Reengineering care transition in public healthcare system

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2013

Sheng, L. (2013). Reengineering care transition in public healthcare system. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/54913>

<https://doi.org/10.32657/10356/54913>

NANYANG
TECHNOLOGICAL
UNIVERSITY

**REENGINEERING CARE TRANSITION IN
PUBLIC HEALTHCARE SYSTEM**

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SCHOOL OF MECHANICAL AND AEROSPACE ENGINEERING

2013

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A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy

2013

Abstract

The rapidly aging population is putting enormous strains on healthcare systems around the world, as elderly people tend to be more vulnerable to chronic diseases. The special medical and social concerns of chronically ill elders are pushing the cash-strapped governments to shift the focus from specialized acute care to integrated continuing care. In Singapore, the concern for seamless integration among acute care hospitals and step-down care facilities is already on the government's agenda. Smooth care transition is critical to achieving the seamless integration of healthcare system.

However, on-going research of care transition is still scarce and lack of in-depth analysis. A large portion of existing research focuses on conceptual discussion with qualitative analyses. Most of these studies are piecemeal projects that only address some aspects of care transition at the operational level. Meanwhile, a considerable amount of other research has exposed the huge complexity in the healthcare system. The complex nature of healthcare system makes it difficult to formulate the messy problems of care transition directly with traditional operations research (OR) methods.

Making use of Singapore's healthcare system as a study case, this research explores ways in which to achieve more effective and robust solutions. It leverages on a range of relevant systems theories and methodologies to systemically examine the care transition situation from a systems perspective. The soft systems methodology (SSM) is adopted as an overarching framework and applied to gain appreciation on the problem situation of care transition. Concurrently, a combination of multiple soft and hard operational research methods are integrated into the framework at different stages of the research to investigate

the relevant research problems. Soft systems methodology-multi-method framework is proposed.

This research firstly enquires into the care transition situation with the intent to gain a comprehensive picture of the current situation. Multiple face to face interviews with various medical staff are conducted to identify the problems in the care transition. These identified problems are then grouped and structured based on their causal relationships. From the structured problem expression, the research problem is scoped to be care transition plan and process improvement. Need for changes is analyzed using viable system model. An ‘aggregative’ care transition model is proposed to achieve these changes. Discrete event simulation is adopted to compare the ‘AS-IS’ process and the ‘TO-BE’ process. The simulation result shows that the proposed ‘aggregative’ care transition model is superior to the current ‘third party’ care transition model in terms of healthcare expenditure and system accessibility.

More rigorous methods for further improvement of the care transition process are developed to achieve optimal solutions by answering how, when and where to discharge patients. For how to discharge patients, a two-stage optimization approach is proposed by converting the care transition process into a network optimization problem. The objective function of the first stage of the optimization is to minimize the duration of a process. Participating activities are selected from various candidate activities and their topological structure is determined to make the process a feasible solution. The second stage of the optimization decides who should perform each of these selected activities to achieve the best service quality of the care transition with resource constraints. The optimal solutions are obtained

using the IBM ILOG CPLEX Optimization Studio. The optimal care transition process design from the two-stage optimization model is generally consistent with the previously proposed ‘aggregative’ care transition model, which is based on the qualitative analysis.

With the objective of further smoothing the care transition process and improving healthcare system performance, this research provides decision support on when and where to discharge patients. A simulation model of patient flow at system level is developed to reflect the correlations among: disease severity, length of stay (LOS), health status, discharge policy, care transition decision and readmission rate. A finite state discrete Markov chain is adopted to capture the transition of patients’ health status during their stay in the hospital and predict their length of stay. The objective is to minimize the cost subject to several system performance requirements. The tradeoff between length of stay (LOS) and readmission rate is balanced through the simulation based optimization. Different optimization scopes are considered and compared. The optimal solutions are searched based on Genetic Algorithm (GA). Optimal computing budget allocation for constrained optimization (OCBA-CO) is incorporated into the search algorithm to reduce the computational time. The optimal solution set indicates that different stakeholders would prefer different solutions with their own objectives. To reduce the healthcare system cost and cycle cost per patient, community hospitals should take on more responsibilities.

The results of this research would make the care planners to transfer needy elders within the healthcare system safer and faster, which would further enable the current system to care for more patients with better care quality at a lower cost.

Acknowledgement

First and foremost, I want to express my deep thanks to my supervisor Associate Professor Yeo Khim Teck, who introduced me to the field of healthcare system. Besides, his keen insight, continuous encouragement, valuable comments as well as his expectation for high quality research are important drives to the on-going development of this research.

I am full of gratitude to my co-supervisor Dr. Mao Jian Feng, who spent a great deal of time in discussing various issues of this research. Numerous valuable suggestions offered by him helped me a lot in identifying the research questions and developing the simulation models. His vast and versatile knowledge together with his patience will never be forgotten.

I am very grateful to my hospital mentor Dr. Ian Leong, who provided much background knowledge and information supports for this research. I want to extend my appreciation to Dr. Khai Pang Leong in Tan Tock Seng Hospital, Mr Denies Hsu in National University Hospital for their help in contacting relevant institutions for this research. I am no less grateful to the reviewers of on my confirmation report, Dr. Chen Songlin and Dr. Park Taezoon for their comments and suggestions. I would also like to express my appreciation to the technician of ADAM lab, Teo Hai Beng, and secretary of the systems and engineering management division, Shahida bte Musni, for their kindness and support.

A special thank you is reserved to Associate Professor Shou Yongyi, Professor Wu Xiaobo in Zhejiang University, Mr Salah Haridy Gad, Ms. Liang Zhong, Ms. Wang Hongyan, Ms. Liu Guiqin, Ms. Li Yan and all my dear friends for their unyielding patience and continuous help to support my academic pursuits. Last, but not least, I am indebted to my family members for their continued love that gives me strength to push my limits.

Table of Contents

ABSTRACT	I
ACKNOWLEDGEMENT	IV
LIST OF FIGURES.....	VIII
LIST OF TABLES.....	IX
1 INTRODUCTION	1
1.1 BACKGROUND	1
1.2 RESEARCH PROBLEM AND MOTIVATION	4
1.3 ORGANIZATION OF THE THESIS	6
2 LITERATURE REVIEW	10
2.1 HEALTHCARE SYSTEM AND ITS COMPLEXITY	10
2.2 HEALTH SERVICE RESEARCH	13
2.3 HEALTHCARE SYSTEM IN SINGAPORE	15
2.3.1 <i>Singapore's Healthcare System</i>	15
2.3.2 <i>Challenges from Aging Population</i>	18
2.3.3 <i>Responses to the Challenges</i>	22
2.4 EXISTING RESEARCH ON CARE TRANSITION	24
2.4.1 <i>What is care transition: definition, components and existing models</i>	24
2.4.2 <i>Care transition and healthcare system performance</i>	29
2.4.3 <i>Barriers to effective care transition</i>	32
2.4.4 <i>Summary</i>	37
3 RESEARCH METHODOLOGY	41
3.1 SOFT SYSTEMS METHODOLOGY: RESEARCH FRAMEWORK.....	41
3.2 MULTI-METHOD APPROACH	45
3.3 SOFT SYSTEMS METHODOLOGY-MULTI-METHOD (SSM-M) FRAMEWORK	47
4 SYSTEMIC ENQUIRY WITH SOFT SYSTEMS METHODOLOGY.....	51
4.1 PROBLEM IDENTIFICATION	51
4.2 PROBLEM STRUCTURE.....	59
4.3 ROOT DEFINITIONS.....	65
4.3.1 <i>Scoping relevant systems</i>	65
4.3.2 <i>Investigation of 'AS-IS' system</i>	66

5 DESIRABLE CHANGES AND RELEVANT CONCEPTUAL MODEL	72
5.1 IDENTIFY THE NEED FOR CHANGES	72
5.2 CONCEPTUAL MODEL FOR IMPROVEMENT	76
5.3 COMPARING 'AS- IS' SYSTEM AND 'TO -BE' SYSTEM VIA SIMULATION	80
5.3.1 <i>Discrete event simulation model</i>	80
5.3.2 <i>Parameter assessment</i>	81
5.3.3 <i>Verification and validation</i>	83
5.3.4 <i>Performance comparison of 'AS-IS' process and 'TO-BE' process</i>	89
5.3.5 <i>Implications from the simulation results</i>	93
5.3.6 <i>Additional advantages of the 'TO-BE' process</i>	96
5.4 FEASIBILITY OF THE CHANGES	97
5.5 SUMMARY AND FURTHER EXTENSION	98
6 ALGORITHMIC APPROACH TO OPTIMAL CARE TRANSITION PROCESS DESIGN.....	100
6.1 INTRODUCTION.....	100
6.2 RELEVANT WORKS	102
6.3 ALGORITHMIC APPROACH FOR OPTIMAL PROCESS GENERATING	105
6.3.1 <i>Projecting business process</i>	105
6.3.2 <i>First stage: what should be done (selecting activities)</i>	108
6.3.3 <i>Second stage: who should do it (allocating resources)</i>	115
6.4 SUMMARY	124
7 DECISION SUPPORT IN PATIENTS TRANSFER	125
7.1 INTRODUCTION.....	125
7.2 CONCEPTUAL MODEL	127
7.3 SIMULATION MODEL DEVELOPMENT	131
7.3.1 <i>The structure of the simulation model</i>	132
7.3.2 <i>Modeling the recovery process of patients with Markov chain</i>	135
7.3.3 <i>Optimization model</i>	138
7.4 OPTIMIZATION ALGORITHM	141
7.4.1 <i>Genetic algorithm (GA)</i>	141
7.4.2 <i>Optimal computing budget allocation (OCBA)</i>	146
7.4.3 <i>Computing efficiency of OCBA-CO-GA</i>	150
7.5 MODEL INPUTS AND EXPERIMENTAL RESULTS.....	151
7.5.1 <i>Model inputs</i>	151
7.5.2 <i>Numerical results</i>	152
7.6 SUMMARY	157

Table of Contents

8 CONCLUSIONS.....	159
8.1 SUMMARY OF THE RESEARCH	159
8.2 PRACTICAL IMPLICATIONS AND THEORETICAL CONTRIBUTIONS.....	162
8.3 POSSIBLE EXTENSIONS	164
REFERENCES	166
APPENDIX 1: DETAIL MODULES OF ARENA MODELS.....	184
APPENDIX 2: PSEUDO CODE OF THE ARENA MODELS.....	193
APPENDIX 3: OPL MODEL FOR THE FIRST-STAGE OPTIMIZATION	201
APPENDIX 4: OPL MODEL FOR THE SECOND-STAGE OPTIMIZATION	203
APPENDIX 5: MATLAB CODE FOR THE SIMULATION MODEL IN CHAPTER 7	205

List of Figures

Figure 1-1 An intergrated care model in Singapore	3
Figure 1-2 Road map of the thesis.....	6
Figure 1-3 Organization of the thesis	7
Figure 2-1Complexity levels of five markets	11
Figure 2-2 Complexity and dynamics in healthcare system	13
Figure 2-3 Annual health expenditure and average healthy life expectancy	15
Figure 2-4 Geographic distribution of public acute care providers in Singapore	16
Figure 2-5 Healthcare system structure in Singapore.....	17
Figure 2-6 Funding of health expenditure	18
Figure 2-7 Proportion of resident population aged over 65 from 2000 – 2030 in Singapore	18
Figure 2-8 Healthcare workforce in year 2000- 2007	20
Figure 2-9 Average daily waiting times for bed (20 Sept. 2009 - 26 Sept. 2009)	21
Figure 2-10 Pyramid model of public healthcare system in Singapore	22
Figure 2-11 Effective care transition framework.....	38
Figure 3-1 The classic form of soft systems methodology (SSM)	42
Figure 3-2 The proposed SSM-M framework	48
Figure 4-1 Expressed problems-----a structured picture of problem situation of care transition.....	64
Figure 4-2 Current process of care transition	68
Figure 5-1 Basic form of viable system model, Beer (1984).....	73
Figure 5-2 Conceptual model of ideal care transition process.....	79
Figure 5-3 Links of different modules of simualtion model with Arena	81
Figure 5-4 WIP and simulation time	84
Figure 5-5 Average daily waiting times for bed (20 Sept. 2009 - 26 Sept. 2009).....	87
Figure 6-1 Classification framework of business process modeling techniques	101
Figure 6-2 Process-object relationship	105
Figure 6-3 Feasible designs of a process.....	106
Figure 6-4 Optimal care transition process design for a specific scenario	114
Figure 6-5 Allocate doctor and nurse with deadline =200 (objective value =220).....	121
Figure 6-6 Allocate doctor and nurse with deadline = 40 (objective value = 210).....	121
Figure 6-7 Allocate 5 types of medical staff with deadline = 200 (objective value = 270).....	121
Figure 6-8 Allocate 5 types of medical staff with deadline = 32 (objective value = 232).....	121
Figure 7-1 Conceptual model	128
Figure 7-2 The structure of the simulation model	133
Figure 7-3 Health status transition	137
Figure 7-4 The structure of a chromosome	142
Figure 7-5 The evolvment of optimal solution along the CPU time.....	150
Figure 7-6 Relationships among the discharge policy, LOS and readmission rate	153
Figure A-1 Module 1 and Module 2 of current ‘third party’ model	185
Figure A-2 Module 3 of current ‘third party’ model	186
Figure A-3 Module 4 of current ‘third party’ model	187
Figure A-4 Module 5 of current ‘third party’ mode	188
Figure A-5 Module 1 and Module 2 of proposed ‘aggregative’ model.....	189
Figure A-6 Module 3 of proposed ‘aggregative’ model.....	190
Figure A-7 Module 4 of proposed ‘aggregative’ model.....	191
Figure A-8 Module 5 of proposed ‘aggregative’ model.....	192

List of Tables

Table 2-1 Hospital admission rate by sex and age (per 1,000 populations)	19
Table 2-2 Admission attendances (public sector hospitals).....	19
Table 2-3 Government healthcare expenditure	21
Table 2-4 Components to achieve smooth care transition.....	26
Table 2-5 Paramount steps to the successful care transition	26
Table 2-6 Operationalized components for effective discharge and care transition	27
Table 2-7 Quality measurement framework of care transition	28
Table 2-8 Care transition intervention activities	37
Table 2-9 Methods adopted to care transition research	39
Table 3-1 Incorporated methods and stages of SSM	50
Table 4-1 Semi-structured interview questions based on Fischer (1989).....	52
Table 4-2 Identified problems in care transition.....	53
Table 4-3 Compare the situation in Singapore with existing research	57
Table 4-4 CATWOE analysis.....	71
Table 4-5 Stakeholder requirements analysis	71
Table 5-1 Proposed changes based on viable system model	76
Table 5-2 Parameters in the simulation models.....	82
Table 5-3 Model validation	85
Table 5-4 Average length of stay based on simulation result.....	86
Table 5-5 Average length of stay by medical service in TTSH (Year 2009)	86
Table 5-6 Utilization of acute beds by clinical departments in TTSH (October 2009)	88
Table 5-7 Statistic of beds in nursing homes (Statistics as at 30 Sept. 2007).....	89
Table 5-8 Comparison of the simulation results of the two processes	91
Table 6-1 Activity set of care transition process design for a specific patient	109
Table 6-2 Notations for the first-stage optimization model.....	111
Table 6-3 Description of objectives and constraints of the first-stage optimization model.....	112
Table 6-4 Tasks in care transition process.....	116
Table 6-5 Task skill level of each role	116
Table 6-6 Notations for the second stage optimization--resource allocation problem	118
Table 6-7 Description of objective and constraints of the second-stage optimization model.....	119
Table 7-1 OCBA procedure (maximizing the probability of correct selection)	147
Table 7-2 OCBA-CO procedure (maximizing the probability of correct selection)	149
Table 7-3 Parameters of the simulation model.....	151
Table 7-4 Limits of constraints and decision variables	152
Table 7-5 Optimal solutions	154

Chapter 1

Introduction

1.1 Background

Population aging has emerged as a global trend at an unprecedented rate. By the year 2030, around 55 countries are estimated to have more than 20% of people older than 65 (James, 2010). These changing demographics are putting enormous strains on healthcare, the largest industry in the world, creating daunting economic challenges (Company, 2012). For example, in the US, the over-65s made up 13% of the population and consumed 36% of the healthcare resources in 2002. The situation is more striking in the UK, where two-thirds of the hospital beds were occupied by the over-65s who accounted for about 16% of the population (Kielstra, 2009). Singapore, as one of the fastest aging societies in Asia, had 9.3% of the population over 65 in 2011. The hospital admission rate of these elders was five times more than those of the working age (MOH, 2011). The reason is that older people tend to be more vulnerable to chronic diseases. 80% of seniors have suffered from at least one chronic disease, which accounts for 75% of global healthcare expenditure (the number seems to increase in the coming years) (Grant, 2010). 25% of an individual's lifetime healthcare expenditures are incurred in the final two years before their death. The consumption of healthcare resources escalates as more people over-65 are dying. Issues on how healthcare systems adjust to the new realities are attracting increasing attention from government agencies and academia globally. Providing patient-centered care via system integration is regarded as a laudable way to reconcile the three competing objectives of healthcare system: equitable access, high quality, and low cost in an efficient way (Kielstra, 2009). The reason

is that frail elderly patients battling multiple chronic diseases are more than any other persons. They need someone to coordinate the various types of essential care and are more frequently transferred from one care provider to another. A successful ‘hand-off’ of care between care providers in different settings is critical to the final result of the patient. Besides, patients over 65 need longer time to recover than the rest of the population. Notably, due to some social problems, a significant amount of these elderly patients stay in the congested acute hospitals when they don’t need to be there medically. Such situation is partially mirrored in the rising healthcare expenditure without corresponding improvements in quality. For example, in Toronto, 10% of acute care beds were occupied by elderly patients who had nowhere else to go (Howlett, 2011). Ideally, a patient should be discharged when the benefits of hospitalization no longer justify the expense. The special medical and social concerns of chronically sick elders are pushing the cash-strapped governments to shift the focus from specialized acute care to integrated continuing care.

Singapore government is gearing up its healthcare system by moving from silo care institutions to a regional integrated healthcare system, where acute hospitals are linked with community rehabilitation hospitals and supported by a network of other community care providers, such as polyclinics, nursing homes, etc. (Lee, 2009). Care transition, which refers to the safe and efficient movement of patients among different sectors or levels of care providers within the healthcare system (Wendy *et al.*, 2010), is a critical way to achieve the consistent care delivery. Hence, it becomes extremely important to seamlessly integrate a wide range of services.

In 2009, the Ministry of Health in Singapore restructured the Agency for Integrated Care (AIC) with the aim to assist and navigate patients to use healthcare services in a more efficient way. The new agency acts as a ‘national care integrator’ to develop a patient-centric and integrated care model that Singaporeans can be proud of. The model is presented in Figure 1-1 with information provided by staff in AIC.

Figure 1-1 An intergrated care model in Singapore

Despite these efforts, configuring all autonomous entities, including acute hospitals, community hospitals, nursing homes and other community care providers is a very complex process due to the different governance structures of the various institutions. Achieving consistent and smooth care transition still remains a challenge. Some healthcare institutions still operate as ‘silos’. Medical staff who provide next stage care often treat the patient without the complete knowledge of the services provided in the previous stage. Various

previous attempts have been made to improve the care transition (Levine, 1998; Kuhn and Giuse, 2001; Coleman, 2003; Moore *et al.*, 2003; Coleman and Berenson, 2004; Venketasubramanian *et al.*, 2008). These initiatives have achieved some results. But most of them have worked only on some aspects of the care transition, rather than examining the problems based on a systemic approach. Study on care transition improvement in a systemic way is urgent and necessary. The size of Singapore makes the systemic study on interaction and integration among different institutions more convenient than many other larger countries.

This research takes care transition in Singapore as an subject of interest with the aim to explore a systemic approach and to develop theoretical methods, which would not only be useful guidelines and tools for achieving smoother care transition in public healthcare system, but also be widely applicable approaches to gain better and fresh understandings of messy and complex problems in many other domains.

1.2 Research Problem and Motivation

The healthcare system is in urgent need of new ways to support effective and efficient use of the limited resources due to the challenges of aging population. With the aim to maintain particular service level and quality, whilst keeping costs down, this research plans to provide policy makers and healthcare planners with approaches to effectively smooth the care transition and to boost the performance of the public healthcare system in Singapore.

A Canadian study claimed that 76% of the decision makers complained about the irrelevance of research and practice in the field of healthcare (Kiefer *et al.*, 2005).

Meanwhile, the review of many Six Sigma projects in the healthcare system pointed out that poor project definition is one of the common causes for project failure (Roland *et al.*, 2006). Therefore, in order to develop a research plan with practical value, we need to appropriately identify and define what the problems are in reality. The preliminary investigation of this research found that the care transition in Singapore involves a wide range of stakeholders with diverse perspectives on the problem nature. The conflicting interests and uncertainties make the care transition situation complex and unpredictable. “What are we trying to achieve” becomes a part of the research, due to such messy problem nature of the research object. It is very difficult to scope the research at the very beginning, since there are no obvious clues as to where the problems are, what should be improved and how to improve.

This research adopts a synthetic, holistic and interdisciplinary approach. It systemically enquires into the care transition situation before taking any action to solve a specific problem. The choice of methods, tools and techniques is situationally responsive. Soft systems methodology is adopted as an overarching framework and into which other methods, either soft or hard, are integrated. For example, semi-structured interviews are integrated into the framework at the initial appreciative stage to generate insights into the problematic situation. Then, cause-effect diagram is applied to structure the identified problems for common understandings. Hence, a clear and comprehensive picture of the current care transition situation in the public healthcare system of Singapore is generated. Cross-functional flowchart is used to depict the current system after the root definitions. Viable system model, in between of soft and hard OR methods, is adopted to provide a conceptual solution. A new care transition process is proposed. A discrete event simulation, one of the hard OR methods, is implemented to validate the superiority of the proposed solution to

current approach. Thereafter, an algorithmic approach for optimal process design is developed to ensure that optimal care transition process is achievable by figuring out what should be done by who at fastest speed with best quality. Finally, a decision support mechanism for care transition on when and where to transfer patients is developed with the objective to further smooth care transition by balancing length of stay and readmission rate. The road map of the whole research is shown in Figure 1-2.

Figure 1-2 Road map of the thesis

1.3 Organization of the Thesis

The organization of the thesis is presented in Figure 1-3. The rest of this thesis is organized into the following seven chapters. Chapter 2 is on literature review. Chapter 3 introduces the research framework and research methods. Chapter 4 presents the investigation into the reality about the problem situation of care transition in Singapore. Efforts to achieve a

smoother care transition are articulated in Chapter 5, 6 and 7. The thesis is then concluded in Chapter 8.

Figure 1-3 Organization of the thesis

Literature review in Chapter 2 starts with a brief description of the healthcare system and its complexity, followed by the development of health service research and more detailed introduction of the healthcare system in Singapore. These content aims at providing a general picture of the context of the care transition. After that, existing research on care transition is reviewed and summarized.

The complexity of the healthcare system indicates the necessity of systems approaches to study the problems of care transition. But the state-of-the-art in care transition research shows that there is sparse mention of systems approaches on care transition research. Therefore, in Chapter 3, soft systems methodology (SSM) is concisely introduced as an overarching methodology. The necessity of multi-method approach is highlighted afterwards. Thereafter, the framework of soft systems methodology with multiple methods (SSM-M), which is proposed based on the retrospect of whole research, is presented as the research methodology.

The work presented in Chapter 4 endeavors to identify the research problem. Soft systems methodology is applied as an overarching framework and problem-structuring tool to explore the care transition situation in depth. Semi-structured interviews are used to capture a range of views of the problem situation. After that, the insights and common understandings are provided with the structured picture on the problem situation. Finally, the research problem is identified by relevant systems scoping and root definitions.

Chapter 5 shows the efforts in developing the conceptual model to achieve a smoother care transition. Needs of changes for current process are identified based on the viable system model. An ‘aggregative’ care transition model is proposed and its superiority over the current ‘third party’ care transition model is validated by the discrete event simulation and modeling based on the Arena software.

Though an improved model is proposed in Chapter 5, it is difficult to ensure that the model is an optimal one due to the limitations of the qualitative analyses. Therefore, in Chapter 6, a two-stage optimization approach is proposed to achieve an optimal process design with

multiple objectives, such as minimized duration of the process and improved service quality. The care transition process is then converted into a network optimization problem. The first stage of the optimization selects the participating activities of a process from various candidate activities and determines their topological structure. The goal of this stage is to obtain a feasible process with the shortest duration time. The second stage of the optimization allocates different tasks to different staff according to their associated skill level. The objective of this stage is to achieve the best service quality of the process with constraints on duration times and the available types of staff. The solution of a test problem is obtained by IBM ILOG CPLEX Optimization Studio V12.2.

Care transition process improvement in Chapter 5 and optimization in Chapter 6 addresses ‘how to’ transfer the patient in a smoother way. To further smooth the care transition, Chapter 7 answers ‘when and where’ to transfer the patients. A discrete event simulation model is developed to capture the complex nature of the patient flow in the whole healthcare system. A new Markov chain model is proposed and incorporated into the simulation model to estimate the length of stay for each patient. Next, genetic algorithm is used to search for the optimal solution. Optimal computing budget allocation algorithm for constrained optimization is then integrated into the genetic algorithm to reduce the computational time. Multiple optimization scopes are considered. The optimal solution set is achieved by balancing the length of stay and readmission rate. Implications on policy making are gained from the optimal solution set. Finally, the summary, theoretical contributions and possible extensions of the research are given in Chapter 8.

Chapter 2

Literature Review

2.1 Healthcare System and Its Complexity

Some researchers articulated that the healthcare system is perhaps more complex than any other area of the economy (Effken, 2002; Runciman *et al.*, 2007). According to Mosby's Medical Dictionary, healthcare system is described as a complete network of agencies, facilities and all providers of health care in a specific geographic area (Douglas *et al.*, 2008). Dictionary of Sociology defines healthcare system as “the arrangements in a given society for the provision of healthcare (both preventive and curative) no matter organized into a coherent system or not”. World Health Report 2000 gives a definition that healthcare system is a set of all people and actions with the primary purpose to improve health, no matter it is integrated or not. Those definitions reflect the large scale of the system with a high variety of agents and interactions.

Modern healthcare systems have evolved and reformed over time with different visions and missions. According to the World Health Report 2000, healthcare systems have existed since people deliberately protected their health and treated diseases. At that time, the systems were very loosely organized and not easily accessed by poor people. With the development of industrialization, around 1940s and 1950s, the first generation of healthcare system reform led to the emergence of national healthcare system in developed countries and extended the social insurance systems into middle-income countries. Later, the requirement of cost-efficiency, equitability and accessibility triggered a second-generation

reform in 20th century, which aimed at increasing the healthcare system accessibility by promoting primary healthcare. However, the poor quality of primary care made the primary service insufficiently utilized. Therefore, the third reform took place and broadened the scope of the modern healthcare systems. It ensures healthcare system accessibility for the poor through gradual convergence and emphasis on financing and subsidies. The current challenges from an aging population, mentioned in Chapter 1, promote the shift from acute care toward the continuing care, which further add momentum to the healthcare system reform.

The work of Rouse (2008) provides some intuitive knowledge of the complexity in the healthcare system. Grounded by information theory, the degree of complexity of each industry has been calculated according to the number of the binary questions that have to be asked to determine the state of network (Rouse, 2008). Healthcare system is ranked second among the five compared fields, both in consumer complexity and total complexity. Figure 2-1 offers a detailed reference.

Figure 2-1 Complexity levels of five markets

Source: Rouse (2008)

A great variety of factors contribute to the complexity of the healthcare system, as shown in Figure 2-2. Firstly, the healthcare system covers a broad area, including the providers and consumers of products and services designed to promote health, no matter if it is preventive, curative, or palliative intervention (World Health Organization, 2000). Secondly, the value of the health services is co-produced by multiple agents, including the providers and consumers (Tien and Goldschmidt-Clermont, 2009). Thirdly, various knowledge and skill sets from multiple stakeholders are needed in the healthcare system. Many organizations and institutions are involved, for example the hospitals, clinics, rehabilitation centers, research institutions, government, pharmacies, non-profit organizations, vendors, suppliers, third-party insurers, and so on. Besides, innumerable individuals play varied roles within the entire system, such as patients, nurses, doctors (geriatricians, neurologists, orthopedic surgeons and psychiatrists etc.), therapists, administrators and so on. Fourthly, inherent uncertainties and variations in treating patients lead to a complicated process which makes it difficult to be standardized. There are thousands of medications, hundreds of clinical laboratory tests and radiological procedures for a physician to choose from. Fifthly, from time to time, people playing different roles have conflicting interests and opinions, especially, when the changes are driven by the administrators, but the consequences are felt by the medical staff. Sixthly, complexities are increased by the rapidly changing context. Variations in a patient's condition and co-morbidity, individual differences, organizational beliefs and culture, resources availability, economics and regulations result in the dynamic nature of the environment (Harper and Pitt, 2004). Seventhly, related technologies and tools are updated at an increasing pace. Their complex interfaces together with their

interdependence further add to the complexity of the healthcare system. Finally, the frequently changing preferences of a human-based system make the system evolve over time.

Figure 2-2 Complexity and dynamics in healthcare system

In summary, the large scale causes complexity on all levels of the healthcare system. Changes in one level of the system may cause some unforeseen impacts on other levels due to the unpredictable actions of individual agents and the non-linear relationships among them.

2.2 Health Service Research

Compared with other research fields, health service research is relatively new with a short history around 60 years. The term "health services research" was formally recognized in 1966 through the establishment of a federal government health services research study sanctioned in United States. The definition and scope of health service research have evolved. In the early 1970s, Sanazaro described health services research as a field that develops methods for improving access to care, moderating the rate of medical care prices, and assuring the effectiveness of care (Berkowitz, 2004). Report of President's Science Advisory Committee (1972) stated, "Health services research seeks to improve the network

for providing health care so that the achievements of biomedical research are readily available to all citizens". Such definition holds a systematic and holistic view of the health service delivery. Later in 1995, Institute of Medicine in America extended the scope of healthcare services with the definition that health service research is a multidisciplinary field of inquiry, both basic and applied, that examines access to, and the use, costs, quality, delivery, organization, financing, and outcomes of health care services to produce new knowledge about the structure, processes, and effects of health services for individuals and populations. Currently, the widely accepted definition comes from Academy Health (2000) of US, which defines health service research as a multidisciplinary field of scientific investigation that studies how social factors, financing systems, organizational structures and processes, health technologies, and personal behaviors affect access to health care, the quality and cost of health care, and longevity and quality of life. Studies in health services research examine outcomes at the individual, family, organizational, institutional, community, and population level. Therefore, according to the definition, this research belongs to the health service research.

Health service research aims to inform policy making by generating and disseminating valid and reliable information and knowledge to identify the most effective ways to organize, manage, finance and deliver high quality care, reduce medical errors and improve patient safety (Agency for Healthcare Research and Quality, 2002). Policy making placed great emphasis on improvement of outcome, but measurement of the outcome is a big challenge of health service research, as mentioned above, health care system is a very complex system with many interventions.

2.3 Healthcare System in Singapore

This research focuses on the improvement of care transition in the context of the public healthcare system in Singapore. Therefore, it is necessary to get aware of the current situation of the healthcare system in Singapore.

2.3.1 Singapore's Healthcare System

According to the last World Health Organization's ranking in 2000, Singapore's healthcare system is ranked 1st in Asia and 6th in the world. It has been regarded as extremely successful in terms of its cost-effectiveness. With the expenditure of 4% of GDP, it has achieved 70 years of healthy life expectancy (John, 2004). Details are shown in Figure 2-3. The success of the Singapore's healthcare system is greatly attributed to the system configuration and its finance mechanism (John, 2004).

Figure 2-3 Annual health expenditure and average healthy life expectancy

Source: John (2004)

There are both public and private healthcare practitioners in Singapore's healthcare system. The public sector plays a dominant role in the national hospital care system, 80% of acute care is provided by 7 public hospitals and 6 national specialist centers, shown in Figure 2-4.

There are 16 private hospitals that provide the remaining 20% of acute care. However, for primary care, 80% services are provided by about 2,000 private, general medical practitioners and the remaining 20% by 18 public polyclinics. Also, there is a comprehensive range of community-based healthcare services catering to intermediate and long-term health service needs, as shown in Figure 2-5. Community-based healthcare service are provided by community hospitals, chronic sickness hospitals, nursing homes, day rehabilitation centers, and other home based service institutions. The mixture of public and private institutions brought free market principles and government controls into play at the same time; this mixture incentivizes more efficient and proactive delivery of healthcare services.

Figure 2-4 Geographic distribution of public acute care providers in Singapore

Source: MOHH (2012)

Figure 2-5 Healthcare system structure in Singapore

Source: summarized by this research based on the data from MOH (2012)

Public expenditure on healthcare in Singapore is only around 1% of GDP, while the remaining, which accounts for 3% of the GDP, is afforded by the patients themselves (John, 2004). The ratio of private expenditure in Singapore is quite high compared with other developed countries, shown in Figure 2-6. The emphasis on individual responsibility for personal healthcare promotes rational consumption of limited healthcare resources. The “3M” financial framework has made a significant contribution to the success of such mechanism. “3M” refers to Medisave, MediShield and Medifund. Medisave is a mandatory deposit of a certain percentage of income for future health related expenditure. MediShield provides low cost catastrophic illness insurance. The third M, Medifund, is a government program that provides funding to support low income Singaporeans with costly medical expenses. In addition, another government funding named Elderfund provides subsidies to voluntary welfare organizations for their post-acute healthcare services.

Figure 2-6 Funding of health expenditure

Source: John (2004)

2.3.2 Challenges from Aging Population

Population aging has become a global trend and brings many challenges to healthcare systems. As the second most rapidly aging society in the world, Singapore will experience a significant change in population structure in the next 20 years (Cheah *et al.*, 2010). It is projected that by the year 2030, 18.7% of Singapore's population will be over 65 years old. The number of seniors in 2030 will be three times the number in 2005 (Committee on Ageing Issues, 2006). More details are presented in Figure 2-7.

