MULTI-OBJECTIVE OPTIMIZATION WITH GENETIC ALGORITHM FOR SPATIAL URBAN LAND-USE PLANNING

Warunee Aunphoklang

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Geoinformatics

Suranaree University of Technology

Academic Year 2017

การหาค่าเหมาะที่สุดแบบหลายวัตถุประสงค์ด้วยขั้นตอนวิธีเชิงพันธุกรรม สำหรับการวางแผนการใช้ที่ดินเชิงพื้นที่ในเขตเมือง

นางสาววารุณี อ้วนโพธิ์กลาง

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรดุษฎีบัณฑิต

สาขาวิชาภูมิสารสนเทศ

มหาวิทยาลัยเทคโนโลยีสุรนารี

ปีการศึกษา 2560

MULTI-OBJECTIVE OPTIMIZATION WITH GENETIC ALGORITHM FOR SPATIAL URBAN LAND-USE PLANNING

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

Thesis Examining Committee

S. Dasananda

(Assoc. Prof. Dr. Songkot Dasananda)

Chairperson

S. Sarapirome.

(Asst. Prof. Dr. Sunya Sarapirome)

Member (Thesis Advisor)

Satith Sangpradid..

(Dr. Satith Sangpradid)

Member

Nittaya Kp

(Assoc. Prof. Dr. Nittaya Kerdprasop)

Member

(Assoc. Prof. Dr. Suwit Ongsomwang)

Member

(Asst. Prof. Dr. Pantip Piyatadsananon)

Member

(Prof. Dr. Santi Maensiri)

Vice Rector for Academic Affairs and Internationalization

(Asst. Prof. Dr. Worawat Meevasana)

Dean of Institute of Science

วารุณี อ้วนโพธิ์ลาง : การหาค่าเหมาะที่สุดแบบหลายวัตถุประสงค์ด้วยขั้นตอนวิธีเชิงพันธุกรรมสำหรับการวางแผนการใช้ที่ดินเชิงพื้นที่ในเขตเมือง (MULTI-OBJECTIVE OPTIMIZATION WITH GENETIC ALGORITHM FOR SPATIAL URBAN LAND-USE PLANNING) อาจารย์ที่ปรึกษา : ผู้ช่วยศาสตราจารย์ ดร.สัญญา สราภิรมย์, 148 หน้า.

การเพิ่มขึ้นของประชากรและการเติบโตทางเศรษฐกิจ ก่อให้เกิดกิจกรรมของมนุษย์ที่ส่งผลกระทบอย่างต่อเนื่องกับการใช้ประโยชน์ที่ดินและการวางแผน โดยเฉพาะอย่างยิ่งในพื้นที่เมือง สำหรับการวางผังเมืองไม่ได้ต้องการแค่การประมาณพื้นที่และหาตำแหน่งของเมืองที่จะมีการขยายตัวในอนาคตเท่านั้น แต่ต้องวางแผนให้เกิดความสมดุลในทุก ๆ ด้านภายใต้วัตถุประสงค์และข้อจำกัดในหลาย ๆ ด้าน การวางแผนที่ดีควรสามารถประนีประนอมความต้องการในแง่มุมต่าง ๆ ที่ขัดแย้งกันได้

เป้าหมายหลักของการศึกษานี้คือมุ่งในการพัฒนากระบวนการและทดลองใช้กับการวางแผนประเภทการใช้ที่ดินในเมืองให้เหมาะสมด้วยขั้นตอนวิธีเชิงพันธุกรรมและการตัดสินใจแบบหลายหลักเกณฑ์ (GA-MODA) ในระดับแปลง ในการศึกษานี้ดำเนินการใน 3 พื้นที่ที่เลือกมาจากพื้นที่เมืองนครราชสีมา โดยประยุกต์กระบวนการ GA-MODA เพื่อสร้างผังการใช้ประโยชน์ที่ดินของปี 2016 และ 2019 ที่สอดคล้องกับ 6 วัตถุประสงค์และ 7 ข้อจำกัด วัตถุประสงค์ในการพิจารณาครอบคลุม การตอบสนองสูงสุดของความเพียงพอของที่อยู่อาศัย การจ้างงาน พื้นที่สีเขียว และความเข้ากันได้กับพื้นที่รอบข้าง การตอบสนองต่ำสุดของต้นทุนการเปลี่ยนแปลงและอัตราการเดินทางระหว่างแปลง เพื่อชีวิตที่ดีขึ้นนั้นข้อจำกัดจึงถูกตั้งค่าให้สอดคล้องกับข้อเสนอแนะทางด้านขนาดพื้นที่และความหนาแน่นประชากรในแต่ละประเภทของการใช้ที่ดิน

ผลลัพธ์ของกระบวน GA-MODA ของปี 2016 ชุดผังการใช้ประโยชน์ที่ดินที่มีค่าวัตถุประสงค์อยู่ที่ Pareto front สำหรับพื้นที่ศึกษา 1 2 และ 3 คือ 26 128 และ 370 ตามลำดับ ในขณะที่ของปี 2019 มี 34 74 และ 115 ตามลำดับ ผังการใช้ประโยชน์ที่ดินเหล่านี้ได้รับการนำไปเปรียบเทียบกับผังการใช้ประโยชน์ที่ดินที่เป็นอยู่ของปี 2016 และผังการใช้ประโยชน์ที่ดินที่คาดการณ์ของปี 2019 ผลลัพธ์ของการเปรียบเทียบแสดงให้เห็นว่าผังการใช้ประโยชน์ที่ดินจาก GA-MODA ดีกว่าผังการใช้ประโยชน์ที่ดินที่เป็นอยู่ของปี 2016 และผังการใช้ประโยชน์ที่ดินที่คาดการณ์ของปี 2019 ทั้งในด้านการอยู่ภายใต้ข้อจำกัด การปรากฏของค่าวัตถุประสงค์บน Pareto front และผลรวมค่าวัตถุประสงค์ที่อยู่บนฐานเดียวกัน ผลลัพธ์นี้ชี้ให้เห็นว่าผังการใช้ประโยชน์ที่ดินจาก GA-MODA ก่อให้เกิดคุณภาพชีวิตของการอยู่อาศัยที่ดีกว่า นอกจากนี้ ยังสามารถยืนยัน

ได้ว่ากระบวนการ GA-MODA เป็นกระบวนการที่สามารถสร้างชุดผังการใช้ประโยชน์ที่ดินที่เหมาะสมอย่างมีประสิทธิภาพ

สาขาวิชาภูมิสารสนเทศ
ปีการศึกษา 2560

ลายมือชื่อนักศึกษา จารุณี อ้วนโพธิ์กลาง
ลายมือชื่ออาจารย์ที่ปรึกษา____________________
ลายมือชื่ออาจารย์ที่ปรึกษาร่วม____________________

WARUNEE AUNPHOKLANG : MULTI-OBJECTIVE OPTIMIZATION WITH GENETIC ALGORITHM FOR SPATIAL URBAN LAND-USE PLANNING. THESIS ADVISOR : ASST. PROF. SUNYA SARAPIROME, Ph.D. 148 PP.

URBAN LAND-USE PLANNING/ GENETIC ALGORITHM/ MULTI-OBJECTIVE OPTIMIZATION

Due to the ever-increasing population and economic growth, human activities have continuous impact on land use and its planning, particularly in urban area. For urban planning, it requires not only estimating and locating the future urban extent but also balancing planning aspects under objectives and constraints. The better planning should be able to compromise the multiple conflicting demands from different aspects. The aim of this study focuses on developing and simulating a procedure for optimal urban class planning using Genetic algorithm and Multi-objectives decision analysis (GA-MODA) in plot level. The methods were employed to operate on 3 case areas which were selected from a part of Nakhon Ratchasima town. GA-MODA process was applied to generating a number of representative plans of 2016 and 2019 that meet the requirement of given 6 objectives and 7 constraints. The objectives cover sufficient housing, employment, open green area, high compatibility, and minimized changing cost and travel rate. For better living, constraints were setup to comply with suggested areas and population densities of urban classes.

From the results of GA-MODA process of 2016, numbers of plans at Pareto front for case area 1, 2, and 3 are 26, 128, and 370, respectively while of 2019 are 34, 74, and 115, respectively. These plans were compared to existing 2016 and predicted 2019 plans. The results show that constraint compliance, being at Pareto front, and sums of normalized objective values (SNOV) of GA-MODA plans are better than of existing 2016 and predicted 2019 plans. It indicates that GA-MODA plans can provide better quality of living. It could also be confirmed that GA-MODA process was the capable method to generate a number of optimal plans.

School of Geoinformatics

Academic Year 2017

Student's Signature Warunee Aunphoklang

Advisor's Signature [signature]

Co-advisor's Signature satith sangpradid.

ACKNOWLEDGEMENTS

I would like to express my deep gratitude to my advisor, Asst. Prof. Dr. Sunya Sarapirome for his supervision, advice, helps with valuable instructions, guidance and suggestions during the study periods at Suranaree University of Technology (SUT). Without his constructive devotion and support, this thesis would not be finished successfully.

I would like to appreciate the co-advisor, Dr. Satith Sangpradid in help, guidance, and discussion on many concerned problems.

I am also very grateful to the chairperson and other committees, Assoc. Prof. Dr. Songkot Dasananda, Assoc. Prof. Dr. Suwit Ongsomwang, Assoc. Prof. Dr. Nittaya Kerdprasop, and Asst. Prof. Dr. Pantip Piyatadsananonfor always being interested in the progress of my work, and for all valuable suggestions and critical comments. I am also very grateful to Suranaree University of Technology for providing scholarship.

I extend my thanks to all the staffs and all of my friends at School of Remote Sensing for their help and support during my study here, especially Mrs. Pimprapai Piphatnawakul, Mr. Athiwat Phinyoyang, Miss Wilawan Prasomsup, Miss Salisa Saraisamrong, Miss Silirak Tanang, and Mr. Patiwat Littidej.

Finally, I would like to express my special thanks to my family for their financial supports, great love, care, and patience during my study.

Warunee Aunphoklang

CONTENTS

CONTENTS (Continued)

Page

CONTENTS (Continued)

CONTENTS (Continued)

CONTENTS (Continued)

LIST OF TABLES

LIST OF TABLES (Continued)

Table **Page**

LIST OF FIGURES

LIST OF FIGURES (Continued)

Figure **Page**

LIST OF ABBREVIATIONS

AqF	=	Aqua Farming
CA	=	Cellular Automata
CA-Markov	=	Cellular Automata and Markov chain Model
D	=	Destination
DOPA	=	Department Of Provincial Administration
DPT	=	Department of Public Works and Town & Country Planning
EI	=	Educational Institution
GA	=	Genetic Algorithm
GA-MODA	=	Genetic Algorithm and Multi-Objectives Decision Analysis
GIS	=	Geographic Information Systems
Gov	=	Governmental Institution, Public Utility and Facilities
HRCom	=	Commercial and High Residential
IDW	=	Inverse Distance Weighted
IW	=	Industrial and Warehouse
LP	=	Linear Programming
LR	=	Low Residential
MODA	=	Multi-Objective Decision Analysis
MR	=	Medium Residential
O	=	Origin
O-D	=	Origin and Destination

LIST OF ABBREVIATIONS (Continued)

OpenG	=	Open land for recreation and environmental quality maintenance
pcu	=	passenger car unit
PHV	=	Peak Hour Volume
PST and P&C Mange Co., Ltd	=	Phisut Technology Co., Ltd. and P&C Management Co., Ltd.
RA	=	Rural and Agricultural
ReDe	=	Area Ready to Develop
RI	=	Religious Institution
RS	=	Remote Sensing
SAOs	=	Sub district Administrative Organizations
ScF	=	Scrub and Forest
SNOV	=	Sums of Normalized Objective Values
STDB	=	Standard Development Bureau of DPT
UnIn	=	Undeveloped Industrial
WA	=	Water or Wetland

CHAPTER I

INTRODUCTION

1.1 Background problems and significance of the study

Due to the increasing population and economic growth, human activities have continuous impact on land use. Those impacts might lead to series of complexities toward environment and land resources development (Huang and Xia, 2001). Land-use planning, one of the important developments, is primary required according to the growth impact. Land-use planning can be defined as the process of allocating different activities or uses to specific units of land within a region (Stewart, Janssen, and Herwijnen, 2004). Thus, urban land-use change and planning have become ever-increasingly complex as a consequence of the growth. Obviously, many green spaces have been transformed into urban land use e.g. residential, industrial, and commercial use. The planning requires not only estimating and locating the future urban extent but also balancing aspects such as provision of enough housing, employment opportunities and conservation of the environment.

In the past, there were a few researches provided both forecast area and indicating the proper class to serve each individual policy. To indicate the proper class, it deals with activities or uses involving residential land, industry, commercial activities, green space, and public service (Cao et al., 2011). This has to compromise the multiple conflicting demands from different groups such as government, merchants, and residents. Urban planning has become a multi-objective problem. Increased inclusion of objectives leads to different demands on the expected results (Stewart, Janssen, and Herwijnen, 2004).

In recent years there are available models used to forecast future changes and trends of urban development and to explore and assess the potential impacts of different policies (Herold, Menz, and Clark, 2001). Among all the numerous developed models, Cellular Automata and Markov chain Model (CA-Markov) is the most accepted model for modelling the growth pattern (Jain, Siddiqui, Tiwari, and Shashi, 2016). A CA-Markov model is a robust approach in the spatial and temporal dynamic modeling of land-use changes because geographic information systems (GIS) and remote sensing (RS) can be efficiently incorporated (Kamusoko, Aniya, Adi, and Manjoro, 2009, quote in Sang, Zhang, Yang, Zhu, and Yun, 2011).

The urban growth areas obtained from forecasting could be identified as certain classes in proportion required by planning policy using multi-objective decision analysis (MODA). In the past, many of these problems could be handled using linear programming (LP) approaches (Guldmann, 1979; Aerts, Eisinger, Heuvelink, and Stewart, 2003). The LP model was first applied in the 1960s to solve problems in urban planning systems through linear or quadratic equations. However, the LP model cannot handle nonlinear and unstructured requirements like spatial interactions between land-use types, it is not suitable for complex urban problems. Within this context, a heuristic algorithm, the genetic algorithm (GA), which is capable of handling the unstructured urban issues, was proposed in the 1970s. The GA is a type of general global optimization algorithm, and it has been shown to be robust and efficient for searching large, complex, and little-understood search spaces such as those of multi objective land-use planning problems. In fact, many researchers have applied a GA to solve multi-objective land-use planning problems, and some meaningful outcomes have been achieved (Huang and Zhang, 2014). Although GA might not be the best method because it provides candidate urban plans by efficient random sampling from all possible combinations of plots which can be one of any available classes in the area, it allows recently available hardware and software capable to better handle processing of sampling plans than to deal with a huge number of all possible combination plans.

In Thailand, the Department of Public Works and Town & Country Planning (DPT) is responsible for urban development and planning as well as building standards and controls. Its mission is to create a better environment and a superior quality of life for people in the kingdom of Thailand. Thailand's overall development strategy is segmented into national, regional, provincial and city/town, community levels. At the national, regional and provincial levels, master plans are created to provide a broad development framework for city/town and community levels. Local and community development plans address specific implementation issues and comply with overall master plans (Kullavanijaya, 2008). However, the plans display types of land use as zones, not in individual plot level.

The Sixth National Economic and Social Development Plan (1987-1991) specified Nakhon Ratchasima province to the main city for development to transportation hub and an industry source of the Northeast region to link to Bangkok. That caused for the rapid development and it is the reason to start comprehensive planning (บริษัท พิสุทธิ์ เทคโนโลยี จำกัด และบริษัท พี แอนด์ ซี แมเนจเมนท์ จำกัด [PST and P&C Mgt Co., Ltd.], 2553).

Currently under Thailand's National Economic and Social Development Plan, Nakhon Ratchasima represents a new growth secondary city which is one of the largest metropolitan populations for a city disconnected from Bangkok's extended metropolitan region. Nakhon Ratchasima Municipality is an urban center of Nakhon Ratchasima province. Municipality gained its present status of the local authority in 1935. Since then the urban area and population have increased many times. Initially, community settlements were confined to being within the old city limits. Around the municipality there are many constraints to growth (Cherdchai and Mayor, 2001).

Parts of municipality can be either lower or over populated. Urban planning or proper class assignment in the plot level is required to moderate over and under populated problems by applying suggested areas and population densities to urban classes. Therefore, the aim of this research was focused on developing a procedure for optimal urban class planning using Genetic algorithm and Multi-objectives decision analysis (GA-MODA) in plot level. GA was focused on generating population of plans for fitness test. MODA was applied to fitness evaluation under given objectives and constraints. Objectives cover sufficient housing, employment, open green area, high compatibility, and minimized changing cost and travel rate. For better living, constraints were setup to comply with 2 suggestions, i.e. 1) suggested areas and population densities to urban classes and 2) suggested population densities for actual/predicted urban class areas. The suggestions were referred to research particularly carried out for the study area.

1.2 Research objectives

There are 2 objectives of the research as follows:

1) To develop and simulate a flexible procedure for urban class planning in individual plot level of selected case areas using Genetic algorithm (GA) and Multi-objectives decision analysis (MODA) to comply with constraints of class areas and population densities obtained from suggestion and estimation.

2) To compare, in terms of being complied with constraints, located at Pareto fronts, and their sums of normalized objective values (SNOV), between:

a) interpreted urban land-use maps and GA-MODA plans of 2016 and

b) predicted urban land-use maps using CA-Markov and GA-MODA plans of 2019.

1.3 Scope and limitations of the study

To achieve objectives of the study, scope and limitation were declared herein. The scope covers from 1) to 7), and 8) is both scope and limitation, while the rests are limitations.

1) CA-Markov model was applied to predicting urban growth of 2019 and compared to the urban growth planning using GA in terms of multi-objective approach.

2) Population and labor force information of 2016 and 2019 used in the analysis were estimated and predicted from statistic data of administrative units recorded by the Department of Provincial Administration (DOPA). GIS interpolation was applied to estimate spatial distribution of population density so that population representative to the study area could be estimated.

3) Urban land-use plots employed as input for GA growth planning were relied on plots from visual interpretation of current year high resolution RS data and plots from CA-Markov prediction model.

4) Destinations of minimized travel rate include facilities, social places available in the study area, and human living class. In case there was no suggested rate for concerning class and no data recorded, such as monastery and park, base density was assumed by filed investigation.

5) There was no officially local identity in the study area. Therefore, there was no such concern in the planning.

6) To allow fair changing cost estimation, any original big plots, particularly agricultural, were allotted to plots having size close to existing developed plots.

7) Urban land-use classification of the study area was modified from classification of DPT so that the changing cost from class to class could be estimated more pragmatically.

8) Based on the planning to achieve the best quality of life, population density of each urban land-use class was relied on the suggestion of the study of PST and P&C Mgt Co., Ltd. (2553) under the supervision of Nakhon Ratchasima City Municipality. The suggestion fits more to the local administration of Nakhon Ratchasima city.

9) Urban LU plots used as input for CA-Markov prediction analysis were visually interpreted from high-resolution remotely sensed data of only 2013 (DigitalGlobe data) and 2016 (QuickBird and WorldView data) due to the availability limitation of data covering the whole study area in the same year. Street view from Google and serious field checks were operated to assure the most accurate and acceptable interpreted results. The result of this interpretation level was normally

regarded as the referent information for accuracy assessment of coarser-scale RS data interpretation. Therefore, the interpretation accuracy assessment of these interpreted results was considered not necessary. Additionally, accuracy assessment of CA-Markov analysis cannot be performed.

10) Surveyed traffic volume data of only few roads are available from PST and P&C Mgt Co., Ltd. (2553). Interpolation of known traffic density segments was performed to obtain traffic volume of unknown road segments.

11) Optimum area extent of the study area or case areas, a number of urban land-use plots, and a number of objectives for decision making were assigned to meet the performance limitation of Matlab® (R2017a) software, the most practical software for GA operation. Three case areas of both 2016 and 2019 were selected to test that all components of the procedure developed for urban planning work properly and were flexible for possible cases. Therefore, the effect from the surrounding of case areas were not considered in the study.

1.4 Study area

1.4.1 Location and administration

The study area of this research is a part of Muang Nakhon Ratchasima comprehensive planning area and located in southeastern corner, as displayed in Figure 1.1. It falls into 6 local administration districts, which are 1 city municipality, 1 subdistrict municipality, and 4 subdistrict administrative organizations (SAOs) as shown in Table 1.1. The study area covers approximately 75 km^2. This area is sub center of CBD urban growth distributed from Muang Nakhon Ratchasima municipality.

Currently, this area has high growth expansion tendency of communities, commercial, malls, governmental institutions, and industrial areas.

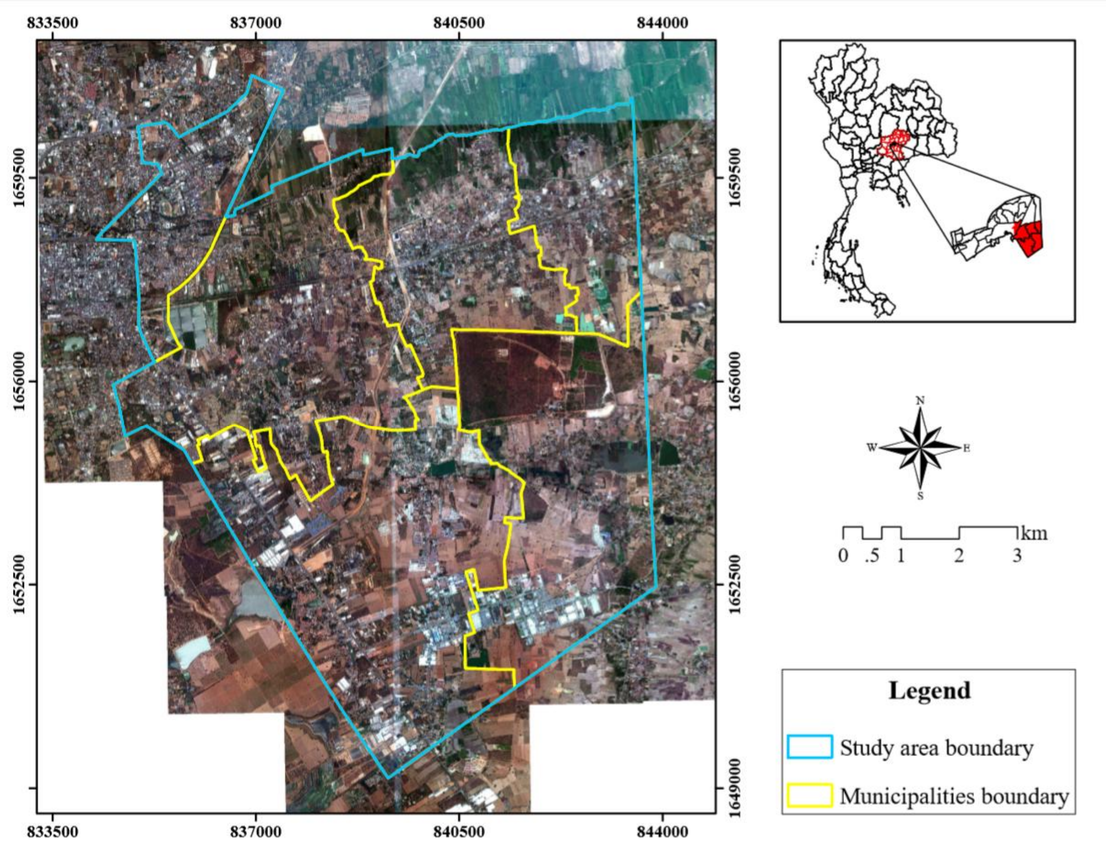


Figure 1.1 SAO and municipalities of the study area.

Table 1.1 Areas of local administration districts in the study area.

No.	Local administration	Area (km^2)
1	Nakhon Ratchasima City Municipality	5.66
2	Hua Thale Subdistrict Municipality	16.53
3	Pha Nao SAO	6.60
4	Maroeng SAO	10.25
5	Nong Raweing SAO	15.60
6	Nong Bua Sa La SAO	20.86
	Total area	**75.52**

1.4.2 Geography and climate

The terrain of the study area is a plain located between the regimes of the Lamtakong and Moon river. The average elevation of the area is about 250 meters above mean sea level. The annual temperature is 26.9 °C and annual rainfall is 1,375.7 mm.

1.4.3 Economics

According to the report of PST and P&C Mgt Co., Ltd. (2553), Cho Ho and Hua Thale subdistrict municipalities, and Nong Raweing SAO show high tendency of fast growing economics of the comprehensive planning area, in terms of commerce or business and industry areas. This reflects proper planning requirement on housing, employment, and facilities.

1.4.4 Population

According to the report of DOPA, population in 2012 to 2015 of 6 local administration districts are shown in Table 1.2. Hua Thale subdistrict municipality has the highest population density (11.81 people/rai). These population data are a source to derive data for case areas.

Table 1.2 Population of years 2012 to 2015 in the study area.

No.	Local administration	2012	2013	2014	2015
1	Nakhon Ratchasima City Municipality	137,579	136,153	134,440	133,005
2	Hua Thale Subdistrict Municipality	25,510	25,716	26,111	26,524
3	Pha Nao SAO	5,008	5,018	5,051	5,086
4	Maroeng SAO	7,414	7,649	7,939	8,107
5	Nong Raweing SAO	11,400	11,617	11,783	11,988
6	Nong Bua Sa La SAO	19,041	20,183	21,145	22,024
	Total	**205,952**	**206,336**	**206,469**	**206,734**

1.4.5 Selected case areas

Due to having big numbers of urban plots in 2016 and 2019 of the study area, this takes great time consuming of the GA-MODA process and over the limit of available software and hardware used in the research. Three case areas of both 2016 and 2019 were selected to confirm that the procedure developed for urban planning was flexible for possible cases. Case areas were selected to test that all components of the procedure work properly. These components are composed of GA process coding, objective functions, constraints, and dominance ranking or fitness procedure.

Three case areas were selected to represent a variety of dense populated areas and areas having obvious change during 2013 to 2016. Urban areas with high-dense populated, medium-dense, and low-dense or suburb areas with difference class distribution were selected as displayed in Figure 1.2. Their population density could be within or out of the range of suggested density based on class areas. Urban plots of case areas were extracted by visual interpretation for 2016 and CA-Markov prediction for 2019 and input into simulation of the developed procedure.

1.5 Benefits of the study

Useful outcomes serving study objectives can be achieved as in the following list:

1) A flexible procedure of GA-MODA process for urban class planning of individual plot level based on suggested class areas and their population densities together with forecasted population. The procedure can be applied to other areas with their own constraints and characteristics.

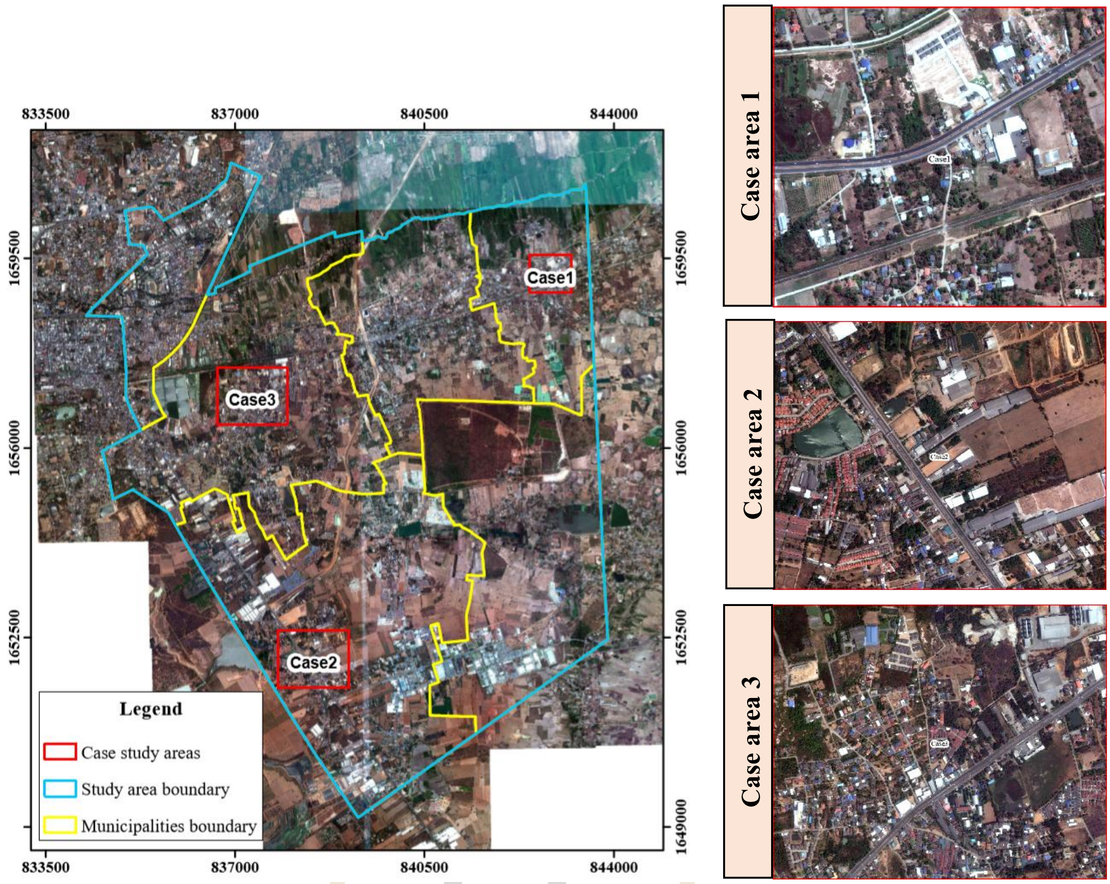


Figure 1.2 The case areas of the study area.

2) The urban class distributions in individual plot level from the visual interpretation of 2016 and prediction using CA-Markov model of 2019.

3) Optimum plans of urban class distribution of 2016 and 2019 in case areas.

4) Multi-objective values of each optimum plans.

5) Comparison results of urban class distributions and multi-objective values of plans.

CHAPTER II

LITERATURE REVIEWS

The main related concepts and theories of this study can be summarized in this Chapter. They include definitions of urban growth, urban land-use classification in Thailand, urban growth prediction modeling, and optimized urban growth planning using Genetic Algorithm. Previous studies are also gathered and discussed.

2.1 Urban growth

2.1.1 Definition of Urban growth

Urban area

Urban area commonly refers to *towns* and *cities - an urban landscape.* The definition of urban area changes from country to country. There are various ways to define what is urban and part of an urban area (Carter, 1981).

Urban growth

Urban growth is a spatial and demographic process and refers to the increased importance of towns and cities as a concentration of population within a particular economy and society. It occurs when the population distribution changes from being largely hamlet and village based to being predominantly town and city dwelling (Clark, 1982).

Hegazy and Kaloop (2015) have described the urban growth is particularly the movement of residential and commercial land to rural areas at the periphery of metropolitan areas, has long been considered a sign of regional economic vitality.

2.1.2 Urban growth pattern and process

Wilson, Hurd, Civco, Prisloe, and Arnold (2003) identified three categories of urban growth pattern: infill, expansion, and outlying, with outlying urban growth further separated into isolated, linear branch, and clustered branch growth that shown in Figure 2.1. The relation (or distance) to existing developed areas is important when determining what kind of urban growth has occurred. The details of urban growth categories are describe in Table 2.1.

Herold, Hemphill, Dietzel, and Clarke (2005) presented a hypothetical schema of urban growth process using a general conceptual representation as shown in Figure 2.2. According to them, urban area expansion starts with a historical seed or core that grows and disperses to new individual development centers. This process of diffusion continues along a trajectory of organic growth and outward expansion. The continued spatial evolution transitions to the coalescence of the individual urban blobs. This phase transition initially includes development in the open space in interstices between the central urban core and peripheral centers. This conceptual growth pattern continues and the system progresses toward a saturated state. In Figure 2.2, this “final” agglomeration can be seen as an initial urban core for further urbanization at a less detailed zoomed-out extent. In most traditional urbanization-studies this “scaling up” has been represented by changing the spatial extent of concentric rings around the central urban core.

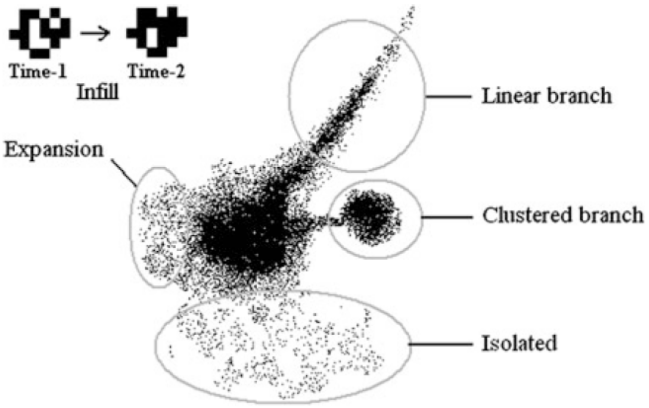


Figure 2.1 Schematic diagram of urban growth pattern (Wilson, Hurd, Civco, Prisloe and Arnold, 2003).

Table 2.1 Details of urban growth categories (Wilson, Hurd, Civco, Prisloe and Arnold, 2003).

urban growth category	**description**
Infill growth	Characterized by a non-developed pixel being converted to urban use and surrounded by at least 40% existing developed pixels.
Expansion growth	Characterized by a non-developed pixel being converted to developed and surrounded by no more than 40% existing developed pixels.
Outlying growth (3 classes)	Characterized by a change from non-developed to developed land-cover occurring beyond existing developed areas.
• *Isolated growth*	Characterized by one or several non-developed pixels some distance from an existing developed area being developed. This class of growth is characteristic of a new house or similar construction surrounded by little or on developed land.
• *Linear growth*	Defined as an urban growth such as a new road, corridor, or a new linear development that is generally surrounded by non-developed land and is some distance from existing developed land. This class is different from isolated growth in that the pixels that changed to urban are connected in a linear fashion.
• *Clustered growth*	Defined a new urban growth that is neither linear nor isolated, but instead, a cluster or a group. It is typical of a large, compact, and dense development.

