An Optimisation-based Framework for Complex Business Process: Healthcare Application

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An Optimisation-Based Framework for Complex Business Process: Healthcare Application

By

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ABSTRACT

The Irish healthcare system is currently facing major pressures due to rising demand, caused by population growth, ageing and high expectations of service quality. This pressure on the Irish healthcare system creates a need for support from research institutions in dealing with decision areas such as resource allocation and performance measurement. While approaches such as modelling, simulation, multi-criteria decision analysis, performance management, and optimisation can – when applied skilfully – improve healthcare performance, they represent just one part of the solution. Accordingly, to achieve significant and sustainable performance, this research aims to develop a practical, yet effective, optimisation-based framework for managing complex processes in the healthcare domain. Through an extensive review of the literature on the aforementioned solution techniques, limitations of using each technique on its own are identified in order to define a practical integrated approach toward developing the proposed framework. During the framework validation phase, real-time strategies have to be optimised to solve Emergency Department performance issues in a major hospital. Results show a potential of significant reduction in patients average length of stay (i.e. 48% of average patient throughput time) whilst reducing the over-reliance on overstretched nursing resources, that resulted in an increase of staff utilisation between 7% and 10%. Given the high uncertainty in healthcare service demand, using the integrated framework allows decision makers to find optimal staff schedules that improve emergency department performance. The proposed optimum staff schedule reduces the average waiting time of patients by 57% and also contributes to reduce number of patients left without treatment to 8% instead of 17%. The developed framework has been implemented by the hospital partner with a high level of success.

DECLARATION

I certify that this Thesis, which I now submit for examination for the award of the degree of Doctor of Philosophy, is entirely my own work and has not been taken from the work of others, save and to the extent that such work has been cited and acknowledged within the text of my work.

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Dublin, Ireland

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ABBREVIATIONS LIST

AWT	Average Waiting Time
ACU	Ambulatory Care Area
AHP	Analytic Hierarchy Process
AIS	Artificial Immune System
ALOS	Average Length Of Stay
ANN	Artificial Neural Network
ANP	Advanced Nurse Practitioner
BPM	Business Process Management
BPR	Business Process Reengineering
BSC	Balanced Scorecard
CARP	Capacitated Arc Routing Problem
CPR	Cardiopulmonary Resuscitation
CSA	Clonal Selection Algorithm
DEMATEL	Decision-Making Trial And Evaluation Laboratory
DES	Discrete-Event Simulation
DFD	Data Flow Diagram
DOE	Design Of Experiments
ED	Emergency Department
EHCI	Euro Health Consumer Index
GA	Genetic Algorithm
GB	Gradient-Based Methods
HMOEA	Hybrid Multi-Objective Evolutionary Algorithm
HSE	Health Service Executive
ICOM	Input, Control, Output And Mechanism
IDEF	Integrated Definition For Function Modelling
IPA	Infinitesimal Perturbation Analysis
KPI	Key Performance Indicators
LRE	Likelihood Ratio Estimator
MCDA	Multi-Criteria Decision Analysis
MCP	Multiple Comparison Procedure
MH	Meta-Heuristics Based Methods

MM	Meta-Model Based Methods
MTS	Manchester Triage System
NHS	National Health Service
NSGA	Non-Dominated Sorting Genetic Algorithm
OO	Ordinal Optimisation
OSTD	Object State Transition Description
OTM	Optimisation Technique Map
PA	Perturbation Analysis
PET	Patient Experience Time
PFD	Process Flow Description
POF	Pareto Optimal Front
PRIME	Preference Ratios In Multi-Attribute Evaluation
R&S	Ranking-And-Selection
RAD	Role Activity Diagram
SB	Statistical-Based Methods
RSM	Response Surface Methodology
SA	Simulated Annealing
SADT	Structured Analysis And Design Technique
SC	Supply Chain
SCM	Supply Chain Management
SHO	Senior House Officer
SMART	Simple Multi-Attribute Rating Technique
SSM	Sequential Selection With Memory
TQM	Total Quality Management
TS	Tabu Search
VRP	Vehicle Routing Problem

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1: INTRODUCTION

1.1 INTRODUCTION

The global economic crisis is continuing to affect the Irish healthcare sector in the form of cuts in finance and reduction in resources. The latest Euro Health Consumer Index (EHCI, 2009) has spotted the slump of the healthcare system in Ireland by ranking it 23rd out of 33 surveyed countries in Europe (Figure 1-1).

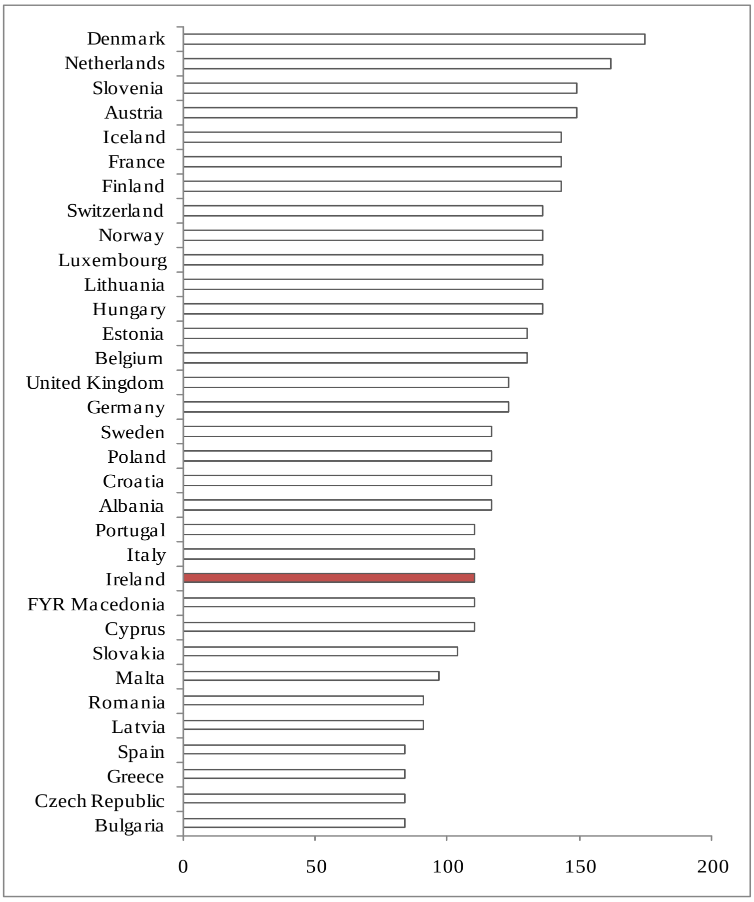


Figure 1-1: Euro Health Consumer Index (EHCI, 2009).

Long waiting lists, overcrowding, and patients dissatisfaction are the main symptoms of the healthcare system in Ireland with over 46,400 adults and children waiting for hospital treatment, according to the latest figures from the Health Service Executive (HSE) in Ireland (HSE, 2010). Many elements are supposed to work in harmony to achieve one goal “better health service”; however, these four elements (Figure 1-2) need to work harder together. Increasing the pressure on the Irish healthcare system leads to calls for involvement of research institutions in many areas. Politicians as well as decision makers are aware that changes are inevitable, due to the pressures which their healthcare system is facing and the need to utilise better decision tools has risen in importance.

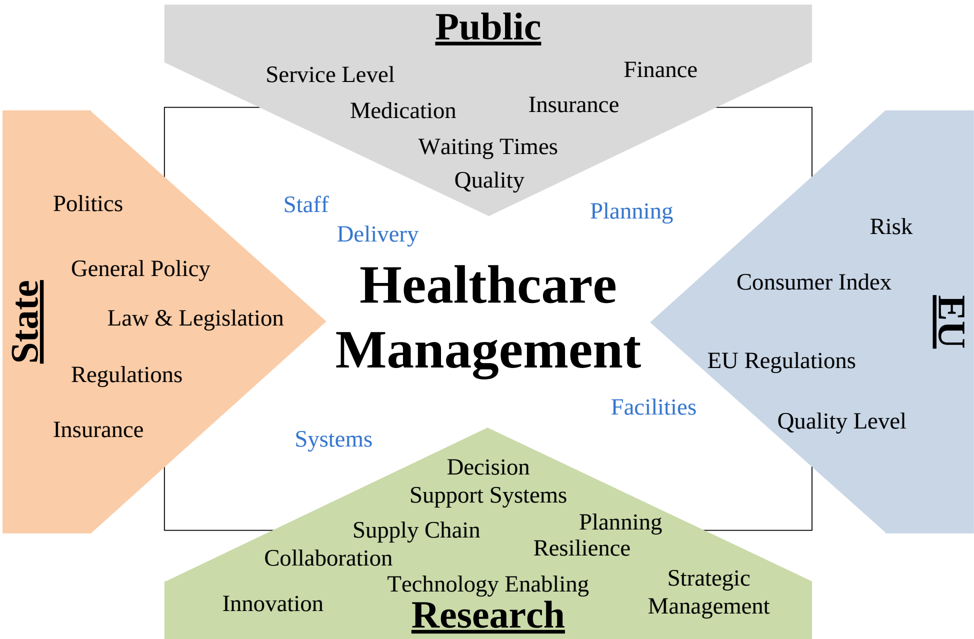


Figure 1-2 Irish healthcare system elements.

Therefore, the HSE is currently under constant pressure to control rapidly escalating expenses, while fulfilling the growing demand for high class patient service level and satisfactory medical treatment. Resolving such challenges requires understanding the complexity of the healthcare system at different levels. Accordingly, service providers and healthcare managers have to recognise the types of sub-systems that constitute the whole healthcare system, the operations within each sub-system, the main bottlenecks and their causes, which actions are efficient and which are not, and the impact of changes and actions on the overall system performance.

However, arriving at a consistent degree of system understanding is an overwhelming task due to the large number and diversity of the organisations and the high level of uncertainty and interdependencies. As a result, service providers and healthcare managers are continuously studying the efficiency of existing healthcare systems and exploring improvement opportunities. The evaluation of such proposed interventions is crucial prior to their actual implementation. Moreover, healthcare managers are challenged by intrinsic uncertainty of the demands and outcomes of healthcare systems; high level of human involvement at both patients level and resource level (doctor, nurses, etc.); limited budget and resources; and large number of variables (e.g., staff scheduling, number of beds, etc).

Patients, on the other hand, in addition to requiring a high level of service quality, are understandably no longer prepared to wait in queues for essential health services. Accordingly, the healthcare service concept has shifted from optimising resource utilisation to finding a balance between service for patients and efficiency for providers (Brailsford and Vissers, 2011). Dealing with these inevitable complexities within healthcare processes and services and addressing the challenges in the decision making process is the focus of this research.

Traditionally, critical decisions are made based on the vast arrays of data contained in clinical and administrative records. This approach cannot succeed to represent the dynamic interaction between the interconnected components of the healthcare system. Consequently, this approach has limited use when it comes to predict the outcomes of changes or proposed actions to the system. Analytical tools are needed to support managers decisions at different levels within the healthcare system. If analytical models are impractical in the healthcare settings it is usually due to the imposed simplifications on the model. Accordingly, important details and features of the underlined systems cannot be captured. Recently, the techniques of Business Process Modelling, Operations Research, Performance Management and Computer Science have been introduced to the management of healthcare provision in different countries such as the UK, USA, and Canada (Henderson, 1995, Murdick *et al.*, 1990, Zairi, 1997, Aktas *et al*., 2007, and Dickenson, 2010). However, there is no public reporting of similar activity within the Irish healthcare services. Typically the effectiveness of such research depends on the specific nature of the problems in the system; it can be reasonably expected that an analysis of healthcare provision in the Irish context would reap benefits in gaining deeper understanding of the problems, and is a step forward for filling the gaps and developing an integrated healthcare management framework towards putting Ireland among the leading countries in providing excellence in healthcare service quality.

1.2 PROBLEM DEFINITION

Health systems are complex. Although a significant fraction of many governments' budgets are allocated to health, results have hardly matched expectations as many health system performance indicators have shown limited improvement. To understand the different levels of complexity of healthcare business processes, first a brief definition of complex business process is given, which in turn is divided into the definition of both complexity and business process.

1.2.1 Complexities of Business Process

Complexity is "a word-problem and not a word-solution" (Alhadeff Jones, 2008, p. 1); at least this is how it used to be considered in many academic and non-academic circles. Wildly varying opinions relating to the actual meaning of the word *complex,* have led to considerable confusion. The term *complex* has been improperly associated with notions such as size, difficulty and order (Edmonds, 1999). Even the difference between what is complex and what is complicated has not always been taken into account. What is important though is that complexity is a pervasive feature of the real-world. The word complex comes from Latin expression *complexus* meaning “embracing or comprehending several elements” that are “plated together, interwoven” (Alhadeff Jones, 2008, p. 2). The terms “complex” and “complexity” were involved in expressions looking to indicate the opposite of simplicity. This is where the confusion between “complex” and “complicated” becomes clearer.

Complicated systems consist of a large number of elements, but these are all “knowable, definable and capable of being catalogued as are all of the relationships" among them; in addition, “cause and effect can be separated" effectively (Snowden, 2003). Examples include are many engineered systems such as aircrafts and vehicles which are predictable and usable because of these properties. On the other hand, complex systems are those where the “whole is more than the sum of its parts", as expressed by Aristotle in the fourth century BC. Complex systems consist of many entities that interact in non-linear ways resulting in complex behaviours at the global level, cause and effects are entangled and thus cannot be separated (Juarrero, 2000). So overall, the system cannot be reduced to just the set of its parts.

To understand the complexity levels within real-world systems, it is essential to describe how their entities are structured. According to Simon (1973), complex systems are composed of large number of interrelated sub-systems, each of the latter (i.e. sub-systems) being structured hierarchically until the lowest level of elementary sub-system is reached. Higher levels in the hierarchy display larger and slower entities, while lower level entities are smaller and faster (Wu, 1999). The interactions between these levels of the system can be classified into: interactions within sub-systems, among sub-systems, and between the system and its environment (Manson, 2001), where the inter-relationships are described by higher order, nonlinear processes rather than just feedback (Costanza *et al*., 1993). Given the properties of sub-systems and their interactions, it is not a trivial matter to infer the behaviour of the whole system (Simon, 1982). Moreover, the behaviour of complex systems is also dependent on the way they interact and integrate within their environment (Polack *et al*., 2010). This is due to the difficulties encountered in the distinction between the system and its environment which make them open systems and far-from-equilibrium (Cilliers, 1998).

Business process is an important variable in understanding the nature and interrelation among activities within complex organisations (Modarres, 2006). It would, however, seem that providing a suitable definition is more difficult than might appear to be the case (Melao and Pidd, 2000). Most of the literature simply quotes (or adapts) the vague definitions put forward by the re-engineering pioneers. Hammer and Champy (1993, p. 35) define a business process as:

> *"a collection of activities that takes one or more kinds of input and creates an output that is of value to the customer. A business process has a goal and is affected by events occurring in the external world or in other processes"*

Hence, in this definition, the product is the focus of the business process. According to Davenport (1993), processes can also be defined as structured set of activities (e.g., cross functionally, or hierarchically within a particular function) designed to produce a specified output for both internal and external customers. That definition implies an *action-focus* with a strong emphasis on how work is performed rather than describing products or services that are a result of a process (Eriksson and Penker, 2000). On the other hand, a *customer-focused* definition is described in Jacobson *et al*. (1994) by concentrating on processes that provide value to customers which require a close collaboration between individuals or groups to achieve individual customer's needs. Their description concentrates on the interface between the internal business process and the customer, which gives an external view of the business process and how it is used by the external actors (Lindsay *et al*., 2003). Complex systems (e.g., manufacturing systems) support and maintain greater numbers of inter-connected and hierarchical processes, where sub-processes are subordinated by a functional relation to their higher-level business process in the hierarchy (Modarres, 2006). Intrinsically, the output of a process tends to be used as an input for adjacent cross-functional processes. As such, variations and changes which result from the interaction between sub-systems (e.g., people, tasks, structure, technology, etc.) will be manifested at the macro (i.e., higher-level) level processes. Hence, the decomposability of higher level vertical processes tends to lead to greater levels of process complexity.

In addition, the complexity of business processes tends to increase as a result of causal connections within hierarchical processes and variability within sub-processes at different level in the system. Moreover, open system, real-world business processes have not only internal relationships, but also external relationships with their environment in order to adapt and survive (Earl and Khan, 1994). Such dynamism is an inevitable feature of business processes that increase complexity levels. Additionally, the flows of resources and products (or services) of business resources are regulated by policies and decisions, which represent explicit statements of actions to be taken in order to achieve a desired result (Pidd, 1996). These interactions between policies and internal structure add another dimension to the complexity of business processes by viewing a process as a set or network of interacting feedback loops (Scherr, 1993; Melao and Pidd, 2000). The process view emphasises the entire process in order to understand how a specific process fits within the larger process and ultimately within the whole system (Harmon, 2007). However, the complexity of hierarchical processes within complex systems tends to reduce the possibility of identifying the risks attached to drastic changes or even opportunities for process improvement. That is, the impact of change on other cross-functional processes, and the likelihood that a particular risk event will occur (Roberts 1994). Nevertheless, organisations need to focus on their core processes rather than individual departments. This is because they represent the flows and relationships that actually add value and produce products or services for customers (e.g., value chain in manufacturing or care chain in healthcare services).

1.2.2 Supply Chain and Healthcare services

The view of an organisation as a chain of interlinked operations or processes emerges from the field of supply chain management (SCM). This is a discipline rooted in business sectors where a set of business tiers are involved in the supply (i.e., upstream) and distribution (i.e., downstream) of products or services between a source and a customer (Mentzer *et al*., 2001) (see Figure 1-3). Similarly, the concept of a supply chain (SC) has been introduced in manufacturing when individual organisations further down the chain tried to reduce the risks of running out of supplies of materials or parts delivered by organisations further up the chain. A number of definitions are used for the ‘supply chain’, however they all share following: supply chain covers all activities from raw materials to distributed products or services; an organisation can be part of more than one supply chain; and every activity of the supply chain should add value to the product for the end customer (Al-Mudimigh *et al.*, 2004).

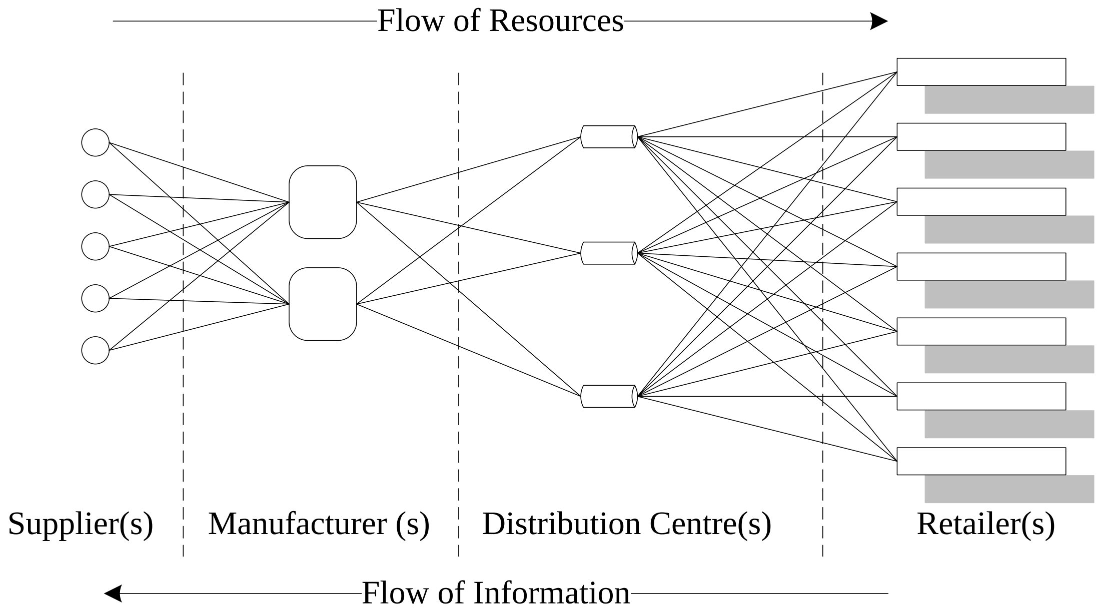


Figure 1-3 Typical supply chain business tiers.

Managing the resulting supply chain networks effectively is challenged by high levels of uncertainty in supply and demand, conflicting objectives, vagueness of information, numerous decision variables and constraints. Christopher (1992, p. 18) provides the following definition of SCM 'The management of upstream and downstream relationships with suppliers and customers to deliver superior customer value'. Therefore, in order to survive, supply chain has to deliver the most value for their customers at the lowest cost (Schary and Skjøtt-Larsen, 2002).

Analogously, the process of service delivery in healthcare can be viewed as the chain of complex processes that require the coordination at different levels in the care chain to provide the necessary care for patients (Figure 1- 4). Healthcare systems (e.g., hospitals) consist of many complex business processes of different types ranging from administrative tasks and protocols, to services provided to patients by doctors and nurses such as assessment and treatment (Andrew, 2001). Healthcare systems are mainly composed of patients and healthcare professionals, in addition to health technology and resources. Every patient who encounters the healthcare system goes through a process (Bevan and Lendon, 2006).

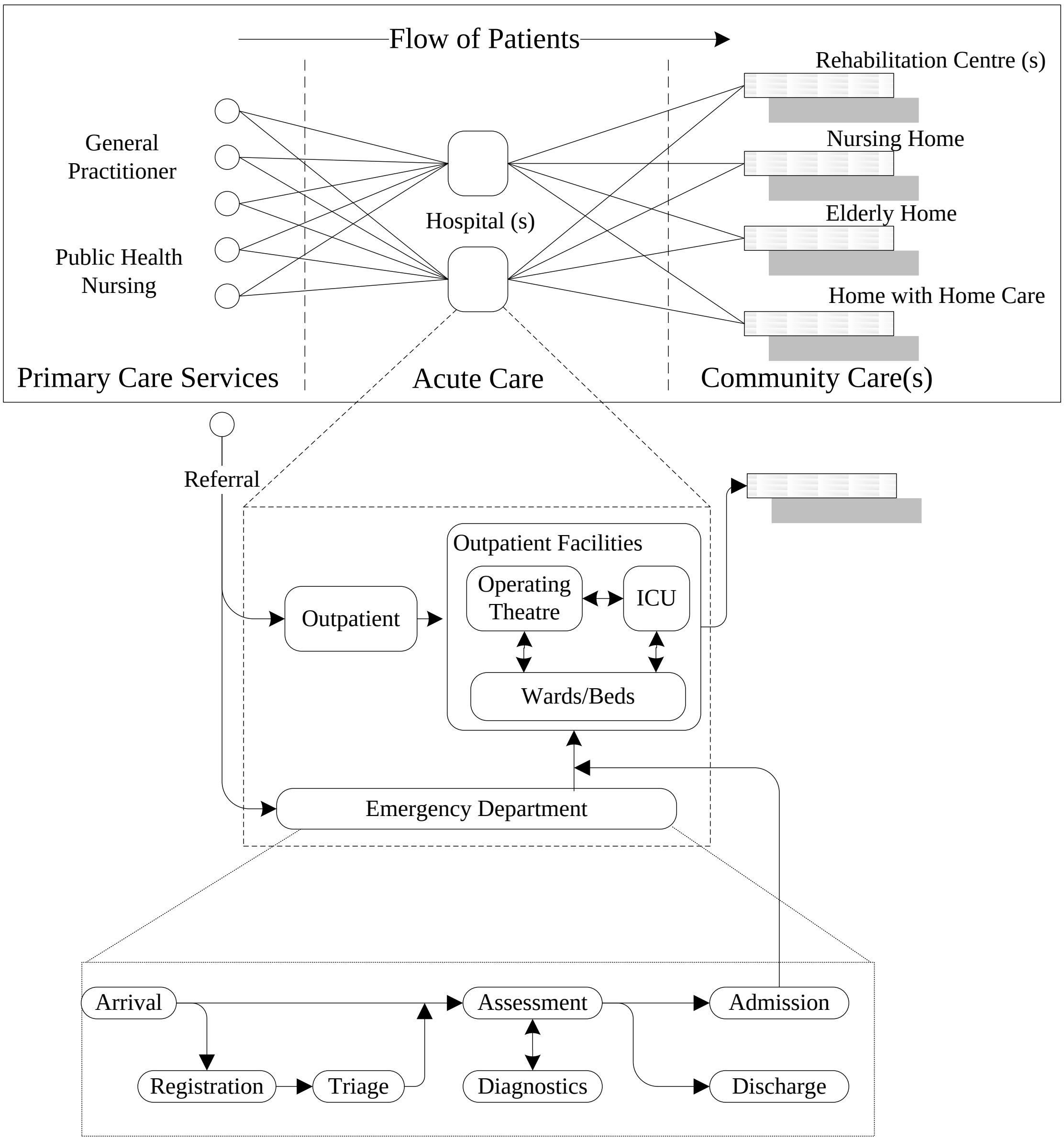


Figure 1- 4 Health care chain.

In general, the healthcare process starts when the patient enters the healthcare system. The patient’s symptoms or complaints can be considered the process input, like raw material in a manufacturing process. A combination of administrative and clinical processes is then triggered by these inputs. Therefore, the healthcare process can be viewed as the interaction of people, equipment, policies, and processes (Bente, 2005).

The medical treatment processes of patients can be seen as a diagnostic–therapeutic cycle (Mans *et al*., 2010). This cycle consists of patient observation, monitoring, medical reasoning and decision making that requires various actions such as determining necessary diagnostic tests and/or therapeutic treatments. The outcomes of these processes are significantly influenced by many factors such as the patient's general health status (co-morbidities), the skill level of staff (e.g., physicians, nurses, technicians, registration clerks, and so forth), and the availability and reliability of proper medical equipments (e.g., labs, X-Rays).

Depending on the patient's medical condition, the output of healthcare process can be an admission order, a medication, or an order for inhalation therapy, which becomes an input for other adjacent cross-functional processes. That is the point at which the responsibility of patient is passed within the healthcare system (i.e. handoff). Healthcare processes may involve hundreds of handoffs that are performed without considering their contribution to the wider care process (Bevan and Lendon, 2006). This type of inter-connection between healthcare processes requires coordination among different people, units, and departments at different levels within the healthcare system (Panzarasa and Stefanelli, 2006). Such interdepartmental collaboration among multiple professions and healthcare units triggers many different types of business processes within healthcare systems including resource planning and allocation, staff scheduling, discharge planning, and bed management. This multifaceted interaction is the origin of the dynamic nature of healthcare processes.

As processes are initiated, changes in technology, healthcare treatments, drugs, and protocols may affect current processes, requiring reparative actions (Anyanwu *et al*., 2003). For example, the discovery of new drugs results in a continuous change in patient care pathways. Consequently, healthcare processes are more likely to be highly complex and dynamic, involving many interconnected elements with mutual influence on each other (Figure 1-5).

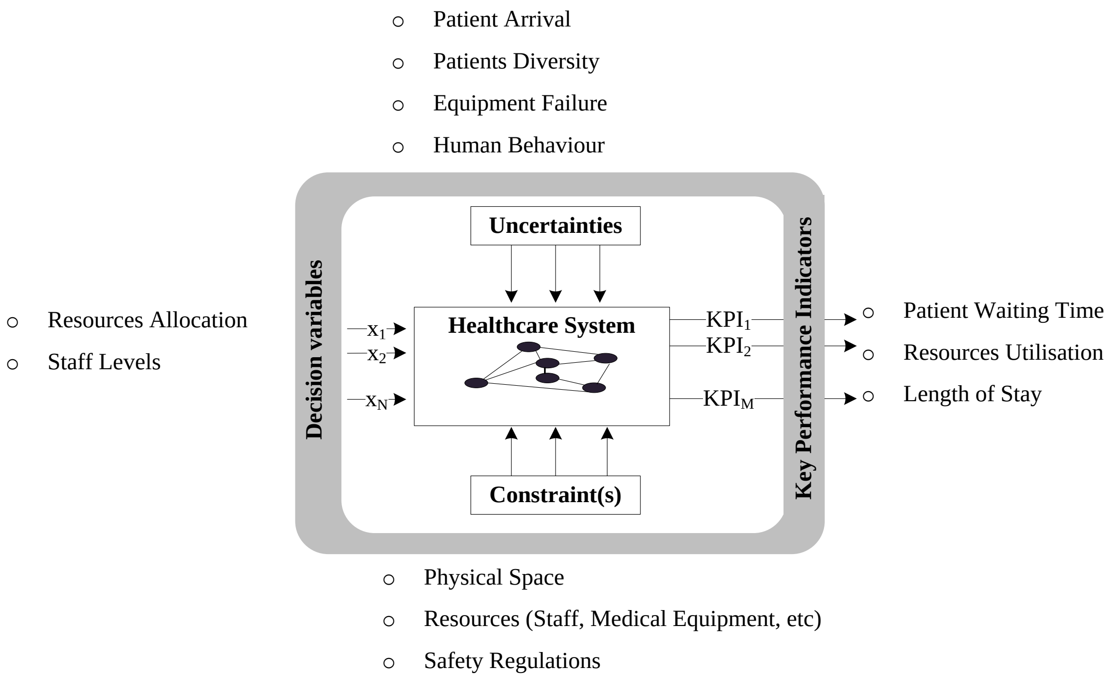


Figure 1-5 Healthcare process complexity.

Such dynamic interactions result in a circular chain of cause and effect relationships between processes that cannot be adequately captured by linear representation. This means that the response of an element in the system to an input can be completely different from what may be intended or predicted because the response will depend on the system's current condition. This indicates that the effects of the same managerial action can be different as they are contingent upon the state of the system when the action is taken. The presence of non-linear relationships makes it difficult to accurately predict the behaviour of health systems and complicates the management decision-making process. Furthermore, healthcare processes involve strong human interactions as they are made and enacted by people with different values, experiences, and expectations. Examples of these human behaviour issues are clinicians motivation, productivity, fatigue, quality of practice, patient anxiety, response to incentives, and the responses of hospital managers to different pressures (Lebcir, 2006). The effects of these aspects of human behaviour are not easily quantifiable which implies that healthcare business processes not only exist in the objective and concrete sense but also they are abstractions, meanings and judgements shaped by subjective construction (Melao and Pidd, 2000). Due to a high labour contribution, the delivery of healthcare services is highly variable and potentially inconsistent. Additionally, existing processes in healthcare have mostly evolved and been adapted to particular circumstances; they are produced and consumed at the same time; and they are not manufactured according to precise standards or can be stored (Vincent, 2010). Despite this resemblance between the healthcare processes and supply chain, the healthcare still lags far behind other sectors such as manufacturing and industry, which widely applied a diversity of sophisticated management tools, such as modelling and simulation, optimisation, and performance management, to improve the quality and efficiency of their business processes.

1.3 RESEARCH MOTIVE

The Irish healthcare delivery system is undergoing rapid change at the present time (DoH, 2007). The goal of these changes is to provide a more efficient, more reliable, more thorough delivery of healthcare services in a manner which meets the needs of the population. However, the healthcare system in Ireland cannot meet the current demands placed on it. For example, emergency departments (EDs) overcrowding has been declared as a "National Emergency" in Ireland since 2006. Several national reports have highlighted a growing demand for emergency care (1.2 million patients attending EDs annually) and a simultaneous decrease in the number of operating EDs. The result has increased crowding, high percentages of patients leaving EDs without being seen and higher morbidity and mortality rates. Additionally, prolonged waiting times have been reported with more than 500 patients on trolleys for hospital admission every day; 18 % of patients are waiting more than 24 hours and 40% between 10-24 hours (HSE Performance Monitoring Report, 2010).

Although Ireland is not alone in experiencing these figures (Schafermeyer and Asplin, 2003, Rowe *et al*., 2006, Forero *et al*., 2010), it is important not to underestimate the sometimes catastrophic consequences this situation has on patients, staff and the healthcare sector. Overcrowding in EDs has become a significant international crisis that negatively affects patient safety, quality of care, and patient satisfaction (Graff, 1999). Therefore, analysing the patient flow in emergency departments to minimise length of stay, improve efficiency, and reduce overcrowding has become a crucial requirement.

Similar problems exist in other parts of the Irish healthcare system. For example, according to Department of Health in 2004, waiting times in many surgical areas are increasing despite the high level of expenditure on reducing waiting lists with over 27,000 people waiting for hospital treatment in the country, from which 16,000 waiting for inpatient care and with the rest waiting for day case treatment. While the popular response is that these problems will be solved by increasing resources, the inefficiency of this approach leads to significant investment and expenses in the system without any guarantee of a complete solution to the problem. The problem must be considered in its full complexity before a solution can be found. Suggestions have been offered with regard to changes in work practice for consultants, hospital doctors, nurses, administrators and other professionals (e.g. radiology) to ease the impact of fluctuating demand on the system. The reluctance to commit to such wholesale changes comes, in part, from not being able to predict the effectiveness of such changes or to understand in full the impact of the change on the working patterns of those involved. There is a need to be able to evaluate changes in delivery practice on the system performance without disrupting the existing provision of services. The danger of such disruption comes from two sources; the changes themselves might make the problem worse and, industrial relations issues are most likely to arise when change is introduced. It is therefore important that change is only introduced where there is clear benefit, which requires that there be some means of demonstrating that the change will be effective and exactly what those effects might be.

Therefore, this study aims to utilise a multi-disciplinary approach to develop an integrated decision support framework that healthcare managers and planners can use in a practical and reflective way. It is envisaged that the research can be expanded to form the basis of a predictive planning and management tool for building new healthcare facilities. For example, evidence based data on the effect of relationships, particularly between physical layout and distribution of services and facilities within a building and staffing requirements can be used to derive optimum layouts and inter-relationships between departments. Variables such as staff levels and costs can be used to define the size of clinical areas that can be supported or alternatively constraints on capital expenditure will determine the size, staffing levels and associated running costs on a department by department basis.

1.4 RESEARCH QUESTION AND OBJECTIVES

This research purposes is to investigate aspects and requirements for developing an integrated decision support framework for managing complex business processes in healthcare facilities. The question that might be raised here is whether there is something so unique and special about healthcare in general and managing healthcare processes in particular, that it requires special attention and dedicated research. Therefore, the aim of the research is to increase the understanding of what is required in order to gain acceptance of decision support tools in the management of healthcare business process. In order to gain acceptance and credibility in healthcare community, the integration between different modeling and decision making tools has shown to be beyond any doubt, that it works both as a tool for learning and decision making in real-world cases. Consequently, the main question in this research is:

"Can an integrated decision support framework be developed for managing complex dynamic business processes in healthcare facilities?"

This main question can be further divided into four major research questions:

RQ1: How applicable are existing solution techniques in handling the dynamics and complexity within healthcare facilities and how efficient are they in supporting their business processes?

RQ2: What are the similarities and differences between complex business processes in the healthcare setting and in the supply chain context?

RQ3: What are the aspects and requirements involved in the design and development of an integrated management framework for complex business processes?

RQ4: How useful is the developed framework for healthcare facilities and to what extent it can be applied?

In order to address these questions and in turn achieve the aim of the research, the main objective has been outlined:

"To develop an integrated optimisation-based decision support framework that is applicable in managing healthcare business process "

Based on this central objective, the specific objectives have been specified and summarised in Table 1-1.

Table 1-1 Research question and corresponding objectives.

Research Questions	Research Objectives
1. How applicable are existing solution techniques in handling the dynamics and complexity within healthcare facilities and how efficient are they in supporting their business processes?.	1. To gain in-depth understanding of existing solution techniques for managing complex business process.
2. What are the similarities and differences between complex business processes in the healthcare setting and in the supply chain context?.	2a. To highlight the relationships and common features of healthcare facilities.
	2b. To explore the common challenges and problems of business processes in the healthcare setting and supply chain context.
3. What are the aspects and requirements involved in the design and development of an integrated management framework for complex business processes?.	3a. To investigate aspects and requirements for developing an integrated decision support framework for managing complex business processes in healthcare facilities.
	3b. To develop an integrated framework for supporting critical decisions.
4. How useful is the developed framework for healthcare facilities and to what extend it can be applied?	4a. To evaluate and validate the proposed framework.
	4b. To deliver cost-effective solutions for healthcare operations managers and planners.
	4c. To optimise operations and offer excellence in healthcare delivery.

1.5 THESIS LAYOUT

The layout of the thesis is illustrated in Figure 1-6.

- Chapter two and three provides a summary of the literature review for the existing solution techniques for complex business process in the context of healthcare and supply chain. This is to gain thorough insights regarding currently applicable approaches for managing complex business process in general and in healthcare in particular.
- Chapter four highlights the research philosophy and approach as the basis to conduct this research. A detailed design of the research process is then given to address the research questions with a description of the research methods and procedures followed to achieve the objectives of this study. Besides, the chapter addresses the gaps in the research those were derived from chapter two and three for the design and development of the integrated framework.
- Chapter five uses a case study of a healthcare facility (e.g., emergency department) to empirically evaluate the developed framework.
- Finally, chapter six concludes the thesis and highlights future work recommendations.

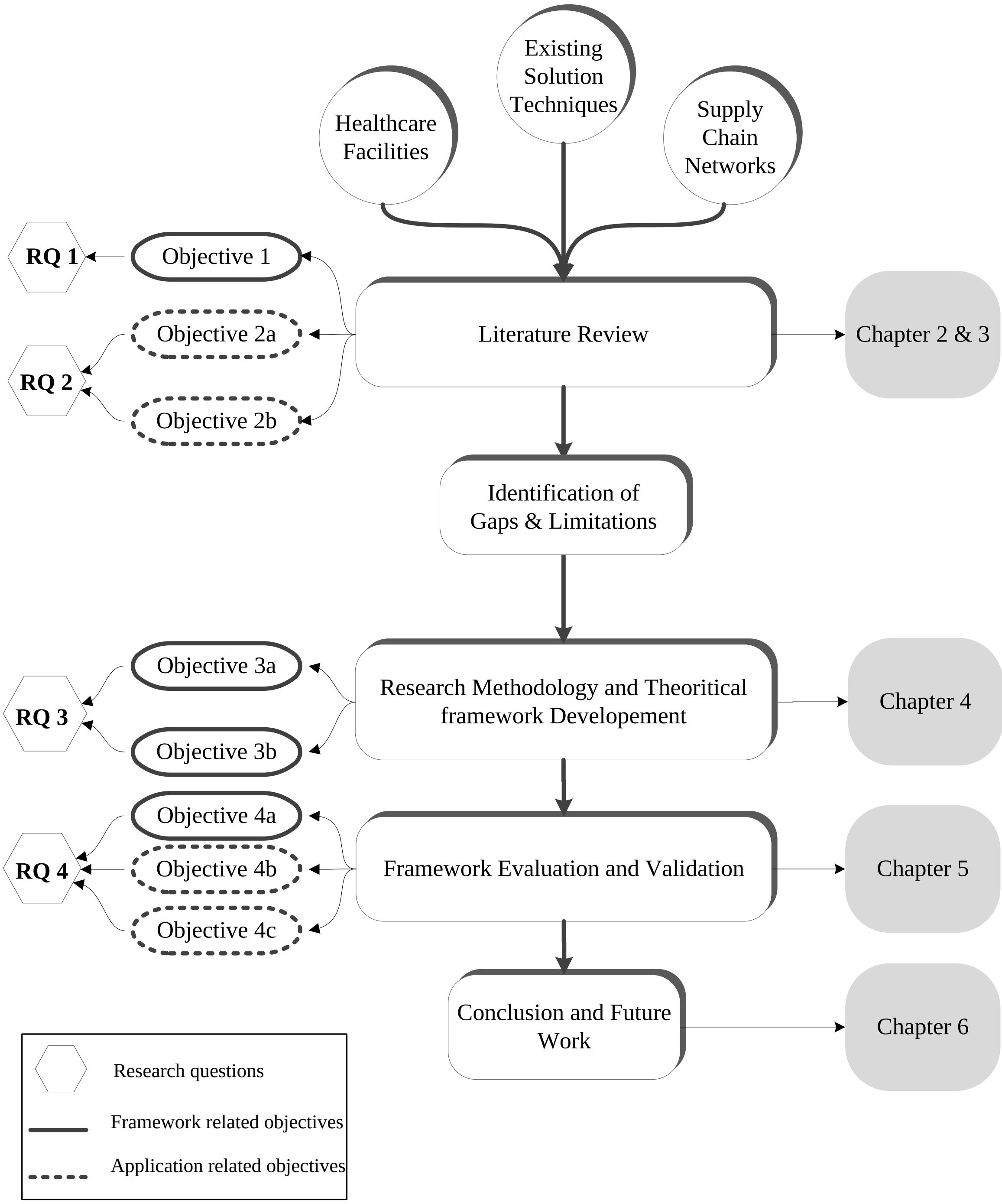


Figure 1-6 Thesis layout and research methodology.

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

From the beginning of the industrial revolution, the onus had been on improving and automating production efficiency and costs (Lindsay *et al*., 2003). At early stage of the 20^{th} century, Frederick Taylor developed his theories of scientific management (Taylor, 1919) which involved breaking the organisation processes down to a cycle of a simple sequence or chain of activities. The basis of such breaking down is that each activity is carried out in the least amount of time possible with the minimum amount of effort.

In Taylor's time, specialisation was the state-of-the-art method to improve efficiency (Davenport, 1995), however, technology did not allow large companies to design processes in a cross-functional or cross-departmental manner. As technology changed with time, the principles of scientific management have also evolved, which was a step in the introduction of business process reengineering (BPR) (Hammer, 1990). As is widely known, BPR is the fundamental rethinking and radical design of business processes to achieve dramatic improvements in critical and contemporary measures of performance, such as cost, quality, service and speed (Davenport, 1993).

In contrast to the radical approach of BPR, total quality management (TQM) philosophy is based on an incremental approach for continuously improving the quality of products and processes (Oakland, 1993). Several authors have illustrated the complementary nature of BPR and TQM (Macdonald, 1995), while others have highlighted their contradictory aspects (Mumford and Hendricks, 1996). The notion of balance between incremental and radical organisational change has been a consistent theme across several research approaches (Burgelman, 1994, Brown and Eisenhardt, 1998, Gavetti and Levinthal, 2000), which resulted in the emergence of the concept of business process management (BPM). BPM is concerned with how to manage processes on an ongoing basis, and not just with the one-off radical changes associated with BPR (Armistead and Machin, 1997).

That process view of systems increases the organisation flexibility to respond to the demands of customers and facilitates increased reliability and consistency in products and service delivery (Garvin, 1995). Therefore, assessing process performance is essential because it provides the capability to identify performance bottlenecks and taking corrective action before these problems escalate (Kueng, 2000). Over the past two decades, several performance measurement systems were introduced in order to offer a solution to the criticisms of traditional financial-based measurement models (Fitzgerald *et al.*, 1991, Kaplan and Norton, 1992, Lynch and Cross, 1995, Neely *et al.*, 2002).

Nevertheless achieving the full potential of performance measurement approaches requires managing issues regarding business process performance improvement and the provision of support to the associated decision-making processes. These issues and the related problems of on currently used performance measurement systems are discussed in Section 2.2 along with the unsuccessful attempts to support decision-makers in such complex systems. This is followed by a discussion about multi-criteria decision analysis (MCDA) tools and simulation modelling in section 2.3 and 2.4 respectively, by highlighting their strengths and how they can contribute to support performance measurement and management of complex business processes. Section 2.5 concludes the chapter.

2.2 PERFORMANCE MANAGEMENT

Performance management is seen as having a key role for supporting the strategic as well as the operational aspects in the decision making process. According to Meliones *et al.* (2001, p. 28):

> *"When dramatic changes are inevitable, developing a strategic focus and examining the business and quality of the healthcare in a measurable and repeatable manner becomes each organisation's opportunity"*

In this section, an overview of the balanced scorecard (BSC) is given as one of the powerful performance management tools (Kaplan and Norton, 1992). This is followed by a discussion about the application of BSC in the healthcare context, along with highlighting its current limitations.

2.2.1 Balanced Scorecard

The balanced scorecard (BSC), one of the main performance measurement frameworks used by organisations, was originally introduced by Kaplan and Norton (1992). The BSC is a systematic methodology that uses strategy-linked leading and lagging performance measures and actions for planning and implementing an organisation's strategy (Kaplan and Norton, 1996). Four performance perspectives are recommended by the balanced scorecard; financial, customer, internal, and innovation and learning. By using the BSC, organisations can ensure a clear link between their strategy, performance measures and the risks of strategic and operational decisions (Kaplan and Norton, 2001). As a conceptual tool, the BSC can also help staff and stakeholders better understand an organisation's key strategies and how activities are related to it. Among the main benefits of applying the BSC are; 1) an excellent way for communicating and gaining insights into strategic initiatives, key objectives, and actions among decision makers and other staff; 2) alignment of the organisation around its mission and strategies and 3) facilitating, monitoring, and assessment of strategy implementation.

2.2.2 Applications of BSC in Healthcare

The BSC was discussed as an appropriate tool for healthcare organisations as early as 1994 where Griffith (1994) places the BSC in the broader notion of championship management. He says that the BSC allows healthcare organisations to track their performance on several dimensions and to establish integrated targets and goals. Several articles have described financial success stories by using BSC in healthcare organisations, whether by solving financial crises (Jones and Filip, 2000, Meliones, 2000, Mathias, 2001) or by reducing costs (Berger, 2004, Gonzalez *et al*., 2006, Colman, 2006). Apart from financial, reasons the BSC has become a regular step in quality improvement within several healthcare organisations (Moullin, 2004). It has become a tool for developing quality plans and for evaluating quality improvement processes (Peters and Ryan, 1999, Colaneri, 1999, Santiago, 1999).

Additionally, to assist progress toward performance targets and quality improvement, Chow-Chua and Goh (2002) established a balance between critical performance measures and quality improvement work which was combined with indicators of non-financial characteristics. The BSC has been also used to measure quality of care and patient satisfaction by Hall *et al.* (2003). The BSC has also been related to the allocation of resources and as a rating and reward tool in several healthcare organisations (Pineno, 2002, Biro *et al*., 2003, Gumbus *et al*., 2003). For example, within the National Health Service (NHS) in the UK, the performance of hospitals is monitored through a BSC-based rating system (Givan, 2005, Patel *et al*., 2008).

Another area for the application of BSC within healthcare organisations is benchmarking, which can be found both internally within different organisations as well as between organisations nationally and internationally. Benchmarking by means of the BSC on a national level has also been found between hospitals in Canada in Ontario (Pink *et al*., 2001), healthcare for veterans in the US (Biro *et al*., 2003), within hospitals in Denmark (Ten Asbroek *et al*., 2004), and within the NHS in the UK (Chang *et al*., 2002).

2.2.3 Performance Perspectives for Healthcare Systems

Although Kaplan and Norton originally emphasised four key perspectives (financial, internal process, customer, and learning and growth), the unique features of healthcare systems have resulted in many innovations and applications of the BSC. Consequently, the number of considered perspectives varies from three (Bevan, 2006, Patel *et al.*, 2008) to as many as six perspectives in Kunz *et al.* (2005) and Peters *et al*., (2007).

Although, some of the scorecards were typical BSCs using the traditional four perspectives, a number of organisations in a wide variety of health care sectors have found it useful to make modifications to Kaplan and Norton's original formulation according to their institutions current conditions. For example, Potthoff *et al*.(1999) report a long-term care organisation creating a balanced scorecard containing the perspectives of "development and community focus", "human resources", and "quality of care and services". Curtright *et al*. (2000) describe how the Mayo Clinic modified the balanced scorecard in line with its core business principles, including the interesting perspectives of "mutual respect and diversity" and "social commitment". Santiago (1999) argues that quality of care and outcomes are important to healthcare organisations and cite the example of Carondelet Health Network that added "outcomes" as a perspective. In addition to adding or modifying perspectives, some organisations modify the basic structure of the balanced scorecard. Rimar (2000) discusses how the physician practice plan at the Yale University School of Medicine demonstrates that it values the customer perspective above others by placing the customer domain at the top of the balanced scorecard. In another approach to tailoring perspectives for an organisation, Zelman *et al*. (1999) focused on adapting the balanced scorecard for academic health centres to reflect the research, teaching, and other unique characteristics of this segment of the healthcare industry. In addition, new perspectives and terminology, for example, clinical perspective, social commitments or employee perspective (Kumar *et al*., 2005, Schmidt *et al*., 2006). Therefore, BSC in healthcare organisations presents a different picture to other industries in relation to the range of perspectives. In healthcare, the BSC scorecard appears more diverse than in other sectors.

The financial perspective in a for-profit setting would show the results of the organisation's strategy from the other perspectives while for a not-for-profit and public sector setting it would show that the organisation achieves its results in an efficient manner that minimises cost (Olve *et al*., 1999). However, it is recommended for not-for-profit organisations to place their customers (patients) – not the financials – at the top of its BSC (Kaplan and Norton, 2001). Moreover, Voelker *et al*. (2001) suggest that the financial perspective can be excluded in some not-for-profit organisations from the BSC since financial performance cannot demonstrate success.

2.2.4 Challenges and Limitations

Although remarkable advances have been made, the theoretical development of effective integrated, balanced and strategically driven performance measurement framework is still challenged by some issues on both the design and implementation levels. While BSC has been applied successfully as a strategic management tool, there are reports of evidence of many failures (Neely and Bourne, 2000). The design of the BSC assumes that an overall vision can be defined and that the units within the organisation are coordinated to accomplish that vision. However, healthcare organisations are traditionally loosely coupled organisations where strategic planning and management are not as vital as in more centralised organisations (Zelman *et al*., 1999). The choice of performance perspectives to be included in the BSC is another main challenge in designing BSCs in healthcare settings. In public healthcare organisations, the focus of scorecards should be on patient health and on the change to the lives of the people who these healthcare institutions are trying to help (Gurd and Gao, 2007). Further, the ranking of these perspectives within the BSC can be questioned (Zelman *et al*., 1999).

Another challenge related to the design of BSC for healthcare facilities is the selection of performance measures that to be used within the scorecard. The BSC is supposed to assist in identifying the most critical measures for monitoring performance and for developing strategy direction. Consequently, the selected measures should support strategic decisions as well as operational decisions. The attention in most of the work presented in the literature focused on how the BSC was designed rather than how it was used within healthcare organisations (Chow *et al*., 1998). Several studies indicate that the BSC was initially regarded as a model for performance measurements with little or no connection at all to strategy implementation (Castaneda-Mendez *et al*., 1998, Griffith, 2000). Healthcare organisations have faced many challenges in implementing the balanced scorecard in the healthcare settings (Zelman *et al*., 2003). For example, many of the measures and indicators in the BSC (e.g., medical staff relations and quality of care) can be difficult to measure and to interpret. This is further challenged by the poor data warehousing of healthcare organisations and the existence of multiple information systems that are not integrated (Dziuk, 2001). Furthermore, the number of performance measures is challenged by the amount of resources tied up in the measurement process, in terms of data collection and analysis and the representation and interpretation of the measures (Gao *et al*., 2006).

Finally, the connections and interactions between the performance indicators within the BSC are, in most articles, assumed and treated as unproblematic issues (Aidemark and Funck, 2009), ignoring the fact that several of the indicators within the BSC can be in conflict and can oppose each other (Patel *et al*., 2008). Providing information about the causal–effect relationships between different types of indicators is then necessary to reduce the split between different views about the performance indicators and to conceptualise the dynamics and operations within the healthcare organisations. However, due to the large number of variables and high levels of uncertainties and dynamics associated with healthcare processes, the BSC alone has limitations in measuring and inferring these relationships between performance indicators.

In summary, an analysis of the literature leads to two major conclusions. First, effectively measuring and managing of process performance is a complex and challenging task. Second, in order to provide a continuous and sustainable performance improvement, then the different stages of the performance measurement and management process starting with the design of measurement systems and their implementation to the analysis of resulted information must be successfully completed in an iterative and not a linear sequence of steps.

In the next two sections, a brief overview of MCDA and simulation modelling is given along with their applications focusing on how these approaches can support the design, implementation, analysis and use of measurement systems, providing an integrated decision support system.

2.3 MULTI-CRITERIA DECISION ANALYSIS

The multi-criteria decision analysis (MCDA) approach takes explicit account of multiple conflicting criteria in decision-making (Zionts, 1979). Multi-criteria methods of dealing with complex problems of decision-making have been developed over the last three decades, in which many alternatives can be evaluated with respect to many quantitative and/or qualitative criteria (Kennerley and Neely, 2002).

2.3.1 Applications

Given the multi-dimensional nature of the BSC, several studies have combined multi-criteria analysis techniques with the BSC. Clinton *et al.* (2002) and Searcy (2004) have used the Analytic Hierarchy Process (AHP) (Saaty, 1990) for the selection of performance measures to be used in the balanced scorecard. Similarly, Karra and Papadopoulos (2005) applied the AHP to develop a BSC for a Cancer Hospital, where the AHP was used to select the most important measures and then to evaluate their weights. Other applications of the AHP method within a BSC system can be found in Reisinger *et al*. (2003), Fletcher and Smith (2004), and Huang (2009); these place emphasis on the development of a performance measurement system in for-profit organisations. Furthermore, Chan (2006) used the AHP to select the appropriate measures for developing an aggregate BSC of 95 acute-care hospitals where 39 indicators are grouped into the traditional four perspectives of the BSC. Moreover, Leung *et al.* (2006) combined the BSC with Analytic Network Process in order to overcome the feedback and interdependence between perspectives and measures. Analytic network process enhances the function of AHP by incorporating interdependent relationships between perspectives or measures (Saaty, 2004).

The decision-making trial and evaluation laboratory (DEMATEL) approach can also be integrated with the analytic network process to deal with the interdependencies among the performance measures (Tsai *et al*., 2008). Other multi-criteria analysis methods have also been applied in the design and evaluation of BSCs. For example, Valiris *et al*. (2005) use the Simple Multi-Attribute Rating Technique (SMART) in order to select appropriate measures for the development of a BSC system in a financial institution. Likewise, Bezama *et al.* (2007) combined several multi-criteria analysis tools in order to develop a BSC model for remediation project. Similarly, Wu *et al.* (2009) applied a fuzzy AHP to estimate the relative importance of the chosen BSC measures, while other multi-criteria analysis methods are used for the performance evaluation of various for-profit organisations.

2.3.2 Discussion

The achievement of high levels of performance on one measure is mostly obtained at the expense of performance on one or more other performance measures, making trade-off among these measures is inevitable (Skinner, 1974). Despite the recognised importance of explicitly dealing with priorities and trade-off between different performance indicators (Banks and Wheelwright, 1979; 1985; Eccles and Pyburn, 1992; da Silveira and Slack, 2001), very little work in the literature has been done to examine the nature of the trade-offs between these measures and their inter-dependencies (Mapes *et al.*, 1997, Neely *et al.*, 2000). Understanding the causes of unsatisfactory performance levels and determining proper corrective actions requires, in most cases, understanding and detailed analysis of the underlined process and the consideration of trade-offs. However, the lack of analytical tools prevents decision makers to effectively process all the information necessary to develop and implement better-informed decisions and plans. Consequently, to deal with the dynamic complexity inherent in business processes, modelling and simulation is required (Senge, 1990; Sterman, 1989). The combined use of qualitative and quantitative modelling enriches the analysis and can provide very useful insights for the design of measurement models and decision support systems.

An overview of literature on modelling and simulation is provided in the next section, highlighting their potential applications and their capabilities to model the dynamic complexity of business process under study.

2.4 BUSINESS PROCESS MODELLING AND SIMULATION

Business process modelling and simulation plays a major role in the perception and understanding of business processes. In most cases, a business process is as expressive and as communicative as the technique that has been used to model it. Therefore, the elements and the capabilities of a business process model play a significant role in describing and understanding a business process. Discrete-event simulation (DES) has proven to be an effective tool for process modelling and improvement (Benneyan, 1997, Jun *et al.*, 1999). For simplicity, from this point and through this thesis the term simulation is used to denote DES to avoid confusion with other types of simulation. An overview of the main modelling techniques is given in the next section. Then, a review of the literature on the application of simulation modelling in the healthcare sector is presented, which is followed by a discussion about the limitations of modelling and simulation.

2.4.1 Process Modelling Techniques

There is abundance of business process modelling techniques with approaches that capture different aspects of a business process, each having distinctive advantages and disadvantages. Authors such as Melao and Pidd (2000), Aguilar-Saven (2004), Ryan and Heavey (2006), Vergidis *et al*. (2008), and Aldin and de Cesare (2009) have provided frameworks for presenting and classifying different business process modelling techniques. The following is a summary for the main techniques that were found as the most frequently used.

