Unwarranted Variations Modelling and Analysis of Healthcare Services based on Heterogeneous Service Data

By

Nagesh Shukla

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy in Engineering

The Digital Lab, Warwick Manufacturing Group

University of Warwick

Coventry, United Kingdom, CV4 7AL

Date: January 2012

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my supervisor Professor Darek Ceglarek, his expertise, understanding, and patience, added considerably to my doctoral experience. His trust, guidance, and support inspired me in the most important moments of making the correct decisions. Also, I would like to thank Dr. Kevin Neailey, Prof. David Williams (Director of the Research School of Health and Life Sciences, Loughborough University), and Prof. Christopher James (Institute of Digital Healthcare, University of Warwick) for their valuable suggestions in improving this thesis.

Most importantly, I would like to thank project members involved in project meetings such as Cris Sievenpiper, Suresh K. Choubey, Richard Frowein, Yuan Chyuan Sheu, Peter Kinhan, Abdek-Malek Aiman, Catherine Tabaka, Bharat Monteiro, Andrew Archibald, James Champion from General Electric Healthcare (US & EMEA); John Keast, Sudi Lahiri, UmutKurttas, Alessandro Cafazzo from University of Warwick; and Dr. Richard Wellings, Dr. Tom Goodfellow, Dr.Santosh Rai, Lowella Wilson, Krystina Hancox, Chris Holt, Dr. Martin Lee, Dr. Tony Kenton, Dr.Arvind Chandratheva, Dr.Aresh Anwar, Dr. Ann Anthony, Carl Holland, Martine Prichard, Jill Foster, Claire Bonniger, Barbara Fowler, Yvonne Brown, Ray Swain.

I would like to thank members of Digital Lifecycle Management Lab such as Prakash, Tirawat Phoomboplab, Duck Young Kim, and Eduardo Izquierdo for their helpful discussions during my doctoral research and training. I am thankful to all the past and present colleagues of the Digital Lab like Saurin Badiyani, Mitan Solanki, Chris Golby, Vibhor Aggarwal, Hardik Raja, Himanshu Patel, Martin Wehle, Nikhil Alexander, Anil George Thomas, Chris Kemp, Srimathi Rajshekhara, and Santosh Kumar Gupta for making my stay at Warwick delightful.

A very special thanks goes to Professor M. K. Tiwari, without whose motivation and encouragement, I would not have considered a doctoral career. Finally, I would like to dedicate this work to my family, who has been greatly supporting me in achieving all my inspirations and ventures.

I acknowledge the financial support from GE-Healthcare and a UK hospital to carry out the research studies discussed in this thesis.

To my parents, brother, and my wife

for their endless love and support

DECLARATION

This thesis is presented in accordance with the regulations for the degree of Doctorate of Philosophy. It has been written and complied by myself and has not been submitted anywhere else. The work in this thesis has been undertaken by me except where otherwise stated.

Signed: Date: 30 January 2012

Nagesh Shukla

LIST OF PUBLICATIONS

Nagesh Shukla, Darek Ceglarek, S. Lahiri, Cris Sievenpiper, Yuan Chyuan Sheu "System And Method for Healthcare Service Data Analysis" *Patent In review at US Patent Office (Aug , 2011)*

Shukla, N., Keast, J., Ceglarek, D., "Role Activity Diagram-Based Workflow Modelling of Imaging Service Delivery Process in Radiology," *INFORMS Service Science Conference*, HKUST, Hong Kong, (2009).

Shukla, N., Keast, J., Ceglarek, D., "Role Activity Diagram-based Process Modelling for Service Delivery Process in Radiology" Favourably reviewed in *IEEE Transactions on Systems Man Cybernetics, Part A*, (2012)

Shukla, N., Lahiri, S., Ceglarek, D., "Pathway Variations Analysis (PVA): Modelling and Simulation" To be *Submitted* to European Journal of Operational Research (2012).

Shukla, N., Ceglarek, D., "Variation Modelling and Improvement in service systems based on Real Time Sensor Data" To be *Submitted* to European Journal of Operational Research, *(2012)*.

Shukla, N., Keast, J., Ceglarek, D., "Simulation modelling of healthcare service delivery processes based on role activity diagrams" *Submitted* to Computers and Industrial Engineering (2012)

ABSTRACT

There is a growing demand worldwide to increase the quality and productivity of healthcare services thereby increasing the value of the healthcare services delivered. To deal with these demands, increasingly importance is being placed on analysing and reducing unwarranted variations in healthcare services to achieve significant savings in healthcare expenditure. Unwarranted variations are defined as the variations in the utilisation of healthcare services that cannot be explained by variation in patient illness or patient preferences. Current modelling and simulation approaches for healthcare service efficiency and effectiveness improvements in hospitals do not utilise multiple types of heterogeneous service data such as qualitative information about hospital services and quantitative data such as historic system data, electronic patient records (EPR), and real time tracking data for analysing unwarranted variations in hospital. Consequently, due to the presence of large amount of unwarranted variations in the service delivery systems, service improvement efforts are often inadequate or ineffective. Therefore, there is urgent need to: (*i*) accurately and efficiently model complex care delivery services provided in hospital; (*ii*) develop integrated simulation model to analyse unwarranted variations *on* a care pathway of a hospitals; and, (*iii*) develop analytical and simulation models to analyse unwarranted variations *from* a care pathway.

Current process modelling methods to represent healthcare services rely on simplified flowchart of patient flow obtained based on on-site observations and clinician workshops. However, gathering and documenting qualitative data from workshops is challenging. Furthermore, resulting models are insufficient in modelling important service interactions and hence the resulting models are often inaccurate. Therefore, a detailed and accurate process modelling methodology is proposed together with a systematic knowledge acquisition approach based on staff interviews.

Traditional simulation models utilised simplified flow diagrams as an input together with the historic system data for analysing unwarranted variations *on* a care pathway. The resulting simulation models are often incomplete leading to oversimplified outputs from the conducted simulations. Therefore, an integrated simulation modelling approach is presented together with the capability to

systematically use heterogeneous data to analyse unwarranted variations *on* service delivery process of a hospital.

Maintaining and using care services pathway within hospitals to provide complex care to patients have challenges related to unwarranted variations *from* a care pathway. These variations from care pathway predominantly occur due ineffective decision making processes, unclear process steps, their interactions, conflicting performance measures for speciality units, and availability of resources. These variations from care pathway are largely unnecessary and lead to longer waiting times, delays, and lower productivity of care pathways. Therefore, methodologies for analysing unwarranted variations *from* a care pathway such as: (i) system variations (decision makers (roles) and decision making process); (ii) patient variations (patient diversion from care pathway); are discussed in this thesis.

A system variations modelling methodology to model system variations in radiology based on real time tracking data is proposed. The methodology employs generalised concepts from graph theory to identify and represent system variations. In particular, edge coloured directed multi-graphs (ECDMs) are used to model system variations which are reflected in paths adopted by staff, *i.e.*, sequence of rooms/areas traversed while delivering services.

A pathway variations analysis (PVA) methodology is proposed which simulates patient diversions from the care pathway by modelling hospital operational parameters, assessing the accuracy of clinical decisions, and performance measures of speciality units involved in care pathway to suggest set-based solutions for reducing variations from care pathway. PVA employs the detailed service model of care pathway together with the electronic patient records (EPRs) and historic data. The main steps of the methodology are: (i) generate sample of patients for analysis; (ii) simulate patient diversions from care pathway; and, (iii) simulation analysis to suggest set-based solutions.

The aforementioned unwarranted variations analysis approaches have been applied to Magnetic Resonance (MR) scanning process of radiology and stroke care pathway of a large UK hospital as a case study. Proposed improvement options contributed to achieve the performance target of stroke services.

ACRONYMS or ABBREVIATIONS

RAD: Role Activity Diagram

DES: Discrete Event Simulation

DoH: Department of Health

NHS: National Health Service, UK

ECDM: Edge Coloured Directed Multigraphs

EPR: Electronic Patient Record

VNM: Value Network Mapping

RFID: Radio Frequency Identification

RF/IR: Radio Frequency/ Infra-Red

RTLS: Real Time Location Systems

MR: Magnetic Resonance

CT: Computed Tomography

ECG: Electro Cardiogram

XSLT: translation style sheet

GUID: Globally Unique Identifiers

UV: Unwarranted Variations

CHAPTER 1: Introduction

1.1 Motivation for the Research

Worldwide, there is a growing demand to increase the quality and productivity of healthcare services. Available estimates in the US suggest that more than half a trillion US dollars got spent on costs associated with *overuse, underuse, misuse, duplication, system failures, unnecessary repetition, poor communication, and inefficiency* (NAE/IOM, 2005). Consequently, improving quality and productivity of the service delivery process is emerging to be a viable step for healthcare organizations worldwide (National Research Council, 2009; NAE/IOM, 2005; National Health Services, 2007; 2003; 2005; UK DoH, 2006, 2010a). To deal with the aforesaid challenges, increasingly importance is being placed on reducing unwarranted variations in healthcare (Wennberg 2002, Fisher, *et al.*, 2003, Appleby *et al.*, 2011, Rightcare NHS, 2010). In US, it is estimated that unwarranted variations in healthcare among Medicare patients can account for up to 30% of healthcare costs (Fisher, *et al.*, 2003). As defined by Wennberg& Cooper (1996), *unwarranted variations (UV) in care* are due to care that is inconsistent with: (i) patient preferences for a particular type of care; or (ii) patient treatment needs. Approaches used in *UV in care* deals with the systematic and routine collation and publication of data to highlight the geographical variations in care in various clinical areas of national importance (Rightcare, NHS 2010; Wennberg, 2002; Appleby, *et al.*, 2011).

However, publicising the existence of *UV in care* at major geographical public health level and their causes does not guarantee that these variations can be tackled at the local health organization level (Appleby, *et al.*, 2011). Furthermore, one of the major recommendations of the report on variations in healthcare highlights the need for development of locally focused incentives to deal with unwarranted variations (Appleby, *et al.*, 2011). Therefore, this thesis extends the definition of *UV in care* to *UV in the service delivery systems* to deal with unwarranted variations at local health organisations level. As illustrated in Table 1.1, *UV in the service delivery systems* are defined as unwarranted variations in care due to care that is affected by: (i) system requirements conformance; and (ii) system related constraints. The *UV in the service delivery systems* deals with the methods to identify and analyse unwarranted variations that leads to actions for reducing these variations at local health organisation level.

Table 1.1: Classification between UV in care and service delivery process

Types of Unwarranted Variations / Characteristics	Unwarranted Variations in Care (Wennberg& Cooper, 1996,Wennberg, 2002, Appleby*, et al.,* 2011)	Unwarranted Variations in Service Delivery Systems (Discussed in This Thesis)
Definition	Unwarranted variations in care due to care that is inconsistent with: (i) patient preferences for a particular type of care; or (ii) patient treatment needs.	Unwarranted variations in care due to care that is affected by: (i) system requirements conformance; and (ii) system related constraints.
Key Scope	Publicises the existence of UV at the *public-health level* that affects patients care	Identifies and reduces UV at the *service delivery system level*(local health organisation level) that affect patients care
Examples	Patients with chronic diseases such as diabetes, living in regions with more physicians per capita will have more consultations and diagnostic tests than other regions (Wennberg, 2002)	Patients routing issues from Emergency Department such as patients send to incorrect hospital wards from ED

To address the UV at service delivery system level, an accurate model of service delivery system is required, which can model complex healthcare processes characterised by collaborations among various medical specialists, complex decisions, sequential, and parallel tasks. Accurate modelling of the service delivery system requires accurate mapping and modelling of the patient journey along the care process as it operationalizes on the hospital floor. Relevant procedures from the patient journey are extracted to accurately develop care pathways. Accurate models of care pathways must then be utilised to identify and analyse UV at service delivery system level.

In this thesis, the unwarranted variations (UV) at the service delivery system level can be classified into: (i) UV *on* a care pathway (for example, delays and bottlenecks); and, (ii) UV due to patient getting unnecessarily diverted *from* a care pathway (for example, patients routing issues from Emergency Department - patients send to incorrect wards from ED).

Unwarranted variations *on* a care pathway (formally defined in Chapter 2, page 37-38) represent variations such as process bottlenecks, patient throughput, wait times and resource utilization. These types of unwarranted variations are common in case of clinical service units such as radiology, where all the patients follow similar procedures (pathway) for diagnostic imaging. In radiology, available estimates indicate that over 1.5 billion imaging procedures were performed in the US (Medicare, 2003) and over 33 million clinical examinations were performed with diagnostic imaging in the UK (Healthcare Commission, 2007). Hence, the increasing needs for imaging services in radiology departments has created considerable bottlenecks in the service delivery process and resulted in longer patient wait time

(Hillman & Neiman, 2003). However, the prohibitive costs of imaging devices severely restrict radiology departments from purchasing additional equipment in an effort to reduce unwarranted variations *on* a care pathway and enhance patient throughput and reduce waiting times.

Unwarranted variations due to the patient getting unnecessarily diverted *from* a care pathway predominantly occur due to patient routing issues from Emergency Department such as patients sent to incorrect wards from ED. Patient diversion from pathway can be a result of ineffective decision making processes, unclear process steps, their interactions, conflicting performance measures for speciality units involved within care pathway, and availability of resources. These unwarranted variations are largely unnecessary and lead to longer waiting times, delays, and lower productivity of care pathways. For example, stroke services dealing with stroke care pathways within UK costs NHS £2.8 billion a year in direct stroke care costs (National Audit Office, 2005). Over 300,000 people live with moderate to severe disabilities as a result of stroke in UK (Adamson, *et al.*, 2005). It is noted that, current stroke services within UK are largely inefficient due to the slower access to better stroke care, *i.e.*, diagnosis and treatment of patients are often late resulting in lower benefit to patients (UK DoH, 2006, 2010b, NAO, 2005).

While process improvement research studies across hospitals is increasingly seen as key to streamline patient care services; however, to date, process improvement studies have been few and far between (National Research Council, 2009; NAE/IOM, 2005). One challenge associated with the lack of improvement studies is the absence of strategies on ways to use large amount of heterogeneous service related data that are generated in hospitals. These data can be qualitative such as clinical staff interviews, workshops related to service delivery process or quantitative such as historic systems data, electronic patient records (EPR), and real time tracking information of staff. Furthermore, conflicting information, missing and unclear data adds difficulty in process improvement efforts. While the information gathered from various sources in hospital is useful, however, there is a lack of systematic knowledge acquisition approaches for information gathering, modelling, and performing meaningful analysis for service improvements. Hence, information from various sources is not used effectively to understand the service delivery process. As a result, without a thorough understanding of service delivery processes in hospital, developing and implementing productivity tools will be incomplete and ineffective.

To address aforementioned issues, Section 1.2 details the research challenges and contributions of the proposed research study.

1.2 Research Challenges and Contributions

In this thesis, methodologies for modelling and simulation analysis of unwarranted variations in health care service delivery systems based on multiple types of service information are proposed. The overall research roadmap and state-of-the-art approaches for analysis of unwarranted variations originating in hospital are illustrated in Fig. 1.1. The main objective of this thesis is to develop methodologies for modelling & analysis of *UV in the service delivery systems* for process improvement. The research challenges identified in achieving this objective, which are addressed by methodologies proposed in this thesis, are as follows:

Research Challenges:

1. Accurate and efficient modelling of the Service Delivery System: Systematic knowledge acquisition based on the use of heterogeneous data and qualitative

information to develop accurate and efficient service delivery system model is essential for reducing unwarranted variation at system level.

Currently, most of the service delivery system model design use a simplified flow chart of patient flow obtained based on on-site observations, group-based debates and brainstorming sessions, complemented with historic patient data. However, this is insufficient in modelling important interactions and relations between clinical staff, equipments and patients causing that the resulting models are often incomplete and with low level of information granularity which leads to the oversimplified outputs from the conducted analysis. This is partly because some of the important information about the service delivery can be missed during unstructured discussions thereby resulting in incomplete data. Therefore, it is necessary to develop a rigorous methodology for effective qualitative data gathering for detailed and accurate process representation.

2. Unwarranted variations *<u>on</u>* a care pathway: The challenges associated with this type of unwarranted variations analysis are mainly related to development of discrete event simulation (DES) models based on simplified process models as input. In addition, the simplified input model assumes that all the patients are following similar, if not same, process steps in care pathways. The sub-challenges are:

    a. Development of DES models for service delivery system analysis based on <u>accurate</u> process models is lacking. There is lack of approach that utilises <u>accurate</u> static process models as necessary input for development of effective dynamic DES models for analysing unwarranted variations *<u>on</u>* a care pathway. The <u>accurate</u> process model helps to identify and represent complex interactions and relations between clinical staff, equipments and patients. Currently, simplified input flow diagrams, used as input for the DES, are not sufficiently accurate to address adequately the issues of UV *on* a care pathway such as low throughputs, bottlenecks, long wait times, and low resource utilization. Conceptual mapping between concepts of process modelling and DES modelling is needed to translate static accurate process models into dynamic DES models.

b. Lack of use of quantitative data from various sources for building DES models: Majority of simulation modelling approaches were focussed only on using historic service system data for identifying process issues related to UV on a care pathway. However, various types of service data available nowadays can be used and integrated together for enhanced simulations. Various types of data available in healthcare service delivery systems are historic system data stored in multiple IT systems, tracking data of patients, equipments, and staff. A systematic approach is needed to define data model which can take inputs from various types of heterogeneous data together with accurate process models for DES modelling.

3. Unwarranted variations due to patient unnecessarily getting diverted *from* a care pathway: Lack of approaches to develop model static and dynamic models for analysing UV *from* care pathway. Traditional approaches were mainly focussed on developing simulation model based on assumption that the same procedures in a care pathway are followed routinely. However, due to unclear decision making steps, patient presenting conditions and resource

availability there are significant UV *from* a care pathway, which makes the improvement suggestions from conducted simulations to be often incomplete and ineffective. The sub-challenges related to this type of unwanted variations in hospital are:

a. Developments of service delivery process models are not scalable for analysis of unwarranted variations *from* care pathway. There are challenges related to representation and development of process models to be not only accurate but also scalable service delivery system model. The scalability of the service delivery process models is needed to: (i) be able to model complex decision making processes embedded within the main service delivery system model; (ii) be able to model care pathway crossing multiple departments/units in a hospital; (iii) be able to generate care pathway for each role or specific service departments. Furthermore, once the scalable process models are developed for identifying UV *from* a care pathway, an approach is needed to integrate these process models with the simulation for analysis.

b. Lack of utilisation of heterogeneous service information from multiple sources related to service delivery systems for analysis of unwarranted variations *from* a care pathway. There are challenges related to development of analytical models for modelling and simulating UV *from* a care pathway by including various types of available service related data such as: (i) patient characteristics data related to disease presentations, and clinical tests (available from electronic patient records, EPRs), and, (ii) real time information about roles (available from tracking systems).Approaches are needed to utilise these information together with the accurate and scalable process models for UV analysis.

To address aforementioned challenges in analysing unwarranted variations in hospital involving service system modelling, simulation and analysis; research methodologies are proposed in this thesis dealing with each of the research challenges. Figure 1.1 illustrates the proposed research indicating various methodologies developed in this research area. The research methodologies and organization of research is discussed below.

The developed methodologies and research contributions of this research are as follows:

1. *Service delivery system modelling methodology based on qualitative procedural information*: This approach aims to develop accurate and effective modelling methodology for complex healthcare service delivery processes combined with systematic and efficient knowledge acquisition approach (see Chapter 4). The knowledge acquisition approach has capabilities for capturing, documenting, and analysis of qualitative procedural information to develop process models of service delivery system. The contributions from this methodology are as follows:
    - Selection of Role Activity Diagram (RAD) as appropriate representation for accurate modelling of complex healthcare service delivery processes
    - Development of systematic knowledge acquisition approach for efficient capturing and documenting of qualitative information neces-

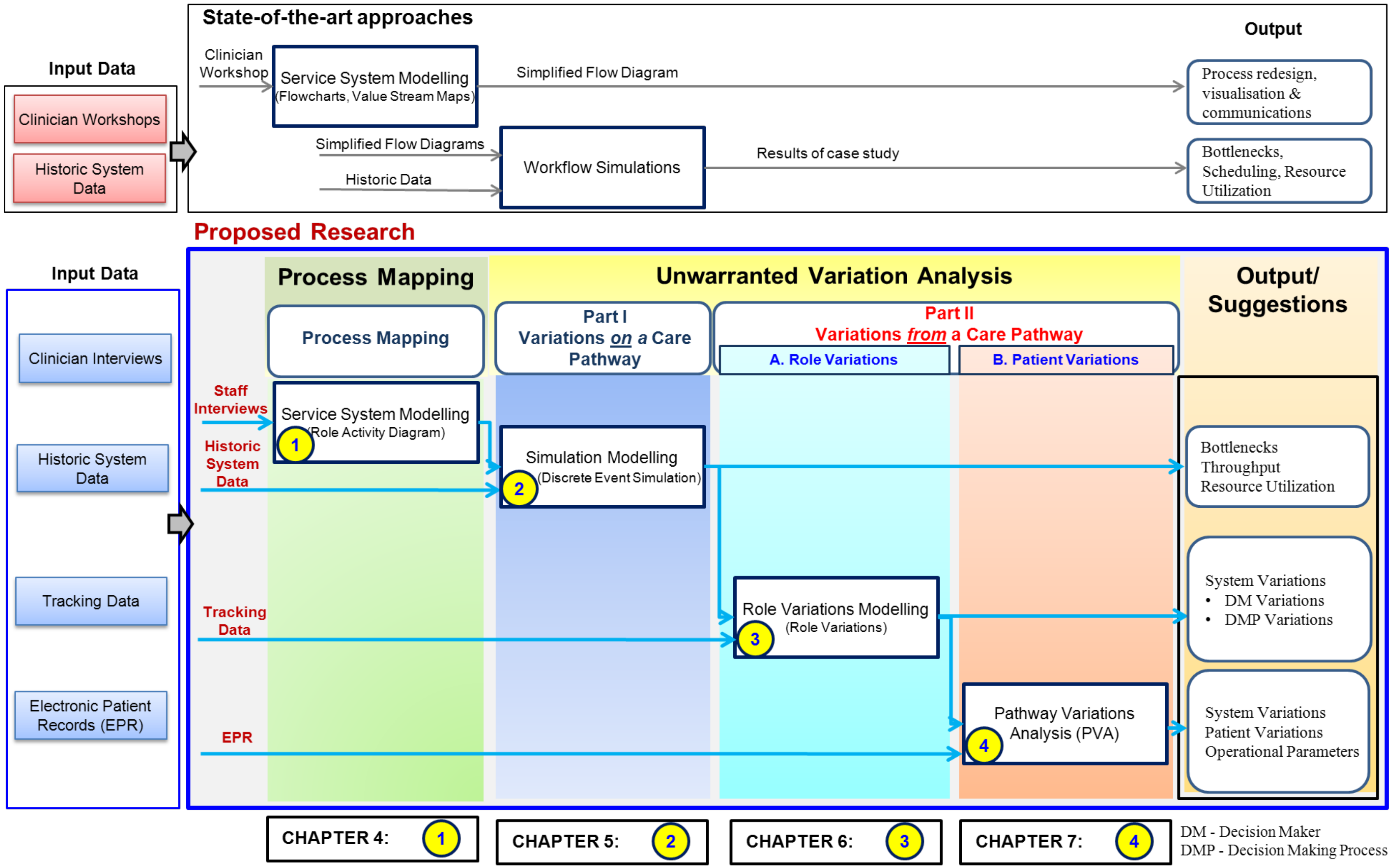


Figure 1.1: State-of-the-art research and proposed on Healthcare Service Improvements

-sary for accurate modelling of complex service delivery processes

- Implementation of the proposed service delivery system modelling methodology to model (i) a Magnetic Resonance (MR) scanning process in radiology unit as well as (ii) stroke care service delivery process in large UK hospital

2. *Modelling and analysis of unwarranted variations <u>on</u> a care pathway using Discrete Event Simulation (DES) integrated with accurate static service delivery system model as input instead of oversimplified workflow models currently used as input to DES*: The DES simulations require process models and large amount of quantitative data for simulations. However, currently there no accurate process models developed which can be used for DES simulations to analyse UV *<u>on</u>* a care pathway. Therefore, the proposed approach develop a systematic methodology for development of dynamic simulations based on accurate representation model of the service delivery system based on RAD together with historic system data (see Chapter 5). The main contributions of this approach are as follows:

    - Integration of accurate service delivery system model based on RAD with the discrete event simulation modelling
    - Systematic methodology for development of discrete event simulation model by integrating various types of quantitative information about healthcare service delivery such as tracking data and historic system data
    - The output from this simulation model can be used to reduce unwarranted variations *<u>on</u>* a care pathway by tackling process issues

such as bottlenecks, low throughput, large wait times, and low resource utilizations

3. Modelling and analysis of unwarranted variations due to patient getting unnecessarily diverted *<u>from</u>* a care pathway:

    - *Modelling and analysis of unwarranted variation of standard operating service delivery processes, specifically, <u>role variations</u> during a care pathway based on tracking information*: The process modelling methods, largely, models the most standard process performed within the service units. However, the unwarranted variations *<u>from</u>* a care pathway plays crucial role in lowering the productivity of service units, therefore, without modelling and analysing unwarranted process variations, the process improvement methods will often be incomplete and unrealistic. Hence, this methodology aims to identify and model the service variations such as decision maker (role) variations and decision making process variations involved within the process based on the real time tracking data (see Chapter 6). The main contribution from this approach are as follows:

        i. Modelling and representing service variations based on the generalized graph theory concepts called as edge coloured directed multigraphs

        ii. Development of learning algorithm based on pattern search for identifying system variations in hospital service units based on real time tracking information of medical staff

iii. Implementation of the proposed method in a radiology service unit within hospital for identifying service variations in roles involved in service delivery

- *Modelling and analysis of unwarranted variation of standard operating service delivery processes, specifically, patient variations (diversion) from a care pathway:* A new approach, Pathway Variations Analysis (PVA), is developed to model and analyse unwarranted variations *from* care pathway (see Chapter 7). The main contributions are:

    i. Identifying sources of unwarranted variations *from* care pathway such as patient diversions from care pathway based on accurate and scalable service delivery system model

    ii. Modelling crucial factors such as decision making process, decision makers, operational parameters, and inter-departmental performance measures leading to patient pathway variations

    iii. Approach to include the information about patient characteristics related to disease presentations and clinical tests for identifying patient diversions and its integration with service delivery system model

    iv. Development of pathway variations analysis (PVA) methodology for identifying, modelling & simulating pathway variations and then for suggesting set-based solutions to reduce patient unwarranted variations *from* care pathway

v. Implementation of proposed methodology on stroke care pathways for unwarranted patient variations reduction in a large UK Hospital

1.3 Organization of Thesis

Chapter 2 discusses the overall classification of the state-of-the-art approaches to highlight key research gaps and limitations in the area of unwarranted variations at the service delivery system level.

Chapter 3 presents a detailed literature review of the approaches used in service delivery process modelling and analysis of unwarranted variations *on* and *from* a care pathway.

Chapter 4 presents an RAD modelling methodology for effective and efficient service delivery process modelling and analysis based on staff qualitative interviews. The RAD modelling methodology considers the interviews of the key staff members (key roles) involved within a service delivery process.

Chapter 5 presents a methodology integrating RAD modelling methodology with the discrete simulation model for analysis and improvements of healthcare service unit. The methodology employs the RAD models that are developed in Chapter 4 together with the quantitative information about the process to develop discrete event simulation model for analysis of unwarranted variations *on* a care pathway.

Chapter 6 presents variations modelling methodology for identifying and modelling unwarranted variations *from* a care pathway such as system variations of a role based on real time tracking data. The methodology considers the RAD model developed in Chapter 4 and identifies most frequently occurring variations. The modelling methodology proposes a variations representation model based on edge coloured directed multigraphs and its learning algorithm from real time tracking data.

Chapter 7 presents a modelling and simulation methodology for unwarranted variations *from* a care pathway such as patient diversions from the integrated care pathway. The PVA methodology uses the RAD modelling methodology of Chapter 4 and identifies the key decisions leading to patient diversion based on EPRs. Then, the RAD of decision making process is developed of the key decisions. Finally, the simulation model is developed from RAD of decision making process and EPRs. The methodology is applied to the stroke care pathway of a large UK hospital and service changes for reducing unwarranted variations from care pathway is suggested.

Chapter 8 discusses the conclusions and future work.

CHAPTER 2: Background Review and Research Limitations

This chapter briefly discusses and classifies overall research done in the areas of hospital service delivery modelling, simulation-based analysis and system improvement based on identifying and reducing unwarranted variations. It also discusses the critical research challenges, which are identified as limitations of the current state-of-the-art approaches. This thesis will address each of the limitation that is identified in this Chapter.

Table 2.1 broadly classifies literature in the area of analysing unwarranted variations in the healthcare services at two levels that affects patient care, namely: *public-health level* and *service delivered system level in hospitals*. Unwarranted variations at *public-health level* is due to care that is inconsistent with: (i) patient preferences for a particular type of care; or (ii) patient treatment needs and generally deal with identifying unwarranted geographical variations in public spending and healthcare activity outcomes (Rightcare, NHS 2010; Wennberg, 2002; Appleby, *et al.*, 2011). Series of maps or atlases are developed to highlight the variations in various clinical areas of national importance to search for unwarranted variations and tackle the causes and drivers of these variations (Rightcare, NHS 2010; Wennberg, J.E., 2002; Appleby, *et al.*, 2011). On the other hand, unwarranted variations at *service delivered system level* in hospitals are due to care that is affected by: (i) system requirements conformance; and (ii) system constraints and can be classified into: (a) unwarranted variations *on* a care pathway (for example, delays and bottlenecks); and, (b) unwarranted variations due to patient getting unnecessarily diverted *from* a care pathway (for example, patients routing issues from Emergency Department).

The proposed research deals with analysing unwarranted variations at the *service delivered system level* originating within the hospital. Literature, in the area of analysing unwarranted variations at the *service delivered system level* in the hospital services, is discussed based on approaches that are extensively used to improve service delivery systems such as – (i) process mapping; and, (ii) simulation modelling.

We will first discuss the literature in the context of (i) process mapping; and, (ii) simulation modelling; and then provide a specific context as it relates to (a) unwarranted variations *on* a care pathway; and, (b) unwarranted variations due to patient getting unnecessarily diverted *from* a care pathway.

The process mapping/modelling is defined as a set of activities for identifying various actions and interactions involved in a particular service delivery processes and its visual representation for process visualization and re-design. Simulation modelling refers to modelling and developing dynamic models of the service delivery system for analysing/estimating the service delivery performances against various "*what-if*" scenarios.

Additionally, these approaches utilize various types of service delivery data for modelling and analysis. These service delivery data are: (i) qualitative data; and, (ii) quantitative data. The qualitative data of the service delivery process is mainly gathe-

Table 2.1: Classification of state-of-the-art approaches for healthcare process improvements

Scope	Approach	Objective	Service delivery data used	Reducing Unwarranted Variations *on* a Care Pathway				Reducing Unwarranted Variations *from* a Care Pathway			
			Key Issues	Qualitative data		Quantitative Data		Qualitative data		Quantitative Data	
				Procedural data	Systematic Knowledge Acquisition	Historic Data/EPR	Tracking Data	Procedural data	Systematic Knowledge Acquisition	Historic Data/EPR	Tracking Data
Public Healthcare Variations	Data Analysis	Geographic Variations		-	-	Wennberg, (2002); Appleby, et al., (2011); Rightcare, NHS (2010)	-	-	-	Wennberg, (2002); Appleby, et al., (2011); Rightcare, NHS (2010)	-
Services Delivery System level	Process Mapping	Static Analysis (Process visualization, redesign)		VSM (Rother & Shook, 2003, Dickson et al., 2008, Jimmerson et al., 2005)	-	Flowchart (Crabbe, et al., 1994) IDEF (Staccini et al., 2006)	-	-	-	-	-
				Service Delivery System Modelling based on RAD(Chapter 4)				**Role Variations Modelling based on Tracking Data (Chapter 6)**			-
	Simulation Modelling	Dynamic Analysis	Quanti-tative data: Historic Data	Molema, et al., 2007; VanBerkel and Blake, 2007; Bayer, et al., 2010; Dodds, 2005; Connelly & Bair, 2004; Brailsford, et al., 2006	**Discrete Event Simulation (DES) Modelling Integrated with Accurate Service Delivery System Model (Chapter 5)**			**Pathway Variations Analysis (PVA) Modelling (Chapter 7)**			-
			Tracking Data				Miller, et al., 2006; 2008	**-**	**-**	**-**	**-**

-red from clinician workshops, group debates, brainstorming or medical staff interviews. The qualitative data of the service delivery process is further classified into procedural data and systematic knowledge acquisition (KA). Procedural information is mainly related to how things are done, which is essential to any process mapping/modelling approach to develop process models. KA refers to the process of gathering and documenting the procedural information for accurate process mapping. Some of the commonly used methods to identify procedural knowledge, *i.e.* KA are based on clinician workshops. However, KA to model complex healthcare services of a hospital based on clinician workshops can be challenging. This is partly due to the fact that some of the important information about the service can be missed during simultaneous discussions with multiple staff; thereby resulting in gathering incomplete procedural data for accurate process modelling. Therefore, a process mapping/modelling methodology to accurately model service system is detailed in Chapter 4 which proposes systematic KA approach to effectively gather and document procedural data.

There are various types of quantitative data, which are available in service delivery systems, such as historic system data, electronic patient records (EPR), real time tracking data. This information is generally used for developing various types of simulation modelling for analysing unwarranted variations *on* a care pathway (see Table 2.1). The behaviour of the service delivery systems under varying system parameters and scenarios can be studied using simulation modelling. It enables process improvement experts to simulate various improvement scenarios that do not yet exist for analysing unwarranted variations occurring *on* a care pathway. Although, simulation modelling is identified to be useful technique for suggesting service improvements; however, traditional simulation models uses simplified flow diagrams, which are unable to represent complex collaborative healthcare services. Furthermore, traditional simulation models relied mainly on historic system data. Thus, outputs from traditional simulation models are often unrealistic and generally less than 10% of the process improvement studies involved any simulation modelling tools (Hulpic, 1998). Therefore, a simulation modelling methodology based on accurate service system model complemented with other quantitative data such as EPR, historic data, and real-time tracking information is proposed for analysing unwarranted variations *on* a care pathway in Chapter 5.

Most of the healthcare process improvement approaches in literature involves analysing unwarranted variations *on* a care pathway. However, there are significant unwarranted variations *from* a care pathway. Largely, these variations are unnecessary and leads to lowering of the efficiency and effectiveness of the services delivered. Traditional approaches, relying on modelling & simulating variations *on* a care pathway, are unable to address the problem of reducing unnecessary variations *from* a care pathway. There are limited research studies that deal with the analysis and reduction of unwarranted variations *from* healthcare services delivered in hospital for overall system level improvements. Therefore, a modelling methodology for service variations such as role variations is proposed in Chapter 6, which utilizes service delivery process model and real-time tracking data for modelling frequently occurring service variation patterns.

In the literature, reducing unnecessary variations by standardizing care delivery processes in healthcare systems or developing & implementation of integrated care pathway (ICP) is identified to be an effective approach (Kitchiner and Bundred, 1999; Pearson, *et al.*, 1995; Wilson, 1998; Archer, *et al.*, 1997; Wentworth and Atkinson, 1996; Willis, *et al.*, 2000). Integrated care pathway (ICP) is a structured multidisciplinary outline of anticipated care plans which details the steps in the care of patients with specific clinical condition or set of symptoms (Campbell, *et al.*, 1998). ICP generally involves multidisciplinary communication among several speciality units in hospital to efficiently provide care to patients. Hence, several research studies have worked on creation of ICPs (Kitchiner and Bundred, 1999; Pearson, *et al.*, 1995; Wilson, 1998; Archer, *et al.*, 1997; Wentworth and Atkinson 1996; Willis, *et al.*, 2000). As a result, ICPs are implemented in predominantly used in hospital to reduce and control care delivery variations in providing care to patients (Panella, *et al.*, 2003). However, effectively implementing ICPs in hospital is often associated with problems due to large variations *from* care pathway. These variations *from* care pathway are largely unnecessary and lead to longer waiting times, delays, and lower productivity of care pathways. For example, patient diversion from care pathway to non-specialty medical units, which compromises the care delivered to patients, is a type of unwarranted variations *from* care pathways. Therefore, pathway variations analysis (PVA) methodology is proposed in Chapter 7 to identify, model and suggest improvements which reduces unwarranted patient diversions or variations *from* care pathway leading to performance improvement. The PVA methodology involves accurate and scalable RAD models of care pathways together with EPR and historic data to identify & simulate variations *from* care pathway for productivity improvements.

Detailed discussions and literature on each of the limitations, discussed in this Chapter and illustrated in Table 2.1, is presented in Chapter 3.

CHAPTER 3: Literature Review

This Chapter builds on the research limitations and research gaps discussed in Chapter 2. Chapters 1 and 2 highlighted the research gaps and discussed about the need to develop methodologies for (see Fig. 1.1 and Table 2.1): (i) service system modelling to accurately model healthcare processes; (ii) modelling and analysis of UV on a care pathway using Discrete Event Simulation (DES) integrated with accurate static service delivery system model; (iii) modelling and analysis of UV from a care pathway, such as, role variations during a care pathway based on tracking information; and, (iv) modelling and analysis of UV from a care pathway, specifically, patient variations (diversion) from a care pathway.

This Chapter mainly discusses literature reviews for each of the aforementioned methodologies in following sections. Section 3.1 discusses the literature in the area of service delivery system modelling and suitability of role activity diagrams (RAD) for accurate modelling of service processes in service systems. Section 3.2 discusses literature in the area of development of DES models for analysis of UV *on* a care pathway, which leads to the need for integrating accurate process models together with quantitative data for simulations (listed under Part I: Reducing UV *on* a Care Pathway). Section 3.3 specifically discusses about UV *from* care pathway and highlighting the need for using accurate and scalable process models. Section 3.3 is then divided into Sections 3.3.1& 3.3.2, which discusses literature reviews in the area of modelling and analysis of two types of UV *from* a care pathway in service systems (listed under Part II: Reducing UV *from* a Care Pathway), namely: *role variations*; and, *patient variations*.

3.1 Service System Modelling to accurately model healthcare processes

This section discusses the literature review in the area of service delivery system modelling illustrated as item 1 in Fig. 1.1.

Many departments in hospital are struggling to manage the increased demand for patient care and reduce wait time for patients to get access to care such as radiology department (Boland, 2006). Hence, there is considerable interest on improving efficiency of service delivery processes within service systems.

The initial step for improving the service delivery system is to acquire thorough procedural knowledge about the process chiefly related to how things are done (Shadbolt and Milton, 1999). This information is complex and frequently qualitative in nature. Traditionally, procedural information in hospitals come from IT systems, manual records maintained by clinical staff, clinician interviews, time and motion studies and subject matter experts (Crabbe *et al.*, 1994; Miller *et al.*, 2006; 2008; White, 2005a, 2005b).

Information derived from the aforementioned sources is generally utilized to build flowchart-based process models (Crabbe *et al.*, 1994), data flow diagrams (Stevens *et al.*, 1974) for analysis and improvement. However, modelling complex service delivery process in service departments based on workshops, brainstorming sessions and discussions with clinical staff can be challenging. This is partly due to the fact that some of the important information about the service can be missed during discussions with staff thereby resulting in inaccurate process model. Furthermore, traditional methods for developing process models from the qualitative data are also inefficient and do not provide scalable process representations. Therefore, it is necessary to have a rigorous methodology for effective qualitative data gathering and handling it for service delivery system process representation (Stead and Lin, 2009).

Several studies have explored models such as flowcharts (Crabbe *et al.*, 1994), data flow diagrams (Stevens *et al.*, 1974), Integrated Definition for Function Modelling (IDEF, Stacciniet *al.*, 2006); and value stream mapping (Rother and Shook, 2003) to examine service delivery process for efficiency improvements, analysis of clinical information systems, and information systems requirements. The details about each of the workflow modelling techniques and their suitability for modelling healthcare processes are discussed in the following paragraphs.

Data Flow Diagrams (DFDs) represents the flow of data within a system and are useful in illustrating information/data flows; activities changing the information; and information storage (Stevens *et al.*, 1974). These models are easily understood and verified. However, DFDs are unable to represent the flow of entities such as patients, and staff within the process, which are useful for healthcare service delivery process modelling and analysis.

Flowcharts are graphical representation of the process in the form of sequences (Crabbe *et al.*, 1994; Lakin, 1996). The process model based on flowcharts represents the process as a sequence of actions and can be easily created with the help of less number of notations. Flowcharts tend to become big when modelling complex processes and hence, these are largely used for high level modelling of the process. Furthermore, a flowchart does not describe the responsibilities or performers.

Process modelling based on the methods described under Integrated Definition for Function Modelling (IDEF) family are mostly focused on IDEF0 and IDEF3 (Aguilar-Savén, 2004). IDEF0 indicates the high level functions of a process illustrating input, output, control, and mechanism associated with each function. Owing to strict rules and notations these are used in computer software. Major limitation associated with IDEF0 based process modelling is that it often tends to be interpreted as a sequence of function or main activities. In addition, an IDEF0 model defines the functions of the process and does not illustrate how the process works. IDEF3 is used to capture the behavioural aspect of a process. It utilizes two modelling methods: (*i*) process flow diagram (PFD) to show how process actually work; and (*ii*) object state transition description (OSTD), which models the object's state transitions within a process. Hence, IDEF3, unlike IDEF0, can describe the process behaviour. However, modelling based on IDEF3 requires lot of data and many partial diagrams when modelling a complex process.

Value stream mapping (VSM) is used in Lean healthcare projects to model the processes (Rother and Shook, 2003). Value stream maps models the process into sequential steps defining process flow and classifies them into value and non-value added steps. Furthermore, VSM maps material and information flows of the process to highlight the bottlenecks. Due to the strong ability of VSMs to represent the process in sequential steps, it has been predominantly utilized in high volume sequential processes. However, in case of processes involving high variety and low volumes VSM tend to become cumbersome in development and frequently unrealistically oversimplify the service delivery system. The service delivery processes in healthcare are largely characterized as collaborative (non-sequential) process and having large process variations. Therefore, sole use of VSM for process modelling in healthcare improvements is often associated with challenges for effective unwarranted variations root cause analysis.

In this thesis, role activity diagram (RAD) is utilized for representing the healthcare service delivery processes. RAD provides graphical representation of the process based on individual roles emphasizing on their responsibilities and interactions (Ould, 1995; 2005). RADs have been shown to be particularly useful in supporting communication. They are easy to understand and present anaccurate and detailed view of the process having multiple interacting roles. They describe how a role object changes state as a result of actions and interactions. Further, RADs can represent sequential, parallel and collaborative processes in detail with the help of multiple interacting roles. Hence, RAD provides a viable opportunity to represent the activities and interactions that are typical in service delivery process in service delivery systems. Therefore, Chapter 4proposes a formal methodology for analysing the staff interviews for efficient and effective RAD-based service delivery system modelling. The methodology gathers the qualitative data about the process from staff interviews, elicits the relevant procedural terms from interviews, and relates the elicited terms to represent the process based on RAD. Hence, RAD modelling methodology proposed in Chapter 4 not only represents service delivery process based on RAD but also utilizes qualitative interviews for modelling and analysis.

Table 3.1 classifies various state-of-the-art process modelling methods based on their ability to graphically represent the service delivery process and their efficiency in capturing and representing the procedural knowledge. The shaded cells of the table represent some of the shortcomings of these methods. However, in comparison, a

RAD-based modelling methodology provides greater opportunities for improving image service processes. It can reduce the overall time needed by improvement projects to gather data and develop models of the service delivery process. Therefore, Chapter 4explores RAD for improving the efficiency of imaging services due to the advantages presented in RAD models.

Table 3.1: Classification of process modelling methods for efficiency improvement in service delivery system

Capability / Methods	Service delivery process representation			Modelling and analysis efficiency
	Type	**State transitions**	**Collaborative processes**	
Data Flow Diagrams	Data flow (-)	No (-)	No (-)	No (-)
Flowchart	Sequential flow of actions (+)	No (-)	No (-)	No (-)
IDEF0	Structural process flow (+)	No (-)	No (-)	No (-)
IDEF3	Behaviour of the system (+)	Yes (+)	No (-)	No (-)
Value Stream Mapping (VSM)	Sequential process flow (+)	Yes (+)	No (-)	No (-)
Role activity diagrams (RAD)	Graphical view of roles and their actions (+)	Yes (+)	Easily represents the collaborative processes (+)	No (-)
RAD based Service System Modelling (Proposed in Chapter 4)	Graphical view of roles and their actions (+)	Yes (+)	Easily represents the collaborative processes (+)	Yes. Methodology is proposed in Chapter 4 (+)

The information about classification capability of process modelling method is as follows:

A. <u>Service delivery process representation</u>: It classifies the process modelling methods based on their ability to graphically represent the service delivery process. This aspect for classification is required as it defines the graphical representation of service delivery process which is critical when analysing the resulting model for efficiency improvements. The service delivery process representation is further classified into:

1. *Type*: It is useful in initial screening of the process modelling methods to represent service delivery process. In order to create the service delivery process model, the process modelling method must be able to detail how the process is being carried out.

2. *State transitions:* As the service delivery process includes various state transitions during the flow, hence it is necessary for the modelling method to have the capability to represent such state transitions.

3. *Collaborative processes*: The imaging service delivery process is considered to be collaborative in nature, *i.e.*, involve individuals collaborating or interacting with each other to deliver services to patients. Hence, the modelling method must be able to represent the interactions among various members of staff involved in imaging service delivery process.

B. <u>Modelling and analysis efficiency</u>: It classifies the process modelling methods based on the efficiency or time involved in capturing and representing the procedural knowledge of the service delivery process model.

Based on abovementioned discussions, RAD is identified to be suitable method for modelling healthcare service delivery processes. A modelling methodology based on interviews to represent service delivery processes as RAD is proposed for improving the modelling and analysis steps in Chapter 4. Next section discusses about the literature in the area of integration of accurate RAD-based service delivery system model with the discrete event simulation modelling for healthcare process improvements, *i.e.*, identifying unwarranted variations *on* care pathways such as bottlenecks, throughput, length of stay, and others (please see item 2 in Fig. 1.1).

PART I: Reducing Unwarranted Variations *on* a Care Pathway

The main objective of this part is to discuss the literature in the area of modelling and analysis of unwarranted variations *on* a care pathway using Discrete Event Simulation (DES) integrated with accurate static service delivery system model (based on RAD) as input instead of oversimplified workflow models currently used as input to DES. As discussed in Chapter 1 (see Fig. 1.1) and Chapter 2 (see Table 2.1), for effective DES modelling and analysis, accurate process models of service systems together with the quantitative data is required. Following section details approaches used in literature in the area of DES modelling in healthcare and their limitations.

3.2 Modelling and Analysis of UV *on* a care pathway using DES integrated with accurate service system model

This section discusses the literature review in the area of service delivery system modelling illustrated as item 2 in Fig. 1.1.

Reducing UV *on* a care pathway for improving the efficiency of service delivery systems entails several challenges including optimum allocation and utilization of resources such as medical staffing; reduced non-productive (non-value added) time periods such as patient waiting time; efficiently identifying and eliminating bottlenecks in the service delivery pathway; and streamlining patient flow across the service department. The majority of the research studies in service delivery system improvements have employed process models such as flowcharts (Crabbe *et al.*, 1994), Integrated Definition (IDEF0) (Staccini, *et al.*, 2006), role activity diagrams (RAD) (Shukla, *et al.*, 2009), data flow diagrams (Stevens *et al.*, 1974) and value stream mapping (Rother and Shook, 2003). These process models are used to document and support service delivery processes in a consistent and uniform manner. Such models aim to support the analysis of a service delivery processes and help in identifying basic problems in achieving the aims of the process. Unfortunately, these static models need to address specific dynamic properties (the behavioural aspects, when things are done) if they are going to be useful in helping improvement experts to predict and understand the implications of change and therefore assist in the making of better decisions.

Few studies related to process improvement have employed DES for analysing the service delivery processes (Lu, *et al.*, 2007; Stemberger, *et al.*, 2004, Hlupic and Robinson, 1998). The behaviour of the service delivery system under varying system parameters and scenarios can be studied using simulation modelling. It enables process improvement experts to analyse various improvement scenarios that do not yet exist. Hence, simulation is a tool by which current service delivery processes can be understood and any improvement changes can be proposed and analysed beforehand. Once a simulation model of the existing service delivery process is developed, various "*what if*" questions can be investigated to predict the performance of process produced by change.

Recently, various simulation software for simulation modelling have improved the application of simulation modelling in process improvements. However, process improvement experts perceive simulation modelling as a complex tool and hence rarely used these techniques for analysis (Harrel, 1996; Hulpic, 1998). In fact, less than 10% of the process improvement studies involved simulation modelling tools (Hulpic, 1998). The main reasons for the lower number of application of simulation modelling tools in process improvement areas (Gladwin and Tumay, 1994; Lingineni *et al.*, 1995): (a) fewer capabilities for integrating simulation software and accurate process modelling approaches, b) extensive simulation modelling expertise necessary to build simulation models, c) use of both, the domain expert and the simulation analyst in the modelling process. About half of the process improvement projects failed to deliver the expected benefits (Hammer and Champy, 1994). This can be explained by the lack of tools to evaluate the (redesigned) process performance before its implementation (Paul, *et al.*, 1998). Otherwise, any challenges arising from the process improvement will only appear once the redesigned processes are implemented, which is costly to correct. Thus, it is necessary to understand and assess how the process will behave when changes have been made before actually implementing them. Following paragraphs details common process modelling methods and discrete event simulation approaches used in literature for process improvements in healthcare.