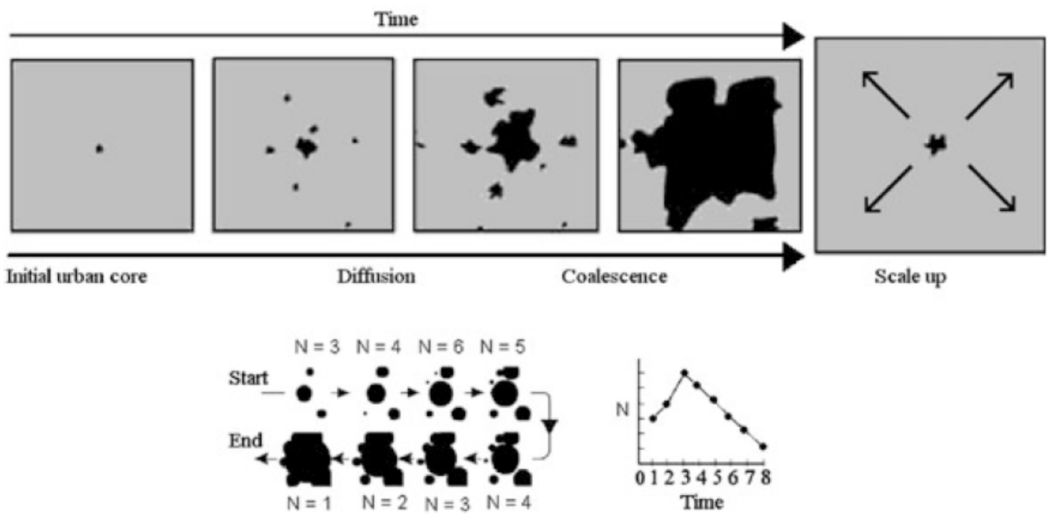


Figure 2.2 Sequential frames of urban growth. The graph on the bottom-right shows N, number of agglomerations, through a sequence of time steps (Herold, Hemphill, Dietzel, and Clarke, 2005).

2.1.3 Urban growth planning

Hall (2002) suggested the definitions of planning and urban planning that can be described as follows:

Planning as a general activity is the making of an orderly sequence of action that will lead to the achievement of a stated goal or goals. Its main techniques will be written statements, supplemented as appropriate by statistical projections, mathematical representations, quantified evaluations and diagrams illustrating relationships between different parts of the plan. It may, but need not necessarily, include exact physical blueprints of objects. Planning today is more flexible, working with far more information and highly complex computerized systems.

Urban and regional planning has many different names e.g. town and country planning, town planning, city planning, physical planning etc.

Urban planning conventionally means something more limited and precise: it refers to planning with a spatial, or geographical component, in which the general objective is to provide for a spatial structure of activities (or of land uses) which in some way is better than the pattern that would exist without planning.

In Thailand, สำนักงานคณะกรรมการกฤษฎีกา (2518), section 4 in Town Planning Act. B.F. 2518 "Town planning" means "the preparation, making and implementation of a general plan and a specific plan in the area of town and related areas or in the country in order to build or develop a new town or a part thereof or to replace a damaged town or a part thereof for the purpose of providing or improving sanitation, amenity and convenience, orderliness, beauty, use of property, public safety, and social security, of improving economy, social affair, and environment, of preserving a place and an object of interest or value in the field of art, architecture, history or antiquity, or of preserving natural resources, landscape of beauty or natural interest."

Specifically proposed for this study, the term of urban class planning is defined as assigning urban land-use classes for plots presenting in the study area so that the all designed objectives and constraints can be served with optimum satisfaction. The purpose of this planning does not include infrastructure development, hazard and disaster zoning and mitigation. The objectives offer optimized housing, employment, open green area, compatibility, and travel rate.

2.2 Urban land-use classification in Thailand

There are various classifications of urban land use applied to different countries. They might be different from country to country based on geography and lifestyles. In Thailand, according to the สำนักพัฒนามาตรฐาน กรมโยธาธิการและผังเมือง [STDB of DPT] (2549), an urban land-use classification can be divided to main land uses and others.

In the main urban land uses can be classified into residence, commerce, industrial, and agriculture. The residence can be separated into 3 subclasses i.e. low density residential, medium density residential, and high density residential. Commerce is commercial land use in community which is sometimes mixed with high density residential. Industrial can be separate into 4 subclasses which are industrial and warehouse, specific industrial, warehouse, and general industrial and warehouse. Rural and agricultural areas have 3 subclasses which are rural and agricultural, conservation area for rural and agricultural, and environmental conservation area for tourism.

Other land uses are available to support the main land-use activities and daily activities of community. The other land uses can be classified into open land for recreation and environmental quality maintenance, governmental institution, public utilities and facilities, religious institution, and educational institution.

In details, DPT classify urban land use totally into 22 classes. A set of classes from town to town can be different. For example, urban land use of Nakhon Ratchasima Municipality city covers 11 classes, i.e. low residential, medium residential, commercial and high residential, industrial and warehouse, specific industrial, rural and agricultural, open land for recreation and environmental quality maintenance, educational institution areas, religious institution, governmental institution and public utility and facilities, and road network.

To serve the purpose of the study that allows pragmatic transformation of classes, urban land use of the study area should be modified to be 16 classes i.e. low residential (LR), medium residential (MR), commercial and high residential (HRCom), rural and agricultural (RA), open land for recreation and environmental quality maintenance (OpenG), scrub and forest (ScF), aqua farming (AqF), area ready to develop (ReDe), industrial and warehouse (IW), educational institution (EI), religious institution (RI), governmental institution, public utility and facilities (Gov), water or wetland (WA), undeveloped industrial (UnIn), railway, and road network. These classes will reflect on compatibility and changing cost matrixes of class transformation. The modified urban land-use classes can be described in Table 2.2.

2.3 Urban growth prediction modeling

Recently, there have been many urban growth models and simulations. Almost all of them were derived from CA models by adding probability, influencing factors, exclusion, policy, etc. They include CA-Markov, SLEUTH, DUEM, Agent Based, URBANSIM, UPLAN, Multi criteria evaluation (MCE)-CA model, GeoCA-Urban and Voronoi-CA (Couclelis, 1985; Couclelis, 1989; Herold, Menz, and Clarke, 2001). Very few do not apply the concept of CA model e.g. logistic regression analysis. Lately, new modified CA models and tools have been used to forecast future urban changes or expansion area, describe and assess trends and impacts of future development, and to express the potential impacts of different policies (Herold, Menz, and Clarke, 2001).

Urban growth models for forecast the urban growth area mentioned above are synthesized and compared. Items compared cover input spatial data and attributes, advantages, limitations, and available software used. The synthetic results are displayed in Table 2.3.

Table 2.2 Description of modified urban land-use classes (modified from DPT classification).

No.	Urban class	Abbreviation	Description
1	Low residential	LR	Single-family homes or semi-detached homes with 1-2 floors
2	Medium residential	MR	Town houses, low-rise apartments (less than 5 floors)
3	Commercial and high residential	HRCom	High-rise apartments, residential and shop buildings, small factory buildings, office and service uses located along arterial roadways, entertainment, banks, cinemas, and department stores
4	Rural and agricultural	RA	Land for agricultural and rural activities
5	Open land for recreation and environmental quality maintenance	OpenG	Area of public land for recreational uses such as parks and playgrounds
6	Scrub and forest	ScF	Scrub and public or community forest
7	Aqua farming	AqF	Shrimp farm, fishing farm, and aquatic animals farm
8	Area ready to develop	ReDe	Land ready prepared for development
9	Industrial and warehouse	IW	Factories (processing and manufacturing), warehousing (storage)
10	Educational institution	EI	School, college, and university

Table 2.2 (Continued).

No.	Urban class	Abbreviation	Description
11	Religious institution	RI	Temple, mosque, shrine, and graveyard
12	Governmental institution, public utility and facilities	Gov	Land for government offices, health center, and public transportation
13	Water or wetland	WA	Water or wetland
14	Undeveloped industrial	UnIn	Undeveloped area in industrial estate
15	Railway	-	Railway
16	Road network	-	Travel paths include expressways, arterial roads (main city roads), and local roads

Table 2.3 Urban growth model comparison.

Model	Input data	S/W	Advantage	Limitation
CA-Markov	- 2-dates land-use data	open source: IDRISI	- Easily to prepare input data - Prototype model - Available MCE modules with varying decision rules	- Limited input data - No more additional influencing factors
SLEUTH	- Slope - Land-use - Excluded - Urban extent - Transportation - Hillshade.	open source: SLEUTH (running through Cygwin s/w on Windows)	- Fit specifically for metropolis - Allow to input data related to policies - Available constraints of growth (Excluded) - Available input data suitable for urban growth analysis	- Fixed number of input data - Software developed for Linux, Unix and need Cygwin s/w to get it run on Windows but inconvenient

Table 2.3 (Continued).

Model	Input data	S/W	Advantage	Limitation
DUEM	- Housing - Industry - Commercial - Vacant - Streets	open source: DUEM	- Develop simple demonstrations of cellular growth. - Allow input the dynamic change status as active and inactive	- Limited input and output land-use classes - Preliminary model derived from CA - Limited number of users
Agent-based	Based on agents and their environment	open source: Swarm, Mason, NetLogo	- Allow to input influence factors as required - Flexible based on researcher knowledge - Can reflect explicit social behavior	- Must have other knowledge or experiences much more than only modeling - Properties of agent are not fixed and can be overlooked or excessed - Can be overly complicated

Among all the numerous developed model Cellular Automata and Markov chain Model is most accepted model for the modelling of the trends of the growth pattern (Jain, Siddiqui, Tiwari, and Shashi, 2016). The capability of hybrid CA-Markov model has been widely employed in predicting changes in land use and land cover. In this hybrid model, Markov chain generates the transition probability matrix while the cellular automata control the evolution and changes in the cells (Ayodeji, 2006; Chang and Chang, 2006; Kamusoko, Aniya, Adi, and Manjoro, 2009). Numerous studies have revealed that the CA-Markov model, which efficiently matches with GIS and RS, is able to devise an appropriate approach in dynamic temporal and spatial modeling of cover/land-use changes (Guan et al., 2011; Myint and Wang, 2006). Hence, the simulation of future growth area of this study will be using a CA-Markov model.

Concept and theory of CA-Markov model are described in the following.

2.3.1 Cellular Automaton (CA)

A discrete dynamic system in which space is divided into regular spatial cells, and time progresses in discrete steps. Each cell in the system has one of a finite number of states. The state of each cell is updated according to local rules, that is, the state of a cell at a given time depends on its own state and the states of its neighbors at the previous time step (Liu, 2009; Wolfram, 1984).

The first important application of the cellular automata came from John Conway's "Game of Life" (Gardner, 1970). "Life" was constructed as a two-dimension grid with two cell states and an eight-cell neighborhood. The two possible states of a cell can be either dead or live. The eight-cell neighborhood includes cells in East, South, West, North, South-west, South-east, North-east, and North-west directions. This type of neighborhood is termed the *Moore Neighborhood*.

The relevant terms used in the CA process can be simply defined as *1) cell*, spatial unit of land use with regular tessellation arrangement, *2) state,* land use/land cover class of a cell, *3) neighborhood,* eight cells surrounding a cell in question, *4) transition rule,* defines how the state of one cell changes in response to its current state and the states of its neighbors, and *5) time*, specifies the temporal dimension in which a cellular automaton exists.

In Conway's "Game of Life", a cell can survive, die, or give birth in successive generations according to the following rules and showing in Figure 2.3:

- *Survival*: A live cell with two or three live neighbors survives into the next generation.

- *Death:* A live cell with less than two or more than three live neighbors dies either of isolation or of overcrowding.

- *Birth:* A dead cell with exactly three live neighbors becomes alive in the next generation.

Using these simple rules, the model is able to generate very complex structures as different cells die, survive, or give birth in successive generations. Figure 2.4 presents a sample of simulation results generated by the model. The “Game of Life” has been a very popular cellular automata model after the paper by Gardner in Scientific American (Gardner, 1970).

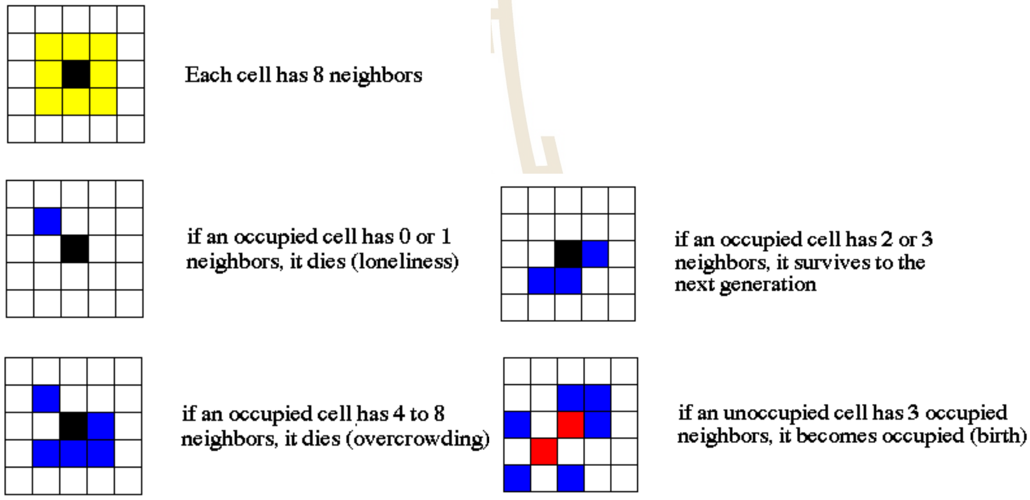


Figure 2.3 Rules of the Cellular Automation “Game of Life” (Biel and Hua, 2012).

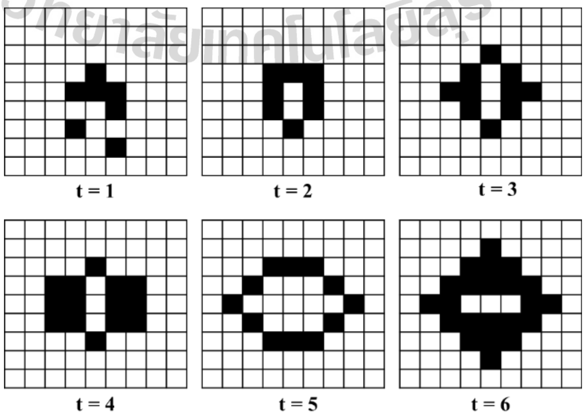


Figure 2.4 A simple simulations based on Conway’s “Game of Life” (Black cells are live, and white cells are dead; *t* is time step) (Liu, 2009).

2.3.2 Markov chain (analysis)

A technique to estimate the probability of occurrence from any original state to any final state after a specific sequence of *n* time steps. It makes use of transition matrixes i.e. transition probability and area matrixes.

Markov chain analysis is used to predict the transition area matrix of land-use change. At first, the original transition probability matrix (denoted by $P_{(N)}$) of land-use type should be obtained from two former land-use maps. Then, according to non-aftereffect of Markov, the transition probability matrix for target simulation periods can be predicted according to Equation (2.1).

$$P_{(N+1)} = P_{(N)} \times P_{(N-1)} \tag{2.1}$$

where $P_{(N+1)}$ is state probability of any times, and $P_{(N-1)}$is preliminary state probability.

If Markov chain has a finite number of states, i.e. *n*, transition probability matrix can be defined as follows:

$$\begin{bmatrix} P_{1,1} & P_{1,2} & \cdots & P_{1,n} \\ P_{2,1} & P_{2,2} & \cdots & P_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n,1} & P_{n,2} & \cdots & P_{n,n} \end{bmatrix} \tag{2.2}$$

Having a transition probability matrix, transition area matrix can be easily obtain, which is performed by Equation (2.3).

$$A = \begin{bmatrix} A_{1,1} & A_{1,2} & \cdots & A_{1,n} \\ A_{2,1} & A_{2,2} & \cdots & A_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{n,1} & A_{n,2} & \cdots & A_{n,n} \end{bmatrix} \tag{2.3}$$

where A is the transition area matrix; $A_{i,j}$ is the sum of areas from the i th land-use class to the j th class during the years from start point to target simulation periods; and n is the number of land-use types.

2.3.3 Simulated land-use change using CA-Markov model

In the CA-Markov model, CA provides a spatial framework. Deciding iteration times, integrating transition area and probability matrixes as the local transition rule of CA, land-use map in the future could be simulated (Yang, Zheng, and Chen, 2014).

2.4 Optimized urban growth planning using Genetic Algorithm

Result from urban growth prediction model and simulation provides urban growth and class changing plots that could occur under certain potential and constraints while urban growth planning deals with not only expansion area extent but also providing suitable classes for all plots to be planned so that the new growth can efficiently and adequately offer good quality of living. The planned urban classes of all plots in the study area should serve an optimum goal based on a set of planning objectives and comply with a set of constraints. The goal of urban growth planning should include optimization of a set of objectives, e.g. housing, employment, class changing cost, neighborhood compatibility, travel rate as well as areas for recreation.

To serve the purpose mentioned above, the research plans to apply GA and MODA as fitness function which is one of meta-heuristic methods. The variation of population of plans can be arranged by GA while MODA is employed to optimize multi-objectives required.

2.4.1 Genetic algorithms (GAs)

The Genetic Algorithm (GA), which is capable of handling the unstructured urban issues, was proposed in this field in the 1970s (Hopkins, 1977; Los, 1978). The GA is a type of general global optimization algorithm, and it has been shown to be robust and efficient for searching large, complex, and little-understood search spaces such as those of multi-objective land-use planning problems (Zhang, Zeng, and Bian, 2010).

GAs are computationally intensive global search heuristics, or meta-heuristics. The central idea behind GAs is to mimic the Darwinian notion that selective breeding seeks optimum individuals in a given environment. (Smith, Goodchild, and Longley, 2007)

Malczewski and Rinner (2015) explain that the basic feature of GA is a multi-directional and global search, while maintaining a population of potential solutions from generation to generation. The population based approach is especially useful for exploring the set of Pareto solutions. Figure 2.5 shows a flowchart of genetic procedure (Deb, 2001).

The procedure covers steps as optimization problem definition, encoding, initialization, evaluation and fitness assignment, selection, crossover, mutation, and new population. A multi-objective optimization problem is firstly defined to involve specifying two or more objective functions and a set of constraints. In order to execute a generic algorithm, each potential solution to the optimization problem is encoded to represent possible solutions in form of chromosomes or genome-like objects. Possible solutions in this study mean possible plans for each plot of urban growth. Chromosomes are made of discrete units, called genes. The gene can be defined as binary, integer or real value.

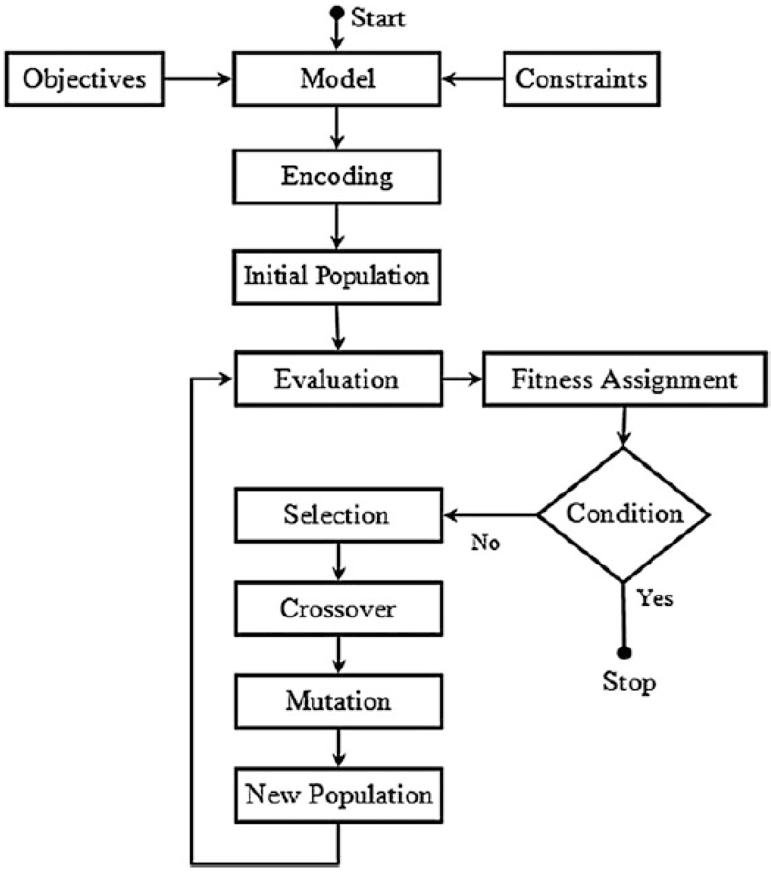


Figure 2.5 A flowchart of genetic procedure (Deb, 2001).

A number of plots or all genes constitute one chromosome, which in this study is also referred to as a land-use plan. The relationship between the components in the GA and the spatial land use in the GIS is illustrated in Figure 2.6. From this figure, a chromosome with a number of genes are equal with the number of plots in each case area. One gene or one plot is assigned an integer (class ID) ranging from one to the maximum number of possible urban land-use classes. Each gene or plot in a chromosome has its old ID and urban class ID.

An optimum solution status of a chromosome or a string of genes will be actually represented by its decision variables or multi-objectives. Once an encoding strategy has been developed, the procedure defines a set of initial chromosomes or solutions/plans. The initial population of solutions is created using a random method.

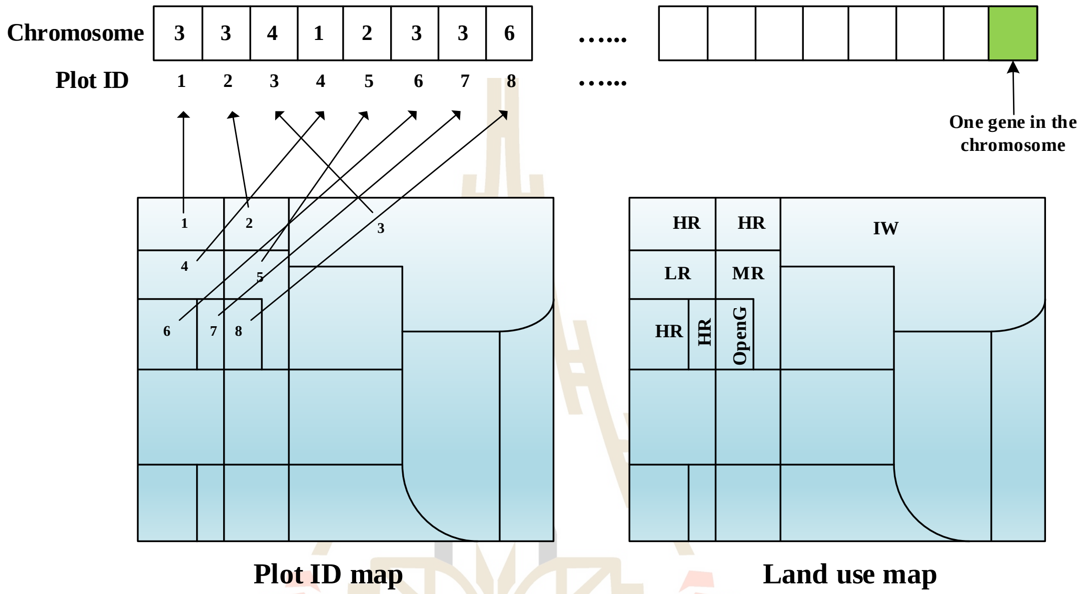


Figure 2.6 Relationship between the components in the GA and the actual spatial land use (Zhang, 2014).

The solutions are then evaluated iteratively using a fitness function. The techniques for fitness assignment are based on the concepts and methods of the conventional multi-objective optimization procedures or MODA. Since the goal or the satisfied condition of generic algorithm is to maximize the fitness of decision variables within the population, the function determines a candidate solution's relative fitness. If the termination condition is not satisfied, then the population is modified using three genetic operators: 1) selection, 2) crossover, and 3) mutation. The detail of genetic operators is explained as follows:

1) Selection

The selection operator chooses the best performing chromosomes in one population to work as parents of successive iterations. There are many methods used to select a suitable parent plan. Almost all methods involve the use of the ratio of the fitness of a certain plan to the summed fitness of the whole population so as to reflect the selected probability of that plan.

2) Crossover

The process crossovers the parents from the selection procedure by exchanging the genes in the mother and father. The main aim of crossover operators is to exploit the existing (best) solutions. The most often used generic crossover methods are one-point, two-point, and uniform crossover operators as shown in Figure 2.7 (Sastry, Goldberg, and Kendall, 2005). The one-point crossover method is started by randomly selecting a crossover point within a chromosome and then interchanges the two parent chromosomes at that point to produce two new offspring as shown in Figure 2.7(a). Figure 2.7(b) illustrates the two-point crossover operator which selects two points randomly and then the elements outside the selected points are inherited from one part of the offspring, and the other elements are replaced by other parent. Uniform crossover evaluates each gene in the parent's chromosomes for exchange based on probability defined by the mixing ratio (or the swapping probability). Typically, the probability of 0.5 is used, as shown in Figure 2.7(c).

3) Mutation:

The process operates on a single offspring. It aims at maintaining genetic diversity from one generation to the next and preventing all solutions in a population to fall into a local optimum. This is accomplished by exploring a single gene or genes in a part of a solution space that their values have not been represented in current solutions, and then altering those parts of individuals in the current generation to be the same values, as shown in Figure 2.8. The process resulted in a set of offspring population for new population process.

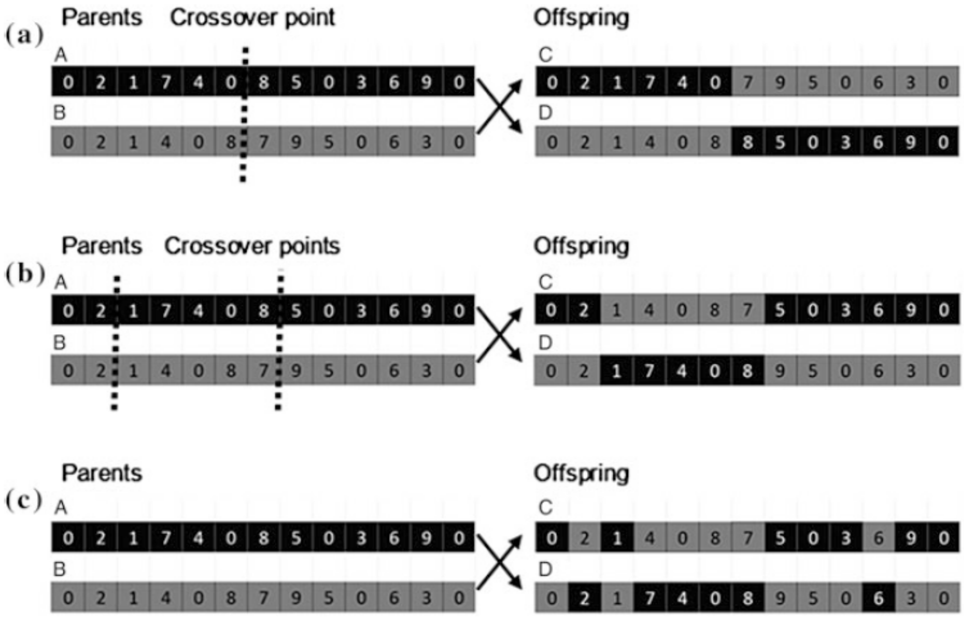


Figure 2.7 Crossover methods: (a) one-point crossover, (b) two-point crossover, and (c) uniform crossover (Sastry, Goldberg, and Kendall, 2005).

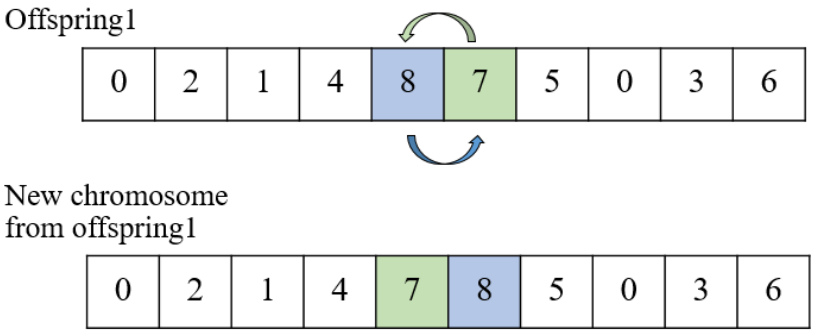


Figure 2.8 Mutation methods to create new solutions (Malczewski and Rinner, 2015).

To generate new population for next iteration, a set of offspring population from mutation is replaced either all parent population or a portion of them.

The iterations of these processes (from evaluation to new population) are continued until a termination condition is satisfied. The termination condition is often defined as a maximum number of generations (iterations) that has to be completed.

2.4.2 MODA

MODA is the effective fitness function of the GA. The available decision methods of MODA to integrate multi-objectives can be classified into 1) weighted-sum (value function) approaches, 2) the metric-based approaches, and 3) Pareto-based (or dominance-based) approaches (Gen and Cheng, 2000).

The most popular method is Pareto-based approach. Instead of providing a single solution or without dominance consideration, the result from Pareto-based approach can provide a set of non-dominated solutions. This allows further flexible consideration to select optimum solution(s) based on a single or a selected group or all objectives.

In this study, the maximin fitness function, one of Pareto approach expressions, is selected to be the decision method for fitness. The function was proposed by Balling (2002). The practical performance of the function is strongly evident in the study of Zhang (2014). The function is employed to measure the goodness of each plan in one generation.

As described by Zhang (2014), the first step of the function is to translate all objectives into the format of "min(Z)", and then let Ob_{ki} as the value of the k-th objective in the *i*-th plan. As for the max(Z) format objective, the objective will be transformed to min(Z) format by following equation.

$$Z = -Z \tag{2.4}$$

Then consider two plans at a time in one generation, the *i*-th plan and the *j*-th plan. The *i*-th plan will be dominated by the *j*-th plan if:

$$Ob_{1i} > Ob_{1j}, Ob_{2i} > Ob_{2j}, \dots, Ob_{ki} > Ob_{kj} \tag{2.5}$$

And this equation is equivalent to the following equation:

$$min\left(Ob_{1i} - Ob_{1j}, Ob_{2i} - Ob_{2j}, \dots, Ob_{ki} - Ob_{kj}\right) > 0 \tag{2.6}$$

Thus, the *i*-th plan is a dominated plan if:

$$\underset{i \neq j}{max}\left(min\left(Ob_{1i} - Ob_{1j}, Ob_{2i} - Ob_{2j}, \dots, Ob_{ki} - Ob_{kj}\right)\right) > 0 \tag{2.7}$$

And the fitness of the *i*-th plan is:

$$f_i = \left[1 - \max_{j \neq i}\left(min\left(\frac{Ob_{1i} - Ob_{1j}}{Ob_{1(max)} - Ob_{1(min)}}, \dots, \frac{Ob_{ki} - Ob_{kj}}{Ob_{k(max)} - Ob_{k(min)}}\right)\right)\right]^p \tag{2.8}$$

In above equation, to normalize the difference of each objective comparing between plan to plan, the difference of maximum and minimum values of objectives in plans of a generation are used to scaling. In Equation (2.8), the scaling factors $Ob_{k(max)}$ and $Ob_{k(min)}$ are the maximum and minimum value of the *k*-th objective.

2.5 Previous studies

Previous researches to identify optimized urban land-use classes using CA-Markov modeling and Genetic Algorithm and MODA (GA-MODA) techniques are gathered and concluded in the follow.

Sang, Zhang, Yang, Zhu, and Yun (2011) studied about simulation of land use spatial pattern of towns and villages based on CA-Markov model. Using land use maps in years 2001, 2006, and 2008, the CA-Markov model that combines the Markov chain analysis and CA models successfully simulated land use changes in Fangshan. From this study, unused land and forest land were the dominant land use types in Fangshan. Since 2001, farm land had been shrinking while forest land and built-up areas had increased quickly. Among the various transformation types, the changes from farm land to built-up land spread most significantly. Regions along railways and main roads as well as rivers with intense human activity had a high local variability of land use distribution. Therefore they became more varied and the spatial pattern of land use changes became more complex. The simulation result by the CA-Markov method showed that its original rate of changes in trends and changes will keep constant from 2008 to 2015. Therefore, it is urgent to strengthen the protection of farm land and water-bodies, to prevent acts of indiscriminate use of farmland in order to promote the protection of farmland and the rational use of land.

Subedi, Subedi, and Thapa (2013) applied CA-Markov model to predicted land-use change in Saddle Creek drainage basin in Florida. Kappa statistics between the actual land-use and that predicted by this model showed an acceptable level of prediction accuracy. The accuracy were well above 80%, the CA-Markov model utilized for this land-use change projection in Saddle Creek drainage basin was considered valid. This model predicted a notable increase in the urban areas (47.3% to 49.4%) and transportation facilities (3.7% to 5%) from 2006 to 2015. On the contrary, agricultural areas are predicted to decline from 14.4% to 12.3% between these periods.

Deep and Saklani (2014) applied CA-Markov model to studied the urban sprawl in Dehradun city, India. The LISS IV images between the year 2004 and 2009 were collected. LULC of these years were generated using unsupervised classification. To achieve the goal, the temporal images of LISS IV were used to analyze the spatial pattern of land cover change in the area and the future growth was modeled by applying CA-Markov model. The results clearly suggest that major changes between the periods of 2004 and 2009 occurred in built up classes (about 27%) followed by agriculture (17.7%) and fallow land (10.2%). The projection as predicted using CA-Markov model suggested a value of kappa coefficient equal 0.91 which indicates the validity of the model to predict future projections. By using the same parameters the projection for the year 2014, The results of forecast for the year 2014 that the major changes will be in agriculture land (18%) followed by mixed vegetation (7%). The built up will be around 12% higher than the projected level of 2009. Modeling suggested a clear trend of various land-use classes' transformation in the area of urban built up expansions.

In 2014, Yang, Zheng, and Chen proposed a new model integrating landscape pattern indexes, Markov Chain and CA model for the simulation of land-use change. Then the model was successfully applied to the simulation of land-use change in Changping, a district of Beijing. Based on land-use maps in years 1988 and 1998, the land-use map in year 2008 was simulated. By analyzing the simulation result, the effectiveness of the model for land-use change simulation was demonstrated. By comparing results simulated by this model and the results simulated by Markov-CA model with the actual land-use map, the advantage of this model in spatial accuracy was shown.

Ebrahimipour, Saadat, and Farshchin (2016) studied about prediction of urban growth through Cellular Automata-Markov chain in Bojnoord city of Iran. CA-Markov model was employed to predict the land-use changes for the next 50 years with 10-year intervals between 2020 and 2070. The results showed that if the process of urban growth and land-use changes in areas around the city persist, the urban areas will double by 2070 compared to 2009, while the agricultural lands will shrink to half. This could provide the context for environmental issues in the future. The detection of changes in different land uses in the future can help managers and policymakers make informed decisions and maintain sustainable resources.

Balling, Taber, Brown, and Day (1999) studied about multi-objective urban planning using Genetic Algorithm (GA), to search the optimal future land-use and transportation plans for a high-growth city for the year 2020 of Provo city in Utah using GA. Objectives included the minimization of traffic congestion, the minimization of costs, and the minimization of change from the status quo. Constraints were imposed to ensure affordable housing for future residents. The GA algorithm searched through 1,991,731 plans to get 10,000 feasible plans which provided enough housing to accommodate the projected future growth. From these 10,000 feasible plans, a global Pareto set of 330 plans was obtained which represents the algorithm’s best plans for the three objectives (travel time, cost, and change) regardless of the relative importance of these objectives. The 330 plans in the global Pareto set must be narrowed by decision makers to a final plan or plans. This narrowing process will inherently involve the relative importance of the objective functions.