2.4.1.1 Flow Chart

Flow charts are the most basic type of diagrams that show the flow of controls and actions of a business process using graphical representations (Lakin *et al*., 1996). Flow charts were initially developed for software specification (Knuth, 1963), but their simplicity and flexibility have attracted managers to adopt this technique for modelling their business processes (Aldin and de Cesare, 2009). The modelling elements of flow charts are simple, yet powerful enough to illustrate the activities that occur within a business process. Given that simplicity, flow charts are effective in fast and informal representation of process representation, and therefore they are effective in communication and discussions between analysts and stakeholders. However, flow charts use a sequential flow of actions and do not support a breakdown of activities (Aguilar-Saven, 2004). Moreover, flow charts lack the necessary semantics to support more complex and standardized constructs (Havey, 2005). Finally, the other hand the technique does not have the means to explicitly represent services, events and rules (Aldin and de Cesare, 2009), and also cannot describe responsibilities or performers in the chart, which results in difficulties to relate the organisational functions or departments to activities (Aguilar-Saven, 2004).

2.4.1.2 Data Flow Diagrams

Data flow diagrams (DFD) are graphical representations that show the functionality of a system, with its underlying processes and flow of data and how information enters and leaves processes (Lee and Wyner, 2003). DFDs enable multi levels of representation by breaking down each process into sub-processes at a lower level (Aguilar-Saven, 2004, Aldin and de Cesare, 2009). These functional decomposition capabilities of DFDs allow for the presentation of more abstract and more detailed representations of the same process, and thus allowing represent the functional dependences among the activities of a business process (Carnaghan, 2006). DFDs also specify the meaning of operations and system constraints by showing where information is stored within the process, and the organisational function to which the activity belongs (Aguilar-Saven, 2004). Additionally, DFDs are simple and easily understood (Shen *et al*., 2004) and accordingly are used for communication and in discussions between analysts and users, as they are also easy to draw, improve and amend (Damij, 2007).

2.4.1.3 Role Activity Diagrams

Unlike flow charts and DFDs that focus more on procedures and data, role activity diagrams (RADs) are a more process-oriented technique that allow a business process to be modelled diagrammatically through roles, goals, activities, interactions and business rules (Ould and Ould, 1995). RAD notation enables the representation of the process in terms of: roles, resources, activities, users, states, and the interaction between participants that represent actions and the speech of acts of a process (Cordes, 2008). Roles are an abstraction of real behaviour that is represented in RAD by grouping activities that carried out by an individual or a group (Phalp *et al*., 1998). Roles enable modeller to refine and modify the process activities without affecting the whole model. The approach provides a flexible and easy to use and understand support that can help stakeholders to visualise the business process so that decisions can be made that leads towards improvements (Aldin and de Cesare, 2009). However, the technique explicitly excludes business objects such as physical resources (e.g., machines), products, and services. Moreover, RAD does not support process decomposition as processes are only presented as a sequence of activities (Aguilar-Saven, 2004).

2.4.1.4 IDEF

The Integrated Definition for Function Modelling (IDEF) is a family of methods that supports a paradigm capable of addressing the modelling needs of an enterprise and its business areas (Aguilar-Saven, 2004). For business process modelling, the most useful members of the IDEF family are IDEF0 and IDEF3. IDEF0 was developed from the Structured Analysis and Design Technique (SADT), which is a methodology to be used as a regimented approach to analysing an enterprise (Marca and McGowan, 1987). IDEF0 is a structural graphical representation of processes or complex systems that allow the analysis and communication of the functional aspect of a system (NIST, 1993). Each process in IDEF0 is described as a combination of activities, inputs, controls and mechanisms in a hierarchical fashion. At the highest level the representation may be of an entire process. The processes can be further decomposed to show lower-level activities. The breakdown of processes may continue until the point is reached where sufficient detail is reached (Colquhoun *et al*., 1993). This hierarchical structure of IDEF0 keeps the model scope within the boundaries and allows the system to be easily refined into more detail until the model is as descriptive as necessary for the decision maker (Kim and Jang, 2002). While IDEF0 shows what is done within the organisation, in terms of its business processes, IDEF3 shows how things work within the system by capturing behavioural aspects of a business process (Aguilar-Saven, 2004). Such behavioural aspects are captured by describing the causal relationships between activities and events of the process. IDEF3 consists of two modelling modes: the process flow description (PFD) and the object state transition description (OSTD). PED describes how things actually work in the business process while OSTD which describes the object's allowable transitions through a particular process. Both PFD and OSTD contain units of information that makeup the description of the whole process and the representation of resource interactions and queuing information (Ryan and Heavey, 2006).

2.4.2 Simulation Modelling in Healthcare

Healthcare managers can apply simulation for assessing current performance, predicting the impact of operational changes, and examining the tradeoffs between system variables (Wierzbicki, 2007). Furthermore, identifying areas of improvement of service through possible reorganisation of existing resources, for example; reorganisation of surgical and anaesthesia care surrounding laparoscopic surgery (Stahl *et al*., 2004); and planning for the geographical locations of new healthcare services taking into account the demographics of the population and the location of the patients who need the services (Harper *et al*., 2005). Simulation is well-suited to tackle problems in hospital departments such as emergency departments and operating rooms, where resources are scarce and patients arrive at irregular times (Jun *et al*., 1999) and effectively combine data mining (Ceglowski *et al*., 2006) for better results. Simulation is also found to be effective for other units such as outpatient clinics, where different alternative configurations can be evaluated and tested (Swisher and Jacobson, 2002).

2.4.2.1 Inpatient Facilities

Efforts to develop DES models in healthcare have been advancing since the late 1980s when Saunders *et al.* (1989) proposed a model to study the impact of key resources on waiting times and throughput. Since that time, simulation models have been used to study the effect of a wide range of health interventions on healthcare processes performance, for example; designing a new house staff work schedule (Dittus *et al*., 1996) or ambulance schedules (Ingolfsson *et al*., 2003); improving capacity utilisation in intensive care units (Kim *et al*., 1999, Litvak *et al*., 2008); and planning healthcare services (Oddoye *et al*., 2009). Patient flow to hospital beds, occupancy levels of beds, and length of stay (LOS) are common areas that have been investigated for many years. For example, in an acute hospital in the UK, the impact of the bed occupancy level on the flow of inpatients has been investigated using discrete-event stochastic simulation models (Bagust, 1999). Results show that hospitals operating at bed occupancy level of 90% or more are likely to face regular bed crises. Hospitals with a bed occupancy level of less than 85% generally avoid a bed crisis as well as the associated risks to patients. Management should therefore plan interventions on a long term basis to match future demand growth (Bagust, 1999). Subsequently, this threshold of bed occupancy (i.e., 85%) has been acknowledged by the national health (NHS) (Bourn, 2000).

Simulation models allow a more accurate interpretation of the utilisation of hospital resources, which in turn supports the hospital management in their decisions on bed usage and patient flow (Harper, 2002). This can be achieved by modelling the flow of patients through the whole hierarchy of hospital. Scenarios can then be used to illustrate the consequence of possible potential decisions suggested by the hospital management. The participation of multiple hospitals in the development phase of simulation models can result in a generic framework that allows for the incorporation of uncertainty or trends in the arrival profiles of patient groups as well as duration variability (e.g. LOS or surgery durations). A more general simulation-based framework was proposed by Harper and Shahani (2002), for the planning and management of hospital beds, operating theatres and workforce. The implementation of their integrated framework resulted in a flattened occupancy rate and a drop of the overall surgery refusal rate from 5% to 3%.

2.4.2.2 Operating Rooms

Performance measures for a surgical unit were investigated by Sciomachen *et al.* (2005) using a simulation model with special focus on wards' productivity in terms of utilisation rate, patient throughput and overruns. The reported results from their model concluded that applying the master surgery schedule reduces the waiting list and the number of overruns by about 25% and 10% respectively. To compare the use of a pooled list with scheduled lists, Vasilakis *et al.* (2006) presented a simulation model that considered surgeons availability, which in turn depended on other clinic activities. A 30% reduction of patients waiting time has achieved using their proposed model under the pooled-list method. A study of a surgical unit using simulation was also presented by Cardoen and Demeulemeester (2007) which shows the effects of the changes bed capacity on the utilisation of beds.

A simulation model was presented by Marcon and Dexter (2007) to examine how standard sequencing rules, such as longest case first or shortest case first, may assist in reducing the peak number of patients in both the holding area and the post anaesthesia care unit. A similar analysis of such sequencing rules was provided in Marcon and Dexter (2006). In this study, however, the authors studied make-span of the unit and the peak number of patients. The make-span represents in this case the completion time of the last patient's recovery. Simulation models can effectively evaluate critical decisions concerning date, room and time assignments (Testi *et al.*, 2007). When patients are scheduled consecutively in an operating room, i.e. without incorporation of idle time, the planned surgery start times (time decision) are determined by sequencing the patients. Niu *et al.* (2007) described a simulation model in which scenarios were tested with adapted resource capacities. In particular, they examined how the LOS of patients varies according to changes in the number of operating rooms, chairs in the holding unit, and available beds. Persson and Persson (2009) developed a simulation model to study how resource allocation policies at the department of orthopaedics affected the waiting time and utilisation of emergency resources, taking into account both patient arrival uncertainty and surgery duration variability.

2.4.2.3 Emergency Departments

Recently calls for improved performance have grown significantly. Therefore, applications for operational decision support are widespread and have become increasingly significant (Eldabi *et al*., 2006). Most of these undertakings have focussed on departmental operations, especially emergency departments (EDs). Performance bottlenecks can be identified and resolved using simulation. In Tan *et al.* (2002), a simulation model was used to compare different alternatives to staff schedules with the current schedule. The results identified the doctor’s station as the bottleneck. The new schedule, generated by queuing analysis, increased the capacity of the bottleneck and hence reduced patient time in the system**.** Similarly, Coats and Michalis (2001) compared different shift patterns *via* simulation and found that the doctor shift pattern that best matched the patient arrival pattern gave the shortest wait times. The effect of physical expansion of the ED on LOS is analysed by Samaha *et al.* (2003). However, physician skills level was not considered in patients service time. In Duguay and Chetouane (2007), a number of alternatives based on adding resources were investigated with the objective of reducing patient waiting times and improving overall service delivery and system throughput. The impact of different patient triage methods on service times has been studied by Connelly and Bair (2004). Yet, variations in patients' arrival rate were not considered. Modelling the complex behaviour of an ED is a challenging task, due to interaction of human and physical resources. Medical staff, for example, are rarely dedicated to one patient or task, they treat several others while waiting for other processes. This diversity of process interaction can be described as multitasking, a common feature of ED operations. Yet, multitasking is rarely considered in DES models of EDs (Gunal and Pidd, 2006). However, Thorwarth *et al.* (2009) examined the impact of staff scheduling on overall utilisation and burnout issues related to over-utilised staff. The tradeoffs between different alternatives such as adding more beds or altering the admission rate was evaluated by Khare *et al.* (2009), where patient LOS is considered as the key performance indicator (KPI). Measuring crowding in an ED was achieved by Hoot *et al.* (2008). The theoretical model was validated with patient data from an academic ED, which facilitated a patient tracking system. Metrics such as patient waiting time, occupancy level, and length of stay, were used to apply Pearson's correlation to achieve a forecast for the short term (eight hours).

Apart from the internal factors, there are many other external factors that affect the crowding level of the ED, for instance, uncertainty in the arrival of patients. Simulation models can effectively be used as a predictive tool to predict the maximum demand level that the ED staff can handle, and consequently determine the required staffing level to meet that increase in demand and at the same time to keep the average waiting time of patients under a certain threshold (Baesler *et al*., 2003). A balance in the utilisation of resources would be attained by analysing the arrival pattern of patients, which can significantly improve staffing planning and resource allocation (Sinreich and Marmor, 2005). Further, the effect of staffing levels was investigated to reduce patient's length of stay (Sinreich and Jabali, 2007). Another factor that contributes highly to the overcrowding of the ED is the shortage in hospital beds. The bed occupancy level has been found to be strongly correlated with average length of stay of patients within the ED (Forster *et al.*, 2003). By using simulation models, Elbeyli and Krishnan (2000) found that adding beds to other specialised units within the hospital decreased the average time of patients waiting to be admitted from the ED. Lane *et al.* (2000) has also examined how reductions in bed capacity in the hospital wards affected patient waiting times in the ED. They examined the ED as part of the larger hospital wide system and considered emergency patients and elective treatment patients.

2.4.3 Limitations

Although a substantial number of simulation studies were reported in the healthcare literature as a decision support tool, most of these studies do not support continual improvement philosophies. A number of performance measures are needed to achieve this continual improvement by representing more than one perspective of the performance. However, most of the reviewed studies consider only small number performance measures such as waiting time and LOS, while other performance measures such as resource utilisation, productivity, and layout efficiency are rarely combined. Linking these measures to international standards and national metrics is mostly neglected. There is a lack of simulation studies that use multiple perspectives of performance, which is pivotal to support not only operational decisions, but also to coordinate diverse staff categories toward the strategic direction and for dealing with the multiple and complex criteria influencing decision making process in healthcare. These limitations can be mitigated by combining BSC and MCDA tools with simulation modelling. The BSC can be used to represent different performance areas in a balanced manner while MCDA tools can explicitly consider the trade-offs among the selected performance measures.

2.5 CONCLUDING REMARKS

Decision makers in both the private and public sectors are under constant pressure to improve the performance of their business processes. However, making informed decisions is challenged by the high level of dynamic complexity and uncertainty of today's business processes; particularly, in the healthcare domain. Therefore, finding effective solutions requires decision makers to change the way they think and consequently, enabling a more effective use of the available information and sophisticated decision support tools. While considerable progress has been made recently towards designing and developing effective decision support systems, there still remain some issues to be addressed. Particularly, helping decision makers 1) to build a better understanding about the underlying process performance, 2) to understand the implications of alternative solutions prior to their actual implementation and 3) to aid in evaluating and eventually selecting appropriate plans and corrective actions. BSC, MCDA, and simulation are approaches that have independently proved their potential to support decision making. There is also a clear potential for these approaches to be integrated and applied in a collaborative manner which can bring new insights to support the different stages of the decision making process. Though simulation can effectively contribute to the understanding of business process, it does not provide the capability of finding the optimum values of decision variables in terms of predefined objective function(s). This is the purpose of optimisation models, which allow decision makers to find the best possible alternatives while their impact on the system performance is evaluated using simulation models. Consequently, the incorporation of optimisation capabilities with decision support systems will significantly help decision makers to find answers for critical decisions such as staff scheduling, resource allocation, and capacity planning, as will be discussed in the next chapter.

CHAPTER 3: BUSINESS PROCESS OPTIMISATION

3.1 INTRODUCTION

Diagrammatic modelling of business process does not add much value without further inspection and analysis of the business process model (Vergidis *et al*., 2008). Likewise, though simulation modelling can effectively contribute to the understanding and analysis of business process, it does not provide the capability of finding the optimum values of decision variables and optimising a business process (van der Aalst *et al*., 2003). An integrated approach toward the improvement of business processes should support the modelling of business process, provide the necessary means to identify performance bottlenecks, and to generate alternative decisions and optimum values for decision variables in terms of specified objectives. Therefore, business process optimisation is the automated improvement of business processes using through the modelling, analysis, of the process and the generation of optimal solutions (Vergidis *et al*., 2008). In this chapter, a brief description of optimisation principles and techniques is provided in Section 3.2 and 3.3 respectively. This is followed by an extensive literature review of optimisation techniques in the supply chain and healthcare contexts in Section 3.4. Finally, the chapter in concluded in Section 3.5.

3.2 OPTIMISATION PRINCIPLES

Optimisation problems can be defined as determining the set of values of the decision variables that are located in the feasible area determined by the underlying system constraints that gives the optimum values of all objective functions. Formally:

$$\text{Optimise} \qquad f_i(x) \qquad i = 1,\ldots,I,$$

$$\text{Subject to:} \quad g_j(x) \le 0 \qquad j = 1,\ldots,J,$$
$$h_k(x) = 0 \qquad k = 1,\ldots,K$$

Where $f_i(x)$ is the objective function i, $g_j(x)$ and $h_k(x)$ are the set of inequalities and equality constraints. The decision variables are represented as a vector $x \in S$; where S is the region of search space that defines all possible combinations of decision variables that satisfy all the constraints. As shown in Figure 3-1, the objective function vector F maps decision variable space S into objective function space Ω (i.e., search space).

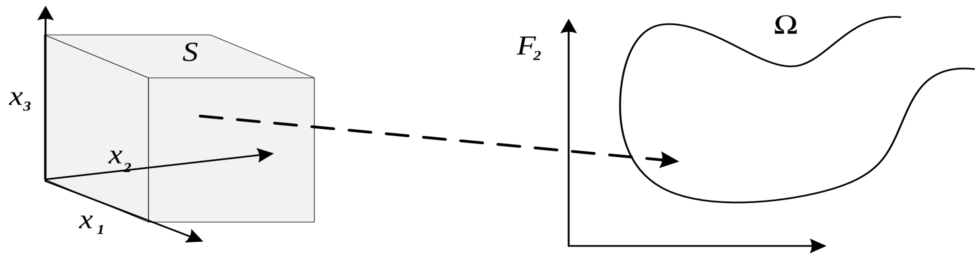


Figure 3-1 Variable space mapping to decision and objective space.

For $i = 1$, it is considered as a single-objective optimisation problem; otherwise it is a multi-objective optimisation problem. Multi-objectives can then be divided into two major categories: the Pareto-based approach and the aggregate-based approach.

3.2.1 Pareto-Based Approach

For multi-objective optimisation problem (i.e., $i \geq 2$), if all the objective functions are to be considered concurrently, it is rare to find a common point x^* that has an optimum value for all the objective functions. Instead, *Pareto optimality* (Censor, 1977) has to be applied that constitutes the origin of multi-objective optimisation.

To define Pareto optimal solutions, domination criteria have to be defined first. A solution $x_1 \in S$ dominates another solution $x_2 \in S$ (denoted as $x_1 > x_2$) if solution x_1 is no worse than solution x_2 in all objectives and solution x_1 is better than x_2 in at least one objective. According to this definition, a solution is Pareto optimal (x^*) if there is exist no x in the feasible search space that decreases some objective function without causing a simultaneous increase in at least another objective function. The Pareto Optimality always gives a set of optimal solutions called non-inferior or non-dominated solutions. The mapping of Pareto optimal set into the objective function space represents the Pareto Optimal Front (POF) as shown in Figure 3-2.

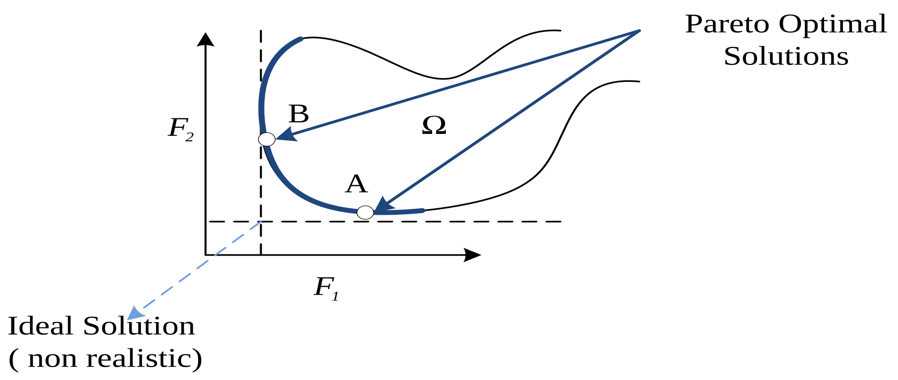


Figure 3-2 A bi-objective optimisation problem.

3.2.2 Aggregate-based Approach

Aggregating functions are used to combine objectives into a single objective function, known as weighted sum aggregation. The weighted sum approach transforms multi-objective optimisation problem into a scalar one by adding all the objectives together using different coefficients (i.e., weights) for each objective, formally:

$$\text{Optimise } F(x) = \sum_{i=1}^{I} w_i f_i(x), \; 0 \leq w_i \leq 1, \text{ and } \qquad \sum_{i=1}^{I} w_i = 1$$

Where w_i are the weighting coefficients of objective function $f_i(x)$. In weighted sum approach, F maps the decision variable space S into a hyper-plane into the objective function space Ω.

In Figure 3-3, for example, a two-objective optimisation problem is represented linearly in the solution space.

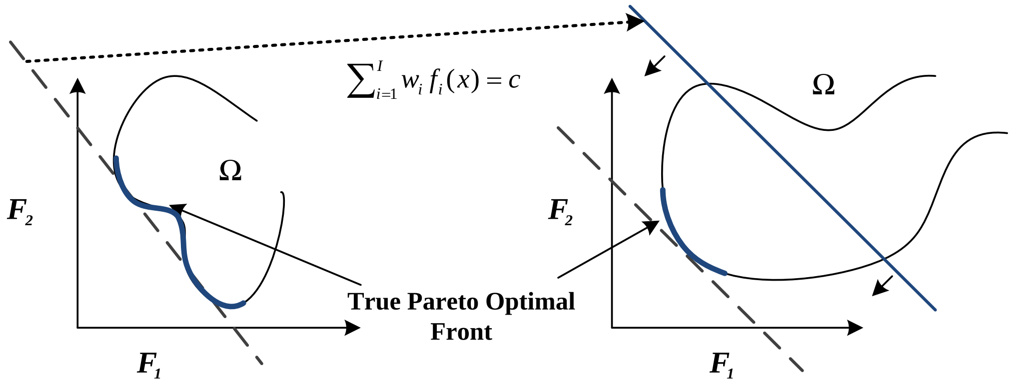


Figure 3-3 Non-convex Pareto optimal front in the decision space.

Therefore, selection of weights defines the slope of the line which in turn leads to the solution point where the line touches the Pareto optimal front. Further, if the Pareto front is non-convex (Figure 3-3), certain solutions are not accessible. Optimisation techniques vary then in their capabilities to find these optimal solution points, and hence in their optimisation results. A brief discussion about the main optimisation techniques is given in the next section.

3.3 OPTIMISATION TECHNIQUES

Business process optimisation entails a wide range of techniques and methods from relevant disciplines such as decision support systems, artificial intelligence, modelling and simulation, expert systems, management science, and operations research. They also support the need for developing queuing, linear programming, and simulation models to represent business processes and to select the optimal design. For example, a schematic representation for the interaction between simulation modelling and optimisation is given in Figure 3-4.

Generally, optimisation techniques can be divided into four main categories: gradient-based methods, statistical-based methods, meta-model-based, and meta-heuristics methods.

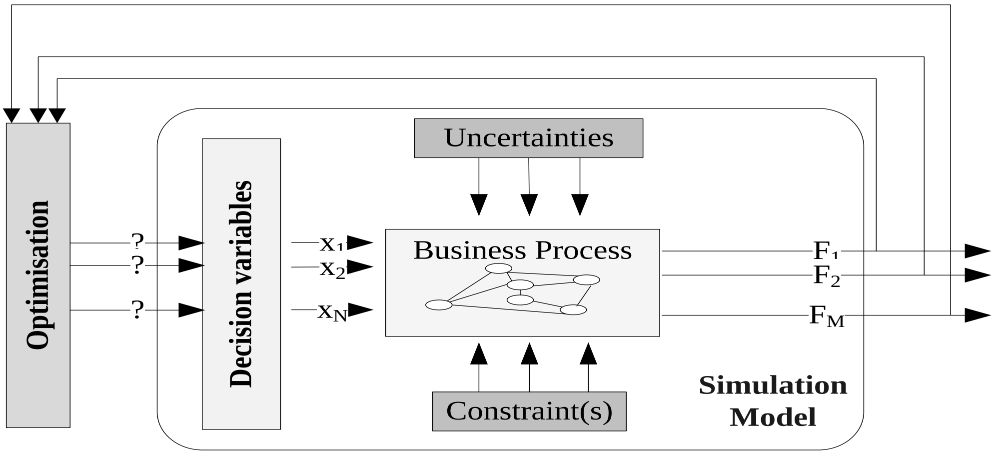


Figure 3-4 Simulation modelling and optimisation interaction.

3.3.1 Gradient-Based Methods

Differentiation is usually used to simplify the objective function in order to find an optimum solution. The gradient-based approach therefore requires a mathematical expression of the objective function. When such a mathematical expression cannot be obtained, there is a need to use an estimation technique to start the solution procedure. The estimated gradient's direction guides the search process to move from one potential solution to another in an iterative scheme in a process called stochastic approximation (Robbins and Monro, 1951). Infinitesimal Perturbation Analysis (IPA) is one of the gradient estimators that are considered to be unbiased (Glasserman, 1991). Its convergence rate has been studied in L'Ecuyer and Perron (1994), while variance reduction and efficient implementation of IPA was investigated in Dai (2000). Another important gradient estimator is Finite Difference Estimation (FDE), which determines partial derivatives of the system performance measures (Dong and Krylov, 2005).

In order to estimate the gradient at each search point, at least ($n + 1$) evaluations of the simulation model are necessary, where n is the number of decision variables. For a more reliable estimate, multiple observations for each derivative are required. On the other hand, Likelihood Ratio Estimator (LRE) estimates the derivative of the performance measure by mathematically differentiating the underlying probability measure of the system (Glynn, 1990).

3.3.2 Meta-Model-Based Methods

While gradient-based estimators are used to estimate the derivatives of the objective function, meta-model-based techniques use an analytical approach to approximate the objective function. The meta-model can then replace part of the simulation model with a mathematical function that mimics the input–output behaviour of that part. Such integration of meta-models simplifies the simulation model in terms of computation time, and consequently simplifies the optimisation process (Reis dos Santos and Reis dos Santos, 2009). In Figure 3-5, the optimisation model interacts with the meta-model, whilst the meta-model approximates the input–output behaviour of the simulation model.

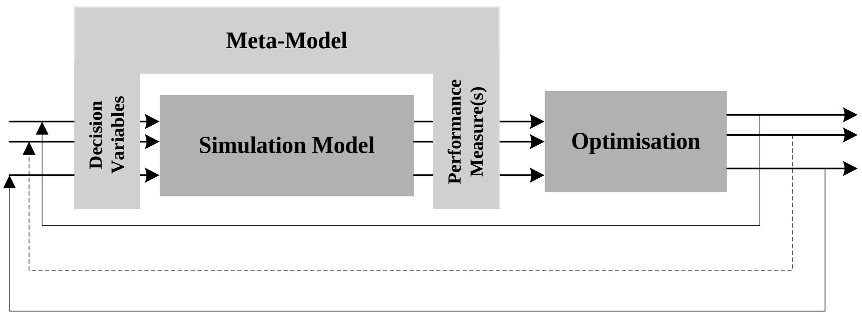


Figure 3-5 A Meta-Model interacts with the simulation and the optimisation models

The Response surface methodology (RSM) is based on procedures that allow regression models to be applied to simulation model responses that are evaluated at several values of decision variables using the design of experiments (DOE) method. A comprehensive study of the use of statistical designs integrated with simulation models can be found in Kleijnen (1998), which focuses on how RSM combines regression analysis, statistical designs and the steepest descent/ascent method to optimise the objective function of the simulated system. On the other hand, kriging (Hussain *et al*., 2002, Keys and Rees, 2004) is an interpolation method that predicts unknown values of a stochastic function which are more flexible than polynomial models and less sensitive to small changes in the experiment design (Meckesheimer *et al*., 2002). Another method is artificial neural networks (ANNs), which has proven to be an effective method to approximate arbitrary smooth functions and can be fitted using stochastic response values (Fonseca *et al*., 2003). ANNs are developed to mimic neural processing, the inputs and outputs of which are linked according to specific topologies.

3.3.3 Statistical Methods

Gradient-based and meta-model-based methods are used for continuous decision parameters. In discrete decision parameters, the problem is to select one of the predetermined system configurations. The task of optimisation algorithms is then to select one of these configurations that optimise system performance based on the selected criteria. Since the system performance is not deterministic, further statistical analysis is required to compare alternatives. Different types of approaches were developed for such optimisation problems, including ranking and selection (R&S), multiple comparison procedures (MCP) and ordinal optimisation (OO). In R&S, there are two main approaches. The first is the indifference zone approach, which finds the decision variable values that make the value of the performance measure different from the optimal performance by at most a small amount (i.e. the indifference zone). On the other hand, subset selection is used to reduce the feasible solution region to a small subset that at least contains the best solution. The indifference zone approach does not require extensive computation efforts and can be applied to a single replication from each solution (Kim and Nelson, 2001). The idea of MCP is to run a number of replications and then evaluate system performance by constructing confidence intervals (Swisher *et al*., 2003). However, it is difficult to precisely determine the best alternative from a set of predefined solutions in terms of absolute values. OO determines which solution is better, rather than focusing on the quantitative difference between the available solutions. In addition, instead of looking for the best alternative, OO selects a good enough solution (Ho *et al*., 2000). This crucial feature of OO makes it a robust optimisation choice when the number of alternatives is very large (He *et al*., 2007).

3.3.4 Meta-Heuristics

Statistical methods are successfully used in the case of discrete decision parameters. However, it is computationally unfeasible to evaluate every possible alternative or all parameter combinations when the solution space is very large. Consequently, determining which alternative(s) to simulate and evaluate is crucial. Also, most of the aforementioned optimisation techniques fail to find an optimum solution when the solution space is highly-dimensional and discontinuous, or when the decision variables are qualitative. Meta-heuristics are used in such cases to efficiently guide the search process towards potential solution points (Bianchi *et al*., 2009).

They ultimately provide balance between exploration of solution space and exploitation of *good* solution(s) in an iterative process by initially starting with a solution (point-based) or set of solutions (set-based or population-based), then in each iteration the search progresses to new, possibly better, solution(s) in the neighbourhood of the current solution. Each meta-heuristic method has its own mechanism to define the neighbourhood structure (Andradottir, 2006). Simulated annealing (SA) is one of the main meta-heuristics that starts with an initial solution, generally chosen randomly. A neighbour of this solution is then generated by a suitable mechanism. The performance of this solution is then calculated. If an improvement occurs, the generated neighbour replaces the current solution. If there is no improvement in the performance, the SA algorithm may accept this solution with some probability to avoid entrapment in a local optimum (Kirkpatric *et al*., 1983).

Another common meta-heuristic method is the genetic algorithm (GA), which works on a population of solutions in such a way that poor solutions are excluded, whereas good solutions evolve to reach their optimum solution (Chaudhry and Luo, 2005). The GA generates an initial population of solutions, which can then be evaluated through a simulation model. This is followed by a selection process in which genetic operators are applied to produce new solutions that are inserted into the population. Figure 3-6 demonstrates the integration process between a GA and a simulation model. This process is repeated until some stopping criterion is reached. Artificial immune system (AIS) is another meta-heuristics optimisation method which seeks to capture some aspects of the natural immune system in a computational framework, either for the purpose of modelling the natural immune system or for solving engineering optimisation problems (Glickman *et al*., 2005).

Tabu Search (TS) is a constrained search procedure, where each step consists of solving a secondary optimisation problem (Glover *et al*., 2007). At each step, the search procedure removes a subset of the search space. This subset changes as the algorithm proceeds and is usually defined by previously considered solutions which are called the reigning tabu conditions (Chelouah and Siarry, 2000).

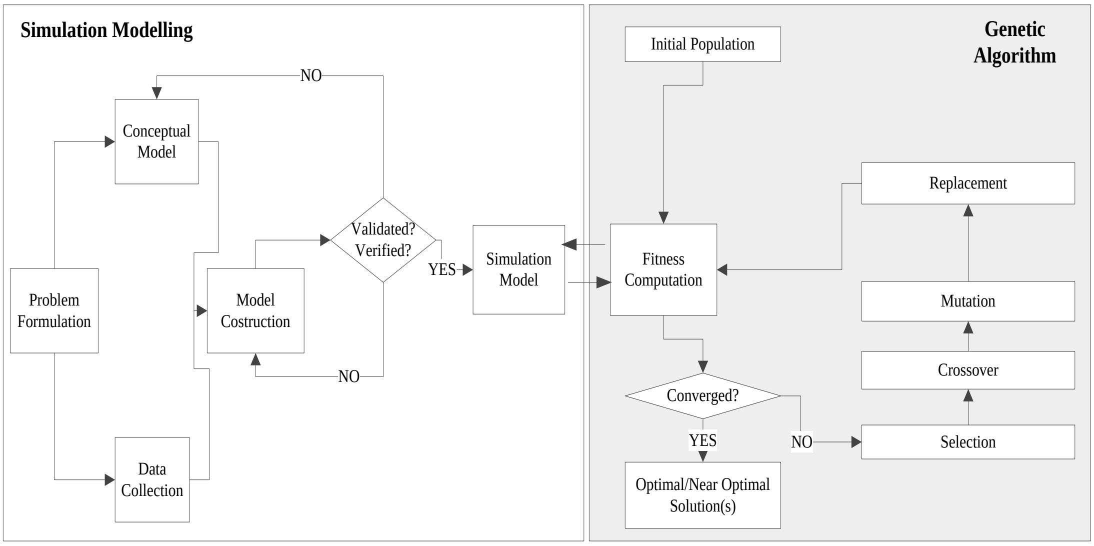


Figure 3-6 A Genetic algorithm integrated with simulation for fitness computation

3.4 OPTIMISATION APPLICATIONS – A REVIEW

Optimisation techniques have contributed to resolve many challenges at different levels of a supply chain (Abohamad and Arisha, 2011). These challenges emerge from the increasing complexity of supply chain networks which is imputable to high level of uncertainty in supply-demand, conflict objectives, and large number of decision variables and constraints. Similar challenges are confronted in managing healthcare processes.

Healthcare can significantly benefit from the application of optimisation techniques in supply chain management. Therefore, and based on the research problem definition discussed in Section 1.2 and the motive of this study (see Section 1.3), a systematic review of the literature has been performed to address the first two research questions and the corresponding objectives (Table 3-1). The resulted body of articles from the systematic review are further critically reviewed and analysed to achieve these objectives and to identify the gaps in the literature.

Table 3-1 The review research questions and their corresponding objectives.

Research Questions	Research Objectives
1. How applicable are existing solution techniques in handling the dynamics and complexity within healthcare facilities and how efficient are they in supporting their business processes?	1. To gain in-depth understanding of existing solution techniques for managing complex business process.
2. What are the similarities and differences between complex business processes in the healthcare setting and in the supply chain context?	2a. To highlight the relationships and common features of healthcare facilities.
	2b. To explore the common challenges and problems of business processes in the healthcare setting and supply chain context.

The methodology followed in the review is based on the process of "systematic review" (McKibbon, 2006) and the literature review framework presented in Eldabi *et al*. (2008) and Jahangirian *et al*. (2011), which are widely used for systematic review of the literature (Naseer *et al*., 2009, Brailsford *et al*., 2009, Jahangirian *et al*., 2010).

The review covered academic, peer-reviewed publications of techniques applied in managing and optimising complex processes in the healthcare and supply chain context. Due to the increased complexity of business processes and the significant advances in the wide application of optimisation techniques over the last decade, the review is limited to the period 2000-2009. Papers that discuss theoretical aspects of optimisation methods are also included to give a background to these techniques. Therefore, the main criteria for inclusion of a paper in this review is that the paper should describe an application in either the healthcare or supply chain context. A number of other exclusion criteria were used at this stage to narrow down and filter out the initial batch of searched academic papers. Because the focus of this research is on the management of business process, papers that discussed disease and medicine are excluded from the review. Further, data visualisation tools, such as CiteSpace (Chen, 2006) were employed to identify irrelevant keywords and subject areas for each domain, and at the same time the most cited references (Naseer *et al.*, 2009, Jahangirian *et al.*, 2010). Following the screening, abstract reading and full-text reviewing of the resulting papers was carried out. Applying filtering mechanisms can result in possible missing of some important articles. Accordingly, reference chasing methods – both backward and forward techniques (Greenhalgh and Peacock, 2005, Jahangirian *et al.*, 2011) – have been applied to identify the key papers and emerging issues. A summary of the review steps methods is given in Table 3-2. Following the selection of the final set of 223 papers, the following attributes were extracted for each article:

1. Application and problem areas: what is the general application orientation of the paper: supply chain or healthcare? What is the specific area of application within the context of these sectors? For example, what is the type of healthcare facility: emergency department, outpatient clinic, intensive care unit or operating room?

2. Techniques and methods: what are the methods applied in the article: modelling, simulation, optimisation or combination of methods? For each method, what is the type of the method? For example, what specific optimisation technique is discussed in the article: mathematical programming, greedy search and heuristics, or meta-heuristics? And if it is meta-heuristics, what is the specific algorithm used: genetic algorithm, tabu search, or stimulated annealing?

Table 3-2 Literature review steps and methodology

Review Step	Methods and Details
Searching	• Database search (SCOPUS and ISI Web of Knowledge) • Reference chasing methods (backward and forward)
Literature Covered	5. Peer-reviewed academic papers
Time Covered	6. 2000-2009
Inclusion Criteria	• Applications in the healthcare and supply chain context • Empirical and methodology studies • All peer-reviewed papers
Exclusion criteria:	• Non-healthcare or non-supply chain Applications • Disease modelling • Cost-benefit analysis • Medical modelling • Non-English language papers • Pre-2000
Sample Size	• Initial search: 3811 • After screening and filtering: 632 • After abstract reading: 174 • After reference chasing: 223
Data Analyses Attributes	• By types of solution technique • By specific methods • By applications and problems • By types of healthcare facility

Through the analysis of literature on business process optimisation in healthcare and supply chain, the common problems and decision areas have been identified and grouped into five main categories as shown in Figure 3-7.

A detailed discussion about each of these problems is presented in the following sections, where each problem is discussed first in the context of supply chain then followed by similar problems in the healthcare sector.

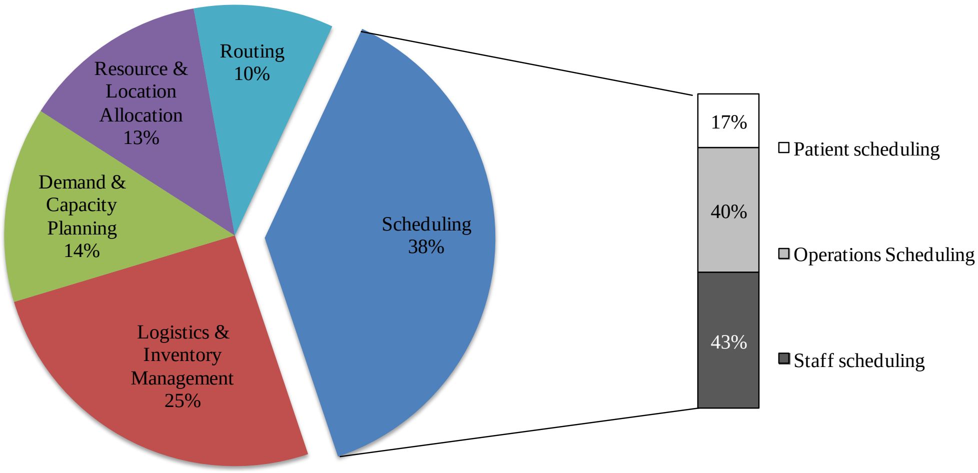


Figure 3-7 Optimisation application areas.

3.4.1 Scheduling

Scheduling is an active area of research in supply chain as well as in healthcare applications for increasing capacity utilisation, cost control measures and improving tactical as well as operational efficiencies of services and facilities. Optimisation techniques are used for a wide range of scheduling problems such as staff scheduling, patient-staff/patient-facilities scheduling, planning and scheduling of operating room surgeries, and production and dispatch planning and scheduling.

The intelligent search capabilities of the genetic algorithms are incorporated with simulation and investigated by Feng and Wu (2006) to find the optimal dispatching schedule for a batch plant. The modelling capability of discrete event simulation and genetic algorithm is presented applied for solving a multi-attribute combinatorial dispatching problem in a flow shop in a manufacturing plant (Yang *et al.*, 2007). Factorial experimental design was used to collect structured data from simulation results which are then used to construct a response surface to optimise the parameters of genetic algorithm. An integrated approach for the planning and scheduling of generalised supply chains is introduced by Amaro and Barbosa-Póvoa (2008). The supply chain is described not only by the traditional forward flow, that links suppliers to customers through factories, warehouses and distribution centres, but also considers the existence of reverse flows where recycling or non-conforming products are returned to factories, for extra processing, or sent to disposal. A mixed integer linear programming is used to model the complex structure of such transportation network. The model provides two levels of information: (1) the optimal aggregated plan for a given planning time domain and (2) its concretization at the scheduling level where detailed information on supply, production, inventory, transportation and recovery of products is optimised based on a pre-defined economical performance criterion. The Pareto dominance concept is applied for solving no-wait flow shop scheduling problems with make-span and maximum tardiness criteria in Pan *et al*. (2008).

Another integrated simulation optimisation framework is developed to minimise the make-span for operations scheduling; operations sequences were improved through genetic algorithm while a simulation model is used to evaluate objective functions under different scheduling schemes in. Meanwhile, a surrogate model based on artificial neural network is designed to predict objective function to decrease the times of running the simulation model (Zeng and Yang, 2009). A large production loss can occur if machine downtime and maintenance actions are neglected during the production scheduling process. Consequently, maintenance and repair strategies for the manufacturing plant have to be considered. The flexibility of simulation models allows the inclusion of several practical aspects of these activities, such as stand-by operation modes, deteriorating repairs, aging and sequences of periodic maintenances. An optimisation method can be then utilised to optimise the components' maintenance periods and the number of repair teams (Marseguerra and Zio, 2000).

A hybrid flow shop scheduling with machine unavailability intervals (due to breakdowns and preventive maintenance) is used to minimise flow time and due date (Allaoui and Artiba, 2004). In their integrated framework, the simulation module evaluates the solutions generated by SA, which are combined with different dispatching rules. The genetic algorithm is modified to deal with distributed scheduling in a multi-factory production with machine maintenance considerations in Chung *et al*. (2009).

Production facilities are more complex than other stages in SC, such as warehouses and distribution centres, in terms of resource constraints and the dynamics of production (Griffiths and Margetts, 2000). Such dynamism and variation in factory schedules might degrade the overall performance of SC. Consequently, integrating production planning and scheduling with other SC units becomes evident. Coordination between two successive stages of an SC is discussed by Mansouri (2005) for a sequencing problem to minimise total set-ups and to minimise the maximum number of set-ups between the two stages. For solving these two NP-hard problems, a multi-objective genetic algorithm solution was proposed which had proven its capabilities of finding Pareto-optimal solutions. An integrated framework based on GA and TS is presented for a distributed hierarchical model for SC planning and scheduling optimisation with a consideration of SC capacity, business strategies and customer requirements (Yin and Khoo, 2007).

A simulation-optimisation framework is demonstrated for production planning, which considered the interdependency between demand and material supplies and the uncertainties emanating upstream and downstream in the SC. Production plans were generated by GA while simulation is used for their evaluation in Sounderpandian *et al*. (2008). A joint production–distribution planning is developed for multi-stage, multi-product SCs where the coordination level between SC components is increased by the parallel processing capabilities of their agent-based simulation framework suggested by Kazemi and Zarandi (2008). Stockton *et al.* (2004) have discussed a wide range of planning decision types, such as aggregate planning, lot sizing within material requirements planning, and production line balancing using GA.

In the healthcare context, planning and scheduling of operating room surgeries has received great attention in the literature. Mostly, there are two types of demand of surgery, namely, emergency and elective. Emergency surgery is unplanned and arrives randomly and must be performed on the day of arrival, on the other hand, elective surgery can be planned ahead. Consequently, the planning problem consists of scheduling elective surgeries in order to minimise the waiting time for elective patients and minimise the overtime costs of the operating rooms. The issues of scheduling operating rooms are discussed by Blake *et al.* (2002) and Blake and Donald (2002). An integer programming model is formulated and solved to develop a consistent schedule that minimises the shortfall between the target of each surgical group and actual assignment of operating room time (also known as block time). A goal programming procedure is applied for minimising idle time and overtime of operating rooms while maximising staff and patients' satisfaction concurrently (Ozkarahan, 2000).

The problem of inpatient surgical scheduling and emergency room scheduling are discussed in details by Carter and Blake (2005), where simulation has been used and proven to be a powerful analysis tool in healthcare. A mixed integer programming model is used to schedule surgical blocks in a medical facility presented in where the availability of resources and schedules of surgeries has a significant impact on the number of patients treated, patients waiting time, and number of cancellations. A system wide model developed to allow management to explore trade-offs between operating room availability, bed capacity, and waiting lists (Santibanez *et al*., 2007). The problem of developing surgery schedules with special considerations of bed occupancy levels was addressed by integrating a mixed integer programming model with meta-heuristic methods to minimise the total bed shortage (Belien and Demeulemeester, 2007). Based on the job shop scheduling problem, Pham and Klinkert (2008) proposed an approach for surgical case scheduling in hospitals. A combination of Monte Carlo simulation and mixed integer programming is used for operating room planning (Lamiri *et al*., 2008), while Hans *et al.* (2008) proposed several constructive and local search heuristics for optimising the assignment of surgeries.

Staff scheduling has been an active area of research in healthcare for increasing capacity utilisation, cost control measures and improving tactical as well as operational efficiencies of services and facilities. In general, the staff scheduling problem is that of assigning shifts to staff having different skills while satisfying as many soft constraints and personal preferences as possible. These constraints include number of consecutive work hours, number of day and night shifts that should be worked by each staff member, staffing requirements according to seniority levels for the day and night shifts, restrictions on the number of consecutive day and night shifts assigned, vacation periods, weekend time-off requests and a fair distribution of responsibilities among staff.

The issues of scheduling physicians in emergency rooms are addressed in Beaulieu *et al*. (2000). Heuristics based on branch-and-bound are used such that the sum of penalties associated with “deviation” constraints is minimised. An integer linear programming model is integrated with tabu search meta-heuristics for scheduling hospital nurse shifts (Valouxis and Housos, 2000). Similarly, mathematical programming and heuristic approaches is used for assigning nurses to critically ill newborn infants (Mullinax and Lawley, 2002). The scheduling of on-call residents problem can also be modelled as a mixed integer program and solved by heuristic procedures (Sherali *et al*., 2002), while genetic algorithms can be used to solve similar problems for resident on-call scheduling considering departmental staffing needs, skill requirements and resident preferences (Wang *et al*., 2007). An integrated framework for solving a nurse-scheduling problem can be provided by combing genetic algorithms with a decoding routine where genetic algorithm solves the unconstrained scheduling problem leaving the constraint handling to the decoder (Aickelin and Dowsland, 2004). The model presented by Felici and Gentile (2004) efficiently solved staff scheduling problems that maximises staff satisfaction using a polyhedral approach. The problem is formulated using an integer programming approach a number of constraints are considered such as workload balancing, shift compatibility, and distribution of days off.

A nurse preference scheduling problem can be solved using a combination of integer programming and heuristics methods (Bard and Purnomo, 2005b). By incorporating a downgrading option, the authors extended the work in Bard and Purnomo (2005a) and improved the quality of schedules. They also presented a model that combines cyclical as well as preference scheduling by formulating an integer programming model in Bard and Purnomo (2007). Based on patient arrival rates, the problem of staff scheduling in emergency rooms can be modelled using queuing models to identify the optimal staffing patterns so that timely care of the patients is optimised and the percentage of patients who leave without being seen is minimised (Green, 2005). A combination of linear programming, constraint programming and meta-heuristics can be effectively used for the problem of home healthcare and nursing to maximise satisfaction of both patients and nurses and at the same time to minimise transportation costs (Bertels and Fahle, 2006). A hybrid approach combining constraint programming with a neighbourhood search meta-heuristic also can be utilised to minimise the number of nurses that visit a patient (Steeg and Schroder, 2008). The Stochastic programming approach can contributes to solving the nurse-to-patient assignment problem, where patients need to be assigned to specific nurses with special skills (Punnakitikashem *et al*., 2008). Along a similar line of research, Sundaramoorthi *et al.* (2009) developed a simulation approach to evaluate nurse–patient assignments. A nurse scheduling methodology is developed by Burke *et al.* (2006) that is more flexible than the traditional fixed period-based approach while combining heuristic ordering with variable neighbourhood search for solving a similar problem is proposed by Burke *et al.*, (2008). Pato and Moz (2008) solved the nurse re-scheduling problem using a genetic algorithm while Moz and Pato (2005) addressed it as a multi-objective problem and solved it using goal programming. Topaloglu (2006) considered the seniority rules when assigning the weekday and weekend day shifts for staff, where branch-and-bound procedure is used to solve scheduling problem.

The quality of service at a hospital emergency department can be improved by utilising simulation and a genetic algorithm to appropriately adjust nurses' schedules without hiring additional staff (Yeh and Lin, 2007). The simulation model is developed to cover the complete flow for the patient through the ED. The GA is then applied to find a near-optimal nurse schedule based on minimising the patients' queue time. Ant colony optimisation approach is applied in Gutjahr and Rauner (2007) to nurse scheduling. The proposed schedules assign nurses dynamically taking into account a variety of soft and hard constraints regarding working date and time, working patterns, nurses qualifications, nurses' and hospitals' preferences, as well as costs. Extensive computational experiments based on simulation models are used to evaluate different scenarios of varying the number of nurses and hospitals. Molema *et al*. (2007) illustrated through a simulation of two case studies that introduction of a part-time work option for doctors can improve service levels and system design. Ahmed and Alkhamis (2008) integrate simulation with statistical methods to design a decision support tool for the operation of an emergency department unit at a governmental hospital. Experimental results show that by using current hospital resources, the optimisation simulation model generates optimal staffing allocation that would allow 28% increase in patient throughput and an average of 40% reduction in patients' waiting time.

Belien and Demeulemeester (2008) integrated the problem of operating room scheduling with nurse scheduling and used linear programming with column generation for solving the joint problem. Grano *et al*. (2009) developed an approach for nurse scheduling for a hospital emergency department that considers both nurse preferences and hospital requirements. An optimised patient–staff/patient–facilities schedule can lead to a considerable cost reduction and an increase in service quality. Queuing models are used by Shmueli *et al*. (2003) for scheduling patients admissions to a hospital intensive care unit. The objective of their model was to maximise the expected number of lives saved by operating at the unit. A hybrid simulation and integer programming approach is used by Persson and Persson (2009) for the problem of scheduling patients for surgery. A single-server model is used by Green (2005) to model cancellations of patient appointments problem. Patrick and Puterman (2006) used simulation to improve resource utilisation for diagnostic services through flexible inpatient scheduling. Another queuing model is developed by Goddard and Tavakoli (2008) to manage patients waiting lists for public health services.

Outpatient appointment scheduling is discussed in Kaandorp and Koole (2007) where a local search procedure was derived with the objective to minimise average waiting times of patients and maximise physician utilisation. Jiang and Giachetti (2008) analysed the flow of patients through outpatient clinics. Their study has demonstrated that parallelisation of activities can reduce the patients length of stay for the patients needing multiple diagnostic or treatment procedures. A Markov decision process is used by Patrick *et al*. (2008) to model patients having varying priorities. An approximate dynamic programming is used to dynamically generate patients' schedules while simulation is used to analyse the quality of generated schedules.

In Ogulata *et al*. (2008), a hierarchical mathematical model was developed for scheduling patients and for assigning staff to patients. The objectives of their model were to balance the workloads of physicians while minimising patients waiting time. Chien *et al*. (2008) have modelled patients scheduling as a hybrid shop scheduling problem where genetic algorithms is used for optimal generation of patient schedules. The objective of their model is to increase the service quality through the reduction of patient waiting times and the increase of resource utilisation. Based on discrete event simulation, Rauner *et al*. (2008) have developed an interactive internet game that illustrates the economic and organisational decision-making processes in hospitals. Healthcare managers, based on various disease categories and budgets, can assess different strategies for capacity planning and patient scheduling.

Table 3-3 summarises the literature on the application of various optimisation methods and their integrations for solving scheduling problems.

Table 3-3 Summary of literature on optimisation techniques for scheduling problems.

<table>
<tr><th colspan="4">Optimisation Methods</th></tr>
<tr><th></th><th></th><th>Meta-Heuristics-Based Methods</th><th>Mathematical Programming</th></tr>
<tr><td rowspan="3">Operations Scheduling</td><td>-</td><td>Pan et al. (2008), Marseguerra & Zio (2000), Chung et al. (2009), Mansouri (2005), Yin & Khoo (2007), Hans et al. (2008)</td><td>Amaro & Barbos (2008), Blake et al. (2002), Ozkarahan (2000)</td></tr>
<tr><td>MP</td><td>Belien & Demeulemeester (2007)</td><td></td></tr>
<tr><td>DES</td><td>Feng & Wu (2006), Yang et al. (2007), Zeng & Yang (2009), Allaoui & Artiba (2004), Sounderpandian et al. (2008), Kazemi & Zarandi (2008)</td><td>Santibanez et al. (2007), Lamiri et al. (2008)</td></tr>
<tr><td rowspan="3">Staff Scheduling</td><td>-</td><td>Wang et al. (2007), Aickelin & Dowsland (2004), Burke et al. (2006), Pato & Moz (2008)</td><td>Topaloglu (2006), Moz & Pato (2005), Green (2005), Belien & Demeulemeester (2008)</td></tr>
<tr><td>MP</td><td>Beaulieu et al. (2000), Valouxis & Housos (2000), Mullinax & Lawley (2002), Sherali et al. (2002), Bard & Purnomo (2005a, 2005b), Bard & Purnomo (2007), Bertels & Fahle (2006), Steeg & Schroder (2008)</td><td></td></tr>
<tr><td>DES</td><td>Yeh & Lin (2007), Gutjahr & Rauner (2007)</td><td></td></tr>
<tr><td rowspan="2">Patient Scheduling</td><td>-</td><td>Kaandorp & Koole (2007), Chien et al. (2008)</td><td>Shmueli et al. (2003), Goddard & Tavakoli (2008), Ogulata et al. (2008)</td></tr>
<tr><td>DES</td><td>Patrick et al. (2008)</td><td>Persson & Persson (2009)</td></tr>
</table>

MP: Mathematical Programming **DES:** Discrete-Event Simulation

3.4.2 Logistics and Inventory Management

Logistical activities may involve transporting raw materials, delivering them for manufacturers, movement of the products to various warehouses, and eventually distribution to customers or healthcare centres. Effective management for these activities may lead to a considerable reduction in SC cost (Christopher, 1999).

In Rao *et al*. (2000), an integrated approach is proposed for the design and deployment of a distribution logistics system under demand uncertainty using simulation optimisation. In their framework, perturbation analysis is combined with simulation to find the optimal configuration of the distribution network of that maximises the total revenues and minimises the total supply chain cost. Based on integer programming models, Rauner and Bajmoczy (2003) developed a decision support system for the allocation problem of medical materials is discussed. Similarly, a multi-objective optimisation heuristic is developed by Swaminathan (2003) for allocating scarce drugs to clinics, with the considerations of the efficiency, effectiveness and equity of the drug-allocation process. Simulation modelling has proven to be an attractive approach for analysing logistics and distribution network (Iannoni and Morabito, 2006). A hybrid optimisation–simulation modelling approach is presented in Ko *et al*. (2006) for managing logistics activities. Genetic algorithms were used to determine the dynamic distribution network structure while uncertainty in demands and travel time are captured by a simulation model. Hospital logistics is addressed in Lapierre and Ruiz (2007) by using a tabu search algorithm to coordinate the procurement and distribution operations while considering inventory capacities. Due to its flexibility, ant colony optimisation has been used by Silva *et al*. (2008) for supplier–logistic systems. A generic supply chain model with suppliers, logistics and distributors is demonstrated in Silva *et al*. (2009) with the objective of minimising the tardiness (i.e., the difference between the release date and the delivery date of the order) of the total orders, minimising the number of orders that are not delivered or delayed, maximising the number of orders that delivered at the correct date, and minimising the total travelling costs of vehicles.