Number of research studies related to improving the service delivery processes in healthcare involving tools such as process mapping and discrete event simulation (Shukla, *et al.*, 2009; Staccini, *et al.*, 2006; Duguay and Chetouane, 2007; Molema, et al., 2007; VanBerkel and Blake, 2007). Researchers in different domains have utilized tools from their areas such as business processes, operations research and industrial engineering for improving service delivery processes. Each of them has some advantages, which can be utilized to improve processes. However, there is lack of interdisciplinary approaches that integrates the above mentioned methods for analysis and suggesting process improvements (Kettinger, *et al.*, 1997; Lingineni, *et* *al.*, 1995; Stemberger, *et al.*, 2004, Hlupic and Robinson, 1998).

In general, qualitative information about service delivery systems is utilized to build process maps of the care process based on flowcharts (Crabbe *et al.*, 1994), data flow diagrams (Stevens *et al.*, 1974), RAD (Shukla, *et al.*, 2009; Patel, 2000), Integrated Definition for Function Modelling (IDEF, Stacciniet *al.*, 2006); value stream mapping (Rother and Shook, 2003) to examine service delivery systems for efficiency improvements, analysis of clinical information systems, and information systems requirements. However, the resulting process models from these approaches are static, which lack the ability to analyse different improvement scenarios.

Numerous research studies have utilized dynamic models based on DES to analyse service delivery systems (Duguay and Chetouane, 2007; Molema, et al., 2007; VanBerkel and Blake, 2007). The discrete event simulation model allowed building dynamic models of the service delivery process. Simulation models of the process are utilized to incorporate various scenarios and analyse them with a view to identifying any bottlenecks or inefficiencies. The majority of these simulation models used for modelling service delivery processes in hospitals were developed based on simplified flow diagrams available in most of the commercial DES software packages such as ARENA, FlexSim, and WITNESS. Although, these simulation models were conveniently built in commercial software packages, however, the flow diagrams used as input were not suitable to represent complex healthcare service delivery systems. This is largely due to the fact that input flow diagrams used of DES modelling are not <u>accurate</u> enough to model the complex healthcare service delivery system processes (as discussed in Section 3.1). The <u>accurate</u> process model helps to identify and represent complex interactions and relations between clinical staff, equipments and patients; which can be used as input for the DES to address adequately the issues of UV *on* a care pathway such as low throughputs, bottlenecks, long wait times, and low resource utilization. Therefore, DES models based on accurate service system model or RADs (discussed in Section 3.1) are needed to effectively and efficiently analyse UV *on* a care pathway.

The aforementioned review of process mapping and DES modelling approaches suggests that it is inappropriate to use any of these approaches alone for process improvements. The use of process modelling alone lacks the ability to analyse and predict the behaviour of processes in case of process changes. On the other hand, simulation models utilizing flow diagrams fail to capture the inherent complexity of the service delivery processes. The information provided by both of these methods complements each other and therefore needs to be integrated for detailed analysis of the processes. Table 3.2 classifies process improvement approaches in the areas of process mapping and discrete event simulation.

Table 3.2: Classification of the approaches used for process improvement

Approaches / Type of analysis		Static analysis	Dynamic analysis
Process Mapping	Flowcharts	Crabbe *et al.*, 1994; Stevens *et al.*, 1974; Stacciniet *al.*, 2006; Shukla, *et al.*, 2009;	-
	IDEF0 & IDEF3		
	Value Stream Mapping (VSM)		
	RAD		
Discrete event simulation (DES)		-	Duguay and Chetouane, 2007; Molema *et al.*, 2007; VanBerkel *et al.* 2007
RAD-based service delivery system model used as accurate input model for the DES simulations		**(Proposed in Chapter 5)**	

The majority of the simulation models rely on simplified flowchart of the patient flow obtained based on on-site observations and interviews, complemented with historic patient data (Duguay and Chetouane, 2007; Molema *et al.*, 2007; VanBerkel *et al.* 2007). However, the resulting workflow model is insufficient in representing the inherent complexity of the process to be modelled. The important interactions between clinical staff, equipment and patients can be missed in simplified models causing the resulting models to be often incomplete and unrealistic. Therefore, role activity diagram (RAD) is used to accurately and efficiently model complex service delivery systems from raw data about the process such as staff interviews (Shukla, *et al.*, 2009). Furthermore, the accurate input service delivery process model will also require more quantitative data, which are coming from EPRs, historic system data, and tracking information. Therefore, Chapter 5discusses a methodology which not only utilizes RAD-based service delivery system model as accurate input model for the DES simulations, but also proposes a data model which can help to use heterogeneous service related data.

Next section discusses about the literature review related to unwarranted variations *from* a care pathway.

PART II: Reducing Unnecessary Variations *from* a Care Pathway

The main objective of this part is to develop methodologies to address two types of UV *from* a care pathway, namely, (i) *role variations*; and (ii) *patient variations* or diversion from care pathway. As discussed in Chapter 1 (see items 3 and 4 in Fig. 1.1) and Chapter 2 (see Table 2.1), the following sections will discuss about the unwarranted variations *from* care pathway and approaches used in the literature to deal with these. Section 3.3 discusses about the causes of UV from care pathways leading to the need for the methodologies to deal with: *role variations* based on tracking information (discussed in Section 3.3.1) and *patient diversion* from care pathway (discussed in Section 3.3.2).

3.3 Modelling and analysis of UV due to patient getting diverted ***from*** a care pathway

Service units in hospital generally operate solely as a service provider to other units in hospital such that it supports care delivery to patients together with other departments. This results in most hospital departments being affected by variations that frequently originates in other department as well as compounding its own variations. Increasingly, efforts are made in literature on analysing the variations sources in service departments thereby streamlining their services (Meitzner and Trewn, 2006; Roobottom, *et al.*, 1995; Hydo, 1995). The main sources of variations in the units are due to: (i) variations in clinician practices; (ii) patient characteristics (number of patients, demographics, mix, diagnosis, and severity); (iii) system variations (resource availability variations, patient and staff scheduling, changeovers/setups of complex equipment); (iv) input/output variations (patient scan request arrival variations, discharge variations). These variations in the case of service department are illustrated in Fig. 3.1.

In particular, the variations in clinician practices includes the methods, techniques, experience utilized by the clinicians to deliver services to patients. The variation associated with the patient characteristics can be due to patient related care choices and demographics among other factors. System variations can arise from resource availability (procedure rooms, beds, doctors, nurses, equipment) and changeovers/setups between consecutive patients. Furthermore, the input/output variations in service department arise due to the patient arrival patterns, and delivery patterns of the service departments. To highlight these variations in service delivery system, not only an accurate process modelling method is required but also method that is scalable. Scalability of RAD models will be important to identify and understand the sources of these unwarranted variations *from* care pathway. Therefore, it is necessary to define variations that can be identified based on the scalability of RADs. Following text details the classification of variations and their types in detail with the help of RADs.

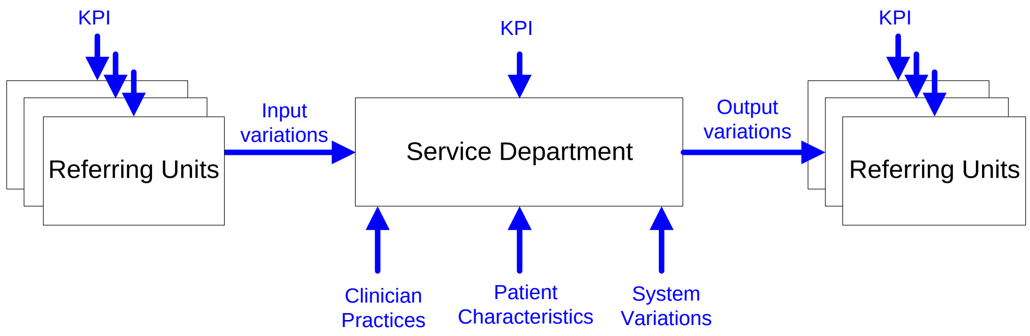


Figure 3.1: Variations sources in service department

Variations in service delivery systems can be represented based on RAD concepts are illustrated in Table 3.3. It defines various types of variations based on RAD concepts such as: *role variation*, *activity variation*, *interaction variation*, and, *time variation*, *patient variation*.

1. The *role variation* occurs when

a. there is unavailability of certain types of roles. These variations results in other roles taking up the additional responsibilities leading to unwanted delays in delivery of services.

b. a role deviates from sequence in which role normally visits rooms/areas for delivering their share of services. These variations are mainly caused when there is unavailability of certain resources (roles searching for resources in various rooms/areas). Generally, *role variations* are a part of system variations leading to unwanted delays within service delivery systems.

Table 3.3: Classification of variations based on RAD concepts

Type	**Interpretation**	**Example (in Radiology)**
Role variation **(Chapter 6)**	These type of variations occurs when there is a staff unavailability or when there is change in staff within a role	Absence of staff such as radiology nurse, clinical consultants
	These variations occur when roles traverse different areas while delivering services	Nurse has to traverse different areas when a wheelchair is unavailable
Activity variation	It mainly occurs when one/ multiple activities are changed or not performed while delivering care to patients	Giving sedation injections to claustrophobic patients for calming anxiety
Interaction variation	These variations occur when interactions are not done or different interactions are performed	Radiology assistant not assisting outpatient to get dressed
Time variation	These type of variations occur when the duration of activities are changed	New radiology technologist takes more time for scans
Patient variation **(Chapter 7)**	These variations occurs when key decision about patients varies which have significant impact on a service system	Stroke patients diverted to non-specialised wards after A&E due to poor decision making

2. *Activity variations*, *interaction variations* occurs when certain activities and interactions varies within a service delivery process change.

3. *Time variations* are mainly when durations of activities or interactions takes longer/shorter time than normal.

4. *Patient variations* occur when certain critical decisions related to patients care varies within a service delivery system. Largely, these variations results in higher unnecessary variations from care pathway and thus resulting in lower productivity of overall service delivery system. These variations are largely due to decision makers, decision making processes, interactions with the other service departments, and resource availability.

Based on abovementioned classification of variations within service departments in hospital, two subsections are detailed each for illustrating state-of-the-art research in variations modelling (each of the following subsection relates to Chapter 6 and Chapter 7).

3.3.1 Modelling and analysis of UV of standard operating service delivery processes, specifically, role variations during a care pathway based on tracking information

This section discusses the literature review in the area of service delivery system modelling illustrated as item 3 in Fig. 1.1. This subsection aims at classifying literature for identifying *system variations* in a service delivery system, therefore, only *role variations* are considered (see Table 3.3).

Realizing improvements in service departments require modelling and analysis of the service delivery system. A number of studies have dealt with modelling/mapping issues of the service delivery system based on information gathered through clinician workshops, interviews and discussions aimed at suggesting process improvements (Crabbe *et al.*, 1994; Jimmerson *et al.*, 2005; Dickson *et al.* 2008; Shukla *et al.*, 2009; Patel, 2000; Staccini *et al.*, 2006). These approaches model the most standard process followed while modelling service delivery system. However, modelling the most standard process is useful when the service unit has only one way of performing activities. Such systematic and controlled processes are predominant in manufacturing sector where majority of processes have a specific way of performing activities. On the contrary, departments in any hospital are usually fast-paced and characterized by uncertainties. Consequently, any improvement provision must first start with the development of a model which can reliably represent process variations in service delivery system.

Table 3.4 presents current literature in the area of process improvement applied in various areas of healthcare service departments. In particular, approaches used in literature can be broadly grouped under service delivery system modelling for process improvements. Approaches in this category are focussed on modelling the most standard process for service delivery. Furthermore, service delivery system modelling relies on identifying all the steps and decisions in a process in diagrammatic form, which is then used for improvement purposes. It describes the flow of information, patients, and staff; decisions made for delivering services; and the essential inter-relationships and interdependence between the process steps. Commonly used approaches in this category are Flowcharts (Crabbe *et al.*, 1994), Integrated DEFinition (IDEF, Staccini *et al.*, 2006), Value Stream Mapping (VSM, Jimmerson *et al.*, 2005, Dickson *et al.* 2008), and RAD (Shukla *et al.*, 2009, Patel, 2000). However, these approaches do not consider modelling of *system variations* such as *role variations* for process improvements.

There are research studies that are focussed on identifying the inefficiencies of the nursing care based on time and motion studies (Hendrich *et al.*, 2008, Hendrickson *et al.*, 1990, Quist, 1992). Hendrich *et al.*, (2008) utilized personal digital assistants

(PDAs), and radio frequency identification (RFID) tags to record time spent by nurses on several care-related activities. This information was then utilized for improving nursing care in hospitals. These studies illustrate time variations with the nursing care and do not deal with the process modelling aspect. Recently, Value Network Mapping (VNM) has been used in modelling business processes at organizational level (Allee, 2002, 2008). VNM models complex business processes in the form of value chain networks including roles, deliverables, and transactions. In VNM, the process is represented in the form of networks illustrating several interacting roles for creating/adding value to the input. VNM is used to model the macro level business processes involving complex interactions in an organization. Further, VNM has the limitation to represent activities performed within each roles involved within service delivery system. Hence, VNM tries to model complex networks at the macro level of details within organization. Hence, these are not included for classification of the approaches in literature in Table 3.4.

Table 3.4: Literature review on the approaches for analysis of UV *from* care pathway

Strategy	Classification			Literature
	Approach	Data gathering		
		Procedural knowledge	Quantitative knowledge	
Service delivery system modelling	Flowchart	-	IT systems, manual records	Crabbe *et al.*, (1994)
	IDEF	-	"	Stacciniet *al.*, (2006)
	VSM	Workshop discussions	Stop watch	Rother and Shook, (2003), Dickson *et al.* (2008), Jimmerson et al., (2005)
	RAD	Individual interviews	"	Shukla *et al.* (2009), Patel, (2000)
Role Variations modelling	Role Variations Analysis	RAD	RTLS based tracking data	**Proposed in Chapter 6**
Patient Variations modelling	Pathway Variations Analysis (PVA)	RAD	Hospital IT systems data, Electronic Patient Records (EPR)	**Proposed in Chapter 7**

As described in Table 3.4, Chapter 6 proposes the variation modelling methodology which models *role variations* occurring within the service delivery system. The *role variations* are mostly reflected in most frequently adopted role paths (*i.e.* sequences of rooms/areas visited by a role for delivering services), which can be electronically tracked, based on the real time tracking systems (RTLS). RTLS allows tracking of roles in service systems and storing the tracking events (*tagID, roomID, time*) in the database which can be analysed to model role variations. Therefore, modelling methodology in Chapter 6 utilizes real time locating system (RTLS) data about paths adopted by roles while delivering imaging services. Nevertheless, it is crucial to identify and reduce system variations which are largely unnecessary and result in longer waiting times and delays.

Next subsection details the literature in the area of modelling and analysis of variations from complex patient care pathway resulting due decision variations.

3.3.2 Modelling and analysis of unwarranted variation of standard operating service delivery processes, specifically, patient variations (diversion) from a care pathway

This section discusses the literature review in the area of service delivery system modelling illustrated as item 4 in Fig. 1.1.

Variations are identified to be major challenge in healthcare systems (Vayda, 1973; Birkmeyer, *et al.*, 1998; Groff, *et al.*, 2000; Smith, 1991). These variations are often linked with the medical errors in care delivery (Sanwlippo and Robinson 2002). Weingart, *et al.*, (2000) estimated that medical error results in 44000–98000 unnecessary deaths each year in US. Therefore, reducing care variations by standardizing care delivery processes in healthcare systems or developing & implementation of integrated care pathway (ICP) is identified to be an effective approach (Kitchiner and Bundred, 1999; Pearson, *et al.*, 1995; Wilson, 1998; Archer, *et al.*, 1997; Wentworth and Atkinson, 1996; Willis, *et al.*, 2000).

Integrated care pathway (ICP) is a structured multidisciplinary outline of anticipated care plans which details the steps in the care of patients with specific clinical condition or set of symptoms (Campbell, *et al.*, 1998). ICP generally involves multidisciplinary communication among several speciality units in hospital to efficiently provide care to patients. Hence, several research studies have worked on creation of ICPs (Kitchiner and Bundred, 1999; Pearson, *et al.*, 1995; Wilson, 1998; Archer, *et al.*, 1997; Wentworth and Atkinson 1996; Willis, *et al.*, 2000). As a result, ICPs are implemented in predominantly used in hospital to reduce and control care delivery variations in providing care to patients (Panella, *et al.*, 2003). However, effectively implementing ICPs in hospital is often associated with problems due to large variations from care pathway. These variations *<u>from</u>* care pathway are largely unnecessary and lead to longer waiting times, delays, and lower productivity of care pathways. For example, patients diversion from care pathway to other medical units, which compromises the care delivered to patients. Therefore, variations from care pathway are crucial for improving the overall performance of care pathway in hospital. Hence, Chapter 7 develops an approach for pathway variations analysis to reduce variations from care pathway for effective and efficient use of complex care pathway in hospital.

The research on identification of variations from care pathways and pathway improvements are limited. Majority of research studies are focused around developing and implementing integrated care pathways within hospital rather than identifying variations from pathway when care pathways are implemented in the hospital (Wilde, 2009, DoH 2006; 2010; Wentworth, *et al.*, 1996; Campbell, *et al.*, 1998). In following paragraphs, issues in care pathway improvements (variations *<u>on</u>* a care pathway) are classified and approaches used in literature for addressing those issues are discussed.

Several issues in improving care pathways based on reducing variations *<u>on</u>* a care pathway have been identified in literature. These issues can be broadly classified into: (i) process redesign and communication; (ii) diagnostic accuracy; and, (iii) efficiency improvements or optimum resource utilisation (see Table 3.5).

Table 3.5: Review of the approaches used in care pathway improvements

Issues \ **Approaches**		**Pathway Modelling**	**Clinical Tests**	**Hospital Operations Simulation**
Variations *<u>on</u>* a care pathway	Process redesign and communication	Crabbe, et al., 1994, Stevens, et al., 1974, Staccini, et al., 2006, Rother and Shook, 2003, Patel, 2000; Shukla, et al., 2009	-	-
	Clinical accuracy	-	Harbison, et al., 2003; Mohd Nor, et al., 2005; Kasner, et al., 1999; Kobayashi, et al., 2009; Chalela, et al., 2007; Wardlaw, et al., 2004	-
	Efficiency improvements /optimum resource utilisation	-	-	Duguay&Chetouane, 2007; Molema, et al., 2007; VanBerkel and Blake, 2007; Bayer, et al., 2010; Dodds, 2005; Connelly & Bair, 2004; Kotiadis& Mackenzie, 2004; Davies, et al., 2002; Brailsford, et al., 2006
Variations *<u>from</u>* a care pathway		**Pathway Variations Analysis (Proposed in Chapter 7)**		

Issues related to process redesign and communications are commonly studied in healthcare literature (Crabbe, *et al.*, 1994; Staccini, *et al.*, 2006; Shukla, *et al.*, 2009; Mould, *et al.*, 2010). Process redesign generally involves review of current processes used in patient pathway before suggesting improvements. The review of existing processes are performed based on the process mapping approaches, which are finally used for process redesign, process documentation, training and communication about existing processes among staff.

Improving diagnostic accuracy for identifying and treating appropriate sub-group of patients within care pathways is identified to be major issue for pathway improvements. Several studies have been conducted by designing and assessing clinical tests to improve diagnostic accuracies (Harbison, *et al.*, 2003; Mohd Nor, *et al.*, 2005; Kasner, *et al.*, 1999; Kobayashi, *et al.*, 2009). This helps in the performance of care pathway by identifying appropriate sub-group of patients for treatment care.

One of the other issues in improving care pathways is optimum utilization of resources for efficiency improvements. This issue have been tackled in previous research studies to develop a prototype model in healthcare for resource planning, bottleneck analysis, and exploring improvement alternatives for care delivery (Bayer, *et al.*, 2010; Dodds, 2005; Connelly and Bair, 2004; Kotiadis and Mackenzie, 2004). It involves simulation modelling of care delivery, which is then used as a decision making tool for different types of scenario based analysis and determining its impact on overall performance.

Several types of approaches are used in literature for solving issues related to variations on care pathway such as process redesign, diagnostic accuracies, and optimum utilisation of resources. The approaches used to address abovementioned issues are then broadly classified into: (i) care pathway modelling; (ii) clinical tests; and, (iii) hospital operations simulation modelling. Pathway modelling refers to the approaches dealing with service delivery system modelling for process redesign. Approaches related to clinical tests deals with the development & assessment of clinical tests for accurate identification of sub-group of patients for treatment in care pathways. Hospital operations simulations approaches deals with the discrete event simulation modelling and analysis of the care delivery. However, there is no approach that deals with the analysis of variations from care pathway. In following paragraphs we discuss more about the abovementioned approaches and their limitations.

Approaches used in care pathway modelling rely on identifying detailed process steps in a care delivery process in diagrammatic form, which is then used for process redesign, documentation, and improvement purposes. Process model describes the flow of information, patients, and staff; decisions made for delivering services; and the essential inter-relationships and interdependence between the process steps. Several studies have explored models such as flowcharts (Crabbe, *et al.*, 1994), data flow diagrams (Stevens, *et al.*, 1974), Integrated Definition for Function Modelling (IDEF, Staccini, *et al.*, 2006); value stream mapping (Rother and Shook, 2003); and role activity diagram (Shukla, *et al.*, 2009) to examine service delivery system for improvements, analysis of clinical information systems, and information systems requirements (see Table 3.5). Shukla, *et al.*, (2009) have proposed that RAD is suitable for service delivery system in healthcare. However, process modelling and redesign alone will have challenges in suggesting overall improvements for care pathways which includes disease specific clinical decisions and hospital operational attributes.

The majority of research in improving care pathways is related to developing effective and efficient clinical tests for accurate diagnosis of patients. Some of the clinical tests involved in complex care pathway such as stroke are FAST (Face Arm Speech Test; Harbison, *et al.*, 2003), ROSIER (Recognition of Stroke in the Emergency Room; Mohd Nor, *et al.*, 2005), NIHSS (National Institute of Health Stroke Scale; Kasner, *et al.*, 1999), OCSP (Oxfordshire Community Stroke Project clinical classification, Kobayashi, *et al.*, 2009), CT/MRI scan (Chalela, *et al.*, 2007; Wardlaw, *et al.*, 2004). These clinical tests are developed with a view to reduce delays in accurately identifying relevant sub-group of patients for treatments using care pathway (see Table 3.5). Reducing delays and accurate diagnosis is necessary in providing access to organized care and initiation of treatment in any care pathway. These studies improves an existing or develops an individual clinical test for improving diagnostic accuracies, however, in general, multiple clinical tests and clinical decisions are involved within a pathway. Furthermore, the clinical decisions are linked with the hospital operations such as KPIs (key performance indicators), and resource utilisation. Hence, overall improvements within care pathways require an approach which considers pathway modelling, multiple clinical tests, and hospital operations.

Research studies are conducted in the literature which deals with simulation modelling of hospital operations for optimum resource utilization, reducing waiting times, LOS, improving throughput, of the care delivery processes (Duguay and Chetouane, 2007; Molema, *et al.*, 2007; VanBerkel & Blake, 2007; Bayer, *et al.*, 2010). Simulation modelling has been applied to various healthcare areas such as a vascular surgery (Dodds, 2005), Accident & Emergency (Connelly and Bair, 2004), intermediate care (Kotiadis and Mackenzie, 2004) or the evaluation of screening programmes (Davies, *et al.*, 2002; Brailsford, *et al.*, 2006). Majority of approaches are based on discrete event simulation modelling of service delivery system to develop an understanding of the impact of service improvements scenarios on the overall performance of pathway (see Table 3.5). Once a simulation model of the existing service delivery system is developed, various "what if" questions can be investigated to predict the performance of process produced by change. Simulation models of the process are utilized to examine various scenarios with a view to identifying any bottlenecks or inefficiencies. The majority of these simulation models in hospitals were developed based on inbuilt flow diagrams available in most of the commercial DES software packages such as ARENA, FlexSim, or WITNESS. Although, these simulation models were conveniently built in commercial software packages, however, initial flow diagrams used were not suitable to represent complexity within complex care pathways. This is partly due to the fact that flow diagrams are best suited to representing sequential processes rather than representing complex integrated and interacting processes common in care pathways. Therefore, use of simulation models alone in complex care scenarios can be challenging.

Researchers in domains such as pathway modelling, clinical test development, and hospital operations simulation have utilized tools from their areas such as process modelling, operations research and clinical decision assessments for reducing variations on a care pathway (see Table 3.5). Each of them has some advantages, which can be utilized to improve pathways. However, there is lack of interdisciplinary approaches that integrates the above mentioned methods for analysis of variations from the care pathway such as patient diversions from care pathway. Therefore, a pathway variations analysis (PVA) methodology is discussed in Chapter 7 that includes the pathway modelling, clinical decision assessment, and operations simulation to analyse pathway variations and suggest improvements (see Table 3.5).

In Chapter 7, Pathway variations analysis (PVA) methodology is proposed to identify, model and suggest improvements which reduces unnecessary patient diversions or variations from care pathway leading to performance improvement of a care pathway.

The next Chapter details the RAD based service system modelling methodology and its implementation on a case study involving MR scanning process of radiology in a large UK hospital.

CHAPTER 4: Service Delivery System Modelling based on Role Activity Diagram

4.1 Introduction

The process modelling of hospital processes is increasingly seen as the significant step in improving the service delivery systems (Reiner, *et al.* 2002). The generation of process models of the service delivery system in hospitals is challenging due to the complexity of the information gathering and managing activities. In-line with this, the research study in this Chapter will focus on developing process models for service delivery systems in hospital such as radiology department. Therefore, following sections discusses about challenges in radiology.

Numerous factors including better patient care, effective diagnosis, and shortage of technologist have driven up demand for imaging services (Pesavento, 2001; 2000; Williams, *et al.*, 2004). This has created considerable bottlenecks in imaging service delivery system ultimately resulting in longer patient wait time (Hillman & Neiman, 2003). Hence, radiology departments are faced with the simultaneous challenges to manage growing demand for scans while reducing wait time for the patients to get access to imaging services (Sachs, 2002; Boland, 2006). Furthermore, prohibitive costs of imaging devices often restrict radiology departments from purchasing them in an effort to enhance patient throughput and reduce waiting times. Hence, improving the efficiency of the service delivery system is emerging to be a viable step for service delivery systems such as radiology departments (Crabbe, *et al.*, 1994; Reiner, *et al.*, 2002; Boland, 2006, Boland, *et al.*, 2008; Aben, *et al.*, 2004; Wendler&Loef, 2004).

Service delivery in radiology departments usually involve complex imaging devices such as magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography-computed tomography (PET-CT), ultrasound, and others; along with highly specialized medical staff such as radiographers, radiologists, and radiology nurses. Healthcare professionals from different departments of a hospital request patient scans from the radiology department in order to diagnose and treat patients. As a result, a radiology department must deal with a large numbers of inpatient and outpatient scan requests on a daily basis.

While service delivery system improvement in radiology is increasingly seen as key to efficient imaging services however, to date, process improvement studies involving radiology have been few and far between. The earlier approaches in modelling service delivery system mostly relied on radiology staff workshops about their involvement in such process. While the information gathered from these workshops is useful however, there is a lack of systematic or formal methodologies for information gathering, documenting, and analysing the imaging processes in radiology department. Without a thorough understanding of accurate processes in radiology departments, developing and implementing productivity tools will be incomplete and ineffective. Therefore, this Chapter provides a systematic methodology for the development of accurate process model of the radiology service delivery system from staff interviews.

There is another research area in the literature widely known as soft operations research (OR), which focuses on problem structuring methods. These methods also utilize qualitative interviews, and discussions for cognitive modelling. Therefore, following paragraph discusses about problem structuring techniques and their comparison with proposed methodology based on individual interviews.

A number of problem structuring methodologies have been proposed in the literature which focuses on structuring the complex problems involving group of decision makers (Rosenhead 1989, Lehaney and Paul, 1996, Robinson, 2001; Mingers and Rosenhead, 2004; Kotiadis and Mingers, 2006). These approaches seek to alleviate or improve situations characterised by uncertainty, conflict and complexity by utilizing discussions, interviews, and workshops about the problem. Strategic options development and analysis (SODA) is one of the problem structuring methods that uses individual's views about the problem situation and develops a cognitive maps of their viewpoint (Rosenhead 1989). These maps are merged together to provide a framework for group discussions and facilitates the analysis of the problem. This methodology is used in various areas for problem structuring such as modelling claim for damages (Ackerman, *et al.*, 1997; Williams, *et al.*, 1995). However, these approaches are applied usually in the situations when a definite scope and different aspects of the process is undefined which is usually characterized by conflicting, uncertain, and complex objectives of the decision makers. Therefore, the proposed methodology is focussed on conceptually mapping complex service delivery process rather than structuring the problem.

The rest of this Chapter is arranged as follows. Section 4.2 details the background of the role activity diagram (RAD) and the proposed approach for efficient RAD model generation based on semi-structured interviews of the key staff. In Section 4.3, the development of software tools for RAD model generation and analysis of radiology department is detailed. Section 4.4 discusses a case study of MR scanning process at the radiology department of one large UK hospital. Section 4.5 provides the comparisons between various process modelling techniques for healthcare processes. Section 4.6 provides applications of the developed RAD model of MR scanning process. Finally, conclusion and comments are presented in Section 4.7.

4.2. Qualitative Modelling of Healthcare Service Delivery System

RAD can be defined as a process modelling method originally developed for effectively modelling collaborative processes (Ould, 1995; 2005). In this study, we employed RAD for modelling service delivery process of a radiology department in a large hospital. Therefore, a clear understanding of the fundamental concepts and notations of RADs is required before any process modelling can be actually performed. Table 4.1 provides some of the fundamental concepts of RAD, general description and examples of their applications in a service unit such as radiology unit. Additionally, Table 4.1 also provides the corresponding graphical representation for each of the RAD concepts which is utilized to model the service delivery process.

In order to efficiently construct RAD model for the service delivery system, a methodology for knowledge acquisition and aggregation is required. The main steps for the RAD-based modelling methodology are illustrated in Fig. 4.1.

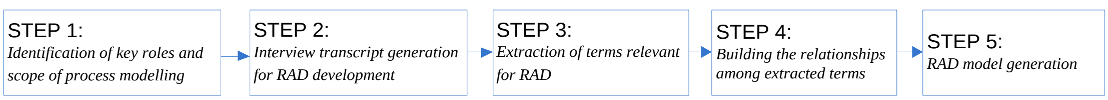
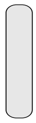
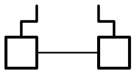
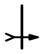
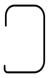


Figure 4.1: Steps involved in the RAD development methodology

Table 4.1: Role Activity Diagram concepts and its descriptions

S. No.	RAD concept	Capability type	General description	Examples in radiology department	Graphical notations
1.	*Role*	Collaboration	A role performs a set of actions in order to fulfil a particular responsibility within a process. Roles are usually performed by an individual, group of people, IT system, and machine or equipment.	*Clinical doctors, porters, nurses, technicians*	
2.	*Activity*	Sequential or Parallel process	An activity is a unit of work performed by a particular role.	*Move patient to changing room, position patient on table*	
3.	*Interaction*	Information flow or Collaboration	People collaborate in order to achieve the service delivery process objective.	*Pass X-ray of the patient from technician to radiology doctors*	
4.	*Part refinement*	Parallel Process	The part refinement symbol refers to the work done simultaneously by a role. This is graphically represented by single thread of activity dividing into parallel threads within a role.	*Patient booking, and printing patient non attendance letters*	
5.	*Case refinement*	Sequential Process	The case refinement is used to represent decision question and possible outcomes.	Decision question: *Does patient require contrast injection*? Outcome: *Yes*, or *No*.	
6.	*Trigger*	Sequential Process	Trigger is an event that starts the activity thread.	*Arrival of patient scan request*	
7.	*State*	State transitions	A state describes what is true either before or after some actions (actions can encompass activities, interactions, and encapsulated processes).	*Scan is finished, patient can have scan*	
8.	*Loop*	Repetition	The loop symbol allows a part of a process to be repeated. The iteration starts at the end of an activity and goes back to a prior activity.	*Multiple attempt to give injection*	
9.	*Replication*	Repetition	This symbol is used to define the nature of the repetition of certain activities in the process.	*Maximum two repeats in giving injections*	
10.	*Encapsulated process*	Hierarchy	The encapsulated process allows us to represent complex sub-processes as a separate diagram and indicating it as a symbol in the main diagram	*Perform patient scanning*	
11.	*Start role*	Other	This symbol is used to initiate a transient role in the main diagram.	*Patient scan request vetting by radiology doctors*	
12.	*Other work*	Other	It represents the other work that does not relate to the main process performed by the role.		
13.	*Stop*	Other	This symbol marks the end of one or more process threads.		

Step 1 of the methodology identifies the scope of the process that is to be modelled together with identifying key roles involved within the process. Step 2 focuses on conducting interviews of key roles and generating interview transcripts.

The process related features and terms are extracted in Step 3. The relationships among the extracted terms are created in Step 4 with the help of various matrices such as action-type, action-role, interaction-role and others to develop the quantitative base for RAD development. Once relationship matrices are created, the RAD model is graphically represented by following the procedure defined in Step 5. A simple example of radiology department is used in this section to illustrate each of the steps. The steps involved in the methodology are detailed below.

The following subsection describes the formal procedure that is proposed in this Chapter to model services delivery process as RAD.

4.2.1 Knowledge acquisition for qualitative modelling of healthcare service delivery processes

In this subsection, the qualitative data regarding the service delivery process is gathered which is used in next sub-section for RAD based model generations.

STEP 1: Identification of key roles and scope of process modelling

One of the main ideas behind improving the efficiency of the service delivery process is to identify and define the scope of the process that is being considered for improvement. The process for improvement is selected based on its impact on the radiology department. The key members of radiology staff involved from the beginning to the end of a selected process are chosen for interviewing in next step.

STEP 2: Interview transcript generation for RAD development

Semi-structured interviews are conducted with the key roles identified in Step 1. These interviews help to gather information about staff roles and responsibilities within the selected service delivery process. The interviews are recorded and subsequently transcribed into a written document. Section 4.4 outlines the selection of members of staff who were interviewed for our case study. Appendix II discusses a set of questions that are generally asked during semi-structured interviews for RAD modelling. Following is a briefly transcribed interview of the radiology nurse to illustrating the methodology steps:

Example 1:

> **Interview Transcript**: "*Radiology nurse will go to the patient waiting in reception, then go through a questionnaire with every patient, this is done to identify whether the patient has metal on them or not. If no metal is found, patient is allowed to change for whatever sort of scan they are having, otherwise failed consenting procedure is used.*"

4.2.2 Knowledge aggregation for quantitative model generation

In this subsection, the qualitative data, gathered in subsection 4.2.1, is used for developing RAD model of the service delivery process.

STEP 3: Extraction of terms relevant for RAD

To construct the RAD of the service delivery systems, it is necessary to have information about the roles involved, activities performed, interactions among the roles and responsibilities, decisions made, resource utilized, and other related issues. The procedural terms that are extracted from the interview transcripts are: roles, actions, decision outcomes, resources, interactions between roles, and their descriptions. The extracted terms are utilized in the next step for relationship building between terms. The main relationships are between – actions and its types, actions and roles, interaction and roles, actions and resource, and descriptions of roles, resources, and actions. The terms extracted from the interview transcript of Example 1 are as follows:

<*Radiology nurse*>, <*go to the patient*>, <*patient*>, <*go through a questionnaire*>, <*whether the patient has metal on them*>, <*allowed to change*>, <*failed consenting procedure is used*>

Where, <*term*> indicates the extracted terms from interview transcript of Example 1. These concepts are utilized in the next step for relationship building.

STEP 4: Building the relationships among extracted terms

The extracted terms in the transcripts are connected with each other in order to construct RAD of the service delivery process under consideration. Therefore, relationship matrices are constructed to relate the extracted terms. The main relationship matrices developed are:

A. Action-Type matrix (**AT**): This relates the extracted terms with the RAD notations such as activity, state, trigger, start role, case refinement, part refinement and encapsulated process. The RAD notations used in this Chapter and related description are given in Table 4.1. In this matrix, the rows represent the extracted terms defined as actions and columns represent the RAD notations. The value of the matrix attribute is 1 if the relation exists between corresponding row and column otherwise it is set to 0. Table 4.2 represents the simple case of **AT** matrix where the extracted actions are denoted as '*Action 1, Action 2,…, Action N*'. Mathematically,

$$[AT]_{ij} = \begin{cases} 1 & \text{if } \textit{Action } i \text{ is of type } j \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Table 4.2: Action-type matrix relating the actions to their types.

Action-Type	*Activity*	*State*	*Trigger*	*Start Role*	*Case refinement*	*Part refinement*	*Encapsulated process*
Action 1	0	0	1	0	0	0	0
Action 2	1	0	0	0	0	0	0
:	:	:	:	:	:	:	:
Action N	1	0	0	0	0	0	0

The **AT** matrix for Example 1 is illustrated in Table 4.3.

Table 4.3: Action-type matrix for the Example 1

Action-Type	*Activity*	*State*	*Trigger*	*Start Role*	*Case refinement*	*Part refinement*	*Encapsulated process*
<go to the patient>	1	0	0	0	0	0	0
<whether the patient has metal on them>	0	0	0	0	1	0	0
<allowed to change>	1	0	0	0	0	0	0
<failed consenting procedure is used>	0	0	0	0	0	0	1

B. <u>Action-Role matrix (**AR**)</u>: This matrix relates the extracted actions with respective roles. It establishes the relationship of action with their corresponding roles which will be helpful in drawing up the process diagrams based on the concepts of the RAD. Table 4.4.a shows the **AR** matrix where row represents the extracted terms and column represents roles. Table 4.4.a relates '*N*' actions with '*R*' roles. Mathematically,

$$[AR]_{ij} = \begin{cases} 1 & \text{if } Action\ i \text{ belongs to } j^{th} \text{ role} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Table 4.4: (a) Generic Action-role matrix; (b) Action-role matrix for Example 1

Action-Role	*Role 1*	*Role 2*	…	*Role 'R'*
Action 1	0	1	…	0
Action 2	1	0	…	0
:	:	:	:	:
Action N	1	0	…	0

Action-Role	*<Radiology nurse>*	*<patient>*
<go to the patient>	1	0
<whether the patient has metal on them>	0	1
< allowed to change>	0	1
<failed consenting procedure is used>	0	1

The **AR** matrix for extracted items of Example 1 is illustrated with the help of Table 4.4.b.

C. Interaction-Roles matrix (**IR**): This relates the interactions between two or multiple roles. The rows in the matrix represent the interactions and the columns represent the roles. Table 4.5.a denotes the format of the **IR** matrix which is constructed with the help of the interview transcripts. Interactions between roles are necessary when performing collaborative tasks and the information about all the interactions can be obtained by carefully extracting the relevant terms from the interview transcripts. Mathematically, the attribute of the matrix **IR** is defined as:

$$[IR]_{ij} = \begin{cases} 1 & \text{if } j^{th} \text{ role is a driver of } i^{th} \text{ Interaction} \\ 2 & \text{if } j^{th} \text{ role is a reciever of } i^{th} \text{ Interaction} \\ 0 & \text{Otherwise} \end{cases} \tag{3}$$

The **IR** matrix for extracted items of Example 1 is illustrated with the help of Table 4.5.b.

Table 4.5: (a) Generic Interaction-role matrix; (b) Interaction-role matrix for Example 1

Interaction-Role	*Role 1*	*Role 2*	*Role 3*	…	*Role 'R'*
Interaction 1	0	2	1	…	1
Interaction 2	1	0	0	…	0
:	:	:	:	:	:
Interaction I	1	0	1	…	0

Interaction-Role	*<Radiology nurse>*	*<patient>*
<go through a questionnaire>	1	1

D. Action-Resource matrix (**AS**): This represents the relationship between the action performed and useful resources consumed. The rows and columns in AS matrix represent the activities and resources. Table 4.6 represents the **AS** matrix for relating activities with their resources.

$$[AS]_{ij} = \begin{cases} 1 & \text{if } \mathit{Action}\ i \text{ involves Resource } j \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Table 4.6: Matrix relating activities with their resources

Activity-Resource	*Resource 1*	*Resource 2*	*Resource 3*	…	*Resource ‘S’*
Action 1	0	0	1	…	1
Action 2	1	0	0	…	0
:	:	:	:	:	:
Action N	1	0	1	…	0

The **AS** matrix for Example 1 does not exist as no resource has been extracted from interview transcript in Step 2.

E. Action-Description matrix, Role-Description matrix, Resource-Description matrix: These matrices are fairly straightforward and are used to retain the knowledge about the terms extracted from the interview transcripts. The rows represent actions, roles, and resources while column represents the description. The matrix attribute value is 1 if corresponding activity or role or resource relates to the description defined for the column; otherwise the attribute value is set to 0.

The abovementioned matrices form the quantitative data structure that is used to develop the RAD model in the radiology department.

STEP 5: RAD model generation

The matrices defined in Step 4 are used to construct the RAD of the service delivery process. In order to represent the RAD graphically, it is imperative to develop a RAD concept library (**T**) which constitutes the RAD graphical notations (illustrated in Table 4.1). The RAD concept library **T** is defined as:

$$\mathbf{T} = (t_1, t_2, t_3 \cdots t_{13}) \qquad (5)$$

Each of the elements in **T** signifies a distinct notation in RAD and there are in total 13 notations. Role symbol is defined by t_1, activity symbol is denoted by t_2, and interaction is denoted by t_3, and so on until loop is denoted by t_{13}. From Step 3, N

actions, R roles, and I interactions are identified which is utilized to develop a procedure for the development of the RAD which is as follows:

1: Set $r=1$, $i=1$, and $j=1$.

2: For r^{th} role, where $r \in (1, 2, 3, \cdots, R)$

draw_shape(t_1) *// drawing the shape of a role*

for i^{th} *action*, where $i \in (1, 2, 3, \cdots, N)$

if $[AR]_{ir} == 1$ then

type=action_type(i) *// get the type of activity*

draw_shape(*type*) *// draw shape of activity type inside // role shape*

End If

End For

End For

3: For j^{th} interaction, where $j \in (1, 2, 3, \cdots, I)$

For r^{th} role, where $r \in (1, 2, 3, \cdots, R)$

if $[IR]_{jr} == 1 \text{ or } 2$ then

draw_shape(t_2) *//draw interaction shape inside role // shape*

End If

End For

End For

4: Join all the RAD notations logically based on the interview transcript

5: End

The RAD diagram for Example 1 constructed from following the above steps is illustrated with the help of Fig. 4.2. The term '*failed consenting procedure of used*' in Fig. 4.2, is a sub-process and hence a represented by encapsulated process symbol. The RAD of the process is not totally automatic and manual interventions are required to define the sequence of RAD symbols. The resulting RAD models are verified with the help of staff by following '*teach back*' method and any inconsistencies or issues are edited and modified manually to reflect the reality.

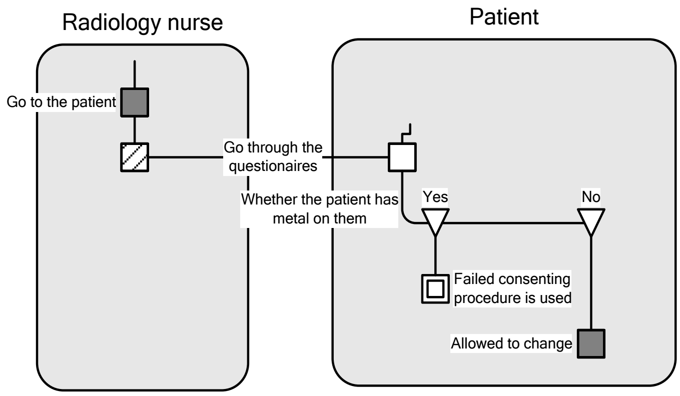


Figure 4.2: RAD for Example 1

The developed RAD model can be further examined to conduct time-based analysis. The following section shows the implementation of the proposed methodology by constructing the software tools necessary to model and analyse the RADs.

4.3. Implementation of RAD Based Qualitative Modelling of Healthcare Service Delivery Process

This section details the development of software tools based on the RAD modelling methodology for each of the four steps (refer Section 4.2). The following subsections provide information about the software tools developed for each step.

4.3.1 Identifying key roles and scope of the process

The scope of the process model and key roles are identified manually based on the communications with senior/clinician manager responsible for managing process performance.

4.3.2 Interview transcript generation based on Microsoft Word

The implementation phase starts when all the qualitative interviews of selected radiology staff are recorded on audio tape as our primary protocol generation technique. Interviews are then transcribed into Microsoft Word documents. Appendix II discusses a set of questions that are generally asked during semi-structured interviews for RAD modelling.

4.3.3 Software tool for extracting RAD concepts

We developed a software toolbar using Microsoft Word to extract terms from the transcribed interviews which were relevant for RAD construction (see Fig. 4.3). Using this tool, the *Action Name, Action Description, Role Name, Role Description, Interaction Name, Decision Question, Resource Name* and *Resource Description* can be marked in the Microsoft Word transcript. To collect more information from interviews, we have included new concepts in our software tool such as *Glossary Item, Glossary Description, Issue Description, Flow Object, Actor Name, and Organisation Name*. These markings are done to extract the relevant terms from the transcripts.

4.3.4 Relationship builder tool

After marking the relevant terms from the Microsoft Word transcripts, the marked term is exported into a matrix based tool which allows relationships between concepts to be defined (see Fig. 4.4). The matrix based tool, as shown in Fig. 4.4, has the same set of matrices that are defined in Step 4. All the matrices defined in

Step 4 are included in the relationship builder tool for defining the relationships. The matrix based tool helps to define relationships between marked terms by entering the attribute values (i.e., 1 or 0) of the matrices.

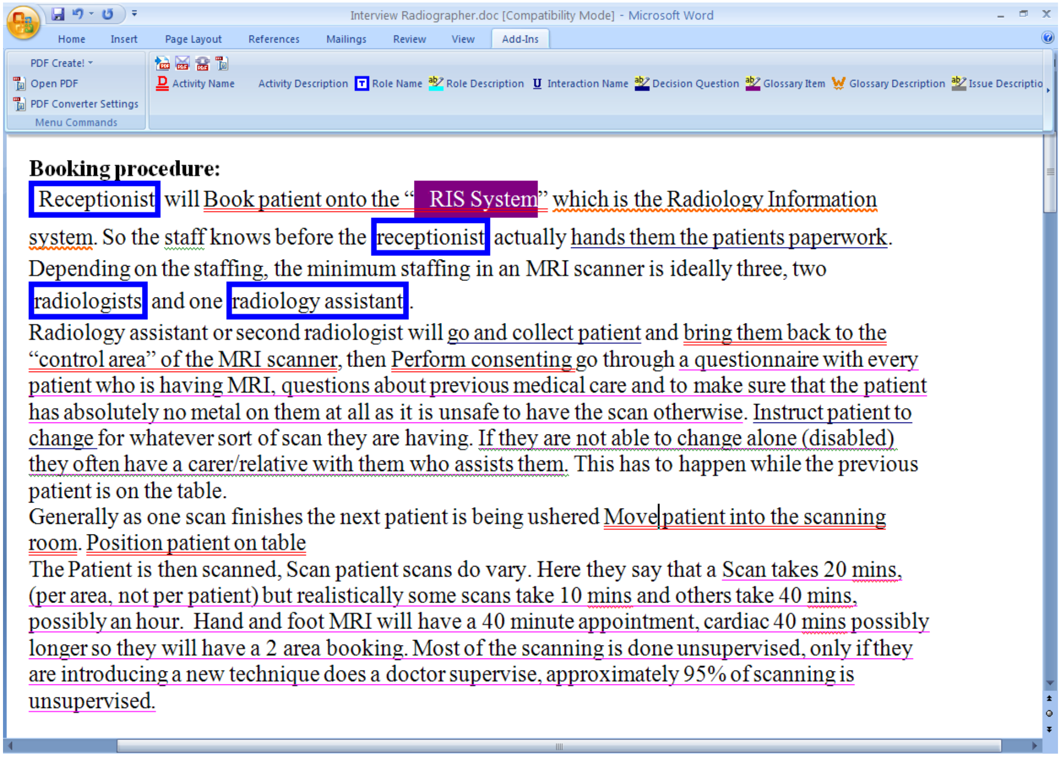
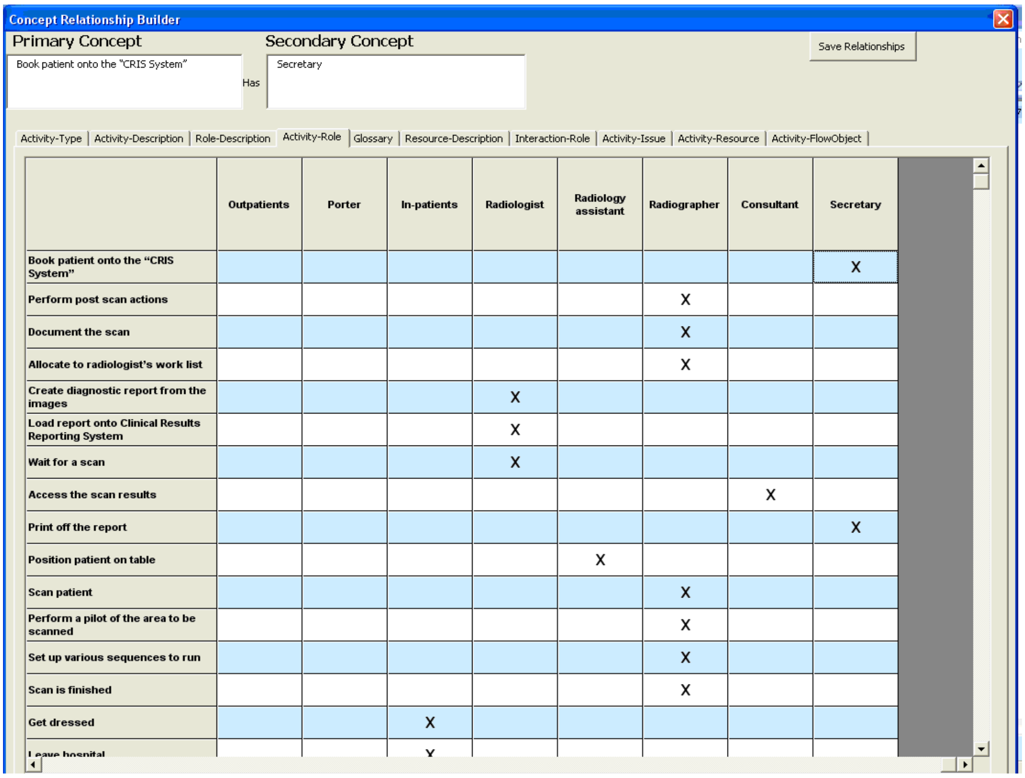


Figure 4.3: Microsoft Word based Mark-Up tool for extracting procedural knowledge concepts

4.3.5 Graphical representation of RAD in MS Visio

The marked terms and their matrix based relationships are then exported to Microsoft Visio where a RAD is automatically generated using the RAD shape library (**T**) in Visio and the algorithm defined in Step5 (see Fig. 4.5). The information about the strict sequence of the activities is not present during the interview transcripts as participants are often unable to describe the activities in strict sequence. However, based upon the interview transcripts, it is possible to create an approximate sequence. The approximate sequence in RAD can be refined by validating it with the selected member of staff that were interviewed. Subsequently, new information from key clinicians can also be added manually to the developed RAD to improve the service delivery process model.



