MULTI-STATE MARKOV POPULATION MODEL FOR HEALTHCARE SERVICE DEMAND

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Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy.

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การศึกษาเกี่ยวกับการเปลี่ยนแปลงโครงสร้างประชากรมีความสำคัญมากเนื่องจากผู้สูงอายุมีการเติบโตอย่างต่อเนื่องทั้งในระดับประเทศและระดับนานาชาติ มีความจำเป็นต้องศึกษาถึงผลกระทบของการเปลี่ยนแปลงโครงสร้างประชากรในระยะยาว ดังนั้นการวิจัยครั้งนี้จึงมีวัตถุประสงค์เพื่อเสนอรูปแบบทางสโตแคสติกส์ สำหรับจำนวนประชากรผู้สูงอายุที่เพิ่มขึ้นที่ต้องการบริการสุขภาพ งานวิจัยนี้นำเสนอแบบจำลองประชากรหลายขั้นตอนโดยวิธีมาร์คอฟที่เปลี่ยนแปลงไปตามเวลาเพื่อคาดการณ์จำนวนประชากรและผู้ป่วยใน และเชื่อมโยง semi-Markov model เพื่อคาดการณ์ระยะวันนอนของผู้ป่วยในโดยเฉพาะเมื่อประชากรสูงอายุเพิ่มสูงขึ้นเพื่อใช้ในการประเมินทรัพยากรในโรงพยาบาลที่ต้องการเมื่อโครงสร้างประชากรที่เปลี่ยนแปลง และยังใช้ในการประเมินความต้องการในการดูแลระยะยาวของชุมชน วัตถุประสงค์ของงานวิจัยนี้ เพื่อคาดการณ์โครงสร้างประชากรและความต้องการผู้ป่วยในโดยเฉพาะผู้สูงอายุที่สูงอายุในการวางแผนสำหรับทรัพยากรเพื่อเพิ่มศักยภาพในการดูแลระยะยาว ความแตกต่างจากการศึกษาอื่น ๆ ก็คือปัญหานี้เชื่อมโยงการเปลี่ยนแปลงประชากร ความต้องการผู้ป่วยใน และความต้องการการดูแลผู้สูงอายุโดยชุมชน โดยใช้แบบจำลอง Markov และSemi-Markov model ข้อมูลจากแบบจำลองที่คาดการณ์ไว้สามารถใช้เป็นข้อมูลเบื้องต้นในการจัดการระบบการดูแลระยะยาว

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MULTI-STATE MARKOV MODEL/SEMI-MARKOV/POPULATION AGING/HEALTHCARE

The study of the change of population structure is very crucial because elderly people have grown continually in both national and international levels. It is necessary to study the impact of population aging in the long run. Therefore, this research aims to propose the stochastic models for increasing aging population who need healthcare service demand. This research applied the multi-states non-homogeneous Markov model from aggregate data for population model and combined semi-Markov model for inpatient length of stay model. The elderly population from population model was also used to evaluate community long-term care demand. The objective of the problem is to predict population structure and the inpatient demand especially, elderly planning for resource and capacity for the elderly inpatient in the long-term care. The difference of this work from other studies is the combination of institutional care and community care using Markov population model and semi-Markov model. The information from the predicted model can be used as preliminary data to manage long-term care system.

School of Industrial Engineering Student's Signature ________

Academic Year 2016 Advisor's Signature ________

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LIST OF ABBREVIATIONS

ACSC	=	Ambulatory Case Sensitive Condition
ADL	=	Activities of Daily Living
BAN	=	Best Asymptotically Normal
CI	=	Cognitive Impairment
CLTC	=	Community Long-term Care
COV	=	Covariance
CTMC	=	Continuous-Time Markov Chains
HCBS	=	Home and Community-based Services
HCC	=	Home and Community Care
ICD	=	International Statistical Classification of Diseases and Related Health Problems
ILTC	=	Institutional Long-term Care
IPD	=	Inpatients
LA	=	Elderly Who Live Alone
LF	=	Live With Family
LTC	=	Long Term Care

LIST OF ABBREVIATIONS (Continued)

ML	=	Maximum Likelihood
NLP	=	Nonlinear Programming
NHV	=	Number of hospital visits
PPS	=	Prospective Payment System
TPD	=	Total patient days
TPM	=	Transition-Probability Model
VAR	=	Variance
WLS	=	Weighted Least Square Estimation

CHAPTER I

INTRODUCTION

1.1 Background

The study of long-term care system is crucial, because elderly people have grown continually in both national and international levels. Recent medical technology makes people live longer in which the life expectancy rate increases and the mortality rate decreases. Furthermore, the fertility rate and the birth rate tend to decline due to social and cultural changes. People nowadays have longer life expectancy than those lives decades ago. These factors are main reasons for an increase of the number of elderly population. This demographic change transforms the society to be an “Aging Society”, namely, there are more than 20% of the population age more than 60 years old. The increasing of the elderly population leads to an increase in the aging dependency ratio, which impacts the economic, the social and the health situations. Considering the elderly gender ratio, statistics show that the female is about 55.1% of the total population in 2010 and it is likely to increase to 56.8% in 2040 because the female generally live longer than the male.

The rapid-growing share of the older population is mainly driven by a reduction in the fertility level, which became evident in 1980, after the declaration of the population policy aiming to promote voluntary family planning. The fertility decline has reduced the proportion of the children and thereby increased the proportion of the older-aged population. (Vipan Prachuabmoh,ed., 2013)

The change of population aging tends to increase both in Thailand, and in other countries. The patient mortality rate and the birth rate have been decreased because the medical technology has been developed continually. These two factors have affected demographic structure for the past decade. There are various studies on the impact of the population changing on the aging society that affects the medical care, the social security system, and the national government budget. In previous research, Lee (2004) presented a framework of stochastic population forecast associated with fertility and mortality which are components of the stochastic population forecast model as shown in Figure 1.1. The amount of population changes from a forecast model can be used for annual budget planning for various types of projects, including Stochastic Medicare, Stochastic Social Security, Stochastic National, Government Budget.

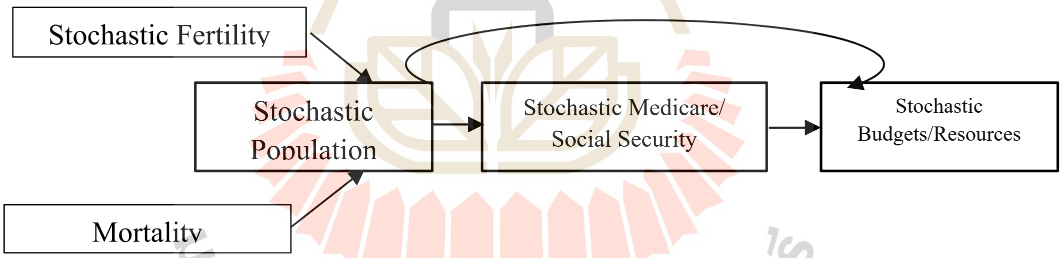


Figure 1.1 The development of demographic stochastic and fiscal stochastic forecasting framework, Source : Lee (2004)

Cornwall and Davey (2004) proposed a changing population age structure in New Zealand that has direct effect on the healthcare demand and the increase of the disability people who need healthcare service in the future. Therefore, long-term care is vital for preparing resources to prepare for the population change. Strunk, Ginsburg, and Banker (2006) studied the demographic changes of the Baby-Boom population in the United States. These changes have affected inpatient demands in the hospitals. The demographic changed were conducted using various factors including fertility rate, mortality rate, and immigration rate. This study yields healthcare demand forecasts for the years 2005-2015 for people in different age groups in order to manage manpower and service planning. There are other numerous studies in the literature that determine the population change model in order to conduct healthcare demand forecasts for manpower and service planning, for example Ehara (2011), Jim, Owens, Sanchez, and Rubin (2012) , Pallin, Espinola and Camargo (2014).

In Thailand, there is a growing trend of the elderly over the past ten years. The rapid increase of the proportion of the elderly from 2010 has changed the structure of the Thai population, which has become similar to the population structure in many developed countries. Such change has affected the social, the economic, the employment, and the resource allocation in the long run. Hence, it is necessary to provide a framework to develop a long-term care system for the elderly in Thailand. This research aims to explore relevant factors in order to develop the framework of the elderly long-term care system, by focusing on managing the resource capacity for the healthcare system in Thailand.

According to the aforementioned reasons, it is essential for any nation to have a strategy to manage and allocate resources for the elderly long-term care. In Thailand, the demographic change and the challenging issues posed by an aging society have led to the issuing of the National Plan for Elderly. The country issued the first 20-year plan for elderly care in 1982. Currently, Thailand has undergone the elderly care plan according to the 2002-2021 blueprint.

The 2nd National Plan for Elderly (2002-2021) is a long-term plan that adds to the first plan a conceptual change from a separated management system for each aspect to an integrated one. The plan comprises of five strategies, which are 1) Strategy for preparing the population for old age. 2) Strategy for promoting the elderly. 3) Strategy for a social protection system for the elderly. 4) Strategy for management of national development and personnel development for the elderly, and 5) Strategy for compiling and developing geriatric knowledge as well as monitoring and assessing the National Plan for Elderly. (Vipan Prachuabmoh, ed.,2013)

This research follows guidelines of the 2002-2021 National Plan for Elderly in Thailand as a foundation to develop a framework for the capacity and the resource planning for elderly long-term care system by incorporating quantitative method as a principal tool to propose a model and recommendation.

Population change into aging society associated with a changing body and affecting health change. Therefore, the demand for care services in hospitals and the demand of care from family and community are likely to increase. The health of the elderly can be divided into three groups according to the characteristics of activity in their daily lives:

1. Well Elderly - The elderly who are healthy and can help themselves. They are active and tend to participate in social events.

2. Home Bound Elderly - The elderly who have chronic diseases or unmanageable complications from many diseases. They can help themselves or need some help. They have limited participation in social activities.

3. Bed Bound Elderly – The elderly who have multiple chronic diseases and complications. They cannot help themselves in the daily routine.

Changes in the health of the population in each age group, especially the elderly, affect the demand for hospital services and the needs of continued care by families and communities. In particular, patients with chronic diseases also require care continually. The emerging to the aging society will increase the number of patients with different levels of chronic diseases. This will unavoidably increase the demand for healthcare services, especially at the hospitals.

Most research in healthcare focus mostly on planning and scheduling. There are not many studies in the literature exploring the long term care planning using operations research methodology. However, there are few studies in capacity and resource planning for long-term care by using operations research. For instance, the methodology of demand planning for long-term care by a simulation Model based on a Markov cycle tree is proposed by Cardoso, Oliveira, Barbosa-Póvoa, and Nickel (2012) to predict the needs of each service and resource requirement. In addition, Lin, Kong, and Lawley (2012) have developed compartment model to simulate the flow of population, with the goal of reducing the cost of long-term care plan to minimize. It is found that the Markov process is appropriate to solve the long-term care problem because of the uncertainty of the demand.

1.2 Problem Definition

Past research shows that healthcare demand in hospitals and elderly long-term care were studied separately, which may not reflect realistic outlook for holistic resource planning. Therefore, this study incorporated the number of population, the annual inpatient demand for all age groups and the elderly long-term care demand into the study model as shown in Figure 1.2

The component of population structure consists of current population in each age, gender group, birth rate, mortality rate and net-migration. The inpatient demands are separated by age groups, gender and chronic, non-chronic and ambulatory care sensitive conditions (ACSC) when population structure changes to the elderly. Relevant factors for the study of elderly population for long-term care are age, gender, chronic/non-chronic, level of dependency and household composition. The inpatient demand affects length of stay (LOS) and annual inpatient days which are important data to providing hospital beds and healthcare staff. The community long-term care demand use to evaluate number of staff especially caregiver in community or patient homes.

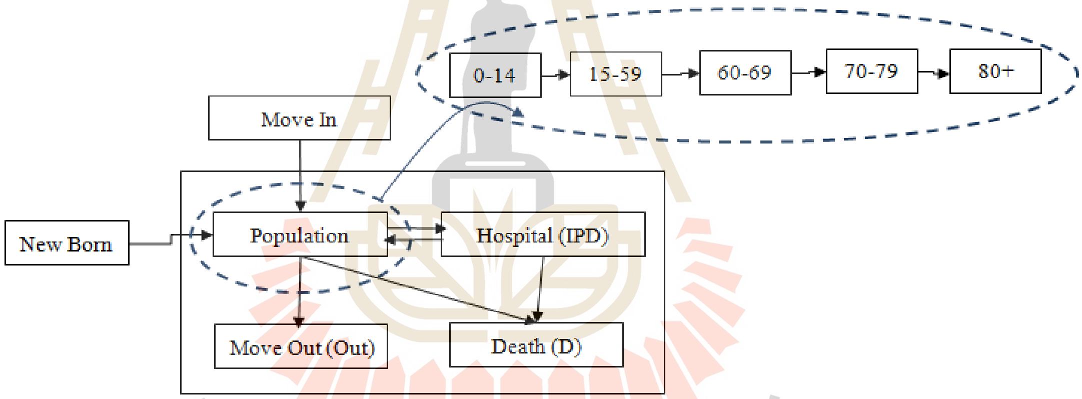


Figure 1.2 The combine of population structure and inpatient demands

The change of population is an uncertain situation so it is necessary to develop a stochastic model in this research. This study applies the multi-states non-homogeneous Markov model from aggregate data for population model and combine with semi-Markov model for inpatient length of stay model. The elderly population from population model also use to evaluate community long-term care demand. The length-of stay result and community long-term care demand used to allocate resources such as the number of beds, the number of medical staffs and formal/informal caregivers. The statistical method analyzes multinomial logit model of Markov chain (Anderson and Goodman, 1957). The asymptotic covariance matrix of weighted least square estimation uses to calculate transition probability of each state for population model.

1.3 Research Objectives

In this research the following objectives will be fulfilled:

1. To propose a stochastic model for population aging with healthcare service demand incorporated.
2. To evaluate the trends of population in each age group and their impacts on the resource planning in the long-run

1.4 Scope of the Study

To accomplish these objectives, the following issues will be considered.

1. The study focuses on the changes of population structure, inpatient demand and long-term care demand for the next 10 years, from 2015-2025 using population data in Nakhon Ratchasima, Thailand as a case study. The forecasted demands will be used to assess the capacity and resource planning for the elderly long-term care.
2. All relevant data used in this study were collected from the healthcare facilities in Nakhon Ratchasima, Thailand.
3. The aggregate historical population information was used to evaluate transition probability function for population model. A sample of individual information from individual database was investigate length-of stay demand of the inpatient model.

4. The resources focus on this research compose of beds and medical staff for inpatient model and informal/formal caregiver for community long-term care

1.5 Basic Assumptions

The basic assumptions of this research are:

1. The change of population structure consists of the following factors birth, morality, net migration, current population
2. The population compose of 5 age groups: (i) ages 0-15 years (child), (ii) ages 16-59 years (working-age), (iii) ages 60-69 years (beginning elderly), (iv) ages 70-79 years (middle elderly) and (v) ages 80 or more (oldest elderly). The gender factor is also the component for each age group.
3. The population change annually. Some of population transfer to next age group by using the transition probability between groups.
4. The change of population can transfer to three inpatient groups by type of chronic disease : (i) chronic (ii) non-chronic (iii) ACSC.
5. The population can be categorized into four age groups ; (i) childhood, (ii) working-age group, (iii) beginning elderly group, (iv) middle elderly group at the beginning of each year can transfer to 9 states as lists below;

   (1)-(3) The population in the each age group in previous year transfer to population in the same age group, the next age group and death in next year

   (4)-(6) The population in the each age group in previous year transfer to 3 inpatient group in the same age group in next year.

   (7)-(9) The population in the each age group in previous year transfer to 3 inpatient groups in the next age group in next year.

6. The population in the oldest elderly group at the beginning of year n can transfer to 5 states as

   (1)-(2) The population in the oldest elderly group in previous year transfer to population in the same age group and death in next year.

   (3)-(5) The population in the oldest elderly group in previous year transfer to 3 inpatient group in the same age group.

7. The inpatient model change within 1 year between 2 stages as alive and death without changing of age group.

8. The causes of inpatient demands occur by many factors. However, due to the limitation of information, this research use aggregate population information and consider the change of each transition using time period and population covariate factors.

1.6 Organization of Dissertation

In this research is organized as follows. Chapter 1 illustrates the significance of the problem and research objectives. In Chapter 2, the relevant literature for long-term care problem and the stochastic Markov Model are discussed. Chapter 3, provides data analysis, Markov model for the multi-states nonhomogeneous Markov population model, the semi-Markov inpatient model, community long-term care model and sensitivity analysis to evaluate resources for long term elderly. The computational results and discussions are proposed in Chapter 4. Finally, in Chapter 5, summary, conclusion, and directions for future research are provided.

CHAPTER II

LITERATURE REVIEW

2.1 Stochastic Markov Model

The demographic change is associated with various uncertainty factors so the stochastic method is an appropriate tool for population change over the future time period. Markov chain is generally used as a tool to predict changes in health status and resource needs. Markov chain has been widely applied to different problems. The review is focused only three approaches that are related to healthcare study : (i) generating Markov model from individual data ; (ii) generating Markov model from aggregated data ; (iii) semi-Markov model.

2.1.1 Markov Model from individual data

A review of non-homogeneous Markov systems presented by Vassiliou (1997), shows that the methodology can be used to solve several problems such as manpower planning, ecological modeling, and social mobility processes. Craig and Newton (1997), generated Markov chain model from non-homogeneous discrete-time data for diabetic retinopathy patients. The model is used to investigate incidence, prevalence, and progression of diabetic retinopathy. The Bayesian estimation is applied to estimate parameters of Markov model. Craig and Sandi (1998) proposed discrete time Homogeneous Markov chain for chronic diseases. They applied maximum likelihood technique to investigate transition matrix. Pérez-Ocón, Ruiz-Castro, and

Gámiz-Pérez (2000) presented nonhomogeneous Markov process to analyze the status of women breast cancer patients. Maximum likelihood Estimation is used to estimate parameters of three state Markov chain, including no relapse, relapse, and death. Erkanli, Soyer, and Angold (2001), conducted non-homogenous Markov regression models for psychiatric disorders and substance abuse problem of American Indian children. Bayesian via Gibbs Sampling is applied to estimate the transition. Another discrete time Markov chain was proposed by Craig and Sendi (2002). This Markov Model is used to evaluate the treatment and care of chronic patients. Transition probabilities are estimated by Maximum Likelihood. It is also found that Mixed effect Markov model, studied by Bizzotto et al. (2011), is applied to sleep architecture problem in insomniac patients. Covariate effects of multinomial Markov chain model consist of age, gender, and BMI. Another research focusing on multi-state continuous time stationary Markov chain was proposed by Eslahchi and Movahedi (2012). This study applied birth-death Markov process to describe the spread of disease in the community. The results of the model can be used as the information to prevent and control the spread of infections in the community. Another Markov model presented by Chao et al. (2014), is used to access diabetes patients in the elderly. The results of the model can be used as the information for health budget planning.

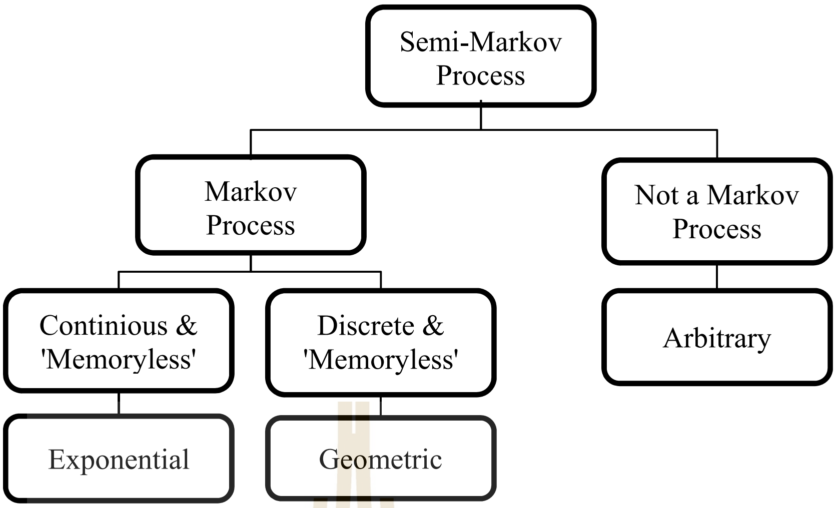
2.1.2 Markov Chain from aggregated data

Generally, maximum likelihood method is used to obtain transition probability for generating Markov model from individual data. However, most data are in aggregated form. Hence, it is necessary to review the tools used to generate Markov model from aggregated data.

Lee, Judge, and Zellner (1968) generated a discrete stationary Markov chain problem from aggregated data. Maximum likelihood estimation and bayesian method were used to estimate transition probabilities. Aggregated root mean square errors were used to measure deviations of each estimation method. MacRae (1977) presented time-varying Markov process for perfect aggregate data of stocks and imperfect aggregate data of stocks. Maximum likelihood estimation and nonlinear least square estimation were used to estimate parameters of perfect observation and imperfect observation, respectively. Kelton (1981) suggested quadratic programming method to estimate parameters for time-independent Markov process with aggregate data. Result shows that this quadratic programming method is not suitable for calculating non-stationary transition probabilities. Kalbfleisch, Lawless, and Vollmer (1983) developed condition least square and approximate maximum-likelihood-estimation to estimate transition probability. This research proposed time-homogeneous Markov model for the biological and sociological problem and extends the model by adding the immigration to the model. Van Der Plas (1983) used conditional least square estimate to generate homogeneous Markov model from macro data. Kalbfleisch and Lawless (1984), Lawless and McLeish (1984), and McLeish (1984) also conducted their studies by using aggregate data to construct time-homogeneous Markov models. They proposed least-square method including weighted least squares, generalized least squares, and ordinary least squares to estimate transition probabilities of Markov models. Another research conducted by Kelton and Kelton (1984), presented hypothesis testing non-stationary Markov Process and stationary Markov Process. They generated hypothesis testing procedure to develop three test stationary models. They applied F-distribution as the test statistics and found the assumptions for the F-distribution by using Monte Carlo study. The extension of generalized linear model was proposed by Liang and Zeger (1986) to analyze the longitudinal data. Asymptotic theory was presented for the general class of estimators in this research. The method from this research assumes a functional form by applying the marginal distribution instead of the joint distribution due to the limitation of longitudinal data. After that, there are other similar research which proposed non-homogeneous Markov model to apply for health expectancies with cross-sectional data such as Davis, Heathcote, and O'Neill (2001); Heathcote, Davis, Puza, and O'Neill (2003). Another similar model conducted by Davis, Heathcote, and O'Neill (2002), applied Markov model to estimate population change and health status. The transition probabilities are obtained in log (odds) function and estimate parameter by weighted least square method.

2.1.3 Semi-Markov model

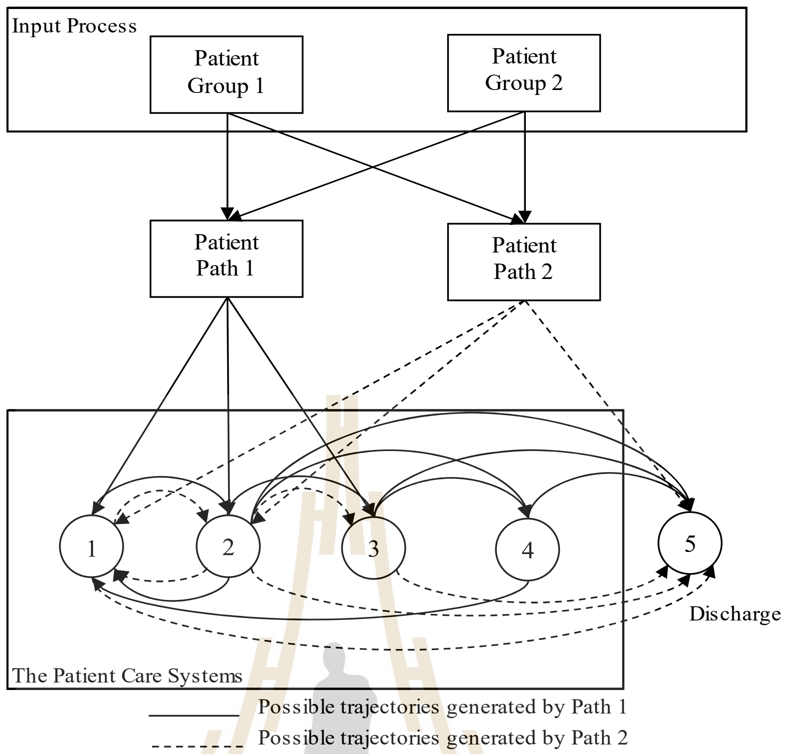
The assumption of Markov models shows that the transition probabilities from one state to each other states depend on the current state of Markov models. In case of Markov assumptions are relaxed, semi-Markov is applied to adapt sojourn times in any states of various problems. Semi-Markov models have an assumption similar to Markov models. The difference between Markov models and semi-Markov models is that time interval between state changes of semi-Markov models is random variables. The relationship between Markov and Semi-Markov Model is shown in Figure 2.1.



Figures 2.1 The relationship between Markov and Semi-Markov Model

Source : Williamson and Suen (2012)

The application of a semi-Markov model for recovery of coronary patients was proposed by Kao (1972). This model estimates length-of-stay in each state and in the whole system and calculates the distribution of recovery population to use for resource planning. The proposed model has the potential to allocate services and resources, planning, utilization to support the study the dynamics of the coronary care system. After that, Kao (1973) applied model from Kao (1972) to study patient movement in the health system in term of semi-Markovian population model shown in Figure 2.2. The model is used to describe patient movements of recovery progress of patients within the system. The developed model is used for short-term forecasting during the period of interest based on available information reported to management.



Figures 2.2 The Patient Care System

Source : Kao (1973)

Valliant and Milkovich (1977) presented the development semi-Markov model to forecast manpower and compare with Markov model. Generally, the semi-Markov seems to be more preferable than the Markov model because the semi-Markov process relaxes the Markov assumptions by allowing the time interval between state changes of semi-Markov models to be random variables. Results did not conclude that the semi-Markov models is more superior to the Markov models due to the limitation of the information. Another of semi-Markov model is presented by Côté and Stein (2007). This research represents an application of semi-Markov processes in outpatient healthcare (patient-care visits in a family practice clinic.). The empirical data were used to develop the model. The performance measure consisted of sojourn time in each state.

The model was used to assist operational decision in the clinic. Next, Gillaizeau, Dantan, Giral, and Foucher (2015) proposed a semi-Markov model to investigate the relationship between the explicative variables and the times-to-events such as disease progression or death. This research investigates the relationship between the variables and the progression of chronic disease, especially to the mortality associated with the disease. The model in this research is semi-Markov additive relative survival (SMRS) model that combines the multistate and the relative survival.

2.2 Long-Term Care problems

The component of long-term care system consists of institutional care and community-based care. Long-term care services need work co-operation among the medical staff, the society and the community. Medical care staff includes nurses, physical therapists, and other non-physicians. Home care service is one of activities to support long-term care elderly to reduce the number of elderly people at the institutional care. There are various topics of long-term care system in the literature as shown in the following details.

2.2.1 Demand Forecasting for Long-Term Care

The initial management of long-term care is concerned about the demand, which is uncertain. It is necessary to study from the previous research to understand the methodology to predict demand.

First of all, Sharma (1980) reviewed the techniques for forecasting needs for home healthcare including Health Systems Agency of Southwestern Pennsylvania, (HSA/SP) model, Florida model, Rhode Island model and a utilization approach. Then, the conclusion is that each approach should be examined empirically to improve the forecasting process. However, these methods are still not suitable for resource and capacity planning in long-term care. Another research about forecasting methodology for the transition of long-term care clients is investigated by Lane D. et al. (1985). This study analyzes three methods of long-term care forecasting, which are State-by-state moving average growth, State-by-state regression analysis and First-order Markov chain with stationary transition probabilities. The study consists of many home and facility placements and care levels. The results show that the Markov method should be suitable as resource planning and allocation tool in long-term care.

Another research relates to the future of informal care in the next thirty years and the result of changes in the demand of informal care to formal services. This research is purposed by Pickard, Wittenberg, Comas-Herrera, Davies, and Darton (2000). A Personal Social Services Research Unit (PSSRU) computer simulation model is applied in this research. The simulation model has produced projections to 2031 for long-term care for England. The PSSRU model is a cell-based (or macro-simulation) model, which has been developed to forecast for long-term care demand for elderly people in England to 2031 under different scenarios. Sensitivity analyses have been analyzed based on the specific assumptions about future trends, including scenarios in which the supply of informal care is seriously restricted. The results of the scenarios have proved of the best for policy by using the PSSRU model. Next, another interesting study is a framework for estimating the future gross cost. It is built around a survival model by Pelletier, Chaussalet, and Xie (2005a). This framework aims to forecast the cost over a period, of each maintaining a group in residential and nursing care which is funded by the local authority. The formulation of the costing structure takes into account survival and cost, and is flexible enough to allow customization to reflect local characteristics.

After that, the estimation of future demand for LTC is conducted by Batljan and Lagergren (2005). This paper presents how projected demographic development may influence future demand for human resources for LTC for older people in Sweden 2000–2030. The analysis of different scenarios is used in the model. The methodology uses information, which divided by age and gender on utilization of current services, number of older people and assumptions on health status changes. There are many changes in demography and health status among the older people. Afterwards, another research is to investigate the long run of the UK system for the provision of long-term care (LTC) conducted by Karlsson, Mayhew, Plumb, and Rickayzen (2006). This study considers demand for LTC and sufficient supply to meet demand. The public budgets are estimating the requirement for formal care. In addition, it involves estimating enough caretakers with current patterns for informal care. The results show long-term care demand for 10 years from now and to the year 2040. In addition, Comas-Herrera, Wittenberg, Pickard, and Knapp (2007) propose the future numbers of elderly with cognitive impairment (CI) in England, the long-term care (LTC) demand and future costs of the care. A macro-simulation (or cell-based) model is developed to produce the projections that are built on an earlier PSSRU model. The future numbers of elderly, future CI rates and functional disability affect the demand for long-term care as testing by sensitivity analysis.

There is another methodology to investigate future demand from older people. Desai, Penn, Brailsford, and Chipulu (2008) conducted system dynamics (SD) to explore ageing population within the budget limitations. SD combines qualitative and quantitative aspects and aims to enhance understanding of the system and the relationships among different system components. The results show that, over the next five years, the number of care requirements will increase continually.

Grey forecasting models is studied by Hsu and Yan (2008) to forecast the disability rate of the aged and the number of aged in the total population. There is another research that applies grey model to analyze the performance of a grey inspired approach, compared with established industrial techniques and highlight the issues raised by the use of grey modeling in regional LTC planning. This research is proposed by Worrall and Chaussalet (2012). However, grey model is still difficult to solve long-term care demand with demographic and health information.

2.2.2 Length of Stay problem for Long-Term Care

Long-term care problems in institutional care are about length of stay of each patient due to the limitation of resources. Marazzi, Paccaud, Ruffieux, and Beguin (1998) studied the development of the statistical analysis of length of stay (LOS) distributions or other consumption variables in health services. The aim of the paper is to assess the adequacy of three widely used models - Lognormal, Weibull, and Gamma - for describing the distribution of length of stay (LOS). The results show the fit of the distributions with one of these models. In the conclusion, statistical methods for case mix description should be improved by more flexible families of models. El-Darzi, Vasilakis, Chaussalet, and Millard (1998) studied the benefits and limitations of flow modeling. The goal of this paper is to build tool for hospital planners to make more efficient for a geriatric department than before. The model is experimented with different policy parameters including emptiness level, bed availability for each compartment, conversion rates, length of stay and admissions. The study develops a simulation model of a queuing system which gives the interaction between emptiness in long-stay care and acute care. Discrete event simulation is used to model the system. Then, what-if analysis is used to allow a greater understanding of bed requirements and effective utilization of resources. The length of stay and the number of clients in each state are estimated the average. The results show that the flow model and the unconstrained simulation are equally viable tools to measure bed occupancy in a geriatric department. However, this research needs more work on the simulation model to experiment with different arrival and admission methods and data from other hospitals.

In addition, McClean and Millard (1998) study a three compartment model consisting of acute care, rehabilitation and long-stay care. The Markov model is used to explain the movements of elderly patients within the hospital system (as shonw in Figure 2.3). By assigning costs to the acute, rehabilitative and long-stay states of the model, this paper determines the costs involved in treating cohorts of patients. Different costs have been attached to each of the three compartments. The result from using the model found that a geriatric medical service to improve the acute management of in-patients became more cost-efficient. This model is useful for Health Care and Social Services planners who require cost information in order to plan their budgets.

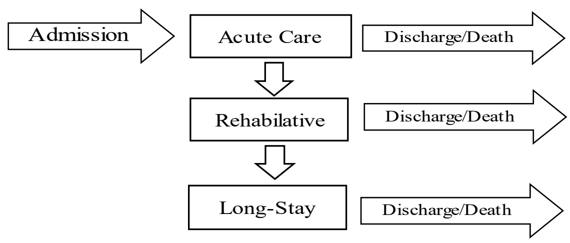


Figure 2.3 Patient flows within a three-compartment geriatric department

Source: McClean and Millard (1998)

Afterwards, length of stay of elderly problem is still crucial to improve long-term care service. Thus, Taylor, McClean, and Millard (2000) considers a census approach to the modeling of the time that elderly patients spend in hospital and then, in the community by using a stochastic Markov model with six compartments. The maximum likelihood estimation is used to fit the model to daily census data. The model is proposed to the hospital administrator to manage bed requirement and resource for elderly. However, the model does still not cover the effect of demographic factors. Therefore, the model to represent the flow of elderly patients is studied by Christodoulou and Taylor (2001). This research uses the continuous time hidden Markov models including the effect of covariates, age and sex. The data are modeled, using a compartmental model, in order to represent the time that the patient has spent in care. Using a hidden Markov model in continuous time, with discrete states, it has been able to show the effects that the covariates age and sex have on the parameter estimates for the mixed exponential fit. However, the model considers only length of stay in the institutional care. Therefore, it is necessity to study more to cover length of stay in community based care.

The problem of elderly patient duration of stay in hospital is still continual study as found by Marshall, McClean, Shapcott, and Millard (2002). This research presents a model to predict the duration of stay distribution of patients in hospital. The paper is to develop such a model to help healthcare managers in the future and facilitate better management of resources. The paper introduces a conditional phase-type model to represent the survival distribution of elderly patients based on the interaction of various patient details recorded on admission to hospital. From model, the anticipated cost of the care of these elderly can also be estimated and allowances for these taken into consideration in the hospital budget. Previous developed bed usage measures do not adequately represent the actual activity or situation in the hospital ward. Therefore, it is necessary to consider new models. After that, Marshall, Vasilakis, and El-Darzi (2005) focused on modeling length of stay and flow of patients. The models were developed from the previous study by using the C-Ph model to represent a continuous distribution. An overview of such modeling techniques is provided to impact and suitability in managing a hospital service. The statistical methodologies build Markov model to measuring and modeling flow.