Logistics is also concerned with the definition of stock levels and allocation of resources. The strategic impact of inventory stored at different stages of the SC is significant. Determining the minimum and maximum levels of inventory and the quantity of order to be placed are major challenges for decision makers. An (s, S) ordering policy specifies these decision variables by placing an order when the level of inventory is below s units, and by specifying the amount of the order by the difference between maximum inventory level (*S*) and the current inventory position. Provided that determining the optimal values of (*s*, *S*) is computationally expensive, simulation-based optimisation is a potential tool for analysing alternatives and finding these optimal values. Infinitesimal perturbation analysis is used by Gavirneni (2001) to compute the appropriate order up-to level in a capacitated SC. Gavimeni (2001) measured the benefit of sharing the inventory parameters of the retailer's ordering policy and demand data with the supplier, which reduced the supplier's cost by a value from 1 per cent to 35 per cent. Ranking and Selection procedures and simulated annealing algorithms are combined by Ahmed and Alkhamis (2002) to find optimal values of (*s*, *S*) inventory policy with the objective of minimising the inventory holding cost, shortage cost and ordering cost. A two-stage integer programming was used for the scheduling of a multi-product batch plant (Engell *et al*., 2004). Haksever and Moussourakis (2005) presented a mixed integer programming model inventory optimisation for ordering multiple inventory items subject to multiple resource constraints. Determining the optimal supply chain configuration is a difficult problem since a lot of factors and objectives must be taken into account when designing the network. Guillen *et al*. (2005) proposed a multi-objective mixed integer linear programming model to capture the complexity of this problem. By using this methodology, the trade-off between the considered objectives (Pareto curve) can be obtained not only for the nominal case, but also when there is uncertainty about some of the parameters defining the production/distribution scenario.

An efficient selection-of-the-best scheme called Sequential Selection with Memory (SSM) is proposed by Pichitlamken *et al*. (2006) to be used during the neighbourhood search. A hybrid between simulation and genetic algorithms is presented by Kochel and Nielander (2005) to define optimal order policies in a multi-echelon inventory system. Additionally, the causal relation between the inventory decision variables and process performance can be constructed using meta-models. Subsequently, the constructed meta-model can be used to determine the base-stock levels of different process stages in order to minimise the backlogging costs at warehouses and the holding costs at supply chain nodes. As an example for such integrated framework, Wan *et al*. (2005) optimised inventory levels for a three-stage SC where each production node has inventories for raw materials and products. In the same fashion, genetic algorithms can be used to generate base-stock levels while being evaluated by simulation models. This integration can be used to minimise the sum of holding and shortage costs in the entire supply chain (Daniel and Rajendran, 2005, Daniel and Rajendran, 2006).

Determining optimal values of stock levels in the stochastic environment of the supply chain is challenged by various sources of uncertainty such as the demand variability. Such demand uncertainty is addressed in Crespo Marquez and Blanchar (2004) by adding in-transit and warehoused inventories to asynchronous production and shipping lead times while optimisation is used for measure the tradeoffs between alternative suppliers. Alternatively, to cope with this uncertainty in demand, Jung *et al*. (2004) proposed a simulation-based optimisation approach that incorporates the concept of safety stock as a time-independent lower bound on the inventory level. However, a key limitation of their approach lies in the large computing times required to address business processes of increasing scope and scale, which consequently may result in more difficulties in determining the relationship between inventory decision variables and process performance.

Due to its gradient estimation capabilities, simultaneous perturbation stochastic approximation (Spall, 1998) can be used in these cases to effectively determine the optimal values of inventory stock levels (Schwartz *et al*., 2006). Similarly, infinitesimal perturbation analysis is used by Zhao and Melamed (2007) to control inventory levels in under demand uncertainty and random production capacity conditions.

Demand and production uncertainty are usually coupled with optimising more than one objective, such as total inventory cost and customer service levels. Lee *et al*. (2008) have presented a multi-objective simulation optimisation framework that integrates simulation, computing budg*et al*location and multi-objective evolutionary algorithms to optimise inventory and replacement policies. Another multi-objective inventory model is proposed by Mahnam *et al*. (2009) for a multi-echelon SC that integrates multi-objective particle swarm optimisation and simulation optimisation. Possibility theory and fuzzy numbers (Zadeh, 1999) are incorporated into their simulation model to handle the uncertainty in SCs. This incorporation has resulted in a flexible decision-making framework that allows linguistic expressions to be used for modelling the reliability of suppliers and to optimise both total inventory cost and fill rate simultaneously.

Inventory control is directly related to the quality of customer service, which is one of the key performance measures in successful SC management. Customer service levels can be computed as the percentage of times that received customer orders are fulfilled by on-hand inventory. The requirements of service levels in a multi-item, multi-echelon distribution system is studied in Caggiano *et al*. (2009) by developing a comprehensive simulation model to compute optimal fill rates over a wide range of base stock levels. In Karaman and Altiok (2009), production management is linked to stock levels in a multi-echelon SC where a simulation-based optimisation framework is developed to analyse SC performance using time averages of inventory, backorder levels and customer service levels as the key performance metrics of the SC. The metrics are then used by the optimisation algorithm to design the SC in order to minimise the expected total system costs. In Yoo *et al*. (2009), a framework is proposed to maintain customer service levels close to the target by stock levels of products at both wholesalers and manufacturers. Such trade-offs between customer service levels and total inventory cost is further detailed in Liao (2009). A summary of the literature work in inventory management is given in Figure 3-8.

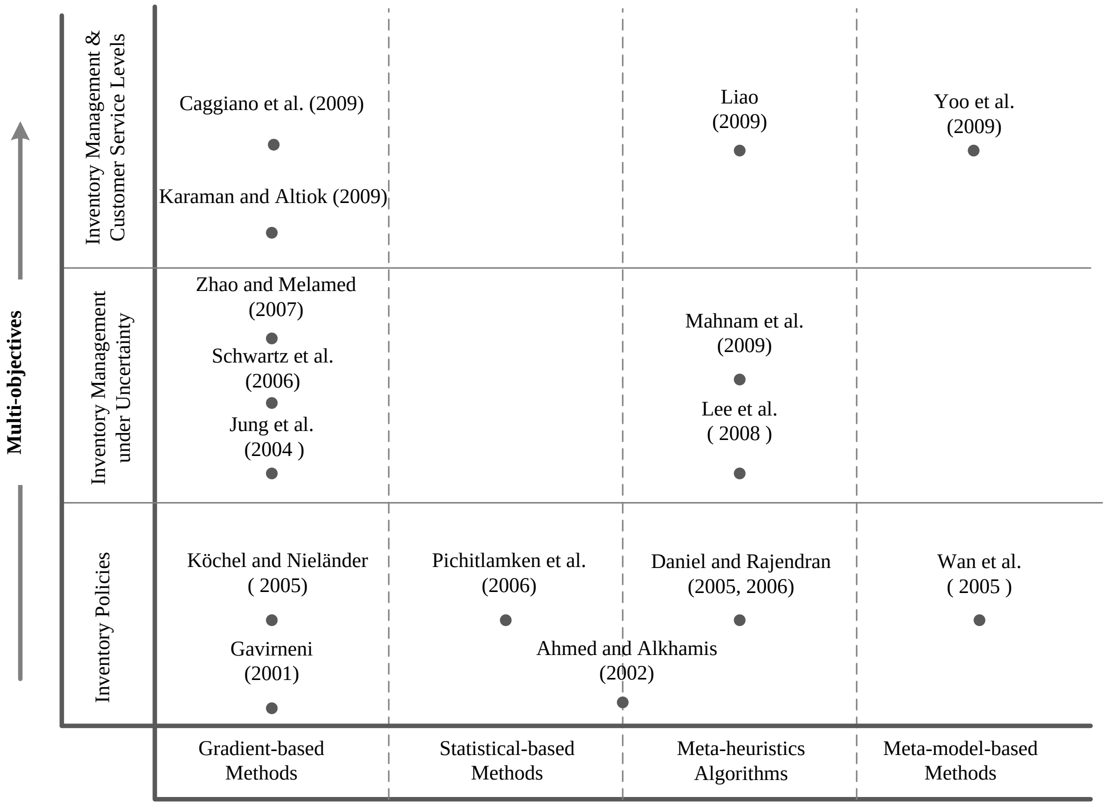


Figure 3-8 Summary of the literature in the area of inventory management

Due to the recent increase in outsourcing, the decision-making process of supplier selection has been complicated by the fact that various criteria must be considered simultaneously. These criteria has been analysed in Ding *et al*. (2005) by considering purchasing costs, transportation costs, inventory costs and total backlogged demands as the target key performance indicators (KPIs). The estimated values of these KPIs – generated by a simulation model – are used to evaluate candidates' supplier portfolios. Such portfolios are created by a GA optimiser, which continuously searches different configurations of the SC, by selecting one or more suppliers plus corresponding transportation modes. This work has been extended in Ding *et al*. (2006) by adopting a multi-objective genetic algorithm for achieving the trade-off between conflicting objectives, e.g. costs and customer service level.

Additionally, the framework addressed not only strategic decisions (e.g. network configuration), but also operational aspects of each proposed network configuration, such as inventory control parameters and transportation allocation. Koo *et al*. (2008) demonstrated another application of simulation–optimisation to support inventory and logistics decisions. The optimisation module generates values of decision variables such as safety stock levels, investment throughput, capacity investment, production cycle time and procurement cycle time, while the simulation model evaluate the performance of the system using the generated values in terms of total revenue, total procurement cost, total operating cost, total product inventory cost and customer satisfaction index.

In the healthcare context, a greedy heuristic procedure is developed by Nicholson *et al*. (2004) for managing the cost of inventory in a healthcare setting. Specifically, the authors compare the service levels and inventory costs of an in-house three-echelon distribution network against an outsourced two-echelon distribution network. A constraint programming optimisation model is developed by Little and Coughlan (2008) determining the inventory needs in hospitals constrained by various product and service levels. Their model is capable of determining optimal stock levels of products restricted by the space, delivery and criticality of the items. In Haijema *et al*. (2007), simulation is combined with Markov dynamic programming for production and inventory management of platelets at a blood bank, and Kopach *et al*. (2008) investigated multi-tier control policies for management of both urgent and non-urgent red blood cell supplies. A simulation–optimisation approach is developed in Rytila and Spens (2006) for managing blood inventory in a blood supply chain. They were able to determine the optimal inventory control of blood stock that minimise outdating and backorder costs while maintaining maximising the blood availability level. Discrete event simulation is used in Katsaliaki and Brailsford (2007) for inventory management in a blood supply chain. The model is used to determine ordering policies with the objective to minimise cost and supply shortages and wastage, and to increase service levels and safety procedures. As more hospitals added to the blood supply chain, the authors extended their work in Mustafee *et al*. (2009) by using distributed simulation to reduce the time needed to executing the model.

3.4.3 Demand and Capacity Planning

The challenges of capacity planning are common between the healthcare and supply chain domain which involves deciding how available limited resources will be allocated to meet customer or patient needs and achieve high level of service quality. Demand uncertainty makes capacity planning a difficult and challenging task, whether the uncertainty in demand is because the variations in forecasts of direct demand or by variability in the business process. Therefore, forecasting activities are widely performed for predicting important aspects such as demand volume and capacity needed.

A two-stage simulation–optimisation framework for rough-cut capacity planning under demand uncertainty is presented by Uribe *et al.* (2003) for a semiconductor manufacturer. The first stage in their framework characterises the optimal response of the manufacturing system under demand uncertainty while these characterisations are used in the second stage to select a tool set with the addition of budget constraints. A multi-scenario, mixed integer linear programming model is proposed by Gatica *et al.* (2003) for the problem of capacity planning under uncertainty that is solved by branch-and-bound technique. This optimisation-based approach selects the final product portfolio and the production planning and investment strategy simultaneously subject to the system uncertainty. The computational efforts needed by this approach are reduced by Levis and Papageorgiou (2004) by adopting a hierarchical approach. The proposed hierarchical methodology employs an aggregate mathematical formulation to determine the strategic decision variables which are then fed into the detailed model in order to derive the operational decision variables. Moreover, required labour force and machines can be predicted by building a multiple regression meta-model based on simulating manufacturing systems (Dengiz *et al*., 2006).

Forecasting activities are widely performed in the various areas of supply chains for predicting important supply chain measurements such as demand volume in order management, product quality in manufacturing processes, capacity usage in production management and traffic costs in transportation management. Jeong *et al.* (2002) presented a computerized system for implementing the forecasting activities required in supply chain management. A linear causal forecasting model is proposed and its coefficients are efficiently determined using guided genetic algorithm. A genetic algorithm is used by O'Donnell *et al.* (2006) to determine the optimal ordering policy that effectively reduced the bullwhip effect. Figure 3-9 shows the application of simulation–optimisation for the planning activities in supply chain.

Capacity planning in the healthcare setting involves deciding how resources will be allocated to meet customer needs and achieve high level of service quality. A queuing model is used by Green and Savin (2008) which addressed increasingly critical hospital capacity planning decisions. Adapted from the overflow model of phone calls in telecommunication, Litvak *et al.* (2008) presented a mathematical model for hospital capacity to treat emergency patients, where simulation is used for validating the results. A queuing model is developed by Mayhew and Smith (2008) to evaluate the emergency departments of hospitals in United Kingdom. The focus was on achieving the government mandated targets by discharging 98% of patients within four hours.

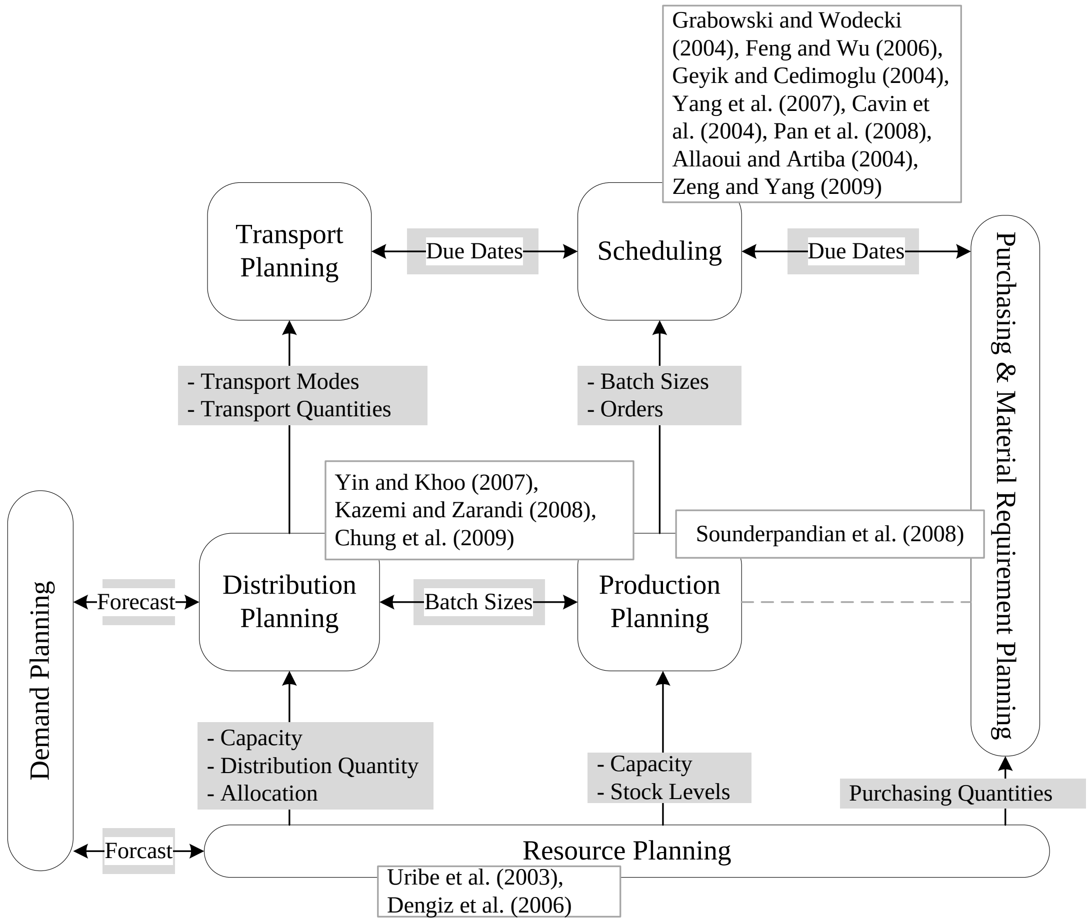


Figure 3-9 Examples of planning activities in supply chain management

A multi-objective optimisation model was developed by Lovejoy and Li (2002) to study the capacity planning problems of operating rooms. The model is integrated with simulation to perform a trade-off analysis between three main objectives: maximising hospital profit; minimising wait to get on schedule; and maximising the reliability of schedule procedure start time. A transient modelling approach using simulation and exponential functions is presented by Paul *et al.* (2006). The modelling approach allows real-time capacity estimation of hospitals of various sizes and capabilities. The parameters of the exponential model are regressed using outputs from designed simulation experiments. Surgery waiting lists were analysed by discrete-event simulation by VanBerkel and Blake (2007). They analysed performance measures for improvement and developed a model for capacity planning decisions.

A stochastic multilevel model is proposed by Oliveira and Bevan (2008) to study and identify the sources of inefficiencies in hospitals. They highlighted various inefficiencies arising from bed distributions, incentives and economies of scale of different kinds of hospitals. Kokangul (2008) provided another combination of deterministic and stochastic approaches for capacity planning problem for a healthcare system. A meta-model using quadratic polynomials is used to obtain a mathematical relationship between the control parameters (e.g., the number of admissions per day, service level and occupancy level) and size of the bed capacity using generated data from a constructed simulation model. Nonlinear mathematical models are then used to determine the optimum size of the required bed capacity based on target levels of the control parameters. Adan *et al.* (2009) optimised the resource utilisation of a cardiothoracic surgery centre. They modelled this problem as a mixed integer program having stochastic lengths of stay.

Similarly, accurate demand forecasting is essential in healthcare planning, its results providing the input to several optimisation problems. Cote and Tucker (2001) discussed common demand forecasting methods for healthcare services such as seasonality analysis, moving average, and trend line. Stepwise autoregressive and exponential smoothing models are used by Xue *et al.*(2001) for analysing and forecasting the continued growth of the end-stage renal disease population in the United States. A market-based healthcare service forecasting study is conducted by Beech (2001) from a broad range of data for estimating the future demand. The data sets include various demographic groupings, discharge utilisation rates, market size and market share by service lines. A facility master plan is developed by Myers and Green (2004) for forecasting future demand along with capacity needs and physician requirements. A comprehensive demand forecasting model is given by Finarelli Jr and Johnson (2004) for healthcare services, while Jones *et al.* (2008) used historical data of patient arrivals at the emergency departments of three different hospitals and considered different forecasting methods such as time series regression, exponential smoothing, moving average and artificial neural network models.

3.4.4 Resource and Location Allocation

Response surface methodology (RSM) has proven to be very effective to address resource allocation problems in manufacturing system. Irizarry *et al.* (2001) applied RSM to facilitate the design process, identify design settings, and optimise the operating factors such as maintenance policy, quality policy, lot size, number of operators. Different Tabu Search (TS) strategies has been investigated by Grabowski and Wodecki (2004) and Geyik and Cedimoglu, (2004) for job-shop parameters for an efficient resource allocation.

A large body of publications in healthcare addressed various issues concerning resource management and location selection, both for healthcare services and medical material. An integer programming model, combined with simulation, is developed by Zhang *et al.* (2008) for allocating operating room capacity with the objective of minimising inpatients' length of stay. The optimal location of healthcare facilities in rural areas is modelled by Rahman and Smith (1999) as a maximal covering location model. The model was solved by heuristic methods. An integer programming model was developed by Branas *et al.* (2000) for a trauma resource allocation problem. The objective of the model was to maximise coverage for severely injured patients. The planning issues hospital location and service allocation is further discussed by Chu and Chu (2000) where a goal-programming model was developed for supply and demand matching. With the goal of maximising coverage for the low-income population, Marianov and Taborga (2001) addressed the location planning for public healthcare centres. Verter and Lapierre (2002) formulated the preventive healthcare facilities location as a mathematical programming model.

A multi-objective decision-support system is developed by Stummer *et al.* (2004) for determining locations and sizes of the medical departments in a hospital network. The objective of the model was to minimise the total costs associated with location-allocation in the hospital plan; the total travel costs incurred by the patients; the number of unit moves necessary to restructure the current allocation; and the number of rejected patients. A simulation model is developed by Harper *et al.* (2005) for the geographical allocation of healthcare services locations. The model considers the necessary resource capacities, variability in patient needs and travel considerations.

A comprehensive overview of blood banking supply chain is presented by Pierskalla (2005) where blood banking locations are addressed. Specifically, they analysed how many community blood centres should be in a region and where they should be located; how supply and demand should be coordinated; and how donor areas should be covered by community blood centres. Daskin and Dean (2005) reviewed location set covering and maximal covering models for addressing the location planning issues in healthcare. Additional location planning problems are discussed by Aaby *et al.* (2006) using simulation modelling. The spatial distribution of the transplant centres is investigated by Bruni *et al.* (2006) using a location model based on mathematical programming. The strategic goal of achieving regional equity in healthcare was considered by allocating transplantable organs across various regions using the proposed model. A mixed integer programming model is presented by Cote *et al.* (2007) for locating new treatment units. The objective of the model was to minimise the patient travelling time, and treatment cost.

Ndiaye and Alfares (2008) have developed a binary integer programming model to determine the optimal locations of primary healthcare units with special consideration of seasonally varying demands. Smith *et al.*, (2009) considered both top-down and bottom-up hierarchical location models for the efficient planning of community health schemes. They proposed a mixed integer programming model for determining the locations of maximal number of sustainable healthcare facilities. Murawski and Church (2009) consider the problem of improving health service accessibility by upgrading links to the existing facility locations of the transport network to all-weather roads. Their integer-programming model is adequate for rural areas of under-developed countries where, during bad weather conditions, accessibility is diminished because of the lack of all-weather roads. Their model addressed a real-world problem scenario in Ghana. More recently, the work by Zhang *et al.* (2009) addressed preventive healthcare facilities network design, regarding the number of facilities and their location, with the aim of maximising the participation of the population in preventive healthcare programmes.

3.4.5 Vehicle Routing

Optimising product delivery from suppliers to customers by vehicles is known as the vehicle routing problem (VRP). A hybrid between tabu search and genetic algorithm is developed by (Tan *et al*., 2001) to solve a vehicle routing problem. The objective in that study was to find optimal route for vehicles that serve a number of customers within predefined time windows at a minimum travelled distance, considering the capacity and total trip time constraints for each vehicle. Tabu search is also investigated in Fu *et al*. (2004) as a way of solving a special kind of VRP called Open-VRP, where vehicles have to revisit their assigned customers in the reverse order. In Tan *et al*. (2006), a hybrid multi-objective evolutionary algorithm (HMOEA) is developed with the objective of minimising the routing distance and the number of vehicles required.

A hybrid multi-objective evolutionary algorithm (HMOEA) is applied to find the Pareto optimal routing solutions for such TT-VRPs. Another genetic algorithm is presented in Lacomme *et al*. (2006) based on the Non-Dominated Sorting Genetic Algorithm (NSGA) for the bi-objective capacitated arc routing problem (CARP). Both the total duration of trips and the duration of the longest trip (make-span) are to be minimised. Zheng and Liu (2006) developed a hybrid intelligent algorithm that integrates simulation and genetic algorithms to minimise the total travel distance of all vehicles.

A hybrid approach between simulation and multi-objective evolutionary algorithms (MOEA) is discussed by Tan *et al*. (2007) for solving a vehicle routing problem under demand uncertainty. In their framework, MOEA searches and generates routes while simulation is used to evaluate the costs of routes in terms of travelling distance, driver remuneration and number of vehicles required. Fuzzy variables are used in Erbao and Mingyong (2009) to deal with uncertainties in demand by integrating simulation and evolution algorithms to minimise the total travelled distance for vehicles. A summary of reviewed articles on vehicle routing problem is given in Table 3-4.

Table 3-4 Optimisation of vehicle routing problems (VRPs)

Author(s)	**Optimisation Algorithm**	**Objective Functions**
Fu et al. (2004)	Tabu Search	Number of vehicles Total travelling cost
Tan et al. (2006)	HMOEA	Number of trucks Routing distance
Lacomme et al. (2006)	NSGA	Total trip duration Longest trip (make-span)
Tan et al. (2001)	Tabu Search Simulated Annealing	Total travelled distance
Zheng and Liu (2006)	Genetic Algorithm/Fuzzy	Total travelled distance
Tan et al. (2007)	MOEA	Total travelled distance Number of vehicles Driver remuneration
Erbao and Mingyong (2009)	DEA/Fuzzy	Total travelled distance

Similarly, optimising the location and routing of emergency vehicles is very critical for efficient delivery of healthcare services. The issues of planning mobile health services are addressed in Hodgson *et al.* (1998) by developing a covering tour model. In their approach, the problem is formulated using integer linear programming model where heuristics methods are used with the objective to minimise mobile facilities travel distances and maximise the coverage area for the population centres within a certain feasible range.

Ambulance service planning and routing is discussed in Henderson and Mason (2005) where a simulation and analysis software tool is investigated for that problem. A fuzzy multi-objective model is presented in Araz *et al*. (2007) for determining the best base location of a limited number of emergency vehicles. The objective of that model was to optimise service levels in terms of maximisation of the population covered by one vehicle; maximisation of the population with backup coverage; and minimisation of the total travel distance. Akjiratikarl *et al*. (2007) proposed particle swarm optimisation for home care worker scheduling to minimise the total distance travelled subjected to the capacity and time constrains.

More near to optimal solutions to solve routing problems for a mobile healthcare facility can be obtained by the combination between Pareo ant colony optimisation and multi-objective genetic algorithms (Doerner *et al*., 2007). Multiple vehicle pickup and delivery problem is considered by Lu and Dessouky (2007) with objective of minimising the total travel cost and the fixed vehicle cost. The problem is formulated an integer programming problem. A branch-and-cut algorithm is developed to optimally solve the problem. A facility location model for ambulances is developed by Ingolfsson *et al*. (2008) for minimising the number of units needed for performing at pre-specified service levels. They incorporated uncertainties and randomness into their convex optimisation mode.

A fixed-charge transportation problem is considered in Jo *et al*. (2008). The problem is modelled as a network model that is associated with additional fixed cost for establishing the facilities or fulfilling the demand of customers. Tree-based genetic representation methods are employed as representation methods to solve the problem. A synopsis of the literature on aforementioned application areas is given in Table 3-5.

Table 3-5 A synopsis of literature on optimisation methods for process management.

		MH	MM	GB	MP
Capacity & Demand Planning	**-**	Jeong *et al*. (2002), O'donnell *et al*. (2006)	Xue *et al*. (2001), Jones *et al*. (2008)		Gatica *et al*. (2003), Levis & Papageorgiou (2004), Green & Savin (2008), Mayhew & Smith (2008)
	DES		Dengiz *et al*., (2006), Paul *et al*. (2006), Kokangul (2008)	Uribe *et al*. (2003)	Litvak *et al*. (2008)
Resource & Location Allocation	**-**				Branas *et al*. (2000), Verter & Lapierre (2002), Cote *et al*. (2007), Ndiaye & Alfares (2008), Smith *et al*. (2009)
	MP	Grabowski & Wodecki (2004), Geyik & Cedimoglu (2004)			
	DES		Irizarry *et al*. (2001)	Harper *et al*. (2005), Aaby *et al*. (2006	Zhang *et al*. (2008)
		MH	**MM**	**SB – GB**	**MP**
Logistics & Inventory Management	**-**	Swaminathan (2003), Lapierre & Ruiz, (2007), Kochel & Nielander (2005)			Haksever & Moussourakis, 2005), Guillen *et al*., 2005), Rauner & Bajmoczy, 2003)
	GB				Engell *et al*., 2004)
	DES	Ko *et al*. (2006), Ko *et al*. (2006), Silva *et al*. (2009), Daniel & Rajendran (2006), Crespo Marquez & Blanchar (2004), Lee *et al*. (2008), Mahnam *et al*. (2009), Liao, (2009), Ding *et al*. (2006), Koo *et al*. (2008)	Wan *et al*. (2005), Yoo *et al*. (2009	Ahmed & Alkhamis (2002), Pichitlamken *et al*. (2006) , Rao *et al*. (2000), Gavimeni (2001), Jung *et al*. (2004), Schwartz *et al*. (2006)	Haijema *et al*. (2007)
		MH		**MP**	
Vehicle & Ambulance Routing	**-**	Tan *et al*. (2001, 2006), Fu *et al*. (2004), Lacomme *et al*. (2006), Akjiratikarl *et al*. (2007), Doerner *et al*. (2007), Jo *et al*. (2008)			
	MH			Lu & Dessouky (2007)	
	DES	Zheng & Liu, (2006), Tan *et al*. (2007), Erbao & Mingyong (2009)			

MH: Meta-Heuristics **DES**: Discrete-Event Simulation **SB**: Statistical-Based
GB: Gradient-Based **MP**: Mathematical Programming **MM:** Meta-Model-Based

3.5 DISCUSSION

The increased complexity of today's business processes has motivated both practitioners and researchers to develop sophisticated, mostly integrated, optimisation methods, resulting in the availability of large number of optimisation techniques. Accordingly, managers and decision makers face numerous difficulties in selecting a proper technique that best suits their needs and the problem under investigation. Improper selection of optimisation technique may result in wrong decisions being made by managers at different levels of the decision making process.

A variety of schemes have been proposed in the literature for classifying optimisation techniques. Decision variables can be used to classify optimisation methods into continuous input parameter methods and discrete input parameter methods (Swisher et al., 2000). Continuous input parameter methods include gradient and non-gradient methods; on the other hand, discrete input parameter methods include statistical methods, ordinal as compared to local optimisation) can be used also to categorise optimisation techniques into local optimisation techniques and global optimisation techniques (Tekin and Sabuncuoglu, 2004). Local optimisation techniques are further divided into discrete decision space methods and continuous decision space methods; global optimisation techniques include meta-heuristics, sampling algorithms and gradient surface methods. However, simulation models are only considered in the aforementioned classifications, which neglect other modelling approaches. Different modelling methods have to be considered to provide a consistent and comprehensive classification of optimisation methods (Beyer and Sendhoff, 2007).

There is a lack of classification schemes which consider different aspects of both the optimisation technique as well as its capability for solving the intended problem. For example, gradient-based optimisation methods are suitable for handling optimisation problems with continuous decision variables. Perturbation Analysis (PA) can estimate all gradients of the performance measure by tracking the propagation of simulation results sensitivity through the system (Ho, 1985). However, to have these tracking capabilities, a deep understanding of the simulation model is required to allow system optimisers to integrate their algorithms into the model. Simultaneous perturbation stochastic approximation (SPSA) overcomes this problem by considering the simulation model as a black box (Sadegh and Spall, 1998). On the other hand, statistical methods are effective when the number of alternatives are small (i.e., finite). Subset selection approaches are most useful when the number of alternatives is quite large. Indifference zone approaches could then be used to select a single solution alternative that is within a pre-specified difference from the true optimum. The major disadvantage of ranking-and-selection (R&S) procedures is the requirement of independence over competing solutions, which precludes the use of most variance reduction techniques. Ranking-and-selection and multiple-comparisons procedures are only powerful for optimisation when the parameter set is discrete.

Regarding scheduling and resource planning problems, these limitations of gradient-based methods and statistical techniques are avoided with more emphasis on meta-models and meta-heuristics. A key advantage of response surface methodology (RSM) is its ability to optimise objective functions with unknown variance along with high levels of uncertainty (Kleijnen *et al*., 2004). RSM can be extended to allow multiple random system responses with multi-constraints (Kleijnen, 2008). For some meta-model-based methods such as artificial neural networks (ANN), special attention has to be given to the training set to avoid over-fitting, which directly affects the meta-model predictive accuracy (Alam *et al*., 2004). The range of application domains solved by meta-heuristics is far greater than other methods. Problem-specific knowledge (e.g. non-standard goals, constraints, objectives and conditions) can be more easily incorporated into the optimisation solution process, which broadens the range of problems to which multi-objective methods are applied. Additionally, meta-heuristic algorithms can handle models with integer variables, discrete variables and/or qualitative variables; whereas continuous variables have to be approximated before the meta-heuristic is applied. More computational efforts are needed at this stage in order to increase the degree of accuracy. Meta-heuristic methods are not function optimisers. That is, their purpose is to seek and find good solutions to the problem, rather than a guaranteed optimal solution (i.e., exact solutions). Therefore, if the model is sufficiently simple, it is more efficient to use mathematical programming methods to obtain an optimal solution, rather than meta-heuristics. Obtaining a guaranteed optimal solution is challenged by the high-level of inter-connected relationships between system variables and the complexity and uncertainty imposed by an ever-changing environment such as healthcare.

Consequently, the integration of optimisation capabilities with other decision support approaches (i.e., BSC, MCDA, and simulation modelling) will provide a more harmonised automation of the managing and improvement business processes by; selecting appropriate optimisation technique(s) for the underlying optimisation problem; selecting appropriate key performance indicators to be optimised; considering the preferences of decision makers regarding their objective(s); handling multiple, mostly conflicting objectives and constraints simultaneously; using the simulation model for evaluating generated values of decision variables; and calculating the aggregated performance for optimal solutions. That potential synergy, initially informed by literature review, brought us to the framework proposed in the next chapter.

CHAPTER 4: RESEARCH METHODOLOGY

4.1 INTRODUCTION

The importance of having relevant research methodology was emphasised by Irani *et al*. (1999) based on the research problem in hand, either related to natural sciences or social sciences both with their corresponding features. However, in deciding how to conduct research or to select its methods, Robson (2002) and Bell (2005) noted that there is no definitive rule regarding how what approach one should select when doing research as it all depends on the nature and scope of research, the sources of data, and the research questions and objectives.

Integrated frameworks for managing complex healthcare business process is a relatively new topic with a limited available of data on applying integration between methods in the healthcare setting, as a consequence an inductive approach has been applied. This was followed by a deductive approach to test and validate the framework. A case study is then used as a research strategy to achieve the research objectives. Finally, several techniques for data collection are employed including observations, interviews, and historical data for the primary data and multiple source data collection for secondary data. A detailed discussion about the aforementioned steps is presented in the next sections.

4.2 RESEARCH APPROACHES

The overall aim of this research is to investigate aspects and requirements for developing an integrated decision support framework for managing complex business process in healthcare facilities. Accordingly, the nature of this research is *applied research,* where the emphasis is on producing relevant practical knowledge. According to Myers (1997), all type of research, whether quantitative or qualitative, is based on some underlying assumptions about what ‘constitutes’ valid research and which research methods are appropriate. Researchers approach their subject *via* implicit or explicit assumptions about the nature of the real world (i.e., ontology) and the way in which it may be investigated (Burrell and Morgan, 1979).

Ontology is the reality that is being investigated in research which concerns the very essence of the studied phenomena and whether ‘reality’ is of an objective (objectivism) or subjective (subjectivism) nature (Perry *et al*., 1999). On the other hand, epistemology refers to the way knowledge is perceived and acquired from real world observations (Becker and Niehaves, 2007). Epistemological assumptions are about what forms of knowledge can be obtained and whether knowledge is something that can be acquired or something personally experienced (Burrell and Morgan, 1979, Eldabi *et al*., 2002). Positivism epistemology deals with the observable reality where knowledge is driven from real observations, objectives and measurable phenomena and represented in the form of hard facts (Phillips and Burbules, 2000). On the other hand, the nature of knowledge in the interpretive epistemology is of a soft and subjective form and based on personal experience. Accordingly, to achieve the aim of this research, a mixture of these philosophies is used. The philosophy of this research can be identified as pragmatism philosophy since positivism and interpretive philosophies are integrated to satisfy all research objectives simultaneously. Using a pragmatist philosophy, the research can be carried out interpretively using the induction approach in order to determine theory or hypotheses, and after that using the stance of positivism to test the hypotheses (Tashakkori and Teddlie, 2003). Figure 4-1 shows the steps of research process utilised to achieve the research objectives.

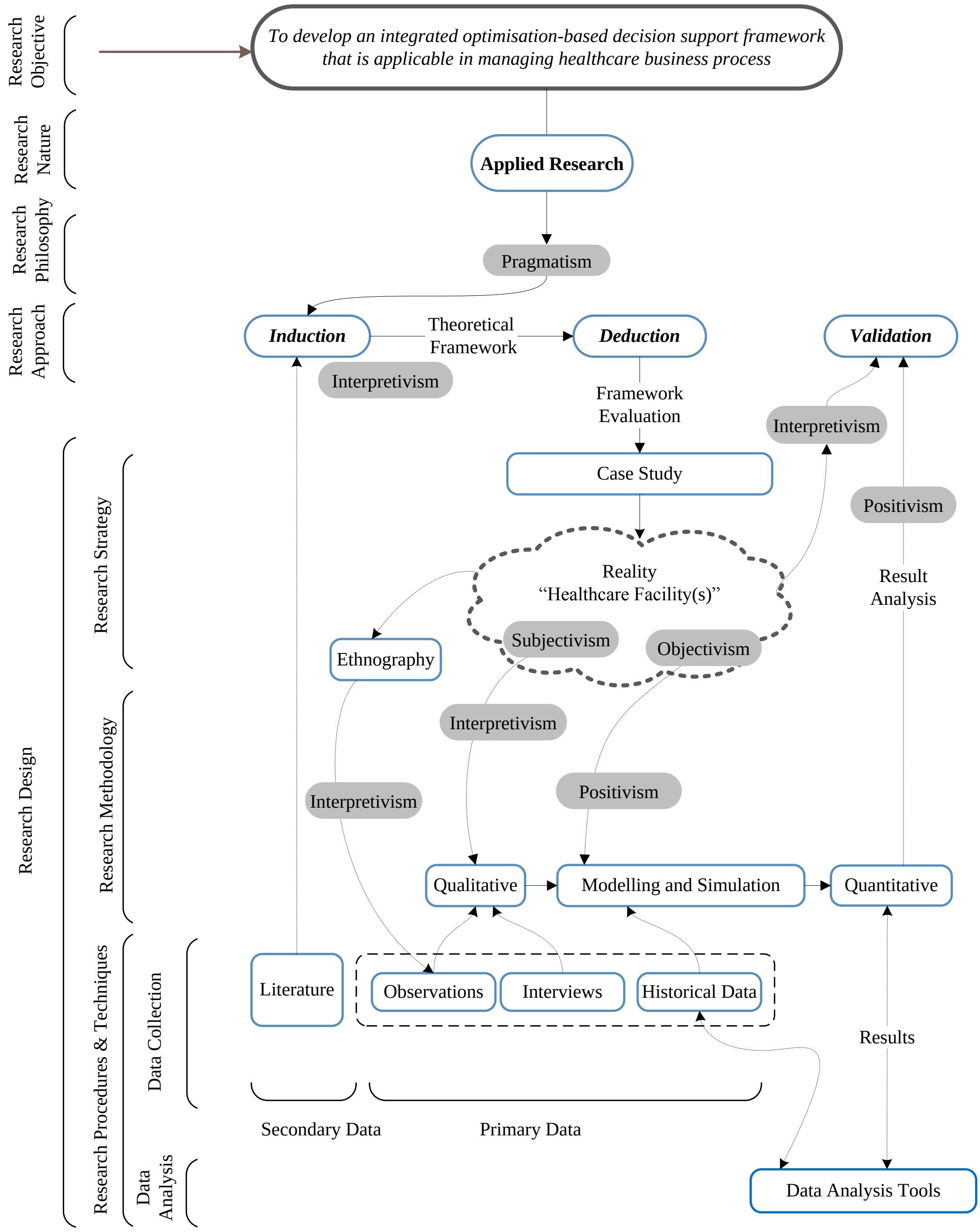
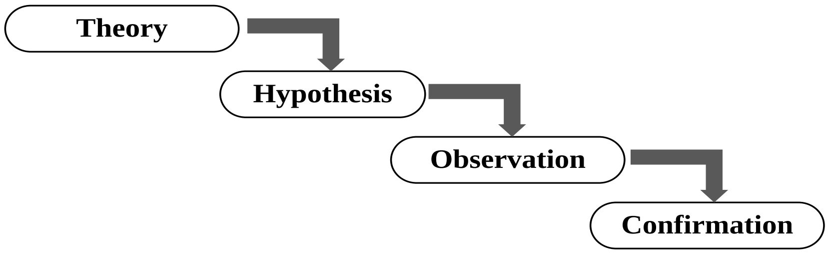


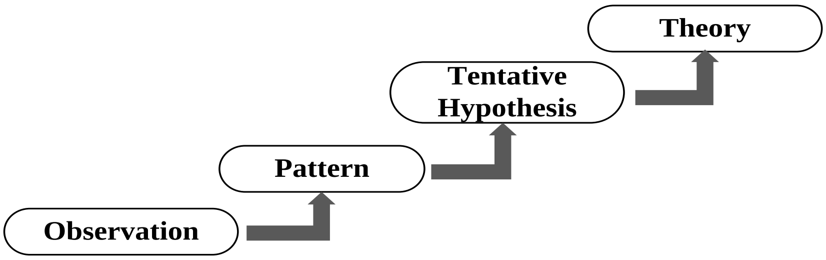
Figure 4-1 Alignment between research steps and research objectives.

There are two major approaches to theory development: deduction theory testing and inductive theory building where the deduction approach is usually based on positivism and the induction approach usually based on interpretivism (Saunders *et al*., 2009). The deductive reasoning, also known informally as 'top-down' approach, starts with the general themes, and then expands upon them with time (Trochim and Donnelly, 2001).

It begins with thinking up from broader more general about a topic of interest, which is then narrowed down into more specific statements and hypothesis that can be tested (Figure 4-2a).



a) A schematic representation of deductive reasoning



b) A schematic representation of inductive reasoning

Source: Trochim and Donnelly (2001)

Figure 4-2 Deductive and inductive reasoning.

While the inductive approach, also known as 'bottom-up' approach, moves from specific observations to broader generalisations and theories (Figure 4-2b). Accordingly, the inductive reasoning starts with specific observations, where patterns are identified and then hypothesis are formulated. Hypotheses then can be evaluated and finally come up with developing more general conclusions and theories.

In this research, the application of integrated tools for improving, managing, and optimising complex business process in the healthcare sector is a new topic, with limited data availability and guidelines on development and deployment of integrated decision support frameworks in a healthcare context. Thus an inductive approach has been applied.

Secondary data is a useful source of knowledge for the pursued research topic since it provides a wide range of related information that are basically collected and analysed by other researches or studies. It includes raw data – not processed before – or compiled data which received some kind of summarising or analysis (Kervin, 1999). Starting the research with secondary data saves a lot of time, cost and effort since research objectives can be met by reanalysing or manipulating the collected data. Many categories of secondary data are defined by several authors including documentary data, survey-based data and multiple source data (Dale *et al.*, 1988, Hakim, 1982, Robson, 2002).

In this research, literature review and other material (reports, surveys and others) are used to collect the preliminary information about managing and improving complex business process. By reviewing the literature a state of knowledge about research elements and their potential integration have been explored. The purpose of secondary data is to support the generation and refinement of the research idea and help to set study's objectives, while the second is to provide the required secondary data that contributes in achieving fowling three objectives:

1. to gain in-depth understanding of existing solution techniques for managing complex business process;
2. to highlight the relationships and common features of healthcare facilities; and
3. to explore the common challenges and problems of business processes in the healthcare setting and supply chain context.

As illustrated in chapters 2 and 3, the literature review has offered a wide view of the applications of solution techniques such as simulation modelling and optimisation and their role in managing complex business process in healthcare and supply chain context.

This was followed by an analysis of the common problems in different types of healthcare facilities, and between these problems and in the supply chain domain. Finally, research gaps are concluded and utilised to develop the integrated framework by providing a clear vision about the aspects and requirements for designing the structure of the framework and its components.

Targeting the first two research questions, an extensive literature review has been conducted systematically on business process modelling and optimisation on healthcare and supply chain. An overview of different types of problems and techniques was constructed. Through more precise scanning for the little available publications on integrated methods in healthcare management and by taking into consideration the main objectives of the healthcare system, a theoretical framework was developed to fill the gaps in the application and techniques, which is detailed in the next section.

4.3 THE PROPOSED INTEGRATED FRAMEWORK

The main objective of this research is to utilise a multi-disciplinary approach in developing an integrated decision support framework for healthcare managers and planners to use in a practical and reflective way. This section discusses the aspects and requirements for developing this framework. The integration between these methods aim to addresses the gaps in the literature as well as providing a practical guidance on managing and improving healthcare business process.

Figure 4-3 gives an overview of the framework where a detailed description of each component is provided through the next sections. Further, the coordination between these components is explained in details along with highlighting their points of integration.

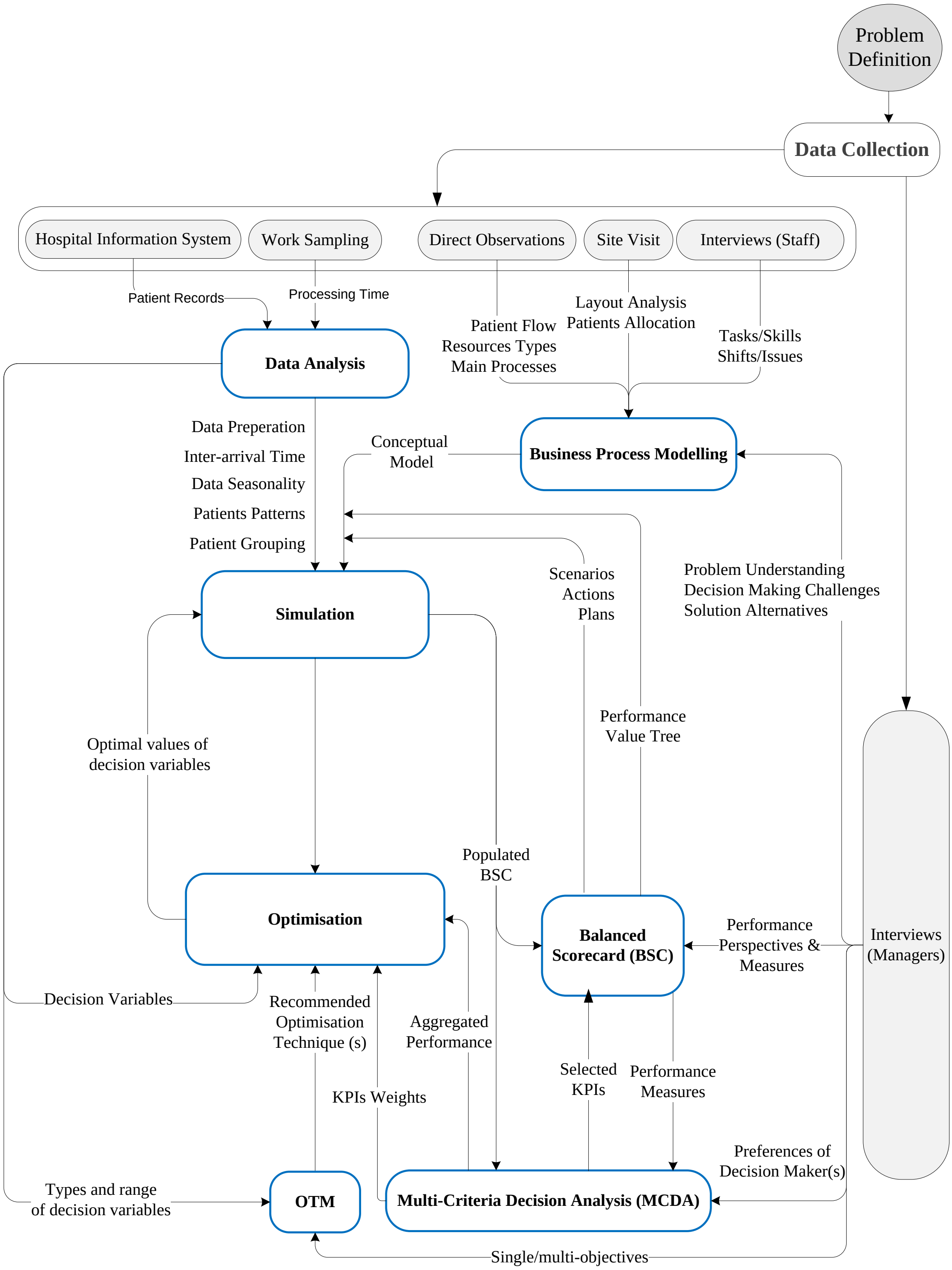


Figure 4-3 An overview of the integrated framework.

4.3.1 Business Process Modelling

Problem definition is one of the key elements in developing the framework. Healthcare systems contain a high level of social interactions that are characterised by complexity and in particular at decision points. Therefore, problems associated with healthcare service delivery and managing patient flow are usually hard to define problems. Gaining a better understanding of the healthcare process is essential for making correct justifiable decisions and providing effective solutions. Accordingly, modelling the underlined business process requires its understanding from the point of view of the individuals who are directly involved in the process of service delivery. The data collection phase combined interview method, focus group, and quality circles with experts and practitioners. This in return provided holistic insights for various system issues and aspects. The underlined business processes are then mapped into a conceptual process model using one of the well-developed modelling languages (i.e. IDEF) where sub-processes and activities are identified. The control flow definition is created by identifying the entities that flow through the system (e.g., patients, staff, and medical resources) and describing the connectors that link the different parts of the process. Finally, the resources are identified and assigned to the activities where necessary. The process model should be verified to ensure that the model does not contain errors and is logically valid.

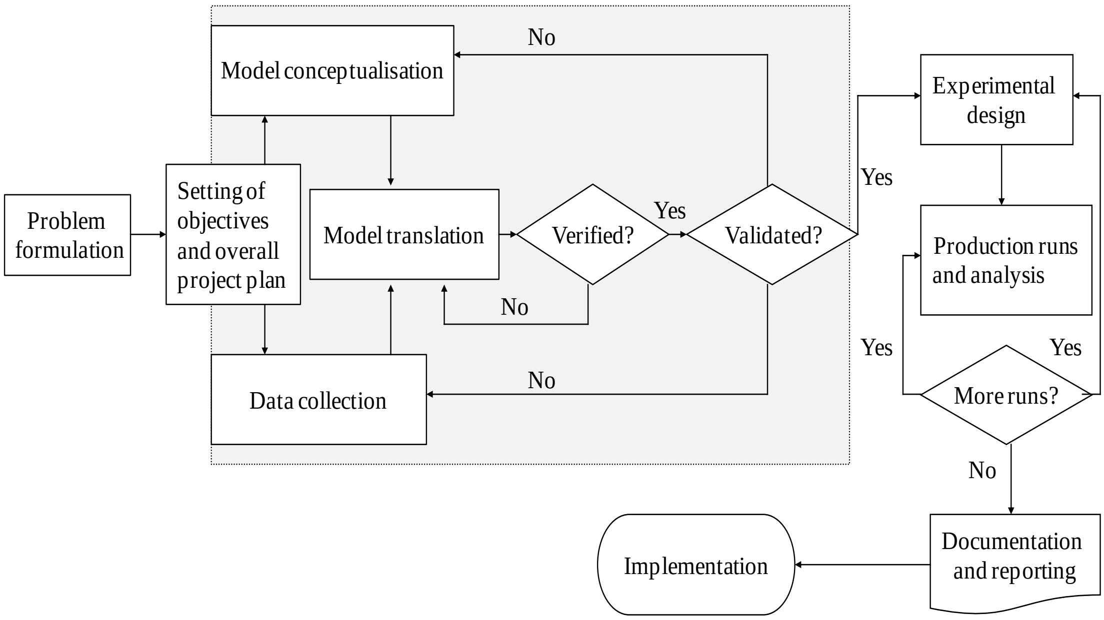
4.3.2 Data Analysis

Interviews and observations have a qualitative nature, which of a great benefit in understanding and modelling of work flow in the healthcare facility. However, to incorporate the time factor, patients records are collected from the hospital information system (HIS), including valuable information about patients and their care steps such as arrival time, mode of arrival, referral type, and time of discharge or admission. The patients data are recorded by different types of staff such as administrators, doctors, and nurses through the stages of patients care. Due to the high level of pressures within healthcare processes, hospital records sometimes lack accuracy and consistency.

Therefore, prior to extracting any set of data from these records, data mining procedures are needed to extract the trustworthy set of records. This is followed by a further analysis of the resulting records for extracting patient arrival patterns, patient groups, distributions and seasonality features. The collected qualitative data through interviews and observations are also used to build a business process model for the healthcare facility, while this model along with the quantitative data (i.e., patients records) are combined in a simulation model to dynamically analyse the healthcare process.

4.3.3 Simulation Modelling

The process models, along with the analysed empirical data are combined into a dynamic simulation model (Figure 4-4) which puts the data collection phase and business process modelling in the context of developing a simulation model.



Source: Banks et al. (1996)

Figure 4-4 Discrete-event simulation developing steps.

According to Banks *et al*. (1996), the simulation procedure starts with the problem formulation. The objective of this step is to:

- Defining the general objectives of the study
- Highlighting specific questions of interest that needs to be answered
- Ensuring and facilitating data accessibility
- Listing the key performance measures onto which the efficiency will be evaluated
- Encapsulating the scope and system configuration of the model
- Setting a time frame for the project

Once all of the issues are discussed, the modeller has got a clear roadmap with goals and milestone to accomplish. Within this stage, it is difficult to foresee all eventualities, but at least the modeller has got a general idea, as well as the stakeholders, of the outcome of the project. Alternatively, Pidd (2004) proposes a technique for problem structuring, where he assumes that the modeller faces a “mess” of which its core components can only be vaguely be described by the stakeholders. The task of the modeller is then to apply structured interview method in order to get as much information out of the “mess” as possible without influencing or manipulating the problem definition.

Accordingly, the data collection phase proceeds to gather relevant information about the underlying processes, which focuses on the retrieval of the data and also on the construction of a conceptual model (i.e., business process model). The quantitative data is either stored in computer databases, written on documents, or recorded on any type of storage medium. Access to the quantitative data may not always be easy because the content may be protected by law and other restrictions, and also because the data may be distributed over various systems. The quality of the data is also a crucial factor, as the simulation model is deeply reliant on it. The modeller has therefore to question the credibility and validity of the data. However, perfect data assemblies that are without error are rare; technical failure of automated input devices and typographical errors by those who input the data are just some reasons for flawed data. The qualitative data can be obtained *via* interviews from the experts. In the healthcare context, experts are those who work in the ED - doctors, nurses, consultants, administrators and managers. However, depending on the role of the expert the information provided may differ and be biased due to the different perspectives of the employees. Based on the gathered data from interviews and observations, the process of building a conceptual model (i.e., business process model) is initiated for application in developing the simulation model. The conceptual model is used in the simulation model for two purposes: first it is guidance for the later actual simulation model, which contains and considers a higher degree of details, and second it is used as a communication platform in order to validate the model with the experts working within the real system.

Once the conceptual model is completed, it is validated with the staff in the facility including managers and medical staff. This is essential step in the credibility of the simulation model and hence its output. Once the conceptual model is validated, the model translation phase begins, which combines the validated conceptual model and the results of the patients' records analysis. The simulation model can either be the programming of code, or modelling with the use of simulation software package, which provides the modeller with tools that are typical and essential for certain modelling. The procedure is often referred as model translation, because it describes the transformation of the abstract conceptual model into a higher detailed complex executable simulation model. Verification during the modelling phase ensures that the model logic reflects the underlying business process. The difference between verification and validation within the context of simulation modelling is that verification ensures that the transformation of the conceptual model has been applied correctly, where validation considers the representation of the model towards the system under investigation (Balci, 1997). Verification and validation is an important part of simulation modelling as these provide the techniques with which the credibility of the model can be guaranteed. Verification of the simulation model is applied by comparing the outcome data of the simulation model with the data obtained during the data collection phase. Once the simulation model is verified and validated, the decision makers can us the replicated model to investigate a number of decisions and alternatives (i.e., what-if scenarios) to foresee the consequences of these decisions. For example, design of experiments (DOE) (Kleijnen, 2008) can be used to test a number of scenarios to obtain answers of these “what-if” statements. Depending on the set up of the model and the number of the parameters, the amount of potential scenarios and experiments increases significantly due to the multiple possible parameter combinations. Following the experimental design, production runs are necessary to provide the data, which is used to analyse the simulation output, where performance measure(s) can be retrieved and compared with the system under investigation.

The final step is then to document, present, and implement the potential alternative. Documentation of the simulation result, as well of the project itself is necessary to follow and to understand the simulation results as well as for the decision making process. Because decision making is based on the results, the value therefore of the presentation should not be underestimated. There are various ways to present simulation results: written reports, graphs and diagrams, and animation. A combination of the three methods is the best suited, however, an animation will probably be best in order to visualise complex relationships within the simulation model. Thus the presentation can be used to increase the transparency of complex systems.

4.3.4 Integration of Balanced Scorecard and Simulation

Although applied in the context of healthcare management, the full potential of the BSC is not recognised due to its limitations and its implementation challenges. In order to alleviate the limitations of the BSC in terms of its measurement capabilities and the lack of inferring the causal-effect among performance measures, an integration between BSC and simulation is proposed in Figure 4-5.