Balling, Powell, and Saito (2004) applied GA for generating future land-use and transportation plans for high-growth cities. GA was used to find a diverse non-dominated set of optimal future zoning and street plans for two high-growth cities in the United States of America. This study had 2 objectives and 3 constraints were formulated for this problem. The constraints required that future plans must have enough housing capacity, employment capacity, and greenspace for the projected future population in the year 2025. The first objective was the minimization of traffic congestion, and the second objective was the minimization of change from the status quo. The result set ranged from a minimum change plan, where undeveloped farmland was rezoned as commercial or residential land, to a minimum traffic congestion plan where commercial and residential usage were spread throughout the cities rather than concentrated in one or two areas.

Cao et al. (2011) chose the example of Tongzhou New Town, China, to demonstrate how the model could be employed to meet three conflicting objectives based on minimizing conversion costs, maximizing accessibility, and maximizing compatibilities between land uses. Using the Genetic Algorithm for multi-objective optimization of land use. The results, in each objective, these tend to be extremes but they definitely reach the best scores with respect to their preferred single objectives. Objective 1 preferred solution is obviously similar to the land-use status quo. Objective 2 preferred solution has the best compatibility with transportation facilities. Objective 3 preferred solution presents the most compatible layout of these land uses. The result of multi-objective used equal weight scenario had the most balanced land-use distribution with respect to compact and required residential land, well-distributed commercial land and green space, as well as industrial land located in three main industrial zones.

Huang and Zhang (2014) developed multi-objective optimization approach to finding sustainable land-use planning for a downtown lake area in central China. A case study of the Donghu Lake watershed was conducted. Donghu Lake is one of the largest downtown lakes in central China, and the watershed area is undergoing rapid urbanization and suffering from nonpoint source water pollution. A multi-objective optimization genetic algorithm of this studied was then developed to search optimal urban land-use plans within the urban extent determined by the urban growth model (CA used). Four objectives were proposed as multiple objectives for the urban planning: housing capacity, employment capacity, reduced nonpoint source water pollution, and compatibility between land uses. They were concluded that CA and GA are successfully used to search for an optimized urban land-use plan for the Donghu watershed. First, all conflicting objectives were incorporated into the process of optimization. Even if the optimal plans do not yield the best solution for single objectives, the optimal plans on the whole provide solutions that satisfy all objectives to the maximum extent. Second, by consideration of the global spatial trend, the spatial distribution of optimal plans was more reasonable than that of the plans that do not consider global distribution. According to the results, the plans allocate heavy industry (HI) and light industry (LI) far from the city center and the central business district (CBD) close to a convenient transportation system.

Zhang (2014) developed the multi-objective optimization for spatial planning of land use. Shenzhen, a rapidly developing city in China, was selected as the case study area to validate the proposed approach. The objectives and constraints in the spatial planning of land use were defined at two different levels based on the land-use principles, local and national policies in China, and characteristics of Shenzhen. At the first level, nine objectives were proposed, namely, maximizing economic benefit, maximizing ecosystem services value, minimizing soil erosion, minimizing non-point source pollution, minimizing carbon emission, maximizing compatibility, minimizing change cost, maximizing accessibility, and minimizing landslide susceptibility. The objectives of spatial planning of land use at the urban level (urban master plan) were subsequently proposed, as follows: maximizing housing capacity, maximizing employment capacity, minimizing changing cost, minimizing pollution from industrial lands, maximizing mixed land uses, maximizing green space, maximizing accessibility, maximizing compatibility, and maximizing spatial equity. The proposed spatial-related objectives were quantified by GIS. Results indicated that the multi-objective optimization based two-level spatial planning could create trade-offs among the conflicting objectives, and a set of solutions is provided as options for decision makers or planners. Moreover, the multi-objective optimization based two-level spatial planning could generated a consistent land-use planning system for Shenzhen.

Mohammadi, Nastaran, and Sahebgharani (2015) studied about sustainable spatial land-use optimization through non-dominated sorting Genetic Algorithm in Baboldasht district of Isfahan. Numerous plans were generated and optimized by non-dominated sorting Genetic Algorithm according to land-use allocation objectives: maximizing compactness, maximizing floor area ratio, maximizing compatibility, maximizing economic benefit, and maximizing mix use. These objectives and constraints were formulated and combined through weighted sum method. The outputs of the model were compared with the current state and GA. The results demonstrate the effectiveness and efficiency of the proposed model and its potential in supporting urban planning and decision making processes through generating numerous land-use alternatives and representing optimal solutions.

CHAPTER III

RESEARCH PROCEDURES

The scope of this study will mainly focus on assigning urban land-use classes using GA-MODA. The objective functions to optimize land-use classes of plots in a plan include maximization of housing capacity, employment capacity, open green area, and neighborhood compatibility, together with minimization of changing cost and travel rate. These functions were operated under constraints of suggested and existing rates of population and labor force densities, class areas, and classes to be preserved.

The conceptual framework of this research was designed and illustrated in Figure 3.1. It includes data collection and preparation, urban interpretation and forecast, optimized urban planning using GA-MODA, and comparison of urban maps and objective values from different years (2016 and 2019).

3.1 Data preparation, interpretation and prediction

Data were prepared, interpreted and predicted in suitable forms for input into Network analysis, CA-Markov analysis, and steps in GA-MODA process.

3.1.1 Urban plots interpretation of 2013 and 2016

Urban plots were required as input for the GA-MODA process to generate optimum urban plans. Urban plots in the study area of 2013 and 2016 were extracted by visual interpretation from QuickBird and WorldView data collected through Google Earth. The urban interpretation was based on modified classification of DPT to be 16 classes. These sets of urban land-use data were further employed for CA-Markov land-use prediction of 2019.

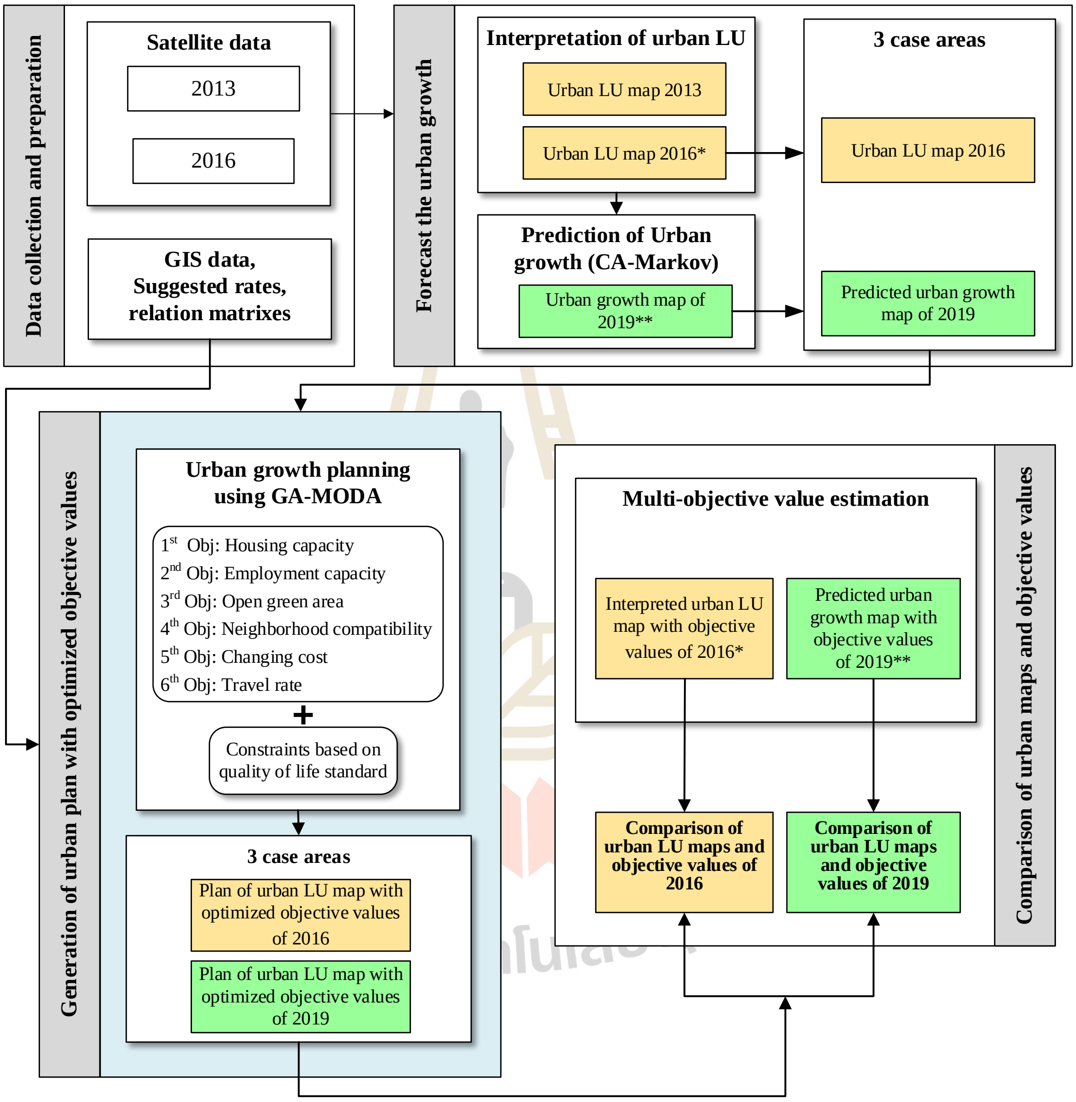


Figure 3.1 Conceptual framework of the study.

To be able to visually interpreted urban land use effectively, the field reconnaissance was required to perceive how characteristics of classes observed in the field corresponding to their appearances in the images. This corresponding could fit in recognition to high spatial resolution images applied and be used as a guide for visual interpretation.

3.1.2 Urban growth prediction of 2019 using CA-Markov model

Urban growth prediction in 2019 of the study area was performed using CA-Markov model available in IDRISI software. The input data were urban land-use maps in 2013 and 2016. The result of CA-Markov model provides land-use transition potential maps derived from matrixes of transition probabilities and areas using Markov chain analysis and spatial allocation by CA spatial filter.

3.1.3 Population and labor force prediction

Population and labor force information of 2016 and 2019 used in the analysis were estimated and predicted from 7 years (2009-2016) of statistic data of administrative units recorded by the DOPA. 2019 information of each local administrative unit was predicted by fitting curve extrapolation. The densities of predicted population and labor force of each unit were then calculated. GIS interpolation was applied to estimate spatial distribution of those densities so that population and labor force representative to the study area could be estimated. However, density estimation using interpolation could cause error when checking with total population of a unit. This was corrected by multiplication of specific coefficient of each unit to each interpolated cell in a unit in order that summation of interpolated cells was equal to the population of the unit. The information estimated was further applied to check consistency with suggested constraints whether actual population could be fit to population from GA-MODA plan. This can assist in population plan and management in urban planning.

3.1.4 Suggested population density and class area

According to the study of PST and P&C Mgt Co., Ltd. (2553) under the supervision of Nakhon Ratchasima City Municipality, for better quality of living and efficient local administration the study suggested the proper percentage of class areas and population densities in living and employment classes. Classes 1, 2, and 3 are directly concerned to housing capacity while classes 3 and 4 are for employment capacity. Rural and agricultural class is considered having very low living and employment rates. It is more likely and easier to be an area changeable to other class.

Population densities of classes i.e. open green area, educational institution, religious institution, and governmental institution were estimated from existing information in 2016 and field investigation to obtain base densities. Proper rate of these class areas are suggested by PST and P&C Mgt Co., Ltd. (2553).

3.1.5 Neighborhood plot identification for compatibility analysis

Neighborhood plot can be identified using Generate Spatial Weights Matrix function of ESRI® ArcGIS™ 10.2. For a given plot, the function provides IDs and a number of neighboring plots. The reciprocal of a number of neighboring plots works as weights and incorporate with the levels of compatibility and plot areas when compatibility value of each plot is estimated in the Objective 4.

Compatibility is considered between classes of a plot and its neighboring plots. STDB of DPT (2549) introduced the levels of compatibility to be high (H), moderate (M), and incompatible (I) in the matrix of classes (Table 3.1). To be able to estimate objective value, the classes in the matrix was modified and compatibility levels are transformed to be 1, 0.5, and 0, respectively. The modified matrix is displayed in Table 3.2. The matrix was relevant to compatibility objective.

Table 3.1 Matrix of land-use compatibility (STDB of DPT, 2549).

Land use class	Low Residential	Residential Preservation	Medium Residential	High Residential	High Commercial and Residential	Commercial	Industrial and warehouse	Specific Industrial	Warehouse	Rural and Agricultural	Rural and Agricultural Preservation	Agricultural Land Reform	Open land for recreation and environmental quality maintenance	Forest Preservation	Educational Institution	Open land for maintain environmental quality and fishery	Culture and tourism conservation	Religious Institution	Governmental Institution, Public Utility and Facilities
Low Residential	H																		
Residential Preservation	H	H																	
Medium Residential	H	H	H																
High Residential	M	M	H	H															
Commercial and High Residential	M	M	H	H	H														
Commercial	M	M	H	H	H	H													
Industrial and warehouse	I	I	I	I	I	I	H												
Specific Industrial	M	I	M	I	M	M	H	H											
Warehouse	I	I	I	I	I	I	H	H	H										
Rural and Agricultural	M	M	M	M	I	I	M	M	H	H									
Rural and Agricultural Preservation	M	M	M	M	I	I	I	M	M	H	H								
Agricultural Land Reform	M	M	M	M	I	I	M	M	M	H	H	H							
Open land for recreation and environmental quality maintenance	H	H	H	H	H	H	M	M	M	H	H	H	H						
Forest Preservation	M	M	I	I	I	I	I	I	I	M	M	H	H	H					
Educational Institution	H	M	H	H	M	M	I	I	I	M	M	M	H	M	H				
Open land for maintain environmental quality and fishery	M	M	M	I	I	I	I	I	I	M	H	H	H	H	M	H			
Culture and tourism conservation	M	M	M	M	M	M	I	I	I	M	M	M	H	H	H	H	H		
Religious Institution	H	H	H	M	M	M	M	M	M	M	M	M	H	M	H	M	H	H	
Governmental Institution, Public Utility and Facilities	M	M	M	M	H	H	M	M	M	M	M	M	H	I	M	M	M	M	H

Note: H = High compatible (1).
M = Moderate compatible (0.5).
I = Incompatible (0).

Table 3.2 Modified land-use compatibility matrix.

No.	Land use class	Low Residential (LR)	Medium Residential (MR)	Commercial and High Residential (HRCom)	Rural and Agricultural (RA)	Open land for recreation and environmental quality maintenance (OpenG)	Scrub and forest (ScF)	Aqua farming (AqF)	Area ready to Develop (ReDe)	Industrial and Warehouse (IW)	Educational Institution (EI)	Religious Institution (RI)	Governmental institution, public utility and facilities (Gov)	Water or wetland (WA)	Undeveloped Industrial (UnIn)
1	Low Residential (LR)	1													
2	Medium Residential (MR)	1	1												
3	Commercial and High Residential (HRCom)	0.5	1	1											
4	Rural and Agricultural (RA)	0.5	0.5	0	1										
5	Open land for recreation and environmental quality maintenance (OpenG)	1	1	1	1	1									
6	Scrub and forest (ScF)	0.5	0.5	0.5	1	1	1								
7	Aqua farming (AqF)	0.5	0.5	0	1	1	1	1							
8	Area ready to Develop (ReDe)	1	1	0.5	1	1	1	1	1						
9	Industrial and Warehouse (IW)	0	0	0	0.5	0.5	1	0.5	0.5	1					
10	Educational Institution (EI)	1	1	0.5	0.5	1	0.5	0.5	0.5	0	1				
11	Religious Institution (RI)	1	1	0.5	0.5	1	0.5	0.5	0.5	0.5	1	1			
12	Governmental institution, public utility and facilities (Gov)	0.5	0.5	1	0.5	1	0	0.5	0.5	0.5	0.5	0.5	1		
13	Water or wetland (WA)	1	1	0.5	1	1	1	1	1	0	1	1	0.5	1	
14	Undeveloped Industrial (UnIn)	0	0	0	0.5	0.5	1	0.5	0.5	1	0	0.5	0.5	0.5	1

Note: 1 = High compatible.
0.5 = Moderate compatible.
0 = Incompatible.

3.1.6 Changing cost matrix

In urban growth process, when a class of plot was transformed to be another class, the difficulty of change was considered in a scale of 0 to 1 of changing cost (Zhang, 2014). The higher value indicates higher difficulty. The values of class changing matrix could be obtained from the survey of expert opinions through interview or questionnaire. This matrix was relevant to changing cost objective. Some classes should be maintained as preserved classes, for example government, religious institutes, industrial and warehouse, open land for recreation, etc.

3.1.7 Road impedance and optimum path analysis

Optimum paths between origins and destinations (O-D) were obtained by network analysis. Every plot in a plan could be both origin and destination. A set of these path was considered the same and could be applied to every plan in the GA process. Impedance of every path together with travel opportunity were used to estimate travel rate. The length and traffic volume of every link (from junction to junction) of road network were used as impedance in the network analysis. Length or distance of every link was attribute of the road network GIS layer. First, topology of road network from RS interpretation, in form of GIS data layer, was checked to guarantee that it can be used for network analysis properly.

Surveyed traffic volume data of only few roads were available from PST and P&C Mgt Co., Ltd. (2553). Interpolation of known traffic density links was performed to obtain traffic volume of unknown links. Then, the total impedance of every link could be estimated by the product of length and traffic volume of a link.

3.1.8 Travel opportunity

Travel opportunity of people in every pair of O-D (TO_{O-D}) was the product of probability of people in a pair of plots and population of the estimated year. The people of a plot was estimated from the plot area and the population density of a plot class. The probability was the division product of people in a plot by the total population of the year estimated. The estimations can be expressed as:

$$TO_{O-D} = (TO_O \times TO_D) \times Pop_{year} \tag{3.1}$$

$$TO_O \text{ or } TO_D = (A_k \times PD_k)/Pop_{year} \tag{3.2}$$

where TO_O or TO_D is the probability of traveling people in plot O or plot D,

A_k is area of plot having class k,

PD_k is population density of class k,

Pop_{year} is population of a study case area in estimated year.

3.1.9 Plot generation

As input data required by GA process, plot IDs, class IDs, and areas as attributes of interpreted and predicted urban plots were prepared using GIS technique. These plots work as genes in a chromosome of GA process. During the process, each urban plan in population generated by GA was composed of all plots containing random class IDs. This variation affects to objective values of each plan.

3.2 Objective function and constraints setup

3.2.1 Objective functions of MODA

Zhang (2014) introduced that to maintain good living conditions in urban areas, a good planning in general should serve the proposes of: first, housing capacity should be sufficient to accommodate the population; second, employment capacity should be sufficient to provide citizens with jobs. These two objectives are the basic functions of cities. Third, the environment in urban areas should be comfortable enough to maintain the quality of life in a city.

For this research, an attempt was trying to generate a set of possible objectives for urban planning so that the good quality of living in the area could be maintained and promoted. These objectives were set based on validity of goal serving and data availability. All objectives should be able to work within the urban plot level. Reasonably, 6 optimized objectives were proposed in order that optimized plans of all plots in a given year of the study area or case areas can be achieved as solutions.

These 6 objectives were 1) to maximize housing capacity, 2) to maximize employment capacity, 3) to maximize open green area, 4) to maximize neighborhood compatibility, 5) to minimize changing cost, and 6) to minimize travel rate. These optimized functions were performed to meet satisfaction of constraints specifically to given objectives, if any.

3.2.1.1 Objective 1: To maximize housing capacity

The first objective was to maximize housing capacity. The total number of housing people of candidate plan *i* is the summation of the product of area of residential classes and their housing density in unit of a number of suggested people per rai. This objective function can be represented by the following equation:

$$Max\ Z_{HC} = \sum_{p=1}^{n}(A_{pk} \times CH_{pk}) \qquad (3.3)$$

where: Z_{HC} is housing capacity (total number of housing people of a plan),

A_{pk} is the area of plot *p*-th with *k*-th urban class,

CH_{pk} is housing density in unit of a number of suggested people per rai for plot *p*-th with *k*-th urban class,

p is plot number in a plan, *p* = 1, 2, 3, …, *n*, and

k is urban class ID, *k* = 1, 2, …, *z*.

Process to calculate maximize housing capacity is shown in Figure 3.2. The residential classes cover low density residential (LR), medium density residential (MR), and commercial and high residential areas (HRCom). Population density of each living class was suggested in Table 4.4. Constraints of this objective include population and areas of residential classes with reference to operating year.

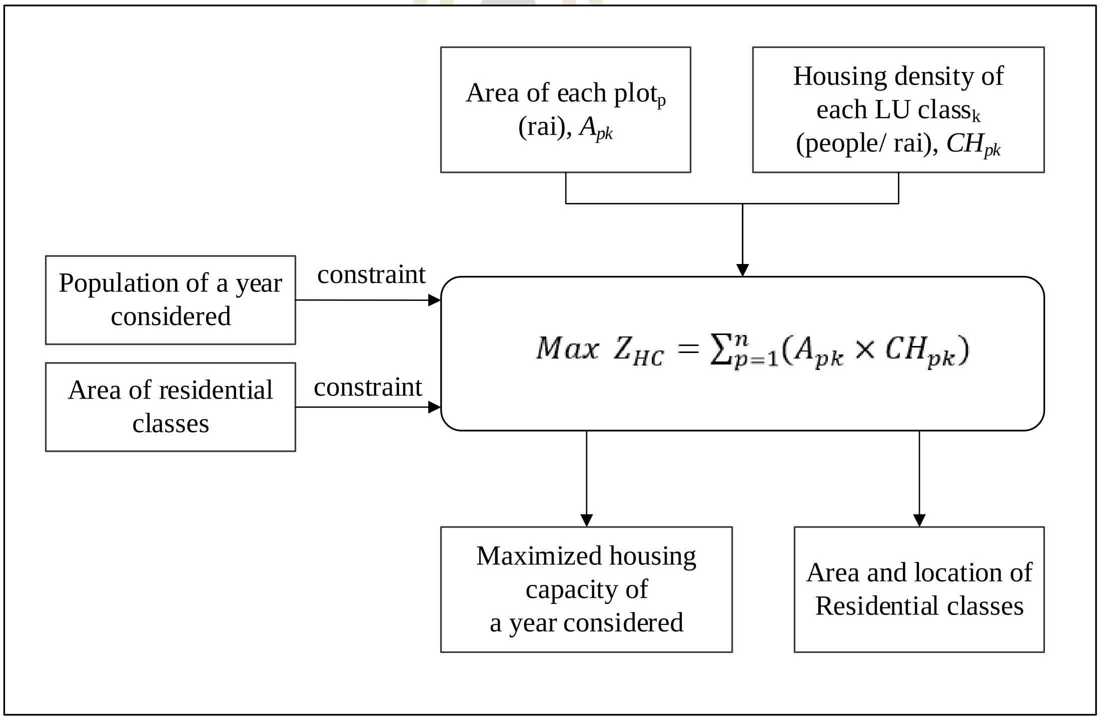


Figure 3.2 The process to maximize housing capacity.

3.2.1.2 Objective 2: To maximize employment capacity

The second objective was to maximize employment capacity. The total number of employment capacity of candidate plan *i* is the summation of the product of area of classes related to employment and their density in unit of a number of suggested people per rai. The objective function can be expressed by the following equation:

$$Max\ Z_{EC} = \sum_{p=1}^{n} (A_{pk} \times CE_{pk}) \tag{3.4}$$

where: Z_{EC} is employment capacity (total number of employment people of a plan),

A_{pk} is the area of plot *p*-th with the *k*-th land-use class,

CE_{pk} is employment density in unit of a number of suggested people per rai for plot *p*-th with *k*-th land-use class,

p is plot number in a plan, *p* = 1, 2, 3, …, *n*, and

k is urban class ID, *k* = 1, 2, 3, …, *z*.

To maximize employment capacity (Figure 3.3), the class areas of commercial and high residential (HRCom), Rural and agricultural (RA) were employed in the function. Population density of each employment class was suggested in Table 4.4. Constraints of the function include population of labor force and area of employment classes.

3.2.1.3 Objective 3: To maximize open green area

The objective was to maximize open green area. The standard or suggested area for open green space can be varied from country to country and different

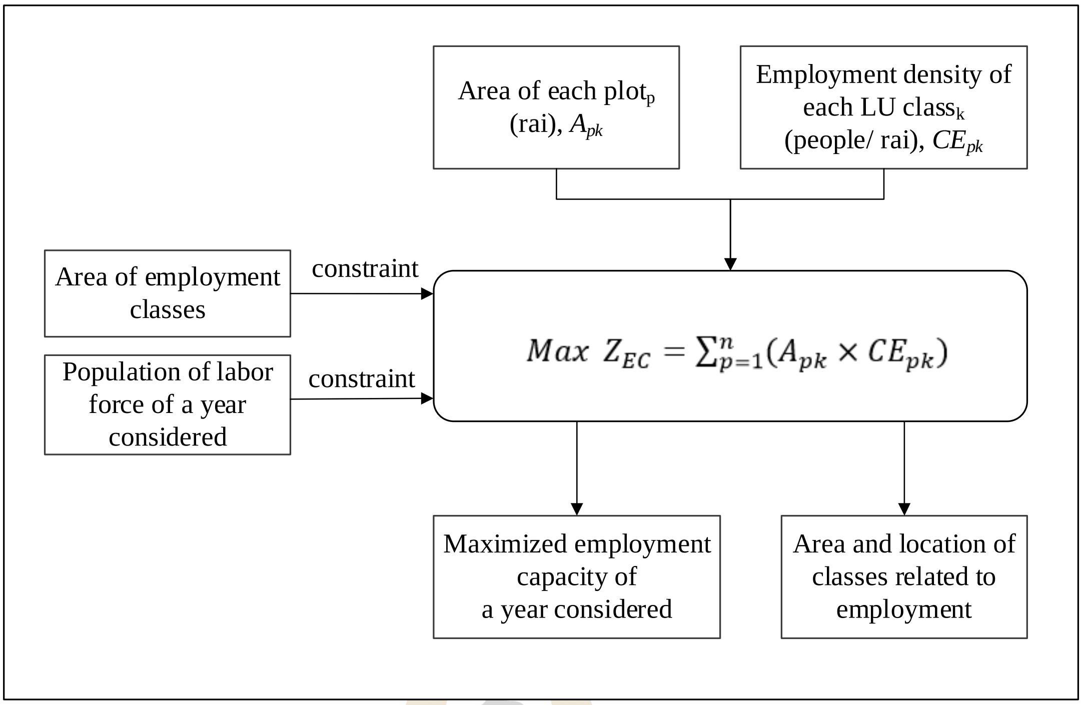


Figure 3.3 The process to maximize employment capacity.

cities. Open green area can be suggested in forms of percentage of town area and square meters per head of population, which very frequent are not the same. The open green area of a particular plan is achieved by summing the plot areas of open green space in a plan. The objective function can be represented by the following equation and Figure 3.4:

$$Max\ Z_{OG} = \sum_{p=1}^{n} A_{pOG} \tag{3.5}$$

where: Z_{OG} is the total area of open green area,

A_{pOG} is the area of plot p-th when k is the open green area class,

p is plot number in a plan, p = 1, 2, 3, …, n, and

k is urban class ID, k = 1, 2, 3, …, z.

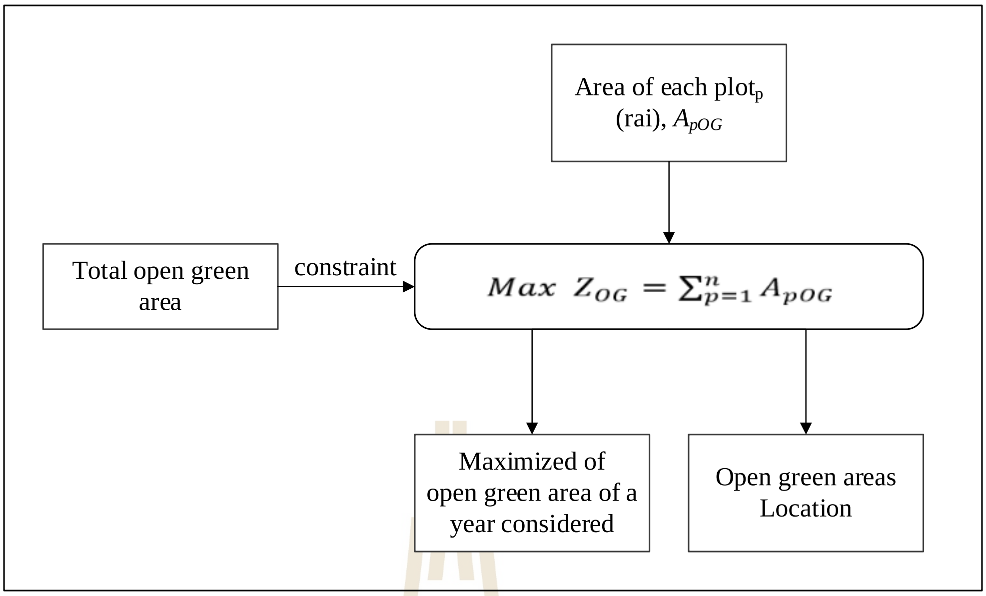


Figure 3.4 The process to maximize open green area.

3.2.1.4 Objective 4: To maximize neighborhood compatibility

To minimize conflicts in neighboring land usage is to maximize neighborhood compatibility (Ligmann, Church, and Jankowski, 2008). Each land-use type has its own neighborhood preference (Cao, Huang, Wang, and Lin, 2012). Therefore, the summed product of compatibility indexes and the areas of a given and neighboring plots including weight is acted as the indicator to reflect the compatibility. In general weight is a reciprocal of a number of neighbor plots. The compatibility is identified as high compatible, moderate compatible, and incompatible. The matrix of neighborhood compatibility was modified from DPT and is displayed in Table 3.2. The compatibility index was ranged from 0 to 1. Higher value indicates higher compatibility. The neighborhood compatibility of the proposed plan can be formulated by Equation (3.6), as displayed in Figure 3.5:

$$Max\ Z_{com} = \sum_{p=1}^{n} \sum_{j=1}^{m \in NB_p} Com_{k,l} \times A_p \times A_j \times W_{pj} \tag{3.6}$$

where: Z_{com} is compatibility of a certain plan,

$Com_{k,l}$ is the compatibility index between the k-th land-use class and the l-th land-use class,

A_p and A_j are the area of p-th plot and neighborhood j-th plot,

NB_p is the a number of neighborhood of p-th plot,

W_{pj} is spatial weight between p-th plot and neighborhood j-th plot,

p is plot number in a plan, p = 1, 2, 3, …, n,

j is a number of neighborhood plots of plot p, j = 1, 2, 3, …, NB_p,

k is urban class ID, k = 1, 2, 3, …, z, and

l is urban class ID of neighborhood plot, l = 1, 2, 3, …, z.

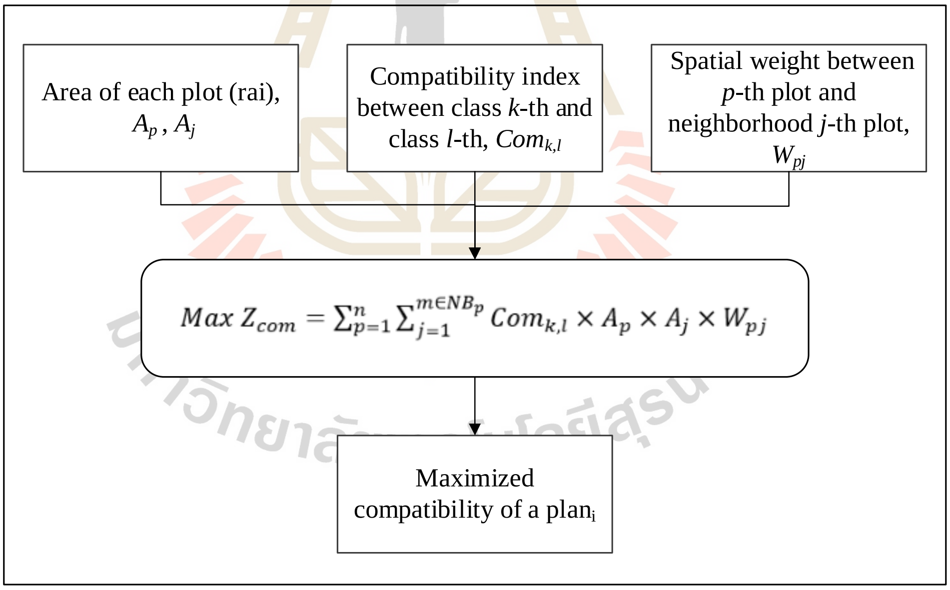


Figure 3.5 The process to maximize compatibility.

3.2.1.5 Objective 5: To minimize changing cost

Changing cost between two land usages indicates the difficulty of changing from a certain kind of land usage to other one (Zhang, 2014). The cost implies economic, social, and cultural conflicts that can occur when a plot class is subject to change. Changing cost is higher when greater effort is required or previous investment will be lost. The changing cost of optimized plan should be minimized. To compute the changing cost of a plan, sum over the changing cost of all changed plots is operated. The objective function of minimizing the changing cost of a plan is displayed in Figure 3.6 and represented in Equations (3.7).

$$Min\, Z_{change} = \sum_{p=1}^{n} CC_{h,k} \times A_p \tag{3.7}$$

where: Z_{change} is changing cost of a certain plan,

$CC_{h,k}$ is the changing cost per unit area from h-th land-use class to k-th land-use class,

A_p is the area of p-th plot,

p is plot number in a plan, p = 1, 2, 3, …, n,

k is former urban class ID, k = 1, 2, 3, …, z, and

h is former urban class ID from 1, 2, 3, …, to z.

In this study, some given classes were considered unchangeable and should be preserved, for example educational institution areas, religious institution areas, open green areas. In specific cases, some certain classes are not allowed to change backward to be less developed classes. HRCom cannot change to be any classes. MR can change to be only HRCom. LR can change to be only MR and HRCom. To meet the condition requirement of specific cases, the coding is developed in the step of sampling class to a certain plot while creating population of plans in GA process. The changing and preservation of classes could be prepared as the matrix of changing cost. To be able to preserve certain classes, Equation (3.7) should be modified to be Equation

(3.8). Plot area was normalized to be between 0 and 1 by the division of maximum plot area in a plan. This control is effective in a constraint.

$$Min\ Z_{change} = \sum_{p=1}^{n} CC_{h,k} \times NorA_p \tag{3.8}$$

where $NorA_p$ is the normalized area of p-th plot (0-1).