Figure 2-7 Proportion of resident population aged over 65 from 2000 – 2030 in Singapore

Source: Committee on Ageing Issues (2006)

The rapidly increase of elderly population in Singapore may cause following problems:

(1) Increased demand

Elderly people are more vulnerable to chronic diseases and need longer time to recover from these diseases. The hospital admission rate of the elderly is five times higher than the rest of the population in Singapore (MOH, 2011), as shown in Table 2-1. Hence, the demand for healthcare resources is rising quickly with the increased amount of seniors in the society. The rate of admission and emergency attendances for elderly people in Singapore is increasing year by year. as presented in Table 2-2, the total number of admissions increased from 415,833 in 2006 to 435,750 in 2008, while the A&E attendances increased from 676,763 in 2006 to 788,539 in 2008, with annual increase rate of 2% and 8% respectively.

Table 2-1 Hospital admission rate by sex and age (per 1,000 populations)

Male (Age)	NO.	Female (Age)	NO.
0 - 14 years	64.3	0 - 14 years	55.1
15 - 64 years	59.3	15 - 64 years	54.5
65 years & above	300.3	65 years & above	263.9

Source: MOH website (2011)

Table 2-2 Admission attendances (public sector hospitals)

Admissions	2006	2007	2008
Total admissions	415833	429744	435750
A&E attendances	676763	752122	788539

Source: MOH website (2011)

(2) Limited resources

Compared with most other developed countries, Singapore faces a relative shortage of medical staff, especially of doctors and nurses, as illustrated in Figure 2-8. The number of

medical staff per 10,000 people in Singapore is approximately half of the number in the US. According to Suhaimi (2009), Singapore had to recruit as many as 1,000 foreign-trained doctors in the past three years to fill up that gap. The shortage would continue for several years until the graduation of extended enrolled medical students.

Figure 2-8 Healthcare workforce in year 2000- 2007

Source: world health statistic,WHO (2009)

In addition, demand for post-acute care is increasing faster than the demand for acute care due to the aging population. More elderly patients need to be transferred from acute hospitals to step-down care institutions, and spend longer time there. Currently, 30% of the hospital beds are for post-acute care, while the remaining 70% is for acute care. The shortage of beds in the step-down care causes some patients staying in acute hospitals even when they no longer need to be there medically. This creates blockages in acute hospitals, which in turn seriously affect the acute ill patients who are waiting for admission.

(3) Healthcare performance

Due to the rising demand and limited resources, the performance of the healthcare system in Singapore has been challenged by rising expenditure, longer waiting time, and increasing readmission rate. The expenditure has almost doubled in the past three years, but healthcare cost is escalating without a corresponding improvement of system accessibility and healthcare quality. The details of the annual healthcare expenditure are shown in Table 2-3.

Table 2-3 Government healthcare expenditure

Expenditure (S\$m)	2006	2007	2008	2009
Recurrent health expenditure (S\$m)	1840	2020	2379	3009
Development health expenditure (S\$m)	96	185	337	773
Government health expenditure/GDP (%)	0.9	0.9	1.0	1.5
Government health expenditure/ Total expenditure (%)	6.5	6.7	7.1	8.7
Government health expenditure per person 1 (S\$)	549	615	745	1002

Source: MOH website, MOH (2009a)

Waiting time became the first rank on the list of patient's complaints (Wong *et al.*, 2007).

Details of the waiting time to admission in public acute hospitals are presented in Figure 2-9.

Figure 2-9 Average daily waiting times for bed (20 Sept. 2009 - 26 Sept. 2009)

Source: Ministry of health, MOH (2009b)

Readmission rates have been used to track the quality of care in public hospitals in Singapore. According to the healthcare performance group of the Ministry of Health, the readmission rate of senior people within 30 days in 2010 is 19% in Singapore public hospitals (Lim *et al.*, 2011). Higher and unexpected readmission rates can be regarded as a service failure.

2.3.3 Responses to the Challenges

In response to the previously mentioned challenges, the Singapore government has restructured the healthcare system from ‘silo or compartmentalized episode care institutions’ to a regionally integrated healthcare system, where acute hospitals are linked to the community hospitals and supported by a network of other care providers in the region. The previous two-cluster healthcare system has been replaced with a ‘pyramid’ model, which is shown in Figure 2-10.

Figure 2-10 Pyramid model of public healthcare system in Singapore

Source: MOH Holdings (2008)

The new model divides the whole system into three layers. On the first layer, providers of the primary care and community care service are spread all over the island to provide one-stop care to patients. If the patient needs more intensive care, he or she will be referred to the secondary care, which is anchored by five regional clusters: the Alexandra Health in the north, National Healthcare Group in the central region, National University Health System in the middle of west, Jurong Health Service in the west, and Eastern Health Alliance in the east. These hospitals refer the most complicated cases to the national centers in the apex of the model (third layer) and transfer stabilized patients back to step-down care institutions for continuous treatment (first layer at the bottom of the pyramid). The new model not only provides the national centers with more resources for patients with complicated conditions, but also gives regional hospitals more space and autonomy in daily operations and management of the network of primary care and step-down care providers. Overall, this model aims at driving the movement towards continuous and integrated patient-centric care through smooth care transition.

MOH Holdings, a holding company of Singapore's public healthcare assets, has been restructured to provide systems-level strategies and promote collaborations across clusters and healthcare institutions. The agency for Integrated Care (AIC) has also been set up to smooth the patient flow between different layers of the pyramid model. These new institutions act as a 'national care integrator' to navigate patients and their families, so healthcare services can be used in a proper and efficient way. It coordinates, manages, and monitors patient referrals from acute hospitals to a great range of intermediate and long-term care providers. Currently, the AIC has recruited 50 care coordinators and dispatched them to public acute hospitals to ensure a smooth care transition of patients from acute hospitals to

community hospitals. Care coordinators have to collaborate with a multi-disciplinary team of doctors, nurses and medical social workers to ensure the smooth transition and a most optimal setting for patients.

The government also guides step-down care institutions, which are run by voluntary welfare organizations through finance incentives. A government fund called the Elderfund has been set up to subsidize voluntary welfare organizations for their post-acute healthcare services. This helps the healthcare system proactively respond to the needs for long-term care in the aging society.

2.4 Existing Research on Care Transition

2.4.1 What is care transition: definition, components and existing models

Care transition is fundamental in achieving beneficial outcomes for patients. The ideal care transition encompasses safe and efficient movement of patients between different sectors or levels of care within the healthcare system (Wendy *et al.*, 2010). It is founded on effective communication and information transfer among the involved stakeholders, dedicated post-discharge follow-up, and consistent, continuing care. Care transition is especially important for elderly patients and other high-risk patients who have multiple comorbidities.

There are multiple points at which a care process can be broken down during the transition. The care plans in previous stage often fail to be fully communicated with the medical staff in the next stage. Sable *et al.* (2011) noticed that lack of structured programs to guide the care transition of young patients with congenital heart disease (CHD), often lead to delayed or inappropriate care, improper timing of the transfer, and undue emotional and financial

stress on the patients, their caregivers, and the healthcare system. Reid *et al.* (2004) reported in 2004 that only 48% of adolescents with CHD underwent successful transition. According to Kripalani (2007), nearly half (49%) of hospitalized patients experienced at least one medical error in medication continuity, diagnostic workup, or test follow-up. It has been reported in their work that 19%-23% of patients suffer an adverse event. Half of these adverse events are considered preventable or “ameliorable”.

A good care transition provides uninterrupted healthcare service that is patient centered, developmentally appropriate, flexible, and comprehensive (Sable *et al.*, 2011). A care-planning tool, which incorporates the needs and preferences of patients, two-way communication, and uniform assessment mechanisms, would be essential for a smooth care transition. For this purpose, Coleman *et al.* (2002) proposed a Care Transition Measurement (CTM), which includes information transfer, patient and caregiver preparation, self-management support, and patient’s preference. After this, Coleman (2003) developed a detail list of essential care components to ensure smooth care transition. The list is presented in Table 2-4. Based on the empirical study of Coleman *et al.* (2004), self-management on medications, patient-centered records, specialist follow-ups after discharge and “red flag” warning symptom have been identified as essential elements in care transition intervention (Coleman *et al.*, 2004).

Table 2-4 Components to achieve smooth care transition

1. Evaluation of potential harm and benefits of an additional transfer
2. Match between the service of next care provider and the needs of the patient
3. Effective communication between the care providers in the two stages: <ol style="list-style-type: none"> a. A uniform care plan to facilitate communication and ensure the continuity of care b. A summary of care provided by the previous care provider c. The patient's goals and preferences d. An updated list of problems, baseline physical and cognitive functional status, medications, and allergies e. Contact information for the patient's caregiver(s) and primary care practitioner
4. Preparation of the patient and caregiver for what to expect at the next stage
5. Consistency of the treatment regimen
6. A follow-up plan
7. An explicit discussion of warning symptoms or signs and contact information of relevant people

Source: Coleman (2003)

Sable *et al.* (2011) identified several paramount steps to the successful transition of a child with special needs from a family-centered pediatric system to a patient-centered adult long-term care system; these steps are in line of the work of Coleman (2003). Details are presented in Table 2-5.

Table 2-5 Paramount steps to the successful care transition

1. A portable and accessible summary of medical and psychosocial information and a care plan should be provided. Comprehensive care that is coordinated and managed through a medical hub.
2. There should be a policy on timing of transfer, and the process is tailored to the development and psychosocial status of each patient.
3. Access to healthcare financing.
4. Education of next stage providers in managing chronic conditions.
5. The patient should demonstrate the ability to manage his or her health care independent of his or her family and pediatric provider.
6. Ongoing, coordinated communication between patients, families, and two-stage healthcare providers to facilitate transition and transfer, including the follow-up after the transfer.

Source: (Sable *et al.*, 2011)

Based on comprehensive review of the care transition relevant factors that result in the hospitalization and complication, Greenwald *et al.* (2007) proposed operationalized components for effective discharge and care transition. Details are shown in Table 2-6.

Table 2-6 Operationalized components for effective discharge and care transition

1. Educate the patient about their diagnoses throughout their hospital stay.
2. Make appointments for clinician follow-up with input from the patient. <ul style="list-style-type: none"> – Confirm that the patient knows where to go and has a plan about how to get to the appointment. – Review transportation options and other barriers to keep these appointments.
3. Discuss with the patient any tests or studies that have been completed in the hospital and discuss who will be responsible for following up the results.
4. Organize post-discharge services and make appointments that the patient can keep.
5. Confirm the medication plan <ul style="list-style-type: none"> – Explain what medications to take, emphasizing any changes in the regimen. – Review each medication's purpose, how to take each medication correctly, and important side effects to watch out for.
6. Reconcile the discharge plan with national guidelines and critical pathways.
7. Review the appropriate steps on what to do if a problem arises.
8. Provide discharge summary to next stage care providers.
9. Assess the degree of understanding by asking patients to explain the detailed plan in their own words.
10. Give the patient a written discharge plan at the time of discharge.
11. Telephone reinforcement of the discharge plan.

Source: (Greenwald *et al.*, 2007)

Soong *et al.* (2013), a group of expert cross several health sectors in Canada, conducted a comprehensive survey of existing research and created an evidence-based checklist include: (1) indication for hospitalization, (2) primary care, (3) medication safety, (4) follow-up plans, (5) home-care referral, (6) communication with outpatient providers, and (7) patient education. The Society of Hospital Medicine also assembled a panel of care transition researchers, process improvement experts, and clinicians to review the literature and developed a similar checklist of processes and elements required for ideal discharge of adult patients (Halasyamani, 2006).

The National Team of Care Transition has proposed a more generic framework with the aim to fill up the measuring gap. The framework has concurrently taken the structure, process

and outcomes into consideration. It encourages all related participants to take action for a smoother care transition. The details have been shown in Table 2-7.

Table 2-7 Quality measurement framework of care transition

Structure
A care coordination hub provides the patient-centric care
A care plan with patient's preference which can be accessed by all related care providers
Integrated and interoperable information system that can be accessed by all providers and patients
Process
Provide care planning medication reconciliation, test tracking, referrals tracking
Follow-up appointment tracking and end-of-life decision making
In time, complete and accurate information with shared accountability
Patient and family education, preparation and engagement in transition
Outcome
Patient's satisfaction of the experience
Providers' satisfaction of the interaction and collaboration
Resource utilization and cost
Health outcomes

Source: NTOCC measures work group (2008)

Currently, there are generally three types of care transition models in practice, namely the 'third party' model, the 'next stage initiation' model and the 'protocol' model. (1) The 'third party' model is the most popular and the most widely adopted model. In this model, an accountable third party, known as care coordinator or case manager, 'bridges' the different care institutions through transition. The third party is expected to be able to identify changes in health status, evaluate and manage multiple complex conditions, manage medications and collaborate with members of interdisciplinary teams and care givers (Coleman, 2003). Maramba *et al.* (2004) reviewed the literature from 1990 to 2002 about the role of nurse in the discharge process. Their study revealed that varied discharge planning processes employ staff nurses, advanced practice nurses, or case managers specifically prepared to implement the discharge planning process. These processes adopted the 'third party' model. (2) The

‘next stage initiation’ model is one of the alternatives to the ‘third party’ model. In this model, the next stage care provider visits the patient and initiates the care transition before the patient leaves current stage. Such pre-discharge visiting benefits the cross-setting communication and smooth information transfer, reduces anxiety and frustration of patients and avoids unnecessary delay and waste (Hollander and Prince, 2002). (3) The third model is the ‘protocol’ model, which provides protocols of patient care in each stage and defines the roles of care providers in different care institutions (Zuckerman *et al.*, 1992). Such model is based on the assumption that every care provider will consistently follow the criteria in the protocols. In addition, there is an evolved version of the ‘third party’ model known as a ‘self-managed’ model, which has already been examined by a large non-profit healthcare system in Colorado, US (Coleman *et al.*, 2006). In this model, the third party is called the transition coach, with the main function to encourage self-management and direct communication between the patients and care providers. This model is more economic, as the role of transition coach is less intensive than the role of care coordinator in the ‘third party’ model.

2.4.2 Care transition and healthcare system performance

Both academia and industry have put a significant amount of effort into examining the linkage between care transition and healthcare system performance. Existing research indicates that the threats of poor care transition can be more formidable than medical errors in a specific site. Conflicting recommendations of self-management and inconsistent treatment programs also have high potential of errors and duplications, which would undermine the benefits achieved in the previous stages and result in further functional dependency and institutionalization (Coleman, 2003). Forster *et al.* (2005) found that poor

communication and the absence of follow up after discharge, caused 11% patients to experience adverse drug events, while 27% of which were preventable and 33% were able to be mitigated. Poor care transition with inadequate follow up and insufficient preparation before discharge would cause patient dissatisfaction and even anxiety (Levine, 1998). Most importantly, poor care transition would ultimately lead to greater use of hospital, emergency, post-acute and ambulatory services, which are associated with higher costs (Institute of Medicine, 2001; Weissman *et al.*, 1999).

On the other hand, a considerable number of research has demonstrated that effective care transition management can improve the healthcare quality and reduce resource utilization by: preventing expensive, avoidable readmission, reducing length of stay in post-acute care institutions, and decreasing redundant diagnostic tests (Rich *et al.*, 1995; Einstadter *et al.*, 1996; Siu *et al.*, 1996; Naylor *et al.*, 1999; Arbaje *et al.*, 2008). Coleman and Berenson (2004) highlighted that the work of a liaison nurse in intensive care institutions can reduce the readmission rate by 8.5%. The severity of the disease of readmitted patients is lower than those without a liaison nurse. Russell (2000) articulated in a similar way that care transition management can decrease the unplanned readmission rate in acute hospitals and reduce the utilization of acute hospital services. Freyer *et al.* (2010) conducted literature review on transition of care from pediatric to adult-focused survivorship services. The result revealed that systematic care transition constitutes the standard of care for young adult survivors of childhood cancer. Naylor *et al.* (2004) used randomized controlled trial to test effectiveness of discharge planning and follow-up services of elderly patients with heart failure by advanced practice nurses, their research found that a comprehensive transitional care intervention for elders hospitalized with heart failure increased the length of time between

hospital discharge and readmission or death, reduced total number of hospitalizations, and decreased healthcare costs, thus demonstrating great promise for improving clinical and economic outcomes. Dedhia *et.al*, (2009) did quasi-experimental pre-post study on care transition of elder people. The result showed that healthcare outcomes can be improved by considering more specific needs of elder patients. Phillips *et al.* (2004) retrieved 832 reports for in-depth screening, of which 19 reports for 18 studies were eligible for analysis. The eighteen studies from 8 countries randomized 3304 elder inpatients with congestive heart failure that have been served with comprehensive discharge planning plus post-discharge support. The result showed that care transition intervention significantly reduced readmission rates and may improve survival rate and quality of life without increasing costs. Hence, monetary benefit can be achieved through care transition management (Coleman *et al.*, 2004).

Despite of those studies, the systematic review by Krieger *et al.* (1988) claimed that existing research designs were not rigorous enough to prove that care transition is cost-effective for non-cardiac patients. It only proved that no negative impacts have been caused. Brand *et al.* (2004) adopted quasi-experimental controlled trial to evaluate a chronic disease management model of transitional care. The study showed that there was no difference in readmission rates, emergency department presentation rates, quality of life, discharge destination or primary health care service utilization. They attributed such result to the lack of robust research methodologies to evaluate the effects of integrated healthcare service within complex and changing environments. Such argument is consistent with the conclusion of Krieger *et al.* (1998). Peikes *et al.* (2009) conducted control experiments on care transition intervention with nurses providing patient education and monitoring (mostly

via telephone) to improve adherence and ability to communicate with physicians. Participants in control group voluntarily joined and paid a service fee. The result indicated that viable care coordination programs without a strong transitional care component are unlikely to yield net Medicare savings. Naylor *et al.* (1999) used random controlled trials to examine the effectiveness of an advanced practice nurse-centered discharge planning and intensive home follow-up intervention for elders at risk for hospital readmissions. Such kind of intervention can reduce the number of readmission times, the time to readmission, and medical reimbursement. But there were no significant improvement in post discharge acute care visits, functional status, depression, or patient satisfaction. Anderson *et al.* (2005) argued that changes in medical management, making it difficult to measure the key elements of a successful care transition program involving education, discharge planning, and transitional care in the outpatient setting. However, they utilized a dedicated education program coupled with comprehensive discharge planning and immediate outpatient reinforcement through a coordinated nurse-driven home health care program. And the result revealed that there was a significant reduction of readmission rates, resulting in a reduction of costs, while the cost of implementing such program is only 10% of the saving gained from the program.

2.4.3 Barriers to effective care transition

There are various barriers that would possibly hinder the achievement of smooth care transition. Firstly, at the system level, diverse local practices in autonomous healthcare institutions, isolated information systems, and absence of strategic collaborations among institutions are major formidable impediments to effective cross-site communication and interaction (Keenan *et al.*, 1998). Currently, most healthcare information systems are

monolithic and limited to in-house use for individual healthcare institution with very few number of intra-enterprise applications. The system designs are technologically driven and have a difficulty to fully reflect the diverse features of the healthcare process (Berg *et al.*, 2003; Blobel, 2006; Institute of Medicine, 2001). Lack of integrated information system can cause limited agreements on the criteria for referral and referral process among different care providers. It also brings difficulties in accessing detailed medical records for next stage care providers (Venketasubramanian *et al.*, 2008). Notably, lack of financial incentive is another impediment for improving care transition across different institutions (Kuhn and Giuse, 2001). Currently, reimbursements in most healthcare systems are directed to particular institutions and quality assurance efforts only concentrate on individual institutions rather than the whole system. Such mechanism discourages professional accountability for the care transition. Furthermore, the financing and contractual relationships between care providers and pharmaceutical manufacturers lead providers to prescribe medications based on their own interests in such a way that causes confusions and even inconsistent regimes for the patients (Coleman, 2003). An absence of rigorously developed indicators to evaluate and monitor the care transition performance also affects the healthcare system (Coleman, 2003). Legislations on patient confidentiality frequently inhibit the smooth care transition (Moore *et al.*, 2003). Variations of drug prices, consultations, and other health services or resource among different healthcare settings make it difficult to transfer patients smoothly (Venketasubramanian *et al.*, 2008).

Secondly, at the institutional level, growing productivity pressures, caused by rising demand, impede extremely busy medical staff from following their patients after discharge (Coleman, 2003). Limited intensive care beds are frequently in shortage, which result in inappropriate

transfer of patient (Wenger *et al.*, 2003). Some of these patients are diverted to step-down care institutions where a new set of staff may lack related skills or be too overwhelmed to provide required services (Coleman, 2003; Wachter and Goldman, 2002). Furthermore, step-down care institutions reject some patients from acute care institutions because of the punishment policy on overstaying in step-down care institutions. The absence of awareness of the capability and capacity of receiving sites can also cause inappropriate transfer and transition (Brewster *et al.*, 2001). Additionally, very few medical staff have the required competency in cross-site collaboration (Coleman, 2003).

Thirdly, at the individual level, most patients lack the initiative to give a voice on how to improve the process of care transition (Coleman and Berenson, 2004). Patients are usually not allowed to express their preferences during the development of a care plan (Gerteis *et al.*, 1993). Moreover, some patients have unrealistic expectations on the performance of the service in the next stage (Coleman, 2003). The socioeconomic situation of a patient is regarded as an important impact factor of pre-discharge and post-discharge interventions in the care transition process (Coleman *et al.*, 2002). On the side of medical staff in the acute care institutions, the ability of step-down care institutions, doctor-patient relationships and high working loads are main impediments to a smooth transition. Insufficient skills and risk adverse attitudes of medical staff in step-down care institutions are also barriers to smooth care transition (Coleman *et al.*, 2002). With comprehensive literature review, Kripalani *et al.* (2007) highlighted important challenges for high quality care transition, including: inpatient-outpatient physician discontinuity, changes and discrepancies in medication regime, self-care responsibilities and social support, poor physician-patient communication. O'connell *et al.* (2003) found communication problems and lack of continuity of care between providers

made it difficult for individuals to negotiate the transition period and increased the burden of care on care givers during the period of transition.

Potential ways to overcome the above mentioned barriers have already been discussed and proposed by some researchers. Laurence *et al.* (2004) outlined a process for improving the integration of care across the rural acute and primary care settings to manage asthma by intensified stakeholder involvement and better communications. Davis *et al.* (2005) proposed to use a liaison nursing staff to improve the communication efficiency between different stakeholders to avoid information missing. Levine (1998) advocated incorporating care transition into Medicare. Cross-setting communication and interventions should be recorded into the document for reimbursement of medical staff to ensure accountability during care transition. Coleman (2003) agreed with Levine's view and believed that incorporating effective discharge into the program of pay for performance is a recommendable way to improve the care transition process. The implementation of such a method needs an effective tool to measure the quality of care transition. Process measures are regarded as particularly well suited tools (Medicare Payment Advisory, 2003; Coleman and Berenson, 2004). To facilitate a constructive process of care transition in response to epidemiological and allied change, awareness of cognitive/psychological factors involved in illness behaviors should not draw attention away from the social determinants and contexts of health (Taylor and Bury, 2007). It would need to identify which patient is in urgent need of care transition and foster collaborations among healthcare institutions. The patients and care providers should be encouraged to function as an integral member (Coleman and Berenson, 2004). Scott *et al.* (2010) explored ways to reduce readmission through care transition intervention, and found that single-component interventions were ineffective in

reducing readmissions by nurse home visits and telephonic support for patients with heart failure, while multi-component interventions demonstrated evidence of benefit in reducing readmissions by as much as 28%. Parry *et al.* (2003) introduced a patient-centered interdisciplinary team intervention designed to improve transitions across sites of geriatric care. The intervention is designed to encourage patient self-management and enhance communication and collaboration between professionals across sites of care, potentially reducing medical errors, missed appointments, and dissatisfaction with care. The details are provided in Table 2-8.

Table 2-8 Care transition intervention activities

Pillar	Medication self-management	Dynamic patient-centered record	Follow-up	Red flags
Goal	Patient is knowledgeable about medications and has a medication management system.	Patient understands, utilizes and manages a personal health record (PHR) for communication and continuity of care plan across providers and settings.	Patient schedules and completes follow-up visit with primary care provider/specialist and is empowered to be an active participant in these interactions.	Patient is knowledgeable about indications that condition is worsening and how to respond.
Hospital visit	Discuss importance of knowing medications and having a system in place.	Explain PHR.	Recommend primary care provider follow-up visit.	Discuss symptoms and drug reactions.
Home visit	Reconcile pre and post-hospitalization medication lists. Identify and correct any discrepancies.	Review and update PHR. Review discharge summary. Encourage patient to update and share the PHR with primary care provider and/or specialist at follow-up visits.	Emphasize importance of the follow-up visit and need to provide primary care provider with recent hospitalization information. Practice and role-play questions for primary care provider.	Assess condition. Discuss symptoms and side effects of medications.
Follow-up	Answer any remaining medication questions.	Remind patient to share PHR with primary care provider/specialist. Discuss outcome of visit with primary care provider or specialist.	Provide advocacy in getting appointment, if necessary.	Reinforce when/if primary care provider should be called.

Source: (Parry *et al.*, 2003)

2.4.4 Summary

Based on the above three subsections, the constructs and impact factors of effective care transition, the relationship between care transition management and healthcare system performance are summarized by a general framework. The details are shown in Figure 2-11. The approaches adopted by researches mentioned above have been summarized in Table2-9.

Figure 2-11 Effective care transition framework

The framework in Figure2-11 indicates that effective care transition can be achieved through a structure with comprehensive constructs and well executed processes. The effective care transition can improve system performance in terms of patient satisfaction, length of stay, average healthcare expenditure, readmission rate, and healthcare system accessibility. However, various barriers at system level, hospital level and individual level may impede the effectiveness of care transitions.

Table 2-9 Methods adopted to care transition research

Methods	Literature	
Literature review	Kripalani <i>et al.</i> (2007)	Halasyamani <i>et al.</i> (2006)
	Soong <i>et al.</i> (2013)	Freyer (2010)
	Laurence <i>et al.</i> (2004)	Phillips <i>et al.</i> (2004)
	Maramba <i>et al.</i> (2004)	Institute of Medicine (2001)
	Keenan <i>et al.</i> (1998)	Medicare payment advisory (2003)
	Levin (1998)	Watcher & Goldman (2002)
	Wendy <i>et al.</i> (2010)	
Interviews, survey, narrative analyses	Reiss (2005)	Hollander & Prince (2002)
	Reiss <i>et al.</i> (2005)	Institute of Medicine (2001)
	Levin (1998)	Laurence <i>et al.</i> (2004)
	Wendy <i>et al.</i> (2010)	O'Connell <i>et al.</i> (2003)
Field observation and process/ medical record review	Greenwald <i>et al.</i> (2007)	Brewster <i>et al.</i> (2001)
	Davis <i>et al.</i> (2005)	Moore <i>et al.</i> (2003)
Expert discussion/ conceptual model discussion /workshops	Sable <i>et al.</i> (2011)	Taylor & Bury (2007)
	Bolbel (2006)	Coleman & Berenson (2004)
	Coleman (2003)	Medicare Payment Advisory (2003)
	Gerteis <i>et al.</i> (1993)	Venketasubramanian <i>et al.</i> (2008)
	Russell (2000)	NOTCC Measures Work Group (2008)
	Kuhn & Giuse (2001)	
Controlled trials	Parry <i>et al.</i> (2003)	Dedhia <i>et al.</i> (2009)
	Scott (2004)	Coleman <i>et al.</i> (2002)
	Naylor <i>et al.</i> (1999)	Coleman <i>et al.</i> (2004)
	Naylor <i>et al.</i> (2004)	Einstadter <i>et al.</i> (1996)
	Brand <i>et al.</i> (2004),	Forster <i>et al.</i> (2005)
	Anderson <i>et al.</i> (2005)	Krieger <i>et al.</i> (1998)
	Peikes <i>et al.</i> (2009)	Siu <i>et al.</i> (1996)
	Weissman <i>et al.</i> (1999)	Wenger <i>et al.</i> (2003)
	Zuckerman <i>et al.</i> (1992)	
Statistic analysis	Arbaje <i>et al.</i> (2008)	Weissberg-Benchell <i>et al.</i> (2007)
	Rich <i>et al.</i> (1996)	

Table 2-9 indicates that most of the care transition literature adopts qualitative analysis with literature review, field observation, interviewer, and conceptual discussion with experts in the domain. Though these qualitative analyses generate many interesting insights, they are not rigorous enough in the nature. There are some research works adopting statistical analysis on the results of controlled trials, which are more rigorous than pure conceptual discussion. But very few researches apply rigorous system-engineering approach to tackle the care transition problems with a holistic view.

Chapter 3

Research Methodology

Existing research on national healthcare system has been narrowly focused on some aspects (Mingers and White, 2010). Efficiency improvements tend to rely on traditional OR. However, as mentioned in section 2.1, the complex nature of healthcare system indicates that it is difficult to directly formulate the messy problem of care transition with traditional OR methods. On the other hand, the ‘whole system’ approach has been found influential in developing health service systems in the UK (Pratt *et al.*, 2005). As systems approach can lead to a more inclusive and less reductionist view of a problematic situation, and therefore more effective and robust solution can be achieved (Ben-Tovim *et al.*, 2007). Though a significant amount of these efforts have been put into studying care transition, (as addressed in the session 2.4), most of these attempts worked only on several aspects of the care transition at operational level. Research on the organizational and inter-organizational level in a systemic way has not been adequately developed. In order to effectively improve care transition as a whole, comprehensive strategies are needed. Hence this research applies a combinative systems approach to examine the care transition problem with a holistic view.

3.1 Soft Systems Methodology: Research Framework

The preliminary investigations of this research on care transition found that the situation is very complex. It involves a wide range of stakeholders with varied perspectives on the problem nature, along with this comes conflicting interests, prominent intangibles and areas of uncertainty. Many researchers have advocated system thinking, especially, soft systems

methodology (SSM) as a basis for analyzing complex organizational operations (Beth *et al.*, 2003; Mawby and Stupples, 2002; Moon and Kim, 2005). As one of the most widely used systems approaches (Van de Water *et al.*, 2006), SSM can tackle the messy problem by allowing diverse and distinctive views to be expressed and embracing multiple objectives without collapsing them into a single measure.

Soft systems methodology (SSM) was first developed as a result of the failure of traditional system engineering approach in some management and social problems, where “there are many clients and decision-makers with conflicting values and the ramifications in the whole system are thoroughly confusing”. It draws from the work of Churchman (1971) on dialectical enquiry and the research of Vickers (1968) on interpretive sociology. The development of SSM has been well documented in three books (Checkland and Holwell, 1997; Checkland, 1999; Checkland and Scholes, 1999).

Checkland (1981) proposed the ‘classic’ form of this methodology, which consists of seven stages, as illustrated in Figure 3-1.

Figure 3-1 The classic form of soft systems methodology (SSM)

Source: Checkland (1999)

Stage 1, Unstructured problem situation. In this stage, observers enter into the problem situation, find out as much information as possible and accept many different views to make the richest initial expression of the situation being studied.

Stage 2, Appreciation and expression of the problem situation. In this stage the observed situation should be displayed in a 'rich picture', which may involve unresolved issues, conflicts, and other problematic or interesting features.

Stage 3, Root definitions. Root definitions are also known as analysis of 'CATWOE', which is a carefully phrased statement of intention expressed in six elements: customers (C), actors (A) transformation (T), worldview/weltanschauung (W), problem owner (O) and environment (E). 'CATWOE' represents a particular outlook on the problem situation. The analysis of 'CATWOE' follows after defining the system boundaries and its objectives.

Stage 4, Conceptual models. The construction of the conceptual models, which can be expressed pictorially, is based on a variety of idea sources. It involves the mapping of process activities and their interconnected sequences guided by the goal of root definitions.

Stage 5, Comparison. The idealized conceptual model(s) is / are compared with the real situation (from Stage 2) to check if there are any gaps.

Stage 6, Feasible and desirable changes. This stage analyzes the feasibility and desirability of the recommended changes in systems, policies, procedures and organization structure as well as 'value' and 'attitude'. If there are unbridgeable gaps, then re-iterate from Stage 3 to

redefine the root definition(s), modify the conceptual model(s), and reconfigure the ‘TO-BE’ model(s).

Stage 7: Action plan. In this final stage of SSM, a master action plan is developed for implementation to reach the desired outcomes.

SSM is structured and rigorous, but non-mathematical. It has been regarded as a general methodology to facilitate system design and redesign in multiple fields that have a wide variety of problem situations (Mingers and Rosenhead, 2004; Wilson, 1990). In particular, healthcare system design, e.g. the development of a new national healthcare system in UK, which incorporated features of local service for primary care, evidence-base medicine with national standards and information system support (Health Department, 1997); the activity model of the new ‘contract’ relationship between healthcare purchaser, and providers (Checkland, 1997); the practice-based approach to link information technology and information system as a whole to support the information needs of healthcare organizations (Checkland and Holwell, 1997); the configuration of health service due to the merge in the national health care system (Checkland, 1999); a national service framework for delivering cost effective services to diabetic patients (Kalim *et al.*, 2004); the design of a totally digital health systems (TDHSs) with interoperability with external systems (Raghupathi and Kesh, 2009), etc.

The applications of SSM also strategy, organization design, and operation in the context of the healthcare industry (Hindle *et al.*, 1995; Lehaney and Hlupic, 1995; Macias-Chapula, 1995; Gaunt, 1998; Lehaney *et al.*, 1999; Mobach *et al.*, 1999; Atkinson, 2000; Adamides and Maniatis, 2001; Clarke and Wilcockson, 2001; Connell, 2001; Lockett and

Grossenbacher, 2003; O'Meara, 2003; Fahey *et al.*, 2004; Stokes and Lewin, 2004; Sachdeva *et al.*, 2007). More information can be found from the literature review by Van de Water *et al.* (2006), which provides a broad and sound summary of the state of the art of SSM both in theoretical development and practical applications. Their work shows that researches on SSM are mainly concerned with: theoretical development of SSM; discussion on the complementarities between hard and soft systems thinking and interdisciplinary research.

The recent theoretical development of SSM introduced two streams of enquiry: cultural analysis and logic-based enquiry, reinforcing the view that SSM is a learning system, which is applied to processes of dealing with the world (Checkland and Scholes, 1999; Checkland and Winter, 2006).