	Outpatients	Porter	In-patients	Radiologist	Radiology assistant	Radiographer	Consultant	Secretary
Book patient onto the "CRIS System"								X
Perform post scan actions						X		
Document the scan						X		
Allocate to radiologist's work list						X		
Create diagnostic report from the images				X				
Load report onto Clinical Results Reporting System				X				
Wait for a scan				X				
Access the scan results							X	
Print off the report								X
Position patient on table					X			
Scan patient						X		
Perform a pilot of the area to be scanned						X		
Set up various sequences to run						X		
Scan is finished						X		
Get dressed			X					
Leave hospital			X					

Figure 4.4: Matrix based tool to relate extracted terms from the transcript

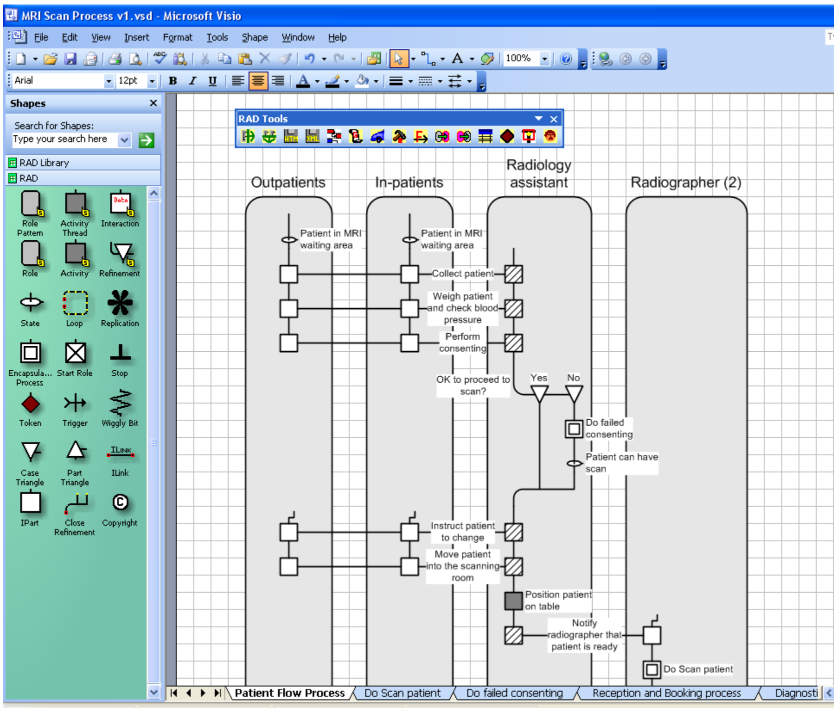


Figure 4.5: MS Visio based RAD stencil for generating RAD models from relationship matrices

The RAD software tools have been discussed in detail and can be accessed in SoW2 (2009a).

Following section shows the application of proposed RAD-based workflow modelling methodology on Magnetic Resonance (MR) scanning process of radiology department.

4.4. Case Study

The case study involves the MR scanning service in the radiology department at a large hospital in UK. The radiology unit has three MR scanners to deal with patient scan requests that generate from different departments in the hospital. Radiographers and radiologists with the help of radiology assistants, receptionists, and porters provide MR imaging services to patients. Each of the MR scanners is assigned two radiographers to scan patients and one radiology assistant to prepare patients for scanning. Several IT systems such including radiology information system (RIS), picture archiving and communication system (PACS), and clinical reporting system (CRS) are used to schedule patient appointments, archive patient scan images, and review patient scan reports. Figure 4.6 illustrates the physical layout of a part of radiology department where MR scanning is performed. It shows two scanners (the third MR scanner is in other part of hospital) and associated rooms for performing the MR scanning procedure. The ethics approval required for this research study was covered under the Comprehensive Research Agreement between collaborative partners University of Warwick, GE Healthcare, and a large UK hospital.

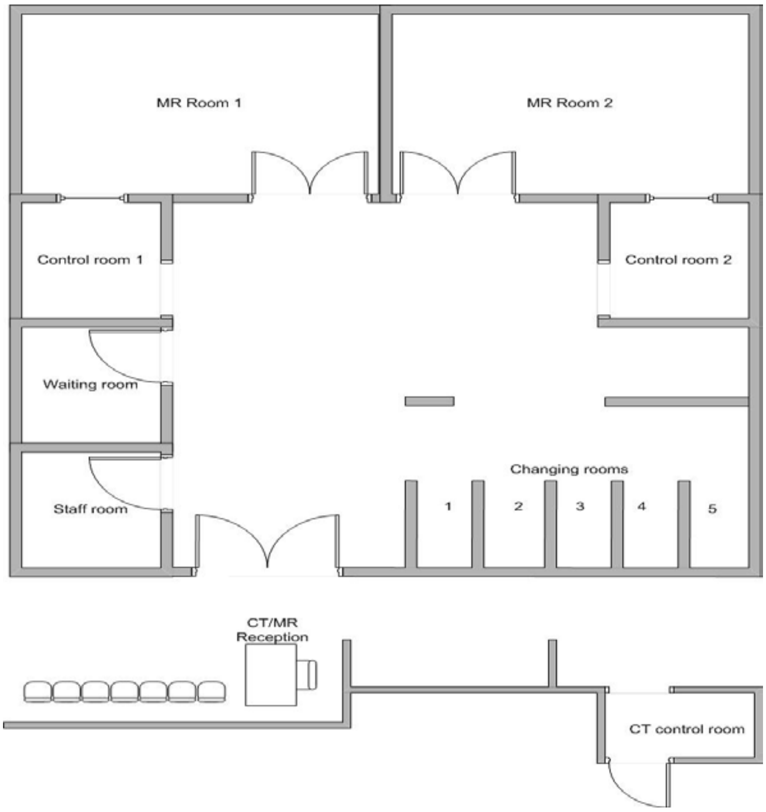


Figure 4.6: Physical layout of the MR imaging services in radiology department

The MR scanning is primarily a medical imaging technique most commonly used in radiology to visualize the structure and function of the body. The patient scan helps the radiologist to monitor and assess patient medical condition. This is sometimes also referred to as diagnostic imaging. The process starts when a patient scan is requested by doctors in other hospital departments. The request contains some questions on patient health that are to be answered by the radiologist. Radiologist answers those questions based on the patient MR scan and his previous medical data available in hospital information systems. The process ends when the radiologist sends the report containing the answers to doctor’s questions.

Doctors from different departments request MR scans for their patients which puts enormous demand on imaging services in the radiology department. The receptionist schedules patients for scan procedures on MR machines, each of which has fixed appointment time slots of 20 minutes per area for patients between 9AM – 5PM (excluding one hour of lunch). The area of the patient indicates a class of scan, *i.e.*, head, heart, abdomen, knee, and others. Due to the large demand for scans from different departments and limited number of available patient appointment slots on the three MR scanners, patients are expected to wait. According to nationally recommended patient care guidelines in UK, no patient should wait more than 18 weeks from doctor's appointment until their treatment (Department of Health, 2006). Imaging services for patients is identified as a major element in the 18 week care pathway. Therefore, the radiology department is under tremendous pressure to meet the targeted wait time guidelines.

Patient MR scanning on MR scanner varies a lot with the age, area to be scanned, health related conditions of patient, and others. Patient scan may require contrast injections or sedation injections or any other setup for performing MR scanning effectively. Paediatric patients or claustrophobic patients requiring sedation involves careful medical monitoring, therefore, it exceeds the 20 minutes/area time allocated for scan. Similarly, disabled patients or the patients requiring contrast liquid for scan can take large amount of time. Whereas, for the physically fit patient without claustrophobia may take less time than 20 min/area. Further, bed ridden inpatients, requiring MR scan, have to be carefully transported from wards and prepared for the scanning. The inpatients on pumps, drips, and others require longer preparation time. Hence, there is lot of variations in scanning different types of patients requiring MR scan.

Specifically, the whole MR patient scanning process can be divided into patient booking process; patient arrival process; patient scanning; and scan review reporting process (see Fig. 4.7).

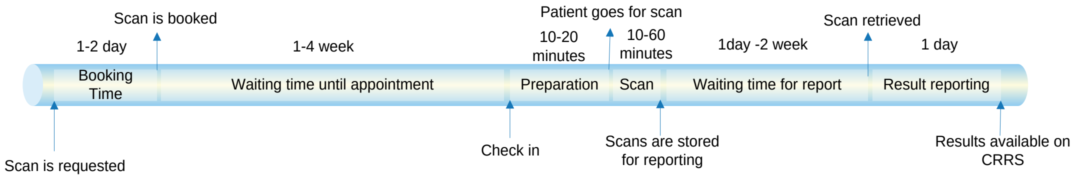


Figure 4.7: Breakdown of the overall time from outpatient request to results availability

Figure 4.7 illustrates that the overall time for MR scanning process can be divided into booking time, waiting time involved until appointment, patient preparation, MR scanning on scanner, waiting time for results reporting, and results reporting. Due to hospital request to improve the efficiency of their MR scanning process, our improvement efforts were focussed on the patient scanning and booking process. The MR scanners are high capital intensive equipments for the hospital, which is required to perform efficiently to meet the rising scanning demand. Efforts were made to improve the patient scanning and booking process of MR scanning process due to: (i) long wait times from scan request to actual MR scanning date (3-4 weeks for outpatients); (ii) average utilization rates of MR scanners are low (~ 40-50%); and, (iii) suggestions identified by improving MR scanning process can be realised in other modalities of radiology such as CT (computed tomography), Nuclear Medicine, X-ray, and Ultrasound which are having similar processes. Therefore, we have looked into the RAD model for specifically improving the scanning process in Section 4.6. In hospital's view, their main priority is to improve the scanner utilization rates and the increased workload thus created for downstream results reporting process can be managed by adopting various options. These options can be: (i) outsourcing the results reporting; and, (ii) adding more staff from hospital for reporting. The effective modelling and improvement of the MR scanning process requires acquiring accurate knowledge about the abovementioned processes from radiology staff. A RAD methodology (see Section 4.2) is applied to model the MR scanning process based on information derived from radiology staff interviews. The subsections below detail the application of the proposed methodology for the RAD based modelling of the MR scanning process.

Knowledge acquisition for RAD modelling of MR scanning process

4.4.1 Identifying key roles in MR scanning process

Initially, the list of roles involved in the MR scanning process is elicited by interviewing the radiology manager, who administers the imaging modalities. The key roles such as receptionist at reception, receptionist at booking department, radiology assistant, radiographer, and radiologist, signifying staff members who participate in the MR scanning process are identified. The two types of receptionists involved in the MR scanning process are (i) receptionist dealing with inpatient and outpatient arrival; and, (ii) receptionist involved in the booking of outpatients in the booking department. These receptionists are identified as Receptionist and Booking Department in the RAD model. Member of staff representing each roles were selected to be interviewed in next subsection.

4.4.2 Interview transcript generation for RAD development

The face to face 30 minute interviews with key roles, identified in subsection 4.4.1, were conducted in the radiology department in one day by project staff. Each selected member of radiology staff was asked to specifically detail their involvement in the MR scanning process from beginning to end. The interviews were recorded using the digital recorder DS-40 from Olympus. After recording, the audio files were transcribed into Microsoft Word (2003).

Knowledge aggregation for RAD modelling of MR scanning process

4.4.3 Extracting RAD concepts based on software tool

The Microsoft Word transcripts of the interviews were marked with the RAD concepts such as actions, interactions, roles, resources, their descriptions, glossary terms and related issues (see Table 4.1), which are useful for creating the RAD model of the MR scanning process. Marking was done using the protocol editor software tool that is developed as a macro for Microsoft Word (2003).

4.4.4 Building relationship matrices based on builder tool

The extracted concepts from the protocol editor were related with each other using the matrix based relationship builder tool (defined in Section 4.3.4). The relationships are defined based on the MR scanning process knowledge obtained after the qualitative interviews of radiology staff.

4.4.5 Graphically representing RAD in MS Visio

Once the marked concepts are related, the relationships were exported to Microsoft Visio, which has the RAD stencil, to construct RAD of the MR scanning process. In order to represent the RAD model clearly, the whole RAD model is divided into four RAD models: patient booking, patient arrival, patient scanning, and diagnostic reporting process. These models were verified with the help of 'teach back' approach, where these models were shown to the same members of staff who were interviewed for editing inconsistencies. This results in the development of verified

RAD representation of the MR scanning process. The logic flow between these RADs is illustrated in Fig. 4.8. Below is the discussion about the RAD model developed for patient booking, patient arrival, patient scanning, and diagnostic reporting of the MR scan process.

The MR scanning process starts when the patient scan request is received by the receptionist of the radiology department from doctors on the ward (for inpatients) or from doctors via e-booking system (for outpatients). This triggers the start of the patient booking process, which is illustrated in Fig. 4.9, to allocate an appointment time to the patient for an MR scan. An outpatient MR scan request card is passed on to the receptionist dealing with the inpatient requests, who works simultaneously on other activities such as monitoring the e-booking system, generating and posting non-attendance letters and other activities. All scan requests are then passed on to the radiologist for vetting. The radiologist decides whether or not the scan request has to be approved. The invalid MR scan requests are removed from booking and the decision is notified to the referring doctors. The scan requests accepted by the radiologist is informed to the receptionist who books the inpatient paper-based card into the radiology information system (RIS) and outpatients scan request is dealt by the outpatient receptionist in the booking department.

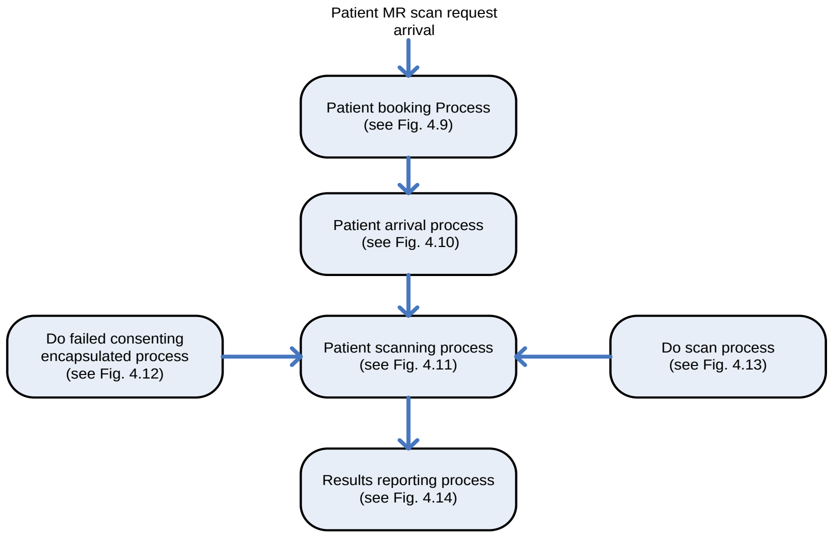


Figure 4.8: RAD models for MR scanning process divided into patient booking process, patient arrival process, patient scanning process, and results reporting process

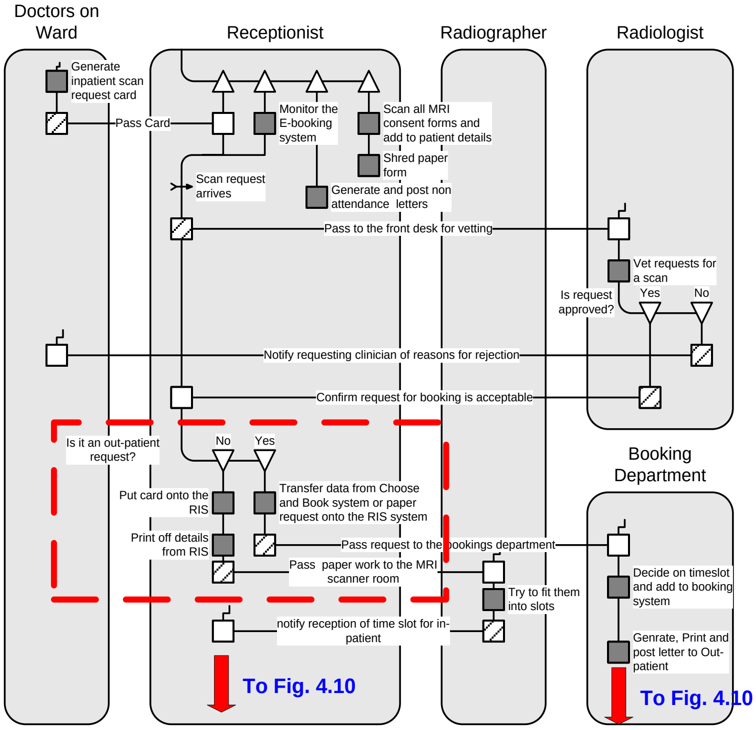


Figure 4.9: Patient booking process for MR scanning process; Highlighted area is a critical process issue (discussed in Section 4.6.1)

Figure 4.10 illustrates the patient arrival process for the actual MR scanning. According to the appointment time, the outpatient arrives in the MR reception area. In contrast, the receptionist books the inpatient into RIS when they receive inpatient

MR scan request. Subsequently, all patient notes and the related consent form are passed on to the radiology assistant for patients with scan appointments.

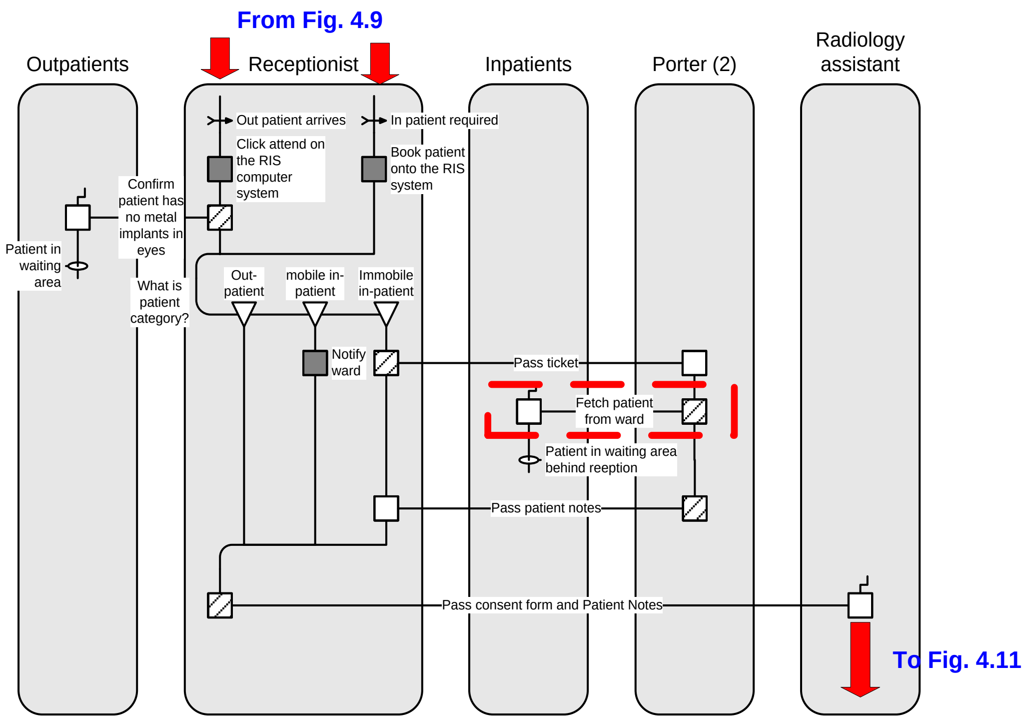


Figure 4.10: Patient arrival process for MR scanning; Highlighted area is a critical process issue (discussed in Section 4.6.2)

Figure 4.11 shows the RAD diagram of the MR scanning procedure where the patient is handled by the radiology assistant and radiographers for scanning. Patients are taken from the MR/CT patient waiting area by the radiology assistant and consenting procedures about the presence of metallic objects in patient body is performed.

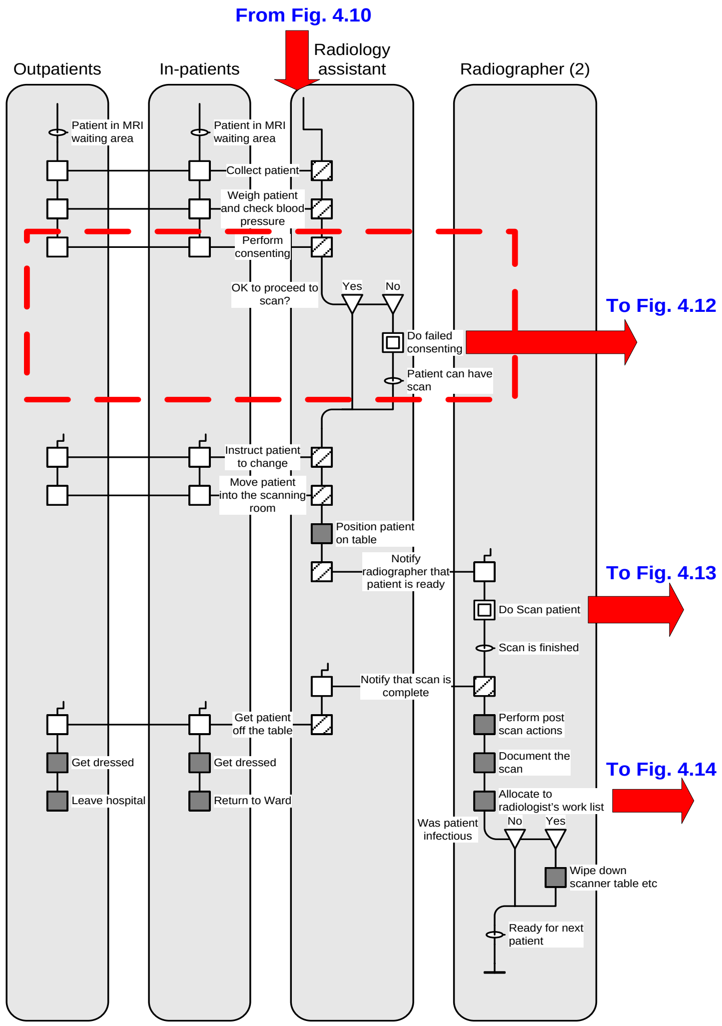


Figure 4.11: MR scanning procedure involving patient, radiology assistant, and two radiographers; Highlighted area is a critical process issue (discussed in Section 4.6.3)

Patients are advised to change into a hospital gown only after completing the consent form indicating that they have met the requirements to proceed with their scanning appointments. Otherwise, the failed consenting procedure is adopted to check for the presence of metallic objects within the patient body. The failed consent procedure is illustrated in Fig. 4.12. The failed consent process involves X-ray scanning and the role of the radiology assistant and the radiologist in order to check for metallic objects in the patient body.

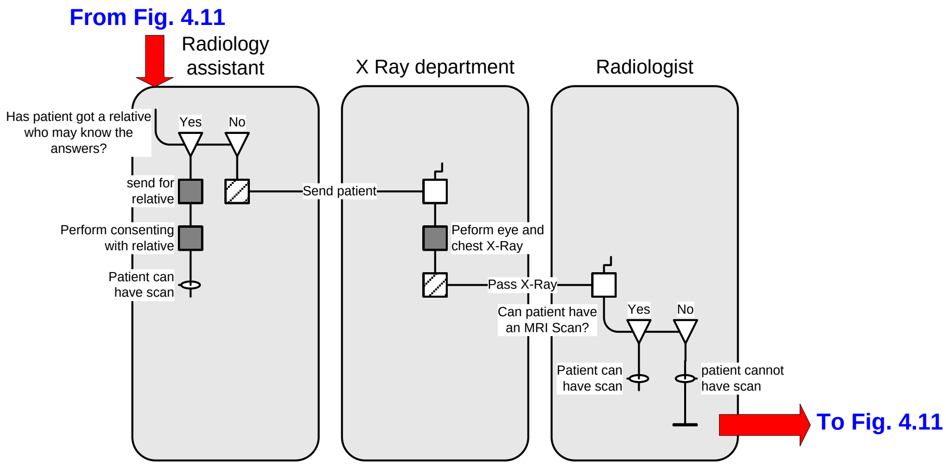


Figure 4.12: RAD showing the encapsulated failed consenting procedure

After the patient has changed into the hospital gown and is ready for the MR scan, this is notified to the radiographers. The patient scan preparation by the radiology assistant is done simultaneously with the previous patient being scanned by the radiographers. Patients are taken to the MRI room by the radiographers and adjustments to the MR scanners are done accordingly. After the scanner adjustments are done, the radiographer leaves the MRI room and goes to the MR control room to do the patient scanning. The encapsulated patient scanning process is represented by the RAD diagram shown in Fig. 4.13.

In some cases, patients are given contrast or sedation injections to improve the quality of scan images. Radiographers are responsible for making the decision about whether to give the contrast injections and sedation to the patients for MR scanning. Contrast injections are useful for scans requiring information about the flow of blood in veins.

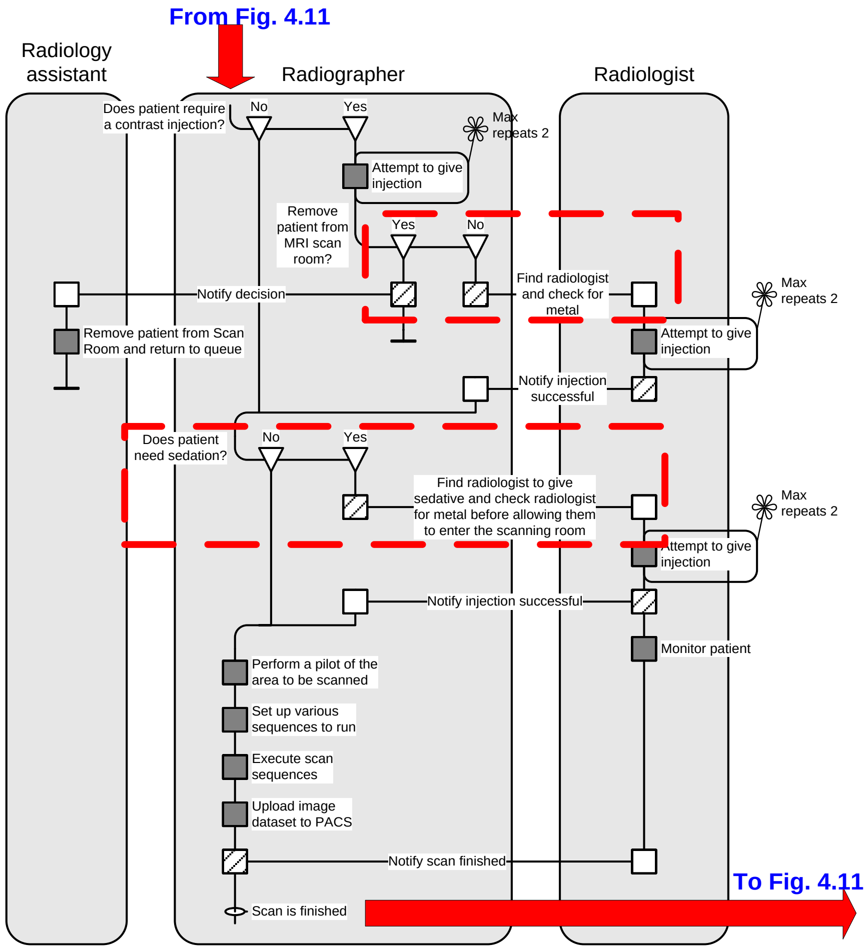


Figure 4.13: RAD showing the encapsulated patient scans process involving radiology assistant, radiographers, and radiologist; Highlighted area is a critical process issue (discussed in Section 4.6.4)

Whereas, sedation is required to calm down claustrophobic or child patients so that MR scan can be performed smoothly. The activities performed by the radiographers and radiologist for sedated patients usually exceeds the duration of the appointment time. After patients are properly placed in the scanner, the radiographer sets up various scan sequences and other operations to run on their workstation. Execution of these activities results in scan images which are uploaded to a PACS and are allocated to a specialist radiologist. The patient is then released from the MRI room and preparations are made for the next patient. The scan is reviewed by the respective radiologist and the results are dictated on the audio tape which is transcribed by the secretary into written document (see Fig. 4.14). The diagnostic report on patient MR scan is then passed on to the doctors requesting the patient scan.

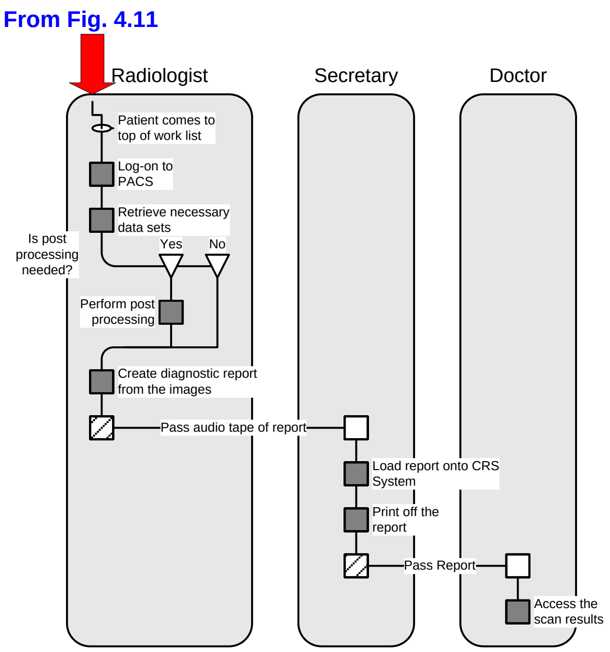


Figure 4.14: Results reporting process for MR scans

The MR scanning process is completed when the scanned images are reviewed and all related results are sent to the referring doctor. In brief, the patient scan requests are booked using patient booking process. Depending upon the appointment date and time, patients arrive in the department for scanning, which is represented by the patient arrival process. Subsequently, patients are scanned by the MR staff to produce images based on the patient scanning process. Further, the patient scan images are reviewed by the radiologists and reported to the referring doctor.

4.5. Discussion and comparison of the RAD-based modelling with VSM and IDEF0

Three service delivery systems modelling methods such as VSM, IDEF0, and RAD is compared and illustrated with the help of Table 4.7 and Fig. 4.15. Table 4.7 classifies IDEF0, VSM, and RAD based on (i) information requirement for modelling; (ii) Characteristics of the process models; and, (iii) applications of the resulting process models. Figure 4.15 illustrates VSM and IDEF0 model which is illustrated in Fig. 4.11 as RAD of the MR scanning procedure.

The developed RAD model can be utilized for a variety of applications including for radiology service delivery process improvements or process redesign as discussed in the following section.

4.6. Qualitative Model Architecture Analysis for Potential Areas of Improvement

The RAD model of the MR scanning process can be used for variety of applications depending upon the specific needs and purpose. This section discusses the three major applications of RAD model of MR scanning process.

RAD based process model can be used to inform about MR scanning processes to radiology staff about MR scanning process, and radiology units of other hospital for comparison and benchmarking. RAD models that are represented in a standard notation on a computer can be shared easily. RAD modelling notations encourage greater precision and clarity, and are less likely to be misinterpreted by the person implementing the design in other units. Hence, the RAD model can be used to document the existing service delivery system for sharing across multiple teams and hospitals.

Table 4.7: Comparisons among VSM, IDEF0, and RAD based workflow modelling

	Information required	Modelling characteristics	Output
IDEF0	**Qualitative**: Clinician workshops and discussions	High level functions of a process illustration	• Visualizes input, output, constraints, and mechanism of the functions within a process • Often interpreted as a sequential process flow
VSM	**Qualitative**: Clinician workshops and discussions **Quantitative**: Time, Resources, and Uptime of the process steps	• Process is represented in terms of sequential steps • Less useful in case of processes involving large variations • Unable to provide enough details about process for its improvement	Helps in identifying problematic steps within a sequential process
RAD	**Qualitative**: Interviews of key process participants	• Sequential, parallel, and collaborating processes can be represented • Can represent variations within the process • Provides detailed and accurate process representation for improvements	• Visualizes process as a set of interacting roles • Helps in identifying the problematic steps and detailed process structure for improvements • Can be easily understood and verified by individual staff associated by following his/her role in RAD

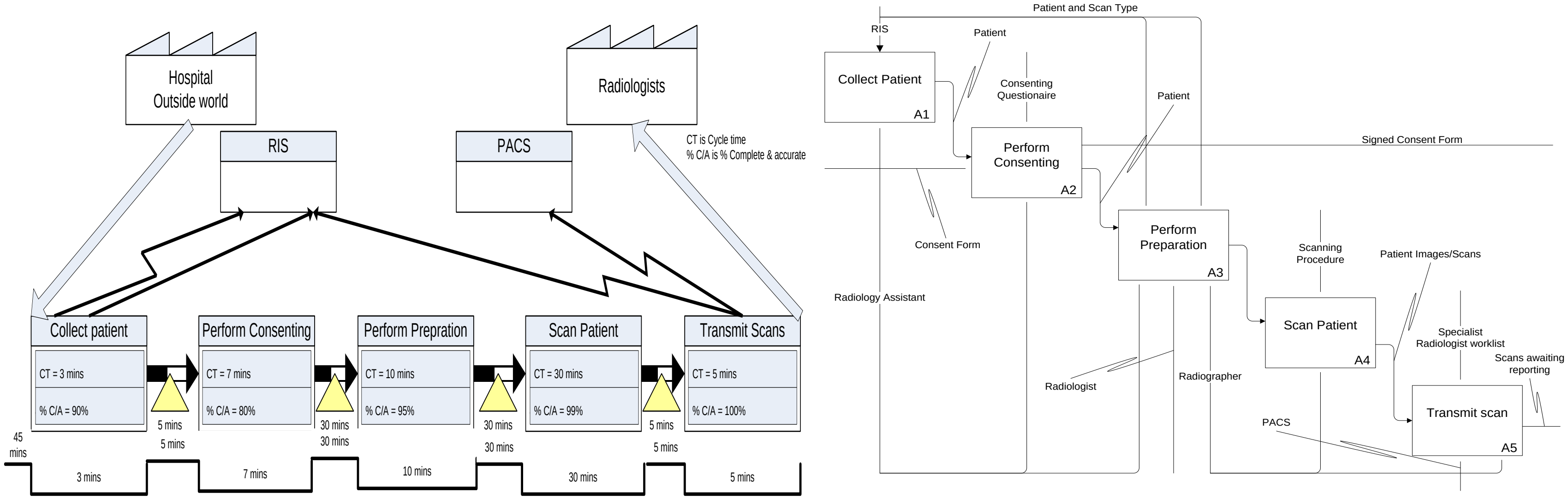


Figure 4.15: Comparison between (a) Value stream mapping; and, (b) IDEF0 model for MR scanning procedure

RAD model of the MR scanning process having standard notations can be used to build the discrete event simulation model for analysing its performance. Based on discrete event simulation model, the current performance of the MR scanning process can be determined and its behaviour in changing internal and external factors can be studied. Discrete event simulating models based on RAD model for MR scanning process can increase the chance of success in the new ways of working before taking the risk and bearing the cost of implementation (discussed in Chapter 5).

The major use of the RAD model of the MR scanning process is for suggesting improvements related to process redesign. Mapping of the existing MR scanning process reveals opportunities for process redesign by illustrating the activities, interactions, and others performed by different roles in the service delivery system that were not apparent beforehand. The improvement areas based on the RAD model can be broadly classified into two:

I. **Primary improvements**: The primary improvements can be identified directly by analysing the graphical representation of RAD model. The primary improvements that can be identified based on the RAD model are duplication of activities, delayed interactions, needless waiting/delays, steps that fail to contribute value to service delivery system, or potential to run in parallel than undertaken sequentially. RAD model of the service delivery system can be analysed based on abovementioned improvement areas for suggesting improvements.

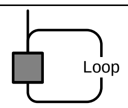
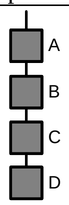
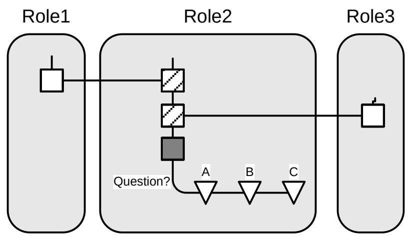
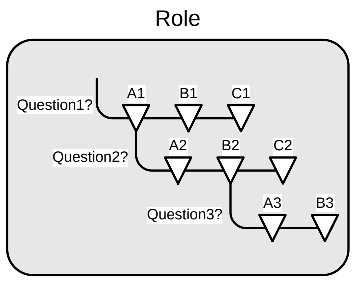
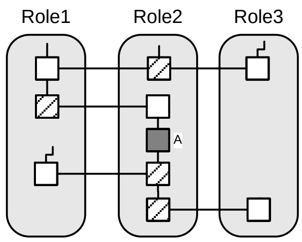
II. **Secondary improvements**: The secondary improvements can be identified by brainstorming about problematic issues in the RAD model of service delivery system. The brainstorming is generally performed among the staff involved process and improvement experts to identify the problematic areas or tasks that are generally delayed or causes problems. Improving the information flows among different roles, use of IT systems are some of the common areas for improvement under this category.

Only primary improvements are detailed in this Chapter as we have defined a set of principles for identifying improvement areas in the service delivery process based on RAD. In particular, RAD model of the MR scanning process, shown in Figs. 4.9-4.14, can be utilized for suggesting improvements based on the improvement principles illustrated in Table 4.8. The following areas of primary improvements were identified based on principles discussed in Table 4.8:

1. <u>Develop an efficient patient booking system by eliminating redundant tasks</u>: Our case study revealed, based on the sensitive RAD architecture (see decision making process in Table 4.8), that the receptionist has to deal with both paper-based card and electronic booking system in the patient booking process (shown in Fig. 4.9). This is due to the fact that the scan request arrives from two sources: (a) the e-booking system and (b) paper-based request cards. This makes receptionist to adopt two ways of booking a patient into the RIS. As a result, some redundant tasks are performed by the receptionist. These tasks are illustrated by the activities such as '*put card onto the RIS*', '*print off details from RIS*', '*transfer data from choose and book system or paper request onto RIS*', and interaction such as '*pass paperwork to MRI scanner room*'. Figure 4.9 illustrates these activities in the RAD model of booking process (refer RAD symbols in red rectangle in Fig. 4.9). The improvements in current booking system can be realised by following the

electronic booking system and taking steps to phase out the paper based cards for booking.

Table 4.8: Identification of areas for improvement based on complexity of service delivery elements of the process

S.No.	Sensitive RAD Architecture	Representation in the model	Potential Impact
1	Individual task complexity	 Repetition of activity	Delays in the service delivery process
2	Long sequence of tasks	 Long sequences activities	Bottlenecks and delays within the process
3	Decision making process	 Decisions requiring large amount of information for decision making	Critical decisions requiring large amount of data (represented as *interactions* and *activities*) for making decisions leads to patient diversions from care process (identified as patients sent incorrectly to different hospital wards).
4	Cascading decision making	 Multiple decisions made by a role	Patient care is delayed as well as patients are diagnosed incorrectly when a large number of critical decisions are made by a role
5	Multiple or long interactions	 Multiple interactions or long interactions	Long and multiple interactions among roles can lead to delays in performing care process steps

2. <u>Improve inpatient scanning</u>: The inpatients requiring MR scans are fetched from the hospital wards by porters as illustrated in Fig. 4.10 by the interaction

‘*fetch patient from ward*’ (see long interactions leads to delays in Table 4.8). It is identified as the time consuming interaction which involves the patient pickup from wards for MR scanning. It is often delayed as moving inpatients in large and busy hospital is time consuming (refer RAD symbols in red rectangle in Fig. 4.10). As a result, inpatients do not arrive timely on their appointment time slot for scanning. This interaction can be improved by better coordination among hospital wards and the radiology porters.

3. <u>Improve inpatient consenting by eliminating unnecessary delays</u>: As per long interactions based sensitive area (illustrated in Table 4.8), consenting procedure is performed on each patient before an MR scan can be performed (as shown in Fig. 4.11 by the interaction ‘*perform consenting*’). Often, this interaction can be time consuming particularly for patients who are unable to provide clear answers to the consenting questionnaires. Our observation suggest that there might be several factors for this delay including due to the confusion that surround some of the questions in the consenting form; inadequate patient command in the English language; unavailability of appropriate translation services, or also due to presenting critical conditions of inpatients. As a result, a translator has to be booked or patient medical history is to be checked before MR scanning. This causes delay for the MR scanning for inpatients. This problem can be reduced by informing the ward nurses, which are taking care of booked inpatient, beforehand about the consenting questions. The hospital ward nurses can get the answers of the consenting questions from the previous medical record of the inpatients. Hence, the answers to the consenting questions for inpatients are readily available for radiology assistant.

4. Better patient preparation: Some of the patients booked for MR scanning require special pre-scan procedures such as sedation and contrast injections (shown in Fig. 4.13 as case refinements '*does patient require contrast injection*' and '*does patient need sedation*'). These techniques are generally employed to keep the claustrophobic or child patient calm in the MR scanners or for accuracy in diagnoses. The radiographers or the radiology assistant has to locate a radiologist in order to monitor patient medical condition during sedation or injecting contrast (see interactions '*find radiologist and check for metal*' and '*find radiologist to give sedative and check radiologist for metal before allowing them to enter scanning room*' in Fig. 4.13). Providing the sedation/contrast injections and finding the radiologist for monitoring takes more than patient appointment time for the patients which can lead to delays. This problem is identified based on the cascading decision making and individual task complexities represented in Table 4.8. The delay can be partly reduced by informing the radiologists beforehand about patients requiring sedation or contrasts.

The aforementioned applications of the RAD model can be useful for the service departments for redesigning and informing staff and other hospitals, discrete event simulation modelling and analysis, and suggesting service improvements. The significance of each of the service improvements detailed for MR scanning process can be evaluated based on the discrete event simulation modelling, which will require the quantitative time related data about the process. The simulation model of the MR scanning process based on RAD model can further help to identify the best possible improvement scenario.

4.7. Summary

This Chapter deals with the quick and reliable development of RAD for service delivery processes in service units. The proposed RAD development methodology considers qualitative interviews of staff, which are involved in the process. The interviews are recorded and then transcribed to get the written document. A mark-up tool is developed to mark related concepts in the interview transcripts. The concepts are matched using matrix based relationship builder using simple tables. These relationships are then exported to Microsoft Visio to draw a RAD of the system. The developed RAD is a flexible tool that can be modified and edited for inconsistencies. The resulting RAD models can be utilized for process improvement purposes, informing the design of the process to others, and can also be applied to develop simulation models of the process. Therefore, the next chapter deals with the challenge of developing the discrete event simulation model of the processes based on RADs and quantitative service data.

Part I: Reducing Unwarranted Variations ***on*** a Care Pathway

CHAPTER 5: Discrete Event Simulation (DES) Modelling Integrated with Accurate Service Delivery System Model

5.1. Introduction

In this Chapter, a methodology is proposed to illustrate simulation model generation based on the accurate modelling of service delivery systems (developed in Chapter 4) and data model to add quantitative service data. In order to illustrate the proposed methodology, service delivery processes of a radiology department is discussed in this Chapter.

Over the past few years, new tools have been developed for process modelling, but mostly without addressing, specifically, their dynamic aspects (Shukla, *et al.*, 2009; Staccini, *et al.*, 2006). Most of the tools only provide simplified representation of complex service delivery system (see Section 3.1 and 3.2 for the limitations of current process modelling approaches). Many of these tools provide some kind of analysis of the process depending on the type of techniques selected for the process representation. However, few of them have been integrated with any form of simulation software (Kettinger *et. al.*, 1997; Lingineni *et al.*, 1995). As a consequence, if an integrated analysis of the organizational processes is desired, a double effort is needed in the modelling process. First, the process has to be modelled using a process modelling tool. Then the analyst or decision maker has to start all over again and model the process using simulation software, even though most of the process definition has already been captured with the process modelling methods. Therefore, this Chapter provides an integral approach, which considers both the static and dynamic aspects, to analyse service delivery system.

This Chapter is organized as follows. Section 5.2 discusses in detail about the methodology used to translate RAD concepts with data models as a discrete event simulation (DES) model. Subsequently, Section 5.3 discusses a case study of MR scanning process of radiology where the proposed method has been applied and improvements were suggested. Finally, Section 5.4 provides a brief summary of the Chapter.

5.2. Methodology for DES modelling based on RAD

In this study, we employed RAD as a process mapping technique for developing a DES model of the service delivery system in a hospital. A clear understanding of the fundamental concepts and notations of RADs is required before any process modelling can be actually performed; therefore Table 4.1 in Chapter 4 provides some of the fundamental concepts of RAD. In order to efficiently construct the DES model for the service delivery system, a methodology for translating the process mapping concepts to DES concepts is required. The following subsection describes the formal procedure to extract and translate the knowledge from accurate process models represented as RADs to build DES models.

5.2.1. Development of RAD model of the service delivery system

The RAD model of the service delivery system is developed based on the modelling methodology, which generates the RAD models from staff interviews (Shukla, *et al.*, 2009, and refer Chapter 4). This methodology analyses the interview transcripts of the staff involved in the service delivery to identify and represent procedural knowledge of the process. This helps to efficiently and effectively develop complex RAD models of the process without loss of information from staff discussions. The main steps of this methodology are illustrated with the help of Fig. 5.1.

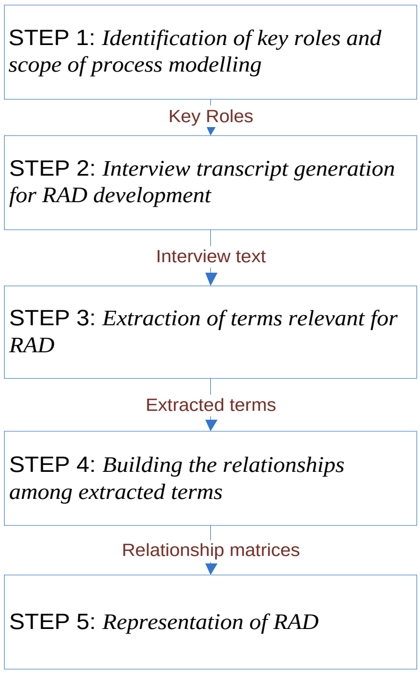


Figure 5.1: RAD-based process modelling methodology from staff interviews

Step 1 identifies key roles involved in the service delivery process and defines the scope of process modelling. Step 2 focuses on generating the input data format for the methodology. It generates the text format of their interviews. The text/terms that are relevant for the construction of RAD model are extracted in Step 3. The relationships among the extracted terms are created in Step 4 with the help of various matrices such as action-type, action-role, interaction-role and others to develop the quantitative base for RAD development. Once relationship matrices are created, the RAD model is graphically represented by following the procedure defined in Step 5.

More information about each of these steps can be obtained in Chapter 4 or in Shukla, *et al.*, (2009).

The implementation of the proposed methodology starts with the development of RAD model for the service delivery system. RAD modelling from clinician interviews is based on software tools developed in Shukla *et al.*, (2009). The software tool takes the Microsoft Word based interview transcripts and helps in generating RAD models of the service delivery system in Microsoft Visio. The main steps in the development of RADs are briefly as follows:

a. *Identifying key roles and scope of the process modelling*

The key roles and process modelling scope is identified as a first step to apply RAD based service delivery process modelling methodology.

b. *Interview transcript generation based on Microsoft Word*

The qualitative interviews of the staff involved in the service delivery system are recorded on audio tape as our primary protocol generation technique. Then the recorded interviews are transcribed into Microsoft Word documents.

c. *Software tool for extracting RAD concepts*

A software toolbar using Microsoft Word is developed to mark (extract) terms or texts from the transcribed interviews which were relevant for RAD construction (see Fig. 5.2.a). These markings are done to extract the relevant terms from the transcripts.

d. *Relationship builder tool*

After marking relevant texts from the Microsoft Word transcripts, the marked text is exported into a matrix based tool which allows relationships between concepts to be defined (see Fig. 5.2.b). The matrix based tool helps to define relationships between marked texts by entering the attribute values (i.e., 1 or 0) of the matrices.

e. <u>*Graphical representation of RAD in MS Visio*</u>

The marked texts and their matrix based relationships are then exported to Microsoft Visio where a RAD is automatically generated using the RAD shape library in Visio (see Fig. 5.2.c). The RAD model once created can be refined by validating it with the staff that was interviewed. Subsequently, new information from key clinicians can also be added manually to the developed RAD to improve the service delivery system model.