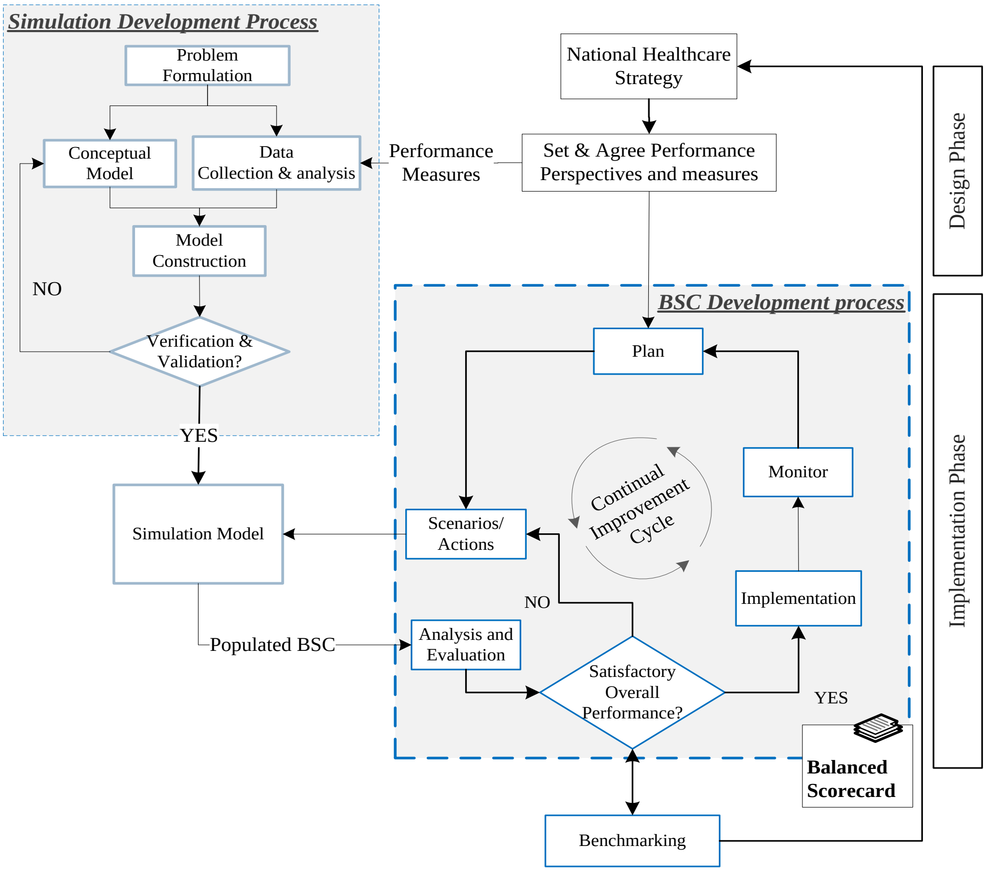


Figure 4-5 Balanced scorecard and simulation modelling integration.

Simulation modelling and BSC can be integrated at the design level and the implementation level. At the design level, the performance perspectives and performance measures collected through interviewing senior managers of the healthcare facility and based on national health strategy (e.g., HSE in Ireland). This is essential to align the performance measures of the healthcare facility (e.g., emergency department) with the strategic objectives of the national health authorities. Consequently, the simulation model will provide quantitative values of the provided performance measures where qualitative measures such as patient satisfaction can be related to measurable indicators such as average waiting time and LOS. Such integration allows the evaluation of a wide range of actions and plans based on the recommendations of national reports and surveys. These plans can then be evaluated in the form of what-if scenarios, with the results are used to populate the design BSC.

The results are then evaluated and interpreted by experts and decision makers, which provide guidance on the implementation of suggested alternatives and plans, as well as set benchmarks of the maximum performance that can be achieved using the available resources and staffing levels. Hence, more practical solutions and plans can be recommended and tested using the simulation model. Therefore, such integration between simulation and BSC helps to focus on strategic visions to obtain desired outcomes, assists in making better decisions, improves communication within the organisation, provides continual feedback on strategies, promotes adjustments to changes and assists both individuals and organisations in achieving their goals and objectives. Moreover, the capabilities of the simulation can provide interesting information about the causal-effect relationships among performance.

4.3.5 Multi-Criteria Decision Analysis

Though limitations of BSC, in terms of its measurement capabilities, are resolved by its integration with simulation, there are still challenges in the selection of the *key* performance measures. In the simulation context, these performance measures are the only inputted from a preceding process in which selection of these measures is performed. The selection of these measures is challenged by the split between different views about the key performance indicators (KPIs). Furthermore, the number of performance indicators (i.e., criteria) delays the evaluation and analysis of the results. This is due to the fact that some of these criteria are of a conflicting nature and oppose each other. Multi-criteria decision analysis (MCDA) tools play a great role addressing these challenges. In effect, MCDA can be used to overcome the selection and evaluation of the key performance measures during the design phase of the BSC. However, such integration is insufficient due to the existence of the limitations in the measurement capabilities of BSC. Consequently, to resolve these challenges, an integration of MCDA, BSC, and simulation is proposed in Figure 4-6.

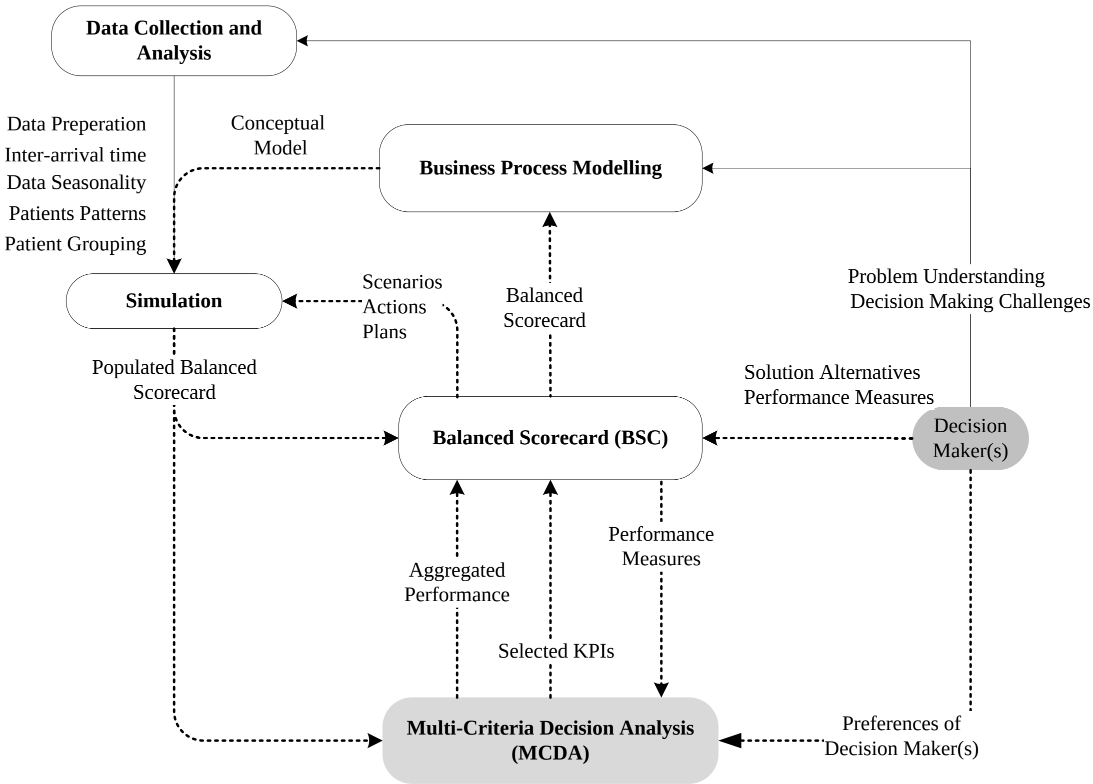


Figure 4-6 Integration of simulation, BSC, and MCDA.

In the design phase of the BSC, MCDA methods can be applied for the selection of appropriate performance measures, where decision-makers can evaluate and prioritise competitive performance measures (i.e., multiple-criteria). The selected performance measures are represented in a *value tree* that represents the selected key performance indicators. Following the KPIs selection, the resulting value tree is passed to the simulation model in the form of balanced scorecard, as explained in the previous section. Due to the large number of performance indicators in the populated BSC, MCDA can effectively aggregate the marginal performance of the indicators considering the preferences of the decision makers regarding the achievement of the defined strategic objective. This dual usage of MCDA within the integrated framework can contributes greatly in the decision making process and in making informed decisions for improving and managing healthcare business process.

4.3.6 Business Process Optimisation: Selection Dilemma

4.3.6.1 Selection Criteria of Optimisation Methods

The literature on business process optimisation has highlighted on the wide variety of optimisation techniques and their applications. Such diversity results in a selection dilemma for managers attempting to optimise their business process. Improper selection of the optimiser may result in inadequate decisions made by managers, which can have critical consequences economically as well as in the people lives, especially in the context of healthcare. Though a variety of schemes have been proposed in the literature for classifying these techniques, only few dimensions of the problem are considered. There is a lack of classification schemes which consider different aspects of both the optimisation technique as well its capability for solving the intended problem. The suitability of the optimisation technique depends on many factors related to the application as well as the optimisation technique. These factors have been identified and discussed in this section.

Optimisation Objective Function: most real-world problems, such as healthcare systems and supply chain networks, are inherently characterised by multiple and mostly conflicting objectives. There are a wide diversity of approaches that can manage multi-objectives such as Pareto-based methods and aggregate-based methods. Optimisation methods are then distinguished according to the underlined multi-objective approach.

Decision Variables Space: in a discrete space, decision variables take a discrete set of values such as the number of beds, medical equipments, locations of healthcare facilities and scheduling rules. On the other hand, in a continuous space, the feasible region consists of real valued decision variables such as throughput rates, staff utilisation, order quantity and reorder quantity in inventory problems. Equally, decision variables can be qualitative (e.g. queuing strategies) or a mixture of discrete and continuous values. Optimisation methods differ in the way they can handle these situations.

Solution Space: solution space is the space of all possible solutions that satisfy all the problem constraints. Some categories of optimisation methods are preferred when the search space is finite, for example the decision alternatives are small or the combination of variable values has a small range. Other categories of optimisation methods are more effective when the solution space is very large or infinite, which is usually associated with continuous variable space, or combinatorial problems where the combination of decision variables is invisible to be enumerated.

Modelling Approach: an optimisation algorithm interacts with the model of the underlined system or process in order to provide optimal values of decision variables. Optimisation approaches are different according to the modelling technique used, whether analytical and deterministic models (e.g., mathematical models) or dynamic stochastic models (e.g., simulation models). Therefore, the modelling approach used for modelling the system performance to be optimised has to be considered to determine a suitable optimisation technique.

Optimisation Searching Mechanism: optimisation methods use different mechanisms for searching for the optimal solution. This is highly dependent on many factors, such as the modelling approach, problem complexity and the objectives of the decision makers. The optimum solution is the vector that gives the global optimum value (maximum/minimum) of the objective function, and avoids the local optimum. Based on the reviewed articles, optimisation methods can be characterised as local search methods, global search methods or guaranteed optimal methods.

4.3.6.2 Optimisation Technique Map (OTM)

Upon the identification of the main factors that contribute to a proper selection of optimisation technique, an Optimisation Technique Map (OTM) is proposed as a classification scheme of optimisation techniques (Figure 4-7). All optimisation selection criteria are included in the classification concurrently: optimisation mechanism, decision variables, solution space and modelling approach. From the right hand side, the OTM begins with the modelling approach to classify the optimisation techniques, then decision variables and solution space are used respectively for further categorisation; on the other hand, the OTM can also be viewed from the left hand side of the figure as a classification of methods in terms of the optimisation mechanism: mathematical programming, gradient-based, meta-model-based and statistical methods, and meta-heuristics.

Adding the “optimisation objective function” to the classification scheme is shown in Figure 4-8. The horizontal dimension represents the searching mechanism of the techniques, while the vertical axis for the nature of the solution space.

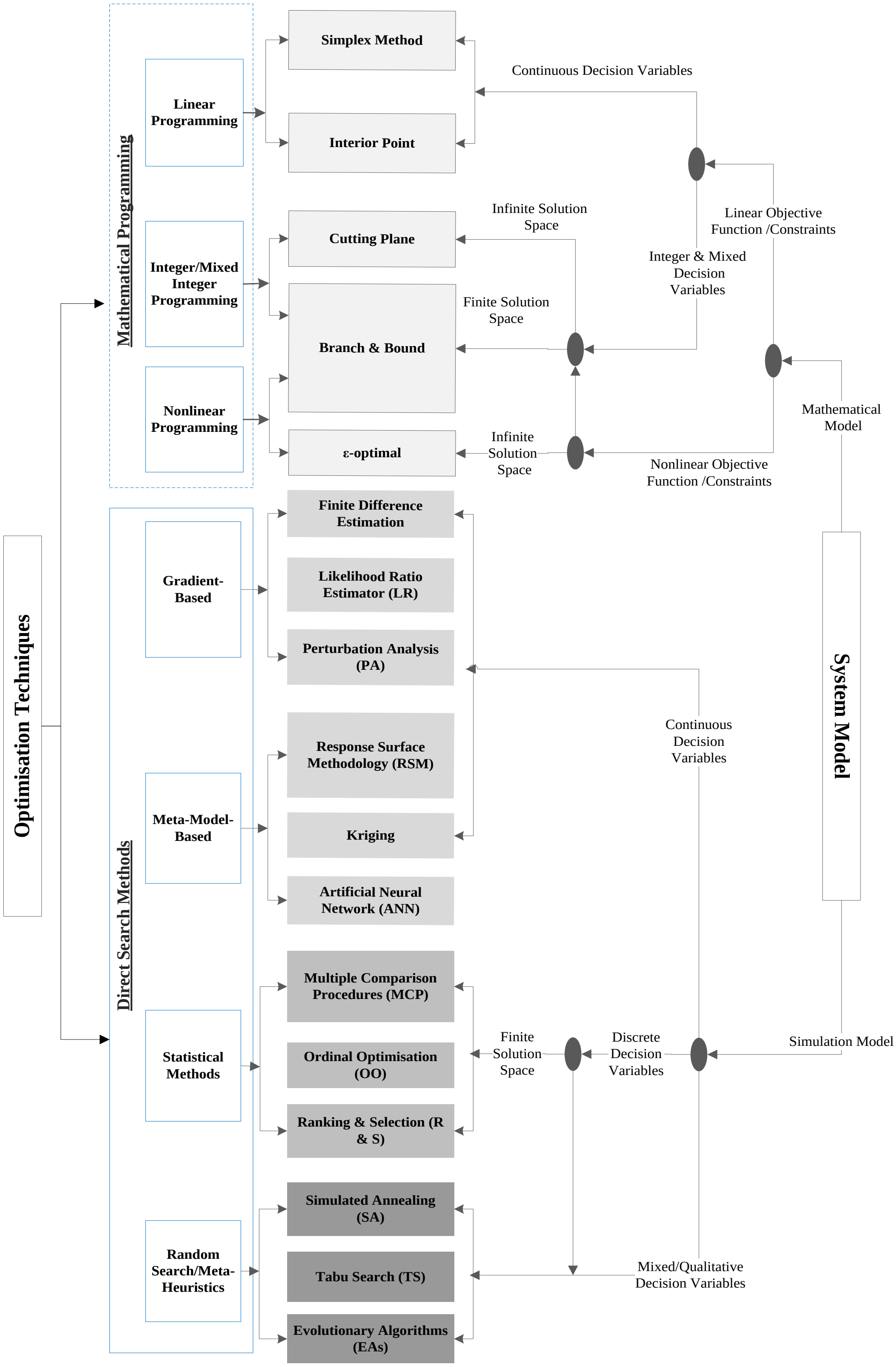


Figure 4-7 Optimisation Techniques Map (OTM).

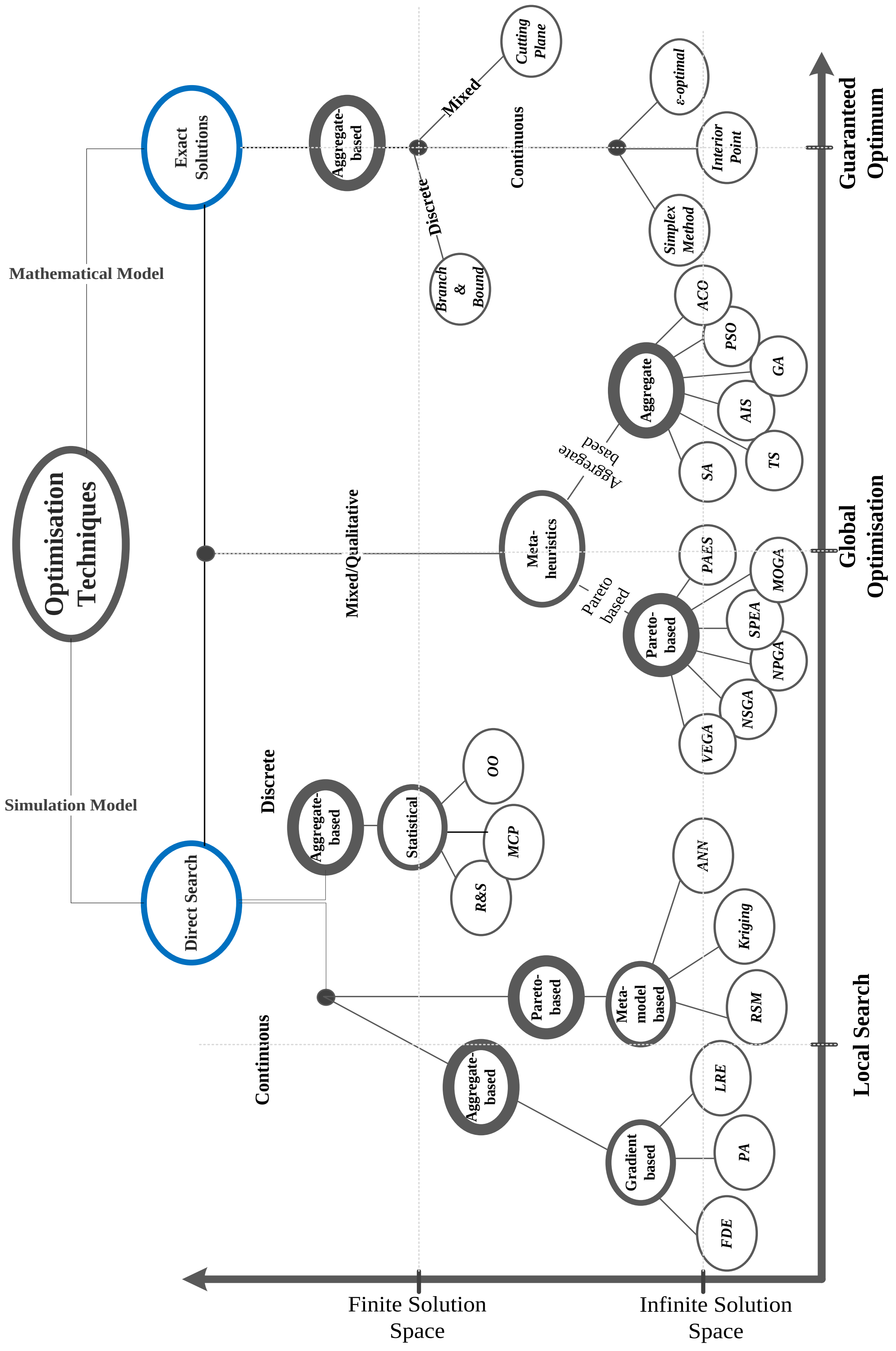


Figure 4-8 A Multi-dimension classification scheme for optimisation methods.

4.3.7 Applying Optimisation

The steps of applying optimisation within the integrated framework are shown in Figure 4-9. Prior to the optimisation, the OTM is used to select an appropriate optimisation technique for the underlying optimisation problem (e.g., capacity planning, resource allocation, and scheduling). The decision variables and its range of values are used to specify the decision variable space (i.e., discrete, continues, or mixed) and whether the solution space is finite or infinite.

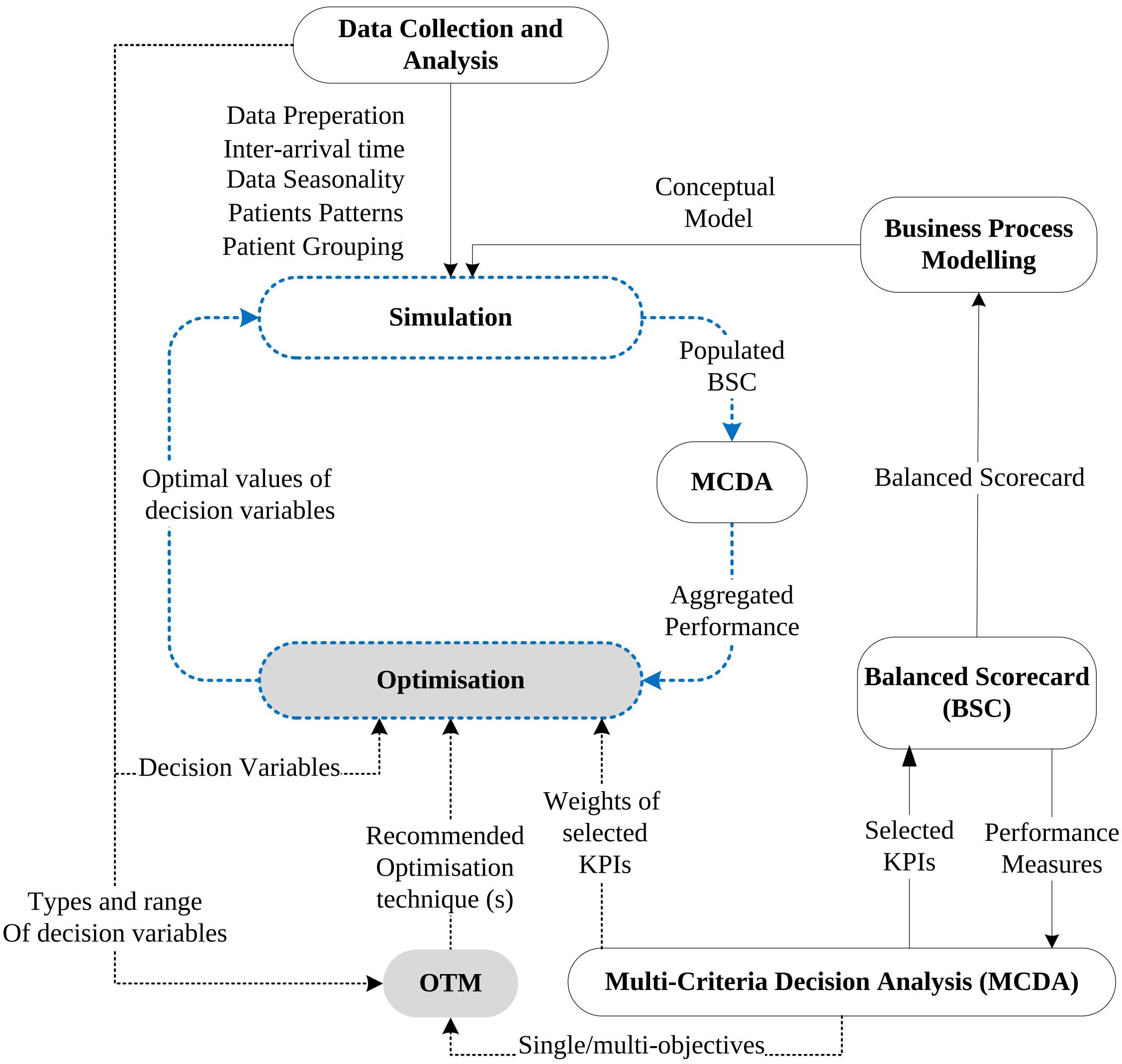


Figure 4-9 The optimisation procedure within the integrated framework.

The selected KPIs are then used, based on the preferences of decision makers, to determine whether the optimisation objective function is single-or multi-objective optimisation problem. In the case of multi-objectives, the weights of the selected KPIs can be used by the optimisation technique for calculating the aggregated performance using the weighted sum approach. Along with the modelling approach (which is simulation modelling in this study); optimisation technique is recommended for starting the optimisation process. The initial values of the decision variables (e.g., the currently used number of medical equipments or beds) are used by the optimisation technique to generate new values towards improving the objective function(s). Thereupon, the simulation runs the scenarios generated by the optimisation model and the BSC is populated with the scenario results. MCDA is then aggregating the performance using the populated BSC (i.e., value tree). The aggregated performance can then be used by the optimisation model to search for better set of values that optimise the required set of objectives.

4.4 RESEARCH DESIGN PROCESS

In order to test the propose framework, a deduction approach is needed. This is achieved by proper selection of the research design for further refinement and development, and to evaluate and validate the framework. The research design is the set of guidelines that form the connection between theory and research, ontological and epistemological considerations, and qualitative and quantitative research (Bryman and Bell, 2007). Further, the process of research design provides the link between the questions that the study is asking, the data that are to be collected and the conclusions drawn (Robson, 1994). A discussion about the design of this research is given in this section in terms of research strategies and methods. The objective is to describe the general plan that links the research paradigm of this research to the research strategies, and subsequently to research methods for collecting and analysing empirical material for the validation of the proposed framework.

4.4.1 Research Strategy: A Case Study

The choice of research strategy is guided by investigating the extent of existing knowledge base, it philosophical underpinnings, and the questions and objectives which it must address (Yin, 2008). Some of these strategies entail deductive approach, others an inductive approach. However, often allocating strategies from one approach or the other can be misleading. Moreover, one or more research strategy can be part of another strategy (Saunders *et al*., 2009). For example, the survey strategy can be used as part of a case study. Therefore, research strategies should not be thought of as being mutually exclusive.

A case study strategy is one that is used as a systemised way of observing (Weick, 1984). A case study strategy was adapted in this research for three main reasons; firstly, the ability to study a phenomena in its natural context; secondly, the possibility of undertaking a deeper investigation in a case study which can provide additional insight which is hard to capture using other alternatives, such as surveys. Finally, the case study strategy does not explicitly manipulate or control variables; rather it studies them in their context. These features are quite suitable for research into identifying an integrated framework where the aim is to perform the study within realistic settings. Therefore, the case study strategy has been employed in this research for the evaluation, refinement, and validation of the developed framework. Due to the common features and challenges between healthcare facilities, the emergency department has been chosen for this research as a case study. The characteristics and features of the ED are similar to those of other hospital departments (e.g., intensive care unit, operating rooms, and radiology department), such as high level of complexity, demand uncertainty, limited resources, and high level of human interactions. The issues of capacity planning, scheduling (staff, operations, and patients), demand planning, and resource allocation are all common between these departments. Moreover, addressing these issues usually involves multiple, often conflicting, objective such as reducing waiting times for patients, increasing efficiency, and achieving a high level of service quality. For these reasons, the ED is a typical case study in the healthcare settings, and a great deal in terms of providing answers to the research questions and to achieve the research objectives. Moreover, studying and improving the ED performance has recently increased and attracted the attention of many authors such as Coats and Michalis (2001), Tan *et al.* (2002), Samaha *et al.* (2003), Connelly and Bair (2004), Gunal and Pidd (2006), Duguay and Chetouane (2007), and Khare *et al.* (2009). A detailed description of the case study used in this research is given in the next section.

4.4.2 An Emergency Department Case Study

The university hospital partner in this research is a an acute, public, voluntary, and adult teaching hospital that holds a unique place in the delivery of healthcare not only to the community of North Dublin but also to the rest of the Republic of Ireland. This 570-bed hospital provides primary, specialised, and tertiary healthcare services, with a 24hr "on-call" ED which services over 55,000 patients annually. The department has officially, 13 monitored trolley spaces; 3 of these trolley spaces (resuscitation area) are reserved for major trauma and critical care patients. The ED also has an ambulatory care area with a capacity of six trolley spaces. Two isolation rooms, 1 psychiatric assessment room, two rapid assessment triage bays, and two triage rooms are also provided by the ED. The layout of the ED is shown in Figure 4-10.

Five distinct areas can be identified: a waiting room for walk-in patients waiting for triage, a diagnostics area (X-Ray and CT scan), an ambulatory care unit area (ACU), a ED resuscitation area (CPR) and an ED major (Majors) assessment area. Patients arrive by ambulance – usually in a critical condition – are routed directly to the resuscitation area, while patients who require their conditions to be monitored stay in the major assessment area. The ambulatory care area is for patients suffering from abdominal pain, headache, limb problems, wounds, head injuries, and facial problems (amongst all other ambulant patients).

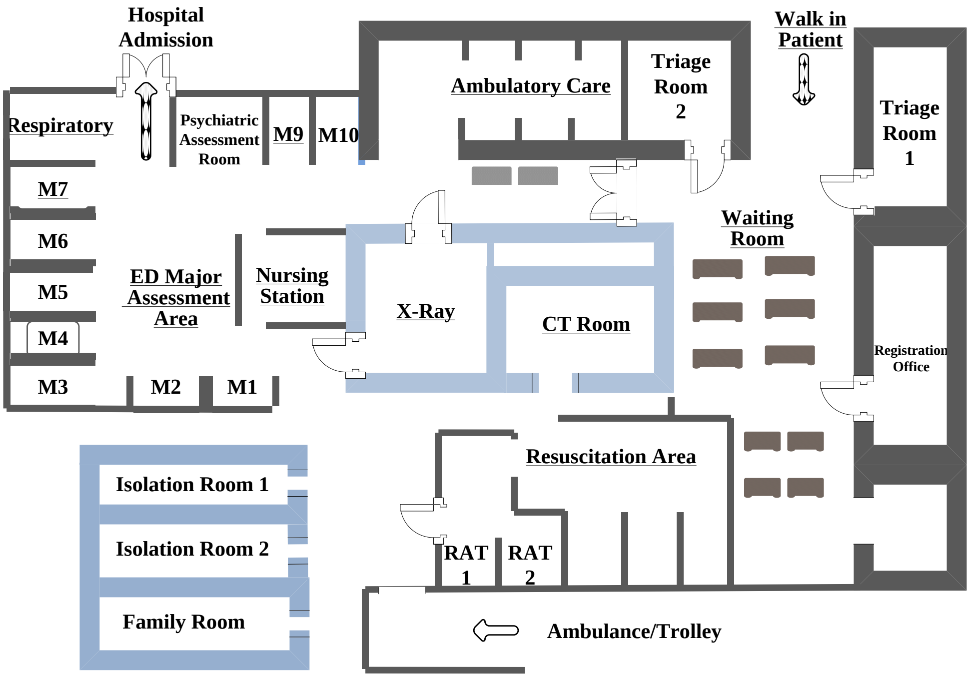


Figure 4-10 ED physical layout and main care areas.

As a 24hr department, the ED has three consultants, two nursing managers, and eleven nurses during the day and nine nurses at night which collectively are divided into six types of nurse; Advanced Nurse Practitioner (ANP), triage nurse, resuscitation nurse, respiratory nurse, majors/minors nurse, and healthcare assistant. Physicians (excluding the 3 Consultants who provide shop floor cover between 9-5 or 8-8 with 24/7 on-call provision) are divided into three types: registrar/specialist registrar, Senior House Officer (SHO), and intern that are distributed as follows when the roster allows: three registrars per day with a 10hr shift starting at 8am, 12pm, and 10pm; two interns with a one shift per day from 8am to 5pm Monday to Friday; and fixed shifts of SHOs during the day and night to keep the ED running by having more than one doctor at specific time (i.e. from 2 to 7 doctors during the day).

According to the task force report in 2007, the overall ED physical space and infrastructure is inadequate. Additionally, the partner hospital is operating at approximately 99% occupancy, according to the task force report in 2007, with resultant difficulty in accommodating surges in numbers of ED admissions. This is often aggravated by delays in patient transfer to critical care (ICU/HDC) beds. Consequently, the hospital is not compliant with volume and wait time targets (6 hour patient experience time target). The ED figures show a clear evidence of overcrowding with an average of 17% of patients leaving the ED before being seen. Moreover, the average time from registration to discharge is 9.16 hrs with 2.58 hrs standard deviation, i.e. 3.16 hrs over the HSE metric (0-6 hrs). Also, the average time from registration to acute admission is 21.3 hrs with a standard deviation of 17.2 hrs, which is 15.3 hrs above the national metric. Obviously, patients to be admitted usually experience a longer LOS than discharged patients due to the delays which can occur between admission referral by an ED doctor, bed allocation, and patient transferral from ED to the allocated bed.

Therefore, the introduction of the proposed framework has the potential to model and manage the aforementioned complexities in a cost neutral, safe and controlled environment, without the need to implement risky and potentially costly change prematurely in real systems. The advantages of modelling and simulation are further highlighted in the next section with a more focus on its usage as a research methodology.

4.4.3 Modelling and Simulation as a Research Method

Quantitative research emphasises a quantification method in the collection and analysis of data that entails a deductive approach to the relationship between theory and research and emphasises the testing of theories (Bryman and Bell, 2007). The quantitative method incorporates the practices and norms of the natural scientific model of positivism, where numbers are assigned to measurements and reality is perceived as an external, objective reality (Hussey and Hussey, 1997). While the quantitative method focuses on the meanings derived from numbers, the qualitative method emphasises on words and its meaning, which entails an inductive approach to the relationship between theory and research (Bryman and Bell, 2007). The qualitative research is then concerned with gaining an understanding of the phenomenon natural setting through observation, rather than the measurement and quantification of the phenomenon (Weick, 1984, Irani *et al*., 1999).

The underlying assumptions of quantitative and qualitative research are seen as contradictory by many authors (Burrell and Morgan, 1979) who argue that there is a mutually exclusive relationship between both strategies. For example, reality is seen objectively by positivist research and is considered measurable, controllable and explainable and therefore many researchers align the epistemology of positivism with the quantitative research (Easterby-Smith *et al*., 2002). Qualitative methods, however, has been brought together with the constructive researches since the methods can deal effectively with the human perspectives, opinions and experiences and conclude findings based on the relationship between subjective parameters (Ticehurst and Veal, 2000). However, several authors have highlighted that researchers who focus on one research approach all the time will possibly lose sight of the bigger picture (Waring, 2000). Similarly, Gable (1994) and Remenyi and Williams (1996) argue that these alternative research methods should be seen as the ends of a continuum. According to (Ticehurst and Veal, 2000), the merits and values of qualitative and quantitative business research are always aligned with different philosophical positions. Moreover, in order to address a wider range of the research aspects, it is necessary to blend quantitative and qualitative methods (Crotty, 1998).

One way to get an understanding of a phenomenon or a complex process is by directly observing it and studying its mechanisms. This delivers knowledge and understanding of how the system reacts to internal and external changes. In order to deepen this understanding, another way is to rebuild this system. Replication is done by building representative models of the original system (i.e., simulation). Once a representative model is established, controlling the parameters of the model allow knowledge to be retrieved about the system behaviour towards changes. Testing of hypotheses can then be conducted using the system model (Law and Kelton, 1991).

The procedure of developing a simulation model (described in Section 4.3.3) is considered as a quantitative method based on the positivist paradigm due to the emphasis on tangible data and results, and the causality and generalisation. However, due to the simulations flexibility to incorporate variability and uncertainty, there are major differences between simulation and other quantitative methods. Simulation, for example, can deal with the variability and complexity of business processes while conventional methods are generally linear and cannot recognise the variability that is inherent in human behaviour. Moreover, it is possible to include and generate both measurable and intangible data and results using the simulation. Generally, simulation can cope with the main limitations of conventional quantitative methods as highlighted in Table 4-1.

Table 4-1 The use of DES to cope with weaknesses of quantitative methods

Quantitative Methods	Discrete Event Simulation
Orderliness and linearity	Deals with non-linear relationships and incorporates feedback loops
Lack of concern over the influence of constraints	Ability to incorporate resources and resource constraints
Exercise in "post-decision rationalisation"	Can be used for problem structuring and discovery
Use of closed survey instrument reduces deeper understanding of what is actually occurring	Possible to include soft variables from open surveys and expert opinions
Relatively weak when used with the objective of discovery; relatively poor discoverability during data collection	Rich in discovering problems during development and processing as well
Methodology of verification rather discovery	Used for enhancing understanding and testing hypotheses
Inability of researchers to observe something without changing it	Provides rich pictures of interactions and helps in objective analysis
Positivism demands an absolute level of generalisation	Offers capabilities to model different possible scenarios
Relies on measurable evidence and therefore influences a high degree of control over the phenomenon	Able to generate measurable evidence as well as intangible evidence
Do not recognise the variability that is inherent in human behaviour	Cope with high levels of variability within/between the modelled variables

Source: Eldabi et al. (2002)

Simulation models provide the flexibility to accommodate arbitrary stochastic elements, and generally allow modelling of all the complexities and dynamics of business processes without undue simplifying assumptions (Terzi and Cavalieri, 2004). Its modelling capabilities incorporate information about problem structure and resources constraints which help decision makers to build better understanding about their processes and safer environment for evaluating and testing solution alternatives. Moreover, simulation can incorporate intangible data as part of the modelling process which is used to understand the behaviour of most complicated business processes (Eldabi *et al.*, 2002). The overall procedure of simulation allows for the retrieval of intangible information with the conjunction of the feedback from the stakeholders – that would be possible to incorporate the feedback either during the verification or the validation phase. However, simulation offers more facilities to deal with the main deficiencies of traditional qualitative methods (Table 4-2).

Table 4-2 DES coping with weaknesses of qualitative methods.

Qualitative Methods	Discrete Event Simulation
The collection and analysis of data are time-consuming and demanding because many types of data are collected	Does not require high volumes of data for development
Large variety of data may inhibit data analysis	Can be used to identify key variables to avoid unnecessary data collection
Qualitative data analysis techniques are also considered "not easy"	May rely on expert opinions for fitting available data
The inability of the researcher to interpret events from the subject point of view without biases	Capable of giving independent picture of the situation by dynamic mimicking
The relationship between theory and research can be weak, as qualitative research approaches are criticised for not instilling theoretical elements	Offers facility for adding or removing any theoretical assumptions whilst examining their impacts
The extent to which qualitative research can be generalised beyond the confines of a particular case, is questioned	It is possible to examine as many hypothetical situations(what-if scenarios) expanded from the base cases
Qualitative research does not offer the pretence of replication, as controlling the research setting destroys the interaction of variables, and therefore affects the underlying philosophy of this research method	Ability to conduct experiments with replications without destroying elements of the model
Unstructured research is endangered of being to be meaningless	The research may start as unstructured yet it becomes more refined and structured in later stages as more understanding is gained from the process
It is possible to loose detachment of the researcher, i.e. "going native"	Researcher is able to experience a simulated environment without risking to loose detachment
Potentially poor reliability, as qualitative research often involves a single event being observed by a single researcher	It is possible to produce reliable qualitative analysis, as model could be replicated and observed by different researchers

Source: Eldabi et al. (2002)

Consequently, simulation models can contain both empirical and a priori knowledge, where both inductive and deductive conclusions can be accessed in the context of the model creation (Becker *et al*., 2005). The deductive approach is a common part in the simulation modelling procedure, where a set of explicit assumptions (i.e., theories) are tested while the results of the model (i.e., observations) can then be investigated inductively (Axelrod, 2007). In all parts of the simulation process, assumptions about the "real world" (ontology) and about human cognition processes (epistemology) come into play. The development of a simulation model and the interpretation and validation of the simulation results, primarily depend on the inherent epistemological orientation of the research study (Becker *et al*., 2005).

Based on the above discussion, the simulation modelling procedure would be applicable as qualitative and quantitative research approach, where the process of modelling and simulation is developed on a sound framework which does not only provide a deeper understanding of the by-products of scientific enquiry but also of the research process itself (Eldabi *et al*., 2002). Due to the complexity of healthcare processes and the unstructured nature of the system behaviour, simulation is used in this study, where quantitative and qualitative data and results are combined.

4.5 RESEARCH TECHNIQUES AND PROCEDURES

4.5.1 Triangulation

Triangulation aims at the integration of multiple data sources in a multi-method design. The basic assumption of triangulation is that the weaknesses in each single data collection method/source are compensated by the counter-balancing strengths of another method/source (Jick, 1979). Triangulation during data collection and analysis serves two goals. First, it is proposed as a near-talismanic method of confirming findings (Miles and Huberman, 1994). In this perspective, data-source triangulation mainly reduces random measurement error (Kumar *et al*., 1993). Second, triangulation is useful in so far as different facets of the phenomenon are investigated through the most appropriate combination of method and sources (Yeung, 1995). In this way, triangulation increases the *internal validity* of the study. Practically, triangulation can be accomplished in many ways. For instance, triangulation during data collection can be performed by interviewing various respondents on the same topic, by interviewing the same respondent on a particular topic more than once, as well as by the combination of primary and secondary data sources. Analytical triangulation can be performed by using dissimilar analytical methods (between-method triangulation) or by using variations within the same basic analytical technique (within-method triangulation) (Begley, 1996).

4.5.2 Primary Data Collection

Primary data collection was commenced to satisfy any additional data required to achieve research objectives. Primary data is defined as the new data which is gathered specifically for the conducted research and has not been collected or analysed before in any other study. The collection of primary data is time and cost consuming as researchers need access to the organisations or research participants on more than one occasion to get the required data. Most research objectives are achieved using a combination of secondary and primary data, however if there are limitations in providing secondary data, the study has to rely completely on the primary data. Three basic methods for primary data collection include:

- Interviews: a conversation between two or more people in which one person (the interviewers) seeks to obtain specific information via asking a series of questions to the other person or persons (the interviewee).
- Observations: careful viewing and documenting for the studied system.
- Historical data: quantifiable data about the studies system under study.

The aforementioned data collection methods were used concurrently in the context of previously discussed case study where the data the data collection phase started in July 2008 (Figure 4-11).

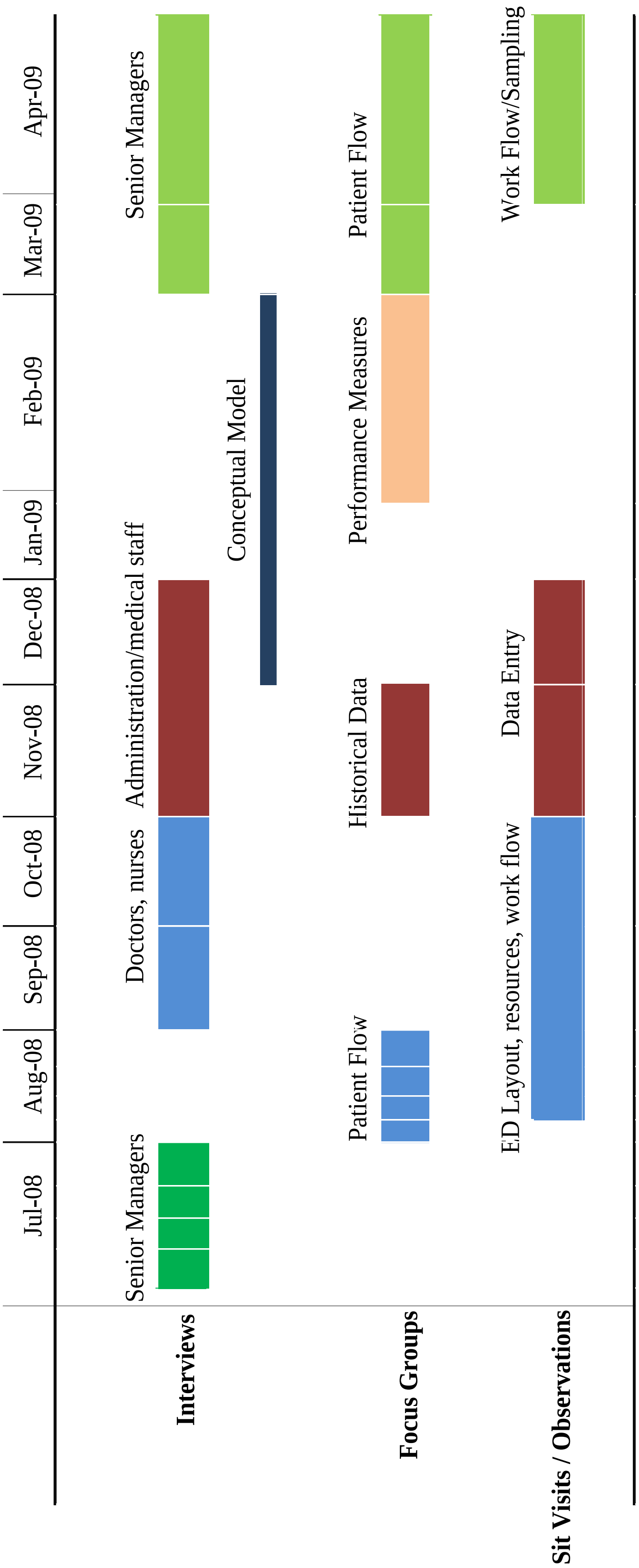


Figure 4-11 Primary data collection through the ED case study

Four preliminary interview sessions with senior managers (two ED consultants and two nursing managers) were carried out in order to get insights about the current challenges they face in managing their department. The current awareness of business process management methods (e.g., simulation modelling, multi-criteria decision analysis, and optimisation) was also a key topic in the discussions and interviews.

A better understanding for healthcare processes, activities, challenges, and variables was acquired with valuable insights of the challenges in the decision making process. The interviews helped to develop significant inputs that critically supported the development and validation phases of the proposed framework. This was followed by constructing a focus group of ED doctors (one registrar and three SHOs) and nurses (a triage nurse, one ANP, and two general nurses) where a weekly meeting was scheduled for discussing issues such as general patient care paths, categories of patients and their complexities, and resources availability and capacity issues. Meanwhile, a number of visits have been made to the ED (i.e., site visits) with an objective to analyse the ED layout that reflects how resources are allocated and utilised within the ED.

Site visits were carried out two times per week where different weekdays were selected at different hours (i.e., morning, afternoon, and night time). This was an essential step in order to observe the variability of care service demand (i.e., patient arrival) and the ED performance at different time intervals. Furthermore different levels of details about the work flow (i.e., patient flow) within the ED were collected in that stage by using two sampling methods. The first was the stationary sampling, where times are taken for specific process steps such as medical assessment time, treatment time, and lab results. The second sample method was to follow certain patients through the system and to note the processes that the patient goes through.

Upon the completion of that stage, the conceptual model phase started where the main ED processes were mapped and detailed into a conceptual process model using IDEF modelling languages. For the validation of the ED conceptual model, it was circulated among the senior managers and the patient flow focus group, where it was then refined through another cycle of interviews and observations. In conjunction with the process mapping phase, a number of interviews with ED senior managers (two consultants, and two nurse managers) has been taken place to collect information about the performance areas and performance measures. Incorporating these measures at that stage was very useful for developing the balanced scorecard for the ED and setting the objectives of the simulation model (i.e., the simulation output).

Concurrently, a focus group for historical data collection started in November 2008 to discuss issues related to electronic patients records, existing information systems, and data entry procedures. That focus group included members from the information system department in the partner hospital. The discussions with that focus group was supported a close observation of the data entry procedures through the patient journey through the ED and by a series of short interviews with the ED staff (e.g. registration staff, triage nurses, and physicians). Initially, and after the approval of the ED consultants, a sample of two months (January 2009 and February 2009) was provided by the information system department. By June 2010, a total of 59,986 anonymous patient records have been collected over a 16-month period (1st January 2009 to 30th April 2010), which was provided by hospital managers, that track the patient data during normal operations by using a real-time patient tracking information system. Each patient record is described by the different patient-level variables such as patient severity index, patient presenting medical complaint, mode of patient arrival, patient attend date/time, time patient seen by doctor, and whether the patient left without seen, discharged, or admitted to the hospital. The analysis of these data is of great value in building a model that account to the pattern of patients arrival and the demand seasonality. A detailed description about the collected data and its analysis is given in chapter 5.

4.5.3 Data Analysis

Having collecting detailed data about the studied facility, the first step is to extract information and knowledge from raw data. A number of ways of analysing case data is presented in Miles and Huberman (1994). A very common starting point is to construct a display of the data. A display is a visual format that presents information systematically so that valid conclusions can be drawn. Displays can be simple arrays, but might also be event listings, critical incident charts, networks, time-ordered matrices, taxonomies (Miles and Huberman, 1994). A number of statistical tests can be applied to check the consistency of the collected data and for the detection of outliers and missing values. Patterns in data can be extracted by discovering clusters or patterns that have similarities or differences; for example, grouping patients according to their severity levels or medical complaints. A number of considerations have to be taken in this step such as the number of combinations between groups. A similar approach is to select pairs of groups and to look for similarities and differences in terms of required resources and care services. With well quantified case data, continuous measures can be developed. This lends itself to simple analysis such as graphing and more sophisticated statistical tests such as seasonality detection and demand pattern. This can be performed on the whole healthcare process (e.g., seasonality) or at the entity level (e.g., patient inter-arrival time for each patient group). Another form of analysis is making predictions (e.g., suggested alternatives from senior managers) and then using the framework to evaluate them. This might consist of gathering, in tabular form, the evidence supporting and evidence working against a prediction and examining it.

A third method is the causal network. A causal network is " a display of the most important independent and dependent variables in a field study and of the relationships among them" (Miles and Huberman, 1994, p. 153); such as the relationships between variables and key performance measures, and inter-dependencies within variables. In the whole process, several tactics for generating meaning were used such as noting patterns, grouping, counting, making contrasts/comparisons, subsuming particulars into the general, noting relations between variables, finding intervening variables making conceptual coherence. As more knowledge became available during the course of the field work and associated conceptualisation, recurrent patterns of interaction between variables within the proposed framework started to emerge. Some variables looked to be connected, while others looked random or unconnected. A detailed data analysis of historical data and framework results is given in chapter 5.

4.6 RELIABILITY AND VALIDITY

According to Hammersley (1992, p. 67):

> *"Validity is another word for truth and reliability refers to the degree of consistency with which instances are assigned to the same category by different observers or by the same observer on different occasions"*

It is particularly important to pay attention to reliability and validity in order to evaluate the quality of the research design in case study research. According to Yin (1994) who cited Kidder and Judd (1986), reliability and validity have a number of dimensions: Construct validity, internal validity, and external validity.

Construct validity is the extent to which correct operational measures are established for the concepts being studied. As Eisenhardt (1989, p. 546) points out:

> *"We are poor processors of information. We tend to leap to conclusions based on a limited set of data, be overly influenced by individuals, ignore basic statistical properties and inadvertently drop conflicting evidence."*

Construct validity is achieved by using multiple sources of evidence (Yin, 1994, Marshall and Rossman, 1999). For this study, triangulation was employed to strengthen construct validity by using multiple sources of evidence for data collection: namely documentation, historical records, interviews, direct observations, and participant observation. Deliberately seeking confirmation from multiple data sources leads to more reliable results. *Internal validity* is the extent to which a causal relationship can be established, whereby certain conditions are shown to lead to other conditions, as distinguished from spurious relationships, while for *external validity*, establishing the domain to which a study's findings can be generalised (Yin, 1994). Accordingly, in this study, a number of validation and verification techniques were performed during the case study to validate the collected data from interviews and observations with staff and senior managers. The analysis of these data has also been validated. Moreover, the results of the framework have been validated statistically as well as qualitatively with decision makers. This is to ensure the internal validity of the framework.

The strategy of the case study method can be divided into a single case study or multiple cases. One of the criticisms of the case study method is that the results cannot be generalised, because they relate to specific situations and localities. In response, Woods (1997) and Yin (2008) argue that multiple-case studies can provide analytical generalisations. There seems to be a general belief that multiple case studies are preferred over single case studies. It is argued that more cases allows for more generalisation and eventually results in a more externally valid outcomes (Leonard-

Barton, 1990). However, this argument relies upon the inappropriate notion of potential statistical significance of multiple case study research (Dubois and Gadde, 2002). As such, the number of cases is not a quality criterion for multiple-case study research (Eisenhardt, 1989). The only argument for switching from single to multiple case study research (at the risk of losing depth) is to create more theory-driven variance and divergence in the data, not to create more of the same.

However, in the context of this study, there are many factors that strengthen its external validity. Due to the common features and challenges between healthcare facilities, the emergency department has been chosen for this research as a case study. The characteristics and features of the ED are similar to those of other hospital departments (e.g., intensive care unit, operating rooms, and radiology department), such as high level of complexity, demand uncertainty, limited resources, and high level of human interactions. The issues of capacity planning, scheduling (staff, operations, and patients), demand planning, and resource allocation are all common between these departments. In addition, addressing these issues usually involves multiple, often conflicting, objectives such as reducing waiting time for patients, increasing the efficiency, and achieving high levels of service quality. Therefore, the framework was used for resolving many of these problems such as capacity planning, staff scheduling, demand planning, and throughput analysis, which are common problems that occurs in other healthcare facilities as well as other service sectors and supply chain business processes. Therefore, it is believed that the empirical evaluation of the framework through all these phases of the case study contributes towards increased confidence in the transferability of findings to a broad range of healthcare settings.

CHAPTER 5: EMERGENCY DEPARTMENT – A CASE STUDY

5.1 INTRODUCTION

Overcrowding is widely prevalent amongst Emergency Departments (EDs) in Ireland and has reached 'National Emergency' proportions in the last decade. Emergency Departments overcrowding is an increasing feature of many healthcare systems worldwide and many of the causes are from outside individual EDs. The evidence to suggest ED overcrowding is associated with poor health outcomes for all patient groups is compelling, as is the proof that these adverse outcomes extend into the wider healthcare system.

Healthcare systems must thus constantly seek cost-effective organisational strategies to reduce ED crowding and improve patient outcomes. However, due to the backdrop of contracting national health budgets, the health service executive (HSE) aims to provide tangible reforms that can lead to better service quality and patient care experiences. As part of its strategy, HSE uses a KPI of a 6 hour maximum Patient Experience Times (PETs) to nationally benchmark quality ED care; yet complex change implementation is constrained by the necessity of maintaining concurrent safe patient-care in a cost-effective fashion. Therefore, the introduction of the proposed framework has the potential to model and manage the aforementioned complexities in a cost neutral, safe and controlled environment, without the need to implement risky and potentially costly change prematurely in real systems. Consequently, the integrated framework has been utilised to determine the best effective ―real-time strategies to improve PETs whilst the considering the difficulty in recruitment of emergency clinical staff.

5.2 EMERGENCY DEPARTMENT PROCESS MAPPING

5.2.1 Patient Flow Analysis

Upon arrival at the ED and registration, walk-in patients (self-referral or GP referral) remain in the waiting area to be triaged. When a patients name is called, depending on triage staff availability, the patient is assessed by a triage nurse. Based on the patient's condition and triage assessment, each patient is assigned a clinical priority (triage category) according to the Manchester Triage System (MTS) that is widely used in UK, Europe, and Australia (Cronin, 2003). The MTS uses a five level scale for classifying patients according to their care requirements; immediate, very urgent, urgent, standard, and non-urgent. Once a triage category is assigned, the patient may be sent back to the waiting room until a bed or trolley is available in an appropriate treatment area, based on the type and intensity of their care requirements.

The patients waiting time depends on the triage category of patient and the availability of both medical staff (i.e. ED physician or ANP) and empty trolleys, which are a prerequisite for a complete and accurate assessment. Following the patients assessment by ED clinician, a decision is made: either the patient is to be discharged or admitted to the hospital. These are the primary care stages which are relevant for all patients, whether they are discharged from or admitted to the hospital. Secondary patient stages are those steps involved in the care of some but not all patients such as diagnostics (e.g. X-Ray and blood test), and second patient assessment by ED doctor. Consultation may be requested by ED staff from a medical/surgical speciality doctor to confirm that a patient should be admitted or to obtain advice on the best possible treatment for the patient who is to be discharged. Figure 5-1 shows a detailed flowchart for patient journey through the ED.

