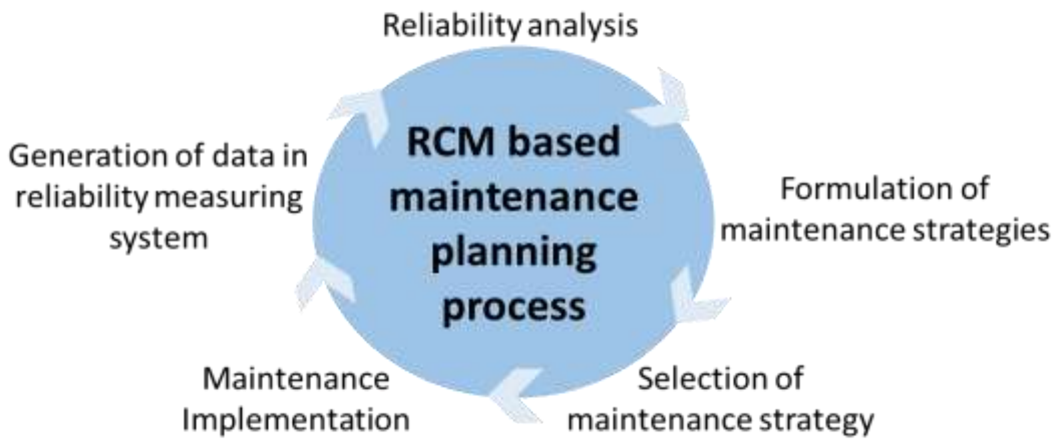


Figure 2-1: RCM based maintenance planning process.

As can be seen in Figure 2-1, the RCM based maintenance planning process is composed of five elements (or stages) that include reliability analysis, formulation of maintenance strategies, selection of maintenance strategy, maintenance implementation and generation of data in reliability measuring system. These are discussed here:

Reliability analysis establishes the reasons for the maintenance by performing risk assessment of the system in which the performance of a system is considered under the given operational environment. There are two steps in the reliability analysis. First the functionally critical sub-systems are identified that have significant influence on the safety, operation and life-cycle cost of the system. In order to make the process cost-effective, only 10% - 20% of the critical sub-systems of the system are considered to make the process cost-effective (Farooq and Vallabh, 2010). In the case of a simple system, the critical sub-systems are obvious and there is no need to use any specific technique to identify them (Emovon et al., 2016).

Next functional failure analysis (denoted as FFA in this study) of the identified operationally critical sub-systems is carried out. The FFA investigates the potential failure modes of the operationally critical sub-systems; whereas, a failure mode is an event that results in a functional failure in the sub-system i.e. failed state (Moubray, 2001). There are different techniques to perform the FFA such as Failure, Modes, Effects and Criticality Analysis (FMECA), fault tree analysis, root cause analysis, failure block diagram analysis and cause consequence analysis. However, FMECA is the most commonly used in practice as there are a number of published guidelines and standards that provide the qualitative and quantitative procedures to be performed in FMECA depending upon the availability of the data. In FMECA, a link is established between the probability of failure modes of components of the sub-system, their effect on the system's mission and functions, and the causes and mechanism of failure modes to determine the risk associated with the failure modes.

Reliability analysis is the core of the RCM process as it answers the first five questions.

Formulation of maintenance strategies involves identification of a maintenance type for each identified critical sub-system, determination of maintenance intervals and optimisation of maintenance resources. Decision logic diagrams are usually used for identification of maintenance types, and the decision factors as per the company's strategical aims are considered in the diagram. Safety is generally measured as first followed by reliability and cost (Cheng and Tsao, 2010). For maintenance scheduling and optimisation, complex algorithms and mathematical models are used. Several strategies are formulated based on different combination of maintenance types and the maintenance interval constraint to the available maintenance resources.

The formulation of the maintenance strategies of the RCM process answers the remaining two questions.

Selection of maintenance strategy strategies involves prioritisation of the formulated maintenance strategies based on their effectiveness in delivering the maintenance objectives. It involves complex decision-making with trade-offs between the achievement of different maintenance objectives. However, there is no established approach which is internationally recognised for prioritisation of maintenance strategies.

Implementation involves the creation of a plan for implementation of the selected maintenance strategies. The plan contains details about quality control and improvement methods for effective execution of the plan maintenance plan.

Generation of data in the reliability measuring system refers to the measurement and monitoring of the reliability based operational performance of a system in terms of KPIs for reliability. As highlighted by (Crespo Márquez, 2007), RCM identifies the maintenance types for a system considering the operating environment under which it operates. Since the operational environment of the urban rail industry is not constrained by some physical boundary, as in production industry, data collected on the KPIs, in addition to measure against the assigned targets, are analysed to characterise the operational performance of a fleet of urban trains.

Since maintenance planning is a closed loop process as shown in Figure 2-1, the outputs of the previous element are the inputs for the next element. The RCM based maintenance planning is mainly guided by the FFA using RCM technique i.e. FMECA. A widely accepted International Standard IEC 60300-3-11 and its identical Australian version AS IEC 60300.3.11-2011 (Standards Australia Committee, 2011) provides a complete guideline for application of RCM technique for maintenance planning. The overall process of maintenance planning in relation to an application of FMECA is shown in Figure 2-2 which is taken from the standard AS IEC 60300.3.11-2011.

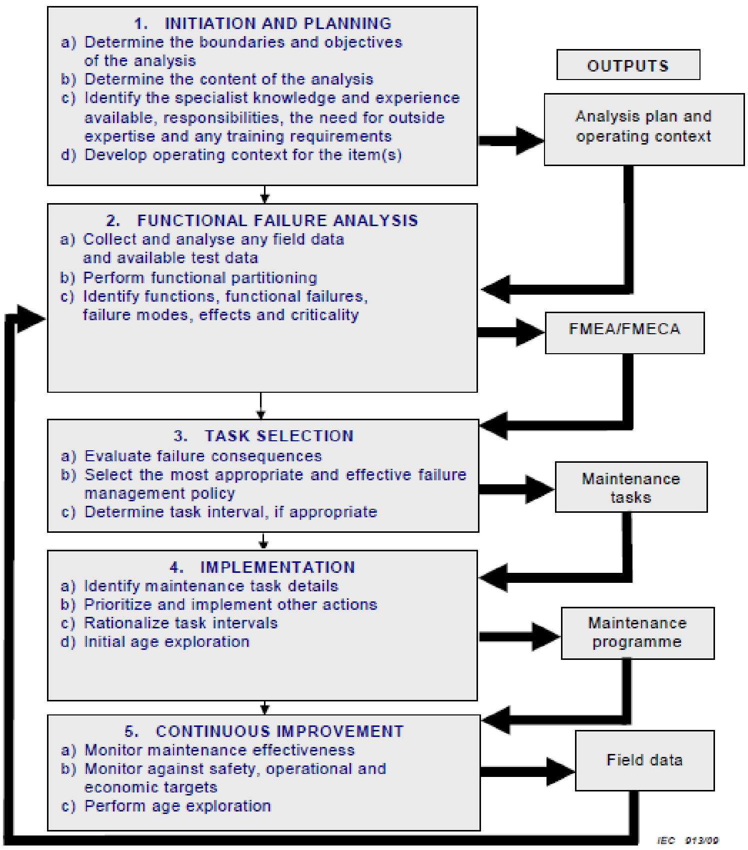


Figure 2-2: An overall process of maintenance planning using RCM technique (i.e. FMECA) as given in AS IEC 60300.3.11-2011

The stages shown in Figure 2-2 are in consistent with the elements of the maintenance planning as shown in Figure 2-1. In Figure 2-2, the first two stages describe the process for conducting the FFA using FMECA i.e. Step 2 of reliability analysis. Stage 2 answers the first five questions about the sub- system's functionality as listed earlier in this section, thus provide deep understanding about failure behaviour of the sub-system. The outputs of second stage establish reasons for determining the maintenance type for each component of each sub-system in Stage 3 which comes under the formulation of maintenance strategies in relation to Figure 2-1. The fourth stage shows implementation of the maintenance plan and the last one involves collection of data on the KPIs for reliability for continuous improvement in the operational performance of the sub-systems. In addition, the standard AS IEC 60300.3.11-2011 provides a decision diagram for assistance in selection of an appropriate maintenance strategy in Stage 3 for failure management of the sub-system. Figure 2-3 shows a decision diagram which is taken from the standard AS IEC 60300.3.11-2011 (Standards Australia Committee, 2011).

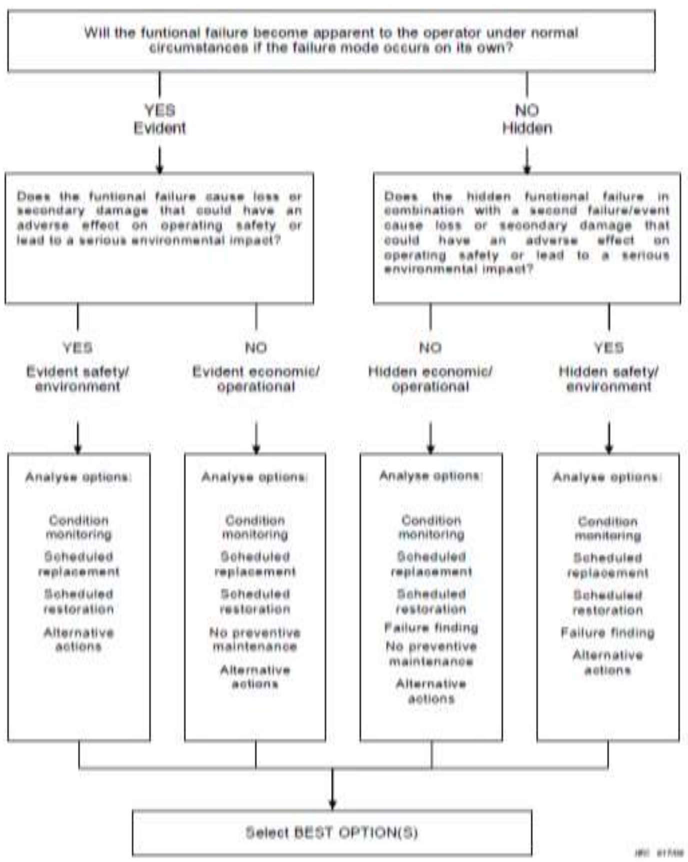


Figure 2-3: RCM decision diagram for selection of an appropriate maintenance strategy as given in AS IEC 60300.3.11-2011

As can be seen in Figure 2-3, the decision diagram first links the failure modes of the sub-system with the consequences in terms of safety and economy, and then use this information in determining an appropriate maintenance type to manage each failure mode of the sub-system (Moubray, 2001, Crespo Márquez, 2007) . The decision diagram is a tree of RCM logics that assists and ensures consistency in making the decisions for the selection of maintenance type for the sub-system, thus answers the last two RCM questions as listed earlier in this section.

In summary, RCM based maintenance planning determines the maintenance needs by investigating functional reliability of a system.

2.3 Review of studies of RCM based maintenance planning for urban train systems

This section presents a critical review of relevant studies available in the published literature of key elements of RCM based MMS. While there may be studies of research conducted within commercial enterprises, these remain confidential and thus there are only a small number of published studies that form the basis of this review. The aim is to establish current approaches to the conventional RCM process through published case studies of urban train systems and to evaluate these approaches to identify their strengths and limitations.

2.3.1 Studies of reliability analysis

There are only a few published studies of RCM based reliability analysis of urban train systems. These studies investigate the urban train systems in different countries particularly China, focusing on the reliability analysis of the different sub-systems of the trains including the brake, bogie, door, and heating, ventilation and air conditioning (i.e. HVAC) sub-systems. In most of the studies, the conventional technique applied for the reliability analysis is FEMCA while in a few others studies, different techniques were applied to overcome limitations of FMECA that include a lack of consideration for (1) the interdependency of the components, (2) random occurrence of FFs or (3) difficulty in obtaining the information related to the failure effects and probability. These studies are reviewed in this section to investigate the approaches including the criteria and the techniques that are commonly used in each step of the reliability analysis.

2.3.1.1 Studies using FMECA

Details of the studies that applied FMECA for FFA of the critical sub-systems are presented in Table 2-2. The criteria that are used to identify the critical sub-systems in Step 1 of the analysis are listed. As shown in the table, while in two studies by (Guan, 2016) and (Catelani et al., 2021) no criterion was reported, in most of these studies the only criterion applied to identify the critical sub-systems in Step 1 of the analysis was FFF. As can also be seen in the table, the technique applied to analyse the FFF data in Step 1 is also listed, but the only study that reported the technique that they used was the study by (Rezvanizaniani et al., 2009) where the researchers applied Pareto analysis, one of the simple descriptive analysis (SDA) techniques.

Details of the functional failure analysis of the critical sub-systems in Step 2 of the FFA are also provided in Table 2.2. As can be seen in the table, in all the studies, the criticality of the failure modes of the critical sub-system was mainly determined using the following measures: ease in detection of the failure modes, frequency of their occurrence and severity of their impact on the functional performance of the sub-system and on the users' safety. Other measures were used in two of the studies. Jaehoon and Hyun-Yong (2013) considered the operational consequences in the computation of severity of the failure modes of the components of the critical sub-system but does not report which ones, while Dinmohammadi et al. (2016) considered the passengers' dissatisfaction.

In addition, the standard procedure of FMECA was applied in five of the seven the studies reviewed. In Feng et al. (2019) FMECA was applied in combination with the fuzzy method, and in Catelani et al. (2021) the authors proposed an improved approach for FMECA to differentiate between the critical and insignificant failure modes of the critical sub-system.

2.3.1.2 Studies using other techniques

Findings from the studies that applied techniques other than FMECA for the FFA of the critical sub-systems in Step 2 of the reliability analysis are presented in Table 2-3.

As can be seen in Table 2-3, none of the listed studies reported how the critical sub-systems were identified in Step 1of the reliability analysis. Only one study by Conradie et al. (2015) reported that they had applied the reliability block diagram in Step 1 not to identify the critical sub-systems but to consider the interdependency of the components of the critical sub-system in the reliability analysis, and thus the KPIs data were not analysed in this study. It is also clearly evident from Table 2-3 that all the listed studies had used different techniques in Step

2 for FFA of the critical sub-systems. Discussion of these techniques is beyond the scope of this study. However, in general these techniques apply the probability or uncertainty theory in the computation of criticality of the failure modes of the components of the critical sub-system based on their frequency of occurrence or failure rate. No information for application of the KPIs for service reliability was reported in any of these studies.

In the studies of FMECA based reliability analysis, FFF is used as the conventional criterion in Step 1 for identification of the critical sub-systems and it is assumed that reducing the FFF in those critical sub-systems will improve functional reliability and thus service reliability. The review of the studies that used the techniques other than the FMECA, shows that the researchers simply state which sub-systems they will use for the analysis and they do not provide any details about the criteria used for the selection of these sub-systems. None of the studies has explained the operational performance characterisation of the sub-systems using the KPIs for reliability. In addition, no specific technique has been identified as a standard tool to identify the functionally critical sub-systems that would ensure uniformity in the analysis across such studies.

By contrast, FMECA is widely used as the standard tool to perform FFA in Step 2 of the reliability analysis. Many studies also present an improved approach for FFA either by modifying FMECA or by developing a new method. Finally, none of the studies have considered the influence of the latent variables in the reliability analysis.

In summary, it is concluded that further research is needed to gain an understanding about the conventional approach of reliability analysis for characterising the operational performance of urban trains using the KPIs data, and how the influence of the latent variables is considered in this approach.

Table 2-2: Summary of the studies of reliability analysis of urban train systems using FMECA					
Authors' names and study year	**Study Country**	**Critical sub-system selected for the analysis**	**Step1: Identification of the critical sub-systems**		**Step2: Functional failure analysis of the critical sub-system**
			Criteria	**Technique for categorisation**	**Criteria for computation of criticality of the failure modes**
Rezvanizaniani et al. (2008) and Rezvanizaniani et al. (2009)	Iran	Wheel sets – bogie	FFF	Pareto Analysis	Detection number, occurrence number and severity number
Cheng et al. (2013)	China	Door	FFF	Not reported	Failure rate, frequency ratio, failure effect probability and working time
Jaehoon and Hyun-Yong (2013)	Korea	Brake	FFF	Not reported	Detectability, frequency and severity based on safety and operational consequences
Dinmohammadi et al. (2016)	Scotland	Door	FFF	Not reported	Likelihood of occurrence based on a failure rate and severity based on economic impacts, social impacts (i.e. passengers' dissatisfaction), safety impacts and environmental impacts
Guan (2016)	China	Brake	Not mentioned	Not reported	Detection number, occurrence number and severity number
Feng et al. (2019)	China	Door	FFF	Not reported	Occurrence, severity, detection and maintainability
Catelani et al. (2021)	From Europe	HVAC	Not mentioned	Not reported	Detection number, occurrence number and severity number

Table 2-3: Summary of studies of reliability analysis of urban train systems using other techniques					
Authors' names and study year	**Study Country**	**Critical sub-system selected for the analysis**	**Step1: Identification of the critical sub-systems**		**Step2: Functional failure analysis of the critical sub-system**
			Criteria	**Technique**	**Technique**
Liming et al. (2010)	China	Door	Not reported	Not reported	Monte Carlo based on Fault tree analysis
Ren and Xing (2014)	China	Door	Not reported	Not reported	FMEA based on fuzzy TOPSIS
Shi et al. (2015)	China	Door	Not reported	Not reported	Monte Carlo based on Fault tree analysis
Conradie et al. (2015)	South Africa	Full coach	Not applicable	Reliability block diagram for interdependency of the sub-systems	Reliability equations
Lin et al. (2016)	China	Bogie	Not reported	Not reported	Complex network theory
Zhu et al. (2016)	China	Bogie	Not reported	Not reported	Fault tree analysis by fuzzy importance degree analysis
Cai et al. (2018)	China	Brake	Not reported	Not reported	Go-Bayes

2.3.2 Studies of prioritisation of the maintenance strategies

There have been only a few studies reported in the literature of the prioritisation of the maintenance strategies of urban train systems as highlighted by (Mohammadi et al., 2020). Since there is no RCM based standard approach which is globally recognised for prioritisation of the strategies as discussed in Section 2.2.5., different approaches have been developed internally by the decision-makers for prioritisation of the strategies in different industries and even within the same industry (Tam and Price, 2008).

This section critically reviews published studies of maintenance optimisation and selection of maintenance strategies. The different approaches are examined including the criteria and the techniques used, and the models and decision-support tools commonly applied in the urban trains systems. In addition, studies of prioritisation of maintenance strategies in other industries are reviewed to explore the approaches used.

2.3.2.1 Studies of urban trains systems

Details of the studies of maintenance optimisation of urban trains systems are summarised and presented in Table 2-4.

It can be seen in Table 2-4 that all studies of maintenance optimisation incorporated measures in the criteria that are related to maintenance planning and capacity planning. While passenger demand was considered in the criteria in the studies by (Wu and Lin, 2016) and (Lin and Lin, 2017), the ultimate objective in both studies was to optimise the maintenance schedule by considering workshop capacity. In addition, the modelling tool commonly used in these studies were variants of the genetic algorithm. In general, because genetic algorithms are known to solve both constrained and unconstrained problems of optimisation by using the natural selection process established in biological evolution (The MathWorks, 2021), a genetic algorithm is a popular choice for dealing with maintenance optimisation problems.

Only three of these studies focus on the prioritisation of the maintenance strategies. The study by (Cheng and Tsao, 2010) involved the selection of the maintenance strategy by using the analytical network process. As can be seen in Table 2-4, although the criteria incorporated functional reliability of the sub-system in terms of failure rate, this study aimed to prioritise the possible maintenance strategies based on their effectiveness in delivering a better ratio of preventive maintenance to corrective maintenance by optimising the replacement interval constrained by the availability of spare parts. This means that the ultimate aim of the approach presented in this study is to optimise the maintenance resources. In addition, in this study, the latent variables were known to the researchers, and factor analysis was applied to condense many latent variables into the high-level categories of quality and efficiency, cost and reliability, and safety. The reliability was represented in terms of condition of a system and the shut down time of the sub-system. However, this is the only study found in which the influence of the latent variables was considered in the approach presented for selection of the maintenance strategy.

The study by (Lu, 2003) proposed a model to prioritise the maintenance strategies based on their effectiveness in accommodating the maximum consumer surplus (i.e. the users' demand) subject to the constraints listed in the criteria in Table 2-4. Since the time the train is out for maintenance impact the operational plan. The performance measures i.e. waiting time and head time variation were incorporated into the development of model to establish a relationship between the existing maintenance and the operational plan. Five simple models were developed within the model to quantify the impact of maintenance time on passengers' spill, service operation, waiting time saving, traincrew and life cycle cost in monetary units. Although the model establishes a relationship between the maintenance and the operational plan, it does not incorporate measures that can assist in quantifying the improvement in operational performance of the sub-systems or train.

The final study of the selection of the maintenance strategy is by (Aslam-Zainudeen and Labib, 2011). The decision-making grid analysis presented in this study for selection of maintenance types was initially developed by (Aslam-Zainudeen and Labib) for application in the automotive industry (Labib et al., 1998), and then they applied it in the manufacturing industry (Labib, 2004). In the 2011 study, (Aslam-Zainudeen and Labib) applied the same approach to identify the maintenance strategies for the critical sub-systems of the fleet of Class 319 operated by First Capital Connect in the UK. This approach is developed on a combination of rules-based approach (i.e. a set of rules that the experts use to reach decisions) and the analytical hierarchy process (Aslam-Zainudeen and Labib, 2011). The sub-systems were ranked in descending order of selected criteria i.e. FFF and delays (in minutes), Pareto analysis was applied to determine the top-most critical sub-systems based on each selected criterion, and each of the identified critical sub-system was then placed in a cell of the decision-making grid (DMG) according to their rank determined against each criterion. Each cell of the DMG suggests a specific maintenance strategy which is determined by the analytical hierarchy process.

Although this study addressed the issue of selection of maintenance strategy, there are some limitations in their approach. This approach is greatly influenced by expert judgement. It is specifically designed to determine the maintenance strategy based on the historical data, and it does not incorporate a procedure that can assist in evaluating the maintenance strategies based on their effectiveness in improving the operational performance of the sub-systems.

2.3.2.2 Studies of prioritisation within urban rail and other industries

There have been a number of relevant studies of maintenance optimisation in other industries, and they are reviewed here according to the industry in which each study occurred.

Automotive and manufacturing industry: Decision-making grid analysis has been applied for maintenance optimisation in the automotive industry (Labib et al., 1998), and in the manufacturing industry (Labib, 2004). These studies were discussed earlier.

Power industry: Li and Brown (2004) developed a simple approach for prioritisation of the maintenance strategies for electric power and distribution industry. In this study the weighted average system reliability index, WASRI, is computed by incorporating the weighted impact of failure rate of the system on each factor of concern individually. These factors included the system interruption frequency, system interruption duration and momentary interruption frequency. The mathematical formulation to measure the impact was the failure rate times the ratio of the factor to the base number and the indexes obtained were the system average interruption frequency index, the system average interruption duration and the momentary average interruption frequency. Thus, WASRI is a sum of three weighted indexes. Since WASRI was derived from the factors that measure the losses in the system, a lower value of WASRI indicates better performance of the system. The ratio of the computed WASRI to the cost associated with the maintenance task was used for prioritisation of maintenance tasks. This approach was then applied for evaluation of the utility system with more than 4000 components and five sub-stations that resulted in reduction in WASRI by 28% constrained within the given budget.

Urban rail industry

Åhrén and Parida (2009) presented an approach to compute an overall railway infrastructure effectiveness (ORIE) based on the concept of overall equipment effectiveness from manufacturing industry. The study does not directly involve the prioritisation of the maintenance strategies; however, it assessed the operational performance of infrastructure by multiplying the infrastructure availability, the infrastructure performance rate and the infrastructure quality rate subject to the maintenance planning. The underlying assumption was that the variation in each of the incorporated measures would not affect the other measures. Although this approach is simple, obtaining each measure involves collection of data or computation of different parameters which are not always possible to access or compute easily. Most importantly the concept of overall effectiveness is applied in the maintenance planning which is based on the total productive maintenance process.

Lai et al. (2015) developed a framework for an optimum allocation of resources between different components of the urban rails system such as trains, signals and tracks by a trade-off between life cycle cost, system reliability (i.e. mean time between failures) and service reliability (i.e. delays in minutes). The framework was composed of two models that are the alternative evaluator (AE) and investment selector (IS). The AE module evaluates all alternatives for each component of the urban rails system and IS determines the best investment alternative for each component based on (i) maximization in service reliability subject to life cycle cost and (ii) minimisation of life cycle cost subject to service reliability. In subsequent studies, (Lai et al., 2017) and (Lu et al., 2017) applied the same framework to develop an integrated model for the development of an optimal investment plan subject to the acceptable life cycle cost, system reliability and service reliability. This framework can be used for prioritisation of the maintenance strategies for urban trains. However, it is a complex model, requires a proven software for application and the underlying concept of its functioning improvement in one measure by compromising improvement in another make it an inappropriate choice.

It is evident from the review that maintenance problems are quite diverse in nature, and thus approaches developed for solving a particular problem are not necessarily suitable for solving other problems. There is currently no approach that involves the prioritisation of the maintenance strategies based on improvement in both functional reliability and service reliability. Thus, further work is needed to develop such an approach and evaluate its performance.

The model presented in the study by (Li and Brown, 2004) for prioritisation of maintenance strategies in the power industry in which multiple measures are integrated into a single index looks promising as the basis for developing a similar model for the urban trains. This is because (i) Li and Brown’s model also aims to improve the reliability (ii) it integrates performance measures that are established based on the indicators that measure the losses in reliability in the same way that the performance measures of urban trains are established based on the KPIs that measure the losses in reliability (iii) it measures the impact of functional failures on each factor of concern individually and (iv) it incorporates weights in the equation that allows the influence of the latent variables to be considered in the evaluation.

Table 2-4: Summary of studies of maintenance optimisation

Authors' names and study year	Aim	Criteria	Modelling tool
Sriskandarajah et al. (1998)	Optimisation of maintenance overhaul scheduling	Total cost of earliness and tardiness (or total penalty for not satisfying the due dates) Maintenance requirements	Developed a genetic algorithm by using a heuristic technique for global optimisation
Lu (2003)	Selection of maintenance strategy based on effectiveness in delivering a maximum consumer surplus	Budget, crew, vehicle capacity, policy Engineering, safety and workshop capacity	Developed a model by establishing a relationship between operational and maintenance plan by integrating performance measures - average wait time and headway variation
Rezvanizaniani et al. (2008)	Optimisation of preventive maintenance interval	Cost Un-necessary maintenance work	Designed a logic tree decision diagram
Cheng and Tsao (2010)	Selection of maintenance strategy based on a ratio of preventive maintenance to corrective maintenance constraint to the number of spare parts	Cost Reliability (in terms of condition) Safety of workers and trains Maintenance quality Work efficiency of staff Quantity of spare parts required and failure rate of trains	Used analytic network process
Park et al. (2011)	Optimisation of preventive maintenance interval	Life cycle cost Availability	Used AvSim software

Han et al. (2011)	Optimisation of mean time to failure (MTTF) and mean time to repair (MTTR)	Life cycle cost Availability	Developed a hybrid genetic algorithm combined with a heuristic method
Aslam-Zainudeen and Labib (2011)	Selection of maintenance types	Rate of occurrence of failure Downtime (delay minutes)	Applied a decision-making grid: hybrid of rule-based approach and the multiple criteria analytic hierarchy process
Umiliacchi et al. (2011)	Optimisation of preventive maintenance processing in sub-system of railway (like rolling stock)	Mission critical fault occurrence Life cycle cost	Applied ontology-based model
Asekun (2014)	Optimisation of maintenance schedule	Cost Reliability	Applied multi objective optimisation model (proposed by Moghaddam, & Usher, 2011)
Wu and Lin (2016)	Optimisation of major maintenance schedule	Cost Peak period passenger demand Workshop capacity	Developed a genetic algorithm with a time-space network
Lin and Lin (2017)	Optimisation of high maintenance plan by assigning schedule to each train and maximizing the utilization of remaining running mileage	Cost Workshop capacity Maintenance rate Peak period passenger demand	Developed a simulated annealing based heuristic algorithm

2.3.3 Studies of the application of data collected in reliability measuring system

While the RCM based maintenance planning studies reviewed in the previous two subsections provide useful knowledge of the application of the data collected on the KPI for functional reliability, these studies do not discuss how the KPIs data for functional reliability and service reliability are analysed for operational characterisation of the sub-systems. Thus, this section presents a review of other studies of application of the KPIs for reliability for improving the reliability of trains. The aim is to develop an understanding of how this data has been applied.

Many studies have been conducted on the use of the KPIs, particularly of the data for services delayed, in the operational planning of urban trains system. Schmöcker et al. (2005) used services delayed data for selection of the service restoration strategy after the occurrence of FF in a train. In this study, the impact of constraints such as service frequency on the effectiveness of the strategy was considered by using simple mathematics calculations and charts. Services delayed data was also applied by Jiang et al. (2007) who used the data to characterise the propagation of delays on the network. The researchers used a model to simulate the impact of changes in availability, buffer time and number of cold standby trains in a fleet on service punctuality and reliability. Other studies that also applied services delayed data were a study by Preston et al. (2009) who used the data to analyse the impact on users and freight trains in monetary units by using the traditional schedule utility approach and then a modelling approach to compute the reliability premiums. In order to develop a model to reduce the services delayed, Alwadood et al. (2012) reviewed (1) the types and causes of services delayed, (2) the impact of services delayed on operator and the passengers in monetary terms and (3) the reduction in services delayed due to various projects by different companies across Asia and Europe.

Some other studies that also applied services delayed data were a study by (Bergström and Krüger, 2013) who applied the services delayed data to analyse the distribution of delays on the network with respect to their vulnerability, space and time in order to identify where the measures for improved reliability need to be provided on the network. Finally, a study by (Barron et al., 2013) who applied data collected on the FFs of trains together with the data on the hours of train delays and on the hours of delays for users. The authors used simple bar charts to analyse the impact of FFs on service reliability and on the users. One further study of the application of data collected in the reliability measurement system was a study by (Bernal et al.) used services delayed data to analyse the impact on ridership by using GIS software and multiple linear regression.

By contrast, there are very few studies of application of KPIs in the maintenance planning. In fact after an extensive literature research, only one study was found. Treurnicht (2012) analysed the FF data to determine the contribution of critical failure modes of the sub-systems of a system of urban trains to the number of services delayed, the number of services cancelled and the delays in minutes. The researchers then used SDA to analyse the data obtained in order to determine the cost for the loss in reliability due to the FFs in trains.

It is clear from the review that studies of operational planning mainly used the data collected on the FFF and the number of services delayed for post disruption management, while only one study of maintenance planning by (Treurnicht, 2012) was found that analysed the KPIs data to determine the contribution of FFF in causing services delayed, services cancelled and delayed minutes to determine the consequential cost of the loss in reliability. Thus, it is still not known what information is assessed from the KPIs data for operational performance characterisation of the sub-systems for maintenance planning, and whether or not SDA is useful in characterising the operational performance of sub-systems. Thus, further research is needed to develop this understanding.

2.4 Review of studies using exploratory multivariate data analysis techniques for big data analysis

The reliability measuring system for an urban train fleet is an amalgamation of the different datasets from the reliability KPIs. This amalgamation results in an enormous amount of data that needs to be analysed using big data analytics tools to extract the maximum useful information from the data in the best possible way. There has been interest in the application of these tools in the railway industry (Thaduri et al., 2015) particularly given the clear advantages they offer over traditional analytical techniques that are based on SDA that only provides a summary of data (D'Agostino et al., 2016). In fact, there are reasonable number of studies that shows applications of different big data analytics tools for operation and maintenance of trains. Fink et al. (2013) applied a combination of conditional restricted Boltzmann machines and echo-state networks for binary time series prediction of occurrence of disruption in railway operation in terms of speed restrictions due to functional failures in tilting system of train; also, Fink et al. (2015) used fuzzy classification with restricted Boltzmann machine and echo-state networks approach for prediction of failures in door system of the train; Fang et al. (2020) applied Mont Carlo Simulation for assessing the criticality of components of railway network in causing disruption on the network; Crespo Márquez et al. (2020) developed a predictive model using a combination of generalised linear models, artificial neural network, decision trees, random forest, gradient boosted trees and support vector machines for designing condition-based maintenance plan for axle bearings of trains. In all these studies, big data analytical tools were applied to approximate the original data for future outcomes. Big data analytical techniques are based on inferential statistics that enables analysts to learn from experience by recognising patterns, dependencies and relationships and to forecast outputs (D'Agostino et al., 2016).

However, due to the complexity of big data, data dimension reduction techniques often need to be employed before statistical inference is performed (Fan et al., 2014). Exploratory multivariate data analysis techniques, such as principal component analysis (PCA) and multiple factor analysis (MFA), that are data dimension reduction techniques are commonly used for analysis of big data in many fields including the rail industry. Such as (Fink et al., 2013) applied PCA to reduce the dimensionality and to extract the important features from the speed restriction data of train for development of a prediction model. PCA is used to analyse a dataset that involves a single dataset, while MFA is used to analyse data involving multiple datasets.

This section aims to provide a review of selected studies that used such techniques to analyse big data in order to understand why these techniques were selected. These studies can be grouped according to whether they involve a single dataset or multiple datasets.

2.4.1 Studies of a single dataset using PCA

PCA, the oldest exploratory multivariate data analysis technique, has been extensively used in scientific studies (Abdi and Williams (2010). PCA orthogonally transforms data that involves many variables that are highly correlated and dependent into data that involves few variables that are uncorrelated and independent from each other. This transformation occurs without much loss of information, and reveals the hidden structure of a dataset (Jolliffe, 2002, Abdi and Williams, 2010). This new set of the few variables which are generated by the linear combination of the many variables is called the principal components. The principal components are the factors that provide insight into the underlying phenomena which is responsible for making the data variables highly correlated. PCA is used to analyse quantitative data and it can be performed either through eigen value decomposition or by singular value decomposition (SVD). However, PCA based on SVD is numerically more precise (Kalisch, 2012) and the computation process is fast.

Some recent studies from different fields show the range of applications of PCA. PCA has been applied to examine the preferences of consumers for mineral and tap water (Platikanov et al., 2017); to investigate the performance of athletes in different decathlon events (Kassambara, 2017b); to identify the key indicators responsible for degradation of insulation cable in a nuclear power plant (De Silva et al., 2017); to evaluate the effect of chemical tests on patients (Qureshi et al., 2017); to characterise the texture of pastries produced in different batches (Dunn, 2019).

Other studies show applications of PCA in urban rail industry. It has been applied to characterise the reliability performance of a train passenger assess system under the tightened-up operating conditions (Turgis et al., 2010); to evaluate the condition symptoms for classification of rail track for maintenance (Żółtowski, 2012); to categorise the trains stations based on their criticality in propagating (Dekker et al., 2019).

Since the ultimate objective of these studies was to enable one choice to be made from the many available, PCA was selected as the technique to use. In PCA, the data are characterised based on the underlying patterns and interrelationships between the data observations and the variables based on the influence of the variables that are not directly observable. Thus, PCA is a useful technique that makes it easier to deal with data sets that involve many variables where the analyst is required to determine which one among them needs to be selected for a particular purpose. It enables the dominant features of data to be extracted by eliminating the less important features. However, although PCA provides a sophisticated way of revealing the underlying causes of recurrent and non-recurrent variability patterns in the data, PCA has been found to sometimes fail to reveal important non-linear patterns from the data, and to be unable to characterise well structures which are not orthogonal to the previous principal component (Lever et al., 2017).

2.4.2 Studies of multiple datasets using MFA

MFA is an extension of PCA which is used to analyse simultaneously multiple data sets that can include both qualitative and quantitative data. Abdi et al. (2013) stated that the first step of MFA is to perform PCA on each dataset individually and then to normalize each dataset by dividing their elements with their first singular value. Normalization is crucial to eliminate the dominant effect of any data set having a larger number of variables than others. All normalized datasets are then fused into one grand table. The second step of MFA is to perform PCA on the grand table.

MFA has also been used in a wide range of fields. Pagès (2005) used MFA to determine the patterns of perceptions defined by several sensory parameters for evaluation of wines by experts; Wang et al. (2011) analysed the data from large scale blackout accidents for performance assessment of electricity firms considering several risks associated with the power grid; Platikanov et al. (2017) determined the preference of consumers for mineral or tap water by studying physiochemical parameters in relation to the rating given by consumers.

MFA has very similar advantages and disadvantages to those of PCA. The basic concept in applying MFA is that the same underlying pattern exists within the different datasets that is responsible for making the datasets similar and dissimilar from each other (De Roover et al., 2012). For this reason, MFA is commonly applied in industries where numerous parameters are used for measurements from several perspectives that are linked with the goals of the particular business and the observations must be characterised with respect to all the parameters. One major limitation of MFA is that it may show a false relationship between the data variables and the latent variables associated with the dimensions for no apparent reason. Hence, for the synthetic non-feasible patterns to be disregarded, it is very important that both PCA and MFA are performed by an analyst who knows all the details of the process.

It is clearly evident from the review that exploratory multivariate data analysis techniques are commonly used in many applications in which big data sets are involved, with PCA used when there is a single dataset and MFA when there are multiple datasets. Both these techniques characterise the data based on the amount of variance explained by the variables in the data that are not directly observable. Thus, these techniques are excellent to use to characterise the operational performance data of urban trains considering influence of the latent variables.

These techniques are discussed in more detail in Chapters 4 and 5 when they are used in the analysis of the complex big data sets from the UTS Melbourne urban train system.

2.5 Summary

This chapter has provided the theoretical background on RCM based MMS and reviewed relevant published studies of RCM based maintenance planning of urban train fleets. From the review of these studies, it is evident that the major gaps in the research are:

(1) It is not known how the conventional approach of reliability analysis uses the KPIs data for characterisation of the operational performance of urban trains for maintenance planning.

(2) There is no clear understanding of how the influence of the latent variables (i.e. the operational constraints) on the operational performance of the sub-systems is considered in the reliability analysis.

(3) It is well-established that FFF is used as the conventional criterion for identification of the critical sub-systems in reliability analysis, but it is not known whether the sub-systems identified as critical using only FFF are also critical for service reliability.

(4) There is no specific tool that can be used to prioritise different maintenance strategies for urban trains that integrate the KPIs for both functional reliability and service reliability while considering the influence of the latent variables.

Hence, the broader aim of this research, as stated in Section 1.3 of Chapter 1, is to investigate the RCM process used by the urban rail industry for trains, and to propose a new improved RCM process that achieves the overall reliability by integrating the performance measures for functional reliability and service reliability, and the influence of latent variables in the process.

The rest of the thesis reports the research undertaken to achieve this aim.

Chapter 3: THE CONVENTIONAL APPROACH OF RELIABILITY ANALYSIS FOR OPERATIONAL PERFORMANCE CHARACTERISATION OF AN URBAN TRAINS FLEET

3.1 Introduction

It is known from Chapter 2 that the reliability analysis realises the operational performance characterisation of an urban trains fleet considering the effect of functional reliability on service reliability for the maintenance planning. However, how the conventional approach of the reliability analysis applies the key performance indicators (KPIs) for the reliability for operational characterisation has not been investigated. Thus, there needs to be an investigation of the conventional reliability approach as stated in the first objective of the research in Chapter 1. This will be achieved through a case study of the urban train service (UTS) in Melbourne in order to acquire the richest possible understanding of the conventional approach.

To accomplish this research objective, the first step is to explain the conventional concept of operational performance characterisation of the sub-systems in the process of reliability analysis. The next step is to demonstrate how the conventional approach works by using it to analyse the data collected from the UTS Melbourne. The final step is to evaluate the usefulness of the conventional approach in transforming the KPIs data into useful information for the maintenance planning.

3.2 Conventional reliability analysis approach for operational performance characterisation of urban trains

This section explains the conventional concept of operational performance characterisation of the sub-systems of an urban trains fleet for the maintenance planning based on the information collected from the UTS Melbourne. Information was collected through one-on-one and group meetings with their maintenance and operational personnel, a review of their internal documents that included the technical maintenance plan, monthly performance reports, diagnostic reports, engineering standards, assets class strategy, faults finding guidelines, reliability growth plan, and site visits. The concept is first discussed to develop an understanding of how the KPIs for reliability are applied for the operational characterisation i.e. what information is investigated from the KPIs data for the maintenance planning? Then, section explores how the operational characterisation is achieved i.e. which an analytical technique is applied for it?

3.2.1 Concept of operational performance characterisation of the sub-systems for maintenance planning

The sub-systems of a complex urban train system have varying importance and challenges to the operation of service, so the operational performance characterisation of the sub-systems provides a lens to the differences in their operational performances for the maintenance planning. This characterisation aims to identify the operationally critical sub-systems by using the KPIs for reliability. The sub-systems are primarily categorised with respect to the functional failure frequency (FFF) for identification of the functionally critical sub-systems. In addition, the sub-systems are categorised with respect to the number of services cancelled and the number of services delayed caused by the FFF of various sub-systems for identification of the service critical sub-systems. This means that the operational performance characterisation of sub-systems using KPIs for reliability is performed in Step 1 of reliability analysis, follow by, functional failure analysis in Step 2. Although findings of Step 2 establish reasons for maintenance requirements of the sub-systems, the findings from Step 1 provides additional support in the decision-making process. However, identification of the operationally critical sub-systems is not as simple as it seems. The repository of operational performance data is very large in size, complex and multivariate given that the data measures the reliability of the multiple sub-systems of a complex system of an urban train in terms of the multiple KPIs under influence of the dynamic operational environment of the urban rail as shown in Figure 3-1.

Figure 3-1: Collection and extraction of operational performance data of the UTS Melbourne for maintenance planning.

The figure shows that inputs from the multiple sources are used to generate a rich repository of operational performance data of the urban trains. This data is then cleaned and processed in order to retrieve the various datasets for operational characterisation.

This big data is aggregated per month and per sub-system for each KPI for reliability. Although the impact of occurrence of functional failures in the sub-systems on the service reliability is measured in terms of number of services cancelled, number of services delayed and passenger weighted minutes, the discussion in this study is only limited to two KPIs for service reliability i.e. number of services cancelled and number of services delayed. The datasets of the monthly FFF profile, the sub-system FFF profile, services cancelled profile caused by the FFF of the sub-systems and the services delayed profile caused by the FFF of the sub-systems are retrieved from the repository of operational performance data as shown in Figure 3-1. These datasets are then used to establish various characteristics to trace and evaluate the trends and patterns of the operational performance of the sub-systems. In general, data for each month of the year for last few years are analysed in order to trace the trends and patterns of the operational performance of the sub-systems within a year and from year to year. This information enables the maintenance planners to trace the reason for changes in operational performance of the sub-systems (if any) in relation to changes in the operational environment of an urban rail system. The operational characteristics are established based on an individual and relative assessment of elements of their relative datasets. Hence, each operational characteristic involves extraction of a specific feature from its relevant dataset that are crucial for a decisive decision-making in the maintenance planning. This study presents and discusses the operational characteristics of the sub-systems systematically in the best interest of supporting the decision-making process of the maintenance planning. Table 3-1 lists the datasets that will be used to obtain the operational characteristics.

Table 3-1: Datasets and the corresponding operational characteristics

Datasets	Operational Characteristics
Monthly FFF profile	**C1** the critical months
	C2 the similar and dissimilar months
Sub-system FFF profile	**C3** the critical sub-systems
	C4 the similar and dissimilar sub-systems
Monthly FFF profile together with sub-system FFF profile	**C5** the relationship between the FFF profiles of sub-systems and the months
Services cancelled profile caused by the FFF of the sub-systems	**C6** the critical sub-systems for services cancelled
Services delayed profile caused by the FFF of the sub-systems	**C7** the critical sub-systems for services delayed
Monthly FFF profile together with the services cancelled profile	**C8** relationship between the FFF and the number of services cancelled
Monthly FFF profile together with the services delayed profile	**C9** relationship between the FFF and the number of services delayed

Operational characteristics C1 to C5 as listed in Table 3-1 aim to establish the operational performance of the sub-systems based on the FFF, while operational characteristics C6 to C aim to establish the operational performance of the sub-systems considering the effect of their FFF on the KPIs for service reliability. The datasets, the operational characteristics obtained from them and their use in maintenance planning are outlined in this section.

3.2.1.1 Monthly FFF profile

The number of reported functional failures from the various sub-systems in a month is used to generate the monthly FFF profile. The monthly FFF profile is analysed for operational characteristics C - the critical months and C2 - the similar and dissimilar months.

Since the aggregated value of the KPI of the different sub-systems in a month gives the monthly value of that KPI, this means that the months represent the individuals in which the data on FFF of each sub-system is recorded. This monthly FFF is applied to categorise the months for identification of the critical months i.e.C1 A month is defined as critical if the FFF in that month not only supersedes the assigned monthly target, but it also makes a major contribution in generating the FFF of the year. Thus, the critical months in a year are the months that have provided the unfavourable operational environment for the operational performance of the sub-systems. Hence, C1 identifies the months in which the problem occurred and there is a need to focus on them in the decision-making process of the maintenance planning to reduce the monthly FFF.

C2 - the similar and dissimilar months differentiates between the similar and dissimilar months based on the contribution of FFF from different sub-systems in generation of the monthly FFF profile. Months that have comparable FFF from the same sub-systems are similar months, and the months that do not have comparable FFF are dissimilar months. It is most likely that the months in which the sub-systems have similar operational performance may have some commonalities in their operational environment, and the months in which the sub-systems have dissimilar operational performance they may not. This means that C2 provides an assessment how the months are related to each other i.e. month-to-month relationship. Hence, C2 can be used to ease the decision-making process in the maintenance planning by dealing with the similar and dissimilar months in the groups instead of managing them one by one.

To sum up, the monthly FFF profile is analysed to establish C1 and C2 by identifying the critical and non-critical months, and the similar and dissimilar months.

3.2.1.2 Sub-system FFF profile

The number of reported functional failures for each sub-system in each month is used to generate the sub-system FFF profile, which is then evaluated for operational characteristics C3 – the critical sub-systems and C4 – the similar and dissimilar sub-systems.

An aggregated value of FFF of the sub-systems in different months gives the sub-system FFF for a year. This sub-system FFF is applied to categorise the sub-systems for identification of the critical sub-systems in a year i.e. C3 – the critical sub-systems. A sub-system is defined as critical if its FFF not only supersedes the assigned target, but it also makes a major contribution in generating the FFF of the year. Thus, the critical sub-systems in a year specify the sub-systems that are functionally unreliable. Hence, C3 identifies the sub-systems that are functionally unreliable and there is a need to focus on them in the decision-making process of the maintenance planning to reduce the sub-system FFF.

C4 differentiates between the similar and dissimilar sub-systems based on their FFF recorded in various months. The sub-systems that have comparable FFF in the same months are similar sub-systems, and the sub-systems that do not have comparable FFF in the same months are dissimilar sub-systems. It is most likely that the sub-systems that have similar operational performance in the months may have some commonalities in their functional reliability, and the sub-systems that have dissimilar operational performance in the months may not have. This means C4 - the similar and dissimilar sub-systems assesses how the sub-systems are related to each other i.e. subsystem-to-subsystem relationship. Hence, C4 can be used to ease the decision-making process in the maintenance planning by dealing with similar and dissimilar sub-systems in groups instead of managing them one by one.

To sum up, the sub-system FFF profile is analysed to establish C3 and C4 by identifying the critical and non-critical sub-systems, and the similar and dissimilar sub-systems.

3.2.1.3 Monthly FFF profile together with sub-system FFF profile

Evaluation of the monthly FFF profile and the sub-system FFF profile as discussed above involve individual assessment of these profiles. An additional useful operational characteristic C5 – the relationship between the FFF profiles of sub-systems and the months is able to be established by the relative assessment of these two profiles in order to analyse the effect of improvement in one profile on the other. This can be interpreted in terms of subsystems-to-months and months-to-sub-system relationships.

The analysis of subsystems-to-months relationship establishes operational characteristic C5(a) - characterisation of the monthly FFF profiles. This operational characteristic explores the monthly FFF profiles to identify the sub-systems that contributed the most in making the months similar and dissimilar This enables a common latent variable to be traced in the operational environment of the months, and makes it possible to understand how its presence or absence can influence the operational performance of various sub-systems. Thus, this identifies the combination of the sub-systems in the decision-making process of the maintenance planning that needs to be focussed on for improvement in the FFF profiles, i.e. the reduction in the FFF of various months.

In addition, the months-to-subsystem relationship aims to establish operational characteristic C5(b) - influence of the sub-system on FFF of the months. It determines the sequence of influence of the sub-system on the months i.e. arrangement of months in descending order based on the FFF of the sub-system. C5(b) is required to analyse how the functional reliability of the sub-system varies in a year as this can facilitate in tracing the seasonal patterns over the years (if any exists). Hence, C5(b) enables the tracing of the latent seasonal variables in the decision-making process of the maintenance planning, so seasonal adjustment factors can be applied for the desired improvement in the operational performance of the sub-system.

To sum up, the monthly FFF profiles in relation to the sub-system FFF profiles are analysed to establish C5(a) and C5(b) by identifying the combination of sub-systems that resulted in similar and dissimilar months, and sequence of months in descending order of FFF of the sub-system in them.

3.2.1.4 Services cancelled and services delayed profiles

The reported number of services cancelled and the number of services delayed caused by the FFF of the sub-systems in various months are used to generate the services cancelled profile and the services delayed profile respectively. These profiles are analysed to obtain operational characteristics C6 – the critical sub-systems for services cancelled and C7 – the critical sub-systems for services delayed.

An aggregated value of the number of services cancelled and the number of services delayed caused by the FFF of the sub-systems in various months gives the corresponding total number of services cancelled and the total number of services delayed for the year. This means that the months represent the individuals in which the data on number of services cancelled and number of services delayed due to the FFF of each sub-system are recorded. The sub-systems are critical for service cancellation if the number of services cancelled not only supersedes their assigned target, but they have also a major contribution in the total number of services cancelled in the year. Similarly, the sub-systems are critical for service delays if the number of services delayed not only supersedes their assigned target, but they have also a major contribution in the total number of services delayed in the year. Identification of the critical sub-systems with respect to the effect of FFF on the number of services cancelled and the number of services delayed show the criticality of the sub-system for service reliability. Hence, C6 and C7 identify the sub-systems that need to be focussed on for improvement in their functional reliability in order to achieve service reliability targets.

To sum up, the services cancelled profile and the services delayed profile are analysed to establish C6 and C7 by identifying the critical sub-systems based on the effect of their FFF on the services cancelled and services delayed profiles.

3.2.1.5 Services cancellation profile and services delayed profile together with monthly FFF profile

Evaluation of the services cancelled profile and the services delayed profile as discussed above involve individual assessment of these profiles. Additional useful operational characteristics C8 - relationship between the FFF and the number of services cancelled and C9 - relationship between the FFF and the number of services delayed are able to be established by assessing the services cancelled profile in relation to the monthly FFF profile, and the services delayed profile in relation to the monthly FFF profile. The relative assessment of these profiles is needed to analyse the effectiveness of the maintenance plan in realising the strategical target for functional reliability together with the strategical targets for service reliability. This can be interpreted through the consolidated analysis of the KPIs in their cause-and-effect structure i.e. FFF-to-number of services cancelled and FFF to-number of services delayed. This implies that C8 and C9 involve the analysis of a one-to-one relationship to determine how the KPIs for functional reliability and service reliability varied together. Hence, C8 and C9 provide information about the relative status of the KPIs in the decision-making process of the maintenance planning.

To sum up, the services cancelled profile and services delayed profile are analysed in relation to the monthly FFF profile to establish C8 and C9 by investigating the relationship between the KPIs for functional reliability and service reliability.

This section shows that operational characterisation is a comprehensive process that involves extraction of trends and patterns of operational performance of the sub-systems. The operational characterisation determines the effectiveness of the maintenance plan in delivering the assigned targets for the KPIs in the face of operational challenges. These operational challenges are the latent variables related to the overall operational environment or the functional performance of the sub-systems in a given reporting month or a combination of both. Finally, this information is integrated into the decision-making process at the strategical level of the maintenance planning to prioritise the sub-systems selected for the maintenance. It also provides guidance in determining the level of maintenance efforts that are required to improve the operational performance of the sub-systems.

3.2.2 Analytical technique for establishing operational characteristics

As stated in Section 2.3.1 of Chapter 2, simple descriptive statistics is conventionally applied for an investigation of the KPIs of any urban train system. This technique is a primary tool for summarising any data as it is easy to perform the analysis and to present the results. Since the data analysis is an expensive process, an analysis is considered to be adequate if it is able to trace whether the trend is up or down and to compare the current values with the historic values (Stenström et al., 2012). Hence, this chapter also applies simple descriptive analysis (SDA) for establishing the operational characteristics of the sub-systems. Given that the KPIs for reliability are established based on the frequency counts of operational failures of the sub-systems, an analytical model for the operational characterisation based on SDA mainly works on the rule of descending order. The different SDA tools that are applied for establishing the different operational characteristics are discussed here.

Pareto curve: Operational characteristics C1, C3, C6 and C7 involve characterisation of the data in terms of detecting the important elements of their dataset. Hence, these characteristics are established by the Pareto analysis. This is simply achieved by arranging the dataset in descending order from the largest to the smallest value of the respective KPI. Data is sorted to rank the elements of the dataset that are then used to explain the level of their criticality. The sorted data is then visualised in a simple vertical bar chart that at a glance identifies the highest and the lowest value of the individuals in the dataset. The individuals involved in the data are then used together with the cumulative percentage of the KPI under study (i.e. FFF, number of services cancelled or number of services delayed) to plot a line graph which is the Pareto curve. Thus, the Pareto chart is a combination of a simple bar chart and the Pareto curve. The value of the KPI is displayed on the left y-axis, the cumulative percentage of the KPI on the Pareto curve is displayed on the right y-axis, and the individuals involved in the data (that are the months or the subsystems) are displayed along the x-axis.

The cumulative percentage of KPI at any point X on the Pareto curve can be computed by the formula shown in Equation 3-1:

$$Cumulative\ percentage\ of\ KPI\ at\ X\ = \left(\frac{Cumulative\ \ KPI\ value\ at\ X}{Total\ value\ of\ KPI}\right) * 100 \qquad \textbf{3-1}$$

Using a table in which the KPI data are arranged in ascending order, the cumulative value is obtained by adding the percentage of KPI at any point X to the sum of all its predecessors, while the total value of the KPI is the sum of KPI value for all months or the sub-systems. Since the data are arranged in ascending order, according to Eq 3.1, the cumulative percentage of KPI at X is greater than or equal to the cumulative percentage of the previous individual, and less than or equal to that of the next individual. The cumulative percentage of the last individual in the dataset is always equal to 100%.

Since the Pareto analysis is applied to measure and categorise the individuals involved in the data, the cumulative percentage is used to determine the number of individuals (i.e. the months or sub-systems) that lie above (or below) a particular cumulative percentage value in the data set. The Pareto principal defines this value at 80% cumulative percentage of KPI as the Pareto principle states that 80% of consequences come from 20% of causes. For this reason, the Pareto principle is also known as 80/20 rule. Thus, to identify the critical months or the critical sub-systems, a cut-off line is marked on the Pareto curve at 80% cumulative percentage of the KPI, and a vertical line from the point of intersection of the Pareto curve and the cut-off line is drawn to the x-axis thus dividing the months or the sub-systems into the critical or non-critical category. All months or sub-systems with cumulative percentage values up to the point where the vertical line meets the x-axis are the critical months or sub-systems, and the all other months with cumulative percentage values greater than the point are the non-critical months or sub-systems.

Based on the interpretation of the 80/20 rule, the identified critical months or the critical sub-systems of the urban train system should be 20% of the months in a year or the sub-systems that account for 80% of their dataset. This signifies in the maintenance planning that there is 80% opportunity for improvement in the operational performance by dealing with only 20% of the elements of the dataset. This theoretically fulfils the requirement for identification of the topmost critical months for establishing C1, and topmost critical sub-systems for establishing C3, C6 and C7.

Composite bar chart: Operational characteristics C2 and C4 characterise the data in terms of detection of relationships between the elements of the same dataset. Hence, these characteristics are established by compositional data analysis. The sub-systems are arranged in descending order of their FFF within each month for establishing C2. The sorted data is then visualised in the composite bar chart that shows the FFF profile of each month by stacking the FFF for each sub-system on top of each other. Hence, the size of the section of each sub-system indicates its contribution in generation of the monthly FFF profile. The sub-systems that have visually comparable sections in the bars of different months have comparable FFF in those months; hence, those months are the similar months. By contrast the sub-systems that have visually incomparable sections in the bars of different months have incomparable FFF in those months; hence those months are the dissimilar months. In the same way, the composite charts for C4 are plotted and interpreted. The only difference is that in case of C4 , the FFF for each month are stacked on top of each other to represent the composition of the FFF profile of each sub-system.

In addition, the advantage of this compositional data analysis is that the same composite bar charts for C2 and C4 can be applied for establishing operational characteristics C5(a) and C5(b) respectively. In the case of C5(a), comparable sizes of sections of the sub-systems in bars of the same months indicate that these sub-systems have the greater contribution in making those months similar. By contrast, the non-comparable sizes of sections of the sub-systems in bars of the same months indicate that those sub-systems have the greater contribution in making those months dissimilar. In the case of C5(b), the months need to be arranged in descending order of their FFF for each sub-system. This sorting of data represents the sequence of influence of an individual sub-system in the FFF profiles of the months.

Combination chart: Operational characteristics C8 and C9 characterise the data by detecting the relationship between the elements of two datasets. Hence, these characteristics are established by using bivariate data analysis. The aim is to trace the pattern of effect of change in one KPI on the other KPI. Therefore, this is achieved by a combination of a composite bar chart with a line curve. The line curve of the monthly FFF profile is combined with the composite bar chart of services cancelled profile for analysing C8 **.** Similarly, the line curve of the monthly FFF profile is combined with the composite bar chart of services delayed profile for analysing C9 **.** A rise or fall in the line curve of monthly FFF together with an increase or decrease in the height of the bars will show the effect of the monthly FFF on the monthly number of services cancelled and the number of services delayed respectively. The analysis can be extended further to measure the effect of the monthly FFF on an individual sub-system by comparing the rise or fall in the line curve with an increase or decrease in the size of section of the same sub-system in the bars of different months.

In summary, SDA is usually applied for operational characterisation of the sub-systems as it offers several simple tools to characterise the data in terms of descriptive parameters that are easy to report. In addition, an analytical model which is based on SDA is budget-friendly.

3.3 Operational performance characterisation of the sub-systems by using SDA

This section first discusses the data and confidentiality concerns, then presents and discusses the results obtained by the application of SDA to the data collected from the UTS Melbourne. The results are discussed to evaluate the usefulness of SDA in establishing the desired operational performance characteristics of the sub-systems.

3.3.1 Data and its confidentiality concerns

Raw data on operational performance of urban trains for six years were collected from the UTS Melbourne. Data were collected in Year 6, and by that time over 2300 train services on 16 different lines were provided by UTS Melbourne each weekday. Over 230 million annual passenger trips were made which is predicted to be increased to 312 million by 2024. Data details are as follows:

1 The focus of this study is only on urban trains not on any other system of urban rail industry such as signal system and infrastructure, thus data on FFF of urban trains were only collected.

2 Data on delays and cancellations in service due to occurrence of FFs in trains were only collected. This means that disruption in service due to occurrence of FFs in any other sub-system of urban rail system such as signals and infrastructure, and due to any other reason, such as strikes and planned maintenance were not included in the data.

3 Trains from four different manufacturers comprised the fleet. Trains from each manufacturer represent one train type in the fleet, and they were coded as A, B, C and D for analysis.

4 No new trains were introduced in these six years. However, the oldest trains i.e. those of train type D, were removed from the service after Year 3.

5 The total fleet was made up of 421 trains excluding train type D. A unit of 3 cars, composed of 2 driving motor cars and one intermediate trailer, were operated as 6-car trains.

6 Train type A was 185 in number, train type B was 72 in number and train type C was 164 in number.

7 All trains of type A, B and C were continuously in operation i.e. no major out of operation period in six years. Similarly, there was no major out of operation period for train type D from Year 1 to Year 3.

8 An average age of train type A, B and C was 30 years, 11 years and 6 years respectively.

9 There were 19 sub-systems on a train that were coded as S1, S2, …., S19. All train types had the same sub-systems.

10 There was a maintenance strategy for each sub-system and there was no major change in it through six years.

Since the focus of this study is on operational performance characterisation of the sub-systems, no information relating to the functional characteristics of the sub-systems such as failure modes or the configuration of the sub-systems was collected. Thus, the analysis presented in this study is limited to the operational characterisation of sub-systems using the KPIs for reliability. Due to the confidentiality concerns of UTS in Melbourne, passenger weighted minutes was not included in the analysis presented in this study. Thus, data was only collected for each KPI for reliability except passenger weighted minutes for each month of the year. Data was processed and cleaned in Microsoft excel. An occurrence of each FF does not result in disruption in service in terms of delays and cancellations. Thus, non-adherence to scheduled arrival time is used as a measure for reduction in operational performance of sub-systems due to the occurrence of FFs. A threshold of 04’59” for on-time arrival was applied to compute the FFF per sub-system and per month. This means that the functional failures that resulted in delays of less than or equal to the threshold of on-time arrival were discarded from the analysis. The number of services cancelled and the number of services delayed were then calculated from the collected data.

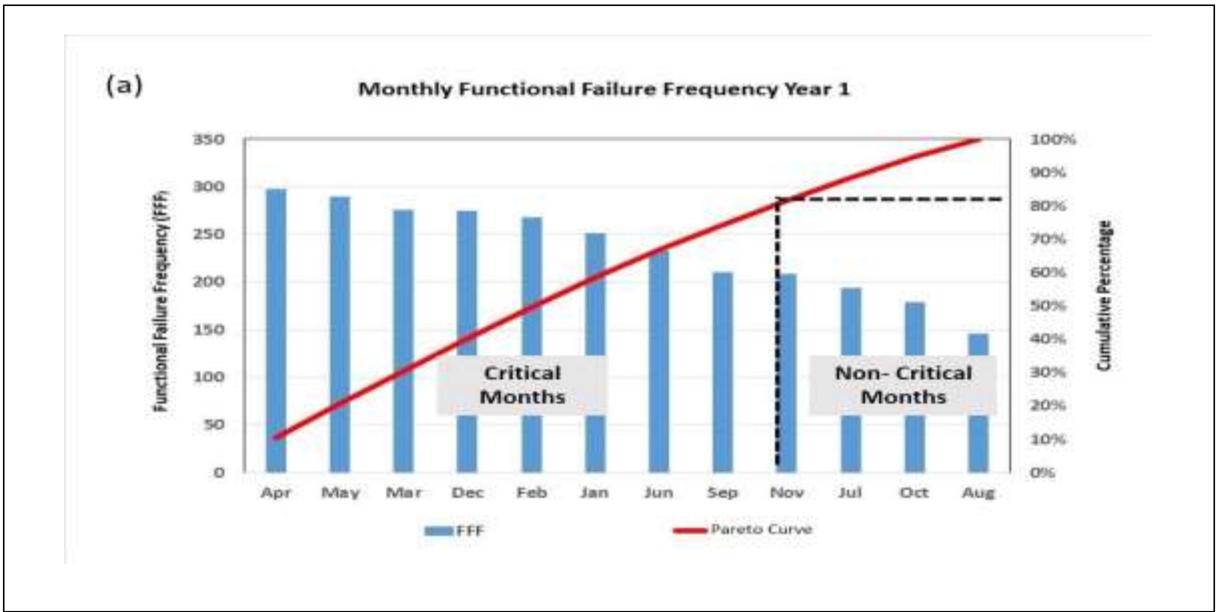
To protect the data, the names of the manufacturing companies and the sub-system were coded to protect the use of confidential data. In addition, the results are only discussed in order to evaluate the conventional reliability analysis approach. Hence, the findings cannot be used to assess the performance of the fleet of the participating franchise by any means.