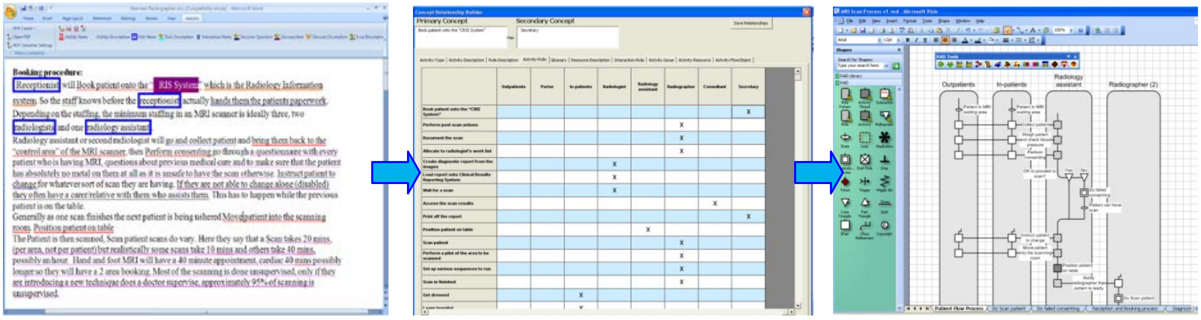


Figure 5.2: (a) Microsoft Word based software toolbar; (b) Matrix based tool to relate marked texts; (c) RAD generation in MS Visio

5.2.2. Data model for RAD based service delivery system

The RAD model developed in previous section consists of the graphical representation of the service delivery system. It represents only the structure of the process, however, it is useful to have comprehensive data model associated with the RADs for analysis and improvements. Therefore, this section details the data model associated with the RAD concepts which can be utilized for DES modelling and analysis.

The data associated with the RAD concepts are detailed as:

1. *Roles*: The data associated with roles are as follows:
    a. Role Name: This defines the names of roles present in RAD model.
    b. Description: It associates the description about role present in RAD model.
    c. Responsibilities: It describes the responsibilities that the role must fulfil. This is a kind of job description.
    d. Experience: It defines the experience associated with a particular role in RAD. Experience will typically be described as a period of time working in a particular role.
    e. Skills: It defines the skills required to perform the assigned service delivery task. Skills may be acquired by attendance on a training course which does not lead to a formal qualification.
    f. Qualification: It associates the qualification with the role in RAD. The qualifications are the formal qualifications that the role performer must have in order to be eligible/legally allowed to perform the role.
    g. Resources: These describe the resources that must be available or are used by the role performer for the duration of the role. Activity resources only need to be available or are used for the duration of the activity.
    h. Number of role performers: It defines the number of people involved in performing a role.
    i. Base location: It defines the initial location of the performers of the roles. This attribute is helpful in building the DES model of the process.
2. Activity: The data attributes associated with the activity is defined as:

a. Activity Name: This defines the name of the activity represented in the RAD model of the service delivery system.

b. Activity Description: This attribute contains the textual description about the activity.

c. Times: This attribute associates different types of time such as planned, actual, optimistic, mean, and pessimistic time. Each of these time elements can be further classified as following time elements:

    i. Time: The main time elements in this category are: time type, duration, value adding time, essential non-value adding, non-value adding time, queuing time, waiting time, indecision time, rework time, value adding ratio.

d. Resources: This attribute associates the resource required to perform the activity and are therefore required until activity duration. The main elements in this attributes are: resource ID, resource name, its description, and type.

e. Location: This defines the area level locations where the activity is performed.

f. Issues: This attribute records the issues which are affect the activity processing.

g. Tasks: This specifically defines list of tasks required to perform an activity.

h. Goals: This attribute describes the goals which are achieved by performing the particular activity.

i. Flow objects: It defines the type of flow objects involved in the activity processing. It can be of four types: *input, output, input/output, constraint*.

3. Interactions, encapsulated process: The data attributes for interactions and encapsulated process are similar to those of activity as these can also be considered as activity.

These are the main data attributes which forms the data model associated with RAD models. The data model together with the RAD concepts can be easily translated or exported to other domains with the help of eXtensible Markup Language (XML). XML is a set of rules for encoding documents electronically (World Wide Web Consortium, W3C). The main purpose for the development of XML was to represent arbitrary data structures and convenient data transfer. RAD models can be encoded into XML format by defined a data structure of the RAD concepts. The data model associated with the RADs can be exported in a XML format defined by a schema.

In order to analyse the RAD, it is necessary to have data model associated with the RAD. Therefore, data entry forms are associated with the RAD symbols in Microsoft Visio. Each RAD symbol has a supporting data entry form which allows inputting of process information (see Fig. 5.3). The data is stored as text or XML in Visio shape properties. Data can be easily added; modified or deleted using forms created in our Visio tool (see Fig. 5.3).

The data model for this phase has been informed by the information requirements of the sorts of analysis that are to be performed. Figure 5.3 shows the form which is associated with the RAD activity symbol. Similarly, data forms are associated with other RAD symbols as well.

Figure5.3 illustrates only the time data form for the activity; however, the data about cost, activity resources, issues, tasks, goals can be further added to the RAD

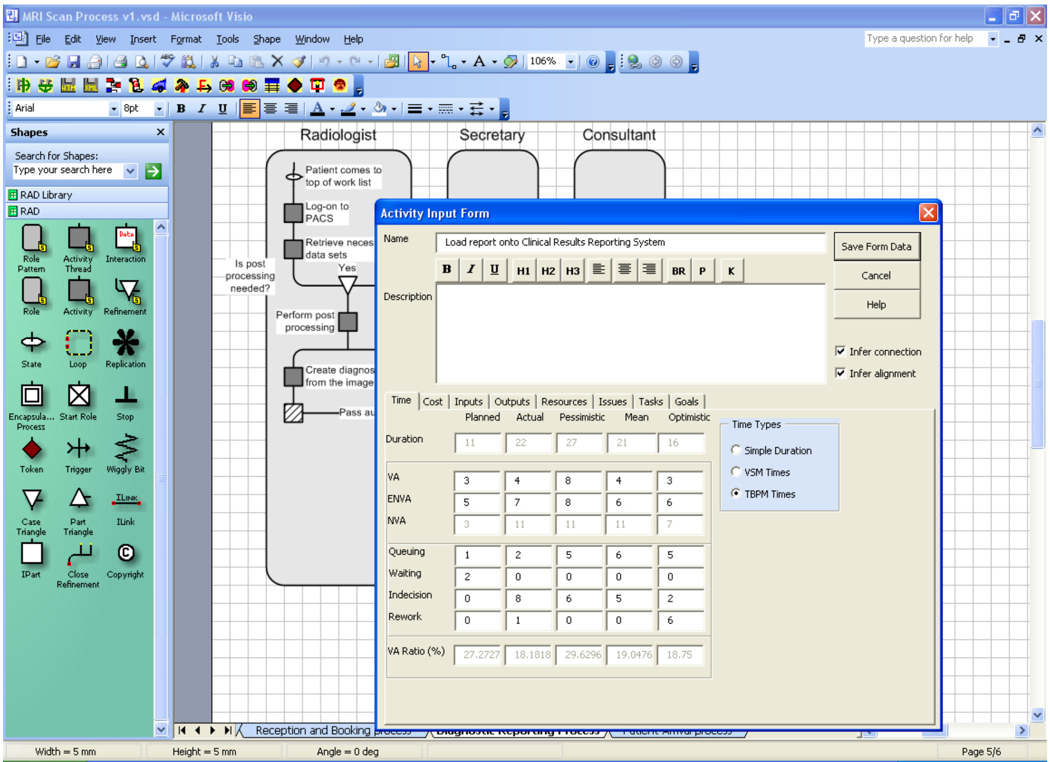


Figure 5.3: Form for entering the time values for RAD activity symbol

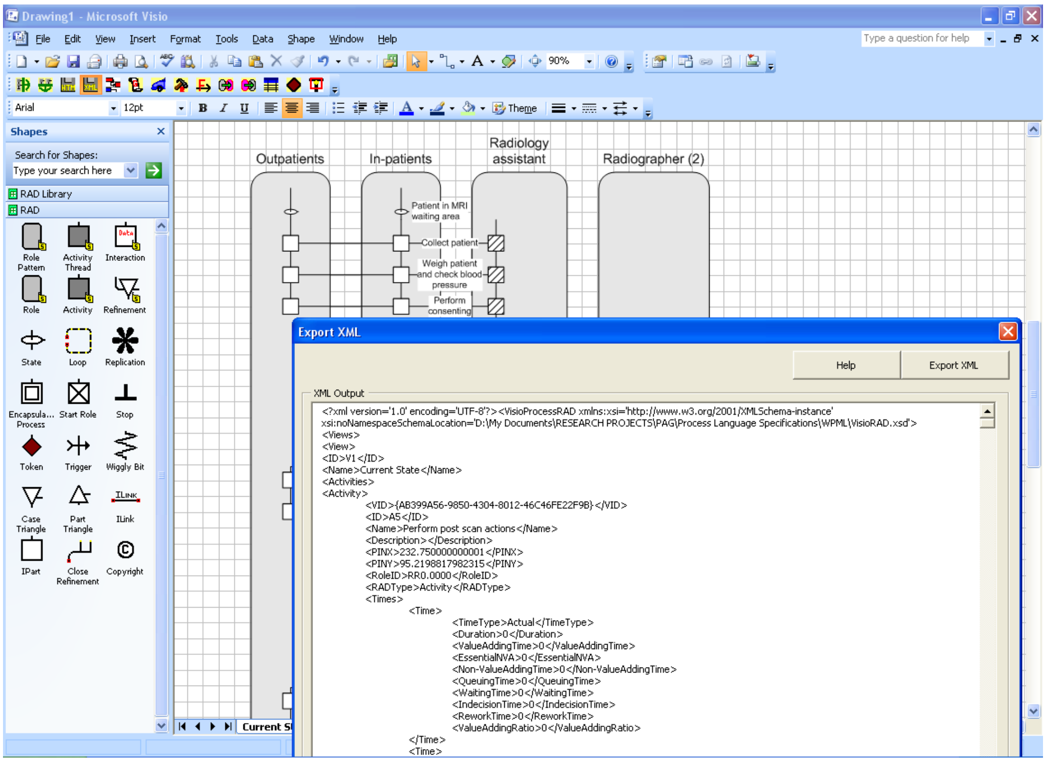


Figure 5.4: XML encoding for RAD model in Microsoft Visio

model. Furthermore, data related to other RAD concepts such as roles, interactions can be added into the RAD model. The RAD model together with data model can be stored as an XML. Figure 5.4 illustrates XML file for the RAD model developed in Microsoft Visio. The RAD toolbar is developed in Microsoft Visio having the functionalities such as generating XML file for the RAD model, website containing RAD model, issue reports and RAD connectivity checking.

5.2.3. Developing DES model based on RAD

In this section, the mapping between RAD concepts such as roles, activities, interactions, decisions, part refinements, case refinements and DES concepts are defined. This is necessary for seamless integration without loss of information and misinterpretation of the service delivery system modelled in RAD (Section 5.2.1, and Section 5.2.2). Understanding DES elements and identifying the relation with the RAD concepts is essential in order to translate the RAD data into DES models.

The details of DES model generation based on the XML of RAD are presented. The discrete event simulation software (from XJ Technologies aka Anylogic) is utilized to interface with RAD software. In order to map RAD concepts in Anylogic based DES model, it is necessary to understand the main elements of DES modelling in Anylogic. Hence, different objects in Anylogic based DES model are discussed in following paragraphs.

The main elements of DES modelling in Anylogic software are discussed in the following text:

1. *Source*: The source object generates the flow entities such as in-patients, out-patients, and emergency patients for the service delivery system. It is often a starting point of a process model. This object generates the entities which may be of generic class Entity or of any user-defined subclass. It also has parameters such as entity arrival types, rates, entities per arrivals, entity shape, and maximum number of arrivals.
2. *Sink*: The sink object disposes of the flow entities. It often represents the end of the process.
3. *Delay*: It delays entities for a specified period of time. It represents the processing time taken to perform any particular activity. Multiple entities can be delayed simultaneously and independently. The parameters of this object include a triangular distribution of delay times, capacity, and statistics.
4. *Network*: This object maintains the network topology and manages resources in Network-Based Modelling. There must be one network object for each network (and there can be multiple networks in one model). Typically, they are used when the processes being modelled are going on in a certain physical space and include movement of entities and resources.
5. *NetworkResourcePool*: It defines a set of network resource units in Network Based Modelling. The objects *NetworkSeize* and *NetworkRelease* are used to access the resource. These resource units cannot exit the network defined. The parameters for this object are resource type, capacity, and speed (if resource is dynamically moving), home location, and shape for resource.
6. *NetworkSeize*: It seizes a given set of network resources in Network Based Modelling. It further sends the seized resources to a specified location and attaches them to the entity (both optionally). This object may be considered

as a Queue for the entities waiting for resources. This object has parameters such as list of resources to be sized, queue capacity, maximum queue capacity, and attach seized resources.

7. *NetworkRelease*: It releases all or some of network resources previously seized by the flowing entity in Network Based Modelling. A list of network resource pools is used to identify the resources to be released. The parameters generally used here are moving resources, and list of resources to be released.
8. *NetworkMoveTo*: It moves the entity to a new network location. If any resources are attached to the entity, they will also move with it. The main parameter under this object is the final destination of the network.
9. *Split*: It creates one or several other entities, for each incoming entity. The new entities created are the exact copy of incoming entity.
10. *Combine*: It waits for the two entities to arrive and produces a new entity. The new entity may be a "completely new", *i.e.* a newly constructed object whose properties possibly depend on the original entities, or it may be one of the original entities, again, possibly modified. Combine is used to re-join the entity with its copy created with Split object.
11. *SelectOutput*: It directs or routes the incoming entities to one of the two output ports depending on probabilistic or deterministic condition. The condition may depend on the entity as well as on any external factors. This is used to sort entities according to a certain criteria, to randomly split the entity flow. The parameters of this object are condition, and selection probability.

The main concepts of RAD modelling are mapped with the concepts of DES modelling for translating the process mapping to DES simulation model. Table 5.1 illustrates the mapping between RAD and DES modelling. The above mentioned list

Table 5.1: Mapping between RAD concepts and DES modelling in Anylogic software

S No	RAD concepts	DES objects	Remarks
1.	*Role*	Resource	In the health service context, roles are usually the people who are interacting with the patient and these map to resources required to perform an activity in the DES model. Because the patient has to provide information through interactions with roles such as the radiology assistant, the patient has to be shown on a RAD diagram as a role. However, in the DES model the patient is the 'Flow object' launched into the model at discrete points in time, passing through the process and leaving the process at the end has work performed on them by the resources used in the process. Each role is defined as *NetworkResourcePool* which is required to perform respective actions and interactions. Presentation shapes are also created
2.	*Activity*	Queue	A queue is needed for each of the activities such that the flowing entities wait until the previous entities have been processed or until all the necessary resources for the activity become available.
		Seize Resources	When all prior flow entities have been processed, the system checks which resources are available and attempts to seize all the necessary resources. When all the necessary resources have been seized the activity can start. *NetworkSeize* seizes resources which are required for performing the activity. *NetworkSeize* also acts as a queue for the flowing entities waiting for resources.
		Delay	The actual activity is simply modelled as a delay of a particular duration. (see 'Time later')
		Release Resources	At the end of each activity resources not needed for the next activity are released. Resources that are common to the current and next activity remain seized for the next activity. *NetworkRelease* releases the resources seized for performing the activity.
		Move	If the 'location' of the current activity and the next activity are different a move is now executed to move the flow entity and any attached resources to a new location. *NetworkMoveTo* moves the flowing entity as well as seized resources to particular locations in the presentation layout.
3.	*Interaction*	As for activity above	A synchronous activity is exactly the same as an ordinary activity except that it is necessary to seize multiple role resources. A physical input/output flow entity is moved to the next single activity that has the flow entity marked as an input. (NB Virtual flow entities where a single electronic document, for example, can be shared between multiple roles are not considered at the moment)
4.	*Part refinement*	Parallel operator	If the flow entity is a physical entity it cannot be divided as a part refinement, therefore it has to be assumed that each of the parallel threads of activity is performed on the entity at the same time. Thus in modelling terms the real flow entity is assigned to the longest duration thread and the other threads are modelled as threads of activities dealing with a cloned or dummy flow entity created at the start of the thread and disposed of at the end. If any of the threads create or use subsidiary flow entities, these need to be created and matched to the main flow entity as necessary. NB parallel threads are only logically possible if the role is performed by multiple actors. *Split* is used in Anylogic for this purpose.
5.	*Case*	Decision	The decision operator only supports binary decisions, so although the RAD notation supports as many decision

	refinement	operator	outcomes as required, it is necessary to restrict the RAD case refinement to a pair of outcomes. *SelectOutput* object directs the incoming entity to a particular activity thread based on some defined conditions.
6.	*Encapsulated process*	Embedded object	An embedded object requires the creation of a separate simulation model from the sub-diagram of the encapsulated process. This is then embedded in the main process. It is necessary to ensure that resources common to both main and sub model are handled correctly. Return points from encapsulated processes are indicated using state symbols in a RAD. Sub model return points have to be properly connected when a sub model is embedded. *Network* defines a new set of process model which performs a particular sub-process
		Activity with representative duration	A simple encapsulated process can be represented as an activity. However the resources seized and durations have to be representative of the sub activity
7.	*Part refinement closure*	Match or combine operator	Where multiple flow entities come together and need to be associated with each other it is necessary to use a match operation where association rules have to be defined manually or a combine operator where flow entities are merged to become new entities or one entity continues while clones are disposed of. *Combine* object waits for incoming entities until they arrive from preceding activity threads and combine them to produce a single entity.
8.	*Case refinement closure*	Connectors	If both the threads following the case refinement act upon the main flow entity it is only necessary to use a connector from each thread connected to a common single connection point. If additional types of flow entity have been created by any of the post case refinement activities then it is necessary to use a merge operator and manually define the merge rules. *Connectors* are used for connecting the activity threads in case of simple case refinements.
9.	*Stop*	Sink	It marks the end of the flowing entity life-cycle.
Non-RAD concepts embodied in the data model associated with each RAD symbol			
1.	Flow Object	*Source*, *NetworkEnter*, *NetworkLe-ave* and *Sink*	Flow objects are defined once for each RAD model and then referenced by each activity or interaction that creates, modifies or consumes the flow entity. Each flow object needs the four DES operators described.
2.	Flow object state	Appropriat-e connection locations for *Source*, *Sink* etc as defined above.	The flow object state in the RAD software offers Input, Output, Input/Output and constraint as options. A flow object is created at an action which has 'output' set, a flow object is disposed of after an activity where it is only an input. A corresponding resource is also created. An action with input/output simply passes the flow object on after an appropriate delay. Where the flow object is marked as a constraint, the resource created by an action as described above has to be seized before the action can proceed.
3.	Location	Location geometry, Optional move operation	Is defined once for each RAD model. The location definition includes the geometry of the area. The location definition is then referenced by actions as necessary to define where the action is performed. Where the location changes from one action to the next, a move operation is performed

of objects in Anylogic simulation software is utilized to translate the RAD concepts into DES model. Table 5.1 defines the Anylogic objects used to build simulation model from RAD.

The mapping defined in Table 5.1 is utilized to translate RAD concepts (in XML format) into DES model in Anylogic. Anylogic stores its data in a proprietary XML format for which there is no published schema. It was thus necessary to generate sample files using the Anylogic graphical user interface and then infer the schema from the sample files. This process is made easier with the use of a tool like Altova's XML Spy, but although this tool infers a schema automatically from a sample, considerable manual intervention was still required. Once the schema for the sending and receiving systems are available, it should be possible using a tool such as Altova Map force or Biztalk Mapper to generate a translation style sheet (XSLT) using a graphical drag and drop approach. However the need to translate the Globally Unique Identifiers (GUIDs) from one format to another, the recursive nature of some elements in the Anylogic file and the use of GUIDs in both schema to provide cross referencing between elements, e.g. the from and to links for connectors reference the start and end activity IDs, make this difficult if not impossible. The approach adopted therefore was to use the schema and a Microsoft visual studio to generate a class library corresponding to the Anylogic Schema with serialisation/deserialization methods built in. Software has then been written to transfer data from RAD classes to the Anylogic classes. The Anylogic data structure is then serialised to provide an Anylogic input file. Currently the export is only one way i.e. from RAD to Anylogic. After the DES model in Anylogic is created, the dynamic parameters in Anylogic simulation model is inputted in following step.

Based on the mapping defined in this section it is possible to build a simulation model based on the process mapping. The DES model of the service delivery system is developed based on the domain mappings defined in subsection 3.4. The DES model of the service delivery system is constructed by translating the XML schema for RADs into DES. By following the above mentioned mapping from RAD to DES model, the structure of the RAD is retained making it easier for the process improvement experts or domain experts in hospitals to understand and become familiar with the simulation model and experiment with it to analyse different process scenarios and runs.

5.2.4. Adding dynamic attributes and validating DES model

The XML document for DES model created in the subsection 3.3 is analysed to eliminate any errors incompatible with the DES modelling. Largely, these errors are due to incomplete information about the dynamic attributes of the DES objects. The dynamic attributes are probabilities of occurrence of several events, arrival rates, capacities of the queues, simulation duration attribute. The DES model generated is analysed for compatibility issues such that a comprehensive DES model of the service delivery system is developed based on the RAD without loss of information.

1. Dynamic presentation information: The main presentation objects required, *i.e.*, representations of the flow entities and role/resource objects are created automatically using default shapes and different colours. However, these aspects of the shapes can be customised. Currently, the location shapes created automatically needs to be moved to the appropriate position on the workplace floor layout. Further, the size of locations on the layout illustrated in an image and movement paths between the locations needs to be defined manually.

2. Linking presentation template with the DES objects: Any dynamic shapes that have been created manually need to be linked with the translated Anylogic objects.
3. Quantitative data to the DES model: The quantitative data is basically the time statistics for the *Delay* objects, arrival types and rates for *Source*, resource capacities for *NetworkResourcePool*, and queue capacities for *NetworkSeize*. The optimistic, pessimistic and mean durations from the RAD model are used to automatically provide the triangular distribution of times need by the *Delay* operator. Arrival rates have to be created manually as this data is currently not part of the RAD model. Resource capacities are set from the quantity field in the RAD model and queue capacities default to large values. These may need to be adjusted manually if there are constraints on queue size. This information helps to build a complete Anylogic simulation model, which can analyse various improvement scenarios. Furthermore, charts for different key performance indexes of the service delivery system can be added to the simulation model to measure the effects of changing scenarios. A default chart for utilisation of resources is created automatically.

The following section presents the application of the developed methodology for building DES model of a process in radiology department. Finally, the improvement cases are also discussed based on the DES model developed in Anylogic.

5.3. Case Study

The case study involves the MR scanning service in the radiology department at a large hospital in UK. For more information about this case study can be obtained in

Chapter 4. Figure 5.5 illustrates the physical layout of a part of radiology department where MR scanning is performed. It shows the two scanners and associated rooms for performing the MR scanning procedure.

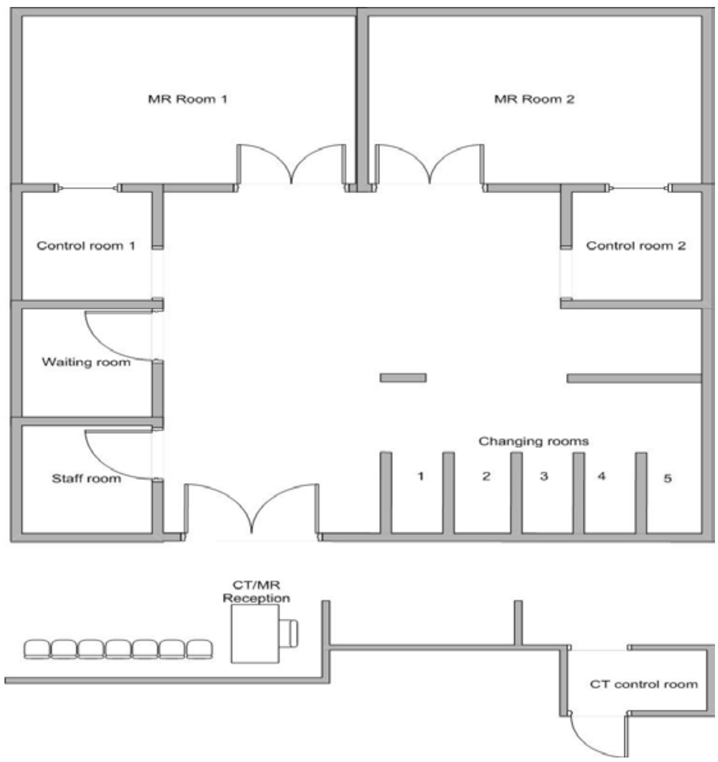


Figure 5.5: Physical layout of the MR imaging service in radiology department

The MR scanning is primarily a medical imaging technique most commonly used in radiology to visualize the structure and function of the body. The process starts when patient arrives for MR scanning process at the radiology department and process ends when the patient scans are finished and uploaded into the PACS for radiologist review/interpretation. Due to the large demand for scans from different departments and limited number of available patient appointment slots on the three MR scanners, radiology department is under tremendous pressure to meet the targeted wait time guidelines.

The proposed RAD based DES modelling methodology is applied to model the MR service delivery process. The methodology developed in Section 5.2 is utilized to build the simulation model of the service delivery system. The subsections below detail the application of the proposed methodology for the RAD based modelling of the MR scanning process.

5.3.1 Development of RAD model for MR Service delivery system

RAD model for MR scanning process is developed based on the modelling methodology developed in Chapter 4 (Shukla *et al.*, 2009). Staff representing different roles such as radiographer, receptionist, radiology nurse, porter, and radiologist were interviewed. The face to face 30 minute interviews were conducted in the radiology department in one day by project staff. Each staff member was asked to detail their involvement in the MR scanning process from beginning to end. The interviews were recorded using the digital recorder DS-40 from Olympus. After recording, the audio files were transcribed into Microsoft Word (2003). The transcribed interviews were utilized to develop the RAD model of the MR scanning process (for more information about RAD-modelling methodology see Chapter 4 or Shukla, *et al.*, 2009). Figure 5.6 illustrates the simplified RAD model of the MR scanning process, *i.e.*, from patients arrival at the MR suite at their appointment times until they exit MR suite after scanning. A simple RAD model is illustrated to show the application of proposed methodology for DES model development from RAD.

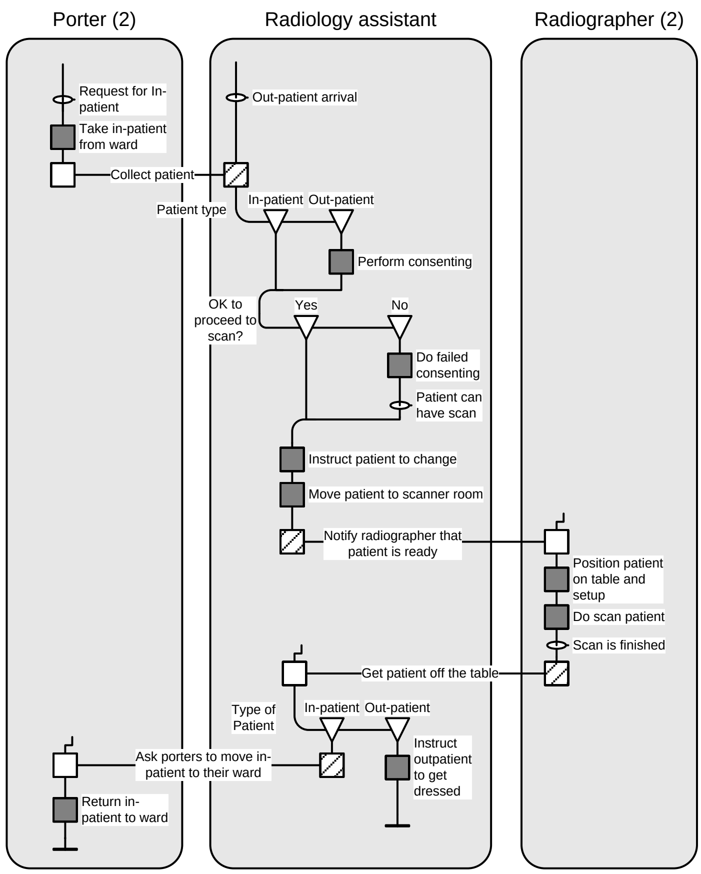


Figure 5.6: RAD model of MR scanning process that is used as a case for developing DES model

Once the MR scanning process is represented as a RAD, data related to each of the RAD concepts such as time durations for activities and interactions; and, experience, skills, resources for each role, are inputted into Microsoft Visio. Then, the RAD model is utilized to generate the XML file input to Anylogic.

5.3.2 Develop DES model for MR scanning process

The RAD model developed in Microsoft Visio is utilized to generate the DES model in Anylogic based on the mapping defined between RAD and DES modelling in Anylogic. The RAD toolbar in Microsoft Visio runs the code needed to do the RAD-Anylogic translation. The resulting process model in Anylogic is illustrated in Fig. 5.7. The translated model in Fig. 5.7 is based on Network based Modelling, hence, it comprises of process flow diagram and network resources diagram. The names of the translated concepts are shortened for clarity and to be valid for modelling.

5.3.3 Input dynamic attributes in DES model

Following information is added into the DES model generated in Section 5.3.2:

4. Dynamic presentation template of MR scanning process: The shapes associated with roles such as porters, radiology assistants, radiographers, patients (inpatients, outpatients, and emergency patients) are created automatically, but movement paths need to be defined manually an image of the workplace added and location objects adjusted to sit over the MR scanning layout. The main areas in MR scanning layout are reception area, MR rooms, control rooms, changing areas, and a waiting room.
5. Linking presentation template with translated DES objects: The shapes, paths, and areas are linked with objects translated from RAD model such that when a process is simulated the dynamic roles and entities flow in the presentation template. The flow in the presentation template will reflect how the MR scanning process is executed for patients.
6. Inputting quantitative data to the DES model representing MR scanning process:

   The additional quantitative data needed by the DES model is added. This is mainly arrival rates for source, and any adjustment of queue capacities. The key performance indicator for the MR scanning process is taken to be the utilization rates of the MR scanners as it affects other performance indicators.

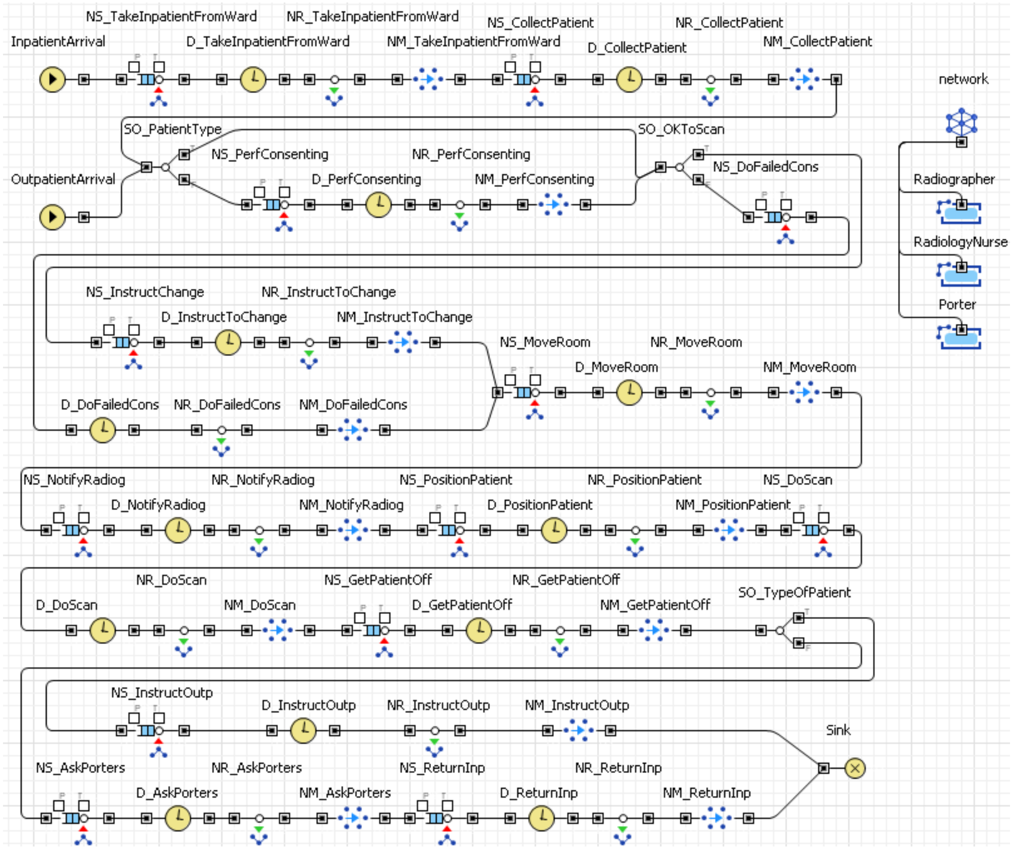


Figure 5.7: DES model presented in Anylogic software based on RAD model of MR scanning process model

Finally, the DES model of MR scanning process in Anylogic is used for analysing various improvement scenarios and its effect on utilization rates of the MR scanning process. The following text illustrates two improvement scenarios and its impact on MR scanning process:

A. <u>Having two tables per MR scanner</u>: Due to the fact that only one MR table is present and dedicated to a scanner, therefore, the MR scanner remains idle when a patient scan ends and next patient is being loaded onto the scanner. The disabled outpatients and inpatients come in wheelchairs or on beds for scanning and they require lifting on to the scanner tables, which become free only when the previous patient's scan is finished. In order to avoid this idle time, an extra MR table is added and its impact on scanner utilization rates are studied. Doing so can reduce wait time. Two scenarios are generated from this improvement case: i) One scanner table per scanner; ii) Two tables per scanner in MR scanning process. These scenarios are simulated and the results are presented in Fig. 5.8. It shows that having two tables per scanner will be useful to improve the utilization rates from 45% to 75%.

B. <u>Performing patient consenting by referring clinicians</u>: The consenting is done for each patients scheduled for MR scan in order to check the suitability of the patient for MR scan. Patient consenting involves set of questionnaires about metal implants in the patient body. This is due to the negative impact of MR scanning process on patients having metal implants. Further, the radiology staffs are less informed about the patient medical history than the referring clinician or GPs. Therefore, it may be better to shift the consenting to the GP level when patients are referred for scans. By having referring consultants or GPs fill up the consenting form when an MR scan is requested the MR process can save up to 15 minutes of time for each patient. The radiology department could be notified of the status of the already conducted consenting procedure by the referring consultant's or GP's office prior to the scan appointment. Two scenarios are simulated based on the DES model obtained and its impact on utilization rates are studied: i) MR scanning process with consenting procedure; and ii) MR scanning process with short consenting procedure (max. 2 minutes). Figure 5.8 illustrates the improvement realized in both of the scenarios.

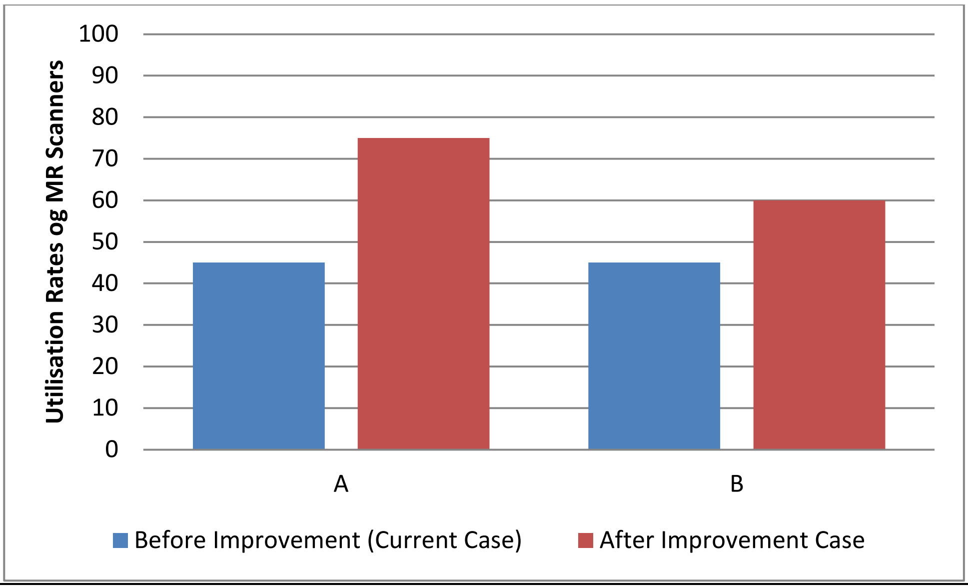


Figure 5.8: Utilization rates of MR scanners for different simulated improvement cases

5.4 Summary

This Chapter proposed a methodology to generate the DES model of complex service delivery system. The methodology employs RAD models of service delivery system obtained from staff interviews and translates RAD concepts into DES modelling objects. Thus, eliminating the complexity involved in building quick and reliable simulation model. The methodology also develops the data model for RAD which can take the inputs from various service data sources such as tracking data, IT systems data, EPRs. The methodology is implemented to develop DES model for MR scanning process for analysis and improvements. The RAD considered in this Chapter was constructed by modelling the most common or standard service delivery system. Hence, it does not include the variations which are predominantly are diverting away *from* a care pathway. Therefore, next Chapter proposes a methodology to model unwarranted variations *from* a care pathway with the help of real time tracking information about the process.

PART II: Reducing Unwarranted Variations ***from*** a Care Pathway

CHAPTER 6: Role Variations Modelling based on Tracking Data

6.1 Introduction

In this Chapter, variations modelling methodology for identifying a type of system variations is proposed (*role variations* defined in Chapter 3.3). The proposed methodology is discussed and implemented in service delivery system such as radiology department. In order to identify role variations, a real time locating system based on RF/IR was specifically implemented in the radiology department of the hospital for this study. The implementation of RF/IR is discussed in SoW2 (2009b,c,d). Therefore, this Chapter includes a brief discussion on imaging processes in radiology department.

The radiology department operates solely as a service unit to other departments in the hospital in that it does not treat a particular disease, but rather supports treatment functions in other radiology departments. These results in radiology department being affected by variations that frequently originate in other departments as well as compounding its own variations. The main sources of variations, as discussed in Chapter 3, in the radiology department are due to: (i) variations in clinician practices; (ii) patient characteristics; (iii) system variations (resource availability variations, patient and staff scheduling, changeovers/setups of complex equipment); (iv) input/output variations (patient scan request arrival variations, discharge variations). This chapter deals with the system variations which are largely unnecessary and leads to lower performance of service units. Particularly, this Chapter proposes a variations modelling methodology for identifying *role variations* which are a part of system variations. The *role variation* occurs when there is unavailability of certain types of roles. These variations results in other roles taking up the additional responsibilities leading to unwanted delays in delivery of services. The *role variation* also occurs when a role deviates from normal day to day sequence in which role visits rooms/areas for delivering their share of services to patients. These variations are mainly caused when there is unavailability of certain resources, for e.g., roles frequently searching for resources can lead to variations in paths. Hence, *role variations* are system variations leading to unwanted delays and bottlenecks.

RAD is recently identified to be one of the suitable techniques for modelling the process in imaging process (Shukla, *et al.*, 2009). However, the resulting RAD model illustrates only the most standard process adopted in service delivery system. Therefore, it is necessary to develop a methodology which can illustrate variations <u>*on*</u> a care pathway.

This Chapter aims at identifying the *role variations* and modelling them for process improvements. The role variations are mostly reflected in most frequently adopted role paths (*i.e.* sequences of rooms/areas visited by a role for delivering services), which can be electronically tracked, based on the real time tracking systems (RTLS). RTLS allows tracking of roles in radiology and storing the tracking events (*tagID, roomID, time*) in the database which can be analysed to model role variations. A modelling methodology based on graph theory concepts, *i.e.*, edge coloured directed multigraphs (ECDM), is utilized to identify and represent the role variations. This modelling method will use RAD models to identify and represent system variations occurring in roles and their paths with the help of ECDMs.

The rest of the Chapter is arranged as follows. Section 6.2 details the background of radio frequency/ infra-red (RF/IR) based real time locating system (RTLS) for hospitals. In Section 6.3, the system variation modelling based on edge coloured directed multigraphs (ECDMs) is discussed in detail. Section 6.4 discusses the learning algorithm for ECDMs from the RTLS tracking database. Section 6.5 details a case study of MR scanning process at the radiology department of one large UK hospital. Finally, summary is presented in Section 6.6.

6.2 Radio Frequency/ Infra-Red (RF/IR) based Electronic Tracking

This section discusses RTLS tracking based on RF/IR system and its deployment in a radiology site. RTLS is used to track and identify the room level location of objects in real time using simple, inexpensive tags attached to or embedded in objects, and readers that receive the wireless signals from these tags to determine their locations. Recently, hybrid RTLS solutions working on the principle of RF and IR waves have been introduced for hospital asset tracking applications (Krohn, 2008). The characteristics of RF and IR waves are used in order to acquire room level and sub-room level accuracy (Crimmins & Saulnier, 1999). RF/IR based RTLS are commercially available and are dedicated to provide solutions for patient, medical device, and staff tracking in hospitals.

The main components of the RF/IR based RTLS are tags, monitors, stars and communication mechanism. The details about the working of these components are presented below:

Tag: It is a battery powered RF/IR tag that can be attached to the object that needs to be tracked in real time (see Fig. 6.1). Tags observe their environment for incoming IR signals with the help of infra-red sensors and periodically report both its own unique code and IR location ID. The IR code represents the area or location where the tag is identified. This communication protocol allows the usage of multiple tags for real time tracking. The tags are also equipped with on-board motion sensors, which allow tags to operate at two different rates: slow when the tag is stationary and fast when the tag is in motion. This provides a method for locating tagged assets with room-level accuracy. The tags have four switches which can be customized for different applications. For example, switches can be used to trigger an alert to indicate tampering if a tag is removed from the object.

Monitor: It is an IR signalling unit which spreads the IR waves to provide a method of locating tagged objects (see Fig. 6.1). Each monitor transmits an IR pulse pattern containing a unique location code. The IR coverage zones are limited by solid physical structures such as walls. A monitor spreads the IR waves, which bounce off effectively from structures and walls to the cover entire room including locations that are not in the direct line of sight to the monitor. Tags in the room having a monitor receive the IR location ID and communicates periodically about its position. The tag's communication is then processed to locate and identify tagged objects within the room. Monitors in RF/IR based RTLS can also communicate with RF. This enables monitors to have constant communication with the stars using RF. Monitors communicate with the stars periodically to report the status of their batteries.

Figure 6.1: RTLS hardware components used in this study: Tag, Monitor, Star

Star: The star interprets and reports RF messages emitted by tags and monitors at larger distances (see Fig. 6.1). Stars communicate the data received from tags to the server running the tracking software interface. The communication between a star and the server is done by using Ethernet. Tag transmissions are processed to track tagged objects in the software. The star allows tracking of large number of tags distributed in several areas.

Communication Mechanism: The basic mechanism of communication between RF/IR based RTLS can be summarized in Table 6.1. As shown in Table 6.1, monitors transmit their location ID using IR and the tag receives the location ID via IR. The location ID and tag ID are then sent to stars via RF which further communicates received data to the server.

Table 6.1: Communication among the RTLS components

	Tag	**Monitor**	**Star**	**Server**
Tag	-	IR waves	RF waves	N/A
Monitor	IR waves	-	RF waves	N/A
Star	RF waves	RF waves	-	Ethernet
Server	N/A	N/A	Ethernet	-

In order to illustrate the deployment of the RF/IR RTLS system, a MR scanning site of the radiology department is considered. Fig. 6.2 illustrates the deployment of tags, monitors, and stars in MR scanning site of radiology unit.

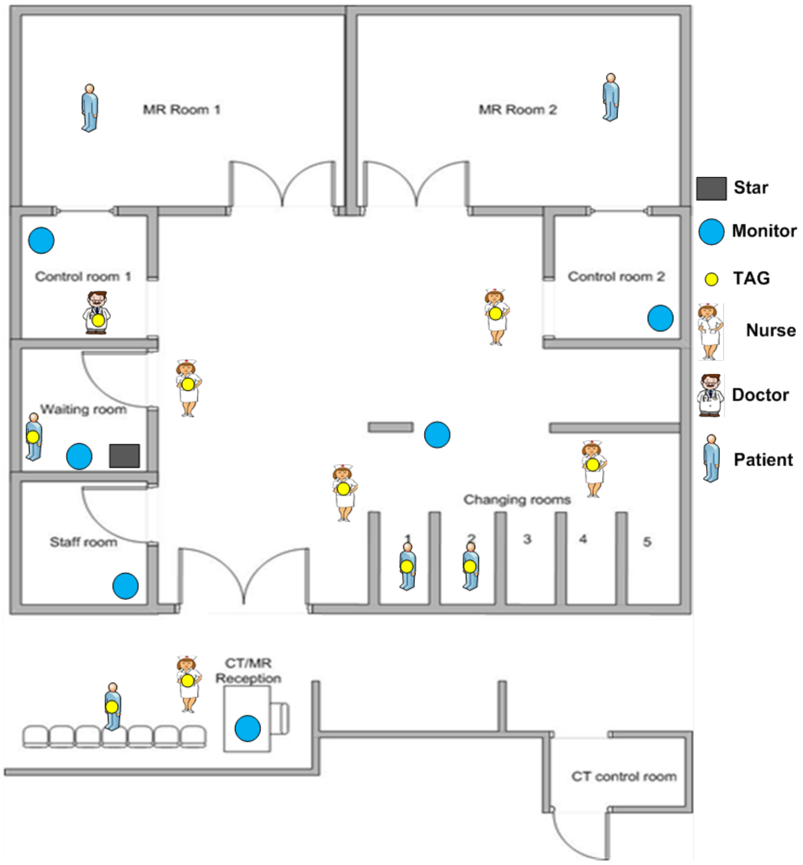


Figure 6.2: Deployment of RF/IR based RTLS in MR scanning site of radiology unit

The deployment illustrates the placement of monitors, and star within different areas of the hospital layout. The tags are attached to patients, nurses and doctors for their real time tracking. Monitors are placed in areas such as waiting room, reception, changing area, and control rooms 1 & 2. These monitors spread the IR waves in their respective areas. These IR waves are correspondingly received by tags attached to patients, doctors and nurses. A tag then transmits its unique ID and IR location ID to a star via RF waves. Subsequently, the tracking information is received periodically by the RTLS and is recorded in the server.

The RF/IR based RTLS tracking solutions are recently introduced and are used in large hospitals for people and equipment tracking and management (Centrak, 2009). So far there are no studies indicating any effect of these systems on patient health. However, care must be taken while using these systems around medical imaging equipment. The RF/IR tags contain metallic batteries to communicate with the monitors and stars for RTLS. Hence, the use of tags has to be avoided when around imaging equipment. This is done by removing the tags from staff and patients before they enter the scanning rooms and then placing the tags back on them again when they egress the scanning rooms. The RF/IR systems were tested in two stages before final deployments at Hospital. The information about these tests/deployment and deployments is presented in SoW2 (2009b,c,d)

The tracking data obtained from RF/IR based RTLS includes crucial information about roles such as (*tagID, roomID, time*). This information is utilized to model frequently occurring patterns in role paths. The following section details the methodology to model role variations arising from radiology service system.

6.3. Modelling the system variations in radiology

This section details the graph based modelling method to represent the system variations (specifically, *role variations*) that occur in the radiology department in form of role variations. The main motivation for developing the graph based model is to represent paths adopted by roles while service delivery. Different rooms/areas within the service delivery site are represented as nodes of the graph based model. In addition, set of directed edges is used to represent role paths. Further, in order to represent various patterns of role paths, concept of coloured edges is utilised. Hence, patterns in role paths are represented in form of edge coloured directed multi-graphs (ECDMs).

A simple illustration of ECDM is shown in Fig. 6.3. The nodes numbered from 1 to 9 represent the rooms/areas of the service delivery site and each set of distinct coloured directed edges represent paths adopted by a role for delivering service. The ECDM illustrated in Fig. 6.3 shows three patterns of role paths, *i.e.*, A, B, and C having green, red, and blue directed edges. The main challenge in modelling patterns is to have a formal and mathematical representation of ECDMs. Hence, the following text is dedicated to provide mathematical representation of ECDM.