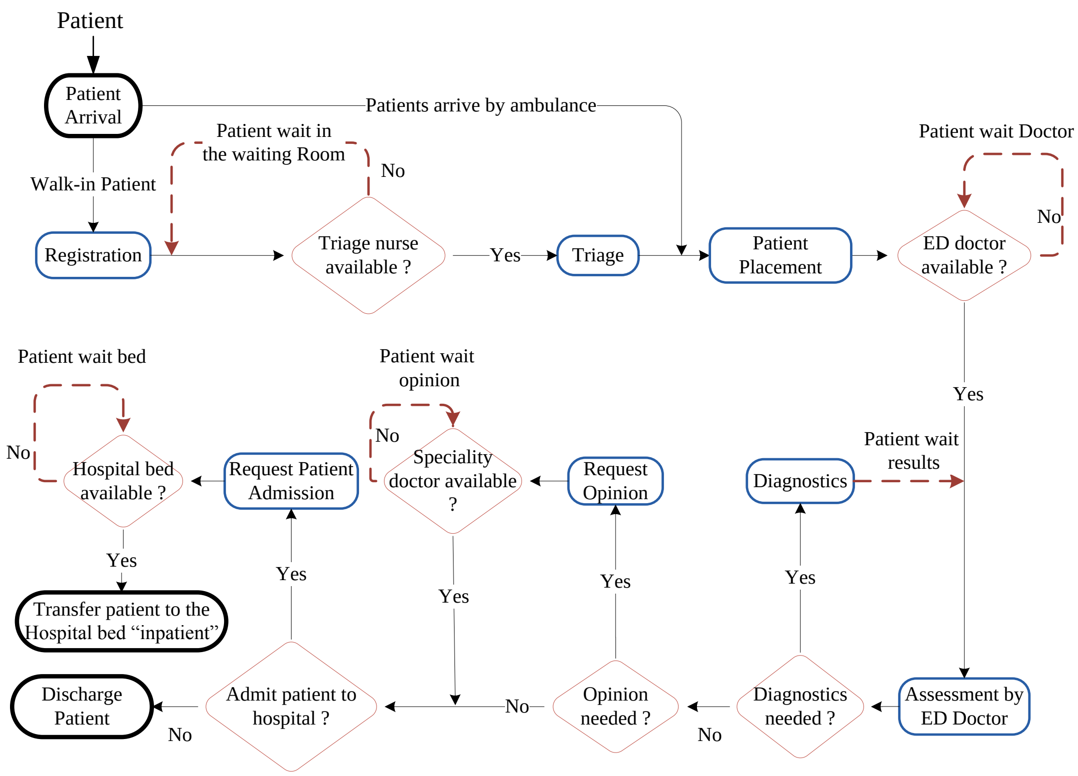


Figure 5-1 Detailed patient flow through the ED.

5.2.2 Patient Routing

The ED layout is used to represent the routes of different patient with various medical complaints and triage categories. For example, for Minor Injury (MI) patients, Figure 5-2 shows the sequence of the steps that take place upon the arrival of minor injury patient. A patient with minor injuries goes to the triage room where patients are triaged and a triage category is assigned (step 1). Then, the patient sent back to the waiting room waiting ED doctor or an Advanced Nurse Practitioner (ANP) (step 2). The triage nurse puts the patient record in a queue in the nursing station corresponding to the patient severity level (i.e., triage category) (step 3). In step 4, the ANP comes from the ambulatory care unit to the nursing station to check for new patients cards in the queue. The ANP then collects the patient from the waiting room (step 5), and then in step 6, the ANP escorts the patient to the ambulatory care unit, where the assessment process starts. The ANP orders X-Ray tests for the patient if needed (step 7, 8).

Depending on the patient condition, the patient is then discharged or waits to be admitted to hospital.

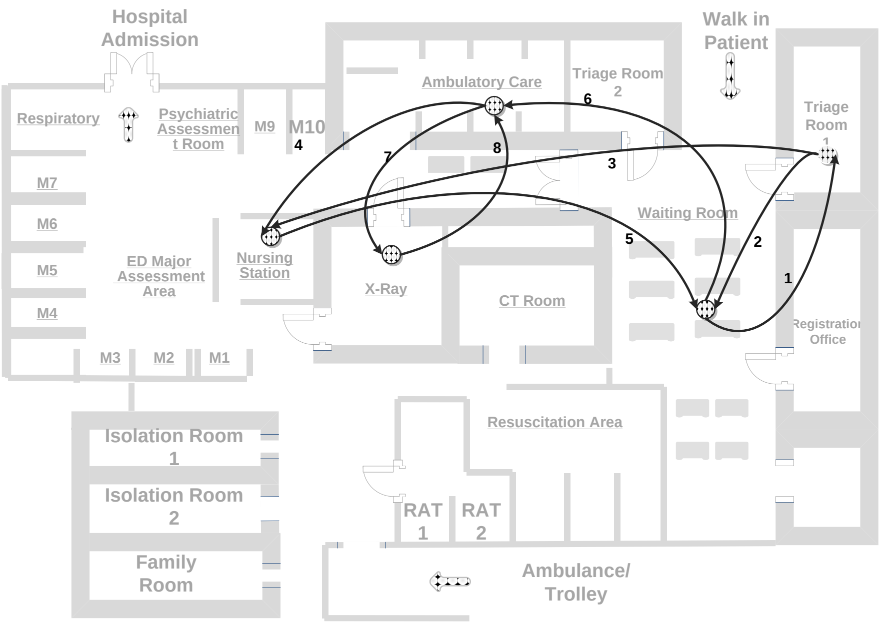


Figure 5-2 Minor injury patients routing steps.

Another example with more complications is the routing steps for patients with Respiratory Problems (see Figure 5-3). While the patient is in the triage room, the triage nurse searches for the respiratory nurse (step 1) and then back to the patient in the triage room (step 2). The patient is then move to the respiratory room (step 3), where the respiratory nurse goes to search for oxygen bottles near the CPR (step 4A) of inside the X-Ray area (step 4B). The nurse then goes back to the respiratory room with the oxygen bottle (step 5A, 5B), usually with help from the ED porters to carry the O2 bottle. The nurse then brings a respiratory mask (step 6, 7) to be used with the O2 bottle. Finally, the nurse records her notes about the patient and his/her status (step 8). In some cases, the respiratory nurse is not available, in which case the triage nurse searches for a doctor or senior nurse to assist in assessing the patient. The respiratory room may not be available, thus patient assessment takes place in another area within the ED, such as a majors trolleys, a minor injuries clinic or a trolley in the ED corridors. Similarly, the routing information about other patient care paths has been analysed and mapped by identifying the movement of patients and resources for each underlying care path.

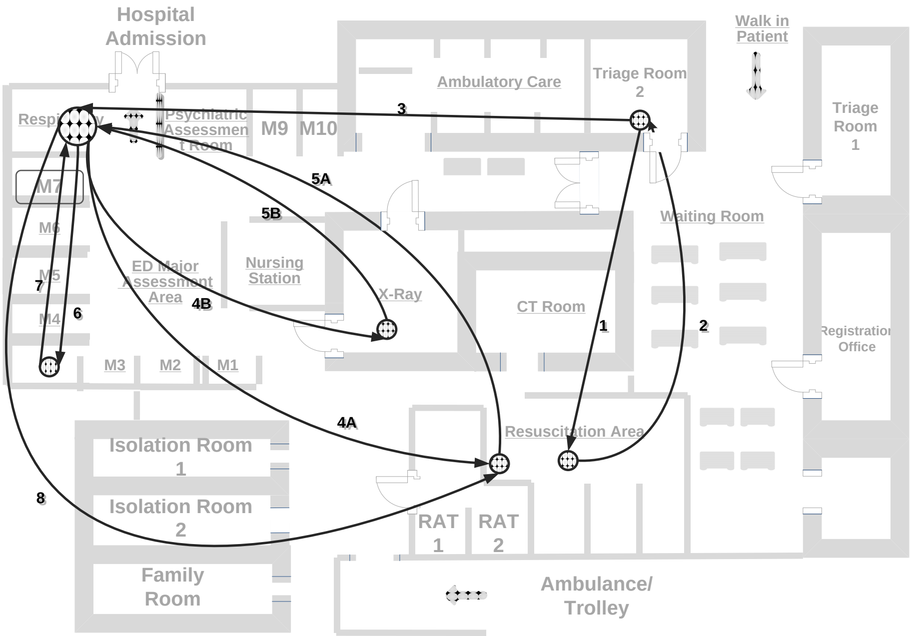


Figure 5-3 Patients with respiratory problems routing steps.

5.2.3 ED Process Mapping

Based on the analysis of patient flow through the ED, a detailed flowchart is built which highlights the common processes and decision points involved in the care of patients through the ED. Each ED process is then broken down into smaller sub-functions with key resources (e.g. staff and medical equipments) at each care stage are identified and detailed using IDEF0. IDEF0 is a powerful tool for modelling complex systems which allows users (e.g. ED managers, decision makers, system analysts) to comprehensively understand the system through modelling decisions, actions, and processes in a hierarchical form. Such an organisational strategy allows the system to be easily refined into more detail until the model is as descriptive as necessary for the decision maker (Kim and Jang, 2002). The top level of the developed IDEF0 model is shown in Figure

5-4. The main unit of an IDEF0 model is an activity block that describes the main function of the process. ICOMs (Input, Control, Output and Mechanism) are represented by horizontal and vertical arrows. Process control (top arrow) can be patient information (e.g. arrival time, triage category, and presenting complaint), safety regulations, or national/international standards whereas process mechanisms are usually the agents/resources which facilitate the activity (e.g. ED physicians, nurses, and physical beds/trolleys).

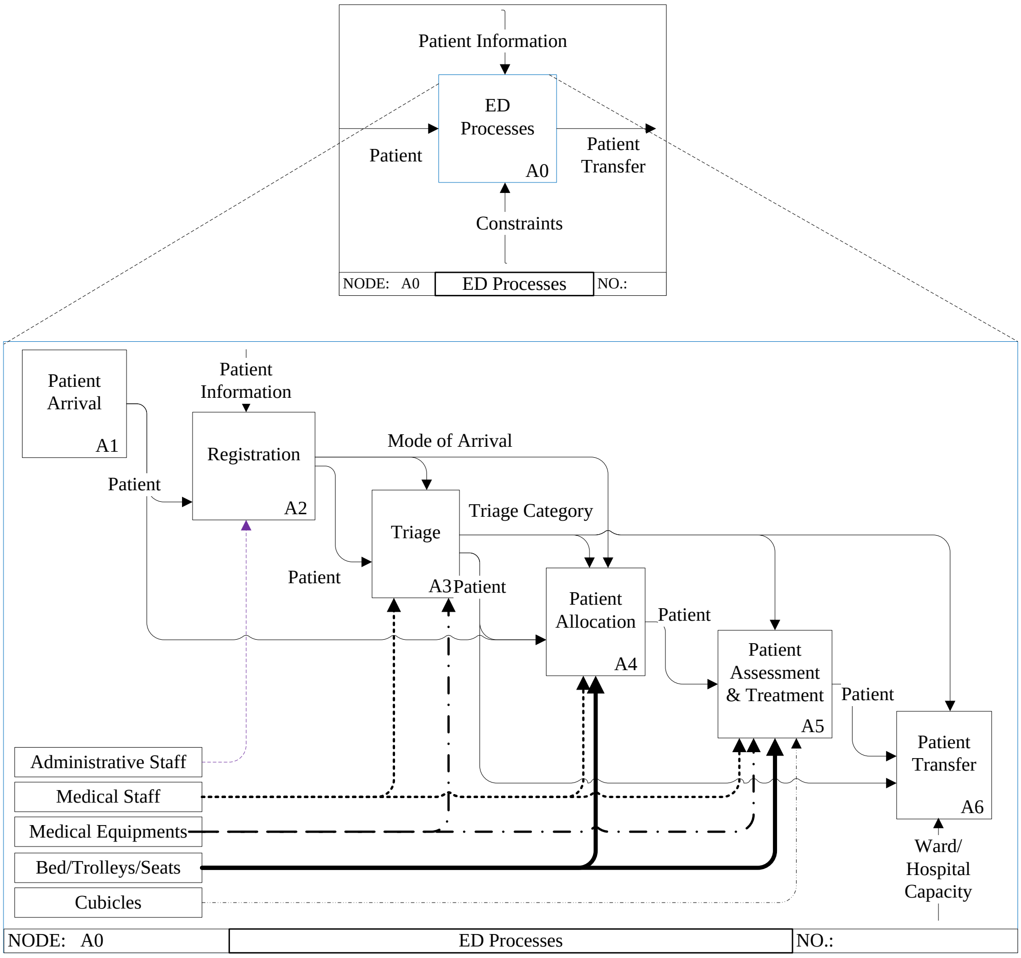


Figure 5-4 Process mapping of main ED processes.

5.2.3.1 Triage Process

The triage process is usually performed inside one of the triage rooms where a number of other activities are also performed such as initial diagnosis and assessment, blood test, patient allocation, and updating patient record (see Figure 5-5). In the initial diagnosis and assessment, the triage nurse asks the patient about his/her complaint and medical history. For each medical complaint, the nurse observes a series of discriminators to specify the triage category of the patient, which indicate the patient's severity level. These discriminators can be measured by recording some vital signs of the patient and/or verbal description from the patient. The triage nurse orders blood test for the patient if needed.

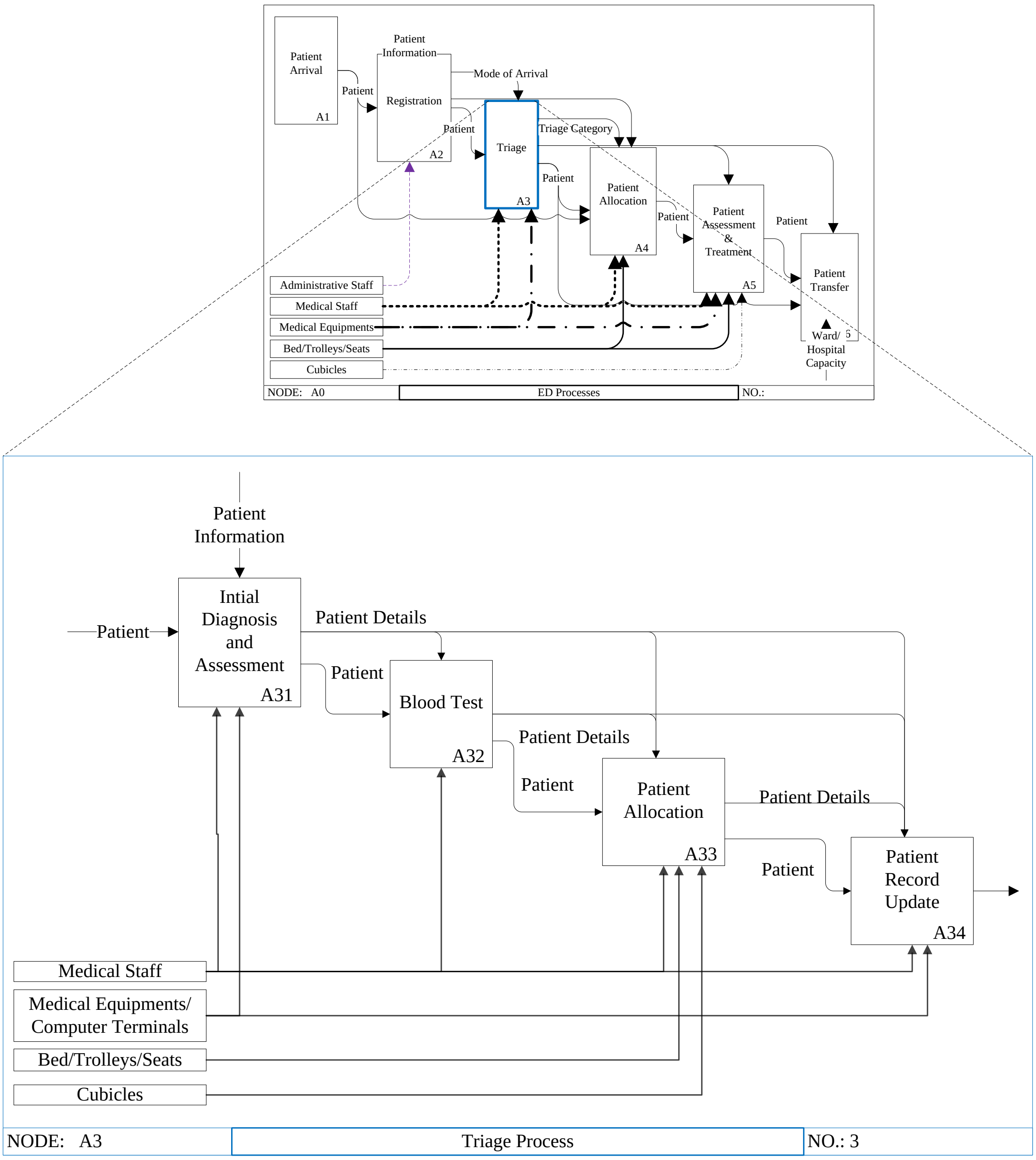


Figure 5-5 Triage process mapping.

The collected patient details along with the lab results, if available, are recorded by the triage nurse in the patient record (soft copy), which in turn is printed out and handed into the nursing area where the patient record is inserted in to a queue corresponding to the patient triage category. Meanwhile the triage nurse works on placing the patient in a proper location based on his/her severity level. The triage process can also be performed, in severe cases, by rapid assessment triage team or inside the ambulance en route to the hospital in accident and major trauma cases. There are many issues concerning the triage process. First, the triage nurse consumes a considerable amount of time searching for available place for the patient, which depends on the availability of ED resources such as cubicles and trolleys. Second, the triage nurse can also be delayed due to interruptions by patients in the waiting room asking about their turn for diagnosis or complaining about longer waiting time.

Finally, the triage nurse can give inaccurate decisions about the patient triage category, which can be altered by the doctor later on in the assessment phase. All these factors contribute to longer waiting times for patients waiting to be triaged which in turn contributes to overcrowding of the ED.

5.2.3.2 Patient Allocation Process

For patients arriving by ambulance, the allocation process is carried out by the rapid assessment triage team or by any floor nurse(s), while for walk-in patients, this process is performed by triage nurse as part of the triage process. For patients who need constant monitoring (e.g., triage category one and two), they are allocated to CPR beds or Majors area trolleys, while for less severe cases, patients are sent to ACU or wait in the X-Ray waiting area inside the ED (Figure 5-6). There are a number of considerations before sending patient to the waiting room again, for example, for patients with unstable vital signs and elderly patients, they should not stay in the waiting room and should be monitored by ED staff while they are waiting a doctor. The patient allocation process depends on the availability of ED resources and in most cases, a time consuming process, which in turn leads to delays for other patients who are waiting to be triaged or to be seen by doctor.

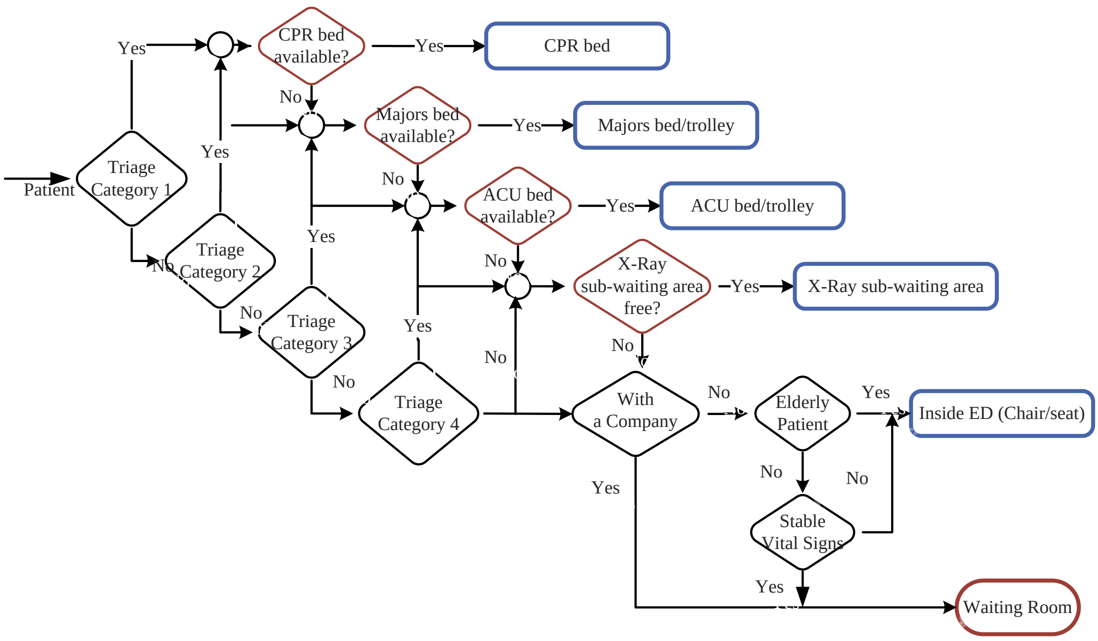


Figure 5-6 Patient allocation detailed flowchart.

5.2.3.3 Patient Assessment Process

The doctor checks the patients records in the nursing station where patients records are located in queues where each queue corresponds to a triage category. The examination process then starts where the required diagnostics (e.g., lab tests, X-Rays) are identified and ordered by the doctor. A documentation process starts after the initial assessment where the doctor writes down the information taken from the patient, medical notes, and treatment possibilities. The patient record is then updated by the doctor in a tracking system while waiting for the lab results. The final diagnosis for the patient is concluded after the arrival of lab results. At this juncture the treatment process is initiated (see Figure 5-7).

There many challenge facing ED doctors in the assessment process. Patients are usually not usually placed at the locations recorded in the patient tracking system. Consequently, the doctor starts searching for the patient in the ED after the selection of the patient records. This typically occurs due to the absence of a proper place for patient assessment not being available due to overcrowding of the ED. Thus doctors have to search for a proper location to complete the assessment process. Doctors experience delays due to insufficient resources such as computer terminals, medical equipment, and nurses. All of the above issues have to be analysed and represented using detailed flowcharts and IDEF0.

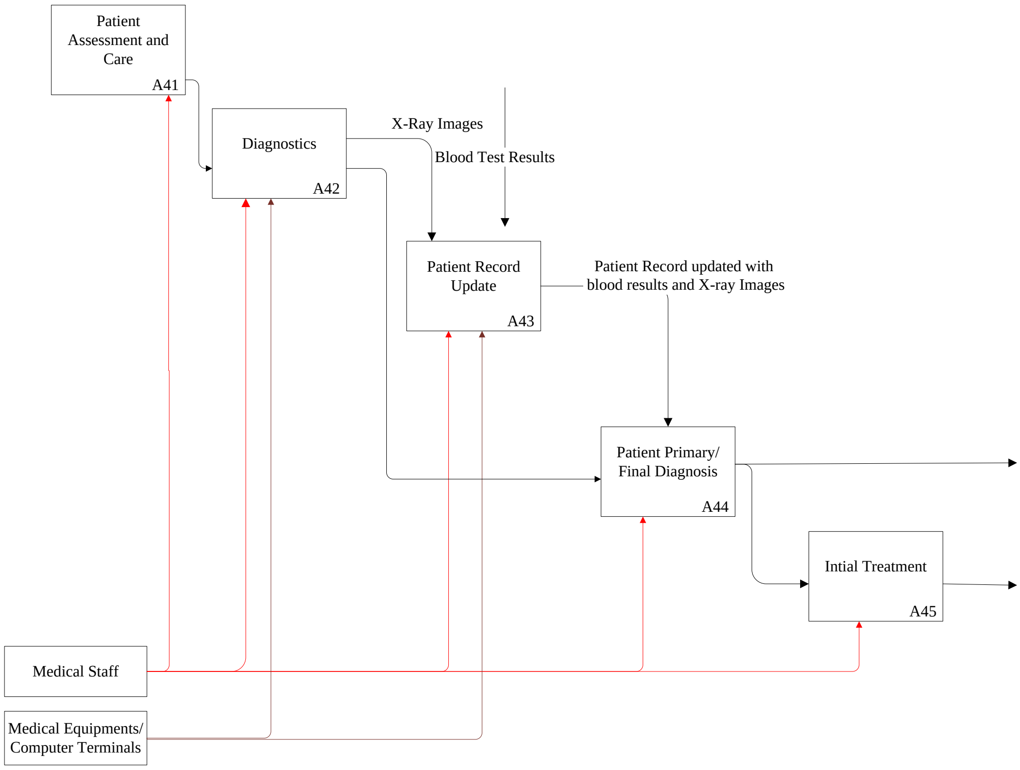


Figure 5-7 Patient assessment process mapping.

5.2.4 Discussion and Remarks

The findings of this stage have highlighted many causes of the overcrowding of the ED. Some of the causes are: the demand for emergency services exceeds the ability of the ED to provide quality care within acceptable time frames; and limited physical space to meet the timely needs of the next patient who needs emergency care. Due to the under-provision in the non-acute sectors (e.g. primary care and community care services, out of hours services, and rehabilitation services), patients who have no place to go for medical care frequently seek the ED for urgent and primary care needs, as a result, attributing to the increase in demands on emergency departments and acute admissions. Moreover, over the last decade, a significant proportion of the Irish population has aged and now exhibit increasingly chronic conditions that require emergency care services. These patients with increased complications or with several acute conditions often require lengthy and complex assessments, thus complicating the evaluation process and making it more time-consuming.

The effect of these factors is usually compounded with the shortage of physical space within the ED to cope with this increased volume of ED visits. Equally the lack of inpatients beds with the studied hospital results in a long *boarding time* for ED patients (i.e., the waiting time of patients to move from the ED to an inpatient bed inside the hospital). On the other hand, hospitals suffer from a significant shortage in experienced and dedicated nursing staff which provides the backbone of care in ED. While many of these factors are outside the immediate control of the hospital, many more are the result of operational inefficiencies in the management of the ED patient flow. In order to identify these performance bottlenecks and operational inefficiencies, a comprehensive simulation model has been developed for the ED.

5.3 EMERGENCY DEPARTMENT BALANCED SCORECARD

5.3.1 Performance Perspectives and Measures

The outcomes of the interviews, focus groups, and quality circles include the agreement on four performance perspectives that formed the ED balanced scorecard: internal ED business processes, learning and growth, patient, and community engagement perspectives (Figure 5-8).

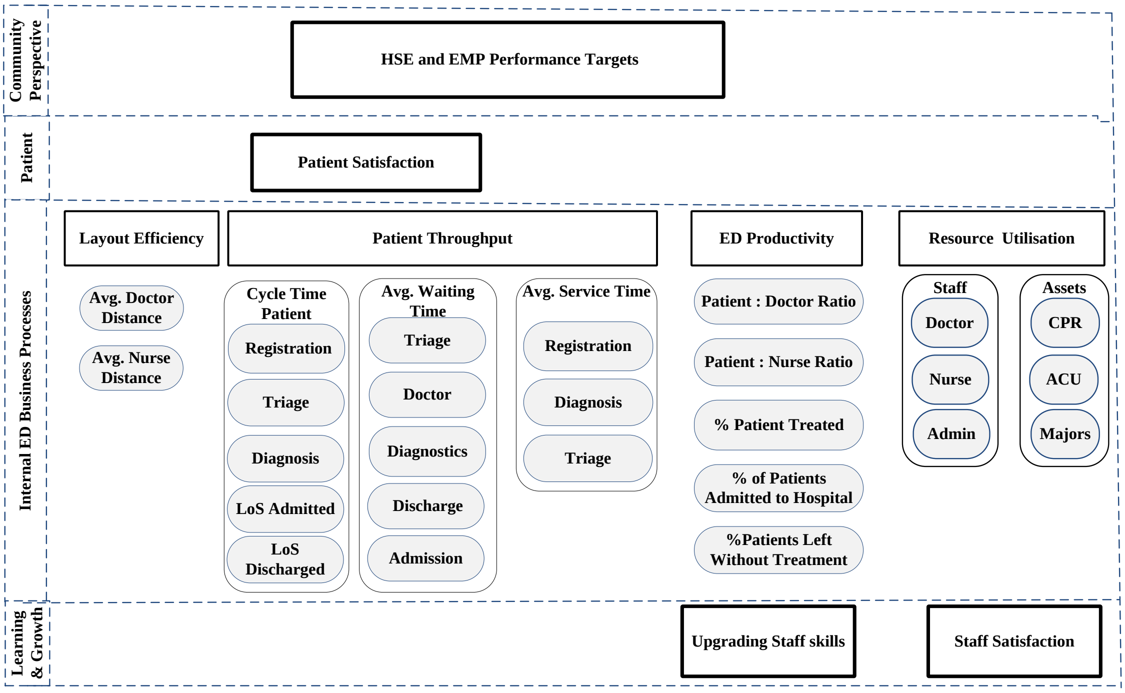


Figure 5-8 The emergency department balanced scorecard

5.3.1.1 *Internal Business Processes Perspective*

The main objective in the internal ED business processes perspective is to improve the ED performance which is driven by layout efficiency, patient throughput, ED productivity, and resources utilisation. The layout efficiency measures the average distance travelled for doctors and nurses per day, while the ED productivity is measured in terms of five indicators: the ratio of patient per doctor, the ratio of patient per nurse, the percentage of patients treated, the percentage of patients admitted to the hospital, and the percentage of patients who left the ED without treatment. The resources utilisation further measured for two types of resources: ED staff (i.e., doctors and nurses, and administrators) and ED assets such as majors trolleys, ambulatory care units (ACUs), and resuscitation rooms (CPRs). The patient throughput is measured through three dimensions: patient average cycle time, patient average waiting time, and patient average service time. The patient cycle time is measured across the different stages of a patients journey in the ED such as registration, triage, treatment, and diagnostics. This includes LOS for both admitted and discharged patients. Similarly, the average waiting time of patients is detailed for each stage, for example, average waiting time for triage, to be seen by ED physician, for Diagnostics (e.g., lab or X-Ray results), for discharge or hospital admission. Detailing these indicators is crucial for the detection of performance bottle necks and for taking effective decisions. Moreover, these indicators/measures of operations may be in fact drivers of others goals such as patient and staff satisfaction.

5.3.1.2 Community Engagement Perspective

The HSE performance targets and the national emergency medicine programme (EMP) are considered in this perspective. The performance target of the HSE is that all patients are processed through the ED in 6 hours or less from time of arrival to time of separation (including admission for designated cases). The overarching aim of the EMP is to improve the safety and quality of patient care in EDs and to reduce waiting times for patients.

5.3.1.3 Learning and Growth Perspective

Due to the critical role of healthcare professionals, two main performance measures are selected in this perspective: staff development and staff satisfaction levels. The staff development is measured in terms of the effect of training the staff to do more than one task and to be dynamically allocated within the ED, while the staff satisfaction levels are related to "internal ED business processes" perspective through the following indicators: staff utilisation, ratio of patients per doctor, and ratio of patients per nurse.

5.3.1.4 Patient Perspective

In designing the ED BSC, "patient" was selected as a sole perspective with and "patient satisfaction" as the main measure for this perspective. The efficiency of internal ED processes impacts the patient satisfaction level, therefore patient average waiting time and patient average length of stay are connected to the patient satisfaction performance measure.

5.3.2 Key Performance Indicators Selection

The balanced scorecard developed in the previous section for the ED includes qualitative as well as quantitative measures. Examples of qualitative measures are the patient satisfaction, staff skills upgrading and staff satisfaction. These measures cannot be measured directly in the simulation model. However, these measures are directly related to the performance measures in the "Internal Business Processes" perspective, which are of a quantitative nature and can be directly measured using simulation. Nevertheless, there is redundancy among performance measures in that perspective (i.e., internal ED business process perspective).

For example, "% of Patients Treated" and "% Patients Left without Treatment" are of complementary meaning. Moreover, some of the ED measures are of a conflicting nature such as staff utilisation and staff satisfaction. Maximising staff utilisation may lead to reaching the burnout level (i.e., 85% utilisation) which decrease the satisfaction level of staff and in turn can deteriorate the whole ED performance. Consequently, to narrow down the list of the measures and to achieve the trade-off between conflicting objectives, MCDA tools are used to systematically select the main key performance indicators (KPIs). The selection process is based on the simple multi-attribute rating technique (SMART) to identify the alternatives and criteria, which are relevant to the decision problem. SMART begins with identifying the alternatives (in this case, performance measures), and specifying the criteria to be used for evaluating these alternatives. The SMART procedure is applied to the performance measures in the "Internal ED business processes" perspective; this is because these measures are interrelated with other performance perspectives and measures, such as patient and staff satisfaction indicators.

Consequently, the 26 performance measures within this perspective are considered the "decision alternatives" for the SMART procedure. Performance measures are then evaluated against the main drivers of the ED performance, namely, layout efficiency, patient throughput, ED productivity, and resource utilisation. Within the SMART procedure, criteria are corresponding to these four performance dimensions. Once the criteria and alternatives were identified, a value tree was produced as shown in Figure 5-9. The root of the tree represents the ED performance, the first level represents the evaluation criteria and finally the second level represents the candidate performance measures (alternatives).

The ED managers (three consultants) have been asked to rank the alternatives (measures) against each criterion from most preferred to least preferred (i.e., from best to worst). The degree of agreement among the ED consultants was very high indicating a high level of consistency or inter-rater reliability (Gwet, 2008).

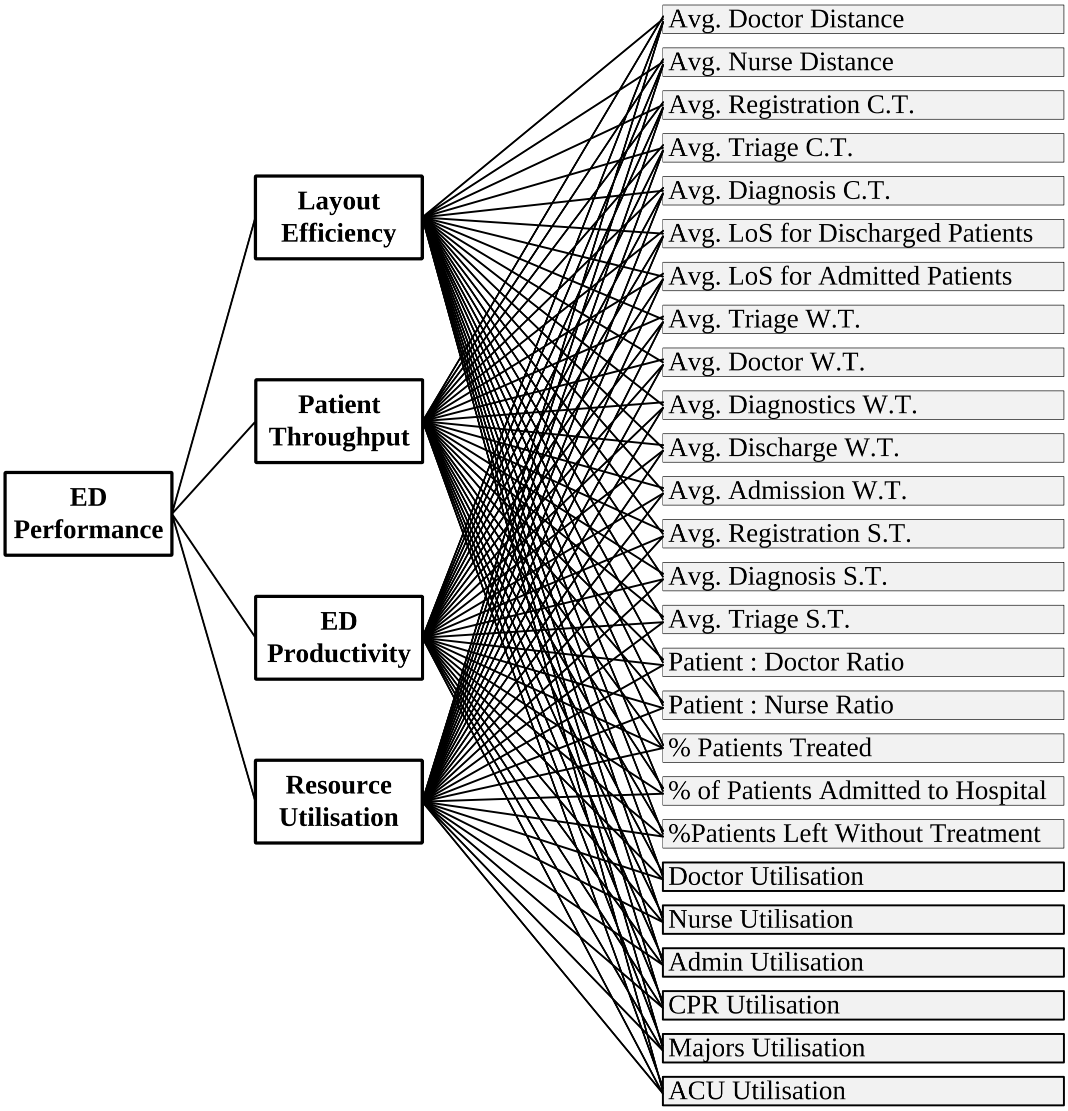


Figure 5-9 Performance measures value tree.

Table 5-1 represents the ED decision-makers' preferences, where a value scale from 0 to 100 is used; Best = 100 and worst = 0, which is an easy scale for decision makers to use (Valiris *et al*., 2005).

For each criterion, the ED managers assign a value of 100 for the most relevant measure, while a value of 0 is assigned to the least relevant one. For example, the average distance travelled by doctors within the ED is the most relevant to the layout efficiency criterion while the average registration service time is the least relevant for the same criterion

Table 5-1 The preference of ED senior manager of measures for each criterion

Performance Measures	Evaluation Criteria			
	Layout Efficiency	Patient Throughput	ED Productivity	Resource Utilisation
Avg. Doctor Distance	100	50	70	90
Avg. Nurse Distance	90	50	70	80
Avg. Registration C.T.	10	60	20	20
Avg. Diagnosis C.T.	20	60	50	20
Avg. Triage C.T.	20	30	50	10
Avg. LoS for Discharged Patients	30	100	30	70
Avg. LoS for Admitted Patients	40	90	30	70
Avg. Triage W.T.	30	20	0	10
Avg. Doctor W.T.	60	70	40	40
Avg. Diagnostics W.T.	10	0	10	10
Avg. Admission W.T.	20	20	10	20
Avg. Discharge W.T.	20	10	10	0
Avg. Registration S.T.	0	10	10	20
Avg. Diagnosis S.T.	20	10	20	10
Avg. Triage S.T.	20	10	10	20
Patient to Doctor Ratio	40	80	90	90
Patient to Nurse Ratio	40	80	80	90
% of Patients Treated	50	90	100	80
% of Patients Admitted	30	60	20	70
% of Patients Left Without Treatment	20	30	30	30
Doctor Utilisation	70	70	90	100
Nurse Utilisation	70	70	90	90
Admin. Utilisation	10	20	30	20
CPR Trolleys Utilisation	70	70	80	80
Majors Trolleys Utilisation	80	70	80	80
ACU Trolleys Utilisation	60	60	70	70

The other set of remaining measures are then rated regarding the most relevant and the least relevant measures and assigned a value ranges from 0 to 100 by the ED manager. Because the evaluation criteria are not equally important, the relative importance of the criteria was ranked by the manager (Table 5-2).

Table 5-2 The relative importance of the evaluation criteria

Rank	Criterion	Value score	Normalised weighting
1	Patient Throughput	100	0.37
2	ED Productivity	80	0.29
3	Resource Utilisation	60	0.22
4	Layout Efficiency	30	0.11

The normalised weighting is calculated by dividing the value score by the total for all value scores i.e. for rank 1, 100/270 = 0.37. The total score for each alternative is then calculated as the weighted average of the value scores for all criteria for that alternative. For example, for "% of Patients Treated" measure see Table 5-3.

Table 5-3 Aggregated weights and values for "% of Patients Treated" measure

Criterion	Value score	Criterion weight	Measure weight
Layout Efficiency	50	0.11	5.56
Patient Throughput	90	0.37	33.33
ED Productivity	100	0.29	29.63
Resource Utilisation	80	0.22	17.78
Total			86.30

Table 5-4 summarises the final weighted scores for all the measures (alternatives), where the rank of each measure is specified.

Finally, a threshold of 50 for the total score for the measures is set by the ED senior managers for the final set of KPIs (Figure 5-10). KPIs are then passed to the simulation model where they are measured and presented as the simulation output.

Table 5-4 The final score and rank of performance measure using SMART

Performance Measures	Total Score	Rank	Performance Measures	Total Score	Rank
Avg. Doctor Distance	70.37	8	Avg. Diagnosis S.T.	14.07	21
Avg. Nurse Distance	67.04	9	Avg. Triage S.T.	13.33	22
Avg. Registration C.T.	33.70	16	Patient to Doctor Ratio	80.74	3
Avg. Diagnosis C.T.	43.70	15	Patient to Nurse Ratio	77.78	5
Avg. Triage C.T.	30.37	17	% of Patients Treated	86.30	1
Avg. LoS for Discharged Patients	64.81	11	% of Patients Admitted	47.04	14
Avg. LoS for Admitted Patients	62.22	12	% of Patients Left Without Treatment	28.89	18
Avg. Triage W.T.	12.96	23	Doctor Utilisation	82.59	2
Avg. Doctor W.T.	53.33	13	Nurse Utilisation	80.37	4
Avg. Lab W.T.	6.30	26	Admin. Utilisation	21.85	19
Avg. Admission W.T.	17.04	20	CPR Trolleys Utilisation	75.19	7
Avg. Discharge W.T.	8.89	25	Majors Trolleys Utilisation	76.30	6
Avg. Registration S.T.	11.11	24	ACU Trolleys Utilisation	65.19	10

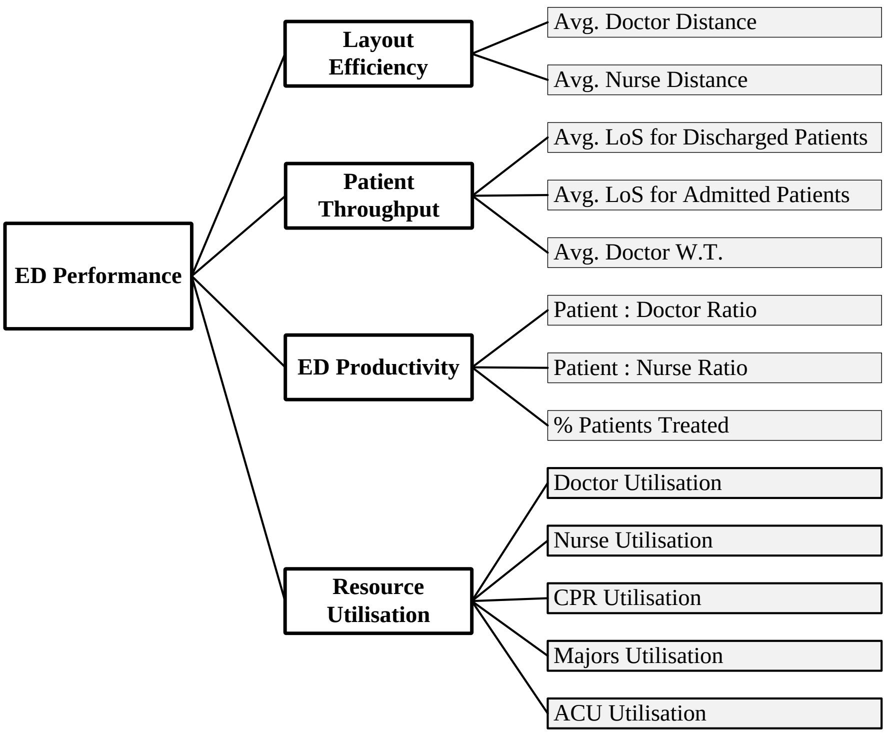


Figure 5-10 ED key performance indicators.

5.4 DATA ANALYSIS

The analysis of empirical data is essential in developing a robust simulation model that considers the time features of the intended system in terms of demand volume and patterns. A thorough analysis of data enables the discovery of different type of patterns (i.e., clustering) that are essential to reduce the complexity of the simulated system in terms of patient groupings and patient allocation and routing analysis. This valuable information is needed to build a comprehensive and representative dynamic model for the underpinned healthcare system. Historical patients records have been gathered for the ED during a 16-month period (1^{st} January 2009 to 30^{th} April 2010) provided by hospital managers. A total of 59,986 anonymous patient records have been collected through the ED information system (patient centre), which is used by ED staff (e.g., administrators, doctors, and nurses) to record data about each patient through the stages of their care. The quality of patients records is subject to level of pressures within healthcare processes, which can significantly affect the accuracy and consistency levels of these records. Therefore, prior to extracting knowledge from these records, data mining procedures are needed to validate records.

5.4.1 Data Description

As shown in Table 5-5, the dataset consists of three tables: Patient Data table, Awaiting Triage and Seen table, and Patient Tracking Data table. Each record in “Patient Arrival Data” table represents one patient using the following attributes: the patient identification number, patient triage category, the HSE triage code, the patient presenting complaint, mode of arrival, gender and patient date of birth, and whether the patient attendance is new or a return attendance and total number of ED attends. With the exception of “Mode of Arrival” attribute, the “Awaiting Triage and Seen” table gives more information about what date and time the patient arrived, triaged, and was seen by an ED physician. Two important flags are also included in that table which indicate if the patient was triaged or not, and if yes, whether the patient was seen by ED physician or left without been seen. Additional redundant information is provided in tables 'Awaiting Triage and Seen' and 'Patient Tracking Data' which shows the patient waiting time, in minutes, from attendance to being triaged, and from being triaged to being seen by ED member are repeated in both tables with the same data fields: namely ' Triage Wait' and ' Seen Response Time' respectively.

Table 5-5 Description of data fields in Patient data tables

Table Name	Patient Arrival Data	Awaiting Triage and Seen	Patient Tracking Data
Table Fields	Patient ID	Patient ID	Patient ID
	Triage Category	Triage Category	Triage Category
	HSE Triage Code	HSE Triage Code	HSE Triage Code
	Presenting Complaint	Attend Date/Time	Attend Date/Time
	Mode of Arrival	Patient Triaged	Patient Triaged
	Gender	Triage Date/Time	Triage Date/Time
	Date of Birth	Presenting Complaint	Presenting Complaint
	New Attendances	Patient Seen	Patient Seen
	Reattendances	Seen Date/Time	Seen Date/Time
	Attendances	Seen Step	Seen Step
		Date of Birth	Date of Birth
		Gender	Gender
		Attendances	Tracking Step Identifier
		New Attendances	Tracking Step Name
		Reattendances	Tracking Step Date/Time
		Triage Wait (mins)	Location
		Seen Response Time (mins)	Tracked by user group
			Seen Wait (mins)
			Triage Wait (mins)
			Attendances
			New Attendances
			Reattendances

Regarding the “Patient Tracking Data” table, each record represents one process stage of the patient journey in the ED. For each tracking step (i.e. process stage), the following attributes were provided: a unique identifier of the tracking step, the name of that step, the date and time, the location within the ED where the step was taken, and the type of user group or staff who performed that step.

5.4.2 Data Preparation and Pre-Processing

There are a number of issues concerning the quality of the dataset. Firstly, there is a lack of consistency in the data tables. For example, the number of patient records in the first and second table is not the same. Additionally, in the “Patient Tracking Data” table, there are multiple entries for the same patient and the same tracking step name but with different timestamp. While these multiple entries can be valid to some tracking steps such as “seen by doctor”, it is invalid for other tracking steps such as “attend” or “triage”. Secondly, there is a great amount of redundant information in the dataset. This is due to the great number of common attributes between the provided tables as highlighted in Table 5-5. Finally, there are missing data values for some attributes, for example, the use of the value “n/a” for some entries in “Triage Category” and “Seen Step” attributes and the value “other” for “Tracked by User Group” attribute.

There are several reasons for such quality issues. Among these reasons is that the majority of patient data is recorded in the tracking information system by the ED staff after the patient has already completed the process stage (e.g. triage, treatment, or discharged). This indicates that the staff member either needed a good memory or made a good guess of the accurate time when the patient has been seen. Additionally, the stressful working conditions within the ED, that have been observed during the observation phases of this research, contribute to a great extend to the accuracy of the data recording process. However, the dataset provides a valuable source for extracted detailed information about patient arrival pattern, patient routing through the different ED processes, and the allocation of critical ED resources such as staff and physical capacity. Prior to the extraction of these parameters, a number of procedures were performed in order to overcome the aforementioned data quality issues and to obtain a trustworthy set of data records.

5.4.2.1 Missing values

Patient records with the value “n/a” in the “Triage category” attribute were removed from the dataset. The removal of these records was supported by many reasons. First, for these records, the range of values of the “HSE Triage code” was not one of the five standard severity levels. It was however an indication that the patient was visiting the ED for the “Wound Care” or other ED clinics. This was confirmed by the finding that the value of the “Patient Triage” field was “No” for all these records and there was no date and time value for the “Triage Date/Time” attribute. The last attribute checked for these patient records was the “Presenting Complaint” which was “No Code Value Recorded” for all the mentioned records.

5.4.2.2 Outlier detection and elimination

In order to detect the outliers in the dataset, the range of values for each attribute in the dataset was analysed. Two attributes were found to have unexplained and extreme values, namely, the “Triage wait (mins)” and the “Seen Response Time” attributes in “Awaiting Triage and Seen” table. For example, in the “Triage wait (mins)” attribute, some patient records have the values “41524” and “7629”, which is corresponding to 28.8 and 5.5 Triage waiting days respectively. After inquiring with the ED staff about these values, they confirmed that these are errors in entering the data in the ED information system; however, they also said that similar values can be valid for other tracking steps such as patients waiting to be admitted to the hospital. Based on the cumulative percent distribution in Figure 5-11 for the triage waiting time attribute, it was found that 95% of patients have a triage waiting time of less than 53 minutes. Patient records with a value greater than this threshold have been identified as an outlier and subsequently have been removed from the dataset.

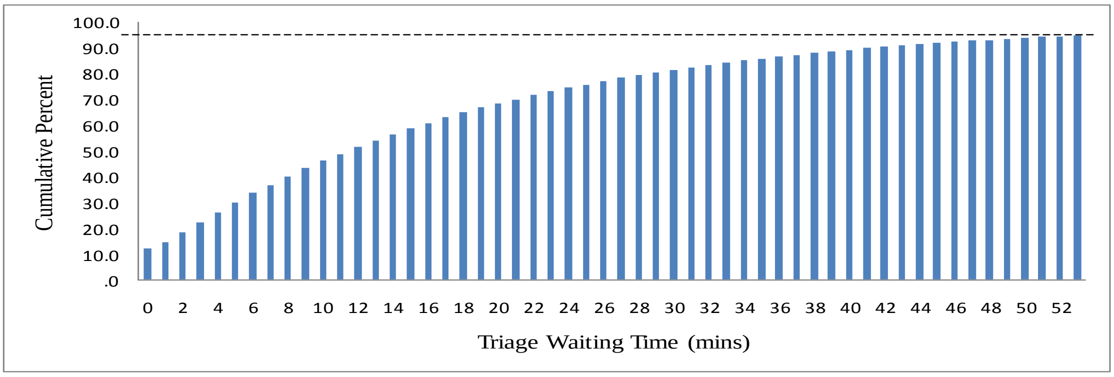


Figure 5-11 Triage waiting time cumulative percentage.

Similarly, a cumulative percent distribution was created for the "Seen Response Time" attribute (see Figure 5-12), where 95 per cent of patient were waiting to be seen by ED staff within a value less than or equal to 544 minutes. Therefore, patient records with a value greater than 544 minutes were removed from all the tables of the dataset.

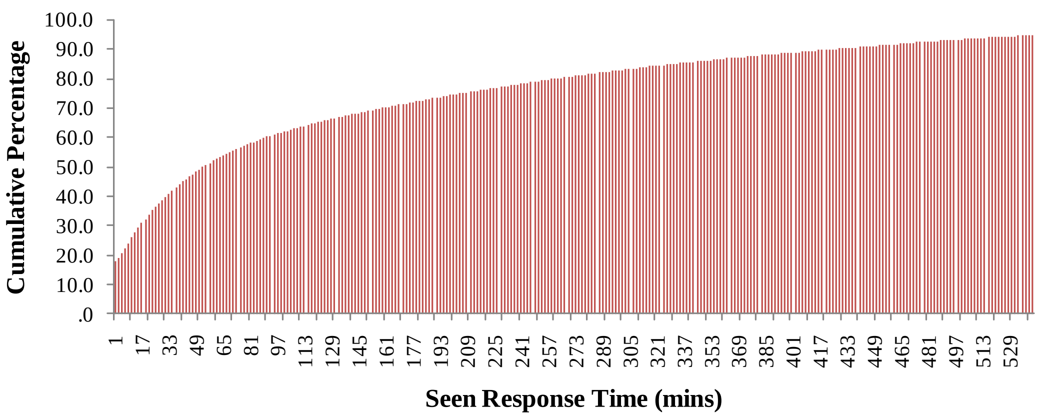


Figure 5-12 Cumulative percentage of first clinical response time.

5.4.2.3 Data Consistency

In the “Patient Tracking Data” table, each record corresponds to one tracking step through the patient journey in the ED. Examples of these steps are: attended, triaged, doctor seen, and discharged. For each of these tracking steps, supplementary data is recorded such as a unique identifier for the step, step name, timestamp, location, and the type of staff performed the step. For each patient, the chronological order of these steps gives complete information about the steps that patient has be put through his or her journey in the ED. However, in that chronological order of patient records, it was found that there are multiple entries for similar steps but with different timestamps. For example, for some patient records, the “attended” step was found repeated consecutively but within few minutes of difference between the timestamps.

While it is possible the same patient attended more than one time to the ED, however, it is unlikely this can happen within minutes. Similarly, for other tracking steps, such as “Triaged” and “Discharged”, the same problem was found. However, for some tracking steps, this assumption is invalid. For example, the “Doctor Seen” step can be repeated for the same patient within a few minutes. For eliminating these inconsistencies within the dataset, both “Triage wait” and “Seen Wait” attribute in the “Patient Tracking Data” table were used to select the step with the right timestamp, and to eliminate the redundant ones. For example, for a repeated “triaged” step, the difference between the patient attendance time and the triage time is calculated for both entries, which corresponds to the patient ‘time to be triaged’ wait. The entry with a match between the calculated triage time and the one recorded in the “Triage Wait” field is the valid record, while the other record is removed from the table. The total number of patient records after these pre-processing procedures is 35,800 and 14,133 for the year 2009 and 2010 respectively, with a total of 49,933 patient records and 83 per cent trustworthy dataset.

5.4.3 Data Extraction, Grouping, and Analysis

In order to developing a comprehensive and representative simulation model of the ED, several parameters have to be investigated and taken into account such as processing times for deferent processes, patient arrival characteristics, patient routing information within the ED, the allocation of resources and medical staff. These parameters can be obtained by analysis of hospital records, staff interviews or by direct observations of the processes.

5.4.3.1 Patient Arrival Pattern

Regarding the patient arrival patterns, different analysis scales has been used to analysis the patient arrival to the ED: monthly, weekly, and daily arrival patterns (see Figure 5-13). Based on the monthly analysis (Figure 5-13a), the seasonality of patient arrival was detected, where the characteristics of patients arrival are similar every four consecutive months. This was supported by the senior managers of the ED where they confirmed this pattern by the stability of the ED staff over each period. Moreover, the patient demand is the highest around working days, whereas the demand is at its lowest levels around weekends (Figure 5-13b). During the course of the day, the demand increases, where the peak is around the midday and which then decays slowly afterwards to its lowest levels during the night time (Figure 5-13c).

These arrival patterns give an overview about the demand for services in the ED and different scales for the patient arrival characteristics. However, it is inaccurate to use only one arrival pattern for all patients in the simulation model. In order to approximate the arrival pattern of patients, patients has to be grouped and each group has its own unique arrival characteristics and patterns.

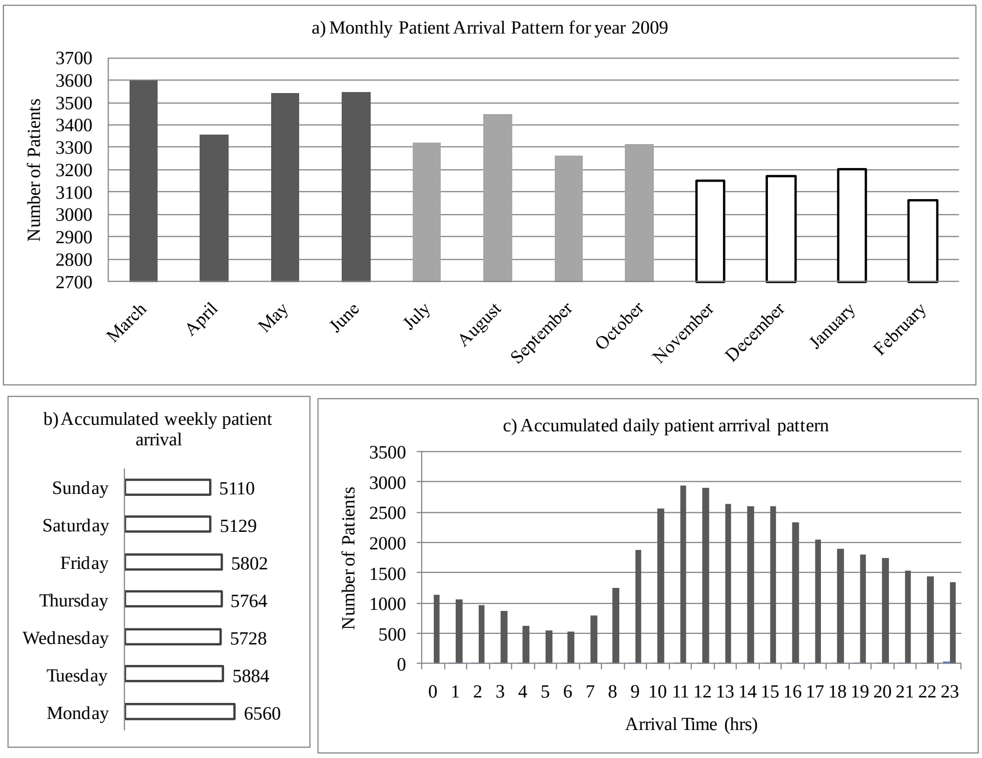


Figure 5-13 Demand seasonality and patient arrival pattern.