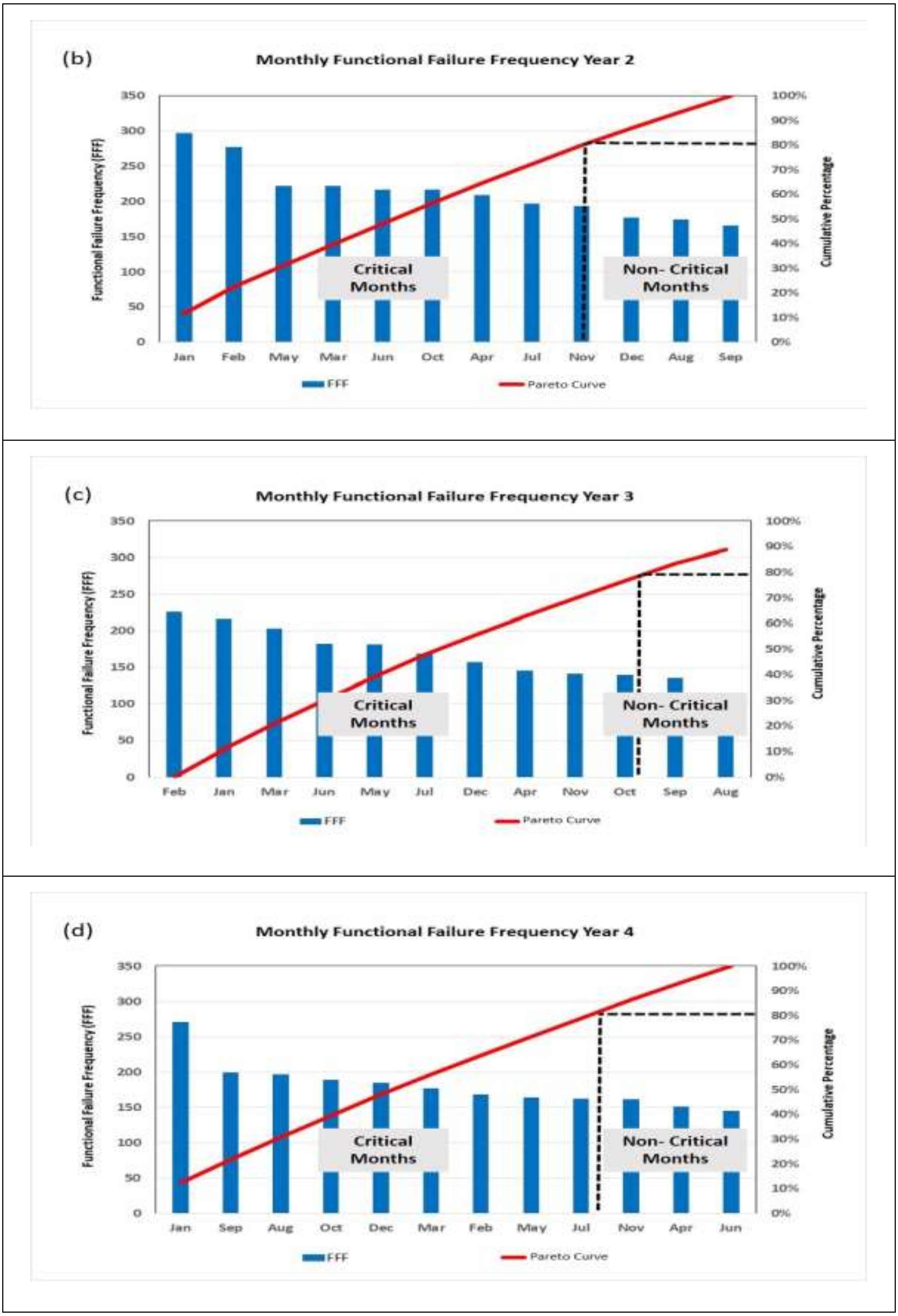
3.3.2 Analysis of the operational characteristics of the sub-systems

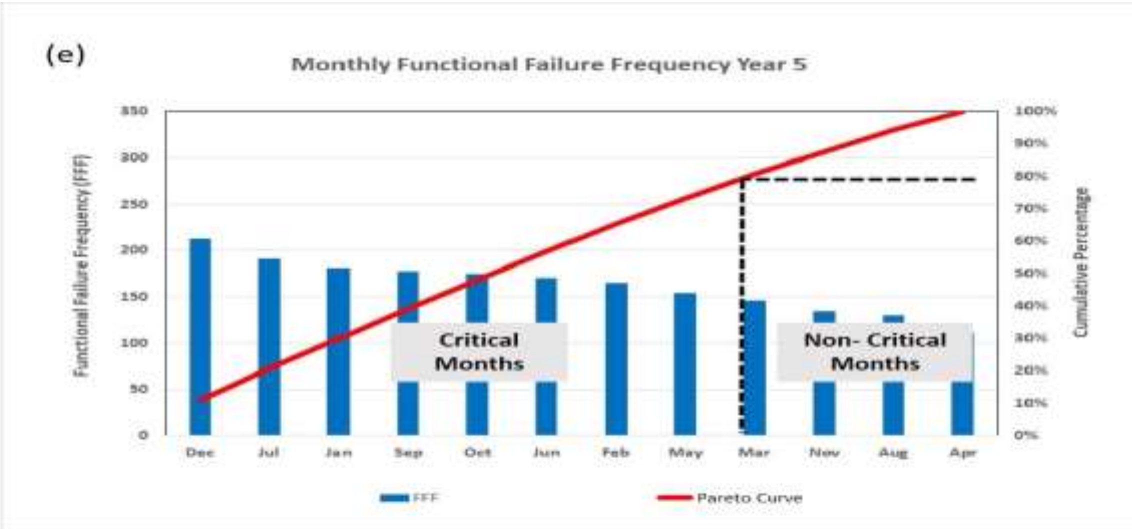
This section presents the operational characteristics of the sub-systems linked to their datasets that were obtained by the application of SDA to the data of the UTS Melbourne. The results are discussed to evaluate the usefulness of SDA in establishing the operational characteristics of the sub-systems.

3.3.2.1 Evaluation of the monthly FFF profile

In order to evaluate the usefulness of SDA to characterise the monthly FFF profile, the monthly FFF profile for each study year is first evaluated based on the FFF for each month to analyse C1 – the critical months. It is then evaluated based on contribution of the FFF from each of the nineteen sub-systems in the FFF of each month to analyse C2 – the similar and dissimilar months. Figure 3-2 shows the mapping of FFF of the months for the six study years in the Pareto charts. Using the Pareto principle, the percentage at which the curve reaches 80% is used to identify the critical and non-critical months.




(b)
Monthly Functional Failure Frequency Year 2
Functional Failure Frequency (FFF)
Cumulative Percentage
0 50 100 150 200 250 300 350
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Critical Months
Non- Critical Months
Jan Feb May Mar Jun Oct Apr Jul Nov Dec Aug Sep
FFF
Pareto Curve
(c)
Monthly Functional Failure Frequency Year 3
Functional Failure Frequency (FFF)
Cumulative Percentage
0 50 100 150 200 250 300 350
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Critical Months
Non- Critical Months
Feb Jan Mar Jun May Jul Dec Apr Nov Oct Sep Aug
FFF
Pareto Curve
(d)
Monthly Functional Failure Frequency Year 4
Functional Failure Frequency (FFF)
Cumulative Percentage
0 50 100 150 200 250 300 350
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Critical Months
Non- Critical Months
Jan Sep Aug Oct Dec Mar Feb May Jul Nov Apr Jun
FFF
Pareto Curve



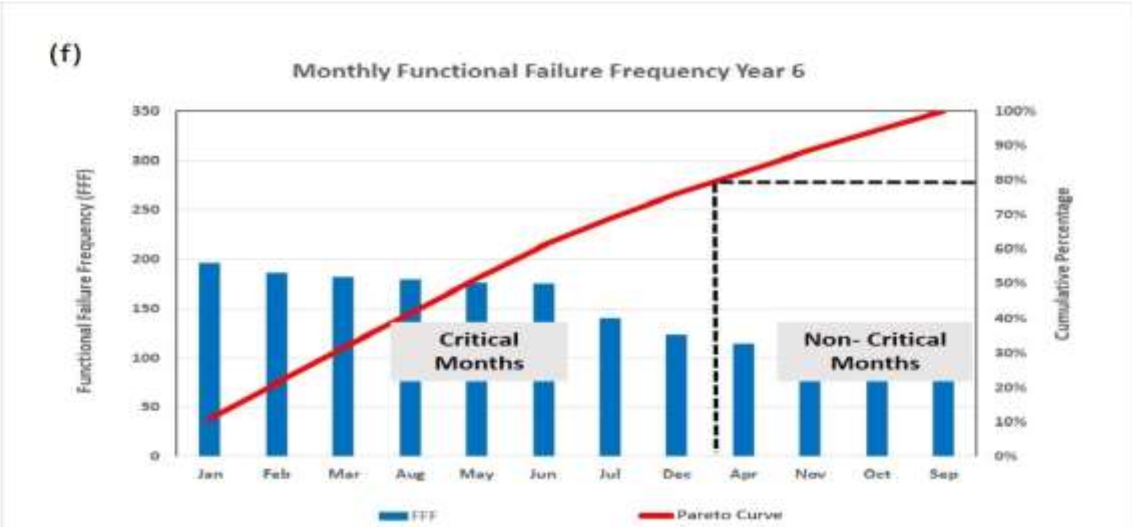


Figure 3-2: Criticality categorisation of the months for identification of the critical months.

Monthly FFF for each study year are mapped in the Pareto chart. Each chart shows the months in descending order of their FFF. On each chart, a cut-off is marked at 80% of cumulative FFF that identifies the months as critical or non-critical.

As can be seen in Figure 3-2, there are 8, 9, 10, 9, 8, 8 months identified as critical in Years 1, 2, 3, 4, 5 and 6 respectively. It is clear that too many critical months have been identified in each year using the Pareto curve. As stated in Section 3.2.2, the application of the Pareto principle aims to identify 20% of the months in the year that account for 80% of the yearly FFF, and then the maintenance plan can focus on those few months to deliver the biggest impact in terms of reduction in the yearly FFF. However, in this case the Pareto principle identified 66.6% of the months as critical in Years 1, 5 and 6; 75% of the months as critical in Years 2, 4 and 10; and 83.3% of the months as critical in Year 3. Hence, it is concluded that identification of only the topmost critical months is not achievable by application of SDA.

To make it easier to analyse whether a particular month is critical or non-critical for any year, the critical and non-critical months for the six study years are presented in calendar order in Table 3-2.

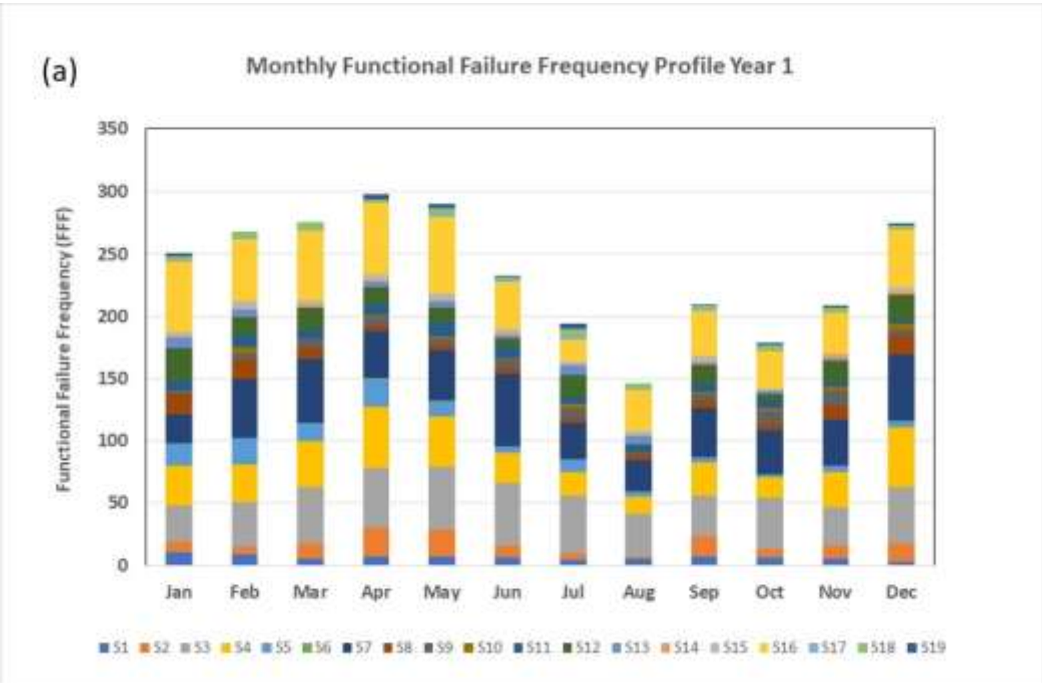
Table 3-2: Criticality categorisation of the months

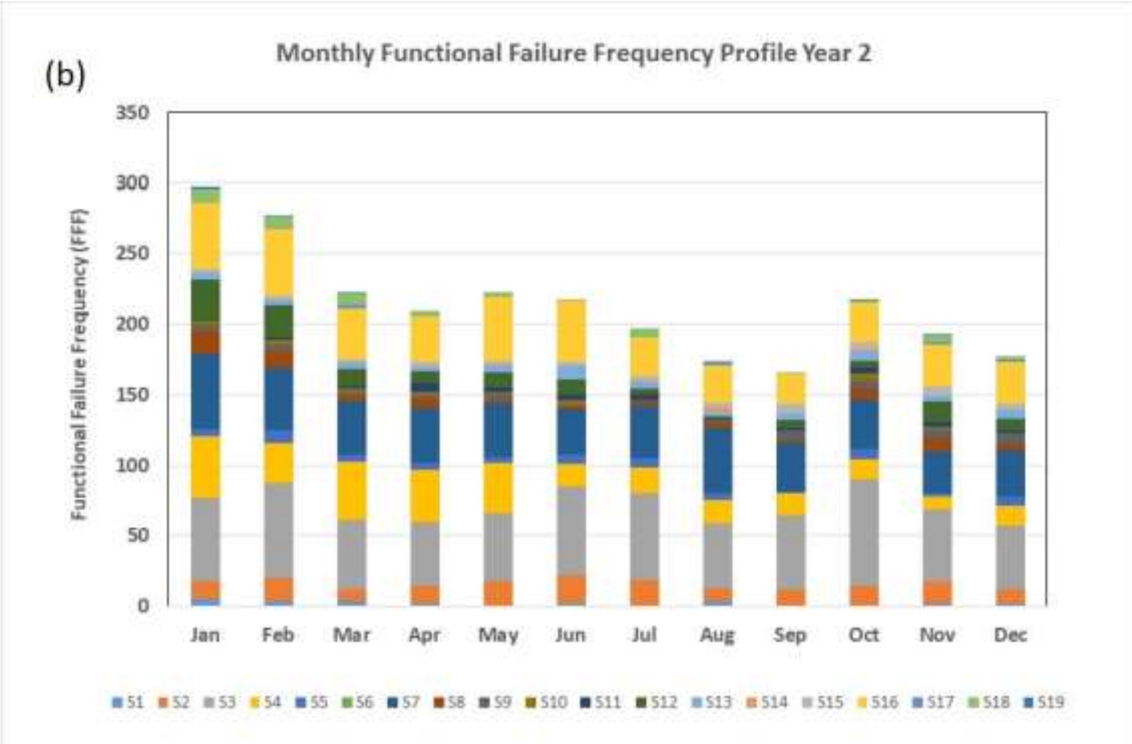
Study Year	Critical months	Non-critical months
1	Jan, Feb, Mar, Apr, May, Jun, Sep and Dec	Jul, Aug, Oct and Nov
2	Jan, Feb, Mar, Apr, May, Jun, Jul, Oct and Nov	Aug, Sep, and Dec
3	Jan, Feb, Mar, Apr, May, Jun, Jul, Oct, Nov and Dec	Aug and Sep
4	Jan, Feb, Mar, May, Jul, Aug, Sep, Oct and Dec	Apr, Jun and Nov
5	Jan, Feb, May, Jun, Aug, Sep, Oct and Dec	Mar, Apr, Aug and Nov
6	Jan, Feb, Mar, May, Jun, Jul, Aug and Dec	Apr, Sep, Oct and Nov

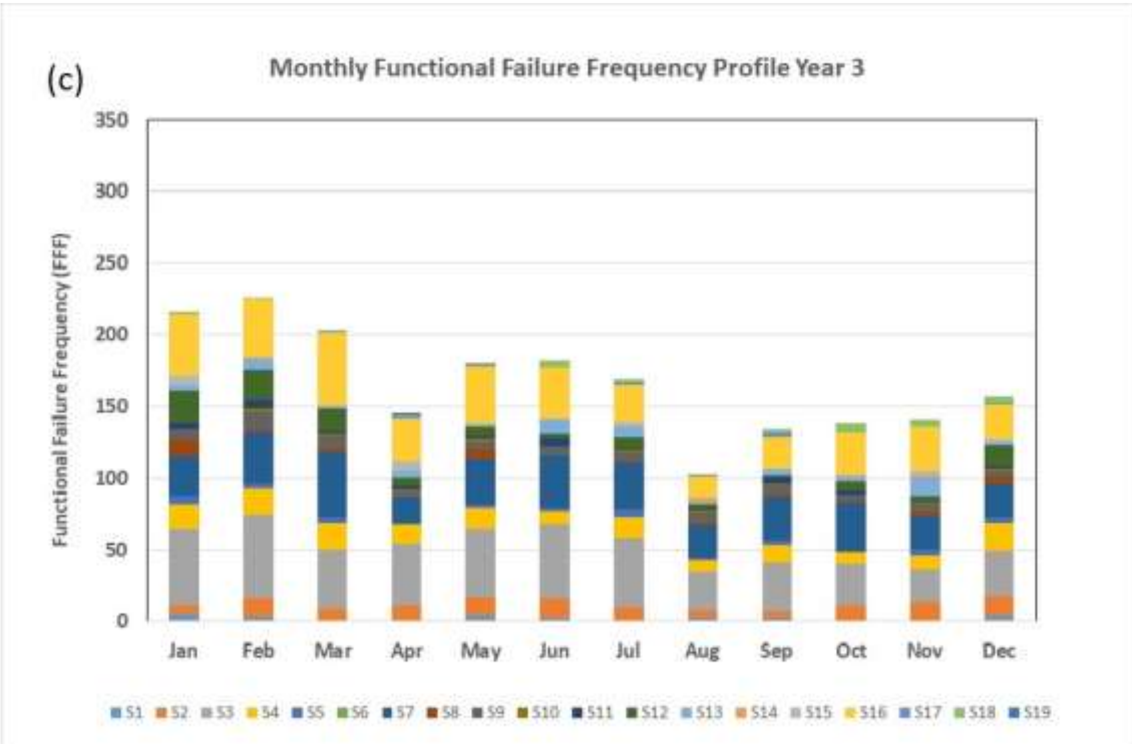
As can be seen in Table 3-2, there are some months that are recurrently identified as critical for the six study years, for instance January and February. However, some of the months are recurrently identified as critical in some years and as non-critical in the other years. For instance, April is recurrently identified as critical and August as non-critical in the first three years, and then April is recurrently identified as non-critical and August as critical in the next three years. There are also some months that occasionally show the non-recurrent pattern. For example, December is non-recurrently identified as non-critical in Year 2. Hence, it is clearly evident that the data contains recurrent and some non-recurrent patterns of the FFF in the months. However, this is unstructured information and thus it does not provide any indication for the latent variables that are responsible for inducing the recurrent and non-recurrent patterns in the FFF of the months.

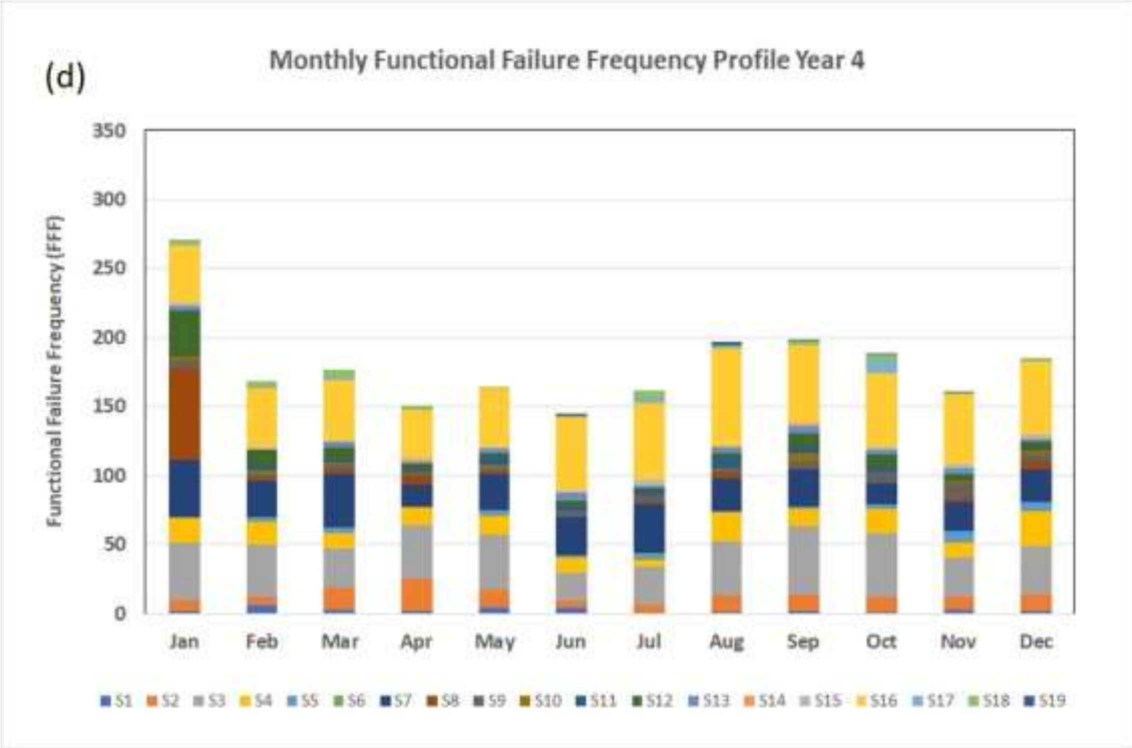
Another major observation is that there are problems with the application of the Pareto principle in the criticality categorisation of the months. For instance, the monthly FFF of July in Years 1, 2, 3, 4, 5 and 6 are 194, 197, 169, 162, 191 and 140 respectively as shown in Figure 3-2.It can also be seen in Table 3-2 that July is categorised as a non-critical month in Year 1, and as a critical month in all the later years even though its FFF in the later years except in Year 2 is less than its FFF in Year 1. Likewise, the monthly FFF of December in Years 1, 2, 3, 4, 5 and 6 are 275, 177, 157, 162, 191 and 140 respectively as can be seen in Figure 3-2. However, it can also be seen in Table 3-2 that December is categorised as a critical month in all study years except in Year 2 in which it is categorised as a non-critical month even though the FFF of December in the later years except in Year 5 is lower than its FFF in Year 2. The reason for this is that the criticality categorisation of the months is relative to the yearly FFF and thus, the change in the criticality of the monthly FFF between the years cannot be meaningfully traced when SDA is used.

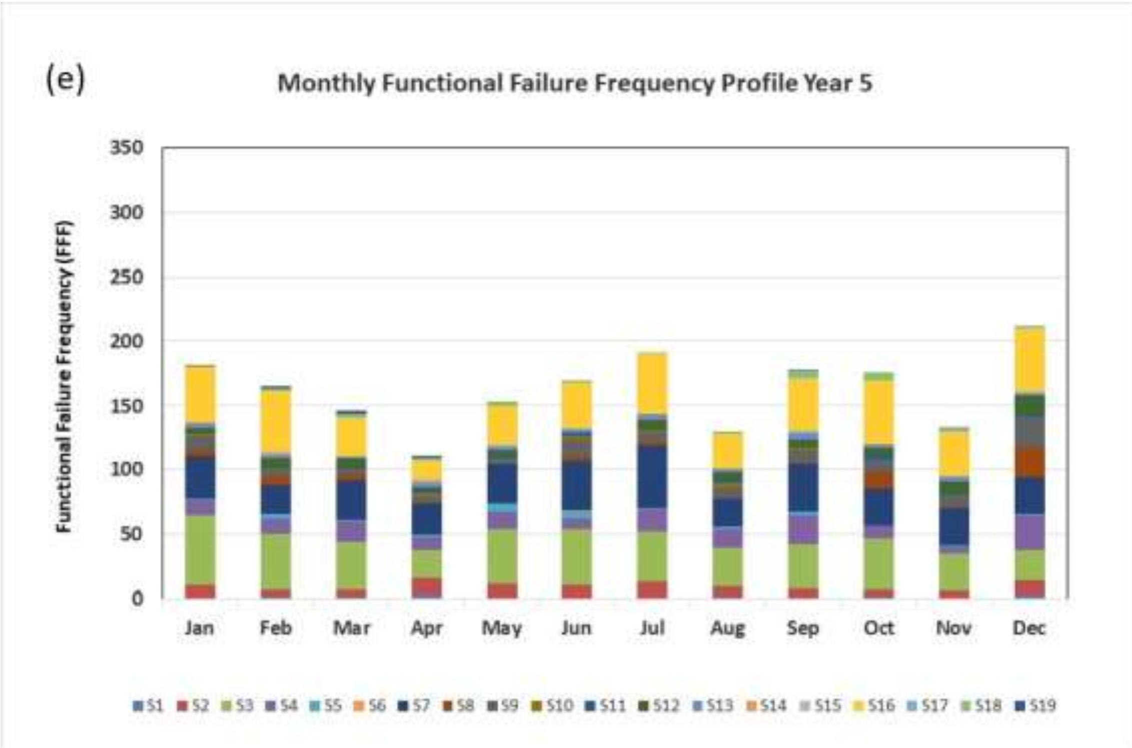
To analyse operational characteristic C2 the similar and dissimilar months, the monthly functional failure frequency profile was plotted in the composite bar charts for the six study years in Figure 3-3.




(b)
Monthly Functional Failure Frequency Profile Year 2
Functional Failure Frequency (FFF)
350
300
250
200
150
100
50
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18 S19


(c)
Monthly Functional Failure Frequency Profile Year 3
Functional Failure Frequency (FFF)
350
300
250
200
150
100
50
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18 S19


(d)
Monthly Functional Failure Frequency Profile Year 4
Functional Failure Frequency (FFF)
350
300
250
200
150
100
50
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18 S19


(e)
Monthly Functional Failure Frequency Profile Year 5
Functional Failure Frequency (FFF)
350
300
250
200
150
100
50
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18 S19

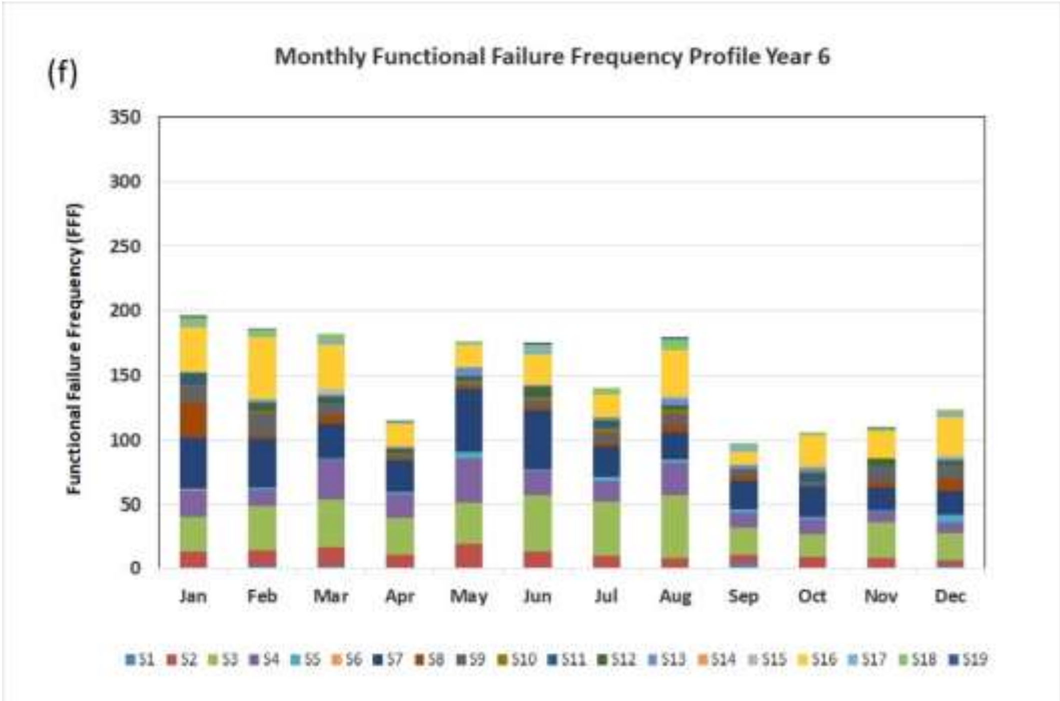


Figure 3-3: Compositional analysis of monthly FFF profiles to differentiate between similar and dissimilar months.

The monthly FFF profiles for each study year are mapped in the composite bar chart. The months are represented by bars and each bar is composed of nineteen sections for the representation of contribution of FFF from each of the nineteen sub-system into the monthly FFF. Thus, on the y-axis the height of bars shows the FFF of the months, while the height of sections shows the FFF of the sub-systems.

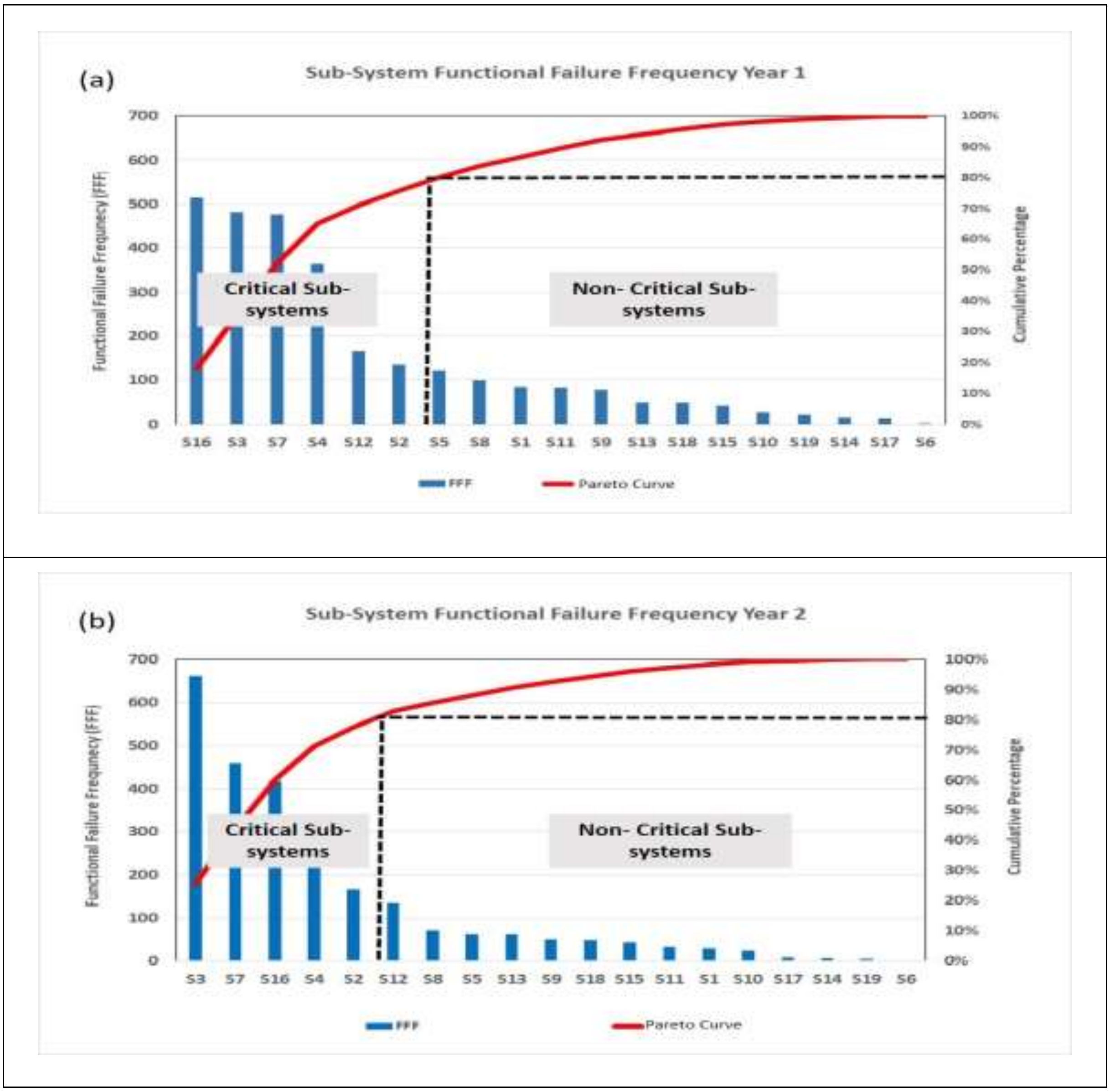
As can be seen in Figure 3-3, it is difficult to compare the monthly FFF profiles because many variables, i.e. 19 sub-systems, are involved. It is also difficult to identify any sub-system with zero FFF in any month because of non-representation of its zero-size section. Thus, this graphical representation of the data by SDA cannot be used to differentiate between the similar and dissimilar months.

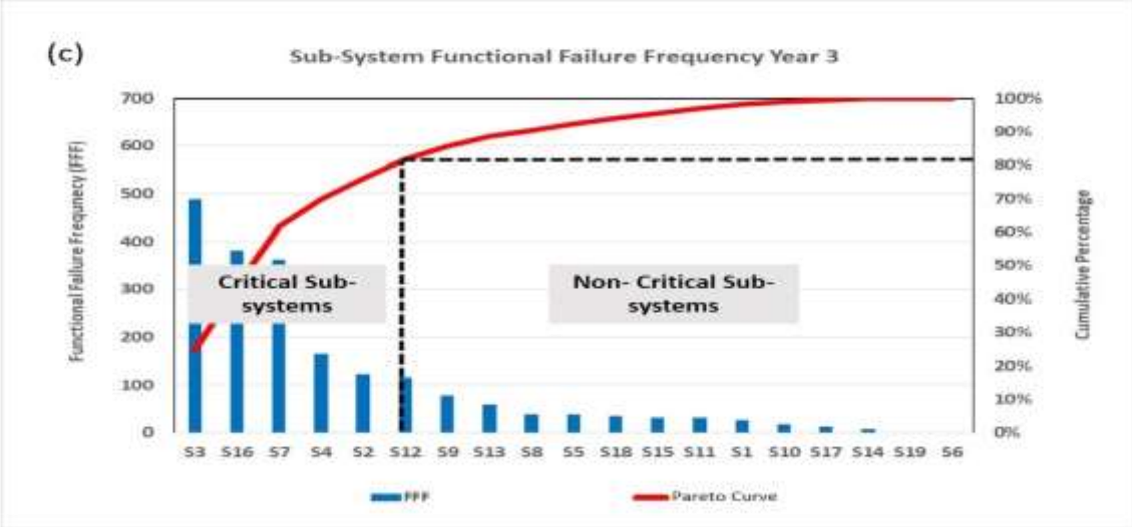
It is concluded that while C1 – the critical months can be established by using SDA, there are major limitations. In addition, C2 the similar and dissimilar months cannot be established by using SDA.

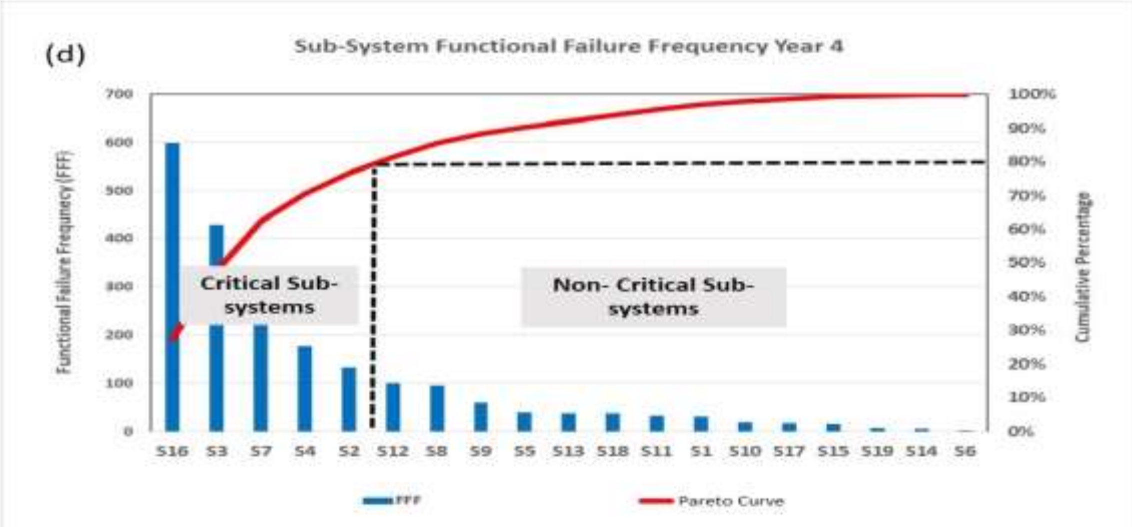
3.3.2.2 Evaluation of the sub-system FFF profile

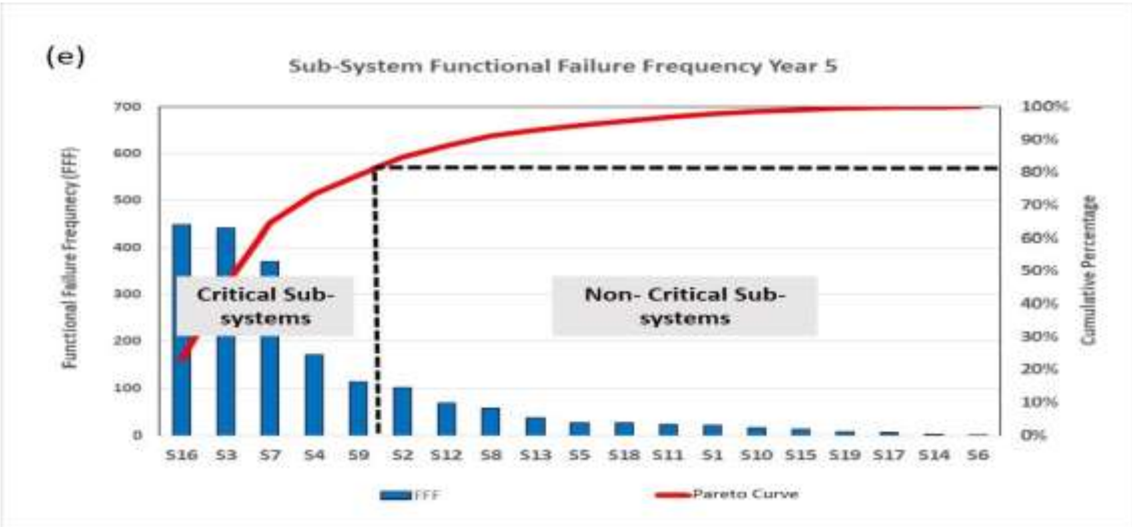
In order to evaluate the usefulness of SDA to characterise the sub-system FFF profile, the sub-system FFF profile for each study year is first evaluated based on the FFF of the sub-systems to analyse C3 the critical sub-systems. It is then evaluated based on the FFF of the sub-systems recorded in different months of the year to analyse C4 the similar and dissimilar sub-systems.

Figure 3-4 shows the mapping of FFF of the sub-systems for the six study years in the Pareto charts. Again, using the Pareto principle, the percentage at which the curve reaches 80% is used to identify the critical and non-critical sub-systems.




(c)
Sub-System Functional Failure Frequency Year 3
Functional Failure Frequency (FFF)
Cumulative Percentage
Critical Sub-systems
Non- Critical Sub-systems
700
600
500
400
300
200
100
0
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
S3 S16 S7 S4 S2 S12 S9 S13 S8 S5 S18 S15 S11 S1 S10 S17 S14 S19 S6
FFF
Pareto Curve


(d)
Sub-System Functional Failure Frequency Year 4
Functional Failure Frequency (FFF)
Cumulative Percentage
Critical Sub-systems
Non- Critical Sub-systems
700
600
500
400
300
200
100
0
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
S16 S3 S7 S4 S2 S12 S8 S9 S5 S13 S18 S11 S1 S10 S17 S15 S19 S14 S6
FFF
Pareto Curve


(e)
Sub-System Functional Failure Frequency Year 5
Functional Failure Frequency (FFF)
Cumulative Percentage
Critical Sub-systems
Non- Critical Sub-systems
700
600
500
400
300
200
100
0
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
S16 S3 S7 S4 S9 S2 S12 S8 S13 S5 S18 S11 S1 S10 S15 S19 S17 S14 S6
FFF
Pareto Curve

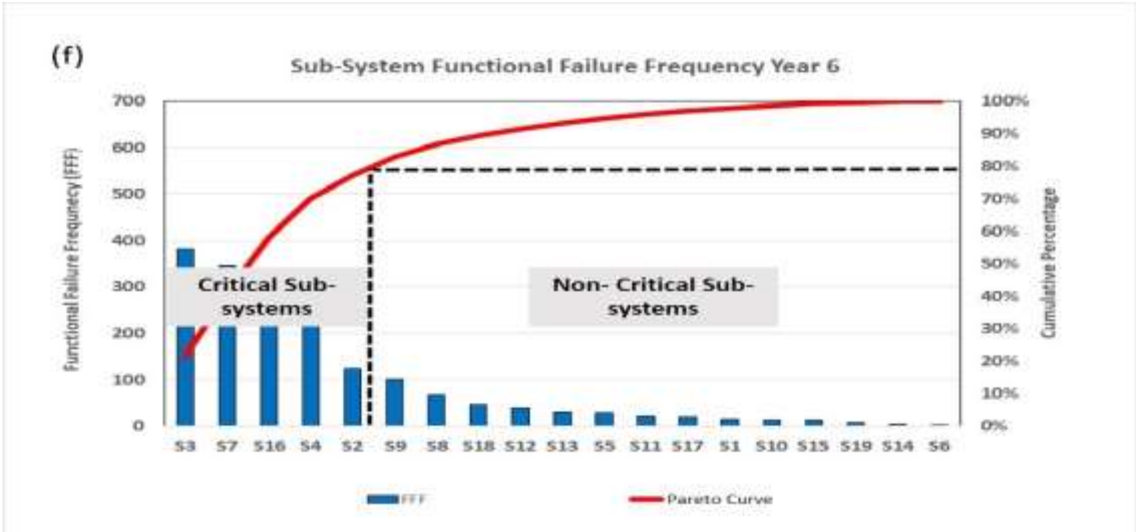


Figure 3-4: Criticality categorisation of the sub-systems based on the FFF for identification of the functionally critical sub-systems.

The FFF of the sub-systems for each study year are mapped in the Pareto chart. Each chart shows the sub-systems in descending order of their FFF. On each chart, a cut-off is marked at 80% of cumulative FFF that identifies the sub-systems as critical or non-critical.

As can be seen from Figure 3-4, there are 6, 5, 6, 5, 5 and 5 sub-systems identified as critical in Years 1, 2, 3, 4, 5 and 6 respectively. It is clear that an application of Pareto principle has resulted in identification of reduced number of sub-systems, but these numbers are much greater than 20% of the sub-systems of the urban train system. In this case, the Pareto principle has identified 31.6% of the sub-systems as critical in Years 1 and 3; 26.3% of the sub-systems in Years 2, 4, 5 and 6. Hence, it is concluded that identification of only the topmost functionally critical sub-systems is not achievable by application of SDA.

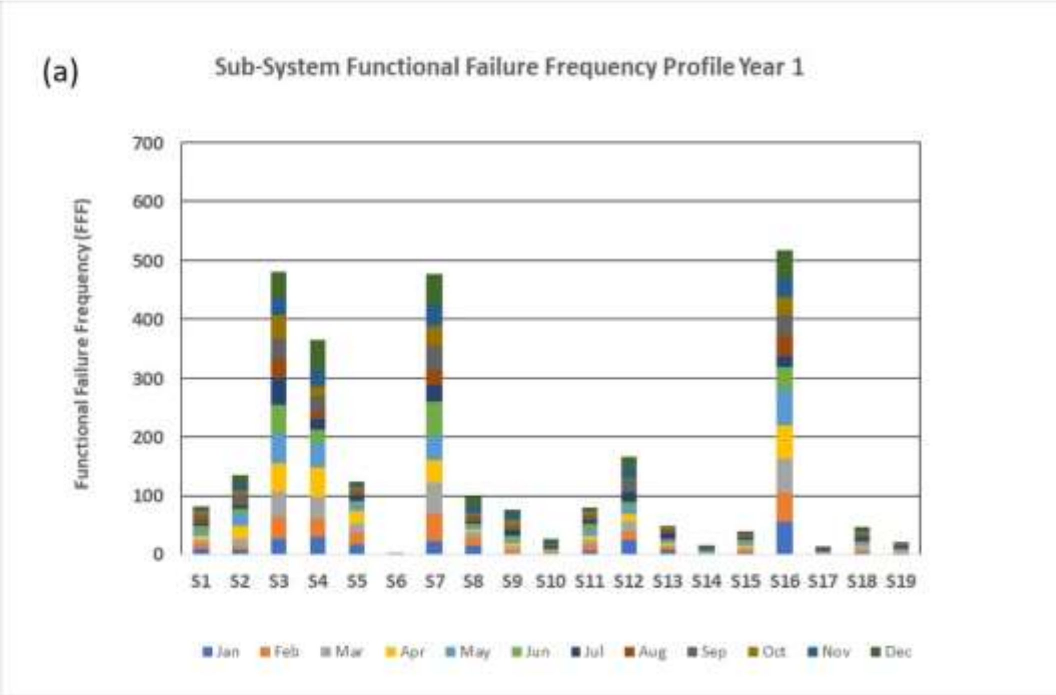
To make it easier to analyse whether a particular sub-system is critical or non-critical for any year, the critical and the non-critical sub-systems for the six study years are presented in their coding order in Table 3-3.

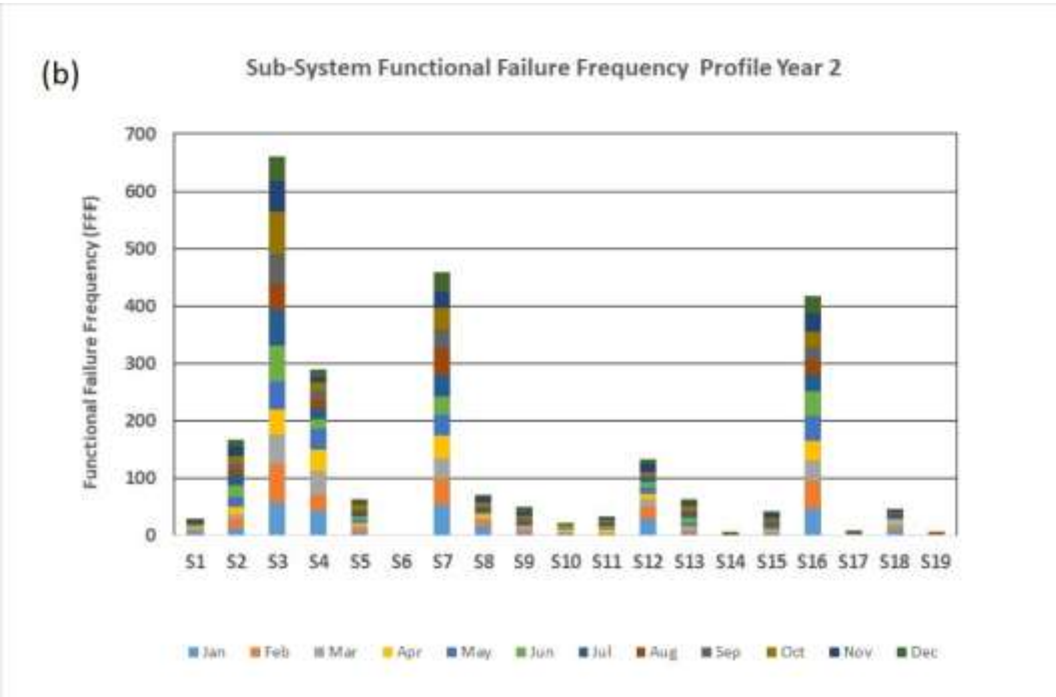
Table 3-3: Criticality categorisation of the sub-systems		
Study Year	**Critical sub-systems**	**Non-critical sub-systems**
1	S2, S3, S4, S5, S7, S12 and S16	S1, S6, S8, S9, S10, S11, S13, S14, S15, S17, S18 and S19
2	S2, S3, S4, S7 and S16	S1, S5, S6, S8, S9, S10, S11, S12, S13, S14, S15, S17, S18 and S19
3	S2, S3, S4, S7 and S16	S1, S5, S6, S8, S9, S10, S11, S12, S13, S14, S15, S17, S18 and S19
4	S2, S3, S4, S7 and S16	S1, S5, S6, S8, S9, S10, S11, S13, S14, S15, S17, S18 and S19
5	S3, S4, S7, S9 and S16	S1, S2, S5, S6, S8, S10, S11, S12, S13, S14, S15, S17, S18 and S19
6	S2, S3, S4, S7 and S16	S1, S5, S6, S8, S9, S10, S11, S12, S13, S14, S15, S17, S18 and S19

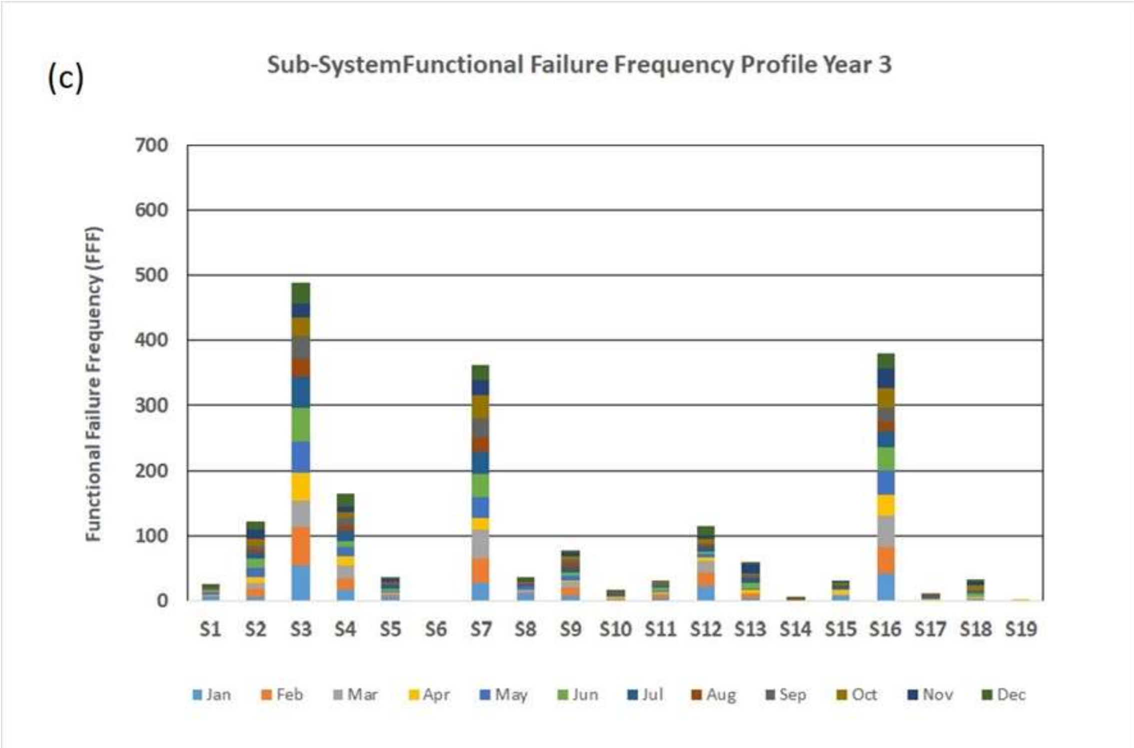
As can be seen in Table 3-3, sub-systems S2, S3, S4, S7 and S16 are recurrently identified as critical for the six study years, and all the other sub-systems are recurrently identified as non-critical. In addition, data has shown some non-recurrent patterns, for instance, S2 is non-recurrently identified as non-critical in Year 5; S5 and S9 are non-recurrently identified as critical in Years 1 and 5. Hence, it is clearly evident that the data contains recurrent and some non-recurrent patterns of the FFF in the sub-systems. However, this is unstructured information and thus it does not provide any indication about the latent variables that are responsible for inducing the recurrent and non-recurrent patterns in the FFF of the sub-systems.

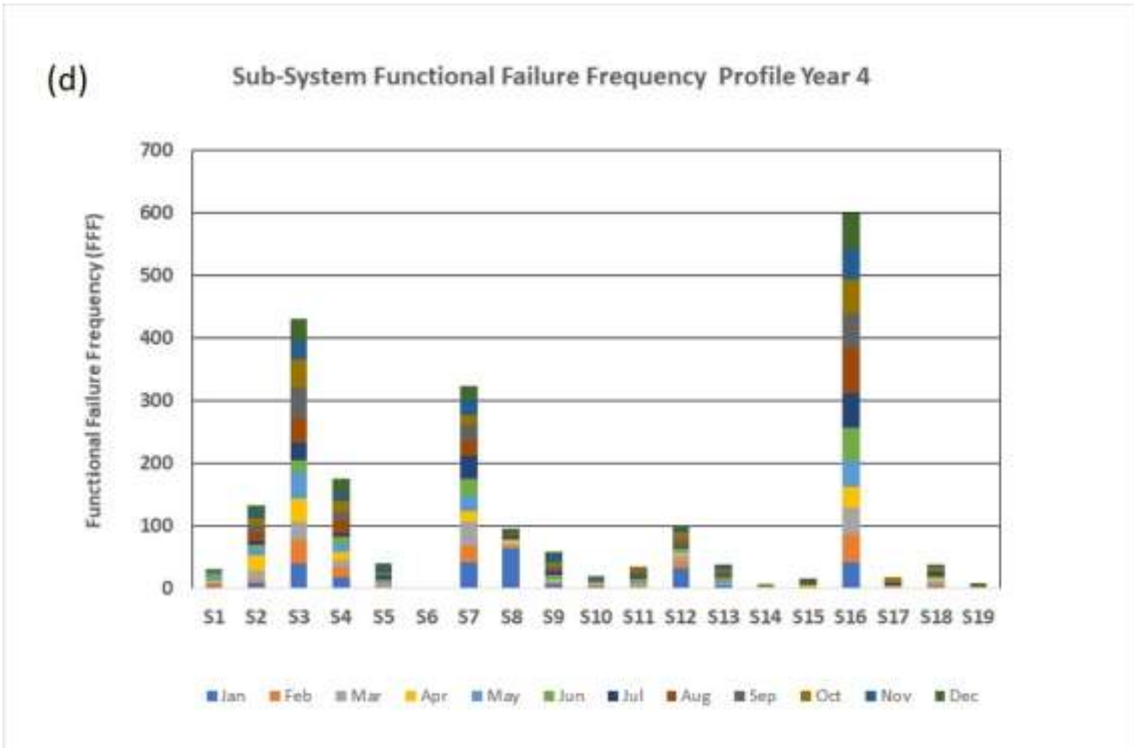
Another major observation is that the application of the Pareto principle for categorisation of the sub-systems does not provide any information that can assist in concluding whether functional reliability of the sub-system has improved or worsened over the years. For instance, the FFF of S3 in Years 1, 2, 3, 4, 5 and 6 are 481, 662, 489, 430, 440 and 382 as shown in Figure 3-4. This clearly shows that the only information which is extractable is a relative increase or decrease in the FFF of S3 between different years. Hence, the yearly trends for change in the criticality of the sub-system with respect to the FFF are not meaningfully traced when SDA is used.

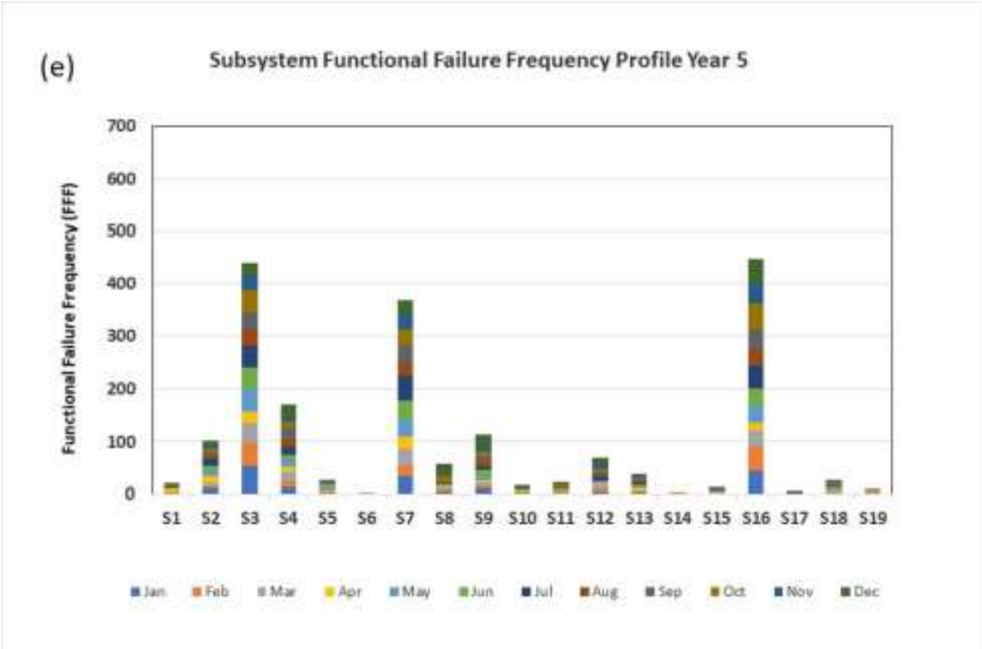
To analyse operational characteristic C4 the similar and dissimilar sub-systems, Figure 3-5 shows the composite bar charts for the six study years.






(c)
Sub-SystemFunctional Failure Frequency Profile Year 3
Functional Failure Frequency (FFF)
700
600
500
400
300
200
100
0
S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18 S19
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec


(d)
Sub-System Functional Failure Frequency Profile Year 4
Functional Failure Frequency (FFF)
700
600
500
400
300
200
100
0
S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18 S19
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec



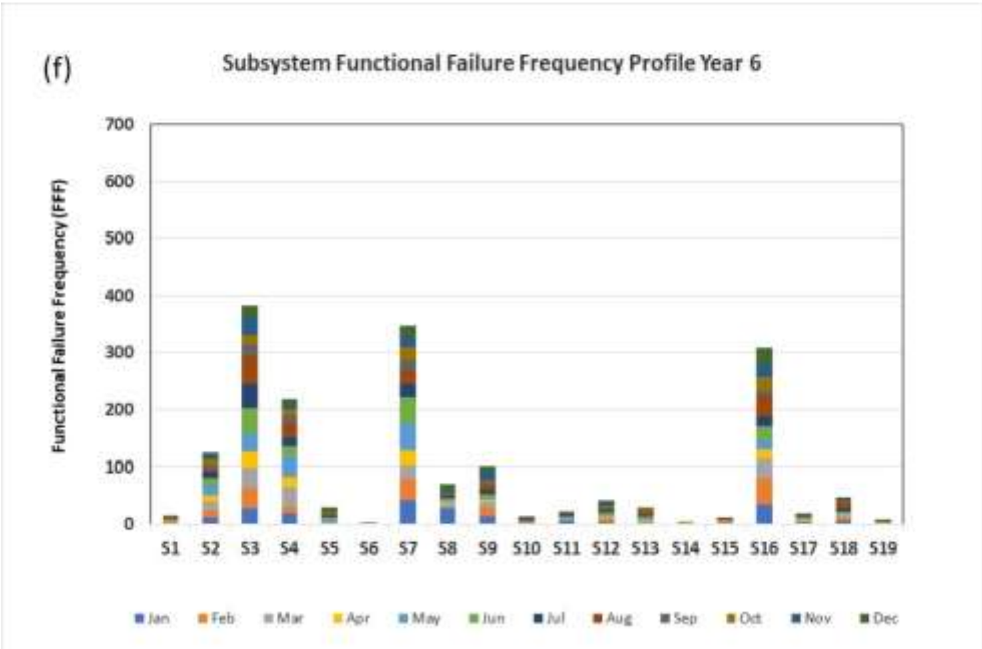


Figure 3-5: Compositional analysis of sub-system FFF profiles to differentiate between similar and dissimilar sub-systems.

The FFF profiles for nineteen sub-systems for each study year are mapped in the composite bar chart. The sub-systems are represented by bars, and each bar is composed of twelve sections representing the FFF of the sub-system in each month of the year. Thus, on the y-axis the height of bars shows the yearly FFF of the sub-system, while the height of sections shows the FFF of the sub-system in the months.

As can be seen in Figure 3-5, it is difficult to compare the sub-system FFF profiles as many variables are involved i.e. 12 months. In addition, there is a significant difference in the FFF of the sub-systems that has resulted in bars of incomparable sizes; furthermore, the sub-systems with zero FFF are not identifiable. Thus, this graphical representation of the data by SDA cannot be used to differentiate between the similar and dissimilar sub-systems.

It is concluded that C3 – the critical sub-systems can be established by using SDA, but with major limitations. Furthermore, C4 – the similar and dissimilar sub-systems cannot be established by using SDA.

3.3.2.3 Evaluation of the relationship between the FFF profiles of sub-systems and months

In order to evaluate the usefulness of SDA for a relative assessment of the FFF profiles of the months and sub-systems, Figure 3-4 can be used to analyse C5 (a) - characterisation of the monthly FFF profiles, and Figure 3-5 can be used to analyse C5 (b) - influence of the sub-systems on FFF of the months.

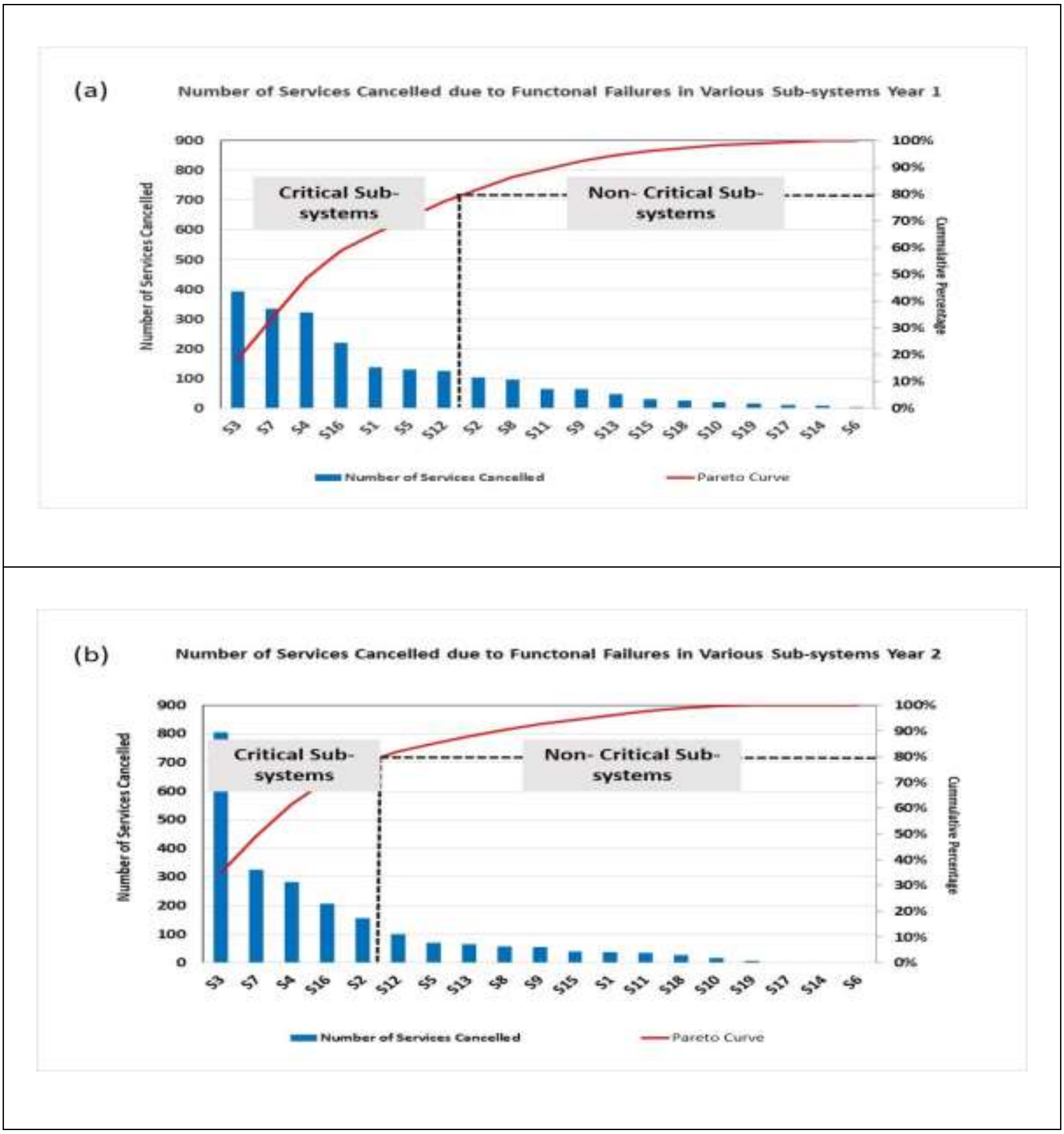
In order to analyse C5 (a) it is required to identify the sub-systems that contributed the most in making the months similar and dissimilar with respect to their FFF. Since an application of SDA has not resulted in differentiation between the similar and dissimilar months as concluded in Section 3.3.2.1, the analysis cannot be extended to identify the sub-systems that make the months similar and dissimilar. Similarly, in order to analyse C5 (b), it is required to identify the sequence of the months in descending order of FFF for the sub-systems in them. As can be seen in Figure 3-5, the months are arranged in their calendar order within a bar for each sub-system. Rearranging the months in descending order of FFF of the sub-systems would require time-consuming and thus costly sorting of the monthly FFF from highest to lowest for one sub-system at a time for the nineteen sub-systems in the six years of data.