3.2 Multi-method Approach

A survey of practitioners about their practical uses of SSM revealed that the most common benefit of SSM is to provide a coherent structure for dealing with the complexity of situations (Mingers and Taylor, 1992; Ledington and Donaldson, 1997). Though SSM is well developed theoretically, its non-mathematical nature implies imprecision and lack of rigor. It focuses more on exploration, learning, and commitment rather than optimization. On the other hand, a complex problem may involve different stages; as a result, different methods are appropriate at different phases (Mingers and White 2010). Hence, once the agreement on the problem nature has been achieved after the problem structuring, other methods, such as traditional operational research (OR) and modeling activities are needed to find effective solutions to the entire problem (Mingers, 2000).

In fact, many practitioners combined SSM with other complementary approaches (Mingers and Brocklesby 1997; Munro and Mingers 2002). The multi-methodology has caused a lively discussion in the field of management science, especially within the systems community (Brocklesby, 1997; Checkland and Holwell, 2004; Greene and Caracelli, 2003; Harwood, 2011; Jackson, 2009; Mingers, 2001; Mingers and Brocklesby, 1997; Tashakkori and Teddlie, 1998, 2002; Pidd, 2004.). Mingers (1997) classified the multiple methodology practice into five categories: (1) one/more methodologies; (2) single/multi paradigm; (3) same or different intervention; (4) whole/part methodology; (5) imperialist/mixed paradigm (Paucar-Caceres and Rodriguez-Ulloa, 2006).

A survey on the multi-methodology by Munro and Mingers (2002) found that most of the combinations are using either all soft OR methods or all hard OR methods, and rarely a mixture of soft and hard OR methods. Mingers and White (2010) also found a degree of separation between the development of soft and hard OR methods. Soft and hard OR methods have frequently been treated as two incompatible extremes due to their different philosophical assumptions (Brown *et al.*, 2006). In contrast, attempts to classify them in disjunction sets, Lane (1999, 2000) and Mingers (2000) pointed out that a combination of several approaches of both soft and hard OR methodologies can lead to more profound debate and discussion, and will benefit the problem owner. In fact many practitioners have used SSM combined with other approaches (Mingers and Brocklesby, 1997; Munro and Mingers, 2002). The number of published papers which combined SSM with other approaches is increasing (Lane, 1998). According to Jackson (2011), there are mainly two ways to handle the difficulties in combining methodologies with different sociological paradigms. The first is the ‘imperialist’ approach where the mixing methodologies are under

the hegemony of some preferred paradigms (Jackson, 1987). Examples such as Checkland and Holwell (2004), Harwood (2011) and Mingers (2005), go down the route of imperialist. The second way is ‘critical systems practice’ approach, advocated by Jackson (2003) and Zhu (2010), which treats hard systems thinking, organizational cybernetics and soft systems thinking as equal partners and supports pluralist vision with different paradigms to get the maximum benefits from them.

3.3 Soft Systems Methodology-multi-method (SSM-M) Framework

Through reflection on the course of integrating multi-methods into SSM framework in this research, soft systems methodology-multi-method (SSM-M) framework is proposed with the aim to provide another option to effectively manage and resolve complex problem by overcoming the limitations of a single methodology or paradigm. It can be regarded as a synthesized and dialectical framework, emerged from integrating multiple methods, principles and techniques. The choice of methods, tools and techniques is situationally responsive. The philosophical principles, concepts and steps of SSM underpin the SSM-M framework. They produced an overarching guideline for taking the study forward and surfacing opportunities for combining multiple methods in a flexible way. Extended from SSM, the SSM-M framework ensures that the analysis is objectively, rather than anecdotally, composed. To some extent, SSM-M aims to improve the rigor of SSM. Details of the proposed framework are elaborated on Figure 3-2.

Figure 3-2 The proposed SSM-M framework

The proposed SSM-M framework demonstrated its own merits throughout the whole research. First, compared with traditional workshop form, this research adopts the semi-structured interview for finding out the problem situation, which is not only more rigorous, flexible and less time pressurized but also effective in eliciting multiple different views from various stakeholders, and minimizing the impact of biased influence of the authority. Second, SSM-M framework uses the causal map as a rich picture instead of the traditional “cartoon-like” pictorial representation of the problem situation in SSM. Causal map is widely used in strategic options development and analysis (SODA). Like traditional SSM rich picture, causal map provides a view of the whole situation and acts as a powerful dialectic tool for conversation, debate and subsequent learning. The advantage of causal map lies in the way it portrays the comprehensive network of divergent problem statements and relationships. The

causal result allows all involved parties to see how their ideas and perspectives connect with each other. Such a way further enables the development of a shared understanding and detection of the emergent properties to increase the rationality of the final decision. Third, SSM-M incorporates change identification, which is supported by the viable system model (VSM). The result of the change identification based on VSM provides rigorous bases for the conceptual model development and could further ensure the viability of the proposed recommendations. Hence, it increases the feasibility and usefulness of a conceptual model. Fourth, the SSM-M framework adopts the discrete event simulation to compare the ‘AS-IS’ system and the ‘TO-BE’ system. Such hard OR method can demonstrate effectiveness and validity of the outcome by probing in a quantitative way if the suggested “culturally feasible” and “systemically desirable” changes and outcomes are really as expected. Fifth, the SSM-M framework contains optimization methods. Such hard OR approaches greatly avoid the subjective nature of SSM. They are not only more rigorous and precise, but can also break the constraint of human intuition, and get testable solutions that may not be achieved by pure qualitative analysis. For example, this research uses mathematical programming and constraint programming to get an optimal care transition process design with quantifiable superiorities over other process design. It adopts combined method of optimal computing budget allocation for constrained optimization (OCBA-CO) and genetic algorithm (GA) to compare the optimal solutions on when and where to transfer the patient from the perspective of different stakeholders. With rigorous nature of hard OR, it is easier to make different stakeholders to realize their roles, contributions, and responsibilities to achieve the best for the whole system. Therefore, conflicting objectives can be aligned and agreement on the process improvement can be reached. All in all, the SSM-M, which is an extended form

of SSM, aims at providing a more comprehensive and rigorous framework to address complex issues. With such multi-method framework, the soft OR can provide the rich picture of the problem situation and identify the interesting research problem, while the hard OR methods can avoid the criticism of ‘contextually naïve’, and provide rigorous solutions that cannot be achieved by soft OR.

How multiple methods are incorporated into the SSM framework is shown in Table 3-1. The rationales of why these methods have been incorporated into the SSM framework are presented in the case research of following chapters.

Table 3-1 Incorporated methods and stages of SSM

Chapters	Research works	Relevant methods	Stages of SSM
Chapter 4	Problem identification	<ul style="list-style-type: none"> • Face to face interview 	Stage 1
	Problem structure	<ul style="list-style-type: none"> • Causal relationship diagram 	Stage 2
	Root definitions	<ul style="list-style-type: none"> • Cross functional flow chart • CATWOE analysis • Stakeholder requirements analysis 	Back to stage 1 Stage 3
Chapter 5	Needs for change	<ul style="list-style-type: none"> • Viable system model 	Back to stage 2 & 3
	Model for process improvement	<ul style="list-style-type: none"> • Cross functional flow chart 	Stage 4
	Comparison of ‘AS-IS’ and ‘TO-BE’ process	<ul style="list-style-type: none"> • Discrete event simulation with Arena • Statistical analysis 	Stage 5
Chapter 6	Feasible process design with minimum duration time	<ul style="list-style-type: none"> • Mathematical programming model • IBM ILOG CPLEX Optimization 	Back to stage 4
	Scheduling relevant staff to maximize the service quality	<ul style="list-style-type: none"> • Constraint programming model • IBM ILOG CPLEX Optimization 	
Chapter 7	Modelling patient flow at system level	<ul style="list-style-type: none"> • Discrete event simulation with MATLAB 	Back to stage 4
	Modelling recovery process	<ul style="list-style-type: none"> • Markov chain 	
	Finding the optimal solution	<ul style="list-style-type: none"> • Genetic algorithm • Optimal computing budget allocation 	

Chapter 4

Systemic Enquiry with Soft Systems Methodology

The importance of smooth care transition has been realized by many hospital administrators and practitioners in Singapore. In spite of the endeavors of Agency for Integrated Care (AIC), achieving consistent and smooth care transition still remains a challenge. With the aim to further smooth the care transition, this research conducts an in-depth systemic enquiry to the problem situation of care transition in Singapore.

As mentioned in earlier chapters, care transition involves multiple stakeholders with different perspectives regarding the problem nature. With this characteristic, soft systems methodology has been adopted as a general methodological framework for the whole study. Going through the steps of SSM helps to gain a deeper understanding of different views of the internal and external stakeholders on the situation of care transition in Singapore.

4.1 Problem Identification

The first step of soft systems methodology is problem identification. In this stage, the study aims at capturing as many views and perspectives as possible and recognizing the need to improve the healthcare system. This research begins by conducting many face-to-face interviews with staff from various levels of hospital operations with different functional roles that have first-hand experience with the problem situation. These interviews are more effective than traditional workshops in eliciting views from various stakeholders. This minimizes the impact of biased influence from senior managers and authority members by letting the voice from all levels to be heard. The interviews were conducted with a semi-

structured questionnaire, which was developed based on the question dialogue proposed by Fischer (1989) on action research. The questions are listed in Table 4-1.

Table 4-1 Semi-structured interview questions based on Fischer (1989)

Have you found any problems during the patient transfer?
Why do you think this is a problem?
When does the problem become extremely significant?
Where does it become a problem?
Who should be responsible for the problem?
Are others interested in the problem?
Do they regard it as a problem?
Are they willing to participate in solving the problem?
Who will suffer if the problem cannot be solved?
Who should solve the problem?
Is it a symptom of another problem?
What will happen if the problem isn't solved?

Source: modified by this research according to Fischer (1989)

Interviews with 31 medical staff working in different levels and institutions of the healthcare system have generated a wealth of information about the problem situation. The results have been coded, merged, trimmed and summarized in Table 4-2. Information from several speeches by relevant government authorities were also collected and incorporated into this list.

Table 4-2 Identified problems in care transition

What is the problem	Why it is a problem	How to solve it	View holders
1. Shortage of beds in step-down care institutions	Causes delay in patient discharge in acute hospital, which negatively impacts the accessibility of the service	Improve resource utilization; Expand resource capacity	Doctors in an acute hospital Care coordinators
2. Errors in information during transfer	Brings adverse results on patients	Standardize the processes; Strengthen monitoring and link errors with staff performance evaluation	Therapists of an acute hospital
3. Patients' inability to manage their own health	Makes patients unable to cope with different care plans developed by different care providers	Improve pre-preparation of transfer Educate patients; Use reminder tools; Follow up patients after discharge	Manager of Agency for Integrated Care
4. Policy of Medisave usage in community hospitals	Discourages transfer from acute hospitals to community hospitals	Increase the usable amount of Medisave at community hospitals; Make transfers more economic	Department administrator of an acute hospital
5. Performance variance of nursing homes	Makes patients unwilling to go to some nursing homes with poor service	Upgrade weak nursing homes; Build more nursing homes	Staff of Ministry of Health
6. Staff shortage at community hospitals	Causes bed closures; Delays patient transfer from acute hospitals	Provide more systemic support for staff training and recruitment	Speech of Permanent Secretary (Health)
7. Difficulty for relevant parties in gaining access to the detailed medical records	Leads to inconsistent care plans, unnecessary duplications and adverse medical events	Build integrated and interoperable information systems or introduce smart cards for medical records	Researchers of National Healthcare Group
8. Different rates of hospitalization subsidy in different institutions	Induces patients to use the most highly subsidized resources rather than the most needed ones	Adjust subsidies policy	Researchers of National Healthcare Group
9. Limited agreement on the criteria of referrals and the process	Referral process becomes inefficient and unpredictable	Advocate related parties to set standards	Researchers of National Healthcare Group
10. Inability to forecast transfer	Leads to inadequate preparations for transfer between different care providers	Develop formal discharge plans once patients have been admitted	Department head of an acute hospital; Director of a community hospital

11. Lack of sound subsidy policies	Inhibits middle-income patients to be discharged from acute hospitals where the services are better and cheaper than step-down institutions	Adjust the subsidy policies	Department head of an acute hospital; Director of a community hospital
12. Ineffective rules in acute hospitals to prevent overstay	Overstay wastes critical resources and increases the healthcare cost	Authorize an institution to monitor and evaluate the situation; Use buffering units; Link overstay with staff performance evaluation	Department head of an acute hospital; Director of a community hospital
13. Community hospitals reject some patients to avoid financial risk	Results in overstay in acute hospitals; Wastes resources	Develop platforms for joint decision making on patient transfer; Set standards for referral and transfer	Department head of an acute hospital; Director of a community hospital
14. Community hospitals are run by volunteer welfare organizations	Have limited funds to improve operations	Ministry of Health should provide more supports and funds to community hospitals	Department head of an acute hospital; Director of a community hospital
15. Difficulties of community hospitals in employing good medical staff	Discourage patients to be transferred from acute hospitals to community hospitals	Ministry of Health should provide more training and support to step-down care providers	Department head of an acute hospital; Director of a community hospital
16. Insufficient participation of geriatric specialists before the transfer of a patient	Some potential problems cannot be detected	Make more formal discharge plans with the participation of geriatric specialties	Researchers of National Healthcare Group
17. Some transitions are determined by the demands for acute beds	May impact the final result of a patient	Make a joint discharge plan with a clear goal; Set standards	Doctor of an acute hospital
18. The follow up plan of discharged patient has not been well executed	Acute hospitals lack the feedback of discharged patients to improve the transfer decisions	Employ more staff; Record feedback and evaluate the execution of the follow up plan	Department administrator of an acute hospital
19. Readmission rate is quite high	High readmission rate indicates bad quality and waste of resources	Make better discharge decisions; Better coordination among different care providers	Doctors, Department administrators of an acute hospital
20. Insufficient communication among care providers at different stages	Lack of information may lead to inconsistent treatment and potentially adverse results for patients	Monitor and ensure timely transfer of all the documents; Staff meet regularly to discuss patients' situation	Nurse of a community hospital
21. Difficulties in transferring some patients from community hospitals to nursing homes	Community hospitals reject some patients who may stay longer than 4 weeks	Adjust the key performance indicators on community hospitals; Develop joint discharge plans; Establish collaborations among different care providers	Therapists of community hospitals; Administrators of an acute hospital and community hospital

Chapter 4 Systemic Enquiry with Soft Systems Methodology

22. Care transition decisions are not linked with the staff performance evaluation	Lacks incentives to improve care transition decisions	Record improper transitions; Link them with staff performance measurement	Researchers of National Healthcare Group
23. Alternative services to nursing home care are too expensive for low-income patients to afford	People with low income cannot afford alternative services in the community; Increase demand on highly subsidised nursing home services	Adjust subsidy policies to allow paying more services in the community with Medisave	Care coordinators
24. Unwillingness of some patients to be transferred from acute hospital	Causes unnecessary overstay in acute hospitals	Upgrade the service level in community hospitals; Adjust the subsidy policies	Care coordinators; Administrator of an acute hospital
25. Risk averse attitude of community hospitals due to their limited operations funds	Community hospitals reject patients who tend to consume expensive resources	Remove the financial barriers; Set risk sharing program	Administrator of a community hospital
26. Lack of integrated information systems within the whole healthcare system	Causes communication errors; Delays information exchange	Build web-based integrated information systems; Use smart cards	Administrators of an acute hospital and a community hospital
27. Discrepancy between expectation of Ministry of Health and actual operations in community hospitals	Community hospitals are used as short term nursing homes with rehabilitation function; Capacity of intermediate care is insufficient	Make consensus on criteria of the transfer of patient to community hospitals; Provide more support to community hospitals	Administrator of a community hospital
28. Ministry of Health's evaluation on the performance of community hospitals linking with overstay	Makes community hospitals reject patients who may overstay	Make more flexible evaluation rules to allow overstay with justification	Administrator of community hospital
29. Limited funds in community hospitals due to the nature of voluntary welfare organizations	Difficult to attract staff with higher skill sets	Government should give more financial support to community hospitals	Administrator of a community hospital
30. Asymmetric information of bed availability in different institutions	Results in repeating referrals and overstay in acute hospital	Closer collaboration; Joint discharge plan	Administrator of a community hospital Care coordinators; Doctors of acute hospitals
31. Long decision time of patients in choosing preferred step-down care providers	Frequently results in overstay in acute hospitals	Inform patients to prepare as early as possible; Implement punishment rules for overstay to accelerate the decision process	Administrator of a community hospital; Care coordinators

32. Healthcare providers are under different authorities	Have different goals; Build barriers for collaboration; Lack of trust	Government should provide more support to community hospitals and strengthen supervision	Administrator of a community hospital
33. Government's emphasis on the individual responsibility	Insufficient subsidies in some public sectors	Adjust financial policy; Give more subsidies to the needy people	Administrator of a community hospital
34. Inconsistency of care plans in different stages	Results in avoidable medical errors and early readmissions	Improve communication between care providers	Administrator of a community hospital
35. Unnecessary overstay of patients in acute hospitals	Wastes resources; Impacts service quality	Strengthen supervision; Smooth discharge process	Administrator of an acute hospital
36. Duplications of some lab tests	Increases healthcare costs and waste critical resources	Optimize process and resource scheduling	Administrator of an acute hospital

The results in Table 4-2 have been compared with the barriers addressed in existing literature. Details are shown in Table 4-3.

Table 4-3 Compare the situation in Singapore with existing research

Addressed factors in literature (details are in section 2.4.3)		Serial NO. of corresponding problems in Table 4-2
System Level		
Collaboration	Diverse local practices	9/34
	Isolated information systems	26
	Lack of formal relationship	30/32
Financial incentive	Medicare reimbursement policy	4/11/28
	Financing and contractual relationships	8
Legislation	Legislation on patient confidential	N/A
Institutional Level		
Resource shortage	Staff shortage	6/15
	Facility shortage	1/21
Performance measure	Productivity pressures of specific roles	20
	Inappropriate measurement on performance	22
Information transfer	Lack of knowledge on other institutions	10/30
Individual Level		
Specialist in AH	Lack of confidence in step-down care	N/A
	Need to show workload statistic	N/A
Patient	Lack of confidence in step-down care	N/A
	Involvement in care planning	31
	Social economic factors	24
Staff in step-down care	Risk-averse attitude	N/A
	Skill limitations	6

This comparison indicates that the barriers to smooth care transition in Singapore are not in line with those addressed in the existing literature. The differences at the system level can be partially attributed to governmental initiatives to smooth care transition. MOH Holdings Company and Agency for Integrated Care have been restructured to minimize system gaps

in Singapore. The legislation of patient privacy has not been a problem for care transition in Singapore. At the individual level, lack of confidence in step-down care is not a problem in Singapore. The reason is because there is an evaluation of the appropriateness of a transfer before discharging a patient from acute hospital to any of the step-down care providers. In Singapore, risk-averse attitude does not show up at the individual level, but rather becomes a problem at the institutional level. Community hospitals reject some patients, who are highly prone to consume expensive healthcare resources, to avoid the financial risk due to the limited operations funds collected by voluntary welfare organizations.

Some problems are unique to Singapore. The problems with serial number 2/3/5/8/12/13/14/16/17/23/25/27/29/33 in Table 4-2 have not been addressed by existing literature. At the system level, they are: errors in information during patient transfer, different hospitalization subsidies rates from different institutions, community hospitals are run by volunteer welfare organizations with limited operations funds, alternative services to nursing home care are too expensive for low-income patients to afford, discrepancy between expectation of Ministry of Health and actual operations of community hospitals, government's emphasis on individual responsibility for personal healthcare leading to insufficient subsidies in the public sector for low-income patients. At the institutional level, problems include: performance variances in nursing homes run by voluntary welfare organizations, ineffective implementation of rules in acute hospitals to prevent overstaying, community hospitals rejecting patients to avoid financial risk, community hospitals wanting to avoid financial risk due to their limited operation's funds, limited funds in community hospitals because of the nature of voluntary welfare organization, insufficient participation from geriatric specialists before the transfer of a patient, transitions are determined by the

demands for acute beds. At the individual level, a patient's inability to manage his or her own personal health has been a problem that has not been addressed in researches on other countries.

4.2 Problem Structure

Framing the identified problems is an important step to achieve an agreement on the problem nature. The 36 identified problems in Table 4-2 are grouped into 26 items, which have no overlap in meaning between each other. Then, the 26 items are structured based on their causal links. The results are illustrated in Figure 4-1, which provides a holistic 'rich picture' of the problem situations. The picture indicates that various factors interactively cause the problems in care transition.

There is a sharp increase in demand for healthcare resources due to the aging society. Controlling cost and maintaining service quality with constraints of current capacity becomes a major challenge for the public healthcare system. How to use the limited critical resources more effectively and how to reduce the waiting time of admission into acute hospitals via smooth care transition are of the major concerns in this study. Based on Figure 4-1, overstay and early readmissions are regarded as important aspects, which can be fixed with better care transition arrangements to decrease resource waste and shorten waiting time. There are mainly five issues that directly lead to overstay, corresponding to the problems 12, 13, 24, 30, 31 as listed in Table 4-2: ineffective rules in acute hospitals to prevent overstay; community hospitals rejecting patients to avoid financial risk; reluctance of patients to be transferred to step-down care providers; inaccurate information of bed availability in different institutions; long decision time of patients in choosing their

preferred step-down care providers. Meanwhile, patient's inability to manage personal health (problem 3) and inconsistent care plans in different stages (problem 34) are main causes of early readmissions.

Each of these issues that cause overstay and readmission has its own origins. For example, the reluctance of patients to be transferred to other institutions (problem 24) is because of the subsidy policy (problems 8 and 11) and inappropriate Medisave usage policy (problem 4). Currently, Medisave cannot be used to pay for expenses in some step-down care institutions and the subsidy rates for step-down care services are much lower than that of acute care for the middle income class. Such policy causes more overstay in acute hospitals.

Policy to discourage overstay can't work effectively (problem 12), because of the staff performance evaluation (problem 22), which is closely linked to patients' satisfaction, but has not been linked with overstay of patients. Under such a policy, doctors tend to allow patients to overstay for a short period with the excuse of medical reasons to increase the patient's satisfaction. The punishment policy of overstay is ineffective in such a situation.

Overstay also occurs if the patient cannot be transferred to his/her preferred step-down care institution in time. He or she needs to wait until the bed is available or apply for the service of another step-down care provider. The negative impacts of the inaccurate information of bed availability in different institutions (problem 30) are exaggerated by the shortage of beds in step-down care institutions (problem 1), and the lack of integrated information systems (problem 26).

Some patients need a longer time to choose their next stage care provider (problem 31), thus postpone the process of care transition and eventually results in overstaying. The shortage of beds in community hospitals (problem 1) and the variation of service prices from institution to institution (problem 8) increase the complexity of the decision. Patients and their families spend long time to check, compare, and discuss before the final decision. Since a patient's needs from step-down care can be identified only after a period of observations in the acute hospitals (problem 10). This constrains early discharge initiatives.

Some patients have nowhere else to go but stay in the acute hospitals, even when they no longer need such level of service. These are the kind of patients who are not fully recovered and would consume expensive healthcare resources if an unexpected situation comes up. Community hospitals tend to reject these kinds of complex cases (problem 13) to avoid financial risk (problem 25). Limited agreement on the criteria for patient transfer and care transition process (problem 9) frequently results in patient rejection by community hospitals (problem 13).

Inconsistent care plans (problem 34) also cause medical errors and unplanned, early readmissions after discharge. Lack of an integrated information system (problem 26) and imperfect follow-up plans (problem 18) make it difficult to achieve a consistent care plan. The problematic care transition plan and process also impedes smooth care transition. The insufficient participation of geriatric specialties before a patient's transfer (problem 16), transitions are impacted by the demands for acute beds (problem 17), difficulties for step-down care providers to gain access to detailed medical records (problem 7), limited agreement on the criteria for patient transfer and care transition process (problem 9), errors

in information during patient transfer (problem 2) are the main problems of care transition plan and process.

Many issues can be partially attributed to the problems in the care transition plan and process (corresponding to problems 2, 7, 9, 16, 17, 20). The shortage of beds in step-down care institutions (problem 1) becomes more serious due to the variations in the demand for post-acute care. However, early discharge for some patients due to high demand for acute beds (problem 17), insufficient communication among staff at different institutions (problem 2) with a limited agreement between care providers on the criteria of referrals and the processes (problem 9) make the needs in a transfer difficult to forecast.

Multiple issues cause a risk averse attitude of the community hospitals (problem 25). Community hospitals are acting as short-term nursing homes while the Ministry of Health (MOH) wants them to take on more responsibilities for providing medical care to unstable patients (problem 27). MOH's rigid punishment policy in overstaying in community hospitals (problem 28) and the difficulties in transferring patients from community hospitals to good voluntary welfare organizations' (VWOs) nursing homes (problem 5, 21) force community hospitals to reject patients with a high potential of overstaying. The rejection of these patients can also be caused by a shortage of staff (problem 6), especially when the high competent staff are needed to handle the complex cases (problem 15) with limited funds they have (problem 29). Lack of fund in community hospitals is also a barrier to implement the integrated information system (problem 26) and to attract high competency staff for community hospitals (problem 15).

With a more in-depth analysis, it is not difficult to know that providers of acute and post-acute care are actually under different authorities (problem 32). Such problem is the root cause for many problems. It causes the problems of care transition plan and process (related to problems 2, 7, 9, 16, 17, 20). It also leads to the discrepancies of the MOH's expectation and the actual operations in community hospitals (problem 27). The expensive substitutions of services of lower cost VWOs nursing homes (problem 23) rather than the shortage of the resources causes the long queue for beds at VWOs nursing homes (related to problem 5, 21). Moreover, there are two main reasons behind the problem for limited funds in community hospitals (problem 29). Firstly, community hospitals are run by voluntary welfare organizations (VWOs) (problem 14). Their operations funds mainly come from public donations. Public want their donations to be used only by people who are poorer than the donators. Therefore, the subsidies for richer people in the community hospitals are relatively low. Besides, the government lays great emphasis on individual responsibility of personal health (problem 34). Hence, the governmental finance support to the step down care institutions is quite limited.

Figure 4-1 Expressed problems-----a structured picture of problem situation of care transition

*The numbers marked in the figure are corresponding to the serial numbers of the problems in Table 4-2

4.3 Root Definitions

4.3.1 Scoping relevant systems

Many factors actively contribute to the problem situation of care transition. The causal links among these problems help us to identify the fundamental problems. The 36 identified problems can be classified into 5 layers according to their cause and effect relationships shown in Figure 4-1. The upper layer is the symptom of the lower layers; therefore, problems in the last layer are the underlying problems in the overall situation. Four underlying problems, which correspond to problems 14, 23, 32, 33 in Table 4-2, are identified. They are community hospitals are run by volunteer welfare organizations; healthcare providers are under different authorities; alternative services to nursing home care are too expensive for low-income patients to afford; the government's emphasis on the individual responsibility. These problems relate to issues of ownership, authority, pricing and responsibility. However, the four identified problems cannot be directly intervened due to the political sensitivities or economic concerns. For example, emphasis on an individual responsibility (problem 33) of personal healthcare does bring problems to the smooth care transition, as it transfers financial burdens to individual citizens. Problem occurs when low-income patients cannot afford the services they need, but the emphasis on individual responsibility would encourage rational consumption of healthcare resources. The comparatively lower tax rates and high demands for other public expenditure in Singapore make the public healthcare system have relatively limited budget. Therefore, the Singapore government would insist on emphasizing the individual responsibility of personal healthcare regardless of its negative impacts on smooth care transition.

It is also difficult to directly smooth the care transition through other three identified fundamental problems. In such a situation, this research goes to the upper level, where there are six interrelated problems.

Based on two criteria: 1. The impact of a problem to the entire healthcare system; 2. The feasibility to make changes to this problem in reality to deliver some interesting results; ‘care transition plan and processes’ is eventually chosen for further investigation as it has the largest number of inter-connections with other problems, which indicates that it has the most profound impact on the whole problem situation, and it is possible to have a new care transition process in reality. At the core of the problem is the absence of an effective discharge plan and process during care transition. Supporting evidence from existing research highlights that formal discharge plan have been associated with a better outcome for patients (Chaboyer *et al.*, 2005; Naylor, *et al.*, 1999), lower cost (Brooten, *et al.*, 1988), and shorter length of stay (Evans and Hendricks, 1993). Wenger *et al.* (2003) claims that a formal discharge plan is an effective way to minimize the service gaps in care transition. In addition, experts in business engineering believe that a successful system starts with an understanding of the business process (Sara and Aguilar-Saven, 2004).

4.3.2 Investigation of ‘AS-IS’ system

Different hospitals have different care transition plans and processes. Hence, this research goes back to stage 2 of the SSM and conducts a case study on Geriatric Department of Tan Tock Seng Hospital (TTSH) in Singapore to better understand the current care transition plan and process. TTSH is the busiest public hospital in Singapore and its Geriatric Department has the most standardized care transition plan and process. Based on the interviews with medical staff, including department directors, managers, nurses, therapists,

social workers, and care coordinators from the acute hospital, associated community hospitals, and the Agency for Integrated Care, the general process of care transition is depicted in a cross functional flow chart in Figure 4-2. There are many business process modeling tools and techniques, but a flow chart has been adopted by this research due to its communication ability, flexibility, and ease of use (Sara and Aguilar-Saven, 2004).

The care transition process begins when the nurse checks if a patient has a care giver within 48 hours after admission into an acute hospital. If the patient has a care giver, the nurse should follow up with the case and provide a brief education and guidance to the care givers on how to take care of the patient after discharge. Otherwise, the nurse refers the case to a care coordinator, who will in turn collect medical, social and economic information about the patient. The care coordinator will recommend several possible step-down care providers to the patient based on his or her specific conditions, such as health status, income and location. The patient and his or her family make a decision within a few days. The availability of all the relevant reports is checked by the care coordinator before the weekly discharge meeting, which is held on a pre-determined day of the week (Patients who stay less than one week in the acute hospital usually do not need any step-down care service after discharge and their discharge decisions are made by doctors individually). During the meeting, relevant medical staff briefly report the medical status of their patients. Estimated discharge time and discharge destination of each patient are discussed. The medical progress of each patient since the previous meeting is reviewed. If the goals of a patient's progress have not been met, the group will find out what the problem is and who should act on it. After the meeting, the doctor informs the patient about the estimated discharge time and suggested care providers in next stage. The final decision is confirmed with the patient by a care coordinator on a later date.

If a patient needs service from a nursing home run by a voluntary welfare organization (VWO) after discharge from the acute hospital, care coordinators will refer the case to a social worker, who will submit an application for the patient to the Agency for Integrated Care (AIC). The AIC is the gatekeeper of all the VWOs nursing homes, the staff in AIC investigates and verifies the eligibility of the transfer to nursing home. The shortage of

resources in VWOs' nursing homes causes a considerable number of patients to wait at home for a period of time until a bed is available. Patients who have no families or friends to take care of them during the wait period are transferred to a buffer step-down care unit that is attached to the acute hospital.

For a patient who needs care from a community hospital, a care coordinator is in charge of the application for the transfer. The community hospital evaluates the rehabilitation potential of the patient. A qualified patient continues to stay at the acute hospital until a bed is available in the specific community hospital. If the application is rejected or there is no vacancy in the community hospital within a short time period, the care coordinator will try other community hospitals or find a private rehabilitation center for the patient. The transfer result is reported to AIC by the care coordinator. After a patient's discharge from the acute hospital, a care coordinator will follow up with the patient via telephone to update on his or her status. If readmission occurs within three months of discharge, the care coordinator will check the reason and try to prevent readmission.

After inquiring about how the current system works, a 'CATWOE' analysis has been conducted to formulate the root definitions, which are used to name the system and to define the 'intent' of a proposed system. Customers (C) are the potential beneficiaries or victims of the process; Actors (A) are the problem solvers; Transformation (T) is the results from the purposeful problem-solving activities; Worldview (W) refers to stakeholders' common belief; Owner (O) is someone who can authorize and stop the activity; Environment (E) means the prevailing constraints. The 'CATWOE' elements in the care transition process are described in Table 4-4 from the perspective of a system engineer at the Ministry of Health.

Table 4-4 CATWOE analysis

Customers	All patients and beneficiaries from the care transition process, including doctors, nurses, therapists, etc.
Actors	Institutional level: Ministry of Health, Healthcare clusters, acute hospitals, community hospitals, nursing homes, Agency for Integrated Care, voluntary and welfare organizations Individual level: doctors, nurses, therapists, social workers, bed managers in acute hospitals, care coordinators, evaluation staff in Agency for Integrated Care, evaluation staff and bed managers in community hospitals
Transformation	Provide a one stop service to discharge stable patient to their preferred institutions at the desired time to reduce overstay and readmission rate, and to drive the cost down
Worldview	Smooth care transitions benefit all the stakeholders in public healthcare system
Owner	Ministry of Health through Agency for Integrated Care
Environment	Singapore is entering into the aging society with a rising demand for healthcare resources

The stakeholders have divergent views on care transition due to different objectives and interests. However, the successful changes would require agreement among all the involved parties. Therefore, it is necessary to address requirements provided by each stakeholder and align their specific objectives before proposing any changes to the process. The details of the stakeholder requirements analysis are shown in Table 4-5.

Table 4-5 Stakeholder requirements analysis

Acute hospitals (AH)	Patients can be properly treated and transferred to the desired step-down care providers at their planned discharge time with a low readmission rate
Agency for Integrated Care (AIC)	All patients can be transferred smoothly by properly allocating the needy patients to the available facilities of voluntary welfare organizations
VWOs community hospitals (CH)	Admitted patients are rehabilitated and discharged within the expected time (usually maximum 4 weeks)
VWOs nursing homes (NH)	Benefit as many low income patients as possible within a controlled operating cost and balanced workload
Ministry of Health (MOH)	High accessibility with an efficient patient flow and a controlled budget to prevent escalation of public healthcare cost without compromising the health service quality
Patients	Receive better care with less charges
Doctors and nurses	Meet requirements of high throughput and patient satisfaction
Care coordinators Social workers	Smooth and high success rate of referral based on the preferred choice of patients

Chapter 5

Desirable Changes and Relevant Conceptual Model

5.1 Identify the Need for Changes

The varying requirements of stakeholders require a rigorous way to align the conflicting objectives and to reach agreement on what changes are systemically desirable and also culturally feasible. In this study the viable system model (VSM) is adopted as a reference model to identify the desirable changes to the current care transition plan and process, it is a holistic and systematic tool that has been widely used for understanding organizations, redesigning business process, and supporting the management of change (Espejo and Gill, 1997). Rather than tinkering with local improvement, VSM offers organization viability for adaption through connectivity, structuring and healthy relationships (Espejo, 2003), and it has already been adopted in various fields (Holloway, 1990; Chan, 2011; Christopher, 2011; Espejo and Kuropatwa, 2011; Khosrowjerdi, 2011; Adham et al., 2012; Ganzert et al., 2012; Jos é Pérez et al., 2012; Kontogiannis and Malakis, 2012). There are some applications of VSM in healthcare research, for example, the healthcare model developed by Beer (1979) to balance pools of people who are healthy and ill; the strategy development of healthcare organization (Markus, 2006); an innovative way to balance multiple targets in the healthcare system (Saviano, 2010); the systemic intervention of public health (Midgley, 2006); quality improvement for the national healthcare system (Holloway, 1990).