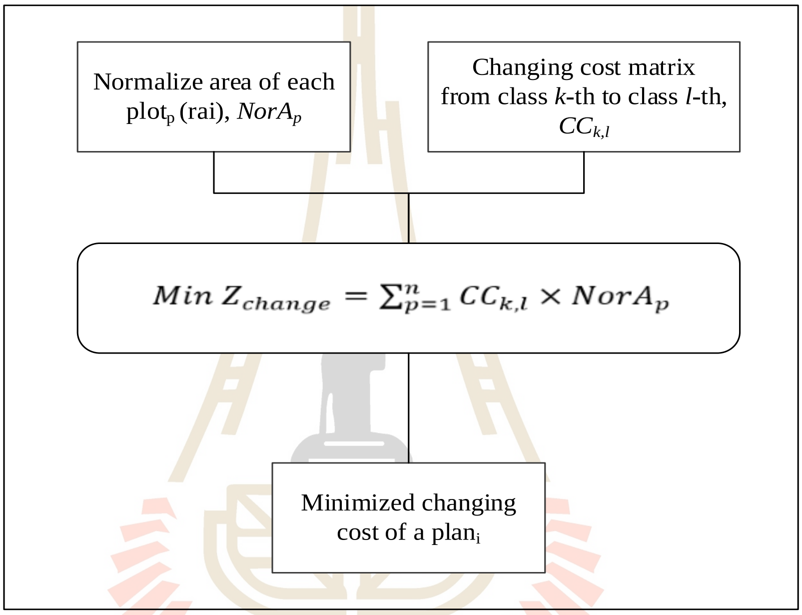


Figure 3.6 The process to minimize changing cost.

3.2.1.6 Objective 6: To minimize travel rate

The optimized plan should have minimization of the traffic congestion where commercial and residential usage were spread throughout the cities rather than concentrated in one or two areas (Balling, Powell, and Saito, 2004). Therefore, this study offers minimizing travel rate based on probability of people to travel from plot to plot of different classes. The travel rate relies on impedance in terms of distance and traffic volume. Thus, the total travel rate of a particular plan in this study was achieved by the summed product of traveling opportunity and impedance of a route from original (O) plot to destination (D) plot (see 3.1.7 and 3.1.8). The opportunity of travel from O plot to D plot will depend on population of those plots. The function of the minimized travel rate can be displayed in Figure 3.7 and represented by the following equation:

$$Min\ Z_{Trans} = \sum_{O=1}^{n} \sum_{D=O+1}^{n} Imp_{O-D} \times TO_{O-D} \tag{3.9}$$

where: Z_{Trans} is total travel rate of a plan,

Imp_{O-D} is the traveling impedance of a route from O plot and D plot,

TO_{O-D} is the travel opportunity of O plot and D plot,

O is origin plot, O = 1, 2, 3, …, n-1, and

D is destination plot, D = O+1, O+2, O+3, …, n.

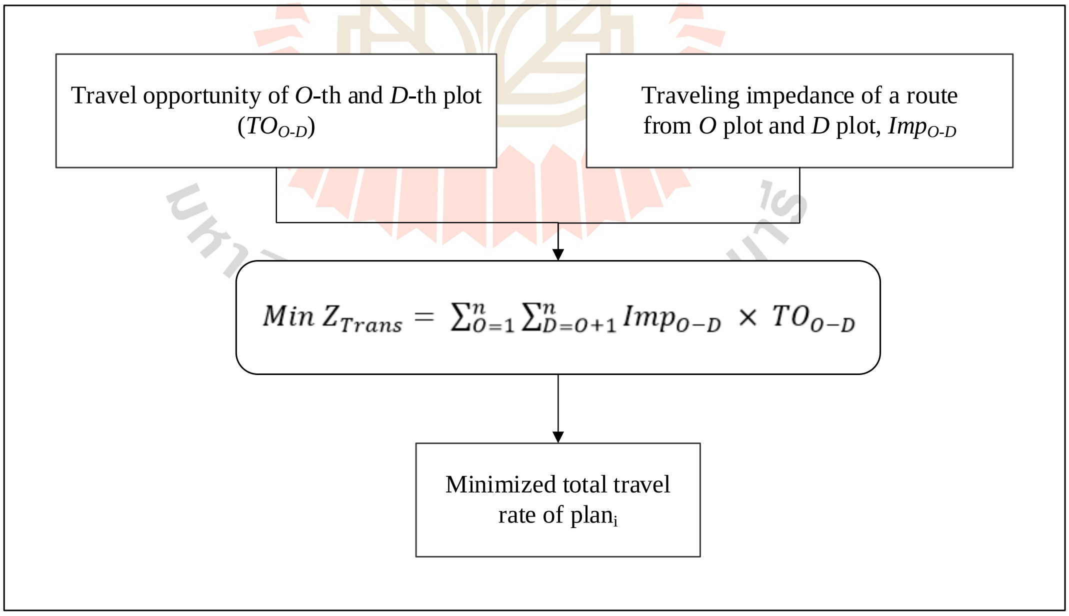


Figure 3.7 The process minimize travel rate.

3.2.2 Constraints setup

In MODA, the analysis of some objectives can be performed successfully with required particular constraints while some do not require. Even though constraints setup in this study case are related to objectives which are effective to some plots, but as a whole they will affect totally to a plan which is composed of plots with different classes formed by random arrangement of GA.

Objectives in the study consist of optimizing housing and employment capacity, and open green areas. These required constraints setup based on suggested land-use rate or specification and existing data and information of study area. For example, constraints of housing capacity relate to populations obtained from suggested areas and population densities to urban classes and suggested population densities for actual/predicted urban class areas. Instead of population, employment capacity relied on labor force availability. These 2 suggested information were applied to forming as upper bound and lower bound of constraint conditions. A suggestion of preserved class such as OpenG can be maintained as lower bound of constraint. Its lower bound follows the suggestion of the Office of Natural Resources and Environmental Policy and Planning (ONEP) (n.d.) which is 10 m^2 per person to create a better environment and a superior quality of life for people.

The purpose of constraint setup was to allow the planning class areas and population able to fall into a range of existing/predicted and suggested conditions. Therefore, the upper bound and lower bound of constraint elements could be practically flexible or varied according to 2 suggestions of case areas. The lower value of existing/predicted area or suggested area/population was set to be lower bound while the higher was set to be upper bound. They were switchable. However, in case the existing/predicted area and population are the upper bound, the adjusted percentages to increase the upper bound are required to allow continuous growth. Regarding constraint 5), in case existing/predicted area of RA class is the lower bound, the adjusted percentages to reduce is required so that changing to be other classes is allowed. The general algorithms to set up constraints was developed. The upper bound and lower bound of constraints in terms of area and population were specifically assigned into relevant classes as listed below.

1) $SuggestPop_L \leq Z_{HC} \leq SuggestPop_U$
2) $SA_1 \times TotalStudyArea \leq \sum A_{p1} \leq Ext/PredA_1 \times Adj$
3) $SA_2 \times TotalStudyArea \leq \sum A_{p2} \leq Ext/PredA_2 \times Adj$
4) $SA_3 \times TotalStudyArea \leq \sum A_{p3} \leq Ext/PredA_3 \times Adj$
5) $SuggestLB_L \leq Z_{EC} \leq SuggestLB_U$
6) $\sum A_{p4} \leq SA_4 \times TotalStudyArea$
7) $\sum_{p=1}^{n} A_{p5} \geq StA_{OG}$

where: Z_{HC} is housing capacity (total number of housing people of a plan)

Z_{EC} is employment capacity (total number of employment people of a plan),

$SuggestPop_L$ is the sum of lower population estimated from either of suggestions of relevant classes in a year considered,

$SuggestPop_U$ is the sum of higher population estimated from either of suggestions of relevant classes in a year considered,

$SuggestLB_L$ is the sum of lower population of labor force estimated from either of suggestions of relevant classes in a year considered,

$SuggestLB_U$ is the sum of higher population of labor force estimated from either of suggestions of relevant classes in a year considered,

A_{pk} is the area of plot p-th with k-th urban class,

SA_1 is percentage of suggested area of a LR urban class,

SA_2 is percentage of suggested area of a MR urban class,

SA_3 is percentage of suggested area of a HRCom urban class,

SA_4 is percentage of suggested area of an RA urban class,

SA_5 is percentage of suggested area of an OpenG urban class,

$TotalStudyArea$ is total study area considered,

$Ext/PredA_k$ is total area of k-th urban class of existing or predicted year,

Adj is percentage of adjust value of a variable,

StA_{OG} is recommended total open green area of the study area based on area per head,

p is plot number in a plan, *p* = 1, 2, 3, …, *n*, and

k is urban class ID, *k* = 1, 2, 3, …, *z*.

3.3 Coding and simulation of GA-MODA process for urban class planning

GA process was coded in Matlab® (R2017a) following the designed structural flow of functions and used to simulate urban class planning of case areas. Interpreted land-use plots of 2016 (with classes of 2013) and CA-Markov predicted of 2019 (with classes of 2016) in case areas were input for the simulation. Prepared data and information of variables of objective functions and constraints mentioned above were input of the process. Selected fitness function of GA process in the study was Pareto approach as expressed in Equation (2.8).

Running GA function of Matlab® (R2017a) can take very long time. The specification of used computer system is the significant variable to control consuming time. The computer specifications employed this study have processor of Intel® Core i7, 2.6 GHz CPU with 12.0 GB RAM and 64-bit Windows 10.

Results of the process were multi-objective values of optimized plans of case areas with respect to 2016 and 2019 urban land use. Every plan could be displayed as a map showing distribution of plots and their urban classes.

3.4 Comparison of urban plan from GA-MODA to 2016 and 2019 urban land use

Optimum plans generated from GA-MODA process were compared to 2016 existing and 2019 predicted urban land use. The elements of plan comparison include maps of urban class distribution, conditions of being complied with constraints and located at the Pareto front including their sums of normalized objective values (SNOV). Any plan complied with constraints indicates that areal extent of each urban land-use class and total population and labor force are in optimum state to attain good quality of living. Even though the SNOV cannot perfectly indicate the better plan as Pareto front can, it can give at least relative comparison among them. High SNOV might appear when only one or two objectives express very high value so that it or they can dominated other objective values. But Pareto approach consider all objective values at once and the better ones are located in the front. This can assure that any plan located at the Pareto front is non-dominated plan.

Data of 2016 were selected to allow possible efficiency comparisons from conventional growth and planning by GA-MODA process. The result should be able to confirm the future comparison to predicted data of 2019.

The urban plan generated by the proposed procedure (GA-MODA) should provide optimum plan with better elements of comparison mentioned above when comparing to 2016 existing and 2019 predicted plans.

CHAPTER IV

RESULT AND DISCUSSION

This Chapter presents input data prepared in forms of tables and maps, constraints table, plans and objective values resulted from GA-MODA process, and comparison of urban land-use maps from existing and GA-MODA process of 2016 and from predicted map using CA-Markov and GA-MODA process of 2019. All relevant aspects of these results are discussed.

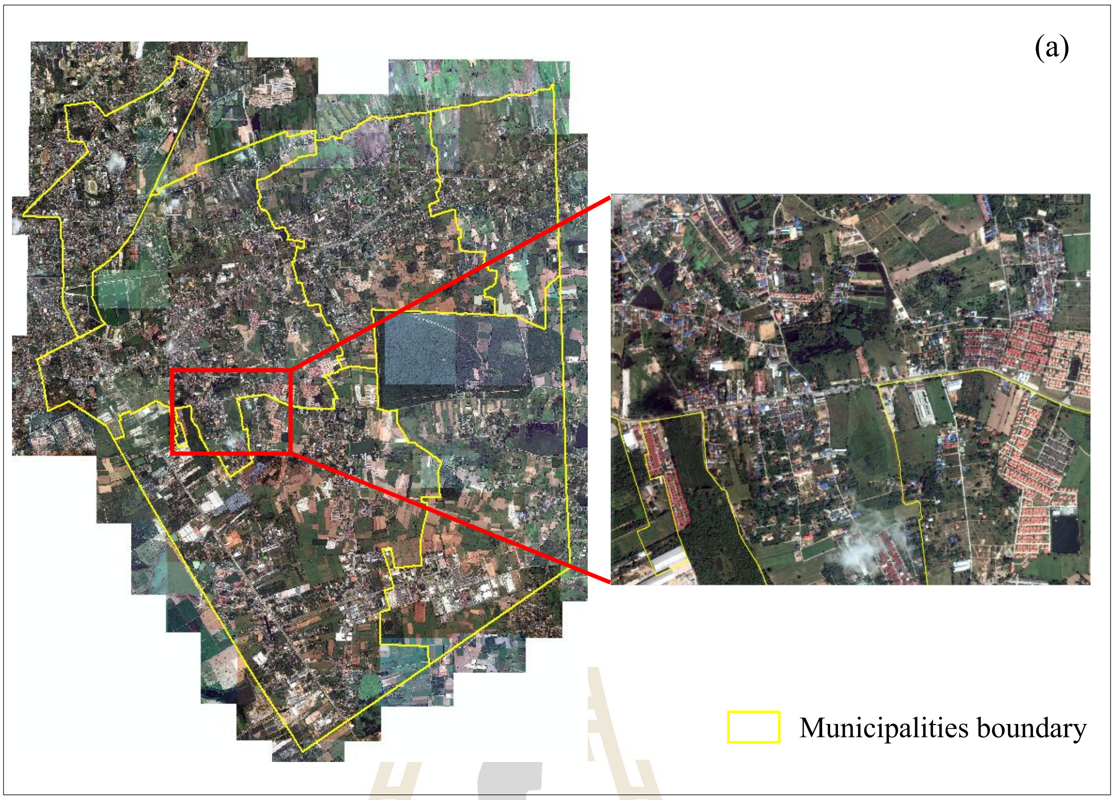
4.1 Input data and information

To serve all objective functions and constraints including plot generation of GA-MODA process, a set of input data and information were prepared. This included Land use/land cover maps in plot level of 2013 and 2016 by visual interpretation and 2019 by prediction using CA-Markov model. Suggested population density working as upper bound and lower bound of objective constraints were adopted from a previous research. Two matrixes of changing cost and compatibility of neighborhood plots were prepared. Road impedance of optimum paths of all O-D were analyzed and incorporated with travel opportunity for travel rate estimation. Population and labor force were estimated and predicted for comparing with ones obtained from optimum plans achieved from GA-MODA process.

4.1.1 Interpreted urban plots of 2013 and 2016

Two hundred and one high spatial resolution satellite images of 2013 from DigitalGlobe data were collected through SAS planet software. Thirty four satellite images of 2016 from QuickBird and WorldView data were collected through Google Earth. The collections were operated under the same interpreted scale (1:4,000). The results of these data were shown in Figure 4.1.

Urban plots were visually interpreted and captured using ArcMap software. The attributes included plot IDs, class IDs, and areas. In this study, urban land-use classes were 16 classes as described in section 2.2 of Chapter II. Visual feature recognition of all modified classes in interpretation process are presented in Appendix A. The number of urban plots in 2013 and 2016 from interpretation were 14,163 and 14,196 plots, respectively. The results of urban plot interpretation are displayed as maps in Figures 4.2-4.3. Due to having too big number of plots in the study area, 3 case areas were extracted as shown in Figure 4.4 so that developed GA-MODA codes, objective functions and constraints could be verified to work properly and achieved results accurately as expected. A number of plots and areas of classes of each case area in 2013 and 2016 are shown in Figure 4.5. Case areas were selected to represent a variety of class variations in different parts of the study area and to represent where obvious change could be observed (see change detection matrixes of case areas in Appendix B).



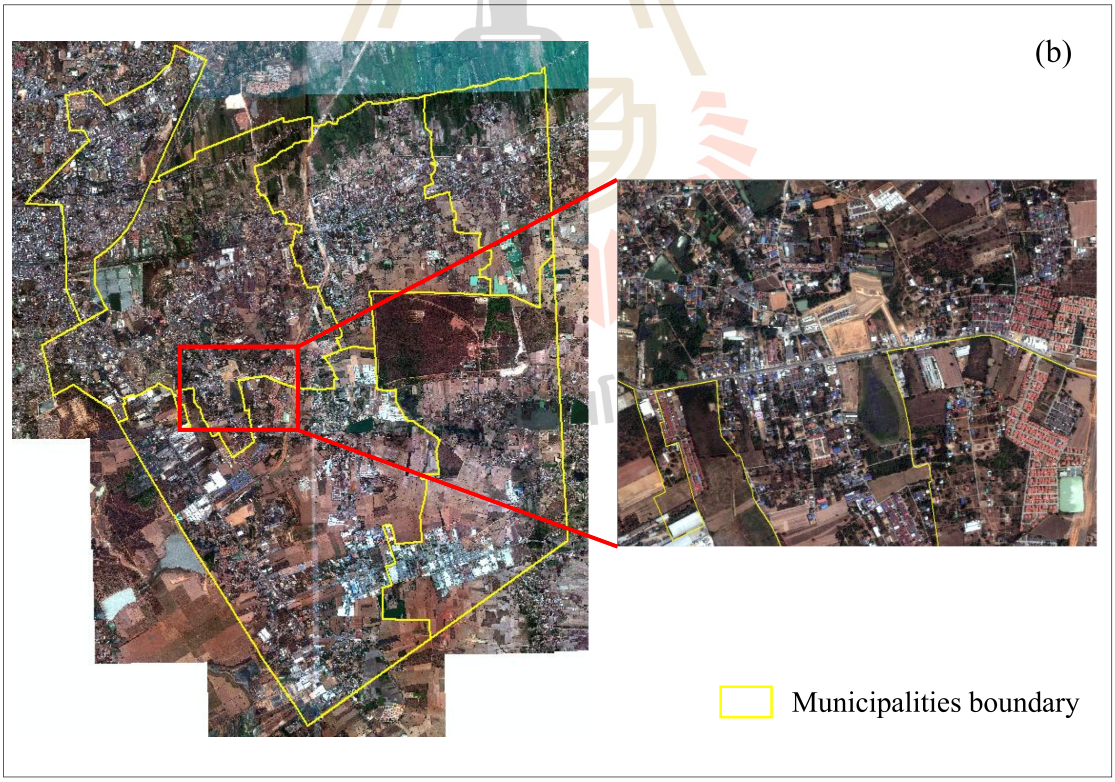


Figure 4.1 High spatial resolution satellite images of year 2013 (a) and 2016 (b).

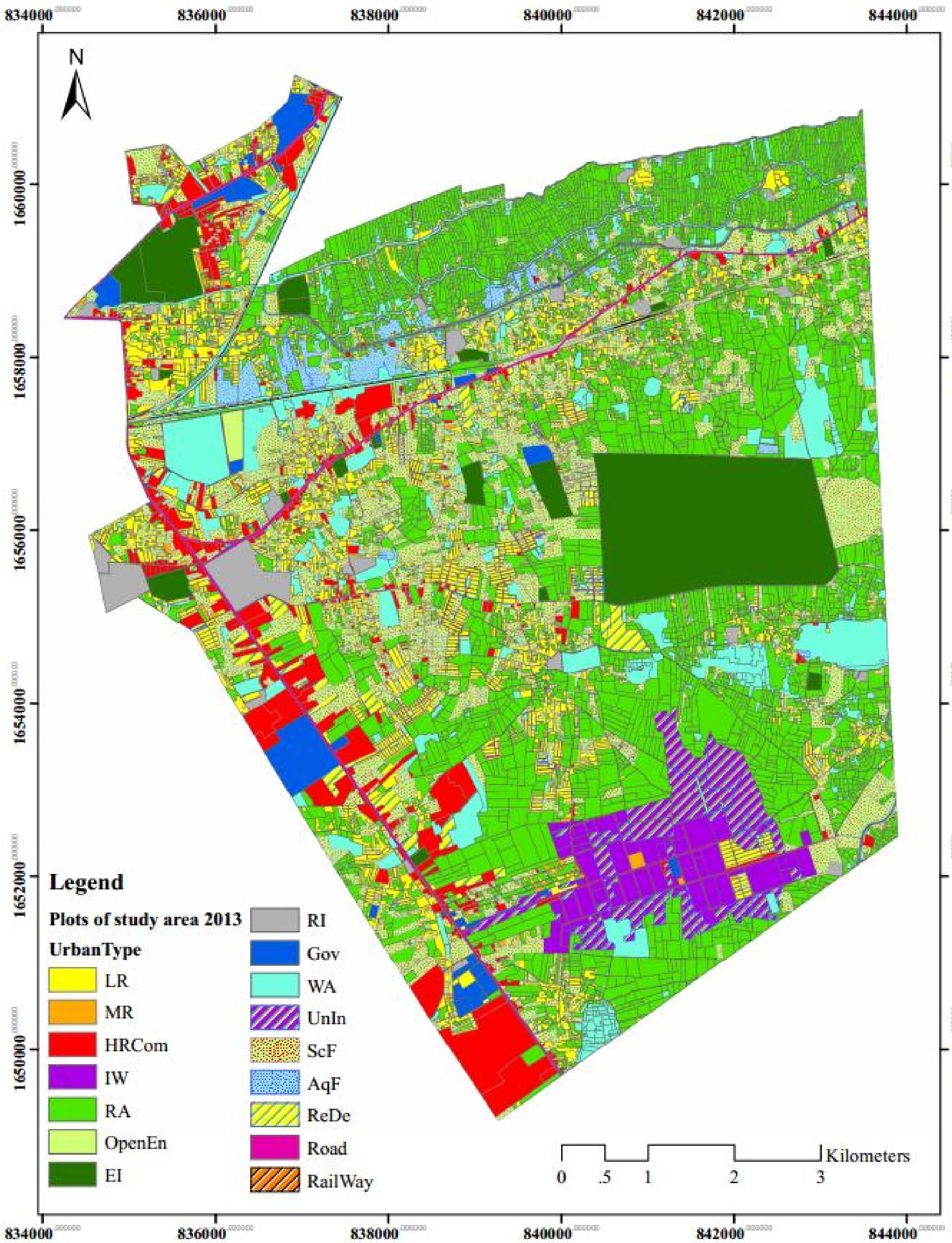


Figure 4.2 Interpreted urban land-use map of 2013.

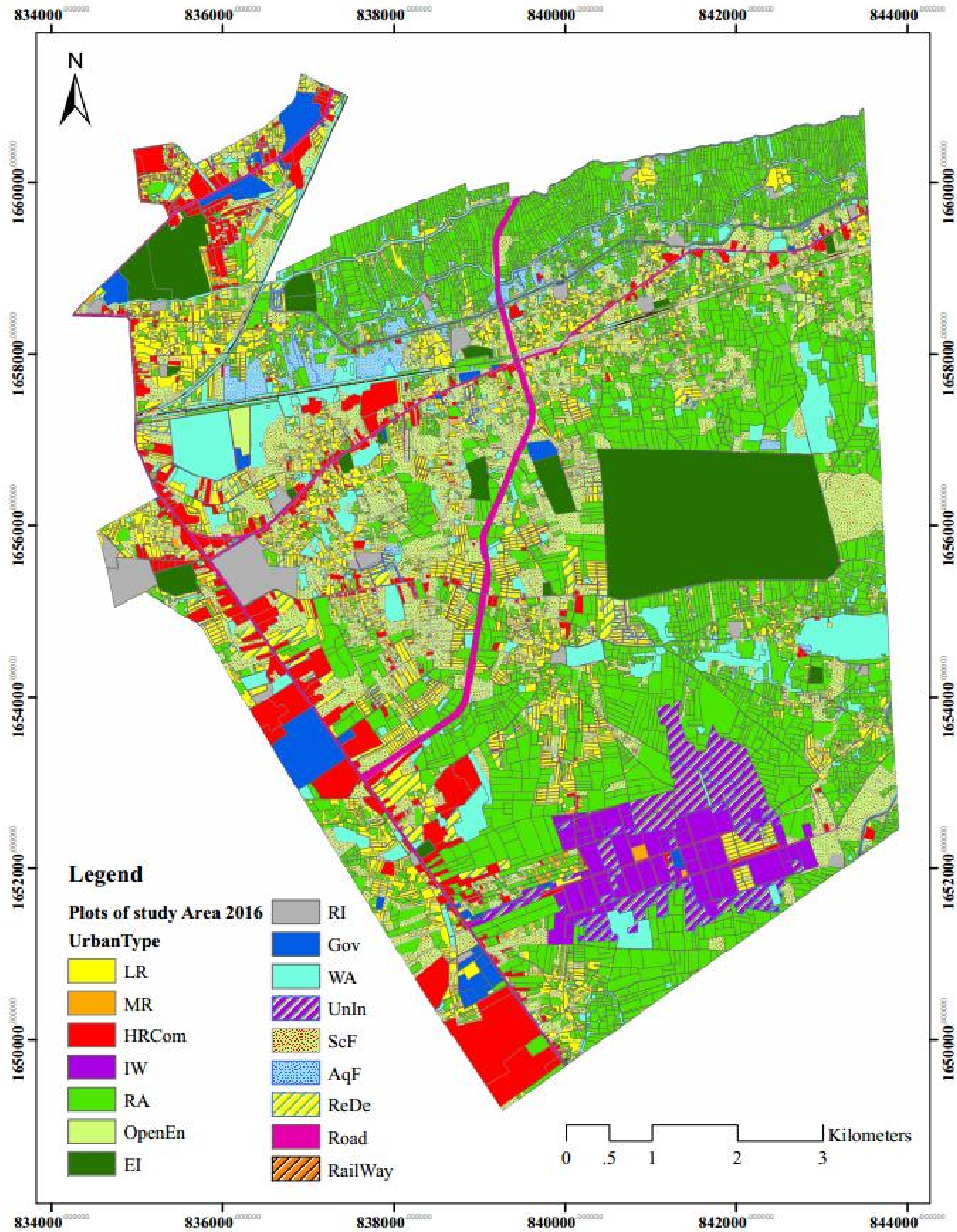


Figure 4.3 Interpreted urban land use-maps of 2016.

.

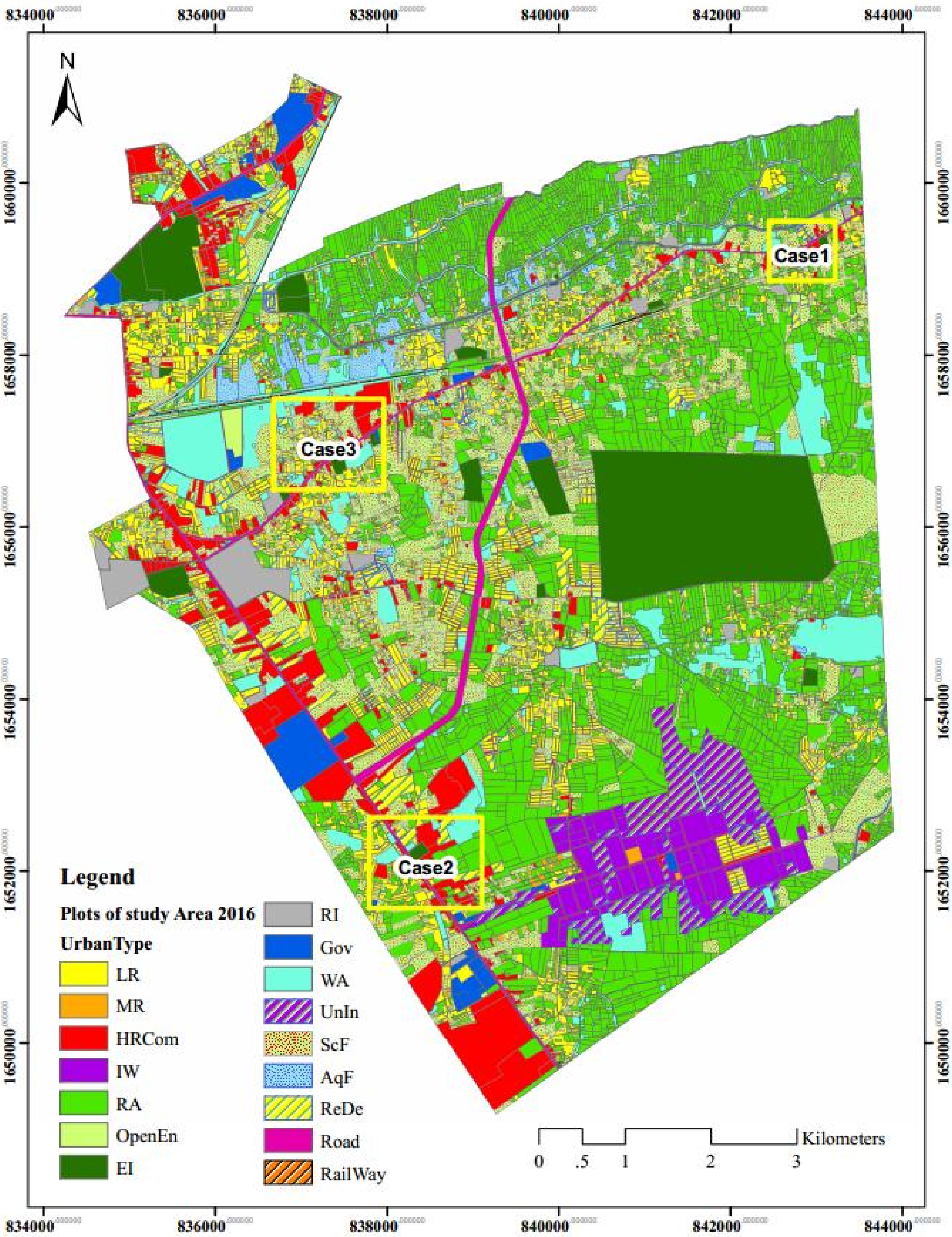
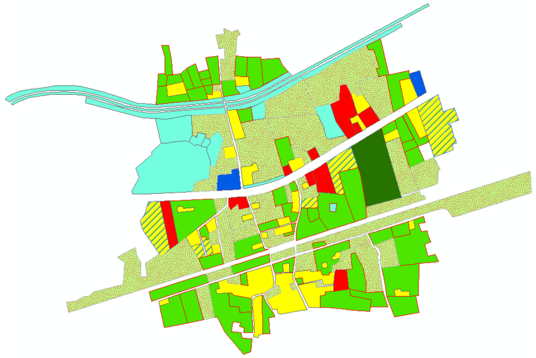


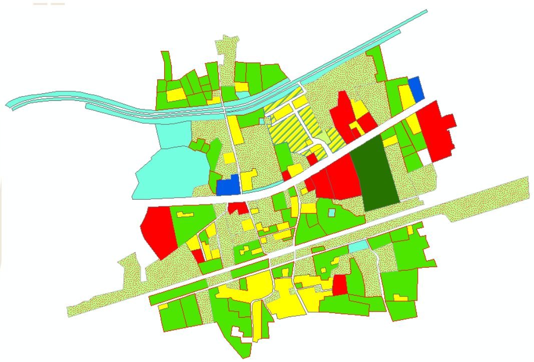
Figure 4.4 Locations of 3 case areas of the research.

Case area 1 in 2013



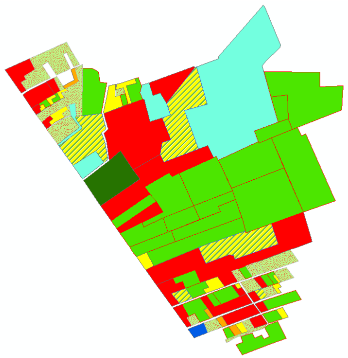
LR	39.06
MR	-
HRCom	16.05
RA	117.99
OpenG	-
ScF	145.57
AqF	-
ReDe	20.16
IW	-
EI	13.28
RI	-
Gov	3.85
WA	54.36
UnIn	-
Total area (rai)	**410.31**
No. of plots	**167**

Case area 1 in 2016



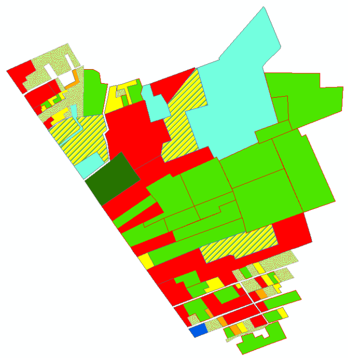
LR	44.04
MR	-
HRCom	37.14
RA	117.72
OpenG	0.70
ScF	129.59
AqF	-
ReDe	12.17
IW	-
EI	13.28
RI	-
Gov	3.85
WA	48.33
UnIn	-
Total area (rai)	**406.82**
No. of plots	**190**

Case area 2 in 2013



LR	15.97
MR	3.30
HRCom	148.80
RA	271.91
OpenG	-
ScF	48.87
AqF	-
ReDe	65.23
IW	-
EI	17.92
RI	-
Gov	1.92
WA	110.89
UnIn	-
Total area (rai)	**684.81**
No. of plots	**94**

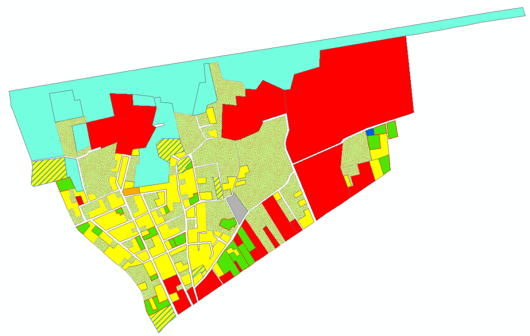
Case area 2 in 2016



LR	17.95
MR	4.25
HRCom	157.86
RA	263.95
OpenG	-
ScF	42.26
AqF	-
ReDe	67.81
IW	-
EI	17.92
RI	-
Gov	1.92
WA	110.89
UnIn	-
Total area (rai)	**684.81**
No. of plots	**96**

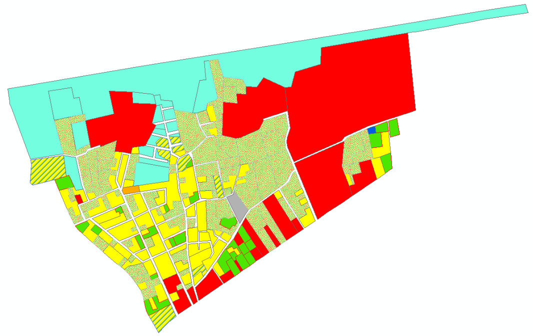
Figure 4.5 Interpreted urban land-use area of each case in 2013 and 2016.