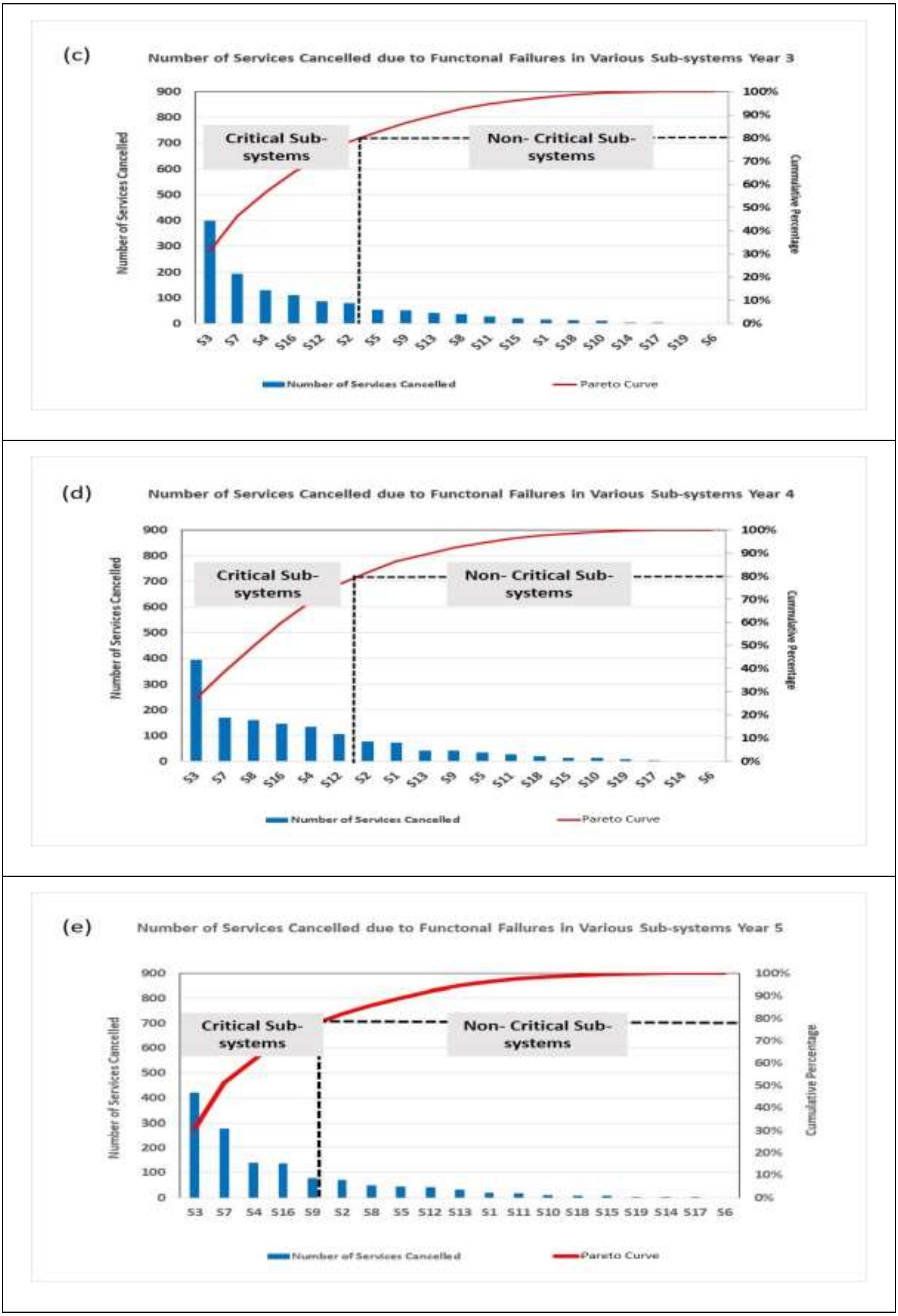
It is concluded that C5 (a) and C5(b) cannot be established by using SDA.

3.3.2.4 Evaluation of the services cancelled profile and services delayed profile

In order to evaluate the usefulness of SDA to characterise the service cancellation profile and the services delayed profile, the service cancellation profile for each study year is first evaluated based on the number of services cancelled to analyse C6 – the critical sub-systems for services cancelled, and then the service delayed profile for each study year based on the number of services delayed to analyse C7 – the critical sub-systems for services delayed.

Figure 3-6 shows the mapping of the number of services cancelled for the six study years in the Pareto charts. Using the Pareto principle as before, the percentage at which the curve reaches 80% is used to identify the critical and non-critical sub-systems.





(c)
Number of Services Cancelled due to Functonal Failures in Various Sub-systems Year 3
Critical Sub-systems
Non- Critical Sub-systems
Number of Services Cancelled
Cummulative Percentage
S3 S7 S4 S16 S12 S2 S5 S9 S13 S8 S11 S15 S1 S18 S10 S14 S17 S19 S6
Number of Services Cancelled
Pareto Curve
(d)
Number of Services Cancelled due to Functonal Failures in Various Sub-systems Year 4
Critical Sub-systems
Non- Critical Sub-systems
Number of Services Cancelled
Cummulative Percentage
S3 S7 S8 S16 S4 S12 S2 S1 S13 S9 S5 S11 S18 S15 S10 S19 S17 S14 S6
Number of Services Cancelled
Pareto Curve
(e)
Number of Services Cancelled due to Functonal Failures in Various Sub-systems Year 5
Critical Sub-systems
Non- Critical Sub-systems
Number of Services Cancelled
Cumulative Percentage
S3 S7 S4 S16 S9 S2 S8 S5 S12 S13 S1 S11 S10 S18 S15 S19 S14 S17 S6
Number of Services Cancelled
Pareto Curve

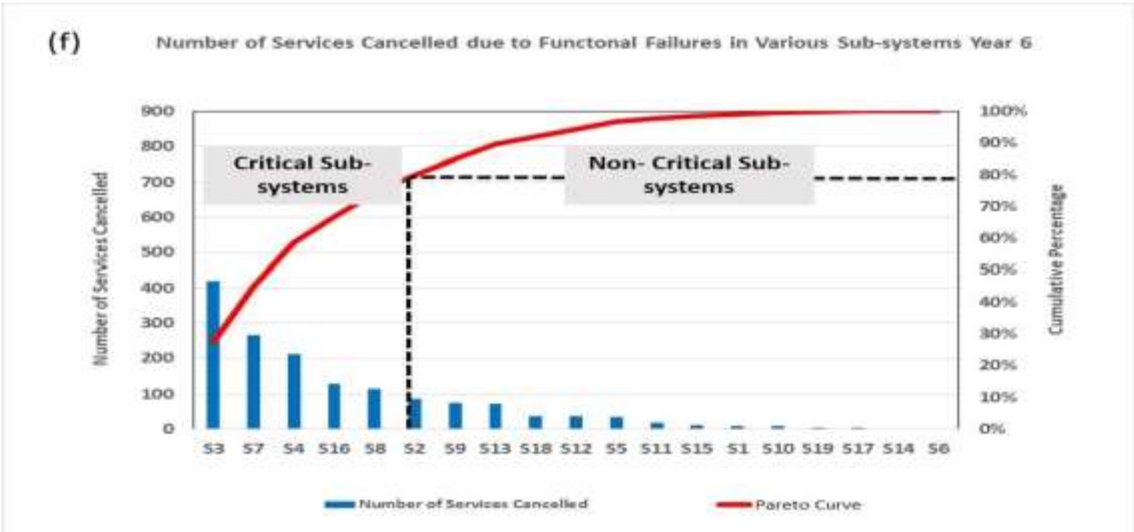


Figure 3-6: Criticality categorisation of the sub-systems based on number of services cancelled for identification of service critical sub-systems.

The number of services cancelled caused by the FFF of the sub-systems for each study year is mapped in the Pareto chart. Each chart graphs the sub-systems in descending order of their number of services cancelled. On each chart, a cut-off is marked at 80% of cumulative number of services cancelled that identifies the sub-systems as service critical or non-critical.

As can be seen in Figure 3-6, there are 7, 5, 6, 5, 5 and 6 sub-systems identified as service critical with respect to the number of services cancelled in Years 1, 2, 3, 4, 5 and 6 respectively. It is clear that too many critical sub-systems have been identified in each year using the Pareto curve. In this case, rather than identifying the 20% of the sub-systems that account for 80% of the yearly number of services cancelled, the Pareto principle identified 36.8% of the sub-systems as critical in Year 1, 26.3% in Years 2, 4 and 5, and 31.6% in Year 3 and 6. Hence, it is concluded that identification of only topmost service critical sub-systems is not achievable by application of SDA.

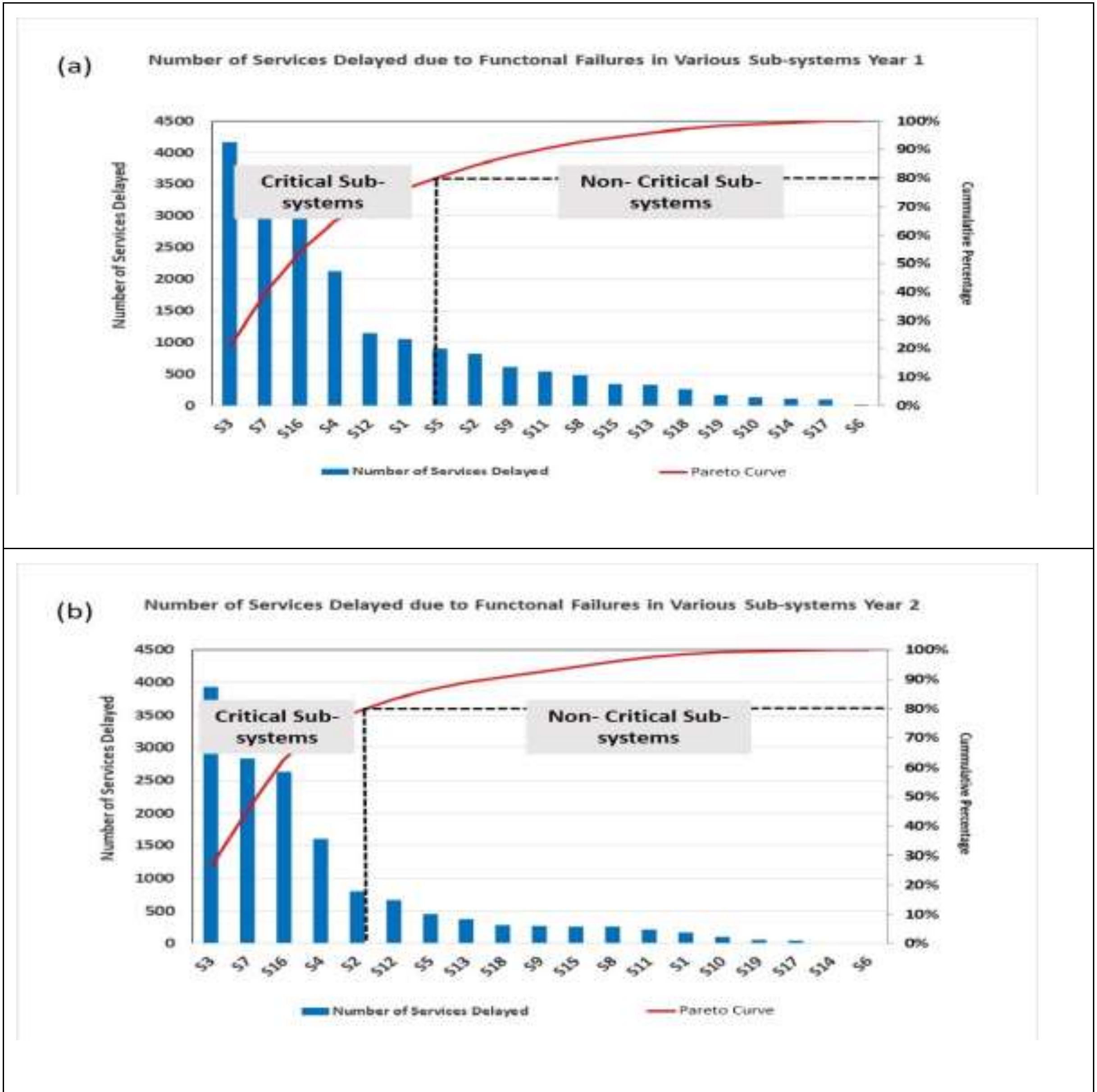
To make it easier to analyse whether a particular sub-system is critical or non-critical for any year, the critical and the non-critical sub-systems for the six study years are presented in numerical order in Table 3-4:

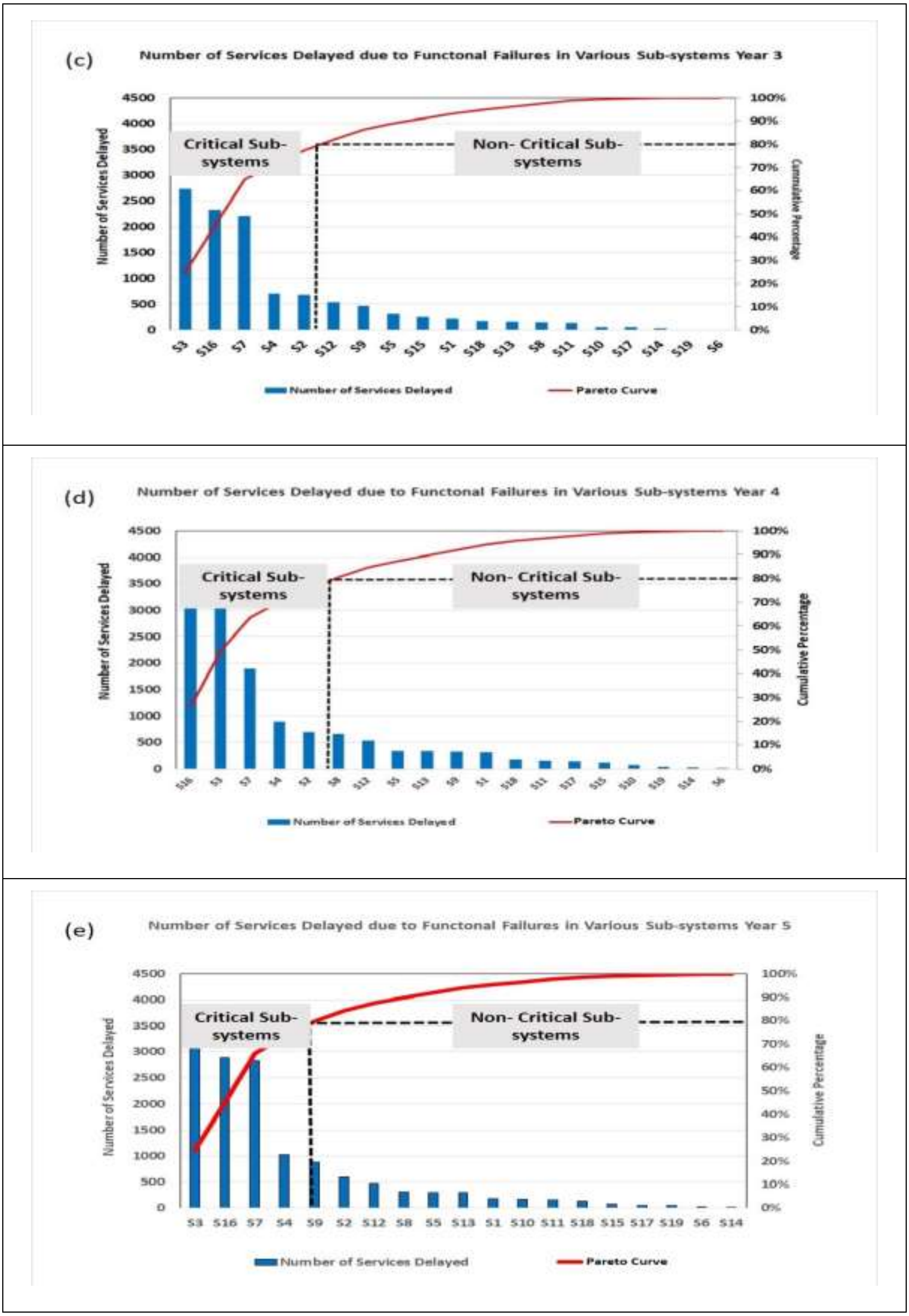
Table 3-4: Criticality categorisation of the sub-systems with respect to the number of services cancelled		
Study Year	**Critical sub-systems**	**Non-critical sub-systems**
1	S1, S3, S4, S5, S7, S12 and S16	S2, S6, S8, S9, S10, S11, S13, S14, S15, S17, S18 and S19
2	S2, S3, S4, S7 and S16	S1, S5, S6, S8, S9, S10, S11, S12, S13, S14, S15, S17, S18 and S19
3	S2, S3, S4, S7, S12 and S16	S1, S5, S6, S8, S9, S10, S11, S13, S14, S15, S17, S18 and S19
4	S3, S4, S7, S8, S12 and S16	S1, S2, S5, S6, S9, S10, S11, S13, S14, S15, S17, S18 and S19
5	S3, S4, S7, S9 and S16	S1, S2, S5, S6, S8, S10, S11, S12, S13, S14, S15, S17, S18 and S19
6	S2, S3, S4, S7, S8 and S16	S1, S5, S6, S8, S9, S10, S11, S12, S13, S14, S15, S17, S18 and S19

As can be seen in Table 3-4, S3, S4, S7 and S16 are recurrently identified as the critical sub-systems for the six study years, and all the other sub-systems are recurrently identified as non-critical. However, there are some non-recurrent patterns in the data as well. For example, S1 is non-recurrently identified as critical in Year 1, S8 in Years 4 and 6 and S9 in Year 5. In addition, some of the sub-systems are recurrently identified as critical in some years and as non-critical in the other years. For example, S2 is recurrently identified as critical in Years 2 and 3, and then it is recurrently identified as non-critical in Years 4 and 5. Hence, it is clearly evident that the data contains some recurrent and some non-recurrent patterns in the number of services cancelled caused by the FFF of different sub-systems. However, this is unstructured information and thus it does not provide any indication for the latent variables that are responsible for inducing these recurrent and non-recurrent patterns in the number of services cancelled.

Another major observation is that the application of the Pareto principle for categorisation of the sub-systems does not establish whether the effect of the FFF of the sub-systems on service reliability has improved or worsened over the years. For instance, the numbers of services cancelled caused by the FFF of S3 in Years 1, 2, 3, 4, 5 and 6 were 392, 804, 399, 396, 421 and 418 as can be seen in Figure 3-6. The only information which is extractable is a relative increase or decrease in the number of services cancelled which does not provide any information about the change in service criticality of that sub-system between different years. Hence, the yearly trends for change in the service criticality of the sub-system with respect to the number of services cancelled are not meaningfully traceable when SDA is used.

To analyse C7 the critical sub-systems for services delayed, Figure 3-7 shows the mapping of number of services delayed for the six study years in the Pareto charts. In this case, the Pareto principle is also used to identify the critical and non-critical sub-systems.




(c)
Number of Services Delayed due to Functonal Failures in Various Sub-systems Year 3
Number of Services Delayed
Cumulative Percentage
Critical Sub-systems
Non- Critical Sub-systems
4500 4000 3500 3000 2500 2000 1500 1000 500 0
100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0%
S3 S16 S7 S4 S2 S12 S9 S5 S15 S1 S18 S13 S8 S11 S10 S17 S14 S19 S6
Number of Services Delayed
Pareto Curve
(d)
Number of Services Delayed due to Functonal Failures in Various Sub-systems Year 4
Number of Services Delayed
Cumulative Percentage
Critical Sub-systems
Non- Critical Sub-systems
4500 4000 3500 3000 2500 2000 1500 1000 500 0
100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0%
S16 S3 S7 S4 S2 S8 S12 S5 S13 S9 S1 S18 S11 S17 S15 S10 S19 S14 S6
Number of Services Delayed
Pareto Curve
(e)
Number of Services Delayed due to Functonal Failures in Various Sub-systems Year 5
Number of Services Delayed
Cumulative Percentage
Critical Sub-systems
Non- Critical Sub-systems
4500 4000 3500 3000 2500 2000 1500 1000 500 0
100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0%
S3 S16 S7 S4 S9 S2 S12 S8 S5 S13 S1 S10 S11 S18 S15 S17 S19 S6 S14
Number of Services Delayed
Pareto Curve

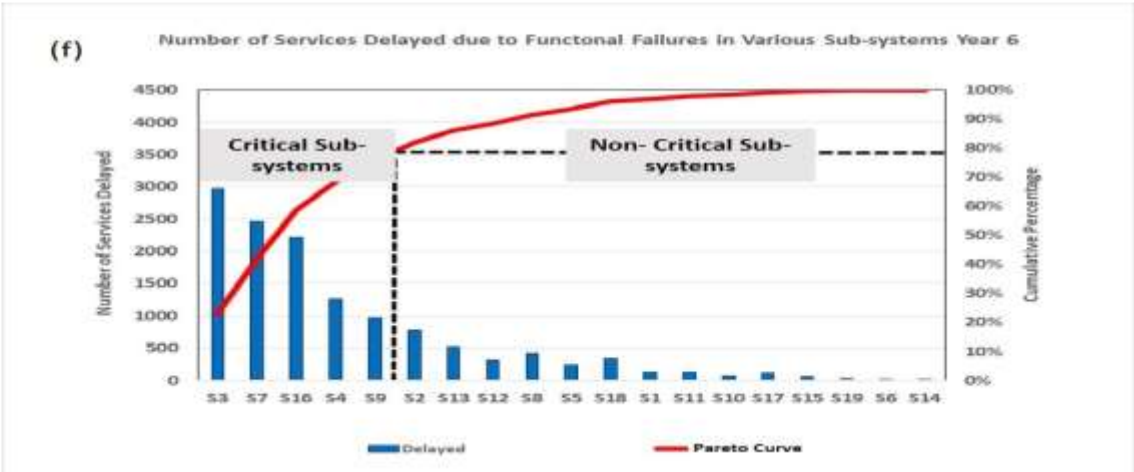


Figure 3-7: Criticality categorisation of the sub-systems based on number of services delayed for identification of service critical sub-systems.

The number of services delayed caused by the FFF of the sub-systems for each study year is mapped in the Pareto chart. Each chart graphs the sub-systems in descending order of their number of services delayed. On each chart, a cut-off is marked at 80% of cumulative number of services cancelled that identifies the sub-systems as service critical or non-critical.

As can be seen in Figure 3-7, there are 7 sub-systems in Year 1 and 5 sub-systems from Year 2 to Year 6 identified as service critical with respect to the number of services cancelled. Thus, 36.8% of the sub-systems are identified as critical in Year 1 and 26.3% in Years 2, 3, 4, 5 and 6. Again, too many critical sub-systems have been identified in each year using the Pareto principle to enable the maintenance plan to be focussed on those few sub-systems to deliver the biggest impact in terms of reduction in the yearly number of services delayed. Hence, it is concluded that identification of only topmost service critical sub-systems is not achievable by application of SDA.

To make it easier to analyse whether a particular sub-system is service critical or non-critical for any year, the critical and non-critical sub-systems for the six study years are presented in their numerical coding order in Table 3-5:

Table 3-5: Criticality categorisation of the sub-systems with respect to the number of services delayed		
Study Year	**Critical sub-systems**	**Non-critical sub-systems**
1	S1, S3, S4, S5, S7, S12 and S16	S2, S6, S8, S9, S10, S11, S13, S14, S15, S17, S18 and S19
2	S2, S3, S4, S7 and S16	S1, S5, S6, S8, S9, S10, S11, S12, S13, S14, S15, S17, S18 and S19
3	S2, S3, S4, S7 and S16	S1, S5, S6, S8, S9, S10, S11, S12, S13, S14, S15, S17, S18 and S19
4	S2, S3, S4, S7 and S16	S1, S5, S6, S8, S9, S10, S11, S12, S13, S14, S15, S17, S18 and S19
5	S3, S4, S7, S9 and S16	S1, S2, S5, S6, S8, S10, S11, S12, S13, S14, S15, S17, S18 and S19
6	S3, S4, S7, S9 and S16	S1, S2, S5, S6, S8, S10, S11, S12, S13, S14, S15, S17, S18 and S19

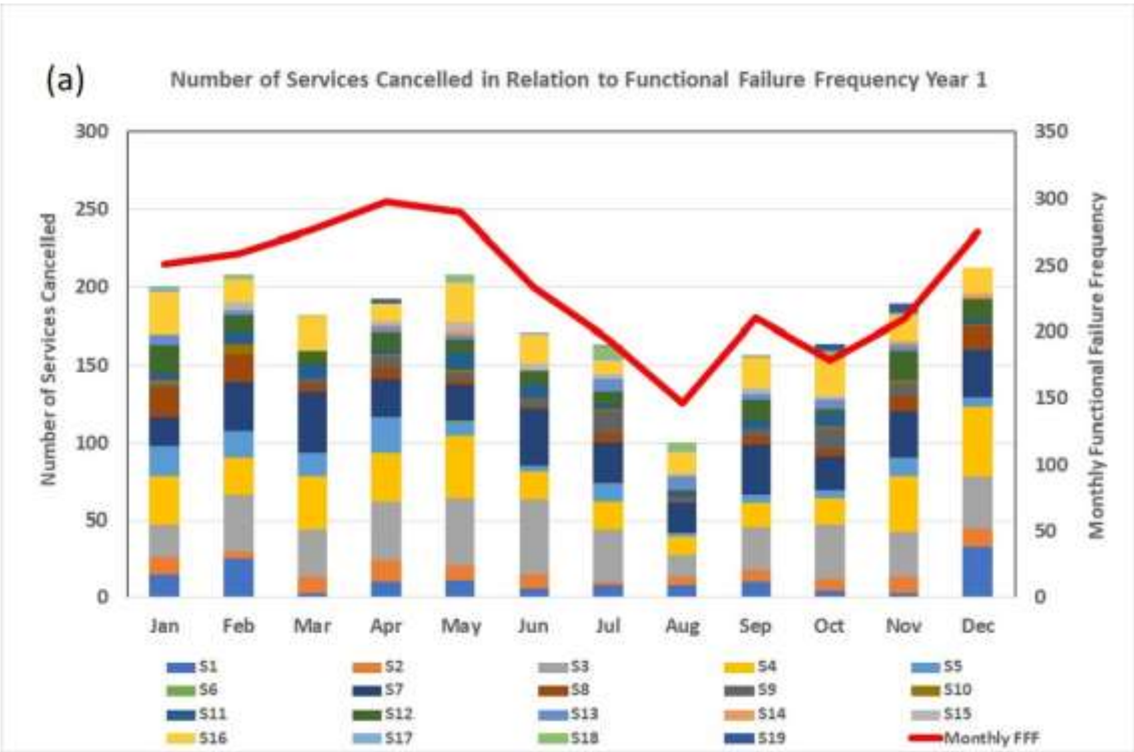
As can be seen in Table 3-5, S3, S4, S7 and S16 are recurrently identified as the critical sub-systems for the six study years, and all the other sub-systems are recurrently identified as non-critical. However, there are some non-recurrent patterns in the data as well. For example, S1, S5 and S12 are non-recurrently identified as critical in Year 1, while there are some sub-systems that are recurrently identified as critical in some years and as non-critical in the other years. For example, S9 is recurrently identified as non-critical from Year 1 to Year 4, and then it is recurrently identified as non-critical in Years 5 and 6. Hence, it is clearly evident that the data contains some recurrent and some non-recurrent patterns in the number of services delayed caused by the FFF of various sub-systems. However, this is unstructured information and thus does not provide any indication of the latent variables that are responsible for inducing the recurrent and non-recurrent patterns of the number of services delayed.

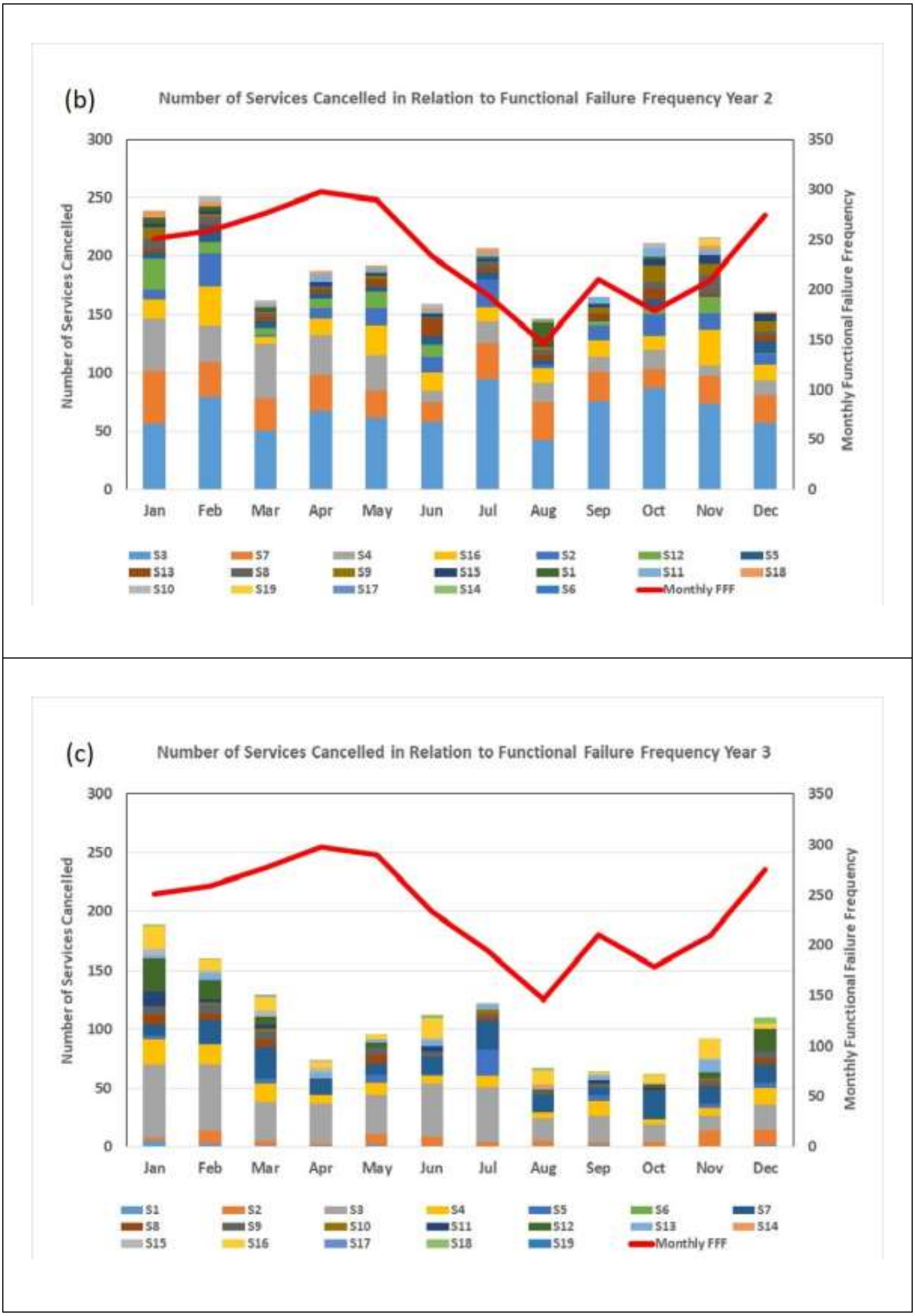
Another major observation is that the application of the Pareto principle for categorisation of the sub-systems does not establish whether the effect of the FFF of the sub-systems on service reliability has improved or worsened over the years. For instance, the numbers of services cancelled caused by the FFF of S3 in Years 1, 2, 3, 4, 5 and 6 were 4164, 3927, 2739, 3054, 3381 and 2973 as can be seen in Figure 3-7. This clearly shows that only information which is extractable is a relative increase or decrease in the number of services delayed which does not provide any information about the change in service criticality of that sub-system between different years. Hence, the yearly trends for change in the service criticality of the sub-system with respect to the number of services delayed are not meaningfully traced when SDA is used.

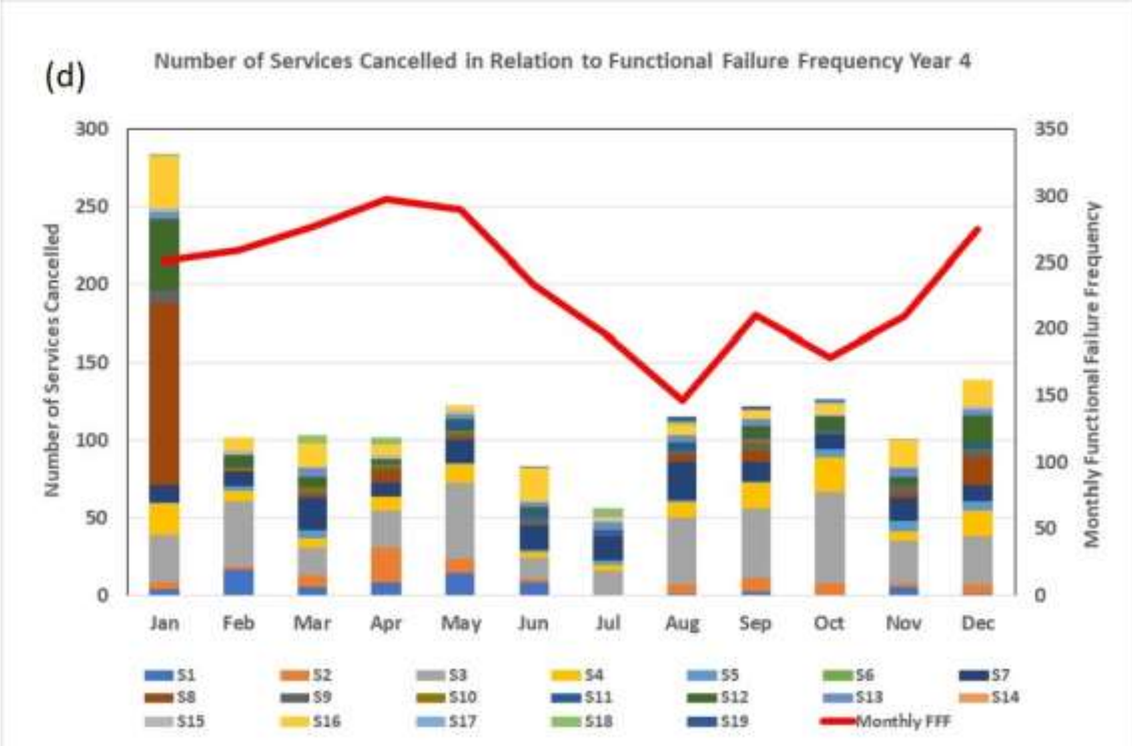
It is concluded that although C6 - the critical sub-systems for services cancelled and C7 - the critical sub-systems for services delayed can be established by using SDA, but with major limitations.

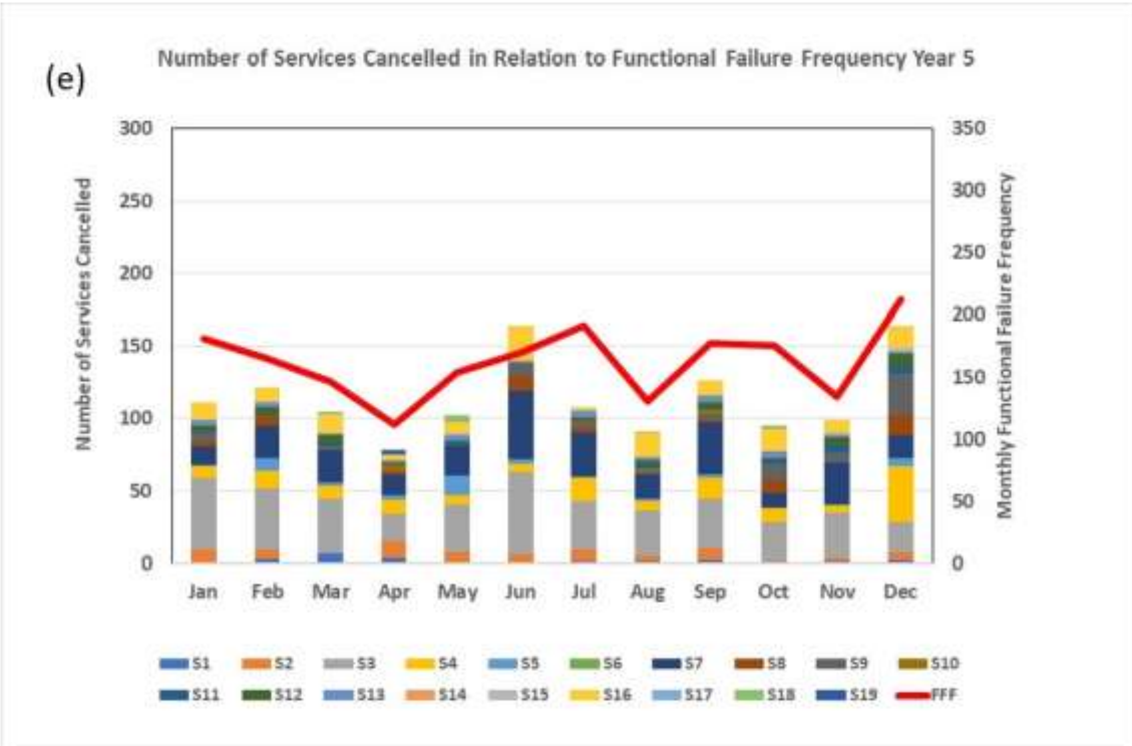
3.3.2.5 Evaluation of services cancelled profile and services delayed profile in relation to monthly FFF profile

In order to evaluate the usefulness of SDA for a relative assessment of the KPIs of service reliability and functional reliability, the services cancelled profile for each study year is first evaluated in relation to the monthly FFF profile to analyse C8 - relationship between the FFF and the number of services cancelled; and then the services delayed profile for each study year is evaluated in relation to the monthly FFF to analyse C9 - relationship between the FFF and the number of services delayed. Figure 3-8 shows the mapping of the monthly FFF and the monthly services cancelled profile for the six study years in the compound charts.




(b)
Number of Services Cancelled in Relation to Functional Failure Frequency Year 2
Number of Services Cancelled
Monthly Functional Failure Frequency
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
S3 S7 S4 S16 S2 S12 S5 S13 S8 S9 S15 S1 S11 S18 S10 S19 S17 S14 S6 Monthly FFF
(c)
Number of Services Cancelled in Relation to Functional Failure Frequency Year 3
Number of Services Cancelled
Monthly Functional Failure Frequency
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18 S19 Monthly FFF


(d)
Number of Services Cancelled in Relation to Functional Failure Frequency Year 4
Number of Services Cancelled
Monthly Functional Failure Frequency
300
250
200
150
100
50
0
350
300
250
200
150
100
50
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
S1
S2
S3
S4
S5
S6
S7
S8
S9
S10
S11
S12
S13
S14
S15
S16
S17
S18
S19
Monthly FFF


(e)
Number of Services Cancelled in Relation to Functional Failure Frequency Year 5
Number of Services Cancelled
Monthly Functional Failure Frequency
300
250
200
150
100
50
0
350
300
250
200
150
100
50
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
S1
S2
S3
S4
S5
S6
S7
S8
S9
S10
S11
S12
S13
S14
S15
S16
S17
S18
S19
FFF

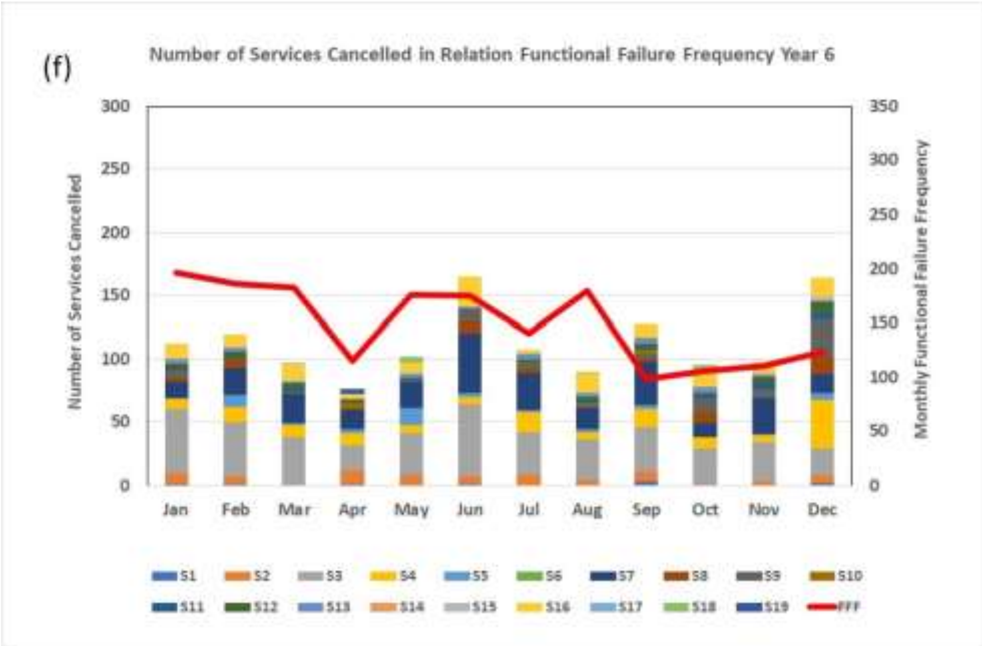
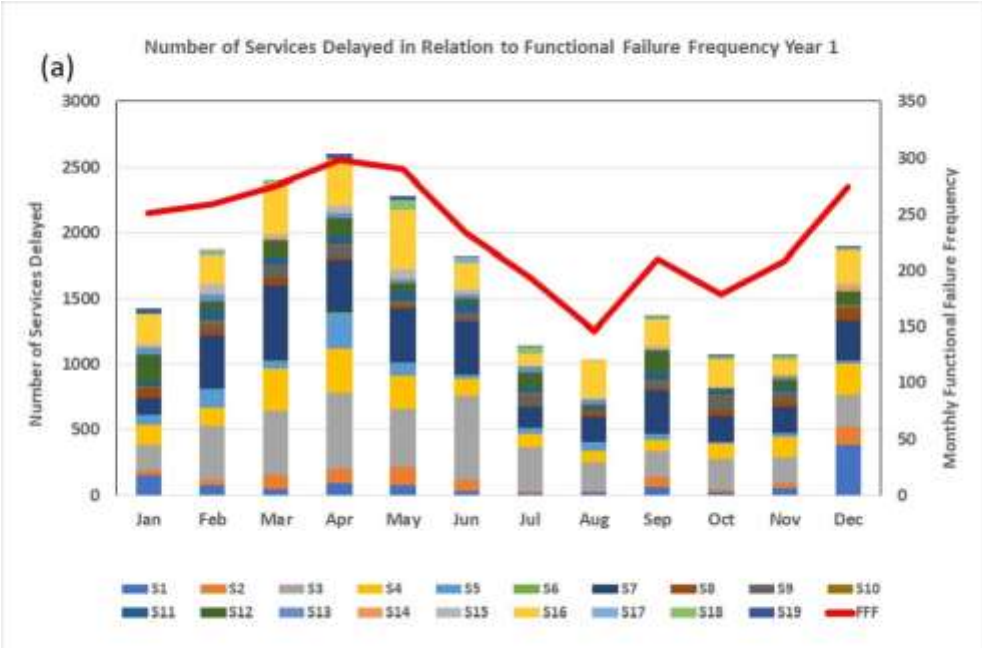


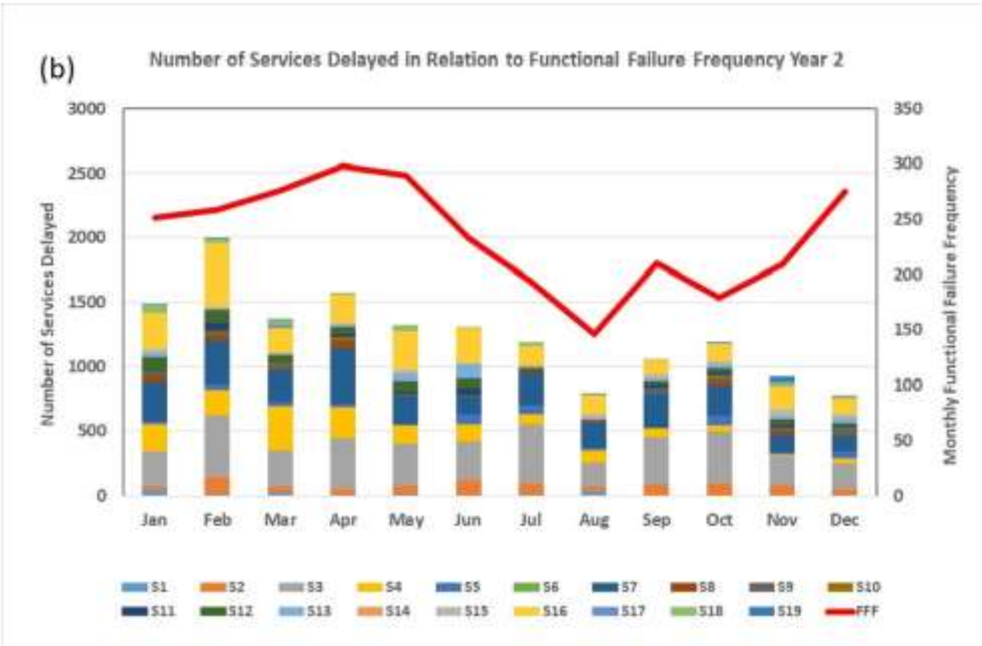
Figure 3-8: Relationship analysis between the monthly FFF and the number of services cancelled per month.

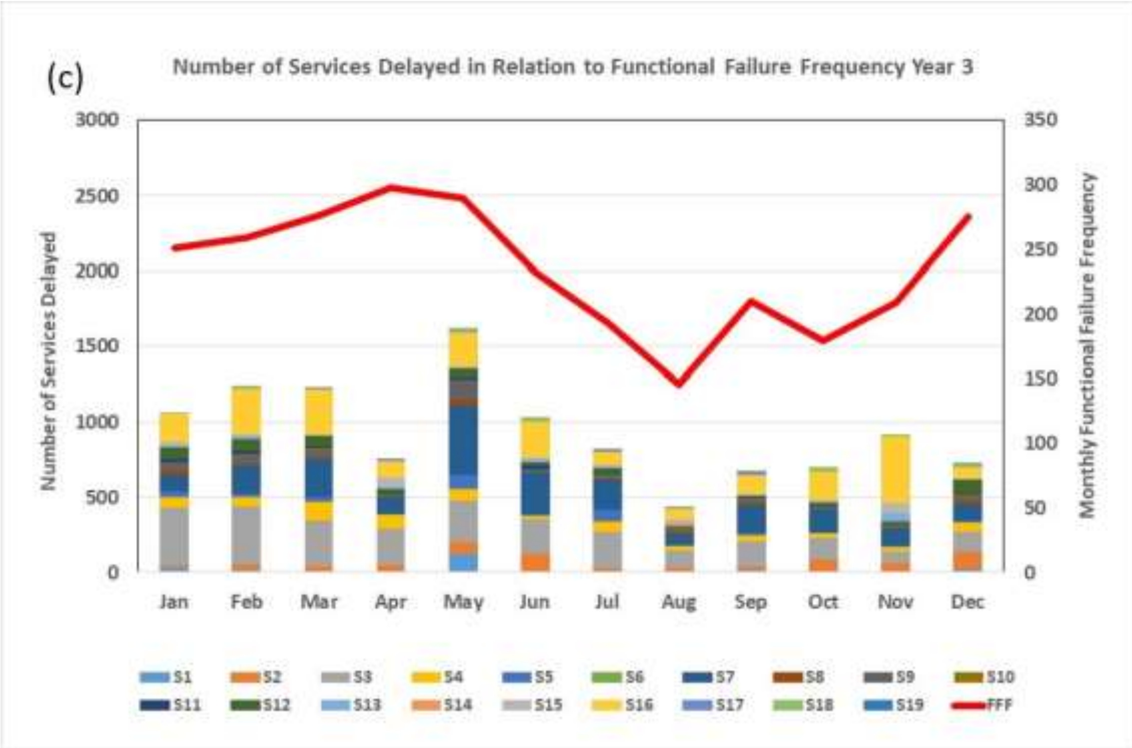
The figure shows the numbers of services cancelled per month with the contribution from the nineteen sub-systems in composite bar charts, and the monthly FFF in the red line curve for the six study years.

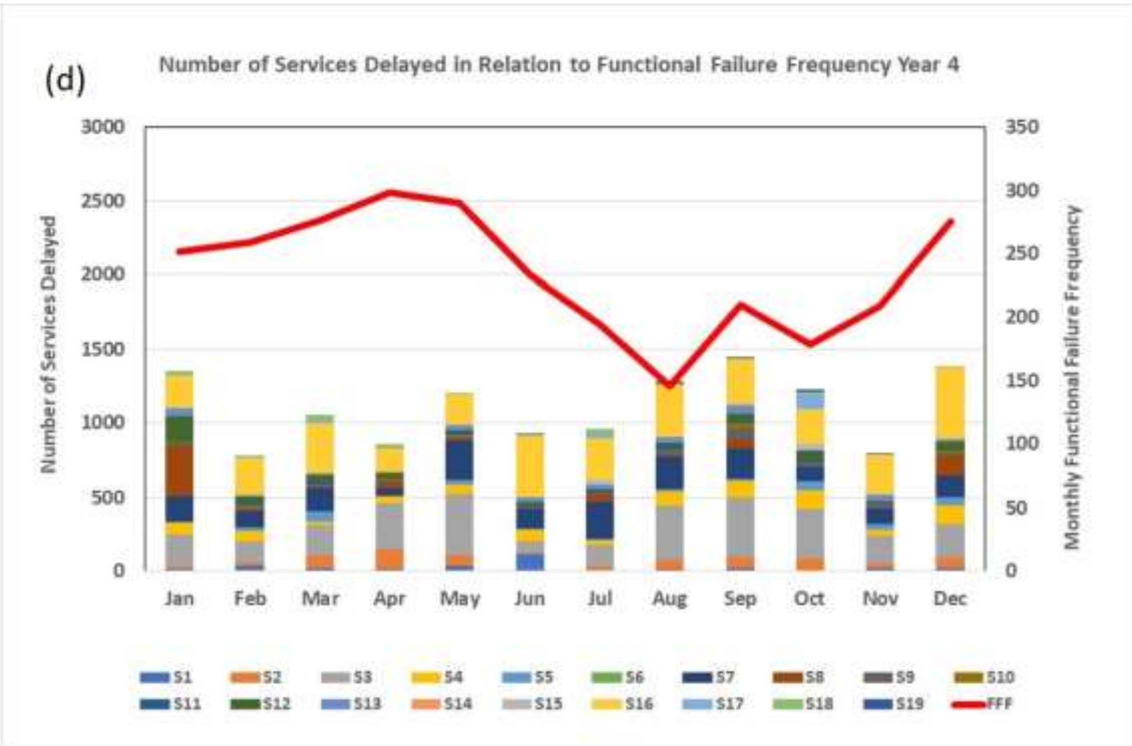
As can be seen in Figure 3-8, for some months an increase in the monthly FFF caused an increase in the number of services cancelled such as from August to September in Year 1, October to December in Year 3 and May to June in year 5, while for the other months an increase in the monthly FFF caused decrease in the number of services cancelled such as from November to December in Year 2, January to April in Year 4 and July to August in Year 6. Similarly, for some months a decrease in the monthly FFF caused a decrease in the number of services cancelled, for example, from July to August in Years 2 and 3, and from March to April in Year 5, while for the other months a decrease in the monthly FFF caused an increase in the number of services cancelled. For example, April to May in Year 1, June to July in Year 2 and August to September in Year 6. Thus, there appears to be some relationships between the monthly FFF and the number of services cancelled per month. However, the relationship is varying from month -to-month and hence, the overall relative status of the two KPIs is not assessable by using SDA.

To analyse C9 - relationship between the FFF and the number of services delayed, Figure 3-9, maps the monthly FFF and the monthly services cancelled profile for the six study years in compound charts.






(c)
Number of Services Delayed in Relation to Functional Failure Frequency Year 3
Number of Services Delayed
Monthly Functional Failure Frequency
3000
2500
2000
1500
1000
500
0
350
300
250
200
150
100
50
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
S1
S2
S3
S4
S5
S6
S7
S8
S9
S10
S11
S12
S13
S14
S15
S16
S17
S18
S19
FFF


(d)
Number of Services Delayed in Relation to Functional Failure Frequency Year 4
Number of Services Delayed
Monthly Functional Failure Frequency
3000
2500
2000
1500
1000
500
0
350
300
250
200
150
100
50
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
S1
S2
S3
S4
S5
S6
S7
S8
S9
S10
S11
S12
S13
S14
S15
S16
S17
S18
S19
FFF

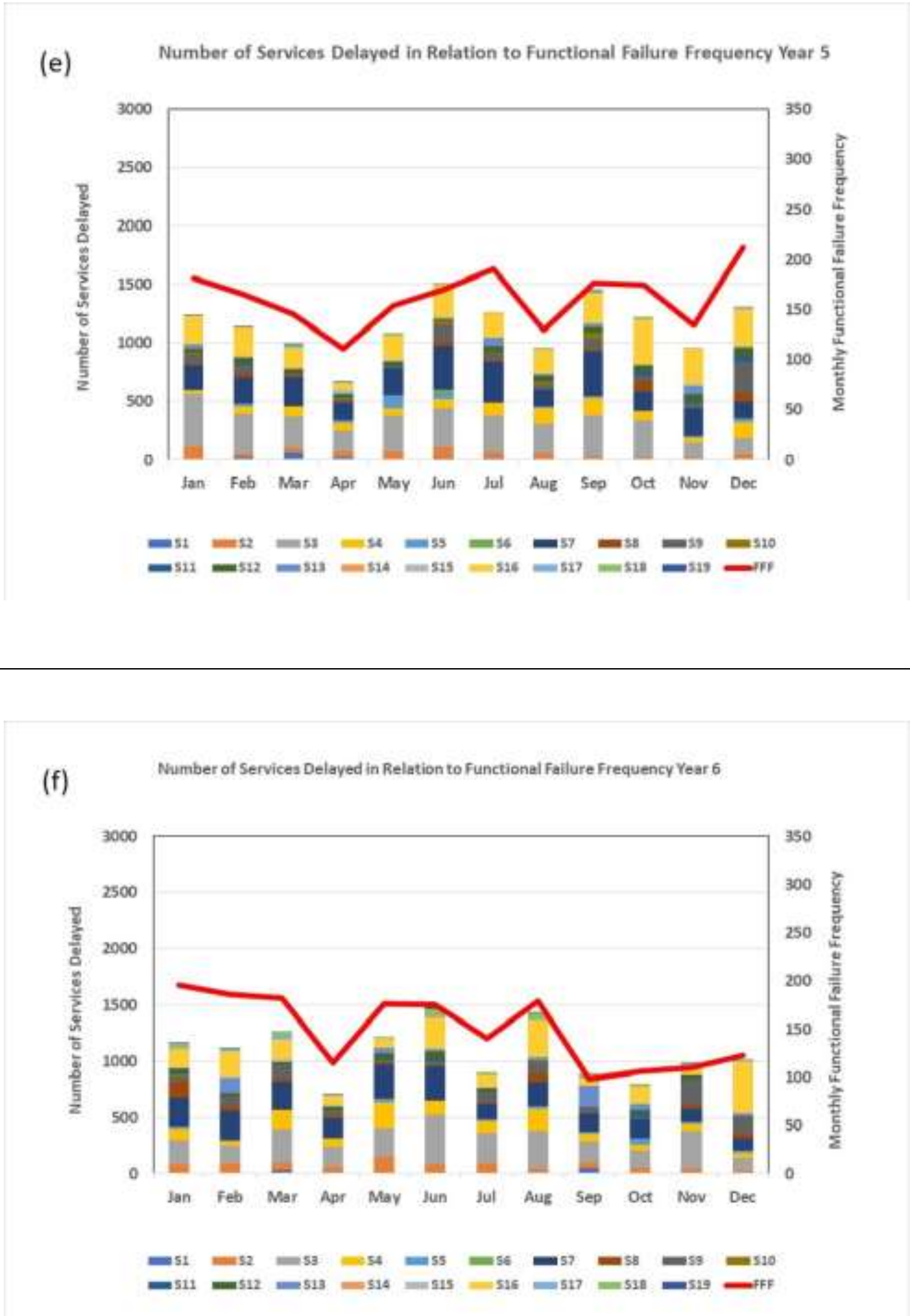


Figure 3-9: Relationship analysis between the monthly FFF and the number of services delayed per month.

The figure shows the numbers of services delayed per month with the contribution from the nineteen sub-systems in composite bar charts, and the monthly FFF in the red line curve for the six study years.

As can be seen in Figure 3-8, for some months an increase in the monthly FFF caused an increase in the number of services delayed such as from August to September in Year1, from October to December in Year 3 and May to June in Year 5, while for the other months an increase in the monthly FFF caused decrease in the number of services delayed such as from September to October in Year 2, July to August in Year 4 and August to September in Year 6. Similarly, for some months a decrease in the monthly FFF caused a decrease in the number of services cancelled, for example, from February to March in Year 2, January to April in Year 3 and June to July in Year 5, while for the other months a decrease in the monthly FFF caused an increase in the number of services delayed. For example, from October to December in Year 1, January to February in Year 2, May to June in Year 5. As identical to the findings of C8, there appears to be some relationships between the monthly FFF and the number of services delayed per month. However, the relationship is varying from month -to-month and hence, the overall relative status of the two KPIs subject to the maintenance plan is not assessable by using SDA.

These findings of C8 and C9 compliment the earlier findings from the literature review, it is not necessary that the more frequent failures cause more disruption, and the less frequent failures cause less (Bergström and Krüger, 2013). Even though, SDA is useful in determining the month-to-month relationship between the FFF and the number of services cancelled, and the FFF and the number of services delayed; however, the overall relative status of the two KPIs is not deducible from this information. Hence, it is concluded that C8 relationship between the FFF and the number of services cancelled and C9 relationship between the FFF and the number of services delayed cannot be established by SDA.

3.4 Evaluation of application of SDA for operational performance characterisation of the sub-systems

The discussion in Section 3.3.2 has shown that SDA is suitable for summarising the operational performance data of urban trains. It has allowed for ease in the data visualisation to analyse operational characteristics of the sub-systems. However, in order to evaluate the overall usefulness of SDA for operational characterisation of the sub-systems, Table 3-6 summarises the information that SDA delivers, and the outcomes that are desired from the analysis.

Table 3-6: Information delivered by SDA and desirables outcomes

Operational characteristics	Status	Limitations	Desirables outcomes
C1 – the critical months	Achievable	Identifies too many months as critical	Identifies only the most critical months
		Only informs whether the monthly FFF increases or decreases over the years	Informs whether the criticality of the months improves or becomes worse over the years
C2 – the similar and dissimilar months	Not achievable	-	-
C3 – the critical sub-systems	Achievable	No indication of the latent variables for the criticality of the sub-systems	Indication of the latent variables for the criticality of the sub-systems
		Only informs whether the sub-system FFF increases or decreases over the years	Informs whether the criticality of the sub-systems improves or becomes worse over the years
C4 – the similar and dissimilar sub-systems	Not achievable	-	-
C5 (a) – characterisation of the monthly FFF profiles	Not achievable	-	-
C5 (b) – influence of the sub-system on FFF of the months	Not achievable	-	-
C6 – the critical sub-systems for services cancelled	Achievable	Identifies criticality based on the number of services cancelled without considering the impact of FFF of the sub-systems	Identifies criticality by considering the impact of FFF of the sub-systems on the number of services cancelled
C7 – the critical sub-systems for services delayed	Achievable	Identifies criticality based on the number of services delayed without considering the impact of FFF of the sub-systems	Identifies criticality by considering the impact of FFF of the sub-systems on the number of services delayed
C8 – relationship between the FFF and the number of services cancelled	Not achievable	-	-
C9 – relationship between the FFF and the number of services delayed	Not achievable	-	-

As evident in Table 3-6, operational characteristics C1 , C3 , C6 and C7 can be established by using SDA, but with major limitations. An analytical model based on SDA uses the feature of the failure frequency counts for identification of the critical months and the critical sub-systems i.e. the higher the frequency counts, the greater the criticality is. However, the criticality categorisation is constrained by the maximum and the minimum value of the KPI data for the analysis period. This results in identification of too many months and sub-systems as critical as there is not a significant difference between their values. In addition, the criticality categorisation of the months and the sub-systems of different years cannot be easily compared. SDA only informs whether the KPI value increases or decreases i.e. whether the trend is upward or downward. Hence, it does not provide any indication for the latent variables that influence the operational performance of the sub-systems. In addition, the findings have shown that even though C6 and C7 can be analysed, the approach is eventually cascaded down to the FFF of the sub-systems. Because SDA is not able to establish the link between the KPIs for functional reliability and service reliability, so this results in general assumption in the maintenance planning process that a reduction in the FFF will help in improving service reliability as well.

Similarly, the analytical model based on SDA uses the feature of the relative comparison of the frequency counts of the KPI in various months and sub-systems for analysing operational characteristics C2 and C4 . Hence, the analysis is only able to explain whether the KPI frequency counts in the months or the sub-systems under consideration are more or less. This interpretation is also only extractable in terms of striking a comparison between the total frequency counts of the KPI for the months or the sub-systems. Hence, the analysis of the month-to-month or subsystem-to-subsystem relationship is not achievable. Since C2 and C4 are not achievable, C5 is not deliverable as it involves the relative assessment of the monthly FFF profile and the sub-system FFF profile. Likewise, operational characteristics C8 and C9 can only be explained in terms of increase or decrease in the in the monthly FFF together with the frequency counts of the KPIs for service reliability. As a result, no conclusion can be drawn about the relationship between the KPIs of functional reliability and the KPIs of service reliability.

In addition, the analysis has revealed the data characteristics that are also useful to develop understanding regarding limitations of the results obtained by SDA. The criticality categorisation of the months and the sub-systems have shown that the data contains some recurrent and some non-recurrent patterns. Also, the graphical representation of the data in composite charts and the compound charts has shown that too many variables are involved in the data i.e. multivariate. Given that the data contains redundant information; hence, there is an inconsistency in the data that has resulted in extraction of meaningless information.

In summary, SDA is not suitable for operational characterisation of the sub-systems. Hence an improved analytical tool is required for operational performance characterisation of the sub-systems.

3.5 Summary

The research presented in this chapter has provided insight into the conventional approach used for operational performance characterisation of the sub-systems for the maintenance planning through the case study of UTS Melbourne. The approach applies the KPIs for reliability for establishment of the operational characteristics of the sub-systems in order to support the decision-making process of the maintenance planning, and achieves this by using SDA as an analytical tool. The demonstration of the approach has shown that SDA is useful in summarising the data both in simple and in more complex composite bar charts that are easy to understand. However, SDA is based on the frequency counts of KPIs for functional and service reliability, and thus only indicates increases or decreases in their values rather than explaining whether each KPI has improved or not. Furthermore, it does not explain the vital relationships between these KPIs and also does not provide any information about the latent variables that have influenced the functional or service reliability. Due to these limitations, while SDA does deliver four operational characteristics to a certain extent, it is not able to deliver all the operational characteristics.

Therefore, it is clear that an improved approach for characterising the operational performance is required. Such an approach is proposed in the next chapter.

Chapter 4: OPERATIONAL PERFORMANCE CHARACTERISATION OF AN URBAN TRAINS FLEET BASED ON A SINGLE (CONVENTIONAL) CRITERION BY USING PRINCIPAL COMPONENT ANALYSIS

4.1 Introduction

The previous chapter presented and assessed the conventional approach of the reliability analysis for operational performance characterisation of an urban trains fleet. It was concluded that simple descriptive analysis which is applied as an analytical tool summarises the data in a manner which is easy to understand, but it is not suitable for establishing the operational characteristics of the sub-systems. Hence, another data analysis technique is needed that can be used for such a big and multivariate dataset. This part of the research focuses on Research Objective 2(a) that seeks to improve the conventional approach which is used to characterise the operational performance of the fleet to enhance its effectiveness in the decision-making process of the maintenance planning.

To achieve this research objective, a new approach is developed in this chapter. In the new approach, the approach is modified by preserving the conventional single criterion for characterisation i.e. functional failures frequency (FFF), while applying an exploratory multivariate data analysis technique called principal component analysis (PCA).

In order to evaluate the suitability of PCA for analysis of the operational performance characteristics of the sub-systems based on the FFF, this chapter first presents the PCA technique and then applies it to the same data which is used in the previous chapter. The data structure for analysis and the software used are described in detail, and the script is validated using several examples. The results of PCA analysis are then presented and finally the performance of the new approach is compared to that of the conventional approach.

4.2 Selection of PCA for operational performance characterisation of the sub-systems

This section explains the applicability of PCA for analysis of the operational performance characteristics of the sub-systems by using the FFF. The data characteristics are first discussed, the analysis objectives are then restated as they are the determinants for selection of an analytical technique for any data. Finally, the usefulness of PCA for analysing the FFF data of urban trains systems is assessed.