According to Beer (1984), a viable system has three basic elements: environment, process, and management. Interactions among the three elements divide the whole system into five subsystems, as presented in Figure 5-1.

Figure 5-1 Basic form of viable system model, Beer (1984)

System 1 - Primary activities: There are several primary activities, which perform at least one function that carry out the transformation. In this research, primary activities are the tasks performed by each stakeholder to successfully transfer a patient to a specific institution during a given period. In the current system, activities can be better arranged. For example, whether the patient has a care giver or not should be identified at the time of admission to initiate the transition plan as early as possible. With integrated information system, choosing and comparing next stage care providers can also be bettered. Moreover, medical report collecting and delivering activities will be done automatically with the integrated information system.

System 2 - Activity coordination: A viable system needs communication channels for coordination and collaboration to support the primary activities and to keep the components as a cohesive whole. Previously, there has been an absence of an integrated and interoperable information systems for the whole healthcare system. Paper and telephone based communication channels can easily result in information delay or incomplete and inaccurate information transfer across the different institutions. The ‘hand over’ of documents between care coordinator and social worker is unnecessary since their functions in care transition are quite similar. Moreover, the waiting time between sending applications and receiving feedbacks is quite long due to problems in communication channels.

System 3 - Audit and control: This subsystem controls and monitors the whole system and makes sure it is working as expected; it supports the organization to co-evolve with other agents in its environment. In the current system, the Agency for Integrated Care has been set up to monitor the care transition result, but they do not monitor care transition demands and plans. Thus, medical staff in acute hospitals are not motivated enough to smooth the care transition.

System 4 - Plan and adaption: This subsystem helps the whole system to interact with the environment and adapt to changes. Currently, at the operating level, aggregated information of the post-acute beds is not available to stakeholders. Step-down care providers cannot access information about transfer needs of patients in acute hospitals until they receive the applications; this increases the difficulty of care transition planning. Besides, lack of systematic feedbacks from patients after discharge hinders the system’s ability to learn quickly from the previous experience, and the improvement of care transition decision

becomes difficult to achieve. At the strategic level, the Ministry of Health and Agency for Integrated Care put great effort into system integration and smooth care transition to make the whole system adapt to the need of an aging society.

System 5 - Policy making: This subsystem balance demand from different parts of the system and steers the system as a whole. Analysis shows that each stakeholder has their own objectives and interests, but currently, the specific policy to reconcile the conflicts of stakeholders has not been well developed. Besides, unfavorable subsidy policy and Medisave usage policy make some patients unwilling to be transferred. To achieve smoother care transition, improvement of existing policies is needed. Moreover, many patients are rejected by the community hospitals due to their high potential to consume expensive healthcare resources when adverse events happen. To avoid this problem, risk sharing mechanism between acute hospital and community hospital should be built and integrated into the care transition process.

According to the above-mentioned needs for changes to each subsystem, the proposed changes and the cooresponding problems (listed in Table 4-2) which can be alleviated are depicted in Table 5-1.

Table 5-1 Proposed changes based on viable system model

VSM subsystems	Identified changes	Serial NO.of addressed problems (in Table 4-2)
1. Primary activities	Rearrange the order of activities in the process to reduce the cycle time (collect information of care giver at the point of admission)	10, 31
	Automate as many activities as possible via integrated information system: collect medical reports, information transfer, etc.	2,7, 10, 12,20, 30, 31, 36
	Joint discharge meeting	2,7,9,10,13,16,17,18,19,20, 25, 30,31,34,35,36
2. Activity coordination	Integrated information system	2,7,9,10,18,20,26,30,31,34,36
	Integrate functions of care coordinators and the social workers in care transition	2,31
3. Audit and control	Measure the contribution of each stakeholders to smooth care transition	2,12, 13, 18,19,20,21,22, 31,34,35,36
4. Plan and adaptation	Updated information of resource availability through the integrated information system. Care transition demand is shared with the relevant parties.	10, 13, 30,31,35
	Expand capacities and upgrade the skill set of the medical staff in step-down care institutions through more financial support	1, 6, 13,15,20,21,24,25,27,29,35
	Educate patients to manage the their personal health	3,7,24,31,34,35
5. Policy making	Adjust the reimbursement policy and link it with care transition results in step-down care institutions	2, 6, 13, 16, 17,18,19,21,25,27,28,34,35
	Adjust the subsidy policy and Medisave usage policy	4,8,11
	Risk sharing mechanism among care providers	13, 18. 25, 27

5.2 Conceptual Model for Improvement

The first two subsystems of a viable system model are closely linked with the process. The last three subsystems can be defined as the connection between the process to the management and environment. Therefore, the new care transition plan and process are proposed based on the identified needs for changes to the first two subsystems; an integrated information system and joint discharge meeting are introduced into the new process. The activities in the process are reorganized and automated by the integrated information system.

The process is also streamlined by removing the unnecessary steps, e.g. integrating the functions of care coordinators and social workers to reduce communication errors and transition delays. With the automation brought by integrated information system, nurses are released from the tasks of checking care giver information of each patient and referring patients without care giver to care coordinators. They only need to provide nursing care and relevant reports in the new care transition process. The role of a nurse in care transition becomes quite similar to a therapist, but with different medical functions. The detailed process is shown in Figure 5-2.

In the new process, information about the care giver would be checked at the time of admission of the patient into an acute hospital. The result would be recorded into the information system, which automatically allocates these patients who are without a care giver to care coordinators. The information system would also record the medical reports, social economic statuses and other relevant information about a patient. Based on the records of medical needs, personal peculiarities, and bed availability in step-down care institutions, the care coordinator would recommend a list of the appropriate step-down care providers for the patient and his/her family to choose. All patients would be classified into groups according to their preferences of next stage care providers. Doctors, nurses and therapists in an acute hospital, care coordinators from AIC, and admission staff from all the community hospitals would attend the weekly joint discharge meeting at the same time, where they can access all the relevant reports and freely pose their questions and opinions on the medical care plan, discharge time and destination. The receiving unit, staff from community hospitals, would evaluate the rehabilitation potential of the patient on the spot based on the records and discussions. The transfer time would be decided immediately after

the evaluation. This integrated information system also benefits the nursing home application by accelerating the information flow. Both community hospitals and nursing homes would update the recent information of their patients and the bed availability via the integrated information system. Reasons of early readmissions are recorded to help the medical staff in acute hospitals to make better discharge and transfer decisions in the future.

Figure 5-2 Conceptual model of ideal care transition process

5.3 Comparing ‘AS- IS’ System and ‘TO -BE’ System via Simulation

5.3.1 Discrete event simulation model

The effect of changes under a varying set of circumstances can be predicted using simulations before the implementation into the systems. Simulation is especially invaluable in modeling inter-organizational processes (Giaglis *et al.*, 1996). This research adopts discrete event simulation to test the feasibility of the proposed care transition plan and process. The ‘what if’ analysis of discrete event simulations enables comparison between different scenarios. It has been widely used in studies on healthcare system due to its ability to represent patient characteristics, resources constraints and clinical decision process. It has been applied in health policy design (Ramwadhoebe *et al.*, 2009), medical decision making (Van Gestel *et al.*, 2010), complex treatment strategy development (Jahn *et al.*, 2010), patient behavior prediction (Brailsford and Schmidt, 2003), resource planning (Coelli *et al.*, 2007; Werker *et al.*, 2009), performance analysis (Villamizar *et al.*, 2011), and so on.

In this research, the discrete event simulation has been used to compare the performance of the ‘AS-IS’ process and the ‘TO-BE’ process. The simulation models are built upon the modeling software Arena (the 12th version). Arena uses the SIMAN processor and simulation language, and it has been widely used in simulating business processes for many companies, such as IBM, UPS, General Motors, etc.

The two simulation models in this research can be divided into five modules, as shown in Figure 5-3. The detailed models are attached in Appendix 1 and the pseudo codes of the models are presented in Appendix 2.

Figure 5-3 Links of different modules of simulation model with Arena

5.3.2 Parameter assessment

The parameters are estimated based on the data obtained from the Geriatric Department of Tan Tock Seng Hospital. Detailed records of each patient are not available to this research because of the authority problems and patient privacy concerns. Kelton *et al.* (1998) suggests that triangular distribution is preferred when detailed data is not available, thus, triangular distribution is widely adopted in this research. Some data are not recorded by the information system and there is no published information in the issued documents. In such a situation, the maximum value, minimum value and average value are estimated based on knowledge from the task owners. The details are shown in Table 5-2.

Chapter 5 Desirable Changes and Relevant Conceptual Model

Table 5-2 Parameters in the simulation models

Parameters	Expressions	Data source
Arrival rate of patient	$3.5e^{-3.5x}$	Published data
Balk tolerance of waiting for admission	$MN(MAX(NORM(7,2),0),12)$	Based on common sense
Estimated LOS at AH	$TRIA(120,255,310)$	Published data
#Delay to check whether has caregiver?	$UNIF(6,48)$	Judgment of interviewed nurse
Percentage of patient with caregiver	48%	Judgment of care coordinator
Actual LOS of patient with caregiver	$TRIA(120,255,310)+NORM(1,10)$	Judgment of doctor
Care coordinator communicates with patient	$TRIA(0.5,1,2)$	Judgment of care coordinator
Delay for family to make decision	$UNIF(24, 96)$	Judgment of care coordinator
#Care coordinator collects reports	$TRIA(0.5,1,1.5)$	Judgment of care coordinator
#Wait to receive all the reports	$TRIA(5,24,48)$	Judgment of care coordinator
#Delay to apply CH	$TRIA(1,3,8)$	Judgment of care coordinator
#Care coordinator applies CH	$TRIA(0.5,1,1.5)$	Judgment of care coordinator
#Waiting time of CH to evaluate patient	$TRIA(1,3,5)$	Judgment of doctor in CH
#Processing time for CH to evaluate patient	$TRIA(0.5,1,1.5)$	Judgment of doctor in CH
#CH delays to inform evaluation result	$TRIA(1,3,18)$	Judgment of doctor in CH
Success rate of patient who applies CH	80%	Judgment of care coordinator
Time to alternative way if rejected by CH	$TRIA(24,72,120)$	Judgment of care coordinator
Waiting time for social worker to take case	$TRIA(48, 96, 120)$	Judgment of care coordinator
Social worker applies NH	$TRIA(0.5,1,1.5)$	Judgment of care coordinator
Time for AIC evaluation feedback	$TRIA(24,36,48)$	Judgment of AIC manager
Processing time for AIC to evaluate patient	$TRIA(2,5,10)$	Judgment of AIC manager
Percentage of qualified applicants	60%	Judgment of AIC manager
Delay of AIC to check bed availability	$TRIA(0.5,0.75,1)$	Judgment of AIC manager
Patients' tolerance of waiting bed in NH	$MN(MX(NORM(3,1),0),4)$	Based on common sense
Delay time for social worker to apply BSC	$TRIA(24,48,105)$	Judgment of care coordinator
Social worker applies BSC	$TRIA(0.5,1,1.5)$	Judgment of care coordinator
#Delay to get confirmation	$TRIA(24,32,48)$	Judgment of AIC manager
#Time for rejected patient to get result	$TRIA(20,48,120)$	Judgment of care coordinator
Find alternative way for rejected patient	$TRIA(48,89,150)$	Judgment of care coordinator
Patient LOS in nursing home	$DISC(0.2,TRIA(1200,3000,5000),0.7,UNIF(4000,8700),1,TRIA(6000,12000,20000))$	Published data
*CC inputs social status processing time	$TRIA(0.5,0.8,1)$	Based on common sense
*Delay for weekly discharge meeting	$TRIA(12,72,120)$	Guessed based on observation
*Delay for final result of discharge meeting	$TRIA(1,3,8)$	Judgment of care coordinator
NO. of beds in AH	78	Published data
NO. of beds in CH	28	Calculated based on published data
NO. of beds in NH	132	Calculated based on published data
NO. of care coordinators	3	Calculated based on published data
NO. of social workers	1	Calculated based on published data
NO. of evaluation staff in AIC	2	Calculated based on published data

Parameters that only used in the model of “AS-IS” process

*Parameters that only used in the model of “TO-BE” process

The time unit is hour

5.3.3 Verification and validation

The verification of simulation models is done interactively to conform to standards. Both of the two models start with module 1: patient admission (details are in Appendix 1-2). The completed module has been run to check whether there is any modeling mistake or not. If the module works as expected, then it would be expanded by adding modules, until the whole model has been built and verified. After that, a wide variety of scenarios are elaborately designed and tested to ensure the robustness of the two models. For example, to detect the logic flaws, all parameters were changed to constant to make the results predictable. The models were also tested under extreme situations. For example, the capacity of nursing homes has been set from 0 to 10,000 to check the robustness of the model. In addition, the models have been run with a replication length of 8,760,000 simulation hours (1000 years) to ensure that models can work for a lengthy simulation. With these tests, simple modeling errors in the initial models can be identified and corrected. Finally, the models are presented to the director of geriatric department in TTSH to ensure they are representing the reality in a correct way.

While the real system is in a steady state, the simulation model starts out with a system where there are no patients and all resources are idle. Hence, initializations of the models are needed before conducting a validation analysis. The simulation model of 'AS-IS' process has been run for 40,000 simulation hours with 10 replications to determine the warm-up period. Multiple replications have been applied to handle the stochastic nature of the model. The number of work in process (WIP) has been used as an indicator of system stability. The result in Figure 5-4 shows that after 20,000 hours, the total WIP has become stable.

Figure 5-4 WIP and simulation time

Therefore, the total time that the model has run is 38760 hours (1 years = 8760 hours) with 30,000 hours used as a warm-up period. 30 replications have been run to gain a statistically reliable result. Then, the simulation results of the ‘AS-IS’ system are compared with the performance of the existing real system to validate the model. (Some data are not available to this research due to the authority problems and patient privacy concerns). Only a rough validation can be provided at the current stage. Number of patients admitted into the acute hospitals, average length of stays, waiting time for admission, number of rejections of admission due to the long queue for acute care beds, bed utilization rates in acute hospital, community hospital, and VWOs nursing homes, are all used as indicators to check the consistency between simulation model and real system, and to represent system efficiency, accessibility and resource utilization rate. The results of the model validation are presented in Table 5-3.

Table 5-3 Model validation

Parameter	Real System	Simulation Results	Difference rate
No. of admitted patient (persons)	2476	2383.9 ±14.11	3.72%
Average length of stay (hours)	10.97	11.42±0.21	4.10%
Waiting time (hours)	[1.6, 5.8]	4.776 ±0.44	N/A
Rejection rate of AH admission	5%	0.454 ±0.005	9.17%
Resource utilization rate (AH)	0.96	0.928 ±0.01	3.33%
Resource utilization rate (CH)	0.9	0.933 ±0.01	3.67%
Resource utilization rate (NH)	0.84	0.797 ±0.01	5.12%

The half width shown in the column of ‘simulation results’ is calculated by the equation:

$$H = t_{\alpha, \nu} \times \frac{\bar{S}}{\sqrt{n}}$$

Where, α is the confidence level. ν is the degree of freedom in the t-distribution. $\bar{S}$ is the standard deviation. n refers to the number of replications. In this research $\alpha=95\%$, $n=30$, $\nu=n-1=29$, therefore $t_{\alpha, \nu}=1.697$.

(1) System efficiency: throughput

In the geriatric department of TTSH, there were 2016 patients admitted directly and 310 patients transferred in from January to December in the year 2008. So the total number of admission in the real system is 2476; while Table 5-3 shows that in the current simulation model, the average admission number of 30 replications is 2383.9 with the half width of 14.11. The difference is acceptable as the disparity rate is 3.72%, less than 5%. One cause of such gap is the estimation error in the distribution of arrival rate. The simulation model has not taken in the variations of arrival rate (in the real system, the number of admissions

decreases in February as patients try to avoid hospitalization during Chinese New Year. At the end of the festivity, elective admissions return to the normal level. The daily variation and weekly variation also exist in the real system).

(2) System efficiency: average length of stay

The average length of stay (LOS) for different types of patients of the simulation model is shown in Table 5-4. The corresponding data in the real system are shown in Table 5-5.

Table 5-4 Average length of stay based on simulation result

Average length of stay in acute hospital	Days
LOS of patient with care giver	9.56±0.02
LOS of patient transferring to CH	10.22±0.16
LOS of patient accepted by NH	14.55±0.13
LOS of patient rejected by NH	16.85±0.04
LOS of all admitted patients	11.42±0.21

Table 5-5 Average length of stay by medical service in TTSH (Year 2009)

Time	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	YTD
LOS (days)	10.7	10.5	11.0	10.0	11.3	12.6	10.6	12.9	10.4	10.0	11.5	10.1	11.0

Source: Office of quality management, TTSH (2009b)

The average LOS of the simulation model is 11.42±0.21 at a 95% confidence level. According to the data in Table 5-5, the average LOS of the real system was 10.97 in the year 2009. The disparity rate is 4.1%, less than 5%, which means it is acceptable. The estimation errors about the processing time for each task in the care transition process are possible reasons for longer LOS in the simulation model compared to the real system. The information of average LOS in community hospitals and nursing homes in real system are not available to this research. Therefore the simulation results of LOS in these two

institutions are validated by experts in the field, the director of geriatric department in Tan Tock Seng Hospital. The simulation results are considered to be reasonable and consistent with real system.

(3) System accessibility: waiting time

Currently, the waiting times for admissions into the geriatric department of TTSH are not available to this research. The data in the published report of Ministry of Health in Figure 5-5 shows that the average waiting time for a bed in TTSH is around 1.6 hours, while the 95% percentage is 5.8 hours. The 95% confidence interval in the simulation result is [4.34, 5.22]. In the real system, patients from the geriatric department have a lower priority than patients of other departments such as emergency department and cardiology department. Hence, geriatric patients suffer longer waiting time for admissions. In addition, in reality, seriously sick patients can be temporarily diverted to the wards of other departments to reduce the waiting time. Therefore, the waiting time of the simulation model is longer than the average shown in Figure 5-5. But the Head of Geriatric Department thought the simulation result is reasonable according to his knowledge of the system.

Figure 5-5 Average daily waiting times for bed (20 Sept. 2009 - 26 Sept. 2009)

Source: MOH (2009b)

(4) System accessibility: rejection rate

The documented information about rejection rate of admission in acute hospital is not available to this research. The Head of Geriatric Department estimated it is approximately 5%. The 95% confidence interval of the simulation result is [0.449, 0.459]. Since 5% is a rough, estimated value by experts, such difference between the simulation result and the estimation of real system is negligible.

(5) Resource utilization rate

The utilization rates of the four types of beds in the geriatric department in TTSH are presented in Table 5-6, and the average utilization rate is 96% in reality. The 95% confidence interval of the simulation result is [0.918, 0.938]. The difference of performance between the real system and the simulation result is less than 5%, which is significantly small.

Table 5-6 Utilization of acute beds by clinical departments in TTSH (October 2009)

Beds	A1	B1	B2	C	ALL
Utilization rate	209.7	134.4	58	127.2	96.0

Source: Office of clinical governance in TTSH (2009a)

(* The rate is larger than 100% means that some patients have been diverged to the other wards)

Currently there are 29 private nursing homes and 30 nursing homes run by the voluntary welfare organizations in the real system. Bed utilization rates vary among the different types of nursing homes. The data from the real system are presented in Table 5-7. The average utilization rate of real system is around 84%, while the 95% confidence interval of the simulation result is [0.787, 0.807].

Table 5-7 Statistic of beds in nursing homes (30 Sept. 2007)

Types of nursing homes	Total beds	Utilized bed	Utilization rate
Private nursing homes without subsidy	1959	1327	0.68
Private nursing homes with subsidy	1514	1068	0.71
VWO nursing homes without subsidy	901	814	0.90
VWO nursing homes with subsidy	4217	4032	0.96
TOTAL	8591	7241	0.84

Source: MOH's report on bed statistic in nursing homes, Ling (2007)

The bed utilization rate in community hospitals of the real system is not available to this research. However, according to the interview with the Clinical Director of Ren Ci Hospital and Medicare Centre, the average bed occupancy rate of community hospitals is around 70%, but the best community hospital runs at almost full capacity. The occupancy rate at Ren Ci community hospital is around 90%. In the simulation model, the related parameters were evaluated based on the Ren Ci community hospital, which is connected to Tan Tock Seng Hospital. The 95% confidence interval of the simulation result is [0.923, 0.943]. The difference between the real system and the simulation is not significant.

All in all, the simulation model of the 'AS-IS' process has been roughly validated based on the above comparisons. Though some simulation results do not exactly equal to the value of the real system, the differences are negligible. Also that the simulation results have been checked by the Head of Continuing and Community Care in Tan Tock Seng Hospital, and he found that the simulation result is reasonable.

5.3.4 Performance comparison of 'AS-IS' process and 'TO-BE' process

After verification and validation, both models of the 'AS-IS' process and the 'TO-BE' process have been run for 30 replications with 38,760 simulation hours, including 30,000

hours as warm-up period. The simulation results of the key performance of the two models are showed in Table 5-8. The first column is about performance indicators. The second column is the sample mean with half width of the ‘AS-IS’ process results. The third column is the sample mean with half width of the results of ‘TO-BE’ process. The fourth column is the difference between the results of the two models. The last column shows the significance level of performance difference between the two models. Student’s t-distribution is adopted to calculate the significance level of the difference.

Chapter 5 Desirable Changes and Relevant Conceptual Model

Table 5-8 Comparison of the simulation results of the two processes

Variable	‘AS-IS’ Model		‘To-Be’ Model		Difference Rate of Sample Mean	Significance
	Sample Mean $\pm$ Half Width	Half Width	Sample Mean $\pm$ Half Width	Half Width		
Rejected admission	122.6 $\pm$ 14.07		89.1 $\pm$ 11.51		27.32%	0.002 **
Throughput	2383.9 $\pm$ 14.11		2403.6 $\pm$ 12.88		0.83%	0.045 **
NO. patient wait>5hours	672.97 $\pm$ 63.99		536.7 $\pm$ 49.17		20.25%	0.004 **
NO. patient admitted without waiting	1523.9 $\pm$ 64.37		1697.77 $\pm$ 52.53		11.41%	0.001 **
Total waiting time of admission in AH	11418.76 $\pm$ 1111.56		8721.12 $\pm$ 851.38		23.62%	0.001 ***
Waiting time for bed in AH	4.776 $\pm$ 0.44		3.62 $\pm$ 0.34		24.20%	0.001 **
Waiting time for bed in CH	76.83 $\pm$ 8.68		86.8 $\pm$ 9.08		12.98%	0.094*
Waiting time for bed in NH	94.83 $\pm$ 2.9		90.19 $\pm$ 3.42		4.89%	0.045 **
Resource utilization bed in AH	0.928 $\pm$ 0.01		0.916 $\pm$ 0.01		1.29%	0.080
Resource utilization bed in CH	0.933 $\pm$ 0.01		0.935 $\pm$ 0.01		0.21%	0.406
Resource utilization bed in NH	0.797 $\pm$ 0.01		0.797 $\pm$ 0.01		0.00%	0.500
LOS in AH of patients with care givers	229.4 $\pm$ 0.56		229.52 $\pm$ 0.42		0.05%	0.387
LOS in AH of patients transferring to CH	245.2 $\pm$ 3.78		251.53 $\pm$ 4.57		2.58%	0.040 **
LOS in AH of patients accepted by NH	349.2 $\pm$ 3.02		355.87 $\pm$ 3.62		1.91%	0.011**
LOS in AH of patients rejected by NH	404.3 $\pm$ 0.86		356.87 $\pm$ 1.1		11.73%	0.000***
Average AH overstay of patients without care giver	11.82 $\pm$ 0.29		11.57 $\pm$ 0.3		2.12%	0.159
Average AH overstay of patients need CH services	27.45 $\pm$ 3.89		33.33 $\pm$ 4.59		21.42%	0.054*
Average AH overstay of patients need NH services	136.32 $\pm$ 1.1		110.8 $\pm$ 1.25		18.72%	0.000***
Total overstay of patients with care givers	13474.05 $\pm$ 321.88		13371.02 $\pm$ 380.64		0.76%	0.364
Total overstay of patients need CH services	16985.22 $\pm$ 2606.4		20713.45 $\pm$ 2902.84		21.95%	0.058 *
Total overstay of patients need NH services	83472.6 $\pm$ 1191.8		67848.1 $\pm$ 1449.4		18.72%	0.000***

The significance level of performance difference is calculated from the following equation:

$$P\{\hat{X}_2 - \hat{X}_1 = 0\} = F\left(\frac{\bar{X}_2 - \bar{X}_1}{\sqrt{\frac{S_1^2}{N_1} + \frac{S_2^2}{N_2}}}\right)$$

$P\{\hat{X}_2 - \hat{X}_1 = 0\}$ is the probability that the expected value of the performance of the two models are same. $\bar{X}_2$ is the sample mean of the results from the 30 replications of the ‘TO-BE’ model. It is the estimation of the expected value $\hat{X}_2$ of the ‘TO-BE’ model. $\bar{X}_1$ is the sample mean of the results from 30 replications of the ‘AS-IS’ process model. It is the estimation of the expected value $\hat{X}_1$ of ‘AS-IS’ model. F is the density function of the t-distribution. S_1, S_2 respectively refer to the standard deviations of the performance of ‘AS-IS’ model and ‘TO-BE’ model. N_1, N_2 refers to the sample size of the two groups.

Table 5-8 indicates that the ‘TO-BE’ process outperforms the current process in terms of system accessibility (which is represented by rejection rate), waiting time for acute hospital admission and throughput. The average length of stay in the acute hospital of patients who have been rejected by nursing homes has also been significantly reduced due to a decrease of overstay in acute hospital. Based on the comparison of the sample means of the simulation results, for system accessibility, the number of rejected patients due to no bed vacancy in acute hospital can be significantly reduced to a rate of 27.32%. For waiting time, the number of patients who have to wait for more than 5 hours to be admitted into the acute hospital can be reduced by 20.25%. The number of patients who have been admitted without

waiting can be increased by 11.41%, which is significant at the 95% confidence level. As a result, the average waiting time for admission into the acute hospital can be reduced by 24.2% and the total waiting time is reduced by 23.62%. The average waiting time for nursing home is decreased by 4.89%. Although the total throughput of the 'TO-BE' model is slightly increased, there is no significant change in the bed utilization rate of each institution. The length of stay in acute hospitals of patients who need community hospital service is reduced by 2.58% and the length of stay in the acute hospital of patients who are transferred to the nursing homes can be reduced by a rate of 1.91% with the 'TO-BE' model. The length of stay in acute hospitals of patients who need nursing home care but rejected by the AIC has a greatest reduction with a rate of 11.73%. The decrease in the average length of stay is largely attributed to the reduction of overstay. Average overstay in the acute hospital of patients need community service is reduced by 21.45%. The decrease of overstay in the acute hospital of patients who need nursing home care is significant at a confidence level of 95% with 18.72% drop. The decrease of overstay in acute hospitals contributes the improvement of system accessibility and the reduction of waiting time.

5.3.5 Implications from the simulation results

In addition to performance improvements to the healthcare system, the proposed care transition model can bring monetary benefits to the society. The lowest hospital bill for Class C beds in acute hospitals for Singapore citizens is S\$30/day with substantial government subsidies. For foreigners, the same bed charges S\$177/day. The calculation based on the two hospital bills and the total decrease in overstay by 11,999 hours indicates that the 'TO-BE' care transition model can save healthcare expenditure from S\$14,979 to S\$88,495 annually in the geriatric department in TTSH. Meanwhile, the total waiting time for the bed in acute

hospital can be reduced from 11,419 hours to 8,721 hours. Suppose the average wage in Singapore is S\$18/ hour, (the Per Capita GDP is S\$53,143 in Singapore of 2009), the decrease in waiting time can indirectly bring in S\$48,558 monetary benefit annually. If the scale is extended from the Geriatric department in TTSH to the whole public healthcare system, the economic benefit would be quite considerable, around S\$10 million annually. The decreased waiting time for admission in acute hospital will also improve health service quality, as the sick patients can be treated earlier.

The reduced waiting time for admission and increased accessibility to acute service is achieved by significant decrease of unnecessary overstay in acute hospitals with the 'TO-BE' process. The efficient utilization rate of the limited resources increases with the decrease of unnecessary overstay. The unnecessary overstay is reduced due to the elimination of unnecessary information delays, which are achieved by following ways. First, checking whether the patient has a care giver at the admission point and automatically referring the cases without care giver to care coordinators can give a care coordinator more time to collect the social status information of a patient. While in 'AS-IS' process, care transition decisions have frequently been delayed due to the unready information of patients social status. The integrated information system would also significantly reduce the information delays between different care providers, especially acute hospitals, community hospitals and nursing homes. The care transition process is further accelerated by the joint discharge meeting with the acute hospital and community hospital, with which the decision can be made on the spot. Hence, information delays for community hospital service application, patients' qualification evaluation and the feedback from community hospital to acute hospital can be eliminated. Moreover, the integrated information system would increase the

transparency of the information of bed availability in downstream and the demand of step-down care in acute hospital; therefore care coordinator can make better recommendation to a patient, and reduces the rejection and reapplication rate. Reduction of such kind of rework can help to improve the efficiency of the process. Finally, the elimination of the role of social worker in care transition also contributes the improvement of the process by avoiding unnecessary hand overs and delays of information transfer.

Another finding from the simulation results is that the waiting time for a nursing home bed is quite long even though the bed utilization rate of nursing homes is relatively low. Even in the ‘TO-BE’ care transition model, where the waiting time is already reduced, it is still up to 90.2 hours. The long waiting time for nursing home bed in the simulation model is quite consistent with complaints of care coordinators during the interviews. Care coordinators intuitively believed that the shortage of nursing home beds leads to the long waiting time, so resources expansion in nursing homes is needed. But when looking at utilization rate, this may not be a wise solution. Simulation results show that the average bed utilization rate of nursing home is 79.7% in both of the ‘AS-IS’ care transition model and the ‘TO-BE’ care transition model. Therefore, more research should be conducted on how to reduce the waiting time for nursing home beds without further expansion of resources, to concern the continuous trend of aging population.

The bed utilization rates in acute hospital and community hospital are more than 90%. There is no significant change in the ‘TO-BE’ model. Existing research shows that the necessary emptiness should be around 15% to avoid congestion (Horrocks, 1986; Mitchell *et al.*, 1987). Therefore, it is necessary to expand bed resources in those two institutions.

5.3.6 Additional advantages of the ‘TO-BE’ process

In addition to significant improvements in system accessibility, reduction of waiting time and overstays, the proposed new process has several other advantages which are not reflected in the previous discussion. Firstly, communication errors can be effectively reduced with the joint discharge meetings. The medical staff from community hospitals would be able to evaluate the health status of a patient during the meeting, and their confusions and opinions can be expressed freely. Discussions, explanations and solutions can be achieved on the spot. This further ensures the consistency of care plan both for the acute hospitals and community hospitals. Secondly, mutual supervision and interaction among relevant hospitals will be strengthened. For instance, during the meeting, staff in acute hospitals can persuade the specific community hospital to accept certain patients who would be rejected by the current process, by sharing the healthcare responsibilities together. Thirdly, resource and manpower planning can be improved by a smoother exchange of information about transfer needs and bed availability. Fourthly, information on the status of discharged patients from acute hospital will be updated by step-down care providers during the meeting. Such feedback can be valuable to the acute hospitals in improving discharge decisions in the future. Finally, the elimination of the role of social workers in the care transition process removes unnecessary ‘hand over’ of work between social workers and care coordinators, which further reduces the potential of communication errors and delays.

The proposed model is actually the combination of the existing three care transition models (as described in section 2.2.1). The role of care coordinator conveys the idea of ‘third party’ care transition model (Coleman 2003). The participation of medical staff from community hospitals in the joint discharge meeting reflects the idea of the ‘next stage initiation’ care

transition model (Hollander and Prince, 2002). The integrated information system embodies the idea of ‘protocol’ care transition model (Zuckerman et al., 1992). Therefore, the proposed model can be regarded as an ‘aggregative’ model which leverages all the advantages of the above mentioned three models.

5.4 Feasibility of the Changes

The proposed process is based on two important assumptions. First, an integrated information system among different care providers is achievable. Second, all relevant staff are willing to participate in the weekly joint discharge meeting. Currently, the Integrated Health Information Systems Company in Singapore has already taken the first step towards the development of an integrated healthcare information system. For the second assumption, how to fairly allocate the added value of the join discharge meeting to the whole healthcare system is crucial to the successful implementation of the proposed model. Besides, the simulation result implies that the current reimbursement policy may impede the adoption of the ‘TO-BE’ process. Because bed utilization rates in acute hospitals would decrease slightly if the proposed process is implemented. Currently, the government’s reimbursement for an acute hospital is based on bed resource utilization rate. Such policy makes acute care providers focus on increasing their bed utilization rate rather than improving the care transition. Moreover, healthcare expenditure of a newly admitted patient is much higher than the expenditure of a stable patient. Extending the length of stay of some patients would not only increase the reimbursement but also reduce the healthcare expenditure for acute hospitals. However, if the reimbursement policy is changed to be throughput-based, service quality may decline, as acute hospitals may try to discharge the patients as soon as possible

to increase their reimbursement. Therefore, reimbursement policies which are able to balance the multiple objectives of smooth care transition are in urgent need for the implementation of the ‘TO-BE’ process.