Case area 3 in 2013



Land use	Area
LR	68.12
MR	0.81
HRCom	158.76
RA	20.12
OpenG	-
ScF	117.15
AqF	-
ReDe	14.14
IW	-
EI	-
RI	2.26
Gov	0.38
WA	125.16
UnIn	-
Total area (rai)	**506.90**
No. of plots	**203**

Case area 3 in 2016



Land use	Area
LR	80.65
MR	0.81
HRCom	164.88
RA	18.70
OpenG	-
ScF	111.06
AqF	-
ReDe	10.38
IW	-
EI	-
RI	2.26
Gov	0.38
WA	117.45
UnIn	-
Total area (rai)	**506.58**
No. of plots	**223**

Figure 4.5 Interpreted urban land-use area of each case in 2013 and 2016 (Continued).

4.1.2 Predicted urban plots of 2019 using CA-Markov model

The result of CA-Markov model provides land-use transition potential map, as displayed in Figure 4.6, derived from matrixes of transition probabilities and areas using Markov chain analysis and spatial allocation by CA spatial filter. Any big plots, particularly agricultural, were allotted to plots having size close to existing developed plots to allow fair changing cost estimation. In 3 case areas of 2019, the land use map, a number of plots and areas of classes of each case were displayed in Figure 4.7.

4.1.3 Predicted population and labor force

Table 4.1 shows collected population and labor force information of 2009-2016 and growth trending equations of sub-districts used to predict both information in 2019. Trending equations were generated by fitting curve.

To estimate population and labor force of case areas, Inverse Distance Weighted (IDW) was used to distributed original information of sub-districts of 2016 and 2019 (Appendix C). However, the process could provide some error when comparing to the original total ones. Correction coefficients of each sub-district were calculated, as shown in Table 4.2, to fix those errors and obtain more accurate results. The coefficients were calculated from the relationship of $X_{original}$ divided by $X_{interpulated}$, when X is population or labor force. Corrected raster layers were clipped to represent each case area of 2016 and 2019 as shown Table 4.3.

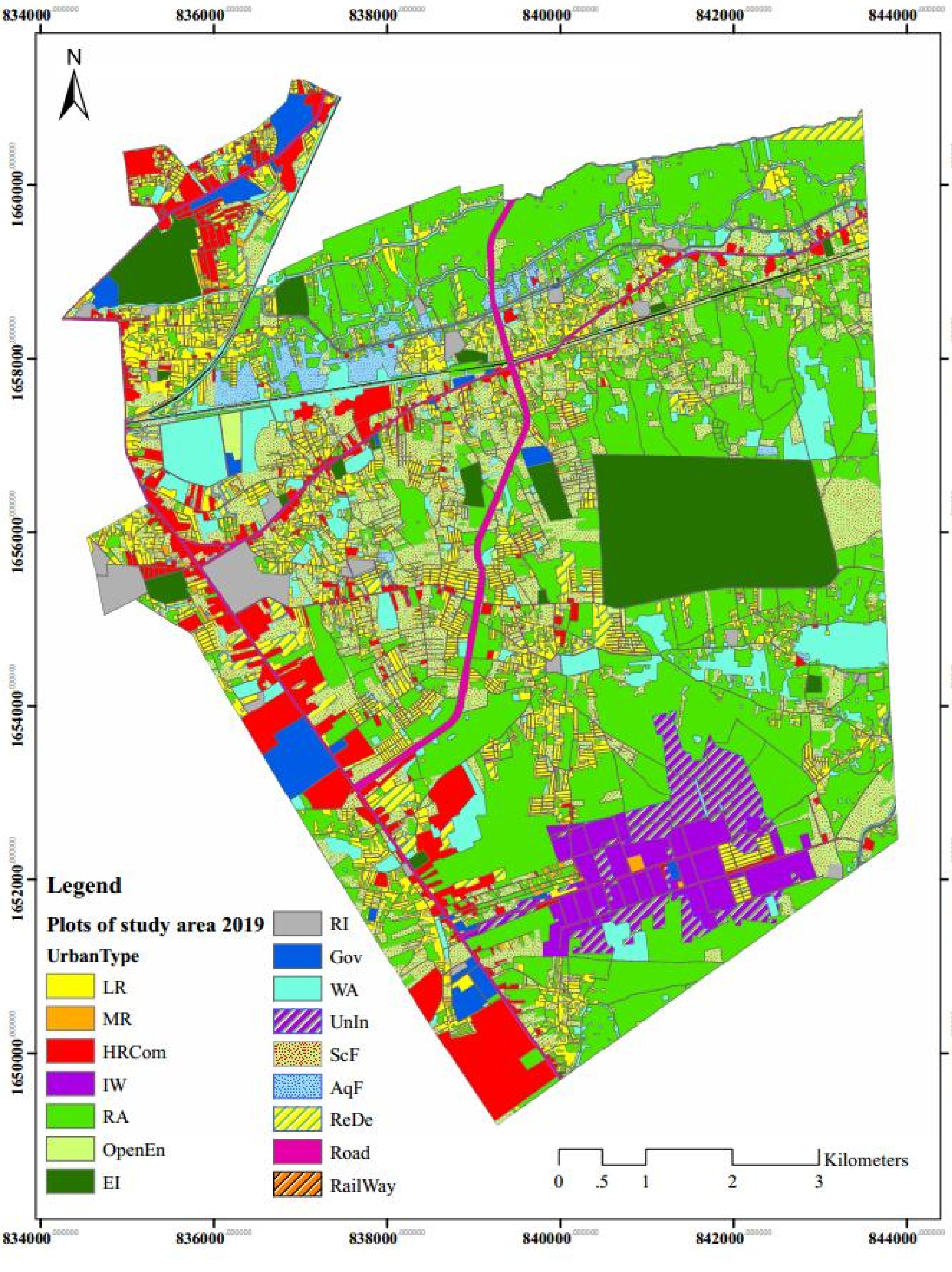
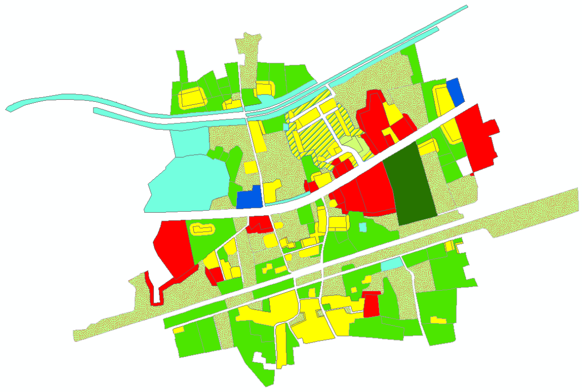


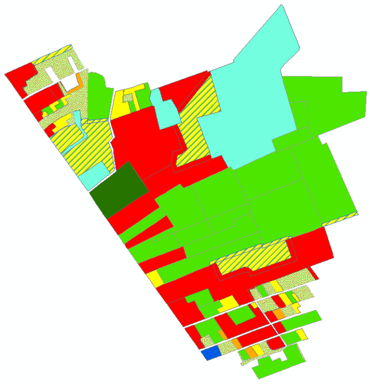
Figure 4.6 Predicted urban land-use map in 2019 from CA-Markov model.

Case area 1 in 2019



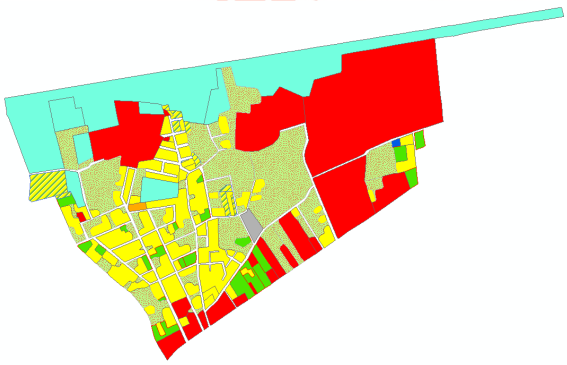
LR	54.38
MR	-
HRCom	45.62
RA	109.63
OpenG	1.72
ScF	118.72
AqF	-
ReDe	11.13
IW	-
EI	-
RI	3.84
Gov	45.31
WA	-
UnIn	-
Total area (rai)	**403.61**
No. of plots	**234**

Case area 2 in 2019



LR	17.93
MR	4.24
HRCom	171.47
RA	258.44
OpenG	-
ScF	38.95
AqF	-
ReDe	62.84
IW	-
EI	17.91
RI	6.91
Gov	1.92
WA	110.89
UnIn	-
Total area (rai)	**684.61**
No. of plots	**118**

Case area 3 in 2019



LR	83.19
MR	0.81
HRCom	165.22
RA	18.33
OpenG	-
ScF	108.89
AqF	-
ReDe	10.04
IW	-
EI	-
RI	2.25
Gov	0.38
WA	117.45
UnIn	-
Total area (rai)	**506.57**
No. of plots	**233**

Figure 4.7 Predicted urban land-use map and class areas of each case in 2019.

Table 4.1 Predicted population and labor force of sub-districts in 2019 based on data of 2009 to 2016.

No.	Local administration	2009	2010	2011	2012	2013	2014	2015	2016	Trend Equation	R^2	Predict 2019
Population												
1	Nakhon Ratchasima City Municipality	143,475	141,714	138,698	137,579	136,153	134,440	133,005	131,286	$y = 59.357x^2 - 2237.4x + 145598$	0.9935	128,169
2	HuaThale Subdistrict Municipality	24,042	24,587	25,013	25,510	25,716	26,111	26,524	26,855	$y = -12.571x^2 + 504.52x + 23595$	0.9961	27,624
3	Pha Nao SAO	4,872	4,917	4,946	5,008	5,018	5,051	5,086	5,082	$y = -2.619x^2 + 55x + 4816.8$	0.9859	5,105
4	Maroeng SAO	6,992	7,063	7,221	7,414	7,649	7,939	8,107	8,287	$y = 6730.6e^{0.0261x}$	0.9871	8,968.91
5	Nongraweing SAO	10,744	10,828	11,049	11,400	11,617	11,783	11,988	12,183	$y = -1.6429x^2 + 232.55x + 10444$	0.9891	12,803
6	Nong Bua Sa La SAO	16,299	17,155	18,148	19,041	20,183	21,145	22,024	22,860	$y = -4.2083x^2 + 995.08x + 15236$	0.999	25,673
	Total population	**206,424**	**206,264**	**205,075**	**205,952**	**206,336**	**206,469**	**206,734**	**206,553**			**208,342**
Labor force												
1	Nakhon Ratchasima City Municipality	96,661	95,382	93,932	93,097	91,397	89,705	88,213	86,751	$y = -35.131x^2 - 1107.6x + 97772$	0.9978	105,705
2	HuaThale Subdistrict Municipality	16,983	17,433	17,767	18,141	18,247	18,468	18,706	18,883	$y = -20.5x^2 + 444.9x + 16599$	0.9931	19,012
3	Pha Nao SAO	3,401	3,409	3,425	3,464	3,431	3,440	3,433	3,426	$y = -2.6131x^2 + 27.173x + 3373$	0.6637	3,356
4	Maroeng SAO	4,923	4,984	5,131	5,280	5,422	5,602	5,700	5,775	$y = -0.8274x^2 + 139.58x + 4745.1$	0.9898	6,180
5	Nongraweing SAO	7,269	7,341	7,510	7,778	7,906	8,031	8,200	8,323	$y = -2.131x^2 + 178.27x + 7046.9$	0.9895	8,750
6	Nong Bua Sa La SAO	11,532	12,164	12,852	13,556	14,361	15,084	15,622	16,226	$y = -7.744x^2 + 755.99x + 10720$	0.9985	18,099
	Total labor force	**140,769**	**140,713**	**140,617**	**141,316**	**140,764**	**140,330**	**139,874**	**139,384**			**161,102**

Table 4.2 Correction coefficients of each sub-district for population and labor force.

No.	Local administration	Population			Labor force		
		$X_{original}$	$X_{interpulated}$	Coeff.	$X_{original}$	$X_{interpulated}$	Coeff.
	Year 2016						
1	Nakhon Ratchasima City Municipality	131,286	87,577	1.4991	86,751	58,611	1.4801
2	HuaThale Subdistrict Municipality	26,855	22,694	1.1833	18,883	15,786	1.1961
3	Pha Nao SAO	5,082	6,898	0.7366	3,426	4,709	0.7274
4	Maroeng SAO	8,287	8,728	0.9494	5,775	6,049	0.9546
5	Nongraweing SAO	12,183	31,819	0.3829	8,323	21,904	0.3800
6	Nong Bua Sa La SAO	22,860	30,152	0.7582	16,226	20,934	0.7751
	Year 2019						
1	Nakhon Ratchasima City Municipality	128,169	87,278	1.4685	105,705	69,015	1.5316
2	HuaThale Subdistrict Municipality	27,624	23,504	1.1753	19,012	16,631	1.1432
3	Pha Nao SAO	5,105	7,112	0.7178	3,356	4,902	0.6845
4	Maroeng SAO	8,969	9,273	0.9671	6,180	6,481	0.9536
5	Nongraweing SAO	12,803	33,296	0.3845	8,750	26,970	0.3244
6	Nong Bua Sa La SAO	25,673	31,917	0.8043	18,099	24,526	0.7379

Table 4.3 Population and labor force in 2016 and 2019 of each case area.

Case area	Year 2016		Year 2019	
	Population	Labor force	Population	Labor force
Case area1	221	148	215	136
Case area2	499	361	590	386
Case area3	1,398	987	1,433	976

4.1.4 Suggested population density and class area

For better quality of living, the proper percentage of class areas and population densities in living and employment classes were adopted from the study of PST and P&C Mgt Co., Ltd. (2553) under the supervision of Nakhon Ratchasima City Municipality as listed in Table 4.4. Field investigation for classes of OpenG, EI, RI, and Gov were added to fulfill the list. Information in Table 4.4 was further applied as constraints of objectives and to travel opportunity estimation. This suggestion was applied with 3 case areas to estimate suggested population, labor force, and class areas to be constraints based on 2 method of suggestions, i.e. 1) suggested areas and population densities to urban classes and 2) suggested population densities for actual/predicted urban class areas. Suggested population and class area of each case area were displayed in Table 4.5.

Table 4.4 Modified urban land-use class and parameters of relevant MODA objectives.

No.	Urban land-use class	Population density (persons/rai)	Suggested area (%)	Preserved class	Obj.1	Obj.2	Obj.3	Obj.4	Obj.5	Obj.6
1	Low Residential (LR)	3	34.09	-	C	-	-	✓	✓	✓
2	Medium Residential (MR)	10	10.03	-	C	-	-	✓	✓	✓
3	Commercial and High Residential (HRCom)	15	4.08	-	C	C	-	✓	✓	✓
4	Rural and Agricultural (RA)	0.5	36.51	-	-	C	-	✓	✓	✓
5	Open land for recreational and maintain environmental quality (OpenG)	*2*	4.95	✓	-	-	C	✓	✓	✓
6	Scrub and forest (ScF)	-	-	-	-	-	-	✓	✓	✓
7	Aqua farming (AqF)	-	-	-	-	-	-	✓	✓	✓
8	Area ready to Develop (ReDe)	-	-	-	-	-	-	✓	✓	✓
9	Industrial and warehouse (IW)	10	3.20	✓	-	-	-	✓	✓	✓
10	Educational Institution (EI)	*0.8*	2.06	✓	-	-	-	✓	✓	✓
11	Religious Institution (RI)	*1*	0.62	✓	-	-	-	✓	✓	✓
12	Governmental Institution, Public Utility and Facilities (Gov)	*2.5*	2.06	✓	-	-	-	✓	✓	✓
13	Water or wetland (WA)	-	-	✓	-	-	-	-	-	-
14	Undeveloped Industrial (UnIn)	-	-	✓	-	-	-	✓	✓	✓

Note: C : information of a class works as objective constraint(s).

✓ : a class relevant to objective.

xx : investigation to obtain base densities.

\- : a class non- relevant to objective.

Table 4.5 Suggested population densities and class areas of each case area.

No.	class	Suggest areas	SuggestPop from SuggA*SuggP	Existing area	SuggestPop from ExistA*SuggP	Suggest areas	SuggestPop from SuggA*SuggP	Existing area	SuggestPop from ExistA*SuggP
Case1 (2016)						**Case1 (2019)**			
1	LR	138.68	416.05	44.04	132.13	137.59	412.78	54.38	163.13
2	MR	40.80	408.04	0.00	0.00	40.48	404.83	0.00	0.00
3	HRCom	16.60	248.97	37.14	557.06	16.47	247.01	45.62	684.25
4	RA	148.53	74.26	117.72	58.86	147.36	73.68	109.63	54.81
5	OpenG	20.14	40.27	0.70	1.40	19.98	39.96	1.72	3.44
6	ScF	0.00	0.00	129.59	0.00	0.00	0.00	118.72	0.00
7	AqF	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	ReDe	0.00	0.00	12.17	0.00	0.00	0.00	11.13	0.00
9	IW	13.02	130.18	0.00	0.00	12.92	129.16	0.00	0.00
10	EI	8.38	6.70	13.28	10.62	8.31	6.65	13.28	10.62
11	RI	2.52	2.52	0.00	0.00	2.50	2.50	0.00	0.00
12	Gov	8.38	20.95	3.85	9.62	8.31	20.79	3.84	9.60
13	WA	0.00	0.00	48.33	0.00	0.00	0.00	45.31	0.00
14	UnIn	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Case2 (2016)						**Case2 (2019)**			
1	LR	233.45	700.35	17.95	53.86	233.38	700.15	17.93	53.80
2	MR	68.69	686.86	4.25	42.49	68.67	686.66	4.24	42.41
3	HRCom	27.94	419.10	157.86	2,367.85	27.93	418.98	171.47	2,572.02
4	RA	250.02	125.01	263.95	131.97	249.95	124.97	258.44	129.22
5	OpenG	33.90	67.80	0.00	0.00	33.89	67.78	0.00	0.00
6	ScF	0.00	0.00	42.26	0.00	0.00	0.00	38.95	0.00
7	AqF	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	ReDe	0.00	0.00	67.81	0.00	0.00	0.00	62.84	0.00
9	IW	21.91	219.14	0.00	0.00	21.91	219.07	0.00	0.00
10	EI	14.11	11.29	17.92	14.33	14.10	11.28	17.91	14.33
11	RI	4.25	4.25	0.00	0.00	4.24	4.24	0.00	0.00
12	Gov	14.11	35.27	1.92	4.80	14.10	35.26	1.92	4.80
13	WA	0.00	0.00	110.89	0.00	0.00	0.00	110.89	0.00
14	UnIn	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note : SuggA: suggest class areas.

SuggP: suggest population densities.

SuggestPop: suggest population.

ExistA: existing area.

Table 4.5 Suggested population densities and class areas of each case area (Continued).

No.	class	Suggest areas	SuggestPop from SuggA*SuggP	Existing area	SuggestPop from ExistA*SuggP	Suggest areas	SuggestPop from SuggA*SuggP	Existing area	SuggestPop from ExistA*SuggP
Case3 (2016)						**Case3 (2019)**			
1	LR	172.80	518.41	76.20	228.60	172.69	518.07	83.19	249.56
2	MR	50.84	508.42	0.81	8.13	50.81	508.09	0.81	8.13
3	HRCom	20.68	310.22	162.93	2,443.97	20.67	310.02	165.22	2,478.28
4	RA	185.07	92.54	19.33	9.67	184.95	92.47	18.33	9.16
5	OpenG	25.09	50.18	0.00	0.00	25.08	50.15	0.00	0.00
6	ScF	0.00	0.00	117.15	0.00	0.00	0.00	108.89	0.00
7	AqF	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	ReDe	0.00	0.00	10.41	0.00	0.00	0.00	10.04	0.00
9	IW	16.22	162.21	0.00	0.00	16.21	162.10	0.00	0.00
10	EI	10.44	8.35	0.00	0.00	10.44	8.35	0.00	0.00
11	RI	3.14	3.14	2.26	2.26	3.14	3.14	2.25	2.25
12	Gov	10.44	26.11	0.38	0.95	10.44	26.09	0.38	0.94
13	WA	0.00	0.00	117.43	0.00	0.00	0.00	117.45	0.00
14	UnIn	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note : SuggA: suggest class areas.
SuggP: suggest population densities.
SuggestPop: suggest population.
ExistA: existing area.

4.1.5 Neighborhood plot identification for compatibility analysis

The neighborhood plot identification resulted in providing plot IDs, number of neighboring plots and spatial weight of its neighboring plots in form of table format. For example from Figure 4.8, plot number 14 had 5 neighboring plots which are 10, 15, 16, 125, and 129. Their spatial weights is 0.2 of each, estimated by averaging for a number of neighboring plots from the total weight of 1.

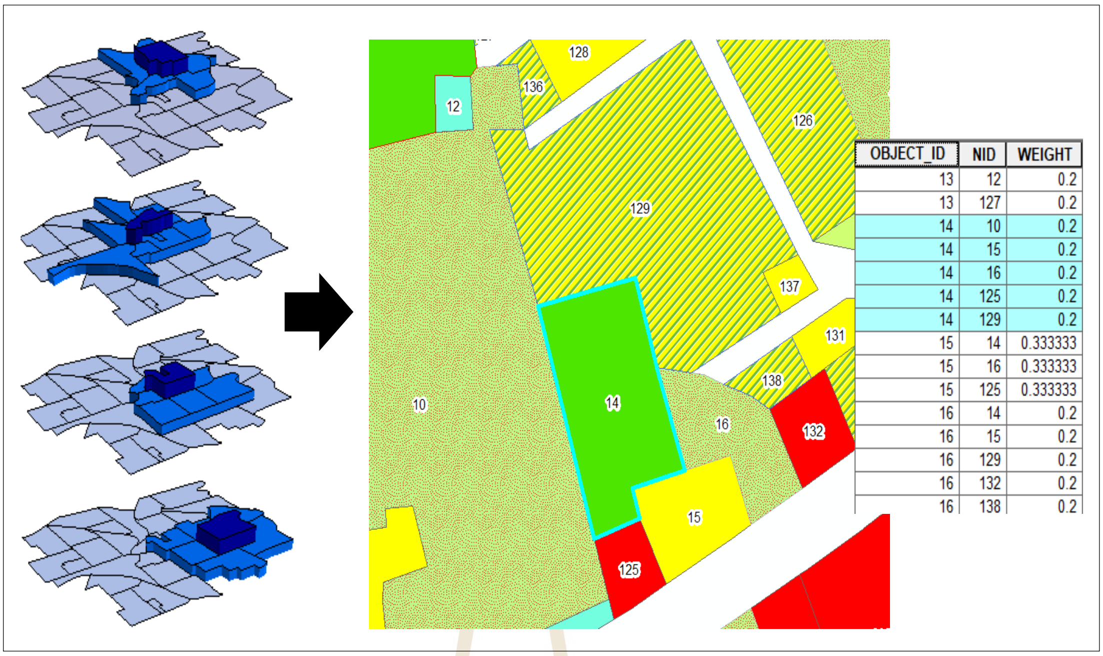


Figure 4.8 An example result of neighborhood plot identification and weight estimation.

4.1.6 Changing cost matrix

The cost of class changing matrix was obtained from the survey of expert opinions through semi-interview and questionnaire. Ten experts included staffs of DPT of Nakhon Ratchasima and urban planning management lecturers. The questionnaire form was displayed in Appendix D. The class changing cost matrix was displayed in Table 4.6. The changing costs were normalized to be 0 to 1. The values interval from expert was 0.18 to 0.77. Many changes between classes were identified as unchangeable, shown as dark cells in the table. The highest changing cost falls into the changing of ReDe to AqF (0.77) while the lowest is LR to MR (0.18).

Table 4.6 Matrix of class changing cost.

No.	Land use class	Low Residential (LR)	Medium Residential (MR)	Commercial and High Residential (HRCom)	Rural and Agricultural (RA)	Open land for recreation and environmental quality maintenance (OpenG)	Scrub and forest (ScF)	Aqua farming (AqF)	Area ready to Develop (ReDe)	Industrial and Warehouse (IW)	Educational Institution (EI)	Religious Institution (RI)	Governmental institution, public utility and facilities (Gov)	Water or wetland (WA)	Undeveloped Industrial (UnIn)
1	Low Residential (LR)	-	0.18	0.35	**	**	**	**	**						
2	Medium Residential (MR)	**	-	0.24	**	**	**	**	**						
3	Commercial and High Residential (HRCom)	**	**	-	**	**	**	**	**						
4	Rural and Agricultural (RA)	0.25	0.35	0.55	-	0.28	0.54	0.41	0.42						
5	Open land for recreation and environmental quality maintenance (OpenG)					-									
6	Scrub and forest (ScF)	0.53	0.58	0.71	0.35	0.40	-	0.66	0.64						
7	Aqua farming (AqF)	0.68	0.73	0.72	0.42	0.44	0.56	-	0.55						
8	Area ready to Develop (ReDe)	0.29	0.38	0.45	0.46	0.53	0.75	0.77	-						
9	Industrial and Warehouse (IW)									-					
10	Educational Institution (EI)										-				
11	Religious Institution (RI)											-			
12	Governmental institution, public utility and facilities (Gov)												-		
13	Water or wetland (WA)													-	
14	Undeveloped Industrial (UnIn)														-

Note: ■ : preserved class.

** : not allow to change.

4.1.7 Road impedance and optimum path analysis (incorporate with travel opportunity to obtain objective of travel rate)

1) Road network

The road network data layer from RS interpretation was polygons of an urban land-use class. These road polygons were converted to lines of polygon boundaries using ArcGIS Polygon to line function as shown in Figure 4.9(a). Then, centerlines were generated from these polygon boundaries to represent line feature of the road network (Figure 4.9(b)).

Figure 4.9 Road polygons from RS interpretation were converted to lines of polygon boundaries (a). Centerlines of road network were then generated from them (b).

The topology of road network data layer was checked to guarantee that it can be used for network analysis properly.

2) Road impedance

Traffic volumes as impedance of all roads in the network were estimated from few available road information. This information was predicted for 2016 and 2019 by PST and P&C Mgt Co., Ltd. (2553). Traffic densities were first estimated from average peak hour volume (PHV) per m^2 of road area of working days as shown in Table 4.7.

Table 4.7 Average of vehicle quantities ratio and traffic density in 2016 and 2019.

No.	Road name	Workday PHV (pcu/hr)	Average PHV (pcu/hr)	Road area (m^2)	Traffic density (pcu/hr/m^2)
	Year 2016				
1	Phetmatukhla (inbound)	1,028	804.5	268,760.60	0.002993
2	Phetmatukhla (departure)	581			
3	Ratchasima - Chok Chai (inbound)	1,531	1,416	311,497.72	0.004545
4	Ratchasima - Chok Chai (departure)	1,301			
	Year 2019				
1	Phetmatukhla (inbound)	1,335	1,045.00	268,760.60	0.003888
2	Phetmatukhla (departure)	755			
3	Ratchasima - Chok Chai (inbound)	2,243	2,075.00	311,497.72	0.006661
4	Ratchasima - Chok Chai (departure)	1,907			

Note: PHV: Peak Hour Volume.
pcu: passenger car unit.

Interpolation of known traffic density links from above data was performed to obtain traffic volumes of unknown links. The grid cell sizes of interpolation were in a series of 1,000, 500, 100, and 1 meter. Traffic volumes of all links of both years were then estimated. Road impedance in links of 2016 and 2019 (Figure 4.10) were between 0.000233-199 and 0.000333-291, respectively. The impedance of road network was used for network analysis to obtain the optimum paths of all O-D. Optimum paths between all O-D in 2016 and 2019 of 3 case areas were 36,100, 9,216, and 49,729 paths and 76,176, 13,924, and 54,289 paths, respectively.

4.1.8 Plot generation

Plot IDs, class IDs, and areas were attributes extracted from interpreted and predicted land-use maps of case areas. They were prepared in form of table to input into GA-MODA process (as examples displayed in Table E1 of Appendix E). These were initial data for candidate plan generation in the GA process. Optimum plans resulted from GA-MODA process were in form of tables which could be converted to display as maps of optimum urban land-use plans.

4.2 Setup constraints

Objective constraints of each case area of 2016 and 2019 were finally setup as shown in Table 4.8. The lower and upper bound of each constraint were related to the suggested population density and class area as mentioned in 4.1.4. In every case areas, existing/predicted area of HRCom become upper bound of constraint 4). Therefore, 25 percentage increment was required to allow continuous growth in this limit. This practice helps promote the area to have higher opportunity to be one of the transportation and industrial hubs of the region. The upper bounds of constraints 1) and

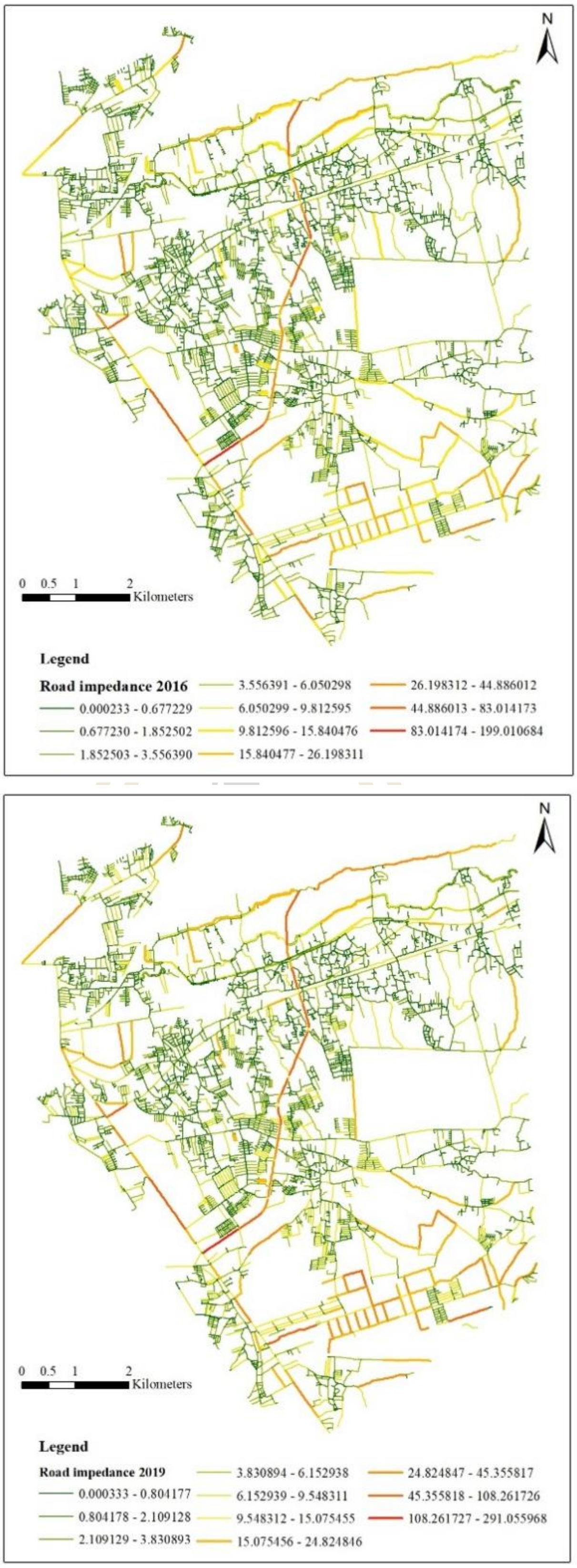


Figure 4.10 Road impedance in 2016 and 2019.

5) which were mainly dependent on the class area were also adjusted due to this practice. Regarding of constraint 5), existing/predicted area of RA class became the lower bound. 25 percentages reduction was required so that changing to be other classes could happen. Finally, the algorithm for flexible constraint setup was developed and an example of constraint setup of case area 1 of 2016 are shown in the Appendix F.

Table 4.8 Sets of constraints of each case area in 2016 and 2019.

	Year 2016	**Year 2019**
Case area 1	Housing capacity:	
	1) $381 \leq Z_{HC} \leq 1{,}520$	1) $410 \leq Z_{HC} \leq 1{,}673$
	2) 44.04 (Ex) $\leq \sum A_{i1} \leq$ 138.68 (Sug)	2) 54.38 (Ex) $\leq \sum A_{i1} \leq$ 137.59 (Sug)
	3) 0 (Ex) $\leq \sum A_{i2} \leq$ 40.80 (Sug)	3) 0 (Ex) $\leq \sum A_{i2} \leq$ 40.48 (Sug)
	4) 16.60 (Sug) $\leq \sum A_{i3} \leq$ 46.42 (Ex*25%)	4) 16.47 (Sug) $\leq \sum A_{i3} \leq$ 57.02 (Ex*25%)
	Employment capacity:	
	5) $293 \leq Z_{EC} \leq 771$	5) $288 \leq Z_{EC} \leq 929$
	6) $\sum A_{i4} \leq$ 148.53 (Sug)	6) $\sum A_{i4} \leq$ 147.36 (Sug)
	Open green area:	
	7) $\sum A_{i5} \geq$ 1.38 (Std)	7) $\sum A_{i5} \geq$ 1.35 (Std)
Case area 2	Housing capacity:	
	1) $515 \leq Z_{HC} \leq 4{,}347$	1) $515 \leq Z_{HC} \leq 4{,}602$
	2) 17.95 (Ex) $\leq \sum A_{i1} \leq$ 233.45 (Sug)	2) 17.93 (Ex) $\leq \sum A_{i1} \leq$ 233.38 (Sug)
	3) 4.25 (Ex) $\leq \sum A_{i2} \leq$ 68.69 (Sug)	3) 4.24 (Ex) $\leq \sum A_{i2} \leq$ 68.67 (Sug)
	4) 27.94(Sug) $\leq \sum A_{i3} \leq$ 197.32 (Ex*25%)	4) 27.93 (Sug) $\leq \sum A_{i3} \leq$ 214.33 (Ex*25%)
	Employment capacity:	
	5) $513 \leq Z_{EC} \leq 3{,}092$	5) $513 \leq Z_{EC} \leq 3{,}344$
	6) $\sum A_{i4} \leq$ 250.02 (Sug)	6) $\sum A_{i4} \leq$ 249.95 (Sug)
	Open green area:	
	7) $\sum A_{i5} \geq$ 3.12 (Std)	7) $\sum A_{i5} \geq$ 3.69 (Std)

Table 4.8 (Continued).

	Year 2016	Year 2019
Case area 3	Housing capacity:	
	1) $547 \leq Z_{HC} \leq 4{,}082$	1) $568 \leq Z_{HC} \leq 4{,}124$
	2) 76.20 (Ex) $\leq \sum A_{i1} \leq$ 172.80 (Sug)	2) 83.19 (Ex) $\leq \sum A_{i1} \leq$ 172.69 (Sug)
	3) 0.81 (Ex) $\leq \sum A_{i2} \leq$ 50.84 (Sug)	3) 0.81 (Ex) $\leq \sum A_{i2} \leq$ 50.81 (Sug)
	4) 20.68 (Sug) $\leq \sum A_{i3} \leq$ 203.66 (Ex*25%)	4) 20.67 (Sug) $\leq \sum A_{i3} \leq$ 206.52 (Ex*25%)
	Employment capacity:	
	5) $318 \leq Z_{EC} \leq 3{,}147$	5) $317 \leq Z_{EC} \leq 3{,}190$
	6) $\sum A_{i4} \leq$ 185.07 (Sug)	6) $\sum A_{i4} \leq$ 184.95 (Sug)
	Open green area:	
	7) $\sum A_{i5} \geq$ 8.74 (Std)	7) $\sum A_{i5} \geq$ 8.96 (Std)

4.3 GA-MODA plans and objective values of case areas

GA-MODA process was coded to run in MatLab® (R2017a) following the designed structural flow of functions as shown in Appendix G. The code was used to generate initial plans and extract target plans that meet the requirement of research objectives.