The FFF is documented per month and per sub-system producing big and redundant data. However, in each case the FFF is cascaded down at the sub-system level; therefore, the sub-systems are the observable variables for the FFF data. This data shows recurrent and non-recurrent patterns in the measurements of FFF for various months and the sub-systems. This is also evident from the findings of Chapter 3 that some months and sub-systems were repetitively identified as critical or non-critical, while some months and sub-systems were non-repetitively identified as critical or non-critical. These patterns indicate the dependency of the FFF on the characteristics of the month and the sub-system. The FFF of the month depends on the operational environment of that month which is a product of a combination of different variables such as abrupt changes in the weather, unforeseen issues in the technology, and unexpected changes in the variables related to infrastructure, maintenance planning and the operational planning. Similarly, the FFF of the sub-system depends on functional reliability of that sub-system which is a product of multiple variables related to its inherent design characteristics, and the design and implementation of its maintenance plan such as unexpected changes in the maintenance interval and complexities in executing the maintenance activities due to the configurational dependency of the sub-systems. These variables related to both the operational environment of the month and functional reliability of the sub-system influence the operational performance of the sub-systems individually and in relation to each other. The variables induce similarities and dissimilarities in their FFF profiles that result in similar and dissimilar months and similar and dissimilar sub-systems. However, their influence cannot be observed directly from the FFF data as the FFF is just a simple count of non-performance of the sub-systems as discussed in Section 3.3.3 of Chapter 3. Therefore, these variables are called the “latent variables” as explained in Section 2.2.2 of Chapter 2.

It is important to consider the influence of these latent variables to accurately characterise the operational performance of the different sub-systems. This influence is traceable by means of exploring the latent structure of the data which is constructed within the data by the latent variables. In order to understand the latent structure, let us take an example – it might be recurrently found from the data that the FFF profile of the sub-systems X and Y are highly correlated. However, the correlation between the FFF of the two sub-systems is not feasible as the sub-systems of a complex system like urban train may have configurational dependency but their functional failures are independent from each other. This implies that there is no dependency between the FFF profile of X and Y; however, there might be a correlation if a third variable is considered i.e. the latent variable (Shyrane, 2011). For example, on investigation data might show that sub-systems X and Y incur high FFF on passing the operational mileage above a specific value. This shows that a correlation exists between the operational mileage and the FFF profile of sub-system X, as well as a correlation between the operational mileage and the FFF profile of sub-system Y. Hence, the operational mileage is the underlying reason for similarities in the FFF profiles of both sub-system X and Y.

This implies that the correlation between the observable variables and the latent variables exists within the data in a hidden manner; therefore, it is called the latent structure. If the latent variables are considered, the correlation between the observable variables become weaker and this will result in a clear manifestation of the latent structure of the data i.e. the correlation between the observable variables and the latent variables (Shyrane, 2011). This provides an opportunity to measure the influence of the latent variables on the observable variables. An understanding of the latent structure will enable the reliability analyst (who knows all the maintenance and the operational history) to recognise the latent variables and learn from the historical decisions and events influencing the operational performance of the sub-systems, thus resulting in data-driven decision-making. Hence, considering the influence of the latent variables in the analysis can be incorporated to enhance the conventional complement the conventional approach of the reliability analysis for operational performance characterisation of the sub-systems.

In order to explore the latent structure of the data, it is first necessary to know what information needs to be extracted from this data. As discussed in Section 3.2.1 of Chapter 3, the objective of analysing the operational performance characteristics of the sub-systems based on the FFF is to evaluate the monthly and the sub-system FFF profiles individually and in relation to each other. The operational characteristics of interest in the historical FFF data are:

C1 the critical months
C2 the similar and dissimilar months
C3 the critical sub-systems
C4 the similar and dissimilar sub-systems

C5 the relationship between the FFF profiles of sub-systems and months

(a) characterisation of the monthly FFF profiles in relation to the sub-system FFF profiles

(b) influence of the sub-system on the monthly FFF profiles

The extraction of this information from the big data by elimination of the less important or redundant information requires the application of a multivariate data analysis technique. PCA offers great potential as a possible technique since it removes redundancy from the data and extracts important information from the data based on the proportion of variance explained by the latent variables in the data (Steorts, Abdi and Williams, 2010, Jolliffe and Cadima, 2016, Hartmann, 2018a). Variance is a measure of a dispersion and when a variable has a larger variance, it indicates that this latent variable contains larger information. Abdi and Williams (2010) state that PCA first orthogonally transforms correlated original variables into the coordinate system of un-correlated variables. There are then fewer new variables than original variables and the new variables, called the principal components, represent the latent variables. PCA then projects the original data into the coordinate system of the PCs. The first PC represents a direction on which the data projection shows the largest variance. The second PC is orthogonal to the first PC and it is found in the direction that shows the next largest variance after the first PC and so on. This orthogonal transformation results in a minimum loss of the original information from the data (Abdi and Williams, 2010). The orthogonal properties of PCA makes it an appropriate choice (Dunia et al., 1996) for analysis of the FFF data of an urban trains fleet.

Other advantages of PCA are:

(i) it can be performed to analyse the latent structure within data without labelling the PCs (Raschka, 2014, Steorts);

(ii) it extracts the important characteristics of a dataset without losing much of its original information (Shang, 2011, Tibshirani, 2013); and

(iii) it provides visual tools that make the presentation and discussion of the results easier (Shang, 2011).

In addition, PCA has been successfully applied in various industries including the rail industry. Żółtowski (2012) applied PCA to the data of rail track condition symptoms for the classification of the track for condition-based maintenance while (Dekker et al., 2019) applied PCA for analysis of the delays data of the urban trains. In Dekker’s study, train delays data from ProRail in the Netherlands was investigated. The data matrix was composed of the disrupted days of the week in the rows and the stations on the network in the columns. The extent of propagation of accumulated train delays at stations is influenced by several latent variables related to both the technical components of the railway system and the human elements such as network capacity, station operational capacity, human decisions for re-routing or cancellation of services. Typically, the raw data is summarised as train delays time and frequency of train delays which does not provide any information about the patterns of transition regime in the train delays framework due to the influence of these latent variables. However, it is crucial to consider influence of the latent variables to identify the critical stations for the development of an improved train management plan. PCA was used to identify the stations on the railway network that were critical for the delays dynamics of the system at macro-scale, and it was found that all stations identified as critical were located on the three busiest train lines that carried international passenger trains and connected the major cities in the Netherlands. Hence, the latent variable that makes the stations critical for the delays dynamics of the system at macro-scale was their geographical location. Thus, this study established PCA could be used to identify not only the critical stations, but also the underlying reason for their criticality. In summary, PCA is a multivariate data analysis technique that can be used to effectively analyse the latent structure within the operational performance data of any urban trains fleet; thus, PCA was selected for use in this study.

4.3 Data analysis plan

This section explains the data analysis plan which was designed for the application of PCA to the urban trains data in this study. The data and the software used for the analysis are first presented, and its script design outlined and then validated through examples. The usefulness of PCA as a complex decision-making process is highlighted.

4.3.1 Data collection and structure

The same data that was collected from the UTS Melbourne for SDA as reported in Chapter 3 was used in this chapter for PCA. In Chapter 3, the FFF recorded for 12 months of the year for 19 different sub-systems of the urban train system (that were coded as S1, S2,…, S19) for the six study years was used for analysing the operational characteristics merely based on the FFF. Hence, in this chapter the same FFF data was structured in a 12x19 matrix for the analysis;

wherein, the months in rows represent the individuals in which the FFF were documented, and the sub-systems in columns represent the original variables from which the FFF were measured. Data for each month of the year for last few years are analysed in order to trace the trends and patterns of operational performance of the sub-systems within a year and from year to year. This information enables the maintenance planners to trace the reason for change in operational performance of the sub-systems in relation to change in operational environment of urban rails.

4.3.2 Software and script design

MATLAB version 9.4 (R2018a) by (The MathWorks Inc) was used to perform PCA. It has an inbuilt function - PCA () in its statistics and machine learning toolbox. An algorithm of this function is based on the singular value decomposition (The MathWorks Inc., 2019). The singular value decomposition is slightly more numerically precise than the eigenvalue decomposition (Kalisch, 2012, The MathWorks Inc., 2019). It performs stable computation for data that has more variables than the individuals (Donev, 2011, Kalisch, 2012). .

Based on the data characteristics, the script was designed with the following considerations to perform PCA on the raw data for each study year:

(1) **Data centring:** the inbuilt function- PCA () in MATLAB2018a by default centre the data before running PCA. Data centring does not affect the resulting PCs (Raschka, 2014) besides it improves the interpretability of the results (Eriksson et al., 2013).

(2) **An unscaled PCA** – unscaled PCA is an appropriate choice when variables are measured in same unit and their absolute values matters (Tibshirani, 2014, Taylor and Bacallado, 2019). Since the FFF is observed for all the sub-systems in each month in the same unit, and their absolute values is of concern so, unscaled PCA was considered.

(3) **Covariance matrix** – a covariance matrix is recommended for PCA computation when variables scale is same. The computation of a covariance matrix is based on the raw data that accounts the actual dispersion in the data (Tinsley & Tinsley, 1987 as cited inField, 2013). An advantage of using a covariance matrix is that it determines the loadings of the original variables which are easy to interpret. The inbuilt function of PCA() in MATLAB2018a by default computes the covariance matrix of the data after centring it. It was incorporated in the script design.

The script designed to perform PCA in MATLAB is presented in Appendix A.

4.3.3 Validation of script and justification for selection of PCA

Two published studies that use PCA were selected for validation of the designed script based on the availability of their data. One example (Dunn, 2019) was taken from the food manufacturing industry and another example (Kassambara, 2017) was taken from the sports industry. In both examples, the variables in the original data were measured in different units; therefore, an additional step was required for standardisation of the data before performing PCA. For this, an inbuilt function z-score in MATLAB was used and the script was then run on the standardised data. The same results as reported in Dunn 2019a were obtained in our work; however, in the second example (Kassambara) different results with values with opposite signs were obtained in our work. This is due to the differences in coding or the use of a different software package (Jolliffe and Cadima, 2016). However, the interpretation of the results does not change because of the change in the signs (The MathWorks, 2019). In Easy (2020), the published results are identical as that were obtained from the designed script. Hence, the results obtained with the designed script validate the script design and its functioning. The obtained results for both examples were mapped into the typical plots of PCA and are presented in Appendix B**.** In order to establish that PCA can be used to reveal the latent structure of the data, the key findings of both examples are discussed here.

In the first example the data involved are measurements of various physical properties of pastry samples from different batches. Despite the same manufacturing process being used, pastries are produced with varied texture. This is due to the influence of the latent variables such as variations in baking temperature and overhandling of the dough. Therefore, food scientists apply PCA for texture characterisation of the pastry samples considering the influence of the latent variables for process control and monitoring. In Dunn's study, it was found that the pastry samples that obtained positive scores on principal component I (PC-I) were brittle, flaky and light due to high percentage of oil, more crispiness, low density and small fracture angle. By contrast, the pastry samples that obtained negative scores on PC-I were chewy, hard and brittle due to low percentage of oil, less crispiness, high density and larger fracture angle. This implies that the latent variable associated with PC-I is essential for production of fine texture pastries. By comparison, the pastry samples that obtained positive scores on principal component II (PC-II) were hard due to high value on the hardness scale and the low percentage of oil. This implies that the latent variable associated with PC-II needs to be resolved to adjust the hardness of the pastries. All this information informs the decision-makers that, in order to improve the process, it is required to adjust the variable related to the hardness of the pastry without changing the other properties.

In the second example, the data involved are performance scores of various athletes in the different events of a decathlon. Different variables like athlete physique and skills required to win decathlon events influence the scores performance. Hence, the sports scientists applied PCA for evaluation of the scores performance. In Kassambara's study, it was found that the athletes that obtained positive scores on PC-I had high scores in X400m, X100m.hurdle, X100m and long jump in comparison to shot put, discus and high jump. It is important to note that having high scores in the former group of events and low scores in the latter group of events represents poor performance. This suggests that the latent variable associated with PC-I is related to speed. It was also found that the athletes were distributed in ascending order of their total scores from positive direction to negative direction of PC-I. This implies that a decrease in influence of the associated latent variable can result in an increase in the total scores of the athletes. On PC-II, it was found that the athletes that obtained positive sores on PC-II had high scores in X1500m and pole vault in comparison to high jump. This suggests that the latent variable associated with PC-II is related to strength. All this together indicates that the athletes in quadrant I are weak in speed, but strong in strength events; the athletes in quadrant II are good in both speed and strength events; the athletes in quadrant III are good in speed, but weak in strength events; and the athletes in quadrant IV are weak in both speed and strength events. This information is utilised by the coaches for training purpose and in selection of the athletes for construction of a balanced team for the future events.

Both examples show that an application of PCA facilitates in investigating, visualising and interpreting with ease the latent structure of the dataset. Using PCA enables the analyst to differentiate between the individuals (entities that are represented in the rows) based on the similarities and dissimilarities in their profiles. The inner-structure of the PCs clarifies how the data variables interact individually and in relation to each other considering the influence of the latent variables. In addition, PCA also reveals which variables contribute the most in making the profiles of individuals similar and dissimilar. All this information jointly enables the decision-makers to recognise the latent variables and to formulate the improvement strategies accordingly.

4.3.4 Relevancy between examples and the urban trains data

The complexity of the selected examples in terms of their data characteristics and analysis objectives is comparable with the complexity of the present urban trains study. The data characteristics and the analysis objectives are summarised in Table 4-1:

Table 4-1: Data characteristics and analysis objectives of examples and urban trains

	Example 1	**Example 2**	**Research Project**
Data characteristics			
Highly correlated variables	✓	✓	✓
Redundancy	✓	✓	✓
Recurrent and non-recurrent patterns	✓	✓	✓
Multivariate	✓	✓	✓
Complexity	✓	✓	✓
Analysis objectives			
Identification of new un-correlated variables	✓	✓	✓
Reduction in number of variables	✓	✓	✓
Extraction of important features by elimination of less important features	✓	✓	✓

As can be seen n Table 4-1, the data characteristics are the same. When the data is multivariate, complex, redundant and involves highly correlated variables, it is quite challenging for analysts to characterise it. In any industry where the data has similar characteristics to those listed in Table 4-1, data analysts is interested to extract important information from the data but with minimum loss of information. The objective of the analysis is to characterise the rows and columns of their data matrix individually and in relation to each other. In both examples, PCA enabled the desired objectives to be achieved by making the information more interpretable and easier to visualise.

In summary, PCA is clearly able to analyse successfully data with similar characteristics to the operational performance data of urban trains in this study.

4.3.5 Application of PCA to the urban trains data

The yearly matrix X of the FFF of each study year was analysed using PCA. This section discusses the computational process used in PCA for analysing the data of urban trains.

As discussed in Section 4.3.1, X is a matrix of order 12 x 19 where the rows are the 12 months of the year and the columns are the 19 sub-systems. Each individual element in X is represented by x_{ij} which implies that x - FFF lodged in i^{th} month by j^{th} sub-system. This means that the elements of i^{th} row forms a p-dimension vector of i^{th} month denoted by M_i and the elements of j^{th} column forms a n-dimension vector of j^{th} sub-system denoted by S_j. PCA orthogonally transforms X into a set of r-PCs which is equal to the minimum (number of rows, number of columns) minus one (Adams et al., 2001, Smoliński et al., 2002). Given that the minimum (12,19) minus one is equal to 11; hence, it generates 11 PCs for each study year. The structuring of the PCs explains the latent structure within X based on the common latent variables. The PCs are the directional vectors (Hartmann, 2018b, Dunn, 2019), and in matrix form each PC is a loading vector of order 19 x 1. The PCs can be labelled by the related latent variables, but recognition of the latent variables needs complete details of the maintenance and the operational history of the study period. In this study, the requisite information could not be obtained due to restricted access to the data and the confidentiality concerns, so the PCs were simply labelled as principal component I, principal component II and so on. Using the SVD, PCA decomposes the data matrix X into a product of left and right singular vectors denoted by U and V respectively and a square matrix D of singular values as shown in Equation 4-1.

$$\mathrm{X} = \mathrm{UD}V^t \qquad \textbf{4-1}$$

with $U^TU = V^TV = I$.

The matrix U is of order 12 x 11, D is of order 11x 11 and V^t is of order 11 x 19. The algorithm first conditions the matrix X to centre by each column for computation of $X^tX = \sum_i M_i M^t$. It is proportional to the covariance matrix for the variables of M_i (i.e. the covariance matrix of the sub-systems). Then, X^tX is diagonalized which results in VD^2V^t. The first resultant matrix V is the orthogonal matrix of the right singular vectors and it is denoted by $\{V_r\}$. This spans the system of the monthly FFF profile and provides an orthonormal basis for $\{M_i\}$. The matrix V is basically the set of PCs that contains the coefficients of the sub-systems on the PCs, and it is equivalent to the loading matrix of the sub-systems (i.e. V = W) (Surawski et al., 2017) . The loading of each sub-system on each PC explains its correlation with the latent variable. The loadings of p – subsystems on k^{th} PC is represented by [$w_{1,k}$, $w_{2,k}$, $w_{3,k}$ ..., $w_{p,k}$], while the second resultant matrix D is a matrix of singular values that contains only non-zero values along its diagonal. Provided that each singular value is associated with one PC, there were 11 PCs for each study year. The singular values describe a magnitude of the variance captured by the corresponding PC. Hence, the singular values explain the strength of influence of the latent variables in generation of X. The first singular value is more important than the second, and the second singular value is more important than the third, and so on (i.e. $\sigma_1 > \sigma_2 > \ldots\ldots \sigma_r$). This means that the singular values are arranged in the descending order of their importance. This also indicates the importance of information within each PC i.e. the first PC is the most significant, and the last PC (which is eleventh PC in this study for each study year) is the least important. The squared of singular values produced eigenvalues of PCA which are proportional to the variance of the PCs. The next step is a computation of U which is a matrix of left singular vectors and it is represented by $\{U_r\}$. The algorithm computes U by using a relation XVS^{-1}. This spans the system of FFF profile per sub-system and forms an orthonormal basis for {Sj}. Finally, the algorithm projects X into the new coordinate system of the PCs by using a relation UD which is equivalent to XV=XW (as V=W). The resultant matrix represents the factor scores of the months denoted by T. The scores are obtained by mapping each row of X on the system of the PCs. The scores of the i^{th} month on the k^{th} PC is represented by $\mathbf{t}_{i,k.}$ and this is obtained by the product of p – dimension vector of i^{th} row of X with the p- dimension vector of k^{th} column of V=W. It is expressed as:

$$\mathbf{t}_{i,k} = \mathbf{x}_{i,1} * \mathbf{w}_{1,k} + \mathbf{x}_{i,2} * \mathbf{w}_{2,k} + \mathbf{x}_{i,3} * \mathbf{w}_{3,k} \text{ ---, } \mathbf{x}_{i,p} * \mathbf{w}_{p,k} \qquad \textbf{4-2}$$

Equation 5.2 shows that the scores are the composite measures of the months on the PCs and each month has one score along the direction of each PC. Consistent with the order of importance of the PCs, the scores of months on the first PC are more important than those on the second PC and so on. As UD = T and V= W, equation 4-1 can be rewritten as:

$$\mathrm{X} = UDV^t = (UD)V^t = TW^t \qquad \textbf{4-3}$$

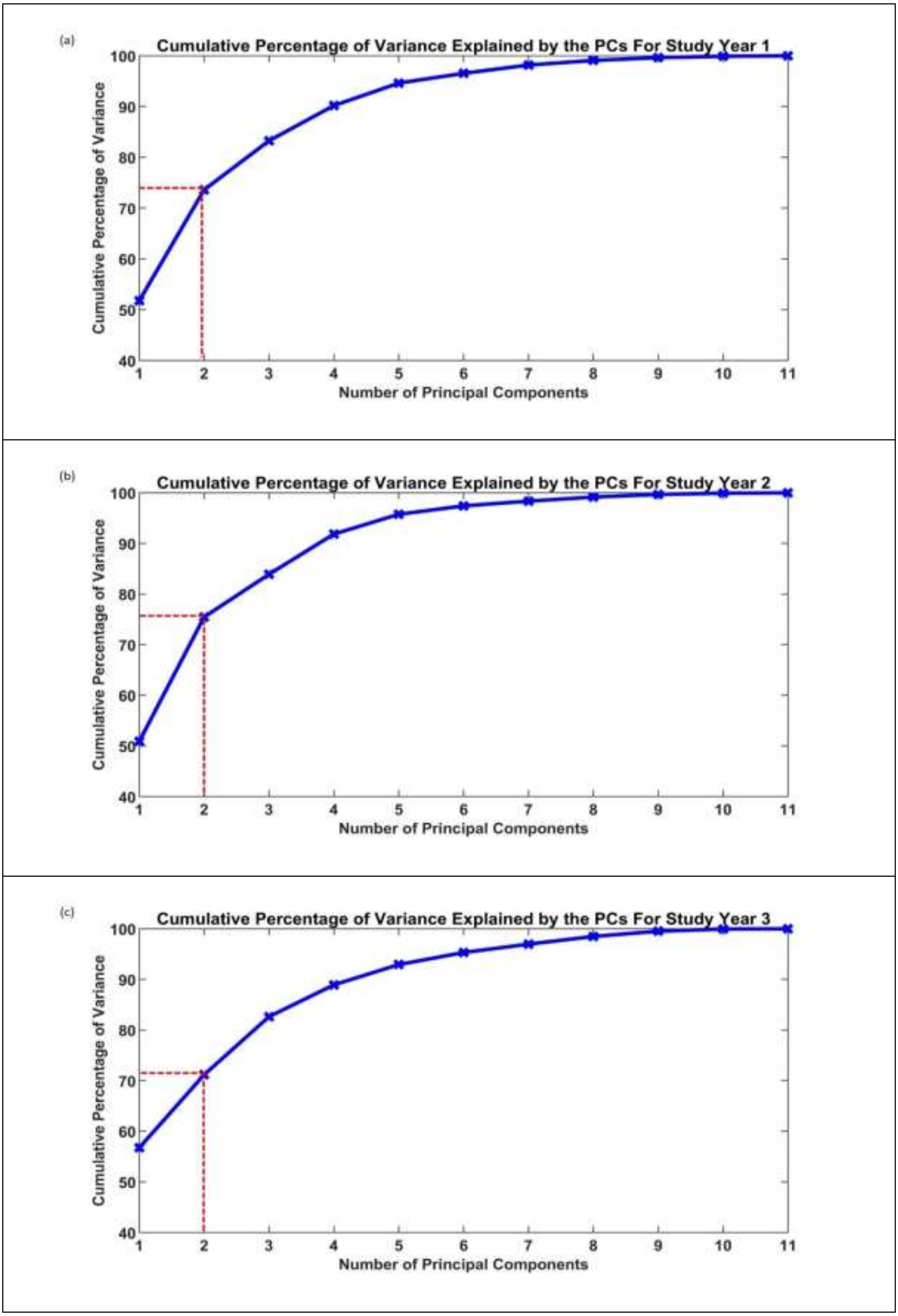
Equation 4-3 shows that PCA transforms X into the scores of months, i.e. T, and the loadings of the sub-systems, i.e. W. The information within both resultant matrices is arranged from order of high to low importance consistent with the arrangement of the singular values. Equation 4-3 also shows that X is a product of T and W^t. The transformation of X into T and W^t discloses the latent structure that exists within the data. Thus, PCA can be used to transform the urban trains data into meaningful information.

4.4 Analysis of the operational performance characteristics using PCA

This section discusses the results obtained by the application of PCA to the urban trains data for the six study years. The aim is to evaluate whether PCA can establish the desired operational characteristics of the sub-systems.

4.4.1 Selection of the number of principal components for further analysis

As discussed in Section 4.3.5, PCA generated 11 PCs for each study year. As these PCs were arranged in order of importance from highest to lowest, the first PC accounted for the greatest variation in the data and the last PC the least, so a selection of an adequate number of PCs is required for a better approximation of the yearly matrix X of the FFF. This number of PCs can be determined from the cumulative percentage of variance plot that is a plot with the number of PCs on the x-axis and the cumulative percentage of variance explained by them on the y-axis. A cut-off value for the cumulative percentage of variance needs to be defined to determine the number of PCs to be retained for further analysis. It is recommended to retain at least as many the PCs, so that the cumulative percentage of variance explained by them is no less than 70%. (Jolliffe, 2002, Yang, 2015, De Silva et al., 2017). Figure 4-1 presents the cumulative percentage of variance plots for all six study years.


(a)
Cumulative Percentage of Variance Explained by the PCs For Study Year 1
Cumulative Percentage of Variance
Number of Principal Components
(b)
Cumulative Percentage of Variance Explained by the PCs For Study Year 2
Cumulative Percentage of Variance
Number of Principal Components
(c)
Cumulative Percentage of Variance Explained by the PCs For Study Year 3
Cumulative Percentage of Variance
Number of Principal Components

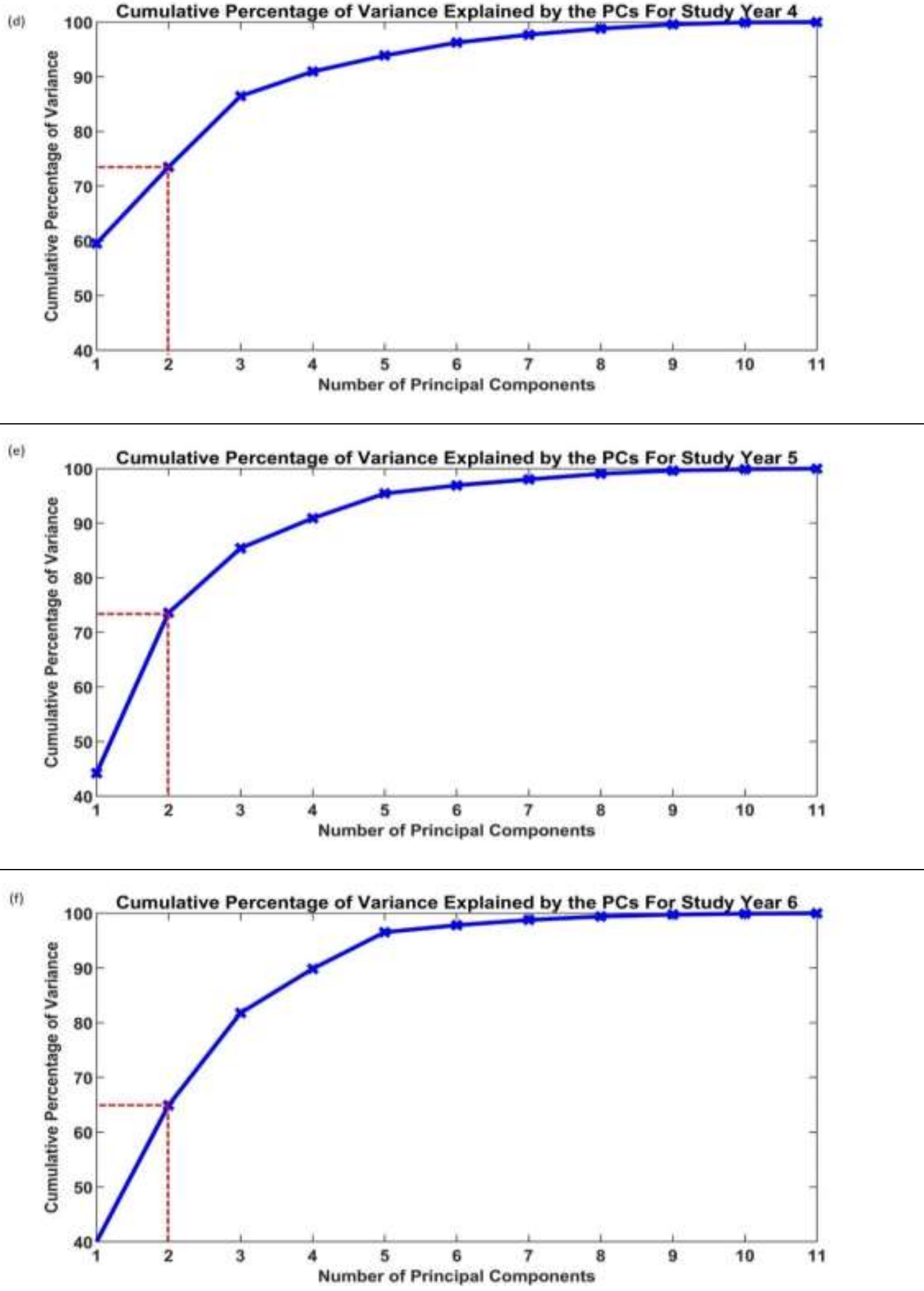


Figure 4-1:Cumulative percentage of variance plot for each study year.

A red dotted on each chart shows the cumulative percentage of variance which is explained by PC-I and PC-II in each study year.

As can be seen in Figure 4-1, if we retain one PC, the cumulative percentage of variance is approximately 52%, 51%, 57%, 60%, 44% and 40% in study years 1,2,3,4,5 and 6, respectively. This shows that PC-I alone explains more than half of the total variance in the X (i.e. the matrix of FFF) except in years 5 and 6. However, if we retain two PCs, then the cumulative percentage of variance is about 74%, 75%, 71%, 73%, 74% and 65% in years 1,2,3,4,5 and 6 respectively. This means that PC-II alone explains the variance by 22%, 25%, 14%, 14%, 29% and 25% in the study year 1,2,3,4,5 and 6, respectively. However, if we retain three PCs, then the cumulative percentage of variance is about 83%, 84%, 83%, 87%, 85% and 82% in years 1,2,3,4,5 and 6 respectively. This means that PC-III alone explains the variance by 9%, 9%, 12%, 14%, 11% and 17% in the study year 1,2,3,4,5 and 6, respectively. The percentage of variance captured by PC-III in each study year is sufficiently smaller than the percentage of variance captured by PC-I and PC-II. In addition, as can be seen in Figure 4-1, there is a significant dropped in the percentage of variance between the PCs from PC-III to onward until the curve is levelled off in all study years. The greater percentage of variance captured by the PC is a theoretical indicative of important information that we want to detect, while the PCs with the little variance are indicative of data noise. Hence, PC-III and the subsequent PCs can be discarded from the analysis. Whereas, the cumulative percentage of variance explained by PC-I and PC II exceeds from the minimum requirement of capturing 70% of the total variance in study years 1-5 and is 65% in year 6. The cumulative percentage of variance of 65% is taken as sufficiently close to 70% for our purposes, so in this study, the cut-off of 65% for the cumulative percentage of variance is deemed to be acceptable for determining the number of PCs. Hence, only PC-I and PC-II are retained for further analysis as they are considered sufficient to explore the latent structure of X in all the study years.

4.4.2 Evaluation of the monthly functional failure frequency profile

In order to understand the latent structure of the monthly FFF profile, the factor scores of the months were mapped in the coordinate system defined by PC-I and PC-II. In this section, first we discuss how the features of scores plot can be used to evaluate the monthly FFF profile. We then define the criteria to analyse the requisite operational characteristics related to the monthly FFF profile (i.e. C1- the critical months and C2 - the similar and dissimilar months), and finally, we interpret the scores plots obtained for each study year.

4.4.2.1 Features of the scores plot for evaluation of the monthly FFF profile

The first feature of the scores plot is the position of the months on each PC which corresponds to the scores of the months on the PCs. The position of the months on each PC can be used to analyse the month-to-PC relationship, i.e. the extent of influence of the characteristics of the PC in the construction of the monthly FFF profile. The position of the months are the signed distances from the origin of the plot, where the sign indicates a positive or negative relationship between the month and the PC, and the distance numerically quantifies the strength of a relationship. Together the sign and the distance explain the month-to-PC relationship. Thus, the months with high positive scores are strongly related to the PC; the months clustered near the origin are moderately related and the months with low negative scores are weakly related to the PC. This enables the months to be categorised as critical, moderately critical, and non-critical. This scores-based categorisation clearly indicates that the FFF of the critical sub-systems in the critical months is higher than the average score, close to the average in the moderately critical months (Eriksson et al., 2013, Dunn, 2019) while it is lower than the average in the non-critical months. In brief, the critical months can be identified considering influence of the latent variables which means the achievement of operational characteristic C1-critical months.

The second feature of the scores plot is the distribution of the months along the PCs. This distribution can be used to analyse the month-to-month relationship (i.e. whether they are similar or dissimilar) considering the influence of the latent variables associated with each PC. When the rows of X are multiplied by the coefficients of the same PC, this results in distribution of the similar months in the same direction of the PC and of the dissimilar months in the opposite direction of the PC. It can be stated as that the months with scores with the same sign are similar, and the months with scores with different signs are dissimilar in their FFF profiles. This means that the larger the distance between positions of any two months on the PC, the greater the dissimilarities between their monthly FFF profiles. Similarly, as smaller the distance between positions of any two months on the PC, as greater the similarities between their monthly FFF profiles. The relationship of the months to the PC is the reason for distributing them near or at a distance from each other. Hence, the distribution of the months along the PCs reveals which months are similar and which months are dissimilar. Thus, the similar and dissimilar months can be differentiated considering the influence of the latent variables which means the achievement of operational characteristic C2-similar and dissimilar months.

In summary, the features of the scores plot can be used to analyse the latent structure of the monthly FFF profile and can develop a clear understanding about influence of the latent variables in construction of the monthly FFF profile individually and in relation to each other.

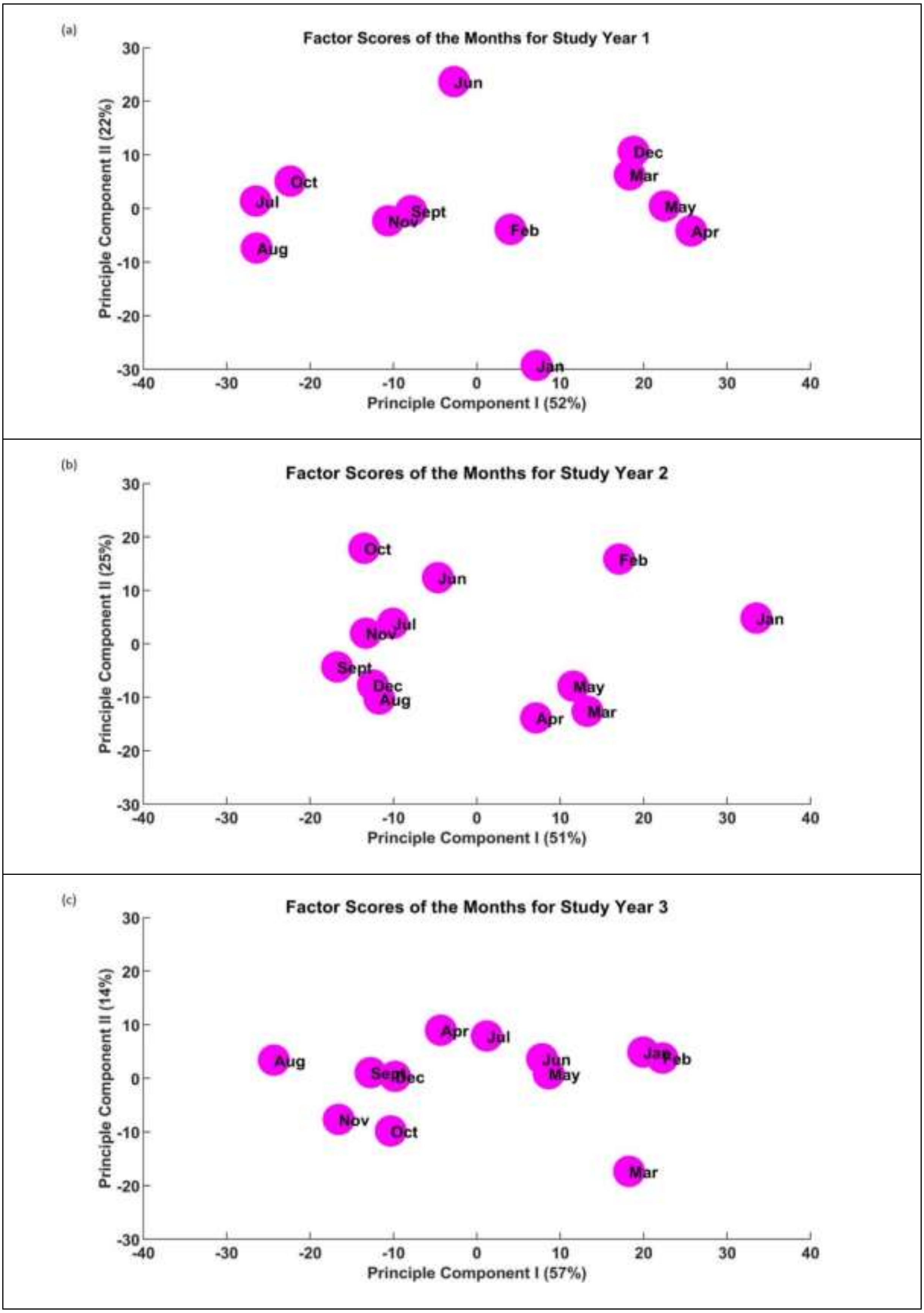
4.4.2.2 Criteria for evaluation of the monthly FFF profile

To identify C1- the critical months, a simple approach based on the scores of the months on the PCs is adopted to define the criterion for the criticality categorisation of the months. The ranges for criticality categories of the months are defined in such a way that they best fit values to the lowest negative and the highest positive score of the months on the PCs for each study year. The months with scores ≥ +10 are defined as critical, the months with scores between -10 and +10 are defined as moderately critical, and the months with scores ≤ -10 are defined as non-critical.

To differentiate between C2 - the similar and dissimilar months, the criterion is defined based on the relative distribution of months along the PCs is used. The months distributed in the same direction of the PCs (i.e. the months within the same criticality category) are defined as similar to each other, the months clustered near the origin of the plot have some similarities and some dissimilarities (i.e. the months within the category of moderately critical) and the months in the opposite directions of the PCs are dissimilar (i.e. the months in the different criticality categories).

4.4.2.3 Analysis of the operational characteristics in relation to the monthly FFF profile

The factor scores of the months for the six study years are plotted in Figure 4-2. The scores plot for each study year shows the position of each month on PC-I and PC-II, and the relative distribution of months along the length of each PC.


(a)
Factor Scores of the Months for Study Year 1
Principle Component II (22%)
Principle Component I (52%)
Jun
Dec
Mar
Oct
Jul
Nov
Sept
Feb
May
Apr
Aug
Jan
30
20
10
0
-10
-20
-30
-40
-30
-20
-10
0
10
20
30
40
(b)
Factor Scores of the Months for Study Year 2
Principle Component II (25%)
Principle Component I (51%)
Oct
Jun
Feb
Jan
Jul
Nov
Sept
Dec
Aug
May
Mar
Apr
30
20
10
0
-10
-20
-30
-40
-30
-20
-10
0
10
20
30
40
(c)
Factor Scores of the Months for Study Year 3
Principle Component II (14%)
Principle Component I (57%)
Apr
Jul
Aug
Jun
May
Feb
Sept
Dec
Nov
Oct
Mar
30
20
10
0
-10
-20
-30
-40
-30
-20
-10
0
10
20
30
40

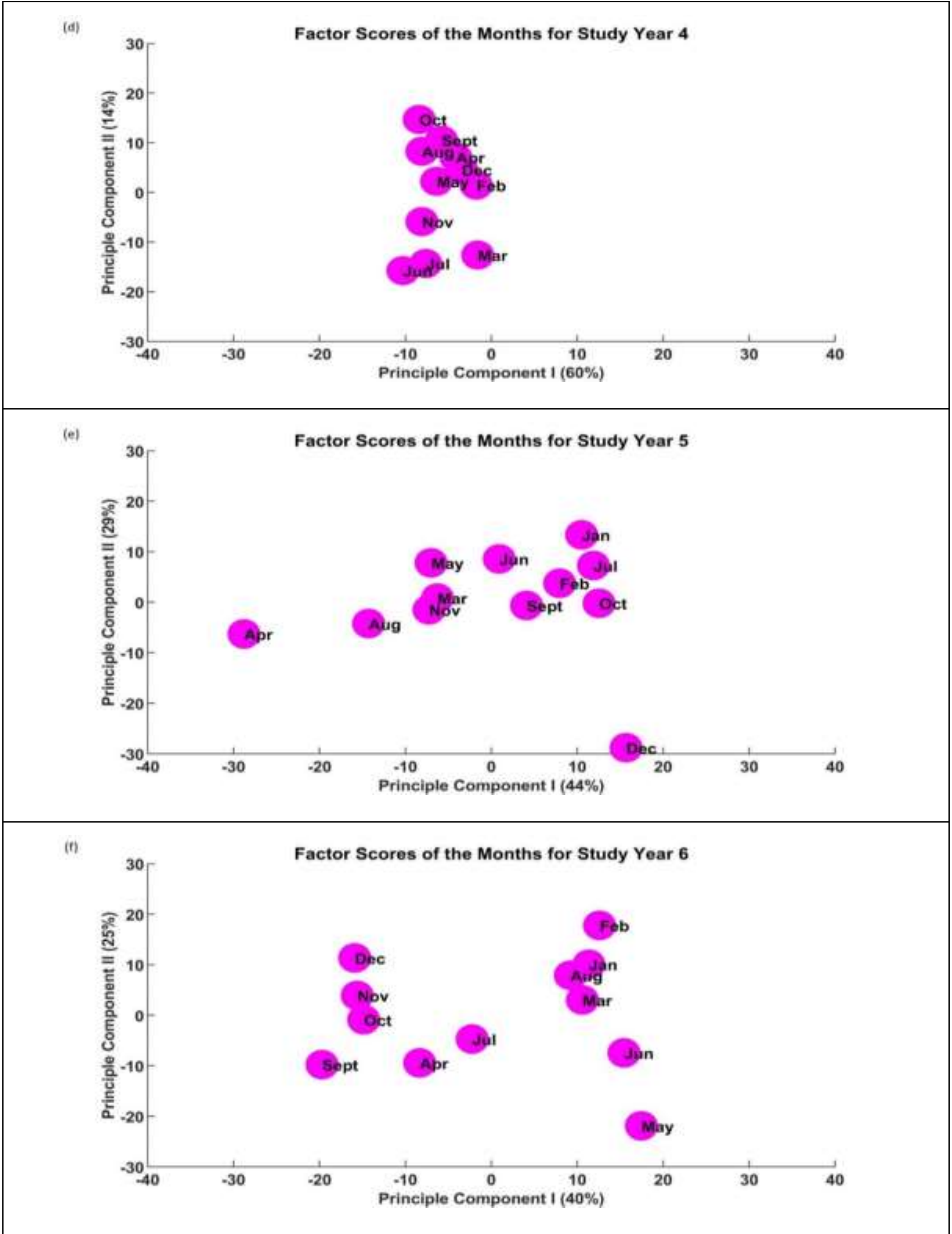


Figure 4-2 : Factor scores plot for six study years for evaluation of the monthly FFF profiles.

In each plot, the x-axis represents PC-I and the y-axis represents PC-II, and the percentage of variance captured by PC-I and PC-II are given with the axis titles. Each scatter plot graphs the scores of months on PC-I along the x-axis and the scores of months on PC-II along the y-axis.

In order to determine the critical months, the months were categorised based on their scores on PC-I and PC-II and the results are presented in Table 4-2 and in Table 4-3.

Table 4-2: Criticality categorisation of the months in relation to PC-I

Study Year	Critical months	Moderately critical months	Non-critical months
Year 1	March, April, May and December	January, February, June, September, and November	July, August, and October
Year 2	January, February, March and May	April and June	July, August, September, November, October and December
Year 3	January, February, and March	April, May, June, July, October and December	August, September and November
Year 4	January	February, March, April, May, July, August, September, October, November, and December	June
Year 5	January, July, October and December	February, March, May, June, September, November	April and August
Year 6	January, February, March, May and June	April, July and August	September, October, November, and December

Table 4-3: Criticality categorisation of the months in relation to PC-II

Study Year	Critical months	Moderately critical months	Non- critical months
Year 1	June and December	February, March, April, May, July, August, September, October, and November	January
Year 2	February, June and October	January, July, August, September, November, and December	March, April, and May
Year 3	-	January, February, April, May, June, July, August, September, October, November, and December	March
Year 4	September and October	January, February, April, May, August, November, and December	March, June, and July
Year 5	January	February, March, April, May, June, August, September, October, November, and December	December
Year 6	January, February and December	March, June, July, August, October, and November	April, May and September

As can be seen in Table 4-2, in relation to PC-I, there are 4, 4, 3, 1, 4 and 5 months are identified as critical in the study years 1, 2, 3, 4, 5 and 6 respectively. Table 4-3 shows that in relation to PC-II, there are 2, 3, 0, 2, 1 and 3 months are critical in the study years 1, 2, 3, 4, 5 and 6 respectively. This means in order to improve the FFF profiles of this number of the critical months, the maintenance plan needs to be focussed on the characteristics of only two variables (i.e. PC -I and PC-II). Hence, PCA has successfully reduced the number of variables that must be dealt with and provides a clear indication of the reason for the criticality of the months which is explainable by the inner-structure of the related PC. It is also evident from Table 4-2 and Table 4-3 that some of the months that are critical in relation to PC-I are also critical in relation to PC-II. For example, December in year 1, February in year 2, and January in years 5 and 6 are critical in relation to both PCs. This is the variance partitioning effect that explains the spread in the characteristics of the operational environment of these months. It can also be seen in Table 4-3 that there is no month critical in relation to PC-II in year 3. Further, as it can be seen in Table 4-2 that August is non-critical in relation to PC-I from years 1 to 3, moderately critical in year 4, non-critical in year 5 and critical in year 6; however, Table 4-3 shows that August is moderately critical in relation to PC-II in all study years. The examples of these months show that the scores-based categorisation enables the monthly FFF profiles to be evaluated within a year, year-to-year and over many years. Hence, the yearly trends for change in the criticality status of the months are traceable with ease by using PCA. Overall, it is concluded that PCA has successfully categorised the months considering the influence of the latent variables.

Table 4-2 and Table 4-3 also provide information about similar and dissimilar months. As can be seen in Table 4-2, March, April, May and December are similar months in relation to PC-I in year 1, as are July, August and October. By contrast, March, April, May and December are dissimilar to July, August and October, whereas January, February, June and December are similar in some ways and dissimilar in other ways with each other in their FFF profiles. The results for each year can be interpreted in the same way. Thus, the months can be differentiated based on the similarities and dissimilarities in their FFF profiles considering the influence of the latent variables by the application of PCA.

In summary, the scores plot provides a clear understanding of the latent structure of the monthly FFF profile and enables the achievement of both operational characteristics C1 - the critical months and C2 - the similar and dissimilar months.

4.4.3 Evaluation of the sub-system FFF profile

In order to understand the latent structure of the sub-system FFF profile, the weights of the sub-systems by which they were loaded on PC-I and PC-II were mapped in the coordinate system defined by both PCs. In this section, first we discuss how the features of loading plot can be used to evaluate the sub-system FFF profile. We then define the criteria to analyse the requisite operational characteristics related to the sub-system FFF profile i.e. C3-the critical sub-systems and C4 -the similar and dissimilar sub-systems, and finally, we interpret the loading plots obtained for each study year.

4.4.3.1 Features of the loading plot for evaluation of the sub-system FFF profile

The first feature of the loading plot is the position vectors of the sub-systems in the coordinate system defined by PC-I and PC-II. An imagination of the component vectors of the position vector of each sub-system explains the sub-system-to-PC relationship, i.e. the extent of variance of the sub-system FFF profile represented by that PC in generation of X (i.e. FFF data matrix). The length of the component vector corresponds to the magnitude of weight of the sub-system on the PC which varies between 0 to 1, and its direction can be positive or negative depending on the sign of the weight. The positive direction indicates the positive relationship between the sub-system and the PC, and the negative direction shows the negative relationship between them. Together the length and direction of the component vector explains the subsystem-to-PC relationship. This means that the component vectors with loading close to +1 indicates the strong influence of the sub-systems in construction of the PC while loadings close to zero shows a weak influence (Minitab, 2020), and the negative loadings indicate an absence of relationship (Burstyn, 2004). Hence, the high positive loading sub-systems are critical in relation to the latent variables associated with the PCs; whereas, the small negative loadings are non-critical in relation to the latent variables associated with the PCs. This enable the sub-systems to be categorised as critical and non-critical. Thus, the critical sub-systems can be identified considering influence of the latent variables which means the achievement of operational characteristic C3 - the critical sub-systems.

The second feature of the loading plot is the relative direction of the position vectors of the sub-systems with reference to the origin of the plot. The relative direction of the position vectors explains the subsystem-to-subsystem relationship (i.e. whether they are similar or dissimilar) considering influence of the latent variables associated with the PCs. The orthogonal transformation of the linear combination of the columns of X results in directionally parallel vectors of the sub-systems that are similar, non-parallel vectors of the sub-systems that are similar in some ways and dissimilar in other ways, anti-parallel vectors of the sub-systems that are dissimilar and perpendicular vectors of the sub-systems that do not have any correspondence in their FFF profiles. Hence, the relative direction of the position vectors of the sub-systems with reference to the origin reveals which sub-systems are similar and which are dissimilar in relation to each PC. Thus, similar and dissimilar sub-systems can be differentiated considering influence of the latent variables which means the achievement of operational characteristic C4-similar and dissimilar sub-systems.

In summary, the features of the loading plot can be used to analyse the latent structure of the sub-system FFF profile and can develop a clear understanding of the influence of the latent variables in the construction of the FFF profile of the sub-systems individually and in relation to each other.

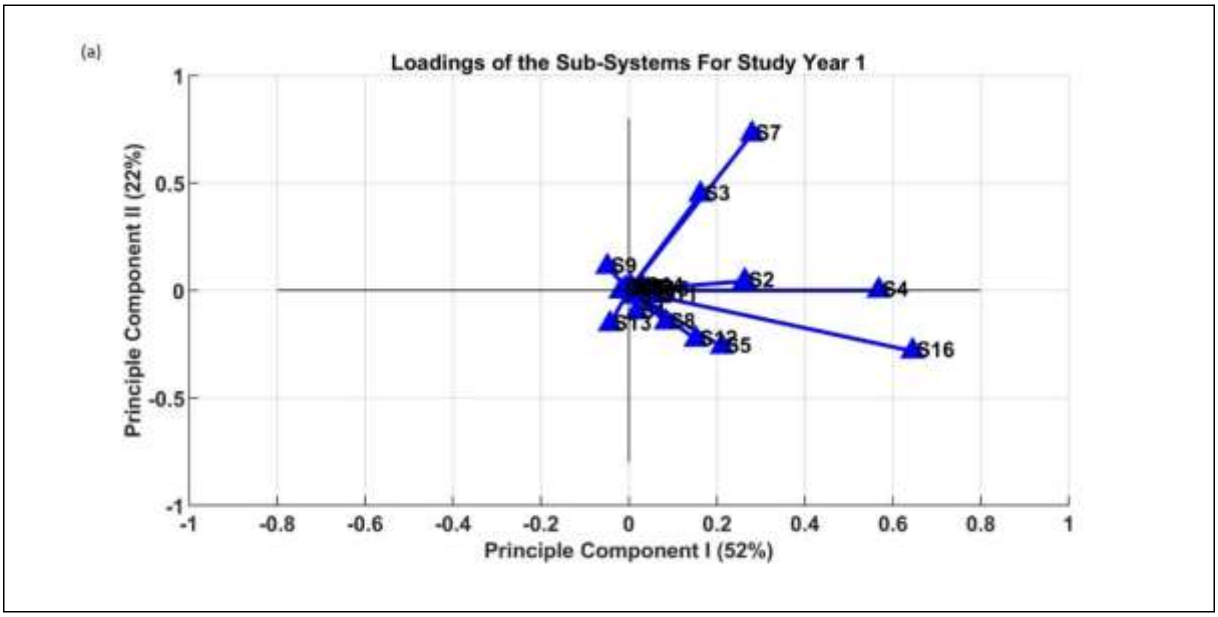
4.4.3.2 Criteria for evaluation of the sub-system FFF profile

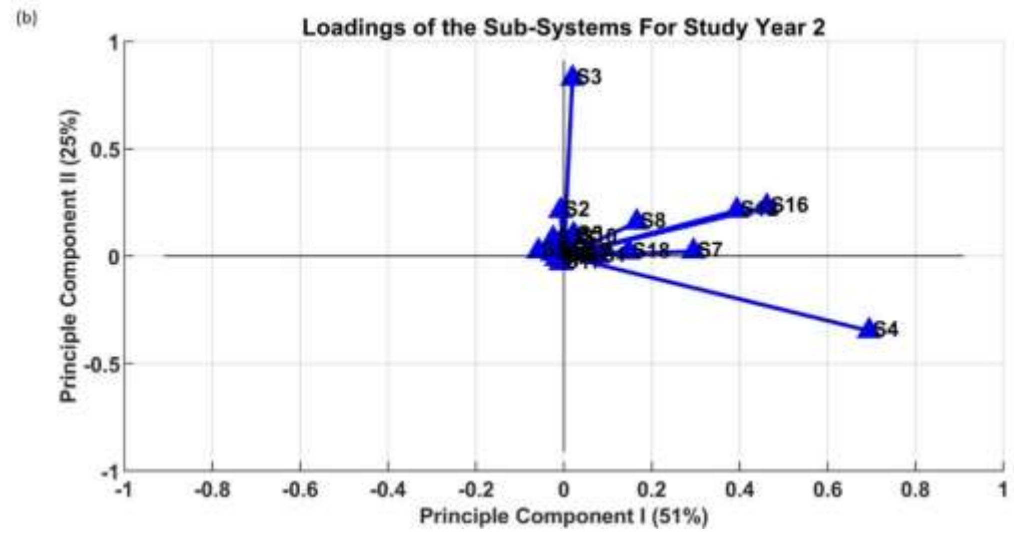
To identify C3- the critical sub-systems, a standard approach based on the loadings of the sub-systems on the PCs is adopted to define the criterion for the criticality categorisation of the sub-systems. Since loadings vary between -1 and +1; therefore, it is required to define the cut-off loading value to categorise the sub-systems as critical and non-critical. The published cut-off loading values are 0.25 (Peres-Neto et al., 2003) , 0.3 (Lebart et al. (1982) as cited in Jolliffe, 2002, Peres-Neto et al., 2003), 0.5 (Lirn et al., 2014) and 0.7 Jolliffe (1972) as cited in Jolliffe (2002). Defining a very high cut-off value (close to +1) will result in the selection of too few variables; similarly, defining a very low cut-off value (close to 0) will result in the selection of too many variables. (Burstyn, 2004) stated in his study that the loadings $< +0.3$ are insignificant and the negative loadings are not of concern in PCA. Hence, in this study the cut-off value is defined at +0.3 loading which implies that the sub-systems with loadings $\geq +0.3$ are the critical sub-systems, and the sub-systems with loadings $< +0.3$ are the non-critical sub-systems.

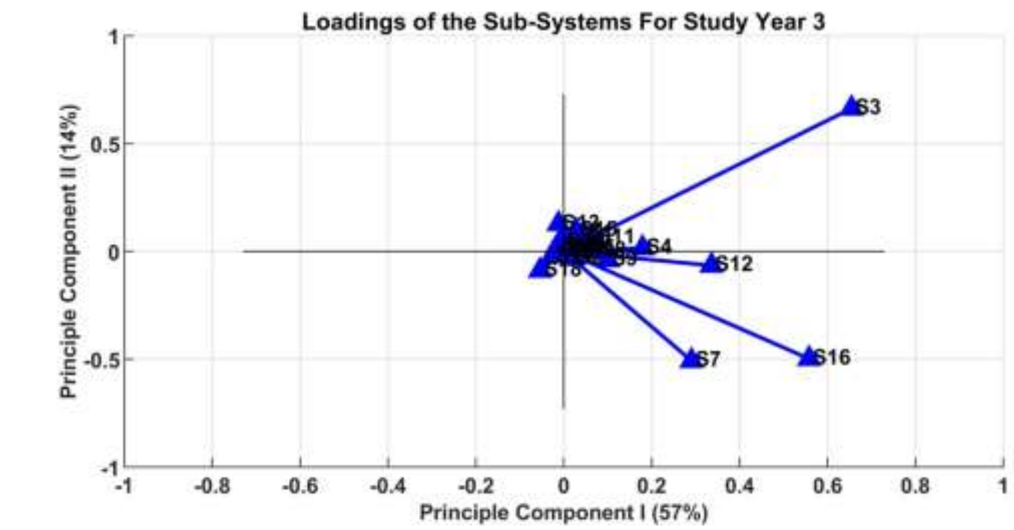
To differentiate between C4 -the similar and dissimilar sub-systems with respect to each PC, the criterion is defined based on the relative location of the position vectors in the quadrants of the coordinate system defined by PC-I and PC-II. The relative location of the position vectors in the quadrants elucidates the relative direction of the vectors which in turn provides an indication of the relationship between the sub-systems. For example, the position vectors of the dissimilar sub-systems with respect to both PCs are directionally anti-parallel; therefore, they are placed in diagonally opposite quadrants (Surawski et al., 2017, Dunn, 2019, Hartmann, 2018b). Using this concept, the criterion is defined as if the position vectors of the sub-systems are located in the same quadrant, and this indicates that they share some similarities in their FFF profile with respect to both PCs. If the vectors of the sub-systems are in the adjacent quadrants, this indicates that they share some similarities with respect to the PC that defines the mutual boundary between the quadrants, and they share some dissimilarities with respect to the other PC. Similarly, if the vectors are in diagonally opposite quadrants, this indicates that they share some dissimilarities in their FFF profile with respect to both the PCs. Also, if the vectors of the sub-systems meet at a right angle, this indicates that there is no correspondence in their FFF profile.

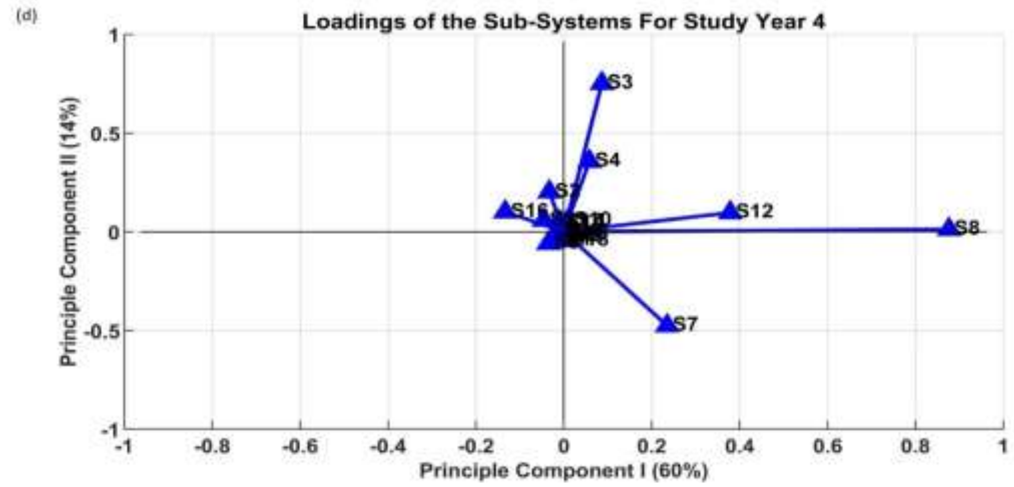
4.4.3.3 Analysis of the operational characteristics in relation to the sub-system FFF profile

The loading plots of the sub-systems for the six study years are presented in Figure 4-3. The loading plot for each study year shows the position vector of each sub-system and their relative distribution in the coordinate system defined by PC-I and PC-II.




(b)
Loadings of the Sub-Systems For Study Year 2
Principle Component II (25%)
Principle Component I (51%)
S3
S2
S8
S16
S18
S7
S4


Loadings of the Sub-Systems For Study Year 3
Principle Component II (14%)
Principle Component I (57%)
S3
S4
S12
S7
S16


(d)
Loadings of the Sub-Systems For Study Year 4
Principle Component II (14%)
Principle Component I (60%)
S3
S4
S12
S8
S7

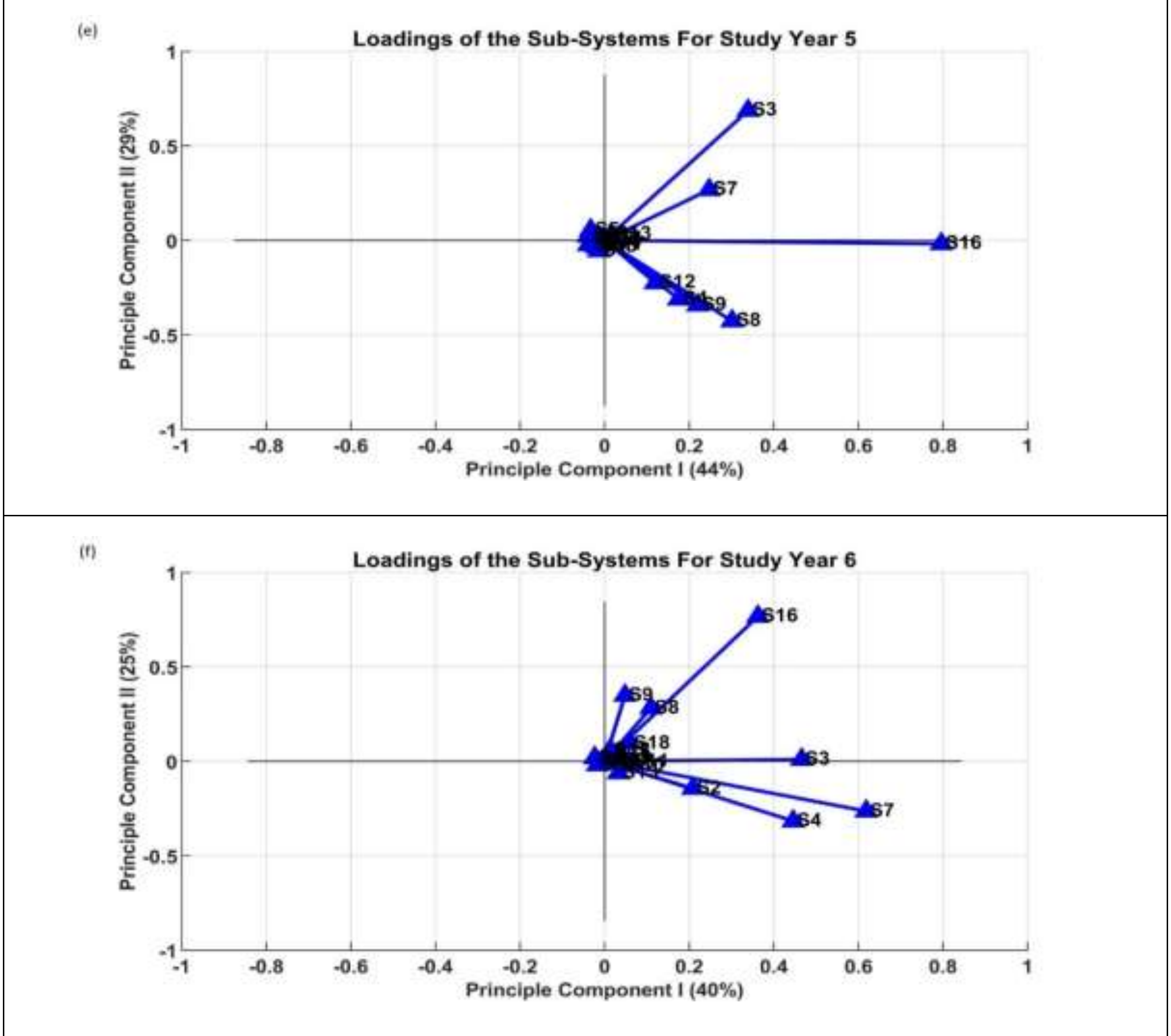


Figure 4-3:Loading plot for six study years for evaluation of the sub-system FFF profiles.

In each plot, the x-axis represents PC-I and the y-axis represents PC-II, and the percentage of variance captured by PC-I and PC-II are given with the axis titles. Each loading plot graphs the weights of the sub-systems on PC-I along the x-axis, and the loadings of the sub-systems on PC-II along the y-axis.

In order to determine the critical sub-systems, the sub-systems in the six study years were categorised based on their loadings on PC-I and PC-II and the results are presented in Table 4-4 and Table 4-5.