5.5 Summary and Further Extension

The needs of changes to current care transition plan and process has been identified based on the viable system model. A conceptual model for improvement has been proposed, and its superiority over current care transition plan and process has been validated by discrete event simulation. The simulation results indicate that the proposed ‘TO-BE’ process surpasses the ‘AS-IS’ process in terms of system accessibility, waiting time, and length of stay.

The ‘TO-BE’ process model is proposed based on rigorous qualitative analysis, but its superiority over the ‘AS-IS’ process cannot ensure that it is the best process. The reason is that design based on qualitative analysis is largely constrained by a designer’s intuition. A better model of care transition plan and process may exist, but has not been identified by the qualitative analysis in this research. Therefore, more rigorous methods of optimal process design are needed to further improve the care transition. More details are addressed in Chapter 6 about how to transfer patient in an optimal way by figuring out what should be done and who should do it.

Despite efforts to incorporate as many details as possible, the simulation model in this chapter is only an abstract of reality, which might have not captured a few details. For example, in the current simulation model, when to transfer the patient depends on the length of stay and bed availability in the next stage, and where to transfer the patient is decided by

percentages calculated from the historical data. While in reality, those decisions are determined through interactions among multiple factors. Hence, more in-depth discussion of when and where to discharge patients will be presented in Chapter 7 to further improve care transition.

Chapter 6

Algorithmic Approach to Optimal Care Transition Process Design

As mentioned in chapter 5 that qualitative analysis on a process is largely constrained by a designer's intuition, implying imprecision and lack of rigor. It is feasible for a better process design but may not be reliable enough for obtaining an optimal process design. Therefore, this chapter is going to propose a rigorous quantitative approach to achieve an optimal care transition process design with consideration of multiple objectives.

6.1 Introduction

Process management has been a continuing research theme (Gupta *et al.*, 2006; Sprague, 2007; Voss, 2007; Craighead and Meredith, 2008). The popularity of business process reengineering (BPR) has been growing since 1990, after when the importance of business process has been widely recognized (Sara and Saven, 2004). Business process reengineering (BPR) is an indispensable tool that breaks away from conventional 'wisdom' and reinvents the process with continuous improvements in efficiency, financial performance, and customer satisfaction (Klassen and Menor, 2007). However, business process reengineering (BPR) has not always brought the desired outcomes; failures indicate the need for improvements in existing methods and tools.

There are various process modeling methodologies each with a different purposes, such as the Integration Definition Family (IDEF), Computer Integrated Manufacturing Open Systems Architecture (CIM-OSA), and Petri-Nets and Object-Oriented Modeling

(Sara and Saven, 2004), shown in Figure 6-1. A considerable number of process modeling tools have been developed using the above mentioned methodologies, for example ARIS, First Step, Prime Objects, TEMAS and SysML with simulation function (Zakarian, 2001). These methodologies and tools support systematic and well-defined representation of processes, evaluate particular characteristics of a process (such as resource utilization, cost, and speed), and check the resource consistency (Sadiq and Orłowska, 2000).

Figure 6-1 Classification framework of business process modeling techniques

Source: Sara and Saven (2004)

Despite the analytical capabilities of these methodologies and tools, BPR still largely depends on qualitative analysis, which is constrained by a designer's intuition. It is a challenge to achieve the most optimal design for a large-scale complex process using description-oriented models. On the other hand, quantitative rigorous methods of optimal process design are far from well developed (Hofacker and Vetschera, 2001). The difficulties in translating the elements and constraints of a process into mathematical format, and the

large fuzzy searching space of feasible solutions with the multiple criteria to define the ‘optimality’ of a process, inhibit the development of quantitative-based methods (Hofacker and Vetschera, 2001).

With the aim to achieve an optimal design of care transition process, this research proposes a two-stage optimization approach with the concerns to both efficiency and quality. The first stage of the optimization selects elements of a process from various candidate activities and determines their topological structure. The second stage of the optimization allocates different resources to these selected activities. The first stage aims at generating a feasible solution with minimal duration time, and the goal of the second stage of the optimization is to achieve the best quality by appropriately allocating the staff to perform the activities based on their task-skill associated levels. The proposed optimization approach can also be applied in other fields with complex processes.

6.2 Relevant Works

Hofacker and Vetschera (2001) took the first step towards mathematical modeling in optimal process design; their model concerned an entire range of possible designs, some of which might be beyond the imagination of a human designer. Mathematical programming, genetic algorithm and the branch and bound method have been used to search for optimal solutions. Computational experiments have found that applied genetic algorithm results in a very weak performance. The branch and bound method has the best computational performance, but its superiority over mathematical programming decreases as the number of activities in a process increases. Their model considered one objective function, minimum duration time and two types of resources, information resources and consumable physical

resources. The information resources, which are renewable resources, once generated, can be reused by many others activities simultaneously, e.g. the prescription for a specific patient. The consumable physical resources, which are non-renewable, once consumed, the available amount will be decreased, such as a painkiller medicine. Due to the simplification, this model is not suitable to deliver an optimal solution to most of complex business process designs in reality.

Grounded on the work of Hofacker and Vetschera (2001), Vergidis *et al.* (2007) extended the single objective model to be a two-objective model. More constraints were added into the model to make it a better representative of real-life processes. Three evolutionary algorithms have been tested to find an optimal solution for such a highly constrained model: Non-Dominated Sorting Genetic Algorithm II (NSGA2), Multi-Objective Particle Swarm Optimization (MOPSO), and Strength Pareto Evolutionary Algorithm II (SPEA2). The performance of the optimization algorithms drops significantly with increased complexity of process designs. In spite of the above-mentioned extensions, the most optimal design of care transition process cannot be achieved directly through this model, because the extended model does not consider the non-consumable physical resources, such as doctors, nurses and hospital beds in the healthcare system. Once occupied by an activity, such resources cannot be used by other activities; but once been released, they will be available again to other activities. Besides, in the care transition process, some activities can be executed using alternative resources or other functional roles in the system. A method to assign tasks to different roles to balance the trade-off between quality and efficiency is needed for the optimal care transition process design.

To some extent, the optimal design process for care transition in this research is similar to the resource-constrained project scheduling problem (RCPSP). Each patient can be treated as an individual project with a begin and an end. Both research problems decide on a sequence of tasks to minimize the completion time. But there are some differences. In RCPSP, the tasks needed to be scheduled are fixed and known. The required resources and the precedence of each task are given in advance in the RCPSP. While in the problem of optimal care transition process design, the participating activities are selected from a large set of candidate activities and the sequence of the participating activities is determined based on their required inputs, which are either the initial global inputs or the outputs from other activities. Hence, the optimal process design problem is much more complicated than RCPSP due to the extra decision variables in choosing participating activities. Besides, in the problem of optimal process design, the functional role to execute each task is alternative and who will be assigned to execute which task is finally decided by the optimization model.

There are some other methods with quantitative analysis for business process optimization, but they are evaluation-oriented rather than optimization-focused. For example, Zakarian (2001) integrated fuzzy reasoning with Integration Definition Family (IDEF) process modeling techniques to evaluate the candidate processes and select the best one. Aytulun and Guneri (2008) used Graphical Evaluation and Review Technique (GERT), a project based process scheduling method, to evaluate the duration time of a process based on topological equations. Kwak and Chang (2002) developed a multi-criteria mathematical programming model to aid resource allocation for business process reengineering in the healthcare system. Shimizu and Sahara (2000) combined the IDEF modeling technique with the Analytic Hierarchy Process (AHP) to evaluate candidate processes. However, in all of

these methods, the candidate processes are created largely based on intuitive knowledge of the process designer and the number of candidate processes is quite limited. Hence, these methods may not be comprehensive enough to find a real optimal solution for care transition.

Due to the limitations of above mentioned methods in optimal care transition process design, a two-stage optimization approach with multiple objective functions is proposed in this research that would automatically generate an optimal process using a rigorous method. The details of the proposed approach are elaborated in the following sections.

6.3 Algorithmic Approach for Optimal Process Generating

6.3.1 Projecting business process

A business process is composed by a flow of interconnected activities transforming inputs into outputs with the aim to create values for customers. The main characteristics of a care transition process can be simply described by Figure 6- 2.

Figure 6-2 Process-object relationship

Source: Aytulun and Guneri (2008)

Figure 6-2 indicates that a general care transition process involves a set of activities, a set of human resources and a set of information resources. These sets are interconnected to fulfill specific goals of transition. Therefore, the process design of care transition can be regarded as selecting and scheduling the activities to generate specific information resources with the constraints of human resources. The resource transformation process is depicted in Figure 6-3. There are multiple ways to achieve a specific objective. Different ways require different input resources and generate different outputs with varied cost, quality and duration times.

Figure 6-3 Feasible designs of a process

A general care transition process involves three types of resources: consumable physical resources, non-consumable physical resources and information resources. Consumable physical resources in the care transition process are medicine, papers, etc., they rarely influence the transition process. Therefore, to simplify the model, only information resources and non-consumable physical resources are considered in the design of an optimal care transition process. Both the specialist facilities such as X-ray, CT-scan, MRI, etc. and human resource, such as doctor, nurse, therapist, etc. are considered as non-consumable physical resources.

The mathematical form of the elements of care transition process can be expressed in the following way: Set $A = \{a_1, a_2, \dots, a_N\}$ includes N candidate activities and set $R = \{r_1, r_2, \dots, r_M\}$ includes M alternative resources. The set R is composed of two subsets: an information resource set IR and a human resource set HR . The set $GI \subset R$ is the initial input resource set of the whole process and the set $GO \subset R$ is the final output resource set of the whole process. A feasible design of the process must be able to generate all the resources in the set GO . Each activity a_i has several attributes, such as duration time, cost, and so on. The attributes of activity a_i can be represented by a vector $Atr_i = (atr_{i1}, atr_{i2}, \dots, atr_{ik})$. The input and output resources of activity a_i are respectively marked by the set IN_i and OUT_i . The activity a_i can only be executed until all its required input resources in IN_i are available. The resources in OUT_i will be generated and available to other activities once a_i has been completed. A process design $P = \{(a_i, s_i, IN_i)\}$ is a set of ordered pairs (a_i, s_i, IN_i) , where a_i represents an activity, s_i is the starting time of the activity a_i and IN_i is the required inputs of the activity. All possible process designs can be generated by selecting different activities and scheduling them in different sequences based on their input requirements and output resources. In a feasible process design, all the resources in IN_i should be available at some time if the activity a_i is included in the process and all the resources in the global output set GO should be produced by at least one of the participating activities.

6.3.2 First stage: what should be done (selecting activities)

The first stage of the process optimization is inspired by the research on project management and project scheduling to meet requirements. The goal is to select the participating activities and decide their topological structure to generate a process with minimum duration time. The topological structure is subject to precedence constraints, in which the starting time of a specific activity is no less than the time that all the required input resources of this activity become available. Since process designs are determined by a combination of participating activities from set A , the applicability and reliability of the optimal process design depends largely on the accuracy and the granularity level of the activity set A .

There are multiple scenarios for the current care transition process and different types of patients that go through different processes. For example, the patient who doesn't have a care-giver and has little hope to recover is highly recommended to be transferred to a nursing home, while a patient with a care-giver and a high rehabilitation potential is recommended to community hospital. Here, the care transition process of the unrecovered patients with care-givers and having high rehabilitation potential of the hip fracture is taken as a testing case for the proposed two-stage optimization approach of process design.

The global input set GI , global output set GO , activity set A , input resources set IN_i , output resources set OUT_i and the duration time of each candidate activity can be predefined after consulting healthcare experts. The precise duration time of each candidate activity in set A is difficult to collect and acquire due to authority constraints and the absence of relevant records. Since the essence of the model is independent of the parameter setting, the idea of finding the optimal process design is illustrated by adopting the estimated duration

times. The details are shown in Table 6-1, in which 22 activities are considered and their corresponding inputs, outputs, and duration times are listed.

Table 6-1 Activity set of care transition process design for a specific patient

Global Input : I(1) Patient admitted; I(18) Discharge meeting time			
Required Input	Alternative activities	Output	Duration
I(1)	1. Check care giver	I(2) Care giver information	0.5
I(1)	2. Medical care	I(3) Medical report	4
I(2)	3. Refer the case	I(4) Case owner	0.5
I(4)	4. Follow up with the case	I(5) Feedback of the case	1
I(3)	5. Nursing care	I(6) Nursing report	3
I(3), I(6)	6. Therapy care	I(7) Therapy report	5
I(6)	7. Estimate the discharge time	I(8) Transfer needs	0.5
I(2), I(8)	8. Collect social economic status	I(17) Social economic status	3
I(8)	9. Communicate with the family	I(9) Transfer decision	0.5
I(9)	10. Check bed availability	I(10) Confirmation of decision	0.5
I(3), I(6), I(7)	11. Access the report manually	I(11) Combined reports	1
I(11)	12. Weekly discussion on discharge plan	I(22) Final transfer decision	2
I(22)	13. Apply CH	I(13) CH application form	1
I(13)	14. Evaluate the rehabilitation potential	I(20) Evaluation result	1
I(20)	15. Transfer the patient to CH	I(15) Transfer result	1
I(15)	16. Follow up	I(21) Feedback of the transfer	1
I(18)	17. Update info. of bed availability	I(19) Bed availability info.	1
I(3), I(6), I(7), I(18)	18. Joint discharge meeting	I(22), I(20)	2
I(10)	19. Submit an application to AIC	I(14) Nursing home application	1
I(5)	20. Evaluate social-economic status	I(16) Nursing home qualification	1
I(16)	21. Contact specific nursing home	I(12) Nursing home acceptance	0.5
I(12)	22. Transfer patient to NH	I(21) Feedback of the transfer	1
Global output: I(22) Final decision; I(20) Rehabilitation potential; I(21) Feedback of the transfer			

There are many process designs that transform the global inputs into the global outputs. In order to efficiently identify the optimal process to realize the transformation, a mathematical

model has been built based on the works of Hofacker and Vetschera (2001) and Vergidis *et al.* (2007), follows as:

$$f(P) = \min \max_{j \in GO} (RCT_j) \quad (1)$$

s.t.

$$A_i \leq \chi_j \quad \forall j \in IN_i; i = 1, \dots, N \quad (2)$$

$$\chi_j \leq \sum_{i=1}^N g_{i,j} A_i \quad \forall j \notin GI \quad (3)$$

$$\chi_j \geq 1 \quad \forall j \in GO \quad (4)$$

$$S_i \geq RCT_j - M(1 - A_i) \quad \forall j \in IN_i; i = 1, \dots, N \quad (5)$$

$$RCT_j \leq S_i + D_i + M(1 - A_i) \quad \forall j \in OUT_i; i = 1, \dots, N \quad (6)$$

$$RCT_j \geq S_i + D_i - M(1 - A_i) - M(1 - \lambda_{i,j}) \quad \forall j \in OUT_i; i = 1, \dots, N \quad (7)$$

$$\lambda_{i,j} \leq A_i \quad \forall j \in OUT_i; i = 1, \dots, N \quad (8)$$

$$\sum_{i: j \in OUT_i} \lambda_{i,j} \geq 1 - M(1 - \chi_j) \quad \forall j \notin GI; i = 1, \dots, N \quad (9)$$

$$A_i \in \{0, 1\} \quad \forall i = 1, \dots, N \quad (10)$$

$$\lambda_{i,j} \in \{0, 1\} \quad \forall j \in OUT_i; i = 1, \dots, N \quad (11)$$

Equation (1) states that the objective is to minimize the completion time of the last output of the whole process in the set GO , which means to reduce the duration time of the whole process. Equations (2)-(9) state the constraints of the process. The notations used to describe the above model are listed in Table 6-2 and a brief explanation of each equation in the model is presented in Table 6-3.

Table 6-2 Notations for the first-stage optimization model

Symbol	Definition
P	A process design
RCT_j	The time that resource j is produced and becomes available
$j \in GO$	Resource j is a global output of the process
A_i	A binary variable indicating whether activity i has been selected to compose the process. $A_i = 1$, activity i has been selected
χ_j	A binary variable indicating the availability of resource j . $\chi_j = 1$, resource j is available
$g_{i,j}$	$g_{i,j} = 1$ indicating that resource j can be generated by activity i
N	Total number of activities
GI	A set of global input resources of the process
GO	A set of global output resources of the process
S_i	The start time of activity i
M	A positive infinite
IN_i	A set of required inputs of activity i
D_i	The duration time of activity i
OUT_i	A set of output of activity i
$\lambda_{i,j}$	A binary variable, $\lambda_{i,j} = 1$ indicating activity i is used to generate resource j

Table 6-3 Description of objectives and constraints of the first-stage optimization model

$f(P) = \min \max_{j \in GO} (RCT_j) \quad (1)$	
Minimize the whole process duration by minimizing the available time of t the last global output.	
$A_i \leq \chi_j \quad \forall j \in IN_i; i = 1, \dots, N \quad (2)$	
If activity i has been selected ($A_i = 1$), then all the input information resource must be available ($\chi_j = 1$) at some stage of the process.	
$\chi_j \leq \sum_{i=1}^N g_{i,j} A_i \quad \forall j \notin GI \quad (3)$	
The information resource j cannot be available if there is no initial input or no activity produces such information.	
$\chi_j \geq 1 \quad \forall j \in GO \quad (4)$	
The global output resource of the process must be available.	
$S_i \geq RCT_j - M(1 - A_i) \quad \forall j \in IN_i; i = 1, \dots, N \quad (5)$	
If resource j is the input resource of activity i , then the starting time of activity i must be after the resource j has been produced.	
$RCT_j \leq S_i + D_i + M(1 - A_i) \quad \forall j \in OUT_i; i = 1, \dots, N \quad (6)$	
$RCT_j \geq S_i + D_i - M(1 - A_i) - M(1 - \lambda_{i,j}) \quad \forall j \in OUT_i; i = 1, \dots, N \quad (7)$	
If resource j is the output of activity i , and activity i has been used to generate resource j , then the resource available time exactly equals to the complete time of the activity.	
$\lambda_{i,j} \leq A_i \quad \forall j \in OUT_i; i = 1, \dots, N \quad (8)$	
If activity i is not participating into the process, it cannot be used to generate resource j .	
$\sum_{i: j \in OUT_i} \lambda_{i,j} \geq 1 - M(1 - \chi_j) \quad \forall j \notin GI; i = 1, \dots, N \quad (9)$	
If a resource is not a global input, but is available at some stage, then it must be produced by some activities.	
$A_i \in \{0, 1\} \quad (10)$	
The control variable whether an activity is selected or not must be binary.	
$\lambda_{i,j} \in \{0, 1\} \quad (11)$	
The variable indicating whether an activity is used to produce a specific resource or not must be binary.	

The mathematical expression of the process is rather complicated compared to its graphical representation. The model is highly constrained and there are a large number of discrete binary variables and binary matrices, which result in a highly fragmented search space for a feasible solution. Currently, no effective algorithm has been found to solve such complex problem. Algorithms addressed by Hofacker and Vetschera (2001) and Vergidis *et al.* (2007) have serious limitations in dealing with the scalability requirements of complex processes. Hence, this research attempts to use IBM ILOG CPLEX Optimization Studio V12.2 to search for the optimal solution. IBM ILOG CPLEX Optimization Studio is an integrated development environment of the Optimal Programming Language (OPL). It provides the fastest and most robust way to build optimization models for various planning and scheduling problems. Problems with millions of variables and constraints can be solved quickly, reliably, and accurately with this tool. Its mathematical programming engine has been adopted to solve the first stage of the optimization problem in this research. The detailed code of the OPL model can be found in Appendix 3.

The results from the optimizer shows that six activities among twenty two candidates have been selected to compose the specific care transition process of patients who have care givers and need to be transferred to community hospitals. The details are shown in Figure 6-4. The global input of the whole process is I_1 (the records of admitted patients), and I_{18} (the discharge meeting time). When a patient with a care giver is admitted into an acute hospital, he/she will first go through A_2 (medical care), which generates I_3 (the medical care report). Based on I_3 (the medical care report), he/she is sent for A_5 (nursing care) with the output of I_6 (the nursing care report). With the medical care report and nursing care report, A_6 (a

specific therapy) is designed, which finally delivers I_7 (the therapy care report). After a few iterations of medical care, nursing care and therapy, a joint discharge meeting A_{18} is held to discuss where to transfer the patient. Information about rehabilitation potential I_{20} and the final decision of the next stage care provider I_{22} will be available after the meeting. The patient is transferred to the community hospital A_{15} based on his/her rehabilitation potential. After the transfer, the patient will be followed up according to the transfer result I_{15} and a feedback of the care transition I_{21} will be generated.

Figure 6-4 Optimal care transition process design for a specific scenario

Results from the first stage of the optimization model are slightly different than the ‘AS-IS’ care transition process and the ‘TO-BE’ care transition process proposed in Chapter 5. Compared to the ‘TO-BE’ process in Chapter 5, the optimal care transition process design for such specific type of patients does not have the need to estimate transfer needs and communicate with patient and their families before the discharge meeting. Such differences justify the necessity of developing an algorithmic approach for process optimization design. The optimal design of a general process for all types of patients is achievable by finding out the optimal design for each type of the patients and synthesizing these optimal designs into a

general process, which covers all the scenarios. The model here is proposed to illustrate the idea and provide guidelines to the practitioners on how to achieve an optimal process design rather than generating an optimal care transition process which can be used directly in practice. Therefore, the focus of this research is not to examine all the scenarios with different types of patients to generate a general optimal care transition process.

6.3.3 Second stage: who should do it (allocating resources)

A process with minimum duration time has been generated at the first stage of the optimization by selecting participating activities and determining their topological structure. The second stage of the optimization aims at exploring ways to allocate human resources to execute those selected activities to achieve the best quality under different scenarios, which can be achieved by maximizing the total task associated skill levels in the process.

In reality, a medical staff handles multiple tasks with multiple patients every day. The health care service is delivered to the patients discretely rather than continuously. The total time that medical staff spends on a patient may be less than 20 hours, but a patient would stay in the hospital for more than 10 days, since they need extra time to recover physically. To simplify the problem, this research assumes that there are five patients in each period who need the care transition. All care transition tasks should be completed within the due date, as there is a limitation on the length of stay for each patient. These constraints and duration time of each task in the process are predefined, as shown in Table 6-4.

Table 6-4 Tasks in care transition process

Tasks	Duration times (hours)	Preceding tasks
A2 Medical care	4	
A5 Nursing care	3	Medical care
A6 Therapy care	5	Nursing care
A18 Joint discharge meeting	2	Therapy care
A15 Transfer patient to CH	1	Joint discharge meeting
A16 Follow up	1	Transfer patient to CH

There are five types of roles among the medical staff and at least one of the five is required for each task in the process. Each type has a varying skill level associated with the tasks. If a role has a skill level of zero, it cannot be assigned to the task. A staff can only work on one task at a time. Each task, once started, cannot be interrupted. The skill level of each role for each task is roughly estimated and shown in Table 6-5. It is possible to accurately estimate the tasks associated skill level for each role through proficiency tests. In this way, an optimal staff allocation is achievable for direct application.

Table 6-5 Task skill level of each role

Tasks	Staff				
	Doctor	Nurse	Therapist	Care coordinator	Other role
(A2) Medical care	9	0	0	0	0
(A5) Nursing care	7	9	5	3	3
(A6) Therapy care	5	7	9	5	3
(A18) Joint discharge	9	9	9	9	9
(A15) Transfer patient to CH	3	7	7	9	5
(A16) Follow up	3	3	3	9	5

The problem in the second stage of optimization is quite similar to the traditional resource constrained multiple projects scheduling problem, but there are two major differences. First,

each task in the care transition process can use alternative human resources. Which resources will be used to perform the task is unknown and is determined by the optimization algorithm. Second, in the care transition process, there is a special task named joint discharge meeting, which requires all the resources that have been used in performing its preceding tasks for all the patients. The joint discharge meeting of all the patients is held at the same time, which can only start after all the preceding tasks of each patient have been completed. The start date of each task is subject to capacity constraints of staff resources over time. Due to such characteristics of the problem, a specific model is needed for the second stage of the optimization, which can be formulated as:

$$f = \max_{M_{ijm}, S_{ij}} \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \sum_{m=1}^{N_m} K_{mj} \times M_{ijm} \quad (1)$$

s.t.

$$S_{ij} \geq F_{ik} \quad \forall i, j, k \in P_j \quad (2)$$

$$\sum_{m=1}^{N_m} M_{ijm} = NM_j \quad \forall i, j \quad (3)$$

$$E_{ij} \cap E_{ab} = \emptyset \quad \forall (i, j) \neq (a, b) \& j, b \notin J, \text{ if } M_{ijm} = M_{abm} = 1 \quad (4)$$

$$E_{ij} \cap E_{ab} = \emptyset \quad \forall j \neq b \& j, b \in J, \text{ if } M_{ijm} = M_{abm} = 1 \quad (5)$$

$$S_{ij} + D_j = F_{ij} \quad \forall i, j \quad (6)$$

$$F_{ij} \leq D \quad \forall i, j \quad (7)$$

$$S_{ij} = S_{kj} \quad \forall i, k, \text{ if } j \in J \quad (8)$$

Equation (1) states that the objective of the model is to maximize the quality of care transition for all the patients by finding out who should execute which task at what time. The sequence is decided by staff availability. Equations (2)-(8) state the precedence constraints

and resources constraints (staff availability). The notations used to describe the above model are listed in Table 6-6. A brief explanation of each equation in the model is displayed in Table 6-7.

Table 6-6 Notations for the second stage optimization--resource allocation problem

Symbol	Definition
M_{ijm}	$M_{ijm}=1$, staff m is selected to execute task j for patient i
S_{ij}	The starting time of task j for patient i
N_i	Number of patients, $i=1 \dots N_i$
N_j	Number of tasks of a care transition process, $i=1 \dots N_j$
N_m	Total number of staff
K_{mj}	The skill level of staff m on task j
F_{ij}	The completing time of task j for patient i
NM_j	Predefined value: number of roles required for task j
E_{ij}	Interval variable of the duration of task j for patient i $E_{ij}=\{t: S_{ij} \leq t \leq F_{ij}\}$
D_j	The duration time of task j
D	Deadline of all the tasks
J	A set of special tasks, which require to be held at specific time with all the resources used in their preceding tasks.
P_j	Set of the precedence of task j

Table 6-7 Description of objective and constraints of the second-stage optimization model

$$f = \max_{M_{ijm}, S_{ij}} \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \sum_{m=1}^{N_m} K_{mj} \times M_{ijm} \quad (1)$$

Objective function: maximize the total task-associated-skill level of the care transition processes for all the patients by appropriately allocating the resources and arranging the sequence of all the tasks.

$$S_{ij} \geq F_{ik} \quad \forall i, j: k \in P_j \quad (2)$$

Precedence constraint: each task can only start after all of its foregoing tasks have been finished.

$$\sum_{m=1}^{N_m} M_{ijm} = NM_j \quad \forall i, j \quad (3)$$

Resource requirement constraint: The total number of roles used to perform task j for patient i should equals to the number of roles required by task j .

$$E_{ij} \cap E_{ab} = \emptyset \quad \forall (i, j) \neq (a, b) \& j, b \notin J, \text{ if } M_{ijm} = M_{abm} = 1 \quad (4)$$

$$E_{ij} \cap E_{ab} = \emptyset \quad \forall j \neq b \& j, b \in J, \text{ if } M_{ijm} = M_{abm} = 1 \quad (5)$$

$E_{ij} = \{t: S_{ij} \leq t \leq F_{ij}\}$ is the interval variable of the duration time of task j for patient i

The staff (role) can only execute one task at a time. There is no overlap between the scheduling times of the two tasks which are performed by the same staff, unless the tasks are the same special tasks of two patients.

$$S_{ij} + D_j = F_{ij} \quad \forall i, j \quad (6)$$

Time constraint: The finishing time of task j for patient i equals to the starting time of task j for patient i plus the duration time of task j .

$$F_{ij} \leq D \quad \forall i, j \quad (7)$$

All the tasks should be finished within the due date.

$$S_{ij} = S_{kj} \quad \forall i, k, j \in J \quad (8)$$

The same special tasks j for all the patients should be performed simultaneously.

The problem is solved by using the constraint-programming (CP) engine in the IBM ILOG CPLEX optimization studio. The engine can solve difficult optimization problems that have complex, combinatorial constraints. It performs a set of logical inferences to decrease the available domains for variables. No assumptions are needed on the mathematical properties of the solution space such as convexity, linearity, etc. Optimality is achieved by ensuring that no better solution can be found than the current solution. The detailed OPL code of the second stage of the optimization problem is illustrated in Appendix 4.

Four scenarios with different types of staff and different deadlines are examined. The first scenario assumes that there are only one doctor and one nurse in the acute hospital to perform all the tasks of care transition for the five patients, and all care transition processes should be finished within 200 hours, which is a loose deadline. The detailed schedule of each task for the five patients is shown in Figure 6-5. The second scenario sets a tighter deadline with 40 hours. There are still only one doctor and one nurse to execute all tasks. The detailed schedule is presented in Figure 6-6. The third scenario includes five roles that are elaborated in Table 6-5 to execute all the tasks with a loose deadline of 200 hours. The fourth scenario constrains the five roles to perform all tasks with a tight deadline of 32 hours. The detailed schedules for the third and fourth scenarios are shown in Figure 6-7 and Figure 6-8 respectively. The numbers 1-6 marked in the colored rectangles in the figures correspond to the task sequences for each patient. The six activities are medical care, nursing care, therapy, joint discharge meeting, transfer patient to community hospital, and follow up. The length of rectangle represents the duration time of the task and the color of the rectangle indicates which staff is used to execute the task.

The comparison between the results of the first and second scenarios shows that when there is only one doctor and one nurse available to perform all the tasks for all the patients, the main function of doctor should focus on medical care if the constraint of deadline is loose and the nurse will take the remaining tasks. Since both the doctor and nurse have the same skill level on the task of ‘follow up’, the doctor can also follow up some cases to get feedbacks and improve the care transition decision. However, if the policy makers want to accelerate the process as fast as possible with the limited staff resources and set quality as the second objective, then, in addition to the medical care, the doctor should take some responsibility as a therapist, and be responsible for some patient transfer and follow up. Compared to the first scenario, the second scenario can finish all the tasks for all of the patients in 40 hours with the total service quality reduced by 5%. When there is a shortage of the staff in a given period, the optimal allocation of staff resources to tasks in care transition will follow the second scenario.

Comparison between the first scenario and the third scenario indicates that both quality and speed of the care transition process can be improved when more types of staff are available. In the third scenario, the doctor takes responsibility of medical care, the nurse is in charge of nursing care, and the therapist provides the service of therapy, while the remaining tasks would be completed by the care coordinators. The total quality of the processes would be 270 (270 is the sum of skill-level of each tasks for all patients, it indicates the service quality) with a total duration time of 44 hours, while the value of the total skill-level is only 220 in the first scenario with a total duration time of 54 hours. Though five roles have been introduced in the third scenarios, the last role named “other” has never been allocated to any

tasks. Therefore, with a loose deadline, 4 types of roles are enough to achieve the fastest speed and best quality. Introducing other additional roles would be a waste of the resource.

The result in the third scenario does not mean that the role of “other” is always useless. If the deadline is very tight, then the role of “other” would have a chance to participate in some tasks to accelerate the process and maintain considerable quality. For example, in the last scenario, all the roles perform some tasks in the care transition process. The optimal result of the last scenario reached the fastest process duration of 32 hours with a total quality value of 232. The fastest speed is only 40 hours with a total quality value of 210 in the second scenario. In the fourth scenario, the doctor focuses on medical care, while the nurse helps the therapist with tasks in therapy. All the roles participate in patient transfer and follow up in the last scenario. Such two tasks are finished by the care coordinator alone in the third scenario. The results indicate that when the deadline is tight, all the staff should help the care coordinator in tasks of patient transfer and follow up to accelerate the process. Results also show that the role of “other” cannot contribute a lot either to the speed or the quality of the care transition regardless of the deadline. These results are consistent with the proposed changes in Chapter 5, which advocates eliminating the role of the social worker in the care transition.

Eventhough the model of the second stage of the optimization included characteristics of alternative resources and special tasks such as the joint discharge meeting; it is still a simplified version of the real situation. First, this model supposes all the five patients come at the same time, while in reality, the arrival rate of the patients are stochastic. Hence the deadlines of the care transition for each patient are different. Second, current model has a

fixed number of each type of staff, while in reality; this number varies. Finally, this model assumes that the duration time of a task is constant with different roles, while in reality, the higher skill level of the staff, the faster he or she performs a task.

6.4 Summary

The two-stage model of optimal process design in this chapter aims at complementing rather than replacing the prevailing qualitative methods of process design. The proposed algorithmic tool is an initial attempt to provide a rigorous method and break the limitations of a designers' intuition. The first stage of the optimization selects participating activities to compose a process with shortest duration time. Grounded on a determined structure and pre-selected activities of the process, the second stage aims at maximizing service quality by appropriately allocating the staff to tasks. Currently, the two-stage model assumes that different roles have the same processing time on a specific task. A more sophisticated model should be built, where the first stage selects participating activities to temporarily generate all feasible process designs rather than providing an optimal process as the current model does. Then, the second stage would allocate the staff to perform the tasks based on varied processing time and skill levels of staff associated with the tasks. A queuing network model should be adopted in the second stage optimization and more details should be incorporated into the model in the future.

Chapter 7

Decision Support in Patients Transfer

The care transition process improvement in Chapter 5 and optimization approach in Chapter 6 addressed ‘how to’ transfer patients in a smoother way. To further improve care transition, scientific decisions on ‘when and where’ to transfer the patients are needed, because inappropriate decision will impede the achievement of smooth care transition. In this chapter, theoretical models and methods are developed to provide decision support for achieving an optimal decision on ‘when and where’ to transfer the patients. It can be used as decision-making tool in real health service delivery with the precise data input.