Another research which focuses on the length of stay of elderly in institutional long-term care is proposed by Xie, Chaussalet, and Millard (2005). The development of a Markov continuous model in this paper is to study the length of stay for elderly moving within and between two compartments, which are residential home care and nursing home care. Maximum likelihood is used to estimate parameter of the model. The model developing in this paper could help planning authorities to understand the overall pattern of usage of resources for elderly people in their catchment area. Other similar research to improve length of stay problem are studied by Pelletier, Chaussalet, and Xie (2005b) and Xie, Chaussalet, and Millard (2006). The paper presents a model-based approach with high-level length-of-stay patterns of residents in long-term care. Two applications are presented to show the potential use of this approach. In addition, the model has been extended to incorporate residents' features, and is able to provide additional insights into the behavior of the flow of residents in institutional long-term care (ILTC) system. There is software, which is presented by Xie, Chaussalet, Toffa, and Crowther (2006) to implementation of a forecasting framework. The software is used to provide useful information to local authority budget planners involved in long term care. Feedback shows that the tool can help care planner and manager to gain more understanding in terms of length-of-stay of residents under their care, and provides quantitative inputs into their decision making on budget planning for long-term care.

2.2.3 Community -Based Care problem in Long-Term Care

Greene, Lovely, Miller, and Ondrich (1995) studied the capability of community long-term care (CLTC) services to reduce nursing home use when services are allocated strategically. This paper uses data from the National Long-Term Care Channeling Demonstration to determine the performance associated with the use of nursing home in the types of community service. The problem applies a large-scale nonlinear programming (NLP) problem and use a logistic transition-probability model (TPM) to determine the relationship between use of community services and nursing home use. Then, the mathematical optimization model is applied to minimize total population nursing home, which used as a function of community service under the total expenditure constraint. The result shows that reductions in nursing home use can be produced without increasing community expenditures.

2.2.4 Long-Term Care Capacity Planning

This part consists of all topics including demand forecasting, length-of stay and community care for long-term care to plan for capacity and resource in long run. Initially, Katsaliaki, Brailsford, Browning, and Knight (2005) studied a project carried out within Hampshire Social Services. The study aims to investigate possible care pathways for older people after discharge from hospitals. This problem is very important because many elderly patients experience delayed discharge from acute beds, because post-acute care services such as home care are insufficient. A discrete-event simulation is used to analyze the system capacities and to estimate the associated reimbursement costs. “Intermediate Care” has been introduced to offer as an alternative option for elderly patients to overcome the “bed-blocking” problem. The services are examined in terms of capacity and appropriateness. This paper fulfils the need to record and evaluate the new post-acute packages which are introduced by the Social Services. Another model determines the resources that will be demanded for provision of long-term care of the frail elderly. Lagergren (2005) developed a new model to estimate the future needs of publicly financed long-term care of frail elderly. Applying the ASIM III-model aims to solve problems. The model provides estimations on the amount of public long-term care services per age group, gender, marital status and degree of disability both retrospectively for the period 1985–2000 and prospectively according to the same terms for the period 2000–2030.

In addition, Hare, Alimadad, Dodd, Ferguson, and Rutherford (2009) developed a deterministic multistate Markov model of the Home and Community Care (HCC) system. The model validates and predicts for future client counts for various HCC client groupings. The model makes several steps forward in terms of research and modeling of HCC. First, the models of HCC appear to be only concerned with publicly funded residential care environments but this model study including home care and non-public fund care. Second, the model predicts both the changes in the age demographics and the changes in the relationship between age and health status.

The development policies were proposed to ensure optimal allocation of scarce healthcare resources conducted by Garg, McClean, Meenan, and Millard (2010). This approach can efficiently be used to forecast resource requirement and resource allocation within the demand or resource constraints. The patient flow was modeled through the care system as a discrete time Markov chain. A discrete time nonhomogeneous Markov models can be efficiently used in more sophisticated admission scheduling and resource requirement forecasting and allocation.

The system dynamic model is also used to development of long-term care facilities in Taiwan. The improvement structure of long-term care facilities in Taiwan is composed of the four levels including satisfaction, service quality, the administrative skill and medical care personnel and facility hardware resources. The model of causal relationships in this research can also increase the understanding of the developmental process of LTC facilities in other developing countries (Hsiao and Huang, 2012). Another dynamic system model is proposed by Brailsford et al. (2012). They developed a system dynamics model for both supply and demand in health and social care with formal and informal. System dynamics is an ideal tool to explore the variable, which is clearly a crucial factor in the provision of informal care and may potentially have a significant impact on the entire social care system, but is very difficult to estimate accurately. Similar study by system dynamic is found in recent year as Ansah et al. (2014).

In addition, the optimal control problem is proposed by Lin, Kong, and Lawley (2012) to determine the optimal level of the infrastructure capacity for a publicly funded home and community-based services (HCBS) program. This research develops a compartmental model (as Figure 2.4) to simulate the population flows through the publicly funded LTC system with a systematic analysis. The objective of the optimal control problem is to minimize the total spending on LTC and potential acute care for LTC patients over an extended period.

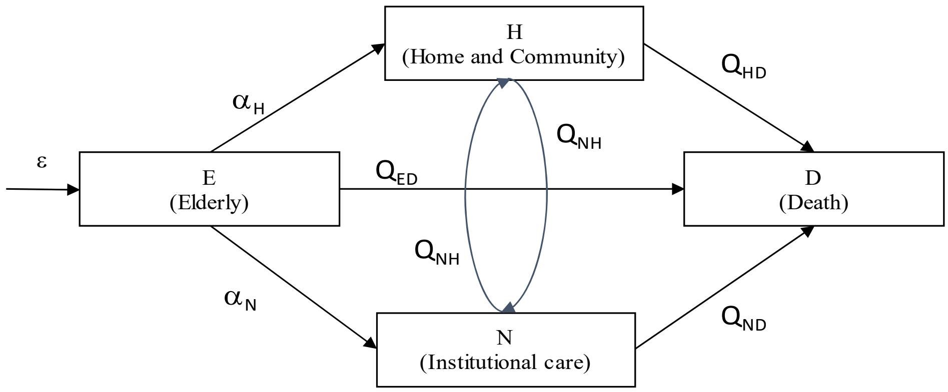


Figure 2.4 The compartmental model for HCBS capacity planning.

Source: Lin, Kong, and Lawley (2012)

Another simulation model is presented by Ragab, Abo-Hamad, and Arisha (2012). This paper describes a project aiming to present modeling and simulation to specify elderly care pathways within healthcare. The frail patients who are admitted to acute care and a new intermediate care beds are introduced as alternative interventions. The healthcare executives are interested in simulating to evaluate the impact on the performance of the new elderly care system. The simulation model with the statistical analysis is developed to enable the management to assess the current system within the critical financial and performance issues. One of simulation model is presented by Zhang, Puterman, Nelson, and Atkins (2012). The model applies a methodology to set long-term care capacity levels over a multi-year planning. The approach integrates demographic and survival analysis, discrete event simulation, and optimization to solve the problem. Cardoso et al. (2012) proposed a simulation model which is based on a Markov cycle tree structure to predict demand for LTC services annually. The objective of the study is to inform the planning of the services at the small-area level in the recent years. The simulation model is multiservice to predict the annual number of each long-term care service (including formal care and informal home-based care, ambulatory services and institutional services), the resources or services that are required to satisfy the need (including informal caregivers, domiciliary visits, consultations and beds) and the costs. The model is validated by using past data and is applied to Portugal at the Lisbon borough level to forecast the 2010–2015 period. Due to data imperfection and uncertainty related to predicting future LTC demand, the scenario was analyzed with probabilistic sensitivity analysis using Monte Carlo simulation. The results show that the model provides information critical for informing the planning and financing of long-term care networks.

2.2.5 Utilization improvement for Long-Term Care

Medicare's Prospective Payment System (PPS) for hospital services in the United States has increased both using nursing home care and resource, since earlier hospital discharge some convalescent care from the hospital to homes and nursing homes. Garber (1989) presented the background of a study of the factors of long-term care utilization by the disabled elderly and analyzes utilization of hospital, home healthcare, and nursing home. Another paper by Doyle and Masland (1997) proposed the development process over the traditional fragmented care along with financing methods through integrating patient administration responsibilities into one particular provider organization. This paper reviews new program to maintain elders with physical and mental disabilities in home and community-based programs, and to minimize the use of acute and long-term institutional care. All services are not integrated into each program. It means that some obtain only primary and acute care but some others obtain only the continuum of long-term care. However, the key focus is full of services, which consist of primary care, acute care and long-term care services. The result describes in terms of improving care and cost saving.

The improvement of utilization for long-term care system is developed by Xie, Chaussalet, Thompson, and Millard (2002). This research studies modeling of a multidisciplinary review panel which match long-term care levels to elderly requirements (as shown in Figure 2.5). The objectives of the review panel are to assess an older person's needs, and to achieve a placement decision that best meets those needs, thus ensuring that resources are used efficiently.

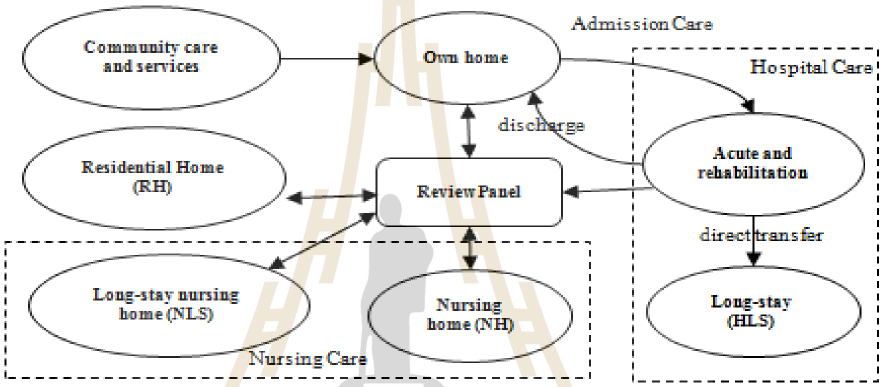


Figure 2.5 Operation of the review panel in London Borough of Merton

Source: Xie, Chaussalet, Thompson, and Millard (2002)

This paper proposes the decision process of review panel and estimate decisions of each applicant's attributes by applying logistics regression for the prediction model. A two-stage approach is used as a decision model to determine whether an applicant should be placed in each compartment and to check the consistency of the review panel's decisions. Graphical decision model is also used to solve this problem by Xie, Chaussalet, Thompson, and Millard (2007). The research proposes an aid to the placement of elderly in institutional long-term care in a London borough, in the UK. The prediction model uses a combination of syndromic decision rules and hierarchical logistic regression to fulfill some of the difficulties encountered in an earlier study (H. Xie et al., 2002). This model can be a useful decision-aid to staff in long-term care, such as social workers, geriatricians and nurses, in providing continuous monitoring and on-going assessment of the appropriateness of placements in order to match the resident requirements, as well as providing an independent assessment and recommendation.

In addition to wealth and utilization planning, long-term care insurance is another vital requirement which should prepare for elderly. Robinson (1996) presented a health status transition model to develop as some part of LTC insurance pricing model. Model features, estimation, and applications are discussed. This paper applies a Continuous-Time Markov Chains (CTMC) to solve problem. The model provides transition rates to alter with the sex and age of each person. The long-term care transition model discussed in this paper is used to simulate monthly insured health status histories. Then, second-stage model is applied that simulated long-term care service utilization and policy benefit payments for individual health status.

An integral part of retirement planning is studied by Gupta and Li (2004). The research divided retirement planning into two phases including pre-retirement and post-retirement. On the basis of four interrelated models which are health evolution, wealth evolution, LTC insurance premium and coverage, and LTC cost structure. The study develops a framework for optimal long-term care insurance purchase decision in the pre-retirement phase. To develop the optimal decisions, Post-retirement LTC costs and LTC insurance premiums and coverage are tested. A dynamic programming problem is used to formulate the problem. Sensitivity analysis of the optimal decisions is performed for the retirement age and dependence of premiums on the health condition of the planner.

2.3 Ambulatory Care Sensitive Conditions (ACSC)

Ambulatory care sensitive conditions (ACSCs) are health conditions of potentially preventable inpatient admissions to help reduce hospital resources and expenses. If there is a good and effective healthcare management system, ACSC patients can be treated by primary care. Sanmartin, Khan, and Team (2011) proposed the study of ambulatory care sensitive conditions (ACSC). The ACSC is an indirect indicator of the efficacy of primary care and of the ability of the system to manage chronic diseases such as diabetes, heart failure, chronic obstructive pulmonary disease (COPD), and asthma. ACSC hospital admissions are often referred as avoidable hospitalizations and used as a measure of the effectiveness of primary care and community care. This study is the first national assessment of many of the hospital-related factors associated with ACSC. The specific characteristics of this study are to focus on patients with at least one ACS condition. This study is based on a linkage survey and hospital information that provides comprehensive information about the patient's characteristics, access to primary care and hospitalization related to the ACSC. Understanding the role these factors may play in primary care may reduce the risk of hospital admissions from ACSC.

Additionally, Freund et al. (2013) studied hospitalizations with ambulatory care–sensitive conditions (ACSCs). The primary care can help to prevent the need for hospital admission from ACSCs. This research investigates the complex causes of hospitalization from the perspective of primary care physicians by interviewing 12 primary care physicians in Germany. In summary, the cause of hospitalization are categorized into 5 main reasons : system-related, physician-related, medical, patient-related, and social. Primary care physicians have suggested that strategies to avoid hospitalization may focus on after-hours care, optimal use of ambulatory services, high-risk patient monitoring, and initiatives to improve patient intentions, ability to seek timely help and patient adherence to medication.

Another research of ambulatory care sensitive conditions (ACSCs) is proposed by Galarraga, Mutter, and Pines (2015). The ACSCs are acute care diagnoses to improve primary care. The objective of this research is to study the cost differences for ACSC visits differ among three hospital-based settings (outpatient, emergency department [ED], and inpatient) and differences in physician and facility costs. The methodology of this research analyzes secondary analysis of data (2005 through 2010) from the Medical Expenditure Panel Survey and apply linear regression models. The results show that ACSC visits as inpatients are the most expensive. Expanding outpatient care resources and improving the health management of chronic patients to avoid inpatient conditions that affect the most expensive expenses. After that, Longman, Passey, Ewald, Rix, and Morgan (2015) proposed the demographic indicators of ambulatory care sensitive conditions (ACSCs). The objective of the indicators is to be used as a representative for the feasibility of accessing services in Australia with chronic ACSCs patients to reduce preventable admissions.

Ambulatory care sensitive hospitalizations (ACSH) is widely used to study the quality and effectiveness of primary care, presented by Lugo-Palacios and Cairns (2015). The data from 248 general hospitals in Mexico during 2001 to 2011 use to estimate a fixed impact model to explain the relationship between ACSH rates to patients and community factors. This study found a strong association of ACSH rates with economic and social conditions, health provision and health insurance, even after the latent control of the potential for launching insurance.

2.4 Chapter Summary

From previous studies, the demographic structure consists mainly of birth, death, and migration. However, there are not many studies of migration on population change affecting the healthcare demand. The change of population to elderly society affects health status of population, especially chronic diseases and the healthcare demand in the hospitals. In addition, the use of hospital services is also essential to prepare to support inpatient demand in aging society. Therefore, this research study on demographic changes to aging society and relate to inpatient demand and long-term care demand. The change of population includes birth, death and migration factor. The population groups are specified by age and gender. The population transfer into 3 groups of diseases consisting of chronic, non-chronic diseases and Ambulatory Care Sensitive Conditions (ACSC) or the disease in case of inpatients who can be controlled with outpatient services. The length-of stays of patients in each year are investigated by semi-Markov Model. The annual elderly from population model use to investigate type of elderly by household situations, level of dependency and chronic/nonchronic factors in order to allocate of staff for long-term care.

CHAPTER III

RESEARCH METHODOLOGY

3.1 Research Framework

It is clear from Chapter I that the population change has impact on managing resources especially to accommodate the increasing of elderly. According to the literature review in Chapter II, Markov chain is suitable tool to predict the number of population in the study. The framework of this study is put into three models. Model 1 is a Markov chain model to determine the number of population and inpatients annually according to age groups and genders. Model 2 is a semi-Markov chain model to determine the length of stay (LOS) of the population when require hospital service. The forecast data from model 1 are used as input information for model 2. Model 3 also uses the result from model 1 to determine the number of caregivers required each year to provide long term care service. The framework is shown in Figure 3.1.

Data used in this study can be categorized into two types, aggregate population data and sample of individual data. Aggregate data used for model 1 compose of annual population data, annual new born data, annual death data, and annual inpatient data. Individual data used to analyze the number of daily admission for model 2.

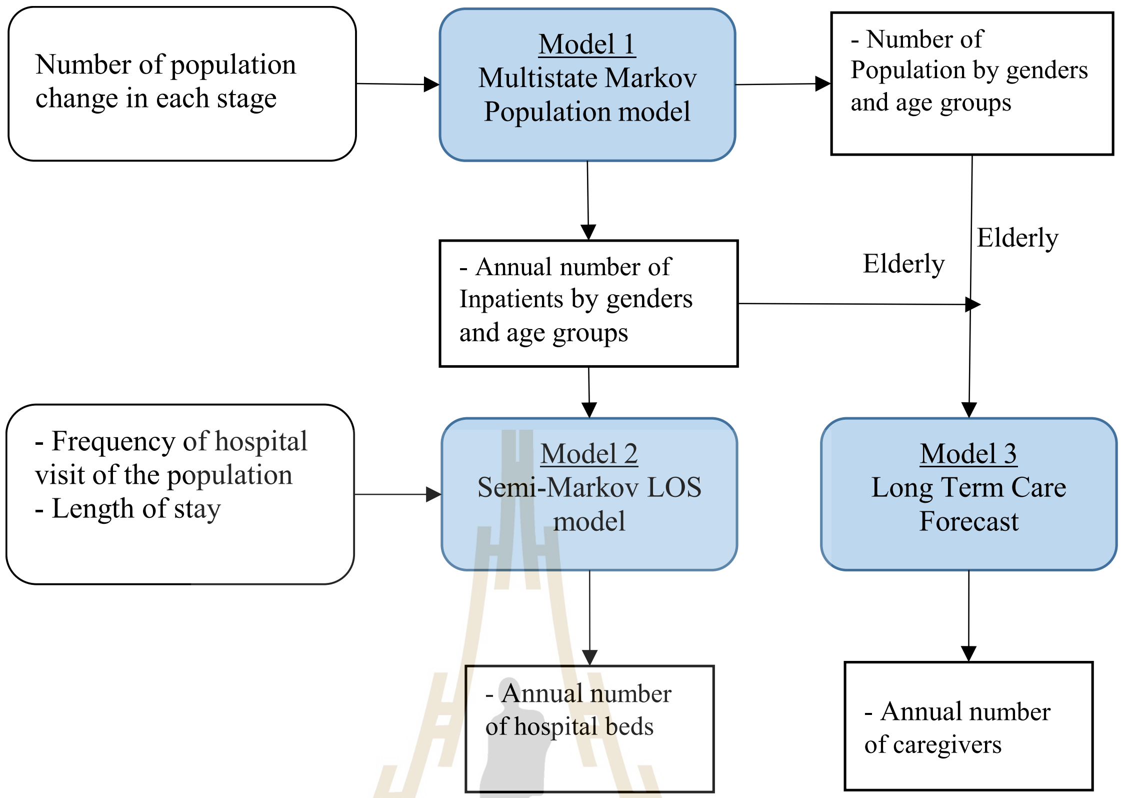


Figure 3.1 Research Framework

3.2 Model I : Markov Population Model

The study is to develop non-homogeneous Markov model to predict population and an annual demand of all hospitals in a certain area. The objective of this research aims to predict annual population and annual inpatient demands separated by Chronic, Non-chronic and Ambulatory Care Sensitive Conditions (ACSC) when population structure change to the elderly. The study examines both the changes in the age and gender demography together with the factors of birth, death and net migration.

Ambulatory Care Sensitive Conditions (ACSC) are one of the key factors of quality and effectiveness of primary care services (Lugo-Palacios and Cairns, 2015). The ACSC inpatients can be reduced by effective treatment in primary care.

Identification of ACSC patients is separated by a primary diagnosis of ICD-10 and secondary diagnosis and procedure of ICD-9 CM (Supol Limwattananont, 2011) as lists below.

i. Epilepsy ICD-10: [G40 and G41]

ii. COPD ICD-10: [J41-J44, J47]

iii. [J10.0, J11.0, J12-J16, J18, J20, J21, J22] which secondary diagnosis is ICD-9 CM: J44

iv. Asthma ICD-10: [J45 and J46]

v. HF-PE ICD-10 : [I50 และ J81] without procedure of ICD-9 CM[33.6, 35, 36, 37.3, 37.5, 37.7, 37.8, 37.94 and 37.98]

vi. Diabetes ICD-10 : [E10.0, E10.1, E10.6, E10.9, E11.0, E11.1, E11.6, E11.9, E13.0, E13.1, E13.6, E13.9, E14.0, E14.1, E14.6 and E14.9]

vii. HT ICD-10 : [I10 and I11] without procedure of ICD-9 CM[33.6, 35, 36, 37.3, 37.5, 37.7, 37.8, 37.94 and 37.98]

Assumptions

1) The change of population structure on each gender consists of the following factors birth, morality, net migration, current population

2) The population compose of 5 age groups: (i) ages 0-15 years (child), (ii) ages 16-59 years (working-age), (iii) ages 60-69 years (beginning elderly), (iv) ages 70-79 years (middle elderly) and (v) ages 80 or more (oldest elderly). The gender factor is also the component for each age group.

3) The population change by annually. Some of population transfer to next age group by using the transition probability between groups.

4) The change of population can transfer to three inpatient groups by type of chronic diseases : (i) chronic (ii) non-chronic (iii) ACSC.

Data analysis

The data flow of model I is shown in Figure 3.2

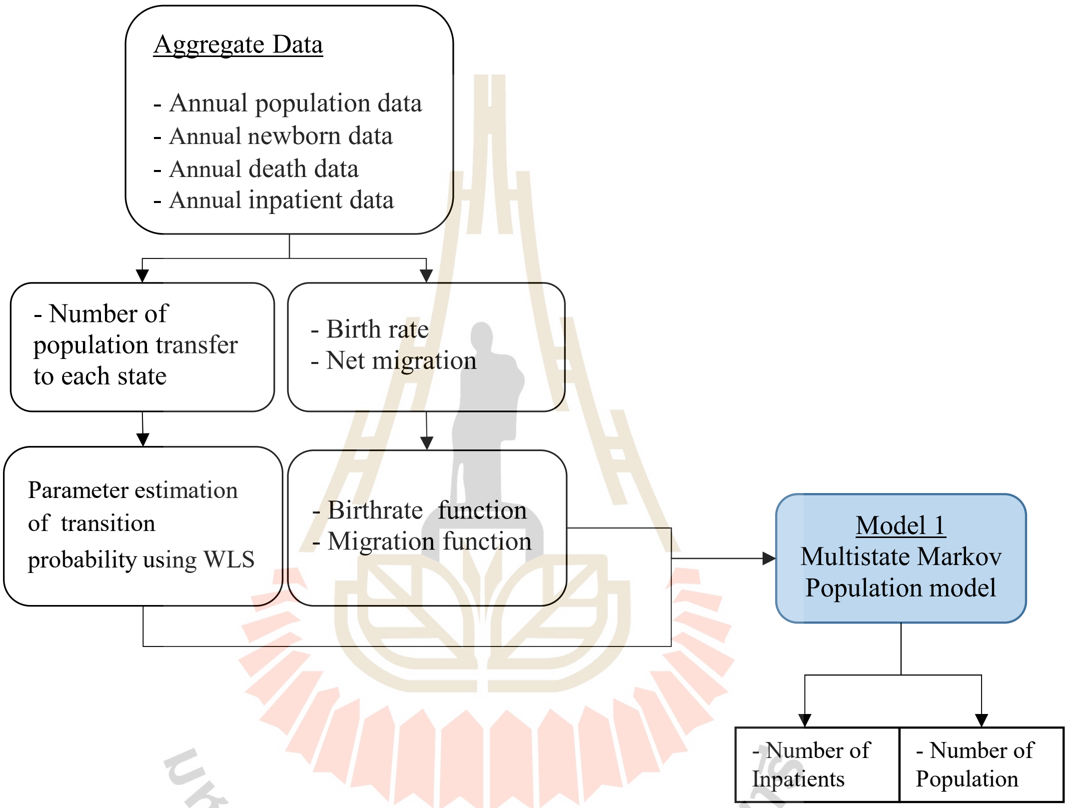


Figure 3.2 Data flow of model I

Sets

Let A – Set of age group; A={[0,15],[16-59],[60-69],[70-79],[80+]}

T – Set of year; T={2015,…,2025}

IP - Set of inpatient types; IP ={Chronic, Non-Chronic, ACSC}

S_1 – Set of state transition, S_1={ [$Pop_{(a)}$ → $Pop_{(a)}$], [$Pop_{(a)}$ → $Pop_{(a+1)}$,], [$Pop_{(a)}$ → $Inp_{(k,a)}$], [$Pop_{(a)}$→ $Inp_{(k,a+1)}$], [$Pop_{(a)}$→ Death]}

G – Set of gender ; G={Male, Female}

Indices

i , j: the i^{th} state and the j^{th} state of the population state $i, j \in S$

t: the t^{th} year , $t \in T$

g: the g^{th} gender , $g \in G$

a: the a^{th} age group , $a \in A$

k: the k^{th} inpatient group , $k \in IP$

Variables

Let $Pop_{(g,a,t)}$ – Population gender g, in age group a at year t

$p_{agij}(t)$ - the probability of the transition of population age group a, gender g transfer from state i at time t-1 to state j at time t.

$n_{agij}(t)$ - the number of individuals of population age group a, gender g transfer from state i at time t-1 to state j at time t.

$Inp_{(g,a,k,t)}$ – the number of inpatient gender g, age group a, disease k at time t

1) Birth rate – Calculate newborn rate per population gender (g) per year (t) from 2007-2014 as equation (3.1) and calculate linear regression of birth rate and time.

$$BirthRate_g(t) = \frac{NewBorn_g(t)}{Population_g(t-1)} \quad (3.1)$$

2) Net migration – Calculate net migration by applying cohort component method (Smith, Tayman, and Swanson, 2006) and vital statistic (VI, 1970) to 5 age groups and each gender. Using equations (3.2) and (3.3), then estimate net-migration rate function with population covariate

$$\text{Net-migration}_{(g,a,t)} = \text{NewBorn}_{(g,t)} + \text{Pop}_{(g,a,t-1)} - \text{Pop}_{(g,a\rightarrow a+1,t-1\rightarrow t)} - \text{Death}_{(g,a,t)} - \text{Pop}_{(g,a,t)} \quad ;\text{ for age(a)} = 1 \quad (3.2)$$

$$\text{Net-migration}_{(g,a,t)} = \text{Pop}_{(g,a,t-1)} - \text{Pop}_{(g,a\rightarrow a+1,t)} + \text{Pop}_{(g,a-1\rightarrow a,t-1\rightarrow t)} - \text{Death}_{(g,a,t)} - \text{Pop}_{(g,a,t)} \quad ;\text{ for age(a)} > 1 \quad (3.3)$$

3.2.1 Model

The calculation begins with analyzing historical data to estimate birth rates, transition probability rates between age groups, transition probability rates to hospitals, net-migration rate and mortality rate. These transition rates are the composition of one-year transition matrix for each gender. The transition matrices are used to estimate annual population changes and annual demand in hospitals during period 2007-2025. The result shows inpatient demand separated by chronic, non-chronic and ACSC types.

The model consists of two sub-Markov models from Figure 3.3 The models are population transfer model and inpatient transfer model by gender . The process of sub model-1 (population transfer model) comprise of states as following details.

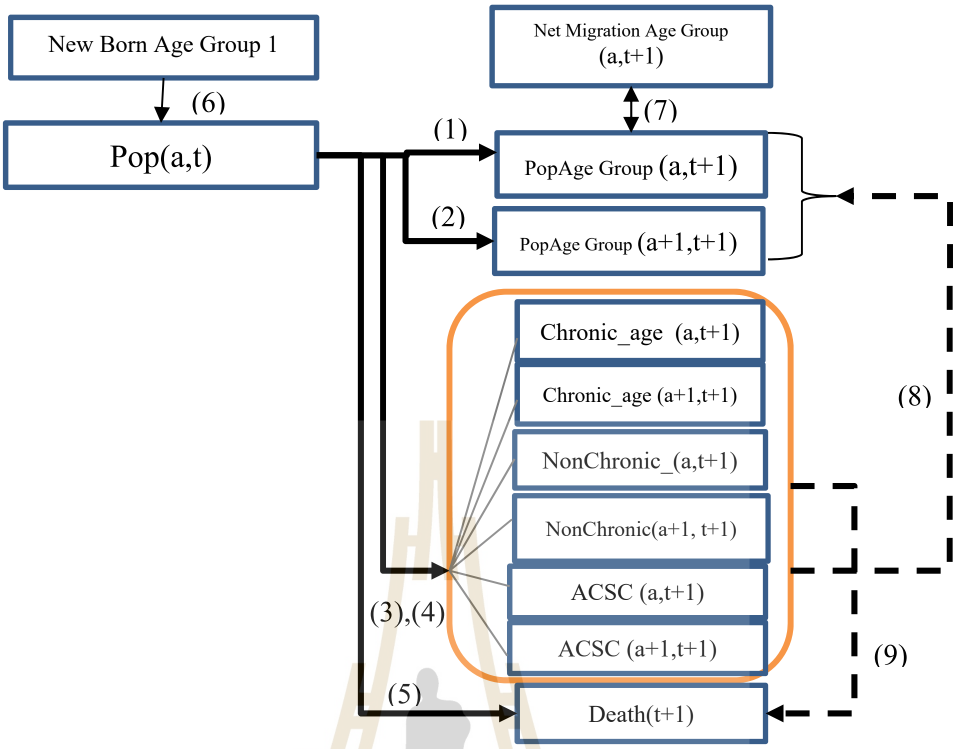


Figure 3.3 Transition probability states of each gender

1) population age (a) at the end of year (t) transfer to population who are not inpatients in year (t+1) in age group (a) ; (a = 1..5)
2) population age (a) at the end of year (t) transfer to population who are not inpatients in year (t+1) in age group (a+1) ;(a = 1..4)
3) population age (a) at the end of year (t) transfer to inpatients group disease (k) in year (t+1) in age group (a) ;(a = 1..5, k=1..3)
4) population age (a) at the end of year (t) transfer to inpatients group disease (k) in year (t+1) in age group(a+1) ;(a = 1..4, k=1..3)
5) population age (a) at the end of year (t) transfer to dead population outside hospital in year (t+1) ;(a = 1..5)
6) New born (t+1) add to population age (1) at year (t+1) ;(a = 1)

7) Net migration age (a) at year (t+1) ± population age (a) at year (t+1) ;(a = 1..5)

The process of sub model-2 (inpatient transfer model) comprise of states as lists below.

8) Inpatient age (a) group disease (k) at year (t+1) transfer back to population age (a) at year(t+1) ;(a = 1..5,k=1..3)
9) Inpatient age (a) group disease (k) at year (t+1) transfer to death state (in hospital) at year(t+1) ;(a = 1..5,k=1..3)

Annual population change shows the transfer flow of each state due to the changing age and illness situation, as shown in Figure 3.4. As follow the step of Markov model in Figure 3.3 and 3.4, the end population of each gender at year (t+1) can calculate as equations (3.4, 3.5 and 3.6).

pop (g,a,t+1) = [pop(g,a,t) - pop(g,a,t) → pop (g,a+1,t+1) + Newborn (g,t+1) ± Net migration(g,a,t+1) - death outside hospital (g,a,t+1) – pop(g,a,t) → $\sum_k \text{inp}\ (g, a, k, t+1)$ – pop(g,a,t)→ $\sum_k \text{inp}\ (g, a+1, k, t+1)$] + [$\sum_k \text{inp}\ (g, a, k, t+1)$ - dead inpatient in hospital (g,a,t+1)]

; for g,=1,2 , a=1 (3.4)

pop (g,a,t+1) = [pop(g,a,t) - pop(g,a,t) → pop (g,a+1,t+1) + pop(g,a-1,t) → pop (g,a,t+1) ± Net migration (g,a,t) - death outside hospital (g,a,t+1) – pop(g,a,t) → $\sum_k \text{inp}\ (g, a, k, t+1)$ – pop(g,a,t)→ $\sum_k \text{inp}\ (g, a+1, k, t+1)$] + [$\sum_k \text{inp}\ (g, a, k, t+1)$ - dead inpatient in hospital (g,a,t+1)]

; for g,=1,2 , a=2..4 (3.5)

$$pop\,(g,a,t+1) = [pop(g,a,t) + pop(g,a\text{-}1,t) \rightarrow pop\,(g,a,t+1) \pm \text{Net migration}\,(g,a,t) - \text{death outside hospital}\,(g,a,t+1) - pop(g,a,t) \rightarrow \textstyle\sum_k inp\,(g,a,k,t+1)\,] + [\textstyle\sum_k inp\,(g,a,k,t+1) - \text{dead inpatient in hospital}\,(g,a,t+1)]$$

; for g,=1,2 , a=5 (3.6)

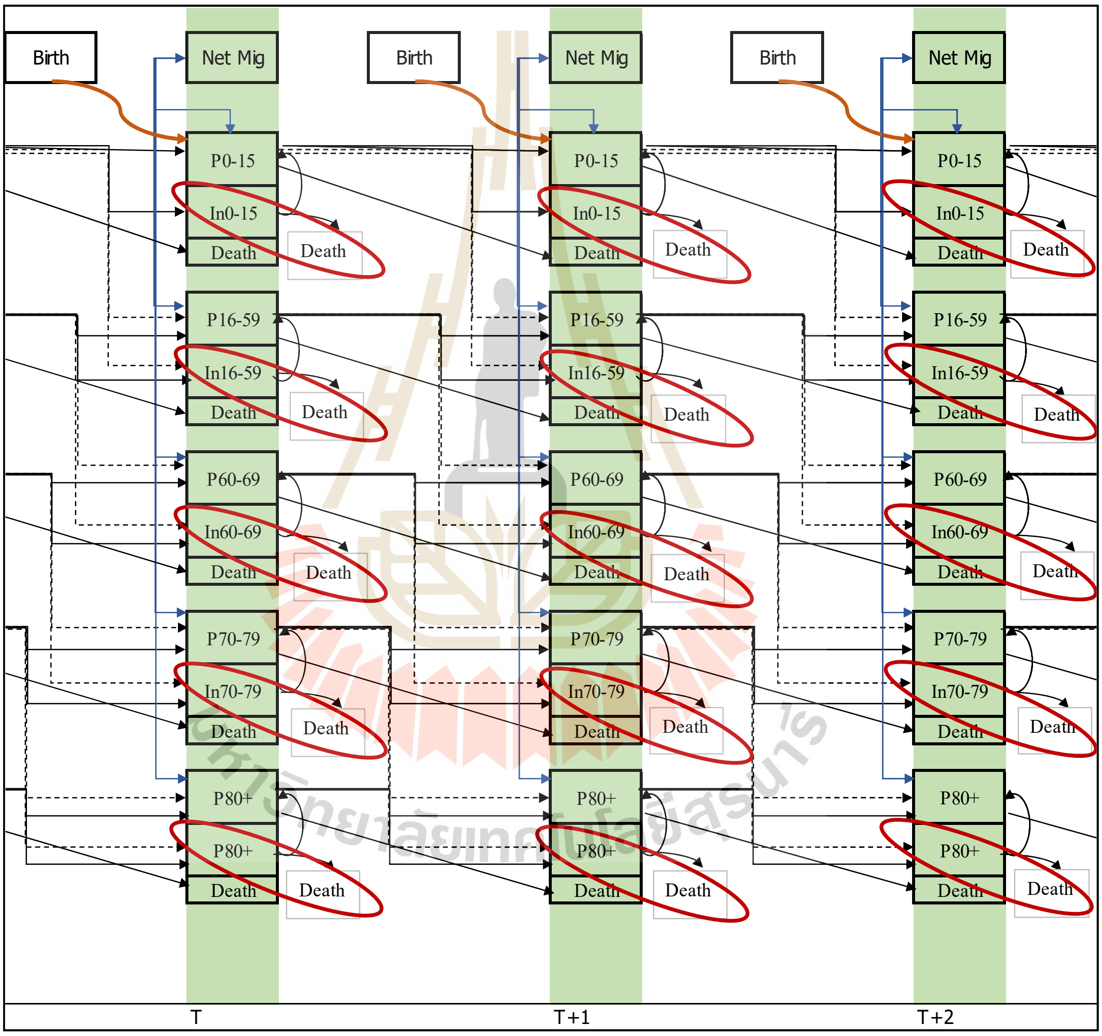


Figure 3.4 State transition between age groups

3.2.2 Markov Chains

In this section, we present non-homogeneous discrete time Markov model base multinomial logit formulation from MacRae, (1977).