The modelling based on ECDM is based on the generalized graph theory concepts. Hence, the graph based models existing in literature are reviewed and suitable graph based model is selected for ECDM. Recently, McGuffin and Schraefel, (2004) introduced new types of generalized graph based models and compared them based on their capability to be used for information navigations representation. The purpose for the development of these models was to generate flexible models which can be used to efficiently and effectively analyse complex and multi-dimensional information. One of the graph based models defined under this category is the zzstructure (McGuffin and Schraefel, 2004), which can represent or subsume multiple instances of other graph based representations. Zzstructures generalize various data structures such as lists, 2D arrays, and trees. Zzstructures are directed multigraphs which can have multiple edges between pair of nodes and each edge has associated colour and direction. In addition, zzstructure must also satisfy the following restriction:

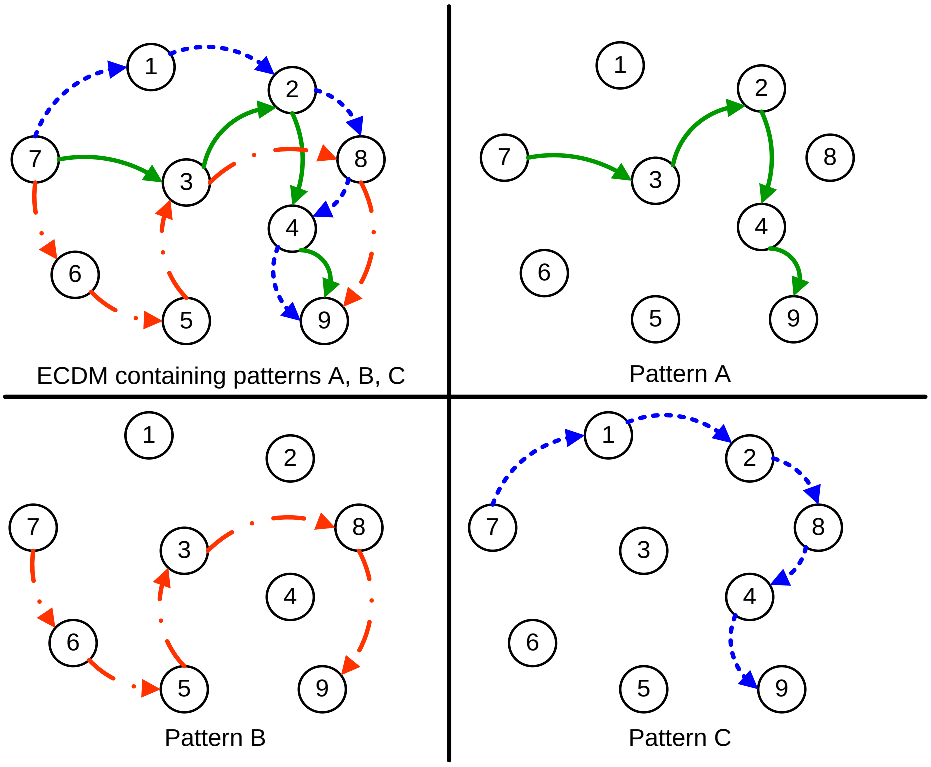


Figure 6.3: Example of ECDM representing patterns A, B, and C, each pattern represents role paths within service delivery site

<u>Restriction R</u>: each node in a zzstructure must have at most one incoming/outgoing edge of each colour.

Due to restriction R in zzstructure, each coloured role paths should form path that do not intersect within same colour. However, in a healthcare setting, patterns of role paths can violate restriction *R* as they can visit one room/area more than once in the service delivery path. Hence, zzstructures without restriction '*R*' are used for modelling ECDMs. This enables the ECDMs to represent multiple complex role paths. Following text details the mathematical representation of ECDMs.

An ECDM can be defined in terms of graph theory as $\mathbf{G} = (\mathbf{V}, \mathbf{E})$, where $\mathbf{V}$ is the set of areas (i.e., nodes) in the service delivery site defined as

$\mathbf{V} = (v_1, v_2, v_3, \dots, v_n)$. $\mathbf{E}$ is the set of directed edges or individual movements, *i.e.*, $\mathbf{E} = (e_1, e_2, e_3, \dots)$ between areas in $\mathbf{V}$. The l^{th} edge (e_l) of $\mathbf{G}$ is equivalent to $v_i \to v_j$, *i.e.*, directed from area v_i to v_j. The direction and the edges associated with each pair of area (v_i, v_j) is denoted by the adjacency matrix **A**. The attribute value $\{a_{ij}\}$ of **A** is the number of edges with source area v_i and target area v_j. Mathematically,

$$\{a_{ij}\} = \#\, of\ edges\ from\ v_i to\ v_j \qquad \forall\ (v_i, v_j) \in \mathbf{V} \tag{1}$$

A function $f(.)$ is defined for mapping the edges to the colours or patterns of role paths such that:

$$f : \mathbf{E} \to \mathbf{C} \tag{2}$$

where, $\mathbf{C}$ is defined as the set of 'K' frequent patterns of role paths $(c_1, c_2, c_3, \dots c_K)$ for an ECDM. The k^{th} pattern of a role will have a set of edges which are to be represented by colour c_k. Therefore, the attribute value a_{ij} of **A**, representing edges from v_i to v_j, is divided into K patterns of role paths. In particular, the division of a_{ij} classifies edges into different patterns of role paths. The division of a_{ij} edges into colours defined by **C** is such that:

$$a_{ij} = \sum_{k=1}^{K} q_{ijk} \,, \tag{3}$$

where, q_{ijk} is the number of edges originating from the i^{th} area and terminating on the j^{th} area of $c_k^{\text{ th}}$ colour or belonging to k^{th} pattern of role paths. The division of a_{ij} classifies all the edges into respective variation patterns of role paths. However, the sequences of the role paths are represented mathematically. Therefore, let us consider $\mathbf{S}^k$ which represents the sequence of edges that is represented by the c_k colour. The sequence $\mathbf{S}^k$ comprises the order of nodes v_i $\forall\, v_i \in \mathbf{V}$ traversed by a role. Therefore, for all patterns of role paths are represented by colours in $\mathbf{C}$, there is a sequence of the edges represented mathematically by $\mathbf{S}^k$. Hence, the aforementioned formulation represents the patterns of role paths mathematically in the form of ECDMs. Considering the above mathematical notations, the restriction 'R' of zzstructure can also be formulated as

$$R :\to 0 \le q_{ijk} \le 1 \qquad (v_i, v_j) \in \mathbf{V}; c_k \in \mathbf{C} \quad . \tag{4}$$

This represents that an area can have at most one incoming and one outgoing edge. However, the above restriction is not present in ECDMs and therefore these are utilized to represent variations in role paths adopted for service delivery.

The tracking data gathered by RTLS is utilized for learning of ECDMs. The learning of ECDMs involves an algorithm which can analyse tracking database to elicit patterns in role paths. The next section provides information about the development of a learning algorithm for ECDMs.

6.4. Learning algorithm for ECDM

This section details the algorithm proposed for learning ECDM from the tracking database. A properly learned ECDM represents paths adopted by a role in the service delivery system. It is necessary to develop an effective learning algorithm for constructing ECDMs from the tracking database. The analysis conducted using inadequately learned ECDMs will provide misleading results that do not reflect accurate information on role paths. The tracking database obtained by deploying the

RTLS system (tags, monitors, stars) generates large amount of events data which is in the form of tuple (*tagID*, *roomID*, *time*). These events reflect the location of individuals performing particular role while delivering patient services. This information about the process can be utilized to construct ECDMs by defining a formal algorithm for learning from events database. The overall methodology for learning ECDMs is illustrated in Fig. 6.4.

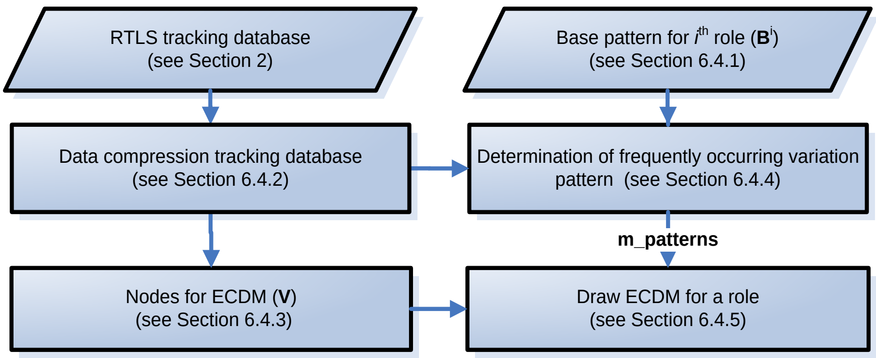


Figure 6.4: Flowchart representing overall learning methodology for ECDM from tracking data

Following paragraphs discusses the steps involved in the learning algorithm which identifies patterns of the role paths.

6.4.1 Determining standard role path for service delivery

The initial step for learning algorithm is to gather information about the standard path of roles, which are most commonly adopted for delivering patient services. This information can be gathered from discussions with senior clinicians involved or by observation and discussions with the relevant staff. The RAD model developed in Shukla, *et al.*, (2009) can also be used for eliciting standard paths together with location information.

An Activity-Location-Role table can be constructed to relate locations (rooms/areas) with the service delivery activities for a particular role (see Table 6.2). As per definition, roles can be radiographer, radiology nurse, receptionist, and radiologist. Table 6.2 is used to get standard paths for each role, which will be utilized in next steps to elicit other patterns from the tracking database.

Table 6.2: Activity-Location-Role table for *i*th role

Locations / Activities	A	B	C	D	E
Activity (*i*, 1)	1	0	0	0	0
Activity (*i*, 2)	0	0	2	0	0
Activity (*i*, 3)	0	0	0	0	3
Activity (*i*, 4)	4	0	0	0	0
Activity (*i*, 5)	0	0	0	5	0
:	:	:	:	:	:

An Activity-Location-Role table relates activities of i^{th} role with the areas within service delivery site. While relating the activities with locations, the sequence of activities is also defined to get the standard or base pattern (for example, the base pattern for receptionist can be Reception, Patient Changing Area, Control Room, Patient Changing area, and Reception). Now onwards, the standard path is referred in this Chapter as base pattern $\mathbf{B^i}$ of i^{th} role. The structure of the table is shown by an example in Table 6.2. The rows represent activities (for example, register patient on arrival, go to control room, forward scan request to radiographer, return back to reception) and columns represent the locations (for example, Reception, Patient Changing Area, Control Room, Waiting Room). Activity (*i*, 1) denotes the 1st activity performed by i^{th} role in service delivery system. Based on the attribute value of the table it is possible to create base pattern of a role. For example, the base pattern for the example shown in Table 6.2 is $\mathbf{B^i} = (\mathrm{A, C, E, A, D})$. The base pattern obtained in this step is used together with the RTLS tracking database for modelling and analysis.

6.4.2 Filtering the tracking database

The initial data obtained from the tracking database can contain erroneous, incomplete, and redundant data which must be screened and filtered out. Similar to all other RTLS, the RF/IR system generates a stream of events data of the form (*tagID, roomID, time*) where *tagID* is the unique code associated with the Tag which is attached to the individuals performing particular roles. RoomID is the code of the monitor under which the tag was identified, and time represents the time at which a tag was identified. If all the events associated with a particular *tagID* are sorted on time scale and grouped, they will form a pattern of the role paths. Hence event are grouped into stages which can be represented in the form of (*tagID, roomID; time in, time out*). In order to study the patterns of role paths, the absolute time can be discarded and only relative duration can be utilized. Hence, the movement stages can be developed in form (*tagID, roomID, duration*). This procedure greatly reduces the number of redundant events in the database and helps to focus on patterns.

6.4.3 Identifying number of areas involved in service delivery

This step details the identification of areas $\mathbf{V} = (v_1, v_2, v_3, \ldots, v_n)$ for ECDM. It is the main element to construct the ECDM. In RF/IR based RTLS, the monitors which are installed in different areas of the service delivery site are considered to be the nodes for ECDM. These areas are represented as nodes in ECDM. The patterns of role paths between nodes will have to be defined to develop the ECDM. Following subsection discusses about determining the patterns of role paths from tracking database.

6.4.4 Determination of patterns of role paths

This step extracts frequently occurring patterns of role paths from the RTLS tracking database. The frequently occurring sequences of areas in tracking database are defined as patterns of role paths. The frequently occurring patterns different from base pattern characterizes that system variation occurs while delivering services. The events obtained from subsection 6.4.2 comprise of three attributes – *tagID*, *roomID*, *duration*. Since, in this Chapter we are interested to identify various patterns occurring within the process, therefore, only *tagID*, *roomID* is utilized for analysis.

Let us consider, **L** to be a set of distinct *roomID*s and pattern **E** is a nonempty subset of **L**. That is

$$\mathbf{E} \neq \phi; \mathbf{E} \subset L \quad . \tag{5}$$

There are N of events (or *roomID*s) in the tracking database for a particular *tagID*. The tracking database can be defined as $\mathbf{D} = \{D_i\}_{i=1}^{N}$, where the i^{th} event $D_i \in \mathbf{L}$. The dataset **D** is constructed by extracting the *roomID*s corresponding to a particular *tagID*. Based on base pattern defined in subsection 6.4.1, $\mathbf{B}^{\mathrm{i}}$ for the i^{th} role is used to construct the ECDM for the i^{th} role. $\mathbf{B}^{\mathrm{i}}$ is utilized to extract the patterns of role paths from **D**. The events in $\mathbf{B}^{\mathrm{i}}$ is termed as base events. Patterns in **D** which are similar to the base pattern $\mathbf{B}^{\mathrm{i}}$ are identified. Three types of variations in base pattern that can be extracted by the proposed algorithm are as follows:

A. Variation type 1: These variations are due to random events that occur between two consecutive base events in $\mathbf{B}^{\mathrm{i}}$. Number of events that can occur in between two consecutive base events are restricted by threshold α . This is done to restrict the size of pattern in the search space otherwise the search space will increase exponentially. The patterns crossing this threshold are infeasible and are not considered further. This is due to the fact that if a role is being interrupted during its designated activities it will be reflected by some events occurring between two consecutive base events. On the other hand, if the number of in-between events is large then it is assumed that the role has started performing new activities that is not reflected in base pattern.

B. <u>Variation type 2</u>: These represent variations in patterns signifying that a role has either missed some of the activities to be performed in the rooms defined in base pattern by missing base events or has done those activities in different rooms. The missing of base events is also restricted by threshold β. It is assumed that if a role is missing more than β base events in a pattern then the role is following completely different path and hence is not included as frequently occurring pattern.

C. <u>Variation type 3</u>: These are represented by deviation in the base patterns due both types of variation, i.e., variation 1 and variation 2. These patterns are restricted by thresholds α and β.

The steps in an algorithm based on $\mathbf{B}^{i}$, α , β, and **D** has been defined below. The steps are as follows:

Step 1: Get the information about tracking database **D**, base patterns ($\mathbf{B}^{i}$) for all roles, α , and β.

Set $i=1$.

Step 2: For i^{th} role do following sub-steps:

Step 2.1: Call function *extract_patterns* with attributes **D**, $\mathbf{B}^{i}$, and α .

// *This is done to extract patterns corresponding to Variation type 1* //

Step 2.2: Assign extracted patterns to $\mathbf{m\_patterns}$

Step 2.3: Generate pseudo base patterns based on $\mathbf{B}^{i}$ and having maximum of β missing base events.

Step 2.4: Assign all the pseudo base patterns to $\mathbf{pseudo\_B} = \{\mathbf{P}_1, \mathbf{P}_2, \mathbf{P}_3 ...\}$

Step 2.5: For each $\mathbf{P}_j$ where, $j \in (1, 2, \ldots, |\mathbf{pseudo\_B}|)$ do

Step 2.6: Call *extract_patterns*(**D**, $\mathbf{P}_j$, α) considering base pattern to be $\mathbf{P}_j$.

//*This is done to extract the patterns defined by Variation type 2 & 3. That is, the patterns extracted in this step can have at the most* β *missing base events and* α *random events in between base events* //

Step 2.7: Append the extracted patterns to $\mathbf{m\_patterns}$

End For

End For

Step 3: For m^{th} pattern in $\mathbf{m\_patterns}$, where $m \in (1, 2 .... |\mathbf{m\_patterns}|)$ do

Step 3.1: Call function *frequency* with $m\_pattern_m$ to evaluate the significance of the variation pattern

Step 3.2: Assign the frequency of the pattern to f_m

Step 3.3: If $f_m < F$, then discard the $m\_pattern_m$ in $\mathbf{m\_patterns}$.

End If

End For

Step 4: Output the $\mathbf{m\_patterns}$ as qualified variation patterns

Step 5: $i = i + 1$ and Goto Step 2 until $i > |\#roles|$

In the above steps, two additional functions *extract_patterns* and *frequency* have been used to illustrate the methodology for identifying frequently occurring patterns of role paths from tracking database. The steps involved in *extract_patterns* function are detailed as follows:

Step 1: Get the input $\mathbf{D} = \{D_i\}_{i=1}^{N}$, $\mathbf{B} = [b_1, b_2 \ldots b_k \ldots b_{|\mathbf{B}|}]$ (base pattern) and α as the argument to the function

Step 2: Set $c = 1$ and $k = 1$

Step 2.1: For all $i \in \{1, 2 \ldots. N\}$ set $index = 0$

Step 2.2: If $(D_i = b_k)$

THEN $k = k + 1$

ELSE $index = index + 1$

End If

Step 2.3: If $index \leq \alpha$

THEN $candi\_pattern(c) = D_i$ and $c = c + 1$

ELSE $k=1$, $c=1$, $index=0$, and CLEAR *candi_pattern*

End If

Step 2.4: If $k=(|\mathbf{B}|+1)$

Output *candi_pattern*

CLEAR *candi_pattern*

$c=1$, and $k=1$

End If

End For

Step 3: End *extract_pattern* function

The steps for the *frequency* function are straight forward and hence are not detailed. The output of frequency function is to provide the number of times each pattern in $\mathbf{m\_patterns}$ exist in database **D**. The output is stored in the vector $\boldsymbol{f}$ having the frequencies of each of the patterns in database **D**.

The output of the above algorithm is the **m_patterns** which comprise of the patterns of role paths.

6.4.5: Constructing the ECDM for a role

The frequently occurring patterns (**m_patterns**) identified in subsection 6.4.4 is utilized for constructing the ECDM of a role. Each movement pattern in **m_patterns** is represented by different edge colours $c_k \in \mathbf{C}$ in the ECDM. The movement patterns in **m_patterns** can be directly mapped to the sequence of edges defined by $\mathbf{S}^k$ in the

ECDMs of c_k colour (see Section 6.3). As per the definition of ECDM, the patterns of role paths are a set of coloured edges between different nodes or areas (obtained in subsection 6.4.2). The values of q_{ijk} for all *i, j,* and *k* are also identified based on the **m_patterns**.

Section 6.5 presents a case study of MR scanning process of the radiology department where variation modelling methodology has been applied. The RF/IR tracking was done in the MR scanning site and the data gathered was utilized to implement the proposed methodology. The following section details the application of the proposed methodology.

6.5. Case Study

The case study involves the MR scanning service in the radiology department at a large hospital in UK (see Section 4.4 for more information about this MR scanning process).The main areas of the MR scanning service delivery site are CT/MR reception area, changing area, waiting room, control room 1, MR room 1, control room 2, and MR room 2 (see Fig. 6.2). The ethics approval required for this research study was covered under the Comprehensive Research Agreement between collaborative partners University of Warwick, Hospital, and GE Healthcare.

The RF/IR based RTLS was deployed in the MR scanning site of the radiology unit (the RTLS deployment is same as illustrated in Fig. 6.2). The main areas that are tracked are CT/MR reception area, changing area, waiting room, control room 1, MR room 1, control room 2, and MR room 2. The power levels of the monitors were appropriately modified as per the size of rooms/areas such as Control Room 1 & 2 (IR Power Level 7), Waiting Room (IR Power Level 7), Patient Preparation Area (IR

Power Level 7), and CT/MR Reception Area (IR Power Level 15) . More information about the RF/IR deployment can be found in SoW2 (2009d). Monitors are installed in each of the areas except MR room 1 and MR room 2 to ensure proper scanning procedures and to ensure patient and staff safety as discussed in the previous sections. Hence, five monitors are installed in CT/MR reception area, changing area, waiting room, control room 1, and control room 2. These monitors spreads IR signals within each area which is picked up by tags associated with staff performing roles to communicate their position to the star which receives information about the location of tags and communicates that to the server which stores the information as events database. In order to ensure the highest level of safety, the monitors were installed after conducting a site analysis to adjust IR power levels to the MR scanning site requirements. Furthermore, project staff with the help of hospital officials made an arrangement to prevent the entrance of staff and patients having tag to the MR rooms to ensure safety procedures are followed.

To ensure smooth data collection, the star and server workstation was installed in waiting room of the MR scanning site. Tailored information sheets about the study and type of RF/IR based data gathering procedures were circulated among radiology staff and patients to inform them of the study and also to seek their voluntary participation. The radiographers, receptionist and radiology assistant that were willing to participate in the study were provided tags at the start of their shift each day to track their paths. The receptionist was informed about the type of study and was asked to provide information sheets inviting patients to the study when registering them on arrival. Patients willing to voluntarily participate in the study were provided tags by project staff.

Project staff was at hand at all times to remove and collect tags from MR scanning staff and patients before they entered the MR scanner rooms (MR room 1 and MR room 2). The tags were given back to staff upon egress from the MR rooms. All tags were carefully collected from patients when they egress the MR scanning site after examination and from staff at the end of their shifts. This process of data gathering was conducted over a period of one week to gather sufficient information about the paths adopted by staff within MR scanning site. The data was continuously recorded in the workstation placed in waiting room in the form of events comprising of attributes such as (*tagID, roomID, time*). In order to model system variations in the MR scanning process of the radiology department, the proposed variations modelling methodology based on ECDM is applied.

6.5.1 Determining base pattern for role

The roles involved in MR scanning process are receptionist, radiographers, and radiology assistant. These roles are required move between different areas of MR scanning site in order to deliver services to patients. The base pattern of radiographer role is identified based on their involvement in MR scanning process. The RAD model of the MR scanning process is utilized together with locations information for identifying base pattern of the role. More information about the MR scanning process is discussed in detail in Chapter 4 (Shukla, *et al.*, 2009). This is done to develop Activity-Locations matrix for radiographer role (see Table 6.3). These matrices also define the precedence relationship among locations (rooms/areas) and activities performed by radiographer role.

The base pattern of the radiographer based on Table 6.3 can be identified to be **B** = (D, B, F, D) or (E, B, F, E). The radiographer (positioned at location D & E) collects patients from the changing area and performs final check about patient consenting in changing area. Then patient is taken to the MR scanner room where the scanner table is positioned and setup operation corresponding to the type of scan is performed in MR scanner room. Finally, radiographer sets up various scan sequences to run on scanner in control room 1. The base pattern is utilized by the learning algorithm to analyse the tracking database obtained by deploying RF/IR based RTLS.

Table 6.3: Activity-Locations-Role matrix for radiographer role

Activities \ **Locations**	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Look at the patient arrival list	0	0	0	1	0	0	0
Collect patient from the changing area	0	2	0	0	0	0	0
Perform final check about consenting	0	2	0	0	0	0	0
Position and setup MR scanner for patients	0	0	0	0	0	3	0
Start various scan sequences to run on patients	0	0	0	4	0	0	0

A = CT/MR reception; B = Changing area; C = Waiting room; D = Control room 1; E = Control room 2; F = MR room 1; G = MR room 2

6.5.2 Compressing the tracking database

The events data for all the radiographer tags are extracted from the tracking database. The events data is stored in form of (*tagID, roomID, time)*. The tracking database is then compressed by grouping the similar events data as (*tagID*, *roomID*, *duration*)(see subsection 6.4.2). Since the proposed variations modelling methodology based on ECDMs deals with the rooms/areas visited by a role, therefore, the database containing a list of the rooms visited by staff performing radiographer role are considered in this case study. The compressed database is represented as **D**, which contains the list of *roomID*s traversed by each tags associated with the staff performing radiographer role.

6.5.3 Identifying nodes for ECDM for radiographer

The nodes of the ECDM for radiographer role are determined by identifying distinct *roomID*s present in the compressed database obtained in subsection 6.4.2. For current example, the distinct nodes for ECDM are identified as ‘A’, ‘B’, ‘C’, ‘D’, ‘E’, ‘F’, ‘G’.

6.5.4 Determination of role variations in radiographer role

The role variations are identified based on the base pattern ($\mathbf{B}$) and tracking database (**D**) for radiographer role identified in subsection 6.4.1 and subsection 6.4.2. The threshold parameters for extracting the variations 1, 2 and 3 is $\alpha = 3, \beta = 1$ and the threshold parameter for qualifying the pattern, *i.e.*, $F = 15$. The pattern identification for radiographer role is defined as follows:

Step 1: Input **D**, base pattern $\mathbf{B} = (\mathrm{D}, \mathrm{B}, \mathrm{F}, \mathrm{D})$ or (E, B, F, E), parameters $\alpha = 3$ and $\beta = 1$.

Set $i = 1$

Step 2: For the clinician do following sub-steps:

Step 2.1: Call *extract_patterns*(**D**, **B**, α).

Step 2.2: Assign extracted patterns to $\mathbf{m\_patterns}$

Step 2.3: Pseudo base patterns having at most $\beta = 1$ missing base events in $\mathbf{B} = (\mathrm{D}, \mathrm{B}, \mathrm{F}, \mathrm{D})$ is generated, *i.e.*, (D,B,F,D), (B,F,D), (D,F,D), (D,B,D), and (D,B,F).

Step 2.4: Assign all five pseudo base patterns to $\mathbf{pseudo\_B} = \{\mathbf{P}_1, \mathbf{P}_2 ... \mathbf{P}_5\}$

Step 2.5: For each $\mathbf{P}_j$, where, $j \in (1, 2, \cdots, 5)$ do

Step 2.6: Call *extract_patterns*($\mathbf{D}$, $\mathbf{P}_j$, α)

Step 2.7: Append the extracted patterns to $\mathbf{m\_patterns}$

End For

Step 3: For m^{th} pattern in $\mathbf{m\_patterns}$, where $m \in (1, 2, \ldots, |\,\mathbf{m\_pattern}\,|)$ do

Step 3.1: Call *frequency*($m\_pattern_m$)

Step 3.2: Assign the frequency of the pattern to f_m

Step 3.3: If $f_m < F$, discard $m\_pattern_m$ in $\mathbf{m\_patterns}$.

End If

End For

Step 4: Output $\mathbf{m\_patterns}=\left(\mathrm{D, A, B, D, B, F, D}\right)$ as qualified patterns of role paths.

Step 5: End

The variation pattern obtained by the proposed methodology is **m_patterns** = (D,A,B,D,B,F,D); (E,A,B,E,B,F,E). It illustrates that there are variations in the involvement of radiographer role in MR scanning process. The pattern identified by the proposed algorithm illustrates that there are areas such as A, B, D which is frequently adopted by the radiographers in order to perform MR scanning. Therefore, the path variation in the radiographer role is to be analysed by constructing ECDM for radiographer path patterns.

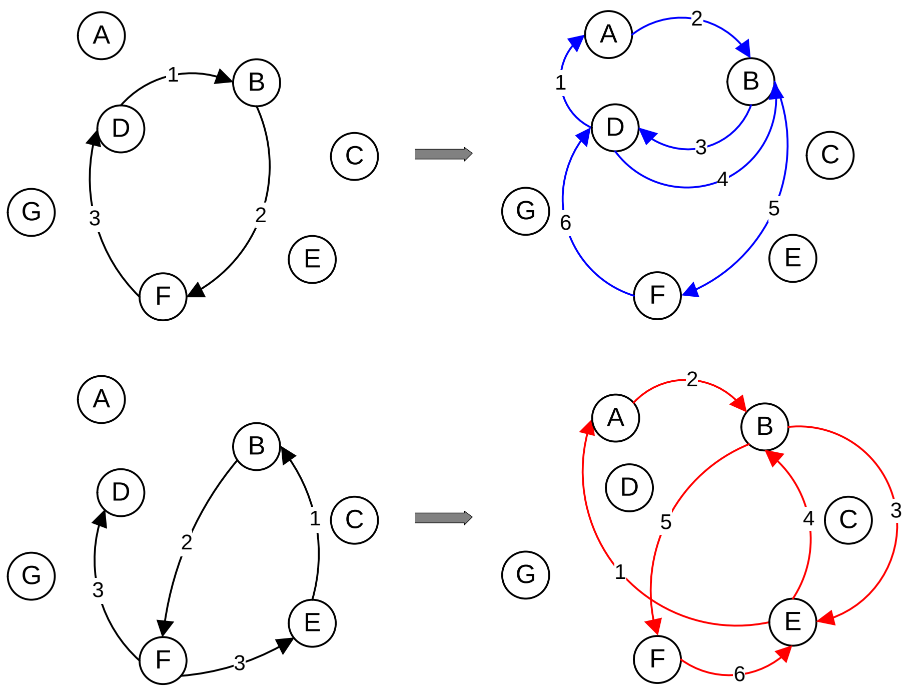
6.5.5 ECDM representation for radiographer

The path variation obtained in the form of movement patterns **m_patterns=**$\left(\mathrm{D,A,B,D,B,F,D}\right);\left(\mathrm{E,A,B,E,B,F,E}\right)$ is represented by obtaining the sequence ($\mathbf{S}^{k}$). The movement pattern of the radiographer in **m_patterns** is represented as *blue* and *red* coloured edges in ECDM. Hence, the sequence is represented as:

$$\mathbf{S}^{blue} = (\mathrm{D,A,B,D,B,F,D})\ \mathbf{S}^{red} = (\mathrm{E,A,B,E,B,F,E}) \qquad (6)$$

The base pattern and the variation patterns for the radiographer role are represented in Fig. 6.5 in the form of ECDM.

The overall application of the methodology on the case study is illustrated in Fig. 7. The radiographers have to frequently visit additional areas such as A, B, D or A, B, E apart from base pattern (D, B, F, D) or (E, B, F, E). The main reason for this variation in the radiographer movement can be explained by the fact that the radiographers were performing the activities defined for the radiology assistants, who were not present. The radiology assistants have to take patients from CT/MR reception area (A) to the changing area (B) where they perform consenting procedure about the presence of metallic objects in patient body. Patients are advised to change into a hospital gown only after completing the consent form indicating that they have met the requirements to proceed with their scanning appointments.



a. Base pattern b. Pattern in radiographer paths

Figure 6.5: ECDM representing base pattern and frequent patterns in paths adopted by staff performing radiographer role

The radiology assistant moves back to the control room 1 or 2 (D or E). In contrast, radiographers have to perform these activities when there are no or shortage of radiology assistants. In effect, radiographer has to perform the additional tasks, which are defined for radiology assistant. This leads to the unnecessary delays and increases waiting time for patients requiring MR scans. Radiographers are required to concentrate on MR scanning performed on patients, recording patient medical condition on radiology information system, and allocating the resulting images to the specialist radiologists. Hence, when radiographer takes up additional responsibilities such as of the radiology assistant, it delays the process and patient to patient time increases. Usually, radiographers remain in the control rooms (D, E) and are responsible for taking patients, prepared for scan, from the changing area (B) or waiting area (C) to the MR rooms (F, G) for performing the MR scanning. Hence, the variations modelling methodology was able to identify the role variations in the radiographer role. The variations in radiographer paths are studied in detail with the staff performing radiographer role. This led to the identification of reasons for variations in radiographer role. The summary of overall steps in the approach is illustrated in Fig. 6.6.

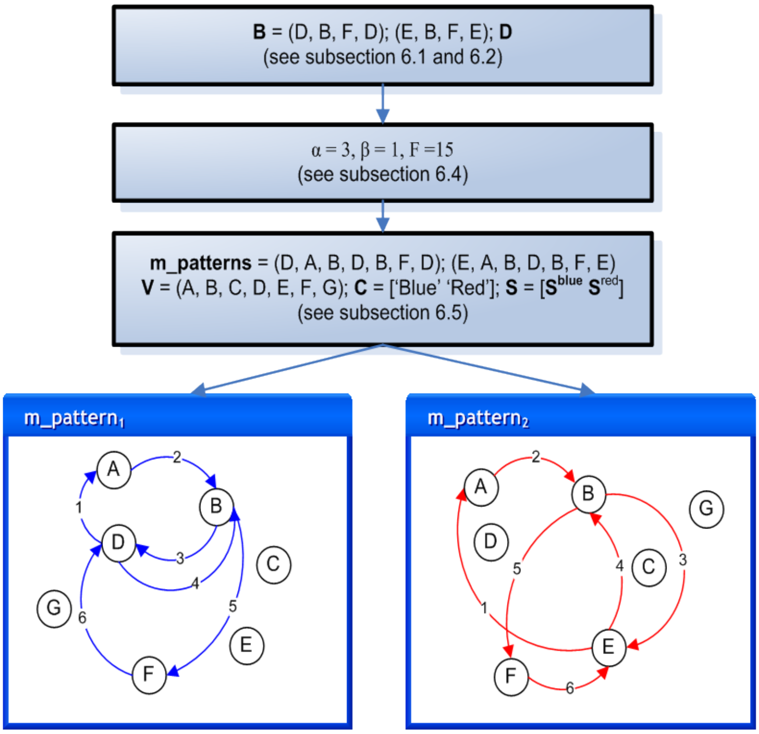


Figure 6.6: Proposed variations modelling methodology on radiographer role in MR scanning process

Thus, the proposed methodology is able to identify and represent the role variations in the roles. The variations are represented in form of ECDMs which is analysed to identify the root causes of the problems such as shortage of radiology assistants. The Matlab Code for identifying role variations from care pathway is presented in Appendix I.

6.6. Summary

This Chapter presents a methodology for modelling the system variations occurring in the radiology department based on the RF/IR based RTLS. The methodology models the system variations in form of patterns of role paths involved in the service delivery system. The patterns are represented in ECDMs, which are generalized representation technique in graph theory. The system variations such as role variations are identified with the help of this methodology. These variations lead to unnecessary delays, waiting, lowering of patient throughput in the radiology. This Chapter mainly dealt with the *role variations* *from* a care pathway. The following Chapter discusses about the unnecessary patient pathway diversions *from* care pathway to reduce unwarranted variations at service system level.

CHAPTER 7: Pathway Variations Analysis (PVA): Modelling and Simulation

7.1 Introduction

In this Chapter, a methodology for analysing unwarranted variations *from* care pathway in a service delivery system is discussed. The methodology uses scalable RADs of the service systems together with the EPRs to model and simulated *patient variations*.

Maintaining and using care pathway within hospital to provide complex care to patients have challenges related to variations from pathway. These variations from care pathway predominantly occur due ineffective decision making processes, unclear process steps, their interactions, conflicting performance measures for speciality units involved within pathway, and availability of resources. These variations from care pathway are largely unnecessary and lead to longer waiting times, delays, and lower productivity of care pathways. Traditional approaches in healthcare pathway improvements are mainly focussed on reducing variations *on* care pathway such as bottlenecks, throughput within pathway rather than variations from the care pathway. State-of-the-art approaches dealing with reducing variations *on* care pathway for healthcare pathway improvements are based on developing simplified flow diagrams of the care delivery processes (such as value stream mapping, flowchart) and discrete event simulation modelling from patient historic data. However, these approaches prove to be ineffective as accurate and scalable care pathway model and large amount of heterogeneous service delivery data is required to model and analyse variations from care pathway. Therefore, pathway PVA methodology is proposed which simulates patient diversions from care pathway by modelling hospital operational parameters, assessing the accuracy of clinical decisions, and performance measures of speciality units involved in care pathway to suggest set-based solutions for reducing variations from care pathway. The main steps of the methodology are: (i) generate sample of patients for analysis; (ii) simulate patient diversions from care pathway; and, (iii) simulation analysis to suggest set-based solutions. The developed methodology has been applied to stroke care pathway of a hospital the case study for modelling and analysis of variations from stroke care pathway. The Proposed methodology has been implemented in a large hospital within the UK, which contributed to the stroke services achieving their performance target.

The rest of the Chapter is arranged as follows. In the next section, the proposed approach for modelling and simulating variations in care pathway is detailed. Section 7.3 discusses a case study of stroke care pathway in a large UK hospital. Finally, a summary of the Chapter is presented in Section 7.4.

7.2 Pathway Variations Modelling & Simulation Methodology

In this section, variations modelling & simulation methodology is described to identify variations from care pathways for service improvements. Overall methodology is described into three major steps as illustrated in Fig. 7.1 and these steps are discussed in detail in following subsections.

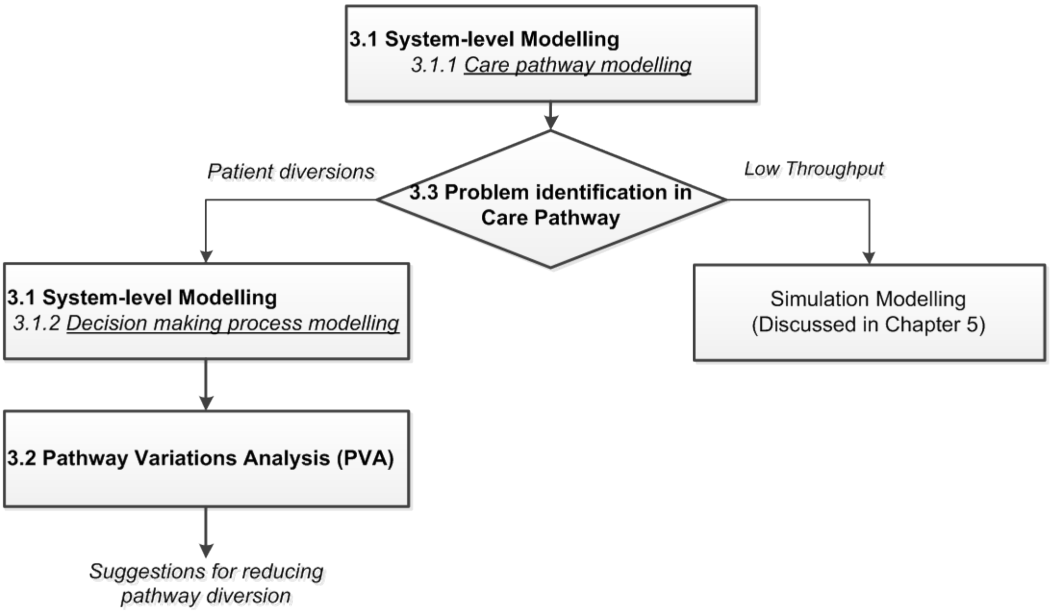


Figure 7.1: Proposed approach for variations analysis in care pathways

In Fig. 7.1, proposed approach starts with system-level modelling of care pathway of hospital, which is considered for analysis. The care pathway modelling involves representation of processes involved within a particular care pathway of a hospital such as activities, interactions, roles, and decisions (see Section 7.2.1.1 for more information about care pathway modelling). Once care pathway model a hospital is developed, problem with care pathway of a hospital is identified using steps defined in problem identification in care pathway (see Section 7.2.3 for details). This step generally identifies two types of problem: (i) low throughput of patients treated by care pathways; and, (ii) patient diversions from care pathway. This chapter mainly focuses on patient diversions, therefore; analysis methodology for low throughput problem is not discussed. Furthermore, details of analysis methodology for patient diversion problem are discussed in Section 7.2.3. Patient diversions analysis method discussed in Section 7.2.3 identifies critical decisions within care pathway which significantly leads to patient diversions from pathway. These critical decisions are then modelled in detail in decision making process modelling (see Section 7.2.1.2) defined in system-level modelling. Once the decision making process is modelled, pathway variations analysis methodology (see Section 7.2.2) is utilized for simulation modelling and solution generation for reducing patient diversions from pathway.

Following subsections details each of the steps of the methodology.

7.2.1 System-level modelling of the healthcare service delivery

In this sub-section, the system level modelling of healthcare service delivery system is performed. The system-level modelling is defined in this step as two sub-step procedure: (i) integrated care pathway modelling in a hospital; and (ii) clinical decision making process modelling. These steps require process mapping or modelling to identify and represent complex collaborative service delivery processes followed in hospital. Care pathway and clinical decision making process models helps to understand interactions among medical speciality units (including accident & emergency (A&E), which is considered to be first point of entry in several care pathways), roles involved in providing care, and decision making steps. Details about each of the sub-steps are provided as follows:

7.2.1.1Care pathway modelling

Currently, integrated care pathways within hospital are generally modelled or represented based on simplified flowcharts for process mapping and representation. The pathway model based on flowcharts represents stroke care process as a sequence of various steps, which can be easily created with the help of less number of notations. However, flowcharts tend to become big when modelling complex processes and hence, these are largely used for high level modelling of the process. Moreover, details about roles interacting within pathway to provide patient care services are not represented. Therefore, a suitable process modelling approach based on role activity diagram (RAD) is used for modelling complex care pathway in hospital. Steps involved in RAD based modelling of care pathway is based on the RAD modelling methodology for service delivery system discussed in Shukla, *et al.*, (2009). This is due to the fact that a care pathway can be considered as a service delivery system involving multi-disciplinary clinical teams for patient care. RAD models developed in Shukla, *et al.*, (2009) were for diagnostic imaging process for all patients who are coming to radiology with scanning request without considering the type of disease. However, process mapping based on RAD in care pathways will be complex as care process for patients suffering from a particular type of disease is being modelled, for example stroke. Process mapping in stroke care pathways will involve modelling various roles, their activities, interactions among them, decisions performed, and simultaneous activities. RAD based modelling methodology utilizes interviews of key staff, involved in care pathway, for representing procedures in care pathway followed in hospital. More detailed information about the RAD modelling methodology based on staff interviews can be obtained in Shukla, *et al.*, (2009, 2011) or see Chapter 4.

7.2.1.2 Decision making process modelling

In this sub-step, decision making processes which are crucial in delivery of care to patients within pathway are modelled. The modelling of crucial decision making processes helps to analyse variations originating from care pathway established in hospital. In general, complex decision making process within care pathway involves following:

Decision Maker(s): The decisions about patient diagnosis and transfer within pathway involves medical specialist role. These roles are central to the decision making processes and performs necessary steps for clinical decision making based on several tests, patient conditions, disease and historical patient information. These are represented in RAD models as roles.

Interactions among roles: The decision making regarding patient conditions within pathway can involve multiple roles. This is due to various medical tests that are performed by various medical specialists along the pathway. These roles are critical to the final decision made by the decision maker on patient conditions. For example, in case of stroke pathways, stroke diagnosis within A&E involves tests such as blood test, CT (computed tomography) scan, ECG (electro-cardiogram) scan, ROSIER (recognition of stroke in emergency room), FAST (face, arm, speech, time), which requires various interacting roles.

Information sources: Majority of clinical decision processes requires various types of information related to patient conditions, which are critical to the diagnosis and final treatment of patients.

Abovementioned features of clinical decision making add to the complexity of decisions and hence all the steps are modelled for analysis.

Attempts have been made in literature to investigate the clinical decision making processes (Graber, 2003; Gordon & Franklin, 2003). The clinical decision making utilized decision trees in these studies to assess potential outcomes. The research study in Wu, *et al.*, (2005), used decision trees which assisted nurses to assess patient conditions and provide patient care. However, there are drawbacks in the use of decision trees where structure can be inaccurate or decision points may have incorrect probabilities associated with them (Banning, 2007). Furthermore, decision trees assumes the knowledge about decision making is available and is accurate; however, in case of complex diseases there can be variations in patient conditions, which can invalidate the decision making based on decision trees. Decision trees deals with the clinical conditions of a particular disease, however, clear representation of decision makers involved, interactions involved within decision making steps, and information required for decision making is not available. Therefore, RAD based mapping is scaled to model the clinical decision making process, which has the capability to illustrate decision makers, interactions, and information used for making decisions in care pathway.

The critical decisions of care pathways are modelled by interviewing the key decision maker(s) to model detailed steps performed to make decisions about patient in a care pathway. The key information that is captured by interviewing key decision maker is to (*i*) identify clinical steps or sub decisions required to make final decision; (*ii*) interactions involved between multiple role while assessing patient conditions for decision making; and, (*iii*) information required in each sub steps for decision making. These interviews are recorded and RAD based modelling methodology is applied to model the decision making process (see Chapter 4 or Shukla, *et al.*, 2009, 2011).

The abovementioned sub-steps helps to model complex care pathway and decision making process of a hospital. These models are used in next step for pathway variations analysis.

7.2.2 Pathway Variations Analysis (PVA)

In this section, simulation modelling and analysis methodology is discussed for variations from care pathway. The care pathway model and decision making process model developed in Section 7.2.1 is used in this step to analyse pathway variations. The pathway variations such as patient diverted to non-speciality wards are largely due to the ineffective push and pull factors among the multiple specialty units involved within care pathway. The speciality unit's patient push is defined as delivering patient care services and sending patients off to succeeding speciality unit (within the care pathway) regardless of succeeding speciality unit's capacity to handle incoming patient demand. On the other hand, the speciality unit's pull is defined as its response (delivering patient care) resulting from incoming patient demand. Figure 7.2 illustrates the patient movements from one speciality ward to another starting from A&E. In Fig. 7.2, patients can be transferred from one speciality unit to another unit in the care pathway or patients can be discharged. However, due to the mismatch of push and pull factors among speciality units in the care pathway; patients are diverted from the care pathway. The patient diversions from care pathway to other medical units compromises the care delivered to patients. Therefore, in PVA methodology, push and pull factors among the speciality units are modelled and analysed in order to reduce the patient diversion from the care pathway.

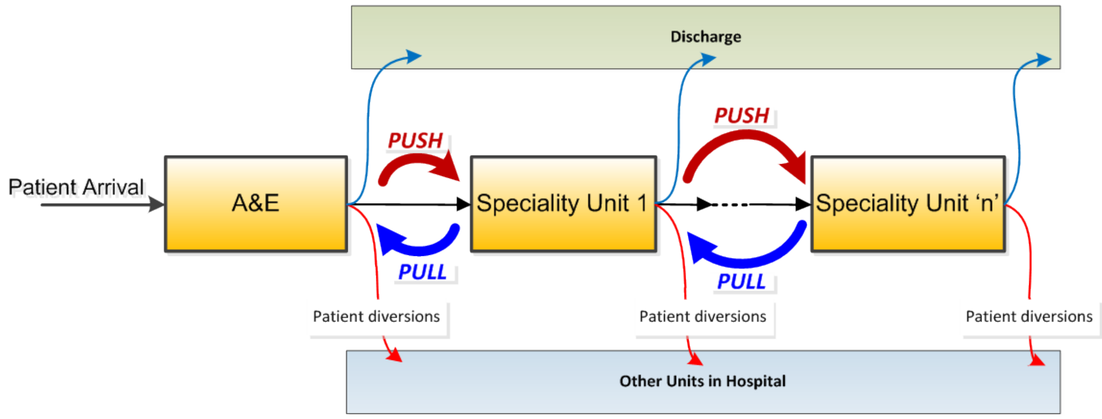


Figure 7.2: Push and Pull between speciality units involved in patient care pathway

Pathway variations or patient variations from care pathway are used interchangeably in the rest of the chapter. The main steps of PVA are – (i) generate a sample of patients for analysis; (ii) modelling push and pull factors to simulate patient flow on pathway; and, (iii) simulation analysis and suggestions. The details of the steps involved in PVA are discussed as follows:

7.2.2.1 Generate sample of patients

In this step, a pool or a sample of patients are virtually generated for analysis in next sub-section. The sample of patients in created based on the following parameters which are used for simulation analysis in next step:

A. Sample Size: Sample size is crucial parameter in generating sample of patients for analysis. Let us consider i^{th} patient of the sample such that$i \in (1,2, \ldots, N_{pts})$, where N_{pts} is the total number of patients (or sample size of the sample of patients to be generated) coming to A&E in a time period T (in days; for *e.g.* week, or month, or year).

B. Patient Arrival Time: The patient arrival time at A&E plays a major role in provision of care to patients as A&E is identified to be the crucial entry point for patients on pathway. Therefore, this model considers i^{th} patient arrival time as $\boldsymbol{Pt_{arrival}}(i) \in [00:00, 23:59]$ and has particular distribution. This helps in modelling patient arrival during a particular day.

C. Patient presenting conditions: Particular care pathway in hospital is used for treatment of a particular type of disease such as stroke, diabetes. Patients coming to A&E for treatments can be broadly classified into disease which is treated in care pathway and disease mimics. Disease mimics are the patient conditions which mimics symptoms of disease treated in care pathway but are different and thus are not suitable for care provided in disease care pathway. Disease mimic patients coming to A&E affect pathway variations as care providers in A&E can put patients on disease care pathway, which compromises the care provided to patients and lowers the productivity of care pathway. Therefore, sample of patients generated for analysis are from two patient groups: disease (defined by $\boldsymbol{disease}$) and mimics (defined by $\boldsymbol{mimics}$). Patient groups are further classified into $\boldsymbol{Pt_{type}}$ categories such that $k \in \left(1,2,\dots,\left|\boldsymbol{Pt_{type}}\right|\right)$ based on patient presenting conditions. The classification is done based on the results of clinical tests that are done for stroke diagnosis in A&E. The patient type category of i^{th} patient is mathematically represented as:

$$\boldsymbol{P_{type}}(i) = k : k \in \left(1,2,\dots,\left|\boldsymbol{Pt_{type}}\right|\right) \forall i \in (1,2,\dots,N_{pts}) \qquad (1)$$

$$\boldsymbol{Pt_{type}} = \boldsymbol{disease} \cup \boldsymbol{mimics} \qquad (2)$$

$$\boldsymbol{disease} \cap \boldsymbol{mimics} = \emptyset \qquad (3)$$

Based on abovementioned defined parameters, sample of patients is generated for analysis. The sample of patients generated in this step is used in next step for simulation modelling for pathway variations analysis.

7.2.2.2 *Modelling push and pull factors to simulate patient flow on care pathway*

In this step, simulation model is developed, which models push and pull factors between speciality units that are crucial for analysing patient diversions. The resulting model will be used to simulate the flow of patients in the sample of patients (generated in Section 7.2.2.1). Following sub-steps are used for developing a generic push and pull pathway model for pathway variations analysis:

***Push factors*:**

A. Decision makers: In this sub-step, the effect of decision makers involved in making critical decisions ($\boldsymbol{CD}$) within care pathway are mathematically modelled for analysis. The information about identifying critical decisions ($\boldsymbol{CD}$) is provided in Section 7.2.3. The effect of decision maker factor is classified into regular working hours and after work hours. This is due the fact that, during after working hours, hospital has reduced specialist staff for diagnosis and providing care which reduces the quality of critical decisions (represented in $\boldsymbol{CD}$); thus resulting in more patients getting diverted to other speciality wards. As a result, the performance of clinical decision making in care pathway is lowered during after working hours. Patient arrival time $\boldsymbol{Pt}_{\boldsymbol{arrival}}(i)\forall i \in (1,2,\dots,N_{pts})$ is classified into patient arriving in ED in regular working hours and after work hours. A decision variable $\boldsymbol{decision}_{\boldsymbol{arrival}}(i)\forall i \in (1,2,\dots,N_{pts})$ is defined to classify patients arriving in regular work hours and after work hours. Mathematically,

$$\boldsymbol{decision_{arrival}}(i) = \begin{cases} 1 & if W_{start} \le \boldsymbol{Pt_{arrival}}(i) \le W_{end} \\ 0 & Otherwise \end{cases}$$

$$\forall i \in (1,2,\dots,N_{pts}) \quad (4)$$

where, W_{start} and W_{end} are start and end time of the regular working hour of a shift. The outcome of $\boldsymbol{decision_{arrival}}(i)$ of i^{th} patient classifies patient arrival in regular and after working hours.