5.4.3.2 *Patient Grouping*

In order to categorise patients, there were two main options: the triage category and the medical complaint. The triage category has been selected to categorise patients over the medical complaint. This selection was for three main reasons; firstly, the number of triage categories is very small (five triage categories are used in the ED). Secondly, patients usually have more than one medical complaint, for example, a patient with chest pain can also suffer from respiratory problems.

Consequently, there are an infinite number of combinations of medical complaints and hence it cannot be used to categorise patients. Finally, according to the ED consultant, they recommended categorising patients according to the triage category. From their perspective, this is more convenient for the representation of patients and also they are interested in breaking down the analysis for each triage category, rather than medical complaints. As shown in Figure 5-14, urgent patients (triage category 3) represent the largest group of new attendees to the ED annually (58% on average) who are presented to the ED with a wide range of medical complaints and aging conditions.

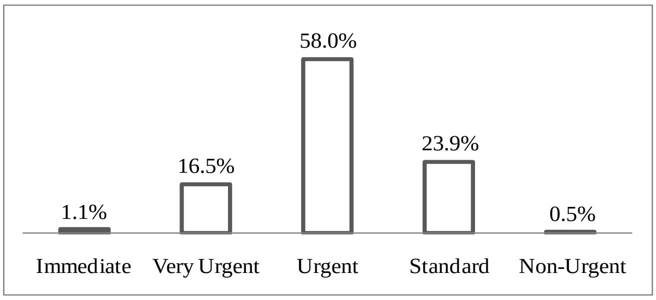


Figure 5-14 Triage category distribution.

Due to the small percentage of “Non-Urgent” patients (0.5%), and based on senior managers suggestions, this patient group has been merged with the “Standard” patient group. This is not only because their small percentage but also for the similarities in the medical conditions and care paths for both patient groups. Likewise, the “Immediate” patient group is combined with the “Very Urgent” patient group. The mode of arrival for each group is then extracted from the dataset (Figure 5-15), which is essential to determine the distribution of walk-in patients and those who arrive by ambulance. This will be used in the simulation model to determine the percentage of patient that will go through the registration and triage process.

Inter-arrival Time for Patients: for each patient group, an estimation of patient arrival distribution is used to replicate the arrival pattern in the simulation model. The Poisson distribution is commonly used to represent these arrival patterns in the literature. For example, Bowers and Mould (2004) investigated the arrival pattern of an orthopaedic trauma centre which resulted in a stochastic pattern, where the Poisson distribution produced the best fit. This distribution was varied in their means to adjust to arrival hour, day and season which is then applied to the simulation model. Another example of fitting distributions to arrival data can be obtained by (de Bruin *et al*., 2007), where the frequencies – according to the grouped arrival minute category – display an exponential distribution, which is later, also shown to be Poisson.

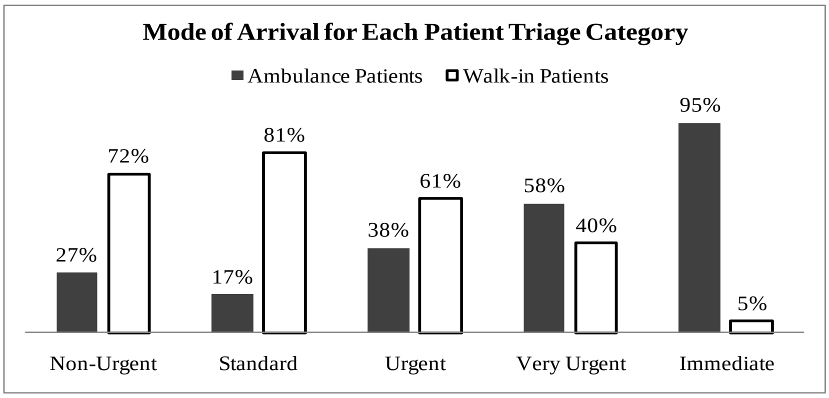


Figure 5-15 Patient arrival mode distribution.

From the simulation perspective, the inter-arrival data is required, not the arrival time, which describe the time delay between two consecutive patient arrivals. To do so, the difference between the arrival times of patients is obtained for each group. For example, for “Urgent” patients group, Figure 5-16 shows the sequential inter-arrival time of 54 patients arriving on the same day, where the inter-arrival time ranges from 1 minute and 54 minutes.

Figure 5-16 Inter-arrival time pattern – urgent patient.

These inter-arrival times are then grouped into time slots where the relative frequency (i.e., percentage) of each time slot is accumulated and represented in a histogram (see Figure 5-16a). This is followed by the determination of a fitted distribution for each inter-arrival histogram using Stat::Fit software, which is a curve fitting program that fits analytical distributions to data. For example, Figure 5-17b shows different possible distributions for the inter-arrival time for “Urgent” patient group. The best fit distribution is then determined for each patient group and validated by using Kolmogorov Smirnov goodness of fit test with a 5 % significance level.

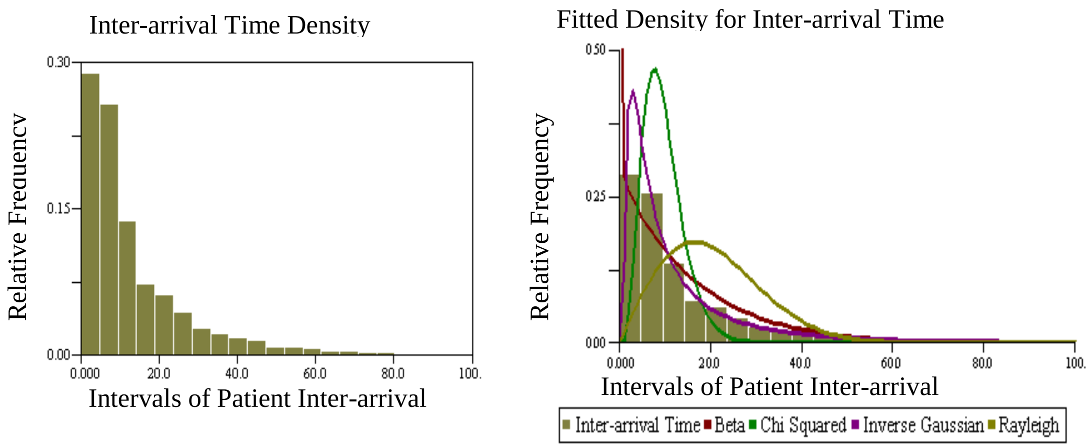


Figure 5-17 Relative frequency diagram – urgent patients.

5.4.3.3 Patient Complaints

An important aspect in developing a simulation model is which level of details to be considered in order to build a representative model, without considering all irrelevant details. For example, about 80 per cent of “standard” patients (triage category four) visit the ED with 7 common medical complaints out of 50 presenting complaints in the Manchester Triage System (MTS) that is used by the ED staff. This is known as the Pareto’s principle or the 80-20 rule and used in many analyses and simulation studies (Forces, 2001, de Bruin *et al.*, 2007). Accordingly, for each triage category, medical complaints that represent about 80 per cent of patients are considered in the simulation model. Table 5-6 shows the patients' complaints that represent 80% for each triage category with each cell represents the percentage of patients in the triage category that have the corresponding medical complaint. The summation of each column in the table (i.e., triage category) is approximately 80% according to the Pareto principle.

Table 5-6 Complaints-based on the Pareto principle.

Presenting Complaints	Triage Category				
	Immediate	Very Urgent	Urgent	Standard	Non-Urgent
Unwell Adult	11%	14%	18%	8%	39%
Limb Problems		7%	11%	47%	13%
Collapsed Adult	46%	6%	4%		
Apparently Drunk					26%
Chest Pain		14%	9%		
Abdominal Pain in Adults		9%	12%		
Overdose and Poisoning	9%	4%			
Shortness of Breath		8%	4%		
Back Pain		4%	5%		
Assault		2%	3%	4%	
Diabetes	8%				
Wounds				8%	
Head Injury			3%	4%	
Fits	7%				
Headache		3%	2%		
Falls		2%	3%		
Abscesses and Local Infections				3%	
Facial Problems				3%	
Mental Illness		3%			
GI Bleeding		2%			
Urinary Problems			2%		
Diarrhoea and Vomiting			2%		
Total Percentage	81 %	78 %	79 %	77 %	78 %

ED Resuscitation Area ED Major Assessment Ambulatory care Minor Injuries Provision

The presentation-priority matrix shown in Table 5-6 also displays the most appropriate disposition of each patient group according to the MTS recommendations. For example, a patient presenting with a limb problem and allocated to the standard priority should be seen in a minor injury area, while a patient with chest pain allocated to the very urgent priority is best seen in the resuscitation room. However, these disposition recommendations are subject to the availability of the care services in the ED, the current pressures on them, and the crowding status of the ED.

5.4.3.4 Patient Allocation and Routing Analysis

Based on the analysis of patients allocation within the ED (Table 5-7), the ED staff failed to fully implement the recommendations of the MTS concerning the disposition of patients, which is due to the overcrowding of the ED. For example, in Table 5-7, 88% of immediate patients are seen in the resuscitation room and 9% in the majors' cubicles, while only 40% percent of very urgent patient are seen in inappropriate assessment areas. Moreover, due to the overcrowding status of the ED, the majority of standard and non-urgent patient are assessed and treated in inappropriate areas (e.g., chairs) or wait in waiting areas.

Table 5-7 Analysis of patient allocation within the emergency department

ED Areas	**Triage Category**				
	IMM	VURG	URG	STD	NURG
Resuscitation Room	88%	25%	2%	0%	0%
Majors Area	9%	15%	8%	1%	0%
Ambulatory Care Unit	0%	12%	10%	20%	11%
Majors Chairs	0%	7%	6%	1%	1%
Rapid Assessment Triage	3%	12%	7%	2%	2%
Waiting Room	0%	14%	56%	74%	85%
X-Ray Sub-Wait Area	0%	15%	12%	4%	1%

IMM: Immediate **VURG**: Very Urgent **URG**: Urgent **STD**: Standard **NURG:** Non-Urgent

Through their journey within the ED, patients go through different stages of care, depending on the acuity and severity level of their cases. Based on the analysis of patient flow, the main stages of care (i.e., tracking steps) have been identified: patient arrival, triaged, seen by doctor, seen by advanced nurse practitioner (ANP), referrer to opinion, referrer to admission, waiting admission, admitted to the hospital, and discharged. These steps were broken down for each triage category, from the patient arrival until the patient was discharged from the ED or admitted to the hospital. Following each stage of care, there are different routing possibilities for patients, which is subject to their conditions and the requirements for their treatment.

For example, the patient after being referred for opinion can be discharged, referred to admission or admitted directly to the hospital. Thereupon, for each stage, the different possibilities of routing are determined for each triage category and its distribution was estimated based on the patient records. This routing information was then validated with the ED staff in order to have robust and reliable routing information. Figure 5-18 shows a detailed flowchart representation of patient routing for all triage categories, where the number on each connection represents the percentage of patients from one tracking step to the following one.

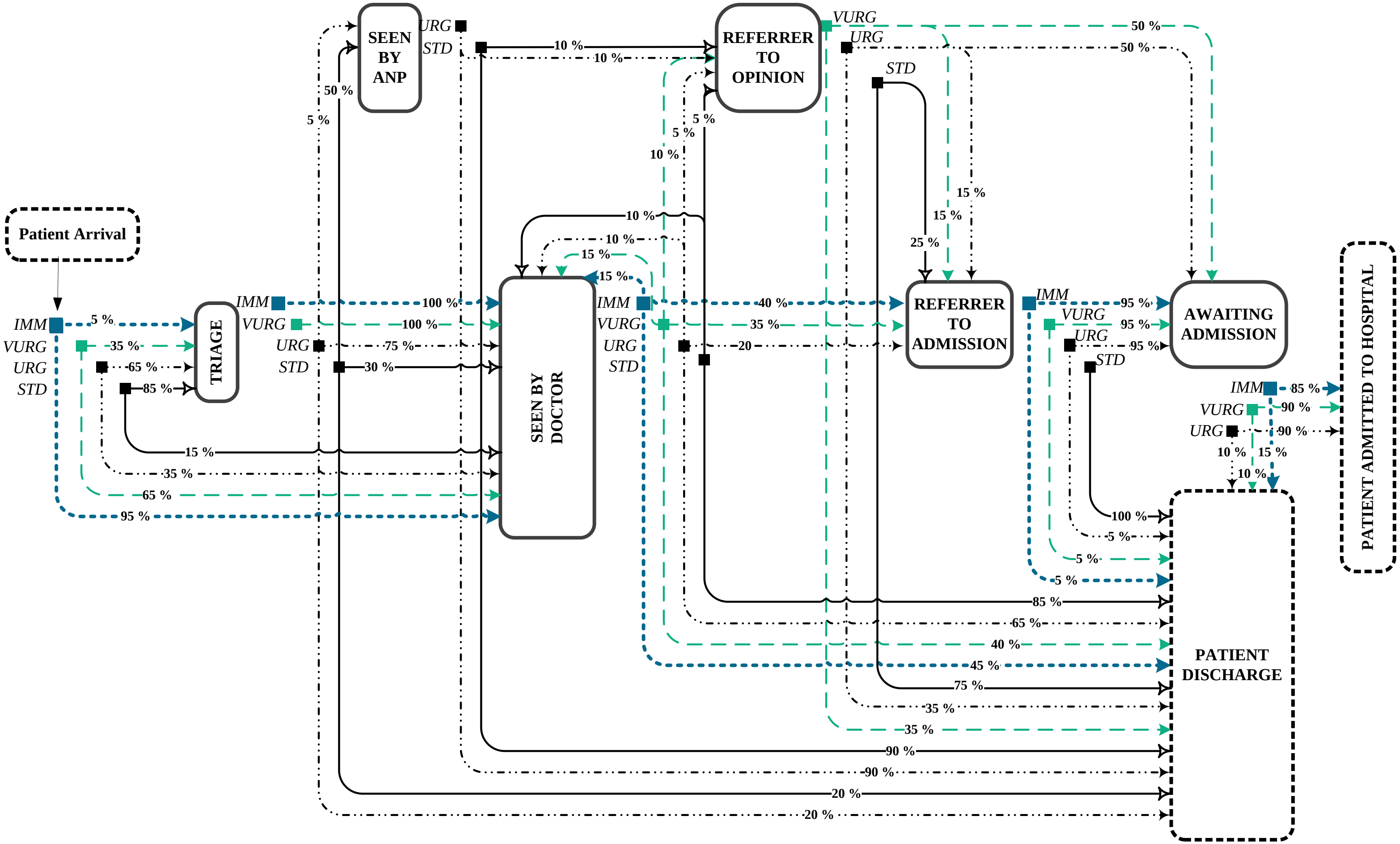


Figure 5-18 Main ED processes and patient routing.

5.5 EMERGENCY DEPARTMENT SIMULATION MODEL

5.5.1 Model Construction

Based on the ED business process model, the designed BSC, and the empirical data analysis, a comprehensive simulation model for the ED was constructed using Extend Suite v.7 simulation package. Modules of the simulation model were connected to resemble the ED business process model, where blocks are connected similar to the conceptual flow chart, which eases the model construction phase. Accordingly, the top-level of the simulation model define the overall model structure, where sub-level blocks containing additional modules with more details. Object-oriented programming was used to customise pre-defined block for constructing the ED simulation model. A database was used to save the measured KPIs after each simulation run (i.e., replicate), followed by exporting the populated BSC in a tabular form for future analysis and validation.

5.5.2 Simulation Model Verification and Validation

To reduce the model development cycle time and to increase the confidence in the simulation model results, the verification and validation were carried out all the way through the development phases of the ED simulation model. After each model development phase, the model was verified and validated with respect to other previously completed phases. For the verification process, the model logic is verified to ensure that the patients follow the correct care path as expected. This was achieved by visual tracking of patients using animation and by checking intermediate output values such as queue lengths and waiting times between processes. The conceptual model had been documented and validated by circulating the document among ED senior managers and senior nursing staff. This was crucial in ensuring that the logic of the model and ED activities was correct. All distributions determined from the data and used in the model were validated by using Kolmogorov Smirnov goodness of fit test with a 5% significance level (Massey, 1951). Simulation variables – such as patients inter-arrival time, mode of arrival, presenting medical complaints, processing time, routing and allocation – were initialised based on the analysis of empirical data and also the analysis of the ED layout and patient flow given in previous sections. Queues at each stage of patient care (e.g. triage, seen by doctor, awaiting admission, and discharge) were set as empty and idle. A warm-up period of two months was found to mitigate any bias introduced by the initial conditions of the simulation model. The simulation outputs are shown in the form of performance value tree (section 5.4.2) that represents the main KPIs of the ED performance.

However, in order to validate the simulation model results, only three KPIs were used, namely average waiting time for doctor (A.W.T), average length of stay for discharged patients (D_ALOS), and average length of stay for admitted patients (A_ALOS). The actual values of these KPIs were calculated from the analysis of the collected patients records. Each of these three KPIs was further explored for each triage category patients to provide a robust validation of the simulation output. A total number of p KPIs were used for validating the simulation output, where $p = 12$. The simulation model was run for $n=10$ independent replications to obtain independent and identically distributed (iid) of aforementioned p KPIs, with each replicate re-initialised by different pseudo-random number seed. Table 5-8 shows the simulation output for the p KPIs for all n replications. For each KPI, a $100(1 - \alpha)$ % two-sided confidence interval was constructed with $\alpha = 0.05$. As show in Table 5-9, the t-value for all the KPIs is less than t-critical which is the upper $(100\alpha/2)^{th}$ percentile of the t distribution with $n - 1$ degrees of freedom (i.e. $t_{n-1}(\alpha/2)$).

Table 5-8 ED simulation output

	Key Performance Indicators (KPIs)											
	A.W.T (mins)				ALOS (hrs)							
					Discharged Patients (D_ALOS)				Admitted Patients (A_ALOS)			
TC	VURG	URG	STD	AL	VURG	URG	STD	AL	IMM	VURG	URG	AL
R1	56.00	249.87	290.07	186.84	9.67	10.82	5.12	8.91	18.52	19.38	23.19	21.44
R2	56.13	265.04	310.97	193.88	9.79	11.28	5.36	9.22	23.27	18.18	22.97	20.37
R3	55.45	187.26	254.42	143.63	9.89	10.74	4.98	8.88	17.07	2.26	20.69	21.79
R4	63.11	248.46	290.76	188.83	10.38	11.22	5.32	9.24	15.61	19.46	24.85	23.90
R5	59.25	249.36	242.18	186.49	9.83	10.76	5.13	8.89	15.82	20.11	23.78	22.99
R6	59.55	204.77	247.21	158.61	9.15	9.73	4.77	8.08	14.89	17.10	22.14	20.34
R7	56.39	357.86	312.04	242.00	10.38	13.16	5.48	10.08	14.64	20.30	24.17	21.90
R8	57.33	207.26	240.91	157.41	10.62	11.89	5.26	9.69	12.66	21.53	23.18	18.11
R9	72.25	202.89	239.28	159.88	11.75	10.21	4.87	8.48	14.73	19.12	22.64	20.99
R10	60.51	202.08	216.40	156.72	9.02	8.72	6.56	8.00	17.32	18.71	25.06	21.09
μ_{av}	55.99	262.17	265.97	189.02	10.23	10.01	5.45	9.16	15.45	20.22	24.05	21.98

A.W.T: Average Waiting Time **TC:** Triage Category **R_i:** Replicate i **IMM:** Immediate **URG:** Urgent
ALOS: Average Length of Stay **μ_{av}:** Actual Value Mean **AL:** All Patients **VURG:** Very Urgent **STD:** Standard

Therefore, the null hypothesis that the simulation model output represents the actual system (i.e. $\mu = \mu_0$) is not rejected for all the KPIs with at least 95% confidence level.

Table 5-9 Simultaneous confidence intervals of ED key performance indicators

			μ_{av}	$\bar{x}$	s	t-value $\lvert t \rvert$: $\frac{\bar{X}-\mu_0}{s/\sqrt{n}}$	t-critical: $t_{n-1}(\alpha/2)$	CI_ Half Length: $t_{n-1}(\alpha/2)\left(s/\sqrt{n}\right)$	CI of $\bar{x}-\mu_{av}$: CI Left	CI Right
A.W.T (mins)		VURG	55.99	59.60	05.07	2.25	2.262	03.62	-00.01	07.24
		URG	262.17	237.48	50.14	1.56	2.262	35.86	-60.54	11.18
		STD	265.97	264.43	33.61	0.15	2.262	24.04	-25.59	22.50
		AL	189.02	177.43	28.63	1.28	2.262	20.48	-32.07	08.88
ALOS (hrs)	D_ALOS	VURG	10.23	10.05	00.79	0.73	2.262	00.56	-00.75	00.38
		URG	10.01	10.85	01.20	2.23	2.262	00.86	-00.01	01.70
		STD	05.45	05.28	00.50	1.05	2.262	00.36	-00.52	00.19
		AL	09.16	08.95	00.65	1.00	2.262	00.47	-00.68	00.26
	A_ALOS	IMM	15.45	16.45	02.91	1.09	2.262	02.08	-01.08	03.08
		VURG	20.22	17.62	05.53	1.49	2.262	03.95	-06.56	01.35
		URG	24.05	23.27	01.30	1.90	2.262	00.93	-01.71	00.15
		AL	21.98	21.29	01.58	1.38	2.262	01.13	-01.82	00.44

$\bar{x}$: Point estimate mean **s:** Point estimate standard deviation CI: Confidence Interval

In order to obtain a lower bound on the overall level of confidence of the simulation output, Bonferroni inequality (Appendix B) was used for constructing individual confidence levels of the p KPIs at $1 - \alpha/p$, with $\alpha = 0.05$ and $p = 12$. This resulted in a new t-value of 4.297 for each KPI, and consequently new confidence intervals (Table 5-10).

Table 5-10 Simultaneous and Bonferroni confidence intervals

			t-critical = 2.262			t-critical = 4.297		
			CI_ Half Length	CI of $\bar{x} - \mu_{av}$		CI_ Half Length	CI of $\bar{x} - \mu_{av}$	
			$t_{n-1}(\alpha/2)(s/\sqrt{n})$	CI Left	CI Right	$\boldsymbol{t_{n-1}}(\alpha/2\boldsymbol{p})(\boldsymbol{s}/\sqrt{\boldsymbol{n}})$	CI Left	CI Right
A.W.T (mins)		VURG	03.62	-00.01	07.24	6.89	-3.27	10.49
		URG	35.86	-60.54	11.18	68.13	-92.80	43.44
		STD	24.04	-25.59	22.50	45.67	-47.21	44.13
		AL	20.48	-32.07	08.88	38.89	-50.49	27.31
ALOS (hrs)	D_ALOS	VURG	00.56	-00.75	00.38	1.07	-1.25	0.89
		URG	00.86	-00.01	01.70	1.63	-0.786	2.47
		STD	00.36	-00.52	00.19	0.68	-0.85	0.51
		AL	00.47	-00.68	00.26	0.89	-1.10	0.68
	A_ALOS	IMM	02.08	-01.08	03.08	3.95	-2.95	4.95
		VURG	03.95	-06.56	01.35	7.51	-10.11	4.91
		URG	00.93	-01.71	00.15	1.76	-2.54	0.99
		AL	01.13	-01.82	00.44	2.14	-2.83	1.45

Therefore, an overall confidence of interval of the simulation output was obtained with at least 95 % that all the p KPIs lie in the p-dimensional "box" defined by the p confidence intervals. Due to the large number of KPIs, the resulted Bonferroni intervals was wider than the simultaneous confidence intervals (Table 5-10), and thus not precise. To avoid the inflated error rate (i.e. α) that resulted from using separate confidence intervals, a joint confidence region was constructed, based on Hotelling's T^2 distribution which is a generalisation of the univariate t-distribution. The main three KPIs were chosen for calculating the T^2 value, namely, the A.W.T, A_ALOS, and D_ALOS for all patients. Based on the correlation matrix of these three means, the Hotelling's T^2 value was 3.027 (Appendix B gives a description about the computation procedure). The T^2 was then multiplied by $(n - p)/(np - p)$ with $n = 10$ and $p = 3$. Such transformation of T^2 yields an exact F distribution with p and $n - p$ degrees of freedom. A 95% confidence region for mean vector all was then constructed such that the transformed T^2 (0.785) is less than the upper $(100\alpha)^{th}$ percentile of the F distribution ($F_{p,n-p}(\alpha)$ = 4.346 and α = 0.05). This procedure gave a formula for the simulation model confidence region as an ellipsoidal region, the exact shape of which depends on the magnitude and sign of the covariance of the KPIs. For simplicity, Figure 5-19 shows confidence regions between each pair of the three main ED KPIs along with their individual confidence intervals.

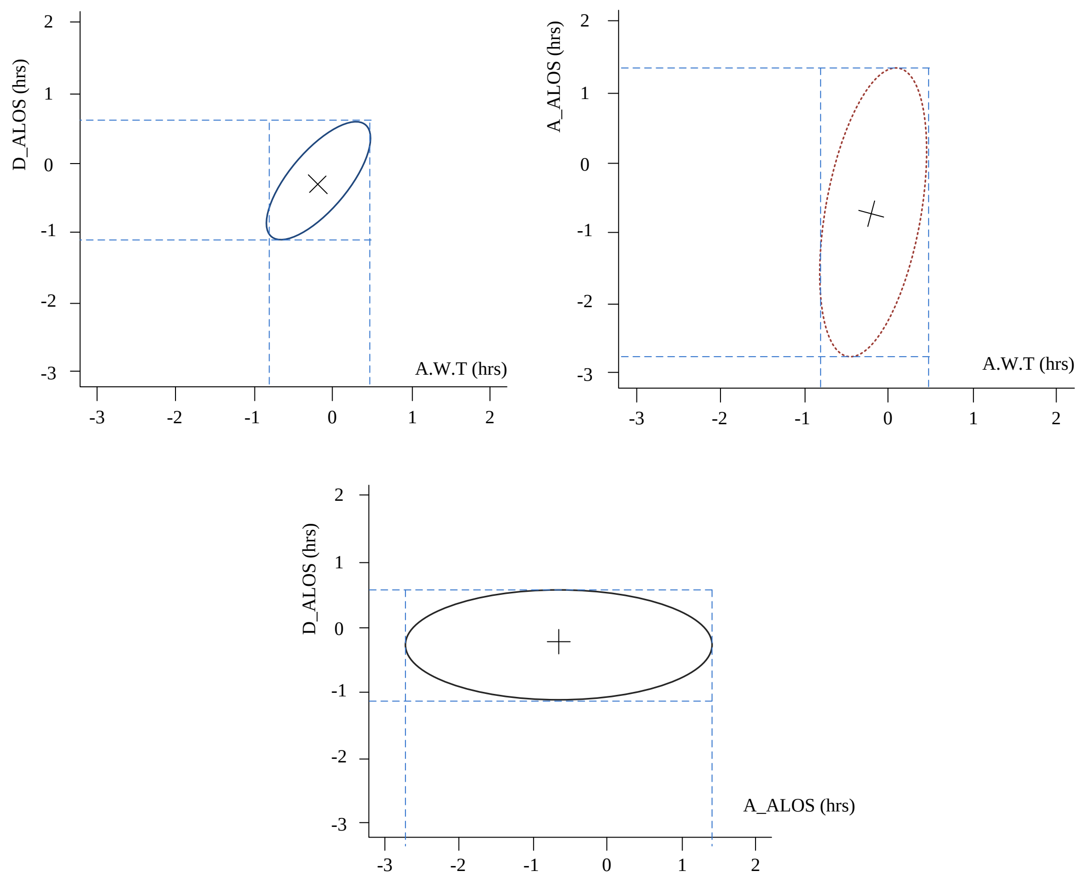


Figure 5-19 Confidence regions and intervals of ED KPIs.

5.6 REAL-TIME STRATEGIES FOR THE EMERGENCY DEPARTMENT

5.6.1 The Three Basic Strategies

5.6.1.1 Scenario Design

The simulation scenarios tested were the impact of variation in medical staffing, increasing clinical assessment space and finally assessing the impact of incorporating a ‘zero-tolerance’ policy regarding exceeding the national 6-hour boarding PET (i.e., length of stay). Distinct study scenario variables (Table 5-11) were added to the simulation model and run for a 3 month continuous blocks. The three months was chosen for the stability of ED staffing levels offer this period, according to the ED managers.

Table 5-11 Simulation variables for base scenario and scenario 1, 2, and 3.

	Decision Variables		
	Access Block (zero-tolerance PET)	Physical capacity (number of trolleys)	Additional physician shift
Base Line	Yes	13	-
Scenario 1	Yes	19	-
Scenario 2	Yes	13	1 SHO [9pm to 7am]
Scenario 3	No	13	-

The principle variables introduced had increased clinical assessment capacity (extra 6 trolley cubicles), increased clinical assessors (1 Senior House Officer shift at night), and absolute compliance with the national 6 –hour admission target for ED boarders. These scenarios were suggested by the ED senior managers to evaluate the intended new extension of the hospital which will include rebuilding of key parts of the hospital including the ED. Expanding the capacity of the ED may eventually necessitate a corresponding increase in the staffing levels. Therefore, the hospital managers and the planners of the new ED express their interest to evaluate the effect of capacity expansion and increasing the staffing levels against the effect of unblocking critical performance bottlenecks such as the access block from the ED to the hospital.

5.6.1.2 Results Analysis

The results of the simulation model showed that adoption of the scenario 3, which is absolute enforcement of the national 6-hour admission target (Table 5-12) had the greatest impact on the patients ALOS at every stage of the patient journey through the ED, especially amongst patients who are ultimately discharged directly from ED care (48% improvement in ALOS).

Table 5-12 Simulation results of scenario 1, 2, and 3.

Key Performance Indicators (KPIs)		Base Line	Capacity Expansion		Increasing Staff		Zero Tolerance	
			O/P	↑↓	O/P	↑↓	O/P	↑↓
Patient Throughput	A.W.T Doctor (hrs)	2.96	2.50	15%	2.80	5%	1.80	39%
	ALOS Dis. Pts. (hrs)	10.23	8.40	18%	9.80	4%	5.30	48%
	ALOS Adm. Pts. (hrs)	21.30	18.20	15%	19.80	7%	5.70	73%
Resource Utilisation	Doctor Utilisation	81%	84%	4%	73%	10%	86%	7%
	Nurse Utilisation	82%	87%	7%	83%	1%	74%	10%
	CPR Utilisation	91%	86%	6%	91%	0%	87%	5%
	Majors Utilisation	94%	82%	13%	92%	2%	85%	10%
	ACU Utilisation	93%	75%	19%	94%	2%	83%	11%
Layout Efficiency	Avg. Doctor Distance (km/d)	3.24	3.63	12%	2.83	13%	3.91	21%
	Avg. Nurse Distance (km/d)	6.48	7.32	13%	6.55	1%	5.34	18%
ED Productivity	Patient : Doctor Ratio	7.34	7.52	2%	7.14	3%	7.9	8%
	Patient : Nurse Ratio	9.84	10.22	4%	10.16	3%	10.8	10%
	% Patients Treated	83%	85%	2%	90%	8%	96%	16

Scenarios 1 and 2 resulted in minimal improvements and these changes were not clinically significant or palatable for patients. Scenario 3 reduced an over-reliance on overstretched nursing resources, whilst improving the utility of physicians as well as expected improving the PETs of boarders. The more potentially expensive change Scenarios 1 and 2 had a negligible impact on ED boarding times. AHP was then used to evaluate these scenarios considering the ED decision makers preferences (Appendix C). The AHP comparison matrix for the four main performance criteria of the ED and their corresponding weights are represented in Table 5-13. For simplicity, LE was given as an abbreviation for Layout Efficiency, PT for Patient Throughput, PR for ED Productivity and RU for Resource Utilisation.

Table 5-13 The comparison matrix for the main KPIs in ED performance criteria.

	LE	PT	PR	RU	Resulting AHP Weight
LE	1	0.125	0.167	0.25	0.046
PT	8	1	3	6	0.581
PR	6	0.33	1	3	0.285
RU	4	0.167	0.33	1	0.116

A comparison matrix for each criterion in Figure 5-9 was then constructed to obtain the weights of individual KPIs (i.e., the leaves of the performance value tree). Table 5-14 shows the comparison matrix for the three KPIs that represent the Patient Throughput criterion and their AHP weight.

Table 5-14 The comparison matrix for the KPIs of the Patient Throughput criterion.

	ALOS Dis.	ALOS Ad.	A.W.T Doc.	AHP Weight
ALOS Dis.	1	0.33	4	0.304
A.LOS Ad.	3	1	3	0.575
A.W.T Doc.	0.25	0.33	1	0.121

The same process of pair comparison among KPI's for each main criterion was repeated until the last level was reached. Figure 5-20 shows the final weights for all the levels in the performance value tree.

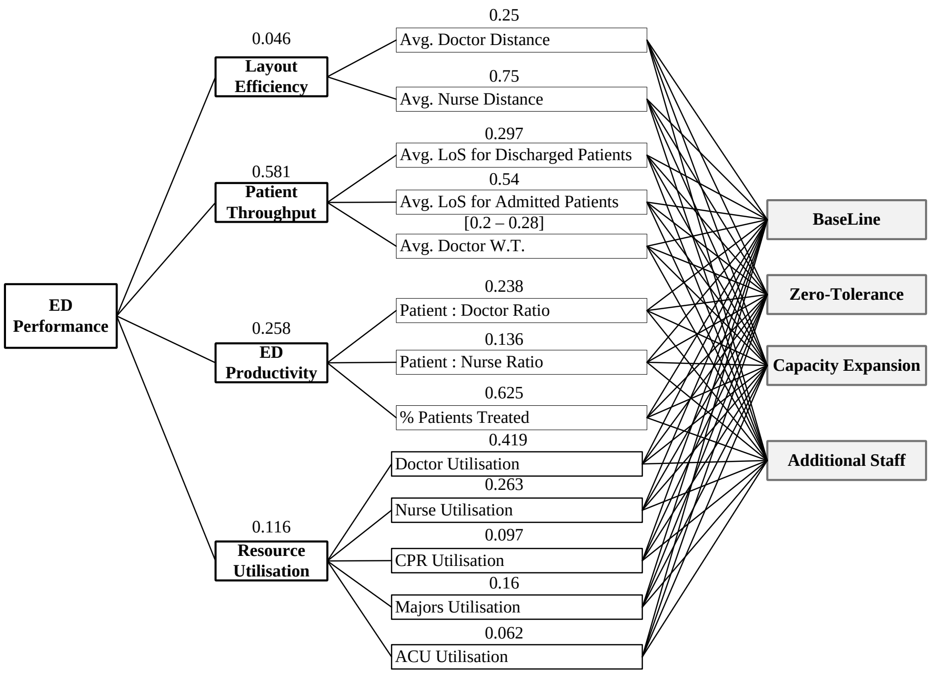


Figure 5-20 AHP weighted value tree.

Upon the determining the weights, the acceptable range for each KPI was determined by the ED manager. For example, the utilisation of staff – for nurses or doctor – had a range between 50% and 85%. This is to avoid the burnout level of the staff (85 %) and at the same time avoid under-utilisation of resource. Similarly, the LOS KPI specified a range between 0 and 6 for both admitted and discharged patients; this is to measure the achievement level of each scenario taking into consideration the HSE target (6-hours maximum LOS). Following assigning acceptable ranges, a value function was then used for each individual KPI to describe the importance and desirability of achieving different performance levels of each KPI based on its measurement level from the simulation model. For example, the desirability increases from 0.5 to 1.0 when the percentage of treated patients increases from 70% to 100% as shown in Figure 5-21.

Given the results of the simulation model in Table 5-12 and the AHP preference model, the final value for each scenario including the base line scenario (current ED) was aggregated and summarised in Table 5-15.

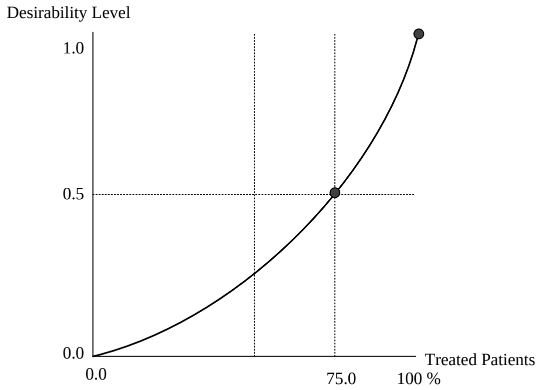


Figure 5-21 Percentage of patients treated value function.

Table 5-15 Weighted results for all scenarios against the baseline scenario.

	Base Line	Zero-Tolerance	Capacity Expansion	Increasing Staff
Resource Utilisation	0.11	0.19	0.14	0.108
ED Productivity	0.169	0.215	0.18	0.194
Patient Throughput	0.214	0.546	0.38	0.289
Layout Efficiency	0.031	0.029	0.034	0.031
ED Performance	0.524	0.98	0.734	0.622

The implementation of the "zero-tolerance" strategy had the greatest impact on the throughput of patients (54.6% increases), and on the overall ED performance (Figure 5-22). Accordingly, the zero-tolerance scenario is clearly a recommended strategy for the ED.

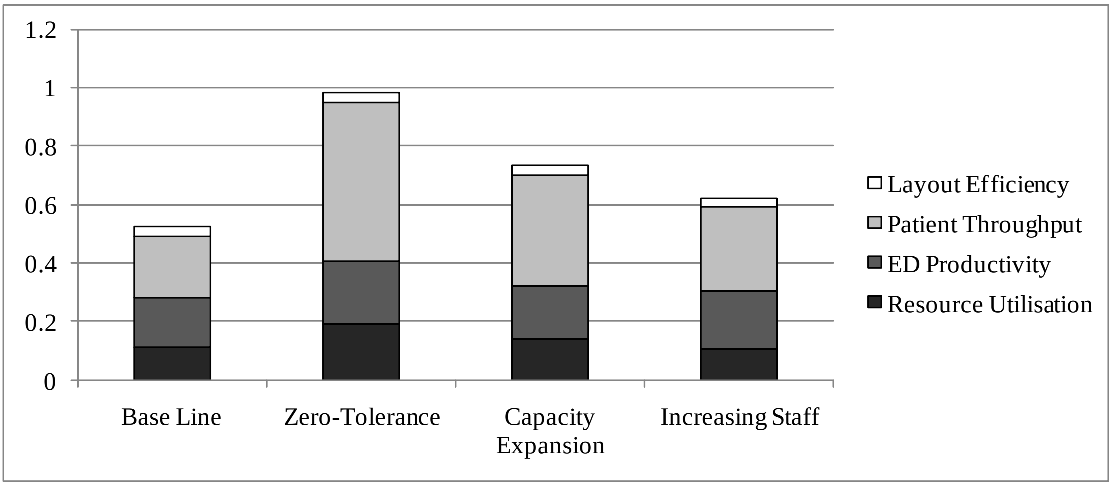


Figure 5-22 The ED performance for all the scenarios against the current ED.

5.6.1.3 Sensitivity Analysis

A sensitivity analysis was performed to explore how the ED performance may change in each strategy regarding the changes in variables. This is essential because recognising the aspects to which the decision is sensitive enables the ED manager to concentrate on, or possibly reconsider the issues, which may cause changes in the decision. Due to the increase of the ALOS for the current ED above 6-hrs, the performance of the current ED deteriorated at all levels, while adding more staff and increasing the capacity of the ED was needed at this stage. However, enforcing the 6-hrs target (i.e., zero-tolerance scenario) outperformed these more expensive scenarios (i.e., Capacity expansion and Additional staff) as shown on Figure 5-23.

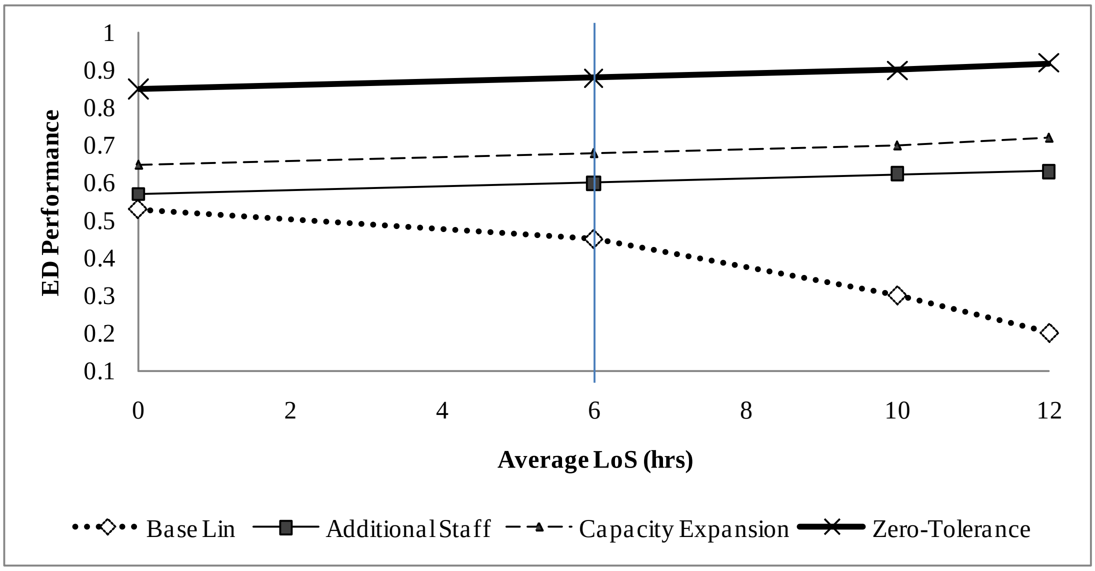


Figure 5-23 The change in ED performance with average LOS for all scenarios.

The performance of the current ED will deteriorate due to over-utilisation of staff because they have reached their burnout level (Figure 5-24). Staff burnout (85% utilisation) can be better mitigated by increasing the staffing level on the ED than expanding the physical capacity of the ED which does not lower the work load on an individual staff member.

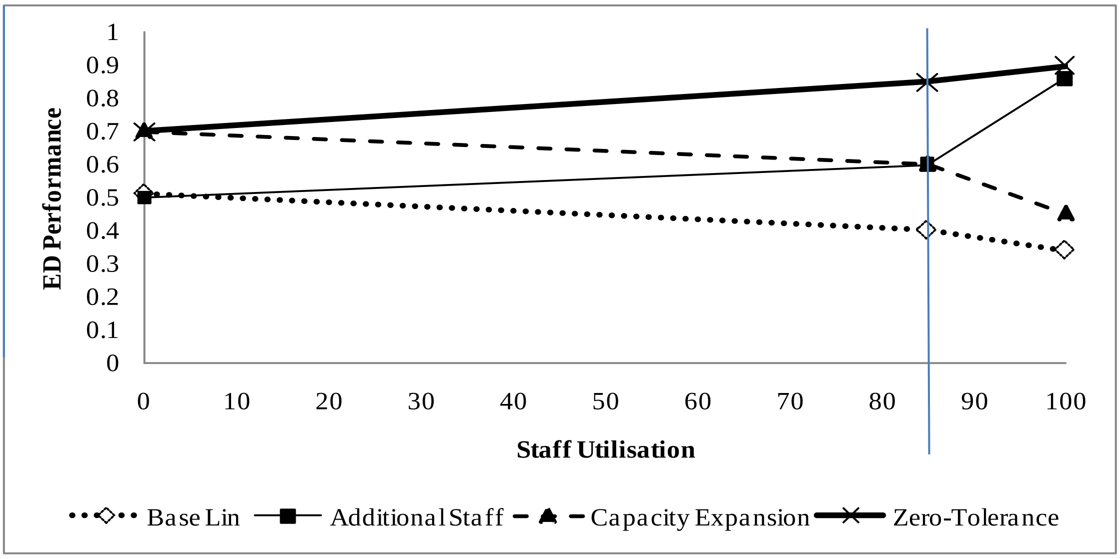


Figure 5-24 ED performance with the burnout level of staff.

5.6.2 Achieving Targets – Real-Time Strategies for the ED

5.6.2.1 Design of Experiments

The basis of the three basic strategies tested in the previous section is that the same demand pattern (i.e., patient arrival time) does not change according to the changes in ED capacity or staffing levels. However, the increase in ED physical capacity will eventually lead to more patients arriving at the ED. The effects of changes in the three principle variables that were introduced in the previous section were considered to evaluate the effect of the expected increase in demand. Table 5-17 shows the decision variables, namely the physical capacity represented with number of trolleys, the staffing level, and the access block which represents the absolute compliance with the national 6 –hour admission target for ED boarders. Every variable has two levels of changes as shown in Table 5-16.

Table 5-16 Simulation variables and their changing levels.

	Access Block	Physical Capacity	Staffing Level
Number of Levels	2	2	2
Level 1	No	13	Same Staff
Level 2	Yes	19	One SHO Shift

A full factorial design of experiments (DOE) is used to evaluate all combinations between the different levels of changes of the aforementioned variables (Table 5-17).

Table 5-17 Scenario design for the three basic strategies and their combinations.

	Decision Variables		
	Access Block	Physical Capacity (trolleys)	Staffing Level
Base Line	Yes	13	-
Scenario 1	No	13	-
Scenario 2	Yes	19	-
Scenario 3	Yes	13	1 SHO [9pm to 7am]
Scenario 4	No	19	-
Scenario 5	No	13	1 SHO [9pm to 7am]
Scenario 6	Yes	19	1 SHO [9pm to 7am]
Scenario 7	No	19	1 SHO [9pm to 7am]

5.6.2.2 Analysis of Results

With expected increase in patients arrivals, resolving the access blockage from the ED to the hospital (i.e., scenario 1) resulted in a significant decrease in admitted patients LOS from 21.3hrs to 7.75hrs with a 49% decrease in the average distance travelled by nurses (Table 5-18).

Table 5-18 Simulation Results of the first three scenarios.

Key Performance Indicators (KPIs)		Base Scenario	Scenario 1 (no blockage)	Scenario 2 (increase capacity)	Scenario 3 (more staff)
Patient Throughput	A.W.T Doctor (hrs)	177.43	204.05	185.85	98.68
	ALOS Dis. Pts. (hrs)	8.95	9.78	9.38	7.53
	ALOS Adm. Pts. (hrs)	21.30	7.75	19.65	19.00
ED Productivity	Patient : Doctor Ratio	7.34	7.47	7.52	7.14
	Patient : Nurse	9.94	10.22	10.22	10.16
	% Patients Treated	83%	83%	85%	94%
Resource Utilisation	Doctor	81%	80%	79%	63%
	Nurse	82%	71%	82%	83%
	CPR	81%	67%	80%	79%
	Majors	91%	85%	87%	88%
	ACU	90%	85%	87%	85%
Layout Efficiency	Avg. Doctor Distance (km/d)	3.24	2.86	2.83	3.25
	Avg. Nurse Distance (km/d)	6.48	3.32	6.35	6.72

The significant decrease in patients ALOS is a result of the availability of ED resources that were utilised by patients awaiting admission. For example, physical beds and trolleys that were occupied by patients waiting admission were available for new emergency patients, especially acute patients. Moreover, nursing staff that were frequently monitoring patients in critical medical conditions in corridors or trolleys could be reallocated to more pressurised areas in the ED. The expectation that increasing the number of trolleys (i.e., scenario 2) will decrease the patient A.W.T was proven wrong due to the shortage in staffing levels to meet the growing increase of patients arrivals. Such decrease in waiting time was attained on the short term, as patients waited doctors inside the ED and utilised the new trolleys. However, due to the crowded ED and the insufficient number of staff, the A.W.T of patients, particularly less acute patients, A.W.T increased by 15 % and consequently the ALOS of discharged patients increased by 5% (Figure 5-25). This effect cascaded back through the ED progressively with more patients waiting on trolleys to be admitted to the hospital. As a result, there was no space left to meet the timely needs of the next patients who needed emergency care.

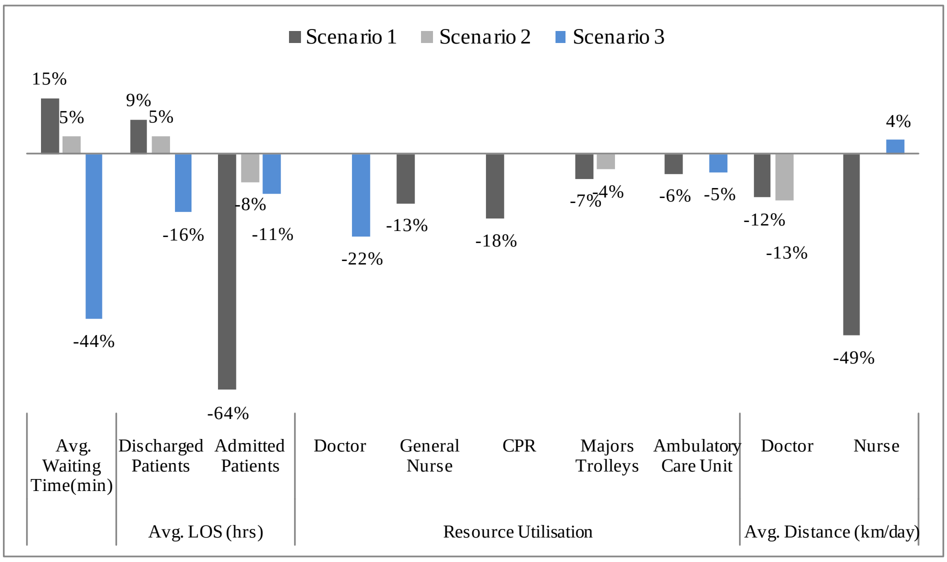


Figure 5-25 Comparison of base scenario against scenario 1, 2, and 3

On the other hand, adding one SHO doctor from 9pm to 7am inn scenario 3 would reduce the queue length in the waiting room that keeps building up over the night time (especially weekends). Subsequently, the average waiting time of patients would shorten by 44% (98.68mins) and the percentage of treated patients will increase to 94%. Nevertheless, the average LOS of patients is still beyond the national metric (6hrs compared to 7.53hrs for discharged patients and 19hrs for admitted patients).

5.6.2.3 The ED Preference Model

A preference model was then developed to analyse the combined effects of decision variables (scenario 4 – 7) against all KPIs simultaneously. Based on base line scenario, and the results the first three scenarios (Table 5-18), along with the simulation results of the simulation output for their combinations (Table 5-19), PRIME (Appendix C) was used for building the ED preference model.

Table 5-19 Simulation results of scenario 4, 5, 6, and 7.

KPIs		Scenario 4	Scenario 5	Scenario 6	Scenario 7
Patient Throughput	A.W.T Doctor (hrs)	141.32	110.80	105.20	99.25
	ALOS Dis. Pts. (hrs)	8.47	7.45	7.54	7.36
	ALOS Adm. Pts. (hrs)	6.91	6.55	18.81	6.36
ED Productivity	Patient : Doctor	7.69	7.28	7.23	7.31
	Patient : Nurse	10.19	10.43	10.34	10.44
	% Patients Treated	90%	94%	93%	95%
Resource Utilisation	Doctor	71%	61%	63%	60%
	Nurse	67%	69%	83%	68%
	CPR	64%	62%	79%	62%
	Majors Trolleys	70%	74%	83%	64%
	ACU	75%	73%	81%	68%
Layout Efficiency	Doctor	2.50	2.89	2.87	2.62
	Nurse	2.65	2.84	6.45	2.47

The main reason behind the selection of PRIME is due to the uncertainty of the ED managers about the expected increase of patients arrival, therefore the imprecise preferences of the ED mangers were used to construct weighted intervals of the ED KPIs as shown in Figure 5-26.

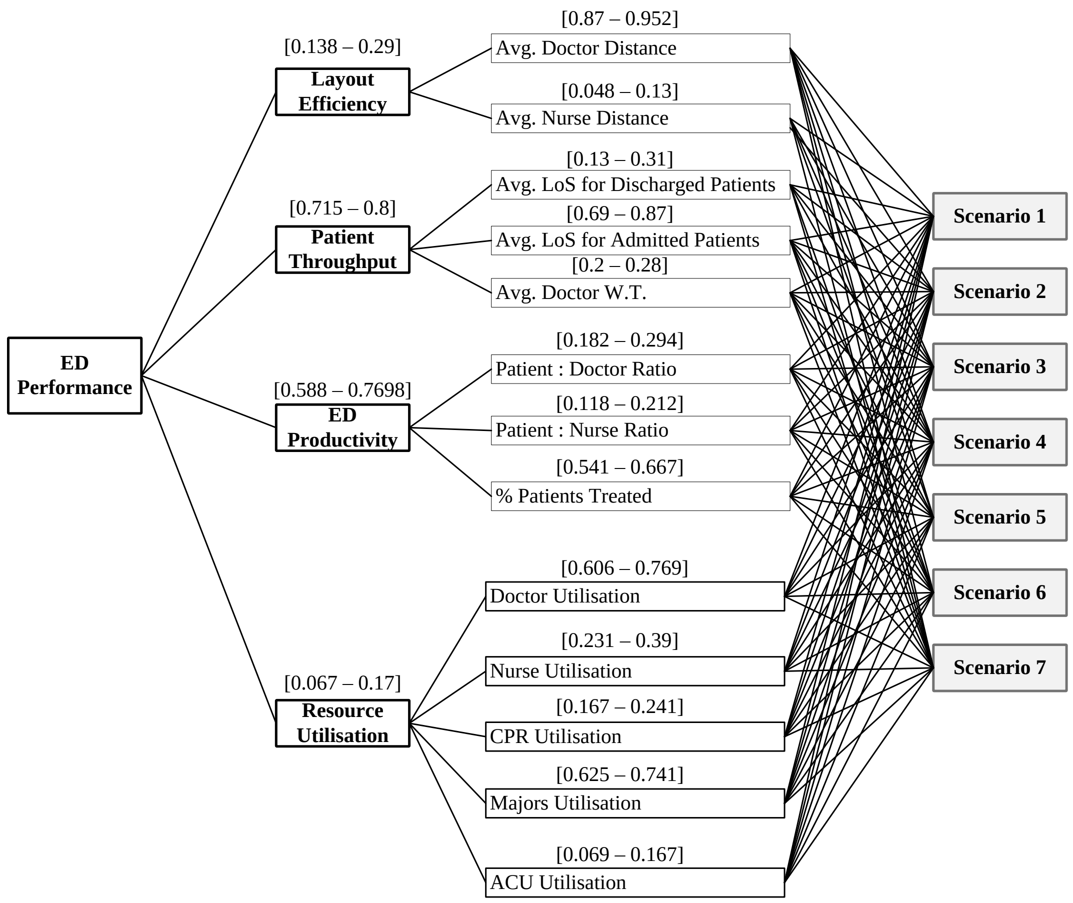


Figure 5-26 The weighted value tree of the ED KPI's using PRIME.

The marginal performance of the KPIs was then aggregated using the PRIME value tree and resulted in a performance value interval for each scenario Figure 5-27. An increase between 38% and 54% in the performance is achieved for scenario 1 while the expansion of the physical ED capacity (scenario 2) enhanced the ED performance only by 8% to 19%. By the visual inspection of value intervals in Figure 5-27, scenario 1, scenario 2, scenario 3, and scenario 6 are dominated by scenario 4, scenario 5, and scenario 7 respectively.