Let $p_{agij}(t)$ be the probability of the transition of population age group a, gender g transfer from state i at time t-1 to state j at time t.

$$p_{agij}(t) = P\left(X_{agt} = j \mid X_{ag(t-1)} = i\right) \text{ for i,j =1,2,.,m, a=1..5,g=1,2,t=0,1..T} \quad (3.7)$$

From the previous study, Anderson and Goodman (1957) presented that Markov model from count data was estimated by using multinomial distribution for both homogeneous and non-homogeneous Markov chains.

Let $n_{agij}(t)$ be number of population age group a, gender g transfer from state i at time t-1 to state j at time t.

$$n_{agi}(t-1) = \sum_{j=1}^{m} n_{agij}(t) \quad \text{for i =1,2,…,m , a=1..5, g=1,2, t=0,1..T} \quad (3.8)$$

And $$\sum_{j=1}^{m} p_{agij}(t) = 1 \quad \text{for i =1,2,…,m , a=1..5, g=1,2, t=0,1..T} \quad (3.9)$$

Calculate maximum likelihood estimation for $p_{agij}(t)$ is

$$\hat{p}_{agij}(t) = \frac{n_{agij}(t)}{n_{agi}(t-1)} \quad \text{for i,j =1,2,…,m , a=1..5, g=1,2, t=0,1..T} \quad (3.10)$$

The condition distribution of $n_{agij}(t)$ given $n_{agi}(t-1)$ has the same distribution formulation of the multinomial distribution.

The parameterization process of non-homogeneous Markov chains in this research transforms multinomial distribution into a linear function by multinomial logit transformation. The multinomial logit function shows the relationship between transition probability and time-dependent covariates. Due to lack of data availability, covariate or independent variable in this research use only time calendar and all population of each age at time t-1.

The transition probability show in odds function which is the relation of $p_{agij}(t)$ state i to state j and $p_{agii}(t)$ is reference state of odds as equation (3.10) and logit function in equation (3.12).

$$\pi_{agij}(t) = \frac{p_{agij}(t)}{p_{agii}(t)} \quad \text{for i,j} = 1,2,\ldots,m,\ j \neq i,\ a=1..5,\ g=1,2,\ t=0,1..T \qquad (3.11)$$

$$\ln(\pi_{agij}(t)) = \theta_{agij}(p(t)) = f(\bar{\beta};\bar{x}), \quad \text{for i,j} = 1,2,\ldots,m,\ j \neq i,\ a=1..5,\ g=1,2,\ t=0,1..T \qquad (3.12)$$

When $\bar{\beta}$ are vectors of parameters and $\bar{x}$ are vectors of covariates or variable of logit function and rewrite equation (3.11) to probability function of parameter and covariate vectors as equations (3.13) and (3.14)

$$p_{agij}(t) = \left(\frac{\exp(\theta_{agij}(p(t)))}{1 + \sum_{j \neq i} \theta_{agij}(p(t))} \right) \text{for i,j} = 1,2,\ldots,m,\ a=1..5,\ g=1,2,\ t=0,1..T \qquad (3.13)$$

$$p_{agii}(t) = \left(\frac{1}{1 + \sum_{j \neq i} \theta_{agij}(p(t))} \right) \text{for i,j} = 1,2,\ldots,m,\ a=1..5,\ g=1,2,\ t=0,1..T \qquad (3.14)$$

Let $n_{agi}(0)$ be number of individuals of population age group a, gender g at state i at time t=0 , and the moment of multinomial distribution show as equations (3.15), (3.16), (3.17), and (3.18)

Mean

$$\mathrm{E}\left(n_{agij}(t)\right) = n_{agi}(0) \times p_{agij}(t) \tag{3.15}$$

Variance

$$Var\left(n_{agij}(t)\right) = n_{agi}(0) \times \left(p_{agij}(t) \times (1 - p_{agij}(t))\right) \qquad \text{for} \qquad i{=}j \tag{3.16}$$

Covariance

$$\mathrm{cov}\left(n_{agij}(t)\right) = -n_{agi}(0) \times p_{agij}(t) \times p_{agii}(t) \qquad \text{for} \qquad i \neq j \tag{3.17}$$

Variance - Covariance Matrix , $V_{agi}(n(t))$, *of* $n_i = (n_{i1}, n_{i2}, \ldots, n_{im})'$ *is given by*

$$V_{agi}(n(t)) = \begin{bmatrix} Var_{11} & Cov_{12} & \ldots & Cov_{1m} \\ Cov_{21} & Var_{22} & \ldots & Cov_{2m} \\ : & : & : & : \\ Cov_{m1} & Cov_{m2} & \ldots & Var_{mm} \end{bmatrix}_{ag} (t) \tag{3.18}$$

From equation (3.10) $\hat{p}_{agij}(t) = \dfrac{n_{agij}(t)}{n_{agi}(t-1)}$, the *Variance - Covariance Matrix of* $p_i = (p_{i1}, p_{i2}, \ldots, p_{im})$ *is given by*

$$Cov_{agi}(p(t)) = V_{agi}(p(t)) = \frac{1}{n_{agi}(t-1)} \times \begin{bmatrix} Var_{11} & Cov_{12} & \ldots & Cov_{1m} \\ Cov_{21} & Var_{22} & \ldots & Cov_{2m} \\ : & : & : & : \\ Cov_{m1} & Cov_{m2} & \ldots & Var_{mm} \end{bmatrix}_{ag} (t) \tag{3.19}$$

3.2.3 Weighted Least Square Estimation

The parameterization for Markov multinomial logit model in this research are applied by using weighted least square estimation (WLS). From the previous study, we found that the weighted least square method in one of the most popular algorithms applying for Markov chain from aggregate data. Therefore, in this research, we use WLS to estimate parameters of multinomial logit Markov model for demographic change.

Weighted least squares (WLS) is a parameter estimation technique which extends from ordinary least square due to non-constant variance. Agresti and Kateri (2011) show the advantage of WLS for parameter estimation as following details. Firstly, WLS has a standard form to apply for various models easily. Secondly, WLS is one of the parts of Maximum likelihood estimation technique by using iterative WLS. Finally, when WLS and ML estimators are asymptotically equivalent. The estimation algorithm from both is in group of best asymptotically normal (BAN).

Asymptotic Covariance Matrix

Logit response function equations (3.11) and (3.12) assume to normal distribution

Let $\tilde{\bar{\theta}}_{agi}(p_n(t))$ be a vector of logit response function on sample size n from state i and $\tilde{\bar{\theta}}_{agi}(p_n(t))$ =[$\tilde{\bar{\theta}}_{agi1}(p_n(t)), \tilde{\bar{\theta}}_{agi2}(p_n(t)),...\tilde{\bar{\theta}}_{agim}(p_n(t))$] for age group a and gender g.

For large sample, suppose that the cdf of $\sqrt{n}\left(\tilde{\bar{\theta}}_{agi}(p_n(t)) - \bar{\theta}_{agi}(p(t))\right)$ converse to a $N(0, \phi V_{agi} \phi')$ cdf.

$$\sqrt{n}\left(\tilde{\bar{\theta}}_{agi}(p_n(t)) - \bar{\theta}_{agi}(p(t))\right) \xrightarrow{d} N(0, \phi V_{agi} \phi') \tag{3.20}$$

From equations (3.11) and (3.12), $\theta_{agij}(p(t))$ show as equation (3.21).

$$\theta_{agij}(p(t)) = \ln(p_{agij}(t)) - \ln(p_{agii}(t))$$ for i,j =1,2,…,m , a=1..5, g=1,2, t=0,1..T

(3.21)

From delta method (Agresti & Kateri, 2011)

Let ϕ_i be the Jacobian (m-1)×m matrix.

$$\phi_i = \frac{\partial \theta_{ij}(p(t))}{\partial p(t)} = \frac{\partial}{\partial p}\left(\ln(p_{ij}(t)) - \ln(p_{ii}(t))\right) = \frac{1}{p_{ij}(t)} - \frac{1}{p_{ii}(t)}$$ for i,j=1..m

and i≠j

$$\phi_i = \begin{bmatrix} -p_{ii}^{-1} & p_{i2}^{-1} & 0 & 0 & 0 & 0 \\ -p_{ii}^{-1} & 0 & p_{i3}^{-1} & 0 & 0 & 0 \\ -p_{ii}^{-1} & 0 & 0 & : & 0 & 0 \\ -p_{ii}^{-1} & 0 & 0 & 0 & : & 0 \\ -p_{ii}^{-1} & 0 & 0 & 0 & 0 & p_{im}^{-1} \end{bmatrix} \quad (3.22)$$

Thus, asymptotic covariance Matrix ($V_F(t)$) of log odds is

$$V_F(t) = \phi_i \times V_{agi}(t) \times \phi_i' \quad (3.23)$$

From minimizes the quadratic loss function form of WLS

$$\left[\bar{\theta}_{agi}(p(t)) - f(\beta; x)(t)\right]' \times V_F^{-1} \times \left[\bar{\theta}_{agi}(p(t)) - f(\beta; x)(t)\right] \quad (3.24)$$

and $f(\beta; x) = \beta x$

Where

β - Set of parameters

x - Set of covariates

Calculate parameter of logit when $\overline{b}_i$ is vector of parameter β_{ij} from equation (3.25) and x is matrix of known constants of covariates.

$$\overline{b}_i = \left(\overline{x}' V_F^{-1} \overline{x}\right)_i^{-1} \times \left(\overline{x}' V_F^{-1} f(\beta; x)\right)_i \tag{3.25}$$

From equation (3.20), the weighted least square estimator has an asymptotic normal distribution, with estimated covariance matrix in equation (3.25)

$$Cov(\overline{b}_i) = \left(\overline{x}' V_F^{-1} \overline{x}\right)_i^{-1} \tag{3.26}$$

Goodness of fit test

The hypothesis test show null hypotheses as equation (3.27)

$$LossFunction \quad \overline{\theta}_{agi}(p(t)) - f(\beta; x)(t) = 0 \tag{3.27}$$

Hypothesis test

The null hypothesis of homogeneity is as

$$\text{H}_0\text{: } \beta = 0 \tag{3.28}$$

The lists of models to compare types of covariates (x) in the same form of equation (3.24) are shown below.

Model A : none of covariate of matrix x or accept null hypothesis $\beta = 0$

Model B : covariate of matrix x ; x is Number of population

Model C : covariate of matrix x ; x is Year

Model D : covariate of matrix x ; x is Number of population and Year

Use F distribution with (q,v) degree of freedom to test hypothesis

$$F_{q,v} = \frac{(SSR_r - SSR_u)/q}{SSR_u / v} \tag{3.29}$$

SSR_r – Residual of loss function equation (3.27) for null hypothesis or Model A with q degree of freedom and SSR_u for the other test (Model B ,C , and D) with v degree of freedom.

3.3 Model II : Inpatient semi-Markov model

From previous section, two sub Markov models are in population model including population age transfer model and inpatient transfer model in a year. The inpatient transfer model consists of two state transition as shown in Figure 3.5. The state of inpatient to discharge and inpatient to death. Times between discharge and death are called length of stay (LOS). In this model, LOS will be investigated by semi-Markov model for five age groups, gender and three types of diseases.

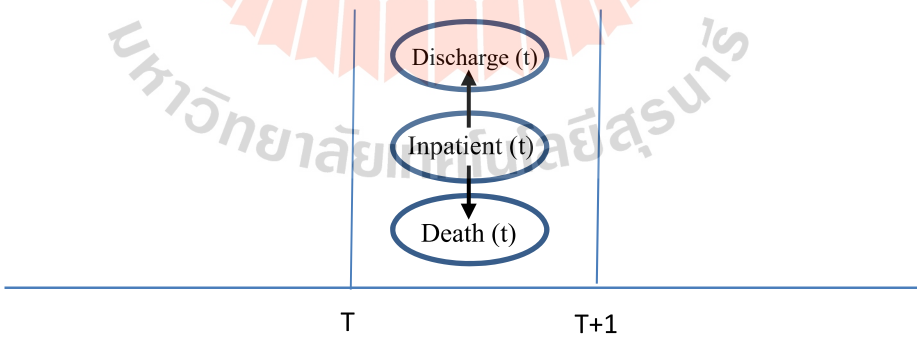


Figure 3.5 Inpatient transfer model

Assumptions

1) Transition occurs within one year so no any age groups change between states.

2) All inpatients will be discharged in a year.

3) Length of stay are in daily unit.

4) Semi-Markov model in this study is a discrete model.

5) Holding time proportions do not change for each year based on inpatients individual sample data from 43 files health data center database

Data analysis

The data flow of model 2 is shown in Figure 3.6

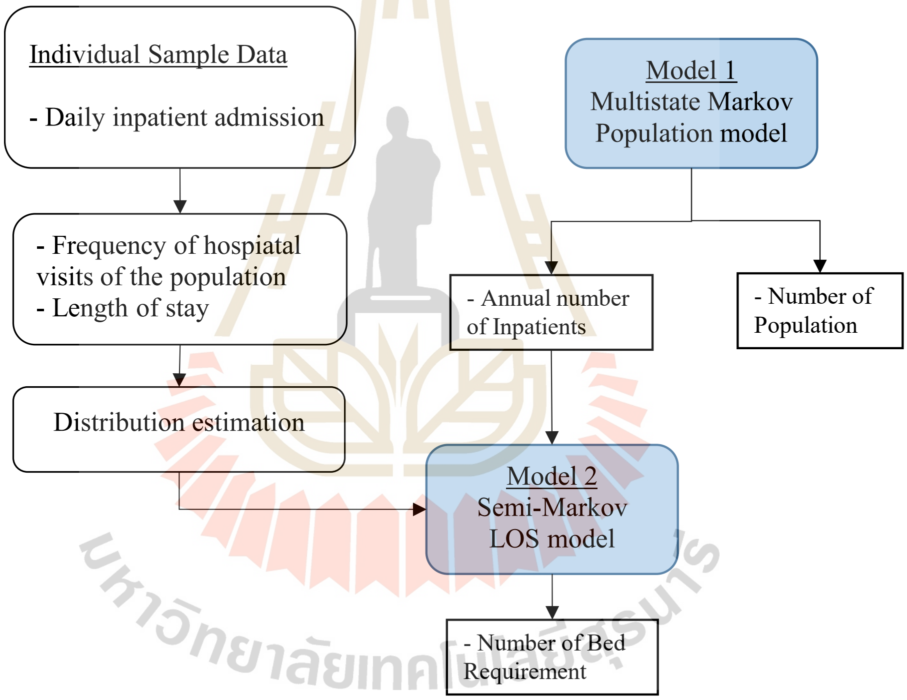


Figure 3.6 Data flow of model II

1) Inpatients disaggregated by gender, age group 5 groups and 3 diseases groups – Total inpatients by gender in 298 main cause of illness from 2007-2014 are disaggregates by age proportion from sample inpatients of each disease group.

2) A number of time visit hospitals – fit distribution of the number of time visit hospitals of inpatients by age groups, diseases, and gender from sample inpatient individual data.

3) The length of stay in hospitals – fit the distribution of length of stay in hospitals of inpatients by age groups, diseases, and gender from sample inpatient individual data.

Sets

Let S_2 – Set of state transition, S_2={ [$Inp_{(a)}$ → $Pop_{(a)}$], [$Inp_{(a)}$→ Death]}

G = {Male, Female}; set of each gender

A = {[0-15],[16-59],[60-69],[70-79],[80+]} ; set of age groups

I = {Chronic, Non-chronic, ACSC} ; set of inpatient types

D = {1,..,d} for set of time day(s) in a year

Indices

i , j: the i^{th} state and the j^{th} state of the inpatient state $i, j \in S_2$

n : the n-th - state transition number n

d: the d^{th} day , $d \in D$

g: the g^{th} gender , $g \in G$

a: the a^{th} age group , $a \in A$

k: the k^{th} inpatient group , $k \in IP$

Variables

p_{ij} - The transition probability of the semi-Markov chain of inpatients moving from state i to j (i,j = 1,..s2)

h_{ij} *(d)*- The holding time (sojourn time) mass function - propability that inpatients in state i will spend *d* days in state i before go to state j destination, when d_{ij} is discrete.

φ_{ij} *(d)* The probability that inpatients will be in state j on day t from state i on day 0

3.3.1 Discrete time semi-Markov model

The semi-Markov models in this study consist of state space and set of information as the following. State space $S_2 = \{1, 2\}$; set of inpatients as 1 for inpatients discharge to survive population and 2 for inpatients to dead in hospital population.

The sojourn time distribution in state i is defined as

$$h_i(d) = P(X_{n+1} = d | J_n = i), i \in S_2, n, d \in D \qquad (3.30)$$

The sojourn time cumulative distribution in state i is defined as

$$H_i(d) = P(X_{n+1} = d | J_n = i) = \sum_{l=0}^{t} h_i(l)\, , i \in S_2, n, l, d \in D \qquad (3.31)$$

Applying discrete semi-Markov model to predict the length of stay, the interval transition probability that inpatients will stay in state j (survive population or pass away) on day d from state i (hospitals) on day 0 is defined as

$$\varphi_{ij}(d) = \delta_{ij}[1 - H_i(d)] \sum_{r \in S2} p_{ir} + \sum_{r \in S2} p_{ir} \sum_{l=1}^{t} h_{ir}(l) \varphi_{rj}(d - l)$$

Where δ_{ij} - the Kronecker symbol , $\varphi_{ij}(0) = 1$ for i=j otherwise $\varphi_{ij}(0) = 0$

and $\delta_{ij} = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases}$; $i, j, r \in S_2,\ l, d \in D$ (3.32)

From Markov population model, the results show number of population for each age and gender groups and number of acute care as inpatients for each types of diseases by annually. Calculate number of hospital visits (NHV) per year t of inpatients (IPD) as following details.

$$NHV_{a,k,g,t} = IPD_{a,k,g,t} \times (proportion\ of\ NHV)_{a,k,g} \times (NHV\ of\ each\ proportion)_{a,k,g}$$

$$, for \quad g \in \{1,2\}, t \in T, k \in \{1,\ldots, K\} \quad (3.33)$$

The number of hospital visits (NHV) from Markov population model are used to calculate total length of stay per year as following details.

$$LOS = NHV \times P_{ij} \times H_{ij} \quad (3.34)$$

Calculate total patient days (TPD) from equation 3.35

$$TPD_t = \sum_g \sum_a \sum_k LOS_{g,a,k}(t) \quad , for\ t \in T \quad (3.35)$$

Calculate number of annual bed requirement as following details.

$$BedRequirement_t = \frac{TPD_t}{365} \quad , for\ t \in T \quad (3.36)$$

$$Bed\ Occupancy\ Rate_t = \frac{TPD_t}{(Bed\_Capacity)_t \times 365} \quad , for\ t \in T \quad (3.37)$$

3.4 Long-term care model

From previous section, the study investigate population structure change from 2015 to 2025 which combine demand of inpatient care. The population who are transferred to inpatient states are defined as acute care patients. In this section, the study will focus on elderly population. Elderly people need more intensive care than other group due to their personal health problems. Long term care systems for elderly are divided by level of elderly health. In this study, the factors that impact to level of long term care are level of dependency and household situation. The data flow of Model 3 is shown as Figure 3.7

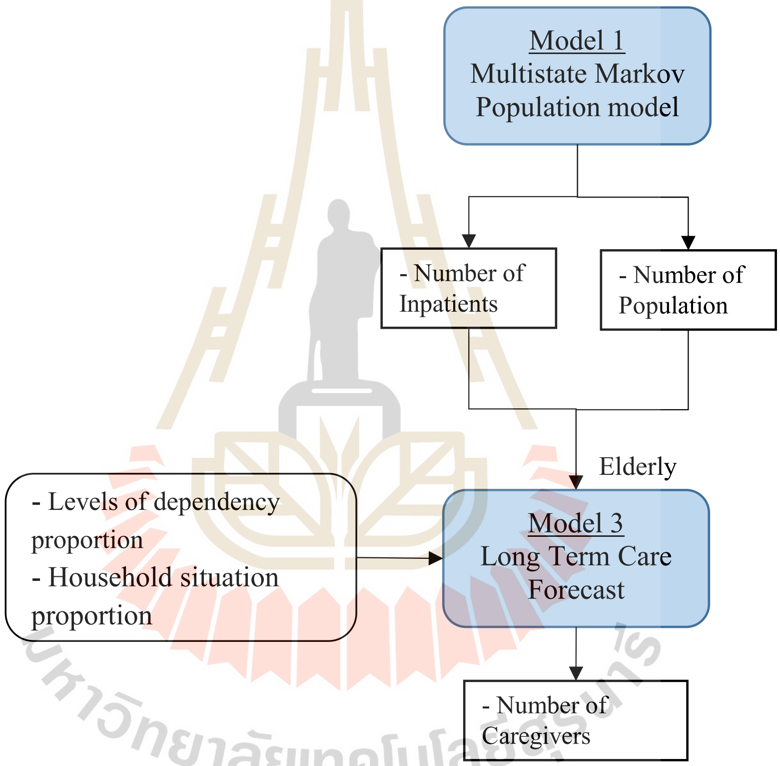


Figure 3.7 Data flow of model III

The details of factors need to consider as following details.

1) Levels of dependency mean level of practice daily activity by themselves as 3 levels

   a) Level 1 no dependency - elderly who can do all activities of daily living (ADL) without assistance.

b) Level 2 light dependency – elderly who need assistance to do activities of daily living for one activity.

c) Level 3 heavy dependency – elderly who need assistance to do activities of daily living more than one activities.

2) Household situation concern about elderly who live alone (LA) or live with family (LF).

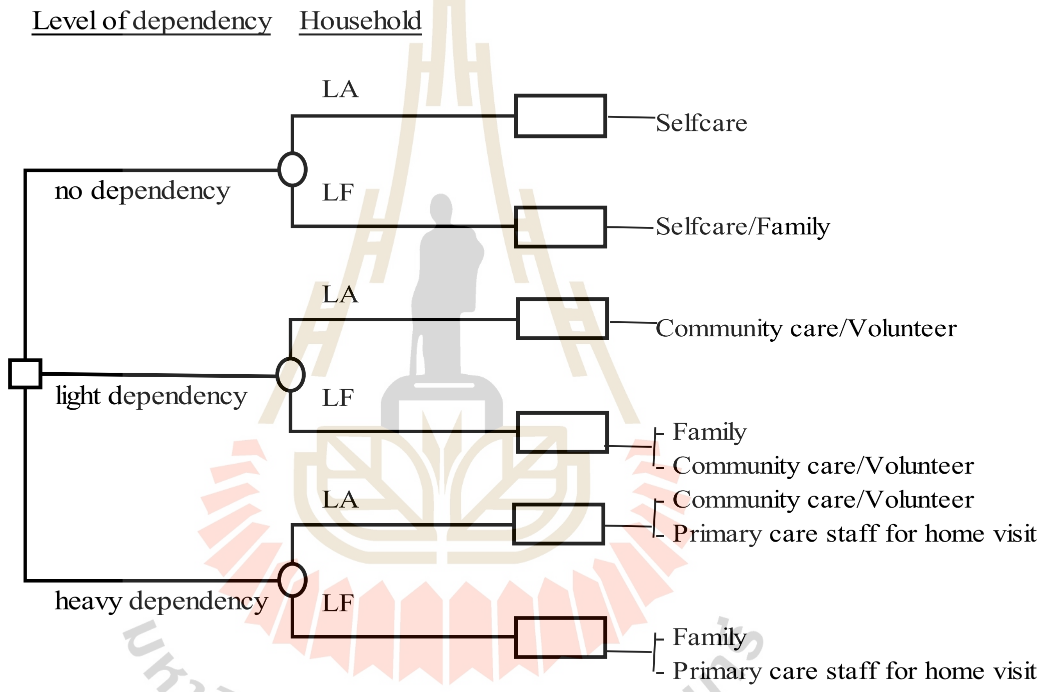


Figure 3.8 Level of long term care diagram and Staffing

Level of care in this research can be classified as lists.

- The elderly who live alone (LA) and heavy dependency need more care from medical care staff at primary care unit.
- The elderly who live alone (LA) and light dependency need more care from care staff at primary care unit.

- The elderly who live with family (LF) and heavy dependency need care from family.

Data Analysis

The information of level dependency and household situation for each elderly group is based on data survey from National health survey.

Table 3.1 Level of Elderly dependency

Age	2009						2014					
	Male			Female			Male			Female		
	1	2	3	1	2	3	1	2	3	1	2	3
[60-69]	0.887	0.106	0.007	0.855	0.139	0.006	0.829	0.150	0.021	0.792	0.186	0.022
[70-70]	0.858	0.125	0.017	0.786	0.202	0.012	0.766	0.195	0.039	0.630	0.307	0.063
[80+]	0.790	0.168	0.042	0.686	0.246	0.068	0.671	0.268	0.061	0.510	0.375	0.115

Remark : 1- no dependency, 2- light dependency, 3- heavy dependency

Table 3.2 Household composition – percent of elderly who live alone

Year	1994	2002	2007	2011	2014
%	3.6%	6.3%	7.7%	8.6%	8.7%

The analysis number of long-term care demand will be applied monte-carlo simulation to investigate proportion of long-term care factors due to the lack of information of joint probability of household composition and level of dependency.

Assumptions:

1) Proportions of level of Elderly dependency distribution are based on uniform distribution of each age and gender.
2) Proportion of household composition are based on uniform distribution as last three survey data.
3) The standard level of all elderly per community care staff is 7 elderly per 1 staff

4) The standard level of elderly who is in dependency level 2and 3 and elderly who live alone per home care staff is 7 elderly per 1 staff.

5) The standard of elderly who is in dependency level 3 per home visit medical staff is 200 elderly per 1 staff.

The number of long-term care demand will be analyzed by simulation of each level of household composition. The trend of level of dependency and household by live alone grow continually therefore, sensitivity analysis will be proposed in the next section.

3.5 Data sources

The information input to the model consists of population data and inpatient data.

1) Population data disaggregated by gender and age from 2007-2014 comprises of

- Annual newborn data and annual population data (The bureau of registration administration [BORA] ,2014)
- Annual death data (National Statistical Office [NSO], 2014) and the number of death disaggregated by age, gender from (Nakhon Ratchasima Provincial Public Health Office, 2014) and (Health Information System Development Office [HISO], 2014)
- Total number of death in hospitals (Bureau of Policy and Strategy [BPS], 2014)

2) Inpatient data consists of aggregate data and individual sample data

- Annual inpatient data from 2004 – 2014 from: (Bureau of Policy and Strategy, 2011, 2012, 2013, 2014)
- Total inpatient data disaggregated by gender and the main causes of illness 298 groups from (BPS, 2014)
- Inpatients Individual sample data from 43 files health data center database from Nakhon Ratchasima Provincial Public Health Office, total 235,362 records from 2012-2014

Inpatient data are disaggregated by chronic, non-chronic and ACSC groups by using ICD-10 and lists of chronic diseases ICD-10 codes from 43 files health data center database.

3.6 Sensitivity Analysis

Many factors impact to the system, in this research, the uncertainty analysis will study the change of level net-migration in Markov population model, the change of level length of stay in semi-Markov model and the change of ACSC inpatients decrease from Markov population Model based on assumption that if the primary care unit serve ACSC patients continually, the acute care of ACSC patients to hospital will be decrease. The elderly inpatients who stay in hospitals more than 1 months decrease to long term care model. The assumption on this case is based on the long-term care system can help to decrease the acute care for the heavy dependent elderly. The levels of uncertainty analysis for each model are proposed to evaluated level of resource requirement.

Table 3.3 Lists of scenario test

Scenarios	Details
1	- Net migration -30%, and +30%
2	- Number of ACSC inpatients , -25%, -40%,+25%, +40%
3	- 25% of elderly inpatients who stay in hospitals more than 1 months decrease to long term care.
4	- Household composition increase 1% by annually

3.7 Chapter Summary

In this chapter, the research methodology is presented including research framework, research procedure, data analysis, models and sensitivity analysis. The research framework consists of combining the stochastic method including nonhomogeneous Markov model and semi-Markov model. The multistate nonhomogeneous model analyze demographic population change from aggregate data. The population model transfer from each age group and gender to next states including inpatient state, population state and death state by annually. The research procedure present the study of the change of population structure impact to healthcare demand and long-term care from previous research. The data analysis using in this research consists of aggregate data and individual data. The analysis of aggregate data use to estimate transition probabilities of each states of non-homogeneous multistate Markov population model.

The models consist of Markov population model, inpatient semi-Markov model and long-term care estimation model. The result from Markov population model compose of number of population and inpatient demand during 2015-2025. The inpatient demand from previous model and holding time distribution from individual data is used to analyze length of stay (LOS) using semi-Markov model and estimate number of bed requirement from LOS. The long-term care requirement are estimated by the data from Markov population model and semi-Markov model. After that, test sensitivity analysis to evaluate result due to uncertainty situation. Finally, analyze result, conclusion and future suggestion.

CHAPTER IV

RESULTS AND DISCUSSIONS

This chapter provided the information related to the parameters of Markov model. The results of Markov model, semi-Markov model and long term care are shown in this chapter. The sensitivity aim to analyze the effect of uncertainty situation impacting the resource requirement of the model.

4.1 Markov population model

4.1.1 Parameter estimation

1) Birthrate Function

There are different parameters relating to the newborn rates of each gender. The parameters of birthrate function from equation (3.1) and new born data in Table A1 by gender are shown in Table 4.1 (based on time-dependent with year covariate).

Let

$f_{birth\_rate}(t)$ be the function of birth rate per population gender. It can be defined as

$$f_{birth\_rate}(t) = \alpha + \beta y(t) \tag{4.1}$$

Table 4.1 Parameters of Birthrate by population gender

Parameters	Male	Female
Constant(α)	0.223673	0.368025
Year $y(t)$	-0.00011	-1.78E-04

2) Net Migration

The net migration rates per population in this research are calculated from aggregate population data by cohort component method from equations (3.2) and (3.3). We fit the distributions by graphical and use fourier distribution for all net migration rate distributions. The equation of distribution function of net-migration rate per total population by gender is shown in equation (4.2) and the parameters are shown in table 4.2

$$f_{netmigrati\,onrate}(t) = a_0 + a_1 \times \cos(x \times w) + b_1 \times \sin(x \times w)$$

$$+ a_2 \times \cos(2 \times x \times w) + b_2 \times \sin(2 \times x \times w) \tag{4.2}$$

Table 4.2 Parameters of net migration rate by population genders

Parameter		a_0	a_1	b_1	w	a_2	b_2
Male	[0-15]	0.00136	0.00006	0.00001	0.00018	-0.00007	0.00024
	[16-59]	0.00014	-0.00257	0.00107	0.00018	0.00272	0.00108
	[60-69]	0.00006	0.00015	0.00009	0.00018	-0.00030	-0.00002
	[70-79]	-0.00008	-0.00002	0.00006	0.00019	0.00013	0.00012
	[80+]	-0.00004	0.00003	0.00017	0.00013	0.00013	0.00017
Female	[0-15]	0.00105	0.00018	-0.00017	0.00017	-	-
	[16-59]	-0.00162	0.00111	0.00153	0.00009	-	-
	[60-69]	0.00000	0.00004	0.00017	0.00012	0.00006	-0.00003
	[70-79]	0.00014	0.00021	0.00024	0.00008	-0.00001	0.00017
	[80+]	-0.00006	-0.00015	-0.00017	0.00019	0.00012	-0.00012

3) Markov Transition Probability

The logit functions are parameterized as polynomial in year calendar and total population of each age group covariates. The comparisons of F-distribution test from equation (3.29) for hypothesis test equation (3.28) are shown in Appendix D. In Table D1 and D2, we compare F-distribution test of models B, C and D with null hypothesis to discover which factors affect transition. In case of rejecting the null hypothesis and accepting the other hypothesis of model B, the number of population can be used as covariate of logit transition probability function. In case of rejecting the null hypothesis and accepting the other hypothesis of model C, the year calendar can be used as covariate of logit transition probability function. In case of rejecting the null hypothesis and accepting the other hypothesis of model D, the number of population and the year calendar can be used as covariates of logit transition probability function. In case of accepting the null hypothesis of model B and C, covariate matrices of logit transition probability function are constant. In case of rejecting the null hypothesis of all models, compare F-test value and choose the most of F-test value.

The result of selected parameters of logit function are shown in Table 4.3 for male and Table 4.4 for female. Parameters of logit function from equation (3.11) of each state for male and female are calculated by using equation (3.24).