Table 4-4: Criticality categorisation of the sub-systems in relation to PC-I		
Study Year	**Critical sub-systems**	**Non-critical sub-systems**
Year 1	S4 and S16	S1, S2, S3, S5, S6, S7, S8, S9, S10, S11, S12, S13, S14, S15, S17, S18 and S19
Year 2	S4, S7, S12 and S16	S1, S2, S3, S5, S6, S8, S9, S10, S11, S13, S14, S15, S17, S18 and S19
Year 3	S3, S7, S12 and S16	S1, S2, S4, S5, S6, S7, S8, S9, S10, S11, S13, S14, S15, S17, S18 and S19
Year 4	S8 and S12	S1, S2, S3, S4, S5, S6, S7, S9, S10, S11, S13, S14, S15, S16, S17, S18 and S19
Year 5	S3, S8 and S16	S1, S2, S4, S5, S6, S7, S9, S10, S11, S1 2, S13, S14, S15, S17, S18 and S19
Year 6	S3, S4, S7 and S16	S1, S2, S5, S6, S8, S9, S10, S11, S12, S13, S14, S15, S17, S18 and S19

Table 4-5: Criticality categorisation of the sub-systems in relation to PC-II		
Study Year	**Critical sub-systems**	**Non-critical sub-systems**
Year 1	S3 and S7	S1, S2, S4, S5, S6, S8, S9, S10, S11, S12, S13, S14, S15, S16, S17, S18 and S19
Year 2	S3	S1, S2, S4, S5, S6, S7, S8, S9, S10, S11, S12, S13, S14, S15, S16, S17, S18 and S19
Year 3	S3	S1, S2, S4, S5, S6, S7, S8, S9, S10, S11, S12, S13, S14, S15, S16, S17, S18 and S19
Year 4	S3 and S4	S1, S2, S5, S6, S7, S8, S9, S10, S11, S12, S13, S14, S15, S16, S17, S18 and S19
Year 5	S3	S1, S2, S4, S5, S6, S7, S8, S9, S10, S11, S12, S13, S14, S15, S16, S17, S18 and S19
Year 6	S9 and S16	S1, S2, S3, S4, S5, S6, S7, S8, S10, S11, S12, S13, S14, S15, S17, S18 and S19

As can be seen in Table 4-4, in relation to PC-I, there are 2, 4, 4, 2, 3 and 4 sub-systems identified as critical in study years 1, 2, 3, 4, 5 and 6 respectively. Table 4-5 shows that in relation to PC-II, there are 2, 1, 1, 2, 1 and 2 sub-systems identified as critical in study years 1, 2, 3, 4, 5 and 6 respectively. This means that in order to improve the FFF of these number of the critical sub-systems, the maintenance plan needs to resolve only two variables i.e. the latent variables associated with PC-I and PC-II. This criticality categorisation also explains the inner-structure of the PCs, and using this information the latent variables can be traced from the maintenance record and the FFF of these critical sub-systems can be improved. Hence, PCA has successfully reduced the number of variables to deal with and provides a clear indication of the latent variables that influenced the operational performance of the sub-systems. In addition, as can be seen in both tables, some sub-systems are identified as critical in relation to both PCs, for instance, S3 in year 5 and S16 in year 6 are critical in relation to both PCs. This is the variance partitioning effect that explains the spread in the characteristics of functional reliability of these sub-systems i.e. these sub-systems have the characteristics of the latent variables associated with both PCs. It can also be seen in both tables that S4 is critical in relation to PC-I in years 1 and 2, and S3 in years 5 and 6, whereas S16 is identified as critical in relation to PC-I in all the study years except in year 4. Similarly, S3 is critical in relation to PC-II in all the study years except in years 3 and 6. The examples of these sub-systems proves that the loading-based categorisation of the sub-systems enables the FFF profiles of the sub-system to be evaluated within the same year, from year-to-year and over many years. Hence, the yearly trends for change in functional reliability of the sub-systems in relation to the PCs are easily traceable by using PCA. Overall, it is concluded that PCA has successfully categorised the sub-systems considering the influence of the latent variables.

In order to determine C4 - the similar and dissimilar sub-systems, the location of the sub-systems must be located in the quadrants. The critical sub-systems are of concern; therefore, for analysis of C4 only the critical sub-systems listed in Table 4-4 and Table 4-5 were considered. Figure 4-3 shows that these critical sub-systems are located in either quadrant I or in quadrant IV or on the boundary between these quadrants and these locations are summarised in Table 4-6.

Table 4-6: Location of critical sub-systems in quadrants of the coordinate system defined by PC-I and PC-II

Study Year	Critical sub-systems in quadrant-I	Critical sub-systems on boundary between quadrant I and IV	Critical sub-systems in quadrant-IV
1	S3, S7	S4	S16
2	S16, S12, S3	S7	S4
3	S3	-	S16, S7, S12
4	S8, S12, S3, S4	-	-
5	S3	S16	S8
6	S9, S16	S3	S7, S4

As can be seen in Table 4-6, in year 1, S3 and S7 are similar sub-systems in relation to PC-I and PC-II. S3 and S7 are also similar to S4 and S16 in relation to PC-I. By contrast, S3 and S7 are dissimilar to S16 in relation to PC-II, and S3 and S7 do not have any correspondence with S4 in relation to PC-II. The results for each year can be interpreted in the same way. Thus, the sub-systems can be differentiated based on the similarities and dissimilarities in their FFF profiles considering the influence of the latent variables by the application of PCA.

In summary, the loading plot provides a clear understanding of the latent structure of the sub-system FFF profile and enables the achievement of both operational characteristics C3-the critical sub-systems and C4 -the similar and dissimilar sub-systems.

4.4.4 Relationship analysis between the FFF profiles of the sub-systems and the months

To analyse C5- the relationship between the FFF profiles of sub-systems and months, the scores plot of the months was superimposed on the loading plot of the sub-systems to produce a bi-plot. The use of common axis in both plots provide relevancy for overlaying the scores of the months on the loadings of the sub-systems. However, the scales of axis in the both plots are different; therefore, the biplot function in MATLAB automatically scales the scores of months to adjust them well in the plot. This results in an approximate representation of scores and loadings in a compromised space; thus, the bi-plot is interpreted in terms of the direction of the vectors and the distribution of the points along them.

In this section, first we discuss how the features of bi-plot can be used to analyse the relationship between the FFF profiles of the sub-systems and the months. We then define the criteria to analyse the requisite operational characteristics related to relationship analysis between the two profiles i.e. C5(a) – characterisation of the monthly FFF profile and C5(b) – influence of the sub-system on the monthly FFF profiles, and finally, we interpret the loading plots obtained for each study year.

4.4.4.1 Features of the bi-plot for relationship analysis between the FFF profiles of sub-systems and the months

The first feature of the bi-plot is the relative distribution of the months with reference to the relative direction of the position vectors of the sub-systems in the coordinate system defined by PC-I and PC-II. This can be useful to analyse the subsystems-to-months relationship i.e. identification of the sub-systems that contributed the most in making the months similar and dissimilar in their FFF profile. Provided that the months and the sub-systems are in intact with their characteristics in relation to the PCs. Therefore, the months that are distributed in the direction of parallel vectors are similar in relation to the sub-systems represented by that vectors; likewise, the months that are distributed in the direction of non-parallel vectors are similar in some ways and dissimilar in other ways in relation to the sub-systems represented by that vectors; the months that are distributed on the opposite directions of the directionally anti-parallel vectors are dissimilar in relation to the sub-systems of that vectors. Hence, the relative distribution of the months considering the relative direction of the vectors enables to identify the sub-systems that contributed the most in making the months similar and dissimilar. Thus, the monthly FFF profiles can be characterised in relation to the sub-system FFF profiles which means the achievement of operational characteristic C5(a) – characterisation of the monthly FFF profile.

The second feature of the bi-plot is relative distribution of the months along the length of position vector of any sub-system. This can be used to analyse the months-to-subsystem relationship i.e. influence of an individual sub-system in the construction of FFF profiles of the months. Using the concept discussed by (Kohler and Luniak, 2005, Kroonenberg, 2008), the months that are distributed far away in the direction of the vector, they have the FFF of the sub-system above than its average FFF; the months that are distributed near the origin, they have the FFF of the sub-system close to its average FFF; the months that are distributed far away in the opposite direction of the vector, they have the FFF of the sub-system below than its average FFF. Hence, the relative distribution of the months along the length of the vector of the sub-system provides an approximate indication of influence of the sub-system in the construction of monthly FFF profiles. Thus, influence of the sub-system in the construction of monthly FFF profiles can be determined considering influence of the latent variables which means the achievement of the operational characteristic C5(b) – influence of the sub-system on the monthly FFF profiles.

In summary, the features of the bi-plot can be used to analyse the FFF profiles of the months together with the FFF profiles of the sub-systems and can develop a clear understanding how these two profiles are related to each other.

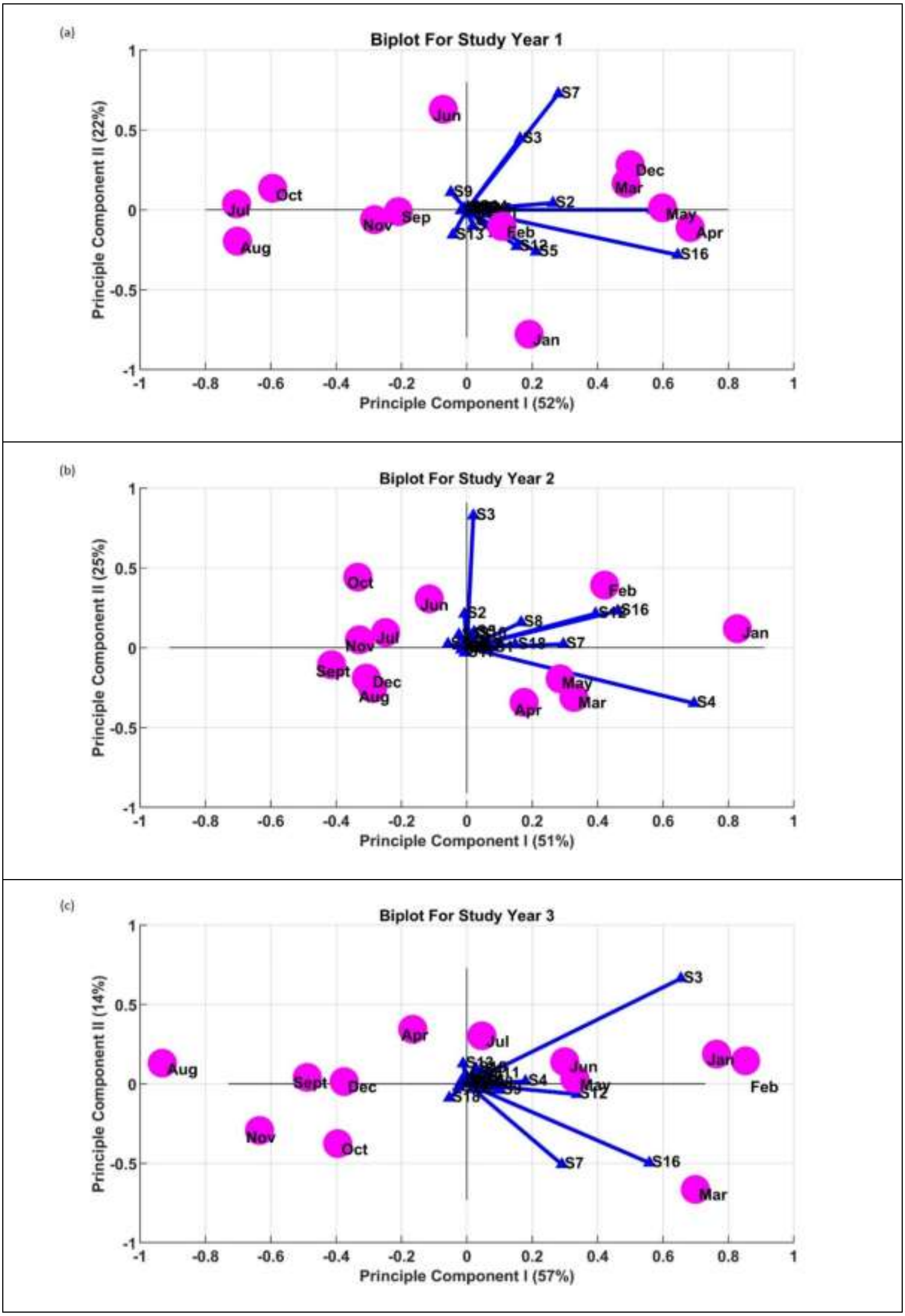
4.4.4.2 Criteria for relationship analysis between the FFF profiles of sub-systems and the months

To analyse C5(a) – characterisation of the monthly FFF profile, the criterion is defined based on the location of the months and the vectors in the quadrants of the coordinate system of PC-I and PC-II. If the vectors are located within the same quadrant as that of the months, the months are similar in their FFF profiles with respect to the FFF of those sub-systems in relation to both PCs. Likewise, if the vectors are in one of the adjacent quadrants in which the months are located, the months are similar in some ways with respect to the FFF of the sub-systems in relation to the PC which defines the boundary between those quadrants, and they are dissimilar in the other ways with respect to the FFF of the sub-systems in relation to another PC. If the vectors are located in the quadrant which is diagonally opposite to the quadrant in which the months are located, the months are dissimilar with respect to the FFF of the sub-systems in relation to both PCs.

To identify C5(b) – influence of the sub-system on the monthly FFF profiles, the approach as discussed by Kohler and Luniak (2005) and demonstrated by (Marcresearch) is adopted. Firstly, the vector of the sub-system which is required to be analysed is extended in both directions. Then, a perpendicular line is drawn on the vector close to the outer edge of the plot, but in the direction of the vector. This perpendicular line is required to be moved in the opposite direction of the vector of the sub-system. The sequence in which the perpendicular line hits the points of the months is the sequence of influence of the FFF of the sub-system in the construction of the FFF profile of the months.

4.4.4.3 Analysis of operational characteristics in relation to the FFF profile of sub-systems and the months

The bi-plots of the sub-systems for the six study years are presented in Figure 4-4. The bi-plot for each study year shows the relative distribution of the months and sub-systems in the coordinate system defined by PC-I and PC-II.


(a)
Biplot For Study Year 1
Principle Component II (22%)
Principle Component I (52%)
Jun
S7
S3
Dec
Mar
Oct
Jul
Sep
Nov
S9
S2
May
Apr
Feb
S13
S12
S5
S16
Aug
Jan
(b)
Biplot For Study Year 2
Principle Component II (25%)
Principle Component I (51%)
S3
Oct
Feb
Jun
S2
S16
S8
Jan
Jul
Nov
S18
S7
Sept
Dec
May
Aug
Mar
S4
Apr
(c)
Biplot For Study Year 3
Principle Component II (14%)
Principle Component I (57%)
S3
Apr
Jul
Jan
Jun
Aug
S13
S4
Sept
Dec
May
Feb
S12
S18
Nov
Oct
S7
S16
Mar

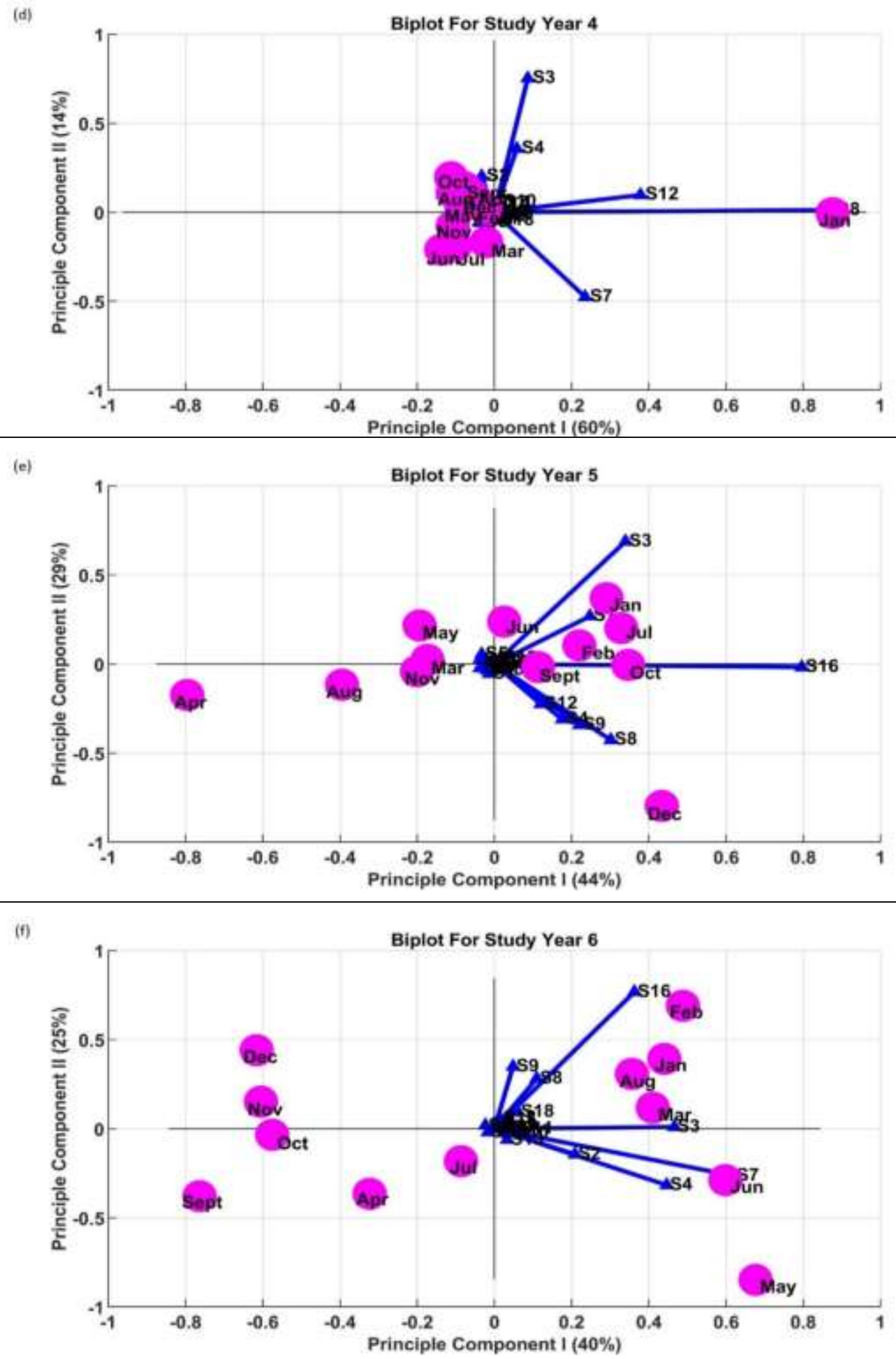


Figure 4-4: Bi-plots for six study years for evaluation of relationship between the FFF profiles of the months and sub-systems.

In each plot, the x-axis represents PC-I and the y-axis represents PC-II, and the percentage of variance captured by PC-I and PC-II are given with the axis titles. Each bi-plot graphs the months and sub-systems in the compromised space.

It is of interest which critical sub-systems contributed the most in making the critical months similar and dissimilar in their FFF profiles; therefore, only the critical sub-systems and the critical months were considered for the analysis of characterisation of the monthly FFF profiles in relation to the sub-system FFF profiles. It can be seen in Figure 4-4 that the critical sub-systems are located either in quadrant I, IV or at the boundary between quadrants I and IV (i.e. positive PC-I), while the critical months are located either in quadrant I, II or IV. The location of the critical sub-systems for each study year can be tallied from Table 4-6, and the location of the critical months for each study year are presented here in Table 4-7.

Table 4-7: Location of the critical months in the coordinate system of PC-I and PC-II

Study Year	Critical months in quadrant I	Critical months in quadrant II	Critical months in quadrant IV
Year 1	March, May and December	June	April
Year 2	January and February	June, and October	March and May
Year 3	January, February and July	April	March
Year 4	January	September and October	-
Year 5	January, July and October	-	December
Year 6	January, February, March and August	December	May

The relative location of the critical sub-systems in Table 4-6 were paired up with the relative location of the critical months in Table 4-7 for each possible combination that resulted in eight different scenarios as shown in Table 4-8. Using this information, the last column in Table 4-8 summarises the characteristics of the FFF profiles of the critical months in relation to the FFF profiles of the critical sub-systems.

Table 4-8: Possible characteristics of the FFF profiles of the critical months with respect to the location of the critical sub-systems in the coordinate system of PC-I and PC-II

Scenario	**Location of the critical sub-systems**	**Location of the critical months**	**Possible characteristics in the FFF profiles of the critical months in relation to the critical sub-systems**
I	quadrant I	quadrant I	The FFF profiles of the critical months are similar in relation to the loadings of the critical sub-systems on both PCs.
II	quadrant I	some are in quadrant I and some are in quadrant II	The FFF profiles of the critical months are similar in relation to the loadings of the critical sub-systems on PC-II, and they are dissimilar in relation to the loadings of the critical sub-systems on PC-I.
III	quadrant I	some are in quadrant I and some are in quadrant IV	The FFF profiles of the critical months are similar in relation to the loadings of the critical sub-systems on PC-I, and they are dissimilar in relation to the loadings of the critical sub-systems on PC-II.
IV	quadrant IV	quadrant IV	The FFF profiles of the critical months are similar in relation to the loadings of the critical sub-systems on both PCs.
V	quadrant IV	some are in quadrant I and some are in quadrant IV	The FFF profiles of the critical months are similar in relation to the loadings of the critical sub-systems on PC-I, and they are dissimilar in relation to the loadings of the critical sub-systems on PC-II.
VI	quadrant IV	some are in quadrant II and some are in quadrant IV	The FFF profiles of the critical months are dissimilar in relation to the loadings of the critical sub-systems on both PCs.
VII	on the boundary between quadrants I and IV	some are in quadrant I and some are in quadrant IV	The FFF profiles of the critical months are dissimilar in relation to the loadings of the critical sub-systems on PC-I.
VIII	on the boundary between quadrants I and IV	some are in quadrant I and some are in quadrant IV	The FFF profiles of the critical months are similar in relation to the loadings of the critical sub-systems on PC-I.

Using the information given in Table 4-8, it can be concluded that May, March and December in year 1 are similar in their FFF profiles in relation to the loadings of S3 and S7 on both PCs (i.e. scenario I). They are similar in their FFF profiles to June in relation to the loadings of S3 and S7 on PC-II, but they are dissimilar in their FFF profiles in relation to the loadings of S3 and S7 on PC-I (i.e. scenario II). They are also dissimilar in their FFF profiles to June in relation to the loadings of S4 and S16 on PC-I (i.e. scenario VII). Likewise, they are also similar in some ways in their FFF profiles to April in relation to loadings of S3 and S7 on PC-I; however, they are dissimilar in the other ways in their FFF profiles to April in relation to S3 and S7 on PC-II (i.e. scenario III). They are also similar in their FFF profiles to April in relation to loadings of S4 and S16 on PC-I (i.e. scenario VIII). In the same way, the results for each study year can be interpreted. Hence, the relative location of the critical sub-systems and the critical months provides information about how their FFF profiles are related to each other.

In order to trace the seasonal trends of the FFF of the sub-systems, the operational characteristic C5(b) – influence of the sub-system on the monthly FFF profiles was only analysed for the sub-systems S3, S4, S7 and S16 that were identified as critical in most of the study years. Using the defined procedure, the sequence of influence of these critical sub-systems on the monthly FFF profile are presented in Table 4-9, Table 4-10, Table 4-11 and Table 4-12 respectively.

Table 4-9: Sequence of influence of S3 on the FFF profiles of the months

Year	Sequence of months										
1	Jun	Dec	Mar	May	Apr	Feb	Sep	Oct	Jul	Nov	Aug	Jan
2	Oct	Feb	Jun	Jan	Jul	Nov	Sep	Dec	May	Aug, Mar	Apr	-
3	Jan	Feb	Jul	Apr	Jun	May	Dec	Sep	Aug	Nov	Oct	Mar
4	Oct	Sep	Aug	Apr	Dec	Jan	Feb	May	Nov	Mar	Jul	Jun
5	Jan	Jul	Jun	Feb	Oct	May	Sep	Mar	Nov	Aug	Dec	Apr
6	May	Jun	Feb	Jan	Mar	Aug	Jul	Apr	Oct	Nov	Dec	Sep

Table 4-10: Sequence of influence of S4 on the FFF profiles of the months												
Year	**Sequence of months**											
1	Apr	May	Dec	Mar	Jan	Feb	Jun	Sep	Nov	Oct	Jul, Aug	-
2	Jan	Mar	Feb	May	Apr	Jun	Aug	Jul	Dec	Nov	Sep	Oct
3	Not identified as critical in this year											
4	Jan	Oct	Sep	Aug, Apr	Dec	Feb, May	Nov	Mar	Jul	Jun	-	-
5	Not identified as critical in this year											
6	May	Jun	Mar	Jan	Aug	Feb	Jul	Apr	Oct	Nov	Sep	Dec

Table 4-11: Sequence of influence of S7 on the FFF profiles of the months												
Year	**Sequence of months**											
1	Dec	Jun	Mar	May	Apr	Feb	Sep	Nov	Oct	Jul	Jan	Aug
2	Jan	Feb	Mar	May	Apr	Jun	Jul	Aug	Dec	Oct, Nov	Sep	-
3	Mar	Oct	Nov	May	Feb	Jan	Jun	Dec	Sep	Jul	Aug	Apr
4	Jan	Mar	Jul	Jun	Nov	Dec	Feb	May	Apr	Sep	Aug	Oct
5	Not identified as critical in this year											
6	May	Jun	Mar	Jan	Aug	Feb	Jul	Apr	Oct	Nov	Sep	Dec

Table 4-12: Sequence of influence of S16 on the FFF profiles of the months												
Year	**Sequence of months**											
1	Apr	May	Jan	Mar	Dec	Feb	Sep	Nov	Jun	Aug	Oct	Jul
2	Jan	Feb	May	Mar	Jun	Apr	Oct	Jul	Nov	Dec	Aug	Sep
3	Mar	Feb	Oct	Jan	May	Jun	Nov	Dec	Jul	Sep	Apr	Aug
4	Not identified as critical in this year											
5	Dec	Oct	Jul	Jan	Feb	Sep	Jun	Mar	Nov	May	Aug	Apr
6	Feb	Jan	Aug	Mar	Dec	Jun	Nov	Jul	Oct	Apr	May	Sep

It can be seen from the tables that there is no consistent pattern in the FFF of the sub-systems in various months over the years. For instance, in Table 4-12, in Year 1 April is first in the sequence; in Year 2, it is sixth ; in Year 3, it is eleventh, in Year 4, it was non-critical; in Year 5, it is twelfth and in Year 6, it is tenth in the sequence. Hence, no particular seasonal trend is traceable for any of the critical sub-systems. Thus, the presence of a seasonal trend can be analysed for any sub-system considering the influence of the latent variables.

In summary, the bi-plot provides a clear understanding of the relationship between the two profiles and enables the achievement of both operational characteristics C5(a)-characterisation of the monthly FFF profile and C5(b) – influence of the sub-system on the monthly FFF profiles.

4.5 Comparison of the results obtained by SDA and PCA

In this section, the performance of the simple descriptive analysis presented in Chapter 4 is compared with the performance of PCA.

4.5.1 Identification of the critical sub-systems by SDA and PCA

Identification of the critical sub-systems is the core of operational characterisation of the sub-systems; therefore, the results obtained for the critical sub-systems by application of both techniques are compared here. Table 4-13 presents the critical sub-systems identified as critical using SDA from Table 4-4 in chapter 4, and those identified as critical using PCA from Table 4-4 and Table 4-5 in this chapter.

Table 4-13: Comparison of critical sub-systems identified by SDA and PCA			
Study year	Critical sub-systems identified by application of SDA	Critical sub-systems identified by application of PCA	
		PC-I	PC-II
Year 1	S1, S3, S4, S5, S7, S12 and S16	S4 and S16	S3 and S7
Year 2	S2, S3, S4, S7 and S16	S4, S7, S12 and S16	S3
Year 3	S2, S3, S4, S7, S12 and S16	S3, S7, S12 and S16	-
Year 4	S3, S4, S7, S8, S12 and S16	S8 and S12	S3 and S4
Year 5	S3, S4, S7, S9 and S16	S3, S8 and S16	S3
Year 6	S2, S3, S4, S7, S8 and S16	S3, S4, S7 and S16	S9 and S16

Table 4-13 clearly shows that PCA has identified fewer sub-systems as critical than SDA. This is because as PCA orthogonally transforms the data that results in removal of redundancy from the data and extraction of important information (i.e. identification of the critical sub-systems in relation to the PCs) by supressing the less important ones, while SDA simply works on the failure frequency count that results in identification of too many sub-systems as critical. Furthermore, PCA has identified the critical sub-systems in relation to the PCs which indicates the underlying causes for the criticality of the sub-systems; by contrast, this information is not obtainable by SDA. Hence, it is concluded that PCA is clearly an appropriate choice for the analysis of the operational characteristics of the sub-systems.

4.5.2 Operational performance characteristics delivered by SDA and PCA

A comparison between SDA and PCA is performed here in order to evaluate their effectiveness in delivering the operational characteristics of the sub-systems from C1 to C5 i.e. the operational characteristics based on the FFF. Table 4-14 compiles the findings that were presented in Table 4-6 in chapter 4 and in the previous section of this chapter.

Table 4-14: Comparison between SDA and PCA in delivering the operational characteristics of the sub-systems based on FFF		
Operational Characteristic	**SDA**	**PCA**
C1 - the critical months	Achievable but with limitations	Achievable
C2 - the similar and dissimilar months	Not achievable	Achievable
C3 - the critical sub-systems	Achievable but with limitations	Achievable
C4 - the similar and dissimilar sub-systems	Not achievable	Achievable
C5(a) - characterisation of the monthly FFF profiles in relation to the sub-system FFF profiles	Not achievable	Achievable
C5(b) - influence of the sub-system on the monthly FFF profiles	Not achievable	Achievable

Table 4-14 clearly shows that PCA has successfully delivered all the operational characteristics of the sub-systems. Thus, it is concluded that PCA provides an excellent approach for the operational performance characterisation of the sub-systems.

4.6 Summary

This chapter has developed the new approach for operational performance characterisation of the sub-systems by partially modifying the conventional approach. The new approach preserves the conventional single criterion for characterisation i.e. FFF, and replaces the analytical technique i.e. SDA by PCA. The demonstration of the new approach by its application to the FFF data of the urban trains that was collected from the UTS Melbourne has shown the transformation of the big data of urban trains into coherent information. PCA has successfully established the five different operational performance characteristics that are based on the FFF, and it has provided a clear insight into the latent structure of the FFF profiles of the months and the sub-systems individually and in relation to each other. In addition, the results of PCA are presented in plots that provide rich information and are easy to interpret. The comparison of the results obtained from PCA with those of SDA has proved that PCA can be used for establishing the operational characteristics of the sub-systems considering influence of the latent variables; thus, enabling the better decision-making in the process of maintenance planning for the fleet of urban trains.

However, despite its significant advantages, PCA can only deal with a single criterion for the data characterisation. Therefore, PCA cannot be applied for operational characterisation of the sub-systems based on the multi-criteria i.e. operational characteristics that involves the KPIs for both functional reliability and service reliability. Hence, the next chapter aims to apply a technique, which is an extended version of PCA, for identification of the critical sub-systems by using the multi-criteria.

Chapter 5: OPERATIONAL PERFORMANCE CHARACTERISATION BASED ON MULTIPLE CRITERIA USING MULTIPLE FACTOR ANALYSIS

5.1 Introduction

In the previous chapter, a new approach was developed for operational performance characterisation of the fleet of urban trains by preserving the conventional single criterion (i.e. functional failure frequency) while applying PCA. It was concluded that PCA can be used to establish five of the operational characteristics of the sub-systems considering the influence of the latent variables; however, it cannot be used to obtain the other four operational characteristics that need to be established based on multiple criteria in line with Research Objective 2(b). Hence, another technique is needed that not only characterises the operational performance of the sub-systems considering the influence of the latent variables, but that can establish the operational characteristics considering the KPIs of both functional reliability and service reliability. This is required in order to evaluate whether there are differences in the critical sub-systems identified based on multiple-criteria that entail the concerns of main stakeholders and those identified as critical based on the single criterion.

This chapter reports the development of this multiple criteria approach obtained by pairing the KPIs in their cause-and-effect structure (i.e. FFF-and-number of services cancelled, and FFF-and-number of services delayed), and then applying a technique called multiple factor analysis (MFA) which is an extension of PCA.

This chapter first presents The MFA technique explaining why it was selected for operational characterisation based on multiple criteria. Next the data structure based on multiple criteria for analysis and the software used are described in detail, and the script is validated using an example. The results of the multiple criteria approach are then presented and compared to the results obtained using the single criterion approach developed in Chapter 4. Finally, the chapter concludes by recommending an improved analytical framework for the reliability analysis.

5.2 Selection of the multiple factor analysis technique

This section explains why MFA was selected as the multiple-criteria analysis method for the operational performance characterisation of the sub-systems. The data characteristics are first discussed and the usefulness of MFA for analysing the operational performance data of urban trains is then assessed.

The discussion in Section 3.3.2 of Chapter 3 clearly shows that the data collected on the number of services cancelled and the number of services delayed contain redundant information, they are multivariate, and show recurrent and non-recurrent patterns in measuring the KPIs in various sub-systems. As discussed in Section 4.2 of Chapter 4, the presence of recurrent and non-recurrent patterns in the data indicates the influence of the latent variables. Therefore, for accurate characterisation of the performance of the sub-systems, it is important to consider the influence of the latent variables and this can be achieved by investigation of the latent structure within the data.

Before considering the technique for analysis, it is important to know what information needs to be extracted from the data. To achieve Research Objective 2(b), the operational characteristics from C6 to C8 (listed in Section 3.2.1 of Chapter 3) need to be evaluated based on the multiple criteria that are defined by the KPIs of both functional reliability and service reliability. For convenience, these operational characteristics are listed here again:

C6 the critical sub-systems for services cancelled

C7 the critical sub-systems for services delayed

C8 relationship between the FFF and the number of services cancelled

C9 relationship between the FFF and the number of services delayed

Analysis of these operational characteristics by applying multiple criteria requires the application of a technique that can characterise the sub-systems considering various KPIs for reliability, and can describe the complex relationships between the KPIs. MFA is a promising technique that is designed to deal with complex multiple datasets, and can be used to find the common latent structure between them. It has been extensively used in many fields including sensory science, molecular biology, environmental science, ecology, surveys analysis and in time series studies. MFA can be applied in any industry that involves wide data bases (Kassambara, 2017a).

Due to its flexibility and robustness, MFA has been increasingly used in engineering and business studies in recent years. Some of these studies apply MFA to analyse data that involve variables entailing the concerns of stakeholders. For example, Wang et al. (2011) analysed large scale blackout accidents data for performance assessment of electricity firms considering several risks associated with the power grid; Visbal-Cadavid et al. (2020) evaluated sustainable development data of higher education institutes for their performance assessment considering several outcome indicators; and Duarte and Campos (2020) studied the inter-organisation collaborative network data for evaluation of improvement in performance of organisations considering several attributes. These studies succeeded in identifying the individuals that are critical in relation to the concerns of different stakeholders by considering the influence of the latent variables and the relationships between the variables. Hence, the successful application of MFA in these studies clearly shows MFA offers great potential to analyse data which is complex, multivariate and involves multiple datasets.

Additionally, MFA has the great advantage that it is based on PCA which has already been used to analyse the urban trains data in the previous chapter. MFA performs a global analysis on a set of variables that is measured on the same individuals or on the same variables that are measured on different individuals (Pages, 2004, De Tayrac et al., 2009, De Roover et al., 2012). MFA investigates the similarities and differences between the different datasets based on the common latent structure (De Roover et al., 2012). Abdi et al. (2013) states that the first step in MFA is to perform PCA on each dataset separately, and then to normalise each dataset by dividing all the elements by the first singular value obtained for that dataset using PCA. This transformation ensures that the first singular value of each data set is equal to 1 which nullifies the dominant effect of any dataset in the common solution (Abdi and Valentin, 2007, Abdi et al., 2013). In the second step, all normalised datasets are combined into a grand table, and then PCA is applied to the grand normalised datasets for global analysis, thus establishing the common scores for the individuals and the loadings of the variables on the dimensions (i.e. the constructed principal components). This means that dimensions represent the latent variables in MFA. The common scores provide an assessment of the individuals in the global space i.e. from the perspectives of all the datasets, while the loadings determine the relationships between the variables.

In the current research, the sub-systems need to be characterised considering the KPIs of both functional reliability and service reliability, and the relationships between these KPIs. In addition, the individuals need to be evaluated in relation to each dataset which can be utilised to compare the performance of the sub-systems with respect to the types of trains in the fleet. Thus, MFA was selected to characterise the operational performance of the sub-systems based on multiple criteria.

5.3 Data analysis plan

This section explains how the data were analysed using MFA. The data and the software used for the analysis are first presented, and the script design is outlined and then validated through an example. The usefulness of MFA in characterising the individuals in the data considering all variables in all datasets is highlighted.

5.3.1 Data collection and structure

To characterise the sub-systems based on the effect of FFF of the sub-systems on the number of services cancelled and on the number of services delayed, MFA was performed on the two datasets. The data obtained using SDA and reported in Chapter 3 were used to carry out this analysis. Since data re-structuring is required in order to expose the influence of the latent variables that are common between datasets (Xu and Goodacre, 2012), the data were structured into groups with respect to the different types of trains in the fleet. The four different types of train in the UTS fleet in Melbourne were coded for analysis as A, B, C and D. No new trains were introduced in six years. However, the oldest trains i.e. those of train type D were removed from the service after Year 3 as discussed in Section 3.3.1 of Chapter 3. Thus, all four groups i.e. A, B, C and D were analysed for the first three years, and when train type D was removed from service after study Year 3, the three remaining groups were analysed for the last three years. In each group, the first variable was FFF in both datasets, while the second variable was the number of services cancelled and the number of services delayed in Set I and Set II respectively. The variables were measured on the 19 different sub-systems that were coded as S1, S2. …., S19 in Chapter 3. Thus, the data for each train type was structured into a 19 x 2 matrix, wherein, the sub-systems in rows represent the individuals that were assessed for reliability, and the KPIs in columns represent the original variables that were used for measuring reliability. The matrices for train types were then combined in grand matrices X_1 and X_2 for Set I and Set II respectively, resulting in a 19 x 8 grand matrix for study years 1, 2 and 3 with four types of train as the groups, and a 19 x 6 grand matrix for study years 4, 5 and 6 with three types of trains as groups.

5.3.2 Software and script design

The analysis was performed in RStudio version 3.5.0 by R Core Team (2018). The script for MFA in RStudio by Kassambara (2017a) was used as an example. The multivariate data analysis packages FactoMine version 2.4 (Husson et al., 2008) and Factoextra version 1.0.7 (Kassambara and Mundt, 2008) were used for the script design. FactoMine offers an inbuilt function – MFA (), while FactoExtra provides functions that are easy to use for visualisation and quick extraction of the results from the analysis (Husson et al., 2008). Based on the data characteristics, the following points were considered in the pre-processing of the data and in assigning the values to various arguments within the function of MFA ():

(1) **Scaled data:** Functional failures are measured in frequency (i.e. counts for a given reported period), while the KPIs for service reliability are measured in terms of numbers that are caused by the occurrence of functional failures in the sub-systems. As we discussed in Section 5.3.2 of Chapter 5, data scaling is required when variables are in different units. Data scaling is also required when the datasets vary in their ranges which is the case with the datasets of FFF and the KPIs for service reliability. Therefore, data scaling was required before performing the analysis in this study. The min-max scaling technique is recommended when there is a difference in the ranges of the datasets (Lakshmanan, 2019, Bhandari, 2020). Hence, the min-max scaling was applied for re-scaling the ranges of all the datasets to the scale of [0 100].

(2) **Number and type of groups:** In case of both Set I and Set II, the four types of trains for years 1, 2 and 3, and the three types of trains for years 4, 5 and 6 were defined as active groups, and the Null value was assigned to the number of supplementary groups. By default, the argument "group" balances the influence of each group of variables in the construction of the dimensions (Kassambara, 2017a).

(3) **Number and type of variables:** There were two variables in each group and all groups of variables were quantitative. RStudio by default standardises the quantitative variables to unit variance in order to make them comparable.

Additionally, the supporting packages named as devtool version 1.13.5 (Wickham et al., 2018), ggplot2 (Wickham, 2009), ggrepel version 0.9.1 (Slowikowski et al., 2021), Rarpack version 0.11-0 (Qiu and Mei, 2016), rJava version 0.9-9 (Urbanek, 2017), xlsx version 0.6.1 (Dragulescu and Arendt, 2018) and Xlsxjars version 0.6.1 (Dragulescu, 2014) were incorporated in the script for expediting the process, for better visualisation of the results, and for quick extraction and importation of the results.

The script designed to perform MFA in RSTUDIO is presented in Appendix C.

5.3.3 Validation of the script

Based on the availability of detailed data, a study by Kassambara (2017b) that used MFA for quality characterisation of the wines was selected for validation of the designed script. In Kassambara's study, 21 samples of wines from different origin were evaluated against 27 sensory variables those were structured in four groups. The groups were named after the sensory tests that included the odour test, visual test, odour after shaking test and the taste test. The number of variables in these groups were 5, 3, 10 and 9 respectively. The designed script was used for performing MFA on this data in RStudio. The values for the different arguments were assigned as per the given data, and the same results as reported by (Kassambara) were obtained. Hence, it validates the script design and its functioning. The typical MFA plots for obtained results were mapped and are presented in Appendix D. In order to develop understanding about usefulness of MFA in revealing the common latent structure that exists between and within the multiple datasets, the key findings of the example are presented here.

The production process of all wine samples only differs with respect to the type of soil for the wine fields. This results variation in the quality of winesS; thus, the sensory scientists apply MFA for characterisation of the wines considering influence of all variables in all groups. In Kassambara's study, dimension I represented the common structure between all groups and within each group. In relation to it, it was found that the wine 1DAM had the highest common scores, while the wines IVAU and the 2ING had the least common scores. The cross checking with the raw data showed that IDAM was the most intense and harmony wine among all samples, while IVAU and the 2ING were the least intense and the harmony wines. The second structure represented by dimension II was related to three groups i.e. odour, odour after shaking and taste, but it was not related to vision. The wines T1 and T2 attained the highest common scores on this dimension. The cross checking with the raw data informed that these wines were spicy and had vegetal characteristics. Hence, it was concluded that the latent variable associated with dimension I is essential for production of highly intense and harmony wine, while the latent variable associated with dimension II is necessary for spiciness and vegetal characteristics in the wine.

The above example clearly shows that MFA reveals the common structure that exists between and within the study groups. This enables the characterisation of the individuals involved in the study considering all variables within all groups, and the analysis of the relationships between the variables. This example in terms of its complexity and the analysis objectives is similar to the present study. Hence, MFA can also be applied to the operational performance data of the urban trains.

5.3.4 Application of MFA to the urban trains data

The yearly matrix X_1 for FFF-and-number of services cancelled for Set I and the yearly matrix X_2 for FFF-and-number of services delayed for Set II were analysed using MFA. The computational process is the same for both sets; the only difference is in terms of the involvement of the KPI for service reliability. Hence, the computational process is explained here only by using the yearly matrix X_1 comprising the data from the four groups A, B, C and D. As defined in Section 5.3.1, the yearly $X_{1,}$ also called the grand matrix X_1 or the global matrix, is of order 19 x 8. This can be represented as $X_1 = [X_A| X_B| X_C| X_D]$. Each individual element in X_1 is represented by x_{ijk} which implies that the x value is lodged by i^{th} sub-system on j^{th} KPI in the k^{th} group. This means that the elements of i^{th} row form a p-dimension vector of i^{th} sub-system denoted by S_i, and the elements of j^{th} column that fall in the k^{th} group forms an n-dimension vector of j^{th} KPI denoted by R_j.

The first step of MFA is to perform PCA on the matrix of each group individually by using the same computational steps as outlined in Section 4.3.5 of Chapter 4. The weight for each group is then established by taking the inverse of its first singular value (i.e. σ_1) obtained by PCA. If the weight is represented by α, then the α weights for k groups can be stored in a J by 1 vector denoted by **a**. It can be represented as **a** = $[\alpha_A 1^T_{|A|}, \alpha_B 1^T_{|B|}, \alpha_C 1^T_{|C|}, \alpha_D 1^T_{|D|}]$; whereas, 1_k shows J_k by 1 vector of ones i.e. J= 8 by 1 vector. To obtain the normalised matrix for each group without disturbing their internal structure, the weight for the group is multiplied with all the elements within that group (Josse et al.). This normalisation adjusts the highest variance of each group to unit that nullifies the influences of the groups (Josse et al., Abdi et al., 2013).

The normalised matrices for the four groups are then concatenated into the grand normalised matrix Z_{X1} (also called the global matrix) of order 19 x 8. This global matrix for operational performance of the fleet of urban trains can be represented as $Z_{X1}= [Z_A| Z_B| Z_C| Z_D]$. Using PCA, MFA decomposes Z_{X1} into a product of three matrices i.e. the matrices of the left and right singular vectors (denoted by U and V respectively) and a square matrix D of singular values as shown in Equation

5-1:

$$Z_{X1} = U_{X1} D_X V^t_{X^t_1} \qquad \text{where } U^t{}_x{}^t{}_1 M U_{x1} = V^t{}_x{}^t{}_1 A V_{x1} = I \qquad \textbf{5-1}$$

In comparison to Equation 4.1 in Chapter 4, the decomposition of Z_{X1} involves two additional definite matrices M and A that represent the constraints on its rows and its columns respectively. The matrix M is a diagonal matrix of order 19 x 19 which is established by using M = diag{m}, while m is a vector of equal masses that are assigned to the individuals (i.e. the sub-systems) by using m = 1/I. Likewise, A is a diagonal matrix of order 8 x 8 which is established by using A = diag{$\mathbf{a}$}, while **a** is a vector of α weights. These constraints are applied to ensure the orthogonality of the matrices U_{x1} and V_{x1}.

The matrix V_{x1} is the first resultant matrix which spans the operational performance of the sub-systems and provides an orthonormal basis for $\{S_i\}$. V_{x1} is the matrix of the set of dimensions that contains the coefficients of the KPIs on the dimensions. Given that the number of individuals is greater than the number of variables, the orthogonal transformation of Z_{X1} results in the number of dimensions being equal to the number of variables (Adams et al., 2001); hence, 8 dimensions are produced. The scree plot maps the number of dimensions and the percentage of variance explained by each of the extracted dimension. This plot is used to determine the number of dimensions to be retained for further analysis. The columns of Vx_1 represents the set of dimensions; thus, it is a matrix of order 19 x 8.

MFA determines the first dimension in a direction that represents the greatest link between all groups (Husson, Visbal-Cadavid et al., 2020). The second dimension is orthogonal to the first dimension and it is determined by the next greatest link between the groups and so on. In this way, in addition to the general results of the standard PCA, MFA reveals the relationship between the dimensions and the groups of variables, and between different groups of variables.

This information is mapped in the plot known as groups representation which can be used to compare the operational performance of different types of train in the fleet considering the influence of the common latent variables.

The second matrix D is a diagonal matrix of singular values representing the amount of variance captured by each dimension; hence, it is of order 8 x 8. The singular values are in descending order of their importance and they explain the magnitude of influence of the latent variables in the construction of Z_{x1} which is the normalised matrix of X_1. The final matrix U_{x1} spans the KPIs for reliability and forms an orthonormal basis for {Rj}; hence, U_{x1} is a matrix of order 19x8. We also know from Section 4.3.5 of Chapter 4 that Equation

5-1 can be re-written as:

$$Z_{X1} = (U_{X1}D_{X1})\, V_{X_1^t}^{t} = T_{X1}W_{X_1^t}^{t} \tag{5-2}$$

In Equation 5-2, T_{X1} stores the common factor scores for the sub-systems considering the influence of all variables of all groups. The common scores of the sub-systems can be plotted in a similar way to the scores plot in PCA. Thus, the representation of the sub-systems in the global environment of MFA characterises the sub-systems with respect to their operational performance in all types of train. Hence, it can be used to identify the sub-systems that are critical in the overall train fleet.

Considering the group structure of the matrix Z_{X1}, the common scores for the sub-systems can be split into their partial scores, i.e. scores of the sub-systems with respect to the group of each type of train in the fleet. The partial scores for the k^{th} group can be computed by multiplying the data matrix of the group with its loading matrix considering the diagonal matrix A_k of α weights for the group i.e. $T_k = Z_kA_kW_k$ (Abdi et al., 2013). Using the partial scores of the sub-systems for the four types of trains, the matrix for the common scores of the sub-systems i.e. T_{X1} can be written as shown in Equation 5-3:

$$T_{X1} = 1/4(Z_A\, A_AW_A + Z_BA_BW_B + Z_C\, A_CW_C + Z_D\, A_DW_D) \tag{5-3}$$

Equation 5-3 clearly shows that the common scores for the sub-systems are the average of the scores for the sub-systems from the four groups. Hence, the contribution of the different types of train in the common scores for the sub-systems can be analysed. The partial scores can be superimposed on the common scores plot of the sub-systems to identify the sub-systems critical with respect to the types of train in the fleet. Another term W^t_{X1} in Equation 5-2 stores the loadings of the KPIs for reliability on dimensions. MFA plots the loadings of the sub-systems on the dimensions in a two-dimensional circle (also called a correlation circle) with a unit radius. This plot is useful for analysing the relationship between the KPIs for reliability and the latent variables associated with the dimensions. In addition, the principal components obtained by individual PCA of each group can be projected on the correlation circle defined by the dimensions obtained from MFA. The correlations of the principal components of each group with the dimensions of MFA are used as coordinates for the mapping. This is referred to as a partial axes plot and it is useful for analysing the relationship between the principal components of each individual analysis and the dimensions of the global analysis.

Equation 5-2 shows that MFA transforms the normalised matrix of original data into the common scores of the sub-systems, i.e. T_{X1}, and the loadings of the KPIs for reliability on the dimensions, i.e. W_{X1}, by imposing constraints on its columns and the rows. This transformation results in the generation of several plots that provide insight into the common latent structure within and between the datasets. Since the computational process for X_1 has shown, it has also shown the process for X_2. Thus, MFA can be used to analyse the functional failures data of the urban trains together with the services cancelled data, and the services delayed data.

5.4 Set I: Analysis of operational performance characteristics based on the impact of FFF on the number of services cancelled

This section discusses the results obtained for Set I by the application of MFA to the urban trains data for the six study years. The aim is to identify the critical sub-systems with respect to the impact of FFF of the sub-systems on the number of services cancelled, and to analyse the relationship between the FFF and number of services cancelled.

5.4.1 Selection of the number of dimensions for further analysis

As explained in Section 5.3.4, the decomposition of matrix X_1 results in the number of dimensions equivalent to the number of KPIs involved in its construction. Matrix X_1 for Years 1, 2 and 3 generated a set of 8 dimensions and for Years 4, 5 and 6 a set of 6 dimensions. We also know from Section 4.4.1 of Chapter 4 that it is important to retain an adequate number of dimensions for the best approximation of the original data matrix.

From different approaches for the selection of number of dimensions, the scree plot was selected. This plot is a line plot which is mapped between the number of dimensions on the x-axis and the variance explained by them on the y-axis (Yang, 2015, De Silva et al., 2017). The amount of variance which is explained by the dimensions can be represented by both singular values and the eigenvalues depending on the selection of the matrix decomposition method and the software package. These values are interchangeable, but it is easier to communicate the variance when it is given as a percentage. The FactoMine package in RStudio represents the percentage of variance explained by each of the dimensions on the y-axis. It also provides an option to plot the scree plot as a line chart, a bar chart or a combination of both. By default, it generates the scree plot as a combination of both line chart and the bar chart (STHDA: Statistical tools for high-throughput data analysis), which is also used in this study.

The scree test is applied for determining the number of dimensions to be retained for further analysis. According to the scree test, the number of dimensions before or up to the elbow point that joins the steep and the flat parts of the plot (i.e. a bend) in the scree plot are adequate for an approximation of the original data matrix (Yang, 2015, De Silva et al., 2017). The steep part indicates an explanation of the maximum percentage of variance in the data by the number of dimensions that fall on it. By contrast, the flat part indicates an explanation of a small or negligible percentage of variance in the data by the number of dimensions that fall on it. Hence, it is better to retain the number of dimensions before or up to the elbow point rather than the number of dimensions after the elbow point that add little or no more information (McDonald, 1985). To decide between the number of dimensions to be retained before or up to the elbow point, we combine the scree test with the cumulative percentage of variance explained by the dimensions. As discussed in Section 5.4.1 of Chapter 5, the minimum recommended number of dimensions corresponds to a cumulative percentage of variance of 70% (Jolliffe, 2002, Yang, 2015, De Silva et al., 2017).

The scree plots for all six study years are presented in Figure 5-1.

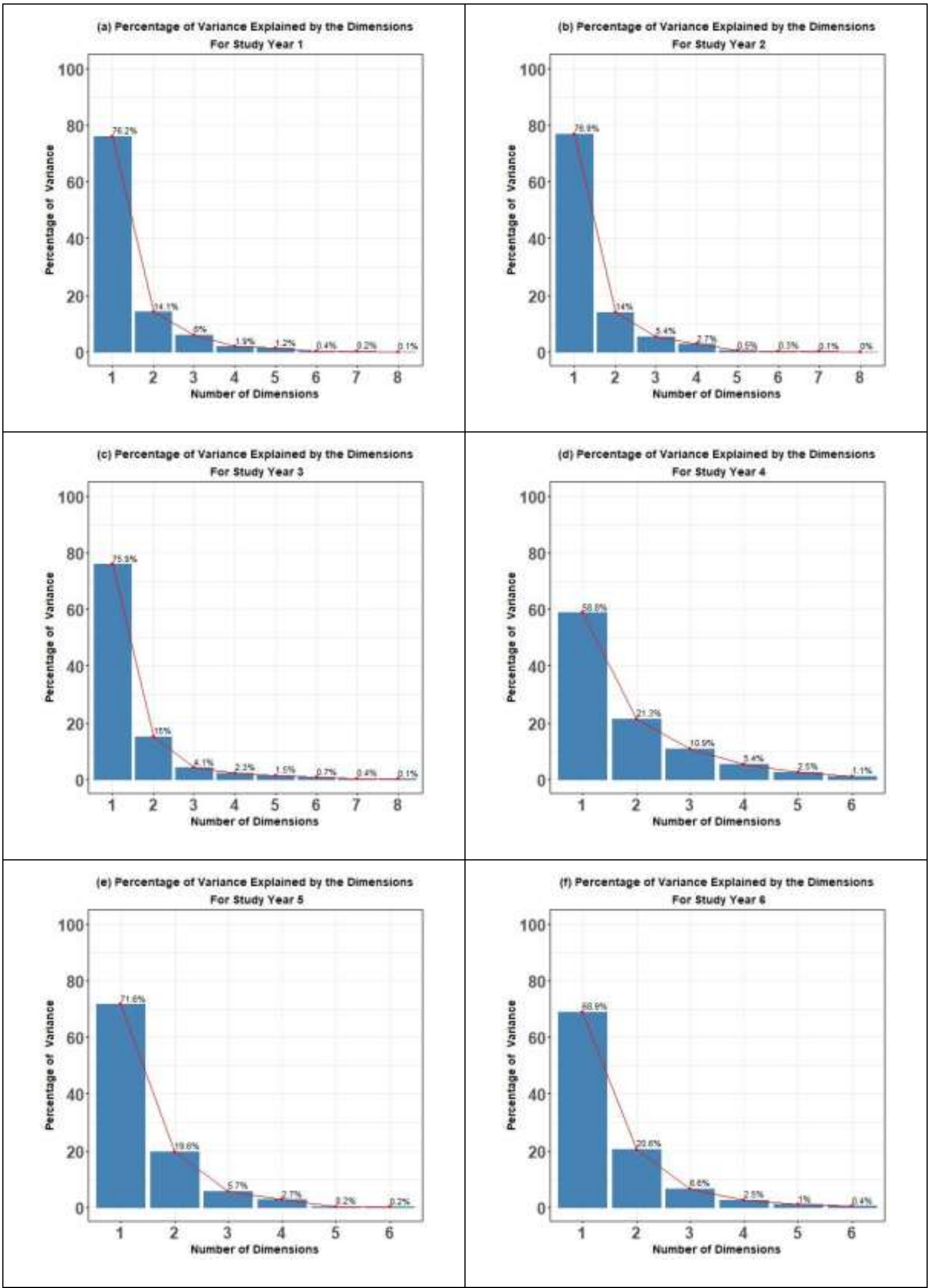


Figure 5-1: Scree plot for the six study years showing the percentage of variance explained by each dimension.

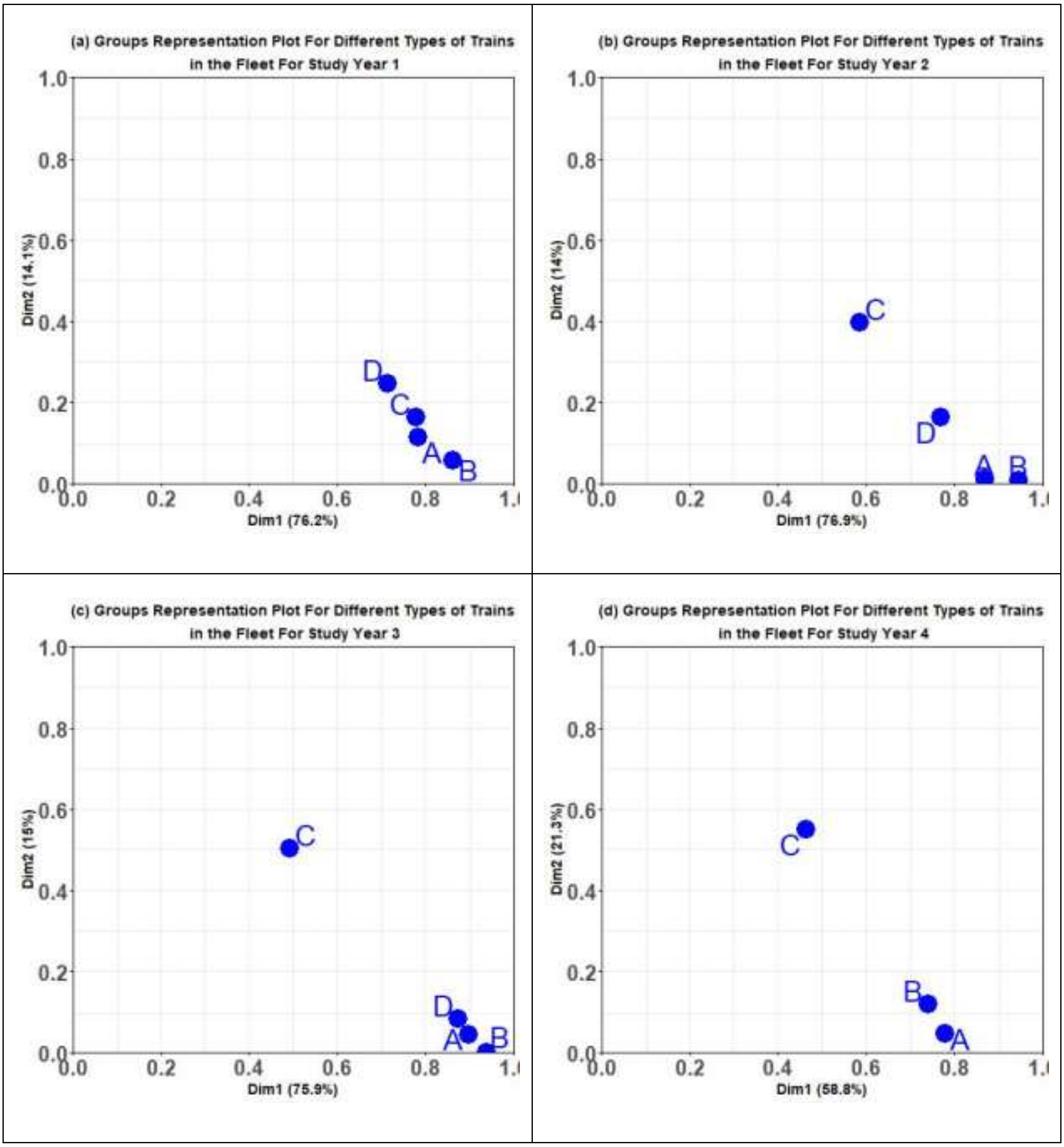
As can be seen in Figure 5-1, the elbow point appears at dimension II in the scree plot of each study year. This implies that only dimension 1 or both dimensions I and II can be retained for further analysis. Using the cumulative percentage of variance approach, Figure 5-1 also shows that if we retain only dimension 1, the cumulative percentage of variance is 76.2%, 76.9%, 75.9%, 58.8%, 71.6% and 68.9% for study years 1,2,3,4,5 and 6, respectively. This shows that dimension I alone explains the cumulative percentage of variance in X_1 (i.e. the global matrix of operational performance of urban trains established on FFF and the number of services cancelled) greater than the minimum threshold of 70% except in years 4 and 6. In addition, the percentage of variance explained by dimension II is 14.1%, 14.0%, 15.0%, 21.3%, 19.6% and 20.6% in study years 1,2,3,4,5 and 6, respectively. This means that if we retain both dimensions I and II, the cumulative percentage of variance is 90.3%, 90.9%, 90.9%,80.1%, 91.2% and 89.5% in years 1,2,3,4,5 and 6 respectively which far exceeds the minimum threshold for each study year. Even though dimension I alone is almost enough to serve the purpose, the mapping of the results in two-dimensional space is better for visualisation of the results. Hence, both dimensions I and II are retained for investigating the latent structure of X_1.

5.4.2 Characterisation of operational performance of different types of train in the fleet

The operational performance of the different types of train in the fleet can be compared based on the strength of the relationship between the performance of each train type and the two dimensions i.e. influence of the latent variables on the operational performance of train types. The amount of variance (also known as inertia) explained by each dimension can be used as a measure of strength of this relationship, and it is equivalent to the sum of variance of the performance of each train type (also known as the partial inertia). The proportion by which the partial inertia of each train type contributes to the total inertia of the dimension defines the strength of the relationship of its operational performance with the latent variable associated with the dimension. This implies that a larger proportion is an indication of a strong relation between the operational performance of the train type and the dimension. Hence, the partial inertias obtained for the different types of train were mapped in the groups representation plot.

In this plot, the partial inertias define the coordinates for the mapping of the train types in the coordinate system defined by dimensions I and II. The coordinates vary between 0 and 1; thus, a cut-off value needs to be defined to categorise the train types in the fleet as strongly related and weakly related to the dimension. The groups representation plot is analogous to the loadings plot (Abdi et al., 2013), so the cut-off value at 0.3 loadings that was chosen in Section 5.4.3.2 of Chapter 5 can be used. Hence, the train types with coordinates ≥ +0.3 on the dimension are strongly related, while the train types with coordinates < +0.3 on the dimensions are weakly related.

Figure 5-2 presents the groups representation plots for the different types of train in the fleet for the six study years.



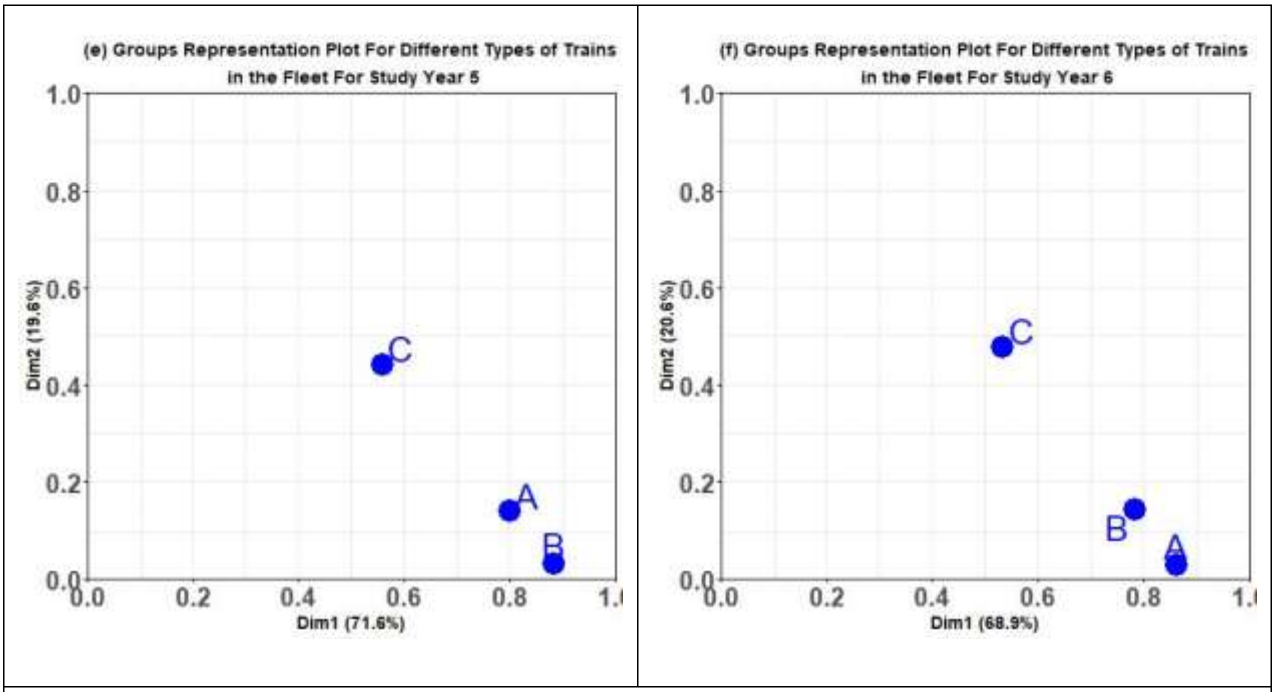


Figure 5-2: Groups representation plot for the six study years.