7.1 Introduction

Medical staff are need to make rational decision in the face of rising demand and increasing medical cost. The captivated reimbursement for inpatient care has increased pressures on hospitals to reduce length of stay. Consequently, elders with complex health needs are being discharged from hospitals earlier (Naylor *et al.*, 1999). Ideally, a patient should be discharged only when the benefits of hospitalization no longer justify the expense, however, the shortage of beds would force clinicians to discharge patients before their situations become stable, which leads to high readmission rates. Readmitted patients may consume more acute care resources than those who would have stayed longer and gained better recovery without readmission. On the other hand, unnecessary delays of discharge for some patients would not only increase medical care cost but also compromise the care of other acutely ill patients due to bed blockage. Reducing waste and unnecessary utilization of

limited healthcare resource is in the interest of all involved parties, including care providers, patients, and the government. It is crucial to manage the tradeoff between patients' length of stay (LOS) and readmission rate. Existing studies indicate that the choice of next stage care providers also plays an important role in reducing delayed discharge and the rate of readmission (Lim *et al.*, 2006). For example, if too many patients are discharged to the community hospital, congestion in the community hospital will not only lead to higher readmission rates but also inefficient resource configuration and increased healthcare expenditure. Hence, decisions on when and where to discharge the patients in the acute hospital are critical to achieve smooth care transition.

Although both researchers and practitioners have tried to provide guidelines for appropriate timing of patient discharges, most of them have mainly focused on the individual level without taking a holistic picture at a system-wide level (Franklin and Jackson, 1983; Lim *et al.*, 2006). The complexity of the legal and ethical aspects of discharge decisions creates barriers to the study of optimal discharge policy at an extended organizational level (e.g. between acute hospital and community hospital). It is crucial to understand how individual decision makers interact with each other and influence the overall performance of the healthcare system. By far, most relevant research has only dealt with the performance improvement of a single aspect or has focused on utilization rate and throughput (Duguay and Chetouane, 2007; Mielczarek and Uziako-Mydlikowska, 2010).

To achieve safer, faster, cheaper, and better care service, this research focuses on providing decision support on when and where to discharge patients by considering multiple aspects of system performance. The aim is achieved by fulfilling three main tasks. First, a new method

is proposed to estimate the length of stay. The finite state discrete Markov chain is adopted to represent system dynamics and capture the transition of the health status of patients at different stages. Second, a simulation model of patient flow is developed to reflect correlations between disease severity, length of stay (LOS), health status, discharge policy, care transition decision, and readmission. Third, a genetic algorithm incorporated with an optimal budget allocation algorithm for constrained optimization is used to search for an optimal solution. The optimal solution is achieved by balancing the tradeoff between the length of stay and readmission rate; as a result the medical cost is minimized with constraints on other performance measurements, such as waiting time, decrease rate, etc. Different optimization scopes are considered and compared. This research can help healthcare planners and policy makers to identify cost-effective strategies to respond to the challenges of the aging population. The proposed simulation model can also be used for the resource planning in specific institutions or the treatment of a specific disease.

7.2 Conceptual Model

A myriad of research has widely agreed that severity of disease, length of stay, readmission rate and other patient particulars are highly correlated (Hannan *et al.*, 2003; Lim *et al.*, 2006; Aujesky *et al.*, 2009; Chi *et al.*, 2008; Novotny and Anderson, 2008; Tan *et al.*, 2009; Vest *et al.*, 2010). However, most discussions are limited to a linear relationship among two or three factors. There are few, if any, models that examine the complex non-linear relationship among these factors in a systemic way. Little is known about how the discharge policy and transition decision impact the length of stay, readmission rate, and other aspects of system performance.

Therefore, this research has conducted various interviews with a wide range of medical staff who have firsthand experiences in the system. With the collected ideas about how the system works, a conceptual model is proposed to present the complex relationships between health status (HS), length of stay (LOS), initial disease severity, discharge plan, care transition decision and readmission rate. Details are depicted in Figure 7-1.

Figure 7-1 Conceptual model

Once a patient is admitted into an acute hospital (AH), his or her health status (HS) will be checked and updated along the time of admission. Random and nonrandom factors such as environment, disease severity, and patients' physical characteristics can affect the health status, but this research only considers the two most critical factors: namely length of stay (LOS) and initial disease severity. The evolvement of health status is reflected by a Markov model. The health status of a patient can be calculated based on the examination of the Cumulative Illness Rating Scale (CIRS) organ impairment scores, the Mini-mental State Examination (MMSE) scores, the Shah modified Barthel Index(BI) scores, and the Triceps Skin Fold Thickness(TSFT) (Leong *et al.*, 2009). In this research, a higher score represents a worse health status.

After a period of stay, the patient may be discharged from an acute hospital to another place. At the weekly meeting of all related medical staff, when and where to discharge the patient will be discussed. The doctors, nurses, and therapists report on the condition of the patient according to the previously mentioned medical tests. In this way, the health status of a patient is known to all the participants of the meeting. Then, a discharge plan is made based on the health status and length of stay of this patient. After that, the care coordinator reports the social economic status of this patient. The report includes whether the patient has a family member to take care of him or her or not, whether the patient or his or her family is able to afford the step-down care service after discharge or not, whether the environment of the home is suitable for the patient to recover or not, and so on. With this information, the medical staff will discuss where would be best to discharge this patient. Usually, a patient who has recovery potential and is not stable enough to return home will be sent to a community hospital. If the patient has no recovery potential, he or she will be sent home or to a nursing home, this will be determined based on his or her social economic condition. Generally, most patients who can afford private nursing services are sent to a private rehabilitation center or a nursing home. The most important social economic factor in care transition for the majority cases is whether the patient has a care giver or not. Hence, in this research, when it comes to social economic condition, it refers to whether a care giver is available.

The discharge health status and discharge time are decided by the discharge policy with two manageable parameters, namely the ‘the minimum dischargeable health status’ and the ‘allowed maximum length of stay’. The patient leaves the acute hospital when his/her health status value is equal to or less than the ‘the minimum dischargeable health status’. However,

if the patient's LOS reaches the allowed maximum length of stay, he/she will still be discharged even his or her health status value is larger than the threshold of dischargeable status.

Where the patient goes after being discharged from the acute hospital is determined by the care transition decision. There are three controllable parameters to the health planners: the 'lower threshold of HS to home', the 'upper threshold of HS to home', and 'threshold of HS to nursing home (NH)'. A patient will go back home if his or her health status value is lower than the 'lower threshold of HS to home'. If a patient has a care giver and his or her health status value is larger than 'upper threshold of HS to home', she or he will also go back home after being discharged. A patient with no care giver and his/her health status value is larger than the 'threshold of HS to nursing home' will go to a nursing home. Patients in other situations will go to a community hospital (CH). That means either a patient with a care giver and his/her health status value is between 'lower threshold of HS to home' and 'upper threshold of HS to home' or a patient without a care giver and his or her health status is between the 'lower threshold of HS to home' and the 'threshold of HS to nursing home' is qualified to go to community hospital.

The patient's health status will be continually updated, regardless of where he or she stays after being discharged from the acute hospital. A change of health status after discharge is associated with the health status at the discharge point and the place in which he or she stays after discharge. Normally, with the same health status, a patient in the community hospital is recovered faster than the one at home or a nursing home due to the better medical care that he or she received. The discharged patient will be readmitted to an acute hospital if his or

her health status deteriorates to a risky level. Therefore, readmission is determined by a patient's health status after discharge, which depends on his/her health status at the discharge point and the place where he/she stays after discharge.

This research is set out to achieve cheaper, safer, faster, better health care service. The objective can be met by finding the optimal discharge policy, with best values for the 'minimum dischargeable health status' and 'allowed maximum LOS', and optimal care transition decision, with best values for 'lower threshold of HS to home', 'upper threshold of HS to home', and 'threshold of HS to nursing home (NH)'. Patients in the healthcare system suffer from many types of diseases; changes of health status follow different patterns due to characteristics of different diseases. It is difficult to compare the severity of different diseases. Therefore, this research only focuses on one common geriatric disease, hip fracture, to illustrate the proposed method.

7.3 Simulation Model Development

The healthcare system is a finite multi-server non-stationary queuing system. The complexity of this problem leads to the adoption of discrete event simulation, which has been proved to be an effective tool to provide solutions to complex systems by many researchers (Mielczarek and Uziółko-Mydlikowska, 2010). Modeling and simulation of patient flow is a well-researched area, but most existing research only focus on one healthcare institution, treating it as an independently functioning entity. This research intends to model the patient flow in and out of multiple connected healthcare institutions by considering complex relationships among length of stay (LOS), health status (HS), discharge plan, care transition decision, and readmission. The difficulties in predicting a patient's LOS

make it necessary to propose a new method to model the recovery process of a patient in each stage. Stochastic processes have been widely applied in modeling medical phenomena (Dumitrescu and Popescu, 1995). Several papers predict LOS and recovery using a Markov model, but in existing Markov models, the predication of length of stay is made based on arrival rate, transfer rate or discharging rate (Kao, 1972; Broyles *et al.*, 2010). In this research model, LOS is predicted based on the changes of health status, which corresponds more with reality. Details about the complete simulation model and the Markov model are presented in following sections. This simulation model focuses on the function of community hospitals. Since a patient without recovery potential would be transferred back to home or nursing home depending on whether he or she has a care giver, this simulation model would simplify the situation by neglecting bed capacities in nursing homes.

7.3.1 The structure of the simulation model

A discrete event simulation model is developed to simulate the whole process described in the conceptual model. The simulation model is developed on the platform of MATLAB (R2009a) with the aim to effectively search for the optimal solution based on customized algorithm. Its structure is shown in Figure 7-2.

Figure 7-2 The structure of the simulation model

In this model, there is only one entity (patients of the geriatric department) with multiple attributes, two types of resources (beds in the acute hospital and beds in the community hospital) and seven types of events (corresponding to the events in Figure 7-2), which are managed by the event list. An event is put into the event list and will be triggered when the system proceeds to the exact occurrence time of this event. Once an event is triggered, several activities will happen sequentially or concurrently. The main activities and processes are shown in Figure 7-2. Multiple variables are used to update the system's status and collect statistical data.

The simulation works in the following sequence: once it begins, the first patient is created with attributes such as arrival time, severity of the disease, whether he or she has a caregiver, etc. Then Event 1(arrival) of this patient is put into the event list. When the simulation

proceeds to the arrival time of this patient, the event list will be updated by deleting Event 1 for this patient. This triggers the creation of next patient, and Event 1 of the newly created patient is put into the event list. Arrived patient is admitted into the acute hospital as long as there is an available bed; otherwise the he or she will be put into a block list (Queue 1 in Figure 7-2). A discrete Markov model is applied to update the patients' health status continuously during their stay in the acute hospital (details are in the next section). In most cases, after a period of stay in the acute hospital, the health status value (severity level) of a patient can drop to a dischargeable level before reaching the allowed maximum length of stay in the acute hospital, but sometimes a patient may be still not stable enough when his or her length of stay reaches the allowed maximum. Both situations can trigger Event 2 (initial discharge of this patient). There is a small chance that the patient may die in the acute hospital, this only happens if his or her health status reaches the highest severity level. In such a situation, the occupied acute bed will be released accordingly.

When Event 2 occurs, the care transition decision will be initialized to check the patient's next destination, which is decided based on the information of the care giver and the health status of a patient at the initial discharge point (which reflects recovery potential). If the next destination is home or a nursing home, the acute bed is released immediately. Otherwise, if the destination is a community hospital, the patient releases the acute bed after occupying an empty bed at the community hospital, which is Event 3 (admission to community hospital). However, if there is no bed available in the community hospital, the patient will be put into another block list (Queue 2 in Figure 7-2) and continue his or her treatment at the acute hospital. The same Markov model keeps updating the health status of the patient until he or she is admitted into the community hospital (Event 3). Sometimes, the patient fully recovers

(Event 5 happens) before a bed in community hospital is open due to the long waiting time. In such a circumstance, the patient leaves Queue 2 and changes his next destination from the community hospital to home.

Once a patient is admitted into the community hospital, a similar Markov model with a different transition matrix is applied to update his or her health status. The patient could possibly die in the community hospital if his or her health status hits the decease state, the highest severity level of health status. Otherwise, a patient will be discharged to home if his or her health status reaches a safe level or his length of stay exceeds the allowed maximum at the community hospital. A patient will be readmitted (Event 4) into an acute hospital if his health status deteriorates to the readmission level.

After the patient goes back home, no matter whether from an acute hospital or community hospital, the health status of the patient may become worse again. Once the health status reaches a certain severity level, the patient will be readmitted (Event 4) to the acute hospital. The severity level for readmission varies from patient to patient according to their tolerance of health deterioration. If the patient dies at home or stays at home for more than three months without readmission, the system will close the case of the patient.

7.3.2 Modeling the recovery process of patients with Markov chain

Some research on the predicted length of stay uses the distribution of service rate to decide the length of stay, which may not be suitable for elderly people suffering from chronic diseases (El-Darzi et al., 1998). The length of stay of chronically ill elder patients mainly depends on their recovery capacities rather than the servicing rate of the medical staff.

Differential equations were also adopted by some researchers to predict the length of stay based on the arrival and discharge rate, which treats the whole process as a black box (Emre and Kamran, 1998; Harrison and Escobar, 2010; Marshall *et al.*, 2004). In this research, a new way is proposed to predict the LOS by utilizing a discrete Markov model that reflects the evolvement of the health status of a patient.

The treatment of patient can be considered as a process progressing through different health statuses, evolving towards a discharge point or deceased state. The next health status depends on the previous status. Although health statuses change continuously, clinical updates are made periodically. The discrete time Markov process is adopted, in the simulation model, there are three Markov chains corresponding to the recovery processes of the three stages, i.e., acute hospital, community hospital and home/nursing homes. The models are similar to each other, but with different transition matrices (details are shown in Appendix 5). In the Markov chain, the state is defined as the severity of disease that a patient is suffering. There are eleven possible states corresponding to different severity levels. They are S_0 (totally recovered), S_1 (slightly sick), S_2 (mildly sick)... S_8 (seriously sick), S_9 (dying), S_{10} (deceased) with corresponding transition matrix, $P = [a_{i,j}]_{11 \times 11}$, where $a_{i,j}$ is the probability that a patient's health changes from one status i to another status j in each period. The transition matrix has the following characteristics:

$$P = [a_{i,j}]_{11 \times 11} = \begin{bmatrix} A' & 0 & 0 & 0 \\ 0 & A'' & 0 & 0 \\ 0 & 0 & B' & 0 \\ 0 & 0 & 0 & B'' \end{bmatrix} \quad \begin{cases} \sum_{j=0}^{10} a_{i,j} = 1 (\forall i) \\ a_{i,j} > 0, \text{ if } |i-j| \leq \xi_i \\ a_{i,j} = 0, \text{ if } |i-j| > \xi_i \end{cases}$$

The cumulative transition probability of each state equals to 1. When the severity of the disease is mild or moderate, the probability of transition to a higher severity level (worse condition) is very low or even zero. If the severity of the disease is serious, it has high probability to enter into both a higher status and a lower status. In this research, the transition can jump to a different status rather than being restricted transiting to a neighboring status.

Figure 7-3 Health status transition

The transition process will stop if the health status reaches one of the safe states $M = \{S_0, S_1, \dots, S_m\}$ or deceased state. The safe states $M = \{S_0, S_1, \dots, S_m\}$ refer to these health statuses with patients safe enough to be discharged from the acute hospital. When the LOS reaches to the allowed maximum length of stay, the transition process also stops. Hence the length of stay of a patient with initial health state S_k is determined by the following equation:

$$LOS_{(k)} = \begin{cases} T_{(k)} & \text{if } T_{(k)} < T'_{(k)} < T_{\max} \\ T'_{(k)} & \text{if } T'_{(k)} < T_{(k)} < T_{\max} \\ T_{\max} & \text{if } T_{\max} < T'_{(k)} \text{ \& } T_{\max} < T_{(k)} \end{cases}$$

$T_{(k)}$ is the sojourn time from the initial state S_k to a safe state S_l , where $S_l \in M$. $T'_{(k)}$ is the time from the state S_k to S_{10} (deceased). $T_{\max}$ is the allowed maximum length of stay

in each healthcare institution. The complexity of predicting the next transition status and the length of stay in this model makes the mathematical solution difficult to be achieved. Therefore, the simulation is based on MATLAB (R2009a) to estimate the length of stay.

7.3.3 Optimization model

As mentioned earlier, this work aims at providing a decision support tool for achieving safer, cheaper, faster and better care service. (1) Safer is represented by the readmission rate and decrease rate in the whole health care system. (2) Cheaper can be achieved by reducing the annual operational costs in the acute hospital and the whole healthcare system as well as the cost per patient in the acute hospital and the whole healthcare system. (3) Faster is measured by system accessibility, which is waiting time to be admitted into the acute hospital. (4) Better is a general concept referring to the overall performance. Since the cost per patient is implicitly related to the LOS, it is considered as a performance indicator in the optimization. System accessibility, instead of LOS, is used to measure ‘faster’ for a more patient-centric result, because a long waiting time can quickly deteriorate the health of the patient during the waiting and make the patient stay longer after being admitted.

When and where to discharge patients are critical to achieve these objectives. According to current practices, two variables are controllable for when to discharge the patient (optimal discharge policy):

(1) α_{AH_D} --- the threshold of a patient’s health status value that make it is safe to discharge him or her from the acute hospital (which corresponds to the S_m in section 7.3.2 and the ‘minimum dischargeable health status’ in section 7.2).

(2) T_{AH} --- the maximum allowed length of stay (which corresponds to the $T_{\max}$ in section 7.3.2 and the ‘allowed maximum length of stay’ in section 7.2).

Three variables can be controlled for where to discharge the patient (optimal care transition decision):

(1) ϕ_{low} --- the lower bound of the health status value to go back home (‘lower threshold to home’ in section 7.2). If a patient’s health status value is smaller than or equal to ϕ_{low} , he/she will be discharged home.

(2) χ_{upp} --- the upper bound of the health status value that a patient is allowed to return home (the ‘upper threshold to home’ in section 7.2). If a patient has a care giver and his or her health status value is larger than χ_{upp} , he or she will go back home after leaving the acute hospital.

(3) η_{NH} --- the limit to transfer to a nursing home. If a patient is without a caregiver and his or her health status value is larger than η_{NH} , he or she will be discharged to a nursing home (the ‘threshold to nursing home’ in section 7.2).

If a patient has a care giver and his or her health status value is between ϕ_{low} and χ_{upp} , or if a patient is without a care giver and his or her health status value is between ϕ_{low} and η_{NH} , he or she will be discharged to a community hospital.

To achieve the most optimal discharge plan and care transition decision, a simulation-based optimization problem is formulated with the general form shown below. Both the annual cost and cost per patient are considered in two different optimization scopes: the acute hospital and the whole healthcare system.

$$\text{Min } Z$$

$$\text{s.t. } X_{readmit} \leq y_{readmit} \quad (1)$$

$$X_{decease} \leq y_{decease} \quad (2)$$

$$X_{wait} \leq y_{wait} \quad (3)$$

$$z_{\alpha} \leq \alpha_{AH_D} \leq y_{\alpha} \quad (4)$$

$$z_T \leq T_{AH} \leq y_T \quad (5)$$

$$z_{\phi} \leq \phi_{low} \leq y_{\phi} \quad (6)$$

$$z_{\chi} \leq \chi_{upp} \leq y_{\chi} \quad (7)$$

$$z_{\eta} \leq \eta_{NH} \leq y_{\eta} \quad (8)$$

$$\phi_{low} \leq \alpha_{AH_D} \quad (9)$$

$$\alpha_{AH_D} \leq \chi_{upp} \quad (10)$$

$$\alpha_{AH_D} \leq \eta_{NH} \quad (11)$$

As mentioned earlier, the rising health care expenditure would be the biggest challenge that the aging population would bring to the cash strapped government. Therefore, four different objective functions of Z are considered corresponding to the costs of different optimization scopes, which are, $Z_{annu_AH}, Z_{avr_AH}, Z_{annu_SYS}, Z_{avr_SYS}$. Z_{annu_AH} represents the annual operational cost of acute hospital, Z_{avr_AH} refers to the cost per patient in an acute hospital, Z_{annu_SYS} stands for the annual operational cost of the whole healthcare system with the

penalty of decease and Z_{avr_SYS} presents the cycle cost per patient in the whole healthcare system. The equations (1)-(3) show the constraints of other system performance measures: the readmission rate $X_{readmit}$, decease rate $X_{decease}$ and waiting time to be admitted into an acute hospital X_{wait} . All these parameters are evaluated by the simulation result. The equations (4)-(8) represent the value ranges of the five decision variables.

7.4 Optimization Algorithm

The integer-nonlinear nature of the optimization problem in this research makes it difficult to reach a solution through mathematical analysis (Gen and Cheng, 2000). Searching for the optimal solutions to such kind of problems in an efficient way is one of the most difficult problems in optimization (El-Sharkawi, 2008). Therefore, a simulation-based optimization with meta-heuristic search algorithm is considered. In this part of the research, a genetic algorithm (GA) is proposed. Optimal computing budget allocation algorithm for constrained optimization (OCBA-CO) is incorporated into the genetic algorithm to improve the computational efficiency.

7.4.1 Genetic algorithm (GA)

Genetic algorithm is an adaptive search technique that solves problems by mimicking the process of natural evolution. As an evolutionary algorithm, genetic algorithm became popular through the work of Holland (1975). Genetics show that hereditary factors of parents are passed to their offspring through a crossover of chromosomes, which carries the hereditary information. During this process, mutation can randomly happen to the new generation due to errors in copying heritage information. Only the fittest can survive and

pass the hereditary to their offspring. Inspired by the evolution in nature, the basic genetic algorithm has following steps:

(1) Initialization

The first step of the genetic algorithm is to randomly generate an initial population with n chromosomes, which corresponding to the n coded possible solutions to the given problem. The chromosome structure of this study is given in Figure 7-4, where the genes are the values of the five decision variables (controllable parameters) in the optimization model and are given with their original form.

α_{AH_D}	T_{AH}	ϕ_{low}	χ_{upp}	η_{NH}
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Figure 7-4 The structure of a chromosome

Though the objective function is to minimize the cost, it is subject to constraints of readmission rate, decease rate, and waiting time. Hence, a feasible solution, composed by five numbers with this structure in Figure 7-4 should satisfy constraints on readmission rate, decease rate, waiting time, and their own value ranges.

A small population size can quickly reach convergence, but may have a high risk to be trapped in a local optimal solution. There are no standard rules to choose population size, as it varies due to the problem nature. In this research, the population size for each generation is fixed at 100.

(2) Reproduction

The solution to a problem solved by genetic algorithm has been evolved. Therefore, multiple iterations are needed to generate a new population used in the optimal solution. The new population is generated through evaluation, selection, recombination, and mutation. Following are the details:

(2.1) Evaluation and selection

Before generating a new population, parent chromosomes are selected based on the fitness value of each chromosome in current population, which is computed according to the objective function (here it is to minimize the cost). The smaller the objective function value, the better fitness of a chromosome and the larger chance that it will be selected as a parent to generate the next generation. This study takes the following steps to select parent chromosomes.

- 1) Calculate the fitness value of each chromosome using $f_i = C_{\min}/C_i$, where C_i is the objective function value of the i th chromosome. $C_{\min}$ is the objective function value of the best chromosome that has been found.

- 2) Roulette wheel selection is adopted to select the parent chromosomes. $r = u \times F_{\text{total}}$,

where u is a random number in the range $[0, 1]$. $F_{\text{total}} = \sum_{i=1}^n f_i$ is the total fitness of

the population. $F_i = \sum_{j=1}^i f_j$ is the cumulative value of f_i . Select i th chromosome

when $F_{i-1} < r < F_i$. If $r < F_1$, then select the first chromosome.

- 3) Repeat the second step to select another parent.

(2.2) Recombination (crossover)

This step mates the two parent chromosomes to generate a new chromosome. If $u < P_c$, then the crossover happens; where u is a random number between the range $[0, 1]$; P_c refers to the fixed crossover ratio, which is a parameter of the genetic algorithm. If $u < P_c$, then the offspring is generated by the formula $of = u \times P_1 + (1-u) \times P_2$; otherwise, $of = P_1$; where P_1 and P_2 are parent chromosomes. In this research, the crossover ratio $P_c = 0.8$.

(2.3) Mutation

Mutation is a second operation of the genetic algorithm that explores new search spaces. It aims at maintaining diversity of the population to avoid being trapped into a local optimum. All the genes of each chromosome have a mutation chance. In this research, mutation happens to genes by introducing small changes within their boundaries. It is done in the following way:

- 1) Select the mutation position by generating a random number u , ranging from $[0, 1]$, for each gene. If $u < P_m$, then a mutation will happen to this gene, otherwise the mutation will not be performed. P_m is a predetermined mutation probability, in this research $P_m = 0.1$.
- 2) The mutation is implemented by generating a uniform random number u within $[0, 1]$. If $u < 0.5$, then $g_{ij} = g_{ij} + d$, otherwise, $g_{ij} = g_{ij} - d$; where g_{ij} is the j th gene of the i th chromosome, and d is the positive increment.

(2.4) Check constraint satisfaction

Whether solutions satisfy all constraints or not is checked after a mutation operation. First, the constraints about the relationships among the decision variables are checked. If $\alpha_{AH_D} > \chi_{upp}$ or if $\alpha_{AH_D} > \eta_{NH}$, or if $\phi_{low} > \alpha_{AH_D}$, their values will be exchanged. α_{AH_D} is the first gene of the chromosome, representing the threshold of health status value that indicate if a patient is stable enough to be discharged from the acute hospital; ϕ_{low} is the third gene that refers to the lower bound of the health status value, which shows if a patient can return home; χ_{upp} is the fourth gene, which stands for the upper bound of the health status value when a patient goes back home. η_{NH} is the last gene, that describes the health status limit to transfer to a nursing home. Second, the constraint on the value range of each decision variable (“gene”) is checked. If the mutated gene is smaller than its lower bound value, it will be set as equal to the lower bound value, or if the mutated gene is larger than its upper bound value, then it will be set as equal to the upper bound value. Finally, multiple replications are run to check the satisfaction of constraints (such as readmission rate, decease rate, waiting time), on the system performance, this was presented in equations 1-3 of the optimization model in section 7.3.3.

(3) Termination

There are mainly four types of terminating criteria in the literature: (1) reaching the maximum number of generations; (2) obtaining a specific value of the objective function; (3) objective function stop improving; (4) reaching the maximum times of fitness evaluation (Taleizadeh *et al.*, 2010). This study adopts the oldest choice and terminates the algorithm

after a specific number of generations. The more generations, the better exploitation of promising solutions, but the algorithm performs better at the expense of a longer simulation time. After incorporated with OCBA-CO, fixed simulation replications of computing budget is adopted by this research. Once the simulation budget reached, the simulation stops.

7.4.2 Optimal computing budget allocation (OCBA)

The stochastic nature of the simulation optimization requires multiple replications to generate a credible estimation of the objective function. The solution (“chromosome”) will not be considered as the candidate for best solution if one of the three constraints on the system performance cannot be satisfied after looking at the results from multiple replications of the simulation. It would be waste of computing budget, and if the evaluation on the objective function is not precise enough, the simulation noise (variance of each design) would lead the algorithm in a wrong search direction or slow down the convergence. Hence, a more efficient way to conduct the simulations is needed. The optimal computing budget allocation (OCBA) proposed by Chen and Lee (2010) is regarded as a potential solution. Literature review by Lee *et al.* (2010) articulated that the integration of OCBA and search algorithms is an effective way to improve the simulation efficiency. OCBA has been integrated with Nested Partition (NP) (Chen *et al.*, 2009; Shi *et al.*, 1999), Evolutionary Algorithm (EA) (Lee *et al.*, 2008; Schmidt *et al.*, 2006), Genetic Algorithm (GA) (Zhang and Wang, 2004; Yan *et al.*, 2008), etc.

Instead of using an identical number of replications for each possible solution, which is inefficient, OCBA improves efficiency by considering both sample means and variance. To maximize the probability of a correct selection, a larger proportion of computing budget is

allocated to critical designs during the evaluation of possible solutions, while less computational effort is expended on non-critical designs, which are not likely to represent the best design. The basic procedure of OCBA is summarized in Table 7-1. For more details about the development of the algorithm, please refer to the book by Chen and Lee (2010).

Table 7-1 OCBA procedure (maximizing the probability of correct selection)

INPUT	k : number of designs ; T : total computing budget; Δ : incremental computing budget; n_0 : initial simulation replications for each of the k designs. $n_0 \geq 5$ and $(T - kn_0)$ is a multiple of Δ .
INITIALIZE	Perform n_0 simulation replications for all designs; $N_1^l = N_2^l = \dots N_k^l = n_0$.
LOOP	WHILE $\sum_{i=1}^k N_i^l < T$ DO
UPDATE	Calculate sample means $\bar{J}_i = \frac{1}{N_i^l} \sum_{j=1}^{N_i^l} X_{ij}$, and sample standard deviations $s_i = \sqrt{\frac{1}{N_i^l} \sum_{j=1}^{N_i^l} (X_{ij} - \bar{J}_i)^2}$, $i = 1, \dots, k$, X_{ij} is the simulation output of j -th simulation replication for design i . Using the new simulation output, find $b = \arg \min_i \bar{J}_i$.
ALLOCATE	Increase the computing budget by Δ and calculate the new budget allocation, $N_1^{l+1}, N_2^{l+1}, \dots, N_k^{l+1}$, according to $(1) \frac{N_i^{l+1}}{N_j^{l+1}} = \left(\frac{s_i(\bar{J}_b - \bar{J}_j)}{s_j(\bar{J}_b - \bar{J}_i)} \right)^2, \text{ for all } i \neq j \neq b, \text{ and}$ $(2) N_b^{l+1} = s_b \sqrt{\sum_{i=1, i \neq b}^k \left(\frac{N_i^{l+1}}{s_i} \right)^2}$
SIMULATE	Perform additional $\max(N_i^{l+1} - N_i^l, 0)$ simulation runs for design $i, i = 1, \dots, k; l = l + 1$.
END OF LOOP	

OCBA has been extensively adopted and continuously developed by Chen and his colleagues since it was invented in 1995. There are multiple extended versions of OCBA with different application goals. For example, OCBA-m was invented to select an optimal subset for m good enough designs (Chen *et al.*, 2007, 2008), MOCBA was developed to select a Pareto optimal set (Chen and Lee, 2009; Lee *et al.*, 2004, 2010), optimal computing budget allocation for constrained optimization (OCBA-CO) was proposed for selecting the best feasible solution for a single objective optimization with stochastic constraints (Pujowidianto *et al.*, 2009; Lee *et al.*, 2012), OCBA-OSD was developed for selecting the best by using regression analysis (Brantley *et al.*, 2008), OCBA-CE was created for extended cross-entropy methods (He *et al.*, 2010), etc.

The objective function and the first three constraints in the optimization model of this study need to be estimated using simulation. Hence, it is risky to directly adopt the basic procedure of OCBA mentioned in Table 7-1, as it is not specifically developed for problems with stochastic constraints. Instead, OCBA-CO, an extended version of OCBA is applied in this study. It is an allocation rule that addresses the simulation budget allocation problem by considering feasibility and optimality issues at the same time. The procedure of OCBA-CO used by this study was proposed by Lee *et al.* (2012), which is presented in Table 7-2.

INPUT	k : number of designs (possible solutions); T : total computing budget; Δ incremental computing budget; n_0 initial simulation replications for each design. $n_0 \geq 5$ and $(T - kn_0)$ is a multiple of Δ .
INITIALIZE	Perform n_0 simulation replications for all designs; $N_1^l = N_2^l = \dots N_k^l = n_0$.
LOOP	WHILE $\sum_{i=1}^k N_i^l < T$ DO
UPDATE	<p>Calculate sample means $\bar{J}_{hi} = \frac{1}{N_i^l} \sum_{j=1}^{N_i^l} X_{hij}$, and sample standard deviations $s_{hi} = \sqrt{\frac{1}{N_i^l} \sum_{j=1}^{N_i^l} (X_{hij} - \bar{J}_{hi})^2}$ of the H performance measures.</p> <p>$h=0, \dots, H$, X_{hij} is the simulation result of j-th replication of objective function (for $h=0$) and constraint measures (for $h=1, \dots, H$) for design i.</p> <p>Using the new simulation output, find $b = \arg \min_i \bar{J}_{0i}$ s.t. $\bar{J}_{hi} \leq c_h, \forall h \neq 0$, the non-best designs belong to the following two sets:</p> $\hat{\Theta}_o = \{i \mid i \neq b, (\bar{J}_{qi} - c_q) / s_{qi} \leq (\bar{J}_{0i} - \bar{J}_{0b}) / s_{0i}\},$ $\hat{\Theta}_F = \{i \mid i \neq b, (\bar{J}_{qi} - c_q) / s_{qi} > (\bar{J}_{0i} - \bar{J}_{0b}) / s_{0i}\}.$ <p>where $q = \arg \min_{h \neq 0} P(\bar{J}_{hi} \leq c_h) \forall i$</p> <p>Afterwards, update the noise-to-signal ratio:</p> <p>if $i \in \hat{\Theta}_F$, $\eta_i = s_{qi} / (\bar{J}_{qi} - c_q)$ if $i \in \hat{\Theta}_o$, $\eta_i = s_{0i} / (\bar{J}_{0i} - \bar{J}_{0b})$ $\eta_b = s_{qb} / (\bar{J}_{qb} - c_q)$</p>
ALLOCATE	<p>Calculate the new budget allocation, $N_1^{l+1}, N_2^{l+1}, \dots, N_k^{l+1}$, according to</p> $N_i^{l+1} = \alpha_i^{l+1} (kn_0 + (l+1)\Delta) \quad \text{given that} \quad \frac{\alpha_i^{l+1}}{\alpha_j^{l+1}} = \left(\frac{\eta_i}{\eta_j} \right)^2 \quad \text{for all } i \neq j \neq b;$ $\alpha_b^{l+1} = \max(\alpha_{ob}^{l+1}, \alpha_{fb}^{l+1}), \text{ where } \alpha_{ob}^{l+1} = s_{0b} \sqrt{\sum_{i \in \Theta_o} \left(\frac{\alpha_i^{l+1}}{s_{0i}} \right)^2} \text{ and } \frac{\alpha_{fb}^{l+1}}{\alpha_i^{l+1}} = \left(\frac{\eta_b}{\eta_i} \right)^2$ <p>for all $i \neq b$. Adjust the allocation for each design accordingly so that</p> $\sum_{i=1}^k \max(0, N_i^{l+1} - N_i^l) = \Delta.$
SIMULATE	Perform additional $\max(N_i^{l+1} - N_i^l, 0)$ simulation runs for each design $i, i=1, \dots, k; l=l+1$.
END OF LOOP	

7.4.3 Computing efficiency of OCBA-CO-GA

Due to the stochastic nature of the simulation, each possible solution needs to be simulated with multiple replications to get a reliable optimal solution. Genetic algorithm has been adopted as a searching algorithm for the optimal solution. In order to improve the computing efficiency, the algorithm of optimal computing budget allocation for constrained optimization is incorporated into the traditional GA, which named OCBA-CO-GA. The performance of combined algorithm named OCBA-CO-GA and traditional GA is presented in Figure 7-5.