Table 4.3 Parameters of the logit function of male for each state

States	Covariates	[0-15]	[16-59]	[60-69]	[70-79]	[80-+]
θ_{12} (Pop1_-->Pop2)	Constant	-457.58	-15.229	102.838	-3.0744	0
	pop	4.8E-05	1.3E-05	0	0	0
	year	0.21972	0	-0.0525	0	0
θ_{13} (Pop1_-->Death)	Constant	-203.84	-15.708	-2.9479	-0.112	580.157

States		Covariates	[0-15]	[16-59]	[60-69]	[70-79]	[80-+]
		pop	0	1.2E-05	-2E-05	-8E-05	0
		year	0.09804	0	0	0	-0.2896
θ_{14}	(Pop1_-->ACSC1)	Constant	-1.3765	-68.483	-2.8093	-1.8237	307.122
		pop	-1E-05	0	0	0	0
		year	0	0.03155	0	0	-0.1531
θ_{15}	(Pop1_-->Chronic1)	Constant	-1.7734	-72.375	-2.7173	-1.7877	266.385
		pop	-1E-05	0	0	0	0
		year	0	0.03394	0	0	-0.1329
θ_{16}	(Pop1_-->NonChronic1)	Constant	1.08282	-2.8173	-0.7923	-0.8153	310.551
		pop	-9E-06	0	-1E-05	0	0
		year	0	0	0	0	-0.1544
θ_{17}	(Pop1_-->ACSC2)	Constant	-268.16	-161.3	-4.5312	-300.03	0
		pop	0	0	0	0	0
		year	0.12966	0.07651	0	0.147	0
θ_{18}	(Pop1_-->Chronic2)	Constant	-3.2544	-7.2587	-4.545	-4.1243	0
		pop	-1E-05	0	0	0	0
		year	0	0	0	0	0
θ_{19}	(Pop1_-->NonChronic2)	Constant	-68.747	-6.1984	-2.4195	-3.0348	0
		pop	0	0	-1E-05	0	0
		year	0.03158	0	0	0	0

Table 4.4 Parameters of logit function of female for each state

States		Covariates	[0-15]	[16-59]	[60-69]	[70-79]	[80-+]
θ_{12}	(Pop1_-->Pop2)	Constant	-443.259	-119.907	94.40829	-146.642	0
		pop	4.99E-05	0	0	0	0
		year	0.212718	0.05744	-0.0483	0.071458	0
θ_{13}	(Pop1_-->Death)	Constant	-186.789	-7.31793	90.67852	127.1182	0.41318
		pop	0	0	0	0	-9.6E-05
		year	0.089336	0	-0.04748	-0.06496	0
θ_{14}	(Pop1_-->ACSC1)	Constant	-2.50532	-4.97077	-2.83943	-2.17238	203.9115
		pop	-1.2E-05	0	0	0	0
		year	0	0	0	0	-0.10222
θ_{15}	(Pop1_-->Chronic1)	Constant	-2.49002	-4.31315	-2.70374	-1.90739	204.9811
		pop	-1.2E-05	0	0	0	0
		year	0	0	0	0	-0.10254
θ_{16}	(Pop1_-->NonChronic1)	Constant	-51.1771	-2.31673	-0.35778	70.67384	251.9695
		pop	0	0	-1.4E-05	0	0
		year	0.024583	0	0	-0.0356	-0.12542

States	Covariates	[0-15]	[16-59]	[60-69]	[70-79]	[80-+]
θ_{17} (Pop1_-->ACSC2)	Constant	-4.95686	-7.26305	-3.7695	-4.52864	0
	pop	-9.7E-06	0	-1.2E-05	0	0
	year	0	0	0	0	0
θ_{18} (Pop1_-->Chronic2)	Constant	-4.28946	-7.12719	-3.50575	-4.09963	0
	pop	-9.7E-06	0	-1.2E-05	0	0
	year	0	0	0	0	0
θ_{19} (Pop1_-->NonChronic2)	Constant	-4.83056	-6.04055	-1.93664	106.1879	0
	pop	0	0	-1.8E-05	0	0
	year	0	0	0	-0.05437	0

The transition probabilities from equations (3.13) and (3.14) are calculated by logit functions from parameters in Tables 4.3 and 4.4. The observed and fitted transition probabilities of each state are shown in Figures 4.1- 4.18. The trends of probability rate of population in year(t) age (a) of male transfer to the same age group (a) in year t+1 are shown in Figure 4.1. The probability rates of “childhood” age group and “working age” age group slightly decrease, on the other hand, the probability rates of “beginning elderly” and “middle elderly” age groups slightly increase and highly increase in “eldest elderly” age group.

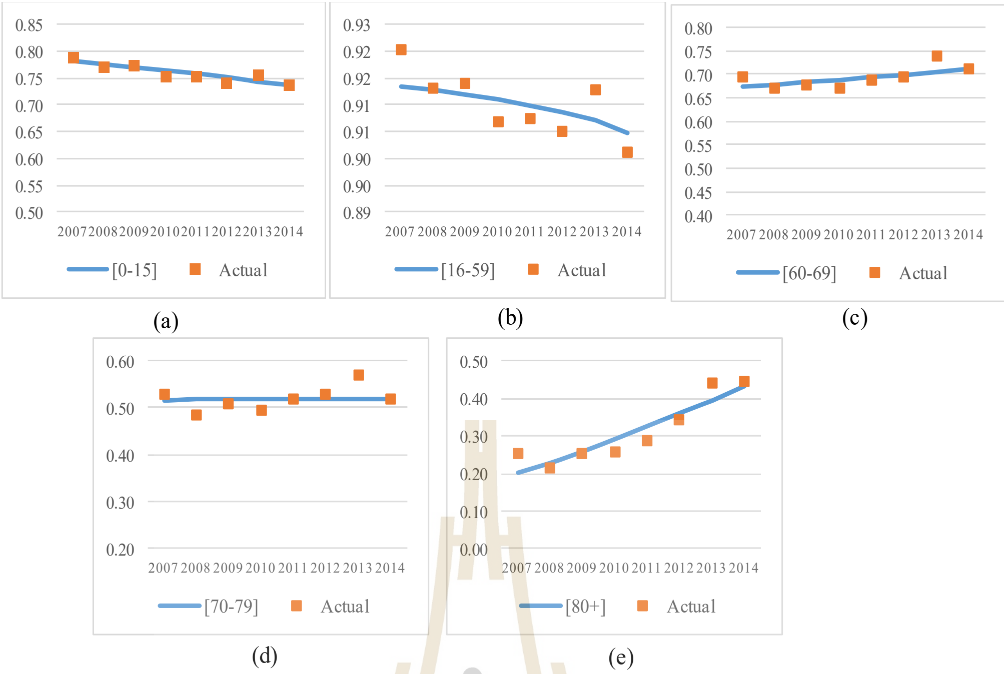


Figure 4.1 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Male)* [*State i* - population current age in year(t) to *State j* - population at current age group in year (t+1)] ; (a) [0-15] (b) [16-59] (c) [60-69] (d) [70-79] (e) [80+]

The probability rates of male population in year(t) age (a) transfer to the next age group (a+1) in year t+1 are shown in Figure 4.2. The trends show that transfer rates slightly increase in childhood group to working age and working age to beginning elderly while, beginning elderly group transfer to middle elderly increasing rapidly.

The transition probability function of male population age [70-79] in year(t) transfer to population age [80+] in year t+1 ,shown in Figure 4.2 (d), are constant meaning that there are no factors that have any effect on transition probability of models B and C as shown in table D1.

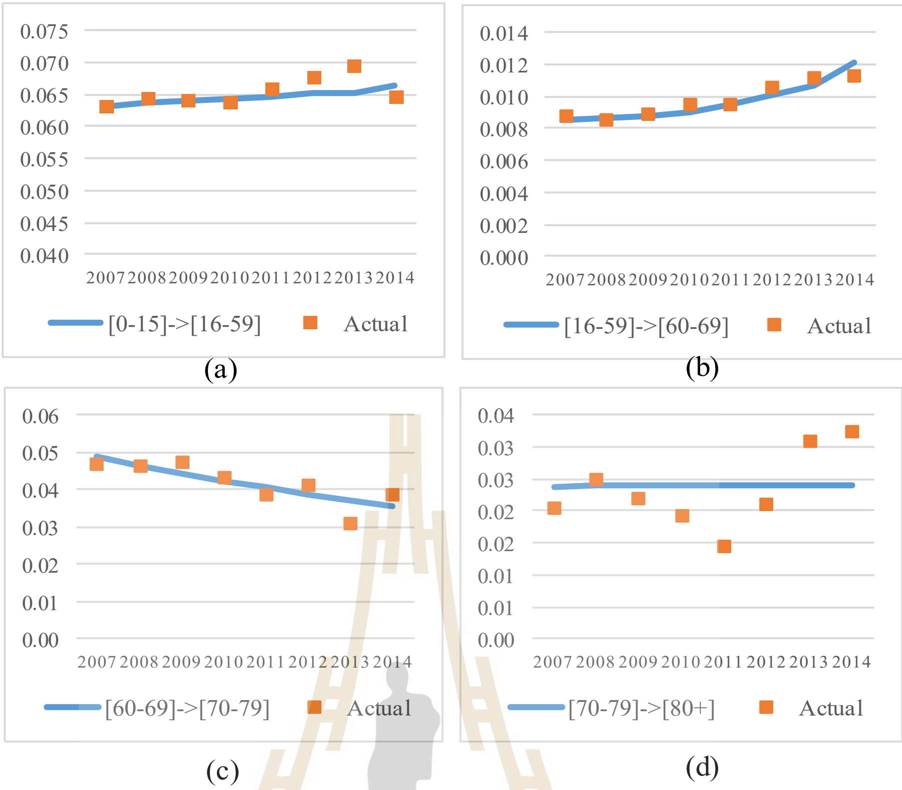


Figure 4.2 Comparison of fitted values and observed values of transition probabilities (pij) (Male) [State i - population current age in year(t) to State j - population at next age group in year (t+1)] ; (a) [0-15] → [16-60] (b) [16-59] → [60-69] (c) [60-69] → [70-79] (d) [70-79] → [80+]

The transition rates of population male age (a) to ACSC in-patients age (a) are shown in Figure 4.3. The transition rate to ACSC in-patients childhood age tends to increase while the transition rates of working age, beginning elderly age and middle elderly age are rather stable and the transition rate to ACSC in-patients oldest elderly age tend to decrease. The transition rates of population male age (a) to ACSC in-patients age (a+1) are shown in Figure 4.4. The transition rates of working age population to beginning elderly age ACSC highly increases and others are rather constant rates.

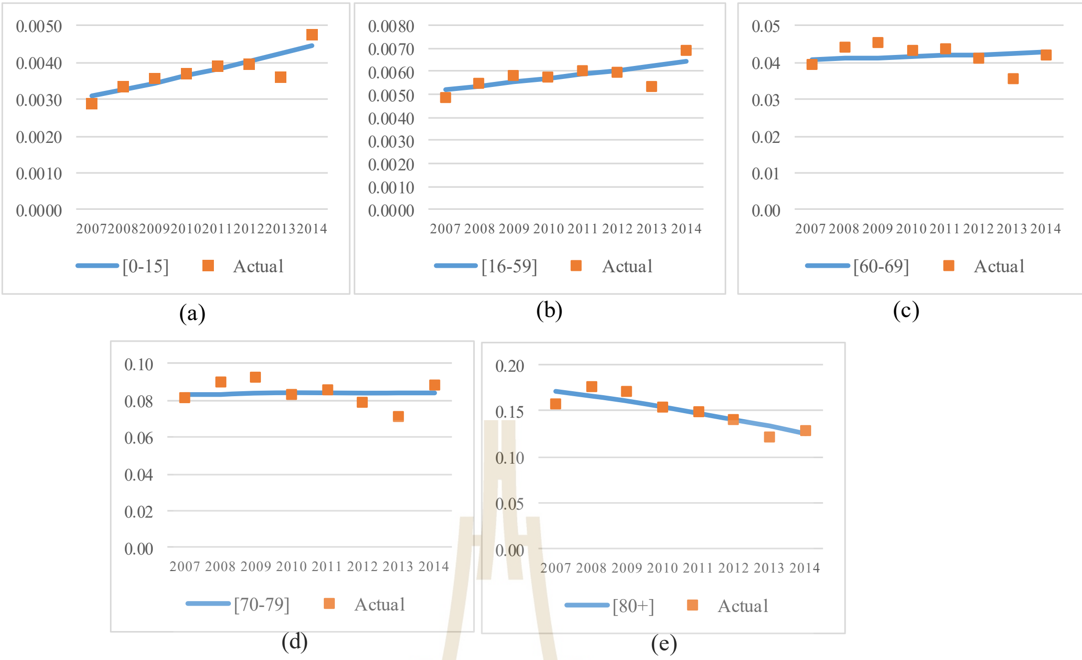


Figure 4.3 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Male)* [*State i* - population current age group in year(t) to *State j* ACSC inpatient current age group in year(t+1)] ; (a) [0-15] (b) [16-59] (c) [60-69] (d) [70-79] (e) [80+]

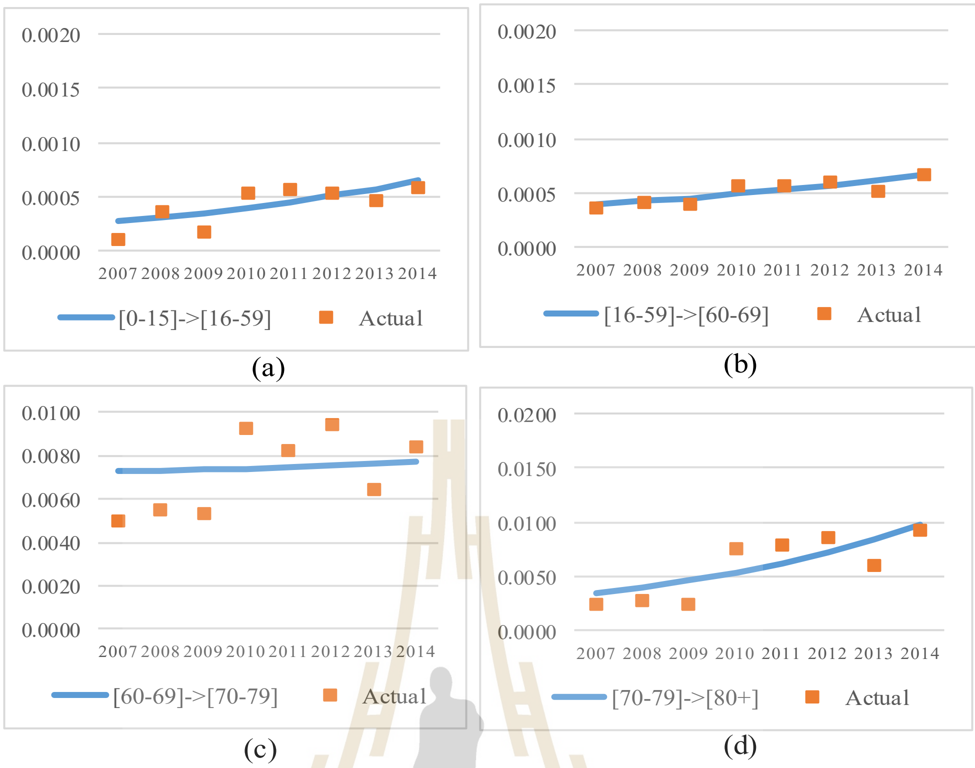


Figure 4.4 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Male)* [*State i* - population current age group in year(t) to *State j* - ACSC inpatient next age group in year(t+1)] ; (a) [0-15]→[16-60] (b) [16-59]→[60-69] (c) [60-69]→[70-79] (d) [70-79]→[80+]

The transition rates of population male age (a) to chronic inpatients age (a) are shown in Figure 4.5. The transition rates to chronic inpatients childhood age tends to highly increase while, the transition rates of working age, beginning elderly age and middle elderly age are rather stable and the transition rate to chronic inpatients oldest elderly age tend to decrease. The transition rates of population male age (a) to chronic inpatients age (a+1) are shown in Figure 4.6. The transition rates of childhood population to working age slightly increase and other rates are rather constant.

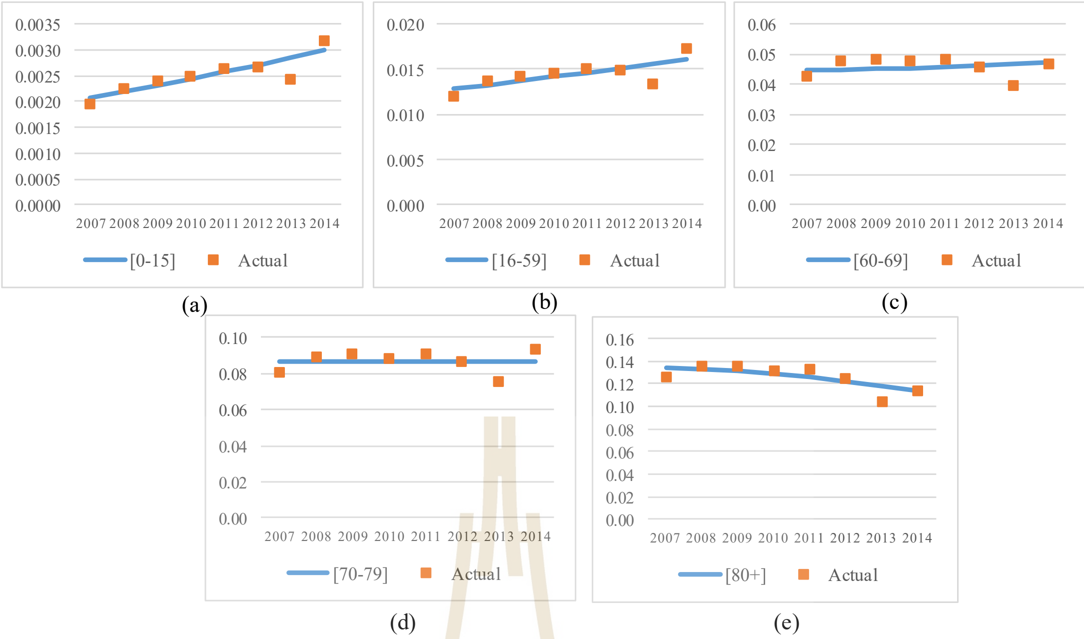


Figure 4.5 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Male)* [*State i* - population current age group in year(t) to *State j* – Chronic inpatient <u>current age</u> group in year(t+1)] ; (a) [0-15] (b) [16-59] (c) [60-69] (d) [70-79] (e) [80+]

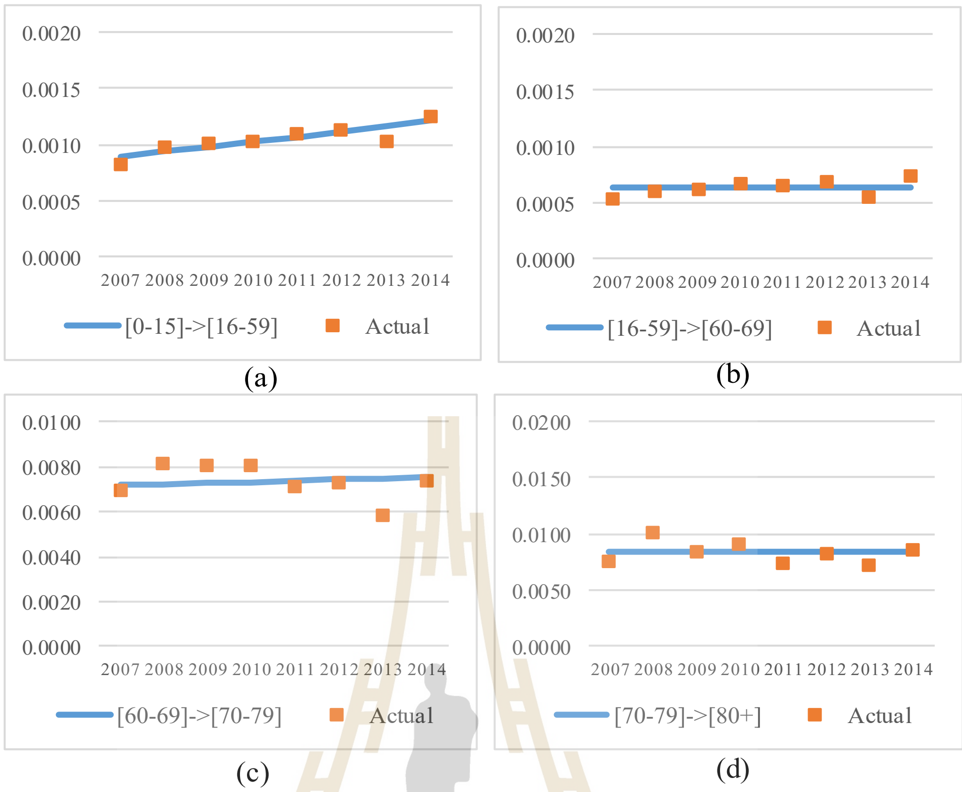


Figure 4.6 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Male)* [*State i* - population current age group in year(t) to *State j* - Chronic inpatient next age group in year(t+1)] ; (a) [0-15]→[16-60] (b) [16-59]→[60-69] (c) [60-69]→[70-79] (d) [70-79]→[80+]

The transition rates of population male age (a) to non-chronic in-patients age (a) are shown in Figure 4.7. The transition rates to non-chronic in-patients childhood age tends to increase while, the transition rates of working age and beginning elderly are rather stable and the transition rates to non-chronic in-patients of middle elderly age and oldest elderly age tend to slightly decrease. The transition rates of population male age (a) to non-chronic in-patients age (a+1) are shown in Figure 4.8. The transition rates of childhood population to working age slightly increase. The transfer rates between male population beginning elderly age(a) to non-chronic inpatients age(a+1) slightly decrease and other rates are rather constant.

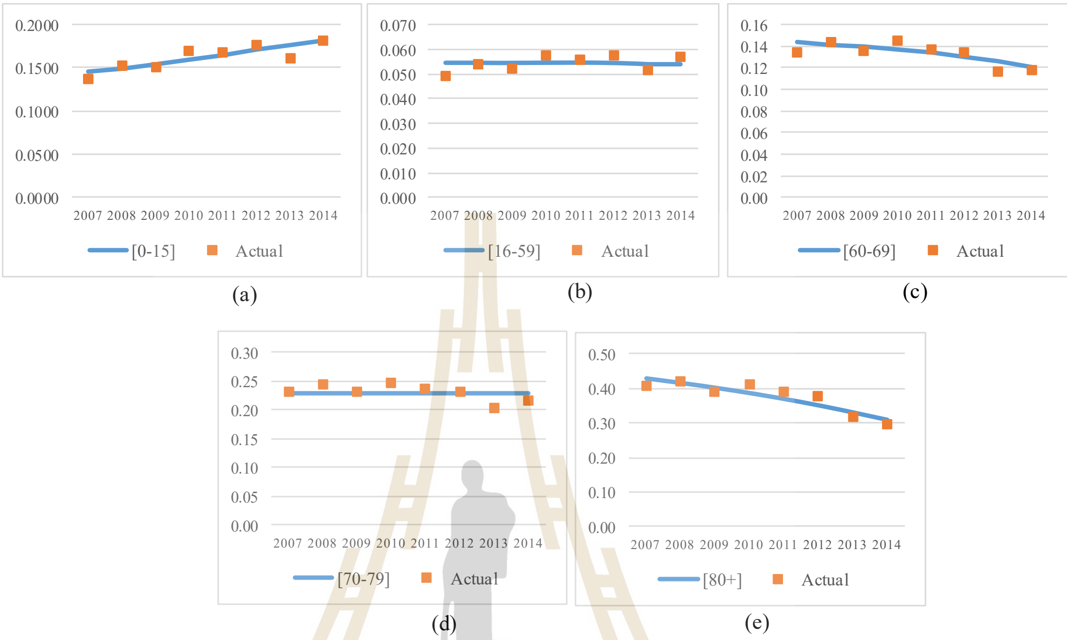


Figure 4.7 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Male)* [*State i* - population current age group in year(t) to *State j* – Non-chronic inpatient <u>current age</u> group in year(t+1)] ; (a) [0-15] (b) [16-59] (c) [60-69] (d) [70-79] (e) [80+]

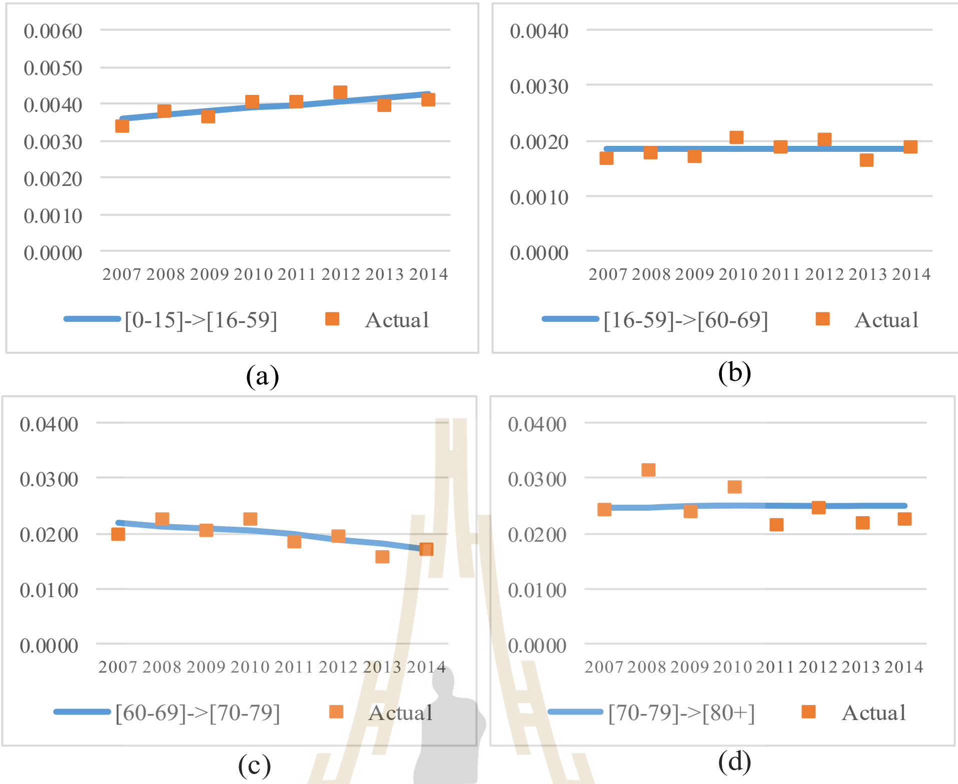


Figure 4.8 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Male)* [*State i* - population current age group in year(t) to *State j* – Non-chronic inpatient next age group in year(t+1)] ; (a) [0-15]→[16-60] (b) [16-59]→[60-69] (c) [60-69]→[70-79] (d) [70-79]→[80+]

The trend of transition rates of male population to death outside hospitals propose in Figure 4.9. The transition rates to death of state childhood and working age are continual growth. However, the transition rates to death of other elderly states tend to decrease.

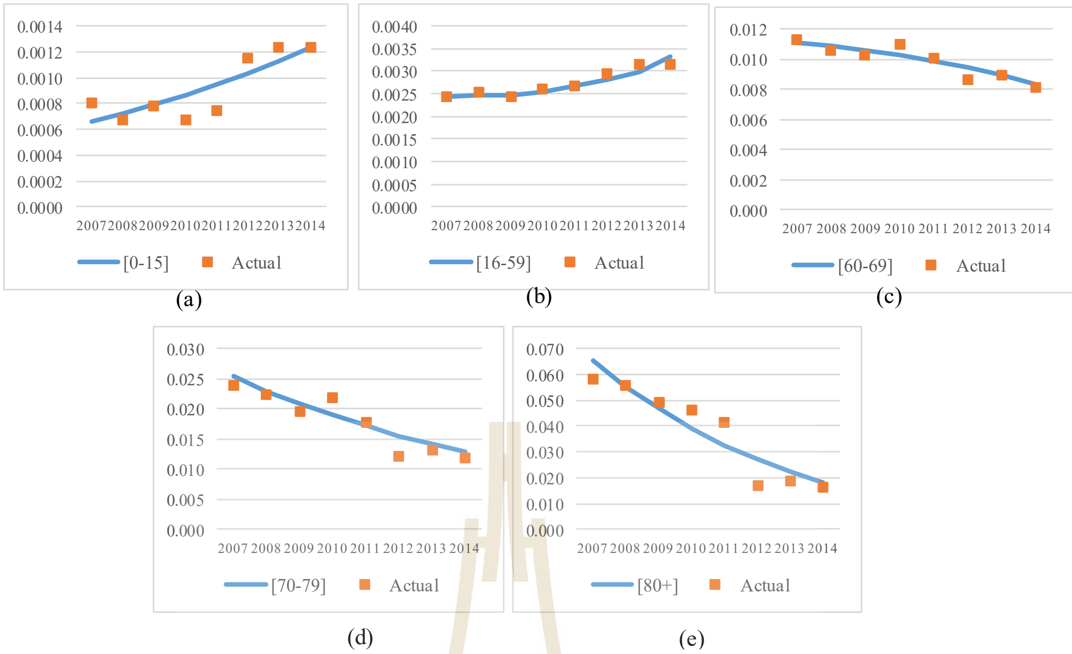


Figure 4.9 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Male)* [*State i* - population current age group in year(t) to *State j* – death all outside hospitals in year(t+1)] ; (a) [0-15] (b) [16-59] (c) [60-69] (d) [70-79] (e) [80+] (Male)

The trend of probability rates of population in year(t) age(a) of female transfer to the same age group (a) in year t+1 are shown in Figure 4.10. The probability rates of age group childhood and working age slightly decrease while the probability rates of age group beginning elderly, middle age elderly and eldest elderly age tend to increase.

The probability rates of female population in year(t) age (a) transfer to the next age group (a+1) in year t+1 are shown in Figure 4.11. The trends show that transfer rates slightly increase in childhood group to working age and working age to beginning elderly and middle elderly age to oldest elderly age while beginning elderly group transfer to middle elderly tend to decrease.

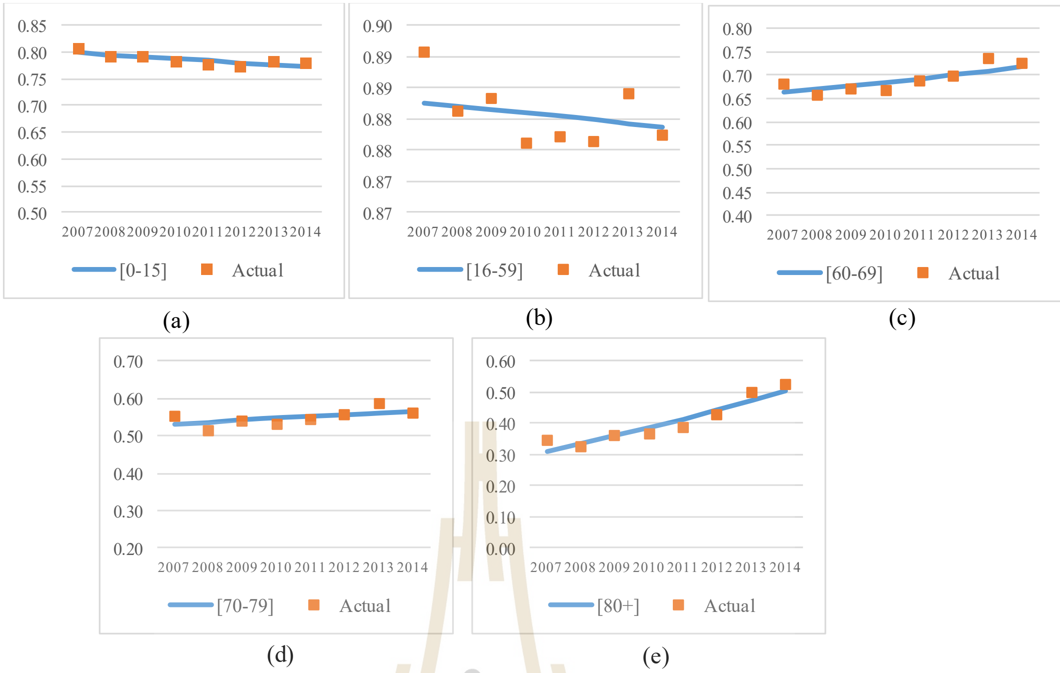


Figure 4.10 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Female)* [*State i* - population current age in year(t) to *State j* - population at current age group in year (t+1)] ; (a) [0-15] (b) [16-59] (c) [60-69] (d) [70-79] (e) [80+]

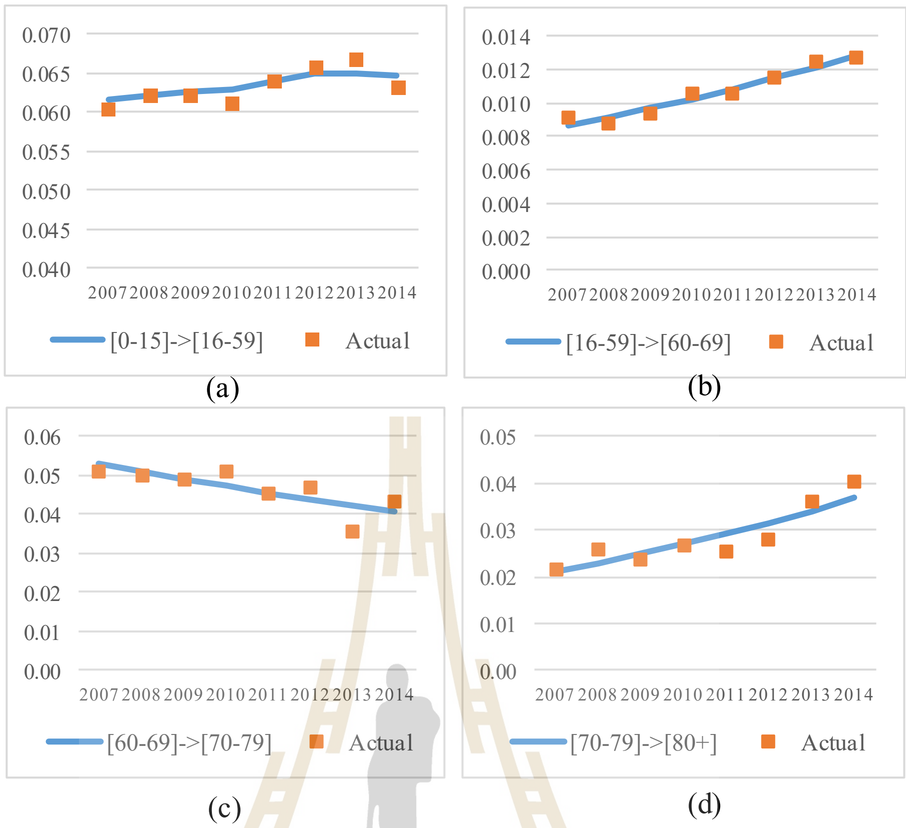


Figure 4.11 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Female)* [*State i* - population current age in year(t) to *State j* - population at next age group in year (t+1)] ; (a) [0-15] → [16-60] (b) [16-59] → [60-69] (c) [60-69] → [70-79] (d) [70-79] → [80+]

The transition rates of population female age (a) to ACSC in-patients age (a) are shown in Figure 4.12. The transition rates to ACSC in-patients childhood age tend to increase while the transition rates of working age, beginning elderly age and middle elderly age are rather stable. The transition rates to ACSC in-patients oldest elderly age tend to decrease. The transition rates of population female age (a) to ACSC in-patients age (a+1) are shown in Figure 4.13. The transition rates of beginning elderly age to middle elderly age ACSC slightly decrease and others are rather constant rates.