The distribution of types of train along the length of each dimension is a measure of the proportion of their partial inertia in the inertia of the dimension. The greater the distance between the point (representing the train type) and the origin of the plot on any dimension, the greater is its proportion in the inertia of the dimension.

As can be seen in Figure 5-2, in relation to dimension I the performances of all train types involved in each year are strongly related to this dimension for the six study years. In relation to dimension II, only the performance of train type C is strongly related to this dimension in all study years except Year 1 in which the performances of all train types are weakly related. Overall, this shows that the operational performance of train types A, B and D is strongly related to the latent variable associated with dimension I, while the operational performance of train type C is strongly related to the latent variable associated with both dimensions I and II. However, in order to analyse whether the relationship is positive or negative, it is required to investigate the inner-structure of the dimensions

These findings also indicate that the latent structure associated with dimension I is common between and within the groups of train types A, B, C and D for the six study years, while the latent structure associated with dimension II only exists within the group of train type C except in Year 1. In other words, the latent variable associated with dimension I is crucial for the operational performance of all train types, while the latent variable associated with dimension

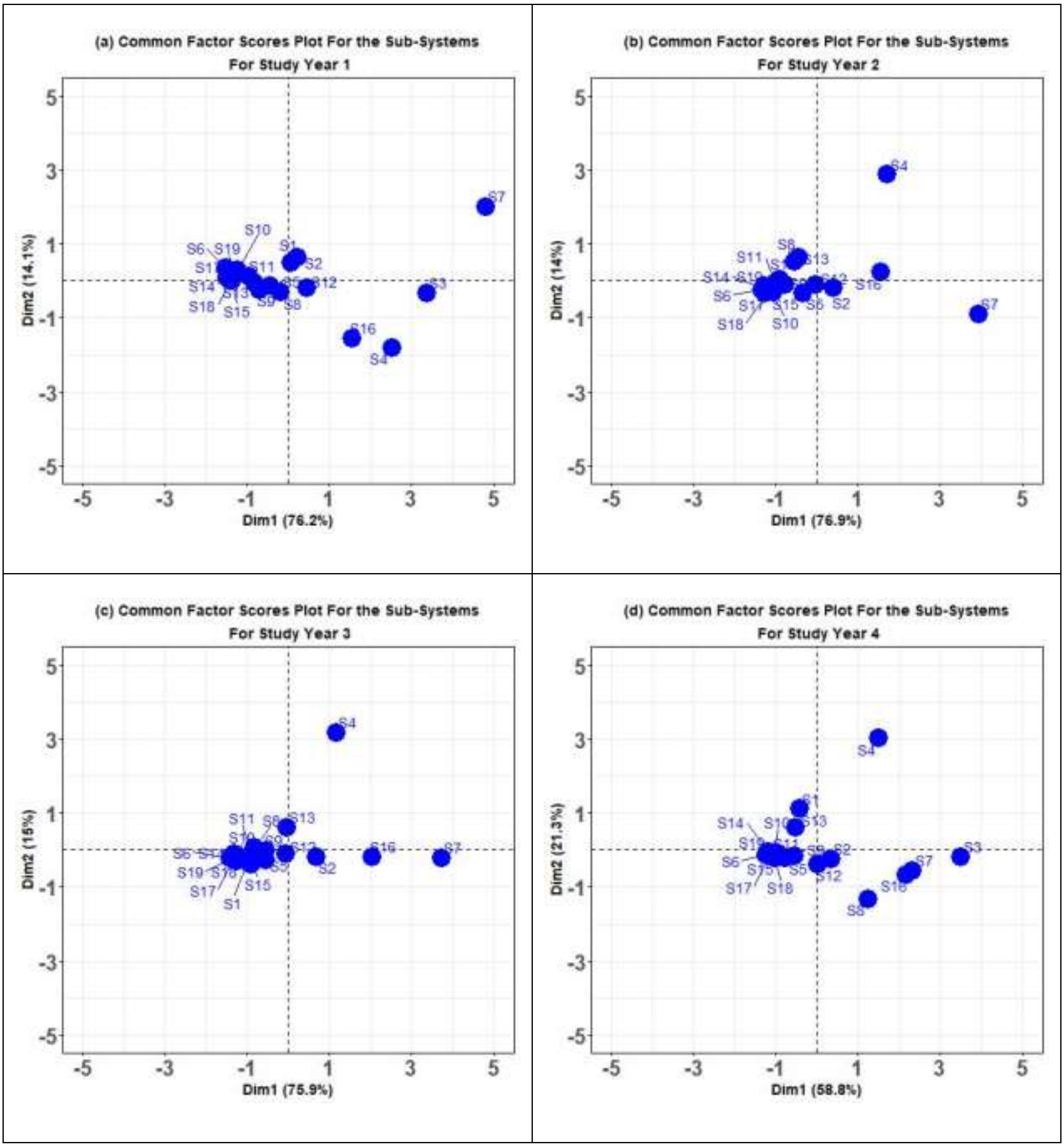
II is only crucial for the operational performance of train type C. Hence, it is concluded that MFA clearly reveals how the operational performances of different train types are related to each other in terms of common latent variable that affects their operational performance.

In summary, using MFA enables to compare the operational performances of different train types considering strength of their relationship with the dimensions, and it exposes the similarities in the latent structure which is common between and within the groups of train types.

5.4.3 Characterisation of operational performance of the sub-systems based on FFF-and-number of services cancelled

In order to identify the critical sub-systems considering the effect of their FFF on the number of services cancelled, the common factor scores of the sub-systems were mapped in the coordinate system defined by dimensions I and II. This plot provides insight into the characteristics of the performance of the sub-systems for all train types in the fleet. As only the critical sub-systems are of interest, a cut-off method is adopted to define the criterion. Considering the distribution of the sub-systems along the length of each dimension for each study year, the cut-off value is defined at +1 common scores. This implies that the sub-systems with the common scores $\geq +1$ are the critical sub-systems, and the sub-systems with the common scores $< +1$ are the non-critical sub-systems.

The common factor scores plots for all the sub-systems for the six study years are presented in Figure 5-3.


(a) Common Factor Scores Plot For the Sub-Systems
For Study Year 1
Dim1 (76.2%)
Dim2 (14.1%)
(b) Common Factor Scores Plot For the Sub-Systems
For Study Year 2
Dim1 (76.9%)
Dim2 (14%)
(c) Common Factor Scores Plot For the Sub-Systems
For Study Year 3
Dim1 (75.9%)
Dim2 (15%)
(d) Common Factor Scores Plot For the Sub-Systems
For Study Year 4
Dim1 (58.8%)
Dim2 (21.3%)

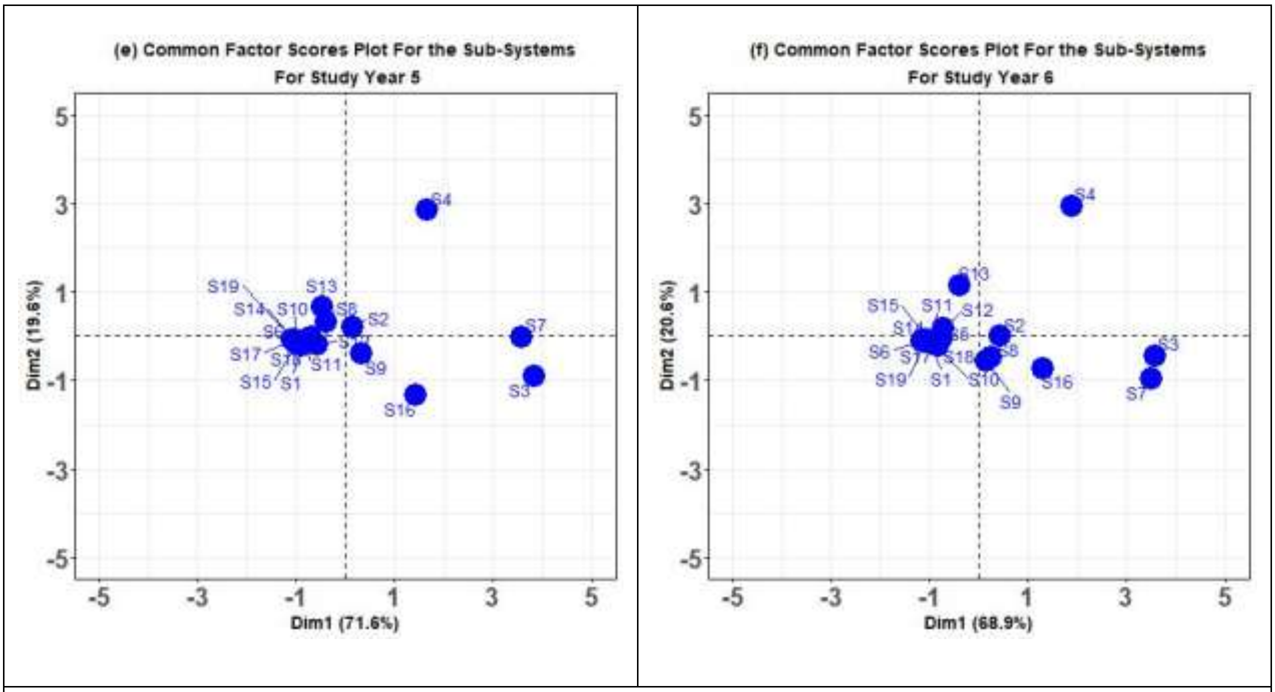


Figure 5-3: Common factor scores plot of the sub-systems for the six study years based on FFF-and-number of services cancelled.

In each plot, the x-axis shows the common scores of the sub-systems on dimension I, and the y-axis shows the common scores of the sub-systems on dimension II. The position of the sub-systems on each dimension indicates the criticality of their operational performance in relation to the dimension.

As can be seen in Figure 5-3, some sub-systems are distributed on the positive direction of the dimensions, while most of the sub-systems are distributed on the negative direction of the dimensions. When the rows of Z_{x1} are multiplied by the coefficients of the same dimensions this results in distribution of the similar sub-systems in the same direction of the dimension and of the dissimilar sub-systems in the opposite direction of the dimension. For the sub-systems distributed on the positive direction, their FFF and the effect of their FFF on the number of services cancelled are influenced by the characteristics of the dimensions, while for those distributed on the negative direction, their FFF and the effect of their FFF on the number of services cancelled are not. Hence, this distribution clearly differentiates the sub-systems that are operationally unreliable from those that are operationally reliable based on the combination of their FFF and the effect of their FFF on the number of services cancelled. However, to identify the critical sub-systems the defined criterion was applied. The sub-systems that are critical in relation to dimension I and dimension II are presented in Table 5-1.

Table 5-1: Critical sub-systems based on the FFF-and-number of services cancelled		
Study Year	**Critical sub-systems in relation to dimension I**	**Critical sub-systems in relation to dimension II**
Year 1	S3, S4, S7 and S16	S7
Year 2	S3, S4, S7 and S16	S4
Year 3	S3, S4, S7 and S16	S4
Year 4	S3, S4, S7, S8 and S16	S1 and S4
Year 5	S3, S4, S7 and S16	S4
Year 6	S3, S4, S7 and S16	S4

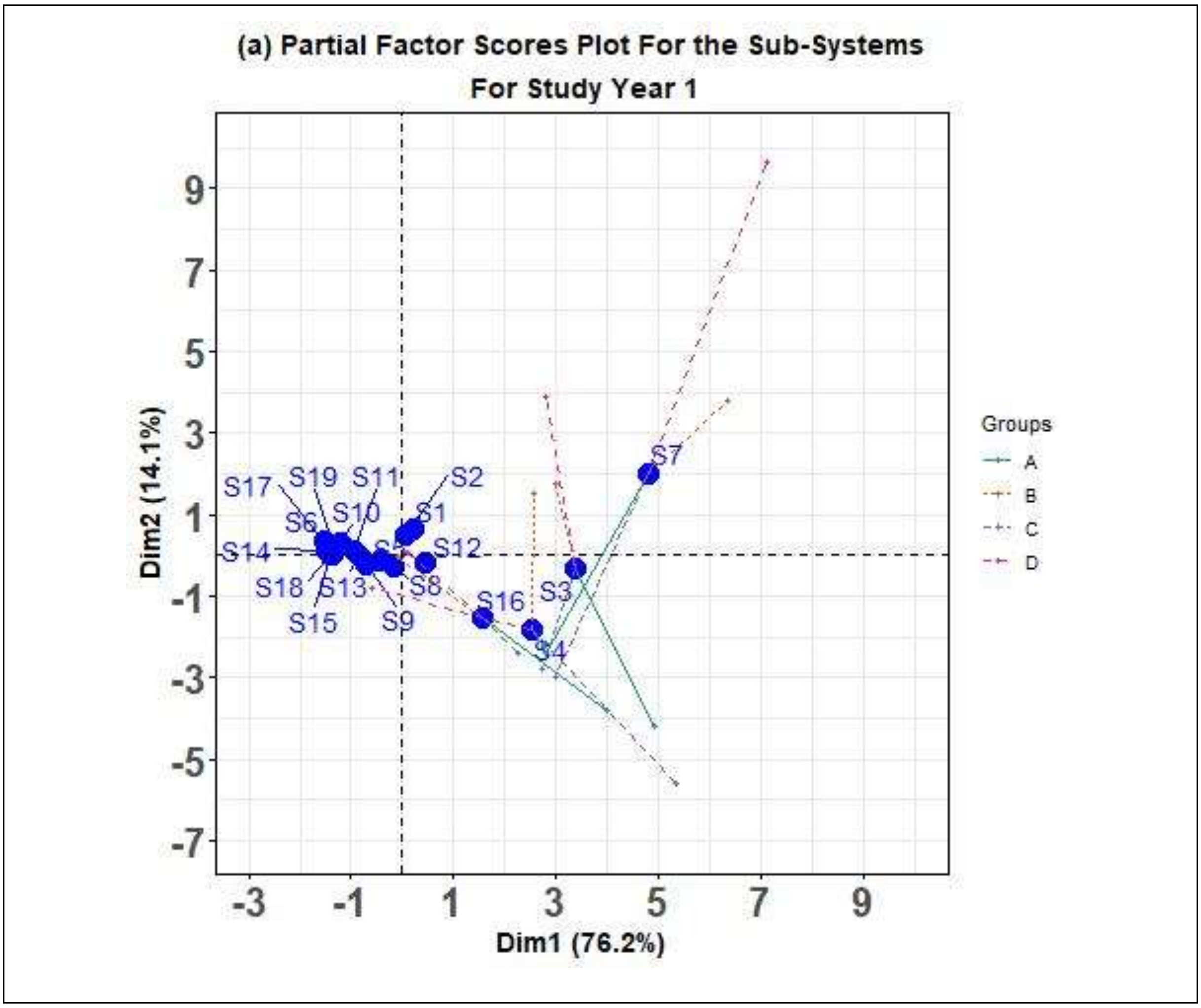
As can be seen in Table 5-1, in relation to dimension I, only 4 out of 19 sub-systems are critical in all study years except in Year 4 when 5 sub-systems are identified as critical. Similarly, in relation to dimension II, only 1 sub-system is identified as critical in all study years except in year 4 when two sub-systems are identified as critical. Hence, MFA successfully reduces the number of sub-systems to be dealt with. In addition, since MFA identifies the critical sub-systems related to the dimensions, to improve the operational performance of these critical sub-systems subject to FFF and number of services delayed, the improvement strategies need to be focussed on the characteristics of dimensions I and II. Thus, MFA provides a clear indication of the reason for the criticality of the sub-systems.

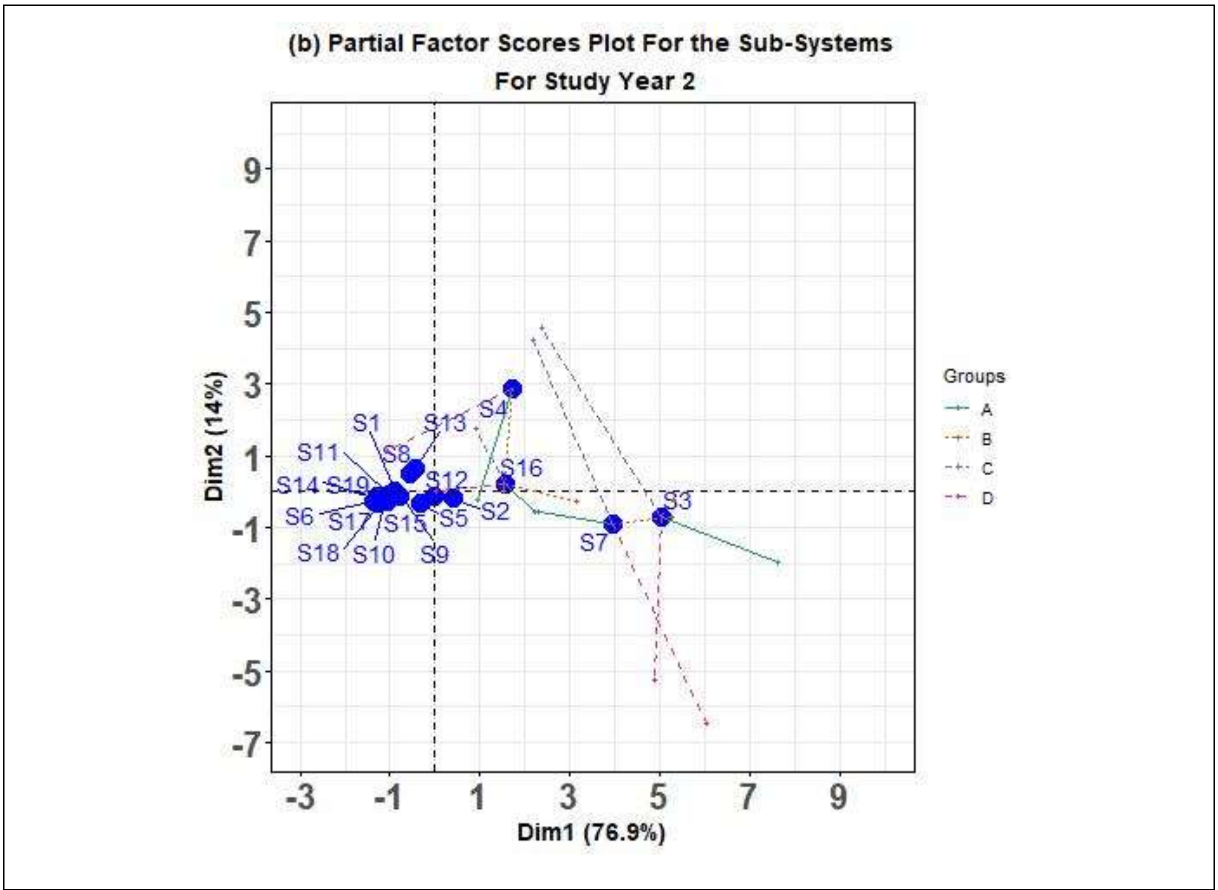
It is also evident from Figure 5-3 in relation to dimension I, S3 is the most critical sub-system followed by S7 and S16 in Years 2-5, while S7 is the most critical followed by S3 and S16 in Years 1 and 6. By contrast, in relation to dimension II, S4 is the only critical sub-system for the six study years. Since the same three sub-systems in the same criticality sequence are identified as critical in relation to dimension I in Years 2-5 and in Years 1 and 6, this could be because of the association of the same latent variable in Years 2-5, then another latent variable in Years 1 and 6. Similarly, the same sub-system is identified as critical in relation to dimension II for all study years, this could be because of the association of the same latent variable.

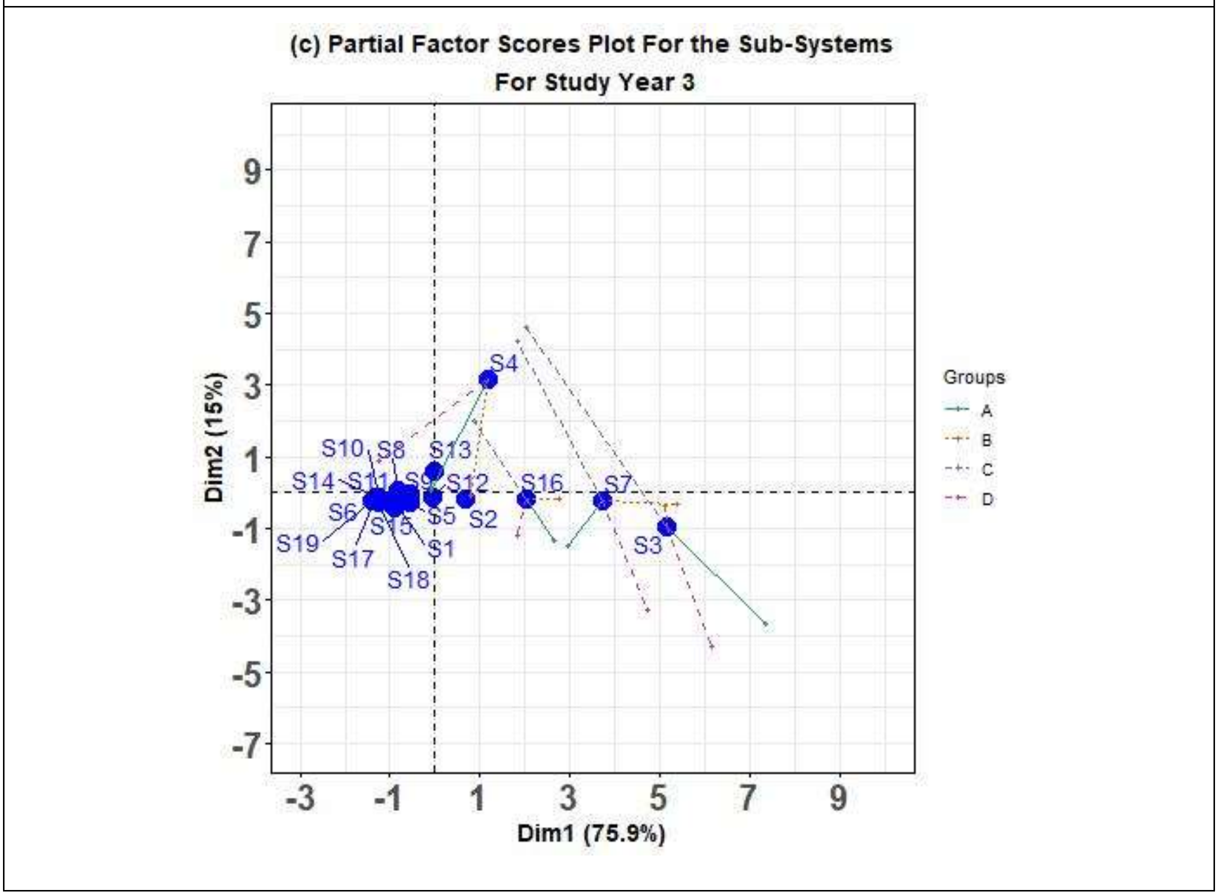
In addition, Table 5-1 shows that in relation to both dimensions, S7 is identified as critical in Year 1, and S4 is identified as critical in all other years. This can be explained by the variance partitioning effect that describes the spread in the characteristics of the operational performance of these sub-systems i.e. their operational performance tends to be influenced by the characteristics of both dimensions.

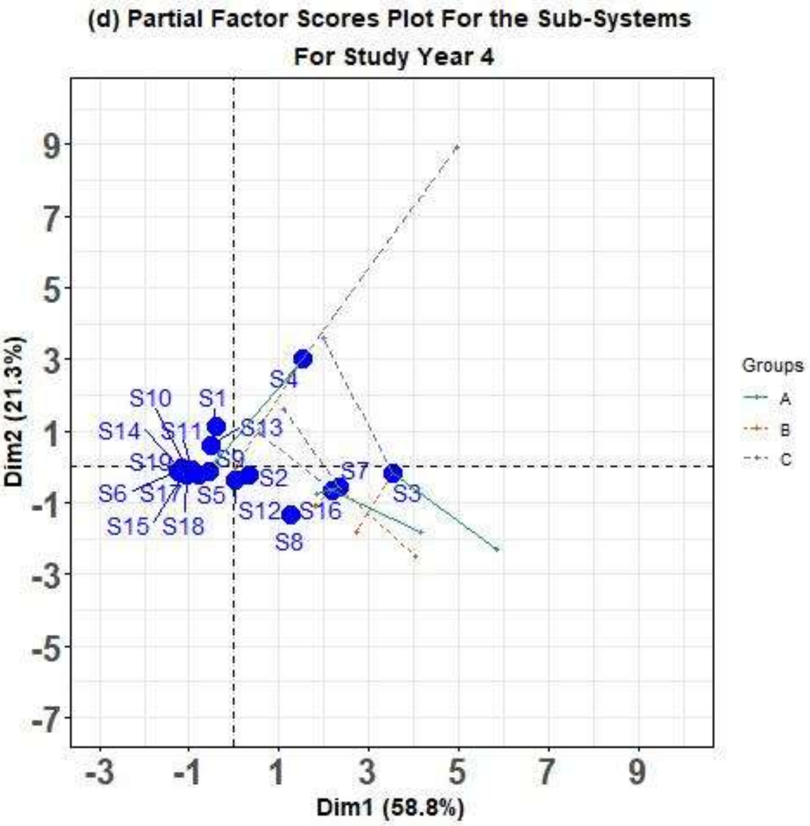
In summary, MFA allows the critical sub-systems to be identified based on FFF-and-number of services cancelled for the overall train fleet and thus, operational characteristic C6 - the critical sub-systems for services cancelled is hereby achieved.

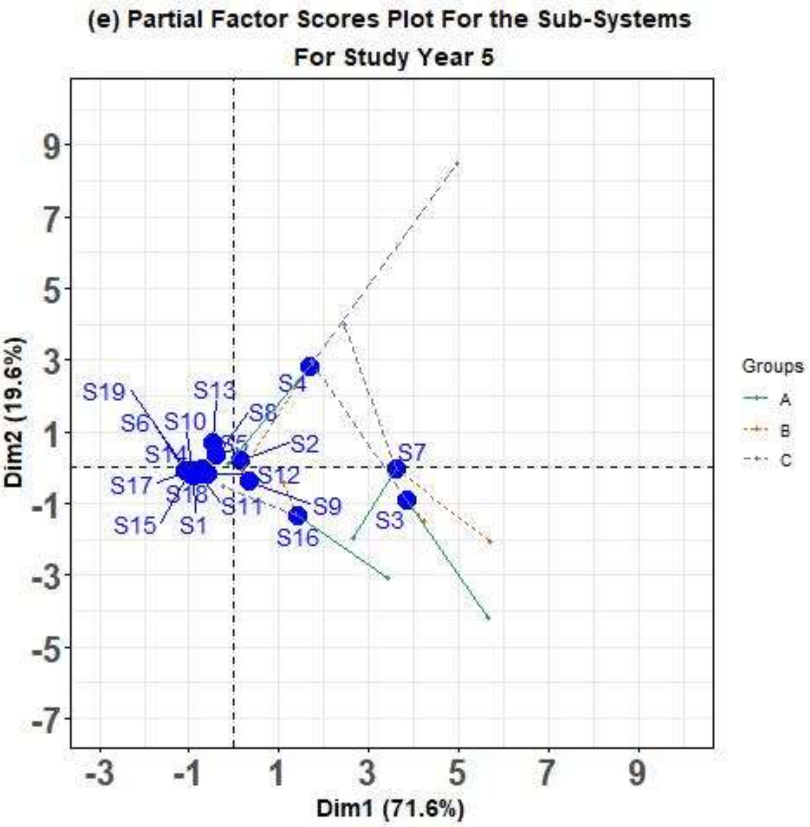
In order to identify the critical sub-systems for each train type in the fleet, the partial scores of the sub-systems were superimposed onto the common scores plot which is presented in Figure 5-4. Since the sub-systems S3, S4, S7 and S16 were the ones identified as critical in all study years, they are the only ones considered here to trace pattern for the operational performance with respect to each train type over these years.




(b) Partial Factor Scores Plot For the Sub-Systems
For Study Year 2
Dim2 (14%)
Dim1 (76.9%)
Groups
A
B
C
D
S1
S2
S3
S4
S5
S6
S7
S8
S9
S10
S11
S12
S13
S14
S15
S16
S17
S18
S19


(c) Partial Factor Scores Plot For the Sub-Systems
For Study Year 3
Dim2 (15%)
Dim1 (75.9%)
Groups
A
B
C
D
S1
S2
S3
S4
S5
S6
S7
S8
S10
S11
S12
S13
S14
S15
S16
S17
S18
S19


(d) Partial Factor Scores Plot For the Sub-Systems
For Study Year 4
Dim1 (58.8%)
Dim2 (21.3%)
Groups
A
B
C


(e) Partial Factor Scores Plot For the Sub-Systems
For Study Year 5
Dim1 (71.6%)
Dim2 (19.6%)
Groups
A
B
C

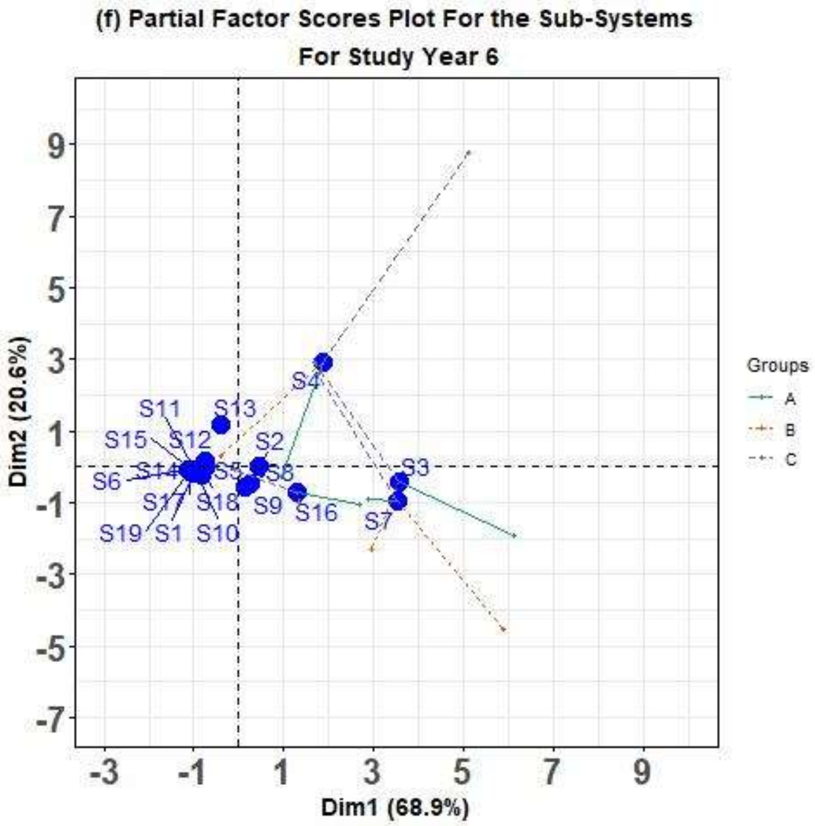


Figure 5-4: Partial factor scores plot of the sub-systems for the six study years based on FFF-and-number of services cancelled.

In each plot, the points representing the common scores of the critical sub-systems are in the centre, they are connected by the dotted lines to the points representing the partial scores for the critical sub-systems with respect to each train type. The relative distance and direction of the partial points of the sub-systems from the origin of the plot provide an indication of the contribution of each train type in the generation of the common scores of the sub-systems.

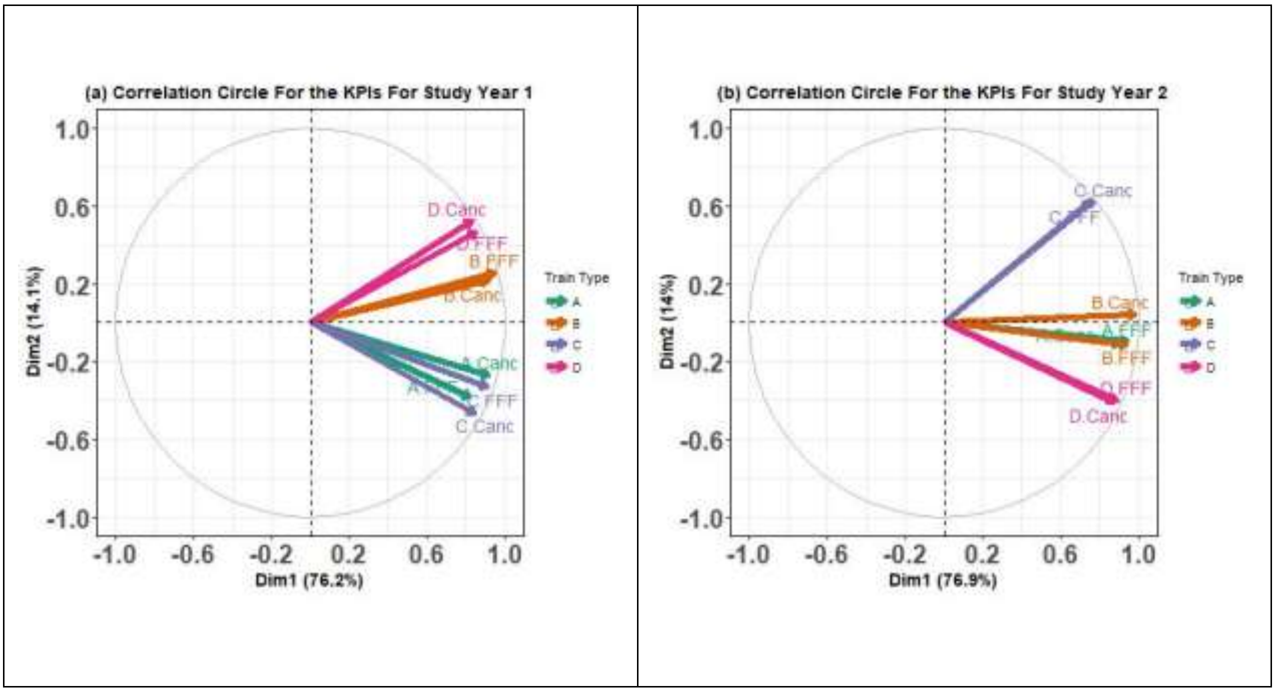
As can be seen in Figure 5-4, for the six study years, S3 is characterised by high values for train type A; S4 is characterised by high values for train type C; S7 is characterised by high values for train type D in years 1 and 2 and for train type B in all other study years; S16 is characterised by high values for the train type A except in years 2 and 3 when it shows high values for train type B. Overall, this shows that S3, S4, S7 and S16 are the most critical in relation to the train type A, C, B and A respectively. This means in order to deliver the biggest impact for the combined reduction in FFF and the number of services cancelled for train type A, it is required to focus on S3 and S16; and for train types B and C, it is required to focus on S7 and S4 respectively.

In summary, the common scores plot enables operational characteristic C6 - the critical sub-systems for services cancelled to be established for the overall train fleet, and superimposition of the partial scores for the sub-systems on this common scores plot further enables the critical sub-systems for each type of train in the fleet to be identified.

5.4.4 Relationship between the FFF of the sub-systems and the number of services cancelled

In order to analyse the relationship between the FFF and the number of services cancelled, the loadings of the KPIs on dimensions I and II were mapped in the correlation circle. Since in the data structuring the KPIs were grouped in columns for each train type, loadings for KPIs are obtained with respect to each train type involved in the study year. This plot provides insight into the relationship between the KPIs and between the KPIs and the dimensions. The plot is interpreted in the same way as was PCA loadings plot as reported in Section 4.4.3.2 of Chapter 4. Thus, the same cut-off value of 0.3 can be used to categorise the KPIs as critical and non-critical in relation to the dimensions. Hence, the KPIs with loadings ≥ +0.3 on each dimension are defined as critical, while the KPIs with loadings < +0.3 are defined as non-critical.

The correlation circles for the KPIs for each study year are presented in Figure 5-5.



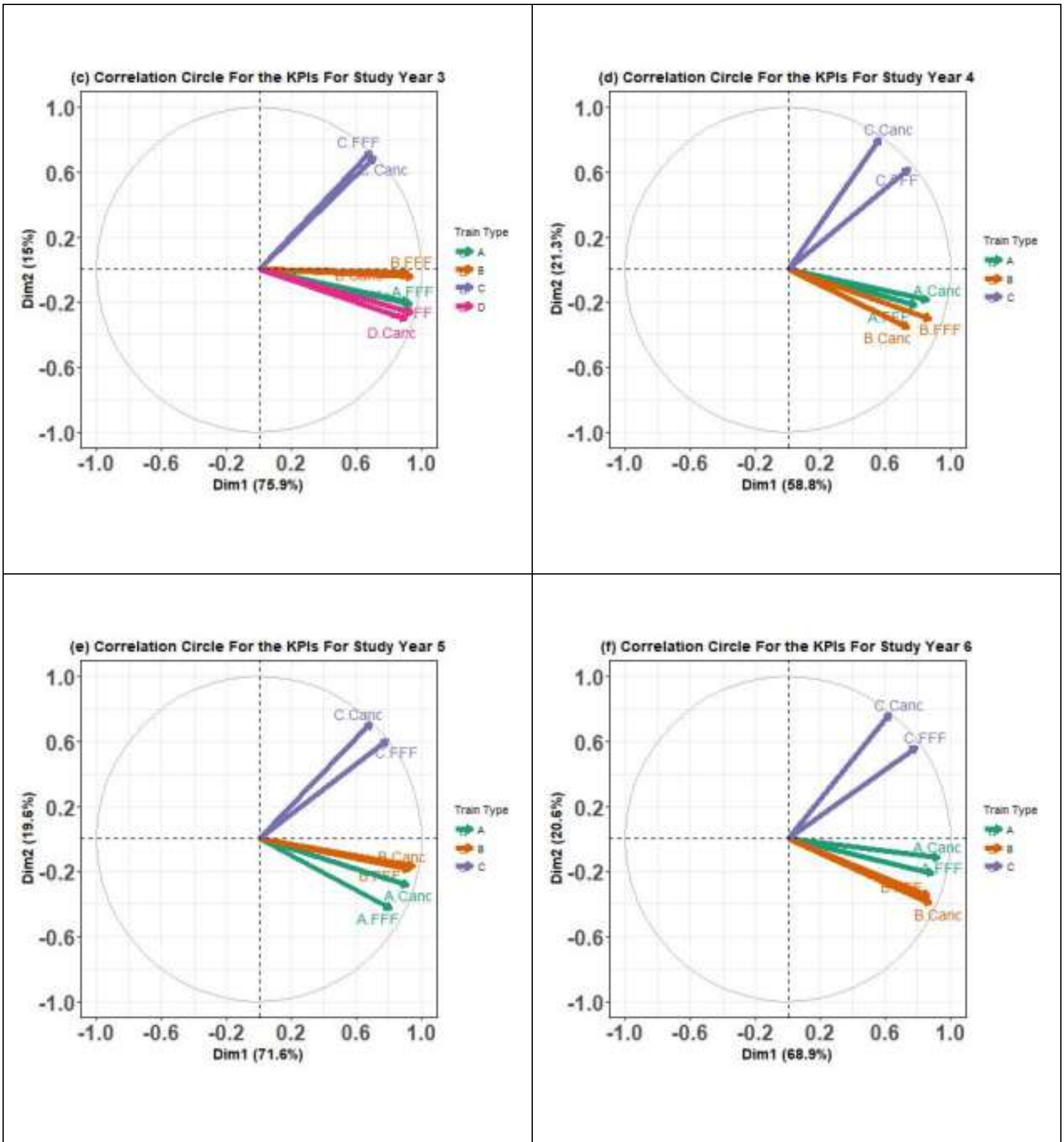


Figure 5-5: Correlation circle for the KPIs for six study years.

The KPIs are represented by vectors which originate from the origin of the plot. The smaller the angle between the vectors, the stronger the relationship between them. In addition, the relative length and direction of the vectors with respect to the origin indicate the relationship of the KPIs to each dimension. In this figure, colours represent the train types.

As can be seen in Figure 5-5, the vectors representing the FFF and the number of services cancelled for each train type are grouped together, and the angle between them is quite small.

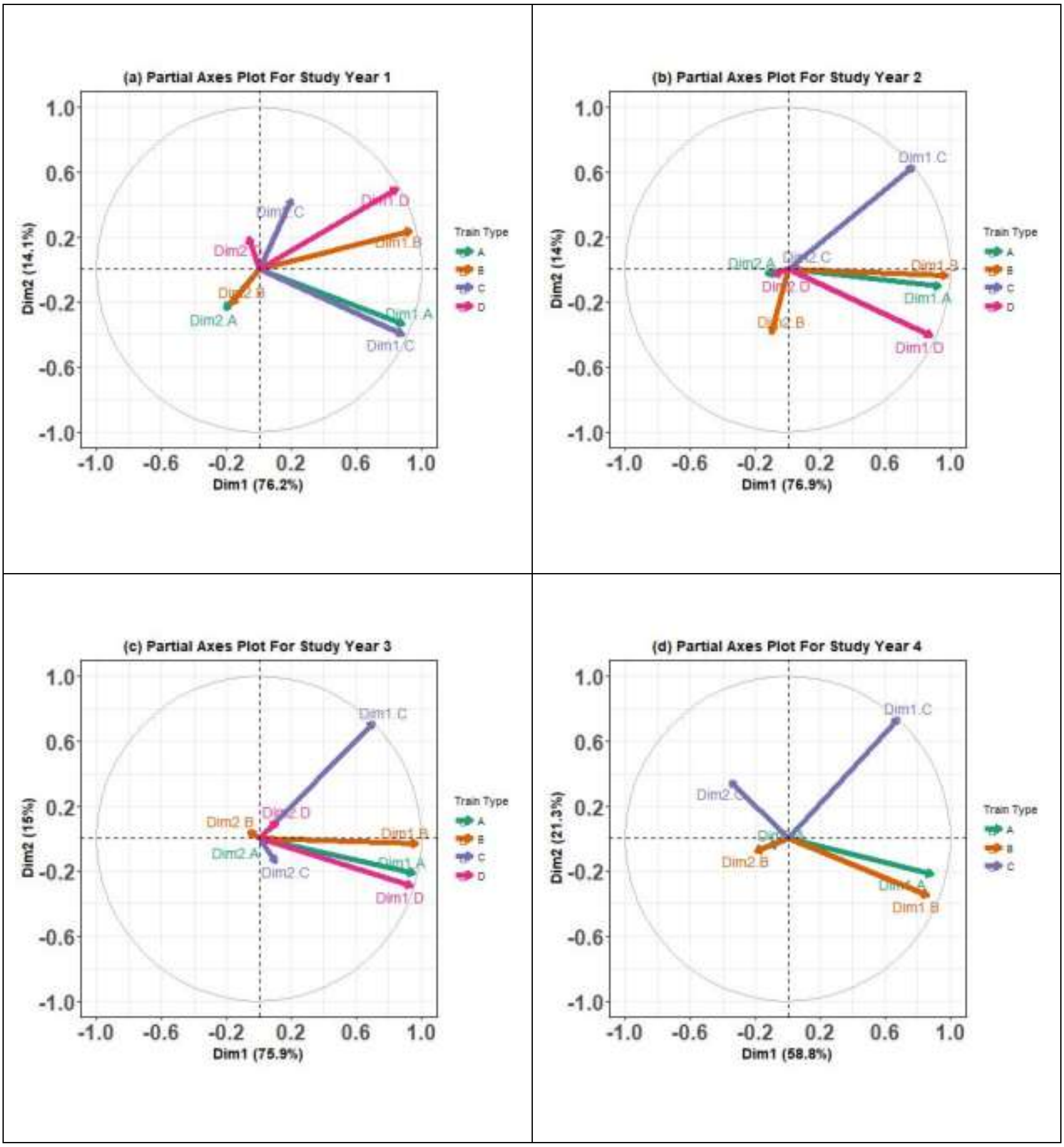
This means that the FFF and the number of services cancelled for each train type are positively related to each other for the six study years, thus establishing operational characteristic C8 – the relationship between the FFF and the number of services cancelled. In addition, in relation to dimension I for the six study years, Figure 5-5 shows that both KPIs (i.e. the FFF and the number of services cancelled) for all the train types are critical, while in relation to dimension II, the KPIs for train type C are critical except in year 1 in which the KPIs for train type D are critical. This means that the operational performance of all train types is positively related to dimension I, while the operational performance of only train type C is positively related to dimension II. Hence, these findings provide additional information reported in the earlier findings of Section 5.4.2 regarding the operational performance of different types of trains in relation to dimensions I and II.

In summary, MFA has enabled operational characteristic C8 - the relationship between the FFF and the number of services cancelled to be established, as well as the relationship between the KPIs and the two dimensions.

5.4.5 Relationship between the latent structure of PCA of each train type and MFA of the overall fleet

In order to analyse relationship between the latent structure of the datasets of each train type and the dataset for overall fleet of trains, MFA was used to generate the partial axes plot. In this plot the principal components obtained by the individual PCA of each train type are superimposed over the dimensions obtained by MFA of the overall fleet as discussed in Section 5.3.4, thus providing insight into the relationship between the PCs of each train type and the dimensions of MFA. Since the partial axes plot is analogous to the correlation circle, the same cut-off value at coordinate of 0.3 can be used to analyse whether the PCs of PCA for each train type are strongly related or weakly related to the dimensions of MFA. This means that the PCs of the train types with coordinates $\geq +0.3$ on a particular dimension are strongly related to that dimension of MFA, while those with coordinates $< +0.3$ are weakly related to that dimension.

The partial axes plot for the six study years are presented in Figure 5-6.



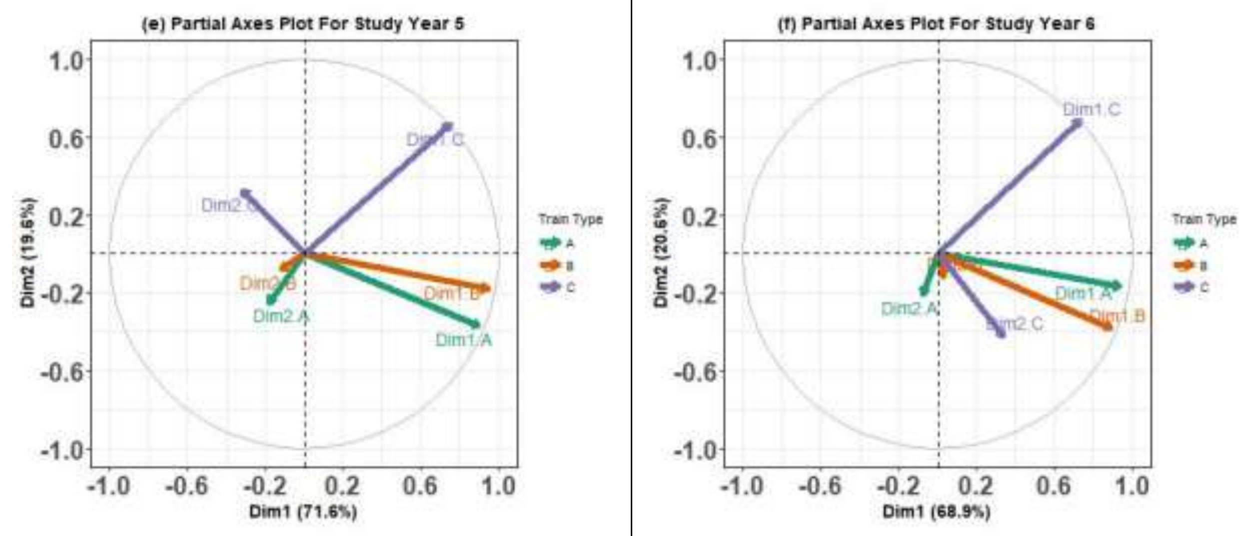


Figure 5-6: Partial axes plot for the six study years.

The relative length and direction of PCs for each train type with reference to the dimensions of MFA indicate the relationship between them. In this figure, colours represent the train types.

As can be seen in Figure 5-6, for the six study years, PC-I for all train types are strongly related to dimension I of MFA. However, in year 1, PC-I of train types B and D and PC-II of train type C are strongly related to dimension II of MFA; from years 2 to 6 only PC-I of train type C and in years 4 and 5 both PCs I and II of train type C are strongly related to dimension II of MFA. Hence, these results show that the variance explained by dimension I in X_1 (i.e. the global matrix of operational performance of urban trains) is related to the operational performance of all train types in the fleet, but the variance explained by dimension II in X_1 is only related to the operational performance of train type C except in Year 1. These findings agree well with the findings reported in Sections 5.4.2 and 5.4.4.

In summary, using MFA enables the relationship between the latent structure that exists within the dataset of each train type and in the dataset of overall fleet of trains to be realised.

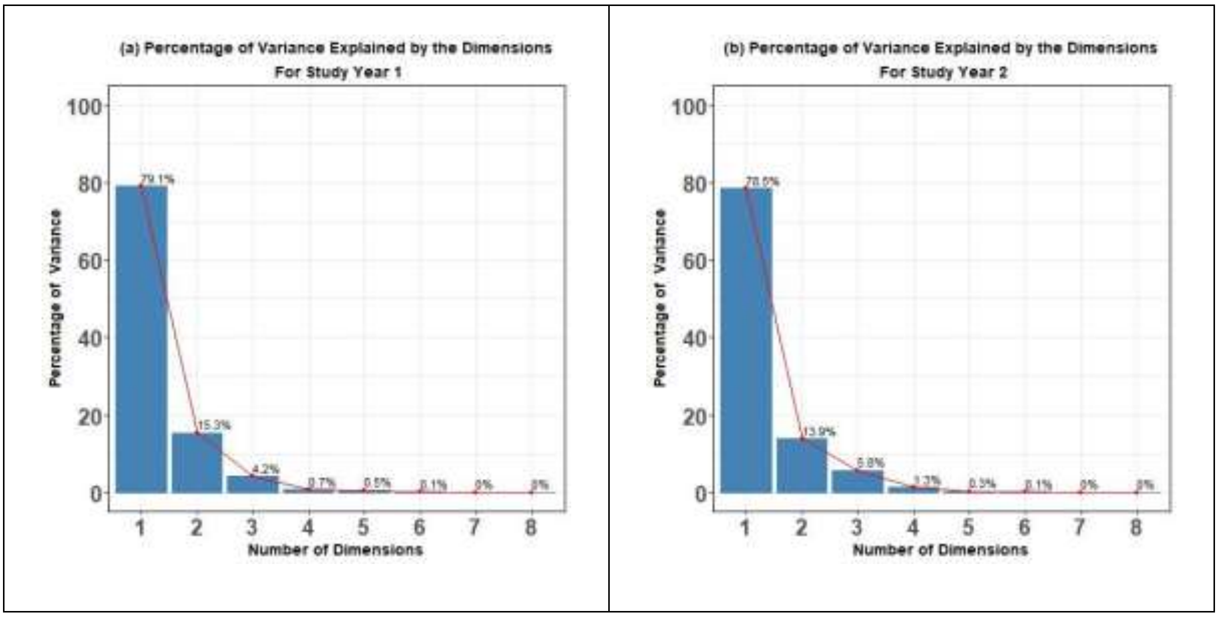
5.5 Set II: Analysis of operational performance characteristics based on the impact of FFF on the number of services delayed

This section discusses the results obtained for Set II by the application of MFA to the urban trains data for the six study years. The aim is to identify the critical sub-systems with respect to the impact of FFF of the sub-systems on the number of services delayed and to analyse the relationship between the FFF and the number of services delayed.

While the data in each dataset are different, both datasets I and II are similar in their structure and are analysed using MFA, with the results being mapped in similar plots. Thus, the criteria and the arguments for interpretation of the plots presented here are essentially the same as those given in the previous section.

5.5.1 Selection of the number of dimensions for further analysis

Similar to matrix X_1, matrix X_2 for Years 1, 2 and 3 generated a set of 8 dimensions and for Years 4, 5 and 6 a set of 6 dimensions. In order to select the number of dimensions to be retained for further analysis from a set of dimensions for each year, the scree plots for the six study years are presented in Figure 5-7. To determine the number of dimensions to be retained before or up to the elbow point, the scree test is combined with the cumulative percentage of variance explained by the dimensions as discussed in Section 5.4.1



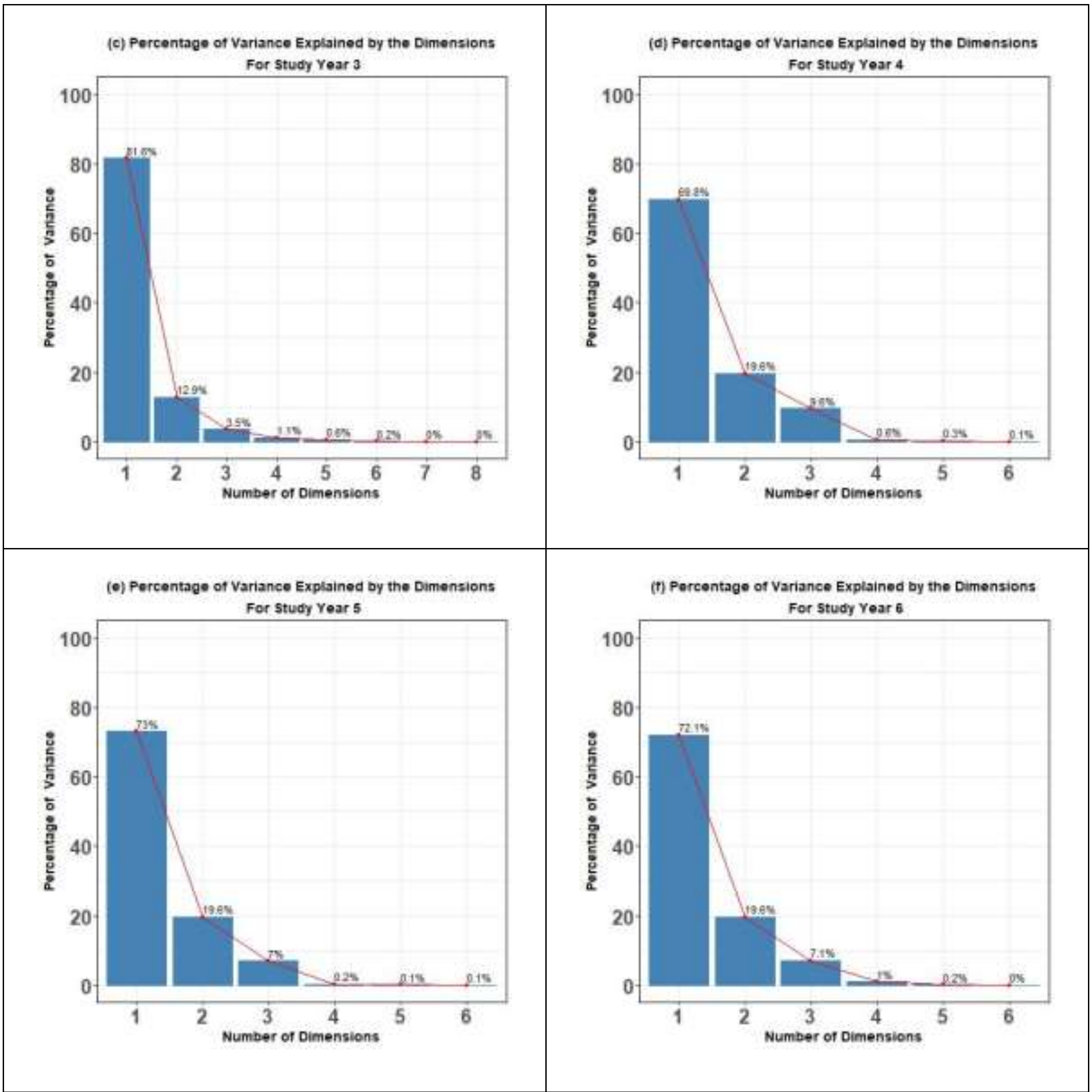


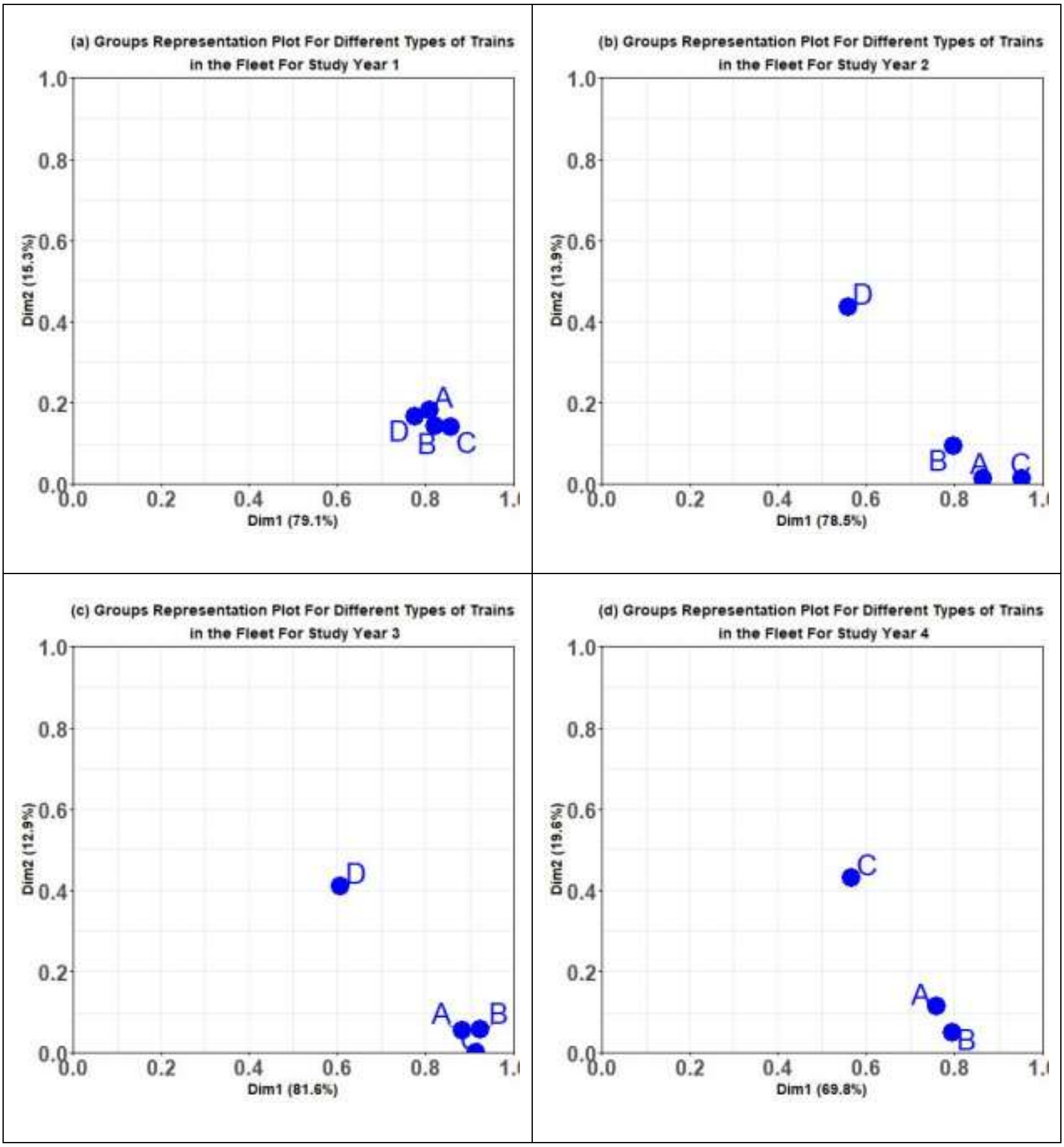
Figure 5-7: Scree plot for the six study years showing the percentage of variance explained by each dimension.

As can be seen in Figure 5-7, the elbow point appears at dimension II in the scree plot of each study year as in Figure 5-1. Hence, the argument for retaining dimensions presented here is essentially the same argument that was presented in Section 6.4.1. Since the elbow point appears at dimension II, only dimension 1 or both dimensions I and II can be retained for further analysis. Using the cumulative percentage of variance approach, Figure 5-7 shows that if we retain only dimension 1, the cumulative percentage of variance is 79.1%, 78.5%, 81.6%, 69.8%, 73.0% and 72.1% for study years 1,2,3,4,5 and 6, respectively. This shows that dimension I alone explains the cumulative percentage of variance in X_2 (i.e. the global matrix of operational performance of urban trains established on FFF and the number of services delayed) greater than the minimum threshold of 70% except in years 4 and 6. In addition, the percentage of variance explained by dimension II is 15.3%, 13.9%, 12.9%, 19.6%, 19.6% and 19.6% in study years 1,2,3,4,5 and 6, respectively. This means that if we retain both dimensions I and II, the cumulative percentage of variance is 94.4%, 92.4%, 94.5%,89.4%, 92.6% and 91.7% in years 1,2,3,4,5 and 6 respectively which far exceeds the minimum threshold for each study year. Even though dimension I alone is sufficient to serve the purpose, the mapping of the results in two-dimensional space is better for visualisation of the results. Hence, as with X_1 in Section 5.4.1, both dimensions I and II are retained for investigating the latent structure of X_2.

5.5.2 Characterisation of operational performance of different types of train in the fleet

To compare the operational performance of different types of train in the fleet, the groups representation plot for each study year was produced by mapping the partial inertias of train types in the coordinate system defined by dimensions I and II. The cut-off value at 0.3 coordinate, as was chosen in Section 5.4.2, is used here to categorise the train types as strongly related or weakly related to the dimensions. This means that the operational performance of the train types with coordinates $\geq +0.3$ are strongly related to the latent variable associated with the dimension, while the train types with coordinates $< +0.3$ are poorly related to this latent variable.

Figure 5-8 presents the groups representation plots for the different types of train in the fleet for the six study years.


(a) Groups Representation Plot For Different Types of Trains in the Fleet For Study Year 1
Dim1 (79.1%)
Dim2 (15.3%)
A
B
C
D
(b) Groups Representation Plot For Different Types of Trains in the Fleet For Study Year 2
Dim1 (78.5%)
Dim2 (13.9%)
A
B
C
D
(c) Groups Representation Plot For Different Types of Trains in the Fleet For Study Year 3
Dim1 (81.6%)
Dim2 (12.9%)
A
B
D
(d) Groups Representation Plot For Different Types of Trains in the Fleet For Study Year 4
Dim1 (69.8%)
Dim2 (19.6%)
A
B
C

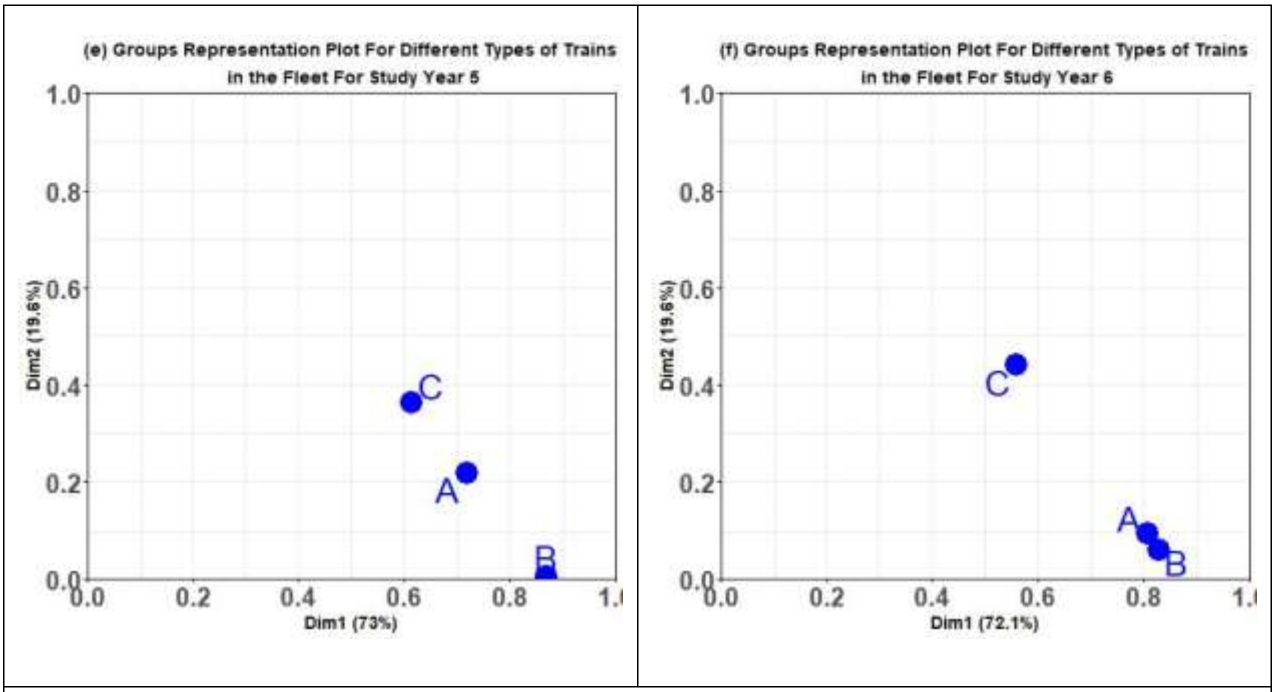


Figure 5-8: Groups representation plot for the six study years.