Figure 7-5 The evolvement of optimal solution along the CPU time

The simulation model has been run with 1-year simulation horizon with two different optimization algorithms. Figure 7-5 presents the evolvement of the best solution along the consumed CPU-time; the result indicates that OCBA-CO-GA is more reliable than

traditional GA. OCBA-CO-GA can reach a good enough solution much faster with a given computing budget. Hence, it is a good choice when the total computing budget is very limited compared to the large solution searching space.

7.5 Model Inputs and Experimental Results

7.5.1 Model inputs

Most parameters in this model are estimated using the data in Tan Tock Seng Hospital (TTSH), the largest hospital that provides service to the greatest amount of elderly patients in Singapore. Details are elaborated in Table 7-3.

Table 7-3 Parameters of the simulation model

Measures	Distribution	Measures	Distribution
Arrival	Exponential $\lambda = 0.286$	No. of beds in AH	Determined=105
Has care giver	Bernoulli $P=0.3$ (has)	No. of beds in CH	Determined=30
Initial disease severity	Discrete probability(HS=1~9) (0.01,0.06,0.15,0.25,0.4,0.68,0.88,0.95,1)	Tolerance for deterioration	Discrete probability (ΔHS 1~3) (0.5,0.8,1)
Cost in AH/day	Determined=\$440	Cost /transition	Determined=\$10
Cost in CH/day	Determined=\$140	Cost/death	Determined=\$100000

The probability of health status transition can be estimated from historical data. Currently, historical data are not available due to authoritative concerns. Hence, the transition probability in this model is an estimation based on the doctors' experiences. But it is reliable to gain insights about the strategic planning. The details of the three transition matrices and the code of simulation model are presented in Appendix 5.

The value range of the constraints and decision variables are decided by the largest tolerances of the current system performance, as is shown in Table 7-4. The decease rate is a bit higher than the average value in the real system. Because in this study, the patients are elderly people who tend to die when suffering from a serious disease.

Table 7-4 Limits of constraints and decision variables

Constraints		Readmission rate	$X_{readmit} \leq y_{readmit} = 0.4$
		Decease rate	$X_{death} \leq y_{death} = 0.10$
		Waiting time	$X_{wait} \leq y_{wait} = 72$
Decision Variables	When	Discharged from AH when health status $\leq \alpha_{AH_D}$	$\alpha_{AH_D} \in \{0, 1, 2, 3\}$
		Maximum allowed length of stay T_{AH} in acute hospital	$T_{AH} \in \{15, 20, 25\}$
	Where	Go back home if health status $\leq \phi_{low}$	$\phi_{low} \in \{0, 1, 2, 3\}$
		Go home if patient has care giver and health status $\geq \chi_{upp}$	$\chi_{upp} \in \{5, 6, 7, 8\}$
		Go nursing home if a patient without care giver and health status $\geq \eta_{NH}$	$\eta_{NH} \in \{6, 7, 8\}$

7.5.2 Numerical results

The total number of patients in the system becomes stable after running the simulation for 1,000 hours. So the simulation model ran for 9,760 hours with 1,000 hours as warm up period. Experiments are conducted to examine the complex relationships among various factors. One example is presented: how α_{AH_D} , the minimum dischargeable health status, impacts the LOS, readmission rate, and decease rate. Other decision variables are kept unchanged during the experiments ($T_{AH} = 25, \phi_{low} = 1, \chi_{upp} = 8, \eta_{NH} = 6$). Results in Figure 7-6 indicate that the relationships between the discharge policy (minimum dischargeable health status), LOS and readmission rate are nonlinear. But there is a significant tradeoff

between LOS and readmission rate. The nonlinear relationship partially explains why readmission is so difficult to predict in the real world. When α_{AH_D} is small, the readmission rate can be high, but the deceased rate is low. A large value of α_{AH_D} would cause a high readmission rate and decrease rate. The discharge policy cannot totally control the length of stay and discharge health status of a patient. For example, a large value of α_{AH_D} would lead many patients to be discharged to community hospitals and cause a bed shortage. The shortage of beds in the community hospital would make the other dischargeable patients stay longer than they need to in the acute hospital. During the wait for step-down care, their health status in the acute hospital is updated and generally becomes smaller than α_{AH_D} when they are finally discharged.

Figure 7-6 Relationships among the discharge policy, LOS and readmission rate

The complex relationships among those factors make a simulation-based optimization necessary. Results with different optimization scopes are examined and compared. A high death penalty, with \$100,000 per death, has been added to the cost of the whole healthcare system. The solutions are shown in Table 7-5. Solution 1 is regarded as the best solution for

minimizing the total annual cost in the whole health care system and achieving the lowest cycle cost per individual patient. However, administrators of acute hospitals may prefer solution 2, as it can minimize the annual cost of acute hospitals and shorten waiting time. While doctors in acute hospital may choose solution 3, because of the comparatively low decease rate and the cheapest cost for patient in the acute hospital, which can increase patient's satisfaction.

Table 7-5 Optimal solutions

Decision variables						Constraints			Objectives: minimize cost			
	When to		Where to			Wait (hour)	Readmit	Decease	Scope: Acute hospital		Scope: whole health care system	
	α_{HSD}	T_{AH}	ϕ_{low}	χ_{upp}	η_{NH}	X_{wait}	$X_{readmit}$	X_{death}	Annual *10 ⁷ (\$)	Single *10 ³ (\$)	Annual *10 ⁸ (\$)	Single *10 ⁵ (\$)
1	2	25	1	8	6	24.8	0.2551	0.0451	1.5421	4.9908	1.6079*	0.7068*
2	3	15	1	6	6	2.3	0.2462	0.0965	1.3886*	4.6816	3.1224	1.4141
3	3	15	2	6	6	21.4	0.3881	0.0698	1.5288	4.1273*	2.8566	1.2931

For discharge time, both administrators and doctors in acute hospital would prefer to discharge the patient as early as possible (once the health status of a patient reaches a dischargeable level) to reduce overstay (discharge a patient who has stayed for more than 15 days but is still not healthy enough, which indicates low potential to recover). For the benefit of the entire healthcare system or individual patients, the best discharge policy is to discharge the patient when he or she is relatively stable and extends the maximum length of stay to 25 days to allow slow recovering patient having more time to reach a stable condition.

When it comes to discharge location, administrators in the acute hospital would prefer to discharge the maximum number of patients to the community hospitals to reduce risk. They only want the healthiest patients to go back home (whose health status value is less than 1, so the patient can recover at home by taking medicines). Patients with very low potential to recover (whose health status value is more than 6) are also discharged back home if they have a care giver or to nursing homes if they do not have a care giver. That's because administrators need to reduce the chance of bed blockage in acute hospitals. Discharging too many patients to the community hospitals will cause bed shortage there, which leads to some dischargeable patients staying at the acute hospitals much longer until beds in community hospitals are available. Doctors in the acute hospital are concerned with both the benefits of the patients and the performance of their hospitals. They tend to make less greedy decisions, discharging patients who really need the step-down care (whose health status value is between 2 to 6) to the community hospitals. For the benefits of the whole healthcare system, community hospitals should take more responsibility, and accept more patients with a wider range of health statuses (accepting patients whose health status value is between 1 to 8) to reduce the decrease and readmission rate within the system.

The performance of healthcare systems around the world has been scolded for its high cost, long waiting time, and unplanned early readmissions. Results in Table 7-5 provide explanations for such phenomena. In most healthcare systems, especially the health care system in Singapore, discharge plans and care transition decisions are made by medical staff who care most about individual patient's satisfaction in the acute hospital. Therefore, solution 3 is a dominating solution in today's healthcare system.

However, from Table 7-5, it is obvious that, shifting the focus from individual healthcare providers to the whole healthcare system not only decreases the cost per patient but also significantly improve the quality of healthcare service, which is indicated by death rate. According to the simulation results, the death rate can be dropped from 9.65% to 4.51%, with 53% decrease. While the cycle cost per each individual patient in the whole system can be dropped from \$141410 to \$70680, which is around 50% decrease, while their expenditures in acute hospital would only increase 6% from \$4681 to \$4990. The annual cost of acute hospital only increases 11% from their optimal base line. Achieving 49% saving (including the death penalty) of the whole healthcare system with 11% increase in operational cost of acute hospital is impressive. The healthcare system could provide more reimbursement to the acute hospitals to incentivize them to be more collaborative to achieve the optimal solution at the system level, so that every stakeholders can enjoy the benefits of the performance improvement of the entire healthcare system. However, in order to make better use of current healthcare resources, the healthcare system oriented solution (solution 1) may increase the average waiting time to achieve the lower death rate, lower cost and better quality. Shifting from the focus of each doctor to the whole healthcare system, (from solution 3 to solution 1) more benefits can be gained. With slightly increase in waiting time and expense in acute hospital, patient can enjoy 35% drop of readmission rate and death rate, and 45% of cost reduction in the entire healthcare system. Therefore, compared with current practice, holistic oriented solution can bring greater benefit to the individual patients and the entire healthcare system.

In fact, to respond to the challenges of an aging population, the Ministry of Health in Singapore is moving toward the solution 1 by calling for system integration, which prevents

the selfish decisions (solution 2) of individual care provider. Meanwhile, the government emphasizes the importance of care transition and upgrades some community hospitals to let them take more medical care responsibilities, treat patients with more severe diseases, rather than acting as medium-term nursing homes with low medical skills. A special institution called the Agency for Integrated Care has been set up to guide the patient flow and improve care transition. Solutions from this research provide quantitative evidence to show how discharge policy and care transition decisions can impact a health care system's performance. Though no dominated solution is found, the insights from this research can help the decision makers to act more rationally, and it can be a useful theoretical support to strategy development by government and care planners.

7.6 Summary

Public healthcare cost is rising due to aging population. This research aims at minimizing the total cost and cost per patient in the public healthcare system by balancing the length of stay and readmission rate. A discrete event simulation model of the patient flow in the whole healthcare system was developed using the MTALAB (R2009a) platform. A new method based on the Markov chain was incorporated into the simulation model to predict the length of stay and changes of health status. Complex relationships among health status, length of stay, discharge policy, care transition, and readmission were captured in the model. An optimal discharge policy (when to discharge) and care transition decisions (where to discharge) were obtained to achieve the lowest cost within different optimization scopes. The optimal solution set shows that different stakeholders in the healthcare system would prefer different solutions. Multiple criteria of the system performance were considered while

searching the optimal solution. Although no dominated solution was found, the results provide interesting insight and useful theoretical references to the care planners and decision makers.

In the future, to achieve a more practical solution, the model needs to balance the benefits of different stakeholders. In addition to cost and quality, both performance of the system and benefits to individuals should be considered when searching for the optimal discharge policy and care transition decisions. More flexibility would be needed for discharging specific patients. For instance, when the LOS of a patient reaches the maximum allowed time, the model should evaluate the risk to this patient if transferred to a different healthcare institution, rather than discharging him or her directly according to the rigid rules. Also, sensitivity analysis should be conducted in the future to test whether the changed parameters impacts the optimal solution.

Chapter 8

Conclusions

8.1 Summary of the Research

The aging population has emerged as a global trend, increasing at an unprecedented rate. Elderly people tend to be more vulnerable to the chronic diseases and need longer time to cure and recover. Hence, the demand for healthcare resources is mounting quickly. Such a situation increases the challenges for healthcare systems around the world, especially in developed countries. Functional integration of the national healthcare system has been regarded as a commendable way to respond to these challenges. Smoother care transition will play a critical role in achieving this seamless integration. Various attempts have been made to improve the care transition, but achieving consistent and smooth care transition remains a challenge due to the governance structures of the different institutions and conflicting objectives of stakeholders. Existing research on the care transition only addressed some aspects of the care transition at an operational level with few rigorous quantitative analyses.

After a review of the state of the art of healthcare system and care transition research, this research uses Singapore as a case study on how to improve care transition in public healthcare systems in response to challenges presented by an aging population. This research leverages a range of relevant systems theories and operational research methodologies. The research problem has been identified and refined with the development of the research. Soft systems methodology has been adopted as an overarching framework for the whole research;

and other methods were integrated into the framework at different stages of the research to explore potential solutions.

Applying soft systems methodology, problems of current care transition system have been identified through face-to-face interviews with medical staff of different functional roles within the healthcare system. Identified and analyzed problems have been grouped and structured according to their cause-effect relationships. Based on the structured problem expression, improving care transition plan and process has been identified as a potential solution in alleviating the current problem situation. Hence, a deeper investigation on current care transition plan and process has been conducted, and the detailed process has been mapped in a cross functional flowchart.

The needs for change in the current care transition system have been identified using the viable system model. An ‘aggregative’ care transition model has been proposed to meet the needs for change. Discrete event modeling and simulation have been adopted as a follow up to compare the ‘AS-IS’ process and the ‘TO-BE’ process. Simulation results show that the proposed ‘TO-BE’ process with ‘aggregative’ care transition model is superior to the ‘AS-IS’ process with ‘third party’ model in terms of healthcare expenditure and system accessibility. However, the superiority of the ‘TO-BE’ process, over the ‘AS-IS’ process cannot ensure the ‘TO-BE’ process is the most optimal choice, as it is developed based on qualitative analysis and may be constrained by a designer’s intuition. More rigorous methods with quantitative analysis are needed for further improvement of the care transition process by figuring out how, when, and where to discharge patients.

For how to discharge patients, a two-stage optimization approach has been proposed to decide what should be done and who should do it. The first stage of the optimization selects the participating activities from various candidate activities and determines their topological structure with the aim to obtain a feasible process that has the shortest duration time. Based on the selected activities and their topological structure, the second stage of the optimization decides who should perform each of these selected activities to ensure the best quality. The optimal solutions of the two stages have been respectively searched with the mathematical program and constraint program of the IBM ILOG CPLEX Optimization Studio V12.2. Results indicate that the optimal care transition process design from the two-stage optimization approach is consistent with the ‘aggregative’ care transition model proposed in Chapter 5.

To further smooth the care transition process, this research provides decision support for when and where to discharge patients. A simulation model of patient flow at the system level has been developed to capture the correlations between disease severity, length of stay (LOS), health status, discharge policy, care transition decision, and readmission. A finite state discrete Markov chain has been adopted to represent the dynamics of change in health status of a patient at different stages. The optimal solution has been searched by balancing the tradeoff between the length of stay (LOS) and readmission rate. The objective is to minimize cost without impairing other performance measurements. Different optimization scopes have been considered and compared. Optimal computing budget allocation (OCBA-CO) has been incorporated into the Genetic algorithm (GA) to improve computing efficiency. The optimal solution set indicates that different stakeholders would prefer

different solutions according to their own objectives. Also to reduce the system costs and cycle cost per patient, community hospitals should take on more responsibilities.

8.2 Practical Implications and Theoretical Contributions

This research has systemically investigated the current status of care transition in the public healthcare system in Singapore. With a holistic view, it has opened a new level of understanding and introduced fresh thinking to the existing problems in care transition. The new care transition model, the two stage optimization approach for process design, and the decision support mechanism for patients discharge which are proposed by this research would be able to assist care providers to transfer needy elderly patients within the healthcare system more smoothly. This would further enable the current system to care for more patients with better care quality at a lower cost. Though the study has been conducted in the context of Singapore, the proposed methods can be referenced by healthcare systems in other countries. This research also provides care managers and planners with a new way to tackle the complexity and messy problem in healthcare systems. Such experience can be extended to other industries, where situations are complex. The two stage optimization approach for optimal process design can be applied to other business process design and redesign. The decision support mechanism for when and where to discharge patients can also be applied to other situations, where patient transfer is needed, for example, from an intensive care unit in the emergency department to the general wards.

In addition to bringing fresh thinking to the existing problems in care transition with a holistic view, this research also provides healthcare planners and researchers with a multi-method framework named soft systems methodology-multi-method framework (SSM-M), a

more rigorous framework extended from SSM. In fact, though soft OR has been around for 40 years, its impact is still frequently overlooked by the OR society due to the subjective nature of the ‘soft’ modeling. It yields insights rather than testable results, implying imprecision and lack of rigor. However, hard OR also has some limitations and frequently been criticized as mathematically sophisticated but contextually naive tool (Ackermann, 2011). The endeavor of this research shows the possibility of freedom for researchers and practitioners to use the mix-method and leverage the complementary advantages of multiple methods in an informed and effective manner without being confined to a particular method or paradigm.

This research can be regarded as ‘pragmatic’ or ‘eclectic’ science. The choice of methods, tools and techniques is situationally responsive, with a synthetic and holistic approach. Soft systems methodology (SSM) has been adopted as an overarching framework. Multi-disciplinary theories and methodologies have been integrated into the framework at different stages of the research to effectively address the problem.

The theoretical contributions of this research can be summarized as: Firstly, this research revealed that SSM is much more than a problem structure tool or a complementarity to hard OR methods. It is a very useful overarching methodology, which needs to be combined with other tools in a flexible and creative way adjust to different scenarios. The SSM-M framework, extended from SSM by leveraging the strengths of multiple methods, provides a more comprehensive and rigorous framework to address the complex issues. Secondly, this research developed a simulation model of the patient flow at the system level, while existing research has primarily focused on individual institutions. This model captured the nonlinear relationships of health status, length of stay, readmission, discharge policy, and care

transition decision. Thirdly, a new method was proposed to estimate the length of stay by adopting a finite state discrete Markov chain to represent system dynamics and to capture the transition of a patient's health status during their residence in the healthcare system. Fourthly, this research adopted an algorithmic approach for optimal process design based on the two-stage optimization, while most business process reengineering methods are still description-oriented without any rigorous mathematical model.

All in all, taking care transition in Singapore as a subject of interest, this research developed a better care transition process model, a two stage optimization approach for optimal care transition process design, and a decision support mechanism on when and where to transfer the patient, with a proposed systemic approach named soft systems multiple methods framework (SSM-M). The proposed methods and framework would not only be useful guidelines and tools for achieving smoother care transition in public healthcare system, but can also be widely applicable approaches to complex problems in many other domains. Therefore, the research objectives have been successfully accomplished.

8.3 Possible Extensions

As mentioned in section 6.4, the two-stage optimization approach for optimal process design in this research assumes that the processing time of different staff (roles) of a specific task is equal to a pre-decided constant. In future models, queuing theory and stochastic processing time with heterogeneous distribution of different roles on a specific task will be adopted to capture the dynamics of the process during the second stage of the optimization. In addition, the future model will consider the varied numbers of different types of medical staff.

The model presented in chapter 7 assumes that when and where to discharge patients only depend on critical factors such as the health status and care givers. In reality, the discharge of a patient is decided by a complex process with interactions between multiple stakeholders. Hence, more sophisticated models will be proposed to further smooth the care transition process in the future. Agent-based simulation model would construct a better matchmaking mechanism that would accelerate the process and improve service quality. Despite this effort, some high risk patients may still not be able to find a matched service provider for next stage care, because community hospitals may reject high risk patients to avoid the potential financial risk. To solve this problem and achieve the optimal results at the system level, community hospitals should accept higher risk patients by sharing the risk with the acute hospitals. However, as autonomous institutions, both community hospitals and acute hospitals aim at maximizing their own benefits or payoffs according to their specific decision rules. Therefore, a co-adaptive risk sharing strategy for care transition will be developed in the future, as it is critical to reach a win-win situation for all parties and to further smooth care transition.

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Appendix 1: Detail Modules of Arena Models

The modules of current ‘third party’ care transition model of Arena are shown in Figure A-1, Figure A-2, and Figure A-3, Figure A-4 respectively. And modules of proposed ‘aggregative’ model are presented in Figure A-5, Figure A-6, and Figure A-7, Figure A-8 respectively. The corresponding pseudo code of these modules is attached in Appendix 2.

Figure A-1 Module 1 and Module 2 of current 'third party' model

Figure A-2 Module 3 of current 'third party' model

Figure A-3 Module 4 of current 'third party' model

Figure A-4 Module 5 of current 'third party' mode

Figure A-5 Module 1 and Module 2 of proposed 'aggregative' model

Figure A-6 Module 3 of proposed 'aggregative' model

Module 4: Care Transition to Community Hospital of Process

Figure A-7 Module 4 of proposed 'aggregative' model

Module 5: Patients' Transition to Nursing Home of Proposed Process

Figure A-8 Module 5 of proposed 'aggregative' model

Appendix 2: Pseudo Code of the Arena Models

The words underlined represent each element of the modules that has been presented in Appendix 1. The words shown in italics are explanations.

- **Code of Module 1: Patient Admission**

- Create arrivals of patient who needs admission**

- Arrival rate: Random (Expo) =3.5hour

- Record number of patients who need admission**

- Assign entity attributes of arrival time and tolerance waiting time**

- Attribute: Arrival time =TNOW,

- Balk Tolerance=MIN (MAX (norm (7, 2), 0), 12)

- // Tolerance of number of peoples in queue ahead*

- Check Bed Availability // Decide Module**

- If

- NR (Bed in AH) < MR (Bed in AH) //Bed available in Acute hospital

- Record Number of Patient Admitted without waiting**

- Else if

- NR (Bed in AH) == MR (Bed in AH) && NQ (Seize bed in AH.Queue) <= Balk Tolerance *// Bed is not available, but patient will choose to wait*

- Assign Variables**

- Variable: Patient Total Waiting Time=

- Patient Total Waiting Time+ (TNOW - Arrival Time)

- NO of Waiting patient=NO of Waiting patient +1

- Else *//Bed is not available and patient cannot wait*

- Assign Entity Type of Patient**

- Entity Type= Rejected Patient**

- Record number of rejected patient**

- Dispose Patient**

Size Bed in AH // rejected patient won't size bed

Assign Variables and attributes of admitted patient

Entity type=Admitted Patient

Attribute: Admitted Time=TNOW,

Estimated LOS in AH=Estimated LOS=TRIA (120,255,310)

// Estimated LOS is an expression TRIA (120,255,310)

Variable: Total Admitted Patient=Total Admitted Patient+1

Check how many admitted patient is waiting longer than 5 hours

// use decide module with expression

If Expression: (TNOW - Arrival Time) >5

Record Number of admitted patient waiting longer than 5 hours

Else

Record Number of admitted patient within normal waiting time

Delay to wait nurses' initial classification, whether patient has care giver or not

Delay time =Time Delay for Classification=UNIF (6, 48)

Check patient with Care giver or not // decide module, decide 2 way by Chance

48% patient has care giver // go to Module 2

52% patient doesn't have care giver // go to Module 3

• **Code of Module 2: Stay and Discharge of Patient with Care Giver**

// Check patient with Care giver or not // decide module, decide 2 way by Chance

// 48% patient has care giver // go to Module 2

// 52% patient doesn't have care giver // go to Module 3

Assign variables, entity type of patient with care giver

Entity Type=C_Patient // patient with care giver

Variable NO of C_Patient=NO of C_Patient+1 // number of patient with care giver

Delay to receive treatment in acute hospital

Delay time =Acutal LOS=Estimated LOS+NORM(1,10)

// Acutal LOS is an expression

Check whether patient is overstayed? // decide module with expression

If

Acutal LOS>Estimated LOS // There is overstay

Assign Variables of Overstay

Variable NO of Overstay by C_Patient=NO of Overstay by C_Patient+1

Total Overstay of C_patient=Total Overstay of C_patient

+MAX((TNOW - Admitted Time)-Estimated LOS in AH,0)

Else // do nothing

Release Bed in AH // C_patient has been discharged back to home

Record average actual Length of stay of patient with care giver in AH

// Time interval with attribute admitted time

Dispose Admitted C Patient

• **Code of Module 3: Patient's Next Stage Institutions Preference Checking**

// Check patient with Care giver or not by nurse

// 48% patient has care giver // go to Module 2

// 52% patient doesn't have care giver // go to Module 3

Assign variable of patient without care giver

NO of NC_Patient=NO of NC_Patient+1 // number of patient without care giver

Process: care coordinator communicate with patient or family member

// to collect initial social economic information

Process time =TRIA(0.5,1,2)

Action=seize delay release

Resource: Seize resource set of care coordinator and save Care Coordinator Index

Delay for Family Decision

// suggestion of next institution has been propose by discharge meeting

Delay time =UNIF(24, 96)

Process: Care coordinator collected related reports

Process time =TRIA(0.5,1,1.5)

Action=seize delay release

Resource: Seize resource set of care coordinator

And select specific member with set index= Care Coordinator Index

Delays to wait all the reports are ready

// sometimes when care coordinator request for report, it may be not ready.

Delay time=TRIA (5, 24, 48)

Decision to transfer patient to CH or NH // 2-way by chance

50% of patient prefers CH // *continued to be processed by Module 4*

50% of patient prefers NH // *Continued to be processed by Module 5*

• **Code of Module 4: Patient's Transition to Community Hospital**

//Decision to transfer patient to CH or NH

// 50% of patient prefers CH (continued to be processed by Module 4)

// 50% of patient prefers NH (Continued to be processed by Module 5)

Assign entity type of patient without caregiver and wants to be transferred to CH

Entity type=NCCH_Patient // *without care giver & want to be transferred to CH*

Delay to apply CH //

Delay time =TRIA (1, 3, 8)

// multiple tasks of care coordinators, some of which not include in the model

Process: care coordinator apply CH

Process time =TRIA (0.5, 1, 1.5)

Action=seize delay release

Resource: Seize resource set of care coordinator

And select specific member with set index= Care Coordinator Index

// need to seize same care coordinator for all related task

Delay for evaluation

Delay time= TRIA (1, 3, 5) *//other tasks of occupied time of evaluator in CH*

CH evaluate patient's rehabilitation potential and other risks

Process time=TRIA (0.5, 1, 1.5)

Delay to inform result

Delay time=TRIA(1,3,18)

// need to check resource in CH and inform in a batch

Decide whether patient will be accepted by CH // 2 way by chance

80% referred patient has potential

Seize bed in CH

Delay: wait to be stable enough to transfer in CH

Delay time=MAX (Estimated LOS in AH-(TNOW-Admitted Time),0)

20% patient was rejected by CH

Assign variable and entity type of NCCH Patient Rejected

Variable: NO of Rjected NCCH_Patient=NO of Rjected NCCH_Patient+1

Entity type=NCCH_Patient Rejected

// patient who has no care giver and wants to be transferred to CH but rejected

Delay to Find Optional Way

Delay time=TRIA (24, 72,120)

Release bed in CH *// patient leaves acute hospital*

Assign attribute of length of stay of NCCH Patient

NCCH_Patient LOS in AH=TNOW - Arrival Time

Decide: Check whether patient have been overstay *// 2 ways by condition*

If NCCH_Patient LOS in AH - Estimated LOS in AH > 0 *// there is overstay*

Assign vaiables of NCCH Patient Oversty in AH

Variable: NO of NCCH_Patient Overstay=NO of NCCH_Patient Overstay+1

NCCH_Patient Oversty in AH=NCCH_Patient Oversty in AH

+ MAX(NCCH_Patient LOS in AH-Estimated LOS in AH,0)

Else *// do nothing*

Decide Patient Type *// whether patient have sized bed in CH (2ways by condition)*

If

Entity type==NCCH_Patient Rejected *// Patient rejected by CH*

Dispose patient

Else *// patient has seized a bed in CH*

Delay; Patient stay in CH *// recover in CH until discharge*

Delay time=TRIA (240,480,600)

Release bed in CH *// leave CH*

Dispose patient *// share the same dispose module*

- **Code of Module 5: Patient's Transition to Nursing Home**

//Decision to transfer patient to CH or NH

// 50% of patient prefers CH (continued to be processed by Module 4)

// 50% of patient prefers NH (Continued to be processed by Module 5)

Assign attribute and entity type of patient will be transferred to nursing home

Attribute: Estimated LOS in AH=TRIA (120,255,310)

Entity type=NH Patient

Delay for social worker to handle

//suppose the transfer of case from cc to SW needs time

Delay time=TRIA (48, 96, 120)

Process: Social worker apply Nursing home

Action=seize delay release

Process time=TRIA (0.5, 1, 1.5)

Delay: Wait for AIC's evaluation

Delay time=TRIA (24, 36, 48)

// including the delay for handle and delay for related proof collected

Process: AIC Evaluation Patient Qualification

Action=seize delay release

Process time=TRIA(2,5,10)

Decide applicant is qualified for VWOs NH or not // 2way by chance

75% qualified

25% rejected

If patient qualified

Delay to check bed availability in Nursing home

Delay time=TRIA(0.5,0.75,1) *// suppose AIC check bed availability at fixed time*

Decide Bed available@ NH?

if NR(Bed in NH) < MR(Bed in NH) *// Bed available*

Seize bed in NH

ELSE

Decide: Check length of waiting time //2way by chance

25% will wait for long time

If patient will not wait for long time

Seize bed in NH

Assign entity type of patient will go to NH

Entity type=NH_Accepted Patient *//after seized a bed*

Delay to be stable to NH

Delay time=MAX(Estimated LOS in AH-(TNOW-Admitted Time),0)

Record length of stay of NH accepted patient

Else //patient wait for long time transfer to BSC

Assign entity type of NH Accepted but go to BSC patient

Entity type=NH_BSC Patient

Delay for social worker to apply BSC

Delay time=TRIA(24,48,105)

// AIC inform the result at fix time, social worker may also be occupied by other tasks

Process: Social worker apply BSC

Action=seize delay release

Process time=TRIA (0.5, 1, 1.5)

Delay to confirm // BSC people need time to evaluate

Delay time= TRIA (24, 32, 48)

Delay to Transfer

Delay time= MX(Estimated LOS in AH-(TNOW-Admitted Time),0)

Record BSC_Patient LOS // length of stay in AH of patient transfer to BSC

Else // Patient not qualified for VWO NH

Delay to inform the result

Delay time=TRIA (20, 48,120)

Assign entity type and variable

Entity type=NCCH_Patient Rejected

Variable: NO of Rejected NH_Patient+1

Delay to find optional way for rejected patient

Delay time=TRIA(48,89,150)

Delay to be stable enough for transfer

Delay time=MAX(Estimated LOS in AH-(TNOW-Admitted Time), 0)

Record rejected patient's length of stay

Assign Variable of total overstay

NH_Patient Overstay in AH=NH_Patient Overstay in AH+MAX ((TNOW-Admitted Time)-Estimated LOS in AH, 0)

Release bed in AH

Decide: check Patient's type

If entity type=NH_Accepted Patient // *go to nursing home*

Delay: recover in nursing home

Delay time=TRIA (400, 876, 1314)

Release bed in NH

Else if entity type=NH_BSC Patient

Process: wait in BSC of NH bed

Action=seize delay release

Process time=TRIA (240, 960, 1960)

Else // *do nothing*

Dispose Patient

Appendix 3: OPL Model for the First-Stage Optimization

```

/*****
 * OPL 12.2 Model
 * Author: Administrator
 * Creation Date: Feb 25, 2011 at 9:06:21 PM
 *****/

int ActivityType=...;
int GInputType=...;
int GoutputType=...;
int GInputInform=...;
int M=9999;
int ResourceType=...;
int ResourceProduce[1..ActivityType][1..ResourceType]=...;
int ActivityInput[1..ActivityType][1..ResourceType]=...;
int GoutputR[1..ResourceType]=...;
int GinputR[1..ResourceType]=...;
float Activityduration[1..ActivityType]=...;

dvar int+ ActivityControl[1..ActivityType];
dvar int+ ResourceControl[1..ResourceType];
dvar int+ ActivityStartTime[1..ActivityType];
dvar int+ ResurceAvailableTime[1..ResourceType];
dvar int+ UsedActivityProduce[1..ActivityType][1..ResourceType];

/***** Obejective function*****/
minimize
max (j in ResourceType-GoutputType+1..ResourceType)
    ResurceAvailableTime[j];

/***** Constrains *****/
subject to {

forall(a in 1..ActivityType)
forall(j in 1..ResourceType)
if(ActivityInput[a][j]==1)
{ActivityControl[a]<=ResourceControl[j];}

forall(j in ResourceType-GInputType..ResourceType)
sum (a in 1..ActivityType)
ResourceProduce[a][j]*ActivityControl[a]>=ResourceControl[j];

forall(j in 1..ResourceType)
ResourceControl[j]>=GoutputR[j];

forall(a in 1..ActivityType)
forall(j in 1..ResourceType)
if(ActivityInput[a][j]==1)
{ActivityStartTime[a]>=ResurceAvailableTime[j]-M*(1-ActivityControl[a]);}

forall(a in 1..ActivityType)
forall(j in 1..ResourceType)

```

```

if(ResourceProduce[a][j]==1)
{ResourceAvailableTime[j]<=ActivityStartTime[a]+Activityduration[a]+M*(1-
ActivityControl[a]);}

forall(a in 1..ActivityType)
forall(j in 1..ResourceType)
if(ResourceProduce[a][j]==1)
{ ResourceAvailableTime[j]>=ActivityStartTime[a]+Activityduration[a]-M*(1-
ActivityControl[a])-M*(1-UsedActivityProduce[a][j]);}

forall(a in 1..ActivityType)
forall(j in 1..ResourceType)
UsedActivityProduce[a][j]<=ActivityControl[a];

forall(a in 1..ActivityType)
forall(j in ResourceType-GInputType..ResourceType)
if(GinputR[j]==0)
sum(a in 1..ActivityType:ResourceProduce[a][j]==1)
UsedActivityProduce[a][j]>=1-M*(1-ResourceControl[j]);

forall(a in 1..ActivityType)
ActivityControl[a]>=0;
forall(a in 1..ActivityType)
ActivityControl[a]<=1;

forall(a in 1..ActivityType)
forall(j in 1..ResourceType)
UsedActivityProduce[a][j]>=0;

forall(a in 1..ActivityType)
forall(j in 1..ResourceType)
UsedActivityProduce[a][j]<=1;}