The results from plot generation process of each case area were input for the simulation using a set of constraints displayed in Table 4.8. The population size of each running was defined as 3,000 plans. For each case area, this number of plans was input into GA-MODA process to compute objective values and to check how many plans were complied with constraints. The plans complied with constraints were proceeded to check whether they were located at Pareto front and ranked by Pareto approach. The ranking process was performed to compare their fitness values (see Equation (2.8)).

Table 4.9 shows numbers of plans of each case area of 2016 and 2019 which complied with constraints and numbers of plans which were at the front in Pareto approach including their fitness values. The minimum and maximum of fitness values of each case area are only displayed in the Table 4.9. In 2016, numbers of plans at the front of Pareto approach for case area 1, 2, and 3 are 26, 128, and 370, respectively while in 2019, there are 34, 74, and 115, respectively. All plans of each case area of both years which were complied with constraints and were at Pareto front including their objective values and ranks are displayed in Appendix H.

Table 4.9 The GA-MODA results of each case area in 2016 and 2019.

Case area	Year 2016				Year 2019			
	Complied with constraints	Plans of Pareto	Min	Max	Complied with constraints	Plans of Pareto	Min	Max
Case area 1	33	26	0.63	0.98	41	34	0.65	0.98
Case area 2	167	128	0.82	0.99	101	74	0.52	0.99
Case area 3	710	370	0.74	0.99	185	115	0.85	0.99

4.4 Comparison of urban plans from GA-MODA to 2016 and 2019 urban land use

Optimum urban land-use plans resulted from GA-MODA process were expected to be better than existing plan of 2016 and predicted plans of 2019. Therefore, there were 3 ways to compare existing 2016 and predicted 2019 plans with GA-MODA plans: 1) to check if they were complied with constraints, 2) to check if they were at Pareto front, 3) to compare their sums of normalized objective values (SNOV).

To be comparable, ranges of constraints and objective values of GA-MODA plans and existing/predicted plans were summarized and displayed in Table 4.10. Objective values of optimum GA-MODA plans of each case area are displayed in range because GA-MODA process provided results as a set of plans. Population and labor force of existing/predicted plans shown in the Table were estimated from interpolation.

4.4.1 Being complied with constraints

According to Table 4.10, in each case area, constraint parameters of existing 2016 and predicted 2019 plans, with respect to objectives of open green areas, housing and employment capacities, were checked whether they were complied with constraints or not. Only open green area of case area 1 in 2019 was complied with constraint while the rests were not. There were 3 cases out of 6 in the objective of housing capacity complied with constraints while the rests were lower than the lower bound. For the objective of employment capacity, there were 2 out of 6 complied with constraints while the rests were lower than the lower bound.

It is essential to note that all objectives of optimum GA-MODA plans were complied with constraints and located at Pareto front. Therefore, based on this comparison element, it can be concluded that they can provide better quality of living than existing 2016 and predicted 2019 plans.

Existing and predicted plans of all case areas of both years show that their populations and labor forces are lower than the lower bound of range of GA-MODA plans. For good quality of living, it indicates that the areas can support more population growth which in turn being able to provide more labor force. Open green of each case area of existing and predicted plans are much lower than ones of GA-MODA plans.

Table 4.10 Constraints and corresponding objective values of each case area of GA-MODA plans and existing 2016 and predicted 2019 plans.

Plan	Housing	Employment	Open green	Compatibility	Changing cost	Travel rate
2016						
Constraint case1	381 - 1,520	293 - 771	≥ 1.38	-	-	-
Existing case1	221	148	0.70	666	1.17	17,937
GA case1	678 - 1,137	488 - 612	36.27 - 130.61	522 - 754	4.64 - 5.51	24,843 - 52,140
Constraint case2	515 - 4,347	513 - 3,092	≥ 3.12	-	-	-
Existing case2	499	361	-	5,216	0.098	135,530
GA case2	2,416 - 3,216	2,348 - 2,488	5.47 - 165.39	4,040 - 6,693	0.57 - 0.95	148,136 - 312,085
Constraint case3	547 - 4,082	318 - 3,147	≥ 8.74	-	-	-
Existing case3	1,398	987	-	1,981	0.03	11,443
GA case3	3,214 - 3,471	2,649 - 3,011	9.29 - 44.24	1,900 - 2,062	0.67 - 0.90	29,788 - 37,741
2019						
Constraint case1	410 - 1,673	288 - 929	≥ 1.35	-	-	-
Predicted case1	215	136	1.72	542	0.62	35,554
GA case1	1,312 - 1,477	772 - 878	18.01 - 72.25	484 - 578	4.81 - 6.91	79,153 - 105,814
Constraint case2	515 - 4,602	513 - 3,344	≥ 3.69	-	-	-
Predicted case2	590	386	-	3,980	0.11	195,390
GA case2	2,562 - 3,106	2,478 - 2,681	36.52 - 155.20	3,127 - 4,787	0.65 - 1.06	183,162 - 275,070
Constraint case3	568 - 4,124	317 - 3,190	≥ 8.96	-	-	-
Predicted case3	1,433	976	-	2,021	0.026	24,478
GA case3	3,357 - 3,503	2,767 - 3,052	9.52 - 31.30	1,959 - 2,078	0.65 - 0.81	88,056 - 103,298

Then, this attribute of each case should be strongly promoted. Compatibility of existing and predicted plans fall into the ranges of corresponding objectives of GA-MODA plans. Therefore, based on these objectives they were considered equivalent and can be maintained. Travel rate of all case areas of both years were lower than the minimum rates of GA-MODA plans because their urban classes provided lower population which caused lower travel opportunity and rate.

4.4.2 Locating at Pareto front

These 2 plans of each case area were also added into the list of optimum GA-MODA plans to perform Pareto approach. The results revealed that they were not located at the Pareto front and resulted in not available fitness value. It can be concluded that plans of existing 2016 and predicted 2019 were completely dominated by optimum GA-MODA plans. Based on this comparison element, GA-MODA plans can provide better quality of living than existing 2016 and predicted 2019 plans.

4.4.3 SNOV comparison

The results of comparison of SNOV in all case areas of both years are displayed in Tables I1-I6 of Appendix I. The higher SNOV indicates the better urban plan. Table 4.11 shows the results of plan comparison of each case area between optimum GA-MODA plans and plan of existing 2016 and predicted 2019. Even though SNOV cannot point out perfectly better plans but it can imply or confirm results of above 2 comparison elements. From the Table, almost all of SNOVs of GA-MODA plans in each case area of 2016 are better than of existing plans while in year 2019 all of SNOVs of GA-MODA plans are better than of predicted plans.

Table 4.11 Comparison results of SNOV of plans of GA-MODA, 2016, and 2019.

	>	<
2016		
Case1	23 (0.0500 - 0.6290)	3 ((-0.1442) - (-0.00115))
Case2	121 (0.03591 - 1.0721)	7 ((-0.21538) - (-0.03507))
Case3	369 (0.00048 - 0.7840)	1 (-0.00465)
2019		
Case1	34 (0.1097 - 1.0326)	-
Case2	74 (0.09175 - 1.2222)	-
Case3	115 (0.00287 - 0.74652)	-

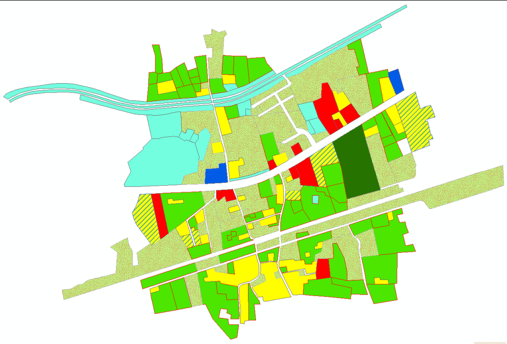
Note: 1) > : a number of optimum GA-MODA plans having higher SNOV than of a plan in a year considered.
< : a number of optimum GA-MODA plans having lower SNOV than of a plan in a year considered.
2) the range of SNOV differences in plan comparison.

From above 3 elements of comparison, final conclusion can be stated that GA-MODA plans were better than not only existing 2016 plans but predicted 2019 plans. They absolutely indicate that according to the plans they are capable to provide better quality of living. It could also be confirmed that GA-MODA process was the capable method to generate a number of optimal plans having higher comparison elements than of existing 2016 and predicted 2019 plans.

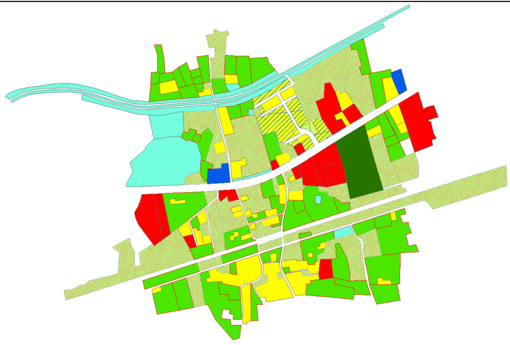
For more obvious comparison and being able to display in form of spatial land-use maps, top 3 on the basis of fitness value of GA-MODA plans were selected to compare with existing and predicted plans of each case area. Land-use maps of these comparison plans of each case area are displayed in Figures 4.11-4.16. Their fitness values, objective values and SNOV are shown in Table 4.12.

Case 1

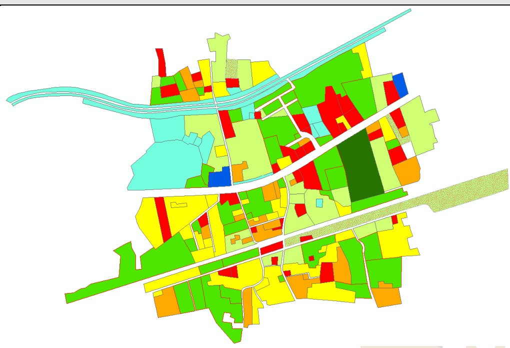
Urban LU map 2013



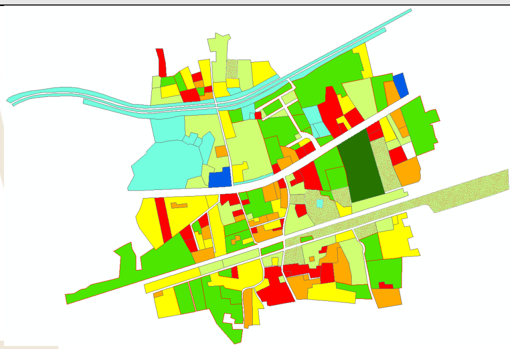
Urban LU map 2016



GA-MODA urban LU map 2016 rank 1



GA-MODA urban LU map 2016 rank 2



GA-MODA urban LU map 2016 rank 3

Legend

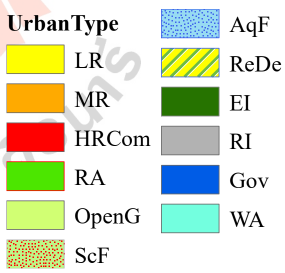


Figure 4.11 Existing and GA-MODA land-use map for case area 1 of 2016.

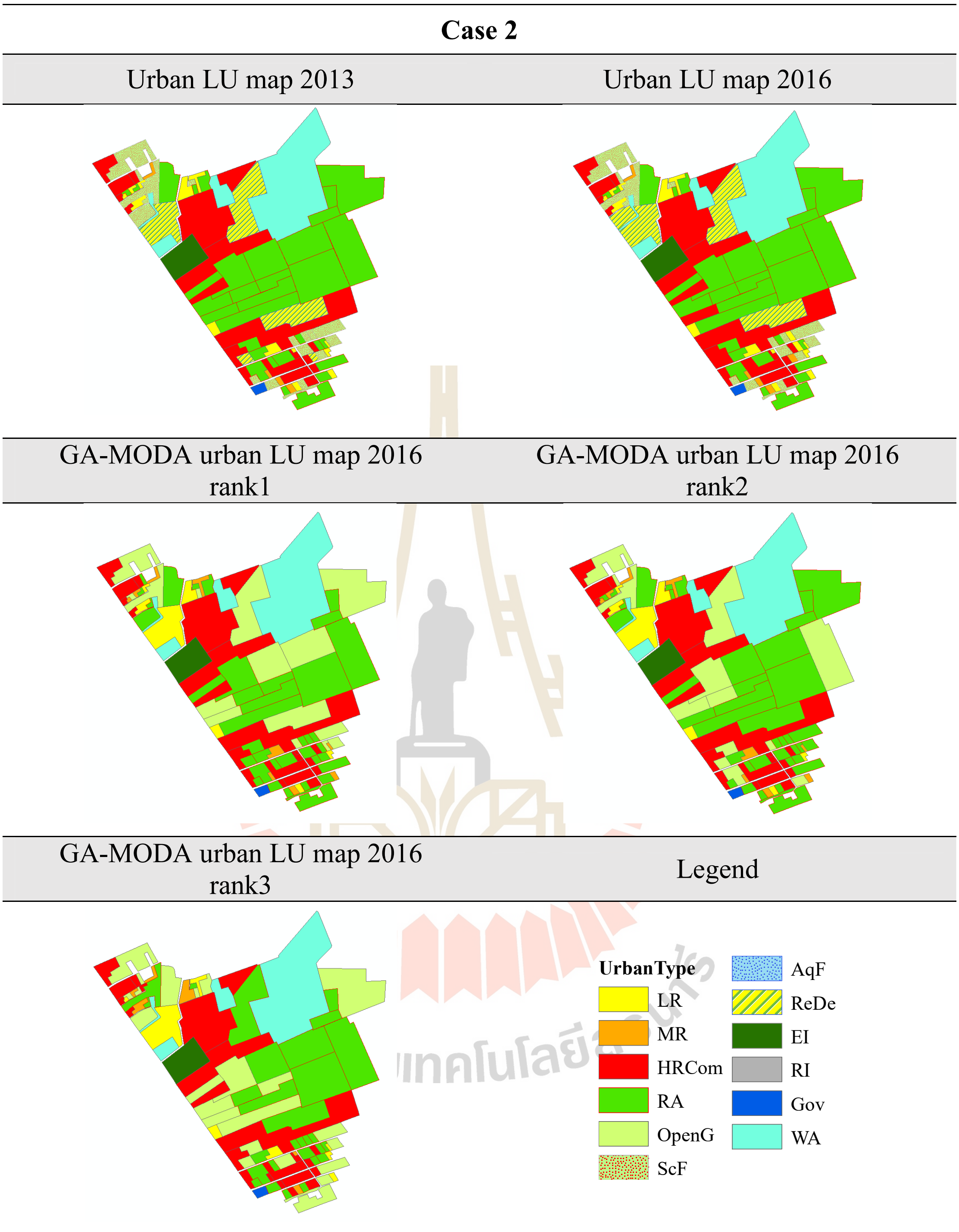
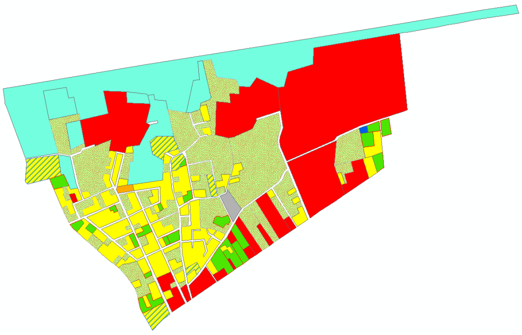


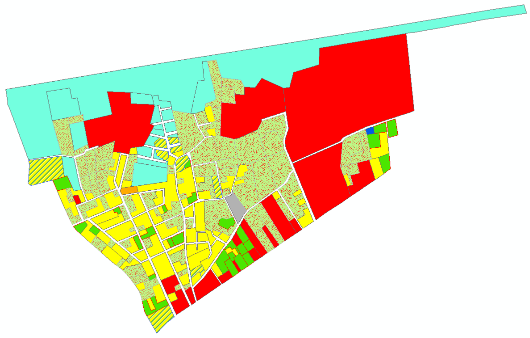
Figure 4.12 Existing and GA-MODA land-use map for case area 2 of 2016.

Case 3

Urban LU map 2013

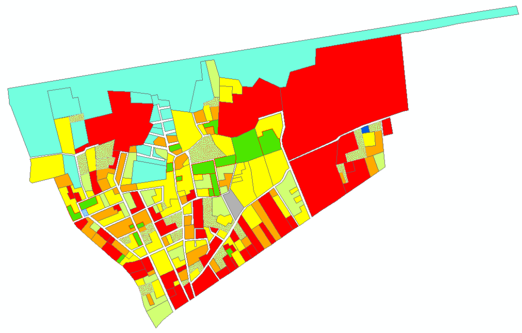


Urban LU map 2016

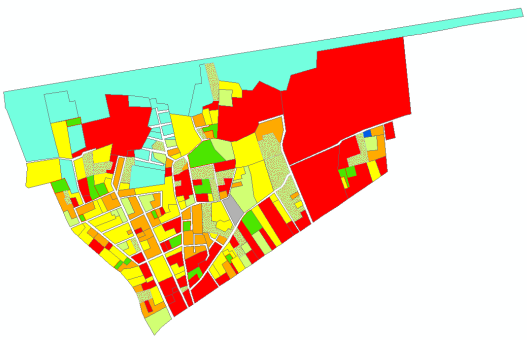


GA-MODA urban LU map 2016 rank1

GA-MODA urban LU map 2016 rank2



GA-MODA urban LU map 2016 rank3



Legend

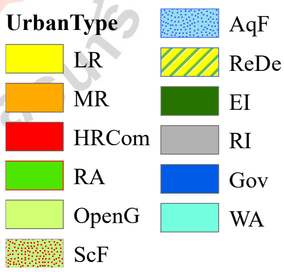


Figure 4.13 Existing and GA-MODA land-use map for case area 3 of 2016.

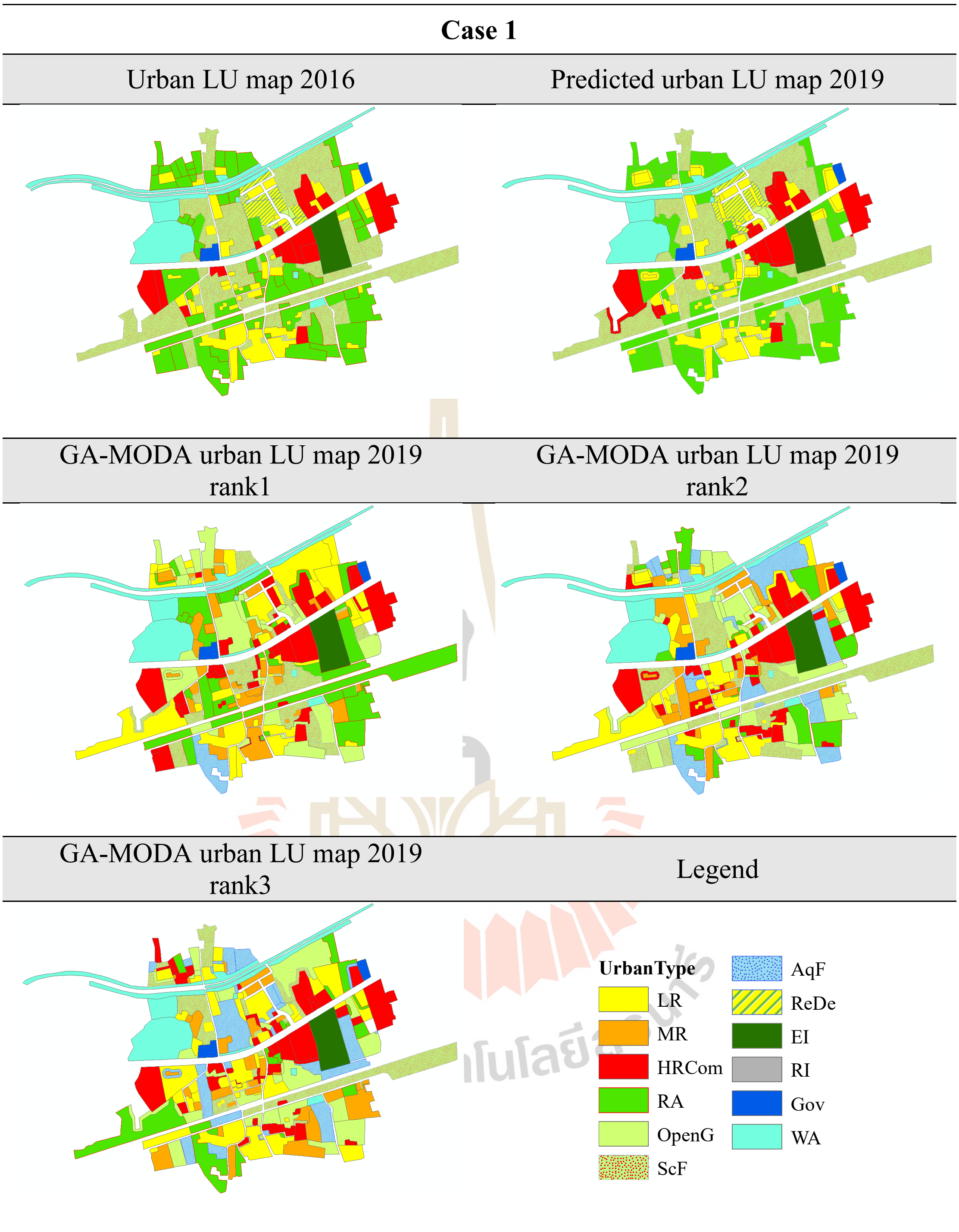
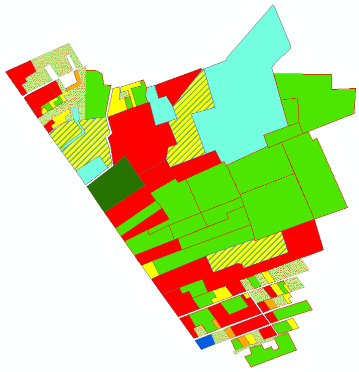


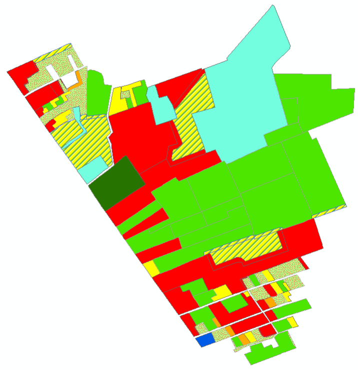
Figure 4.14 Predicted and GA-MODA land-use map for case area 1 of 2019.

Case 2

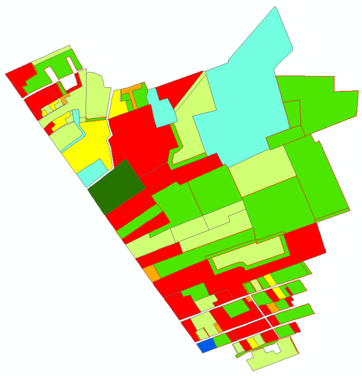
Urban LU map 2016



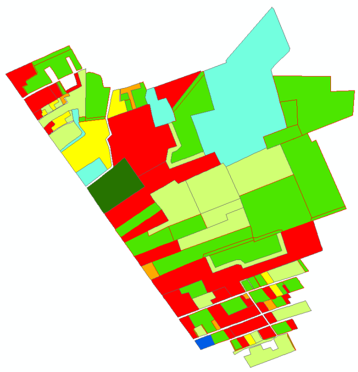
Predicted urban LU map 2019



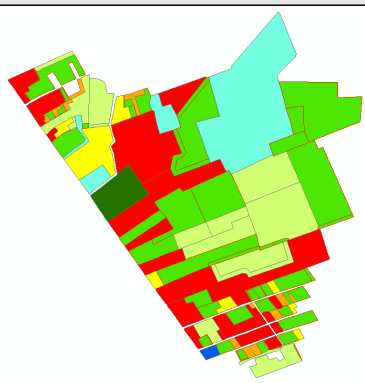
GA-MODA urban LU map 2019
rank1



GA-MODA urban LU map 2019
rank2



GA-MODA urban LU map 2019
rank3



Legend

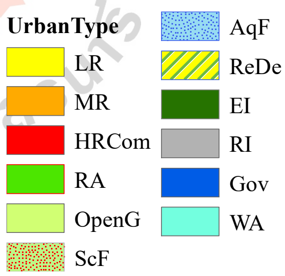


Figure 4.15 Predicted and GA-MODA land-use map for case area 2 of 2019.

Case 3

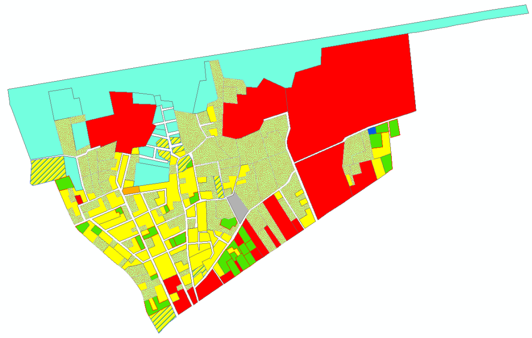
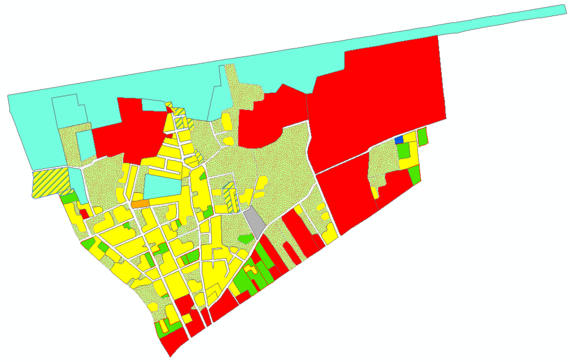
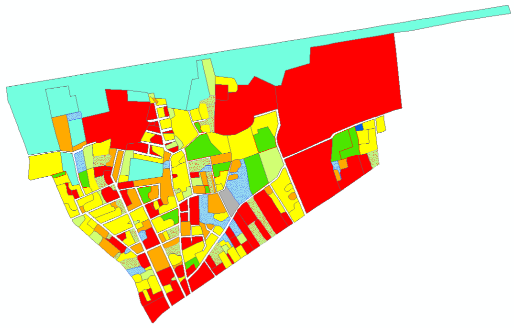
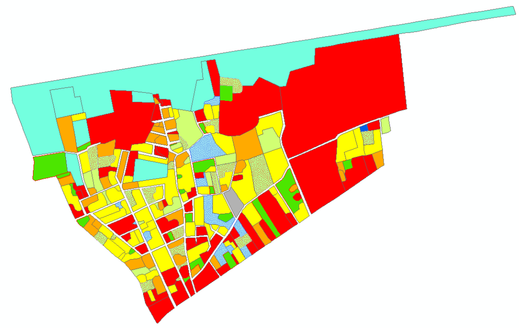
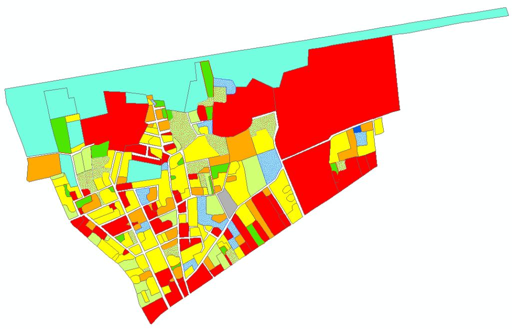
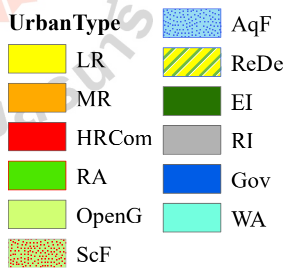
Urban LU map 2016	Predicted urban LU map 2019
	
GA-MODA urban LU map 2019 rank1	GA-MODA urban LU map 2019 rank2
	
GA-MODA urban LU map 2019 rank3	Legend
	

Figure 4.16 Predicted and GA-MODA land-use map for case area 3 of 2019.

Table 4.12 Plans having top 3 of fitness values, their objective values and SNOV.

	Fitness	Objective value 1	Objective value 2	Objective value 3	Objective value 4	Objective value 5	Objective value 6	SNOV
2016								
Case1								
Existing	-	687.70	616.17	0.70	666.07	1.17	17,937.00	3.36
GA Rank 1	0.9807	1,071.81	609.82	64.26	620.84	4.98	43,436.72	3.51
GA Rank 2	0.9775	1,074.70	604.29	64.09	614.10	5.00	40,537.66	3.55
GA Rank 3	0.9559	835.59	609.31	88.07	725.16	5.06	31,827.33	3.83
Case2								
Existing	-	2,464.20	2,499.82	NA	5,215.80	0.098	135,530.00	3.21
GA Rank 1	0.9980	2,415.57	2,348.92	164.55	6,297.95	0.78	180,311.28	4.23
GA Rank 2	0.9976	2,415.57	2,368.99	124.42	6,300.35	0.71	161,206.02	4.12
GA Rank 3	0.9970	2,434.88	2,377.73	158.83	5,335.26	0.87	182,080.88	3.96
Case3								
Existing	-	2,723.26	2,482.54	NA	1,980.50	0.0298	11,443.00	3.30
GA Rank 1	0.9992	3,460.12	2,914.46	23.31	1,975.57	0.82	34,882.50	3.61
GA Rank 2	0.9991	3,394.84	2,794.42	27.02	1,999.03	0.73	34,291.55	3.76
GA Rank 3	0.9990	3,433.30	2,851.70	22.02	1,996.32	0.70	33,850.24	3.72
2019								
Case1								
predicted	-	847.39	739.07	1.72	541.97	0.62	35,554.00	3.13
GA Rank 1	0.9826	1,391.57	854.07	55.00	558.14	5.48	92,548.72	3.97
GA Rank 2	0.9809	1,357.01	846.22	52.82	548.12	5.67	86,740.60	3.92
GA Rank 3	0.9783	1,411.34	846.55	56.77	540.85	5.18	92,098.40	4.02
Case2								
predicted	-	2,668.23	2,701.24	NA	3,979.70	0.105	195,390.00	3.08
GA Rank 1	0.9967	2,613.40	2,581.96	135.63	3,991.12	0.75	197,077.57	4.08
GA Rank 2	0.9933	2,613.40	2,588.20	123.14	4,510.93	0.76	193,497.90	4.12
GA Rank 3	0.9925	2,562.46	2,489.97	131.16	4,083.23	0.77	190,283.63	4.03
Case3								
predicted	-	2,735.98	2,487.44	NA	2,020.50	0.026	24,478.00	3.36
GA Rank 1	0.9945	3,479.60	2,919.29	16.43	2,032.71	0.70	97,390.01	4.00
GA Rank 2	0.9941	3,448.84	2,980.23	25.05	2,021.58	0.73	97,729.12	4.24
GA Rank 3	0.9937	3,478.14	2,954.40	17.41	2,044.21	0.73	96,996.31	4.00

Note: NA: not available.

- : fitness value is not available because of not being at Pareto front.

By visual comparison of urban land-use maps, the better plan cannot be identified. This is to confirm why fitness value of Pareto front approach is necessary. As known, plans located at Pareto front are non-dominated plans. Their fitness values resulted from considering all objectives in GA-MODA process at once can be effectively identified ranks of non-dominated plans. Theoretically, the higher fitness value indicates the better plan.

Considering maximized values of objective 1-4 (housing, employment, open green, and compatibility) of all case areas of both years, ones of GA-MODA plans are apparently the same or higher than of the existing/predicted ones. When considering minimized values of objective 5 and 6 (changing cost and travel rate) of all case areas of both years, ones of GA-MODA plans are higher than existing/predicted ones. The results can explain that housing capacity, employment capacity, open green area, and compatibility of GA-MODA plans are better while changing cost and travel rate are subordinate.

It is obvious that travel rate of GA-MODA plans can be comparatively higher when their populations are higher than suggested population. It can be explained that higher population with more distribution can trigger higher travel activity. Similar to what mentioned above, objective values of existing 2016 and predicted 2019 plans were analyzed to shown that they were not located at Pareto front and resulted in not available fitness value. This indicates that they were completely dominated by corresponding GA-MODA plans. The result is strongly confirmed by SNOV. SNOV of all GA-MODA plans are higher than of existing 2016 and predicted 2019 land use.

CHAPTER V

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The main goal of this study is to plan urban land use spatially in a level of individual plot using GA-MODA for 2016 and 2019. The objectives of the study are to develop and simulate a flexible procedure for urban class planning of selected case areas using GA-MODA to comply with constraints, and compare results between existing/interpreted and GA-MODA plans of 2016 and between CA-Markov predicted and GA-MODA plans of 2019. The comparison result of 2016 was use to confirm the result of 2019 if they go in same direction. The existing urban land use of 2016 was considered as the fact while of 2019 was relied on the prediction. GA was used to focus on generating population of plans for fitness test. MODA was applied to fitness evaluation under given objectives and constraints. Objectives cover sufficient housing, employment, open green area, high compatibility, and minimized changing cost and travel rate. For better living, constraints were setup to flexibly comply with 2 suggestions: 1) suggested areas and population densities to urban classes and 2) suggested population densities for actual/predicted urban class areas.

The study results provide, from each case area, GA-MODA plans with fitness values were complied with constraints of objectives and were at Pareto front. The results serves the first research objective completely.

To be evident that GA-MODA plans were better than existing and predicted plans, the comparison base on 3 aspects 1) if they complied with constraints, 2) if they were at Pareto front, and 3) if SNOV of GA-MODA plans were better than existing and predicted plans. The results show that there are no existing and predicted plans completely comply with constraints while all GA-MODA plans do. No one of existing and predicted plans was located at the Pareto front while all GA-MODA plans were. More than 90 percentage of GA-MODA plans having higher SNOV than of existing and predicted plans. These comparisons serve the second research objective. To be able to guide the planning management, objective values were also compared so that it can tell preservation or promotion of which objectives of existing and predicted plans could be advised.

As a result, it could be confirmed that GA-MODA process is the capable method to generate, for each case area, a number of optimal plans having higher comparison elements than of 2016 and 2019 plans. The flexible GA-MODA procedure designed in this study can balance all objectives to meet the optimizing values which are better than of existing and predicted plans. The procedure was designed to be able to apply to other areas with their own constraints and characteristics.