The distribution of types of train along the length of each dimension is a measure of proportion of their partial inertia in the inertia of the dimension. The greater the distance between the point (representing the train type) and the origin of the plot on any dimension, the greater is its proportion in the inertia of the dimension.

As can be seen in Figure 5-8, in relation to dimension I for the six study years, the performances of all train types involved in each year are strongly related to this dimension. In relation to dimension II, in Year 1, all train types are weakly related to this dimension; in years 2 and 3, only train type D is strongly related; in years 4, 5 and 6, only train type C is strongly related. Overall, this shows that the operational performance of train types A and B are strongly related to dimension I, while the operational performance of train type C is strongly related to dimension I for the first three years, and to both dimensions I and II for the last three years. In addition, the operational performance of train type D is strongly related to both dimensions I and II for all years except in Year 1 when it is weakly related to dimension II.

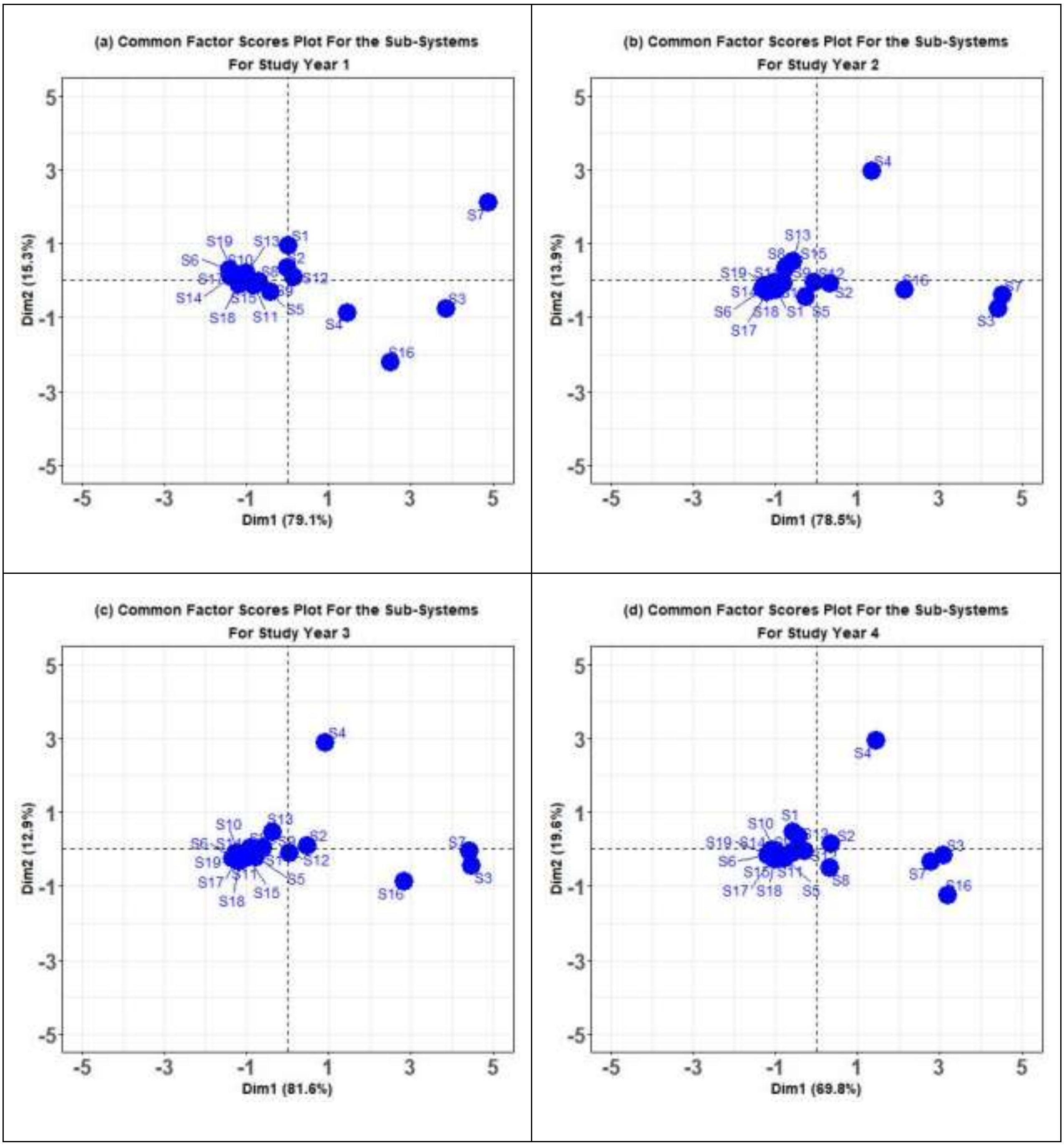
These findings also indicate that the latent structure associated with dimension I is common between and within the groups of train types A, B, C and D for the six study years, while the latent structure associated with dimension II only exists within the group of train type D for Years 2 and 3, and it only exists within the group of train type C for Years 4-6. In other words, the latent variable associated with dimension I is crucial for the operational performance of all train types, while the latent variable associated with dimension II is crucial only for the operational performance of train type D. However, after the removal of train type D from the fleet, dimension II represents the latent variable which is crucial only for the operational performance of train type C. Hence, it is concluded that MFA clearly reveals how the operational performances of different train types are related or not related to each other in terms of common latent variables that affect their operational performance.

In summary, using MFA enables to the operational performances of different train types to be compared considering the strength of their relationship with the dimensions, and it exposes the similarities in the latent structure which is common between and within the groups of train types.

5.5.3 Characterisation of operational performance of the sub-systems based on FFF-and-number of services delayed

In order to identify the critical sub-systems considering the effect of their FFF on the number of services delayed, the common factor scores of the sub-systems were mapped in the coordinate system defined by dimensions I and II. The cut-off value at +1 common scores as defined in Section 5.4.3 is used to categorise the sub-systems as critical and non-critical considering all train types in the fleet. This means that the sub-systems with the common scores ≥ +1 are the critical sub-systems, and the sub-systems with the common scores < +1 are the non-critical sub-systems.

The commons scores plots for the sub-systems for the six study years are presented in Figure 5-9.


(a) Common Factor Scores Plot For the Sub-Systems
For Study Year 1
Dim2 (15.3%)
Dim1 (79.1%)
(b) Common Factor Scores Plot For the Sub-Systems
For Study Year 2
Dim2 (13.9%)
Dim1 (78.5%)
(c) Common Factor Scores Plot For the Sub-Systems
For Study Year 3
Dim2 (12.9%)
Dim1 (81.6%)
(d) Common Factor Scores Plot For the Sub-Systems
For Study Year 4
Dim2 (19.6%)
Dim1 (69.8%)

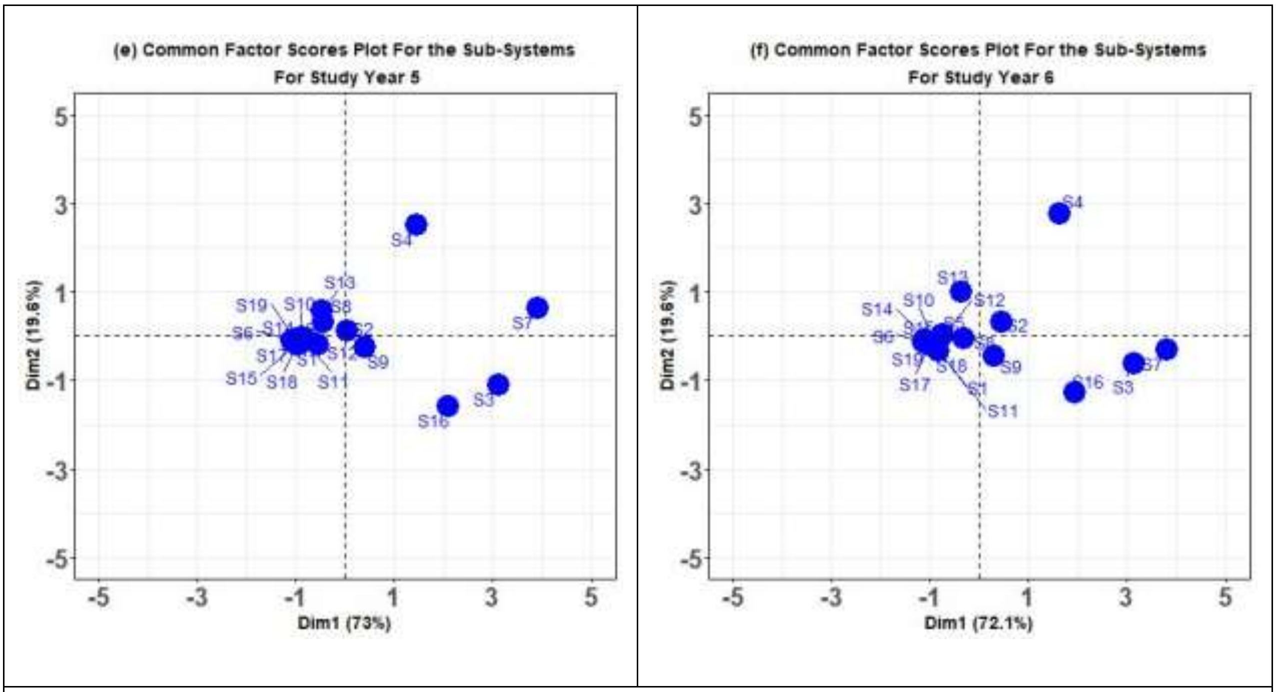


Figure 5-9: Common factor scores plot of the sub-systems for six study years based on FFF-and-number of services delayed.

In each plot, the x-axis shows the common scores of the sub-systems on dimension I, and the y-axis shows the common scores of the sub-systems on dimension II. The position of the sub-systems on each dimension indicates the criticality of their operational performance in relation to the dimension.

As can be seen in Figure 5-9, some sub-systems are distributed on the positive direction of the dimensions, while most of the sub-systems are distributed on the negative direction of the dimensions. When the rows of Z_{x2} are multiplied by the coefficients of the same dimensions, this results in distribution of the similar sub-systems in the same direction of the dimension and of the dissimilar sub-systems in the opposite direction of the dimension. This distribution of the sub-systems clearly differentiates the sub-systems that are operationally unreliable from those that are operationally reliable based on the combination of their FFF and the effect of their FFF on the number of services delayed as discussed in Section 5.4.3. However, to identify the critical sub-systems, the defined criterion was applied and the sub-systems that are critical in relation to dimension I and dimension II are presented in Table 5-2

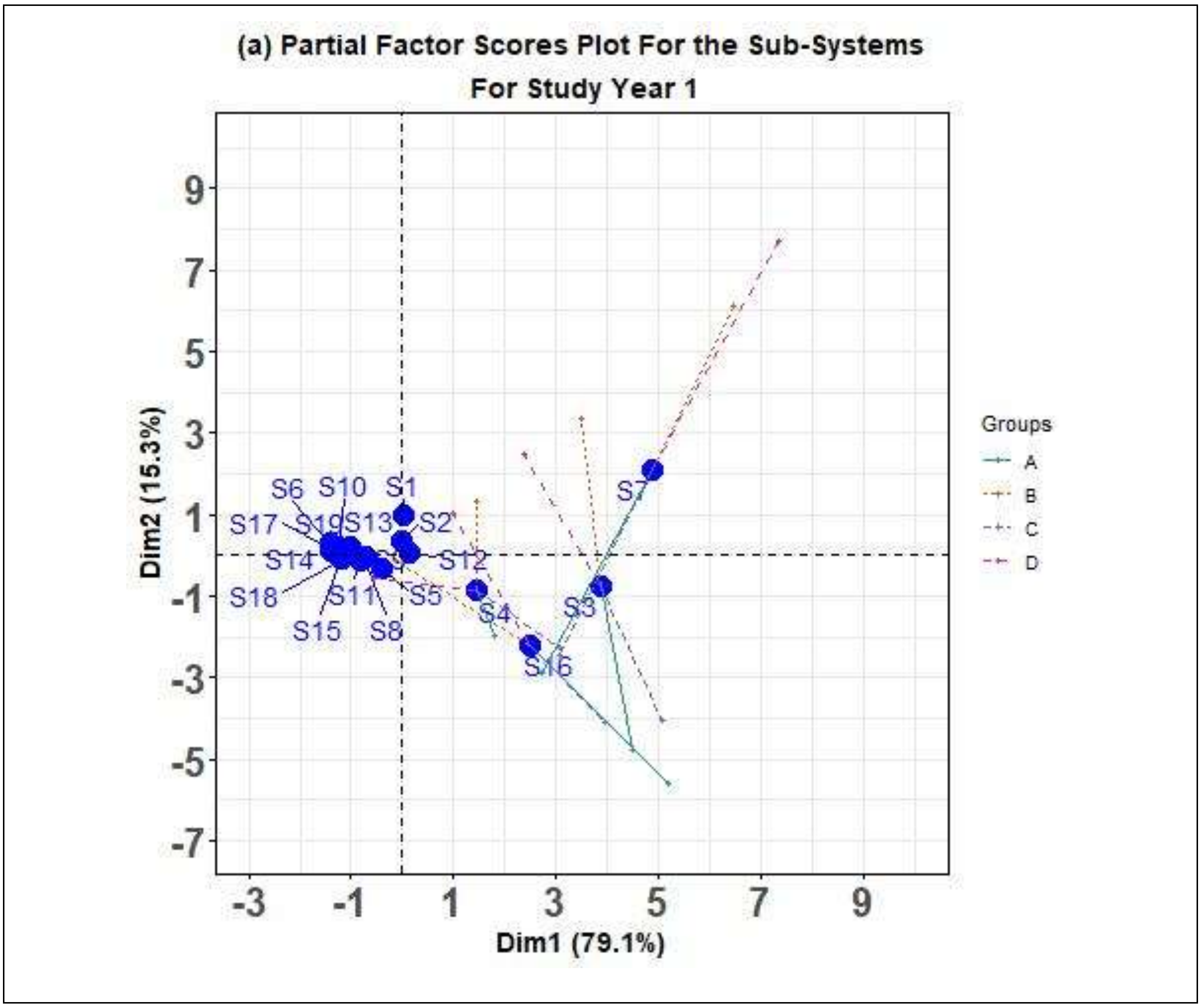
Table 5-2: Critical sub-systems based on the FFF-and-number of services delayed		
Study Year	**Critical sub-systems in relation to dimension I**	**Critical sub-systems in relation to dimension II**
Year 1	S3, S4, S7 and S16	S7
Year 2	S3, S4, S7 and S16	S4
Year 3	S3, S4, S7 and S16	S4
Year 4	S3, S4, S7 and S16	S4
Year 5	S3, S4, S7 and S16	S4
Year 6	S3, S4, S7 and S16	S4

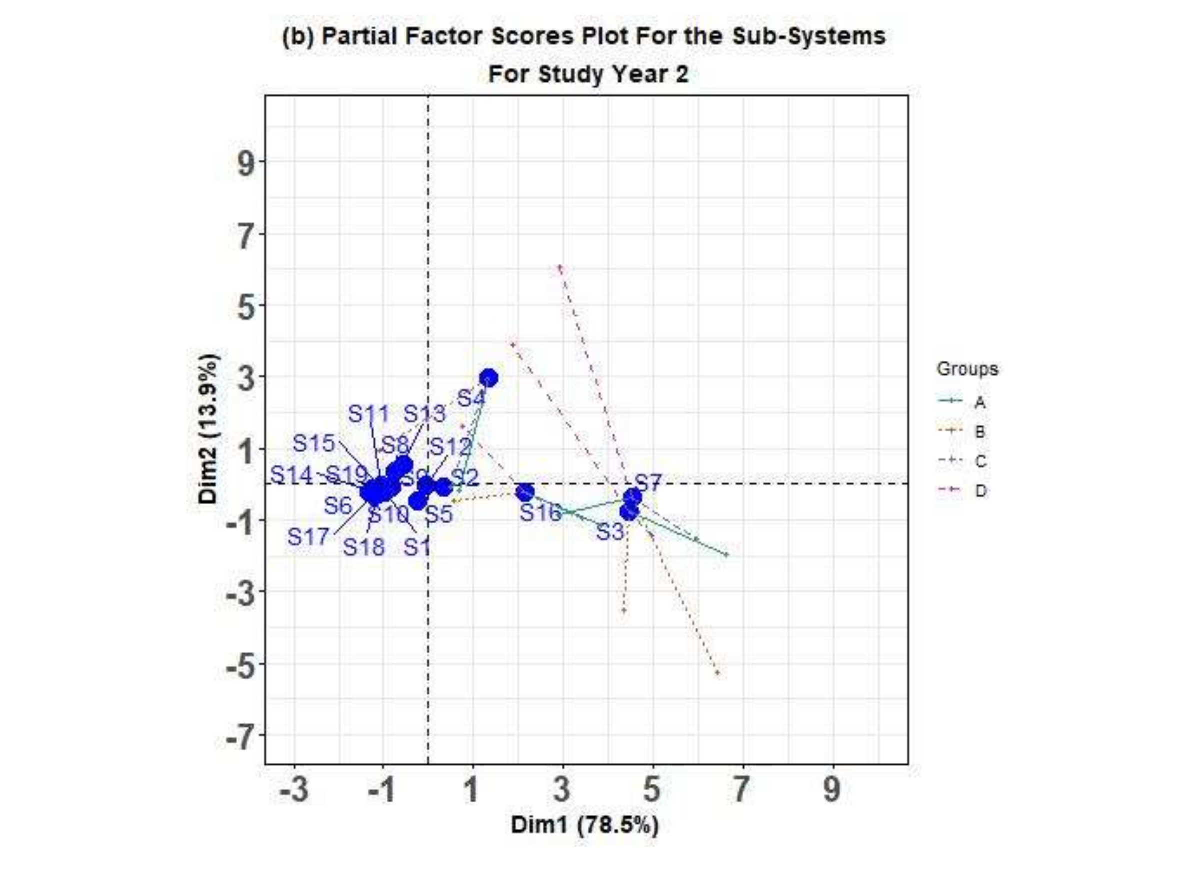
As can be seen in Table 5-2, for the six study years, only 4 out of 19 sub-systems are critical in relation to dimension I, while only 1 sub-system is critical in relation to dimension II. Hence, MFA successfully reduces the number of sub-systems to be dealt with. In addition, since MFA identifies the critical sub-systems related to the dimensions, to improve the operational performance of these critical sub-systems subject to FFF and number of services delayed, the improvement strategies need to be focussed on the characteristics of dimensions I and II. Thus, MFA provides a clear indication of the reason for the criticality of the sub-systems.

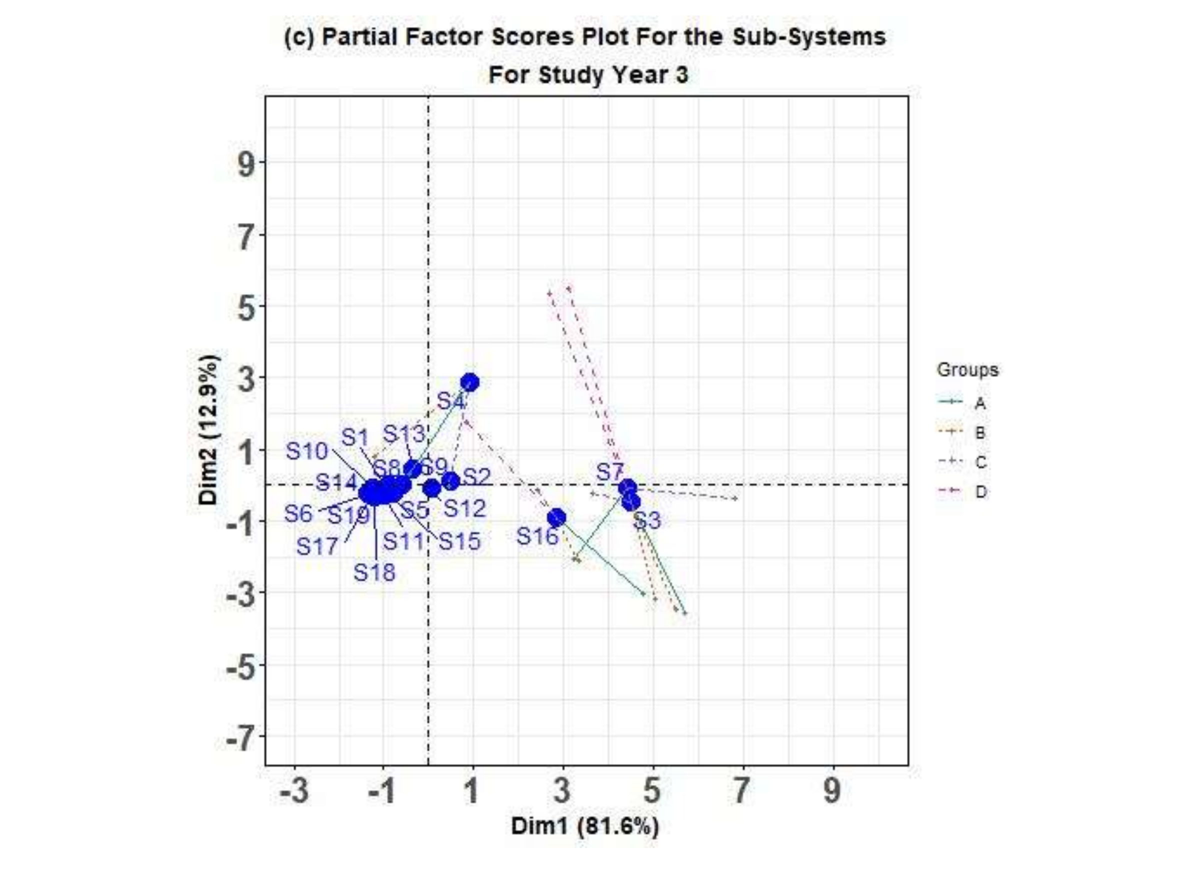
It is also evident from Figure 5-9, in relation to dimension I, S7 is the most critical sub-system followed by S3 and S16 for the six study years. By contrast, in relation to dimension II, S7 is the only critical sub-system in Year 1, and S4 is the only critical sub-system in Years 2-6. Since the same three sub-systems are identified as critical in relation to dimension I for all study years, this could be because of the association of the same latent variable. Similarly, the same sub-system is identified as critical in relation to dimension II for all study years except Year 1, this could be because of association of the association of one variable in Year 1, then another latent variable in Years 2 to 6.

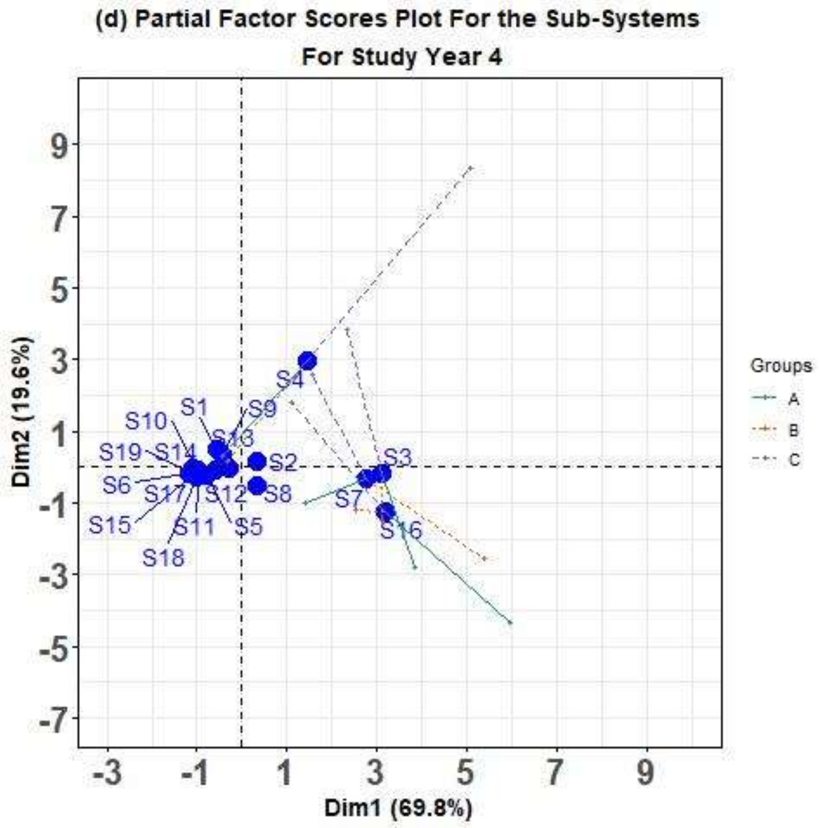
In addition, Table 5-2 shows that in relation to both dimensions, S7 is identified as critical in Year 1 and S4 is identified as critical in all other years. This can be explained by the variance partitioning effect as discussed in Section 5.4.3. These findings suggest that the operational performances of S7 in Year 1 and S4 in Years 2-6 tend to be influenced by the characteristics of both dimensions.

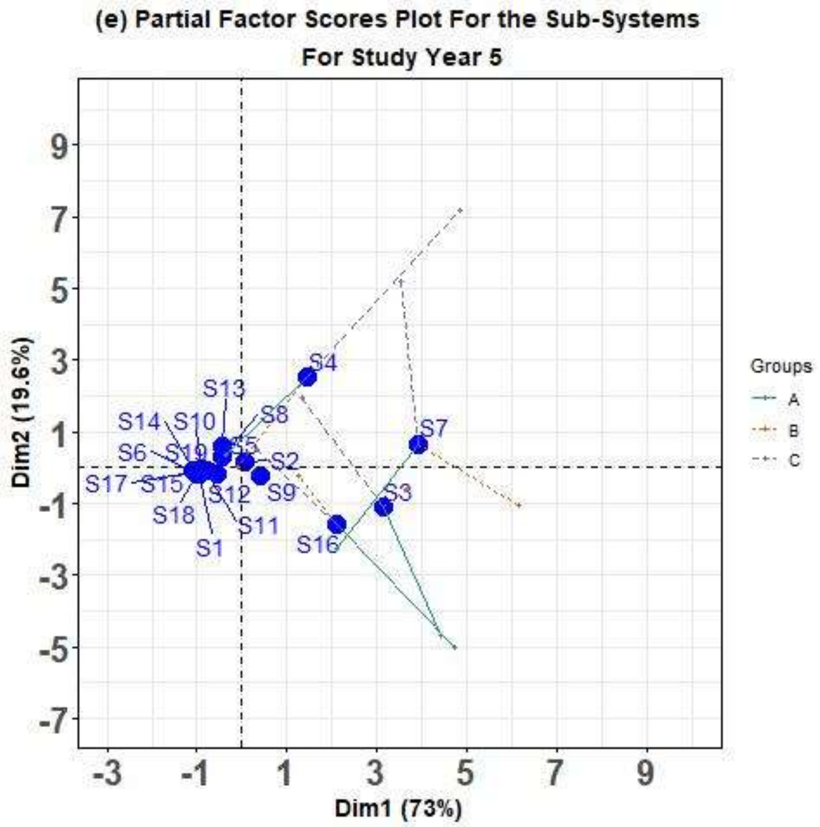
In summary, MFA allows the critical sub-systems to be identified based on FFF-and-number of services delayed for the overall train fleet. Thus, operational characteristic C7 - the critical sub-systems for services delayed is hereby achieved. In order to identify the critical sub-systems for each train type in the fleet, the partial scores of the sub-systems were superimposed onto the common scores plot which is presented in Figure 5-10. Since sub-systems S3, S4, S7 and S16 were the ones identified as critical in all study years, they are the only ones considered here to examine their operational performance with respect to each train type over these years.




(b) Partial Factor Scores Plot For the Sub-Systems
For Study Year 2
Dim2 (13.9%)
Dim1 (78.5%)
S4
S11
S13
S15
S8
S12
S14
S19
S2
S6
S10
S5
S16
S7
S3
S17
S18
S1
Groups
A
B
C
D


(c) Partial Factor Scores Plot For the Sub-Systems
For Study Year 3
Dim2 (12.9%)
Dim1 (81.6%)
S4
S10
S1
S13
S14
S8
S9
S2
S7
S6
S19
S5
S12
S3
S16
S17
S11
S15
S18
Groups
A
B
C
D


(d) Partial Factor Scores Plot For the Sub-Systems
For Study Year 4
Dim1 (69.8%)
Dim2 (19.6%)
Groups
A
B
C
S1
S2
S3
S4
S5
S6
S7
S8
S9
S10
S11
S12
S13
S14
S15
S16
S17
S18
S19


(e) Partial Factor Scores Plot For the Sub-Systems
For Study Year 5
Dim1 (73%)
Dim2 (19.6%)
Groups
A
B
C
S1
S2
S3
S4
S5
S6
S7
S8
S9
S10
S11
S12
S13
S14
S15
S16
S17
S18
S19

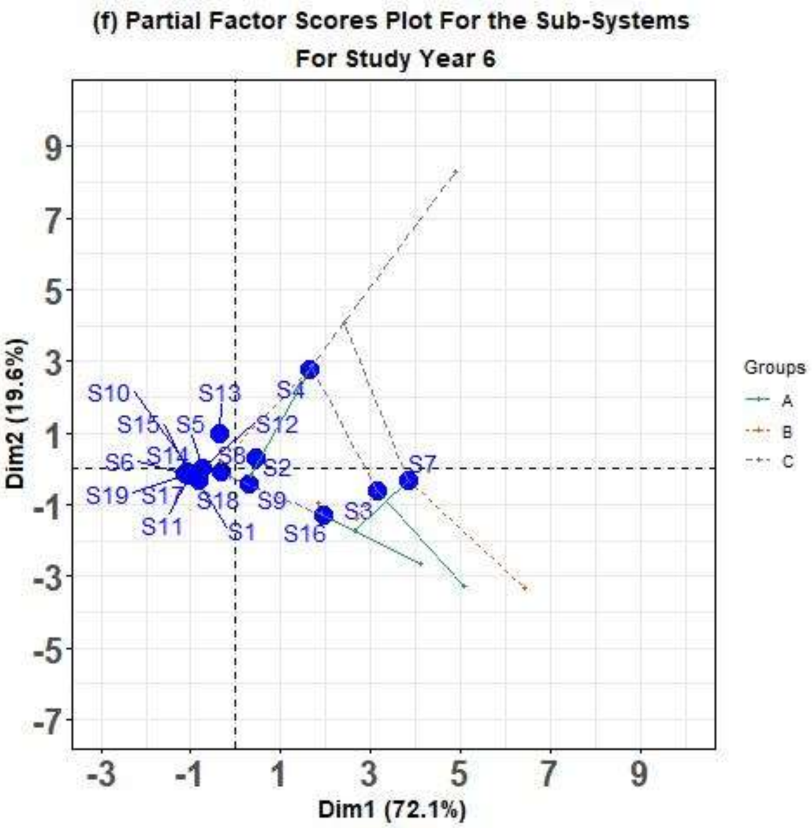


Figure 5-10: Partial factor scores plot of the sub-systems for the six study years based on FFF-and-number of services cancelled.

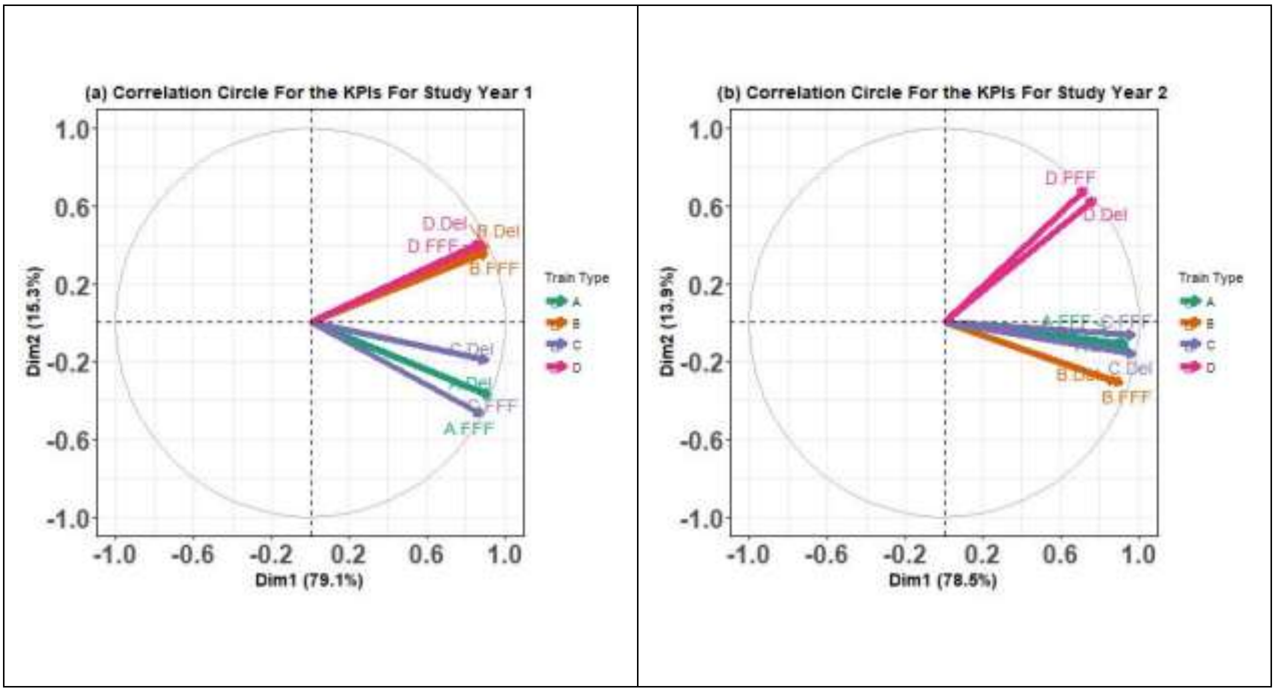
In each plot, the points representing the common scores of the critical sub-systems are in the centre, they are connected by the dotted lines to the points representing the partial scores for the critical sub-systems with respect to each train type. The relative distance and direction of the partial points of the sub-systems from the origin of the plot provide an indication of the contribution of each train type in the generation of the common scores of the sub-systems.

As can be seen in Figure 5-4, S3 is characterised by high values for train type C in Year 1 and by high values for train type A for Years 2-6, S3 is characterised by high values for train type A; S4 is characterised by high values for train type C; S7 is characterised by high values for train type D in Years 1 and 2 and high values for train type B for Years 3-6; S16 is characterised by high values for train type A in all study years. Overall, this shows that S3, S4, S7 and S16 are the most critical in relation to train type A, C, B and A respectively. This means that in order to deliver the biggest impact for the combined reduction in FFF and the number of services delayed in train type A, it is required to focus on S3 and S16; and in train type B and C, it is required to focus on S7 and S4 respectively.

In summary, the common scores plot enables operational characteristic C7 - the critical sub-systems for services delayed to be established for the overall train fleet, and superimposition of the partial scores for the sub-systems on this common scores plot further enables the critical sub-systems for each type of train in the fleet to be identified.

5.5.4 Relationship between the FFF of the sub-systems and the number of services delayed

In order to analyse the relationship between the FFF and the number of services delayed, the loadings of the KPIs on dimensions I and II were mapped in the correlation circle. The cut-off value at loadings of 0.3 as defined in Section 5.4.4 is used to categorise the KPIs as critical and non-critical in relation to the dimensions. This means that the KPIs with loadings ≥ +0.3 on each dimension are defined as critical, while the KPIs with loadings < +0.3 on the dimensions are defined non-critical. The correlation circles for the KPIs for the six study years are presented in Figure 5-11.



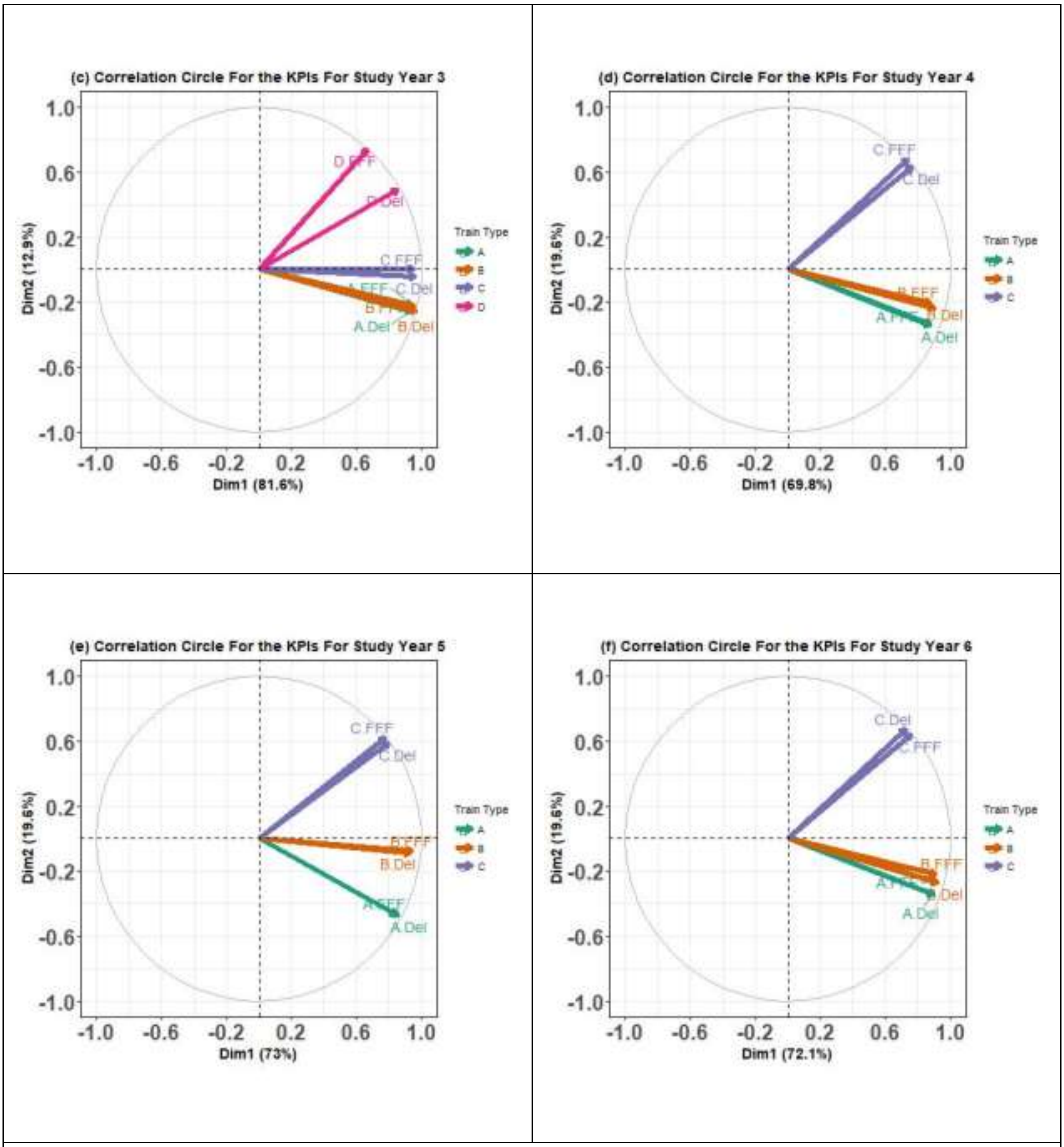


Figure 5-11: Correlation circle for the KPIs for the six study years.

The KPIs are represented by vectors which originate from the origin of the plot. The smaller the angle between the vectors, the stronger the relationship between them. In addition, the relative length and direction of the vectors with respect to the origin indicate the relationship of the KPIs to each dimension. In this figure, colours represent the train types.

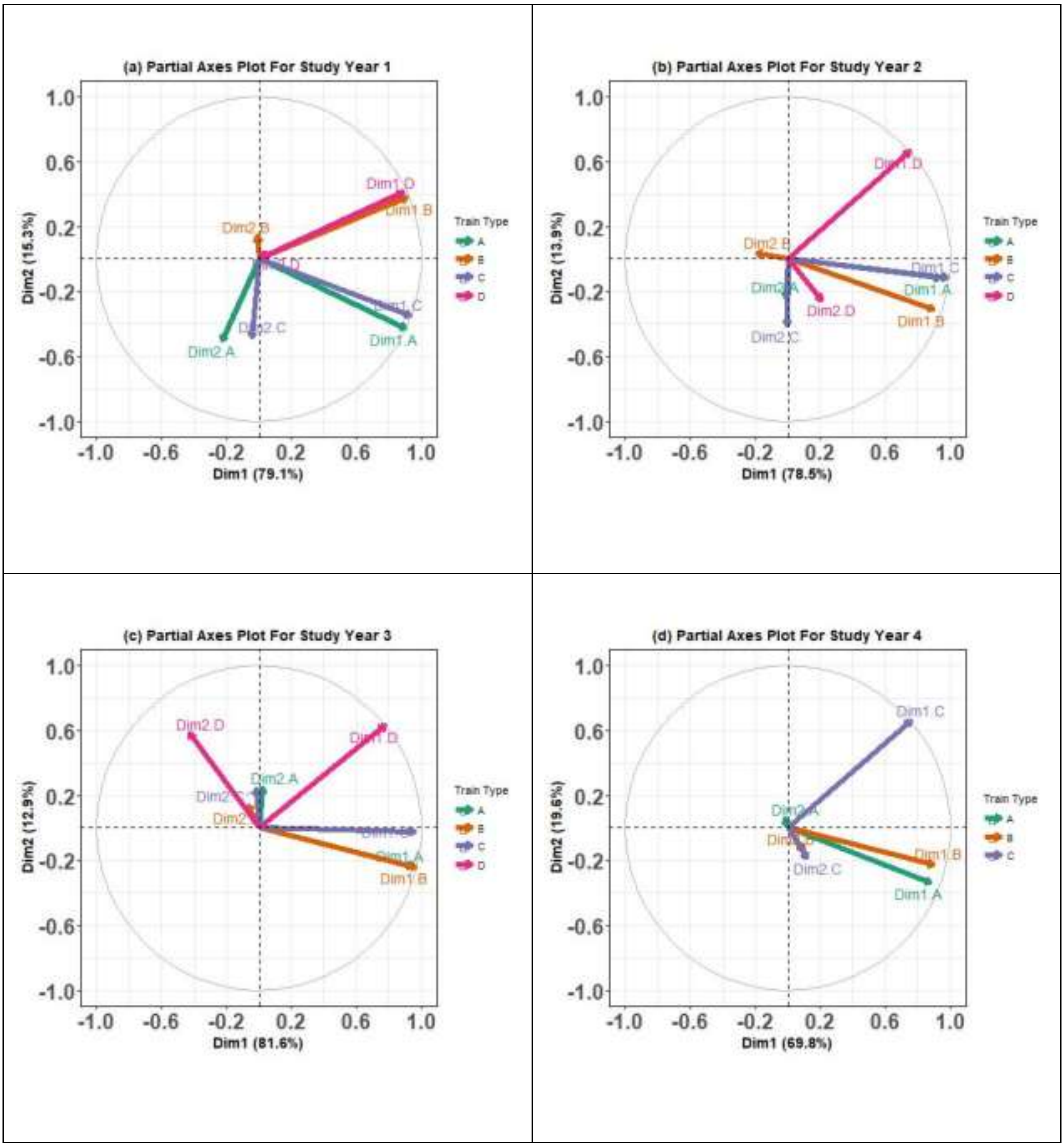
As can be seen in Figure 5-11, the vectors representing the FFF and the number of services delayed for each train type are grouped together, and the angle between them is quite small. This means that the FFF and the number of services delayed for each train type are positively related to each other for the six study years, thus establishing operational characteristic C9 – the relationship between the FFF and the number of services delayed. In addition, in relation to dimension I for the six study years, Figure 5-11 shows that both KPIs (i.e. FFF and the number of services delayed) for all train types are critical, while in relation to dimension II, the KPIs only for train type D are critical in years 2 and 3, and then the KPIs only for train type C are critical in years 4, 5 and 6. This means that the operational performance of all train types is positively related to dimension I, while in relation to dimension II the operational performances are positive only of train type D in Years 2 and 3 and only of train type C in Years 4-6. Hence, these findings provide additional information to the earlier findings reported in Section 5.5.2 regarding the operational performance of different types of trains in relation to dimensions I and II.

In summary, MFA has enabled operational characteristic C9 - relationship between the FFF and the number of services delayed to be established, as well as the relationship between the KPIs and the two dimensions.

5.5.5 Relationship between the latent structure of PCA of each train type and MFA of the overall fleet

In order to analyse relationship between the latent structure of the datasets of each train type and the dataset for overall fleet of trains, MFA was used to generate the partial axes plot. As discussed in Section 5.4.5, this plot superimposes the principal components obtained by PCA of each individual train type over the dimensions obtained by MFA of the overall fleet, thus providing insight into the relationship between the PCs of each train type and the dimensions of MFA. The cut-off value at coordinate of 0.3, as chosen in the previous section, is applied here to analyse whether the PCs of PCA for each train type are strongly related or weakly related to the dimensions of MFA. This means that the PCs of the train types with coordinates $\geq +0.3$ on a particular dimension are strongly related to that dimension of MFA, while those with coordinates $< +0.3$ are weakly related to that dimension.

The partial axes plot for the six study years are presented in Figure 5-12.



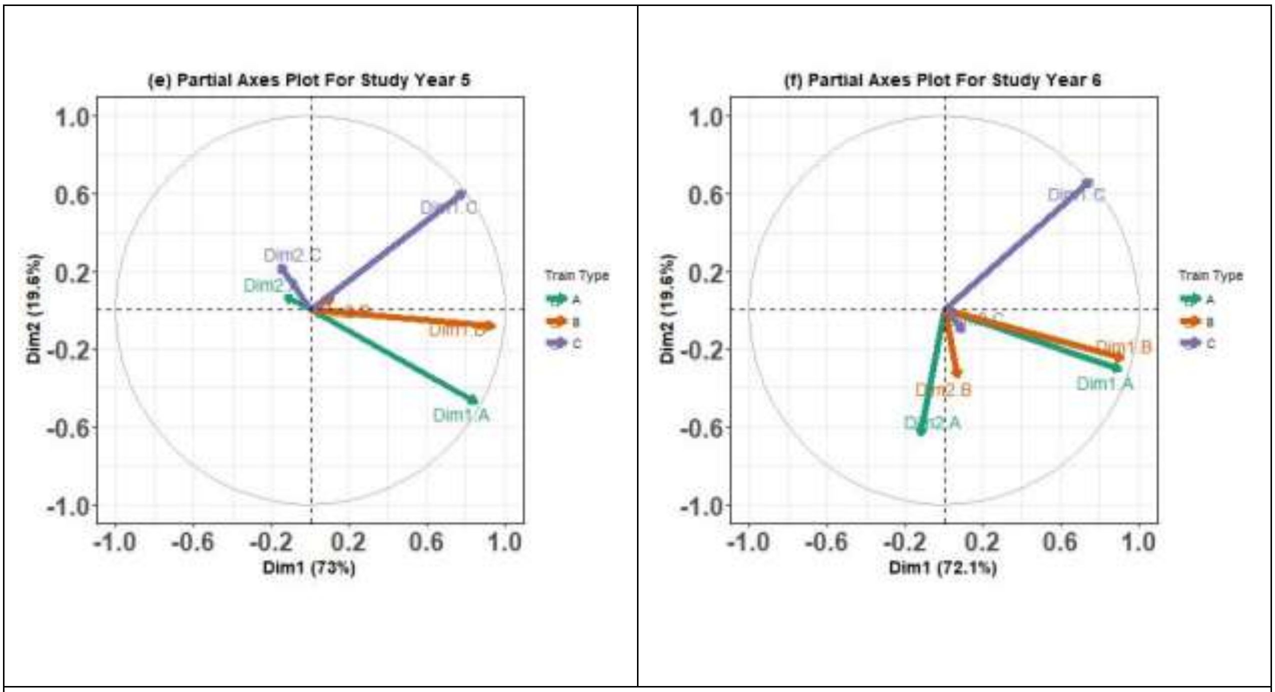


Figure 5-12:Partial axes plot for the six study years.

The relative length and direction of PCs for each train type with reference to the dimensions of MFA indicate the relationship between them. In this figure, colours represent the train types.

As can be seen in Figure 5-12, for the six study years, PC-I for all train types are strongly related to dimension I of MFA. However, in year 1, PC-I of train types B and D; in Year 2, only PC-I of train type D; in Year 3, both PC-I and PC-II of train type D; and in years 4-6 only PC-I of train type C are strongly related to dimension II of MFA. Hence, these results show that the variance explained by dimension I in X_2 (i.e. the global matrix of operational performance of urban trains) is related to the operational performance of all train types in the fleet, but the variance explained by dimension II in X_2 is related to the operational performance of train types B and D in Year 1, only train type D in Years 2-3, and then only train type C Years 4-6. These findings agree well with the findings reported in Sections 5.5.2 and 5.5.4.

In summary, using MFA enables the relationship between the latent structure that exists within the dataset of each train type and in the dataset of overall fleet of trains to be realised.

5.6 Comparison of the results obtained by single criterion using PCA and multiple criteria by using MFA

In order to establish whether the sub-systems identified as critical by using PCA based on the single conventional criterion are the same as the sub-systems identified as critical by using MFA based on multiple criteria, the critical subsystems identified are listed in Table 5-3 and are compared. The sub-systems identified as critical using PCA are taken from Table 4-4 and Table 4-5 in Chapter 4, and those identified as critical using MFA are taken from Table 5-1 and Table 5-2 in this chapter.

Table 5-3: Comparison of the critical sub-systems identified using PCA based on the single conventional criterion and using MFA based on the multiple criteria

Study year	Critical sub-systems identified using single criterion, FFF	Critical sub-systems identified using the FFF-and-number of services cancelled	Critical sub-systems identified using the FFF-and-number of services delayed
Year 1	S3, S4, S7 and S16	S3, S4, S7 and S16	S3, S4, S7 and S16
Year 2	S3, S4, S7, S12 and S16	S3, S4, S7 and S16	S3, S4, S7 and S16
Year 3	S3, S7, S12 and S16	S3, S4, S7 and S16	S3, S4, S7 and S16
Year 4	S3, S4, S8 and S12	S1, S3, S4, S7, S8 and S16	S3, S4, S7 and S16
Year 5	S3, S8 and S16	S3, S4, S7 and S16	S3, S4, S7 and S16
Year 6	S3, S4, S7, S9 and S16	S3, S4, S7 and S16	S3, S4, S7 and S16

As can be seen in the Table 5-3, the characterisation of the sub-systems using MFA based on FFF-and-number of services cancelled and on FFF-and-number of services delayed results in the identification of the same critical sub-systems except in Year 4. In year 4, the variation in the subsystems identified as critical for both datasets is likely to be associated with the latent variable which is more critical for service cancellations than services delayed. In all other years, the same subsystems are identified as critical and this is likely to be because of the association of the same latent variables to the dimensions of both datasets.

More importantly, as can be seen in the table, there are differences between the sub-systems identified as critical using PCA based on the single conventional criterion and those identified using MFA based on multiple criteria in all years except in Year1. This shows that characterising the sub-systems based on only FFF results in the identification of the sub-systems that are functionally critical, but not necessarily those that are also service critical. Hence, characterising the sub-systems based on multiple criteria successfully identifies the sub-systems that are critical concerning to both functional reliability and service reliability and brings the concerns of all main stakeholders into the analysis, thus providing more accurate identification of the critical sub-systems for maintenance planning.

5.7 Recommended analytical framework for the reliability analysis of urban trains

As discussed in the literature review in Chapter 2 and in the investigation of the conventional approach of reliability analysis for operational characterisation of the sub-systems reported in Chapter 4, FFF is a widely accepted criterion for identification of operationally critical sub-systems. However, from the previous section it is clear that the sub-systems identified as critical based on a single criterion are not necessarily the same as those identified based on multiple criteria. This means that critical sub-systems identified based only on the FFF in Step 1 of reliability analysis are only considered for functional failure analysis in Step 2 as discussed in Section 2.2.5 in Chapter 2. Since maintenance planning is a closed loop process as shown in Figure 2-1 in Chapter 2, there is an implication for this discrepancy on the effectiveness of the whole process of maintenance planning. Due to this reason, the strategical targets of service reliability cannot be ensured through maintenance planning. Hence, a multiple criteria-oriented framework for reliability analysis is needed to meet the diverse concerns of the multiple stakeholders associated with the operational performance of urban trains.

To achieve such a framework, a number of modifications to the conventional framework are recommended, and the steps in this proposed framework are shown in the flowchart shown in Figure 5-13.

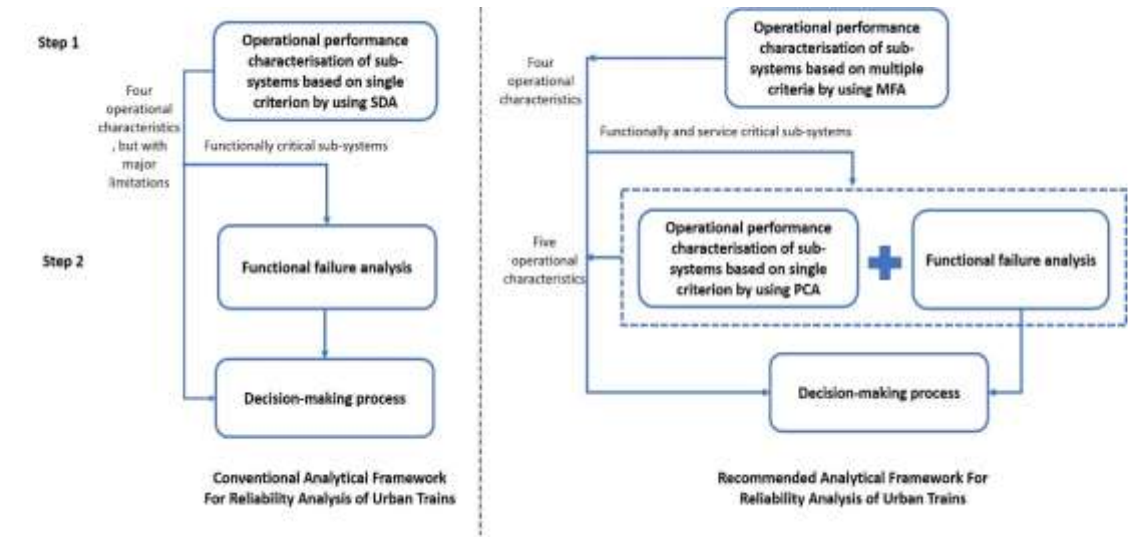


Figure 5-13: Recommended framework for reliability analysis in comparison to conventional framework.

As shown in Figure 5-13, the first step in the conventional analytical framework involves operational characterisation of the sub-systems based on single criterion (i.e. FFF) by using SDA. It establishes four operational characteristics, but with major limitations as reported in Section 3.4 of Chapter 3. The critical sub-systems that are identified in the first step are only functionally critical, and they are used as inputs in the second step for functional failure analysis. Information from both steps is used in the decision-making process. It is clearly evident from the flow of information that the selection of the single criterion and the technique in the first step governs the whole process.

An improved approach is presented in Figure 5-13. As can be seen, in the first step multiple criteria are applied by using MFA, and four operational characteristics are established. To consider the KPIs in their cause-and-effect structure, MFA is performed on the two data sets (i.e. one data set for the FFF-and-the number of services cancelled, and another data set for the FFF-and-the number of services delayed) as reported in this chapter. This step ensures that the critical sub-systems are identified considering the combined effect of the KPIs for functional reliability and service reliability. In addition, this step provides insight into the common latent structure between the two data sets. Hence, the findings from step 1 will enable improvements in the interdepartmental communication and strategies that will result in the achievement of both the strategical targets of functional reliability and service reliability subject to the maintenance plan.

The second step is to characterise the sub-systems identified as critical in the first step based on the single conventional criterion (i.e. FFF) by using PCA in parallel to the standard functional failure analysis of those sub-systems. In this step the detailed operational characteristics of these critical sub-systems are analysed with respect to the monthly FFF profile and the system FFF profile as carried out in the work presented in Chapter 5, and five operational characteristics are established that provide insight into the latent structure within the FFF data. Hence, findings from this step will enable improvements in the intradepartmental communication and strategies leading to a better maintenance plan. Finally, the findings from both steps are used in the decision-making process.

In summary, this section presents an improved approach for the reliability analysis of the urban train system.

5.8 Summary

This chapter has presented the development of an improved multiple criteria approach for the operational performance characterisation of the fleet of urban trains. This approach applies the KPIs for functional reliability and service reliability in their cause-and-effect structure by using MFA. Using MFA, the four operational performance characteristics have been successfully established that could not be obtained using PCA. The comparison of the results obtained based on multiple criteria by using MFA with the results obtained based on the single criterion by using PCA has clearly shown that the critical sub-systems must be identified based on multiple criteria for improved maintenance planning. Hence, an improved framework has been proposed for the reliability analysis of the fleet of urban trains.

Since the findings of the reliability analysis are used as inputs of the maintenance planning, the next chapter presents the development of a multiple criteria model for prioritisation of the maintenance strategies based on an overall improvement in reliability of the sub-systems.

Chapter 6: DEVELOPMENT OF A MODEL FOR RELIABILITY PERFORMANCE-BASED PRIORITISATION OF THE MAINTENANCE STRATEGIES

6.1 Introduction

The previous two chapters reported the development of an improved reliability analysis approach in the RCM process for operational performance characterisation of the sub-systems of the urban train fleet. The improved approach is based on the KPIs for both functional reliability and service reliability and the effect of the latent variables on the reliability. However, it was established in the literature review that the current maintenance models do not incorporate the KPIs for both functional reliability and service reliability and the influence of the latent variables to prioritise different maintenance strategies in the maintenance planning. Thus, a new model needs to be developed that incorporates all measures for reliability for prioritisation of the maintenance strategies based on their effectiveness at delivering improvement in the overall reliability of the sub-system. This is the final research objective of this research.

To achieve this research objective, this chapter proposes a reliability performance-based model named Overall Sub-System Reliability Index (OSRI) to prioritise the maintenance strategies. The model enables the overall reliability of the sub-system to be computed in a composite index. The index is based on a calculation of the impact of change in the FFF of the sub-system on the change in the number of services cancelled and of services delayed due to the proposed maintenance strategy. In the development of the model, the same approach as was used in developing a multiple criteria approach for operational performance characterisation of the sub-systems is used as reported in Chapter 5. In other words, the KPIs for functional reliability and service reliability in their cause-and-effect structure are integrated into the proposed model and the influence of the latent variables on the operational performance of the sub-system assessed using MFA is taken into consideration.

This chapter first proposes the model, and then demonstrates how it can be used. In the model demonstration, the data used and the assumptions made are first discussed. Two hypothetical maintenance scenarios are then developed, and the results obtained using the model for each scenario are discussed in detail. Next, the model is validated by using a mixed approach based on the available evidence from the literature and expert opinion of maintenance managers from UTS Melbourne. Finally, the usefulness of the model in maintenance planning is outlined.

6.2 Development of an overall sub-system reliability index model

The concept of this model is based on a model named the Weighted Average System Reliability Index (known as WASRI) developed by Li and Brown (2004) for prioritisation of the maintenance strategies for a distribution system in the power and electricity industry. The WASRI was discussed in Section 2.3.2 of Chapter 2 with models used in other industries. Since Li and Brown's model is based on the impact of a system's failure on each factor individually and incorporates the weights to consider the relative extent of impact of the system's failure on each factor, a similar model is developed in this work.

The proposed reliability index model is established using the basic equation of risk assessment, where the risk assessment measures the loss of reliability due to the occurrence of functional failures in the train system. This equation states that the risk equals the probability of failure multiplied by the consequences (Farmer et al., 1990, Todinov, 2006, Webster, 2011). The probability of failure for the sub-system can be determined by the failure rate of its functional reliability, denoted by λ, which is equivalent to the reciprocal of MDBF (Lai et al., 2017, Qin and Jia, 2019) and the consequences are the sum of the number of services cancelled, C, out of the total number of services scheduled for operation, N, and the number of services delayed, D, out of the total number of services, N. Thus, the overall reliability of i^{th} sub-system, denoted by OSR_i, can be expressed as:

$$OSR_i = \left(\lambda \text{ x } \frac{C}{N}\right)_i + \left(\lambda \text{ x } \frac{D}{N}\right)_i \qquad \textbf{6-1}$$

Equation 6-1 shows that the impact of λ on C and D is measured individually in the computation of OSR_i. We know from Section 2.3.3 of Chapter 2 that the MDBF is a ratio of the total sub-system distance, d, to the functional failure frequency of the sub-system, that is FFF. Thus, λ in Equation 6-1 can be replaced by these terms in order to expand the equation in terms of KPIs for functional reliability and service reliability as shown in the following equation:

$$OSR_i = \left(\frac{FFF}{d} \text{x} \frac{C}{N}\right)_i + \left(\frac{FFF}{d} \text{ x} \frac{D}{N}\right)_i \qquad \textbf{6-2}$$

It is clear from Equation 6-2 that the KPIs both for functional reliability and service reliability are integrated in their cause-and-effect structure in the computation of $OSRI_i$. However, it is also important to consider in the computation of $OSRI_i$ how FFF causes C and D. Since the distributions of occurrence of services cancelled and services delayed due to the occurrence of functional failures in i^{th} sub-system are unknown, a simple assumption is made that both C and D vary linearly to the failure rate of the i^{th} sub-system. Given this, the first term of Equation 6-4, $\frac{FFF}{d} X \frac{C}{N}$, determines the average number of services cancelled and the second term, $\frac{FFF}{d} X \frac{D}{N}$, determines the average number of services delayed due to the occurrence of functional failures in the i^{th} sub-system over a given sub-system distance. Hence, these terms can be named as the i^{th} sub-system average cancellation index (denoted as $SACI_i$) and the i^{th} sub-system average delays index (denoted as $SADI_i$) respectively. Thus, Equation 6-4 can be simplified as follows:

$$OSRI_i = SACI_i + SADI_i \qquad \textbf{6-3}$$

Equation 6-3 shows that $OSRI_i$ is the sum of two service interruption indexes, so $OSRI_i$ is a measure of the operational performance risk of the i^{th} sub-system. This means that the smaller the OSRI of the sub-system, the better its operational performance. However, the contribution of each index in the computation of $OSRI_i$ is governed by the extent to which the latent variables influence the operational performance characteristics of the i^{th} sub-system, i.e. the number of services cancelled and the number of services delayed due to the functional failures in the i^{th} sub-system. According to the weighted risk assessment, the variation in the importance of each risk factor or index can be incorporated by assigning weights to them (Holt et al., 2005). Hence, in order to capture the operational performance characteristics of the sub-system in the computation of $OSRI_i$, weights w_1 and w_2 need to be assigned to the indexes SACI and SADI respectively. These weights can be obtained by using MFA to analyse the datasets of FFF-and-number of services cancelled, and FFF-and-number of services delayed as reported in the previous chapter. So, Equation 6-3 can now be expressed as:

$$OSRI_i = w_1 X\, SACI_i + w_2\ X\, SADI_i \qquad \textbf{6-4}$$

Equation 6-4 can be used to compute the change in the OSRI of the i^{th} sub-system before maintenance and after maintenance using the proposed maintenance strategy to evaluate the effectiveness of the strategy in improving the $OSRI_i$. In conventional maintenance planning, it is assumed that the proposed maintenance strategy will result in X number of savings in F which results in a reduction in λ after maintenance (Corman et al., 2017). Given that service reliability varies linearly with the change in functional reliability, the values for C and D will be reduced corresponding to the savings in F. This implies that the service interruption indexes (i.e. SACI and SADI) for the i^{th} sub-system will change after maintenance. Hence, the difference between the indexes before and after maintenance is a measure of change in the overall reliability of the sub-system, denoted as $\Delta OSRI_i$, due to the proposed maintenance strategy.

However, in the computation of $\Delta OSRI_i$ it is also assumed that the values for w_1 and for w_2 before and after maintenance do not change because there is no change in the operational environment. Thus, $\Delta\ OSRI_i$, can be given by Equation 6-5.

$$\Delta OSRI_i = w_1 \text{ x } \Delta SACI_i + w_2 \text{ x } \Delta SADI_i \qquad \textbf{6-5}$$

Since OSRI is established on the KPIs that measure the losses in functional reliability and service reliability of the sub-system, the maintenance strategy prioritisation approach is to minimise the OSRI subject to the base OSRI, i.e. a reference value for measuring the improvement which is the value before maintenance of the i^{th} sub-system. Hence, the effectiveness, E, of the maintenance strategy in improving the overall reliability of the i^{th} sub-system is given by:

$$E = \left(\frac{\Delta OSRI_i}{OSRI_{ibase}}\right) \text{X } 100 \qquad \textbf{6-6}$$

Equation 6-6 clearly shows that the larger the reduction in $OSRI_i$, the greater the effectiveness of the proposed maintenance strategy in improving the overall reliability of the i^{th} sub-system.

In summary, a simple model has been developed that can be used for prioritisation of the maintenance strategies for the sub-system based on their effectiveness in improving the overall reliability of the sub-system.

6.3 Demonstration of the model

This section first presents the data and the two simple hypothetical maintenance scenarios used for the demonstration of the model. The model results are then presented and discussed to evaluate whether the OSSRI model can successfully prioritise the maintenance strategies for the sub-systems.