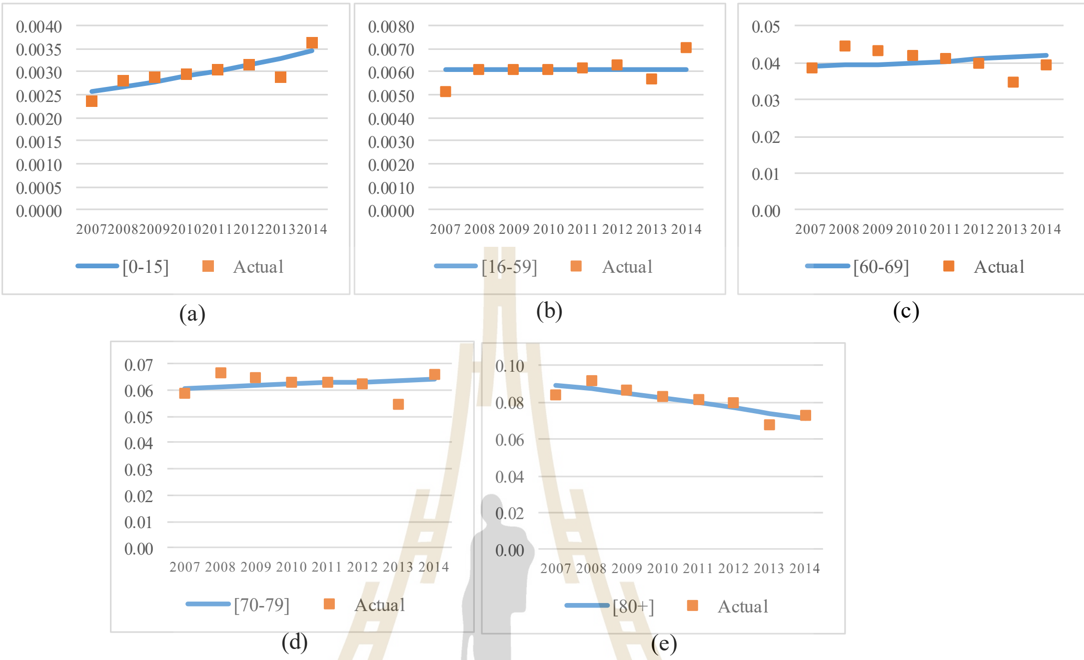


Figure 4.12 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Female)* [*State i* - population current age in year(t) to *State j* – ACSC inpatient at current age group in year (t+1)] ; (a) [0-15] (b) [16-59] (c) [60-69] (d) [70-79] (e) [80+]

(c) (d)

Figure 4.13 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Female)* [*State i* - population current age in year(t) to *State j* – ACSC inpatient at <u>next age</u> group in year (t+1)] ; (a) [0-15] → [16-60] (b) [16-59] → [60-69] (c) [60-69] → [70-79] (d) [70-79] → [80+]

The transition rates of population female age (a) to chronic inpatients age (a) are shown in Figure 4.14. The transition rates to chronic inpatients childhood age tend to highly increase and beginning elderly age and middle elderly age tend to slightly increase. While the transition rates of working age are rather stable and the transition rate to chronic inpatients oldest elderly age tend to decrease.

The transition rates of population female age (a) to chronic inpatients age (a+1) are shown in Figure 4.15. The transition rates of childhood population to working age slightly increase and beginning elderly to middle elderly tend to decrease. Other rates are rather constant.

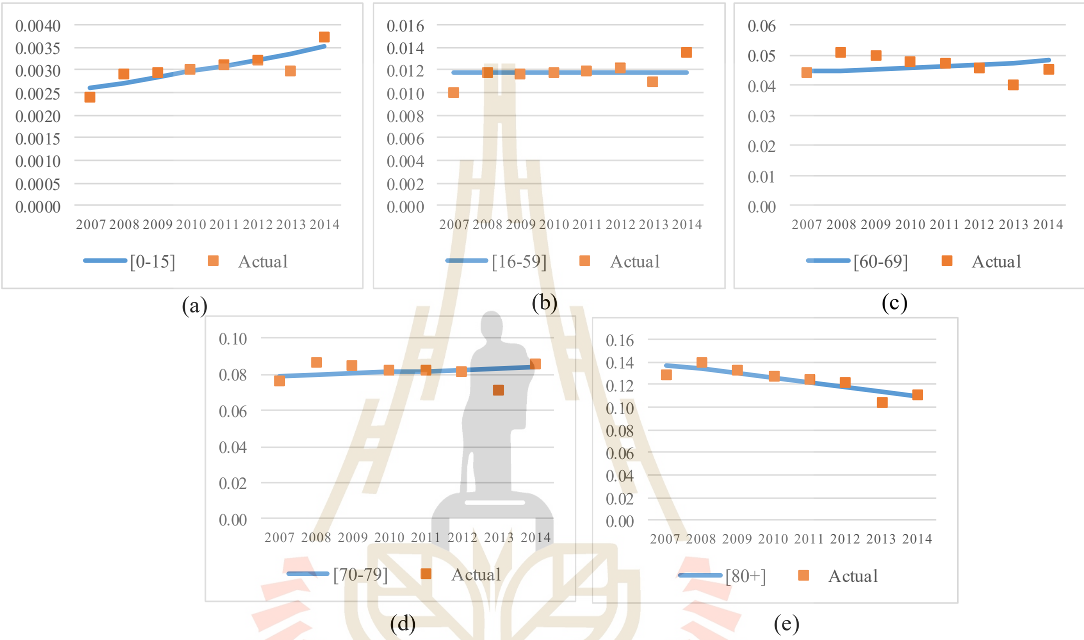


Figure 4.14 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Female)* [*State i* - population current age in year(t) to *State j* – Chronic inpatient at current age group in year (t+1)] ; (a) [0-15] (b) [16-59] (c) [60-69] (d) [70-79] (e) [80+]

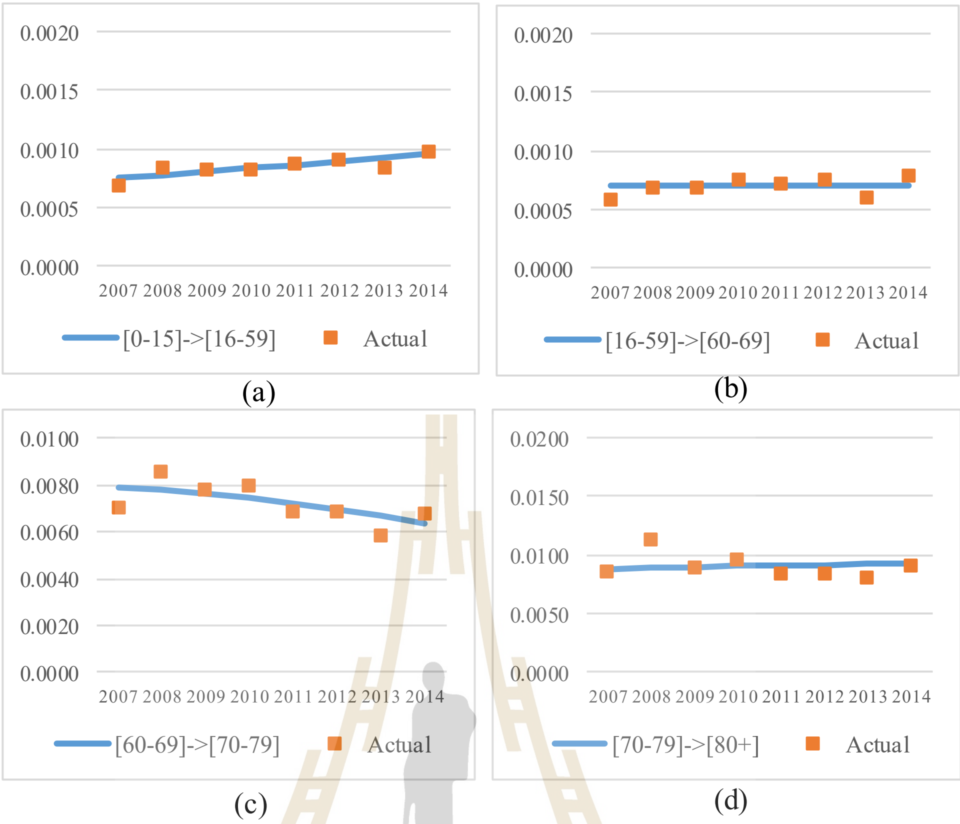


Figure 4.15 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Female)* [*State i* - population current age in year(t) to *State j* – Chronic inpatient at next age group in year (t+1)] ; (a) [0-15] → [16-60] (b) [16-59] → [60-69] (c) [60-69] → [70-79] (d) [70-79] → [80+]

The transition rates of population female age (a) to non-chronic in-patients age (a) are shown in Figure 4.16. The transition rates to non-chronic in-patients childhood age tend to increase while, the transition rates of working age are rather stable. The transition rates of beginning elderly, middle elderly age and oldest elderly age tend to decrease.

The transition rates of population female age (a) to non-chronic in-patients age (a+1) are shown in Figure 4.17. The transition rates of childhood population to working age and working age to beginning elderly age (a) non-chronic inpatients age(a+1) are rather constant. The other rates are rather decease.

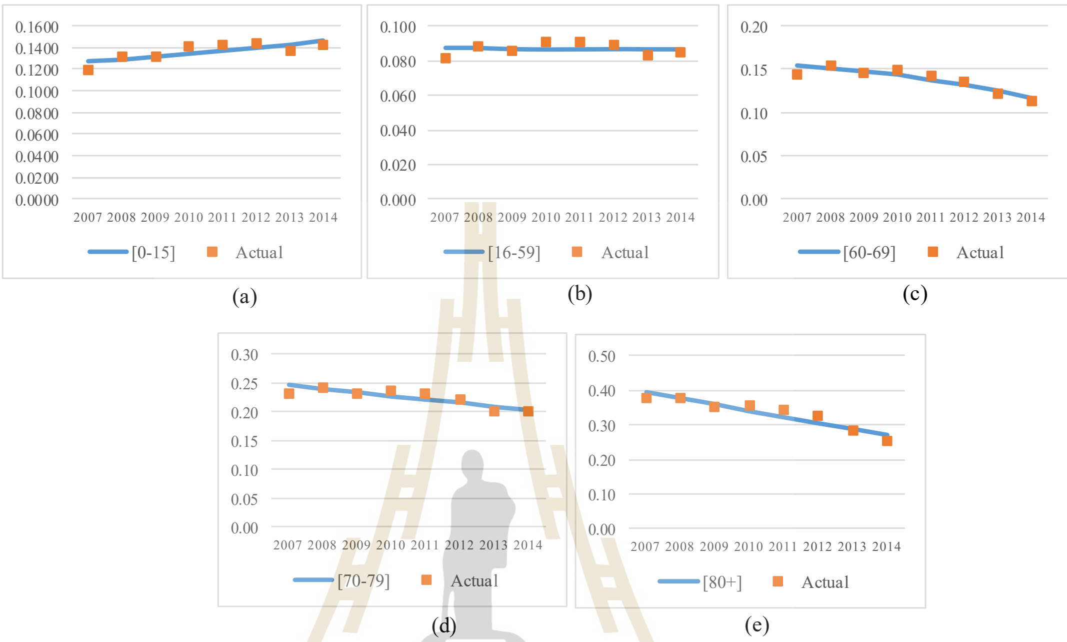


Figure 4.16 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Female)* [*State i* - population current age in year(t) to *State j* – Non-chronic inpatient at current age group in year (t+1)] ; (a) [0-15] (b) [16-59] (c) [60-69] (d) [70-79] (e) [80+]

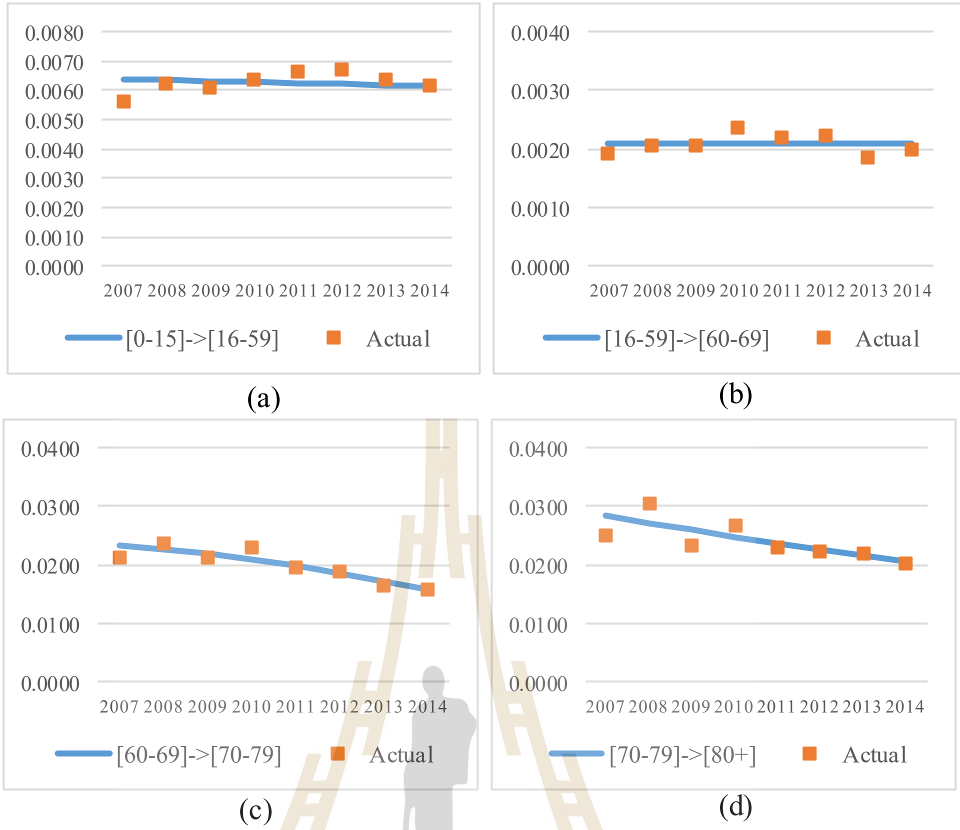


Figure 4.17 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Female)* [*State i* - population current age in year(t) to *State j* – Non-chronic inpatient at next age group in year (t+1)] ; (a) [0-15] → [16-60] (b) [16-59] → [60-69] (c) [60-69] → [70-79] (d) [70-79] → [80+]

The trend of transition rates of female population to death outside hospitals are proposed in Figure 4.18. The transition rates to death of state childhood are continual increasing and the transition rates of working age are constant. However, the transition rates to death of other elderly states tend to decrease.

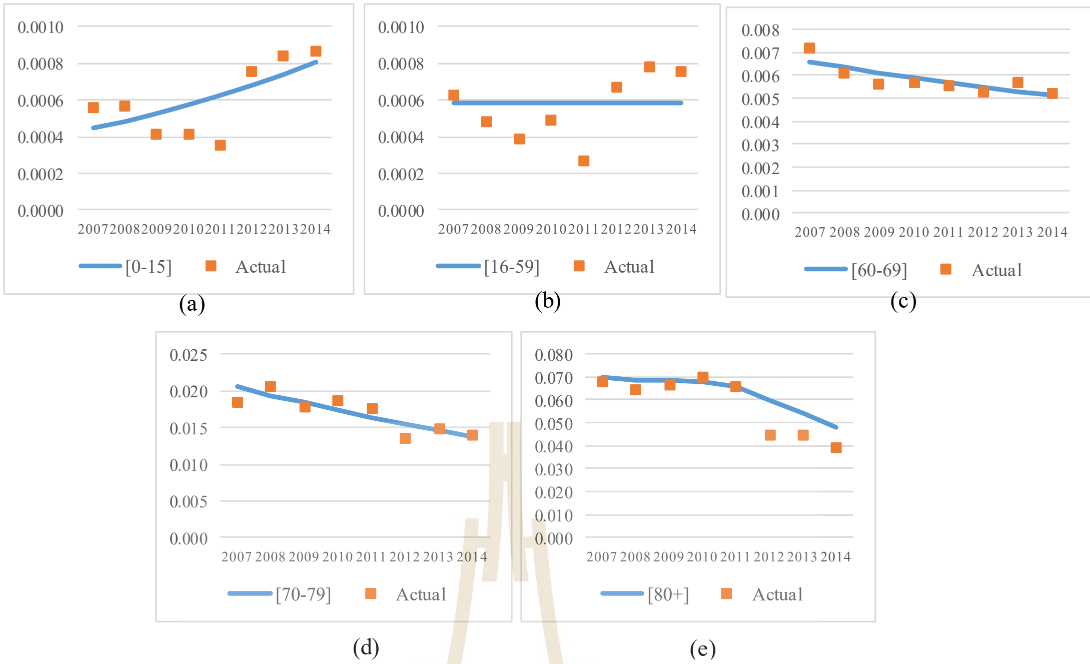


Figure 4.18 Comparison of fitted values and observed values of transition probabilities (p_{ij}) *(Female)* [*State i* - population current age group in year(t) to *State j* – death all outside hospitals in year(t+1)] ; (a) [0-15] (b) [16-59] (c) [60-69] (d) [70-79] (e) [80+] (Male)

4.1.2 Model validation

To compare the efficiency of the forecast results, it is necessary to validate the reliability of the calculations by comparing between real and prediction data using the Mean Absolute Percent Error (MAPE). The historical data from 2007 to 2014 are used to calculate Markov model. Therefore, the validation of the model will compare all data during 2007-2016. The comparison, in Table 4.5, shows that the predictions of population have less difference from the real data. When compare between age groups and genders, it can be found that the predictions of population for childhood and working age have differences between actual and predicted data less than 1%. In the elderly age, there are differences between real and predicted data ranging from 1-4% in male and 1-5% in female. The difference of each age group is due to uncertainty factors such as mortality rate by chronic and net-migration. Thus, the future study should consider the transition rate by considering other impact factors such as type of chronic disease and factor for migration etc. However, the difference or MAPE of total population is less than 1%. Therefore, the predicted population and demand from model can be used to estimate resource requirement.

Table 4.5 Mean Absolute Percent Error (MAPE) between real and predicted values for population during 2010-2016

MAPE	Male					Female					Total
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	
2007	0%	0%	0%	1%	2%	0%	1%	0%	1%	0%	0%
2008	0%	0%	0%	1%	2%	0%	0%	1%	1%	5%	0%
2009	0%	0%	0%	0%	1%	0%	0%	1%	1%	5%	0%
2010	0%	0%	1%	1%	0%	0%	0%	0%	0%	6%	0%
2011	0%	0%	1%	2%	5%	0%	0%	0%	0%	2%	0%
2012	0%	0%	1%	3%	4%	0%	0%	0%	1%	1%	0%
2013	0%	1%	4%	3%	8%	0%	1%	2%	2%	9%	0%
2014	0%	1%	2%	3%	5%	0%	1%	2%	2%	9%	0%
2015	0%	0%	0%	4%	2%	1%	1%	1%	3%	7%	0%
2016	0%	0%	1%	6%	3%	1%	0%	4%	4%	3%	0%
Avg	0%	0%	1%	2%	0%	0%	0%	0%	1%	5%	0%

4.1.3 Number of Population

The transition probability rates of Markov population are applied to calculate number of population and number of inpatients from 2007-2025. The beginning state is population by age and gender group in 2006. The results show the number of population and the number of inpatients by five age groups and each gender in appendix A, Table A1-A8. The summary of all results are shown in Figures 4.19-4.21.

The number of male population Figure 4.19 in group childhood decreases from 288,125 in 2007 to 211,999 in 2025 or decreases 26.4% and population in group working age slightly increase from 831,657 in 2007 to 838,091 in 2025, or increase 0.77%. However, the change of total male population in all elderly age group increase from 123,580 in 2007 to 225,177 in 2025, or increase 45.11%. The number of population of beginning age elderly highly increase from 71,123 in 2007 to 131,615 in 2015 or 85.05% increase. The number of population of middle age elderly increase from 39,515 in 2007 to 47,402 in 2015, or 19.96% increase. The number of population of the oldest age elderly increase from 12,941 in 2007 to 46,161 in 2015, or 256.71% increase. The proportion of total elderly per all male population increase from 9.94% in 2007 to 17.65% in 2025.

The male ACSC patients tend to increase from 2007 to 2015. The number of male elderly ACSC inpatients increases from 9,083 in 2007 to 16,343 in 2025, or increases 44.42%. The number of male elderly chronic inpatients increase from 9,405 in 2007 to 14,629 in 2025, or increase 35.71%. The number of male elderly non-chronic inpatients increases from 27,966 in 2007 to 30,254 in 2025, or increase 7.56%.

The number of female population shown in Figure 4.20(a) in group childhood decreases from 271,778 in 2007 to 198,826 in 2025, or decreases 26.84% and population in group working age decrease from 848,606 in 2007 to 785,227 in 2025, or decrease 7.47%. However, the change of total female population in all elderly age group increase from 152,914 in 2007 to 355,244 in 2025, or increase 131%. The number of population of beginning age elderly highly increases from 80,617 in 2007 to 216,091 in 2015 or 168.05% increase. The number of population of middle age elderly increases from 51,454 in 2007 to 63,467 in 2015, or 23.35% increase. The number of population of oldest age elderly increases from 20,843 in 2007 to 75,686 in 2015, or 263.12% increase. The proportion of total elderly per all female population increase from 12.0% in 2007 to 26.5% in 2025.

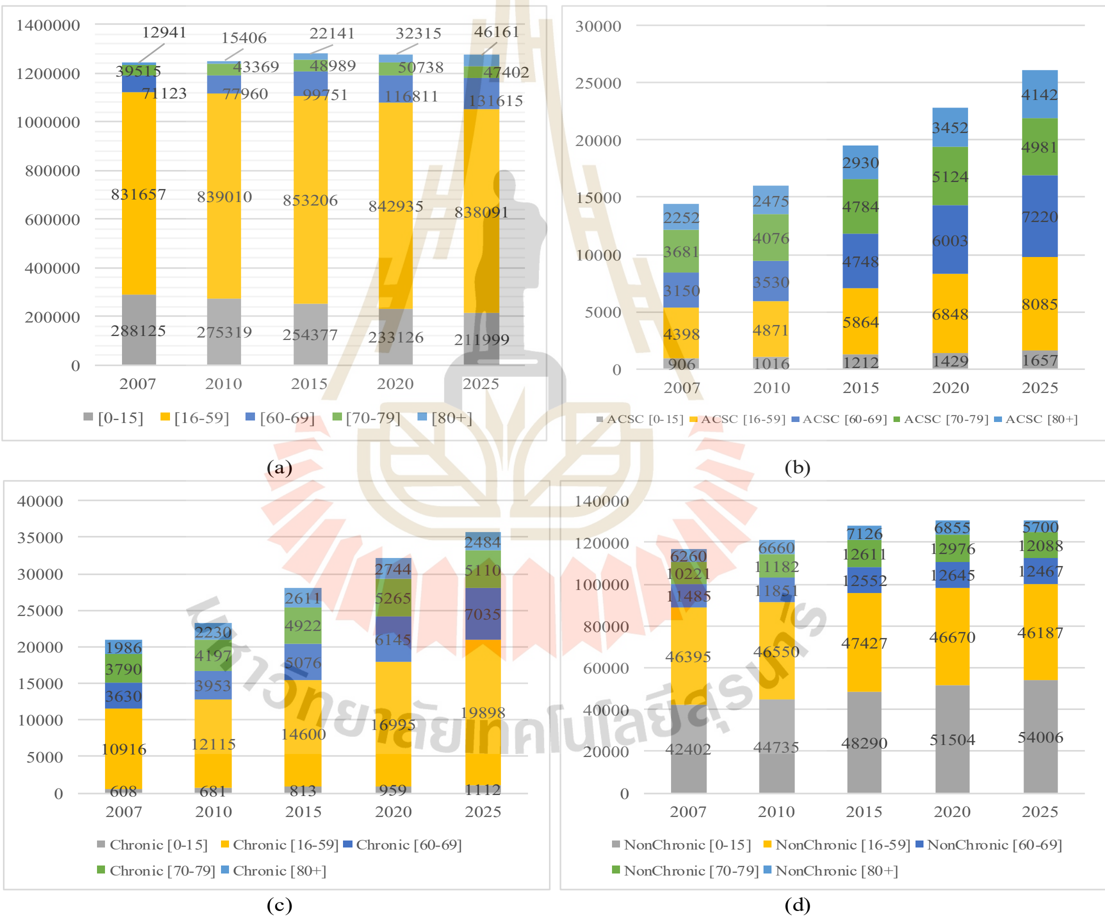


Figure 4.19 Number of Population and Inpatients from Markov models *(Male)* (a) Number of population, (b) ACSC inpatients, (c) Chronic inpatients and (d) Non-chronic inpatients

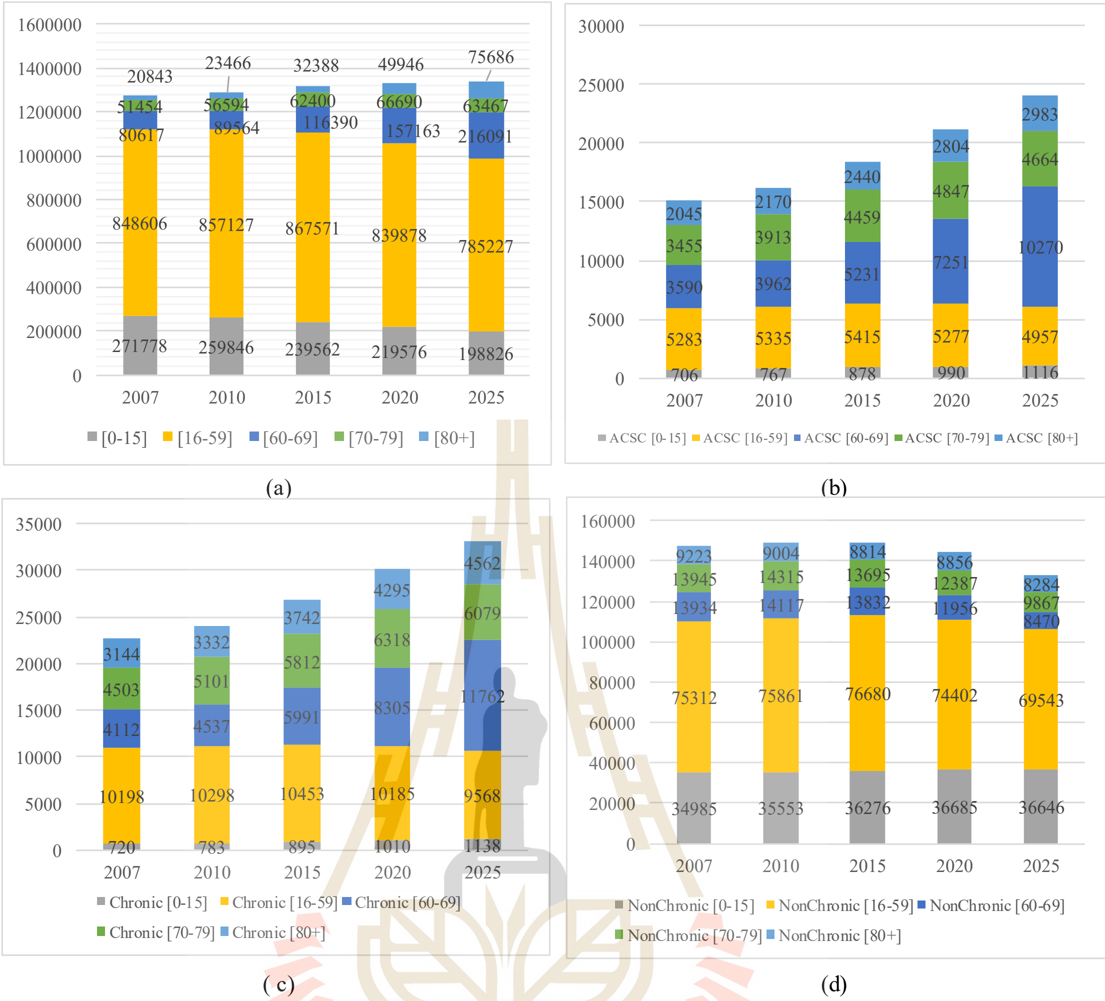


Figure 4.20 Number of Population and Inpatients from Markov models *(Female)* (a) Total number of population, (b) ACSC inpatients, (c) Chronic inpatients and (d) Non-chronic inpatients

The female ACSC patients tend to increase from 2007 to 2015. The number of female elderly ACSC inpatients increase from 9,090 in 2007 to 17,916 in 2025, or increase 49.26%. The number of female elderly chronic inpatients increase from 11,759 in 2007 to 22,404 in 2025, or increase 47.51%. The number of female elderly non-chronic inpatients (Figure 4.20 (d)) decreases from 37,101 in 2007 to 26,621 in 2025, or decrease 39.34%. The number of female elderly non-chronic inpatients tends to decrease as follow transition probability change in Figures 4.16 (c-e) and Figures 4.17 (b-d)

The number of total population Figure 4.21(a) in group childhood decreases from 559,903 in 2007 to 410,825 in 2025, or decreases 26.6% and population in working age group decrease from 1,680,263 in 2007 to 1,623,318 in 2025, or decrease 3.39%. However, the change of total population in all elderly age group increase from 276,494 in 2007 to 580,421 in 2025, or increase 52.36%.

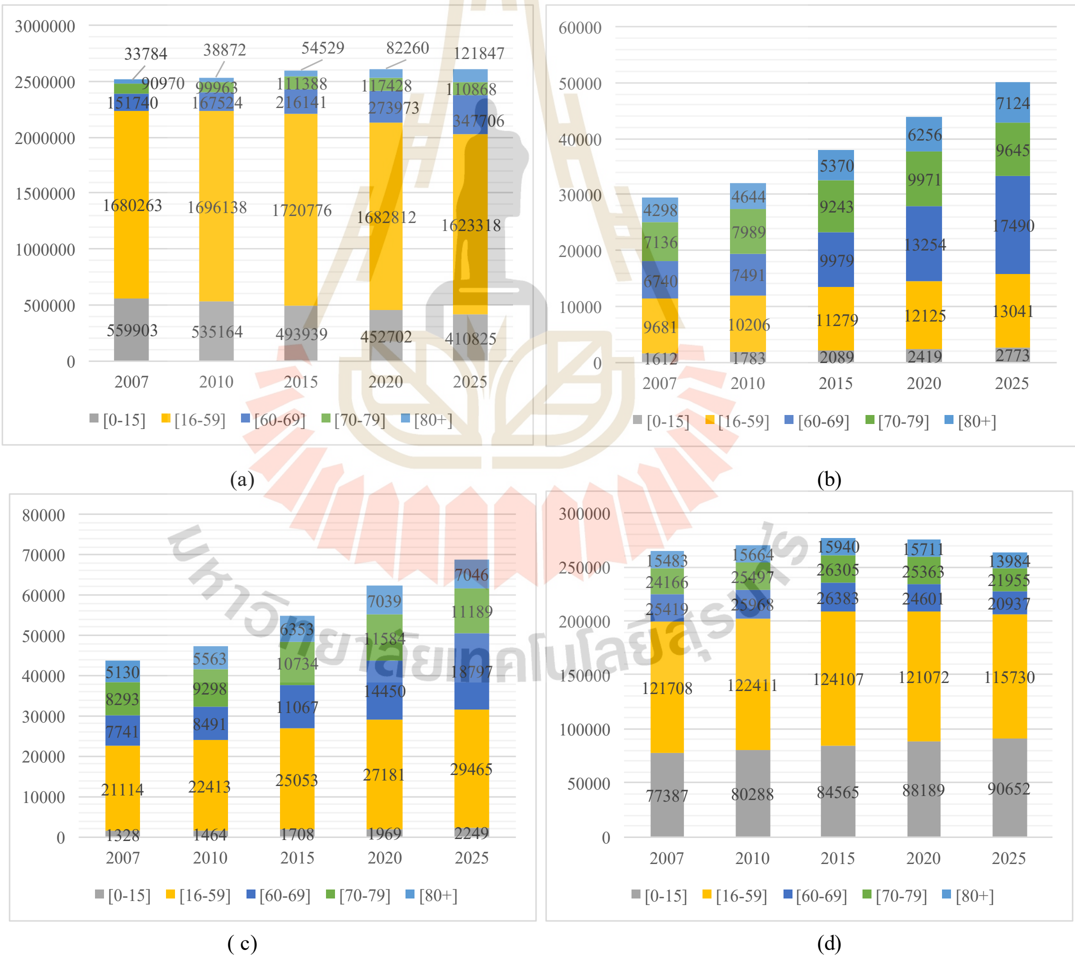


Figure 4.21 Total Number of Population and Inpatients from Markov models (a) Total number of population, (b) ACSC inpatients, (c) Chronic inpatients and (d) Non-chronic inpatients

The number of population of beginning age elderly highly increases from 151,740 in 2007 to 347,706 in 2015, or 129.15% increase. The number of population of middle age elderly increases from 90,970 in 2007 to 110,868 in 2015, or 21.87% increase. The number of population of oldest age elderly increases from 33,784 in 2007 to 121,847 in 2015 or 260.66% increases. The proportion of total elderly per all population increase from 11.0% in 2007 to 22.1% in 2025.

All ACSC patients tend to increase from 2007 to 2015. The number of all elderly ACSC inpatients increases from 18,174 in 2007 to 34,259 in 2025, or increases 46.95%. The number of all elderly chronic inpatients increases from 21,164 in 2007 to 37,033 in 2025 or increases 42.85%. The number of all elderly non-chronic inpatients (fig 4.21 (d)) decreases from 65,068 in 2007 to 56,876 in 2025 or decreases 14.40% because the number of female elderly non-chronic inpatients tends to decrease.

The changes of population for both male and female in childhood group decrease from 2007 to 2025. However, the changes of working age population for male from 2007 to 2025 are still stable but the changes of working age population for female decrease from 2007 to 2025. The proportions of total elderly per all population tend to increase for both male and female. The elderly proportions of ACSC patient and chronic patient are also increase for both male and female. Nonetheless, the female elderly proportions of non-chronic patient decrease from 2007 to 2015 but the male elderly proportions of non-chronic patient slightly increase.

4.1.4 Number of hospital visits

The number of inpatients for each type of diseases from Markov population model is used to calculate number of hospitals visits using equation (3.30). The calculation of number of hospitals visits incorporate individual sample data from

43 files, health data center database. The proportion of number of hospitals visits in one year disaggregated by gender, five age groups and three type of inpatients are shown Tables B1-B6 of appendix B. The summary of number of hospitals visits are shown in Figures 4.22-4.23.