5.2 Recommendation

5.2.1 Constraints of this study were mainly based on the suggestion, for better living quality, on urban class areas and population densities which are belong to the study of PST and P&C Mgt Co., Ltd. (2553). It could be better if the information can be updated to fit to most recent socioeconomic and policy structures of the area. The future research to obtain updated information should be required.

5.2.2 From this study, it is found that available tools used to run GA-MODA process are still not capable well with a big number of plots in the case area and big size of plots can also cause difficulty to obtain optimal plans. An example from this study, only almost 250 plots of case area 1 could take longer than 3 weeks for running. If a plot is too big, it can be difficult to allot attributes to comply with constraints. Agriculture and scrub are more likely changed to more developed class. In this case, they were split to have size not bigger than 2-3 times of average LR and MR plot sizes, which were classes to change to. Therefore, splitting study area to be case areas with suitable number of plots are advised. Too big plots should be split to a number of small plots as well.

5.2.3 Constraints and objectives of the procedure should be adjusted to fit with its own characteristics of study areas.

5.2.4 It is very important to note that GA process focuses on sampling a number of plans expected to represent the population, but do not cover the whole possible plans of the population. Other tools capable to operate with the whole population plans should be sought for and working together with higher efficiency computer system. Tremendous time consuming to run a process could be no longer a problem for such a case. Following this recommendation, it can guarantee that all possible optimize plans will be extracted for comparison and rank.

REFERENCES

REFERENCES

กรมโยธาธิการและผังเมือง, สำนักพัฒนามาตรฐาน. (2549). **เกณฑ์และมาตรฐานผังเมืองรวม พ.ศ. 2549**. กรุงเทพฯ: กรมโยธาธิการและผังเมือง.

สำนักงานคณะกรรมการกฤษฎีกา. (2518). **พระราชบัญญัติ การผังเมือง พ.ศ.2518**. ราชกิจจานุเบกษา. เล่ม 92 ตอนที่ 33 ฉบับพิเศษ., หน้า 1-26.

บริษัท พิสุทธิ์ เทคโนโลยี จำกัด และบริษัท พี แอนด์ ซี แมเนจเมนท์ จำกัด. (2553). **ผังเมืองรวมเมืองนครราชสีมา (ปรับปรุงครั้งที่ 3): เอกสารประกอบการประชุม คณะที่ปรึกษาผังเมืองรวมเมืองนครราชสีมา**. สำนักงานโยธาธิการและผังเมืองนครราชสีมา. (อัดสำเนา)

Aerts, J. C. J. H., Eisinger, E., Heuvelink, G. B. M., and Stewart, T. J. (2003). Using linear integer programming for multi-site land-use allocation. **Geographical Analysis**. 35(2): 148-169.

Ayodeji, O. Z. (2006). **Change detection in land use and land cover using remote sensing data and GIS (A case study of Ilorin and its environs in Kwara State)**. M.S. thesis, University of Ibadan, Nigeria.

Balling, R. (2002). The maximin fitness function for multiobjective evolutionary optimization. In I. C. Parmee and P. Hajela (eds.). **Optimization in Industry** (pp 135-147). London: Springer.

Balling, R. J., Taber, J. T., Brown, M. R., and Day, K. (1999). Multi-objective urban planning using Genetic Algorithm. **Journal of Urban Planning and Development**. 125(2): 86-99.

Balling, R., Powell, B., and Saito, M. (2004). Generating future land-use and transportation plans for high-growth cities using a genetic algorithm. **Computer-Aided Civil and Infrastructure Engineering**. 19: 213-222.

Biel, Y. and Hua, D. (2012). **Population Dynamics in Conway's Game of Life and its Variants** [On-line]. Available: https://www.slideshare.net/pelikan/stars2012 -finalpresentation.

Cao, K., Batty, M., Huang, B., Liu, Y., Yu, L., and Chen, J. F. (2011). Spatial multi-objective land use optimization: Extensions to the nondominated sorting genetic algorithm. **International Journal of Geographical Information Science**. 25(12): 194-1969.

Cao, K., Huang, B., Wang, S. and Lin, H. (2012). Sustainable land use optimization using Boundary-based Fast Genetic Algorithm. **Computers, Environment and Urban Systems**. 36(3): 257-269.

Carter, H. (1981). **The study of Urban Geography**. Australia: Edward Arnold Victoria.

Chang, C. L. and Chang, J. C. (2006). Markov model and cellular automata for vegetation. **Journal of Geographical Research**. 45: 45-57.

Cherdchai, S. and Mayor, L. (2001). **First Meeting of the Kitakyushu Initiative Network (sessionIII): Urban Sustainable Development in Nakhon Ratchasima and Implementation of Pilot Project of the Kitakyushu Initiative** [On-line]. Available: http://kitakyushu.iges.or.jp/activities/network _meetings /first.html.

Clark, D. (1982). **Urban Geography: An Introductory Guide**. London: Taylor & Francis.

Couclelis, H. (1985). Cellular worlds: A framework for modelling micromacro dynamics. **Environment and Planning A: Economy and Space**. 17: 585-596.

Couclelis, H. (1989). Macrostructure and microbehavior in a metropolitan area. **Environment and Planning B: Planning and Design**. 16: 141-154.

Deb, K. (2001). **Multi-objective optimization using evolutionary algorithms**. New York: John Wiley & Sons.

Deep, S. and Saklani, A. (2014). Urban sprawl modeling using cellular automata. **The Egyptian Journal of Remote Sensing and Space Sciences**. 17: 179-187.

Department of Provincial Administration. (2015). **Population data** [On-line]. Available: http://stat.dopa.go.th/stat/statnew/upstat_age_disp.php.

Ebrahimipour, A., Saadat, M., and Farshchin, A. (2016). Prediction of urban growth through Cellular automata-Markov chain. **Bulletin de la Societe Royale des Sciences de Liege**. 85: 824-839.

ESRI. (2010). ArcGis10.2 [Computer software]. New York: ESRI.

Gardner, M. (1970). The fantastic combinations of John Conway’s new solitaire game “Life”. **Scientific American**. 233: 120-123.

Gen, M. and Cheng, R. (2000). **Genetic algorithms and engineering optimization**. New York: John Wiley & Sons.

Guan, D., Li, H., Inohae, T., Su, W., Nagaie, T., and Hokao, K. (2011). Modeling urban land use change by the integration of cellular automata and Markov model. **Ecological Modelling**. 222: 3761-3772.

Guldmann, J. M. (1979). Urban land use allocation and environmental pollution control: An intertemporal optimization approach. **Socio-Economic Planning Sciences**. 13(2): 71-86.

Hall, P. (2002). **Urban & Regional Planning** (4th ed.). London: Routledge.

Hegazy, I. R. and Kaloop, M. R. (2015). Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate Egypt. **International Journal of Sustainable Built Environment**. 4(1): 117-124.

Herold, M. G., Hemphill, J., Dietzel, C., and Clarke, K. C. (2005). **Remote sensing derived mapping to support urban growth theory** [On-line]. Available: http://www.isprs.org/ proceedings/XXXVI/8-W27/herold_hemphill_etal.pdf.

Herold, M. G., Menz, G., and Clarke, K. C. (2001). Remote sensing and urban growth models. Demands and perspectives. Proceedings of the **Symposium on Remote Sensing of Urban areas**. Regensburg, Germany.

Hopkins, L. D. (1977). Land-use plan design-quadratic assignment and central facility models. **Environment and Planning**. 9(6): 625-642.

Huang, B. and Zhang, W. (2014). Sustainable land-use planning for a downtown lake area in central China: Multiobjective optimization approach aided by urban growth modeling. **Journal of Urban Planning and Development**. 140: 1-12.

Huang, G. and Xia, J. (2001). Barriers to sustainable water-quality management. **Journal of Environmental Management**. 61: 1-23.

Jain, S., Siddiqui, A., Tiwari, P. S., and Shashi, M. (2016). Urban growth assessment using CA Markov model: a case study of Dehradun city. Proceedings of **the 9th international geographic union 2016**. Delhi, India.

Kamusoko, C., Aniya, M., Adi, B., and Manjoro, M. (2009). Rural sustainability under threat in Zimbabwe – Simulation of future land use/cover changes in the Bindura district based on the Markov-cellular automata model. **Applied Geography**. 29:

435-447. Quote in Sang, L., Zhang, C., Yang, J., Zhu, D., and Yun, W. (2011). Simulation of land use spatial pattern of towns and villages based on CA-Markov model. **Mathematical and Computer Modeling in agriculture**. 54: 938-943.

Kamusoko, C., Aniya, M., Adi, B., and Manjoro, M. (2009). Rural sustainability under threat in Zimbabwe - Simulation of future land use/cover changes in the Bindura district based on the Markov-cellular automata model. **Applied Geography**. 29: 435-447.

Kullavanijaya, T. (2008). Urban planning policies in Thailand. **Asia-Pacific Housing Journal**. 2(2): 6-73.

Ligmann, Z. A., Church, R. L., and Jankowski, P. (2008). Spatial optimization as a generative technique for sustainable multiobjective land-use allocation. **International Journal of Geographical Information Science**. 22(6): 601-622.

Liu, Y. (2009). **Modelling Urban Development with Geographical Information Systems and Cellular Automata**. New York: CRC Press.

Los, M. (1978). Simultaneous optimization of land use and transportation - A synthesis of the quadratic assignment problem and the optimal network problem. **Regional Science and Urban Economics**. 8(1): 21-42.

Malczewski, J. and Rinner, C. (2015). **Multicriteria Decision Analysis in Geographic Information Science**. New York: Springer Science Business Media.

Mohammadi, M., Nastaran, M., and Sahebgharani, A. (2015). Sustainable spatial land use optimization through Non-dominated Sorting Genetic Algorithm-II (NSGAII): Case study: Baboldasht district of Isfahan. **Indian Journal of Science and Technology**. 8: 118-129.

Myint, S. W. and Wang, L. (2006). Multi criteria decision approach for land use land cover change using Markov chain analysis and a cellular automata approach. **Canadian Journal of Remote Sensing**. 32(6), 390-404.

Sang, L., Zhang, C., Yang, J., Zhu, D., and Yun, W. (2011). Simulation of land use spatial pattern of towns and villages based on CA-Markov model. **Mathematical and Computer Modelling**. 54: 938-943.

Sastry, K., Goldberg, D. E., and Kendall, G. (2005). Genetic algorithms. In E. Burke and G. Kendall (eds.). **Search methodologies: Introductory tutorials in optimization, and decision support techniques** (pp 97-125). United States of America: Springer.

Smith, M. J., Goodchild, M. F., and Longley, P. A. (2007). **Geospatial Analysis: A Comprehensive Guide to Principle, Techniques and Software Tools** (2nd ed.). Leicester: Troubador.

Stewart, T. J., Janssen, R., and Herwijnen, M. V. (2004). A genetic algorithm approach to multiobjective landuse planning. **Computers & Operations Research**. 31(14): 2293-2313.

Subedi, P., Subedi, K., and Thapa, B. (2013). Application of a hybrid Cellular automaton – Markov (CA-Markov) model in land-use change prediction: a case study of Saddle Creek drainage basin, Florida. **Applied Ecology and Environmental Sciences**. 1(6): 126-132.

Wilson, E. H., Hurd, J. D., Civco, D. L., Prisloe, S., and Arnold, C. (2003). Development of a geospatial model to quantify, describe and map urban growth. **Remote Sensing of Environment**. 86(3): 275-285.

Wolfram, S. (1984). Cellular automata as model of complexity. **Nature International Journal of Science**. 311: 419-424.

Yang, X., Zheng, X-Q., and Chen, R. (2014). A land use change model: Integrating landscape pattern indexes and Markov-CA. **Ecological Modelling**. 283: 1-7.

Zhang, H. H., Zeng, Y. N., and Bian, L. (2010). Simulating multi-objective spatial optimization allocation of land use based on the integration of multi-agent system and genetic algorithm. **International Journal of Environmental Research**. 4(4): 765-776.

Zhang, W. (2014). **Multi-objective optimization for spatial planning of land use in Shenzhen**. Ph.D. Dissertation, The Chinese University of Hong Kong, Hong Kong.

APPENDICES

APPENDIX A

VISUAL FEATURE RECOGNITION OF MODIFIED CLASSES IN THE STUDY AREA

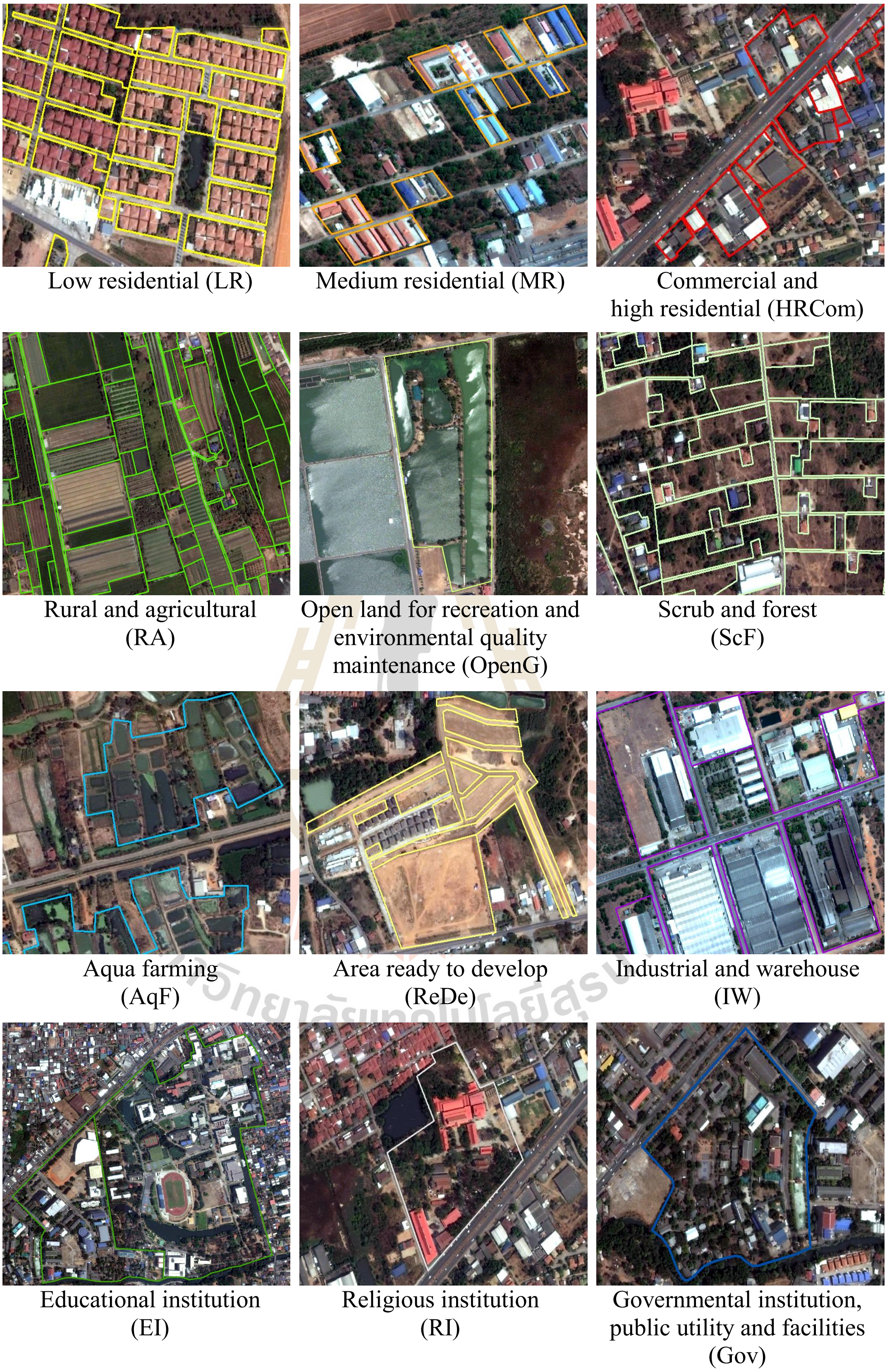


Figure A1 Visual feature recognition of modified classes in the study area.

Water or wetland
(WA)

Undeveloped industrial
(UnIn)

Railway

Road network

Figure A1 Visual feature recognition of modified classes in the study area (Continued).

APPENDIX B

URBAN LAND-USE CHANGING MATRIX OF CASE AREAS DURING 2013-2016

Table B1 Urban land-use changing matrix of case area 1 during 2013-2016.

2016 / 2013	LR	MR	HRCom	RA	OpenG	ScF	AqF	ReDe	IW	EI	RI	Gov	WA	Row Total
LR	39.05	-	-	-	-	-	-	-	-	-	-	-	-	39.05
MR	-	-	-	-	-	-	-	-	-	-	-	-	-	-
HRCom	-	-	16.05	-	-	-	-	-	-	-	-	-	-	16.05
RA	0.47	-	2.57	112.71	-	2.25	-	-	-	-	-	-	-	118.00
OpenG	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ScF	2.87	-	-	1.06	0.27	125.77	-	11.15	-	-	-	-	1.02	142.13
AqF	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ReDe	1.63	-	18.52	-	-	-	-	-	-	-	-	-	-	20.16
IW	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EI	-	-	-	-	-	-	-	-	-	13.28	-	-	-	13.28
RI	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Gov	-	-	-	-	-	-	-	-	-	-	-	3.85	-	3.85
WA	-	-	-	3.96	0.43	1.58	-	1.02	-	-	-	-	47.32	54.31
Colum Total	44.03	-	37.14	117.73	0.70	129.60	-	12.17	-	13.28	-	3.85	48.34	**406.82**

Table B2 Urban land-use changing matrix of case area 2 during 2013-2016.

2013 \ 2016	LR	MR	HRCom	RA	OpenG	ScF	AqF	ReDe	IW	EI	RI	Gov	WA	Row Total
LR	15.97	-	-	-	-	-	-	-	-	-	-	-	-	15.97
MR	-	3.30	-	-	-	-	-	-	-	-	-	-	-	3.30
HRCom	-	-	148.80	-	-	-	-	-	-	-	-	-	-	148.80
RA	0.99	-	6.97	263.94	-	-	-	-	-	-	-	-	-	271.89
OpenG	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ScF	1.00	-	-	-	-	42.27	-	5.61	-	-	-	-	-	48.88
AqF	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ReDe	-	0.94	2.09	-	-	-	-	62.19	-	-	-	-	-	65.22
IW	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EI	-	-	-	-	-	-	-	-	-	17.92	-	-	-	17.92
RI	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Gov	-	-	-	-	-	-	-	-	-	-	-	1.92	-	1.92
WA	-	-	-	-	-	-	-	-	-	-	-	-	110.90	110.90
Colum Total	17.95	4.25	157.85	263.94	-	42.27	-	67.80	-	17.92	-	1.92	110.90	**684.79**

Table B3 Urban land-use changing matrix of case area 3 during 2013-2016.

2016 / 2013	LR	MR	HRCom	RA	OpenG	ScF	AqF	ReDe	IW	EI	RI	Gov	WA	Row Total
LR	66.80	-	1.36	-	-	-	-	-	-	-	-	-	-	68.15
MR	-	0.81	-	-	-	-	-	-	-	-	-	-	-	0.81
HRCom	-	-	158.77	-	-	-	-	-	-	-	-	-	-	158.77
RA	0.79	-	-	19.33	-	-	-	-	-	-	-	-	-	20.11
OpenG	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ScF	-	-	-	-	-	117.13	-	-	-	-	-	-	-	117.13
AqF	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ReDe	3.07	-	2.81	-	-	-	-	8.25	-	-	-	-	-	14.13
IW	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EI	-	-	-	-	-	-	-	-	-	-	-	-	-	-
RI	-	-	-	-	-	-	-	-	-	-	2.26	-	-	2.26
Gov	-	-	-	-	-	-	-	-	-	-	-	0.38	-	0.38
WA	5.59	-	-	-	-	-	-	2.15	-	-	-	-	117.41	125.15
Colum Total	76.23	0.81	162.94	19.33	-	117.13	-	10.41	-	-	2.26	0.38	117.41	**506.90**

APPENDIX C

POPULATION AND LABOR FORCE ESTIMATION

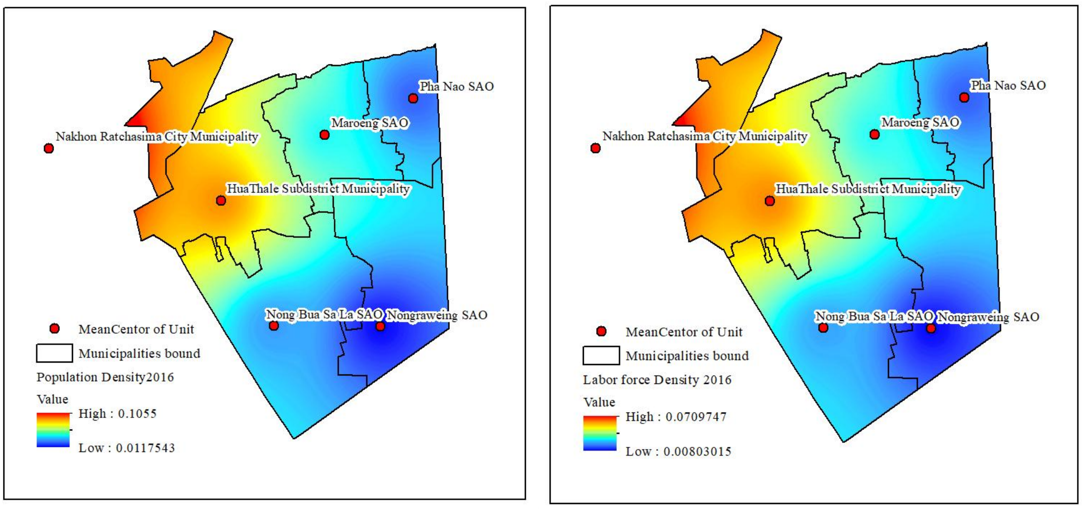


Figure C1 The distribution of population and labor force density in 2016.

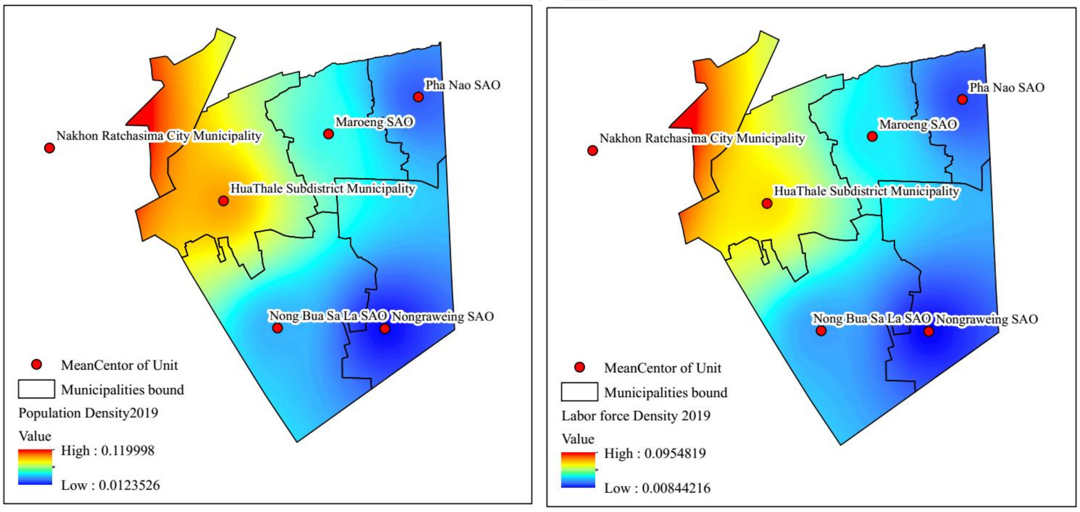


Figure C2 The distribution of population and labor force density in 2019.

APPENDIX D

QUESTIONNAIRE FOR IDENTIFYING CHANGING COST MATRIX OF URBAN LAND-USE CLASSES

<u>แบบสอบถามสำหรับการวิจัย</u>

เรื่อง ความคิดเห็นของผู้เชี่ยวชาญในการกำหนดค่าต้นทุนในการเปลี่ยนแปลง ประเภทการใช้ประโยชน์ที่ดินสำหรับการวางแผนการใช้ที่ดินเชิงพื้นที่ในเขตเมือง

<u>คำชี้แจงในการตอบแบบสอบถาม</u>

1. แบบสอบถามนี้ต้องการวิเคราะห์หาค่าต้นทุนในการเปลี่ยนแปลงประเภทการใช้ประโยชน์ที่ดินจากประเภทหนึ่งไปเป็นประเภทอื่นๆ ซึ่งค่าต้นทุนนี้หมายรวมทั้งด้านความยาก-ง่าย ด้านต้นทุน ด้านเศรษฐกิจ ด้านสังคมและด้านวัฒนธรรมในการเปลี่ยนแปลงประเภทการใช้ประโยชน์ที่ดิน ซึ่งเป็นวัตถุประสงค์หนึ่งสำหรับการทำวิทยานิพนธ์เรื่องการหาค่าเหมาะที่สุดแบบหลายวัตถุประสงค์ด้วยขั้นตอนวิธีเชิงพันธุกรรมสำหรับการวางแผนการใช้ที่ดินเชิงพื้นที่ในเขตเมือง เพื่อให้ได้รูปแบบการจัดสรรประเภทการใช้ประโยชน์ที่ดินอย่างเหมาะสม

2. แบบสอบถามแบ่งออกเป็น 2 ตอน

   ตอนที่ 1 ข้อมูลทั่วไปของผู้ตอบแบบสอบถาม

   ตอนที่ 2 ความคิดเห็นในการกำหนดค่าต้นทุนในการเปลี่ยนแปลงประเภทการใช้ประโยชน์ที่ดิน

3. ขอความกรุณาท่านได้ตอบแบบสอบถาม ตามสภาพความเป็นจริง โดยคำตอบของท่านจะนำไปสรุปผลการศึกษาค้นคว้าในลักษณะภาพรวมไม่มีผลกระทบหรือเกิดความเสียหายต่อท่านหรือผู้อื่น ทั้งทางตรงและทางอ้อมแต่ประการใด หากแต่จะเป็นประโยชน์ต่อการจัดสรรประเภทการใช้ประโยชน์ที่ดินในหน่วยงานของท่านให้ดียิ่งขึ้นต่อไปในอนาคต

ขอขอบคุณในการอนุเคราะห์ในการให้ความร่วมมือของท่าน

วารุณี อ้วนโพธิ์กลาง

นักศึกษาระดับดุษฎีบัณฑิต มหาวิทยาลัยเทคโนโลยีสุรนารี

<u>ตอนที่ 1</u> ข้อมูลทั่วไปของผู้ตอบแบบสอบถาม

<u>คำชี้แจง</u> โปรดทำเครื่องหมาย ✓ หรือกรอกข้อมูลลงในช่องว่าง ที่ท่านเห็นว่าตรงกับสภาพความเป็นจริงของท่าน

1. หน่วยงานของผู้ตอบแบบสอบถาม..
2. ตำแหน่งของผู้ตอบแบบสอบถาม..
3. เพศ

   1. ( ) ชาย 2. ( ) หญิง

4. อายุ

   1. ( ) 20 -30 ปี 2. ( ) 31-40 ปี

   3. ( ) 41-50 ปี 4. ( ) 51 ปีขึ้นไป

5. การศึกษา

   1. ( ) มัธยมศึกษา หรือ ปวช. 2. ( ) ปวส./อนุปริญญา

   3. ( ) ปริญญาตรี 4. ( ) ปริญญาโท

   5. ( ) ปริญญาเอก 6. ( ) อื่นๆ......................................

<u>ตอนที่ 2</u> ความคิดเห็นในการกำหนดค่าต้นทุนในการเปลี่ยนแปลงประเภทการใช้ประโยชน์ที่ดิน

<u>คำชี้แจง</u> ให้กรอกค่าคะแนนลำดับความสำคัญของต้นทุนในการเปลี่ยนแปลงประเภทการใช้ประโยชน์ที่ดินประเภทหนึ่งไปเป็นประเภทอื่นๆ ในอนาคต โดยค่าคะแนนของค่าต้นทุนในการเปลี่ยนแปลงประเภทการใช้ประโยชน์ที่ดิน มีค่าอยู่ระหว่าง 0-10 (ต้นทุนน้อย ไป ต้นทุนมาก) โดยมีรายละเอียดดังนี้

- 0 คือ ไม่มีค่าต้นทุนการเปลี่ยนแปลง
- 1-10 หมายถึง มีค่าต้นทุนในการเปลี่ยนแปลงจากระดับง่ายไปสู่ยาก
- ■ หมายถึง ประเภทการใช้ประโยชน์ที่ดินนั้นห้ามเปลี่ยนเป็นประเภทการใช้ประโยชน์ที่ดินใดๆในอนาคต

<u>ตอนที่ 2</u> ความคิดเห็นในการกำหนดค่าต้นทุนในการเปลี่ยนแปลงประเภทการใช้ประโยชน์ที่ดิน

No.	ประเภทการใช้ประโยชน์ที่ดินในอนาคต / ประเภทการใช้ประโยชน์ที่ดินปัจจุบัน	ที่อยู่อาศัยหนาแน่นน้อย	ที่อยู่อาศัยหนาแน่นปานกลาง	ที่อยู่อาศัยหนาแน่นมากและพาณิชยกรรม	ชนบทและเกษตรกรรม	ที่โล่งเพื่อนันทนาการและการรักษาคุณภาพสิ่งแวดล้อม	ป่าและป่าละเมาะ	พื้นที่ฟาร์มสัตว์น้ำ	พื้นที่ที่พร้อมพัฒนา
1	ที่อยู่อาศัยหนาแน่นน้อย	0							
2	ที่อยู่อาศัยหนาแน่นปานกลาง		0						
3	ที่อยู่อาศัยหนาแน่นมากและพาณิชยกรรม			0					
4	ชนบทและเกษตรกรรม				0				
5	ป่าและป่าละเมาะ						0		
6	พื้นที่ฟาร์มสัตว์น้ำ							0	
7	พื้นที่ที่พร้อมพัฒนา								0

ข้อเสนอแนะ:

APPENDIX E

AN EXAMPLE OF DATA FORM OF PLAN INPUT TO GA-MODA PROCESS

Table E1 An example of data form of existing/predicted plans input to GA-MODA process.

Plot ID	Plot area (rai)	Urban LU class	Normalize plot area
2	3.061	6	0.170379
3	0.741	1	0.041249
4	0.292	6	0.016271
5	1.154	4	0.064238
7	1.275	1	0.070948
8	0.516	1	0.028731
10	0.771	1	0.042941
12	1.377	8	0.076657
13	1.672	1	0.093045
15	0.181	8	0.010060
17	4.951	6	0.275588
19	1.521	4	0.084648
20	0.640	8	0.035615
21	1.304	6	0.072608
22	0.032	8	0.001786
23	1.192	8	0.066357
24	1.464	3	0.081480
25	1.338	1	0.074491
26	1.189	1	0.066163
27	0.987	1	0.054925
28	1.779	1	0.099026
29	4.686	3	0.260849
30	0.732	1	0.040746
31	0.470	8	0.026159
32	0.698	5	0.038867
33	0.197	8	0.010941
34	0.343	8	0.019112
35	0.368	1	0.020494
36	0.040	1	0.002245
37	0.146	8	0.008138
38	4.215	8	0.234603
39	0.773	1	0.043013
40	8.486	3	0.472311
41	0.546	3	0.030410
42	0.331	6	0.018413
43	1.293	4	0.071951
44	1.303	4	0.072515
45	0.893	1	0.049710
⋮	⋮	⋮	⋮
276	0.979	4	0.0545112

APPENDIX F

ALGORITHMS AND AN EXAMPLE OF CONSTRAINT SETUP

For better living, constraints were setup to comply with 2 suggestions:

1) suggested areas and suggested population densities of urban classes and

2) suggested population densities for existing/predicted urban class areas.

A. Algorithms of constraints setup

Algorithms of all constraints are described below:

1) LR area constraint (Constraint 2)

Consider LR class

If

existing/predicted area is <u>lower than</u> the suggested area,
set existing/predicted area to be "lower bound"
and suggested area to be "upper bound"

Else

set suggested area to be "lower bound"
and existing/predicted × 25% to be "upper bound"

Then

LR constraint:
lower bound ≤ Total LR area ≤ upper bound

2) MR area constraint (Constraint 3)

Consider MR class

If

existing/predicted area is <u>lower than</u> the suggested area,
set existing/predicted area to be "lower bound"
and suggested area to be "upper bound"

Else

set suggested area to be "lower bound"
and existing/predicted × 25% to be "upper bound"

Then

MR constraint:
lower bound ≤ Total MR area ≤ upper bound

3) HRCom area constraint (Constraint 4)

Consider HRCom class

If

existing/predicted area is <u>lower than</u> the suggested area,
set existing/predicted area to be "lower bound"
and suggested area to be "upper bound"

Else

set suggested area to be "lower bound"
and existing/predicted × 25% to be "upper bound"

Then

HRCom constraint:
lower bound ≤ Total HRCom area ≤ upper bound

4) Housing Capacity (Constraint 1)

Consider population of LR, MR, and HRCom classes

set lower bound of population =

(lower bound of LR class area × suggested population density of LR class)+
(lower bound of MR class area × suggested population density of MR class) +
(lower bound of HRcom class area × suggested population density of HRcom class),

set upper bound of population =

(upper bound of LR class area × suggested population density of LR class)+
(upper bound of MR class area × suggested population density of MR class) +
(upper bound of HRcom class area × suggested population density of HRcom class),

and set Housing Capacity constraint:

lower bound of Population ≤ Total Population ≤ upper bound of Population

5) RA area constraint (Constraint 6)

Consider RA class

If

existing/predicted area is <u>lower than</u> the suggested area,
set (existing/predicted area × 0.75) to be "lower bound"
and suggested area to be "upper bound"

Else

set suggested area to be "lower bound"
and existing/predicted area to be "upper bound"

Then

RA constraint:
Total RA area ≤ upper bound

6) Labor force (Constraint 5)

Consider population of HRCom (Constraint 4) and RA classes (Constraint 6)

set lower bound of Labor force =

(lower bound of HRCom class area × suggested population density of HRCom class)+
(lower bound of RA class area × suggested population density of RA class),

set upper bound of Labor force =

(upper bound of HRCom class area × suggested population density of HRCom class)+
(upper bound of RA class area × suggested population density of RA class),

and set Labor force constraint:

lower bound of Labor force ≤ Total Labor force ≤ upper bound of Labor force

7) Open Green area (Constraint 7)

Consider OpenG class

StA_{OG} is recommended total open green area based on area per head, 10 m^2/ person.

StA_{OG} = (Number of Population × 10 m^2)/ 1,600 rai

Then set Open Green area constraint:

Total Open Green area ≥ StA_{OG}

B. An example of constraints setup

An example how to set up constraints of case area 1 in 2016 using the developed algorithm.