B. Clinical Decision Making Process: Research studies related to clinical decision making in case of care pathway generally involves diagnostic test performance assessment based on metrics derived from the *confusion matrix*. Clinical tests are assumed to be a binary classification model which classifies each patient into two classes: a true class (a disease is present) and a false class (disease in not present). This results in four possible classifications for each patient: *true positive*, *true negative*, *false negative, false positive*, and *false negative*. These four possible outcomes for stroke diagnosis can be represented in the form of *confusion matrix* illustrated in Fig. 7.3. If a patient is suffering from a particular disease 'X' (that is treated by care pathway) and clinical test indicates positive (i.e., 'X' is present) (Y), then it is considered as *true positive*; if it is predicted as negative ('X' is not present) (N), then it is counted as *false negative*. Further, if the patient is not suffering from the disease 'X' (indicated as 'No-X' in Fig. 7.3) and it is predicted by clinical tests as positive, then it is considered as *false positive*; if prediction is negative, then it is considered as *true negative*. The *true positives* and *true negatives* are correct classifications of the clinical tests.

Given a clinical test and a sample of patient instances, the confusion matrix is constructed and various common metrics for assessing performance of clinical tests are developed. Following are the common metrics used:

$$fp_{rate} = \frac{FP}{TN + FP} \tag{5}$$

$$tp_{rate} = \frac{TP}{TP + FN} \tag{6}$$

$$sensitivity = \frac{TP}{TP + FN} = tp_{rate} \tag{7}$$

$$specificity = \frac{TN}{FP + TN} = 1 - fp_{rate} \tag{8}$$

Predicted class from clinical tests		True Class: **Disease** 'X'	True Class: **Disease** 'No-X'
	Y	*True Positive (TP)*	*False Positive (FP)*
	N	*False Negative (FN)*	*True Negative (TN)*

Figure 7.3: Confusion Matrix for model assessment for diagnosis in care pathway

The $fp_{rate}$is false positive rate (disease 'No-X' patient instances incorrectly classified) of the classification based on clinical tests and tp_{rate} is the true positive rate (disease 'X' instances correctly classified). Further, $sensitivity$ and $specificity$ of a clinical tests used in diagnosis is defined in Eqn. 7 & 8 based on tp_{rate} and fp_{rate}.

In case of complex integrated care pathways, several tests are performed before making final decision about putting patients on the care pathway. Therefore, confusion matrix is to be constructed for overall decision making rather than evaluating individual clinical tests. The hospital IT systems data comprising of patient pathway information is utilized for constructing confusion matrix for decision making. Figure 7.4 illustrates the representation of *TP*, *FP*, *FN*, and *TN* patient instances based on a decision (taken at Ward A) that are made about their referral to ward included under care pathway in hospital (Ward B) or ward which does not comes under care pathway in hospital (Ward C).

Figure 7.4 illustrates that if a patient, whose final diagnosis was 'X', is sent to ward B, then it is considered as *TP*; and if these patients are sent to ward C, then it is considered to be *FN*. However, if a patient, whose final diagnosis was 'No-X', is sent to ward B, then it is considered as *FP*; and if those patients are sent to ward C, then it is considered as *TN*. Therefore, the probability of sending patient with disease 'X' and 'No-X' to ward B based on the decision taken at Ward A is mathematically represented as:

$$p_{A \to B}^{X} = \frac{TP}{TP + FN} \tag{9}$$

$$p_{A \to B}^{No-X} = \frac{FP}{FP + TN} \tag{10}$$

where, $p_{A \to B}^{X}$ and $p_{A \to B}^{No-X}$ are the probability of sending patients to ward B (which provides care for disease 'X') and *TP, FP, FN, TN* are calculated using patient pathway information from hospital database and based on the Fig. 7.4. However, there are some assumptions in this estimation. Assumptions: (*i*) wards under care pathway for disease 'X' deals with patients suffering from 'X', *i.e.*, no patients with other type of illnesses ('No-X') can go to wards under care pathway for disease 'X'; and (*ii*) for computation in Eqn. 9 & 10, patients having final diagnosis as 'X' and most frequently occurring stroke mimic conditions (*i.e.*, 'No-X' patients exhibiting 'X' disease like symptoms) are considered in this study. The probabilities computed in this section related to critical decision is utilized to further develop mathematical model to simulate patient flow in care pathway.

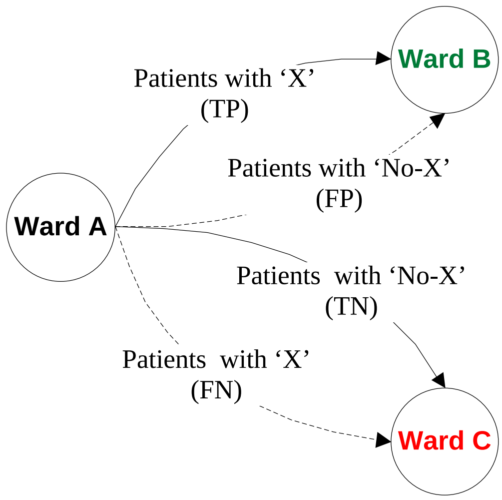


Figure 7.4: Confusion matrix based on patient pathway information; (where, Ward B – where care for disease 'X' is provided and Ward C – where care for disease 'No-X' is provided)

The performance of clinical decision making is determined with the help of probabilities of sending k^{th} type patient ($k \in (1,2,\ldots,|\boldsymbol{Pt_{type}}|)$) to a ward of care pathway during regular work hours ($\boldsymbol{P^{Reg}}$) and after work hours ($\boldsymbol{P^{Aft}}$). Mathematically,

$$\boldsymbol{P^{Reg}} = \left[\alpha_1, \alpha_2, \alpha_3, \ldots \alpha_k \ldots, \alpha_{|Pt_{type}|}\right] \tag{11}$$

$$\boldsymbol{P^{Aft}} = \left[\beta_1, \beta_2, \beta_3, \ldots \beta_k \ldots, \beta_{|Pt_{type}|}\right] \tag{12}$$

where, α_k and β_k are estimated based on Eq^n. (9) & (10) and based on $\boldsymbol{Pt_{type}}(i)$.

A decision variable $\boldsymbol{decision_{prob}}(i)$is defined based on i^{th} patient arrival (*i.e.*, $\boldsymbol{decision_{arrival}}(i)$), $\boldsymbol{Pt_{type}}(i)$, and $\boldsymbol{P^{Reg}}$&$\boldsymbol{P^{Aft}}$. $\boldsymbol{decision_{prob}}(i)$selects probability from $\boldsymbol{P^{Reg}}$&$\boldsymbol{P^{Aft}}$ based on patient type $\boldsymbol{Pt_{type}}(i)$ and arrival type defined by $\boldsymbol{decision_{arrival}}(i)$. Mathematically,

$$\boldsymbol{decision_{prob}}(i) = \begin{cases} \boldsymbol{P^{Reg}}(k) & if \boldsymbol{decision_{arrival}}(i) = 1 \\ \boldsymbol{P^{Aft}}(k) & Otherwise \end{cases} \forall i \in (1,2, \dots, N_{pts}) \quad (13)$$

where, $\boldsymbol{P^{Reg}}(k) = \alpha_k$, $\boldsymbol{P^{Aft}}(k) = \beta_k$, and $\boldsymbol{Pt_{type}}(i) = k$.

Now, the decision to send a patient to ward included in care pathway of hospital based on the decision variable $\boldsymbol{decision_{prob}}(i)$ is mathematically represented as:

$$\boldsymbol{decision_{SendProb}}(i) = \begin{cases} 1 & if R \le \boldsymbol{decision_{prob}}(i) \\ 0 & if\ R > \boldsymbol{decision_{prob}}(i) \end{cases} \forall i \in (1,2, \dots, N_{pts}) \quad (14)$$

where, R is a random number $\in$ [0,1]. $\boldsymbol{decision_{SendProb}}(i) = 1$ simulates that i^{th} patient is sent to wards included in care pathway based on the disease diagnosis and $\boldsymbol{decision_{SendProb}}(i) = 0$ means i^{th} patient is sent to ward which is not included in the care pathway of hospital. Following decision variable defines each incoming patients into $\boldsymbol{disease}$ or $\boldsymbol{mimics}$.

$$\boldsymbol{decision_{Pts}}(i) = \begin{cases} 1 & \forall \boldsymbol{P_{type}}(i) \in \boldsymbol{disease} \\ 0 & \forall \boldsymbol{P_{type}}(i) \in \boldsymbol{mimics} \end{cases} \forall i \in (1,2, \dots, N_{pts}) \quad (15)$$

Abovementioned decision variables are used in next sub-step for estimating overall variations from care pathway in hospital.

C. <u>A&E 4-hour Operational KPI</u>: As ED (Emergency Department or A&E) is common entry point for most of the care pathway; hence operations in ED are modelled in this sub-step. Once, i^{th} patient arrives at ED, clinical interventions are carried out on patients such as: triage, senior intervention following triage (SIFT), ED specialist registrar (SpR) assessment, ED consultant assessment. These interventions for i^{th} patient coming to ED is collectively defined by $\boldsymbol{Pt_{TW}}(i)$. The main components of $Pt_{TW}(i)$ of i^{th} patient are defined as: Triage time ($\boldsymbol{Pt_{Triage}}(i)$), SIFT process ($\boldsymbol{Pt_{SIFT}}(i)$), ED SpR assessment time ($\boldsymbol{Pt_{EDSpR}}(i)$), ED consultant assessment time ($\boldsymbol{Pt_{Consltant}}(i)$), where$i \in (1,2, \dots, N_{pts})$. These sub-interventions time duration of $Pt_{TW}(i)$ are mathematically defined as:

$$\boldsymbol{Pt_{TW}}(i) = \boldsymbol{Pt_{Triage}}(i) + \boldsymbol{Pt_{SIFT}}(i) + \boldsymbol{Pt_{EDSpR}}(i) + \boldsymbol{Pt_{Consltant}}(i) \quad (16)$$

$$\boldsymbol{Pt_{Triage}}(i) \sim D(\mu_{triage}, \sigma_{triage}) \quad (17)$$

$$\boldsymbol{Pt_{SIFT}}(i) \sim D(\mu_{SIFT}, \sigma_{SIFT}) \quad (18)$$

$$\boldsymbol{Pt_{EDSpR}}(i) \sim D\left(\mu_{EDSpR}, \sigma_{EDSpR}\right) \quad (19)$$

$$\boldsymbol{Pt_{Consltant}}(i) \sim D(\mu_{Consltant}, \sigma_{Consltant}) \quad (20)$$

where, $D(\mu, \sigma)$is a distribution having μ as its mean and σ as standard deviation and $D(\mu_{triage}, \sigma_{triage})$, $D(\mu_{SIFT}, \sigma_{SIFT})$, $D\left(\mu_{EDSpR}, \sigma_{EDSpR}\right)$, $D(\mu_{Consltant}, \sigma_{Consltant})$ are assumed to be distributions of Triage time, SIFT time, EDSpR assessment time, and ED consultant assessment time.$\boldsymbol{Pt_{TW}}(i)$ can be modified for particular care pathway by adding or subtracting sub-intervention times in Eqn. (16) for patient sub-groups ($\boldsymbol{P_{type}}(i)$) classified as priority or non-priority in care pathway.

The 4-hour operational KPI in ED is common across NHS trusts in UK due to Department of Health (DoH), UK guidelines for acute care in ED. It suggests that no patients in A&E should wait more than 4 hours in A&E

from arrival to discharge or hospital admission. This leads to the push of patients to speciality units after arrival in ED within 4 hours. The 4-hour operational KPI of ED affects patient diversions to incorrect wards due to time consuming complex clinical diagnostic tests involved in patient diagnosis in ED. The time interventions window ($\boldsymbol{Pt_{TW}}(i), i \in (1,2, \dots, N_{pts})$), is related to 4-hour operational KPI as it effects patient diversions from care pathway to incorrect speciality units. Therefore, a binary decision variable $\boldsymbol{decision_{EDKPI}}(i) \forall i \in (1,2, \dots, N_{pts})$ is defined to consider patients breaching 4-hour KPI of ED. Mathematically,

$$\boldsymbol{decision_{EDKPI}}(i) = \begin{cases} 0 & if \boldsymbol{Pt_{TW}}(i) > 4 \\ 1 & if\ \boldsymbol{Pt_{TW}}(i) \leq 4 \end{cases} \forall i \in (1,2, \dots, N_{pts}) \qquad (21)$$

Therefore, i^{th} patient sent to speciality units or wards correctly or incorrectly is determined by $\boldsymbol{Pt_{SentWard}}(i)$, which is mathematically represented by

$$\boldsymbol{Pt_{SentWard}}(i) = \boldsymbol{decision_{EDKPI}}(i) \times \boldsymbol{decision_{SendProb}}(i) \qquad (22)$$

where, $\boldsymbol{Pt_{SentWard}}(i) = 1$ represents that i^{th} patient is sent to speciality unit correctly; and $\boldsymbol{Pt_{SentWard}}(i) = 0$ represents that i^{th} patient is sent to speciality unit incorrectly, following medical decision making.

<u>Pull factors:</u>

D. <u>Ward Resources</u>: The availability of resources (such as staff, beds) in speciality units within care pathway helps to admit patients from preceding speciality units. However, lower availability of resources can cause patients not being admitted to speciality unit and results in patient diversions. Therefore, bed capacity constraint of speciality units in care pathways is identified to be a factor affecting patient diversion. Resource utilization is modelled as a KPI of speciality wards. In this chapter, we have considered only number of beds as one variable determining the speciality unit's capacity. However, other resource parameters such as staff utilization can be also used for determining speciality unit's capacity.

Beds in Speciality Wards: Let us consider bed capacity of a speciality unit be B_{SU} and average patient length of stay in speciality unit be LoS_{SU} (in days). Then bed utilization in a speciality unit can be approximated as:

$$U_{SU}^{Bed} = \frac{LoS_{SU} \times \sum_{i=1}^{N_{pts}} \boldsymbol{Pt_{SentWard}}(i)}{B_{SU} \times T} \times 100 \tag{23}$$

where, $\sum_{i=1}^{N_{pts}} \boldsymbol{Pt_{SentWard}}(i)$ represents number of patients sent correctly to speciality unit in time duration T (in days).

E. Key Performance Indicator (KPI) of speciality units: There can be KPI of speciality units, which helps speciality units to receive financial incentives by providing care to patients in care pathway. For example, stroke units in the UK have an 80/90 KPI, whereby 80% of the stroke patients should stay more than 90% of their hospital stay in stroke units. This results in pull to admit patients from preceding units to improve KPI of the speciality unit. These KPIs are specific to speciality units, therefore, a mathematical representation of the KPI specific to stroke care is provided in case study.

The push factors such as decision makers, clinical decision making process, and 4-hour operational KPI of ED ensures that patients are referred (push) to speciality units; however, capacity constraints of a speciality unit can restrict patient admissions to the speciality unit. As a result, patients are sent to other speciality units or medical wards incorrectly after ED. Therefore, patient diversions from care pathways can be mathematically represented as:

$$\text{Max}\left(Sent_{SU} = \sum_{i=1}^{N_{pts}} \boldsymbol{Pt_{SentWard}}(i) \times \boldsymbol{decision_{Pts}}(i) \right) \tag{24}$$

$$\text{Subject to: } U_{SW}^{Bed} \leq 80\ \% \tag{25}$$

Eq^{n}. (24) represents objective function which maximises the number of patients being sent to speciality units correctly. Constraint represented in Eqn. (25) represents that the utilization of beds in a specialty unit must be less than 80%. This formulation based on push and pull factors will help to reduce patient diversions and simultaneously monitor the specialty unit's capacity to accommodate increased number of patients referred from ED.

7.2.2.3 *Analysis of Pathway Variations Simulation Model*

In this step, simulation analysis is performed to simulate patient flow in a care pathway and evaluate patient diversions from care pathway based on the simulation model defined in Section 7.2.2.2. The Monte Carlo simulation technique is utilized to simulate patient flow on care pathway. Monte Carlo simulation is a method used for evaluating a model using sets of random numbers and their distributions as input. The main objective of this step is to determine various improvement options to reduce patient diversions from care pathway.

A. Estimating inputs and running the simulation model:

   Inputs to the simulation model are identified based on the simulation model defined in Sections 7.2.2.1 and 7.2.2.2. The inputs to the simulation model are $\boldsymbol{Pt_{arrival}}, \boldsymbol{Pt_{type}}, \boldsymbol{Pt_{Triage}}, \boldsymbol{Pt_{SIFT}}, \boldsymbol{Pt_{EDSpR}}, \boldsymbol{Pt_{Consltant}}$ and probabilities represented in $\boldsymbol{P}^{\boldsymbol{Reg}}$&$\boldsymbol{P}^{\boldsymbol{Aft}}$. The probabilities defined by $\boldsymbol{P}^{\boldsymbol{Reg}}$&$\boldsymbol{P}^{\boldsymbol{Aft}}$are computed based on the procedure defined in section 7.2.2.2.B. The distributions of variables such as$\boldsymbol{Pt}_{\boldsymbol{arrival}}$, $\boldsymbol{Pt}_{\boldsymbol{Triage}}$, $\boldsymbol{Pt}_{\boldsymbol{SIFT}}$,$\boldsymbol{Pt}_{\boldsymbol{EDSpR}}$,$\boldsymbol{Pt}_{\boldsymbol{Consltant}}$are identified such that it closely fits the real data from hospital IT systems or EPR. Hospital IT systems largely stores information about variables related to the care pathways which is utilized to identify closely fitting distributions. Fitting distributions to hospital IT systems data finds the type of distribution (*normal, beta, gamma*, etc) and the value of distribution related parameters (*mean, variance,* etc) that gives the highest probability of producing the observed data. These inputs are then utilized for simulation.

Based on the input distributions and parameter values identified from hospital IT system data, the mathematical model of patient flow in care pathway is coded as a computer program (see Appendix I for Matlab code). The input and output from the simulation model is utilized for historical validation of the simulation model. Since, the historical patient data is recorded in hospital, part of the dataset is utilized to develop simulation model and the remaining hospital IT data is used to validate simulation model. The model output (*i.e.*, patient diversions defined in Eqn. (24)) is compared with that of hospital test dataset and simulation model is validated (for more information refer SoW3, 2010). Once the simulation model is validated, simulation model is utilized for suggesting improvements for reducing care pathway variations.

B. *Analysis of simulation model for set-based improvements:*

The simulation models developed for healthcare services generally focuses on suggesting single parameter change (or individual change) type solutions for service improvements (such as changing number of beds, staff, or removing certain tasks which causes delays). The single parameter change solution means suggesting changing one parameter in the simulation model to generate '*what-if*' scenarios. However, single parameter change solution does not consider the interactions among various parameters as a result of change in one parameter. The inherent inter-related parameters are large in case of complex integrated care pathways where several medical speciality units are involved to provide patient care. Therefore, changes in the modelling parameters for one of the speciality unit in care pathway will affect other unit's performance in the pathway. Hence, single parameter change solutions do not work for inter-related services such as integrated care pathways in hospital. Hence, the simulation model for integrated care pathway must be analysed with the help of set-based solutions.

In set-based solutions for simulation modelling, multiple parameters affecting simulation model is changed simultaneously for generating '*what-if*' scenarios. These changes consider overall performance of care pathways. Push and pull factor in each of the specialty units of care pathway are adjusted to suggest any service improvements. More details about set-based solution are provided in case study.

7.2.3 Problem identification in care pathway

In this section, the problem in integrated care pathways of a hospital is identified with the help of hospital IT systems data storing electronic patient records (EPR).

The EPR is utilized to monitor the performance of care pathways based on crucial key performance indicator (KPI). If the performance target of care pathway is not met, then this step is used to identify problems in care pathway. The hospital IT systems stores information about patient flow within a care pathway, which can be analysed to identify two types of problem: (i) low throughput on care pathway; and, (ii) patient diversion from care pathway. The details about each of these problems are discussed in the following sub-sections.

7.2.3.1 *Low throughput in care pathway*

One of the problems in care pathway within hospital is low throughput of patients treated within care pathways. The lower throughput of care pathway within hospital is mainly due to bottlenecks in one or more service delivery specialty units along the care pathway. EPR data about patients on care pathway such as patient arrival and discharge from each speciality units are used for identifying bottlenecks in the care pathway of a hospital. Solving care pathway throughput issue can only improve patient flow for patients that are correctly placed on care pathway. Therefore, issue of patient diverting from care pathway is crucial for improving the overall performance of care pathways in hospital. In this chapter, we focus on patient diversions from care pathway, therefore, more information about throughput issue or bottleneck identification is not detailed.

7.2.3.2 *Patient diversions from care pathway*

Patient diversion from care pathway is identified to be a major problem for integrated care pathway of hospital. In this sub-step, a systematic procedure for identifying decisions that causes patient diversions from care pathway is discussed based on RAD developed in Section 7.2.1.1 and EPR.

RAD model developed in Section 7.2.1.1 represents care pathway detailing roles involved, activities performed, interactions done, decisions taken and other RAD related concepts. In this Chapter, we focus on *patient diversions or variations* from designated care pathway; hence, decisions represented in RAD leading to such variations are identified and their impact is analysed. RAD model for care pathway is utilized together with the EPR data for identifying critical decisions leading to patient diversions from pathway. Following is the two-step process to identify pathway variations from pathway.

A. <u>*Identifying candidate set of decisions in RAD leading to pathway variations*</u>: The decisions involved within care pathway are graphically illustrated in RAD as a notation called *case refinement*. Therefore, *case refinements* within RAD of pathway are analysed for identifying case refinements leading to pathway variations. This chapter deals with patient diversions, hence, *case refinements* related to patient diversions from one speciality unit to another specialty units in RAD are selected as candidate decisions. These candidate case refinements are mathematically represented as:

$$\boldsymbol{CR} = \left[CR_1, CR_2, \dots, CR_{|CR|}\right] \qquad (26)$$

Figure 7.5 highlights decisions, within a simple process represented in RAD, that results in patient being sent to ward A, B, or C; or classified as other patients (patients not eligible for treatment/care on specialised care pathway). Based on the RAD represented in Fig. 7.5, a conceptual decision making representation is developed (see Fig. 7.6).

Figure 7.6, represents the case refinements ($\boldsymbol{CR}$) present in the RAD of care pathways. Circles in Fig 7.6 represent the case refinements which lead to the patients being sent to wards A, B, or C; or classified as other patients. All decisions within RAD model of pathway are examined to identify the potential sources of patient diversion from care pathway. The candidate set of decisions ***CR*** is analysed in next sub-step with the help of hospital IT systems data or EPR to identify its impact on patient diversion.

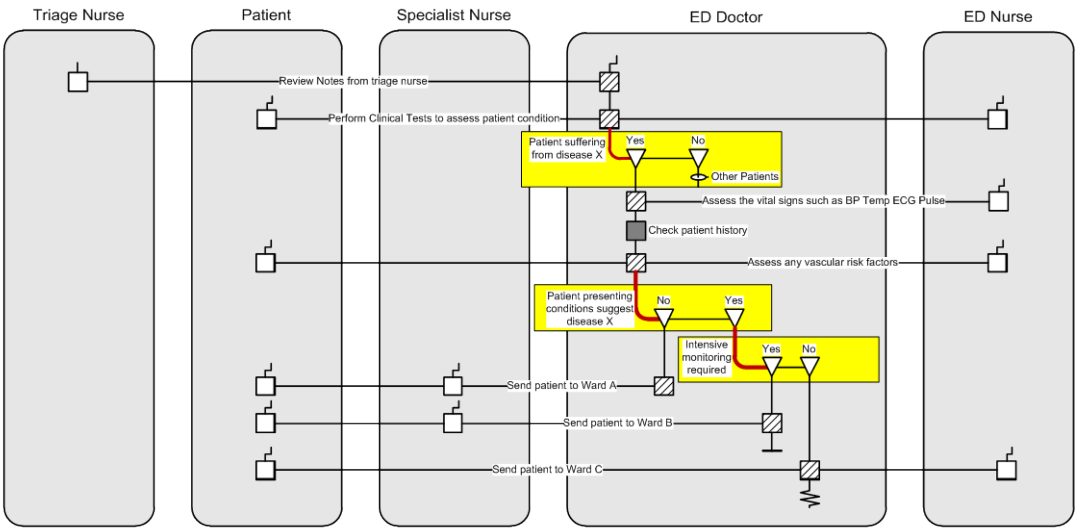


Figure 7.5: RAD of a process illustrating decisions or case refinements included as *CR*

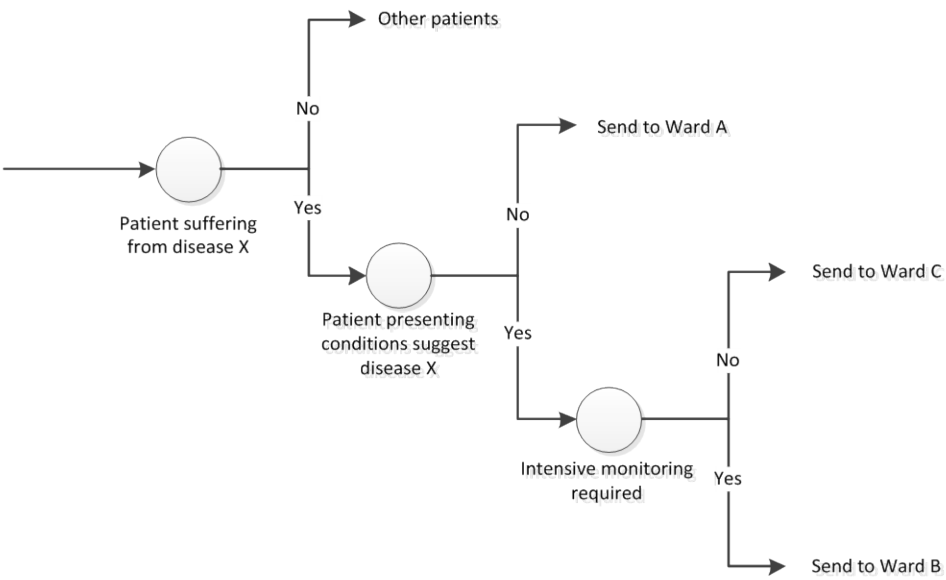


Figure 7.6: Conceptual representation of *CR* represented in RAD

B. *Identifying critical decisions from* $\boldsymbol{CR}$: The candidate set of decisions ($\boldsymbol{CR}$) are analysed in this sub-step to identify critical decision(s) that is (are) significantly affecting patient diversions from pathway. In order to identify critical decisions ($\boldsymbol{CD}$), candidate decisions are mapped to ward-level locations. This is done to provide mapping between decisions in $\boldsymbol{CR}$ and their resulting impact on patient ward level flow on the care pathway. This is analysed with the help of patient pathway data from hospital IT system or EPR. Mathematically, mapping is defined based on matrix $\mathbf{L} = \left[l_{a,b}\right]_{a=1,2,\dots,w;\ b=1,2,\dots,w}$.

$$l_{a,b} = \begin{cases} c & if\ CR_c \in \boldsymbol{CR} : CR_c = decision(a \to b) \\ 0 & if\ decision(a \to b) \notin \boldsymbol{CR} \\ 0 & if\ a = b \end{cases} \tag{27}$$

where, $c \in [1, |\boldsymbol{CR}|]$, a, b represents ward-level locations of patient and $decision(a \to b)$ represents decisions in $\boldsymbol{CR}$ leading to patient being sent to ward b from ward a. w is the total number of wards patients can go to, which can be significantly reduced by grouping incorrect wards as one type of ward.

Once, matrix $\mathbf{L}$ is constructed, the impact of decisions in $\boldsymbol{CR}$ is quantified based on the EPR containing patient ward level movement data. Mathematically, impact of CR_c is assessed as:

$$I_{CR_c} = \frac{\sum_{r=1}^{R} d_{c_a,c_b}^{r}}{\sum_{r=1}^{R}\sum_{a=1}^{w}\sum_{b=1}^{w} d_{a,b}^{r}} \tag{28}$$

where, I_{CR_c} is impact of CR_c on patient pathway based on patient records $r \in [1, R]$. Total number of stroke patient records from hospital EPR (for a given time period) is defined as R. Indices c_a and c_b defines the row and column of **L** which has attribute value $c(c \in [1, |\boldsymbol{CR}|])$. And, $d^r_{c_a,c_b}$ is defined as:

$$d^r_{a,b} = \begin{cases} 1 & if\ pt(a \to b)\ in\ r^{th} patient\ record \\ 0 & else \end{cases} \tag{29}$$

where, $pt(a \to b)$ defines patient sent to ward b from ward a.

The impact of each decision in $\boldsymbol{CR}$ is assessed based on I_{CR_c} defined in Eqn. 28. CR_cwhich significantly leads to patient diversions from the care pathway is selected as critical decision ($\boldsymbol{CD}$) based on threshold Th (if $I_{CR_c} \geq Th$ then $CR_c \in \boldsymbol{CD}$). While evaluating $I_{CR_c} \forall\ c \in [1, |\boldsymbol{CR}|]$ from stroke patient records, there can be decisions where data related to them is not available and therefore those decisions are not considered for further analysis. The critical decisions ($\boldsymbol{CD}$) are then utilized in subsections 7.2.1.2 clinical decision making process modelling; following clinical decision making modelling, pathway variations are analysed based on Section 7.2.2.

7.3 Case Study: Stroke Care Pathways

The case study involves the stroke care pathways (SCP) for acute ischemic stroke (AIS) at the Hospital. Stroke represents a major health problem worldwide (WHO Fact Sheet, 2008) with an estimated stroke care costs NHS £2.8 billion a year in direct care costs (National Audit Office, 2005). Furthermore, over 300,000 people live with moderate to severe disabilities as a result of stroke in UK (Adamson, *et al.*, 2005). As a result, various clinical guidelines have been introduced to improve the stroke care services by developing stroke care pathways (Wilde, 2009, DoH 2006; 2010). The ethics required for this research study was covered under the

Comprehensive Research Agreement between collaborative partners University of Warwick, a UK Hospital, and GE Healthcare.

AIS patients generally arrive at Accident and Emergency (A&E) of a hospital from outside with the help of paramedics, emergency medical services (EMS) or ambulance services. Medical team in A&E then assesses patient based on initial clinical observations and diagnostic imaging. Once AIS case is identified in a patient, acute stroke team of Neurology assesses patients for hyper acute monitoring and treatment (*e.g.* thrombolysis). After hyper acute phase, patients are shifted to acute stroke wards for rehabilitation and physiotherapy treatments. Finally, the process ends when the patients are discharged from the hospital. As such, stroke care pathway within a hospital deals with multiple departments such as Accident & Emergency (A&E), Neurology, Radiology, and Lab Services. Several IT systems storing EPR including patient administration system (e.g. iPM), beds management system (e.g. Extra-Med), clinical reporting system (e.g. CRS) in A&E, radiology information system (e.g. RIS) in Radiology and clinical system (e.g. Dendrite) in Neurology is used for storing stroke patients care related information.

Stroke care pathway in a hospital can be divided into: (i) hyper acute stroke phase; and, (ii) acute stroke phase. This case study deals with the hyper acute stroke phase to illustrate the application of the proposed approach for identifying and solving patient diversion problem. Figure 7.7 illustrates the hyper acute process which is divided into: patient arrival process, medical team assessment, neurological assessment, and hyper acute stroke ward process.

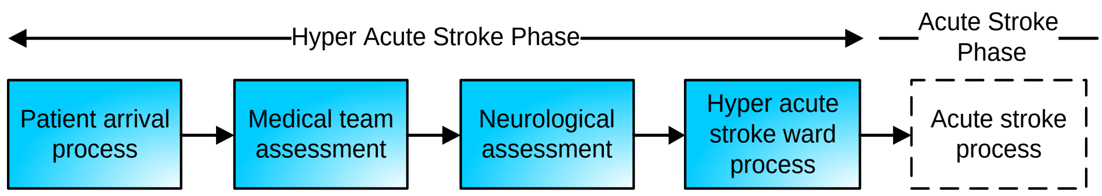


Figure 7.7: Processes involved in stroke care pathway of a hospital

The proposed variations modelling methodology is applied to model, simulate and analyse the hyper acute phase of stroke care pathway of a hospital. The subsections below detail the application of the proposed methodology to stroke care pathway.

7.3.1 System-level modelling of stroke care pathway

In this section, the RAD model of hyper acute phase of stroke care pathway is developed based on interviews of staff involved in stroke care pathway in a hospital. Following sub-step illustrates the procedure for modelling stroke care pathway in a hospital:

7.3.1.1 *Stroke care pathway modelling*

The list of roles involved in the hyper acute phase of stroke care pathway is elicited by interviewing the stroke services manager in hospital, who manages and administers the stroke pathway within hospital. The key roles involved within the hyper acute phase are Paramedics, A&E Receptionist, Resus Sister, Emergency Nurse, Triage Nurse, Stroke Nurse, Neurology Registrar, CT Radiographer, Radiologist, Medical Team in A&E (Consultant/Senior Health Officer (SHO)/Specialist Registrar (SpR)), and Modern Matron are identified. Member of staff performing each roles were interviewed regarding details of their involvement in the stroke pathway from start to end. The interviews were recorded using the digital recorder DS-40 from Olympus. After recording, audio files were transcribed into Microsoft Word (2007). These textual transcripts are utilized to build RAD of the hyper acute phase of stroke care pathway based on RAD modelling steps (see Section 7.2.1.1). The resulting relation between RADs of the hyper acute phase of stroke pathway is logically illustrated in Fig. 7.8. Below is the discussion about the RAD model developed for hyper acute phase of stroke care pathway.

Figure 7.8 illustrates four sub-processes of hyper acute phase of stroke care pathway. Patient arrival process is divided into: (i) FAST (Facial weakness; Arm weakness; Speech problems; Time to call 999) positive patient arrival process; and, (ii) Non-FAST positive patient arrival and medical team assessment process. FAST is a type of clinical assessment performed by Paramedics or Triage Nurses for identifying stroke patients and if positive, pre-alerting acute stroke team (neurology registrar, stroke nurse) while transporting patients to local A&E. If a patient is FAST positive, paramedic staff pre-alerts acute stroke team and then patients are rapidly assessed by stroke team upon arrival at A&E. However, if a patient is non-FAST positive, then patients undergo medical team assessment upon arrival at A&E and then acute stroke team is notified if initial clinical assessment confirms stroke. Both FAST positive and non-FAST positive patients then undergo neurological assessment for stroke confirmation followed by hyper acute stroke ward process where various treatments are provided to respective stroke patients.

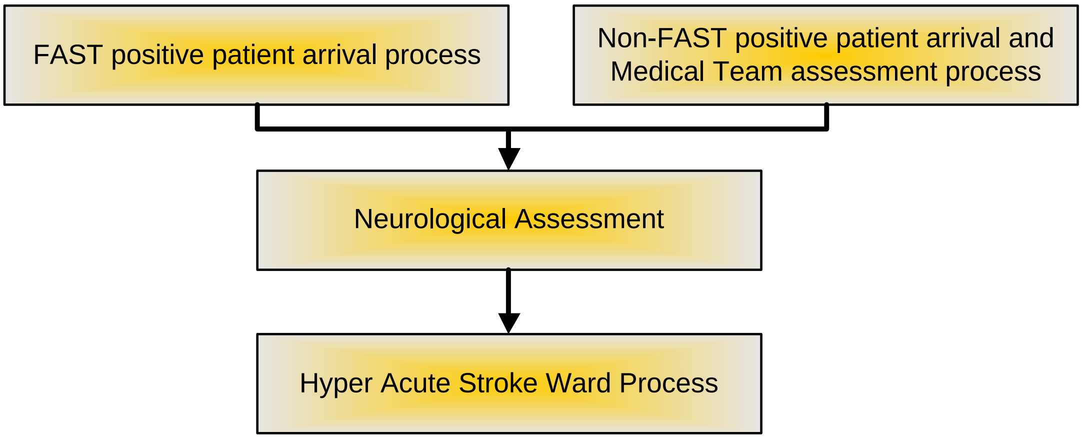


Figure 7.8: Sub-processes of hyper acute phase of stroke care pathway

The stroke care pathway starts with the FAST positive patient arrival at A&E (see Fig. 7.9 related to FAST positive patients). The process starts by a trigger representing paramedic staff arrival at patient location and performing FAST assessment. If patient is found FAST positive, a FAST positive alert is sent to resus sister in A&E by paramedics control room. Resus sister then alerts acute stroke team comprising of stroke nurse (in hyper acute stroke ward), neurology registrar, and emergency department (ED) specialist registrar (SpR). Stroke nurse from the hyper acute stroke ward report to the A&E resus area based on the pre-alert and will wait for patient arrival. Simultaneously, paramedics transport patient to A&E and hands over the patient to resus sister and stroke nurse. Further, paramedics hands over the ambulance log sheet (paramedics form) to the A&E receptionist, who registers patient demographics and medical condition into various IT systems. FAST positive patients are then normalized and initial tests are performed by resus sister together with stroke nurse in resus area followed by neurologic assessments.

Figure 7.10 illustrates the process of non-FAST patient arrival and medical team assessment at A&E. This process starts when patients are identified as non-

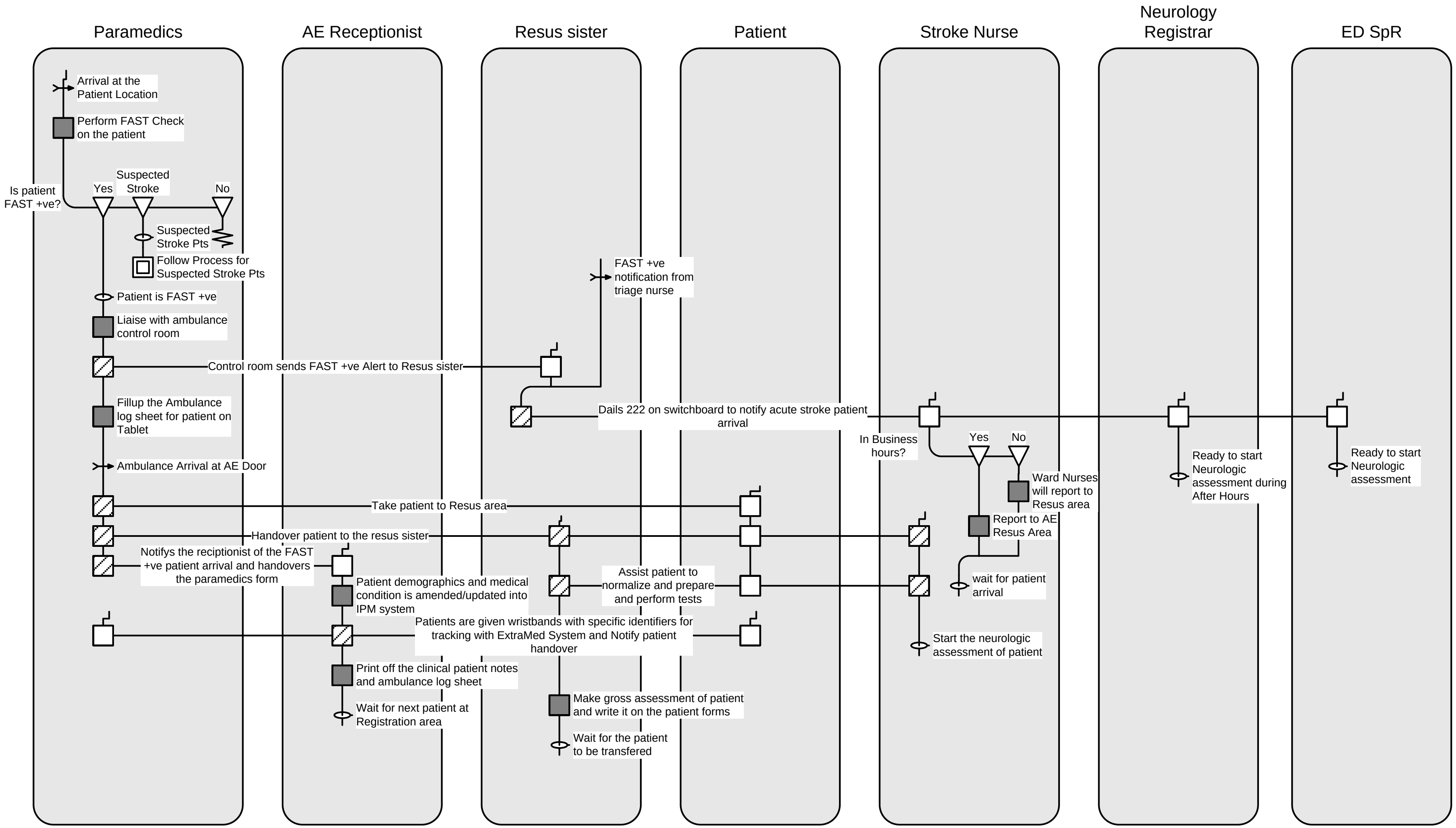


Figure 7.9: RAD for FAST positive patient arrival process

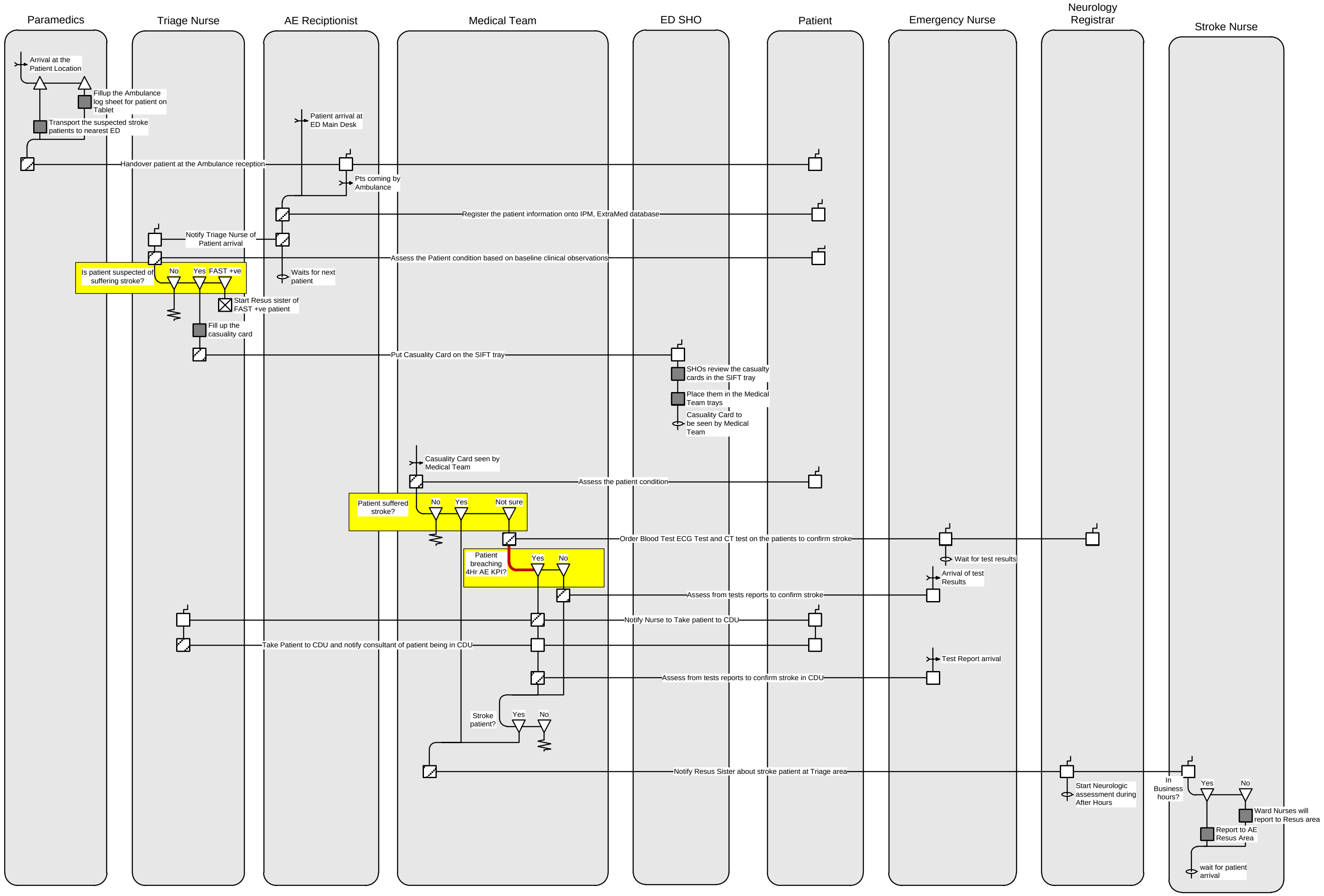


Figure 7.10: RAD of non-FAST positive patient arrival and medical team assessment process

FAST positive by paramedics. These patients are then transported to the local A&E and handovers to A&E receptionist, who registers patient into IT systems and finally notifies the triage nurse of patient arrival and start the triage assessment. Initial patient assessment is performed by the triage nurse and decision is made about patient having suffered stroke. If patient is FAST positive then resus sister is alerted and FAST positive patient process is initiated.

However, if patient is not FAST positive and triage nurse suspect stroke, then medical team in A&E is notified with the help of causality card which details about the patient conditions in triage. Then medical team (comprising of SHO/SpR/Consultant) will assess the patient conditions and if patient conditions are unclear will order blood test, electrocardiogram (ECG) test, computed tomography (CT) scan of the patient. Medical team will send these patients to clinical decisions unit (CDU) if patient is nearing 4 hours of A&E KPI for further assessment based on tests. CDU is a ward used for the patients who has complex presenting conditions and requires final decision about their diagnosis. It acts as a buffer to the A&E for the patients breaching 4 hour KPI of A&E. Then medical team makes decision about the patient diagnosis after receiving the test reports. If patient is identified to have suffered stroke then the neurology registrar and stroke nurse is notified about the stroke patient which is followed by the neurologic assessment.