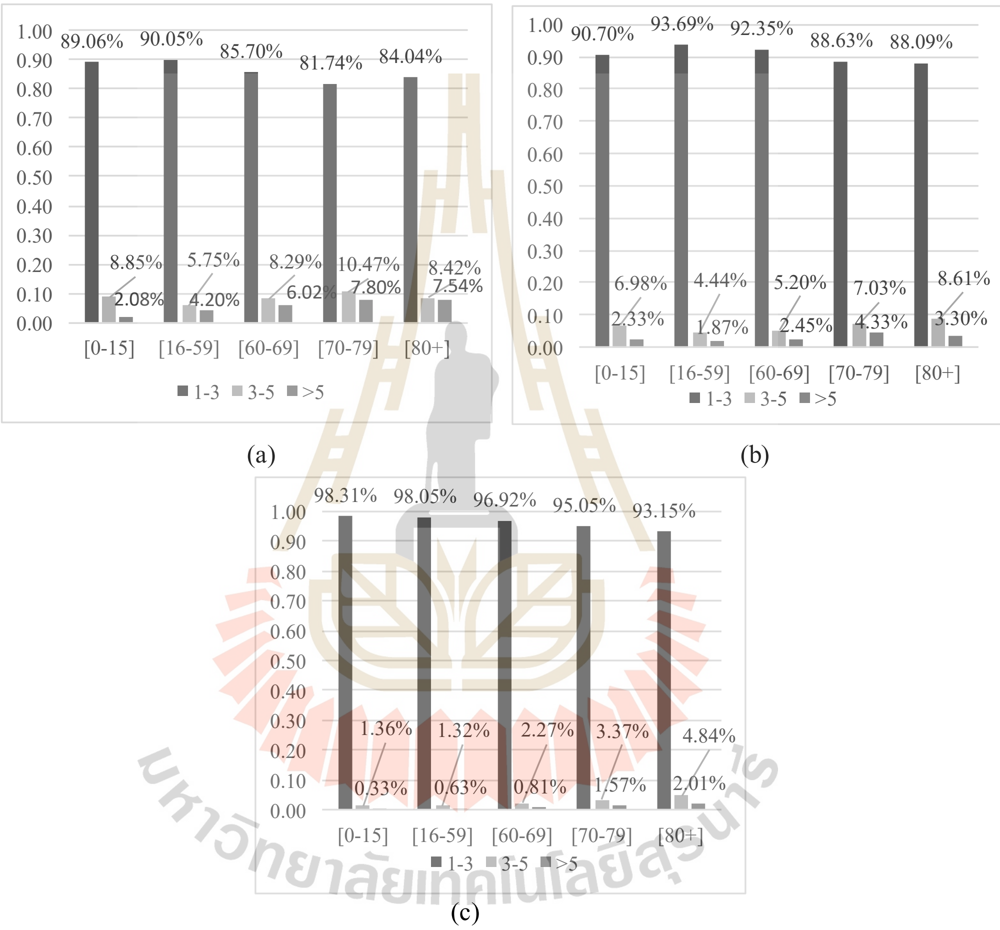


Figure 4.22 Proportion of number of hospital visits (Male) (a) ACSC patients (b) Chronic patients and (c) Non-chronic patients ; by 1-3 times/year , 3-5 times/year and more than 5 times/year

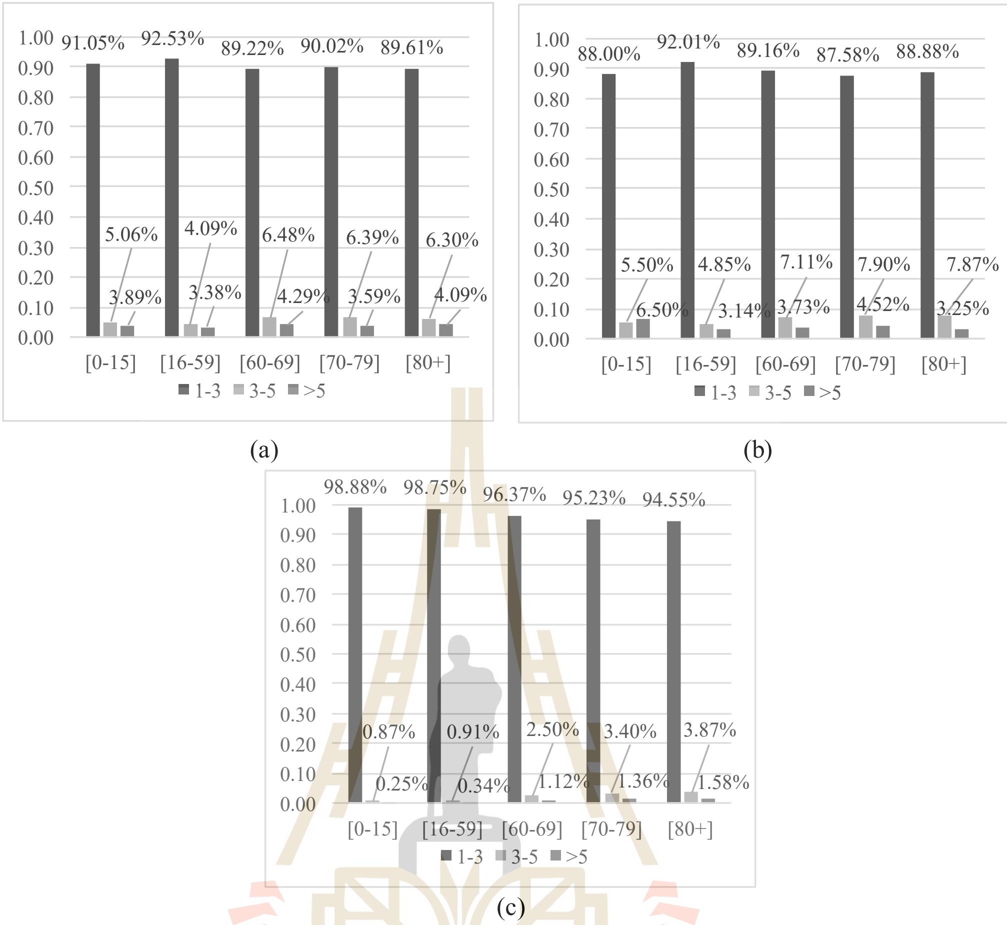


Figure 4.23 Proportion of Number of hospital visits (Female) (a) ACSC patients (b) Chronic patients and (c) Non-chronic patients ; by 1-3 times/year , 3-5 times/year and more than 5 times/year

The proportions of a number of hospital visits show that elderly patients have the frequency to visit hospital more than other age groups in every gender and every type of diseases. The oldest elderly age groups have the most frequency to visit hospitals. The number of inpatients from Markov population and the number of hospital visits is used to investigate an annual incident in patients.

4.2 Semi-Markov Model

4.2.1 Holding Time distribution

The holding time distributions were investigated from individual sample information from 43 files, health data center database are shown in Figure C1-C12 of appendix C. The summary proportions of holding times between states are show in Table 4.6. The proportions of the holding times show that elderly patients have the length of stay or hold in hospitals more than other age groups in every gender and every type of diseases.

Table 4.6 Summary proportion of holding time between states in four groups (1) 5-10 days (2) 6-10 days (3) 11-30 days (4) > 30 days

Gender	Patients	Ages	Holding times (days/time)			
			0-5	6-10	11-30	>30
Male	ACSC	[0-15]	0.9303	0.0663	0.0034	0.0000
		[16-59]	0.8403	0.1238	0.0307	0.0053
		[60-69]	0.8549	0.1162	0.0278	0.0010
		[70-79]	0.8515	0.1170	0.0305	0.0009
		[80+]	0.8349	0.1260	0.0369	0.0023
	Chronic	[0-15]	0.8782	0.0660	0.0508	0.0051
		[16-59]	0.7686	0.1399	0.0863	0.0052
		[60-69]	0.7965	0.1318	0.0678	0.0038
		[70-79]	0.8101	0.1213	0.0641	0.0046
		[80+]	0.7957	0.1234	0.0723	0.0085
	Non Chronic	[0-15]	0.9256	0.0683	0.0057	0.0004
		[16-59]	0.8717	0.0924	0.0331	0.0028
		[60-69]	0.8387	0.1141	0.0428	0.0044
		[70-79]	0.8271	0.1196	0.0498	0.0036
		[80+]	0.7827	0.1510	0.0616	0.0046
Female	ACSC	[0-15]	0.9097	0.0831	0.0048	0.0024
		[16-59]	0.8865	0.0924	0.0208	0.0004
		[60-69]	0.8752	0.1067	0.0161	0.0010
		[70-79]	0.8634	0.1088	0.0273	0.0005
		[80+]	0.8235	0.1394	0.0353	0.0018
	Chronic	[0-15]	0.9393	0.0491	0.0093	0.0023

		[16-59]	0.8001	0.1307	0.0637	0.0055
Gender	Patients	Age	Holding time (days/time)			
			0-5	6-10	11-30	>30
Female	Chronic	[70-79]	0.8327	0.1081	0.0562	0.0030
		[80+]	0.8413	0.1099	0.0469	0.0019
	Non Chronic	[0-15]	0.9400	0.0543	0.0054	0.0003
		[16-59]	0.9346	0.0519	0.0125	0.0011
		[60-69]	0.8617	0.1020	0.0340	0.0022
		[70-79]	0.8440	0.1103	0.0423	0.0035
		[80+]	0.7908	0.1438	0.0605	0.0049

4.2.2 Transition probability

The transition rates of inpatients transfer to discharge/alive population and inpatients transfer to death are calculated by logit function. The parameters of logit function are shown in Table 4.7

Table 4.7 Parameter of logit function for inpatients to discharge

Gender	Patients type	Parameters	Inpatients to discharge				
			[0-15]	[16-59]	[60-69]	[70-79]	[80+]
Male	ACSC	constant	-17.756	-0.320	7.404	20.252	39.072
		year	0.011	0.002	-0.002	-0.009	-0.018
	Chronic	constant	0.633	-0.172	7.027	20.835	37.407
		year	0.001	0.002	-0.002	-0.009	-0.017
	Non-chronic	constant	36.431	38.718	46.976	60.927	81.744
		year	-0.015	-0.017	-0.022	-0.029	-0.040
Female	ACSC	constant	34.746	16.687	23.781	31.483	47.223
		year	-0.015	-0.007	-0.010	-0.014	-0.022
	Chronic	constant	6.522	16.240	21.857	31.226	44.048
		year	-0.001	-0.007	-0.009	-0.014	-0.020
	Non-chronic	constant	62.435	61.514	66.881	76.788	93.253
		year	-0.028	-0.028	-0.031	-0.036	-0.045

The length of stay or total patient day in one year are calculated by equation (3.34) and bed requirement are calculate by equation (3.35). The results are shown in Tables 4.8-4.9. The trend of bed requirement shows that male inpatients need more beds than female inpatients from 2016-2025

Table 4.8 Total patient days before discharged and total patient days before death (Male)

Year	Patient days before discharged				Patient days before death				All Total	No of Beds
	0-15	16-59	60+	Total	0-15	16-59	60+	Total		
2007	145812	257072	254532	657416	6	675	2232	2913	660329	1809
2008	148661	260267	260801	669729	6	697	2398	3101	672830	1843
2009	151499	263441	267023	681963	7	719	2576	3302	685264	1877
2010	154244	267176	274242	695662	7	743	2785	3535	699197	1916
2011	157010	271478	281471	709959	7	769	2995	3772	713731	1955
2012	159669	276071	290094	725835	7	797	3244	4048	729883	2000
2013	162533	280818	296918	740269	8	825	3466	4299	744568	2040
2014	164869	287021	304152	756042	8	859	3679	4546	760589	2084
2015	167284	290285	313910	771479	8	884	3987	4879	776358	2127
2016	169811	293139	320329	783278	9	909	4249	5166	788444	2160
2017	172331	295962	325916	794209	9	933	4515	5457	799666	2191
2018	174753	299341	330033	804127	9	960	4761	5730	809857	2219
2019	177095	303064	333196	813354	9	989	4994	5992	819346	2245
2020	179358	306922	335551	821831	10	1018	5216	6244	828075	2269
2021	181528	310989	337138	829655	10	1049	5425	6484	836139	2291
2022	183601	315218	338020	836840	10	1081	5621	6712	843552	2311
2023	185568	319633	338253	843454	11	1113	5800	6924	850378	2330
2024	187423	324215	337886	849523	11	1147	5963	7122	856645	2347
2025	189156	328975	336967	855098	11	1183	6108	7302	862399	2363

Table 4.9 Total patient days before discharged and total patient days before death (Female)

Year	Patient days before discharged				Patient days before death				All Total	No of Beds
	0-15	16-59	60+	Total	0-15	16-59	60+	Total		
2007	114229	306423	287063	707715	7	315	670	992	708707	1942
2008	115003	307164	292328	714495	7	322	722	1051	715546	1960
2009	115750	307917	295775	719441	7	330	770	1106	720548	1974
2010	116466	308379	299177	724022	7	337	820	1165	725187	1987
2011	117155	308971	302432	728557	8	345	874	1226	729783	1999

Year	Patient days before discharged				Patient days before death				All Total	No of Beds
	0-15	16-59	60+	Total	0-15	16-59	60+	Total		
2012	117812	309864	307959	735635	8	354	942	1304	736939	2019
2013	118431	310857	312207	741495	8	363	1010	1380	742876	2035
2014	119011	311412	316136	746558	8	372	1080	1460	748018	2049
2015	119557	311171	318755	749483	9	380	1146	1534	751017	2058
2016	120067	310340	322142	752549	9	387	1221	1617	754167	2066
2017	120540	308855	326881	756276	9	395	1311	1714	757990	2077
2018	120970	306799	331540	759309	9	401	1406	1817	761126	2085
2019	121351	304265	335526	761143	10	407	1502	1920	763062	2091
2020	121682	301307	339005	761995	10	413	1602	2025	764020	2093
2021	121961	297956	342010	761927	10	419	1703	2132	764060	2093
2022	122186	294233	344410	760829	11	424	1806	2240	763069	2091
2023	122354	290160	346093	758608	11	429	1906	2345	760953	2085
2024	122467	285750	347098	755314	11	433	2002	2446	757760	2076
2025	122520	281007	347594	751121	12	437	2093	2542	753663	2065

4.2.3 Resource requirement

The number of beds required is shown in Figures 4.24-4.25. The elderly need more patient days and beds than other age groups. The male patients tend to need more patient day than female since 2016. The maximum capacity of beds can support all bed requirement. However, we cannot utilize all beds for all patients because all available information is not sufficient to categorize the bed type to each patient in each area. Hence, we assume three levels of beds utilization at 80%, 85%, and 90% according to bed types and hospital areas. The results show that the number of bed need are more than bed support level factor at 80%, 85% and 90%.

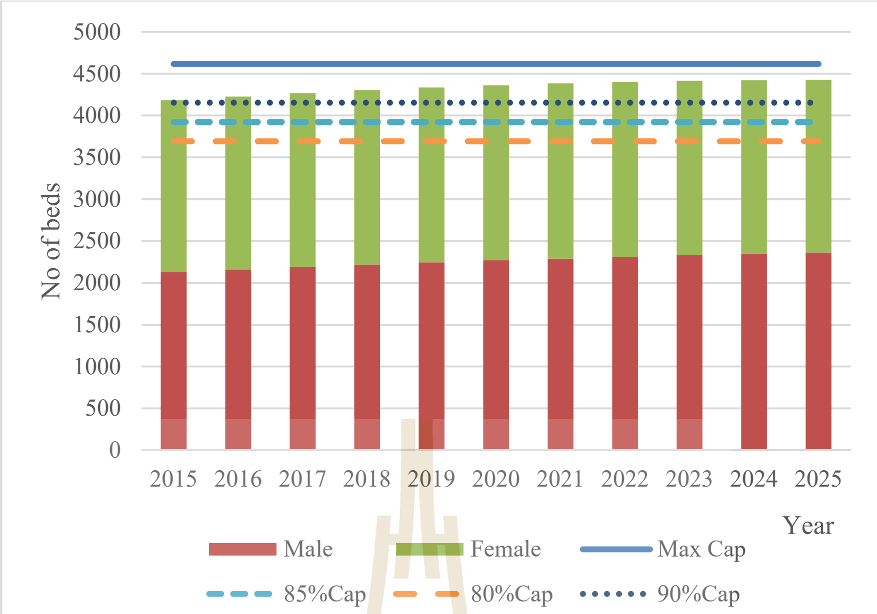


Figure 4.24 Beds requirement by gender

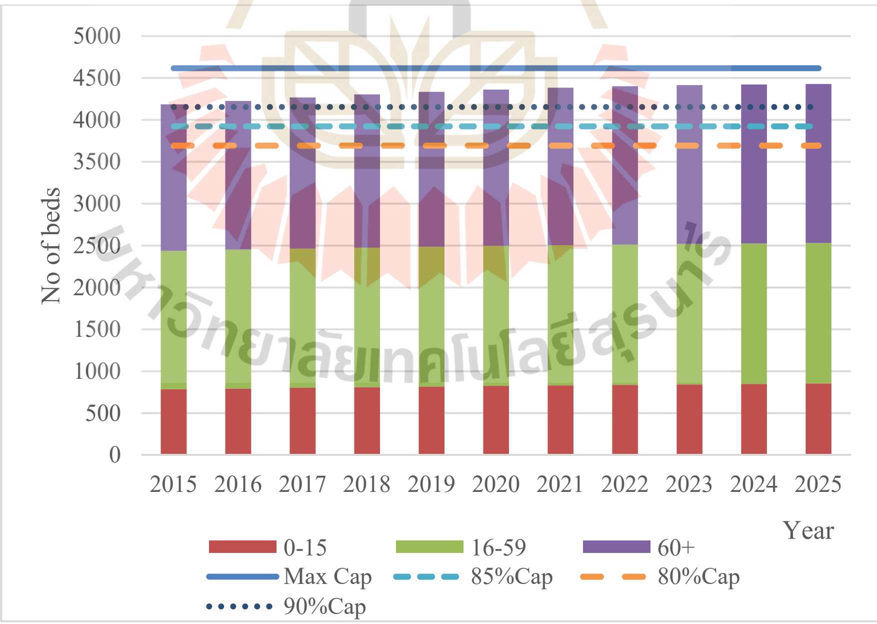


Figure 4.25 Beds requirement by age group

4.3 Long-Term Care Model

4.3.1 Number of long-term care demand

The community care staff are calculated by standard level of community care based on the assumption that one staff can take care of seven elderly as shown in Table 4.10. The trend of elderly who live alone grows continually from 2007-2025. The same trend is for the community care staff requirement.

Table 4.10 Total elderly disaggregated by household type and level of dependency and Community care staff requirement

Household	Live Alone				Live with Family				Community care staff
Dependency	1	2	3	Total	1	2	3	Total	
2007	17856	4171	632	22660	200001	46706	7081	253788	39493
2008	18422	4310	654	23386	206333	48260	7328	261921	40758
2009	19053	4463	679	24195	213402	49973	7604	270979	42168
2010	19772	4631	705	25108	221457	51848	7895	281200	43758
2011	20639	4839	740	26219	231170	54185	8287	293643	45694
2012	21514	5043	773	27331	240973	56470	8656	306099	47633
2013	22504	5267	808	28580	252061	58971	9052	320084	49809
2014	23607	5512	847	29966	264408	61717	9482	335608	52225
2015	24666	5758	887	31311	276275	64475	9928	350679	54570
2016	25770	6030	933	32734	288638	67518	10453	366609	57049
2017	26888	6312	983	34182	301159	70669	11004	382832	59573
2018	28034	6602	1033	35670	314002	73915	11573	399491	62166
2019	29222	6904	1087	37213	327300	77305	12175	416780	64856
2020	30452	7221	1144	38818	341081	80852	12815	434748	67652
2021	31723	7551	1205	40478	355317	84539	13489	453345	70546
2022	33029	7889	1267	42186	369948	88331	14187	472466	73522
2023	34368	8236	1331	43935	384943	92210	14901	492054	76570
2024	35741	8590	1396	45727	400316	96174	15631	512122	79693
2025	37150	8953	1463	47566	416105	100235	16379	532719	82898

The number of live alone elderly with dependency is shown in Table 4.11. This group is elderly who live alone and need assistance to do activities of daily living (ADL) more than or equal one activity. The standard of home care level is one staff per seven dependency elderly.

Table 4.11 Live alone and dependency elderly and home care requirement

Household	Live Alone			Home Care
Dependency	2	3	Total	
2007	4171	632	4804	686
2008	4310	654	4965	709
2009	4463	679	5142	735
2010	4631	705	5336	762
2011	4839	740	5579	797
2012	5043	773	5816	831
2013	5267	808	6075	868
2014	5512	847	6359	908
2015	5758	887	6645	949
2016	6030	933	6964	995
2017	6312	983	7294	1042
2018	6602	1033	7635	1091
2019	6904	1087	7992	1142
2020	7221	1144	8366	1195
2021	7551	1205	8755	1251
2022	7889	1267	9156	1308
2023	8236	1331	9567	1367
2024	8590	1396	9986	1427
2025	8953	1463	10415	1488

Home visit care by medical staff provides primary care unit to support elderly who live alone and need assistance to do activities of daily living (ADL) more than or equal two activities. In general, it is assumed that there should be at least one home care staff per two hundred dependent elderly. The trend of home visit requirement by medical staff are increasing as shown in Table 4.12

Table 4.12 Live alone and dependency elderly and Home visit requirement

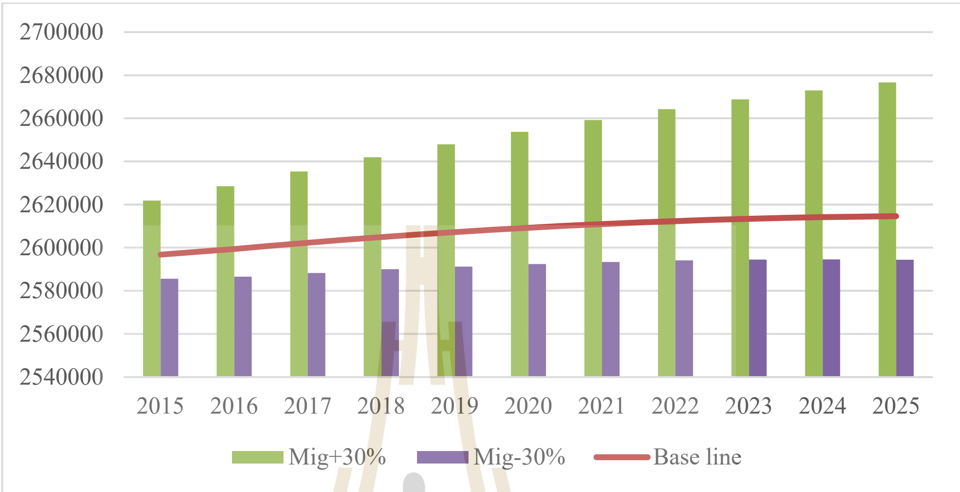
Year	Non acute care	Home visit
	LA,LF &Dep =3	
2007	3988	20
2008	4177	21
2009	4429	22
2010	4690	23
2011	5070	25
2012	5380	27
2013	5754	29
2014	6173	31
2015	6612	33
2016	7144	36
2017	7687	39
2018	8261	42
2019	8887	46
2020	9567	50
2021	10296	54
2022	11064	58
2023	11866	63
2024	12702	68
2025	13572	72

4.4 Sensitivity Analysis

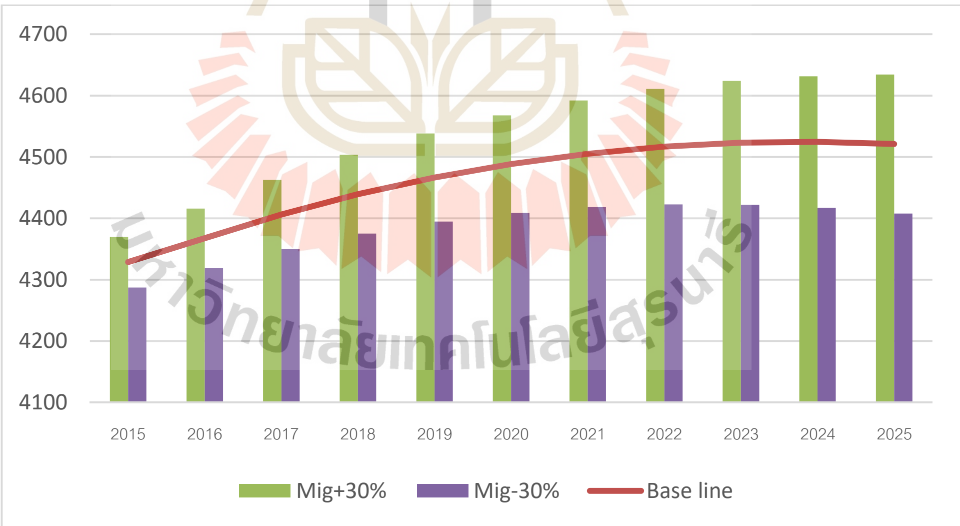
4.4.1 The impact of net migration

To test the change of population model by migration, scenario 1 analyzed the change of population in case that net migration +30% and -30%. The result is shown in Figure 4.26. The trend of population increases when net migration increase 30% from 0.96% in 2015 to 2.41% in 2025. The trend of bed requirement increase when net migration increase 30% from 0.96% in 2015 to 2.50% in 2025. In case of net migration decrease to 30%, both population and bed requirement also decrease. The trend of population decrease when net migration decrease 30% from -0.96% in 2015 to

-2.42% in 2025. The trend of bed requirement decrease when net –migration decrease 30% from -0.95% in 2015 to -2.51% in 2025.



(a) Population



(b) Bed requirement

Figure 4.26 The trend of population in case that net migration +30% and -30% for (a) Population and (b) Bed requirement

4.4.2 The impact of ACSC elderly inpatient

The changes of number ACSC elderly inpatient in 4 levels are shown in Figure 4.27 and 4.28. The sensitivity analysis is shown as following details. The trend of bed requirement decreases when ACSC decrease 25% from 2.64% in 2015 to 3.56% in 2025. The trend of bed requirement decreases when ACSC decrease 40% from 4.22% in 2015 to 5.69% in 2025. The trend of bed requirement increases when ACSC increase 25% from 2.43% in 2015 to 3.99% in 2025. The trend of bed requirement increases when ACSC increase 40% from 4.28% in 2015 to 6.53% in 2025.

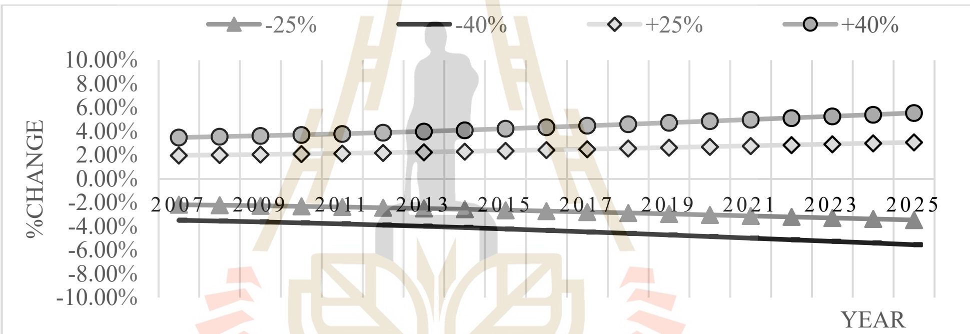


Figure 4.27 Percent of bed requirement change when level of ACSC elderly patients are -25%, -40%, +25% and +40%

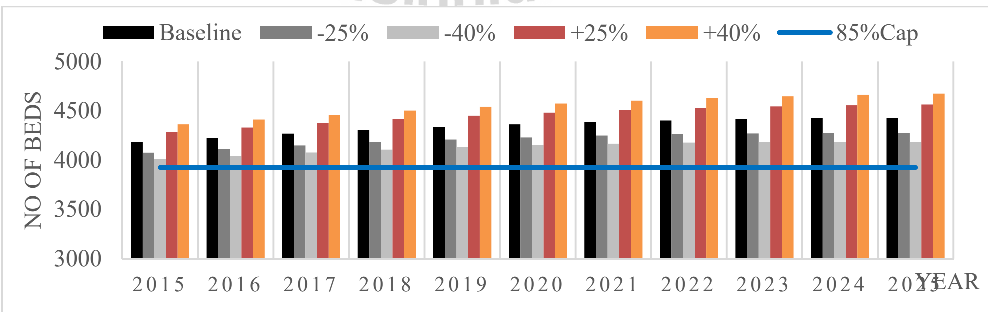


Figure 4.28 No bed requirement when level of ACSC elderly patients are -25%, -40%, +25% and +40%

4.4.3 The impact of LOS level

The study of the impact of elderly patients who live more than one month in hospitals. In this case, we assume that elderly patients who live more than one month need long term care at home. They are treated by medical care staff at home. The study is 75% of elderly who stay in hospital more than one month decrease to long term care as home visit by medical staff. The need of bed requirement slightly decrease as shown in Figure 4.29 and the home visit demand increase in Table 4.13

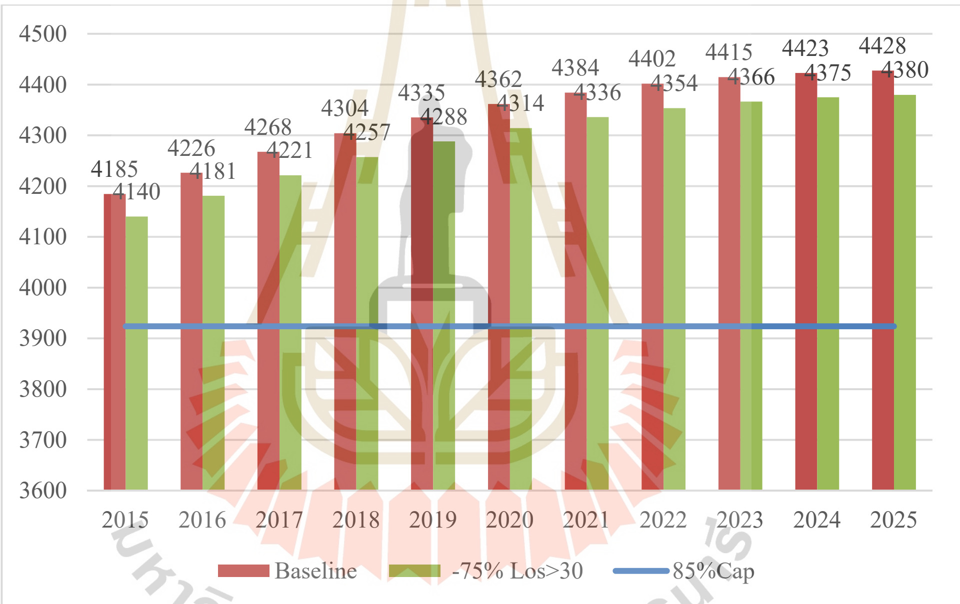


Figure 4.29 The change of elderly who need length of stay more than one month decrease -75% vs bed requirement in one year

Table 4.13 Home visit demand increase from decrease -75% of elderly who need length of stay more than 1 month

Year	Non acute care		Home visit
	LA,LF &Dep =3	From Inpatients	
2007	3988	185	21
2008	4177	189	22
2009	4429	192	23
2010	4690	196	24
2011	5070	199	26
2012	5380	204	28
2013	5754	208	30
2014	6173	211	32
2015	6612	215	34
2016	7144	218	37
2017	7687	221	40
2018	8261	223	42
2019	8887	225	46
2020	9567	226	49
2021	10296	226	53
2022	11064	226	56
2023	11866	225	60
2024	12702	224	65
2025	13572	222	69

4.4.4 The impact of household level

In this case, household level of live alone are increase by annually 1 %. The result shows that number of elderly who live alone and home care requirement increase from 2015 to 2025 as shown in Figures 4.30 and 4.31

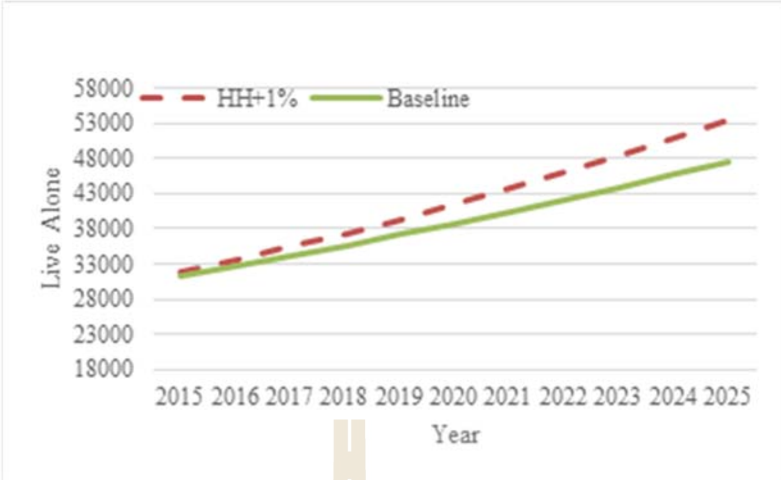


Figure 4.30 The change number of live alone when household rate increase 1% by annually

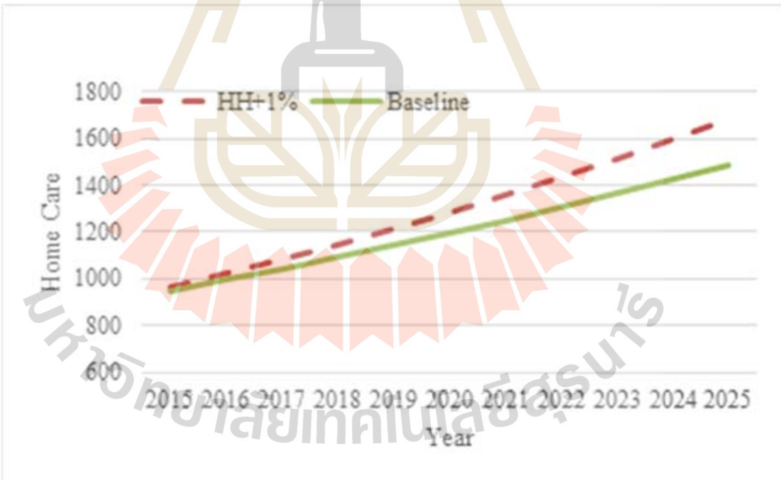


Figure 4.31 The change home care requirement when household rate increase 1% by annually

4.5 Chapter Summary

This chapter discusses the result of purposed model consisting of birthrate function, net migration function, transition probability function, the prediction of population for five age groups and each gender by consider the migration of the population in the proposed model. The demands for hospital services using Markov model show three type of inpatient demand based on disease type as ACSC patient, chronic patient and non-chronic patient. The prediction of long-term care demand for elderly and the analysis of sensitivity are also investigated in this chapter.