6.3.1 Data and software used for the model demonstration

To demonstrate the functionality of the model in the hypothetical maintenance scenarios, the critical sub-systems S3, S7 and S16 for train type A were selected. The data that was used to determine the values for the parameters of the model are UTS Melbourne data from study Year 6 together with assumed data, and these data are described in detail in this section.

1 **Number of functional failures:** Data from Year 6 on the FFF for the selected sub-systems was used to obtain the number of functional failures before maintenance. To determine the value for FFF after maintenance, the FF savings assumed in the scenario from 1 to 10 were subtracted from the FFF value before maintenance.

2 **Weights (w_1 and w_2):** The approach used here is the same as the approach used in Chapter 6 to determine w_1 and w_2. In the previous chapter, MFA was performed on the data for each year for each train type on FFF-and-number of services cancelled, and on FFF-and-number of services delayed. To obtain w1 and w2, MFA was performed for each month of Year 6 on FFF-and-number of services cancelled, and on FFF-and-number of services delayed for Train A.

3 **Total sub-system distance (d):** Data for total sub-system distance was required to be collected. Since the data provided by UTS Melbourne was on the total train distance from Year 6, it was assumed that the total sub-system distance, d, is equal to the total train distance. It was further assumed that d was same for each sub-system before and after maintenance.

4 **Number of services cancelled and the number of services delayed (C and D):** Since forecasting of C and D was beyond the scope of this study, a simplified form of the equation provided in the studies by Lu (2003), Lai et al. (2017), Lu et al. (2017) was used to compute C and D. The equations are given by $C = F\ X\ C_{avg}$ and $D = F\ X\ D_{avg}$. Besides, because the data on C_{avg} and D_{avg} were not provided, the values for these parameters were roughly estimated from the Year 6 data.

5 **Number of scheduled services (N):** Since computation of N is a part of operational planning which was beyond the scope of this study, N number of total trains scheduled for operation in a normal month of 30 days was computed based on basic mathematics. The number of trains scheduled for operation was first calculated for one day by multiplying the number of trains scheduled for operation during a peak hour by the number of peak hours per day, and multiplying the number of trains scheduled for operation during an off-peak hour by the number of off-peak hours per day, and then adding these two numbers together.

The number of trains scheduled for operation during a peak hour was taken from the UTS Melbourne data. It was assumed that a normal day contains 8 peak hours and the number of trains scheduled for operation during an off-peak hour was taken as 70% of the number of trains scheduled for operation in a peak hour.

6 **Proposed maintenance strategies:** Since each maintenance strategy offers some FF savings, there were in total 10 proposed maintenance strategies in correspondence to FF saving from 1 to 10.

7 **Maximum percentage of improvement in the OSRI of the sub-system:** It was assumed that the maximum improvement in the OSRI of any sub-system that could be achieved is limited to 95%. Thus, after arriving at this point, the %OSRI of the sub-system remained constant at 95% despite any more FF savings.

These data were used for modelling by developing spreadsheets for each sub-system in Microsoft Excel by Microsoft Corporation (2019). The results were mapped in simple line curves by using the tool available in Microsoft Excel.

6.3.2 Hypothetical maintenance scenario I

It is assumed that a maintenance plan needs to be designed that promises to improve functional reliability of each critical sub-system S3, S7 and S16 by at least 10% (i.e. the reduction in the

FFF of each critical sub-system should be equal to or greater than 10%). This maintenance plan must also ensure an equivalent improvement (i.e.10%) in the overall reliability of the critical sub-systems associated with the improvement in functional reliability of the critical sub-systems. Hence, a maintenance strategy needs to be selected for each sub-system that satisfies both assigned targets.

Since the operational characteristics of the sub-systems vary each month, the need for the savings in the FFF of each sub-system is different each month. Accordingly, the %OSRI of the sub-system varies from month to month. Hence, the selection of the maintenance strategy for the i^{th} sub-system involves a complex decision-making process which involves a compromise between the improvement in its functional reliability and in its overall reliability in various months of the year. The optimum maintenance strategy for the i^{th} sub-system is the one that commits to deliver the given targets for both the improvement in its functional reliability and in its overall reliability in most months of the year. This strategy for the i^{th} sub-system is achieved by carrying out the following simple steps using the OSRI model:

Step 1 Compute the %OSRI of the i^{th} sub-system for the FF savings from 1 to 10 for each month of the year using the OSRI model.

Step 2 Plot the impact of the FF savings on the %OSRI for the i^{th} sub-system for each month of the year.

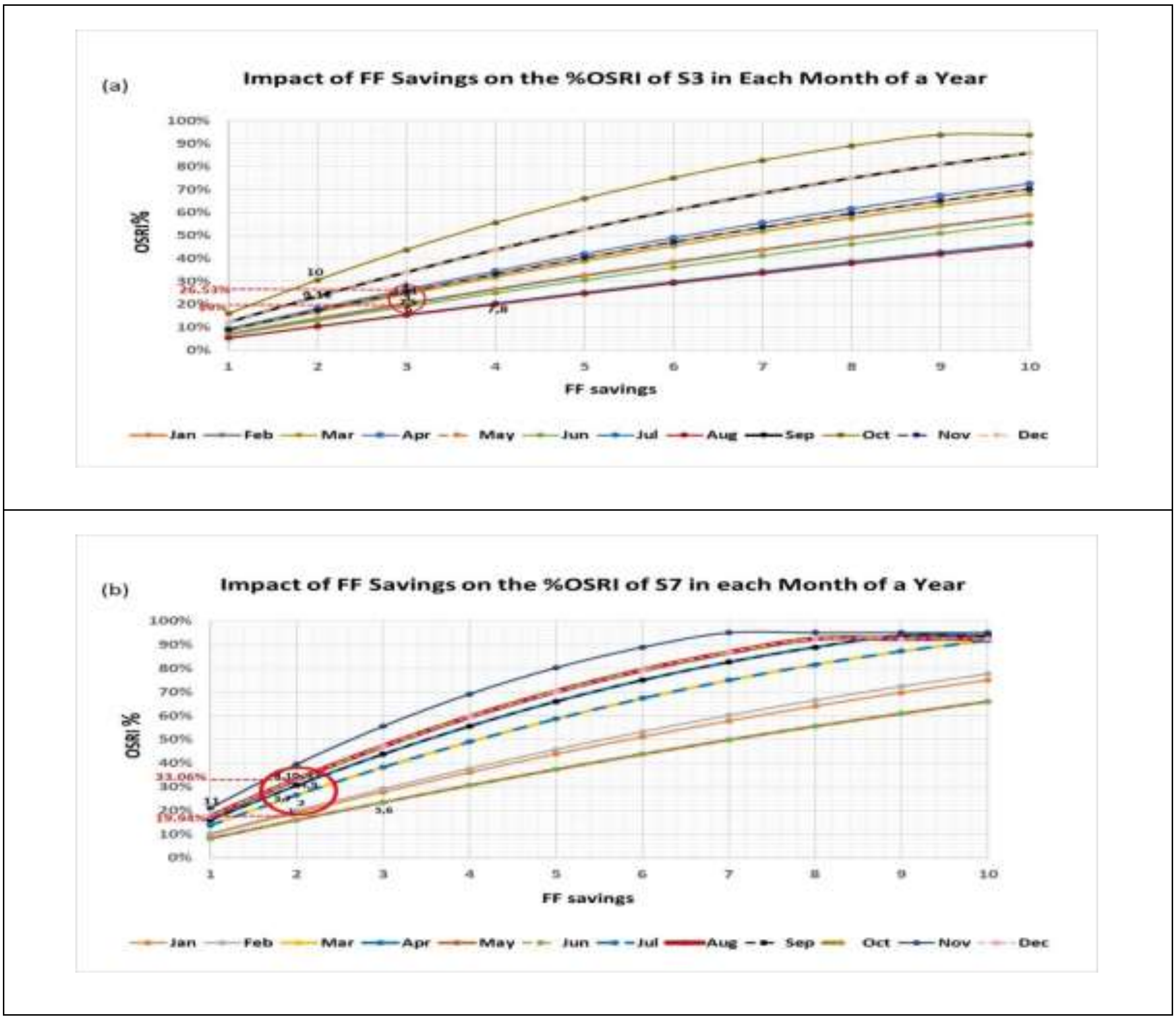
Step 3 On the curve for every month of the year, put the month number (i.e. 1-12) at the point where the number of FF savings provides the required improvement (i.e.10%) in functional reliability of the i^{th} sub-system.

Step 4 Determine the number of FF savings which is required by most of the months to achieve the given target for improvement in functional reliability. This number of FF savings is called the concentrated FF savings number.

Step 5 Assess whether the concentrated FF savings number delivers the desired %OSRI or not.

Step 6 If the desired %OSRI is not achieved by the concentrated FF savings number, repeat steps 4-6 for a higher FF savings number that needs to be negotiated with the owner because of additional cost for maintenance to achieve the given target.

To demonstrate hypothetical maintenance scenario I, the %OSRI of the i^{th} sub-system obtained in Step 1 for each month of the year were used to plot the impact of the FF savings of the i^{th} sub-system on the %OSRI. These plots are presented in Figure 6-1.



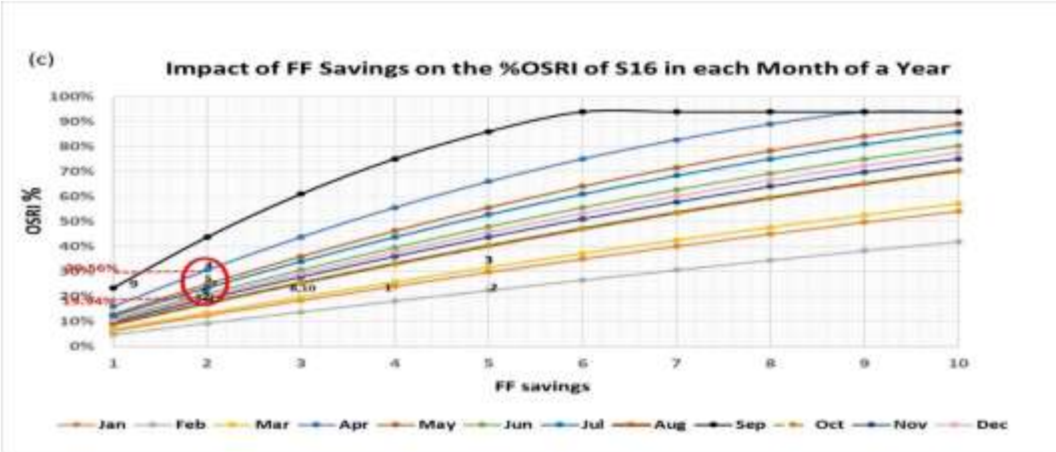


Figure 6-1: Impact of the FF savings on the %OSRI of the ith sub-system in each month of a year.

The point corresponding to the requisite FF savings for 10% improvement in functional reliability for each sub-system is marked on the line curve for the months by the number of the month in the year. The months that require the FF savings by the same number are enclosed in the red circle, thus establishing the concentrated FF saving number. The red dashed lines indicate the minimum and the maximum %OSRI of each sub-system corresponding to the concentrated FF savings of that sub-system.

As can be seen in Figure 6-1, in order to improve functional reliability of S3, S7 and S16 by the given target, the number of FF savings needed for these sub-systems is the same in 7, 9 and 6 months respectively out of the12 months of the year. This means that the concentrated FF savings for S3, S7 and S16 are 3, 2 and 2 in number respectively. In addition, for S3, there are 3 months that require FF savings fewer than 3, and 2 months that require more than 3; for S7, there is 1 month that requires FF savings fewer than 2, and 2 months that require more than 2; and for S16, there is 1 month that requires FF savings fewer than 2, and 4 months that require more than 2. Thus, the maintenance strategy associated with the concentrated FF savings improves functional reliability of S3, S7 and S16 by equal to or greater than 10% in a total of 10, 10 and 7 months respectively. In addition, as can be seen in Figure 6-1, corresponding to the concentrated FF savings for each sub-system, the minimum and the maximum %OSRI of each sub-system are both also greater than the given target i.e. 10%. Thus, it is clear that this maintenance strategy corresponding to the concentrated FF savings is likely to provide both given targets. Figure 6-1 also shows that, in order to deliver these targets for all 12 months, the maintenance strategy associated with the FF savings of 4, 5 and 3 for S3, S7 and S16 respectively must be selected. However, selecting the maintenance strategy that offers the FF savings less than or greater than the concentrated FF savings results in an under-designed and over-designed maintenance plan respectively. Therefore, the maintenance strategy associated with the concentrated FF savings of 3, 2 and 2 is the optimum strategy for S3, S7 and S16 respectively in order to improve their functional reliability together with the improvement in the %OSRI by at least 10%.

Thus, it has been shown that, for this scenario, the OSRI model enables the maintenance strategies to be prioritised for a sub-system based on the impact of the improvement in its functional reliability on the %OSRI in different months of the year.

6.3.3 Hypothetical maintenance scenario II:

It is assumed that a maintenance plan needs to be designed that promises to cumulatively improve functional reliability and the %OSRI of S3, S7 and S16 by x% and y% respectively. Since the sub-systems vary in their operational characteristics, the extent by which functional reliability and thus the %OSRI of the sub-systems can be improved is different for each sub-system. Thus, the given targets are required to be allocated between the critical sub-systems which involves a compromise between the improvement in their functional reliability and in their overall reliability.

In order to assess the contribution of each sub-system, it must be established which sub-systems are maintenance intensive and which can deliver a better index. The sub-systems that are maintenance intensive are those that require relatively more FF savings to achieve the same level of improvement in their functional reliability, while the sub-systems that can deliver a better index are those that result in relatively high %OSRI to achieve the same level of improvement in their functional reliability. Considering this S3, S7 and S16 were evaluated for 10% improvement in their functional reliability in three different months of the year by using the OSRI model. The sub-systems which are maintenance intensive and which can deliver a better can be identified in the following simple steps by using the OSRI model.

Step 1 Compute the %OSRI of S3, S7 and S16 for the FF savings from 1 to 10 for the three months by using the OSRI model.

Step 2 Plot the impact of the FF savings on the %OSRI of each sub-system for each chosen month.

Step 3 On the curve for every sub-system, put the sub-system name (i.e. S3, S7 and S16) at the point where the number of FF savings provides the required improvement (i.e.10%) in their functional reliability.

Step 4 Determine the %OSRI corresponding to the FF savings for each sub-system.

Step 5 Arrange the sub-systems in descending order of their values for the FF savings and for the %OSRI.

To demonstrate hypothetical maintenance scenario II, the %OSRI of each sub-system obtained in Step 1 for each month were used to plot the impact of the FF savings of each sub-system on the %OSRI. These plots are presented in Figure 6-2.

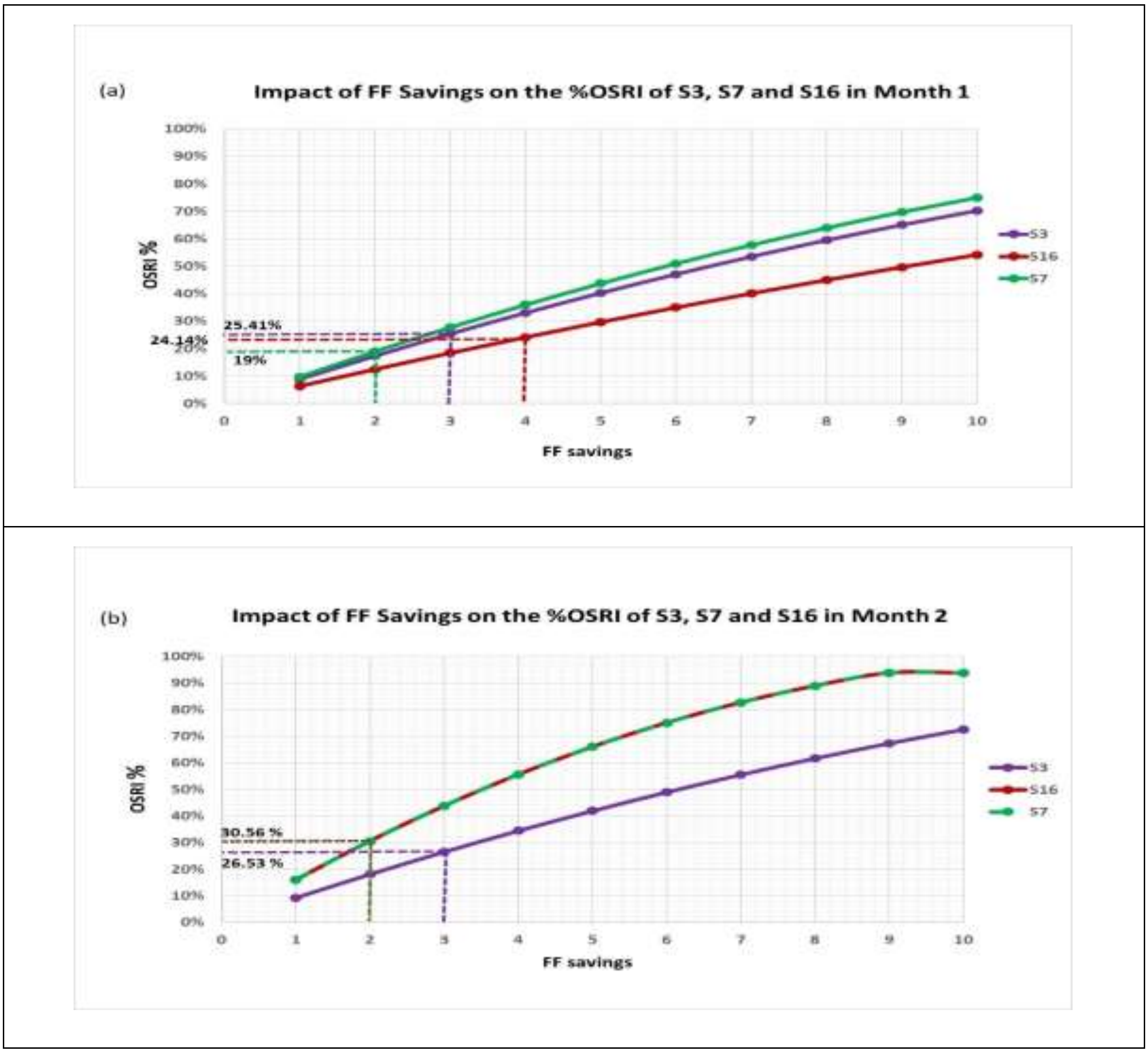


Figure 6-2: Impact of the FF savings on the %OSRI of the three critical sub-systems in each month.

The requisite FF savings for 10% improvement in functional reliability of S3, S7 and S16 and the resultant %OSRI are marked by the dashed vertical and the horizontal lines respectively.

As can be seen in Figure 6-2, for 10% improvement in functional reliability of each sub-system, the sub-system with the highest value for the FF savings on the x-axis is maintenance intensive, while the sub-system with the highest value for the resultant %OSRI on the y-axis delivers a better index. The findings are summarised in Table 6-1.

Table 6-1: Sub-systems in descending order of their values for FF savings and %OSRI for an equivalent improvement in their functional reliability

Month	Sub-systems in descending order of maintenance intensiveness	Sub-systems in descending order of %OSRI delivery
1	S16>S3>S7	S3>S16>S7
2	S3>S7 and S16	S7 and S16>S3
3	S3>S7 and S16	S7>S16>S3

Table 6-1 shows that, in month 1, S7 is the least maintenance intensive, but delivers the smallest %OSRI; in months 2 and 3, both S7 and S16 are the least maintenance intensive, but in month 2, they deliver the same %OSRI, whereas in month 3, S7 delivers a better index than S16. Based on these findings, different combinations of the assigned targets can be allocated to the sub-systems. For example, one combination without considering any other constraints is to allocate a greater proportion of the given target to S3 in month 1, to S7 and S16 in month 2 and to S7 in month 3. Using this combination, the maintenance strategy that offers the improvement in functional reliability and in the %OSRI of the selected sub-systems corresponding to the identified proportions should be selected to achieve the given targets.

In addition, as can be seen in Figure 6-2 (b), the line curve for S16 is exactly the same as the line curve of S7 for month 2. Consequently, both sub-systems are equally maintenance intensive and deliver the same %OSRI. However, the values of the ΔOSRI obtained using the OSRI model showed that the ΔOSRI for S7 is greater than that for S16. This difference in value reflects a difference in their operational characteristics which are considered in the model by the weights w_1 and w_2. This means that in month 2, because of the unfavourable operational environment for S7, it is more difficult to improve the reliability of S7 than it is to improve the reliability of S16. Thus, it can be concluded that since the model is able to capture differences in the operational environment, it is functioning well.

In summary, it has been shown that the OSRI model enables the maintenance strategies to be prioritised for different sub-systems considering the impact of the improvement in their functional reliability on the %OSRI in a given month, and hence the OSRI model can be used to develop a well-balanced and improved maintenance plan.

6.4 Model validation and usefulness

To evaluate the practical utility of the OSRI model, the results obtained using the model are compared to the results of the assessment of the reliability loss conducted by UTS Melbourne for the same year. Using their standard method, the UTS maintenance managers determined two internally used measures for evaluating the loss in reliability of the urban train system, one focused on the performance of the urban train system alone and the other based on the relative performance of the urban train system to that of the other urban rail systems that are not reported here due to confidentiality concerns. The results obtained were a loss in reliability of 0.6%% and of 7% respectively. Although a direct comparison cannot be made between these values and the values obtained using the model, the question is whether the model provides a reasonable estimate for practical maintenance planning purposes.

The values for $\%OSRI_{base}$ obtained for S3, S7 and S16 using the model for each month of the year showed that the minimum cumulative loss in reliability was 0.7% and the maximum cumulative loss in reliability was 4.6%. It can be seen that these values computed using the model do provide a reasonable approximation to the values obtained by the maintenance managers to give them confidence in the performance of this tool.

The simple OSRI model has been developed in order to assist in practical decision-making in the maintenance planning process for an urban train system. It provides a tool that is easy for maintenance managers to compute as it does not involve complex statistical analysis or computer software. The model enables the maintenance strategies for each sub-system alone and all the sub-systems together to be prioritised based on their effectiveness in improving the overall sub-system reliability index, sub-system average cancellation index and sub-system average delay index. Additionally, the model can be used to establish internal benchmarks for improvement in the KPIs for reliability and improve coordination between the maintenance and other departments in the organisation.

6.5 Summary

This chapter has presented the development of a new simple model that enables the maintenance strategies for the sub-systems to be prioritised based on their effectiveness in delivering the strategical targets for reliability. The model explicitly computes the %OSRI of the sub-system by measuring the impact of the improvement in functional reliability of the sub-system due to the proposed maintenance strategy on the number of services cancelled and on the number of services delayed. In the computation of the index, the model considers the influence of the latent variables on the operational characteristics of the sub-system. The demonstration of the model in two hypothetical maintenance scenarios has shown that the model can be used to identify the optimum maintenance strategy for each sub-system by trading-off its functional reliability and the overall reliability, and to identify the best maintenance strategies for a number of sub-systems by trading-off their functional reliability and overall reliability. Hence, the model provides a valuable tool for improving the decision-making process of the maintenance planning.

Chapter 7: CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

7.1 Conclusions

The main aim of this research was to investigate the RCM process used by the urban rail industry for the maintenance planning of trains, and to propose a new improved RCM process that achieves overall reliability by integrating the performance measures both for functional reliability and service reliability, and the influence of latent variables in the process. To achieve this broad aim, the research was divided into three key components:

(1) assessment of the conventional approach of reliability analysis for operational performance characterisation of sub-systems using the KPIs for reliability
(2) development of an improved approach for the reliability analysis by using exploratory multivariate data analysis techniques and by integrating the KPIs both for functional reliability and service reliability
(3) development of a model for prioritisation of the maintenance strategies based on their effectiveness at delivering overall improvement in the reliability of each sub-system and the sub-systems overall.

The conclusions from each of these research components are highlighted here.

7.1.1 Assessment of the conventional approach of reliability analysis

The conventional approach of reliability analysis for the operational performance characterisation of the sub-systems of the urban train system was assessed through a case study of the urban train service in Melbourne. It was found that in this approach the KPIs data are applied in order to establish nine different operational characteristics of the sub-systems using simple descriptive analysis. SDA was found to be useful in summarising the data both in simple and in more complex composite bar charts that are easy to understand. However, SDA is based on the frequency counts of the KPIs for functional and service reliability, and thus only indicates increases or decreases in their values rather than explaining whether each KPI has improved or not. Furthermore, it does not explain the vital relationships between these KPIs or provide any information about the latent variables that have influenced the functional or service reliability. Given these limitations, only four of the nine characteristics of the sub-systems can be established to a limited degree. In addition, this approach does not consider the influence of the latent variables on the operational performance of the sub-systems. This means that the maintenance planning ultimately relies on a simple increase or decrease in the values of the KPIs of the sub-systems and thus does not establish whether each KPI has improved or not both individually and also in relation to each other. This component of the research provides a detailed understanding of the reliability analysis approach in the RCM process currently used to characterise the operational performance of the urban train system in Melbourne, and identifies where improvements could be made in this approach.

7.1.2 Development of an improved approach for the reliability analysis

In this research component, the new improved approach of reliability analysis for operational performance characterisation was developed from the conventional approach in two steps.

First the conventional approach was partially modified by preserving the conventional single criterion for characterisation, i.e. FFF, and by replacing the analytical technique, i.e. SDA, by principal component analysis. Using this approach on the FFF data collected from UTS Melbourne, five operational performance characteristics based on the FFF are successfully established. The results of PCA are presented in plots that provide rich information and are easy to interpret. The comparison of the results obtained from PCA with those from SDA showed that PCA establishes the operational characteristics of the sub-systems considering the influence of the latent variables, thus providing a clear insight into the latent structure of the FFF profiles of the months and the sub-systems individually and in relation to each other. However, since PCA can only be applied for a single criterion, it cannot be applied for characterisation based on multiple criteria that incorporate the KPIs for both functional and service reliability.

Next, an improved multiple criteria approach was developed for the operational performance characterisation using multiple factor analysis. This approach applies the KPIs for functional reliability and service reliability in their cause-and-effect structure by using MFA, and the four remaining operational performance characteristics are successfully established. The comparison of MFA results obtained based on multiple criteria with PCA results obtained based on the single criterion clearly shows that better maintenance planning can be achieved when the critical sub-systems are identified based on multiple criteria. Finally, an improved framework for the operational characterisation was proposed using a combination of PCA based on a single criterion and MFA based on multiple criteria.

7.1.3 Development of a model for prioritisation of the maintenance strategies

In the final component of the research, a simple reliability index model was developed that can be used to compute the overall sub-system reliability Based on the computed values, the maintenance strategies for the sub-systems can be prioritised based on their effectiveness in delivering the strategical targets for reliability. The index explicitly computes the percentage of overall reliability index, %OSRI, of the sub-system by measuring the impact of the improvement in functional reliability of the sub-system due to the proposed maintenance strategy on the number of services cancelled and on the number of services delayed. In the computation of the index, the model integrates the influence of the latent variables on the operational characteristics of the sub-system in terms of weights.

The model can be used to identify the optimum maintenance strategy for each sub-system by trading-off its functional reliability and its overall reliability. It can also be used to identify the best maintenance strategies for a number of sub-systems by trading-off their functional reliability and overall reliability. It provides a tool that is easy for maintenance managers to compute as it does not involve complex statistical analysis or computer software. Hence, the model provides a valuable tool for improving the decision-making process of the maintenance planning.

In summary, in this research a better RCM process for the urban train system has been developed based on an improved approach for the reliability analysis used to characterise the operational performance and a new reliability index model used to select the best maintenance strategies. This RCM process can be used to achieve more effective maintenance planning that in turn will ensure greater service reliability.

7.2 Significance of the work

This section briefly discusses the novelty and scientific contribution of the work presented in this thesis.

This research is the first comprehensive study of operational performance characterisation of the sub-systems of a complex urban train system in the process of RCM based maintenance planning. This research provides a valuable new approach for implementation of the RCM method in the maintenance planning of the urban train systems. While in the conventional approach, a single criterion, the KPI for functional reliability, is used for identification of the critical sub-systems, in the new approach, multiple criteria that integrate the KPIs both for functional reliability and service reliability are used. The operational performance characterisation of the sub-systems based on multiple criteria successfully identifies the sub-systems that are critical with respect to both functional reliability and service reliability, thus, enabling more effective reliability analysis to be performed for improved maintenance planning.

Furthermore, this research provides an improved analytical framework for reliability analysis by developing an advanced two step approach instead of the conventional simple single step approach. The two step process has been designed to overcome the limitations of the conventional approach. In the first step, four operational performance characteristics are established based on multiple criteria using MFA that provide valuable insights into the common latent structure between the two data sets. In the second step, an additional five characteristics are established based on single conventional criterion using PCA that provide insight into the latent structure within the FFF data. Hence, based on the improved understanding of these nine characteristics and the latent structure in the data, the proposed analytical framework will enable significant improvements in the maintenance planning process to be achieved.

In addition, in the conventional maintenance planning process, the maintenance strategies are prioritised based on their effectiveness in delivering maximum improvement in the functional reliability of the sub-systems i.e. maximum reduction in the FFF. However, an improvement in the functional reliability of the sub-systems does not always guarantee an improvement in the service reliability. This research introduces a new approach to prioritise the maintenance strategies based on their effectiveness in terms of overall improvement in reliability by striking a balance between both the functional reliability and service reliability of sub-systems i.e. a reduction in FFF together with a reduction in the number of services cancelled and the number of services delayed.

Finally, this research also develops a model to determine a consolidated index of the overall improvement in reliability of the sub-system when a particular maintenance strategy is used.

This model provides a simple tool that can be used by maintenance planners to evaluate different maintenance strategies.

7.3 Challenges in application of PCA and MFA to the urban trains data

The challenges in application of PCA and MFA to the operational performance data of urban trains are the same as that can be incurred in the implementation of any new technology. An organisation's culture is one of the big barriers that influences the acceptance of changes in the process. To overcome this challenge, PCA and MFA need to be implemented gradually. Another challenge is that staff need training to use PCA and MFA since these methods are exploratory data analysis techniques that require specific knowledge and expertise for application. Communication could be another challenge as the identification of the latent variables associated with the PCs in PCA and with the dimensions in MFA is a process that is based on the agreement of staff within or from the different departments.

7.4 Recommendations for future work

An improved reliability management process for the urban train fleet has been proposed in this research. To extend the findings of this work, the following recommendations for further research are made.

(1) In this research, there were a number of non-disclosure constraints imposed on the reporting of the data provided by UTS Melbourne. In order to de-identify some of the data, the computed principal components reported in Chapter 4 and the dimensions reported in Chapter 5 were kept unlabelled. This has limited the development of a more comprehensive understanding of the underlying phenomena that affect the operational performance of urban trains. It is recommended that further work be carried out to identify the latent variables that could be used for labelling. This would provide a useful understanding of the dynamics of an operational environment of any typical urban trains service, thus leading to improved practices for both maintenance and operational planning.

(2) This research has produced a large amount of information for operational characteristics of sub-systems based on FFF using PCA. Since PCA detects the patterns from historical data that can then be applied for prediction, PCA has a proven track record of application in

predictive analytics. However, since it was beyond the scope of the work reported in this thesis, a model based on historical patterns of operational performance characteristics of sub-systems for prediction of FFF was not developed. Using the findings from PCA reported in Chapter 4, where the historical FFF data was characterised, it would be very useful to develop a model to predict FFF for future maintenance planning. Such a model would enable precise prediction of FFF, thus enabling better maintenance planning.

(3) A good understanding of the effect of using KPIs both for functional reliability and service reliability on the identification of critical sub-systems has been acquired using MFA in Chapter 5, and based on this, much progress has been made in developing an improved approach of reliability analysis for operational performance characterisation. However, in order to detect the patterns from the data by using MFA, it is assumed that there is a linear relationship between the variables. Further research is necessary to better understand whether the relationship between the KPIs is linear or non-linear, and then MFA based on simple PCA (as in this research) or nonlinear PCA can be incorporated in the analysis.

(4) In this study, the simple OSRI model was developed for prioritisation of the maintenance strategies. While this model is able to provide a satisfactory estimation of the overall reliability of sub-system, several assumptions were made in generating data for demonstration of the model as reported in Section 6.2 of Chapter 6. This means that the outputs of the model are based on a combination of actual and generated data. Thus, in order to make the model more accurate, it is recommended that further work be undertaken to calibrate the model based on field findings.

APPENDIX A: SCRIPT DESIGNED TO PERFROM PCA IN MATLAB

A script designed to perform PCA on FFF data of urban trains in MATLAB is presented here. This code was run for each study year separately.

```
%%Principle Component Analysis of Functional Failure Data of Urban Trains:

load('Year1_inputs');

%Compute principal components for functional failure data of urban trains and the variance accounted for by each component:

[coeff,score,latent,explained]=pca(A1);

 w=coeff(:,1:2);
 t=score(:,1:2);
 var=explained;

 %Scree plot for representation of percentage of variability explained by each principle component

figure
plot((cumsum(latent)/sum(latent)*100),'-bx','linewidth',2)
title ('Cumulative Percentage of Variance Explained by the PCs for Study Year 1','Fontsize',14,'Fontweight','bold')
xlabel ('Number of Principal Components','Fontsize',12,'Fontweight','bold')
ylabel ('Cumulative Percentage of Variance','Fontsize',12,'FontWeight','bold')
xlim ([1 11])
ylim ([40 100])

%Score plot for analysing the distribution of months

figure
scatter(score(:,1),score(:,2),250,'m','filled')
title('Factor Scores of the Months for Study Year 1','Fontsize',14,'Fontweight','bold')
xlabel('Principle Component I','Fontsize',12,'Fontweight','bold')
ylabel('Principle Component II','Fontsize',12,'Fontweight','bold')
labels1={'Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sept','Oct','Nov','Dec'};
text(score(:,1),score(:,2),labels1,'Fontsize',12,'Fontweight','bold')
xlim([-40 40])
ylim([-30 30])


%Loading plot for reflection of sub-systems interrelation and identification of most influential sub-systems

systems={'S1','S2','S3','S4','S5','S6','S7','S8','S9','S10','S11','S12','S13','S14','S15','S16','S17','S18','S19'};
months={'Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sept','Oct','Nov','Dec'};
figure
```

```
h=biplot(w,'varlabels',systems,'color','b','LineWidth',1.5,'marker','^','MarkerFaceColor','b','MarkerEdgeColor','b');
title('Loadings of the Sub-Systems For Study Year 1','Fontsize',14,'Fontweight','bold')
xlabel('Principle Component I ','Fontsize',12,'Fontweight','bold')
ylabel('Principle Component II','Fontsize',12,'Fontweight','bold')
xlim([-1 1])
ylim([-1 1])

% to change the variable font
for k = 39:57
   h(k).FontWeight= 'Bold';
end

% to change the variabkle font
for k = 39:57
   h(k).FontSize= 12;
end

%Biplot for determining why months end up in the score plot the way they do

systems={'S1','S2','S3','S4','S5','S6','S7','S8','S9','S10','S11','S12','S13','S14','S15','S16','S17','S18','S19'};
months={'Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sept','Oct','Nov','Dec'};


figure
h1=biplot(w,'Scores',t,'varlabels',systems,'obslabels',months,'markersize',20);
title('Biplot For Study Year 1','Fontsize',14,'Fontweight','bold')
xlabel('Principle Component I','Fontsize',12,'Fontweight','bold')
ylabel('Principle Component II','Fontsize',12,'Fontweight','bold')
xlim([-1 1])
ylim([-1 1])

h1(1:70);

% to change the line width
for k = 1:19
   h1(k).LineWidth = 2;
end

% to change the line color
for k = 1:19
   h1(k).Color = 'b';
end

% to change the line marker type
for k = 20:38
   h1(k).Marker = '^';
end

% to change the line marker size
```

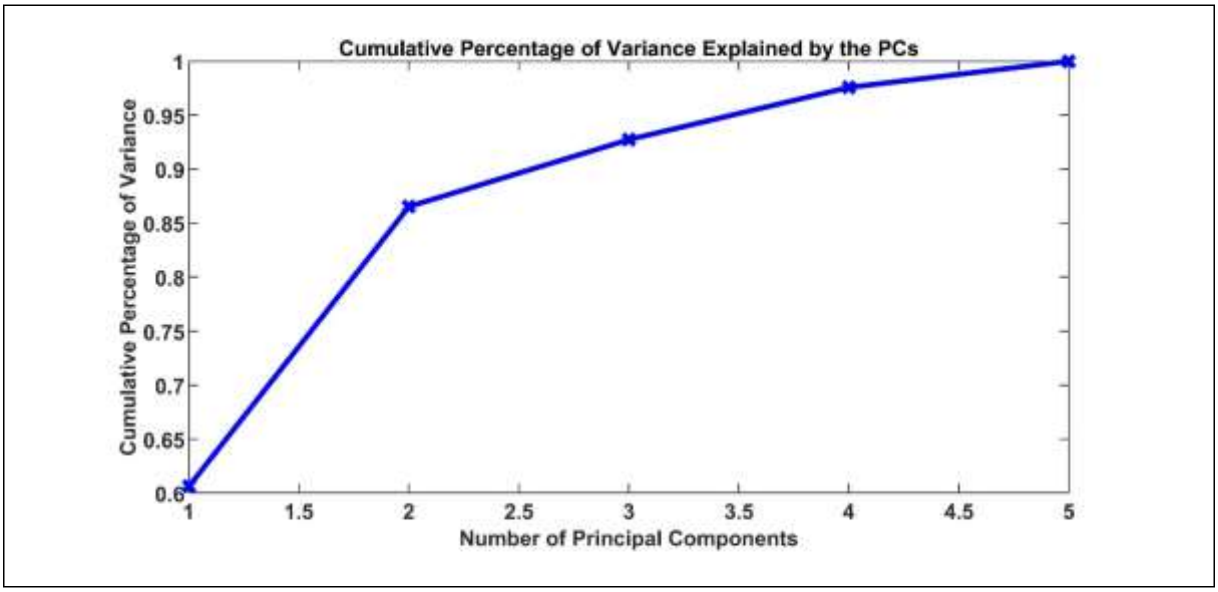
```
for k = 20:38
   h1(k).MarkerSize = 5;
end


% to change the line marker color (filled)
for k = 20:38
   h1(k).MarkerFaceColor = 'b';
end

% to change the line marker color (filled)
for k = 20:38
   h1(k).MarkerEdgeColor = 'b';
end

% to change the variable font
for k = 39:57
   h1(k).FontWeight= 'Bold';
end

% to change the variable font
for k = 39:57
   h1(k).FontSize= 12;
end

% to change the months size
for k = 58:69
   h1(k).MarkerSize =50;
end

% to change the months color
for k = 58:69
   h1(k).Color ='m';
end
```

APPENDIX B: PCA PLOTS OF EXAMPLES

Two published studies that use PCA were selected for validation of the designed script based on the availability of their data. One example (Dunn, 2019) was taken from the food manufacturing industry and another example (Kassambara, 2017) was taken from the sports industry.

These examples were discussed in Section 4.3.3 of Chapter 4, and PCA plots obtained for these examples by using designed script in MATLAB are presented here.

Example 1 - PCA plots of example from food manufacturing industry



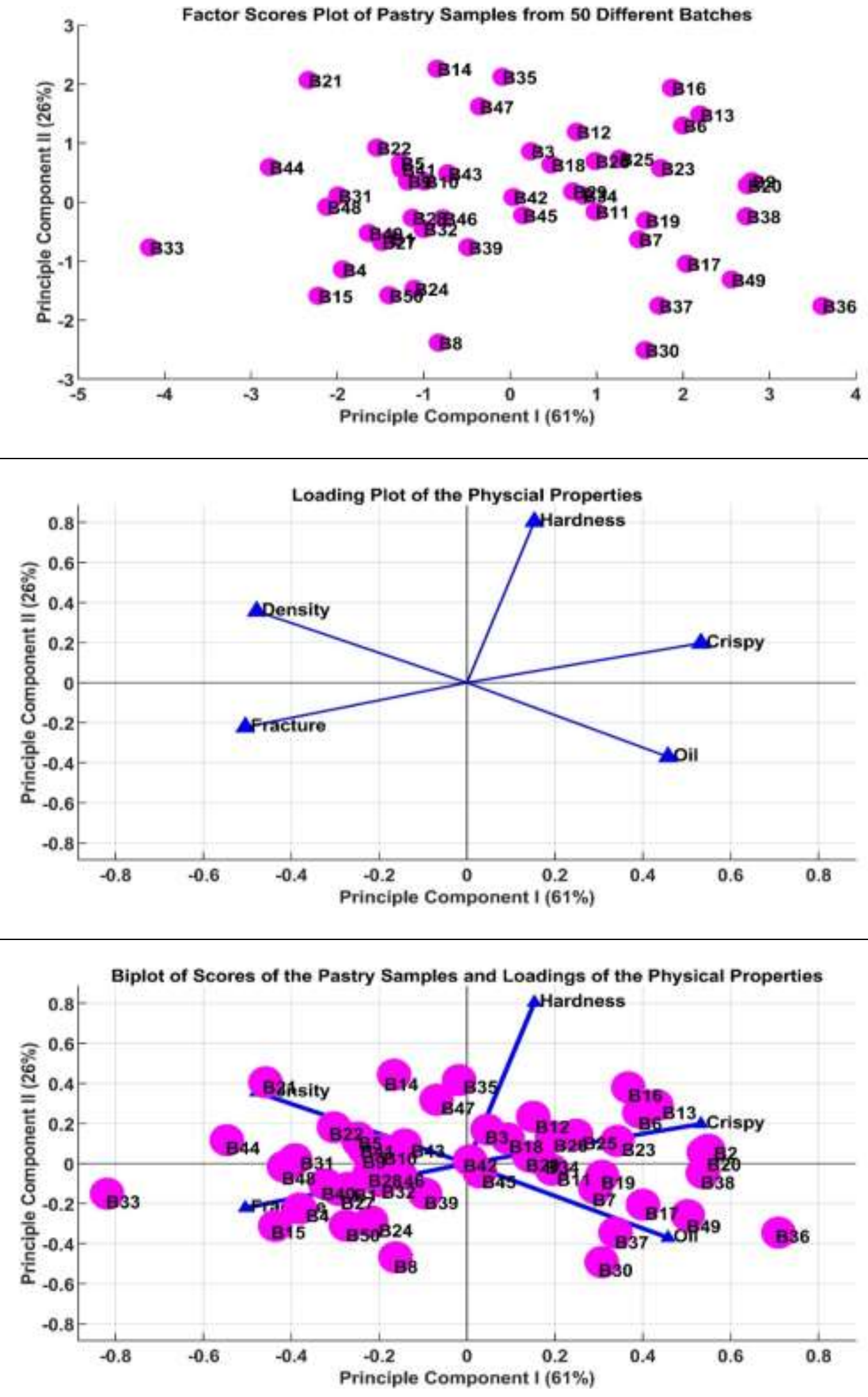
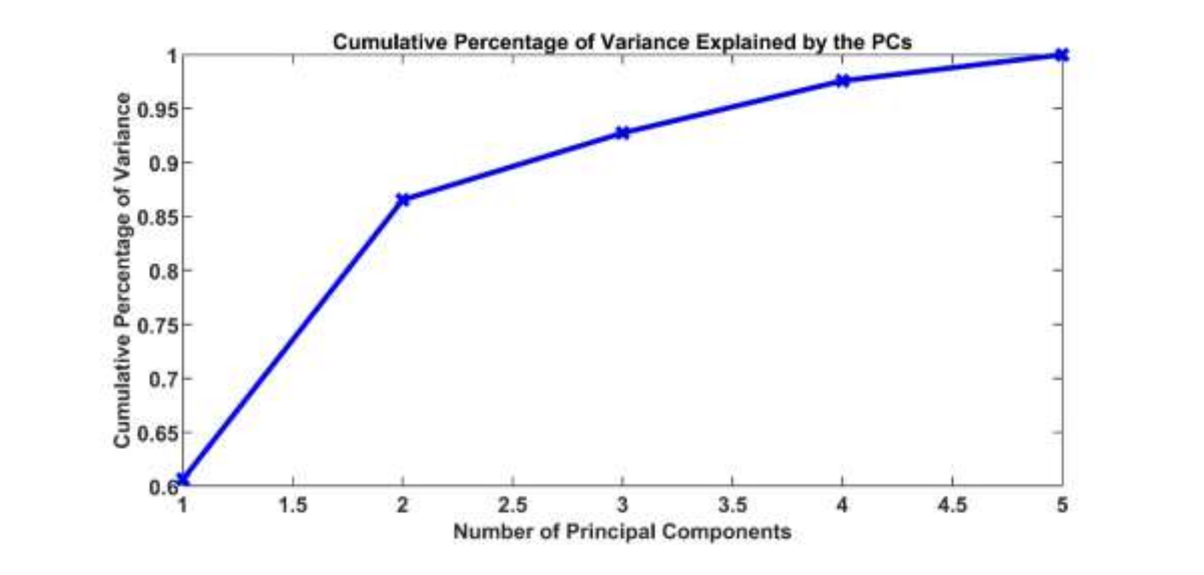
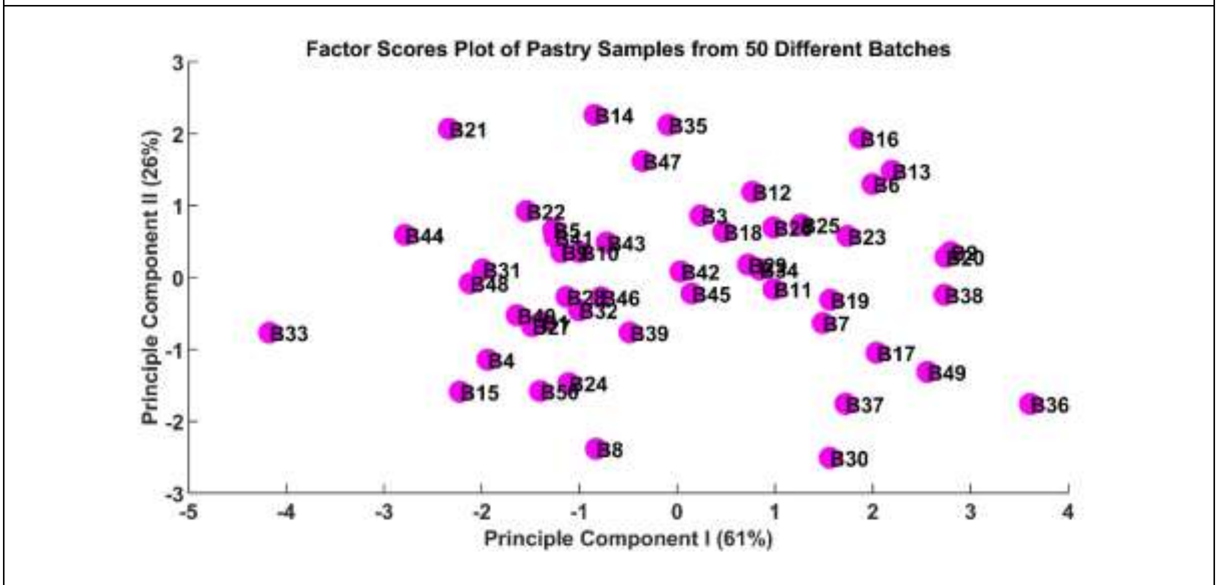


Figure B-1: PCA plots of example 1 from food manufacturing industry

Example 2 - PCA plots of example from sports industry





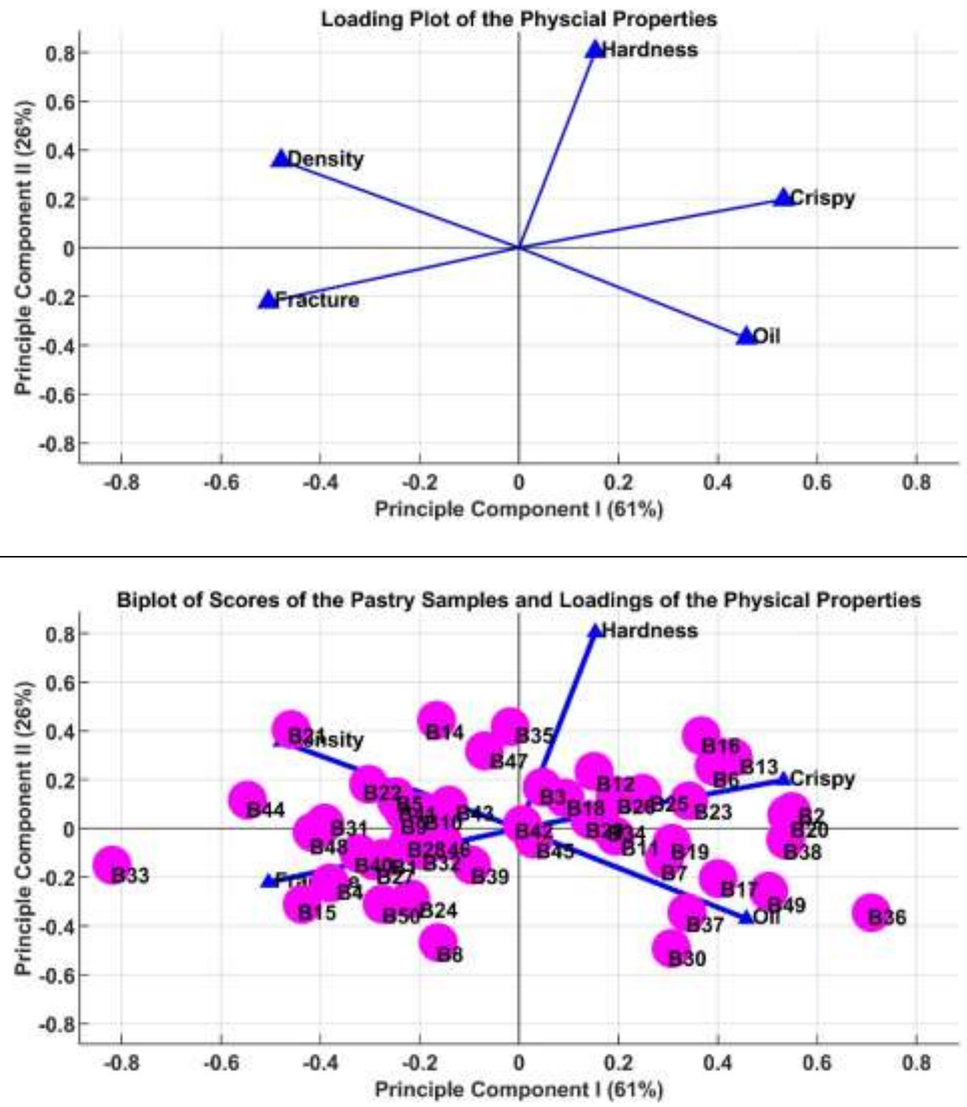


Figure B-2: PCA plots of example 2 from sports industry

APPENDIX C: SCRIPT DESIGNED TO PERFORM MFA IN RSTUDIO

A script designed to perform MFA on Set I: FFF-and-number of services cancelled and on Set II: FFF-and-number of services delayed is presented here. This script was run for each study year separately for each dataset.

```
# get working directory
getwd()
# load libraries
library(FactoMineR)
library(devtools)
library(ggplot2)
library(factoextra)
library(rARPACK)
library(ggrepel)
# import and load data
data1<-read.csv(file.choose(),header=TRUE,row.names = 1,sep=",")
# code for MFA
#Years 1 to 3
res.mfa<MFA(data1,group=c(2,2,2,2),type=c(rep("s",4)),ncp=5,name.group=c("A","B","C","D"),num.group.sup=NULL)
#Years 4 to 6
res.mfa<MFA(data1,group=c(2,2,2),type=c(rep("s",3)),ncp=5,name.group=c("A","B","C"),num.group.sup=NULL)
#outputs
summary(res.mfa,ncp=5,nbelements=Inf)
# Set it globally:
options(ggrepel.max.overlaps = Inf)

## to extract specific information
## screeplot
eig.val <- get_eigenvalue(res.mfa)
head(eig.val)
jpeg('Plot1.jpg')
```

```
fviz_screeplot(res.mfa,addlabels=TRUE, main="Percentage of Variance Expalined by the Dimensions\n For Study Year 1", xlab= "Number of Dimensions", ylab="Percentage of  Variance")+scale_y_continuous(limits =c(0,100),breaks=seq(0,100,20)) +theme(plot.title = element_text(hjust=0.5,lineheight= 1.3, size=14,face = "bold"),axis.title.x = element_text(size=12,face = "bold"),axis.title.y = element_text(size = 12,face = "bold"),axis.text.x = element_text(size=10, face="bold"),axis.text.y = element_text(size=10, face="bold"),panel.border = element_rect(colour = "black", fill=NA, size=0.5))

dev.off()

## Representation of groups of variables

group <- get_mfa_var(res.mfa,"group")

group

jpeg('Plot2.jpg')

fviz_mfa_var(res.mfa,"group", geom=c("point","text"), col.var="blue",repel= TRUE, shape.var = 19, pointsize=5)+scale_x_continuous(limits =c(0,1),breaks = seq(0,1,0.2), expand = c(0,0))+scale_y_continuous(limits = c(0,1),breaks = seq(0,1,0.2), expand = c(0,0))+labs(title ="Groups Representation Plot For Different Types of Trains\n in the Fleet For Study Year 1")+theme(plot.title = element_text(hjust=0.5,lineheight= 1.3, size=14,face = "bold"),axis.title.x = element_text(size=12,face = "bold"),axis.title.y = element_text(size = 12,face = "bold"),axis.text.x = element_text(size=10, face="bold"),axis.text.y = element_text(size=10, face="bold"),panel.border = element_rect(colour = "black", fill=NA, size=0.5))

dev.off()

## Individual Factor Map (Subsystems Profile)

ind <- get_mfa_ind(res.mfa)

ind


jpeg('Plot3.jpg')

fviz_mfa_ind(res.mfa,invisible="quali.var",repel = TRUE,habillage = "none",col.ind = "blue", pointsize=5)+scale_x_continuous(limits =c(-5,5),breaks = seq(-5,5,2))+scale_y_continuous(limits = c(-5,5),breaks = seq(-5,5,2))+labs(title="Common Factor Scores Plot For the Sub-Systems\n For Study Year 1")+theme(plot.title = element_text(hjust=0.5,lineheight= 1.3, size=14,face = "bold"),axis.title.x = element_text(size=12,face = "bold"),axis.title.y = element_text(size = 12,face = "bold"),axis.text.x = element_text(size=10, face="bold"),axis.text.y = element_text(size=10, face="bold"),panel.border = element_rect(colour = "black", fill=NA, size=0.5))

dev.off()

## correlation Circle for analysing variables i.e. sub-systems

jpeg('Plot4.jpg')

fviz_mfa_var(res.mfa, "quanti.var", arrowsize=1, repel = TRUE, palette = "rainbow")+scale_x_continuous(breaks = seq(-1,1,0.4))+scale_y_continuous(breaks = seq(-1,1,0.4))+labs(title="Correlation Circle For the KPIs For Study Year 1")+theme(plot.title = element_text(hjust=0.5,lineheight= 1.3, size=14,face = "bold"),axis.title.x = element_text(size=12,face = "bold"),axis.title.y = element_text(size = 12,face = "bold"),axis.text.x = element_text(size=10, face="bold"),axis.text.y = element_text(size=10, face="bold"),panel.border = element_rect(colour = "black", fill=NA, size=0.5), legend.position = "None")

dev.off()
```

 # (optional) to obtain map with specific partial sub-systems

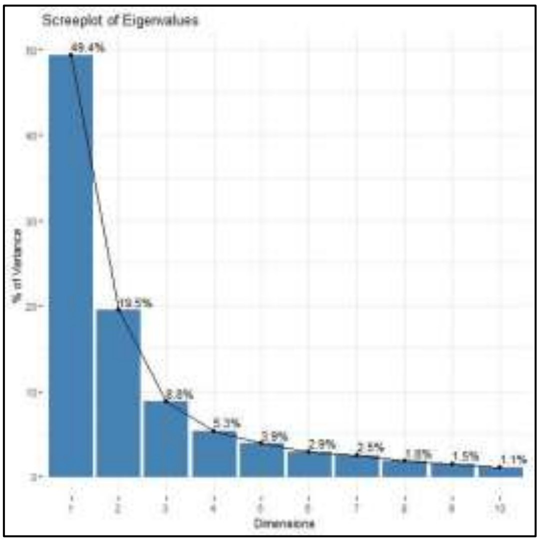
```
jpeg('Plot5.jpg')

fviz_mfa_ind(res.mfa, invisible="quali",partial = c("S3","S4","S7","S16"),col.ind =
"blue",pointsize=5)+scale_x_continuous(limits =c(-3,+10),breaks = seq(-3,+10,2))+scale_y_continuous(limits = c(-
7,+10),breaks = seq(-7,+10,2))+labs(title="Partial Factor Scores Plot For the Sub-Systems\n For Study Year
1")+theme(plot.title = element_text(hjust=0.5,lineheight= 1.3, size=14,face = "bold"),axis.title.x =
element_text(size=12,face = "bold"),axis.title.y = element_text(size = 12,face = "bold"),axis.text.x =
element_text(size=10, face="bold"),axis.text.y = element_text(size=10, face="bold"),panel.border =
element_rect(colour = "black", fill=NA, size=0.5))

dev.off()
```

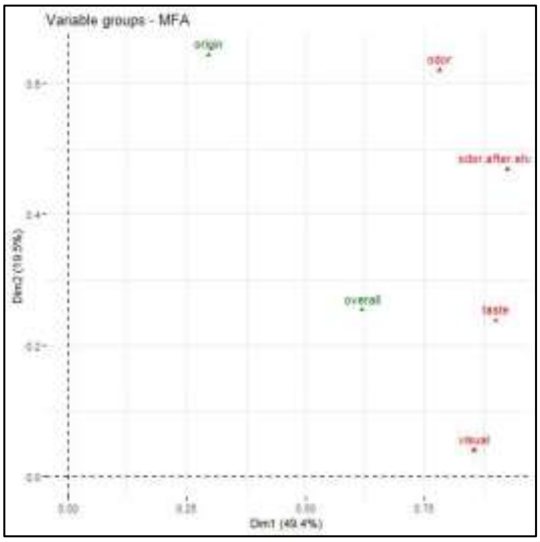
graph of partial axes

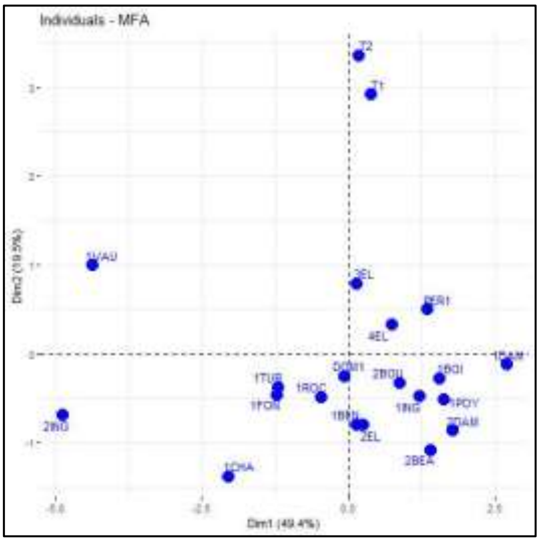
```
jpeg('Plot6.jpg')

fviz_mfa_axes(res.mfa, arrowsize=1, repel = TRUE, palette = "rainbow")+scale_x_continuous(breaks = seq(-
1,1,0.4))+scale_y_continuous(breaks = seq(-1,1,0.4))+labs(title="Partial Axes Plot For Study Year 1")+theme(plot.title
= element_text(hjust=0.5,lineheight= 1.3, size=14,face = "bold"),axis.title.x = element_text(size=12,face =
"bold"),axis.title.y = element_text(size = 12,face = "bold"),axis.text.x = element_text(size=10, face="bold"),axis.text.y
= element_text(size=10, face="bold"),panel.border = element_rect(colour = "black", fill=NA, size=0.5),
legend.position = "None")

dev.off()
```

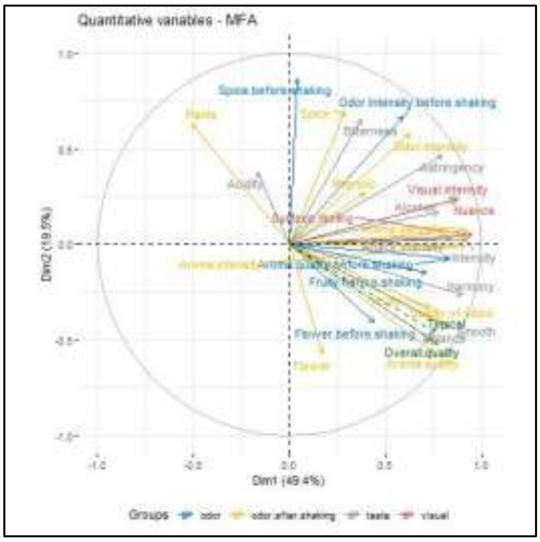
APPENDIX D: MFA PLOTS OF EXAMPLE

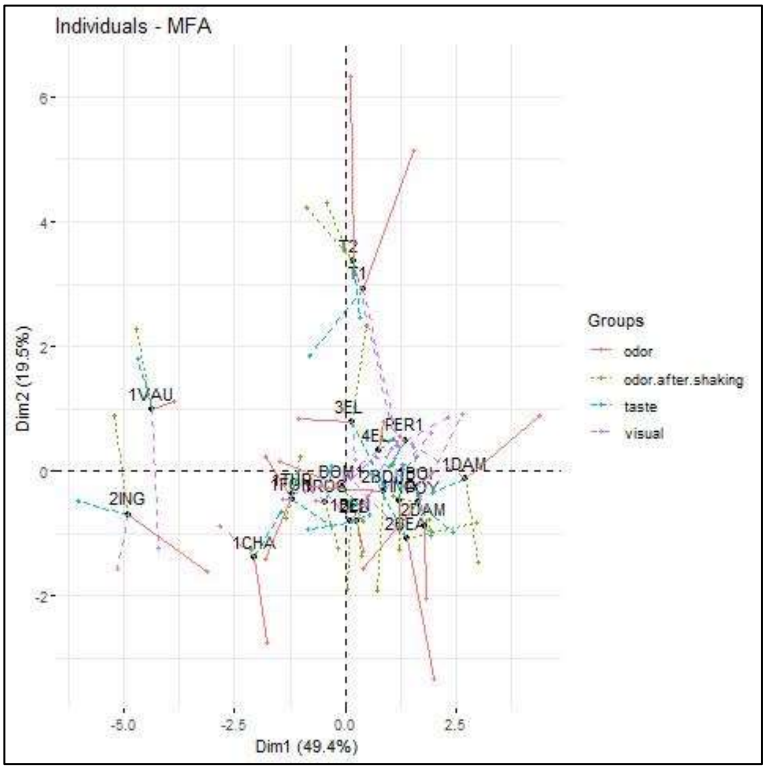
Based on the availability of detailed data, a study by Kassambara (2017b) that used MFA for quality characterisation of the wines was selected for validation of the designed script. In Kassambara's study, 21 samples of wines from different origin were evaluated against 27 sensory variables those were structured in four groups. This example was discussed in Section 5.3.3 of Chapter 5, and the plots obtained by using designed script in RStudio are presented here.











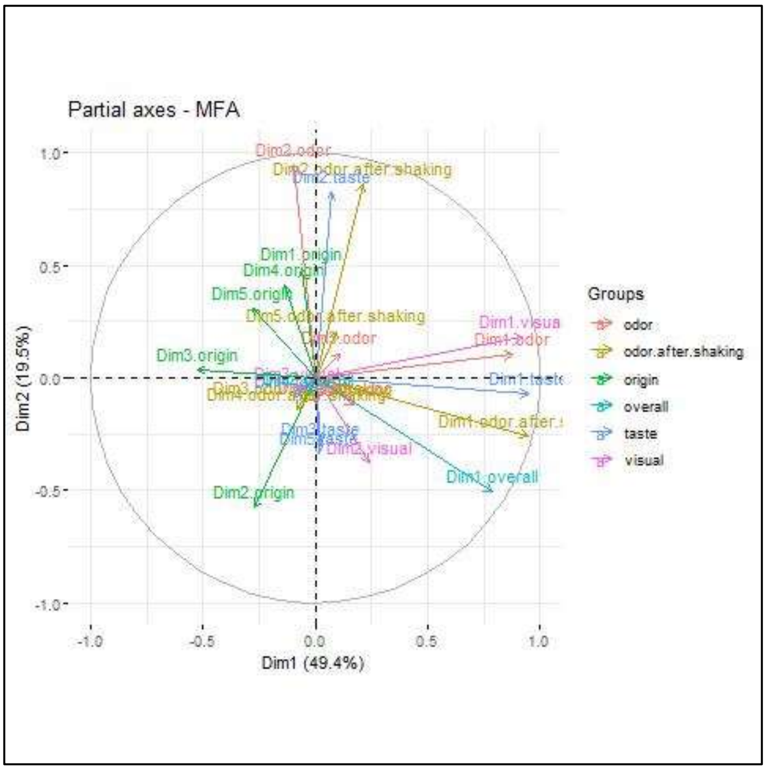
S


Figure D-1: MFA plots of example of a sensory evaluation of wines

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