Figure 7.11 illustrates the neurological assessment process for the stroke patients. Stroke nurse assess the initial patient condition and if conditions are complicated then neurology registrar are called to assess patient otherwise neurology registrar supervises stroke nurse by means of telephone. Then CT scanning is ordered and performed by stroke nurse and CT radiographer. Finally,

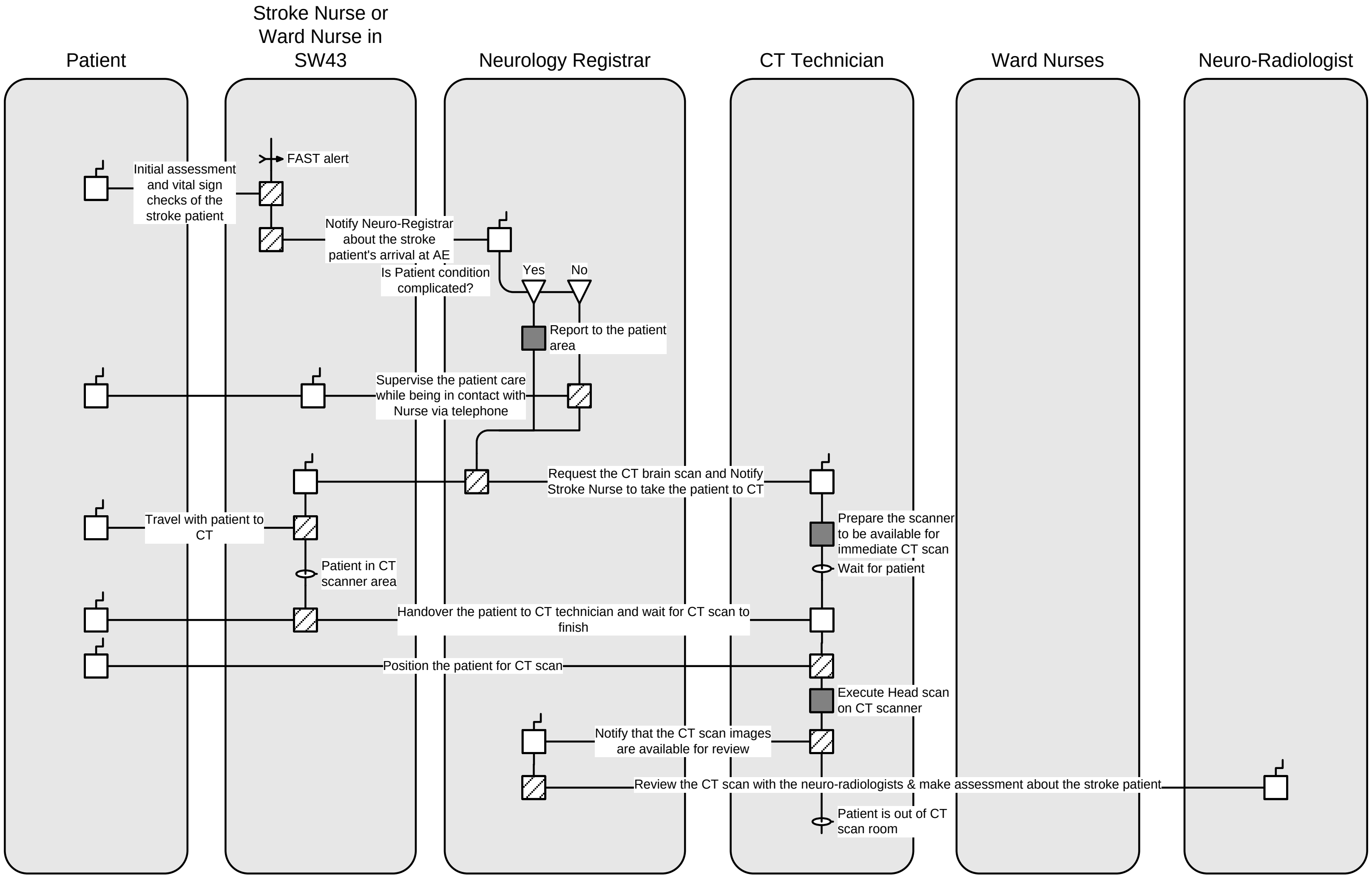


Figure 7.11: RAD of neurological assessment process of stroke patients

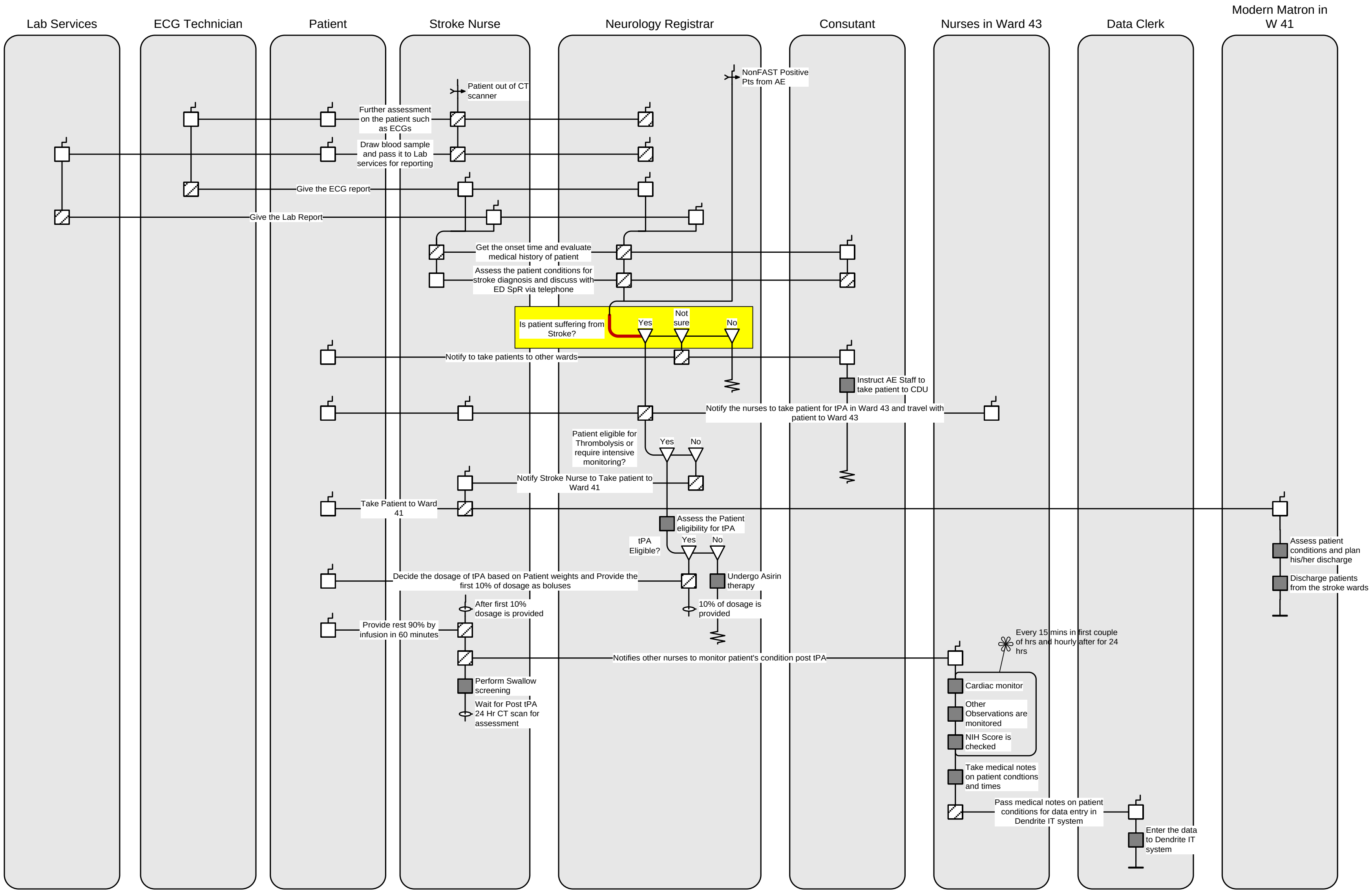


Figure 7.12: RAD of hyper acute stroke ward process

patient is out of the CT scanner and the images are interpreted and reported by the neuro-radiologist.

Figure 7.12 illustrates the hyper acute stroke ward process which is initiated after the neurological assessment of stroke patients. Stroke nurse performs ECG, and blood test in collaboration with ECG technician and Lab services. Reports of these tests together with the assessment of neurology registrar are used to make decision about if a patient has suffered stroke. If patient is identified to be stroke patients, then they are sent to hyper acute stroke wards and thrombolysis (tPA) eligibility is assessed is provided to stroke patients.

The RAD models of stroke care pathways developed are utilized in next subsection to identify critical decisions leading to patient variations from pathways.

7.3.2 Problem identification in stroke care pathway

In this step, the performance of stroke care pathway is monitored based on the EPR data available in hospital. The crucial key performance indicator of the stroke care pathway in which the stroke services are struggling to achieve the targeted performance is 80/90 KPI. 80/90 KPI is defined as more than 80% of total stroke patients coming to the hospital must spend more than 90% of their hospital stay in stroke speciality units. A number of randomized clinical trials are consistently yielding findings wherein *acute stroke patients who spend most of their time at a hospital in a stroke ward/stroke unit experience better recovery outcomes* (Langhorne and Pollock, 2002; Stroke Unit Trialists' Collaboration, 1997). Moreover, UK DoH (2006, 2010) stipulates that *80% of stroke patients must spend 90% of their stay at a hospital in a stroke ward / stroke unit* (80/90

KPI). This contractual expectation, with clinical underpinning, is closely related to stroke care pathway evaluation and DoH (UK) funding policies. Therefore, hospitals attempting to adhere to this performance measure must transport acute stroke patients into a stroke ward immediately upon confirmation of the diagnosis in A&E. Hence, in this chapter we will use 80/90 KPI to evaluate the performance of overall stroke care pathway. Figure 7.13 illustrates the 80/90 KPI performance of stroke care pathway of a hospital based on EPR. Figure 7.13 shows that the stroke care pathway in hospital are not able to achieve their targeted performances.

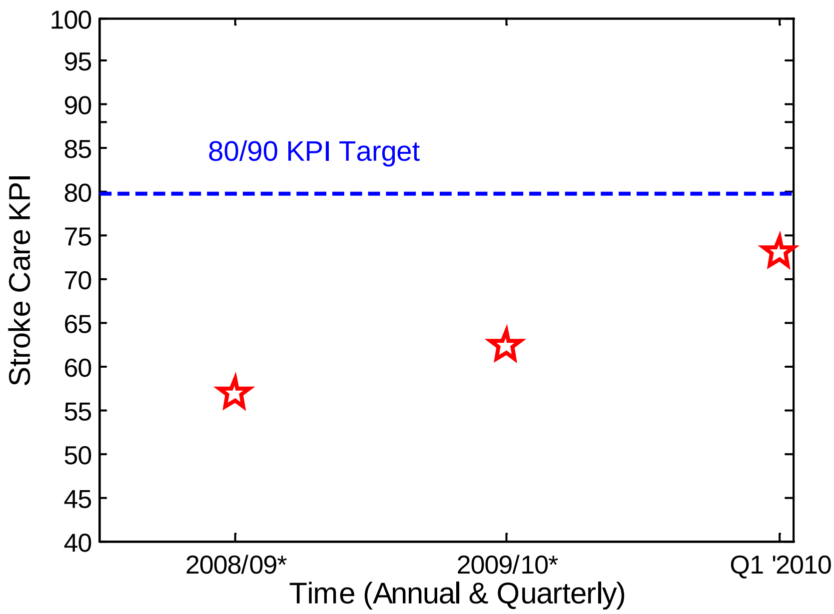


Figure 7.13: Monitoring 80/90 KPI for stroke care pathways

The main reason for the stroke care pathway in hospital not being able to achieve targeted performance is largely due the patient diversions to other non-stroke speciality units; thus significantly reducing stroke patient's length of stay in stroke units. Therefore, in this section, decisions leading to significant patient diversion from the stroke care pathway are identified based on RAD of stroke care pathway and EPR.

RADs of the hyper acute phase of stroke care pathways are used in this subsection to identify decisions that are leading to patient diversion from stroke care pathway (see Section 7.2.3.2). The decision making steps that leads to variations from the pathways is identified based on following sub-steps:

7.3.2.1 Identifying candidate decisions from system model of stroke pathway

As discussed in Section 7.2.3.2, candidate case refinements from RAD model of stroke care pathway are identified which are leading to pathway variation. All the decisions in RAD are analysed to identify case refinements or decisions which leads to patient referral from one speciality unit to another. Therefore, candidate case refinements (***CR***) are highlighted in Fig. 7.10 and Fig. 7.12 which potentially are leading to patient diversion. These decisions are *Is patient suspected of suffering stroke?*, *Patient suffered stroke?*, *Patient breaching 4Hr AE KPI?* in Fig. 7.10; and, *Is patient suffering from Stroke?* in Fig. 7.12. These candidate set of decisions (represented in Fig. 7.14) are further analysed in next step with the help of patient records from hospital IT systems.

*7.3.2.2 Identifying critical decision from **CR***

The EPR data for stroke patients is analysed to identify the impact of the decisions on pathway variations. Stroke patient referrals from A&E and other sources to stroke wards (speciality unit involved in providing stroke care within stroke care pathway), clinical decisions unit (CDU), and other wards such as cardiology wards (CRD), medical wards (MED), surgery wards (SRG), other wards (RGB, W40) are computed and are represented in Fig. 7.15. CDU and other wards are not involved in proving specialist care to stroke patients and thus stroke patients referred to these units are considered as patient diversion from stroke care pathway. Figure 7.15 illustrates the pathway variations from stroke pathway in hyper acute and acute phase based on 5 months of hospital data. The red coloured boxes indicate the non-stroke wards and green colour box represent the stroke wards. The red arrows represent stroke patient diversions and blue arrows indicate correct referral of stroke patients. Therefore, red arrows represent patient diversions in Fig. 7.15. Significant number of stroke patients is diverted to CDU after A&E in Fig. 7.15 (97 from AE and 2 from other sources stroke patients sent to CDU). These patient diversion leads to less number of stroke patients spending most of their hospital stay in stroke speciality units.

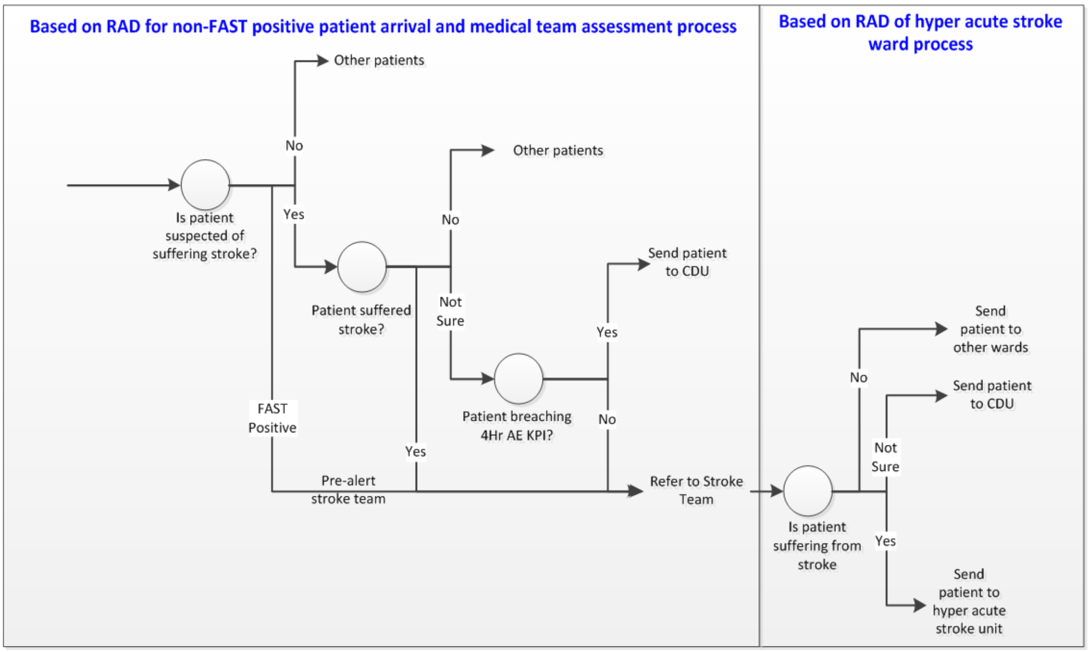


Figure 7.14: Conceptual diagram for the case refinements (*CR*) represented in RADs

Decisions *Patient breaching 4Hr AE KPI?* and *Is patient suffering from Stroke?* are usually taking place in A&E and leads to patients being diverted to

CDU (see Fig. 7.14). Hospital wards are grouped into A&E, Stroke Wards (W41, W42, W43), CDU, and Other Wards (W40, SRG, CRD, MED, RGB) (*i.e.*,$w = 4$). Therefore, the impact (I_{CR_c}) for both of these decisions is computed as:

$$I_{CR_c} = \frac{\sum_{r=1}^{298} d_{1,3}^{r}}{\sum_{r=1}^{298}\sum_{a=1}^{4}\sum_{b=1}^{4} d_{a,b}^{r}} = \frac{97}{97+4+27+2+131+2+8+1} \approx 0.356 \quad (30)$$

where, $d_{1,3}^{r}$ represents decisions leading patient being sent to CDU from A&E.

Let us consider the threshold $Th = 0.20$, then decisions *Is patient suffering from Stroke?* and *Patient breaching 4Hr AE KPI?* are eligible as critical decision (***CD***) leading to significant patient diversions. Decisions *Is patient suffering from Stroke?* and *Patient breaching 4Hr AE KPI?* are considered as one because both of them are leading to same type of patient variation (*i.e.*, from A&E to CDU) and there is lack of data supporting individual decision analysis. These decisions are then analysed in next sub-step based on the interview of *Neurology Registrar* and *Medical Team* (in A&E) about decision making process for identification of stroke in A&E and their referral to stroke wards, CDU, and other wards.

7.3.3 Decision making process modelling

In this sub-section, *neuro SpR* and ED *medical team* is re-interviewed about the decision making process involving other roles, clinical information, clinical tests, and patient medical history for identifying stroke. Patients are sent off to stroke or non-stroke units based on this decision making process (as discussed in Section 7.2.1.2). The interviews are transcribed into textual format and RAD of decision making process is developed based on RAD based modelling methodology. The RAD of decision making process identifies inputs to the decision making process for examp-

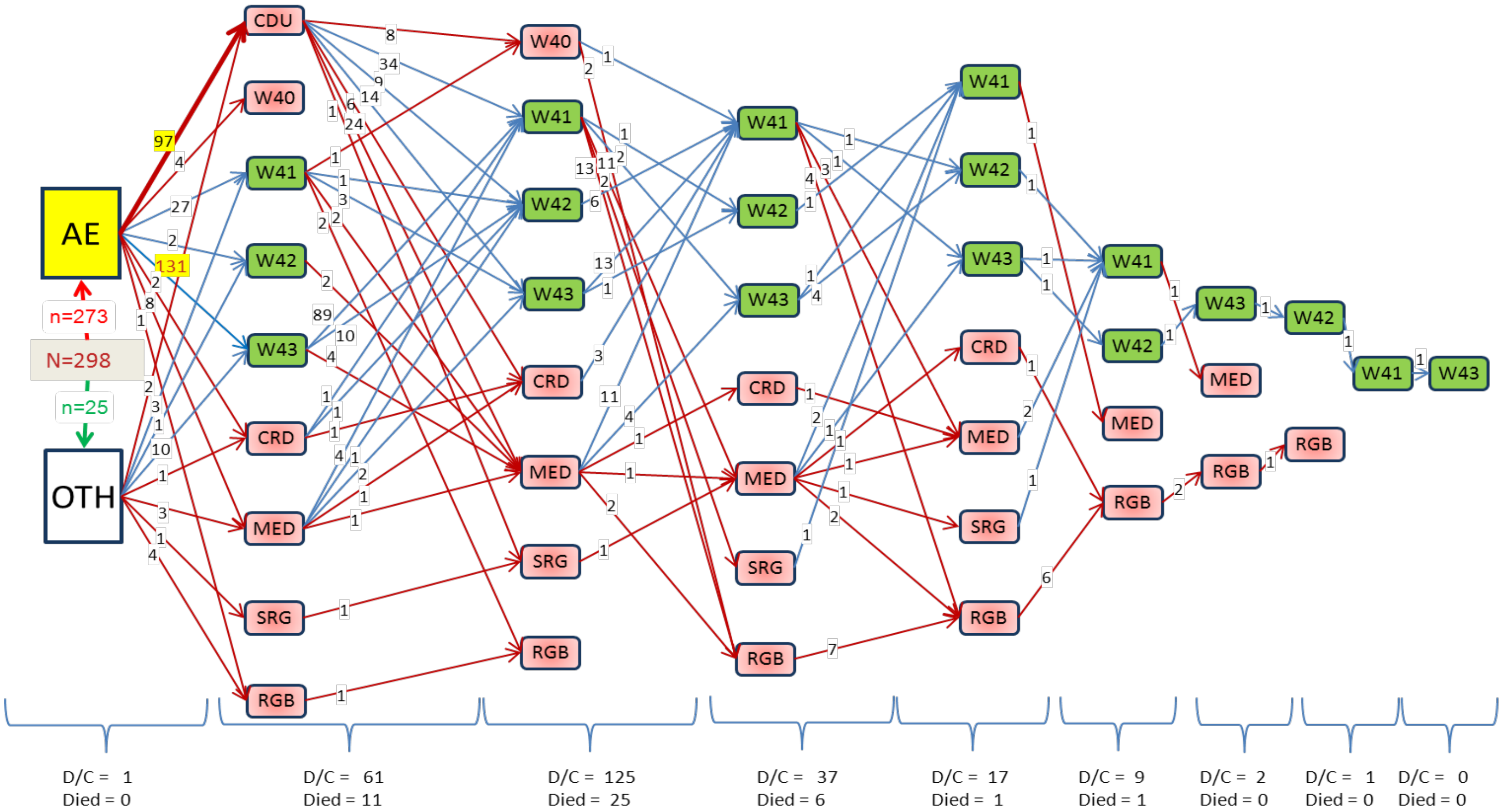


Figure 7.15: Patient diversion from stroke care pathways based on hospital data (April 2010 – August 2010); OTH: other sources; D/C: patient discharged

-le clinical test results, FAST test result, CT scan review by radiologist, stroke onset time, other); decision making steps involved in identifying stroke, and resulting actions that are performed. Figure 7.16 illustrates the RAD model for decision making process adopted by neurology registrar and medical team for identifying stroke. The neurology registrar or medical team doctor will first assess patients based on triage notes or FAST (face weakness, arm weakness, speech, time) test notes from paramedics. Initial assessment is performed, vital signs and medical history is assessed for suspected stroke patients.

For suspected stroke patients, symptom progression, time onset, focal neurological deficits, and vascular risk factors are evaluated to identify whether patient condition suggest stroke or not. If these assessment suggest stroke the differential diagnosis such as ranking based on NIHSS (national institute of health stroke scale), ECG and Blood test, and CT scan are performed to confirm stroke and assess patient treatment options. Based on these assessments, patients are sent to stroke wards or CDU or other wards. RAD model developed for decision making process is then utilized in next step to analyse the pathway variations from stroke care pathway.

7.3.4. Pathway variations analysis (PVA) for stroke care pathway

The stroke care pathway is analysed based on the pathway variations analysis (PVA) methodology discussed in Section 7.2.2. The model is developed for stroke care pathway based on the hospital IT systems data related to stroke care. Details of steps involved in PVA for stroke care pathway are described as follows:

7.3.4.1 *Generate sample of patients for analysis*

The sample of patients is generated based on following parameters:

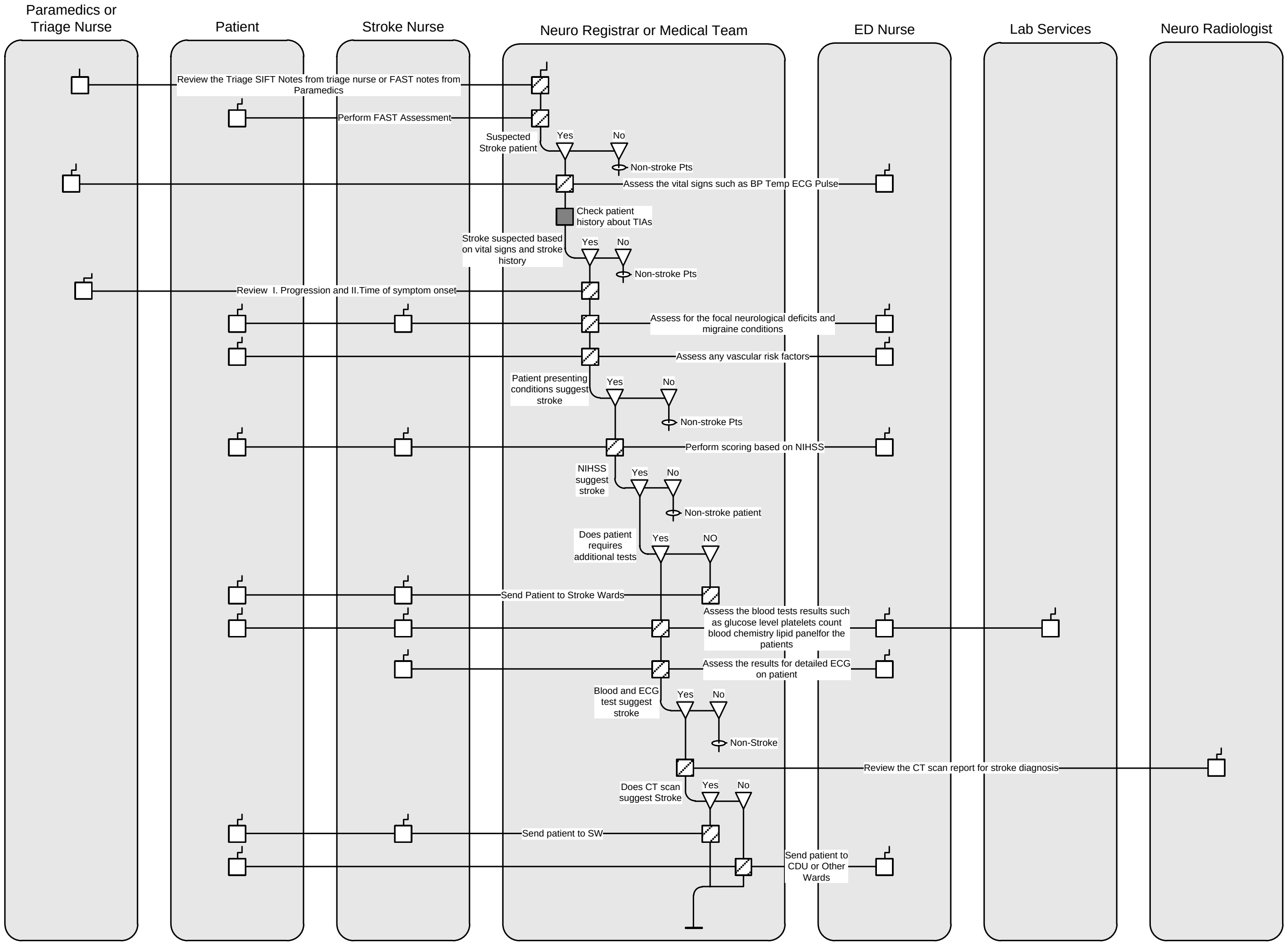


Figure 7.16: RAD of decision making process for identifying stroke

A. Sample size: Parameters such as N_{pts} and T are evaluated based on the hospital data about the patients coming to hospital for stroke related services. The time period time period $T = 30\ days$ is used and number of patients is identified to be $N_{pts} \sim N(105, 9)$.

B. Patient arrival time: The distribution for patient arrival time to A&E ($\boldsymbol{Pt_{arrival}}$) is identified to be:

$$\boldsymbol{Pt_{arrival}} \sim N(13.8, 5.28) \tag{31}$$

$\boldsymbol{Pt_{arrival}}$ distribution is used in next step for simulation modelling and analysis. Figure 7.17 illustrates the patient arrival distribution on the dataset.

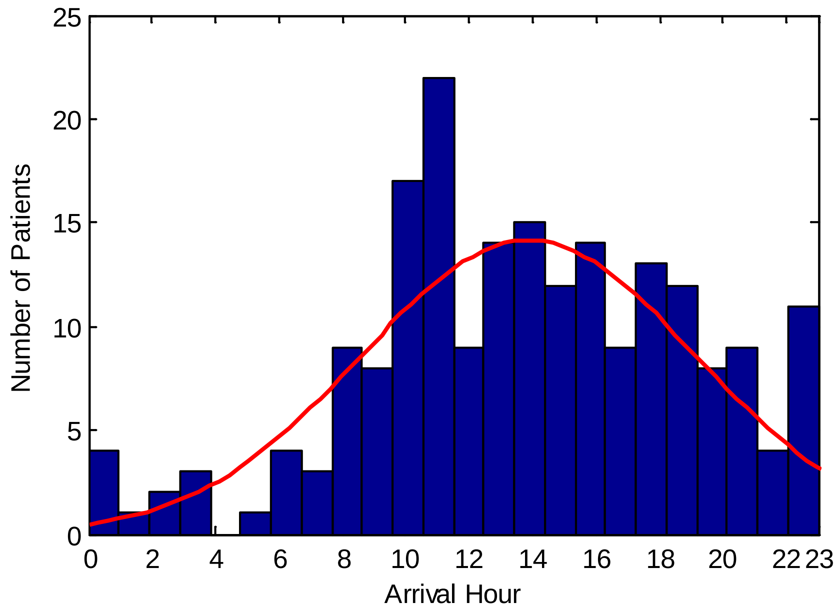


Figure 7.17: Patient arrival time distributions

C. Patient presenting conditions: $\boldsymbol{Pt_{type}}$ is identified with the help of RAD model of the critical decision making process obtained in Section 7.3.3. Each patient type is based on patient clinical test results that are performed by neurology registrar and medical team to identify stroke. Five sub-groups of patients (stroke and stroke mimics) are identified based on major clinical assessment tests such as FAST, focal neurological deficit (FND), symptom onset type, and TIA history. For *e.g.*, 1st type of patients have FAST test as positive; 2nd type of patient have FAST test as negative and FND test as positive; 3rd type of patient have FAST, FND test as negative, symptom onset type, TIA history as positive; 4th type of patients have FAST, FND test as negative, and symptom onset type, TIA history as negative; and, 5th type of patients have all the stroke tests as negative. Therefore, $\boldsymbol{stroke} = \{1,2,3,4\}$&$\boldsymbol{mimics} = \{5\}$represents stroke patients and stroke mimics patients category**.** Therefore,

$$\boldsymbol{Pt_{type}} = \{1,2,3,4,5\}\boldsymbol{:}\ \boldsymbol{stroke} = \{1,2,3,4\}, \boldsymbol{mimics} = \{5\} \quad (32)$$

Based on abovementioned parameters, sample of patients comprising of patients with diagnosis stroke and stroke mimics is created. This sample of patients is used in next steps for simulation modelling and analysis.

7.3.4.2 *Modelling push and pull factors to simulate of patient flow on stroke care pathway*

As defined in Section 7.2.2.2, the push and pull factors among speciality units involved in stroke care pathway leads to patient diversions. These factors are modelled for the stroke care pathway of a hospital are relevant parameters are estimated based on EPR. These factors are estimated as:

Push Factors:

A. *Decision makers in Regular work hours and after work hours*: The quality of decisions is affected during the regular work hours and after work hours. This is due to the presence of neurologist in regular work hours and only medical team in A&E together with neurologist ‘on call’ service takes over during after work hours. The W_{start} andW_{end} (start and end time of regular working hour of a shift) is identified to be 8:00 and 16:00 and this is utilized for evaluating the probabilities defined in Eqs. (9-12) in the next step.

B. Evaluation of decision making process for stroke: The probabilities for sending stroke or stroke mimics patients to stroke wards during regular and after hours are identified from hospital patient records data (see Section 7.2.2.2.B) and are represented as:

$$\boldsymbol{P^{Reg}} = [0.95, 0.55, 0.80, 0.70, 0.05] \quad (33)$$

$$\boldsymbol{P^{Aft}} = [0.95, 0.44, 0.70, 0.50, 0.10] \quad (34)$$

Probabilities $\boldsymbol{P^{Reg}}$and$\boldsymbol{P^{Aft}}$are estimated based on the 3 months data from hospital IT systems about patient flow in the stroke care pathway.

C. A&E 4 Hour Operational KPI: The time distributions for clinical interventions in A&E are identified for $\boldsymbol{Pt_{Triage}}$, $\boldsymbol{Pt_{SIFT}}$,$\boldsymbol{Pt_{EDSpR}}$, $\boldsymbol{Pt_{Consltant}}$in hours. These distributions are identified and represented as:

$$\boldsymbol{Pt_{Triage}} \sim Unif(0.4, 0.6);\ \boldsymbol{Pt_{SIFT}} \sim Unif(0.7, 1.0) \quad (35)$$

$$\boldsymbol{Pt_{EDSpR}} \sim Unif(1.0, 1.5); \boldsymbol{Pt_{Consltant}} \sim Unif(1.2, 2.2) \quad (36)$$

Based on the distributions of $\boldsymbol{Pt_{Triage}}$, $\boldsymbol{Pt_{SIFT}}$,$\boldsymbol{Pt_{EDSpR}}$, $\boldsymbol{Pt_{Consltant}}$; the $\boldsymbol{Pt_{TW}}(i)$ for each of the i^{th} patients is generated. Furthermore, based on the hospital current policy about stroke care, $\boldsymbol{Pt_{TW}}(i)$ is defined as:

$$\boldsymbol{Pt_{TW}}(i) = \begin{cases} \boldsymbol{Pt_{Triage}}(i) & \forall \boldsymbol{P_{type}}(i) = 1 \\ \boldsymbol{Pt_{Triage}}(i) + \boldsymbol{Pt_{SIFT}}(i) + \boldsymbol{Pt_{EDSpR}}(i) + \boldsymbol{Pt_{Consltant}}(i) & Otherwise \end{cases} \quad (37)$$

i^{th}patient such that $P_{type}(i) = 1$ represents patient category defined FAST positive patients, which are referred directly to Acute Stroke Team after *triage* in ED and thus, $\boldsymbol{Pt_{SIFT}}(i), \boldsymbol{Pt_{EDSpR}}(i), \boldsymbol{Pt_{Consltant}}(i)$ times are not included in $\boldsymbol{Pt_{TW}}(i)$ in Eqn. (37).

As discussed in section 7.2.2.2.C, the 4-hour A&E operational KPI, defined by $\boldsymbol{decision_{EDKPI}}(i)$, is used as one of the KPI affecting stroke care pathway.

Pull Factors:

D. Bed utilization KPI of hype acute stroke Ward: As discussed in Section 7.2.2.2.C, the bed utilization KPI is computed based on hyper acute bed capacity in hyper acute stroke ward. Currently, hyper acute stroke ward has 4 beds (*i.e.*, $B_{SU} = 4$) and $LoS_{SU} \approx 3.25$ (estimated using hospital patient records data). Therefore, U_{SU}^{Bed} is estimated as:

$$U_{SU}^{Bed} = \frac{3.25 \times \sum_{i=1}^{N_{pts}} \boldsymbol{Pt_{SentWard}}(i)}{4 \times T} \times 100 \tag{38}$$

These parameters are used in next step to run the simulation model and identify the service improvement scenarios.

E. Stroke Unit KPI: The 80/90 KPI of stroke unit of a stroke care pathway is identified as a crucial factor affecting stroke patients being sent to stroke unit. This KPI is evaluated based on $Sent_{SU}$ and $Sent_{CDU}$ representing patients sent to stroke units and non-stroke units such as CDU. From $Sent_{SU}$ and $Sent_{CDU}$, patients spending more than 90% of their stay at stroke wards are evaluated. Mathematically,

$$OBJ = \frac{f_1 \times Sent_{SU} + f_2 \times Sent_{CDU}}{Sent_{SU} + Sent_{CDU}} \times 100 \quad (39)$$

Parameters f_1 and f_2 are evaluated based on the EPR database storing the stroke patient information. These parameters are utilized to identify patients spending more than more than 90% of their hospital stay in stroke wards (*OBJ*). This is done to evaluate the performance of stroke care pathway based on 80/90 KPI (discussed in Section 7.3.2).

7.3.4.3 <u>*Analysis of stroke care pathway variations simulation model*</u>

As discussed in section 7.2.2.3, Monte Carlo simulation technique is used for simulation analysis. Following sub-steps further discusses the simulation analysis:

A. <u>Running the simulation model for stroke care pathway</u>:

For simulation modelling, a group of patients (N_{pts}) is created based on the distributions of each patient types ($\boldsymbol{Pt_{type}}$). Then for each of i^{th} patients, $\boldsymbol{Pt_{arrival}}(i)$, $\boldsymbol{Pt_{Triage}}(i)$, $\boldsymbol{Pt_{SIFT}}(i)$,$\boldsymbol{Pt_{EDSpR}}(i)$,$\boldsymbol{Pt_{Consltant}}(i)$ are sampled based on Eqs. (33, 35, 36). Then, $\boldsymbol{Pt_{TW}}(i)$ for i^{th} patient is estimated based on $\boldsymbol{P_{type}}(i)$. Then, decision variables $\boldsymbol{decision_{EDKPI}}(i)$ and $\boldsymbol{decision_{SendProb}}(i)$ for i^{th} patient is computed based on $\boldsymbol{Pt_{TW}}(i)$, $\boldsymbol{decision_{arrival}}(i)$. Finally, $\boldsymbol{Pt_{SentWard}}(i)$ is calculated for each of the i^{th} patient and number of stroke patients sent to stroke wards and CDU is computed. The stroke patients sent to stroke wards is represented as $Sent_{SU}$ and stroke patient sent to CDU is represented as $Sent_{CDU}$. A simulation model is developed in MATLAB (2010) software (see Appendix I), which follows the abovementioned procedure for simulation modelling for large number of iterations. After pathway variations are simulated for all N_{pts}

patients, number of stroke patients spending more than 90% of their stay in stroke wards is evaluated (defined in Eq. 39).

The simulation model is then validated and verified based by taking additional three month data and comparing the 80/90 KPI obtained from simulation model and hospital data given the number of patients (stroke and mimics) arriving at A&E. The simulation model developed is then used in next step for suggesting set-based solutions to reduce patient diversion from stroke care pathway.

B. Analysis of stroke care pathway simulation model for set-based solutions:
After running the simulation model of pathway variations of current state, the current percentage of stroke patients spending more than 90% of their hospital stay in stroke wards is 73% (Approx.). After running the simulation model for $T = 30$ days, the utilization of stroke beds is estimated to be $U_{SU}^{Bed} \approx 81\%$.

Improvement options are analysed and their potential realization in hospital scenario is determined. The simulation model developed is used to identify set-based solutions for improving stroke care pathways. In order to suggest changes, average percentages of patient types are illustrated in Table 7.1. Table 7.1 shows the impact of patient types on overall number of stroke patients coming to hospital for stroke care. Patient type 1 to 4 is stroke patients and 5th category is for stroke mimics patients (non-stroke patients having stroke like conditions).

From Table 7.1, patients with negative FAST test and positive FND test (*i.e.* $k = 2,\ k \in \boldsymbol{Pt_{type}}$) is 32.2 % which is largest in stroke patients set ($k \in \boldsymbol{stroke}$). Furthermore, probabilities of sending patients to stroke wards for

$P_{type}(i) = 2$ is $\boldsymbol{P^{Reg}} = 0.55and\boldsymbol{P^{Aft}} = 0.44$ in regular and after hours. Therefore, improving the decision making for patients of 2^{nd} type, *i.e.*, $P_{type}(i) = 2$, can significantly improve number of stroke patients correctly sent to stroke wards, thereby improving *OBJ* (see Eqn. 39). However, increasing the number of stroke patients sent to stroke wards following their diagnosis in A&E, will increase the number of patient coming to stroke wards for stroke care. Therefore, the capacity of stroke wards (i.e., number of beds) will also have to be increased simultaneously with the improvement of clinical decision making for $P_{type}(i) = 2$. Hence, following improvement options are suggested taking into account set-based solutions to increase *OBJ* of stroke services of hospital.

Table 7.1: Average percentages of patients of each $\boldsymbol{k} \in \boldsymbol{Pt_{type}}$

Patient Type ($\boldsymbol{Pt_{type}}$)	**Percentages**
1	24.5
2	32.2
3	07.7
4	05.6
5	30.0

<u>Option A</u>: In this option, patient of type 2, *i.e.*, $P_{type}(i) = 2$, are prioritized after triage in A&E to reduce overall clinical assessment time ($\boldsymbol{Pt_{TW}}(i)$) and training of A&E staff about identifying stroke once patient is identified as FND positive. In simulation model, these changes will be reflected as reduced clinical intervention time for patient of type 2 and higher probabilities for sending stroke patients to stroke wards. That is mathematically represented as:

$$\boldsymbol{Pt_{TW}}(i) = \begin{cases} \boldsymbol{Pt_{Triage}}(i) & \forall \boldsymbol{P_{type}}(i) = 1 \\ \boldsymbol{Pt_{Triage}}(i) + \boldsymbol{Pt_{Consltant}}(i) & \forall \boldsymbol{P_{type}}(i) = 2 \\ \boldsymbol{Pt_{Triage}}(i) + \boldsymbol{Pt_{SIFT}}(i) + \boldsymbol{Pt_{EDSpR}}(i) + \boldsymbol{Pt_{Consltant}}(i) & Otherwise \end{cases} \quad (40)$$

And probabilities of type 2 patients in regular and after work hours are represented as $\boldsymbol{P^{Reg}}(2) = 0.75and\boldsymbol{P^{Aft}}(2) = 0.65$ this is due to the improved decision making due to A&E staff training on stroke patient identification if FND is positive. This improvement suggestion will help to get more stroke patients into stroke wards; hence, bed capacity of the stroke ward will also have to be increased in the analysis. Increasing, $B_{SU} = 5$ (*i.e.*, adding one extra bed in stroke ward) results in $U_{SU}^{Bed} \approx 79\%$.

Option B: In this option, patient of type 2, *i.e.*, $P_{type}(i) = 2$ are fast tracked in A&E (as is done for FAST positive patients, *i.e.*, $P_{type}(i) = 1$). That is reducing $\boldsymbol{Pt_{TW}}(i)$ by removing SIFT time, ED SHO/SpR/Doctor time, Consultant time and considering them as a high priority patients by pre-alerting to acute stroke team for stroke diagnosis. Mathematically, $\boldsymbol{Pt_{TW}}(i)$ can be represented as:

$$\boldsymbol{Pt_{TW}}(i) = \begin{cases} \boldsymbol{Pt_{Triage}}(i) & \forall \boldsymbol{P_{type}}(i) = 1,2 \\ \boldsymbol{Pt_{Triage}}(i) + \boldsymbol{Pt_{SIFT}}(i) + \boldsymbol{Pt_{EDSpR}}(i) + \boldsymbol{Pt_{Consltant}}(i) & Otherwise \end{cases} \quad (41)$$

Since, patients of type 2 in this improvement option are referred directly to acute stroke team after triage (using pre-alerts); therefore, the probability of sending patients will increase (same as type 1 patient) due to better decision making (due to Neuro-SpR and stroke nurse involvement in acute stroke team). Hence, probabilities of type 2 patients in regular and after work hours are represented as $\boldsymbol{P}^{\boldsymbol{Reg}}(2) = 0.95and\boldsymbol{P}^{\boldsymbol{Aft}}(2) = 0.95$. Implementation of this option will result in more number of stroke patients coming to stroke wards for stroke care, therefore, bed capacity is increased based on increment in stroke patient referred to stroke ward. Increasing $B_{SU} = 6$ (*i.e.*, adding two extra beds in stroke ward) results in $U_{SU}^{Bed} \approx 80\%$.

The abovementioned options for improving the stroke services are then simulated with the help of Monte Carlo simulation model and considering increased capacity of stroke wards.

Figure 7.18 illustrates the results of the pathway variations simulation analysis for current, option A and option B. Fig. 7.18 (I) shows the number of patients that are correctly sent to stroke ward, and Fig. 7.18 (II) shows the number of stroke patients that are incorrectly sent off to non-stroke wards verses number of hyper-acute beds available/required for current (4 beds), option A (5 beds), and option B (6 beds). Further, Fig. 7.18 (III) illustrates number of stroke patients incorrectly sent to non-stroke wards for current, option A, and option B; and Fig. 7.18 (IV) illustrates the percentage of stroke patients spending more than 90% of their hospital stay in stroke wards (*OBJ*) verses number of beds required for option A and option B. It is evident from Fig. 7.18, that by improving decision making process (i.e., option A and B) and increase of hyper acute bed capacity (i.e., from 4 to 5 and 6), the 80/90 KPI can increase from 73% to 81 % and 93 % respectively.

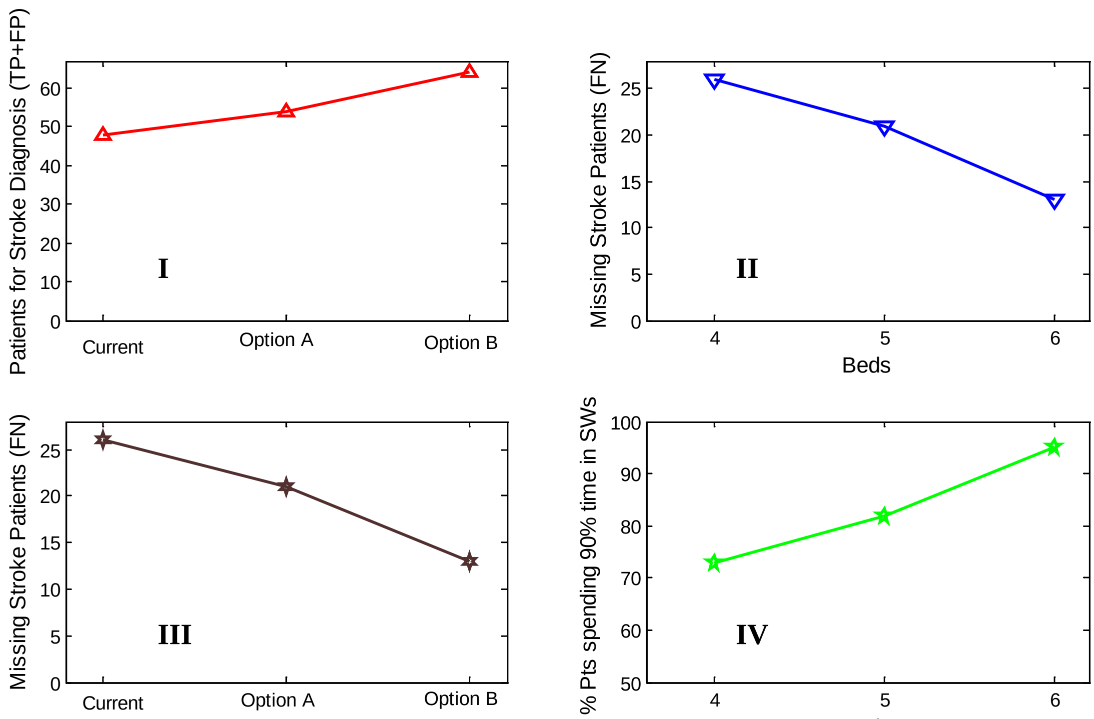


Figure 7.18: Simulation analysis for Current, Option A, and Option B

Based on the results of simulation analysis, set-based solutions were suggested to the hospital to reduce patient diversions from stroke care pathway, which helps hospital's stroke care program to meet their contractual 80/90 KPI. The Matlab Code for simulating the patient diversions from care pathway is present in Appendix I.

7.4 Summary

This chapter proposed a pathway variations analysis methodology for simulation modelling and analysis of patient variations *from* care pathway. PVA methodology models push and pull factors in speciality units leading to patient variations from care pathway. The improvement suggestions help to identify options to reduce these unwarranted variations. The pathway variations analysis methodology employs accurate and scalable RADs, clinical decision making, hospital operations modelling based on push and pull, and Monte Carlo simulation for identifying critical decisions that leads to patient diversions from care pathway. Improvement options are suggested to reduce pathway variations and increase the overall performance of stroke care pathway. A real case study of stroke care pathway of a large UK hospital is employed to illustrate the applicability of proposed methodology for identifying and reducing unnecessary variations *from* a care pathway. Based on the PVA results on the case study, following recommendations/suggestions were made to the hospital:

Recommendation 1: *Re-designed sequence of clinical decision-making by having ED clinicians concentrate their clinical assessment on rapidly detecting presentations of focal neurological deficits (FND) which led to improved diagnostic accuracy of stroke referral from ED to stroke team.*

Hospital Action: Suggestion implemented. Frontline ED clinicians with rotas of three or more months are trained on use of the R.O.S.I.E.R (Recognition of Stroke in Emergency Room) Scale.

Result: Reduced number of stroke patient diverting from care pathway which resulted in improved stroke care KPI from 73% to 88%.

To manage the patient flow due to increased number of stroke patients correctly identified in ED:

Suggestion 2: *Increase hyper-acute stroke unit capacity from 4 beds to 6 beds to manage increased patient flow & eliminate bottlenecks*

Suggestion 3: *Balance bed capacity to manage patient flow variation by relocating entire hyper-acute stroke unit into the acute stroke ward*

Hospital Action: Suggestions implemented Divisional Director of Neurology in consultation with Director of Clinical Pathways & Director of Specialized Networks oversaw implementation of Suggestions 2 & 3.

The next Chapter concludes the research study conducted in this Thesis followed by the future research directions.

CHAPTER 8: Conclusions and Future Work

In this chapter, the contributions and findings of the thesis are summarized. The potential future research is also discussed and outlined.

8.1 Research Contributions

The research proposed in this thesis is based on imperative needs of healthcare service delivery organization to improve existing patient care as well as reducing unwarranted variations *on* and *from* a care pathway. The research aims to effectively model, simulate, and analyse unwarranted variations in hospital services for improvements. Methodologies for analysing unwarranted variations in hospitals based on various types of heterogeneous service data such as tracking data (RFID), electronic patient records (EPR), historic service data and qualitative interviews of medical staff are discussed. The significance of the research proposed in this thesis can be summarized into four major areas which are: (*i*) service delivery system modelling based on qualitative procedural information; (*ii*) simulation modelling and analysis of unwarranted variations *on* a care pathway; (*iii*) unwarranted *role variations* *from* a care pathway modelling and analysis based on real time tracking data and service delivery model; and, (*iv*) unwarranted *patient variations* *from* a care pathway modelling and simulation based on electronic patient records and service delivery model.

(i) *Service delivery system modelling methodology based on qualitative procedural information*:

The significance of service delivery system modelling methodology is that it provides semi-automatic method for accurate and detailed service delivery system model generation based on clinician interviews. The proposed methodology helps in: (a) reducing overall time involved in the development of accurate and detailed process models for process redesign and re-engineering activities; (b) accurately modelling complex healthcare service delivery systems based on qualitative information; and (c) representing collaborative healthcare processes as RAD. In order to show the applicability of the proposed approach for process modelling and static process redesign, a real case study of magnetic resonance (MR) scanning process of radiology department is also discussed. A set of principles such as *Individual task complexity, Long sequence of tasks, Decision making process, Cascading decision making, and Multiple or long interactions* are discussed to identify problem areas in RAD representing MR scanning process. Software tools based on the methodology are also developed to ease the handling of qualitative interviews data and RAD based process modelling.

(ii) *Modelling and analysis of unwarranted variations on a care pathway using Discrete Event Simulation (DES) integrated with accurate static service delivery system model as input instead of oversimplified workflow models currently used as input to DES*

The simulation modelling methodology based on static service delivery model can help the process improvement experts for rapid and extensive analysis of the unwarranted variations *on* a care pathway. The analysis such as bottlenecks identification, low throughput, long waiting times, and low resource utilizations can be easily conducted and their impact on the overall performance of healthcare services can be evaluated. It helps to perform detailed analysis based on RADs and high level process analysis based on simulation models by generating various '*what-if*' improvement scenarios. The integration of accurate process model based on RAD of healthcare services with the simulation modelling helps to reduce overall time involved to develop models for hospital simulations. This integration can help decision makers to analyse various improvement scenarios to improve healthcare services. A real case study of MR scanning process of radiology is included to illustrate the integration of simulation modelling with RAD. Two different process improvement scenarios are discussed based on simulation modelling. These scenarios are: (*a*) *two tables per scanner for simultaneous execution of MR scanning and patient preparation*; and, (*b*) *patient consenting by referring clinicians*.