```

Appendix 4: OPL Model for the Second-Stage Optimization

```

/*****
 * OPL 12.2 Model
 * Author: Administrator
 * Creation Date: Sep 25, 2011 at 9:38:55 PM
 *****/

using CP;
int NbStaff = ...;
int NbPatient = ...;
range Patient= 1..NbPatient;

int Deadline = ...;

{string} Staff = ...;

{string} Tasks = ...;

int Durations[Tasks] = ...;

tuple Skill {
    string staff;
    string task;
    int    level;
};
{Skill} Skills = ...;

tuple Precedence {
    string pre;
    string post;
};
{Precedence} Precedences = ...;

dvar interval tasks [h in Patient][t in Tasks] in 0..Deadline size
Durations[t];
dvar interval wtasks[h in Patient][s in Skills] optional;

execute {
    cp.param.FailLimit = 30000;
}

maximize sum(h in Patient, s in Skills:s.task!="joint") s.level *
presenceOf(wtasks[h][s])+45;
subject to {

    startOf(tasks[1]["joint"])==startOf(tasks[2]["joint"]);
    startOf(tasks[2]["joint"])==startOf(tasks[3]["joint"]);
    startOf(tasks[3]["joint"])==startOf(tasks[4]["joint"]);
    startOf(tasks[4]["joint"])==startOf(tasks[5]["joint"]);

```

```

forall(h in Patient) {

  forall(p in Precedences)
    endBeforeStart(tasks[h][p.pre], tasks[h][p.post]);

  forall(t in Tasks)
    if(t=="joint")
    {sum(s in Skills: s.task=="joint")presenceOf(wtasks[h][s])==NbStaff;
  forall(s in Skills: s.task=="joint")
    {startOf(wtasks[h][s])==startOf(tasks[h][t]);
    endOf(wtasks[h][s])==endOf(tasks[h][t]);}}
    else
      alternative(tasks[h][t], all(s in Skills: s.task==t&& s.level>0)
wtasks[h][s]);

}

forall(w in Staff)
  noOverlap(all(h in Patient, s in Skills:
s.staff==w&&s.task!="joint") wtasks[h][s]);
};

```


Appendix 5: MATLAB Code for the Simulation Model in Chapter 7

```
The optimization algorithm of OCBA-CO-GA
The simulation model of care transition process
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
for aa=2: maxgeneration
    btime=cputime;
    ctime=btime-a_time;
    g_rep=sum(Rep_Num);
    T_rep=T_rep+sum(Rep_Num)
    perform_store(aa-1,:)=[Selected_Chrom,Best_fit,ctime,Best_Rep];
    global_store(aa-1,:)=[global_Chrom,Gloable_min,ctime,T_rep];
    if Best_feas>0
        feas_store(aa-1,:)
        =[Best_feas_Chrom,Best_feas,ctime,Best_feas_Rep]
        global_best_feas_store(aa-1,:)
        =[Gloable_bestf_Chrome,Gloable_bestf,ctime,T_rep];
    end
    xlswrite('ocba_ga_perform13.xlsx',perform_store);
    xlswrite('ocba_ga_feas13.xlsx',feas_store);
    xlswrite('ocba_ga_global13.xlsx',global_store);
    xlswrite('ocba_ga_g_best_feas.xlsx',global_best_feas_store);
    Temp_SYSCost=zeros(pop_size,Rep_no);
    Temp_readm=zeros(pop_size,Rep_no);
    Temp_death=zeros(pop_size,Rep_no);
    Temp_wait=zeros(pop_size,Rep_no);
    newpop=zeros(pop_size,Chromlen);
    FesPop=[];
    TemFit=[];
    Fes_Rep=[];
    Best_feas_Rep=0;
    for i=1:pop_size
        Num_Parent=2;
        Parent_index=zeros(1,Num_Parent);
        for k=1:Num_Parent
            Wheel_pos =rand()*Sumfit;
            cusumfitness=0;
            a=1;
            while(a<=pop_size&&cusumfitness<Wheel_pos)
                cusumfitness=cusumfitness+AFitness(a);
                a=a+1;
            end
            Parent_index(k)=a-1;
        end
        Parent1=pop(Parent_index(1),:);
        Parent2=pop(Parent_index(2),:);
        randcross=rand;
        if randcross<cross_ratio
            newpop(i,:)=round(randcross*Parent1+(1-randcross)*Parent2);
        else
            newpop(i,:)=Parent1;
        end
    end
end
```

```

mutate=rand(1,Chromlen)<mutation_ratio;
for j=1:Chromlen
    if mutate(j)==1
        c=rand;
        if c>0.5
            newpop(i,j)=newpop(i,j)-Increment;
            newpop(i,2)=newpop(i,2)-Increment*5;
            if newpop(i,j)<lov(j)
                newpop(i,j)=lov(j);
            end
        elseif c<=0.5
            newpop(i,j)=newpop(i,j)+Increment;
            newpop(i,2)=newpop(i,j)+Increment*5;
            if newpop(i,j)>upv(j)
                newpop(i,j)=upv(j);
            end
        end
    end
end
tenp1=newpop(i,1);
tenp2=newpop(i,2);
tenp3=newpop(i,3);
tenp4=newpop(i,4);
tenp5=newpop(i,5);
if tenp1>3
    tenp1=3;
elseif tenp1<0
    tenp1=0;
end
if tenp2>25
    tenp2=25;
elseif tenp2<15
    tenp2=15;
else
    tp=round(tenp2/5)*5;
    tenp2=tp;
end
if tenp3>tenp1
    tenp3=tenp1;
elseif tenp3<0
    tenp3=0;
end
if tenp4>8
    tenp4=8;
elseif tenp4<5
    tenp4=5;
end
if tenp5>8
    tenp5=8;
elseif tenp5<6
    tenp5=6;
end
newpop(i,1)=tenp1;
newpop(i,2)=tenp2;
newpop(i,3)=tenp3;
newpop(i,4)=tenp4;
newpop(i,5)=tenp5;

```

```

for j=1: Rep_no
[DischargedNO,AVWaitAH,AHSumCost,AHSingleCost2,TotalCOST2,Singl
eCost3,TotalCOST,SingleCost2,ReAdR,DeathR,AVLOSAH]=
    CareTransitionModel(tenp1,tenp2,tenp3,tenp4,tenp5);
    Temp_SYSCost(i,j)=TotalCOST2;
    Temp_readm(i,j)=ReAdR;
    Temp_death(i,j)=DeathR;
    Temp_wait(i,j)=AVWaitAH;
    Throughput1(j)=DischargedNO;
end
Fitness_SYSCost(i)=
max(0,mean(Temp_SYSCost(i,Temp_SYSCost(i,:)>0)));
C_readm(i)=max(0,mean(Temp_readm(i,Temp_readm(i,:)>0)));
C_death(i)=max(0,mean(Temp_death(i,Temp_death(i,:)>0)));
C_wait(i)=max(0,mean(Temp_wait(i,Temp_wait(i,:)>0)));
St_Cost(i)=
max(0.0000001,std(Temp_SYSCost(i,Temp_SYSCost(i,:)>0)))
St_readm(i)=max(0.0000001,std(Temp_readm(i,Temp_readm(i,:)>0)));
St_death(i)=max(0.0000001,std(Temp_death(i,Temp_death(i,:)>0)));
St_wait(i)=max(0.0000001,std(Temp_wait(i,Temp_wait(i,:)>0)));
M_readm(i)=max(0,(C_readm(i)-ReadT)/St_readm(i))
M_death(i)=max(0,(C_death(i)-DeathT)/St_death(i));
M_wait(i)=max(0,(C_wait(i)-WaitT)/St_wait(i));
M_constrain(i)=max([M_readm(i),M_death(i),M_wait(i)]);
end
Fitness=Fitness_SYSCost
[Best_fit,index] = min(Fitness);
Primili_min=Best_fit;
Selected_Chrom=newpop(index,:)
T=pop_size*Rep_no;
Rep_Num(1:pop_size)=Rep_no;
L=1;
tem_pro=[];
M_Object=zeros(pop_size);
while Best_feas_Rep < M_rep
    FesPop=[];
    TemFit=[];
    Fes_Rep=[];
    for i= 1:pop_size
        if i~=index
            M_Object(i)=(Fitness_SYSCost(i)-Best_fit)/St_Cost(i);
            if M_constrain(i)<=M_Object(i)
                Pro(i)=1/M_Object(i);
                tem_pro=[tem_pro,Pro(i)/(Fitness_SYSCost(i)-Best_fit)];
            else
                Pro(i)=1/M_constrain(i);
            end
        else
            Pro(i)=1;
        end
    end
    allo_r=(Pro.^2)/(Pro(1)^2);
    allo_ob=(St_Cost(index)/Pro(1))*sqrt(sum(tem_pro.^2));
    allo_fb=allo_r(index);
    allo_b=max(allo_ob,allo_fb);
    Total_allo=sum(allo_r)+(allo_b-allo_r(index));
    Allo_N=allo_r/Total_allo;

```

```

Allo_N(index)=allo_b/Total_allo;
T=pop_size*Rep_no+L*increM;
Allo_N_N=Allo_N*increM ;
Allo_crement=max(round(Allo_N*increM), 0);
L=L+1;
for i = 1:pop_size
    if Allo_crement(i)>0
        p1=newpop(i,1);
        p2=newpop(i,2);
        p3=newpop(i,3);
        p4=newpop(i,4);
        p5=newpop(i,5);
        for j=Rep_Num(i): Rep_Num(i)+Allo_crement(i)
[DischargedNO,AVWaitAH,AHSumCost,AHSingleCost2,TotalCOST2,SingleCost3,Tot
alCOST,SingleCost2,ReAdR,DeathR,AVLOSAH]=
        CareTransitionModel(p1,p2,p3,p4,p5);
        Temp_SYSCost(i,j)=TotalCOST2;
        Temp_readm(i,j)=ReAdR;
        Temp_death(i,j)=DeathR;
        Temp_wait(i,j)=AVWaitAH;
        end
        end
        Fitness_SYSCost(i)=
        max(0,mean(Temp_SYSCost(i,Temp_SYSCost(i,:)>0)))
        C_readm(i)=max(0,mean(Temp_readm(i,Temp_readm(i,:)>0)));
        C_death(i)=max(0,mean(Temp_death(i,Temp_death(i,:)>0)));
        C_wait(i)=max(0,mean(Temp_wait(i,Temp_wait(i,:)>0)));
        St_Cost(i)=
        max(0.0000001,std(Temp_SYSCost(i,Temp_SYSCost(i,:)>0)));
        St_readm(i)=max(0.0000001,std(Temp_readm(i,Temp_readm(i,:)>0)));
        St_death(i)=max(0.0000001,std(Temp_death(i,Temp_death(i,:)>0)));
        St_wait(i)=max(0.0000001,std(Temp_wait(i,Temp_wait(i,:)>0)));
        M_readm(i)=max(0,(C_readm(i)-ReadT)/St_readm(i));
        M_death(i)=max(0,(C_death(i)-DeathT)/St_death(i));
        M_wait(i)=max(0,(C_wait(i)-WaitT)/St_wait(i));
        M_constrain(i)=max([M_readm(i),M_death(i),M_wait(i)]);
        Rep_Num(i)=Rep_Num(i)+Allo_crement(i);
        if (C_readm(i)<ReadT && C_death(i)<DeathT && C_wait(i)<WaitT)
            FesPop=[FesPop;pop(i,:)];
            TemFit=[TemFit,Fitness_SYSCost(i)];
            Fes_Rep=[Fes_Rep,Rep_Num(i)];
        end
    end
    Fitness=Fitness_SYSCost;
    [Best_fit,index] = min(Fitness);
    Primili_min=Best_fit;
    Selected_Chrom=newpop(index,:);
    if ~isempty(TemFit)
        [Best_feas,index2] = min(TemFit);
        Best_feas_Chrom=FesPop(index2,:);
        Best_feas_Rep=Fes_Rep(index2)
    else
        Best_feas=0;
    end
end
if ~isempty(TemFit)
[Best_feas,index2] = min(TemFit);

```

```

Best_feas_Chrom=FesPop(index2,:);
Best_feas_Rep=Fes_Rep(index2);
Best_findex=index_store(index2);
Best_feas_M=mean(Temp_SYSCost(Best_findex,1:M_rep));
if Best_feas_M<Gloable_bestf
    Gloable_bestf=Best_feas_M;
    Gloable_bestf_Chrome=Best_feas_Chrom;
end
else
    Best_feas=0;
end
if Best_fit<Gloable_min
    Gloable_min=Best_fit;
    global_Chrom=pop(index,:);
    Best_Rep=Rep_Num(index)
end
for i=1:pop_size
    AFitness(i)=Gloable_min/Fitness(i);
end
Sumfit=sum(AFitness);
pop=newpop;
xlswrite('OCBA_pop.xlsx',pop);
end
b=cputime-a_time;
g_rep=sum(Rep_Num)
T_rep=T_rep+sum(Rep_Num)
perform_store(aa,:)=[Selected_Chrom,Best_fit,b,Best_Rep];
feas_store(aa,:)=[Best_feas_Chrom,Best_feas,b,Best_feas_Rep];
global_store(aa,:)=[global_Chrom,Gloable_min,b,T_rep];
global_best_feas_store(aa,:)=[Gloable_bestf_Chrome,Gloable_bestf,ctime,
T_rep];
xlswrite('ocba_ga_perform13.xlsx',perform_store);
xlswrite('ocba_ga_feas13.xlsx',feas_store);
xlswrite('ocba_ga_global13.xlsx',global_store);
xlswrite('ocba_ga_g_best_feas.xlsx',global_best_feas_store);
display('this is the end of the program, get the result from you .xlsx
file')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%the simulation function of the discharge
function
[DischargedNO,AVWaitAH,AHSumCost,AHSingleCost2,TotalCOST2,SingleCost3,T
otalCOST,SingleCost2,ReAdR,DeathR,AVLOSAH]=CareTransitionModel(P1_Ah_hs,
P2_Ah_max, P3_H_l, P4_H_P,P5_Nh);
global Arrival_Rate
Arrival_Rate=0.286;
NOAcutebed=105;
NOCHbed=30;
AHCharge=440/24;
CHCharge=140/24;
TranCharge=10;
Dthcost=100000;
b=[];
global MaxLOSAH DHSAH RadAH MaxCH DischargeLevelCH HomeMax AHhomeL
AHhomeU AHNH
MaxLOSAH=P2_Ah_max;
DHSAH =P1_Ah_hs;

```

```

AHomeL=P3_H_1;
AHomeU=P4_H_P;
AHNH=P5_Nh;
RadAH=inf;
MaxCH=30;
DischargeLevelCH=0;
HomeMax=90;
global NoInSystem NoInAH NoInCH LNoInSystem LNoInAH LNoInCH LahSever
LchSever NOLeftAHW NODiedAHW Wlimit NOBALK BalkWait PriHS QleaveList
NoInAH=0;
NoInCH=0;
NoInSystem=0;
LNoInSystem=[0 0];
LNoInAH=[0 0];
LNoInCH=[0 0];
LahSever=[0 0];
LchSever=[0 0];
NOLeftAHW=0;
NODiedAHW=0;
NOBALK=0;
BalkWait=0;
Wlimit=2;
PriHS=8;
QleaveList=[0 0 0 0];
SimuTime=9760;
global CurTime CurPatient CurEvent Eventlist
CurTime=0;
Eventlist=[0 0 0];
global NumAttribute Patient NumPatient
NumAttribute=18;
Patient=zeros(1,NumAttribute);
NumPatient=1;
global AHFreeBed CHFreebed QAHAadmit QCHBed Limit
AHFreeBed=NOAcutebed;
CHFreebed=NOCHbed;
QAHAadmit=[];
QCHBed=[];
Limit=inf;
while CurTime<SimuTime
    CurEvent=Eventlist(1,3);
    CurTime=Eventlist(1,2);
    CurPatient=Eventlist(1,1);
    Eventlist(1,:)=[];
    if CurEvent==0
        CreatPatient;
    elseif CurEvent==1
        if AHFreeBed>0
            CreatPatient;
            AHFreeBed=AHFreeBed-1;
            UpdateAHPatient(CurPatient);
            NoInAH=NoInAH+1;
            LNoInAH=[LNoInAH;NoInAH,CurTime];
        else
            CreatPatient;
            UpdateQAHAadmit(CurPatient);
        end
        NoInSystem=NoInSystem+1;

```

```

        LNoInSystem=[LNoInSystem;NoInSystem,CurTime];
elseif CurEvent==2
    if Patient(CurPatient,10)==3|Patient(CurPatient,10)==4
        AHSmoothDischarge(3);
        NoInSystem=NoInSystem-1;
        LNoInSystem=[LNoInSystem;NoInSystem,CurTime];
    elseif Patient(CurPatient,10)==2
        if CHFreebed>0
            CHFreebed=CHFreebed-1;
            AHSmoothDischarge(2);
            NoInCH=NoInCH+1;
            LNoInCH=[LNoInCH;NoInCH,CurTime];
        else
            QCHBed=[QCHBed;CurPatient];
            [Readmitag,LOS,CurHS] =
            recovertime(Patient(CurPatient,7),Limit,0,Limit,1);
            if Patient(CurPatient,7)>=10
                display('event 2')
            end
            if Readmitag~=10
                FinalrecoverT=CurTime+LOS;
                UpdateEventList(CurPatient,FinalrecoverT,5);
            else
                FinalrecoverT=CurTime+LOS;
                UpdateEventList(CurPatient,FinalrecoverT,6);
            end
        end
    end
elseif CurEvent==3
    UpCHBedRelease;
    UpdateHome(CurPatient,2,3);
    NoInSystem=NoInSystem-1;
    LNoInSystem=[LNoInSystem;NoInSystem,CurTime];
elseif CurEvent==4
    a=find(Eventlist(:,1)==CurPatient);
    Eventlist(a,:)=[];
    z=Patient(CurPatient,:);
    Patient=[Patient;z];
    Patient(NumPatient,1)=NumPatient;
    Patient(NumPatient,2)=Patient(CurPatient,2);
    Patient(NumPatient,3)=Patient(CurPatient,17);
    Patient(NumPatient,4)=CurTime;
    Patient(NumPatient,5:15)=inf;
    Patient(NumPatient,17)=0;
    Patient(NumPatient,16)=Patient(CurPatient,16);
    Patient(NumPatient,18)=Patient(CurPatient,1);
if AHFreeBed>0
    AHFreeBed=AHFreeBed-1;
    UpdateAHPatient(NumPatient);
    NoInAH=NoInAH+1;
    LNoInAH=[LNoInAH;NoInAH,CurTime];
else
    UpdateQAHAdimit(NumPatient);
end
    NumPatient=NumPatient+1;
    if Patient(CurPatient,15)==2
        UpCHBedRelease;

```

```

elseif Patient(CurPatient,15)==3
    NoInSystem=NoInSystem+1;
    LNoInSystem=[LNoInSystem;NoInSystem,CurTime];
end
elseif CurEvent==5
    x=find(QCHBed==CurPatient);
    if x>0
        QCHBed(x,:)=[];
        Patient(CurPatient,8)=CurTime;
        Patient(CurPatient,9)=0;
        Patient(CurPatient,10)=99;
        if length(QAHAdimit)==0
            AHFreeBed=AHFreeBed+1;
            NoInAH=NoInAH-1;
            LNoInAH=[LNoInAH;NoInAH,CurTime];
        else
            UpdateHSwaitAH;
        end
        UpdateHome(CurPatient,1,3);
        NoInSystem=NoInSystem-1;
        LNoInSystem=[LNoInSystem;NoInSystem,CurTime];
    end
elseif CurEvent==6
    if Patient(CurPatient,8)>CurTime
        if length(QAHAdimit)==0
            AHFreeBed=AHFreeBed+1;
            NoInAH=NoInAH-1;
            LNoInAH=[LNoInAH;NoInAH,CurTime];
        else
            UpdateHSwaitAH;
        end
        x=find(QCHBed==CurPatient);
        if x>0
            QCHBed(x,:)=[];
            Patient(CurPatient,10)=88;
        end
        Patient(CurPatient,11:17)=inf;
        Patient(CurPatient,14)=10;
        Patient(CurPatient,8)=CurTime;
        NoInSystem=NoInSystem-1;
        LNoInSystem=[LNoInSystem;NoInSystem,CurTime];
    end
elseif CurEvent==7
    UpCHBedRelease;
    Patient(CurPatient,14)=10;
    Patient(CurPatient,15:17)=inf;
    NoInSystem=NoInSystem-1;
    LNoInSystem=[LNoInSystem;NoInSystem,CurTime];
end
end
LNoInSystem=[LNoInSystem;NoInSystem,CurTime];
LNoInAH=[LNoInAH;NoInAH,CurTime];
LNoInCH=[LNoInCH;NoInCH,CurTime];
close all;
stairs(LNoInSystem(:,2),LNoInSystem(:,1),'r')
title('No of patient in the system, AH &CH ');
xlabel('red--system, green---AH,blue---CH ')

```



```

hold on;
stairs(LNoInAH(:,2),LNoInAH(:,1),'g')
hold on;
stairs(LNoInCH(:,2),LNoInCH(:,1),'b')
T=[];
T2=[];
c=0;
for i=1:400:SimuTime
b=sum(QleaveList(:,2)<=i+400);
T=[T;i,b-c];
c=b;
end
c=0;
for i=1:2000:SimuTime
b2=sum(QleaveList(:,2)<=i+2000);
T2=[T2;i,b2-c];
c=b2;
end
stairs(T(:,1),T(:,2),'k')
hold on;
stairs(T2(:,1),T2(:,2),'m')
hold on;
DischargedNO=0;
TotalstayAH=0;
TotWaitAH=0;
TotWaitAH2=0;
NOTreatCH=0;
TotalstayCH=0;
CHTotWait=0;
for i=1:NumPatient-1
    if Patient(i,8)<=SimuTime&Patient(i,1)>395
        if (Patient(i,7)~=88)
            TotalstayAH=TotalstayAH+(Patient(i,8)-Patient(i,5));
            DischargedNO=DischargedNO+1;
            TotWaitAH=TotWaitAH+(Patient(i,5)-Patient(i,4));
        end
        TotWaitAH2=TotWaitAH2+(Patient(i,5)-Patient(i,4));
    end
    if (Patient(i,14)~=88)
        if Patient(i,12)<=SimuTime&Patient(i,1)>395
            TotalstayCH=TotalstayCH+(Patient(i,12)-Patient(i,8));
            CHTotWait=CHTotWait+(Patient(i,8)-
(Patient(i,5)+Patient(i,6)))
            NOTreatCH=NOTreatCH+1;
        end
    end
end
AVLOSAH=TotalstayAH/DischargedNO;
AVAHBedU=TotalstayAH/(CurTime-Patient(396,4));
AHBedUR=AVAHBedU/NOAcutebed;
AVWaitAH=TotWaitAH/DischargedNO;
AVWaitAH2=TotWaitAH2/(DischargedNO+NODiedAHW+NOBALK);
AVQAH=TotWaitAH/(CurTime-Patient(396,4));
NOTreatCH;
AVLOSCH=TotalstayCH/NOTreatCH;
AVCHBedU=TotalstayCH/(CurTime-Patient(396,4));
CHBedUR=AVCHBedU/NOCHbed;

```

```

AVWaitCH=CHTotWait/NOTreatCH;
AVQCH=CHTotWait/(CurTime-Patient(396,4));
if Patient(i,1)>395
    ReAdR1=sum(Patient(:,15)<inf);
    SumTreat=sum(Patient(:,14)<inf)-sum(Patient(:,14)==1)-
        (NOLeftAHW+NODiedAHW+NOBALK);
    ReAdR=sum(Patient(:,15)<inf)/SumTreat;
    DeathR=sum(Patient(:,14)==10)/SumTreat;
end
AHSumCost=TotalstayAH*AHCharge;
AHSingleCost=AHSumCost/DischargedNO;
AHSingleCost2=AHSumCost/(DischargedNO-ReAdR1);
CHSumCost=TotalstayCH*CHCharge;
CHSingleCost=CHSumCost/NOTreatCH;
TotalCOST=AHSumCost+CHSumCost+TranCharge*sum(Patient(:,10)==2)+Dthcost*
    (NODiedAHW+sum(Patient(:,14)==10));
SingleCost2=TotalCOST/(DischargedNO-ReAdR1);
TotalCOST2=AHSumCost+CHSumCost+TranCharge*(sum(Patient(:,10)==2));
SingleCost3=TotalCOST2/(DischargedNO-ReAdR1);
length(QleaveList);
DeathR2=(DeathR*DischargedNO+NODiedAHW)/NumPatient;
AVHS=mean(Patient(Patient(:,7)<=88,3));

function CreatPatient
global NumPatient NumAttribute Patient CurTime Arrival_Rate
if NumPatient~=1
a=zeros(1,NumAttribute);
Patient=[Patient;a];
end
Patient(NumPatient,1)=NumPatient;
Patient(NumPatient,2)=CargiverInf;
Patient(NumPatient,3)=AdmitHS;
Patient(NumPatient,4)=CurTime+exprnd(1/Arrival_Rate);
Patient(NumPatient,5:15)=inf;
Patient(NumPatient,16)=TolerentHS;
Patient(NumPatient,17)=0;
Patient(NumPatient,18)=inf;
UpdateEventList(Patient(NumPatient,1),Patient(NumPatient,4),1);
NumPatient=NumPatient+1;
function UpdateAHPatient(PatientID)
global Patient CurTime MaxLOSAH DHSAH RadAH
Patient(PatientID,5)=CurTime;
[Patient(PatientID,14),Patient(PatientID,6),Patient(PatientID,7)]=recoverytime(
    Patient(PatientID,3),MaxLOSAH,DHSAH,RadAH,1);
if Patient(PatientID,3)>=10
display('updateAHPatient')
end
PlannedDTAH=Patient(PatientID,5)+Patient(PatientID,6);
if Patient(PatientID,14)~=10
    UpdateEventList(PatientID,PlannedDTAH,2);

Patient(PatientID,10)=Where(Patient(PatientID,2),Patient(PatientID,7));
else
    UpdateEventList(PatientID,PlannedDTAH,6);
end
function UpdateEventList(PatientID,EventTime,EventType)
global Eventlist

```

```

Eventlist=[Eventlist;PatientID,EventTime,EventType];
[Order,Index]=sort(Eventlist(:,2));
Eventlist=Eventlist(Index,:);
function x=CargiverInf
    a= rand;
    if(a<0.7)
        x=1;
    else
        x=-1;
    end
function y=TolerentHS
    a=rand;
    if(a<0.5)
        y=1;
    elseif(a>=0.5&a<0.8)
        y=2;
    else
        y=3;
    end
function b=AdmitHS
    a=rand;
    if a<=0.01
        b=1;
    elseif a>0.01 & a<=0.06
        b=2;
    elseif a>0.06 & a<=0.15
        b=3;
    elseif a>0.15 & a<=0.25
        b=4;
    elseif a>0.25 & a<=0.4
        b=5;
    elseif a>0.4 & a<=0.68
        b=6;
    elseif a>0.68 & a<=0.88
        b=7;
    elseif a>0.88 & a<=0.95
        b=8;
    else
        b=9;
    end
function Destination= Where(CareG,CurHS)
global AHomeL AHomeU AHNH
    if (CurHS<=AHomeL | (CareG==1&&CurHS>=AHomeU))
        Destination=3;
    elseif (CareG==-1&&CurHS>=AHNH)
        Destination=4;
    else
        Destination=2;
    end
function AHSmoothDischarge(NexStage)
global Patient CurTime CurPatient CurEvent Eventlist QAHAdimit
AHFreeBed MaxCH HomeMax NoInAH LNoInAH Limit
    if length(QAHAdimit)==0
        AHFreeBed=AHFreeBed+1;
        NoInAH=NoInAH-1;
        LNoInAH=[LNoInAH;NoInAH,CurTime];
    else

```

```

        UpdateHSwaitAH;
    end
    Patient (CurPatient,8)=CurTime;
    Patient (CurPatient,9)=Patient (CurPatient,7);
    if NexStage==3|NexStage==4
        UpdateHome (CurPatient,1,NexStage);
    else
        UpdateCHAdmit (CurPatient);
    end
function UpdateCHAdmit (PatientID)
global Patient CurTime CurPatient CurEvent Eventlist QAHAdimit
AHFreeBed MaxCH HomeMax
RadmitLevel=Patient (PatientID,9)+Patient (PatientID,16);
[Readmitag,LOS,CurHS] =
recovertime (Patient (PatientID,9),MaxCH,0,RadmitLevel,2);
Patient (PatientID,11)=LOS;
Patient (PatientID,12)=Patient (PatientID,8)+LOS;
Patient (PatientID,13)=CurHS;
Patient (PatientID,14)=Readmitag;
if Readmitag==10
    UpdateEventList (PatientID,Patient (PatientID,12),7);
elseif Readmitag==0
    UpdateEventList (PatientID,Patient (PatientID,12),3);
elseif Readmitag==1
    ReadmitTime=Patient (PatientID,8)+LOS;
    UpdateEventList (PatientID,ReadmitTime,4);
    Patient (PatientID,15)=2;
    Patient (PatientID,17)=CurHS;
end
function UpdateHome (PatientID,CurStage,NextStage)
global Patient HomeMax CurTime
if CurStage==1
    RadmitLevel=Patient (PatientID,9)+Patient (PatientID,16);
    [Readmitag,LOS,CurHS] =
    recovertime (Patient (PatientID,9),HomeMax,0,RadmitLevel,3);
elseif CurStage==2
    RadmitLevel=Patient (PatientID,13)+Patient (PatientID,16);
    [Readmitag,LOS,CurHS] =
    recovertime (Patient (PatientID,13),HomeMax,0,RadmitLevel,3);
end
Patient (PatientID,14)=Readmitag;
if Readmitag==1
    ReadmitTime=CurTime+LOS;
    UpdateEventList (PatientID,ReadmitTime,4);
    Patient (PatientID,15)=NextStage;
    Patient (PatientID,17)=CurHS;
end
function UpdateHSwaitAH
global Patient QAHAdimit CurTime Limit NOLeftAHW NODiedAHW Wlimit
NoInSystem LNoInSystem NOBALK BalkWait QleaveList NoInSystem
LNoInSystem AHFreeBed NoInAH LNoInAH
while size (QAHAdimit,1)>0
    BlockedPatient=QAHAdimit (1,1);
    QAHAdimit (1,:)=[];
    waitingtimeH=CurTime-Patient (BlockedPatient,4);
    waitingtimeD=
    round (waitingtimeH/24)+Patient (BlockedPatient,3)/24;

```

```

balkHSLimit=Patient (BlockedPatient,3)+Wlimit;
initialHS4TEST=Patient (BlockedPatient,3);
[Readmitag,LOS,CurHS]=

recovertime (Patient (BlockedPatient,3),waitingtimeD,0,balkHSLimit,0);
if (Readmitag==2|CurHS==10|Readmitag==1)
    Patient (BlockedPatient,6:14)=88;
    Patient (BlockedPatient,5)=
    Patient (BlockedPatient,4)+min (LOS,waitingtimeH);
    Patient (BlockedPatient,3)=CurHS;
    NoInSystem=NoInSystem-1;
    LNoInSystem=[LNoInSystem;NoInSystem,CurTime];
    QleaveList=
    [BlockedPatient,CurTime,initialHS4TEST,CurHS;QleaveList];
    if (Readmitag==2)
        NOLeftAHW=NOLeftAHW+1;
    elseif (CurHS==10)
        NODiedAHW=NODiedAHW+1;
    else
        NOBALK=NOBALK+1;
    end
    if size (QAHAdimit,1)==0
        AHFreeBed=AHFreeBed+1;
        NoInAH=NoInAH-1;
        LNoInAH=[LNoInAH;NoInAH,CurTime];
    end
    else
        Patient (BlockedPatient,3)=CurHS;
        UpdateAHPatient (BlockedPatient);
        break;
    end
end
function UpdateQAHAdimit (Patientag)
global Patient QAHAdimit CurPatient NumPatient PriHS
[QBlength,c]=size (QAHAdimit);
if Patient (Patientag,3)>=PriHS
    if QBlength>0
        B=find (QAHAdimit (:,2)<PriHS);
        if length (B)>0
            insertpoint=B(1);
        else
            insertpoint=0;
        end
        if insertpoint>1
            QAHAdimit=[QAHAdimit (1:insertpoint-1,:);
[Patientag,Patient (Patientag,3)];QAHAdimit (insertpoint:end,:)];
        elseif insertpoint==1
            QAHAdimit=[ [Patientag,Patient (Patientag,3)];QAHAdimit];
        elseif insertpoint==0
            QAHAdimit=[QAHAdimit;Patientag,Patient (Patientag,3)];
        end
    else
        QAHAdimit=[Patientag,Patient (Patientag,3)];
    end
else
    QAHAdimit=[QAHAdimit;Patientag,Patient (Patientag,3)];
end

```



```

0 0 0 0 0 0.7 0.2 0.09 0.01 0 0;
0 0 0 0 0 0 0.68 0.2 0.11 0.01 0;
0 0 0 0 0 0 0.05 0.6 0.2 0.1 0.05;
0 0 0 0 0 0 0 0 0.6 0.28 0.12;
0 0 0 0 0 0 0 0 0 0.58 0.42;
0 0 0 0 0 0 0 0 0 0 1];
Counter=0;
IniHS=HS;
while 1
    if Stage==1
        TP=TPAH;
    elseif Stage==2
        TP=TPCH;
    elseif Stage==3
        TP=TPHOME;
    else
        TP=TPCH;
    end
    chance=rand;
    Temp=TP(IniHS+1,:);
    Temp=cumsum(Temp);
    UpdatedHS=sum(Temp<=chance);
    Counter=Counter+1;
    if Stage~=3
        if(UpdatedHS<=DischargeLevel)
            if (Stage==0)
                Readmitag=2;
            else
                Readmitag=0;
                break;
            end
        end
    end
    if(Counter>=AcuteMax&&UpdatedHS~=10)
        if(Stage~=3)
            Readmitag=0;
        else
            Readmitag=99;
        end
        break;
    end

    if(UpdatedHS>=RadmitLevel&&UpdatedHS<10)
        if(Stage~=1)
            Readmitag=1;
            break;
        end
    end
    if(UpdatedHS>=10)
        Readmitag=10;
        break;
    end
    IniHS=UpdatedHS;
end
LOS=Counter*24;
CurHS=UpdatedHS;

```