CHAPTER V

CONCLUSIONS

5.1 Conclusion

The research combines the Markov population model and the semi-Markov inpatient model. The results from Markov population show the prediction of population for five age groups and each gender by considering the migration of the population in the proposed model. The demands for hospital services using Markov model show three types of inpatient demand based on disease type as (i) ACSC patient, (ii) chronic patient and (iii) non-chronic patient. The results from Markov model show that the proportion of total elderly per all population increase from 11.0% in 2007 to 22.1% in 2025. The all ACSC patients tend to increase from 2007 to 2015. The elderly proportion of all ACSC inpatients increase from 60.6% in 2007 to 72% in 2025. The elderly proportion of all chronic inpatients increase from 47% in 2007 to 60.6% in 2025. The elderly proportion of all non-chronic inpatients decrease from 24.6% in 2007 to 22.5% in 2025.

The changes of population for both male and female in childhood group decrease from 2007 to 2025. However, the changes of working age population for male from 2007 to 2025 are still stable but the changes of working age population for female decrease from 2007 to 2025. The proportion of total elderly per all population tend to increase for both male and female. The elderly proportions of ACSC patient and chronic patient are also increase for both male and female. Nonetheless, the female elderly proportions of non-chronic patient decrease from 2007 to 2015 but the male elderly proportions of non-chronic patient slightly increase.

The average daily demand for beds is growing, especially for those used by the elderly. The male patients tend to need more patient day than the female since 2016. The maximum capacity of beds can support all bed requirement.

The analysis of sensitivity analysis shows that the trend of population and bed requirement will increase when net migration increase. The trend of bed requirement will decrease when the number of ACSC patients decreases. The elderly who live alone and home care requirement increase when household level of live alone increases by annually.

The information from the predicted model can be used as preliminary data to study long-term care system in the future research.

5.2 Limitation of the Study

This research has several limitations in terms of the data availability and the analysis of factors related to the services in the hospitals. In future study, to better reflect the real situation appropriately, the determining of transition probability between states should depend on time changes. In addition, the other factors related to demand services in hospitals should be considered such as type of diseases, patient service areas and other socio-economic factors.

5.3 Applications of the Work

The objective of this research is to develop a framework for demand and resource planning to manage of the elderly long-term care. The study model consists of the three sub models including Markov population model, semi-Markov inpatient model and long term care model. The Markov population model predict demographic and inpatient demand, semi Markov model is used to investigate length of stay of elderly inpatients and long-term care use to evaluate type of care for elderly. It is aimed that this research can use as quantitative tool to predict demands for resources and capacity planning for the elderly long-term care.

5.4 Recommendation for Future Work

1) Markov population model considers more factors that impact of personal health such as BMI, cholesterol level etc. of population to evaluate demands of inpatients when demographic change.

2) Semi-Markov inpatient model considers more activities during stay in hospitals to evaluate the utility of resources and time duration between activity before discharge or death

3) To evaluate long-term care insurance for long term care elderly, the future research should consider time between each state change from each type of elderly and others factor of the taking care elderly.

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APPENDIX A

DATA MODEL

Table A1 Total population, new born and birth rate for male / female

Year	Male			Female		
	Population	NewBorn	BirthRate	Population	NewBorn	BirthRate
2003	1232029	15129	0.012280	1255037	14359	0.011441
2004	1235643	15202	0.012303	1260206	14316	0.011360
2005	1240121	14624	0.011792	1265404	13992	0.011057
2006	1242780	14101	0.011346	1269093	13203	0.010403
2007	1240176	14454	0.011655	1268285	13481	0.010629
2008	1245732	14391	0.011552	1274444	13960	0.010954
2009	1250383	14237	0.011386	1280768	13480	0.010525
2010	1256268	13677	0.010887	1286965	13056	0.010145
2011	1262987	14757	0.011684	1294668	13916	0.010749
2012	1270365	14833	0.011676	1302629	13790	0.010586
2013	1274216	13741	0.010784	1307847	13181	0.010078
2014	1278788	13623	0.010653	1313013	13146	0.010012
2015	1281296	12,928	0.010090	1317544	12,249	0.009297
2016	1282326	12,214	0.009525	1321621	11,834	0.008954

Table A2 Total population age(a),year(t) (Male)

Year	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	Total
2006	292424	830413	69394	38123	12426	1242780
2007	288370	828832	71102	39180	12692	1240176
2008	283780	834524	73151	40458	13819	1245732
2009	279774	838595	75444	42242	14328	1250383
2010	275779	842696	78530	43901	15362	1256268
2011	271963	847576	82069	45502	15877	1262987
2012	267914	852136	86070	47214	17031	1270365
2013	262220	849914	93305	48658	20119	1274216
2014	258359	851740	97360	49832	21497	1278788

Table A3 Population age(a),year(t+1) from Population age(a),year(t) (Male)

Year	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	Total
2007	230771	764108	48149	20101	3128	1066257
2008	222426	756730	47743	18973	2719	1048591
2009	219556	762677	49685	20614	3522	1056054
2010	210820	760364	50594	20962	3715	1046455
2011	207475	764777	54044	22751	4419	1053466
2012	201923	767008	56901	24016	5418	1055266
2013	202706	777930	63696	26944	7485	1078761
2014	193659	765918	66529	25220	8938	1060264

Table A4 ACSC inpatient age(a),year(t+1) from Population age(a),year(t) (Male)

Year	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	Total
2007	847	4056	2746	3089	1963	12701
2008	968	4568	3138	3530	2245	14449
2009	1016	4855	3318	3728	2368	15285
2010	1038	4858	3254	3505	2200	14855
2011	1085	5084	3424	3751	2286	15630
2012	1079	5066	3382	3598	2227	15352
2013	969	4554	3050	3371	2071	14015
2014	1247	5865	3917	4271	2578	17878

Table A5 Chronic inpatient age(a),year(t+1) from Population age(a),year(t) (Male)

Year	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	Total
2007	568	9941	2950	3067	1563	18089
2008	649	11359	3385	3475	1716	20584
2009	681	11924	3551	3663	1880	21699
2010	696	12187	3591	3734	1883	22091
2011	728	12744	3790	3984	2048	23294
2012	724	12672	3737	3921	1985	23039
2013	650	11373	3410	3552	1777	20762
2014	836	14668	4364	4531	2304	26703

Table A6 Non-chronic inpatient age(a),year(t+1) from Population age(a),year(t) (Male)

Year	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	Total
2007	40254	40855	9304	8860	5048	104321
2008	44021	44666	10211	9604	5302	113804
2009	42696	43352	9907	9361	5371	110687
2010	47539	48283	10915	10399	5865	123001
2011	46528	47248	10782	10385	5967	120910
2012	47836	48562	10989	10563	5980	123930
2013	43143	43792	10075	9615	5379	112004
2014	47574	48384	11045	10508	5972	123483

Table A7 Population age (a+1),year(t+1) from Population age(a),year(t) (Male)

Year	[0-15]→[16-59]	[16-59] → [60-69]	[60-69] → [70-79]	[70-79] → [80+]	Total
2007	18476	7288	3251	782	29797
2008	18625	7056	3306	977	29964
2009	18236	7367	3460	889	29952
2010	17906	7948	3254	816	29924
2011	18169	7960	3042	635	29806
2012	18462	8946	3369	954	31731
2013	18651	9500	2646	1462	32259
2014	17016	9591	3621	1579	31807

Table A8 ACSC inpatient age (a+1),year(t+1) from Population age(a),year(t) (Male)

Year	[0-15]→[16-59]	[16-59] → [60-69]	[60-69] → [70-79]	[70-79] → [80+]	Total
2007	33	305	343	94	775
2008	106	349	392	107	954
2009	48	340	387	99	874
2010	152	484	699	321	1656
2011	156	485	646	350	1637
2012	146	506	776	395	1823
2013	124	440	555	283	1402
2014	156	576	782	452	1966

Table A9 Chronic inpatient age (a+1),year(t+1) from Population age(a),year(t) (Male)

Year	[0-15]→[16-59]	[16-59] → [60-69]	[60-69] → [70-79]	[70-79] → [80+]	Total
2007	242	444	479	288	1453
2008	280	495	578	400	1753
2009	286	519	589	340	1734
2010	289	568	610	385	1852
2011	304	559	559	324	1746
2012	306	589	598	374	1867
2013	276	473	504	340	1593
2014	327	634	690	422	2073

Table A10 Non-chronic inpatient age (a+1),year(t+1) from Population age(a),year(t) (Male)

Year	[0-15]→[16-59]	[16-59] → [60-69]	[60-69] → [70-79]	[70-79] → [80+]	Total
2007	996	1400	1384	931	4711
2008	1102	1495	1599	1237	5433
2009	1039	1447	1505	971	4962
2010	1144	1727	1699	1197	5767
2011	1127	1591	1456	944	5118
2012	1172	1732	1611	1126	5641
2013	1063	1398	1365	1030	4856
2014	1078	1606	1599	1095	5378

Table A11 Death outside-hospital,year(t+1) from Population age(a),year(t) (Male)

Year	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	Total
2007	235	2015	787	912	723	4672
2008	194	2111	749	879	709	4642
2009	221	2044	750	795	678	4488
2010	190	2175	828	922	665	4780
2011	207	2249	789	776	641	4662
2012	314	2496	706	555	266	4337
2013	331	2676	768	616	320	4711
2014	325	2672	759	580	328	4664

Table A12 Total population age(a),year(t) (Female)

Year	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	Total
2006	275767	845451	78824	49270	19781	1269093
2007	271504	844339	80553	51091	20798	1268285
2008	267349	849243	82578	52599	22675	1274444
2009	263501	853703	85481	54513	23570	1280768
2010	259927	856389	89302	56492	24855	1286965
2011	256448	860645	93581	58094	25900	1294668
2012	252186	864695	98526	59874	27348	1302629
2013	247259	860682	106804	61335	31767	1307847
2014	243770	861419	112030	62599	33195	1313013

Table A13 Population age(a),year(t+1) from Population age(a),year(t) (Female)

Year	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	Total
2007	222759	753122	53669	27266	6802	1063618
2008	215079	744115	52850	26107	6796	1044947
2009	212076	750101	55453	28377	8200	1054207
2010	206354	747995	57148	28971	8613	1049081
2011	202342	751117	61306	30777	9599	1055141
2012	198755	754306	65215	32353	11079	1061708
2013	197202	764393	72447	35094	13649	1082785
2014	192578	755088	77483	34290	16678	1076117

Table A14 ACSC inpatient age(a),year(t+1) from Population age(a),year(t) (Female)

Year	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	Total
2007	654	4375	3037	2892	1652	12610
2008	772	5164	3595	3388	1898	14817
2009	770	5157	3577	3418	1966	14888
2010	779	5219	3570	3430	1955	14953
2011	793	5306	3669	3551	2026	15345
2012	809	5413	3728	3613	2067	15630
2013	734	4914	3440	3284	1853	14225
2014	905	6067	4213	4038	2307	17530

Table A15 Chronic inpatient age(a),year(t+1) from Population age(a),year(t) (Female)

Year	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	Total
2007	667	8446	3479	3770	2539	18901
2008	788	9969	4118	4418	2915	22208
2009	786	9954	4097	4456	3022	22315
2010	795	10073	4090	4472	3004	22434
2011	809	10242	4202	4628	3112	22993
2012	825	10448	4270	4711	3176	23430
2013	749	9486	3940	4280	2845	21300
2014	923	11711	4825	5265	3545	26269

Table A16 Non-chronic inpatient age(a),year(t+1) from Population age(a),year(t) (Female)

Year	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	Total
2007	33001	68723	11381	11431	7451	131987
2008	35757	74438	12361	12291	7851	142698
2009	35008	72916	12065	12160	7981	140130
2010	37285	77699	12682	12852	8354	148872
2011	37169	77418	12770	13035	8482	148874
2012	36901	76847	12627	12909	8423	147707
2013	34500	71848	11998	12081	7772	138199
2014	35110	73232	12130	12265	7994	140731

Table A17 Population age (a+1),year(t+1) from Population age(a),year(t) (Female)

Year	[0-15]→[16-59]	[16-59] → [60-69]	[60-69] → [70-79]	[70-79] → [80+]	Total
2007	16703	7684	4028	1067	29482
2008	16915	7423	4002	1312	29652
2009	16637	7936	4039	1237	29849
2010	16162	9057	4333	1445	30997
2011	16653	9020	4036	1420	31129
2012	16886	9906	4361	1625	32778
2013	16862	10783	3491	2153	33289
2014	15637	10938	4634	2457	33666

Table A18 ACSC inpatient age (a+1),year(t+1) from Population age(a),year(t) (Female)

Year	[0-15]→[16-59]	[16-59] → [60-69]	[60-69] → [70-79]	[70-79] → [80+]	Total
2007	98	436	426	275	1235
2008	118	506	529	378	1531
2009	115	517	492	305	1429
2010	113	570	524	342	1549
2011	118	543	472	311	1444
2012	121	569	491	317	1498
2013	110	461	442	312	1325
2014	126	596	555	361	1638

Table A19 Chronic inpatient age (a+1),year(t+1) from Population age(a),year(t) (Female)

Year	[0-15]→[16-59]	[16-59] → [60-69]	[60-69] → [70-79]	[70-79] → [80+]	Total
2007	189	500	555	422	1666
2008	227	580	689	581	2077
2009	222	592	641	468	1923
2010	219	652	683	525	2079
2011	228	622	616	478	1944
2012	234	652	639	487	2012
2013	212	528	577	480	1797
2014	243	683	723	554	2203

Table A20 Non-chronic inpatient age (a+1),year(t+1) from Population age(a),year(t) (Female)

Year	[0-15]→[16-59]	[16-59] → [60-69]	[60-69] → [70-79]	[70-79] → [80+]	Total
2007	1542	1635	1682	1238	6097
2008	1694	1741	1917	1563	6915
2009	1623	1742	1750	1236	6351
2010	1686	2023	1963	1462	7134
2011	1722	1890	1734	1304	6650

Year	[0-15]→[16-59]	[16-59] → [60-69]	[60-69] → [70-79]	[70-79] → [80+]	Total
2012	1723	1927	1753	1293	6696
2013	1607	1609	1627	1311	6154
2014	1523	1717	1685	1250	6175

Table A21 Death outside-hospital,year(t+1) from Population age(a),year(t) (Female)

Year	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	Total
2007	153	530	568	909	1337	3497
2008	153	403	491	1052	1337	3436
2009	111	329	464	941	1506	3351
2010	108	415	487	1013	1645	3668
2011	92	231	499	989	1636	3447
2012	194	578	497	785	1155	3209
2013	211	672	564	880	1228	3555
2014	213	648	555	855	1242	3513

APPENDIX B

NUMBER OF HOSPITAL VISIT DISTRIBUTION

Table B1 Number of time visit hospital distribution of ACSC patients (Male)

No of time visit	ACSC				
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]
1	0.61719	0.66283	0.56300	0.53452	0.50877
2	0.20573	0.17468	0.19977	0.18931	0.22105
3	0.06771	0.06297	0.09421	0.09354	0.11053
4	0.05990	0.03318	0.05108	0.06347	0.05439
5	0.02865	0.02437	0.03178	0.04120	0.02982
6	0.00521	0.00880	0.01816	0.02116	0.02281
7	0.00260	0.00812	0.00908	0.02339	0.01228
8	0	0.00609	0.00908	0.00445	0.00702
9	0.00521	0.00406	0.00568	0.00780	0.00877
10	0.00260	0.00203	0.00681	0.00111	0.01053
11	0.00260	0.00271	0.00341	0.00111	0.00351
12	0	0.00135	0	0.00557	0
13	0.00260	0.00068	0.00114	0.00334	0.00175
14	0	0.00339	0.00114	0.00111	0.00351
15	0	0.00068	0.00114	0.00111	0.00175
16	0	0.00135	0.00114	0.00445	0
17	0	0.00068	0	0	0
18	0	0	0	0.00111	0.00175
19	0	0	0	0.00111	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0.00111	0.00175
24	0	0.00135	0.00114	0	0
26	0	0.00068	0.00114	0	0
29	0	0	0.00114	0	0
30	0	0	0	0	0
47	0	0	0	0	0
53	0	0	0	0	0
69	0	0	0	0	0
361	0	0	0	0	0
Total	1	1	1	1	1

Table B2 Number of time visit hospital distribution of Chronic patients (Male)

No of time visit	Chronic				
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]
1	0.62791	0.69482	0.66518	0.59608	0.56671
2	0.22326	0.17726	0.19599	0.20196	0.21234
3	0.05581	0.06482	0.06236	0.08831	0.10187
4	0.06512	0.02823	0.03267	0.04988	0.05882
5	0.00465	0.01620	0.01930	0.02044	0.02726
6	0.01860	0.00565	0.00965	0.01390	0.01291
7	0.00465	0.00417	0.00594	0.00736	0.00717
8	0	0.00221	0.00445	0.00736	0.00574
9	0	0.00221	0	0.00654	0
10	0	0.00074	0.00074	0.00245	0.00430
11	0	0.00098	0.00223	0.00082	0
12	0	0.00098	0.00074	0.00164	0.00143
13	0	0.00025	0	0	0
14	0	0.00025	0.000742	0	0
15	0	0	0	0	0.00143
16	0	0.00025	0	0.00082	0
17	0	0	0	0	0
18	0	0.00049	0	0.00082	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0.00025	0	0.00082	0
22	0	0	0	0	0
24	0	0	0	0	0
26	0	0	0	0	0
29	0	0	0	0	0
30	0	0.00025	0	0	0
47	0	0	0	0	0
53	0	0	0	0.00082	0
69	0	0	0	0	0
361	0	0	0	0	0
Total	1	1	1	1	1

Table B3 Number of time visit hospital distribution of non-chronic patients (Male)

No of time visit	NonChronic				
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]
1	0.83157	0.85849	0.77484	0.73538	0.66655
2	0.12296	0.09846	0.14786	0.16379	0.19232
3	0.02857	0.02356	0.04655	0.05135	0.07264
4	0.01022	0.00962	0.01464	0.02155	0.03390
5	0.00334	0.00358	0.00806	0.01218	0.01453
6	0.00153	0.00258	0.00247	0.00675	0.00796
7	0.00087	0.00133	0.00164	0.00356	0.00484
8	0.00037	0.00093	0.00148	0.00281	0.00138
9	0.00016	0.00044	0.00099	0.00037	0.00138
10	0.00012	0.00020	0.00049	0.00019	0.00173
11	0.00008	0.00016	0.00016	0.00037	0.00035
12	4.1E-05	1.2E-04	0	5.6E-04	1.0E-03
13	8.2E-05	8.1E-05	4.9E-04	3.7E-04	3.5E-04
14	0	8.1E-05	1.6E-04	1.9E-04	3.5E-04
15	4.1E-05	1.2E-04	0	1.9E-04	0
16	0	0	0	0	0
17	0	0	1.6E-04	1.9E-04	3.5E-04
18	0	8.1E-05	0	0	0
19	0	0	0	0	3.5E-04
20	0	4.0E-05	0	0	0
21	0	0	0	1.9E-04	0
22	4.1E-05	0	0	0	0
24	0	0	0	0	0
26	0	0	0	0	0
29	0	0	0	0	0
30	0	0	0	0	0
47	0	4.0E-05	0	0	0
53	0	0	0	0	0
69	0	4.0E-05	0	0	0
361	0	4.0E-05	0	0	0
Total	1	1	1	1	1

Table B4 Number of time visit hospital distribution of ACSC patients (Female)

No of time visit	ACSC				
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]
1	0.595331	0.694132	0.621918	0.610778	0.579216
2	0.217899	0.173681	0.192694	0.202595	0.218058
3	0.097276	0.057499	0.077626	0.086826	0.098807
4	0.031128	0.023118	0.045662	0.032934	0.042589
5	0.019455	0.017783	0.019178	0.030938	0.020443
6	0.019455	0.008299	0.017352	0.008982	0.011925
7	0.015564	0.005928	0.005479	0.006986	0.008518
8	0	0.003557	0.009132	0.008982	0.001704
9	0	0.003557	0.003653	0.003992	0.010221
10	0	0.002371	0.002740	0.001996	0.005111
11	0.003891	0.002964	0.000913	0.000998	0
12	0	0.001778	0	0	0.001704
13	0	0.001778	0	0	0.001704
14	0	0.000593	0	0.001996	0
15	0	0	0.000913	0.000998	0
16	0	0.000593	0	0	0
17	0	0	0	0	0
18	0	0	0.000913	0	0
19	0	0	0	0	0
20	0	0	0.000913	0	0
21	0	0.000593	0	0	0
22	0	0.000593	0	0	0
24	0	0	0	0	0
26	0	0.000593	0	0.00100	0
29	0	0.000593	0	0	0
30	0	0	0.000913	0	0
47	0	0	0	0	0
Total	1	1	1	1	1

Table B5 Number of time visit hospital distribution of chronic patients (Female)

No of time visit	Chronic				
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]
1	0.6050	0.66689	0.595258	0.585484	0.549843
2	0.1950	0.17287	0.201524	0.197581	0.237146
3	0.0800	0.08029	0.094835	0.092742	0.101784
4	0.0400	0.03246	0.047417	0.044355	0.055614
5	0.0150	0.01606	0.023709	0.034677	0.023085
6	0.0150	0.01093	0.015241	0.016935	0.012592
7	0	0.00854	0.006774	0.008871	0.007345
8	0.0200	0.00478	0.005927	0.008871	0.003148
9	0.0100	0.00205	0.002540	0.003226	0.003148
10	0.0100	0.00205	0.002540	0.002419	0.003148
11	0	0.00102	0	0.000806	0.001049
12	0.0050	0.00102	0.000847	0.001613	0.001049
13	0	0	0.000847	0.000806	0
14	0	0.00102	0.001693	0	0
15	0	0	0.000847	0.0016129	0
16	0	0	0	0	0
17	0	0	0	0	0.0010493
18	0.0050	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
24	0	0	0	0	0
26	0	0	0	0	0
29	0	0	0	0	0
30	0	0	0	0	0
47	0	0	0	0	0
Total	1	1	1	1	1

Table B6 Number of time visit hospital distribution of non-chronic patients (Female)

No of time visit	NonChronic				
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]
1	0.859766	0.850934	0.7882762	0.7400919	0.6946862
2	0.106564	0.112932	0.1369111	0.1603963	0.1855245
3	0.022462	0.023646	0.0385439	0.051838	0.0652771
4	0.006498	0.005996	0.0172645	0.0203906	0.0254237
5	0.002166	0.003066	0.0077623	0.0136416	0.0132845
6	0.001271	0.001510	0.0044165	0.0045951	0.0073294
7	0.000377	0.000789	0.0021413	0.0038771	0.0025195
8	0.000283	0.000338	0.001606	0.0010052	0.0025195
9	0.000141	0.000316	0.0010707	0.0020103	0.0018323
10	0.000047	0.000135	0.0005353	0.0004308	0.0004581
11	0.000094	0.000090	0.0004015	0.0001436	0
12	0.000141	0.000068	0.0004015	0.0002872	0.000229
13	0.000047	0.000068	0.0002677	0.0004308	0.0006871
14	0.000047	0.000023	0	0	0
15	0	0	0	0.0001436	0
16	0	2.254E-05	0.0002677	0.0004308	0
17	4.709E-05	2.254E-05	0.0001338	0.0001436	0
18	4.709E-05	0	0	0	0.000229
19	0	0	0	0.0001436	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
24	0	2.254E-05	0	0	0
26	0	0	0	0	0
29	0	0	0	0	0
30	0	0	0	0	0
47	0	2.254E-05	0	0	0
Total	1	1	1	1	1

APPENDIX C

HOLDING TIME DISTRIBUTION

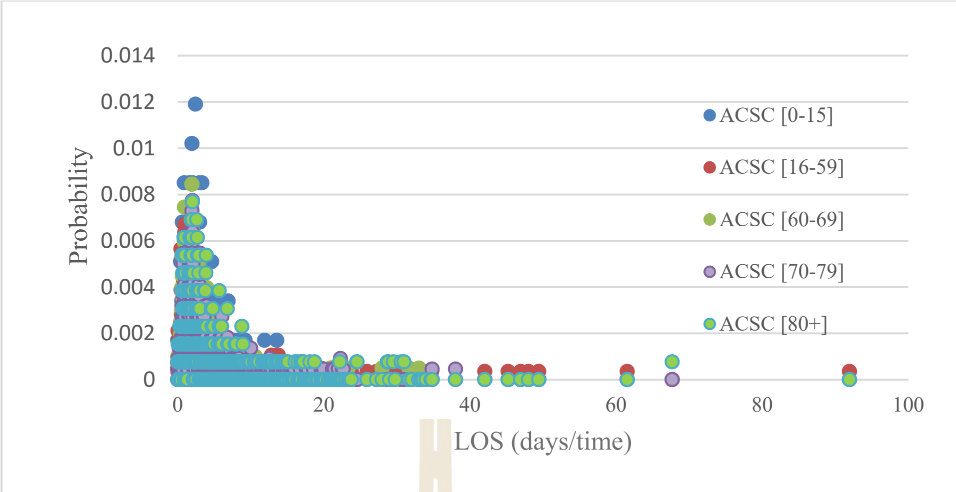

Figure C1 Holding time distribution ACSC inpatient to discharge (Male)

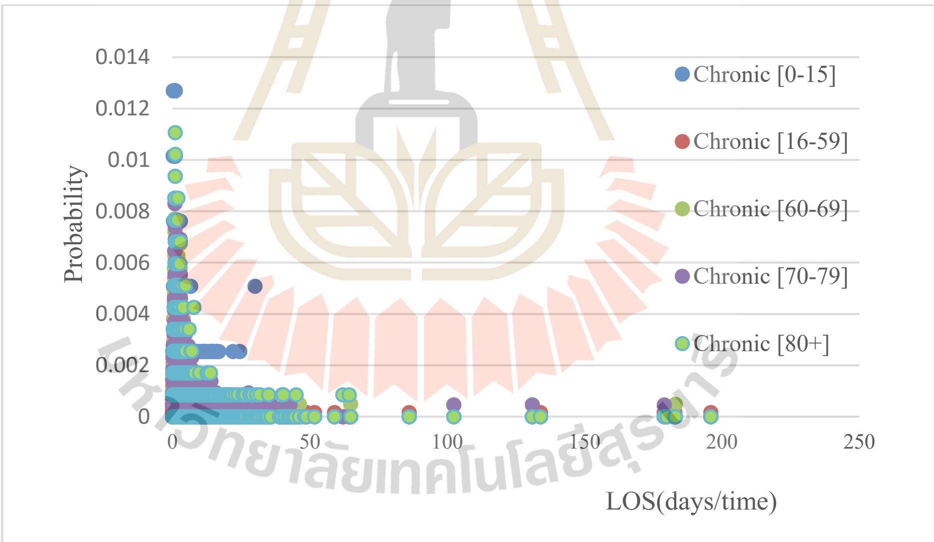

Figure C2 Holding time distribution chronic inpatient to discharge (Male)

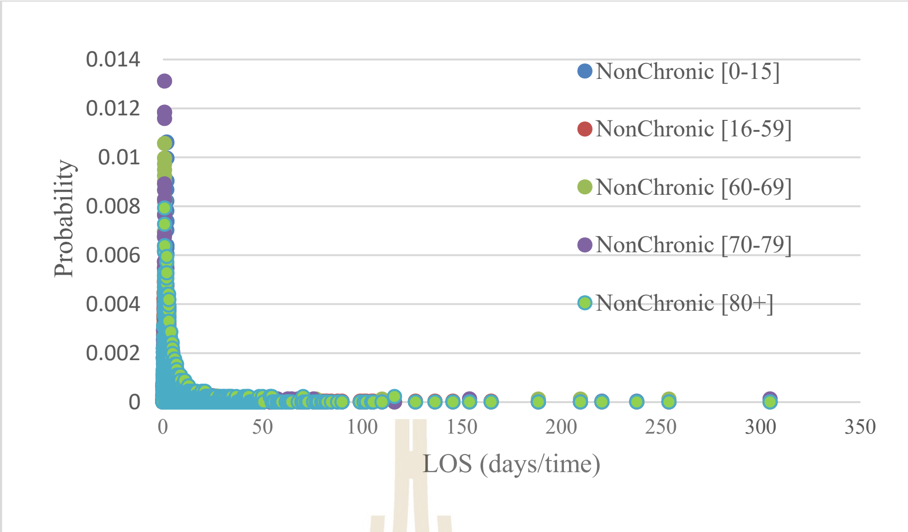

Figure C3 Holding time distribution non-chronic inpatient to discharge (Male)

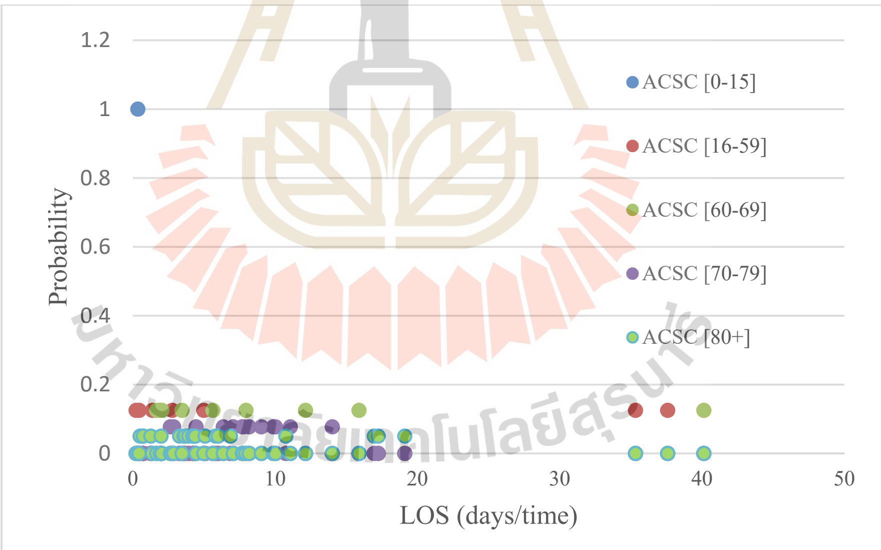

Figure C4 Holding time distribution ACSC inpatient to dead (Male)

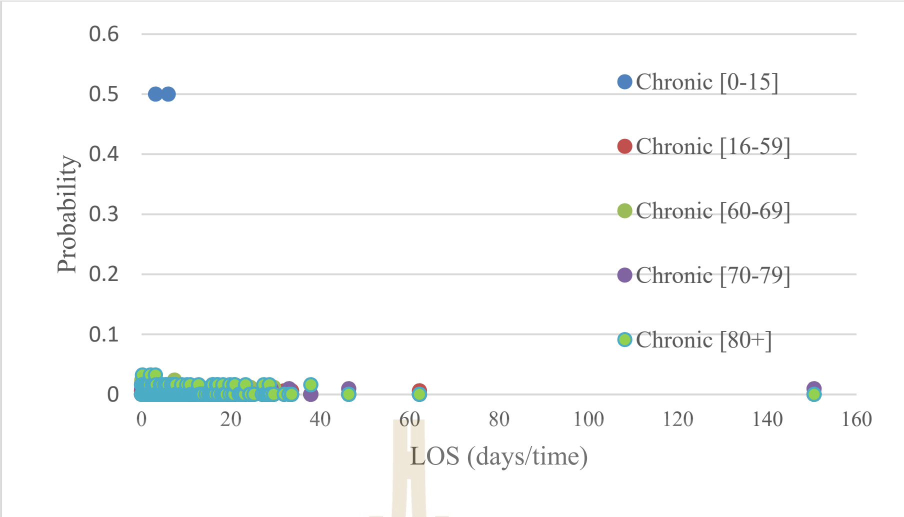

Figure C5 Holding time distribution chronic inpatient to dead (Male)

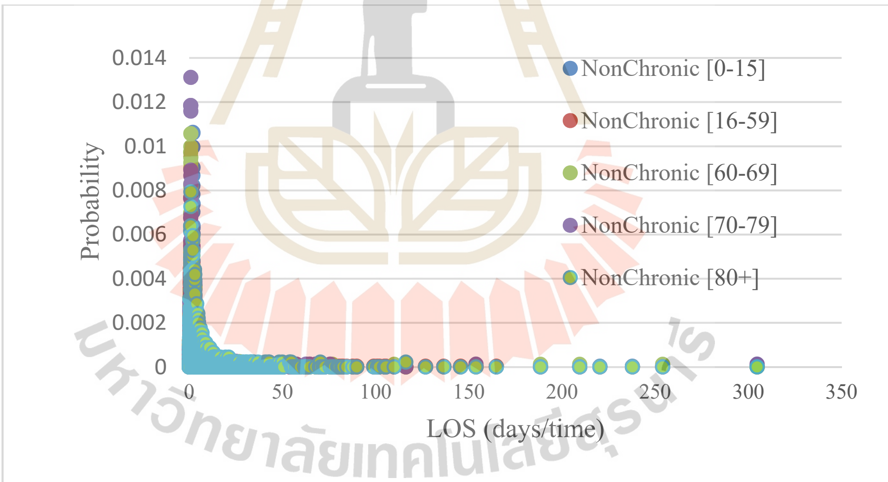

Figure C6 Holding time distribution non-chronic inpatient to dead (Male)

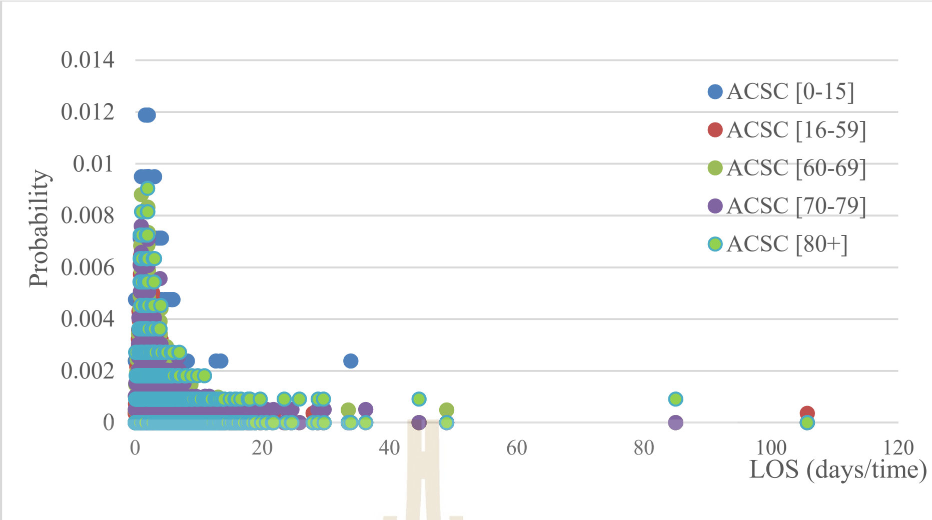

Figure C7 Holding time distribution ACSC inpatient to discharge (Female)