(iii) *Modelling and analysis of unwarranted variation of standard operating service delivery processes, specifically, role variations during a care pathway based on tracking information*

The system variations such as role variations modelling approach based on electronic tracking data can play a significant part in unveiling crucial unwarranted variations from a care pathway, which are largely unnecessary and leads to inefficient care delivery, in hospital services. Modelling system variations in hospital service delivery can help to discover comprehensive process maps central to any process redesign/re-engineering projects in healthcare. Unwarranted role variations *from* a care pathway are modelled with the help of proposed edge coloured directed multigraphs (ECDM) modelling concept and a learning methodology is also proposed to learn ECDM from electronic tracking logs of clinicians. The resulting ECDM helps to identify system variations associated with healthcare service delivery. In order to demonstrate the applicability of proposed methodology, a case study relating MR scanning process is utilized and crucial system variations within care delivery are identified. The proposed methodology can run parallel or remotely to the electronic tracking studies conducted in hospitals for hospital supply chains, patient tracking, and resource tracking as it only requires the tracking logs to be analysed.

(iv) *Modelling and analysis of unwarranted variation of standard operating service delivery processes, specifically, patient variations (diversion) from a care pathway*

Unwarranted variations *from* care pathways have been identified as a major challenge in the success of process improvement studies within hospital. Largely, these variations are due to inherent factors of various service departments involved within complex care pathways and are largely unnecessary which leads to longer waiting times, delays, and lower productivity of service delivery systems. Thus resulting in reduced key performance indicators associated with care pathways. Therefore, a PVA methodology is developed for modelling and simulating care pathway variations to highlight substandard care pathways in terms of efficiency/effectiveness. The PVA methodology identifies major patient variations *from* care pathway such as patient diversions and develops a mathematical model of healthcare operations together with the goodness of decision making processes involved. The mathematical model thus developed is utilized for simulation analysis by analysing electronic patient records stored in Hospital IT systems. Based on simulation analysis, improvement scenarios were suggested which helps in reducing unwarranted pathway variations. The proposed approach integrates three major areas: (a) care pathway modelling; (b) decision making steps within pathway; and, (c) operations model of the hospital services; for modelling and simulation analysis of pathway variations. A case study of stroke care pathways within a hospital is utilized to illustrate the implementation of proposed PVA modelling and simulation analysis methodology. Based on the PVA results on the case study, following recommendations/suggestions were made to the hospital:

Recommendation 1: *Re-designed sequence of clinical decision-making by having ED clinicians concentrate their clinical assessment on rapidly detecting presentations of focal neurological deficits (FND) which led to improved diagnostic accuracy of stroke referral from ED to stroke team.*

Hospital Action: Suggestion implemented. Frontline ED clinicians with rotas of three or more months are trained on use of the R.O.S.I.E.R (Recognition of Stroke in Emergency Room) Scale.

Result: Reduced number of stroke patient diverting from care pathway which resulted in improved stroke care KPI from 73% to 88%.

To manage the patient flow due to increased number of stroke patients correctly identified in ED:

Suggestion 2: *Increase hyper-acute stroke unit capacity from 4 beds to 6 beds to manage increased patient flow & eliminate bottlenecks*

Suggestion 3: *Balance bed capacity to manage patient flow variation by relocating entire hyper-acute stroke unit into the acute stroke ward*

Hospital Action: Suggestions implemented Divisional Director of Neurology in consultation with Director of Clinical Pathways & Director of Specialized Networks oversaw implementation of Suggestions 2 & 3.

8.2 Suggestions for future Work

The research presented in this thesis involves development of modelling and analysis methodologies for analysing unwarranted variations in healthcare service delivery systems based on multiple types of service data. However, further research is to be conducted for performing systematic service conformance analysis of hospital services based on clinical guidelines recommended by National Institute of Health (NIH), National Institute for Health and Clinical Excellence (NICE). The future research can be summarized as follows:

1. *Development of service delivery model from clinical guidelines or gold standards*: Due to the presence of large variations in service delivery to patients, research community in healthcare domain is involved in developing best care plans or clinical guidelines for various types of diseases or patient conditions based on the best available medical knowledge or practice. Clinical guidelines are method for standardization and uniform improvement of the quality of healthcare. Developing service delivery models from comprehensive text based clinical guidelines is challenging. Therefore, modelling methodology has to be developed which can utilize the text based long clinical documents to develop service delivery models (see Fig. 8.1). Text mining algorithms

and medical ontology can be used in the methodology for analysing text based guideline documents and development of service delivery models. The resulting model can be used by clinicians and hospital managers for service improvements and conformance analysis.

2. *Methodology for conformance analysis of hospital services based on clinical guidelines:* Research has to be conducted on developing a methodology which can utilize models from clinical guidelines and hospital service delivery model for process conformance analysis. This approach will highlight part of the hospital services which are not or in accordance with the guidelines. The variations in hospital service delivery can be identified be used for process improvements and provision of standard care to patients (see Fig. 8.1).

3. *Methods for suggesting service improvements based on conformance analysis:* Methods can be developed to improve the service delivery system in hospital by suggesting service improvements and changes (see Fig. 8.1). These methods will help in identifying the impact of the non-conforming processes within hospital and help in reducing the variations in the services.

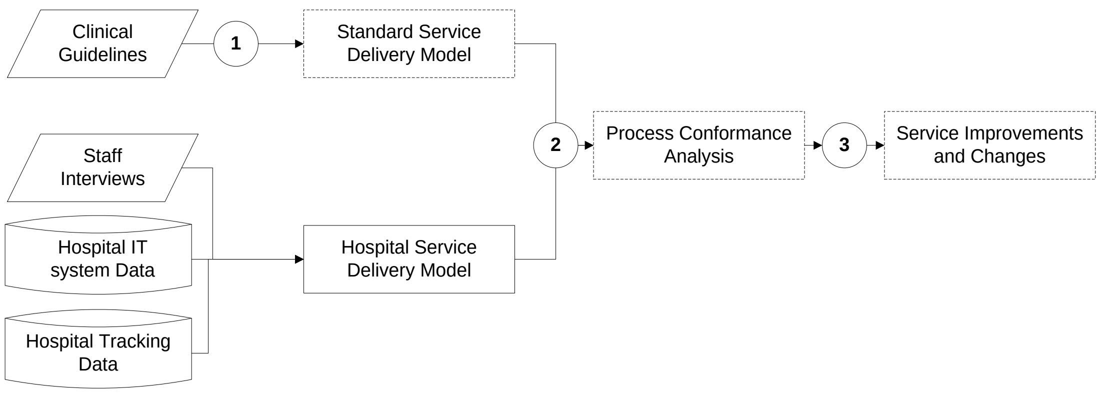


Figure 8.1: Future Research Areas

Work conducted in Chapter 7 related to PVA was a part of a pilot study and further work can be carried out to analyse the benefits of proposed recommendations and implementations in stroke care pathway.

BIBLIOGRAPHY

Aben, G. R., Morita, M., Fors, S. and Switzer, M., **(**2004) "Integrated communication: workflow enhancement in the digital diagnostic radiology department" *CARS 2004 - Computer Assisted Radiology and Surgery*, Vol. 1268, pp. 357-360

Ackermann, F., Eden, C. and Williams, T. (1997) "Modelling for litigation: mixing qualitative and quantitative approaches" *Interfaces*, 27, (2), 48-65.

Adamson, J, Beswick, A. and Ebrahim, S. (2004). "Stroke and Disability".*Journal of Stroke and Cerebrovascular Diseases*, Vol. 13, Pages: 171-177.

Aguilar-Savén, R. S., (2004), "Business process modelling: Review and framework", *International Journal of Production Economics*, Vol. 90, No. 2, pp. 129-149.

Allee, V., (2002) "The future of knowledge: increasing prosperity through value networks" *Butterworth-Heinemann*.

Allee, V., (2008) "Value network analysis and value conversion of tangible and intangible assets" *Journal of Intellectual Capital*, Vol. 9, No. 1, Pages: 5-24.

American Hospital Association, (2004), "The Cost of Caring".

American Stroke Association, (2005), pg. 690

Appleby, J., Raleigh, V., Frosini, F., Bevan, G., Gao, H., Lyscom, T., (2011) "Variations in health care: The good, the bad and the inexplicable", *The King's Fund* Report.

Archer SB, Burnett RJ, Flesch LV, *et al.*, (1997) "Implementation of a clinical pathway decreases length of stay and hospital charges for patients undergoing total colectomy and ileal pouch/anal anastomosis" *Surgery*; 4: 699–705.

Banning, M. (2007) “A review of clinical decision making: models and current research” *Journal of Clinical Nursing,* 17, 187–195.

Bayer, S., Petsoulas, C., Cox, B., Honeyman, A. and Barlow, J., (2010) “Facilitating stroke care planning through simulation modelling” *Health Informatics Journal,* Vol. 16(2), Pages: 129–143.

Birkmeyer JD, Sharp SM, Finlayson SRG, Fisher ES, Wenneber JE (1998) “Variation profiles of common surgical procedures” *Surgery*; 5: 917–923.

Boland GWL. (2006) “Stakeholder expectations for radiologists: obstacles or opportunities?” *Journal of American College of Radiology*, Vol 3, pp. 156-63.

Boland, GWL, Houghton,M.P., Marchione, D.G., McCormick W., (2008), “Maximizing outpatient computed tomography productivity using multiple technologists,” *American College of Radiology*, Vol. 5, No. 8, pp. 900-906.

Brailsford S, Rauner M, Gutjahr E, Zeppelzauer W, (2006) “Combined discrete-event simulation and ant colony optimisation approach for selecting optimal screening policies for diabetic retinopathy” *Computational Manage Sci*, Vol. 4, pages: 59–83.

Campbell, H., Hotchkiss, R., Bradshaw, N., Porteous, M. (1998) “Integrated care pathways” *British Medical Journal*, Vol. 316, Pages: 133-144.

Carter, P.L., Melnyk, S.A., Handfield, R.B., (1995) “Identifying the basic process strategies for time based competition”, *International Journal of Production and Inventory Management*, Vol. 36, Issue 1.

Centrak, (2009) www.centrak.com

Connelly LG, Bair AE. (2004) “Discrete event simulation of emergency department activity: a platform for system-level operations research” *Academy of Emergency Medicine*, Vol. 11, Page: 1177–84.

Crabbe JP, Frank CL, Nye WW (1994) “Improving report turnaround time: an integrated method using data from a radiology information system,” *American Journal for Roentgenology*, 1994; 163:1503–1507.

Crimmins, J. W., Saulnier, J. L., (1999) “IR/RF locator” *US Patent 5917425*.

Davies R, Roderick P, Crabbe D, Raftery P, Patel P, Goddard JR. (2002) “A simulation to evaluate screening for helicobacter pylori infection in the prevention of peptic ulcers and gastric cancers” *Health Care Manage Sci*, Pages: 249–58.

Department of Health UK, www.dh.gov.uk/

Dickson, E. W., Singh, Sabi, Cheung, Dickson S., Wyatt, Christopher C., and Nugent, Andrew S., 2008 “Application of lean manufacturing techniques in the Emergency Department,”*The Journal of Emergency Medicine*, Vol. xx, No. x, pp. xxx, 2008

Dodds S., (2005) “Designing improved healthcare processes using discrete event simulation” Br J Healthcare ComputInf Manage, Vol. 22 (5), pages: 14–16.

Duguay, C., Chetouane, F. (2007) “Modelling and Improving Emergency Department Systems using Discrete Event Simulation” *Simulation*, Vol. 83, Issue 4, Pages: 311-320.

Fisher, D. L. (1966) "Data, Documentation and Decision Tables" *Comm ACM*, Vol. 9, No. 1, pages: 26–31.

Fisher, E.S., Wennberg, D.E., Stukel, T.A., Gottlieb, D.J., Lucas, F.L., Pinder, E.L., (2003) “The Implications of regional variations in Medicare spending Part 2: health outcomes and satisfaction with care” *Annals of Internal Medicine*, Vol. 138, No. 4.

Fishman, G. S. (1995). Monte Carlo: Concepts, Algorithms, and Applications. New York: Springer. ISBN 038794527X.

Forrester, J.W., (1994) "System Dynamics, Systems Thinking, and Soft-OR" System Dynamics Review, Vol. 10, No. 2.

Gladwin, B. and Tumay, K., 1994. "Modelling business processes with simulation tools", *In Proceedings of the 1994 Winter Simulation Conference*, Pages: 114-121.

Goldstein, L. B., Hey, L. A., & Laney, R. (2000) "North Carolina Stroke Prevention and Treatment Survey: Statewide availability of programs and services" *Stroke*, Vol. 31, Issue: 1, Pages:66-70.

Gordon R & Franklin N (2003) "Cognitive underpinnings of diagnostic error" *Academic Medicine,* 78, 782.

Graber M (2003) "Metacognitive training to reduce diagnostic errors: ready for prime time" *Academic Medicine,* 78, 781.

Groff JY, Mullen PD, Byrd T, Shelton AJ, Lees E, Goode J. (2000) "Decision making, beliefs, and attitudes toward hysterectomy: a focus group study with medically underserved women in Texas" *J Women's Health Gend Based Med*; 9: S39–S50.

Hammer, M., and Champy J., 1994. Reengineering the corporation - a manifesto for business revolution, *Nicholas Brealey Publishing*, London.

Harbison, J, Hossain, O, Jenkinson, D, Davis, J, Louw, S. J., and Ford, G. A., (2003)"Diagnostic Accuracy of Stroke Referrals From Primary Care, Emergency Room Physicians, and Ambulance Staff Using the Face Arm Speech Test" *Stroke,* Vol. 34;pages: 71-76.

Harrel, C. and Field K., 1996. “Integrating process mapping and simulation”.*In Proceedings of the 1996 Winter Simulation Conference*, Pages: 1292-1296.

Hay, A.M., Valentin, E.C., and Bijlsma, R.A., (2006) “Modeling Emergency Care in Hospitals: A Paradox - The Patient Should not Drive the Process” *IEEE Proceedings of Winter Simulation Conference*, Pages: 439-445.

Healthcare Commission (2007) “An improving picture? Imaging services in acute and specialist trusts” *Acute Hospital Portfolio Review*, Pages: 1- 48.

Hendrich, Ann, Chow, Marilyn P, Skierczynski, Boguslaw A, Lu, Zhenqiang, (2008) "A 36-Hospital Time and Motion Study: How Do Medical-Surgical Nurses Spend Their Time?" *The Permanente Journal,* Vol. 12, No. 3, Pages: 25-34.

Hendrickson G, Doddato TM, Kovner CT (1990) "How do nurses use their time?" *Journal of Nursing Administration*, Vol. 20, No. 3, Pages: 31–37.

Hillman BJ, Neiman HL. (2003) “Radiology 2012: radiology and radiologists a decade hence—a strategic analysis for radiology from the second annual American College of Radiology forum” *Radiology*; Vol. 227: pp. 9-14.

Hlupic V., 1998. "Business Process Re-engineering and Simulation: Bridging the Gap". In *Proceedings of the European Simulation Multiconference* (ESM’98), *Ed. by Zobel R. and Moeller D., SCS,* Pages: 641-645.

Holloway, R. G., Benesch, C. and Rush, S. R. (2000) "Narrowing the evidence–practice gap" *Neurology*, Vol. 54, Pages:1899-1906

Hulpic, V., Robinson, S. (1998) “Business Process Modelling and Analysis using discrete-event simulation” *Proceedings of the 1998 Winter Simulation Conference*, Pages: 1363- 1369.

Hydo, B (1995) “Designing an Effective Clinical Pathway for Stroke” *The American Journal of Nursing*, Vol. 95, No. 3, Pages: 44-51.

Jimmerson, C., Weber, D., Sobek, DK, (2005) “Reducing waste and errors: piloting lean principles at IHC,” *Joint Commission Journal on Quality and Safety*, Vol. 31, No. 5, pp. 249-257.

Kalra, L., Perez, I., Melbourn, A., (1998) "Stroke risk management: changes in mainstream practice" *Stroke*, Vol. 29, Pages: 53–57.

Kasner, S. E., Chalela, J. A., Luciano, J. M., Cucchiara, B. L., Raps, E. C., McGarvey, M. L., Conroy, M. B., and Localio A. R., (1999) “Reliability and Validity of Estimating the NIH Stroke Scale Score from Medical Records” *Stroke*, Vol. 30, Pages:1534-1537

Kettinger, W., Teng J. and Guha S., 1997.“Business Process Change: A Study of Methodologies, Techniques and Tools” *Management Infomation Systems Quaterly*, Volume 21.Number 1. USA. 55-80.

Kitchiner D, Bundred PE.(1999) “Clinical pathways. A practical tool for specifying, evaluating and improving the quality of clinical practice” *MJA*; 170: 54–55.

Kobayashi, A., Wardlaw, J. M., Lindley, R. I., Lewis, S. C., Sandercock, P. A.G., Czlonkowska, A., (2009) “Oxfordshire Community Stroke Project Clinical Stroke Syndrome and Appearances of Tissue and Vascular Lesions on Pretreatment CT in Hyperacute Ischemic Stroke Among the First 510 Patients in the Third International Stroke Trial (IST-3)” *Stroke*, Vol. 40, Pages: 743-748.

Kotiadis K, Mackenzie M. (2004) “Simulation modelling for intermediate care” *Br J Healthcare Manage*, Vol. 10 (8), pages: 240–6.

Kotiadis, K., Mingers, J. (2006) “Combining PSMs with hard OR methods: the philosophical and practical challenges” *Journal of the Operational Research Society*, 57, 856-867.

Lakin, R. (1996) "BPR enabling software for the financial service industry", *Management Services*, Vol. 40 No.3, pp.18-20.

Langhorne, P. and Pollock, A., (2002) “What are the components of effective stroke unit care?” *Age and Ageing*, Vol. 31, Pages: 365–371.

Lawrence P., (1997) “Workflow Handbook,” *John Wiley & Sons Ltd*, ISBN 0-4719-6947-8.

Lehaney, B., Paul, R., (1996) “The Use of Soft Systems Methodology in the Development of a Simulation of Out-patient Services at Watford General Hospital” *Journal of the Operational Society*, 1996, 47, 864-870.

Leigh, E. (2010) "Progress in improving stroke care" *26th Report of session 2009-10 report, House of Commons*.

Lingineni, M., Caraway B., Benjamin P. and Mayer R., 1995. “A tutorial on PROSIM: A knowledge-based simulation model design”. *In Proceedings of the 1995 Winter Simulation Conference*, Pages: 408-412.

Lu, M., Wah-ho Chan, Jian Ping Zhang, Ming Cao, (2007), “Generic Process Modelling and Simulation Methodology for Integrating Site Layout and Operations Planning in Construction” *Journal of Computing in Civil Engineering*, Vol. 21, No. 6, Pages: 453-462.

McGuffin, M. J. and schraefel, m. c. (2004) A Comparison of Hyperstructures: Zzstructures, mSpaces, and Polyarchies. In: *ACM Conference on Hypertext and Hypermedia*, *2004*, August 9-13, 2004, Santa Cruz, California, USA.

Medicare, (2003) http://www.medicare.gov/

Meitzner, B. and Trewn, J., (2006) “Variation Reduction strategies for IP patient flow through operating rooms” *Society for Health Systems* in Session: *Operational Performance Improvement*.

Metropolis, N.; Ulam, S. (1949)."The Monte Carlo Method".*Journal of the American Statistical Association (American Statistical Association)*, Vol. 44 No. 247, Pages: 335–341.

Miller, M. J., Ferrin, D. M., Flynn, T, Ashby, M, White (Jr.), K. P., Mauer, M G, (2006) “Using RFID Technologies to Capture Simulation Data in a Hospital Emergency Department” *Proceedings of the 38th conference on Winter Simulation, Monterey, California*, Pages: 1365 - 1370.

Miller, M. J., Ferrin,D. M., Shahi, N., LaVecchia, R., (2008) “Using RFID Technologies to Capture Simulation Data in a Hospital Emergency Department,” *Proceedings of the 40th Conference on Winter Simulation*, Pages: 1637-1644.

Mingers, J., Rosenhead, J. (2004) “Problem structuring methods in action” *European Journal of Operational Research*, Vol. 152, pp: 530-554.

Mohd Nor, A., Davis, J., Sen, B., Shipsey, D., Louw, S. J, Dyker, A. G., Davis, M., Ford, G. A., (2005) “The Recognition of Stroke in the Emergency Room (ROSIER) scale: development and validation of a stroke recognition instrument” *The Lancet Neurology*, Volume 4, Issue 11, Pages 727 – 734.

Molema, J J W, Groothuis, S., Baars, I J, Kleinschiphorst, M., Leers, E.G.E, Hasman, A., van Merode, G. G., (2007), “Healthcare System design and Parttime working doctors” *Health Care Management Science*, Vol. 10, Pages: 365-371

Mould, G, Bowers, J, Ghattas, M (2010) “The evolution of the pathway and its role in improving patient care” *QualSaf Health Care*, 19: e 14.

NAE/IOM (2005), Building a Better Delivery System: A New Engineering/Health Care Partnership, Technical report, *National Academy Engineering and Institute of Medicine.*

NAO, (2005) “Reducing Brain Damage: Faster access to better stroke care” HC: 452 2005-2006, ISBN: 010293570X

National Research Council, (2009) “Computational Technology for Effective Health Care: Immediate Steps and Strategic Directions” *Editors: Willam W. Stead and Herbert S. Lin; Committee on Engaging the Computer Science Research Community in Health Care Informatics*, Pages: 1-120.

National Health Services (2003) “Radiology: A National Framework for Service Improvement” Page: 1-15.

National Health Services (2005) “Success factors for reducing waiting times and improving services for patients” *Modernising Radiology Services: A practical guide to redesign*. Pages: 1-112.

National Health Services (2007) “Radiology success factors” Page: 1-1.

Office of National Statistics Health Statistics Quarterly (12) Winter (2001) “Stroke incidence and risk factors in a population based cohort study” *Scottish Stroke Care Audit* (2005/2006)

Ould, M.A., (1995) "Business processes: modelling and analysis for re-engineering and improvement." *Chichester ; New York: Wiley & Sons.*

Ould, M.A., (2005), “Business Process Management: A Rigorous Approach”, *Meghan-Kiffer Press.*

Panella, M., Brambilla, R., Marschisio, S. & Di Stanislao, F., (2008) “Reducing Stroke In-Hospital Mortality: Organized Care Is a Complex Intervention” *Stroke*, DOI: 10.1161/STROKEAHA.108.533877.

Panella, M., Marchisio, S., Di Stanislao, F. (2003) “Reducing clinical variations with clinical pathways: do pathways work?” *International Journal for Quality in Health Care*; Volume 15, Number 6: pp. 509–521

Patel, N. V. (2000) “Healthcare Modelling through Role Activity Diagrams for Process-Based Information Systems Development,” *Requirement Engineering*, Vol. 5, No. 2: Pages: 83-92.

Paul R., Hlupic V., and Giaglis G. M., 1998.“Simulation Modeling of Business Processes”, *In Proceedings of the UK Academy for Information Systems 1998 Conference*, 311-320.

Pearson SD, Goulart-Fisher D, Lee TH. (1995) “Critical pathways as a strategy for improving care: problems and potential” *Ann Intern Med*; 12: 941–948.

Pesavento, P., (2000) “Where have all the radiologists gone?” *Decisions in Imaging Economics,* Vol. 13, Issue: 5, Pages: 48-53.

Pesavento, P., (2001) “A turn-of-the-century census” *Decisions in Imaging Economics,* Vol. 14, Pages: 22-34.

Ploeg, J. (1999) "Identifying the best research design to fit the question. Part 2: qualitative designs" Evidence Based Nursing, 2, Pages: 36-37

Quist BD. (1992) "Work sampling nursing units" *Nursing Management*, Vol 23, No. 9, Pages: 50–51.

Reiner, B., Siegel, E., Carrino, J. A., (2002), “Workflow optimization: current trends and future directions”, *Journal of Digital Imaging*, Vol. 15, No. 3, pp. 141–152.

Rick Kronn, (2008), “The optimal RTLS Solution for hospitals Breaking through a complex environment,” *Journal of Healthcare Information Management*, Vol. 22, No. 4.

Rightcare, NHS (2010) "The NHS Atlas of Variation in Healthcare" Report Available on www.rightcare.nhs.uk/atlas/qipp_nhsAtlas-LOW_261110c.pdf

Robinson, S., (2001) “Soft with a hard centre: discrete-event simulation in facilitation. *Journal of the Operational Research Society*, Vol. 52, pp: 905-915.

Roobottom, C. A., Jewell, F. M., Jones, A., Wells, I. P., (1995) “Variation in Angiographic Practice and Technique Amongst Interventional Radiologists in the UK: Assessment by Postal Questionnaire” *Clinical Radiology*, Vol. 50, Pages: 705-709.

Rosenhead, J. (1989) “Rational analysis for a problematic world: problem structuring methods for complexity, uncertainty and conflict” *John Wiley*, ISBN 0-471-92285-4.

Rother, M., Shook, J. (2003), “Learning to See – Value-stream Mapping to Create Value and Eliminate Muda” *Lean Enterprise Institute*, ISBN: 9780966784305.

Sachs MA. Diagnostic Imaging. January 2002. *SG - 2, LLC*.17-24.

Sanwlippo JS, Robinson CL. *The Risk Management Handbook for Healthcare Professionals*. London: The Partenon Publishing Group Ltd, 2002.

Shadbolt, N., Milton, N. (1999) “From Knowledge Engineering to Knowledge Management” *British Journal of Management*, Vol. 10, pp. 309-322.

Shukla, N., Keast, J., Ceglarek, D, (2009) “Role Activity Diagram-Based Workflow Modelling of Imaging Service Delivery Process in Radiology” *INFORMS International Conference on Service Sciences*, Hong Kong.

Shukla, N., Keast, J.E., Ceglarek, D., (2011) “Modelling Variations in Imaging Service Delivery based on Real Time Tracking Information” *Working Paper*

Smith R. (1991) "Where is the wisdom? The poverty of medical evidence" *Br Med J* 1991; 303: 798–799.

SoW2 Report by Shukla, N, Keast, J, Ceglarek, D. (2009a) "Role Activity Diagram (RAD) development for modelling and analysis of the UHCW radiology service delivery workflow" Progress Report of the Service Delivery Lifecycle and Work Flow collaborative research project between a large UK Hospital, GE-HC and the University of Warwick. Software Tools can be obtained by contacting Darek Ceglarek (d.j.ceglarek@warwick.ac.uk)

SoW2 Report by Shukla, N, Chris Kemp, Ceglarek, D. (2009b) "DualTrak RF/IR system deployment guidelines (Part 1 of 3: Testing the individual variables affecting the tracking)" Progress Report of the Service Delivery Lifecycle and Work Flow collaborative research project between a large UK Hospital, GE-HC and the University of Warwick. Software Tools can be obtained by contacting Darek Ceglarek (d.j.ceglarek@warwick.ac.uk)

SoW2 Report by Shukla, N, Chris Kemp, Ceglarek, D. (2009c) "DualTrak RF/IR system deployment guidelines (Part 2 of 3: Testing the interaction between variables affecting tracking of DualTrak RF/IR systems)" Progress Report of the Service Delivery Lifecycle and Work Flow collaborative research project between a large UK Hospital, GE-HC and the University of Warwick. Software Tools can be obtained by contacting Darek Ceglarek (d.j.ceglarek@warwick.ac.uk)

SoW2 Report by Shukla, N, Chris Kemp, Ceglarek, D. (2009d) "DualTrak RF/IR System Deployment Guidelines (Part 3 of 3: DualTrak Deployment in MR scanning site at UHCW)" Progress Report of the Service Delivery Lifecycle and Work Flow collaborative research project between a large UK Hospital, GE-HC and the University of Warwick. Software Tools can be obtained by contacting Darek Ceglarek (d.j.ceglarek@warwick.ac.uk)

SoW3 Report by Shukla, N, Ceglarek, D. (2010) "Pathway Variations Analysis: case in Point-Stroke" Progress Report of the Integrated Stroke Care Services Pathway (ISCSP) collaborative research project between a large UK Hospital, GE-HC and the University of Warwick.

Staccini, P., Joubert, M., Quaranta, J.F., and Fieschi, M.(2005)"Mapping care processes within a hospital: from theory to a web-based proposal merging enterprise modelling and ISO normative principles" *International Journal of Medical Informatics*, Volume 74, Issues 2-4, pp. 335-344

Stead, W.W. & Lin, H.S. (Eds), (2009) "Computational Technology for Effective Health Care: Immediate Steps and Strategic Directions," *National Research Council*, Washington, DC. Available on the web at: http://www.nap.edu/catalog/12572.html.

Stemberger, M I, Jaklic, J., Popovic, A. (2004) "Suitability of Process Maps for Business Process Simulation in Business Process Renovation Projects" *Proceedings of 16th European Simulation Symposium*, ISBN 1-56555-286-5.

Stevens, W., Myers, G., Constantine, L. (1974) "Structured Design", *IBM Systems Journal*, Vol. 13, No. 2, pp. 115-139.

Stroke Unit Trialists' Collaboration (1997) "Collaborative systematic review of the randomised trials of organised inpatient (stroke unit) care after stroke" *BMJ*, Vol. 314(7088), Pages: 1151-1159.

Tumay, K., 1996. "Business Process Simulation", *Proceedings of the 1996 Winter Simulation Conference*, Pages 93-98.

UK DoH, (2006) "Improving stroke services: a guide for commissioners" Product number: 278329, Gateway reference: 7418, Pages: 50, Copyright holder: Crown.

UK DoH, (2010a) “Equity and Excellence: Liberating the NHS” White Paper available http://www.dh.gov.uk/en/Publicationsandstatistics/Publications/PublicationsPolicyAndGuidance/DH_117353

UK DoH, (2010b) “Department of Health: Progress in improving stroke care”.

van Vliet, EJ, Sermeus, W., van Gaalen, CM, Sol, J C A, Vissers, JMH, (2010) “Efficacy and efficiency of a lean cataract pathway: a comparative study” *QualSaf Health Care*;19:e13.

VanBerkel, P. T., and Blake, J. T., (2007) “A comprehensive simulation for wait time reduction and capacity planning applied in general surgery” *Health Care Management Science*, Vol. 10, Pages: 373-385.

Vayda E. (1973), “A comparison of surgical rates in Canada and in England and Wales” *N Engl J Med*; 23: 1224–1236.

Wardlaw, J. M., Seymour, J., Cairns, J., Keir, S., Lewis, S., and Sandercock, P., (2004) “Immediate Computed Tomography Scanning of Acute Stroke Is Cost-Effective and Improves Quality of Life” *Stroke*, Vol. 35, Pages: 2477-2483

Weingart SN, Wilson RM, Gibberd RW, Harrison B. (2000) “Epidemiology of medical error” *Br Med J*; 320: 774–777.

Wendler, T., Loef, C., (2001) “Workflow management -integration technology for efficient radiology,” *Medicamundi*, Volume 45, Issue 4.

Wennberg, J.E., (2002) "Unwarranted variations in healthcare delivery: implications for academic medical centres" *British Medical Journal*, 325, Pages: 961-964.

Wennberg, D. E., and Wennberg, J. E., (2003) "Perspective: Addressing Variations: Is There Hope For The Future?" *Health Affairs,* Pages: 614-617.

Wennberg, J.E., Cooper, M.M., (1996) “The Dartmouth Atlas of Health Care in United States” Report http://www.dartmouthatlas.org

Wentworth DA, Atkinson RP, (1996) “Implementation of an acute stroke program decreases hospitalisation costs and length of stay” *Stroke,* Vol. 27, Page: 1040-1043.

White K.P., Jr. (2005a) “A Survey of Data Resources for Simulating Patient Flows in Healthcare Delivery Systems,” In *Proceedings of the 2005 Winter Simulation Conference*,pp: 926 – 935.

White, K.P., Jr. (2005b). “Area-Wide Ambulance Diversions: Data Resources for Simulation Modeling” In *Proceedings of the 2005 Winter Simulation Conference*, Ed. M.E Kuhl, N.M. Steiger, F.B. Armstrong, and J.A. Joines, pp. 926-935. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.

WHO Fact Sheet, November (2008) “WHO Media Centre” *Fact Sheet No. 310*.

Wilde, K., (2009) “West Midlands Stroke Research Network Newsletter”, *National Institute for Health Research*

Williams, T., Eden, C., Ackermann, F., Tait, A. (1995) “The effects of design changes and delays of project costs” *Journal of the Operational Research Society*, 46, (7), 809-818.

Williams,C., Maloney,E., McElveny,C. (2004) “Resolving the technologist shortage: A summary of ACR and ASRT efforts to meet the increasing demand for RTs” *Journal of the American College of Radiology*, Vol. 1, Issue 11, Pages 842-847.

Willis B, Kim LT, Anthony T, Bergen PC, Nwariaku F, Turnage RH (2000) "A critical pathway for inguinal hernia repair reduces hospital admissions" *J Surg Res*; 1: 13–17.

Wilson J. (1998) "Integrated care management" *Br J Nurs*; 4: 201–202.

World Wide Web Consortium http://www.w3.org/TR/REC-xml/

Wu SM, Chao Yu YM, Yang CF, Che HL, (2005) "Decision-making tree for women considering hysterectomy" *Journal of Advanced Nursing*, 51, 361–368.

XJ Technologies http://www.xjtek.com/

APPENDIX I

Matlab Code for PVA:

```
%%%%%%% Simulation Model for Shrinking Time Windows %%%%%%%
%%%%%%%               August 2010                  %%%%%%%

clear all;
clc;

pt_conditions=5;
% pt_distributions=           [0.35  0.22 0.24 0.05 0.06 0.08 0.3];
% Percentage of each Patient Category Coming to A&E
% pt_distributions=           [0.245  0.154 0.168 0.035 0.042 0.056
0.3]; % Percentage of each Patient Category Coming to A&E Assuming
30 % non stroke pts
pt_distributions=             [0.245  0.322 0.077 0.056 0.30]; %
Percentage of each Patient Category Coming to A&E without Weekend
consideration
probability_send_sw_regular=  [0.990  0.550 0.800 0.700 0.05]; %
Probability to sending to SWs in Regular Hours
probability_send_sw_after=    [0.990  0.440  0.70  0.50  0.1]; %
Probability to sending to SWs in after Hours + weekends
steps_skipped      =          [4       0     0     0     0 ];  %
Steps that are skipped for patients depending on Conditions


% Fitting the Normal distribution to Time of Admission at the
Hospital
admission_time=[11;11;16;23;23;15;21;18;18;17;18;11;18;7;3;12;14;11;
10;8;11;14;20;15;13;20;23;18;19;18;13;13;8;18;17;21;12;10;23;8;9;19;
12;15;17;23;16;23;19;15;19;3;14;12;14;13;23;13;10;12;14;12;9;19;11;2
1;17;12;17;13;16;6;13;16;17;6;9;11;11;10;10;14;14;15;15;23;15;6;10;1
7;8;19;11;8;0;11;7;19;14;23;8;10;1;20;11;3;2;10;15;18;14;11;12;10;16
;13;16;11;18;0;13;10;23;18;15;21;9;11;21;13;13;12;20;11;11;13;14;10;
13;10;21;19;10;21;16;10;19;8;20;0;8;11;22;13;7;10;21;2;20;18;11;18;1
8;15;20;9;19;21;8;16;22;11;0;20;11;14;17;11;14;16;16;10;16;19;14;9;9
;15;22;10;9;16;15;14;23;14;5;11;16;16;19;22;17;6];
[mu,sigma] = normfit(admission_time); % Returns estimates of the
mean, µ, and standard deviation, ?, of the normal distribution given
the data in admission_time.

tw_LL =[0.4   0.7   0.1   1.2];     % Lower Limit time (in Hrs) for
Triage, SIFT, Medicine, Consultant
tw_UL =[0.6   1.0   1.5   2.2];     % Upper Limit time (in Hrs) for
Triage, SIFT, Medicine, Consultant

% Define Work Hours
start_wrk_hrs=8;
end_wrk_hrs=17;

% % Normal Distribution of patients coming perMonth to Emergency
Department
% (ONLY includes Stroke and Stroke Mimics)
max_iter=1000;
```

```
for num_iter=1:max_iter
    pt_demand_monthly=ceil((randn(1,1) * 10) + 100);
    number_patients=ceil(pt_demand_monthly*pt_distributions); %
Number of Patients for each category
    n=sum(number_patients);
    n_non_stroke=number_patients(pt_conditions); % 9th type of
patient condition are Non-Stroke patients

    % all_patients: 1st field - stroke or non-stroke; 2nd field -
category; 3 and 4 field - start and TW;
    % 5th field tells which ward they went into (SW or CDU)
    all_patients=zeros(n,5);

    for i=1:n
        if i>(n-n_non_stroke)
            all_patients(i,1)=0; % non-stroke pts
        else
            all_patients(i,1)=1; % stroke pts
        end
    end

    k=1;
    for i=1:pt_conditions
        for j=1:number_patients(i)
            all_patients(k,2)=i;   % type of conditions in field 2
            k=k+1;
        end
    end

    % Randomize the all_patients data vector
    all_patients = all_patients(randperm(size(all_patients,1)),:);

    % Assigning the start and end time for patients based on
sampling from Time
    % of arrival


    for i=1:n
        all_patients(i,3)=((randn(1,1) * sigma) + mu); % arrival
time
        if all_patients(i,3)>=24
            all_patients(i,3)=23;
        end
        if all_patients(i,3)<0
            all_patients(i,3)=0;
        end

        TW=0;
        if all_patients(i,2)==1
            TW=((randn(1,1) * 0.2) + 1.5); % Assigning Mean and
Variance time for Category one patients
            %          else if all_patients(i,2)==2
            %
TW=unifrnd(tw_LL(1),tw_UL(1))+unifrnd(tw_LL(4),tw_UL(4));
        else if all_patients(i,2)>=2
                TW=unifrnd(tw_LL(1),tw_UL(1))+
unifrnd(tw_LL(2),tw_UL(2)) + unifrnd(tw_LL(3),tw_UL(3))+
unifrnd(tw_LL(4),tw_UL(4));
            end
            %             end
```

```
        end

        all_patients(i,4)=TW; % Assigning the duration
    end


    for i=1:n

        if all_patients(i,4)>4
            all_patients(i,5)=2; % 2 Represents patient sent to CDU
        else

            if all_patients(i,3)<=8 &&
(all_patients(i,3)+all_patients(i,4)) <=8
                p=probability_send_sw_after(all_patients(i,2));

                % Apply After Hrs Probability
            end

            if all_patients(i,3)<=8 &&
(all_patients(i,3)+all_patients(i,4)) >=8 &&
(all_patients(i,3)+all_patients(i,4)) <=17
                p=probability_send_sw_regular(all_patients(i,2));

                % Apply Regular Hrs Probability
            end

            if all_patients(i,3)>=8 &&
(all_patients(i,3)+all_patients(i,4)) <=17
                p=probability_send_sw_regular(all_patients(i,2));

                % Apply Regular Hrs  Probability
            end

            if all_patients(i,3)>=8 && all_patients(i,3)<=17 &&
(all_patients(i,3)+all_patients(i,4)) >= 17
                p=probability_send_sw_after(all_patients(i,2));
                % Apply After Hrs Probability
            end

            if all_patients(i,3)>17
                if (all_patients(i,3)+all_patients(i,4))>24
                    if (all_patients(i,3)+all_patients(i,4)-24)<=8

p=probability_send_sw_after(all_patients(i,2));

                        % Apply After Hrs  Probability
                    else

p=probability_send_sw_regular(all_patients(i,2));

                        % Apply Regular Hrs  Probability
                    end
                else
                    p=probability_send_sw_after(all_patients(i,2));

                    % Apply After Hrs  Probability
                end
```

```
            end
            probabili(i)=p;
            if unifrnd(0,1)<p
                all_patients(i,5)=1;  % 1 Represents patient sent to
SW
            else all_patients(i,5)=2; % 2 Represents patient sent to
CDU
            end
        end
    end

    sent_SW(num_iter)=0;
    sent_CDU(num_iter)=0;
    sent_non_str_SW(num_iter)=0;
    sent_non_str_CDU(num_iter)=0;

    for i=1:n
        if all_patients(i,1)==1
            if all_patients(i,5)== 1
                sent_SW(num_iter)=sent_SW(num_iter)+1;
            else
                sent_CDU(num_iter)=sent_CDU(num_iter)+1;
            end
        end
        if all_patients(i,1)== 0
            if all_patients(i,5)== 1

sent_non_str_SW(num_iter)=sent_non_str_SW(num_iter)+1;
            else

sent_non_str_CDU(num_iter)=sent_non_str_CDU(num_iter)+1;
            end
        end

    end
    sum_stroke(num_iter)=sum(all_patients(:,1));
    sum_non_stroke(num_iter)=size(all_patients,1)-
sum(all_patients(:,1));
end


% In order to calculate 80/90 KPI from the diverted patients, 91 *
(percent
% correctly sent to Stroke Wards) + 45% (percent incorrectly sent to
Other Wards)


factor_corr_sent=0.91;
factor_wron_sent=0.45;
percent_pts_passing_KPI=(factor_corr_sent*(sum(sent_SW)/max_iter)/(s
um(sent_SW)/max_iter+sum(sent_CDU)/max_iter))+(factor_wron_sent*sum(
sent_CDU)/max_iter/(sum(sent_SW)/max_iter+sum(sent_CDU)/max_iter));
percent_pts_correctly_diverted=(sum(sent_SW)/max_iter)/(sum(sent_SW)
/max_iter+sum(sent_CDU)/max_iter);

aveg_sent_sw=(sum(sent_SW)/max_iter) +
(sum(sent_non_str_SW)/max_iter);
aveg_missing_str_pts=sum(sent_CDU)/max_iter;
```

Role Variations Identification Matlab Code:

```
function candi=freqofpatterns(base_pattern,tol_len)
fid = fopen('patterns.txt', 'a+');
fseek(fid, 0, 'eof');
all_event=['A' 'B' 'C' 'D' 'E' 'F' 'G' 'H' 'I' 'J' 'K'];
track_database=['BDEIAECIJDDBIFKJABHFHAEADFBFHABGDBGACBGHJCFHEBHADHB
FGJKAHKEDBADCFEBHFHAHIDBIFGKHACDABCIKBFCAKHJHACDBCFHADBDAFHADKBIFJHA
DBFEFJBJIEHAKAIDFBAFHADEBKFGHECDBHAJEDADBDHDAFHAFDBJCFHAGDBGFJFCDHJA
DBKBHFKBAHBFAECKDCFGBIBHKFHAGDCBFHBADFCBBICFHIJAHDBCDFHAFDABEFEAHEAE
CHIKDBHFGHADCHFDHBIFDHEFKCHADBFHADBHJFEHIKADBKFHADBFDAHCAIDEBDEBFGIC
AHABDBDFHABDFBFIHAHCDIBFDHFEABGDEBJFDEHACGDBFHADCEJDKBECFEHIADIDBFHA
DBFHDJADBFEHIIADABCBBFHJADBFDHJAHAGDBJCFHADBFHAAGDBDAFEHAKDBFHECBCAJ
DBAFIEDBHADEBJKFJEHEBAKEGDBFHADBFGHADBADEFIEIHCJIADEBFHADBFKHFADIBAF
CDGFHAFDGDJIBEFHADFBCFHCDADBCBFDHADBFDHDADBJFCHKAIHAIFBDBIFHEAKDIBFH
JEADCHFKBFCGAHADIKBJFKHIABCDABFHIACDIKBJCFKBHAHDBFHBGADBFHAKBDBCAFKH
ACDEBAFCDHAIFHBDBGFHIAKAJDBFHKADEDBCFHGADBJCJCFFHKFJAJDBFHCAFBDJFBFC
HFHAKDIBFHIDEJHKDIADBFBCIBKAFHJFADJBFDEHAFDBFHAGADIJBFHBADBFHAFDBEFG
HEADBFHADJIFBFJIEHBIHBADEJJFBFJHAHIJIDFHDBJBFJHJAEBHDBFEHADBGHEFHIAE
DBCFHADBIHFHADHAHEDGABCFKCHIAIADBFHAIDBFHADFBHFHADBEAFJDEHCADCBIFHEC
EADBIBFHADBHAEF'];
i=1;
index=0;
k=1;
cnd=1;
size_base_pattern=size(base_pattern);
size_database=size(track_database);
num_candi=0;
can_no=1;
while i<size_database(2)
    if track_database(i)==base_pattern(k)
        k=k+1;
        if k==2
            search_pointer=i;
        end
    else
        index=index+1;
    end
    if index>tol_len
        index=0;
        if k>1
            i=search_pointer+1;
        end
        k=1;
        cnd=1;
        clear candidate;
    else
        candidate(cnd)=track_database(i);
        cnd=cnd+1;
    end
    if k==(size_base_pattern(2)+1)
        candi(can_no).pattern=strtrim(candidate);
        can_no=can_no+1;
        clear candidate;
        cnd=1;
        k=1;
    end
    i=i+1;
end
```

```
i=1;
Sizecandi=size(candi);
while i<=Sizecandi(2)-1
    for j=i+1:Sizecandi(2)
        result=strcmp(candi(i).pattern,candi(j).pattern);
        if result==1
            candi(j).pattern=['delete'];
        end
    end
    i=i+1;
end
j=1;
for i=1:Sizecandi(2)
    if ~strcmp(candi(i).pattern,'delete')
        candi1(j).pattern=candi(i).pattern;
        j=j+1;
    end
end
clear candi;
candi=candi1;
clear candi1;

Sizecandi=size(candi);

for i=1:Sizecandi(2)
    SizePattern=size(candi(i).pattern);
    fragments =
restrict(track_database,candi(i).pattern,SizePattern(2)); %% Pattern
Matching
    SizeF=size(fragments);
    matching=SizeF(1)-1; %% Computing frequency of patterns having
TOL A&B
    count = fprintf(fid,'%12s %12f\n',candi(i).pattern,matching); %%
Appending the variation patterns (having TOL B) and their
frequencies in Patterns.txt file
end

fclose(fid);



%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%
% % Program for obtaining most frequently occuring patterns and
writes them
% % to Patterns.txt file in the C:\Documents and
Settings\shukla_n.WMGDS\My
% % Documents\MATLAB\Variations Modelling Directory.
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%
fid = fopen('patterns.txt', 'w+');
fseek(fid, -1, 'bof');
clear('patterns.txt') %% Cleared off the previous contents
fclose(fid);
base_pattern=['A' 'D' 'B' 'F' 'H']; %% Base pattern for a role is
inputted here
size_base_pattern=size(base_pattern);
tol_base_events=1; %% Tolerance of the Base Events which can be
absent from the variation pattern TOLERANCE A
```

```
tol_len=2;         %% Tolerance of the Events that could be present
in-between two consecutive base events TOLERANCE B

com_pattern=nchoosek(base_pattern,size_base_pattern(2)-
tol_base_events); %% Storing different combinations (considering
TOLERANCE A) of base patterns in com_pattern
size_com_pattern=size(com_pattern);
for i=1:size_com_pattern(1)
    candis(i).candi=freqofpatterns(com_pattern(i,:),tol_len); %%
Evaluating the frequency of variations patterns (considering
TOLERANCE B) for each patterns in com_pattern
end
% % Goto freqofpatterns function
```

APPENDIX II

Interview Questions for RAD Modelling

In order to develop role activity diagram from the qualitative data that we get from interviews we need to focus on some specific questions. The questions that we should ask to the staff during the interviews and a short description of each question are given below.

Questions

1. **What is the role's involvement to the care process under study?**

This question is related to learn about the role's actions and interactions during the process. Also person should tell us about the responsibilities that he/she have during the process.

2. **What does role do most frequently/most standard during the care process under study?**

This question is related to learn what exactly role does during the stroke care process. To learn what are the actions that role does and what are the interactions that role involved during the stroke care process. This is to learn about most standard process followed for stroke patient by role.

3. **What is the exact starting point of the role's involvement to the care process?**

The aim of this question is to find out when role will start to involve within the process. This information will help us finding out the boundaries between roles and understanding role's drivers to take action.

4. **What is the end point of role's involvement to the care process?**

By asking this question we are trying to learn about when the role passes his /her work to other role and when his/her responsibility ends. Moreover with the information that we get from this question and from the previous question we will learn what the exact boundaries of the role are.

5. **What are the activities, interactions and decisions that role does during the care process?**

We have understood the person's exact role from the previous questions, with this question we will understand what are the actions and interactions that are performed by this role. While learning about interactions we should also ask to the person about other roles that are involved to the interaction. In addition to these, we should learn about the decisions that the role take during the stroke care process. These decisions might be a simple decisions or a serious decisions such as deciding, whether the patient have a stroke or not?

6. **What is the sequence of the task that the role performs?**

This question will help us to learn the order of the actions that the role does during his/her process. We can learn the sequence of the work that the role performs from the previous questions but it is really useful to ask to him/her about the sequence because it will help us to see if we miss a point or not also it will help us putting the actions and interactions in order.

7. **What are the resources that are used by the role during the care process?**

The aim of this question is to learn about what are the tools and the equipments that the role use during his/her role. These resources might be a needle, stethoscope, computer etc.

8. **What are the issues that the role faces during the care process?**

We are trying to learn about what are the problems that the role might have while performing his/her role. These issues can be separated into three dimensions:

- *Problems, challenges* such as; computer problem, lack of any tool, less chairs etc.
- *Constraints* such as; time that the role have to perform his/her action
- *Bottlenecks* such as; waiting for end of a simultaneous action to finish his/her role

After having this information from the role we should also ask for his/her suggestions about how to solve these issues.

9. **What are the simultaneous activities that role involves during the care process?**

The aim of this question is to learn is there any actions that should be done simultaneously by the role and to learn what these actions are. This will also provide us information about role’s work load.

10. Are there any KPIs that the role must follow? If there is what are these KPIs?

This information will help us to find out what the main drivers of the role are and what might build pressure on role’s actions. Also we can understand whether role knows his/her performance measures clearly or not.