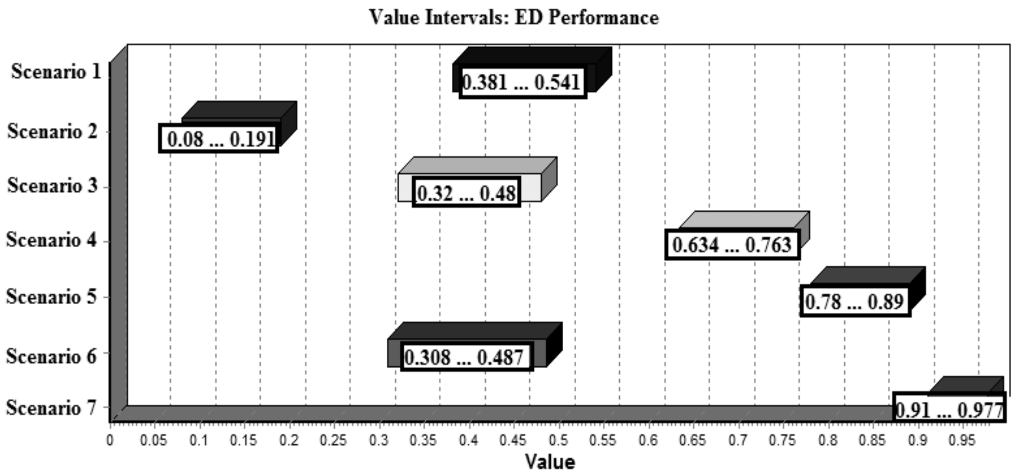


Figure 5-27 Value intervals for all scenarios.

The dominance structure of all the scenarios is shown in Table 5-20, where the "+" highlights that alternative in the row dominates the alternative in the corresponding column, and the "-" indicated that the alternative in the row is dominated by the one in the corresponding column. The effect of inpatient admission blockage (i.e., scenario 1) on the ED performance is greater than that by adding more ED beds or having an additional physician. However, when combined other scenarios, the performance improved significantly. Scenario 7 dominates all other scenarios in terms of ED performance. As shown in Table 5-19, the ALOS for admitted patients is approximately 6-hrs, and percentage of patients treated patients is 95% which meet the national metric for both indicators.

Table 5-20 Dominance structure of all scenarios.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
Scenario 1		+		-	-		-
Scenario 2	-		-	-	-	-	-
Scenario 3		+		-	-		-
Scenario 4	+	+	+		-	+	-
Scenario 5	+	+	+	+		+	-
Scenario 6		+		-	-		-
Scenario 7	+	+	+	+	+	+	

5.7 STAFF SCHEDULING

Unblocking the performance bottleneck highlighted in previous section access necessitates collaboration between different departments within the hospital. Additionally, recruiting clinical staff is not a feasible alternative for the ED given the currently limited budget. More effective solution is achieved using the integrated framework by optimising required staffing level for the ED. Staff scheduling had contributed to resolve the ED overcrowding problem by dynamically adapting the time-varying patient arrival to the ED.

5.7.1 Problem Definition

The scheduling problem for the ED is to create weekly schedules for ED doctors of up to 50 doctors by assigning one of a number of possible shift patterns to each nurse. These schedules have to satisfy working contracts, whilst meeting the variable demand in the arrival of patients. Furthermore, the problem has a special day-evening-night structure as most of the doctors are contracted to work either days/evening or nights in one week but not both. However due to working contracts, the number of days worked is not usually the same as the number of nights.

Due to the combinatorial nature of the scheduling problem and the existence of multi-objective represented in the ED value tree, the optimisation technique map (OTM) developed in section 4.3.6.2 guided the selection process of the optimisation technique to the meat-heuristics optimisation techniques to be used for the scheduling problem. Scheduling problems are challenging for any local search algorithm as finding and maintaining feasible solutions is extremely difficult in the existence of feasible schedules constraints. Accordingly, meta-heuristics optimisation techniques have been used for the scheduling problem. The Genetic algorithm (GA) has been extensively used for scheduling problems in the healthcare and other sectors. However, due to this special structure of the staff scheduling problem, an integration between the GA and the Clonal Selection Algorithm (CSA) has been used (Abohamad *et al.*, 2010, Mohamed Korayem *et al.*, 2010). CSA is an adaptive search algorithm search that is inspired from the natural immune system, where CSA seeks to capture a variety of evolutionary and adaptive mechanisms for improving the searching process. A detailed description of applying the GA/CSA hybrid for finding optimal staff schedule is described in Appendix D.

5.7.2 Problem Formulation

As suggested by the ED manager, the re-scheduling will be for the Senior House Officer Doctors (SHOs) that currently exist in the ED, which is constrained with the feasible doctor work-shifts. For simplicity, doctor will be used instead of SHOs from this point to the end of this section. For keeping the ED running, only twelve SHOs are considered in the schedule, as a roster is used then to rotate the work-stretch for the remaining doctors. A work-stretch is a set of consecutive work-shifts between at least two days off. The work-shift is a period of time within a working day during which a doctor will be assigned. Table 5-21 shows feasible range of available work-shifts provided by the ED managers, where each work-shift has a starting and ending times with a length of 10 hours.

Table 5-21 Feasible work-shifts in the emergency department.

Work-shift	Time	Shift Name
Day shift	06 - 16:00	D1
	08 - 18:00	D2
	10 - 20:00	D3
	11 - 21:00	D4
Evening shift	14 - 00:00	E1
	16 - 02:00	E2
Night Shift	22 - 08:00	N

The day is generally partitioned into generally three working shifts: day, evening and night shifts. The day shift is in turn has 4 types D1, D2, D3, and D4. Each day shift is of 10hrs length but with a different starting working hour. Two available evening shifts: E1 and E2, and only one night shift, namely N. There are several rules and assumptions have to be considered during the optimisation procedure; first, the roster assigned to each doctor must contain only feasible work-stretches; and at least two days off after each work-stretch. In order to address these constraints, a binary representation of the roster had introduced for staff work-shifts (Table 5-22).

Table 5-22 Binary representation of feasible work shifts.

	Day shift				Evening shift		Night Shift
	06 - 16:00	08 - 18:00	10 - 20:00	11 - 21:00	14 - 00:00	16 - 2:00	22 - 8:00
D1	1	0	0	0	0	0	0
D2	0	1	0	0	0	0	0
D3	0	0	1	0	0	0	0
D4	0	0	0	1	0	0	0
E1	0	0	0	0	1	0	0
E2	0	0	0	0	0	1	0
N	0	0	0	0	0	0	1
OFF	0	0	0	0	0	0	0

The work stretch can then be represented in terms of these work shifts as a binary vector W_{7x1} as s work stretch for the whole week. For example, a work stretch for a doctor can be represented as (D1, D1, E2, N, N, OFF, OFF), where each of these consecutive work shifts is replaced by its binary representation in Table 5-22.

Subsequently, the doctor roster is a Vector $R_{12x7,}$ for the total number of SHOs in the ED. Following the encoding of the scheduling problem, the hybrid GA/CSA is then used to find the optimal doctor's roster that maximises the ED performance. The main steps of the GA/CSA are as following:

1. Generate randomly an initial population of N doctor rosters.
2. Calculate the fitness for each individual (i.e., doctor roster) in the current population.
3. Produce new individuals (off-springs) from current population using crossover.
4. Combine the resulted off-springs from step 3 with current population.
5. Select individuals from the combined population that gives the highest fitness values, which will be used to generate new individuals.
6. For each individual, generate clones and mutate each clone according to its fitness.
7. Select the best mutated individual from each group of clones and add it to the population.
8. Delete individuals with lower fitness form the population, then add to the population of the new individuals.
9. Repeat the steps from 2- 8 until the optimal schedule is obtained or to the maximum number of iterations.

According to (Haupt and Haupt, 1998), the initial number of population is $N = 84$, as a multiple of the binary string length, which represents each individual in the population.

5.7.3 Results Analysis

The main reason for the optimisation process is to generate the optimal or near-optimal staff schedule that can improve the ED performance and in turn to minimise the average patient LOS. Therefore, the ED simulation model is used to calculate the fitness of each individual. Each individual is passed to the simulation model as a scenario, where the output is passed in the form of populated balanced scorecard to the AHP tool (section

4.3.7). The aggregated ED performance obtained from the MCDA becomes the fitness value for each individual in the population. After appropriate operations, based on selection, crossover, and Cloning operators, off-springs are obtained to replace some of the individuals (i.e., schedules), which in turn are evaluated and analysed to decide whether to stop or continue through the evolution process.

The final output of the optimisation procedure is the near-optimal doctor schedule for the ED. Table 5-23 shows the optimal weekly work stretches for the ED staff, along with the total number of physician hours for achieved for each day in the week.

Table 5-23 Optimal weekly work stretches for the ED staff.

Work stretch no.	M	T	W	T	F	S	S
1	OFF	D2	D2	D2	D2	OFF	
2	E1	E1	E1	E1	E1	OFF	
3	N	N	N	N	N	N	N
4	OFF						
6	D4	D4	OFF		D4	D4	D4
7	E2	E2	E2	E2	OFF		E2
8	E2	E2	E2	X	X	E2	E2
9	OFF						
10	D1	D1	D1	OFF		D1	D1
11	D2	D2	D2	D2	D2	OFF	
12	N	N	N	N	N	N	X
Daily staffing level (hrs)	90	100	90	70	70	50	50

Using the ED simulation model has resulted in directing the adaptive search capabilities of the GA/CSA algorithm towards obtaining optimal staff working stretches that meet the patient demand which is the highest around working days, whereas the demand is at its lowest levels around the weekends (Figure 5-28).

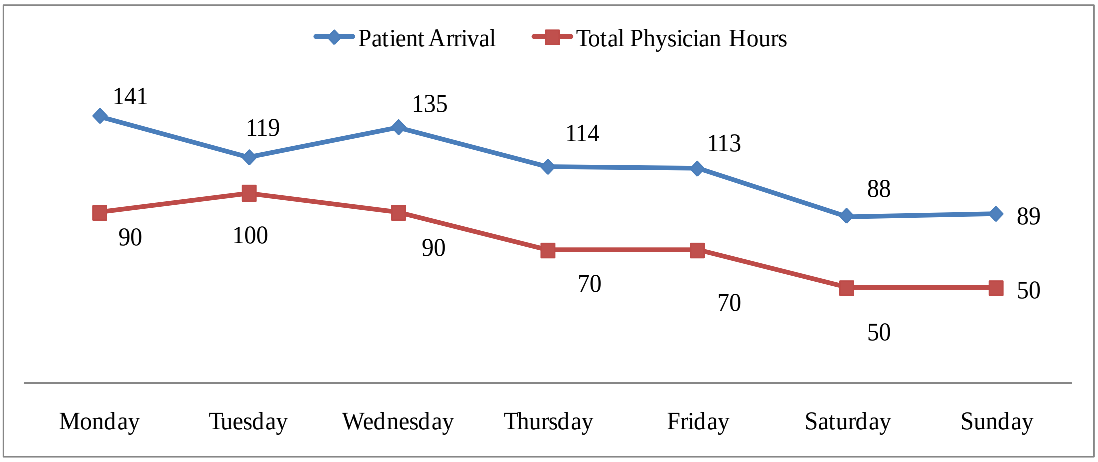


Figure 5-28 The ED optimal staffing levels matching the weekly patient arrival rate.

As a result, the average patient waiting time was reduced by 57% due to the new schedule. Table 5-24 shows that the percentage of treated patients has approached 92% converging on the HSE 6-hours target.

Table 5-24 Simulation results of the optimal staff schedule and the baseline scenario

KPI's	**Base Line**	**Optimal schedule**	↓↑
Avg. A. W.T. (mins)	177.43	75.68	57%
ALOS Discharged Patients (hrs)	8.95	7.13	20%
% Patients Treated	83%	92%	11%

In order to statistically compare the EDs performance of the optimal schedule scenario with the current ED performance (i.e., base line), a confidence interval was constructed for the difference between μ_1 and μ_2 with overall confidence level of $1 - \alpha$, where α = 5%. After two tailed t-test computation, the results implied that there are significant differences in the comparison between the optimal schedule and the current one, which means that the new staff schedule showed improvements in the quality care in the ED. The resulting optimal work shifts accounts for the time-varying characteristics of the daily patient arrival by allocating the optimal staffing level over the ED 24-hours. For example, Figure 5-29 shows the overlapping between staff working shifts on Tuesday, which is one of the busiest days with high patient arrival rate at the ED. Due to the short in staff during the peak times (between 14:00 and 18:00) that resulted in the overcrowding of the ED, the optimal schedule effectively overcome this problem by a dynamic overlapping between staff working shifts to meet such fluctuation in the demand, where the staffing level ranges from 6 to 7 doctors (Figure 5-29).

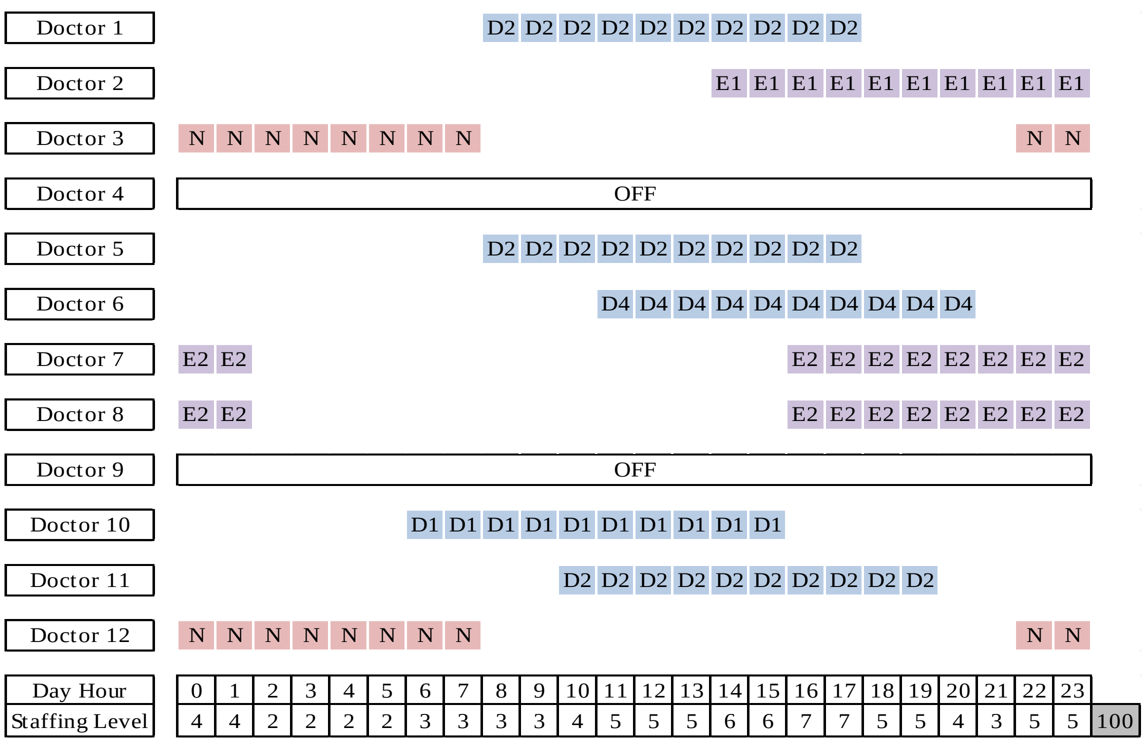


Figure 5-29 Overlapped staff work shifts comply with daily demand fluctuation.

To avoid staff under-utilisation, staff levels were reduced by overlapping between staff shifts to adopt to the slowly decayed patient arrivals rates, where the staffing levels reached its lowest levels during the night time (from 2 to 3 doctors over the night shifts). Due to the consideration of the seasonality in the arrivals of patients during the construction phase of simulation model, the resulted staffing roster comply with the weekly patients arrival pattern as demand is the highest around working days, whereas the demand is at its lowest levels around weekends (Figure 5-30).

	w1	w2	w3	w4	w5	w6	w7	w8	w9	w10	w11	w12
DOCTOR 1	1	2	3	4	5	6	7	8	9	10	11	12
DOCTOR 3	11	12	1	2	3	4	5	6	7	8	9	10
DOCTOR 4	10	11	12	1	2	3	4	5	6	7	8	9
DOCTOR 5	9	10	11	12	1	2	3	4	5	6	7	8
DOCTOR 6	8	9	10	11	12	1	2	3	4	5	6	7
DOCTOR 7	7	5	9	10	11	12	1	2	3	4	5	6
DOCTOR 8	6	7	8	9	10	11	12	1	2	3	4	5
DOCTOR 9	5	6	7	8	9	10	11	12	1	2	3	4
DOCTOR 10	4	5	6	7	8	9	10	11	12	1	2	3
DOCTOR 11	3	4	5	6	7	8	9	10	11	12	1	2
DOCTOR 12	2	3	4	5	6	7	8	9	10	11	12	1

	WEEK 1 WEEK 2 WEEK 3 WEEK 4 WEEK 5
DOCTOR 1	X D2 D2 D2 D2 OFF E1 E1 E1 E1 E1 OFF N N N N N N N OFF D2 D2 D2 D2 D2 OFF
DOCTOR 2	N N N N N N OFF D2 D2 D2 D2 OFF E1 E1 E1 E1 E1 OFF N N N N N N N OFF
DOCTOR 3	D2 D2 D2 D2 D2 OFF N N N N N N OFF D2 D2 D2 D2 OFF E1 E1 E1 E1 E1 OFF N N N N N N N
DOCTOR 4	D1 D1 D1 OFF D1 D1 D2 D2 D2 D2 D2 OFF N N N N N N OFF D2 D2 D2 D2 OFF E1 E1 E1 E1 E1 OFF
DOCTOR 5	OFF D1 D1 D1 OFF D1 D1 D2 D2 D2 D2 D2 OFF N N N N N N OFF D2 D2 D2 D2 OFF
DOCTOR 6	E2 E2 E2 OFF E2 E2 OFF D1 D1 D1 OFF D1 D1 D2 D2 D2 D2 D2 OFF N N N N N N OFF
DOCTOR 7	E2 E2 E2 E2 OFF E2 E2 E2 E2 OFF E2 E2 OFF D1 D1 D1 OFF D1 D1 D2 D2 D2 D2 D2 OFF
DOCTOR 8	D4 D4 OFF D4 D4 D4 E2 E2 E2 E2 OFF E2 E2 E2 E2 OFF E2 E2 OFF D1 D1 D1 OFF D1 D1
DOCTOR 9	D2 D2 D2 D2 D2 OFF D4 D4 OFF D4 D4 D4 E2 E2 E2 E2 OFF E2 E2 E2 E2 OFF E2 E2 OFF
DOCTOR 10	OFF D2 D2 D2 D2 D2 OFF D4 D4 OFF D4 D4 D4 E2 E2 E2 E2 OFF E2 E2 E2 E2 OFF E2 E2
DOCTOR 11	N N N N N N N OFF D2 D2 D2 D2 D2 OFF D4 D4 OFF D4 D4 D4 E2 E2 E2 E2 OFF E2
DOCTOR 12	E1 E1 E1 E1 E1 OFF N N N N N N N OFF D2 D2 D2 D2 D2 OFF D4 D4 OFF D4 D4 D4

Figure 5-30 The optimal staff roster for the emergency department for three months

5.8 FINDINGS

This case study has shown that the developed integrated framework, when properly conceived and designed in a collaborative fashion between scientists and clinicians can provide a valid and verifiable dynamic comparator (i.e., model) to a real-life overcrowded ED. Furthermore development of the computer model allows the safe and non-disruptive study of potential process strategies in an accurate alternative virtual reality without unnecessary disruption to patients, clinicians and healthcare managers.

This low cost framework may also prevent the introduction of potentially expensive unsuccessful strategies to improve patient care and to improve the internal process of the healthcare facility. Whilst increasing medical staffing at busy periods or increasing clinical assessment capacity might seem intuitively beneficial to overall patient LOS, the integrated framework reveals that enforcement of the national KPI 6-hour boarding limit for EDs, would have a significantly greater impact on reducing LOS for all ED patients than increasing medical staff or assessment cubicles. The prolonged waits for admission from the ED increases the total hospital average length of stay and also impacts on the morbidity of elderly patients. Access block therefore, has been shown by the developed framework to have the greatest impact on prolonged waiting time for patients and successful strategies are available to reduce hospital access block especially in situations of ED surge and reduced hospital bed capacity.

Considering the variability in patient arrival rates, the optimised staff scheduling strongly contributed to solving ED crowding problem and reduced the average waiting time for patients significantly by 57% compared to the current waiting time. That is achieved by optimising the staffing level and accordingly the number of physicians hours required to meet such variability in demand.

In conclusion, the use of the integrated framework in hospitals has a significant benefit in ensuring the quality of implementation of strategies and supporting decision makers. It also provides a safer, less disruptive and potentially less expensive tool than instigating de novo untested ineffectual strategies.

CHAPTER 6: CONCLUSION

6.1 INTRODUCTION

Science and technology are advancing at a rapid pace; however, the Irish healthcare delivery system struggles to cope in especially in its ability to provide high-quality service levels consistently. Irish Healthcare systems are in need of fundamental changes in the way care services are managed. Many patients, doctors, nurses, and healthcare providers are concerned that the care delivered is not, essentially, the care that should be received. The frustration levels of both patients and clinicians have probably never been higher. Policy makers, healthcare providers and managers should provide the quality of care that meets people need while improving the efficiency of their business processes based on the best scientific knowledge available. Yet there is strong evidence that this frequently is not the case. Large numbers of disciplined review bodies have reported the scale and gravity in healthcare problems world-wide. More systematic and sophisticated approaches are needed to analyse and manage healthcare processes and to support decision makers and healthcare mangers in the provision of informed decisions and strategies for delivering safe and effective care. The main purpose of this research was to introduce an integrated framework that allows healthcare decision makers to sort out complex issues and to make the best possible use of available resources. The following sections summarise the stages of this research in order to address the gaps in the existing knowledge domain and develop a practical, yet robust framework for healthcare business process management. Subsequently, a discussion of the main research findings is provided which is followed by the main contributions to existing knowledge. Research limitations are then highlighted and finally directions and guidelines of future work conclude the chapter.

6.2 RESULTS DISCUSSION

The developed integrated framework brought together scientists and clinicians to resolve many challenges that face healthcare providers and managers at different levels of the decision making process. Through the development of a detailed and comprehensive model that duplicated a real process, managers used a '*what if'* analysis approach to examine solutions. In this way they can enhance decision making by simulating situations that are too complicated to be modelled mathematically. Furthermore, the integrated framework provides a safe and non-disruptive management environment to assess potential process strategies without unnecessary disruption to the healthcare delivery process. Consequently, potentially expensive unsuccessful strategies can be detected prior to their actual implementation.

The integrated optimisation-based framework has successfully provided real-time strategies for emergency departments to improve patient care, by improving their internal processes. By applying and analysing the results, a number of potential performance bottlenecks have been identified and analysed. One of the main performance bottlenecks in healthcare systems and especially in hospitals is the access blockage from the emergency department to the inpatient facilities within hospitals. The lack of alignment and coordination among hospitals units resulted in unbalanced utilisation of hospital resources which in turn affects the whole care delivery process. Moreover, the prolonged waits for admission from EDs increases total hospital average length of stay and also impacts the morbidity of elderly patients. Increasing medical staffing at busy periods might seem intuitively beneficial to overall patient LOS. However, the reduction in LOS for patients awaiting admission is on average of 7%. This potentially expensive change has limited impact on ED boarding time. Similarly, the impact of increasing the clinical assessment capacity was negligible (15% decrease) compared to the synchronisation of patient flow through the hospital (i.e., enforcing the maximum boarding time from emergency department to hospital beds). Resolving this performance blockage can free valuable resources (e.g., doctors, nurses, and trolleys) consumed by patients waiting for hospital admission, which in turn reduced ALOS by 48 %. Moreover, the average waiting time was reduced by 39 % for patients waiting to be seen by ED clinician, while reducing the over-reliance on overstretched nursing resources, and improving the utility of doctors and nurses by 7% and 10% respectively. The combination of the three strategies produced a higher level of service quality that leads to a significant increase in patient throughput (95% treated patients) and achieved the strategic target of 6-hour maximum patient experience time (i.e., LOS), while accounting for the expected increase in patient arrival rates.

The integrated framework also produces optimal staffing patterns that match the available human resources (i.e., staff) in order to cope with the high uncertainty level in demand. This solution can then helps healthcare managers and provide a useful decision support tool. Optimal staff scheduling capabilities of the proposed framework allocated budgeted physicians to the proper patients at the proper times. Considering the variability in patient arrival rates, the optimised staff scheduling reduced the average waiting time of patients by 57% and also provided a significant increase in productivity (i.e. on average of 92% of patients were treated instead of 83%). The optimised schedule maintained continuity of care delivery for patients while ensuring uniformity of rotation, weekends, days off, and work stretch among available staff.

6.3 RESEARCH OUTCOMES

Due to the high level of complexities and uncertainties embedded in healthcare systems, this research utilises a multi-disciplinary approach to bridge the gaps between researchers and healthcare professionals. The main objective of this research was achieved by developing and implementing an integrated optimisation-based decision support framework that is applicable in managing complex healthcare business process.

Although significant advances were made, over the past two decades, for developing integrated methods and approaches for business process improvement (Clinton *et al.*, 2002, Searcy, 2004, Bezama *et al.*, 2007, Karaman and Altiok ,2009), there are issues have to be addressed to improve business process performance through the provision of support to the associated decision-making processes. The development of a high-level process model prior to the development of the simulation model could greatly help in the collection of relevant information on the operation of the system (i.e. data collection) and, therefore, reduce the effort and time consumed to develop a simulation model (Nethe and Stahlmann, 1999). Although methods from the IDEF approach have been used to support simulation of manufacturing systems (Al-Ahmari and Ridgway 1999; Jeong, 2000; Perera and Liyanage, 2000), their potential has not been explored in the healthcare sector (Brailsford, 2009). The utilisation of IDEF in this research for process modelling has not only improved the quality of simulation models but also it enhanced the communication levels among decision makers and the staff (e.g., doctors and nurses) through modelling the underlined work flow, decision points, and processes in a hierarchical form. This hierarchical structure kept the model scope within the boundaries represented by breaking down processes into smaller sub-functions. Such organisational strategy allowed the system to be easily refined into more details until the model is as descriptive as necessary for the decision maker.

The integration between simulation modelling and balanced scorecard contributed to the alleviation of BSC limitations in terms of its measurement capabilities and the lack of inferring the causal-effect among performance measures, which was highlighted by a number of authors such as Chow *et al.* (1998), Neely and Bourne (2000), Zelman *et al.* (2003), and Patel *et al.* (2008). Further, the combination of multi-criteria decision analysis tools along with simulation and BSC contributed significantly in the decision making process by explicitly dealing with priorities and trade-offs between different performance indicators (Banks and Wheelwright, 1979; 1985; Eccles and Pyburn, 1992; da Silveira and Slack, 2001). Such integration resulted in building a better understanding about the problem structure, the implications of potential corrective actions prior to their actual implementation, and selecting appropriate and informed decisions.

Consequently, the integration between simulation modelling, BSC, and MCDA within the proposed framework has brought new insights to inform and support the different stages of the decision making process. A synergy between supply chain networks and healthcare systems was established to identify the similarities and the lessons that can be learned. Although a number of attempts in the literature to draw such analogy have been introduced (Huijsman and Vissers, 2004, Ahgren and Axelssson, 2007), there is very little work to integrate optimisation techniques with MCDA, BSC, and simulation modelling. The optimisation capabilities of the framework has significantly contributed to the decision making process by offering help to decision makers to find the optimum values of decision variables, particularly for critical decisions such as staff scheduling, resource allocation, and capacity planning. Furthermore, the developed optimisation technique map (OTM) contributed to resolving the selection dilemma that faces system modellers and optimisers. The OTM mitigated the limitations of existing classifications of optimisation methods, which consider only small number of criteria such as decision variables (Swisher et al., 2000), optimisation capabilities (Tekin and Sabuncuoglu, 2004), or system modelling technique (Beyer and Sendhoff, 2007).

Therefore, the integration of optimisation within the framework provided a more harmonised automation of the improvement of healthcare processes. This was achieved by first selecting appropriate optimisation technique for underlying optimisation problem. For example, obtaining optimal schedules for ED staff is a combinatorial problem with multiple constraints and objectives to be satisfied. By considering these factors, the OTM has guided the selection process of the optimisation technique to the meta-heuristics methods to be used for the scheduling problem.

Many researchers have treated the staff-scheduling problem as an optimisation problem or a decision problem. For example, Cheng *et al.* (1997) described the design and implementation of a constraint-based nurse roster system using a redundant modelling approach. They modelled the nurse roster problem as a constraint satisfaction problem (CSP). Feasible solutions to the CSP are the assignments of values to variables satisfying all constraints. Jaumard *et al.* (1998) proposed a generalised linear programming model for nurse scheduling. The configuration of their work is to fulfil the hospital staffing demand coverage while minimising the salary cost and maximising nurse preferences. Carter and Lapierre (1999) extracted the characteristics of the generic emergency room physician scheduling problem and presented the schedule requirements and constraints to establish a mathematical programming model. Their objective function depended on the physician’s preferences. Valouxis and Housos (2000) presented a hybrid methodology for the work-shift a d rest assignment of nursing personnel. An approximate integer linear programming (ILP) model is first solved and its solution is further improved by using local search techniques. The objective function serves to minimise the total cost of rosters by giving a solution with the minimum number of work-shifts and with the maximum desirability. Dowsland (1998) applied tabu search and strategic oscillation for nurse roster problems. The objective is to ensure that enough nurses are on duty at all times while taking account of individual preferences and requests for days off. Yeh and Lin (2007) utilised simulation and GA to adjust staff schedules without hiring additional staff, with the objective to minimise the patients queue time.

However, the aforementioned studies considered only few performance measures which are mostly not related to patient satisfaction and national performance metrics. Moreover, the complete flow of patients through the healthcare facility is neglected. Therefore, the developed framework in this research utilised the BSC as a systematic procedure for the collection of performance measures and KPIs. The selected KPIs, using SMART method, were then represented as the objective functions for the optimisation problem. The initial values of the decision variables (e.g., the currently used staff schedules) were used by the GA to generate new values (i.e., schedules) towards improving the objective function(s). Thereupon, a comprehensive simulation model, which covered the complete patient flow, run the scenarios generated by the GA model and the BSC was populated with the scenario results. AHP was then aggregating the performance using the populated BSC. The aggregated performance was then used by the GA to search for better set of values that optimise the required set of objectives.

Such integrated optimisation features has contributed to significant improvement when applied to a real-world case study of an emergency department, in terms of patient waiting time, LOS, and staff utilisation. The obtained remarkable results outperform recently introduced decision support framework for solving staff scheduling issues, where only optimisation is integrated with simulation (Yeh and Lin, 2007, Gutjahr and Rauner, 2007). Therefore, the integrated framework considered healthcare problems in its full complexity before a solution can be found. It provided a significant aid to the decision makers and facility planners to foresee the consequences of a wide range of plans and potential solutions and predict the impact of the changes without disrupting the existing provision of services, which is another main contribution of this research that provides a practical decision support system that has been not only tested and validated, but also implemented.

6.4 LIMITATIONS

This research contributes towards integrated frameworks for business process management in healthcare systems. Although it has attempted to cover all the different aspects of the decision making process, we do not claim to have exhausted this area. The framework is limited to only to discrete-event simulation (DES), other simulation methods such as system dynamics (SD) and agent-based simulation (ABS) are emerging as potential tools for analysing the inter-connected relationships between healthcare components on the macro-level of the system, the inclusion of these simulation methods into the framework will enhance its utility and wider impact on the healthcare system.

6.5 RECOMMENDATIONS FOR FUTURE RESEARCH WORK

Due to the positive feedback from the executive board of the partner hospital, the framework is currently used to model other hospital units to achieve the alignment and coordination between their processes. Due to its ability to study inter-relationship between healthcare units, the inclusion of system dynamics provides valuable knowledge about the inter-relationships between the studied hospital units.

The integration between the hospital information system and the framework is to be investigated as recommended by the hospital managers. This will be of a great benefit in providing real-time simulation for the healthcare process and for making appropriate decisions in real-time manner. Such integration is to be provided by a web-based intelligent agent to facilitate the decision making process across the whole hospital. The framework is also used in collaboration with the facility planners and project managers of the new extension of the hospital to test the efficiency of the proposed layouts and capacities using the current staffing levels of the hospital.

Consequently, it is envisaged that this research can be expanded to form the basis of a predictive planning and management tool for building new healthcare facilities. For example, evidence based data on the effect of relationships, particularly between physical layout and distribution of services and facilities within building and staffing requirements can be used to derive optimum layouts and inter-relationships between departments. Variables such as staff levels and costs can be used to define the size of clinical areas that can be supported or alternatively constraints on capital expenditure will determine the size, staffing levels and associated running costs on a department by department basis. The optimisation technique map (OTM) can be used as an initial phase to develop a knowledge-based framework (Figure 6-1) for selecting a best-fit optimisation software package (Abohamad and Arisha 2010).

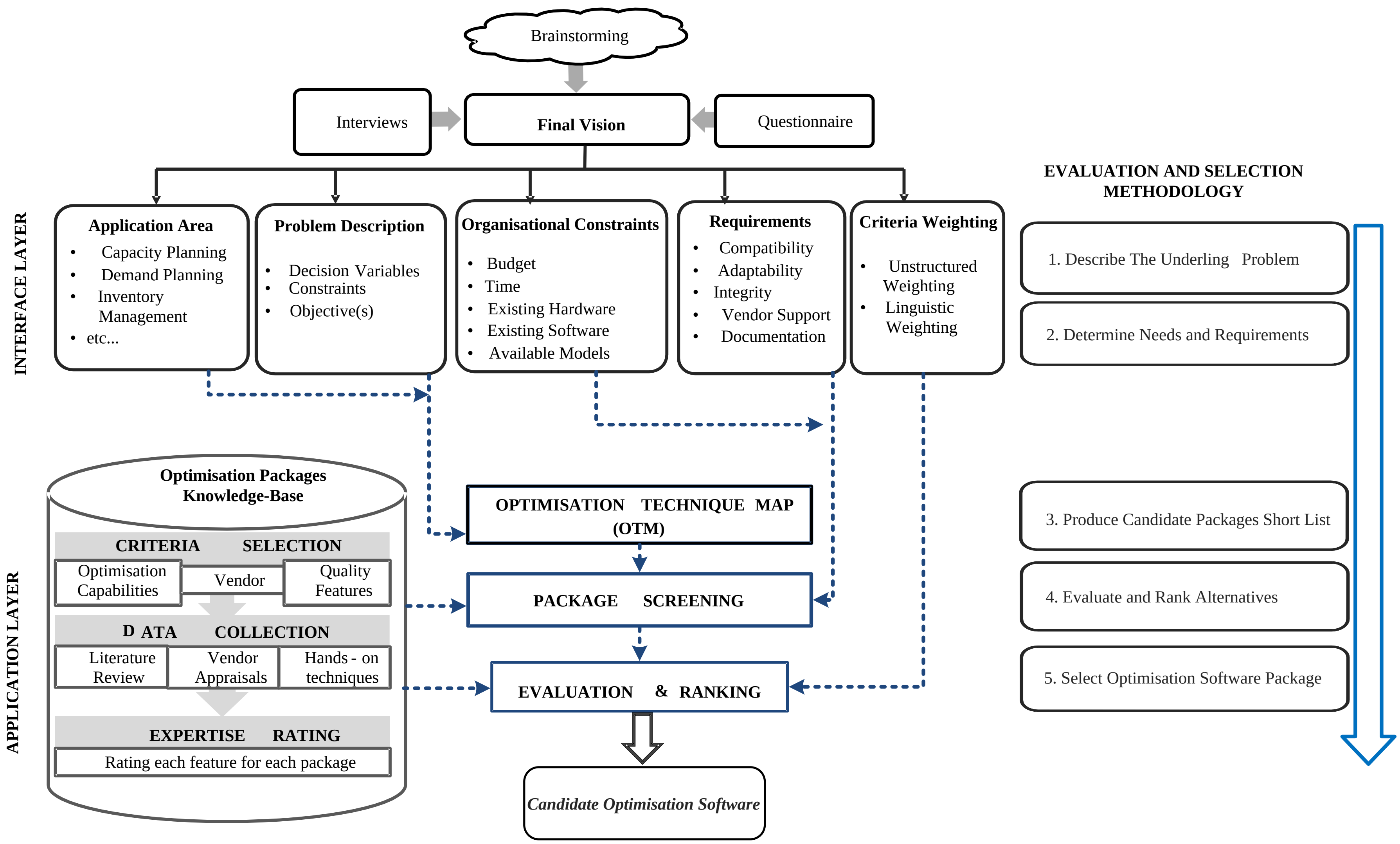


Figure 6-1 A framework for optimisation software selection

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APPENDICES

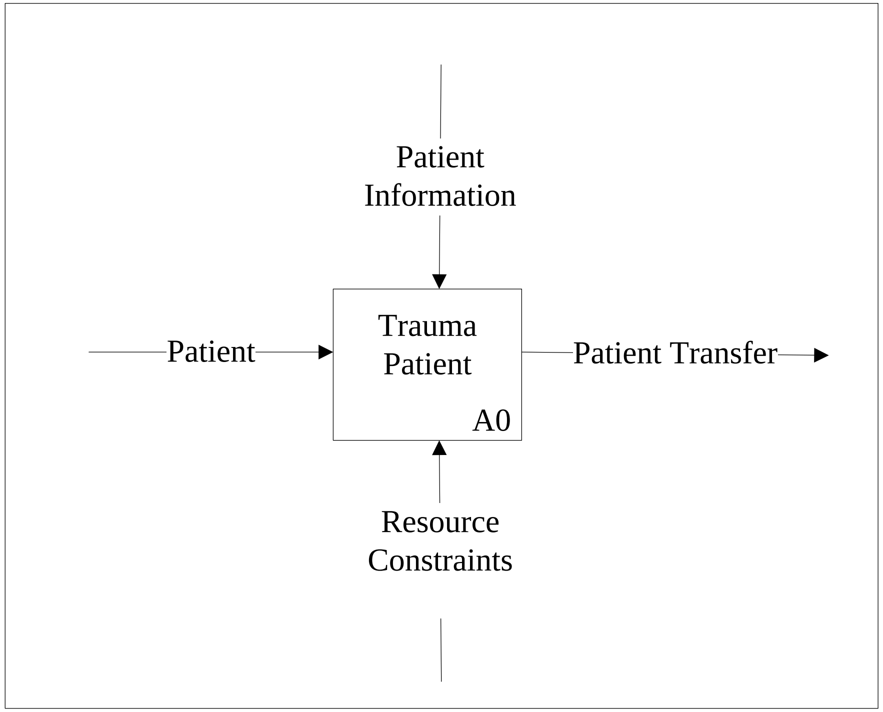
APPENDIX A: PATIENT FLOW PROCESS MAPPING

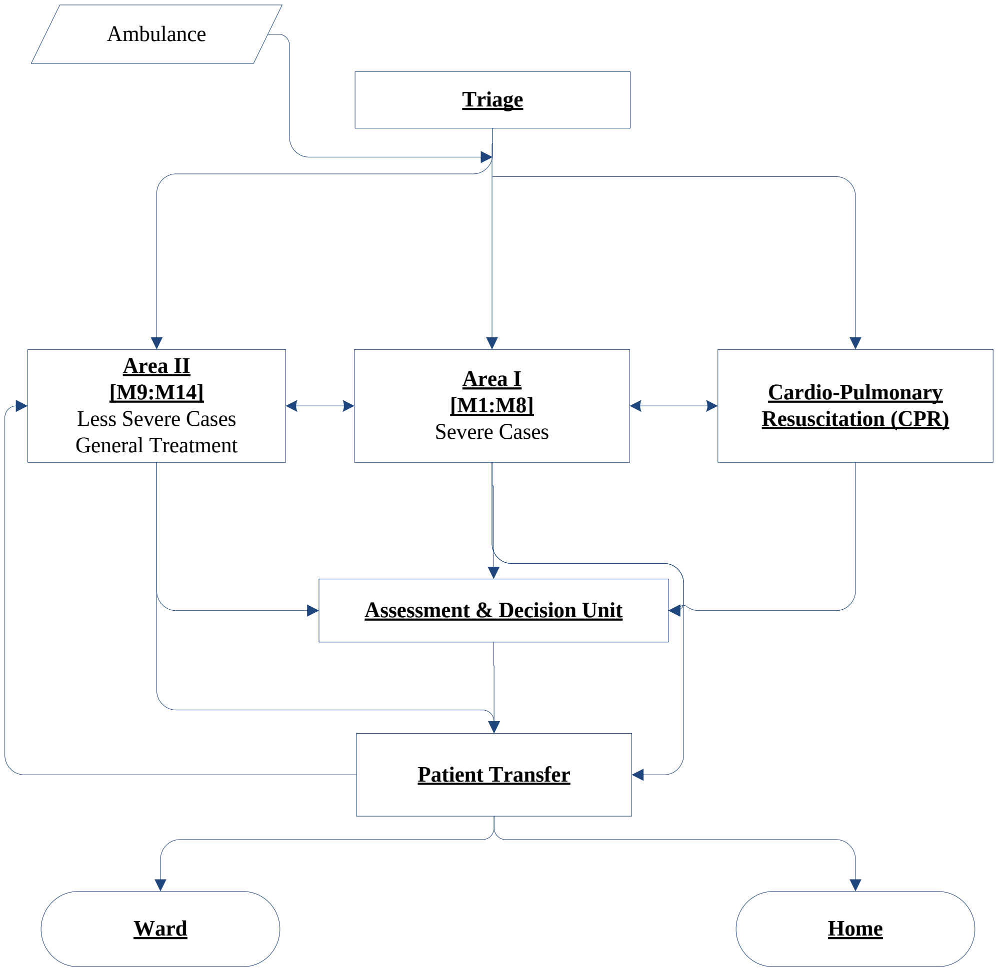
APPENDIX B: STATISTICAL ANALYSIS OF SIMULATION OUTPUT

APPENDIX C: MULTI-CRITERIA DECISION TOOLS

APPENDIX D: GENETIC ALGORITHM AND ARTIFICIAL IMMUNE SYSTEM

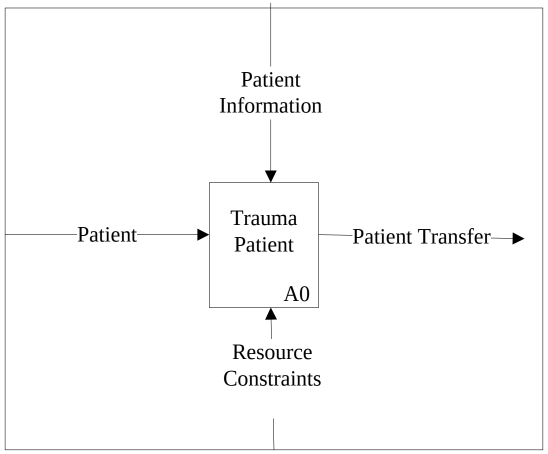
Appendix A: Patient Flow Process Mapping

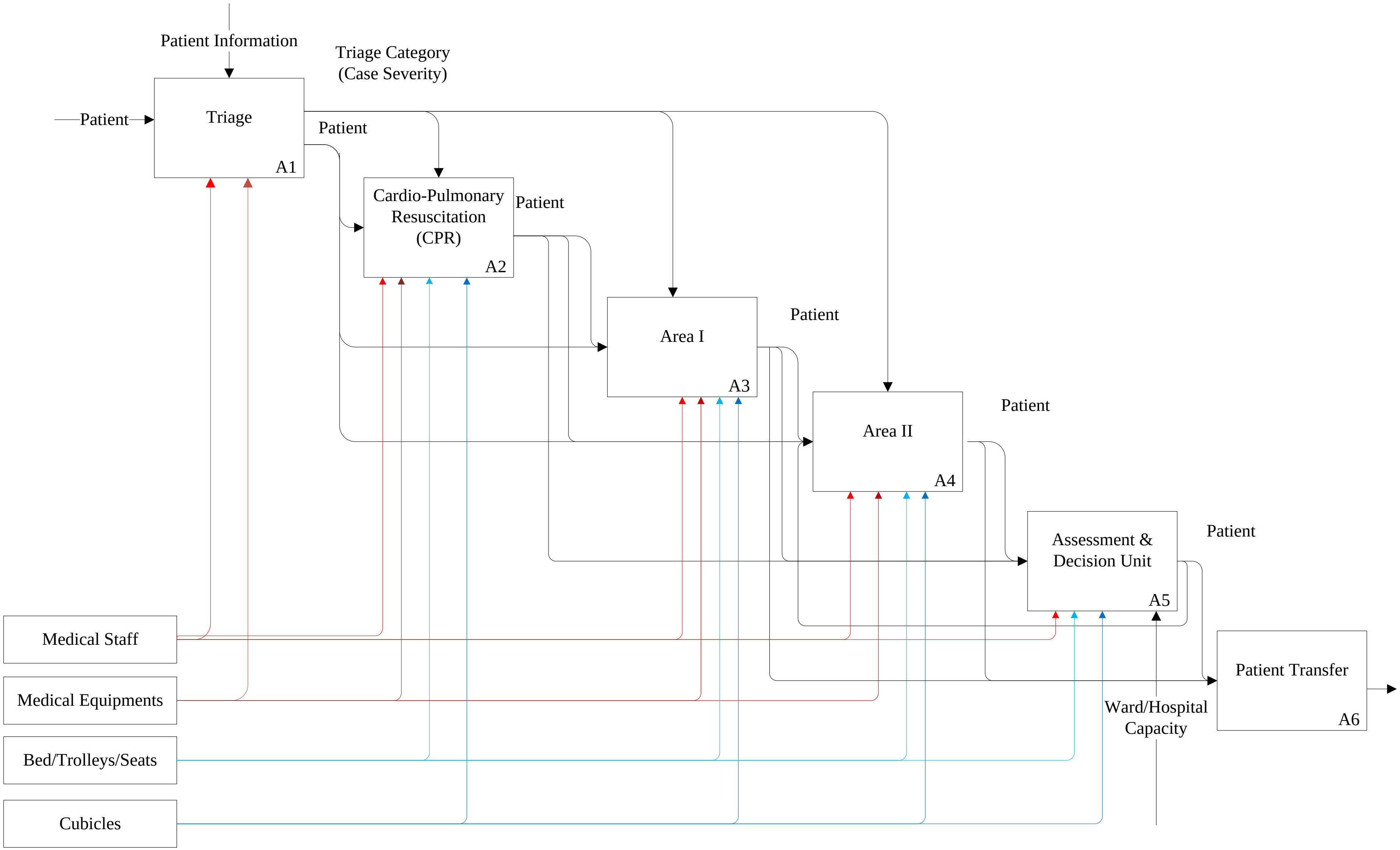


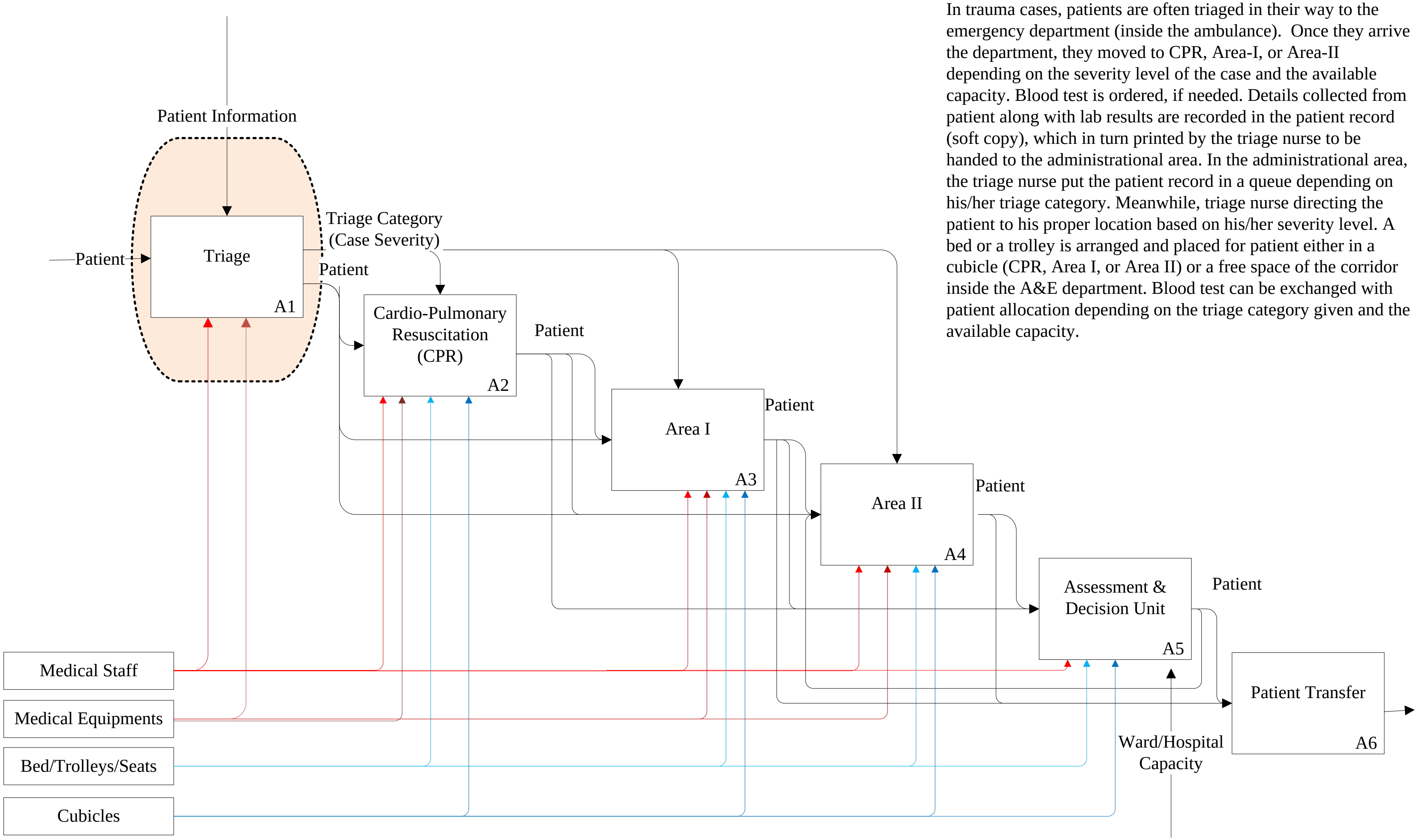


Trauma Patient

Trauma Patient arrive the A&E department via ambulance in which the triage is performed. Patient is then placed in the cardio-pulmonary resuscitation (CRP)/trauma unit. Area-I,II can be used depending on the severity case of the patient. Based on the diagnosis and other lab results, a decision is made about the patient to be hospitalised or sent home.

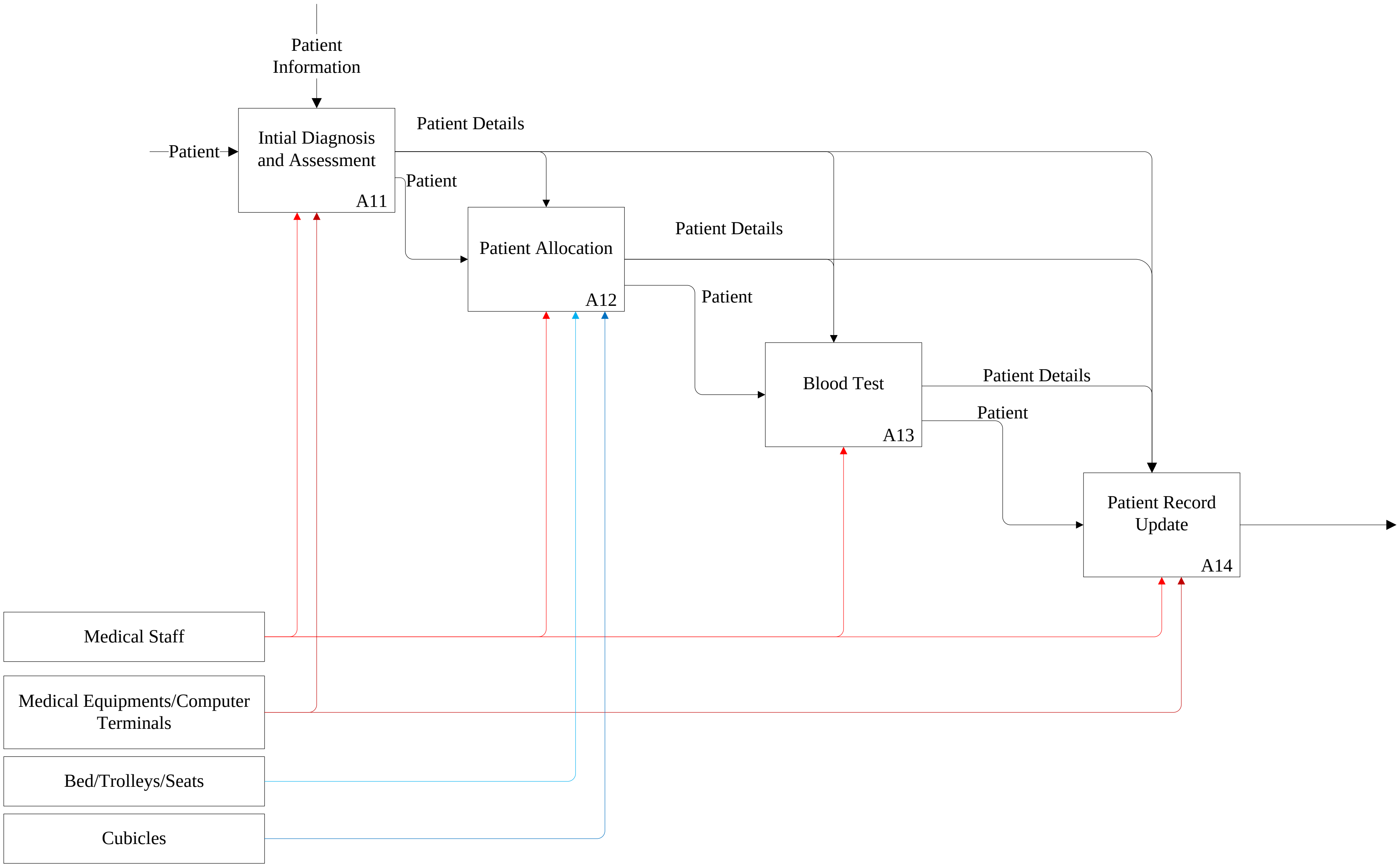



Patient Information
Triage Category
(Case Severity)
Patient
Triage
A1
Patient
Cardio-Pulmonary
Resuscitation
(CPR)
A2
Patient
Area I
A3
Patient
Area II
A4
Patient
Assessment &
Decision Unit
A5
Patient
Patient Transfer
A6
Ward/Hospital
Capacity
Medical Staff
Medical Equipments
Bed/Trolleys/Seats
Cubicles



Triage

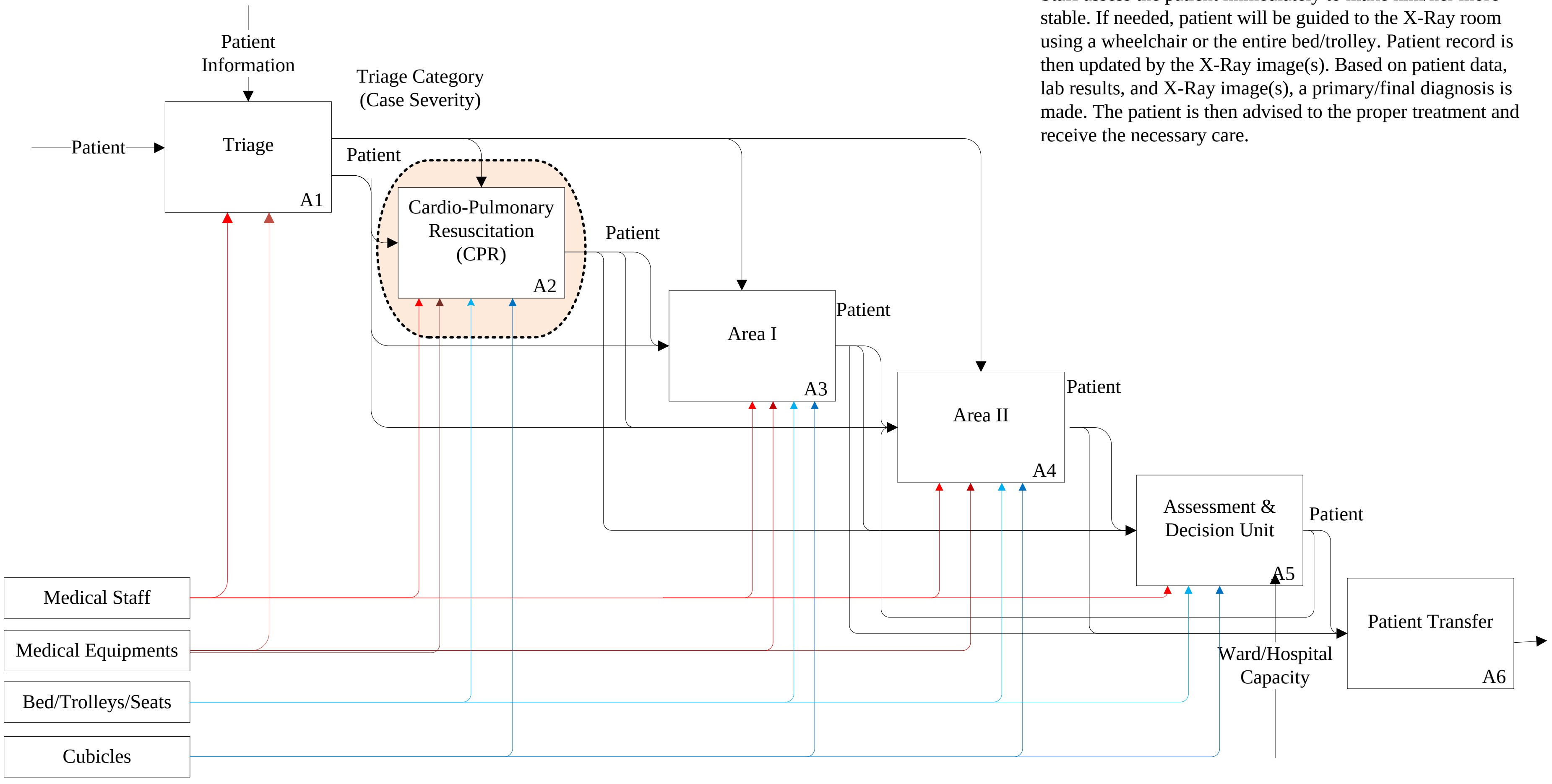
In trauma cases, patients are often triaged in their way to the emergency department (inside the ambulance). Once they arrive the department, they moved to CPR, Area-I, or Area-II depending on the severity level of the case and the available capacity. Blood test is ordered, if needed. Details collected from patient along with lab results are recorded in the patient record (soft copy), which in turn printed by the triage nurse to be handed to the administrational area. In the administrational area, the triage nurse put the patient record in a queue depending on his/her triage category. Meanwhile, triage nurse directing the patient to his proper location based on his/her severity level. A bed or a trolley is arranged and placed for patient either in a cubicle (CPR, Area I, or Area II) or a free space of the corridor inside the A&E department. Blood test can be exchanged with patient allocation depending on the triage category given and the available capacity.