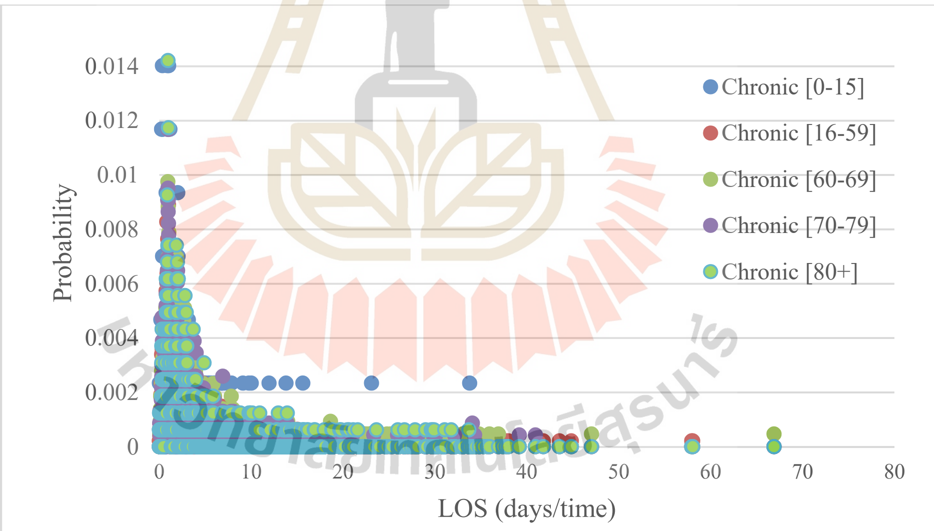

Figure C8 Holding time distribution chronic inpatient to discharge (Female)

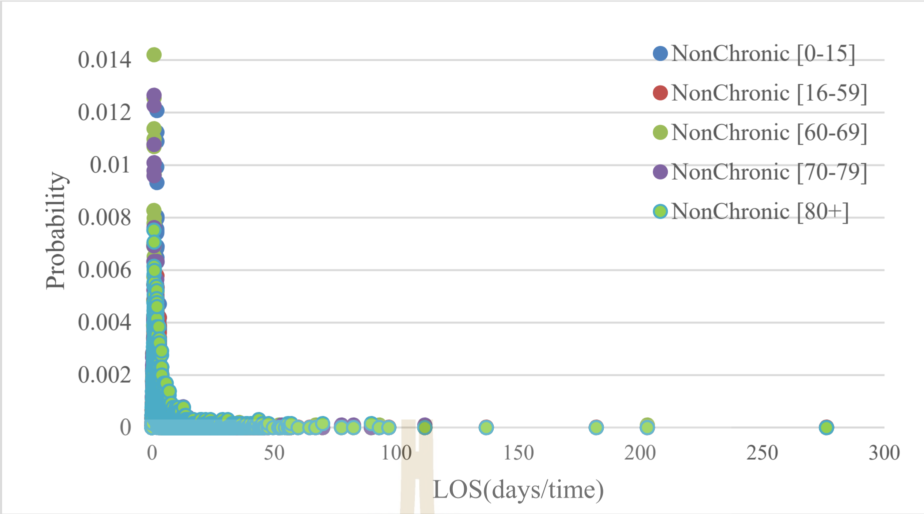

Figure C9 Holding time distribution non-chronic inpatient to discharge (Female)

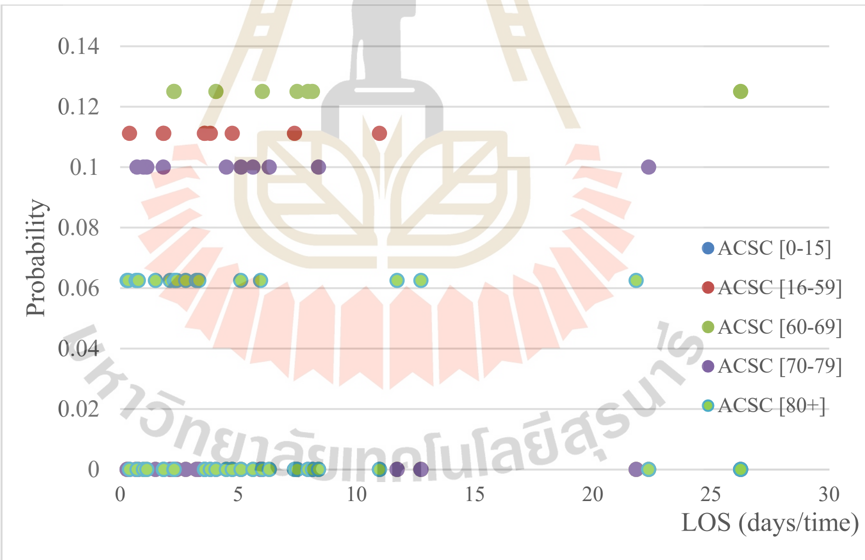

Figure C10 Holding time distribution ACSC inpatient to dead (Female)

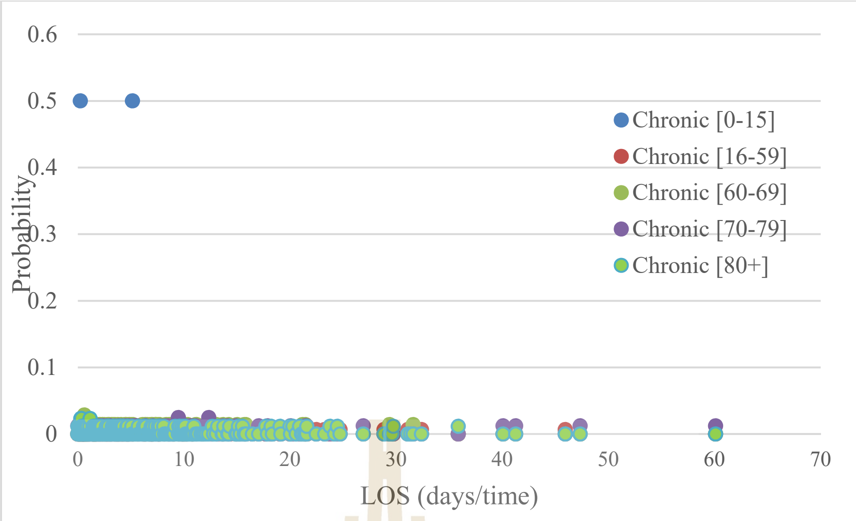

Figure C11 Holding time distribution chronic inpatient to dead (Female)

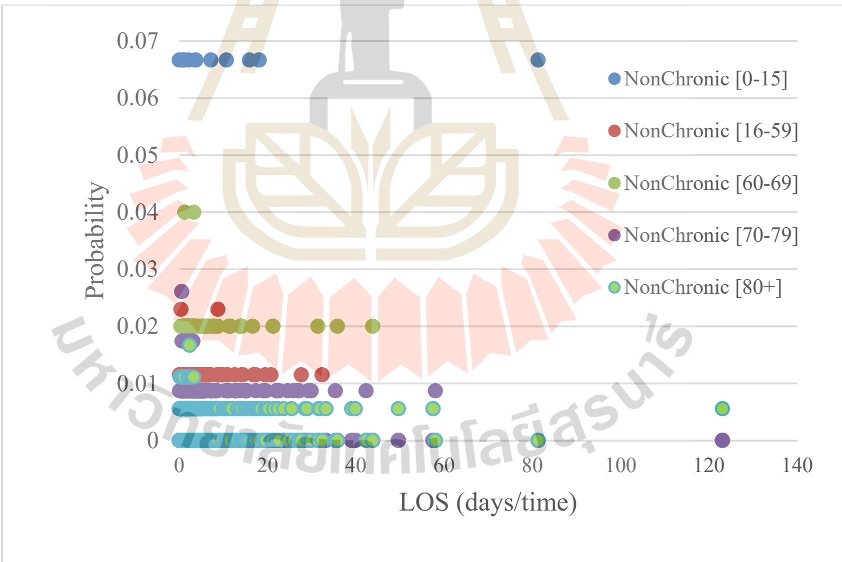

Figure C12 Holding time distribution non-chronic inpatient to dead (Female)

APPENDIX D

F-TEST FOR PARAMETER

Table D1 F-test comparison of other hypothesis test of model B, C and D for transition probability logit function of Male

State	F -Test	$F_{critical_{0.05,q,v}}$	[0-15]		[16-59]		[60-69]		[70-79]		[80-+]	
			F-test	Sig. at p<0.05	F-test	Sig. at p<0.05	F-test	Sig. at p<0.05	F-test	Sig. at p<0.05	F-test	Sig. at p<0.05
θ_{12} (Pop1→Pop2)	F_{model_B}	$F_{0.05,1,6}$	16.531	reject	95.960	reject	7.695	reject	2.597	accept	-	-
	F_{model_C}	$F_{0.05,1,6}$	20.106	reject	84.205	reject	9.847	reject	2.559	accept	-	-
	F_{model_D}	$F_{0.05,2,5}$	100.481	reject	50.133	reject	4.213	accept	-	-	-	-
θ_{13} (Pop1→Death)	F_{model_B}	$F_{0.05,1,6}$	17.902	reject	47.179	reject	41.562	reject	34.325	reject	34.925	reject
	F_{model_C}	$F_{0.05,1,6}$	19.022	reject	68.036	reject	28.558	reject	30.133	reject	36.812	reject
	F_{model_D}	$F_{0.05,2,5}$	8.545	reject	29.488	reject	17.320	reject	16.108	reject	17.114	reject
θ_{14} (Pop1→ACSC1)	F_{model_B}	$F_{0.05,1,6}$	23.614	reject	2.683	accept	1.944	accept	1.598	accept	27.154	reject
	F_{model_C}	$F_{0.05,1,6}$	20.416	reject	6.355	reject	1.806	accept	1.329	accept	37.823	reject
	F_{model_D}	$F_{0.05,2,5}$	17.408	reject	-	-	-	-	-	-	16.299	reject
θ_{15} (Pop1→Chronic1)	F_{model_B}	$F_{0.05,1,6}$	23.717	reject	3.024	accept	1.087	accept	0.321	accept	21.568	reject
	F_{model_C}	$F_{0.05,1,6}$	20.515	reject	7.101	reject	0.938	accept	0.228	accept	25.251	reject
	F_{model_D}	$F_{0.05,2,5}$	17.355	reject	-	-	-	-	-	-	11.109	reject
θ_{16} (Pop1→NonChronic1)	F_{model_B}	$F_{0.05,1,6}$	16.598	reject	1.385	accept	10.451	reject	4.524	accept	41.394	reject
	F_{model_C}	$F_{0.05,1,6}$	16.170	reject	2.519	accept	6.834	reject	3.965	accept	37.450	reject
	F_{model_D}	$F_{0.05,2,5}$	6.993	reject	-	-	5.205	accept	-	-	20.025	reject
θ_{17} (Pop1→ACSC2)	F_{model_B}	$F_{0.05,1,6}$	7.802	reject	9.936	reject	1.507	accept	9.804	reject	-	-
	F_{model_C}	$F_{0.05,1,6}$	7.928	reject	16.594	reject	2.467	accept	10.267	reject	-	-
	F_{model_D}	$F_{0.05,2,5}$	3.338	accept	7.967	reject	2.122	accept	5.028	accept	-	-
θ_{18} (Pop1_→Chronic2)	F_{model_B}	$F_{0.05,1,6}$	22.689	reject	1.942	accept	1.970	accept	1.232	accept	-	-
	F_{model_C}	$F_{0.05,1,6}$	20.705	reject	3.865	accept	1.998	accept	1.056	accept	-	-

State	F -Test	$Fcritical_{0.05,q,v}$	[0-15]		[16-59]		[60-69]		[70-79]		[80-+]	
			F-test	Sig. at p<0.05	F-test	Sig. at p<0.05	F-test	Sig. at p<0.05	F-test	Sig. at p<0.05	F-test	Sig. at p<0.05
	F_{model_D}	$F_{0.05,2,5}$	11.353	reject	-	-	0.842	accept	-	-	-	-
θ_{19} (Pop1→NonChronic2)	F_{model_B}	$F_{0.05,1,6}$	10.002	reject	0.404	accept	8.839	reject	3.980	accept	-	-
	F_{model_C}	$F_{0.05,1,6}$	10.485	reject	0.641	accept	7.168	reject	3.607	accept	-	-
	F_{model_D}	$F_{0.05,2,5}$	4.726	accept	-	-	3.737	accept	-	-	-	-

Table D2 F-test comparison of other hypothesis test of model B, C and D for transition probability logit function of Female

State	F -Test	$Fcritical_{0.05,q,v}$	[0-15]		[16-59]		[60-69]		[70-79]		[80-+]	
			F-test	Sig. at p<0.05	F-test	Sig. at p<0.05	F-test	Sig. at p<0.05	F-test	Sig. at p<0.05	F-test	Sig. at p<0.05
θ_{12} (Pop1→Pop2)	F_{model_B}	$F_{0.05,1,6}$	11.262	reject	78.381	reject	9.509	reject	18.992	reject	-	-
	F_{model_C}	$F_{0.05,1,6}$	12.993	reject	123.737	reject	9.897	reject	20.399	reject	-	-
	F_{model_D}	$F_{0.05,2,5}$	18.959	reject	78.760	reject	4.210	accept	11.367	reject	-	-
θ_{13} (Pop1→Death)	F_{model_B}	$F_{0.05,1,6}$	6.302	reject	3.443	accept	19.763	reject	14.715	reject	29.350	reject
	F_{model_C}	$F_{0.05,1,6}$	6.539	reject	3.195	accept	46.428	reject	15.076	reject	26.736	reject
	F_{model_D}	$F_{0.05,2,5}$	2.975	accept	-	-	26.363	reject	6.468	reject	12.848	reject
θ_{14} (Pop1→ACSC1)	F_{model_B}	$F_{0.05,1,6}$	18.298	reject	1.289	accept	5.695	accept	0.889	accept	30.510	reject
	F_{model_C}	$F_{0.05,1,6}$	16.432	reject	4.418	accept	4.959	accept	0.833	accept	38.253	reject
	F_{model_D}	$F_{0.05,2,5}$	11.370	reject	-	-	-	-	-	-	16.393	reject
θ_{15} (Pop1→Chronic1)	F_{model_B}	$F_{0.05,1,6}$	18.206	reject	1.287	accept	5.704	accept	0.887	accept	30.344	reject
	F_{model_C}	$F_{0.05,1,6}$	16.346	reject	4.415	accept	4.967	accept	0.831	accept	38.646	reject

State	F -Test	$Fcritical_{0.05,q,v}$	[0-15]		[16-59]		[60-69]		[70-79]		[80-+]	
			F-test	Sig. at p<0.05	F-test	Sig. at p<0.05	F-test	Sig. at p<0.05	F-test	Sig. at p<0.05	F-test	Sig. at p<0.05
	F_{model_D}	$F_{0.05,2,5}$	11.349	reject	-	-	-	-	-	-	16.509	reject
θ_{16} (Pop1→NonChronic1)	F_{model_B}	$F_{0.05,1,6}$	9.489	reject	0.078	accept	45.155	reject	11.362	reject	81.244	reject
	F_{model_C}	$F_{0.05,1,6}$	9.669	reject	0.134	accept	18.755	reject	11.700	reject	51.784	reject
	F_{model_D}	$F_{0.05,2,5}$	4.073	accept	-	-	26.989	reject	5.153	accept	35.424	reject
θ_{17} (Pop1→ACSC2)	F_{model_B}	$F_{0.05,1,6}$	13.896	reject	0.766	accept	7.507	reject	2.638	accept	-	-
	F_{model_C}	$F_{0.05,1,6}$	13.142	reject	1.932	accept	7.182	reject	2.587	accept	-	-
	F_{model_D}	$F_{0.05,2,5}$	6.438	reject	-	-	3.169	accept	-	-	-	-
θ_{18} (Pop1→Chronic2)	F_{model_B}	$F_{0.05,1,6}$	13.967	reject	0.765	accept	7.559	reject	2.624	accept	-	-
	F_{model_C}	$F_{0.05,1,6}$	13.225	reject	1.939	accept	7.211	reject	2.575	accept	-	-
	F_{model_D}	$F_{0.05,2,5}$	6.435	reject	-	-	3.189	accept	-	-	-	-
θ_{19} (Pop1→NonChronic2)	F_{model_B}	$F_{0.05,1,6}$	3.733	accept	0.039	accept	33.249	reject	8.963	reject	-	-
	F_{model_C}	$F_{0.05,1,6}$	4.016	accept	0.035	accept	19.528	reject	9.227	reject	-	-
	F_{model_D}	$F_{0.05,2,5}$	-	-	-	-	14.637	reject	4.123	accept	-	-

APPENDIX E

MARKOV POPULATION RESULTS

Table E1 Number of Population (Male) from Markov model

Year	Male					Total
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	
2007	288125	831657	71123	39515	12941	1243362
2008	283825	832449	73008	40775	13589	1243647
2009	279591	834910	75182	42038	14526	1246247
2010	275319	839010	77960	43369	15406	1251063
2011	271114	843722	81356	44725	16648	1257565
2012	266708	848522	85072	45824	17672	1263799
2013	262713	858166	89827	47130	18532	1276368
2014	258612	856608	95193	48271	20445	1279130
2015	254377	853206	99751	48989	22141	1278463
2016	250098	849374	103745	49652	24049	1276918
2017	245848	847113	107274	50175	25941	1276352
2018	241605	845618	110582	50550	27921	1276276
2019	237363	844152	113748	50741	30048	1276051
2020	233126	842935	116811	50738	32315	1275924
2021	228893	841799	119808	50524	34739	1275763
2022	224665	840792	122767	50091	37326	1275641
2023	220439	839839	125709	49430	40088	1275506
2024	216218	838954	128654	48535	43031	1275391
2025	211999	838091	131615	47402	46161	1275267

Table E2 Number of ACSC inpatients (Male) from Markov model

Year	ACSC(Male)					Total
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	
2007	906	4398	3150	3681	2252	14388
2008	942	4549	3265	3819	2308	14883
2009	979	4703	3388	3946	2375	15391
2010	1016	4871	3530	4076	2475	15967
2011	1055	5053	3704	4216	2552	16579
2012	1093	5246	3912	4362	2668	17282
2013	1135	5447	4141	4488	2737	17948
2014	1172	5682	4429	4641	2776	18700
2015	1212	5864	4748	4784	2930	19537
2016	1254	6042	5031	4882	3036	20244
2017	1297	6223	5290	4969	3150	20929
2018	1340	6421	5532	5038	3249	21580
2019	1385	6630	5769	5090	3347	22221
2020	1429	6848	6003	5124	3452	22856

Year	ACSC(Male)					Total
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	
2021	1474	7076	6238	5138	3564	23490
2022	1519	7312	6476	5131	3688	24127
2023	1565	7560	6718	5103	3825	24770
2024	1611	7817	6965	5053	3976	25422
2025	1657	8085	7220	4981	4142	26084

Table E3 Number of Chronic inpatients (Male) from Markov model

Year	Chronic(Male)					Total
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	
2007	608	10916	3630	3790	1986	20929
2008	632	11300	3726	3933	2055	21646
2009	657	11690	3831	4064	2131	22372
2010	681	12115	3953	4197	2230	23176
2011	707	12575	4108	4341	2309	24039
2012	733	13059	4298	4491	2415	24996
2013	761	13563	4506	4620	2473	25923
2014	786	14148	4776	4776	2494	26981
2015	813	14600	5076	4922	2611	28021
2016	841	15039	5333	5021	2672	28906
2017	870	15484	5561	5109	2726	29750
2018	899	15965	5765	5179	2751	30559
2019	929	16472	5959	5232	2755	31346
2020	959	16995	6145	5265	2744	32108
2021	989	17539	6326	5278	2718	32850
2022	1019	18100	6505	5270	2677	33571
2023	1050	18680	6682	5239	2624	34275
2024	1081	19279	6858	5186	2559	34963
2025	1112	19898	7035	5110	2484	35638

Table E4 Number of Non-Chronic inpatients (Male) from Markov model

Year	Non-Chronic(Male)					Total
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	
2007	42402	46395	11485	10221	6260	116764
2008	43193	46436	11604	10565	6363	118161
2009	43978	46454	11723	10875	6478	119508
2010	44735	46550	11851	11182	6660	120978
2011	45495	46722	11996	11502	6770	122486
2012	46223	46919	12150	11823	6955	124071
2013	47006	47115	12294	12075	6995	125485
2014	47638	47528	12444	12368	6933	126911
2015	48290	47427	12552	12611	7126	128005
2016	48969	47239	12611	12746	7163	128729
2017	49645	47028	12641	12864	7180	129358
2018	50290	46887	12654	12945	7116	129892
2019	50909	46779	12655	12985	7003	130332
2020	51504	46670	12645	12976	6855	130650
2021	52069	46570	12626	12915	6673	130853
2022	52604	46471	12598	12797	6463	130934
2023	53107	46376	12562	12622	6227	130894
2024	53575	46281	12518	12386	5972	130731
2025	54006	46187	12467	12088	5700	130446

Table E5 Number of population (Female) from Markov model

Year	Female					Total
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	
2007	271778	848606	80617	51454	20843	1273298
2008	267796	851831	83023	53364	21595	1277609
2009	263721	854270	85922	55047	22508	1281469
2010	259846	857127	89564	56594	23466	1286598
2011	256012	860887	93904	58022	25259	1294084
2012	251872	864968	98765	59200	26954	1301759
2013	247578	867849	104210	60204	28822	1308662
2014	243511	868526	110078	61293	30357	1313764
2015	239562	867571	116390	62400	32388	1318311
2016	235703	864796	123157	63575	35237	1322468
2017	231806	860433	130539	64710	38451	1325939
2018	227804	854734	138655	65664	41872	1328729
2019	223715	847856	147532	66340	45674	1331117

Year	Female					Total
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	
2020	219576	839878	157163	66690	49946	1333252
2021	215413	830865	167529	66692	54634	1335133
2022	211246	820871	178614	66345	59618	1336695
2023	207090	809930	190406	65669	64805	1337899
2024	202950	798050	202899	64697	70160	1338756
2025	198826	785227	216091	63467	75686	1339297

Table E6 Number of ACSC Inpatients (Female) from Markov model

Year	ACSC(Female)					Total
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	
2007	706	5283	3590	3455	2045	15079
2008	726	5302	3685	3622	2112	15447
2009	746	5321	3811	3775	2138	15790
2010	767	5335	3962	3913	2170	16147
2011	787	5352	4150	4044	2196	16530
2012	807	5373	4377	4167	2286	17011
2013	830	5397	4632	4273	2352	17484
2014	855	5413	4919	4365	2416	17968
2015	878	5415	5231	4459	2440	18423
2016	900	5407	5568	4552	2487	18913
2017	921	5388	5931	4645	2574	19459
2018	943	5359	6329	4731	2661	20024
2019	966	5321	6769	4801	2735	20593
2020	990	5277	7251	4847	2804	21170
2021	1015	5225	7776	4867	2869	21752
2022	1040	5167	8342	4857	2925	22331
2023	1066	5103	8947	4819	2964	22898
2024	1091	5033	9590	4753	2983	23450
2025	1116	4957	10270	4664	2983	23989

Table E7 Number of Chronic Inpatients (Female) from Markov model

Year	Chronic(Female)					Total
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	
2007	720	10198	4112	4503	3144	22677
2008	740	10234	4221	4721	3245	23162
2009	761	10271	4365	4920	3284	23601
2010	783	10298	4537	5101	3332	24052
2011	803	10330	4754	5271	3372	24530
2012	823	10371	5013	5431	3510	25149
2013	847	10417	5305	5569	3610	25748
2014	872	10449	5634	5689	3707	26351
2015	895	10453	5991	5812	3742	26894
2016	918	10438	6377	5933	3813	27478
2017	939	10400	6793	6054	3946	28133
2018	962	10344	7249	6167	4079	28800
2019	985	10272	7752	6258	4191	29458
2020	1010	10185	8305	6318	4295	30114
2021	1035	10086	8906	6344	4394	30764
2022	1061	9974	9554	6331	4477	31397
2023	1087	9850	10247	6281	4536	32001
2024	1112	9715	10984	6196	4564	32571
2025	1138	9568	11762	6079	4562	33109

Table E8 Number of Non-Chronic Inpatients (Female) from Markov model

Year	Non-Chronic(Female)					Total
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	
2007	34985	75312	13934	13945	9223	147399
2008	35185	75516	14001	14157	9263	148122
2009	35375	75724	14066	14275	9121	148561
2010	35553	75861	14117	14315	9004	148849
2011	35725	76031	14147	14299	8863	149066
2012	35888	76277	14145	14233	8974	149517
2013	36031	76548	14099	14091	8980	149749
2014	36156	76711	13996	13893	8975	149731
2015	36276	76680	13832	13695	8814	149297
2016	36386	76505	13603	13483	8740	148717
2017	36486	76170	13307	13267	8805	148036
2018	36571	75694	12937	13027	8863	147093
2019	36638	75100	12486	12737	8870	145832
2020	36685	74402	11956	12387	8856	144286

Year	Non-Chronic(Female)					Total
	[0-15]	[16-59]	[60-69]	[70-79]	[80+]	
2021	36714	73606	11353	11977	8828	142477
2022	36724	72718	10688	11510	8769	140408
2023	36716	71743	9975	10995	8661	138091
2024	36691	70684	9231	10443	8498	135547
2025	36646	69543	8470	9867	8284	132811

APPENDIX F

MATLAB CODE

```
%calculate transition probability

%transition probability of population age g at y(t) to age i at year t(+1)

p11 = PopAll.\Pop1_Pop1;

%transition probability of population age g at y(t) to age i+1 at year t(+1)

p12 = PopAll(:,1:4).\Pop1_Pop2;

%transition probability of population age g at y(t) to death all at year t(+1)

p14 = PopAll.\Pop1_Death;

%transition probability of population age g at y(t) to ACSC IPD age i at year t(+1)

p15=PopAll.\Pop1_IPD1_ ACSC;

%transition probability of population age g at y(t) to Chronic IPD age i at year t(+1)

p16=PopAll.\Pop1_IPD1_Chro;

%transition probability of population age g at y(t) to non-chronic IPD age i at year
t(+1)

p18=PopAll.\Pop1_IPD1_NonChro;

%transition probability of population age g at y(t) to ACSC IPD age i+1 at year t(+1)

p19=PopAll.\Pop1_IPD2_ ACSC;

%transition probability of population age g at y(t) to Chronic IPD age i+1 at year t(+1)

p20=PopAll.\Pop1_IPD2_Chro;

%transition probability of population age g at y(t) to non-Chronic IPD age i+1 at year
t(+1)

p22=PopAll.\Pop1_IPD1_NonChro;
```

```
%Calculate log Odds
lnP1_P2=log(p11.\p12);
lnP1_Death=log(p11.\p14);
lnP1_ACSC1=log(p11.\p15);
lnP1_Chronic1=log(p11.\p16);
lnP1_nonChronic1=log(p11.\p18);
lnP1_ACSC2=log(p11(:,1:4).\p19);
lnP1_Chronic2= log(p11(:,1:4).\p20);
lnP1_nonChronic2= log(p11(:,1:4).\p22);
y12= lnP1_P2;
```

```
y14= lnP1_Death;
y15= lnP1_ACSC1;
y16= lnP1_Chronic1;
y18= lnP1_nonChronic1;
y19= lnP1_ACSC2;
y20= lnP1_Chronic2;
y22= lnP1_nonChronic2;
%---------------
% Model_1   x3=blkdiag([1 PopAll(n,g)] );
% Model_2   x3=blkdiag([1 Year(n,1)] );
% Model_3   x3=blkdiag([1 PopAll(n,g) Year(n,1)] );
%----------------
%Example for parameter estimation  Model_3
%----------------
% if numstate = 9 states-population age group (1)-(4)------------------------------------------
%p_all=[p12(:,1:4),p14(:,1:4),p15(:,1:4),p16(:,1:4),p18(:,1:4),p19(:,1:4),p20(:,1:4),p22(:,1:4)];
% y_all=[y12(:,1:4), y14(:,1:4), y15(:,1:4), y16(:,1:4), y18(:,1:4) y19(:,1:4) y20(:,1:4)
y22(:,1:4)];
% for  g=1:r-1
%       j=4*(h-1)+g;
%-----------------------------------------------------------------------------------------------
% if numstate = 5 states- population age group (5)----------------------------------------
% p_all=[p14(:,5),p15(:,5),p16(:,5),p18(:,5)];
% y_all=[y14(:,5), y15(:,5), y16(:,5), y18(:,5) ];  y22(:,1:4)];
% for g=5
%        j=h;
%-----------------------------------------------------------------------------------------------
[m r]=size(PopAll);
numstate=9;
p_all=[p12(:,1:4),p14(:,1:4),p15(:,1:4),p16(:,1:4),p18(:,1:4),p19(:,1:4),p20(:,1:4),p22(:,1:4)];
```

```
y_all=[y12(:,1:4), y14(:,1:4), y15(:,1:4), y16(:,1:4), y18(:,1:4) y19(:,1:4) y20(:,1:4)
y22(:,1:4)];
for h=1:numstate-1
for g=1:r-1
j=4*(h-1)+g;
>> for n=1:m
x3=blkdiag([1 PopAll(n,g) Year(n,1)] );
cov3=[  p11(n,g)*(1-p11(n,g)),    -p11(n,g)*p_all(n,j),
 -p11(n,g)*p_all(n,j)       p_all(n,j)*(1-p_all(n,j)),];
A_data3=[-1/p11(n,g),   1/p_all(n,j)];
varW3=A_data3*(1/PopAll(n,g)*cov3)*A_data3';
var3=varW3;
w3=inv(var3);
y3=[y_all(n,j)];
pd3=x3'*w3*x3;
pd4=x3'*w3*y3;
if n<=1
sum3=pd3;
sum4=pd4;
varWtable3=varW3;
covtable3=cov3;
A_datatable3=A_data3;
Invvarwtable3=w3;
pd1table3=pd3;
pd1table4=pd4;
else
```

```
sum3=sum3+pd3;
sum4=sum4+pd4;
varWtable3=[varWtable3,varW3];
covtable3=[covtable3,cov3];
A_datatable3=[A_datatable3,A_data3];
Invvarwtable3=[Invvarwtable3;,w3];
pd1table3=[pd1table3;,pd3];
pd1table4=[pd1table4;,pd4];
end
end
para3=inv(sum3)*sum4;
>> for n=1:m
x3=blkdiag([1 PopAll(n,g) Year(n,1)] );
cov3=[  p11(n,g)*(1-p11(n,g)),   -p11(n,g)*p_all(n,j),
 -p11(n,g)*p_all(n,j)      p_all(n,j)*(1-p_all(n,j)),];
A_data3=[        -1/p11(n,g),       1/p_all(n,j)];
varW3=A_data3*(1/PopAll(n,g)*cov3)*A_data3';
var3=varW3;
w3=inv(var3);
y3=[y_all(n,j)];
sse3=(y3-x3*para3)'*w3*(y3-x3*para3);
sst3=(y3-mean(y_all(:,j)))'*w3*(y3-mean(y_all(:,j)));
if n<=1
sum_sse3=sse3;
sum_sst3=sst3;
else
```

```
sum_sse3=sum_sse3+sse3;
sum_sst3=sum_sst3+sst3;
end
end
covM3=inv(sum3);
std95inv3=diag(sqrt(sum_sse3*covM3));
SE3=diag(sqrt(covM3));
if g<=1
paratable3=para3;
sumssetable3=sum_sse3;
sumssttable3=sum_sst3;
varWtable3table=varWtable3;
covtable3table=covtable3;
A_datatable3table=A_datatable3;
Invvarwtable3table=Invvarwtable3;
pd1table3table=pd1table3;
pd1table4table=pd1table4;
sum1table3=sum3;
sum2table4=sum4;
covM3table=[covM3];
std95inv3table=std95inv3;
SE3table=SE3;
else
paratable3=[paratable3,para3];
sumssetable3=[sumssetable3,sum_sse3];
sumssttable3=[sumssttable3,sum_sst3];
```

```
varWtable3table=[varWtable3table,varWtable3];
covtable3table=[covtable3table,covtable3];
A_datatable3table=[A_datatable3table,A_datatable3];
Invvarwtable3table=[Invvarwtable3table,Invvarwtable3];
pd1table3table=[pd1table3table,pd1table3];
pd1table4table=[pd1table4table,pd1table4];
sum1table3=[sum1table3,sum3];
sum2table4=[sum2table4,sum4];
covM3table=[covM3table,covM3];
std95inv3table=[std95inv3table,std95inv3];
SE3table=[SE3table,SE3];
end
end
if h<=1
paratableall=paratable3;
sumssetableAll=sumssetable3;
sumssttableAll=sumssttable3;
varWtable3tableAll=blkdiag([varWtable3table]);
covtable3tableAll=blkdiag([covtable3table]);
A_datatable3tableAll=blkdiag([A_datatable3table]);
Invvarwtable3tableAll=blkdiag([Invvarwtable3table]);
pd1table3tableAll=blkdiag([pd1table3table]);
pd1table4tableAll=blkdiag([pd1table4table]);
sum1table3tableAll=blkdiag([sum1table3]);
sum2table4tableAll=blkdiag([sum2table4]);
covM3tableAll=[covM3table];
std95inv3tableAll=[std95inv3table];
SE3tableAll=[SE3table];
```

```
else
paratableall=[paratableall;,paratable3];
sumssetableAll=[sumssetableAll;,sumssetable3];
sumssttableAll=[sumssttableAll;,sumssttable3];
varWtable3tableAll=blkdiag([varWtable3tableAll,varWtable3table]);
covtable3tableAll=blkdiag([covtable3tableAll,covtable3table]);
A_datatable3tableAll=blkdiag([A_datatable3tableAll,A_datatable3table]);
Invvarwtable3tableAll=blkdiag([Invvarwtable3tableAll,Invvarwtable3table]);
pd1table3tableAll=blkdiag([pd1table3tableAll,pd1table3table]);
pd1table4tableAll=blkdiag([pd1table4tableAll,pd1table4table]);
sum1table3tableAll=blkdiag([sum1table3tableAll,sum1table3]);
sum2table4tableAll=blkdiag([sum2table4tableAll,sum2table4]);
covM3tableAll=[covM3tableAll,covM3table];
std95inv3tableAll=[std95inv3tableAll;,std95inv3table];
SE3tableAll=[SE3tableAll;,SE3table];
end
end
Rsquare3=(1-sumssttableAll.\sumssetableAll);
radj=1-(1-Rsquare3)*(m-1)/(m-1-1);
ssr3=sumssttableAll-sumssetableAll;
[rx,cx]=size(x3);
msr3=ssr3/(cx-1);
mse3=sumssetableAll/(m-cx);
Ftest=mse3.\msr3;
```

BIOGRAPHY

Miss. Nuanpan Buransri was born on June 9, 1980 in Prachin Buri, Thailand. She received a B.Eng. in Food Engineering from King Mongkut's Institute of Technology Ladkrabang in 2002. She received M. Eng. in Industrial Engineering from Chulalongkorn University in 2005. After graduation, she served in position of production control section manager at Honda Foundry (Asian) Co.,Ltd. from 2005 to 2010 and supply planner at Hitachi Global Storage Technologies (Thailand) Ltd. from 2010-2011. From 2011 to 2017 she was a Ph.D student in the school of Industrial Engineering at Suranaree University of Technology. Her research interests lie in stochastic model, healthcare logistics and supply chain optimization.