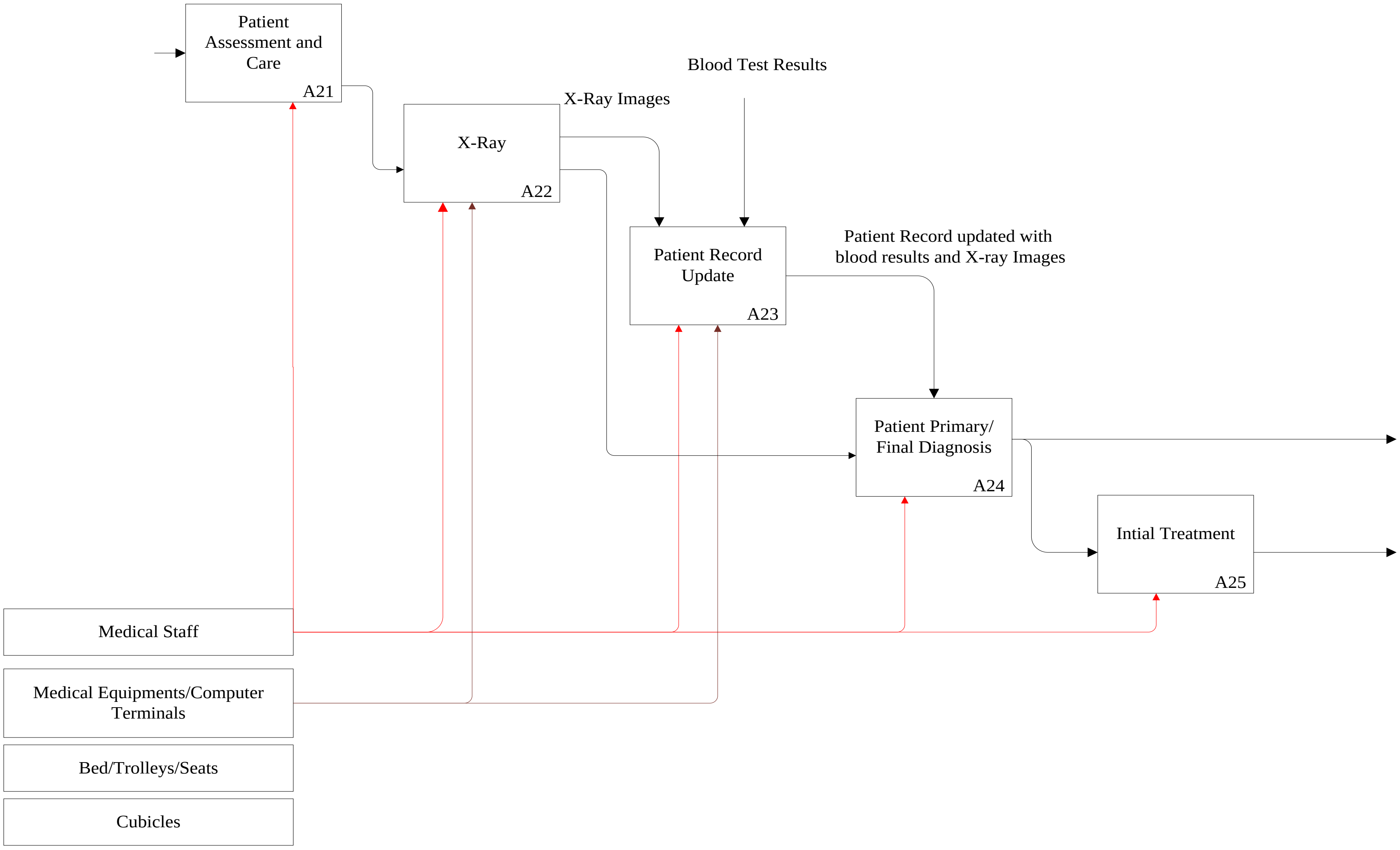

Patient Information
Patient
Intial Diagnosis and Assessment
A11
Patient Details
Patient
Patient Allocation
A12
Patient Details
Patient
Blood Test
A13
Patient Details
Patient
Patient Record Update
A14
Medical Staff
Medical Equipments/Computer Terminals
Bed/Trolleys/Seats
Cubicles

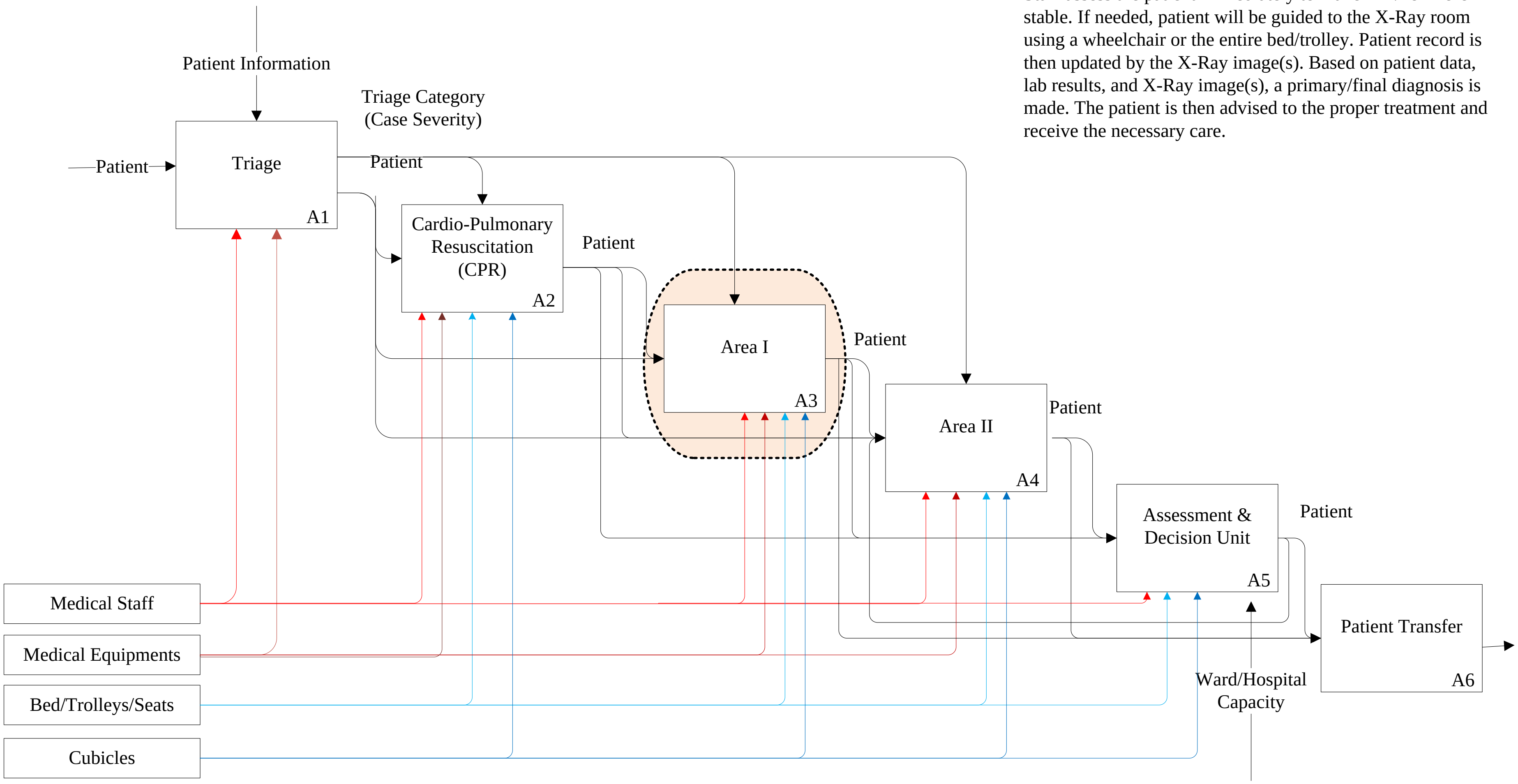
<u>Cardio-Pulmonary Resuscitation (CPR)</u>

The CPR/trauma room is dedicated to trauma cases where it is equipped with monitoring devices and advanced medical equipments.

Staff assess the patient immediately to make him/her more stable. If needed, patient will be guided to the X-Ray room using a wheelchair or the entire bed/trolley. Patient record is then updated by the X-Ray image(s). Based on patient data, lab results, and X-Ray image(s), a primary/final diagnosis is made. The patient is then advised to the proper treatment and receive the necessary care.



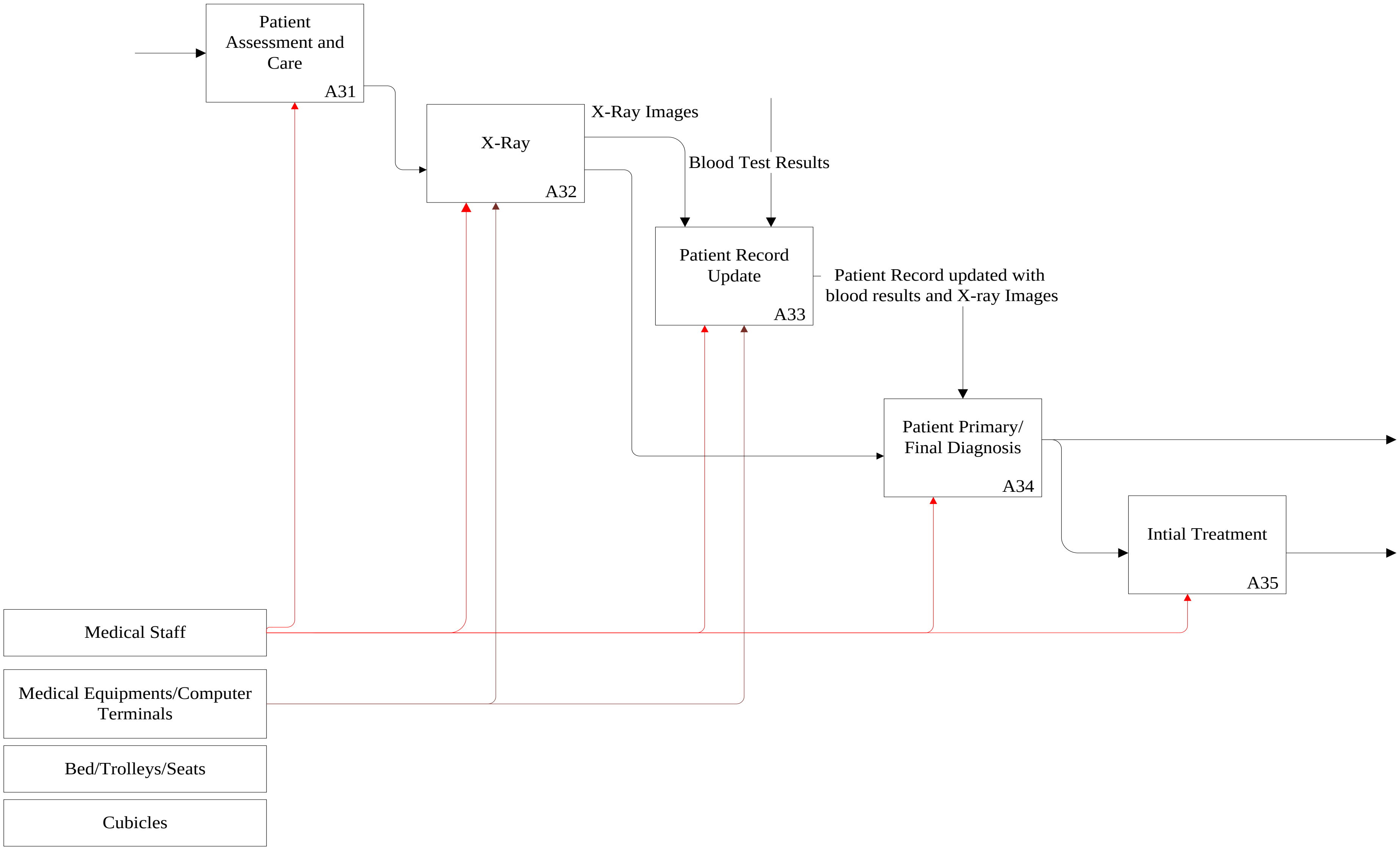

Patient Assessment and Care
A21
X-Ray
A22
X-Ray Images
Blood Test Results
Patient Record Update
A23
Patient Record updated with blood results and X-ray Images
Patient Primary/ Final Diagnosis
A24
Intial Treatment
A25
Medical Staff
Medical Equipments/Computer Terminals
Bed/Trolleys/Seats
Cubicles



Area-I

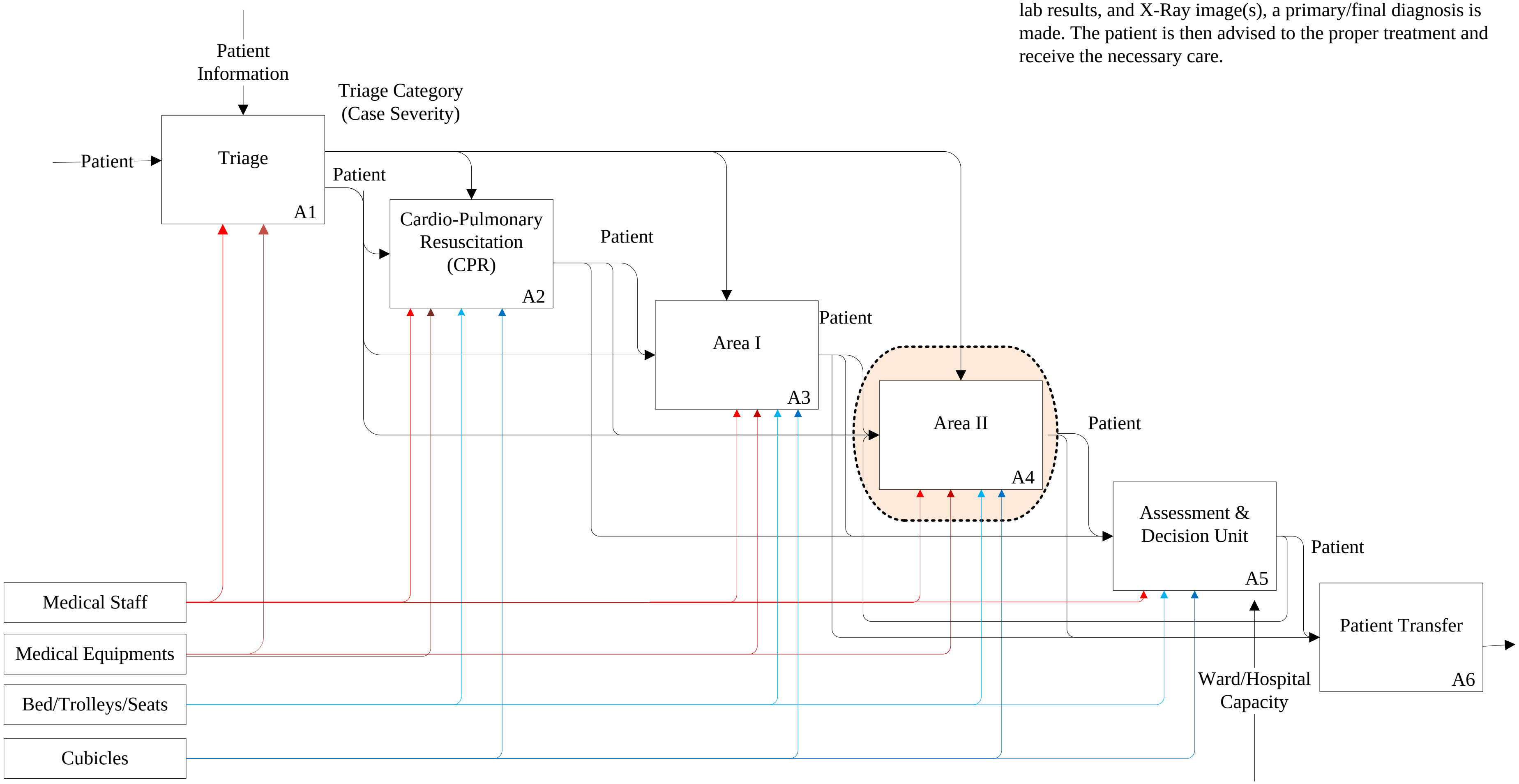
In case of overcrowdings, Area-I,II cab be used for trauma patients.

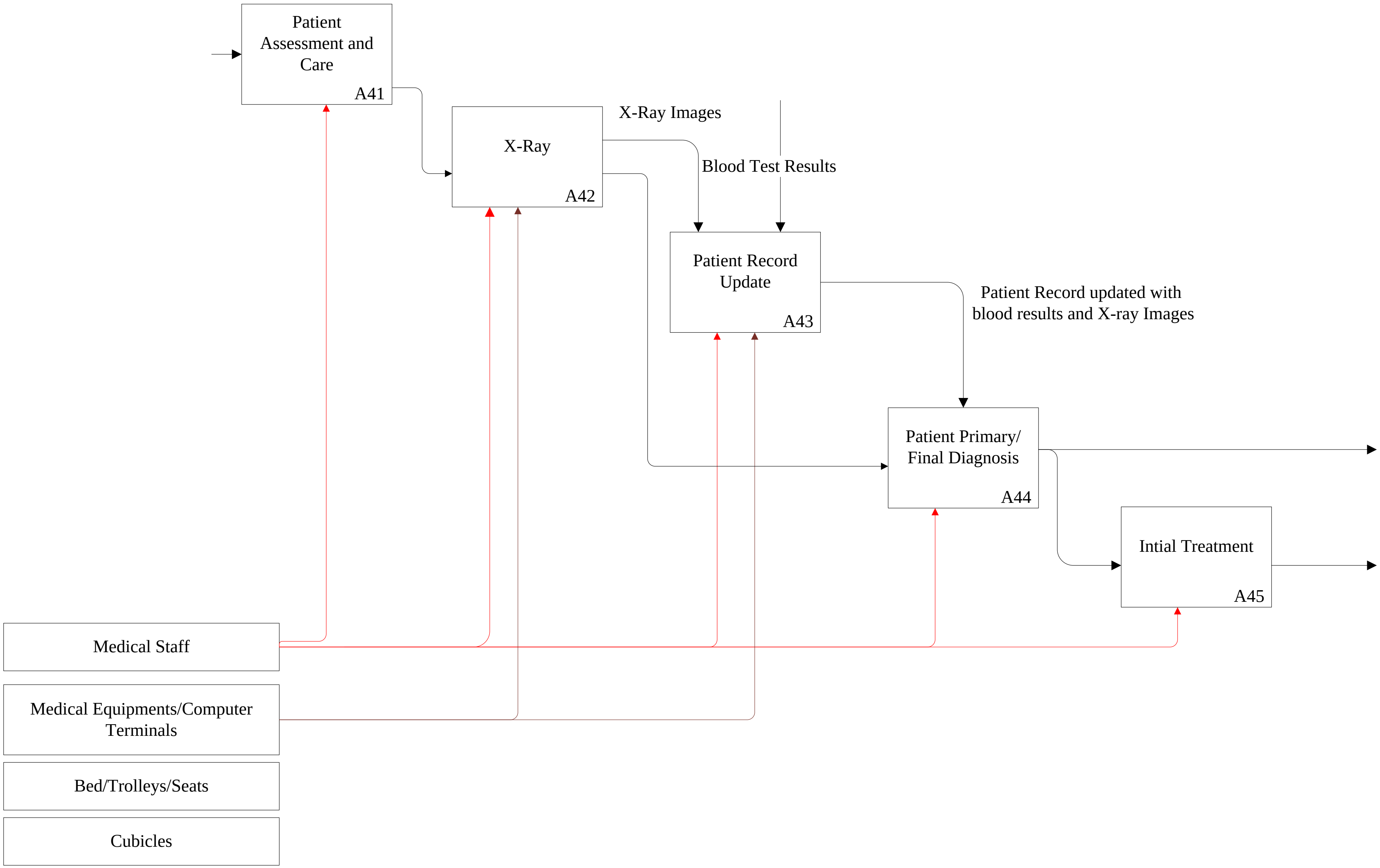
Staff assess the patient immediately to make him/her more stable. If needed, patient will be guided to the X-Ray room using a wheelchair or the entire bed/trolley. Patient record is then updated by the X-Ray image(s). Based on patient data, lab results, and X-Ray image(s), a primary/final diagnosis is made. The patient is then advised to the proper treatment and receive the necessary care.


Patient Assessment and Care
A31
X-Ray
A32
X-Ray Images
Blood Test Results
Patient Record Update
A33
Patient Record updated with blood results and X-ray Images
Patient Primary/ Final Diagnosis
A34
Intial Treatment
A35
Medical Staff
Medical Equipments/Computer Terminals
Bed/Trolleys/Seats
Cubicles

<u>Area-II</u>

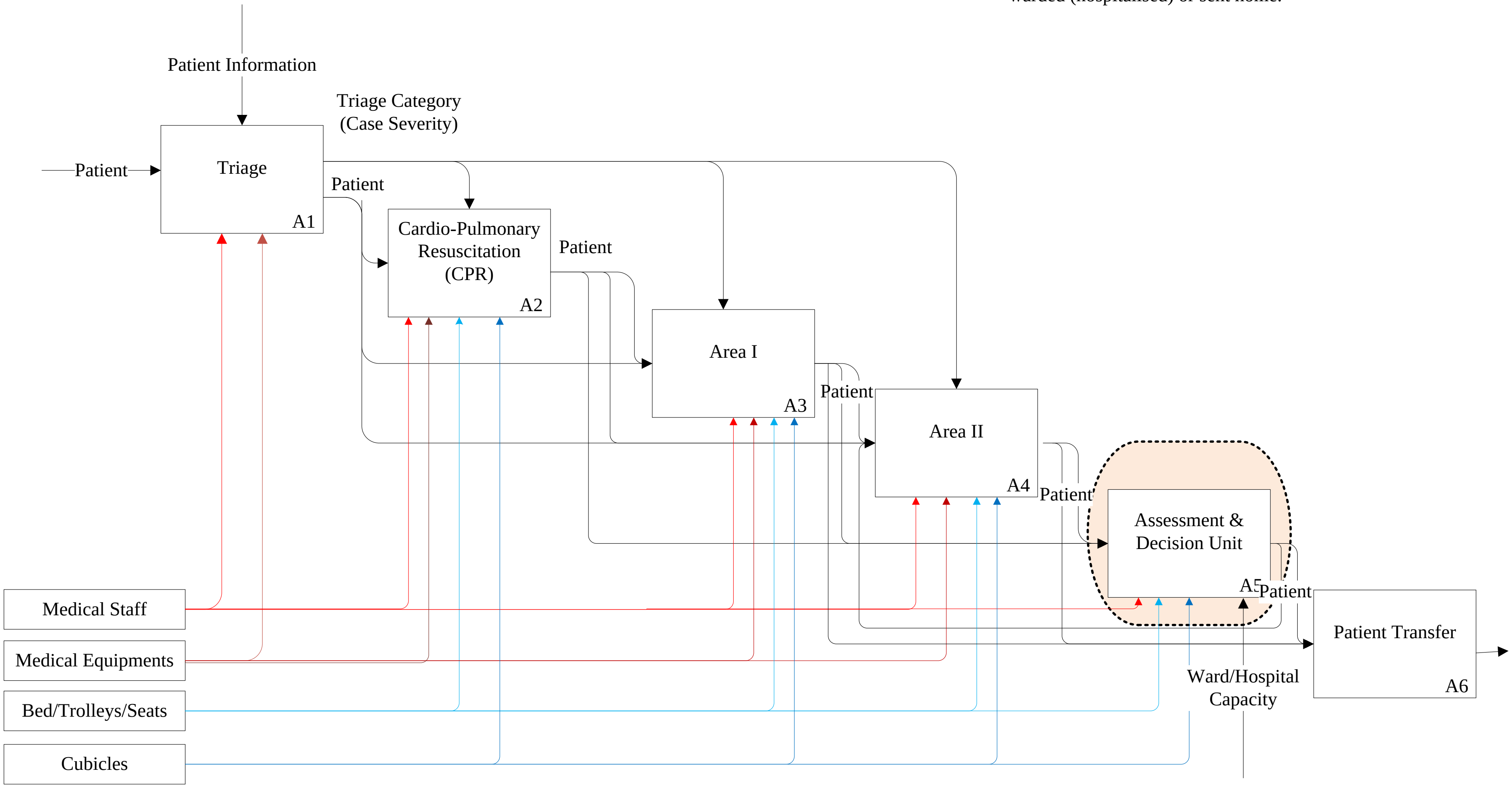
Staff assess the patient immediately to make him/her more stable. If needed, patient will be guided to the X-Ray room using a wheelchair or the entire bed/trolley. Patient record is then updated by the X-Ray image(s). Based on patient data, lab results, and X-Ray image(s), a primary/final diagnosis is made. The patient is then advised to the proper treatment and receive the necessary care.

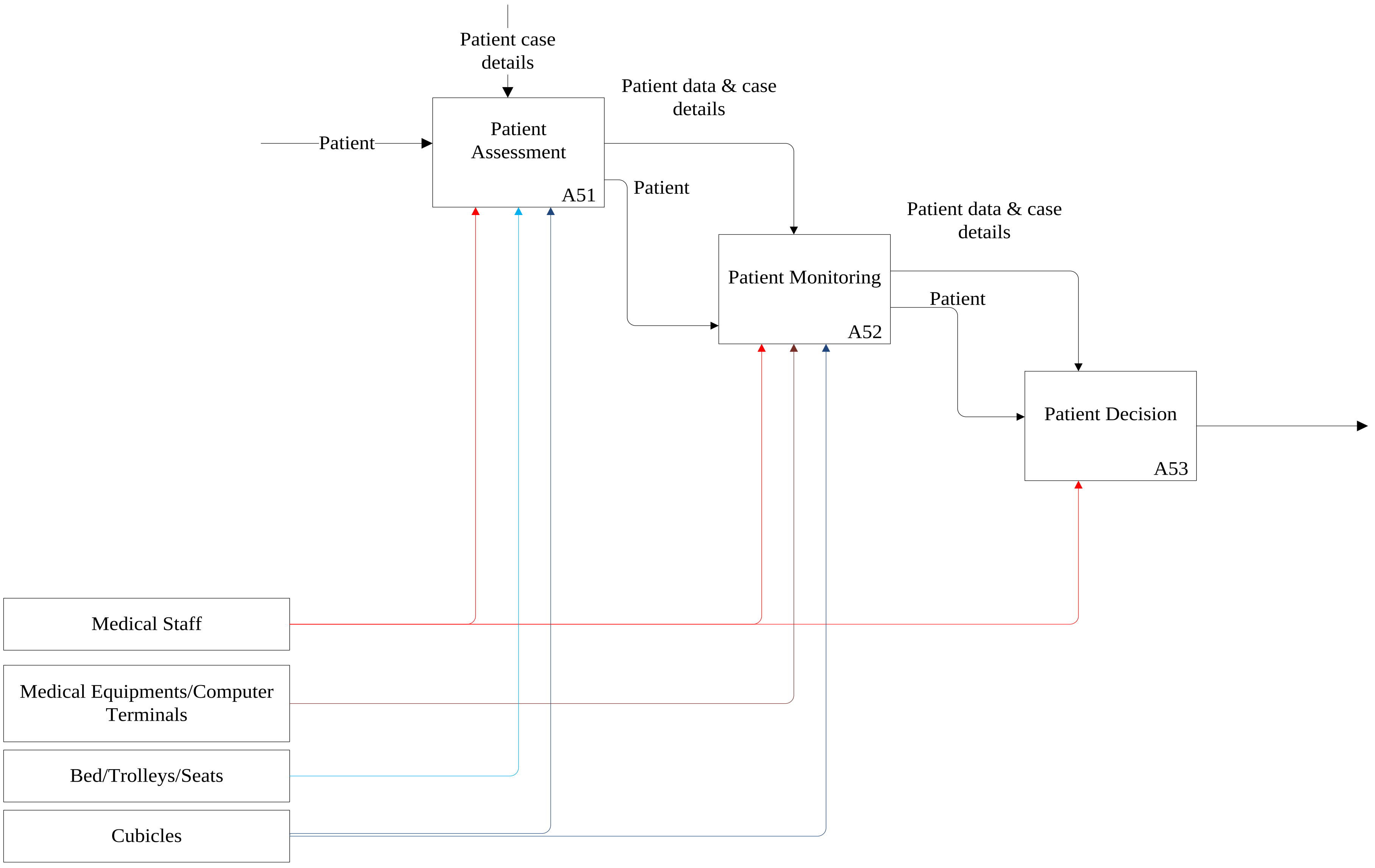


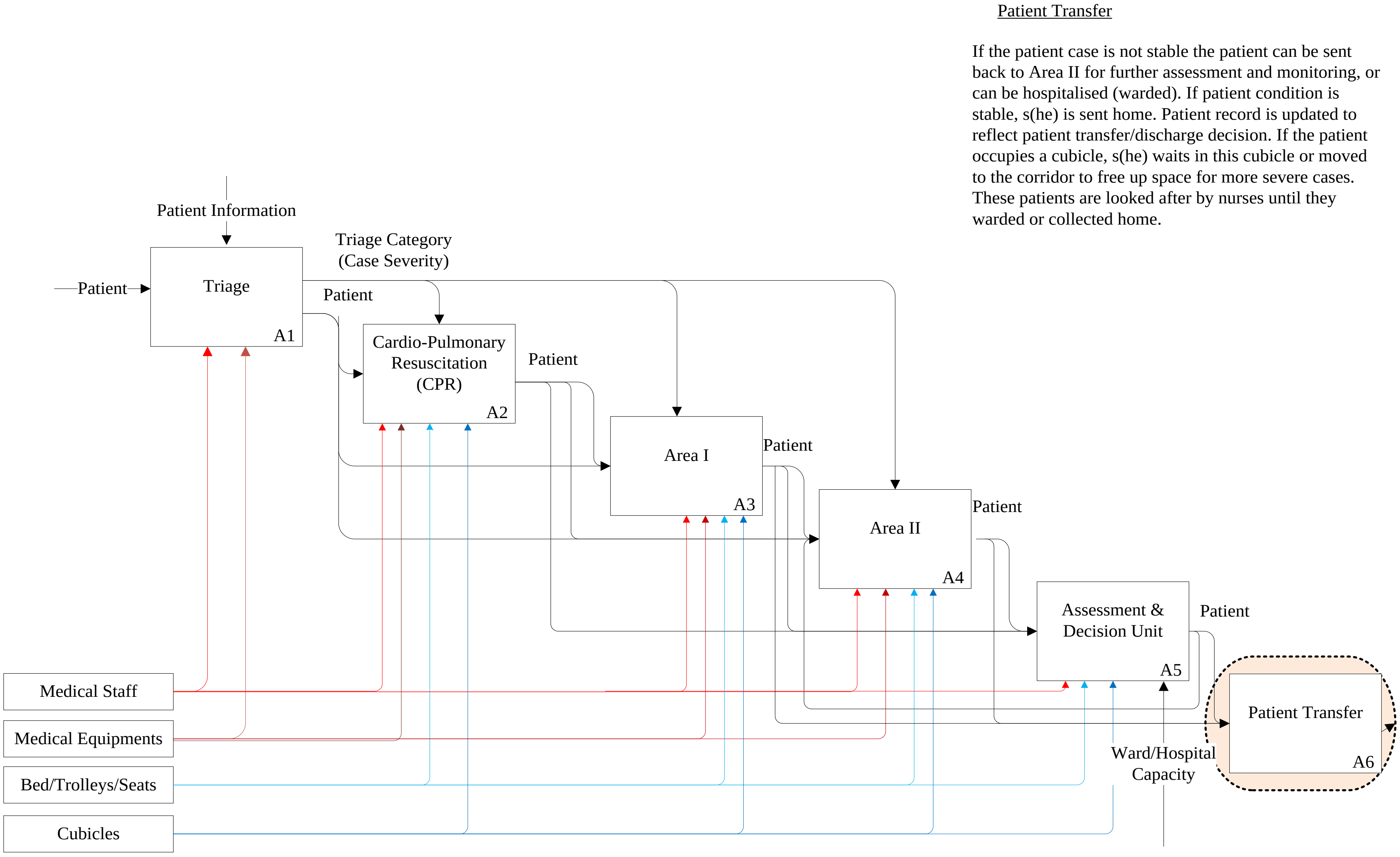

Patient Assessment and Care
A41
X-Ray
A42
X-Ray Images
Blood Test Results
Patient Record Update
A43
Patient Record updated with blood results and X-ray Images
Patient Primary/ Final Diagnosis
A44
Intial Treatment
A45
Medical Staff
Medical Equipments/Computer Terminals
Bed/Trolleys/Seats
Cubicles

Assessment & Decision Unit

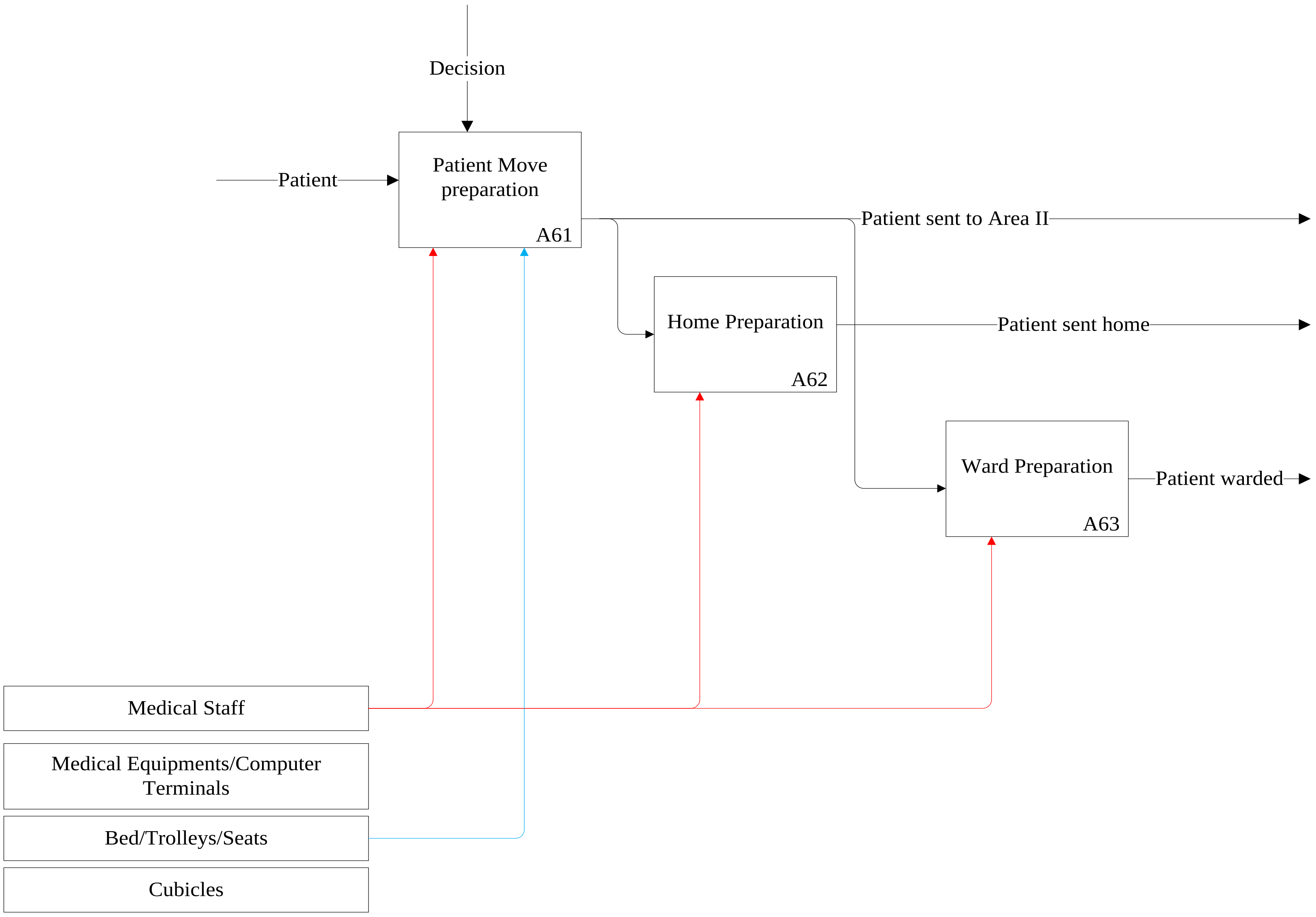
Subject to the patient condition and the monitoring results, a decision about the patient is taken whether the patient will be warded (hospitalised) or sent home.




Patient case details
Patient
Patient Assessment
A51
Patient data & case details
Patient
Patient Monitoring
A52
Patient data & case details
Patient
Patient Decision
A53
Medical Staff
Medical Equipments/Computer Terminals
Bed/Trolleys/Seats
Cubicles



Patient Transfer
If the patient case is not stable the patient can be sent back to Area II for further assessment and monitoring, or can be hospitalised (warded). If patient condition is stable, s(he) is sent home. Patient record is updated to reflect patient transfer/discharge decision. If the patient occupies a cubicle, s(he) waits in this cubicle or moved to the corridor to free up space for more severe cases. These patients are looked after by nurses until they warded or collected home.
Patient Information
Triage Category
(Case Severity)
Patient
Triage
A1
Patient
Cardio-Pulmonary
Resuscitation
(CPR)
A2
Patient
Area I
A3
Patient
Area II
A4
Patient
Assessment &
Decision Unit
A5
Patient
Patient Transfer
A6
Ward/Hospital
Capacity
Medical Staff
Medical Equipments
Bed/Trolleys/Seats
Cubicles


Decision
Patient
Patient Move preparation
A61
Patient sent to Area II
Home Preparation
A62
Patient sent home
Ward Preparation
A63
Patient warded
Medical Staff
Medical Equipments/Computer Terminals
Bed/Trolleys/Seats
Cubicles

Appendix B: Statistical Analysis of Simulation Output

B.1 NOTATION AND DESCRIPTIVE STATISTICS

Data: *p* variables, *n* observations

$\underline{X_1}$	$\underline{X_2}$	...	$\underline{X_p}$
x_{11}	x_{12}	...	x_{1p}
x_{21}	x_{22}	...	x_{2p}
$\vdots$	$\vdots$		$\vdots$
x_{n1}	x_{n2}	...	x_{np}

Data matrix:

$$\mathrm{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix}$$

B.2 DESCRIPTIVE STATISTICS

Sample means:

$$\bar{x}_k = \frac{1}{n}\sum_j x_{jk} \qquad k = 1,2,\ldots,p$$

Sample variances:

$$s_k^2 = s_{kk} = \frac{1}{n}\sum_j (x_{jk} - \bar{x})^2 \qquad k = 1,2,\ldots,p$$

Sample standard deviations:

$$\sqrt{s_{kk}} \qquad k = 1,2,\ldots,p$$

Sample covariance:

$$s_{ik} = \frac{1}{n}\sum_j (x_{ji} - \bar{x}_i)(x_{jk} - \bar{x}_k) \qquad i = 1,2,\ldots,p,\ \ k = 1,2,\ldots,p$$

Sample correlations:

$$r_{ik} = \frac{s_{ik}}{\sqrt{s_{ii}}\sqrt{s_{kk}}} \qquad i = 1,2,\ldots,p,\ \ k = 1,2,\ldots,p$$

B.3 ARRAYS AND MATRICES

$$\underset{(p\,x\,1)}{\bar{x}} = \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \\ \vdots \\ \bar{x}_p \end{bmatrix}$$

Covariance Matrix:

$$S_n = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1p} \\ s_{21} & s_{22} & \cdots & s_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ s_{p1} & s_{p2} & \cdots & s_{pp} \end{bmatrix}$$

$(p\ x\ \ p)$

Correlation Matrix:

$$R = \begin{bmatrix} 1 & r_{12} & \cdots & r_{1p} \\ r_{21} & 1 & \cdots & r_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ r_{p1} & r_{p2} & \cdots & 1 \end{bmatrix}$$

$(p\ x\ \ p)$

$Notes: \quad S_n \text{ and } R \text{ symmetric where } \quad -1 \le r_{ik} \le 1$

B.4 CONFIDENCE INTERVALS

Assume $X_1, X_2, \ldots, X_n$ *independent* $N(\mu, \sigma^2)$ and σ^2 unknown.

$$\boldsymbol{H}_0 : \mu = \mu_0 \qquad\qquad t = \frac{\bar{X} - \mu_0}{s/\sqrt{n}} \quad is \quad t_{n-1}$$
$$\boldsymbol{H}_1 : \mu \ne \mu_0$$

Reject H_0 if:

$$|\,t\,| > t_{n-1}(\alpha/2)$$

Alternatively, since $t_{n-1}^2 = F_{1,n-1}$, reject H_0 if:

$$t^2 = \left(\frac{\bar{x} - \mu_0}{s/\sqrt{n}}\right)^2 = (\bar{x} - \mu_0)\left(\frac{s^2}{n}\right)^{-1}(\bar{x} - \mu_0) > t_{n-1}^2(\alpha/2) = F_{1,n-1}(\alpha)$$

Also, *not* reject H_0 if: $|t| = \left|\frac{\bar{x}-\mu_0}{s/\sqrt{n}}\right| \le t_{n-1}(\alpha/2)$

Or

$$\mu_0 \in \bar{x} \pm t_{n-1}(\alpha/2)\left(s/\sqrt{n}\right)$$ ← 100(1–α) % confidence interval for μ

B.5 MULTIVARIATE GENERALISATION – HOTELLING'S T2

Assume $\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X}_n$ independent $N_p(\mu, \Sigma)$ and Σ unknown.

$$H_0 : \mu = \mu_0$$
$$H_1 : \mu \neq \mu_0$$

Hotelling's T^2 ($n - 1 > p$)

$$T^2 = (\bar{x}-\mu_0)'\left(\frac{S}{n}\right)^{-1}(\bar{x}-\mu_0) = n(\bar{x}-\mu_0)'S^{-1}(\bar{x}-\mu_0)$$

Under H_0, T^2 is: $\frac{(n-1)p}{n-p}F_{p,n-p}$

Reject H_0 at level α if

$$T^2 = n(\bar{x}-\mu_0)'S^{-1}(\bar{x}-\mu_0) > \frac{(n-1)p}{n-p}F_{p,n-p}(\alpha)$$

(Note: $t^2 = T^2$ if $p = 1$)

B.6 CONFIDENCE REGIONS

A 100(1 - α) % confidence region for all **μ:**

$$\boldsymbol{n}(\bar{\boldsymbol{x}}-\mu)'\boldsymbol{S}^{-1}(\bar{\boldsymbol{x}}-\mu) \le \frac{(\boldsymbol{n}-1)\boldsymbol{p}}{\boldsymbol{n}-\boldsymbol{p}}\boldsymbol{F}_{\boldsymbol{p},\boldsymbol{n}-\boldsymbol{p}}(\alpha) = \boldsymbol{c}^2$$

The relationship between confidence region and tests of H_0 is that any $\boldsymbol{\mu}_0$ in 100(1–α) % confidence region is consistent with the data (not reject H_0) at the α level.

B.7 SIMULTANEOUS CONFIDENCE INTERVALS

Assume: X_j *is* $N_p(\mu, \Sigma)$ $\quad\Sigma$ *unknown*

Consider: $a'\mu = a_1\mu_1 + a_2\mu_2 + \cdots + a_p\mu_p$

Simultaneous intervals of 100(1−α) % for all $\boldsymbol{a'\mu}$ given by:

$$a'\bar{x} \pm c\sqrt{\frac{a'Sa}{n}} \qquad \text{Where} \qquad c^2 = \frac{(n-1)p}{n-p}F_{p,n-p}(\alpha)$$

Notes:

- $a' = [1,0,\ldots,0] \Rightarrow a'\mu = \mu_1$
- $a' = [1,-1,\ldots,0] \Rightarrow a'\mu = \mu_1 - \mu_2$, and so forth.
- *a fixed*, 100(1−α)% confidence interval for $a'\mu$ given by

$$a'\bar{x} \pm t_{n-1}(\alpha/2)\sqrt{\frac{a'Sa}{n}}$$

B.8 BONFERRONI INTERVALS

Consider:

$$a_1'\mu, a_2'\mu, \ldots, a_p'\mu$$

And p confidence levels for each component = $1-\alpha_i$ $i = 1, 2 \ldots p$, with confidence intervals:

$$a_i'\bar{x} \pm t_{n-1}(\alpha_i/2)\sqrt{\frac{a_i'Sa_i}{n}} \qquad i = 1,2,\ldots,p$$

Where $\alpha_i = \alpha/p$, have overall confidence level greater than or equal to 1−α.

Appendix C: Multi-Criteria Decision Tools

C.1 ANALYTICAL HIERARCHICAL PROCESS

Analytical Hierarchical Process (AHP) is based on paired comparisons and the use of ratio scales in preference judgements represented in a comparison matrix. The decision maker is asked to give the ratio of weights of the main performance criteria in the form:

$$r_{ij} = \frac{\mathrm{w_i}}{\mathrm{w_j}}$$

Where r_{ij} is the ratio scale between the weights of criterion i (w_i) and criterion j (w_j). The elements on the diagonal, of the comparison matrix are 1. Moreover, only upper triangular matrix is needed where:

$$r_{ij} = \frac{1}{r_{ji}}$$

Therefore, the comparison matrix is a reciprocal matrix. The ratio scale of weights ranges from 1 (equally important) to 9 (extremely more important). The weights are then estimated from the estimates w_i by normalising the elements of the eigenvector corresponding the largest Eigen value of the comparison matrix. The marginal performance of each decision alternative is calculated using the resulted above preference model and aggregated as:

$$\mathrm{V}(x) = \sum_{i=1}^{N} \mathrm{w_i} v_i(x_\mathrm{i})$$

where w_i, $i \in (1,2,..., N)$ corresponds to the relative weight of the KPI_i and $v(x_i)$ is the desirability value of x_i for the corresponding KPI.

C.2 PREFERENCE RATIOS IN MULTI-ATTRIBUTE EVALUATION (PRIME)

The preferences of decision maker(s) in PRIME are assumed to have an additive structure so that the overall value of an alternative (i.e., scenario) equals the sum of its attribute-specific scores,

$$\mathrm{V}(x) = \sum_{i=1}^{N} v_i(x_\mathrm{i})$$

where, N in the number of leave nodes (i.e., twig-level KPIs that have not been decomposed into further lower level attributes in the value tree), x_i is the achievement level of alternative x with regard to the i-th attribute (i.e., KPI), and $v_i(x_i)$ is the single-attribute score associated with the achievement x_i on the i-th attribute. The process of decision maker preference elicitation consists of two phases; score elicitation and weight elicitation. The goal of the score elicitation phase is to rank consequences ordinally with respect to the least and most preferred achievement levels x_i^0 and x_i^* for each attribute i. The same process has been repeated for all the twig-level KPIs. Ordinal rankings become linear constraints of the form:

$$v_i(x_i^j) - v_i(x_i^k) > 0,$$

where $x_i^{\ j}$ is more preferred than $x_i^{\ k}$ in the i-th attribute for alternatives j and k respectively. Following ordinal ranking of achievement levels, further score information is obtained through interval-valued statements about ratios of value differences. The decision maker sets lower and upper bounds [L,U] on the ratio between the value difference from x_i^0 to the achievement level x_i^j and the value difference from x_i^0 to x_i^*:

$$L \leq \frac{v_i(x_i{}^j) - v_i(x_i{}^0)}{v_i(x_i{}^*) - v_i(x_i{}^0)} \leq \mathrm{U}.$$

For the weight elicitation phase, trade-off information about the relative importance of attributes is elicited through interval-valued (i.e., ratio) judgments. A reference attribute (e.g., the most important one) is selected and one hundred points are assigned to it. The decision maker is then asked to assign a range of points [L,U] to the other attributes in accordance with the perceived importance of these attributes:

$$\frac{L}{100} \leq \frac{v_i(x_i{}^*) - v_i(x_i{}^0)}{v_{ref}(x_{ref}{}^*) - v_{ref}(x_{ref}{}^0)} \leq \frac{\mathrm{U}}{100}.$$

This process is repeated for each level in the value tree where the relative importance of KPIs is specified by the decision maker. PRIME converts the imprecise preference model then into preference synthesis structure and consists of; 1) weight intervals of the attributes, 2) value intervals for the alternatives, and 3) dominance structures and decision rules for the alternatives comparison. Weight intervals are obtained by solving the linear constraints imposed on weights (represented by lower and upper inequalities). Following weight interval calculation, value intervals are calculated for each alternative:

$$\mathrm{V}(x) \in \left[\min \sum_{\mathrm{i}=1}^{\mathrm{N}} v_i(x_\mathrm{i}), \max \sum_{\mathrm{i}=1}^{\mathrm{N}} v_i(x_\mathrm{i})\right]$$

While $w_i \in [\min v_i(x_i{}^*), \max v_i(x_i{}^*)]$ are the linear programs that give bounds for the weight of the i-th attribute. The dominance structure for alternatives is then inferred. Computationally, alternative x^j is preferred to x^k in the sense of absolute dominance if and only if the smallest value of x^j exceeds the largest value of x^k, i.e.,

$$\min \sum_{\mathrm{i}=1}^{\mathrm{N}} v_i(x_\mathrm{i}^\mathrm{j}) > max \sum_{\mathrm{i}=1}^{\mathrm{N}} v_i(x_\mathrm{i}^\mathrm{k})$$

Appendix D: Genetic Algorithm and Artificial Immune System

D.1 GENETIC ALGORITHM

GA is a search technique that has a representation of the problem states and also has a set of operations to move through the search space. The states in the GA are represented using a set of chromosomes. Each chromosome represents a candidate solution to the problem. The set of candidate solutions forms a population. In essence, the GA produces more generations of this population hoping to reach a good solution for the problem. Members (candidate solutions) of the population are improved across generation through a set of operations that GA uses during the search process. GA has three basic operations to expand a candidate solution into other candidate solutions. These basic operations are:

- Selection: an objective function (i.e., fitness function) is used to assess the quality of the generated solutions. Solutions with higher fitness values are selected for the following iteration (i.e., generation) of the algorithm.
- Crossover: This operation generates new solutions given a set of selected members of the current population. Crossover exchanges genetic material between two single chromosome parents This set of selected members is the outcome of the selection operation.
- Mutation: biological organisms are often subject to a sudden change in their chromosomes in an unexpected manner. Such a sudden change is simulated in GA in the mutation operation. This operation is a clever way to escape from local optima trap in which state-space search algorithms may fall into. In this operation, some values of a chromosome are changed by adding random values for the current values. This action changes the member values and hence produces a different solution.

Genetic Algorithm pseudo code:

1. Generate initial random population of chromosomes.
2. Compute the fitness for each chromosome in the current population.
3. Make an intermediate population from the current population using the reproduction operator.
4. Using the intermediate population, generate a new population by applying the crossover and mutation operators.
5. If you get a member the population that satisfies the requirements stop, otherwise go to step 2.

D.2 CLONAL SELECTION ALGORITHM

The Clonal selection algorithm (CSA) is a special kind of immune algorithms using the clonal expansion and the affinity maturation as the main forces of the evolutionary process.

CSA Algorithm pseudo code:

1- Generate initial antibodies (each antibody represents a solution that represents the parameters of HMM in our case the *A* and *B* matrices).
2- Compute the fitness of each antibody. The used fitness function computes the average log probability over training data.
3- Select antibodies from population which will be used to generate new antibodies (the selection can be random or according to the fitness rank). The antibodies

with highest fitness are selected such that they are different enough as described later.

4- For each antibody, generate clones and mutate each clone according to fitness.
5- Delete antibodies with lower fitness form the population, then add to the population the new antibodies.
6- Repeat the steps from 2- 5 until stop criterion is met. The number of iterations can be used as the stop criterion.

D.3 HYBRID GENETIC -IMMUNE SYSTEM METHOD

The main forces of the evolutionary process for the GA are crossover and the mutation operators. For the CSA, the main force of the evolutionary process is the idea of clone expansion in which new clones of – potentially good solutions – are generated. These new clones are then mutated and the best of these clones are added to the population plus adding new generated members to the population. The hybrid method takes the main force of the evolutionary process for the two algorithms.

GA/CSA Algorithm pseudo code:

1- Generate the initial population (candidate solutions).
2- Select the (N) best items from the population.
3- For each selected item generate a number of clones (N_c) and mutate each item form (Nc).
4- Select the best mutated item from each group (N_c) and add it to the population.
5- Select from the population the items on which the crossover will be applied. We select them randomly in our system but any selection method can be used.
6- After selection make a crossover and add the new items (items after crossover) to the population by replacing the low fitness items with the new ones.
7- Add to the population a group of new generated random items.
8- Repeat step 2- 7 according to meeting the stopping criterion.

The steps 2 -5 were repeated for a number of times before adding new group of generated solutions**.**

LIST OF PUBLICATIONS

Peer-Reviewed Journals

- **Waleed Abo-Hamad** and Amr Arisha (2011), “Simulation Optimisation Methods in Supply Chain Applications: A Review”, *Irish Journal of Management*, 30 (2), 95-124.
- **Waleed Abo-Hamad,** John McInerney and Amr Arisha (2011), “Virtual ED’: Utilisation of a Discrete Event Simulation-based Framework in Identifying ‘real-time’ Strategies to Improve Patient Experience Times in an Emergency Department”, *Emergency Medicine Journal*, 28, A3-A4.
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- **Waleed Abo-Hamad** and Amr Arisha (2009), “Optimisation Methods in Supply Chain Applications: A Review”, *Proceedings of the 12th annual Irish Academy of Management Conference.* 2 – 4 September 2009, Galway - Mayo Institute of Technology, Ireland.

Conference Abstracts

- **Waleed Abohamad**, John McInerney, and Amr Arisha (2011), “‘Virtual ED’ – Utilisation of a Discrete Event Simulation-based Framework in Identifying ‘real-time’ Strategies to Improve Patient Experience Times in an Emergency Department”, *The Sixth Mediterranean Emergency Medicine Congress (MEMC VI)*, 10 – 14 September 2011, Kos, Greece.

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