1) LR area constraint (Constraint 2)

Consider LR class

If

existing area (44.04) is <u>lower than</u> the suggested area (138.68),
set existing area to be “lower bound”
and suggested area to be “upper bound”

Then

LR constraint:
$44.04 \leq$ Total LR area ≤ 138.68

2) MR area constraint (Constraint 3)

Consider MR class

If

existing area (0.00) is <u>lower than</u> the suggested area (40.80),
set existing/predicted area to be “lower bound”
and suggested area to be “upper bound”

Then

MR constraint:
$0.00 \leq$ Total MR area ≤ 40.80

3) HRCom area constraint (Constraint 4)

Consider HRCom class

If

existing area (37.14) is <u>not lower than</u> the suggested area (16.60),
set suggested area to be “lower bound”
and existing/predicted × 25% to be “upper bound”

Then

HRCom constraint:
$16.60 \leq$ Total HRCom area ≤ 46.42 (or 37.14×1.25)

4) Housing Capacity (Constraint 1)

Consider population of LR, MR, and HRCom classes

set lower bound of population =
(lower bound of LR class area (44.04) × suggested population density of LR class (3))+
(lower bound of MR class area (0.00) × suggested population density of MR class (10)) +
(lower bound of HRcom class area (16.60) × suggested population density of HRcom class (15))
= 381,

set upper bound of population =
(upper bound of LR class area (138.68) × suggested population density of LR class (3))+
(upper bound of MR class area (40.80) × suggested population density of MR class (10))+
(upper bound of HRcom class area (46.42) × suggested population density of HRcom class(15))
= 1,520,

and set Housing Capacity constraint:

$381 \leq$ Total Population $\leq 1{,}520$

5) RA area constraint (Constraint 6)

Consider RA class

If

existing area (117.72) is lower than the suggested area (148.53),
set (existing area × 0.75) to be "lower bound"
and suggested area to be "upper bound"

Then

RA constraint:
Total RA area ≤ 148.53

6) Labor force (Constraint 5)

Consider population of HRCom (Constraint 4) and RA classes (Constraint 6)

set lower bound of Labor force =

(lower bound of HRcom class area (16.60) × suggested population density of HRCom class (15))+
(lower bound of RA class area (117.72 × 0.75) × suggested population density of RA class (0.5))
= 293,

set upper bound of Labor force =

(upper bound of HRcom class area (46.42) × suggested population density of HRCom class(15))+
(upper bound of RA class area (148.53) × suggested population density of RA class (0.5))
= 771,

and set Labor force constraint:

$293 \leq$ Total Labor force ≤ 771

7) Open Green area (Constraint 7)

Consider OpenG class

StA_{OG} is recommended total open green area based on area per head, 10 m^2/ person.

StA_{OG} = (Number of Population (221) × 10 m^2)/ 1,600 = 1.38 rai

Then set Open Green area constraint:

Total Open Green area ≥ 1.38

APPENDIX G

STRUCTURE OF FUNCTION FLOW IN CODING GA-MODA PROCESS

The structure of function flow in coding GA-MODA process comprises four main functions. The output from the earlier main function becomes input of the next function consecutively. The main functions 1) and 2) contain sub-functions to complete the process. The structure of function flow can be described as follows:

1) MainFunction: *to generate population of plans in GA process and estimate their objective values.*

> gaoptimset: *Matlab® functions to create GA options structure*

> CreationFcn: *to create the initial population*

> MutationFcn: *to produce mutation children*

> CrossoverFcn: *to create crossover children*

> StallGenLimit: *to stop the algorithm when meet the assigned limit*

> Generations: *to identify maximum number of iterations before the algorithm halts*

> PopulationSize: *to identify size of the population*

> PopInitRange: *to specify the range of the individuals (classes) in the initial population*

> myFitnessObj: *to estimate objective values of generated plans*

> fitnessObj1: *to estimate values of objective 1 of plans*

> fitnessObj2: *to estimate values of objective 2 of plans*

> fitnessObj3: *to estimate values of objective 3 of plans*

> fitnessObj4: *to estimate values of objective 4 of plans*

> fitnessObj5: *to estimate values of objective 5 of plans*

> fitnessObj6: *to estimate values of objective 6 of plans*

2) MainCheckConstraintsFunction: *to estimate attributes and to check 7 constraints of initial population plans*

> myconstraint1: *to estimate attributes of objectives and to check whether they are complied with constraints or not*

> findConstraint1: *to estimate attributes of objective1*

> findConstraint2: *to estimate attributes of objective2*

> findConstraint3: *to estimate attributes of objective3*

3)TestPlansFunction: *to extract population plans completely complied with constraints*

4) FitnessFunction: *to check if plans are located at Pareto front and to calculate their fitness values*

APPENDIX H

AN EXAMPLE LIST OF MULTI-OBJECTIVE VALUES OF OPTIMIZED PLANS

Table H1 An example list of multi-objective values of optimized plans for case area 1 in 2016.

Ranking from Fitness value	Fitness value of plan	Value of Obj. 1	Value of Obj. 2	Value of Obj. 3	Value of Obj. 4	Value of Obj. 5	Value of Obj. 6
1	0.9807	1,071.81	609.82	64.26	620.84	4.98	43,436.72
2	0.9775	1,074.70	604.29	64.09	614.10	5.00	40,537.66
3	0.9559	835.59	609.31	88.07	725.16	5.06	31,827.33
4	0.9557	775.61	566.22	96.13	711.48	5.45	28,115.49
5	0.9552	1,094.13	608.21	91.07	611.98	5.45	49,595.77
6	0.9496	1,133.47	591.42	81.37	614.73	4.98	49,881.78
7	0.9473	1,029.68	583.57	69.97	678.61	5.15	38,269.50
8	0.9465	1,101.45	589.36	56.79	622.45	5.51	42,973.93
9	0.9438	1,109.18	601.87	92.58	614.79	5.46	47,375.53
10	0.9415	855.83	576.51	66.33	691.82	4.96	27,270.81
11	0.9370	1,125.23	601.64	87.40	610.83	5.37	49,095.59
12	0.9366	1,111.05	590.17	51.84	663.90	5.18	40,300.66
13	0.9261	813.31	554.99	90.97	727.70	4.96	30,107.34
14	0.9173	1,127.14	597.64	85.81	586.62	5.38	52,139.60
15	0.9163	816.10	565.25	130.61	734.10	5.41	33,143.87
16	0.9139	1,126.34	612.09	60.65	566.41	5.07	44,697.70
17	0.9060	1,137.00	608.94	36.27	522.15	5.15	42,034.38
18	0.9000	1,125.96	579.00	42.40	589.88	5.31	40,743.84
19	0.8966	763.96	532.73	102.58	742.33	4.64	25,673.73
20	0.8916	1,108.53	579.10	74.94	679.28	5.27	44,243.26
21	0.8807	795.96	543.63	77.57	720.20	4.74	27,490.11
22	0.8795	1,059.52	579.53	82.00	622.79	4.95	44,313.77
23	0.8343	677.78	488.63	107.25	754.00	4.98	24,843.41
24	0.8197	1,049.50	605.79	58.84	650.72	5.37	38,065.47
25	0.7739	1,042.27	507.73	64.09	621.44	4.94	38,920.15
26	0.6270	858.37	582.58	82.73	700.18	5.34	30,890.05

Table H2 An example list of multi-objective values of optimized plans for case area 1 in 2019.

Ranking from Fitness value	Fitness value of plan	Value of Obj. 1	Value of Obj. 2	Value of Obj. 3	Value of Obj. 4	Value of Obj. 5	Value of Obj. 6
1	0.9826	1,391.57	854.07	55.00	558.14	5.48	92,548.72
2	0.9809	1,357.01	846.22	52.82	548.12	5.67	86,740.60
3	0.9784	1,411.34	846.55	56.77	540.85	5.18	92,098.40
4	0.9713	1,374.19	867.16	69.65	560.05	5.40	95,858.75
5	0.9692	1,433.41	855.03	55.01	550.67	5.76	94,256.40
6	0.9672	1,424.69	866.54	48.29	545.45	5.49	92,417.62
7	0.9588	1,378.93	856.01	57.94	505.32	5.73	88,220.39
8	0.9574	1,356.33	846.90	50.08	536.30	5.63	86,569.63
9	0.9563	1,393.26	856.27	50.77	570.64	6.17	92,008.82
10	0.9558	1,452.71	839.99	72.25	532.32	5.54	105,814.19
11	0.9528	1,421.04	851.43	71.01	564.69	5.50	99,258.58
12	0.9524	1,357.08	799.51	50.07	571.73	5.15	89,124.64
13	0.9494	1,447.10	843.05	52.52	561.08	5.44	98,163.70
14	0.9491	1,385.73	867.29	41.27	497.96	4.94	89,077.60
15	0.9473	1,423.16	843.44	66.79	517.30	4.82	99,798.32
16	0.9466	1,364.94	862.03	34.40	541.71	5.40	87,336.55
17	0.9437	1,437.81	843.21	35.24	501.45	5.90	92,088.39
18	0.9374	1,453.13	867.11	65.95	572.07	6.09	102,898.94
19	0.9348	1,476.99	872.68	52.22	520.26	5.45	104,636.25
20	0.9338	1,469.28	853.38	43.85	511.08	5.71	95,690.75
21	0.9281	1,323.91	870.37	55.53	553.14	5.77	83,770.91
22	0.9272	1,335.79	869.40	63.27	538.17	6.05	84,472.00
23	0.9268	1,311.81	771.50	47.84	569.13	5.39	83,274.80
24	0.9266	1,413.93	837.69	59.29	504.69	4.83	96,813.74
25	0.9223	1,456.44	869.67	37.82	483.55	5.15	98,875.34
26	0.9201	1,373.77	864.72	40.08	493.47	4.81	91,003.29
27	0.9165	1,433.81	872.77	18.01	484.52	5.09	86,037.14
28	0.8902	1,347.01	817.91	29.72	505.91	5.27	79,153.24
29	0.8769	1,420.82	877.98	51.27	571.05	5.61	95,589.82
30	0.8641	1,351.40	873.08	28.80	492.37	6.11	82,776.11
31	0.8611	1,405.77	822.90	47.60	522.03	5.65	89,524.66
32	0.7928	1,396.46	777.44	71.00	549.59	5.83	94,768.94
33	0.7882	1,397.48	873.76	45.68	577.59	5.34	91,665.45
34	0.6498	1,410.54	860.93	19.05	518.22	6.91	90,435.14

Table H3 An example list of multi-objective values of optimized plans for case area 2 in 2016.

Ranking from Fitness value	Fitness value of plan	Value of Obj. 1	Value of Obj. 2	Value of Obj. 3	Value of Obj. 4	Value of Obj. 5	Value of Obj. 6
1	0.9980	2,415.57	2,348.92	164.55	6,297.95	0.78	180,311.28
2	0.9976	2,415.57	2,368.99	124.42	6,300.35	0.71	161,206.02
3	0.9970	2,434.88	2,377.73	158.83	5,335.26	0.87	182,080.88
4	0.9969	2,415.57	2,377.91	106.56	5,258.64	0.75	159,640.47
5	0.9947	2,415.57	2,349.81	161.56	6,389.82	0.78	179,998.19
6	0.9947	2,461.02	2,410.60	128.22	6,261.55	0.72	168,007.82
7	0.9946	2,415.57	2,375.58	111.23	5,336.08	0.73	157,059.39
8	0.9946	2,415.57	2,359.34	143.70	6,411.67	0.75	166,165.81
9	0.9938	2,463.78	2,357.96	135.55	6,191.66	0.78	172,310.57
10	0.9938	2,459.45	2,418.18	113.58	5,359.34	0.73	174,046.44
11	0.9921	2,415.57	2,351.76	158.87	6,408.59	0.80	181,097.25
12	0.9920	2,415.57	2,350.01	162.36	5,436.24	0.85	181,559.81
13	0.9914	2,415.57	2,348.66	165.08	6,447.79	0.82	181,419.26
14	0.9913	2,459.45	2,396.89	156.18	6,302.79	0.78	185,067.31
15	0.9909	2,415.57	2,358.93	144.53	5,471.15	0.86	165,824.12
16	0.9907	2,415.57	2,355.18	152.03	5,418.05	0.79	177,192.12
17	0.9904	2,434.88	2,382.60	147.75	5,981.81	0.83	182,746.29
18	0.9903	2,434.88	2,375.76	161.56	6,382.94	0.79	183,108.86
19	0.9902	2,475.19	2,426.90	123.00	6,356.92	0.73	169,974.00
20	0.9902	2,417.14	2,362.41	137.05	6,232.71	0.73	165,044.51
21	0.9902	2,417.14	2,349.01	163.84	6,496.56	0.79	168,074.56
22	0.9902	2,417.14	2,355.48	150.90	5,521.25	0.78	168,162.47
23	0.9902	2,417.14	2,374.42	113.02	5,295.17	0.70	160,827.92
24	0.9902	2,417.14	2,362.58	136.70	6,200.18	0.75	176,297.93
25	0.9902	2,417.14	2,363.05	135.77	6,248.19	0.76	165,855.58
26	0.9902	2,417.14	2,367.00	127.86	6,113.81	0.72	161,706.26
27	0.9902	2,417.14	2,375.59	110.69	5,137.92	0.71	159,827.32
28	0.9902	2,417.14	2,372.79	116.29	5,059.67	0.73	158,997.77
29	0.9902	2,417.14	2,372.13	117.61	5,014.10	0.76	159,365.11
30	0.9902	2,417.14	2,359.79	142.28	5,027.71	0.80	164,274.41
31	0.9902	2,417.14	2,358.14	145.59	6,423.29	0.79	166,345.84
32	0.9902	2,417.14	2,369.80	122.26	6,096.34	0.65	162,256.75
33	0.9902	2,417.14	2,364.41	133.03	6,284.02	0.73	163,583.06
34	0.9902	2,417.14	2,369.19	123.47	6,387.27	0.70	160,496.23
35	0.9902	2,417.14	2,348.24	165.39	5,902.84	0.83	171,934.06
36	0.9902	2,417.14	2,362.72	101.05	5,909.00	0.79	152,288.20
37	0.9902	2,417.14	2,354.18	153.51	5,678.64	0.83	168,528.14
38	0.9902	2,417.14	2,356.13	149.59	5,590.79	0.82	166,808.91
39	0.9902	2,415.57	2,375.15	112.09	6,007.37	0.71	158,960.24
40	0.9900	2,415.57	2,357.75	146.14	6,196.48	0.77	176,813.11
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
128	0.8179	2,782.93	2,395.01	88.82	5,037.23	0.81	284,784.69

Table H4 An example list of multi-objective values of optimized plans for case area 2 in 2019.

Ranking from Fitness value	Fitness value of plan	Value of Obj. 1	Value of Obj. 2	Value of Obj. 3	Value of Obj. 4	Value of Obj. 5	Value of Obj. 6
1	0.9967	2,613.40	2,581.96	135.63	3,991.12	0.75	197,077.57
2	0.9933	2,613.40	2,588.20	123.14	4,510.93	0.76	193,497.90
3	0.9925	2,562.46	2,489.97	131.16	4,083.23	0.77	190,283.63
4	0.9924	2,562.46	2,495.37	120.37	4,117.49	0.72	186,913.42
5	0.9916	2,718.73	2,680.49	115.20	3,996.56	0.73	242,039.15
6	0.9910	2,663.74	2,625.47	117.26	4,449.32	0.72	200,328.63
7	0.9908	2,562.46	2,503.28	104.54	3,980.92	0.65	185,328.22
8	0.9893	2,613.40	2,595.56	108.42	3,982.58	0.69	206,105.89
9	0.9893	2,562.46	2,477.95	155.20	4,152.48	0.78	211,029.50
10	0.9885	2,562.46	2,494.52	122.05	4,497.24	0.70	186,320.90
11	0.9875	2,563.84	2,500.57	112.63	4,010.55	0.65	200,088.17
12	0.9872	2,562.46	2,504.04	103.02	4,140.94	0.67	196,999.95
13	0.9869	2,709.95	2,677.83	135.84	4,515.10	0.80	209,952.31
14	0.9863	2,613.40	2,597.33	104.88	4,034.77	0.69	190,342.04
15	0.9860	2,658.32	2,626.45	106.50	4,453.75	0.71	196,779.06
16	0.9859	2,693.31	2,677.68	98.67	4,079.13	0.75	217,366.46
17	0.9851	2,562.46	2,491.49	128.12	4,262.60	0.73	187,039.13
18	0.9846	2,614.79	2,578.94	143.72	4,493.49	0.76	197,914.63
19	0.9845	2,673.81	2,659.62	97.07	3,975.70	0.66	216,069.09
20	0.9840	2,562.46	2,500.86	109.38	3,928.67	0.65	186,037.52
21	0.9834	2,613.40	2,599.37	100.79	4,199.02	0.70	190,159.53
22	0.9821	2,562.46	2,505.15	100.79	4,166.86	0.69	183,786.78
23	0.9817	2,668.46	2,553.85	97.92	3,353.11	0.68	197,948.90
24	0.9811	2,562.46	2,494.29	122.53	4,471.85	0.74	186,853.09
25	0.9806	2,650.34	2,622.94	98.09	4,112.55	0.71	195,464.89
26	0.9803	2,562.46	2,483.37	144.37	4,523.66	0.75	193,680.05
27	0.9799	2,562.46	2,489.70	128.78	4,460.79	0.73	186,849.00
28	0.9789	2,651.73	2,603.09	109.60	4,395.08	0.85	192,629.84
29	0.9780	2,921.24	2,596.36	76.04	3,235.74	0.67	241,411.88
30	0.9771	2,650.34	2,606.38	131.21	4,158.99	0.75	203,675.18
31	0.9769	2,613.40	2,599.61	100.33	3,890.39	0.65	204,025.87
32	0.9765	2,710.74	2,664.55	131.64	4,420.31	0.84	229,799.51
33	0.9760	2,770.13	2,629.31	76.60	3,643.48	0.75	209,885.37
34	0.9756	2,629.74	2,549.31	121.57	4,247.32	0.79	197,272.81
35	0.9752	2,663.74	2,633.35	101.48	4,428.91	0.69	195,987.49
36	0.9751	2,562.46	2,495.51	120.08	4,472.31	0.74	186,931.33
37	0.9744	2,562.46	2,487.38	136.35	4,690.88	0.76	189,277.74
38	0.9737	2,641.35	2,567.36	133.89	4,059.78	0.77	202,746.28
39	0.9732	2,879.70	2,619.75	97.92	3,401.62	0.72	226,248.92
40	0.9691	2,668.78	2,615.95	147.73	4,549.69	0.77	210,466.59
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
74	0.5175	3,105.65	2,650.47	50.56	4,149.53	0.72	251,057.78

Table H5 An example list of multi-objective values of optimized plans for case area 3 in 2016.

Ranking from Fitness value	Fitness value of plan	Value of Obj. 1	Value of Obj. 2	Value of Obj. 3	Value of Obj. 4	Value of Obj. 5	Value of Obj. 6
1	0.9992	3,460.12	2,914.46	23.31	1,975.57	0.82	34,882.50
2	0.9991	3,394.84	2,794.42	27.02	1,999.03	0.73	34,291.55
3	0.9990	3,433.30	2,851.70	22.02	1,996.32	0.70	33,850.24
4	0.9989	3,468.27	2,845.79	14.39	1,981.36	0.74	33,909.87
5	0.9989	3,431.65	2,862.48	27.34	2,006.48	0.72	36,993.32
6	0.9988	3,438.80	2,832.31	27.17	2,036.28	0.75	33,972.50
7	0.9988	3,456.43	2,857.35	28.32	2,025.80	0.78	34,600.48
8	0.9987	3,428.09	2,798.72	20.13	1,981.69	0.77	33,602.22
9	0.9986	3,436.94	2,796.12	20.62	1,998.45	0.83	33,799.57
10	0.9986	3,466.30	2,936.46	10.20	1,959.85	0.78	34,876.70
11	0.9986	3,315.14	2,693.86	21.97	1,995.90	0.71	32,317.74
12	0.9985	3,422.97	2,829.93	22.38	2,010.79	0.75	34,822.39
13	0.9985	3,460.72	2,819.31	25.83	2,012.22	0.83	35,154.84
14	0.9983	3,469.91	2,886.39	29.42	2,035.15	0.75	36,452.24
15	0.9983	3,405.71	2,893.20	26.61	1,974.65	0.79	33,566.60
16	0.9982	3,459.18	2,882.36	20.82	1,988.27	0.83	34,858.64
17	0.9982	3,463.67	2,826.74	30.68	2,002.41	0.78	35,858.12
18	0.9982	3,469.75	2,907.14	13.98	2,006.16	0.77	35,223.22
19	0.9981	3,462.25	2,891.25	31.47	1,998.11	0.82	34,873.80
20	0.9981	3,416.13	2,878.95	26.27	1,990.35	0.76	33,743.55
21	0.9981	3,425.63	2,896.95	20.69	1,999.68	0.81	34,149.73
22	0.9980	3,470.25	2,933.50	33.66	2,022.61	0.82	35,725.22
23	0.9980	3,467.44	2,836.04	21.39	1,997.97	0.78	35,821.44
24	0.9980	3,388.60	2,807.08	22.81	1,959.81	0.72	33,605.13
25	0.9980	3,370.20	2,951.32	27.18	1,982.60	0.77	33,234.16
26	0.9980	3,309.43	2,898.75	11.83	1,952.24	0.82	31,995.01
27	0.9980	3,416.62	2,923.16	17.75	2,004.79	0.78	33,114.97
28	0.9980	3,414.01	2,761.57	25.19	2,004.19	0.75	33,856.17
29	0.9980	3,455.82	2,788.83	26.17	2,031.73	0.73	35,093.76
30	0.9979	3,380.51	2,744.95	30.85	2,004.37	0.82	33,076.53
31	0.9979	3,458.29	2,946.27	22.50	1,985.88	0.78	35,408.42
32	0.9979	3,439.88	2,914.16	17.81	1,991.57	0.83	33,643.63
33	0.9979	3,410.54	2,840.28	31.48	1,967.31	0.76	35,075.28
34	0.9978	3,457.32	2,915.62	25.60	2,009.58	0.78	35,538.01
35	0.9978	3,450.14	2,841.32	31.74	2,013.93	0.84	34,889.51
36	0.9978	3,444.21	2,904.48	30.97	1,976.05	0.81	34,491.88
37	0.9978	3,454.98	2,877.37	27.65	2,018.64	0.75	34,174.11
38	0.9978	3,373.18	2,821.92	15.62	1,971.69	0.75	32,563.55
39	0.9978	3,470.39	2,805.40	11.28	1,964.51	0.80	34,859.66
40	0.9978	3,433.13	2,919.48	19.92	1,969.74	0.79	34,246.68
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
370	0.7425	3,395.11	2,673.63	44.24	2,029.25	0.84	35,013.02

Table H6 An example list of multi-objective values of optimized plans for case area 3 in 2019.

Ranking from Fitness value	Fitness value of plan	Value of Obj. 1	Value of Obj. 2	Value of Obj. 3	Value of Obj. 4	Value of Obj. 5	Value of Obj. 6
1	0.9945	3,479.60	2,919.29	16.43	2,032.71	0.70	97,390.01
2	0.9942	3,448.84	2,980.23	25.05	2,021.58	0.73	97,729.12
3	0.9937	3,478.14	2,954.40	17.41	2,044.21	0.73	96,996.31
4	0.9933	3,469.40	2,952.75	16.65	2,039.84	0.78	91,710.06
5	0.9932	3,483.35	2,938.00	14.97	2,002.01	0.71	94,821.91
6	0.9930	3,488.21	2,922.04	17.37	1,997.95	0.73	97,157.06
7	0.9925	3,434.97	2,948.63	16.58	2,019.05	0.74	90,139.38
8	0.9925	3,441.70	2,824.39	18.46	2,054.68	0.73	92,502.61
9	0.9917	3,454.79	2,917.79	22.49	2,045.62	0.71	93,635.76
10	0.9916	3,415.00	2,951.49	24.60	2,046.45	0.72	92,114.21
11	0.9915	3,464.69	2,858.67	15.89	2,047.46	0.71	97,858.72
12	0.9907	3,481.37	2,980.55	18.70	1,993.86	0.75	97,531.62
13	0.9907	3,456.94	2,975.98	21.51	2,055.69	0.68	99,350.32
14	0.9905	3,436.15	2,960.99	16.69	2,002.20	0.77	93,217.47
15	0.9902	3,429.71	2,866.72	18.90	2,025.59	0.69	93,310.76
16	0.9902	3,496.19	2,920.94	20.46	2,035.10	0.75	95,799.89
17	0.9902	3,448.89	2,903.57	26.68	2,074.51	0.74	96,698.54
18	0.9902	3,441.12	2,955.34	22.09	2,023.15	0.67	92,810.92
19	0.9899	3,468.98	2,843.77	25.10	2,033.20	0.71	100,990.40
20	0.9895	3,423.78	2,961.29	25.00	2,058.73	0.78	91,766.76
21	0.9895	3,474.01	2,936.07	15.30	2,027.45	0.74	93,026.82
22	0.9892	3,375.86	2,939.13	21.96	2,049.62	0.66	93,893.55
23	0.9889	3,480.53	3,005.68	26.05	2,017.90	0.73	99,095.77
24	0.9888	3,459.80	3,007.83	19.03	2,001.37	0.69	92,259.78
25	0.9888	3,503.02	2,938.38	13.19	2,039.42	0.79	95,198.99
26	0.9888	3,500.51	2,917.50	26.80	2,048.79	0.80	97,956.10
27	0.9887	3,475.38	2,881.45	12.95	2,005.75	0.72	94,754.39
28	0.9886	3,498.67	2,931.52	16.39	2,037.60	0.66	95,572.87
29	0.9885	3,469.95	2,973.67	31.05	2,028.61	0.75	95,673.77
30	0.9883	3,481.29	2,963.41	24.67	2,020.73	0.74	96,176.20
31	0.9882	3,419.59	2,881.52	25.81	2,073.92	0.74	91,607.84
32	0.9875	3,492.52	2,928.75	23.94	2,026.85	0.75	97,233.10
33	0.9875	3,476.10	2,952.65	10.47	2,014.02	0.70	100,003.81
34	0.9872	3,503.06	3,000.66	19.28	2,022.34	0.75	98,150.60
35	0.9872	3,454.22	2,876.99	17.24	2,027.93	0.77	93,509.84
36	0.9869	3,490.19	2,937.98	17.36	2,011.28	0.75	96,020.75
37	0.9868	3,479.45	2,892.15	30.87	2,057.55	0.79	95,497.24
38	0.9867	3,404.91	2,792.85	26.51	2,024.00	0.69	92,573.36
39	0.9865	3,494.14	2,964.00	14.38	2,002.49	0.80	96,214.56
40	0.9865	3,465.72	2,933.72	27.04	2,026.04	0.71	97,362.17
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
115	0.8486	3,434.71	2,907.73	14.76	2,044.40	0.65	91,048.73

APPENDIX I

AN EXAMPLE LIST OF SNOV

Table I1 An example list of SNOV of optimized plans for case area 1 in 2016.

Ranking from Fitness value	Nor_Value of Obj. 1	Nor_Value of Obj. 2	Nor_Value of Obj. 3	Nor_Value of Obj. 4	Nor_Value of Obj. 5	Nor_Value of Obj. 6	Sum of all Objective
existing urban LU 2016	**0.60**	**1.00**	**0.01**	**0.88**	**0.21**	**0.66**	**3.36**
1	0.94	1.00	0.49	0.82	0.10	0.17	3.52
2	0.95	0.99	0.49	0.81	0.09	0.22	3.55
3	0.73	1.00	0.67	0.96	0.08	0.39	3.84
4	0.68	0.93	0.74	0.94	0.01	0.46	3.76
5	0.96	0.99	0.70	0.81	0.01	0.05	3.52
6	1.00	0.97	0.62	0.82	0.10	0.04	3.54
7	0.91	0.95	0.54	0.90	0.07	0.27	3.63
8	0.97	0.96	0.43	0.83	0.00	0.18	3.37
9	0.98	0.98	0.71	0.82	0.01	0.09	3.58
10	0.75	0.94	0.51	0.92	0.10	0.48	3.70
11	0.99	0.98	0.67	0.81	0.03	0.06	3.54
12	0.98	0.96	0.40	0.88	0.06	0.23	3.51
13	0.72	0.91	0.70	0.97	0.10	0.42	3.81
14	0.99	0.98	0.66	0.78	0.02	0.00	3.43
15	0.72	0.92	1.00	0.97	0.02	0.36	4.00
16	0.99	1.00	0.46	0.75	0.08	0.14	3.43
17	1.00	0.99	0.28	0.69	0.07	0.19	3.22
18	0.99	0.95	0.32	0.78	0.04	0.22	3.30
19	0.67	0.87	0.79	0.98	0.16	0.51	3.98
20	0.97	0.95	0.57	0.90	0.04	0.15	3.59
21	0.70	0.89	0.59	0.96	0.14	0.47	3.75
22	0.93	0.95	0.63	0.83	0.10	0.15	3.58
23	0.60	0.80	0.82	1.00	0.10	0.52	3.83
24	0.92	0.99	0.45	0.86	0.02	0.27	3.52
25	0.92	0.83	0.49	0.82	0.10	0.25	3.42
26	0.75	0.95	0.63	0.93	0.03	0.41	3.71

* Nor : Normalize

Table I2 An example list of SNOV of optimized plans for case area 1 in 2019.

Ranking from Fitness value	Nor_Value of Obj. 1	Nor_Value of Obj. 2	Nor_Value of Obj. 3	Nor_Value of Obj. 4	Nor_Value of Obj. 5	Nor_Value of Obj. 6	Sum of all Objective
predicted urban LU 2019	**0.57**	**0.84**	**0.02**	**0.94**	**0.09**	**0.66**	**3.13**
1	0.94	0.97	0.76	0.97	0.21	0.13	3.97
2	0.92	0.96	0.73	0.95	0.18	0.18	3.92
3	0.96	0.96	0.79	0.94	0.25	0.13	4.02
4	0.93	0.99	0.96	0.97	0.22	0.09	4.16
5	0.97	0.97	0.76	0.95	0.17	0.11	3.94
6	0.96	0.99	0.67	0.94	0.20	0.13	3.90
7	0.93	0.97	0.80	0.87	0.17	0.17	3.92
8	0.92	0.96	0.69	0.93	0.19	0.18	3.87
9	0.94	0.98	0.70	0.99	0.11	0.13	3.85
10	0.98	0.96	1.00	0.92	0.20	0.00	4.06
11	0.96	0.97	0.98	0.98	0.20	0.06	4.16
12	0.92	0.91	0.69	0.99	0.26	0.16	3.93
13	0.98	0.96	0.73	0.97	0.21	0.07	3.92
14	0.94	0.99	0.57	0.86	0.29	0.16	3.80
15	0.96	0.96	0.92	0.90	0.30	0.06	4.10
16	0.92	0.98	0.48	0.94	0.22	0.17	3.71
17	0.97	0.96	0.49	0.87	0.15	0.13	3.57
18	0.98	0.99	0.91	0.99	0.12	0.03	4.02
19	1.00	0.99	0.72	0.90	0.21	0.01	3.84
20	0.99	0.97	0.61	0.88	0.17	0.10	3.73
21	0.90	0.99	0.77	0.96	0.16	0.21	3.99
22	0.90	0.99	0.88	0.93	0.12	0.20	4.03
23	0.89	0.88	0.66	0.99	0.22	0.21	3.85
24	0.96	0.95	0.82	0.87	0.30	0.09	3.99
25	0.99	0.99	0.52	0.84	0.25	0.07	3.66
26	0.93	0.98	0.55	0.85	0.30	0.14	3.77
27	0.97	0.99	0.25	0.84	0.26	0.19	3.50
28	0.91	0.93	0.41	0.88	0.24	0.25	3.62
29	0.96	1.00	0.71	0.99	0.19	0.10	3.94
30	0.91	0.99	0.40	0.85	0.12	0.22	3.49
31	0.95	0.94	0.66	0.90	0.18	0.15	3.79
32	0.95	0.89	0.98	0.95	0.16	0.10	4.03
33	0.95	1.00	0.63	1.00	0.23	0.13	3.93
34	0.96	0.98	0.26	0.90	0.00	0.15	3.24

* Nor : Normalize

Table I3 An example list of SNOV of optimized plans for case area 2 in 2016.

Ranking from Fitness value	Nor_Value of Obj. 1	Nor_Value of Obj. 2	Nor_Value of Obj. 3	Nor_Value of Obj. 4	Nor_Value of Obj. 5	Nor_Value of Obj. 6	Sum of all Objective
existing urban LU 2016	**0.77**	**1.00**	**0.00**	**0.78**	**0.10**	**0.57**	**3.21**
1	0.75	0.94	0.99	0.94	0.18	0.42	4.23
2	0.75	0.95	0.75	0.94	0.25	0.48	4.12
3	0.76	0.95	0.96	0.80	0.08	0.42	3.96
4	0.75	0.95	0.64	0.79	0.21	0.49	3.83
5	0.75	0.94	0.98	0.95	0.17	0.42	4.22
6	0.77	0.96	0.78	0.94	0.24	0.46	4.14
7	0.75	0.95	0.67	0.80	0.23	0.50	3.90
8	0.75	0.94	0.87	0.96	0.21	0.47	4.20
9	0.77	0.94	0.82	0.93	0.18	0.45	4.08
10	0.76	0.97	0.69	0.80	0.23	0.44	3.90
11	0.75	0.94	0.96	0.96	0.15	0.42	4.18
12	0.75	0.94	0.98	0.81	0.11	0.42	4.01
13	0.75	0.94	1.00	0.96	0.14	0.42	4.21
14	0.76	0.96	0.94	0.94	0.17	0.41	4.19
15	0.75	0.94	0.87	0.82	0.09	0.47	3.95
16	0.75	0.94	0.92	0.81	0.17	0.43	4.03
17	0.76	0.95	0.89	0.89	0.13	0.41	4.04
18	0.76	0.95	0.98	0.95	0.17	0.41	4.22
19	0.77	0.97	0.74	0.95	0.23	0.46	4.12
20	0.75	0.95	0.83	0.93	0.23	0.47	4.16
21	0.75	0.94	0.99	0.97	0.17	0.46	4.29
22	0.75	0.94	0.91	0.82	0.17	0.46	4.06
23	0.75	0.95	0.68	0.79	0.26	0.48	3.92
24	0.75	0.95	0.83	0.93	0.21	0.44	4.09
25	0.75	0.95	0.82	0.93	0.20	0.47	4.12
26	0.75	0.95	0.77	0.91	0.24	0.48	4.11
27	0.75	0.95	0.67	0.77	0.25	0.49	3.88
28	0.75	0.95	0.70	0.76	0.23	0.49	3.88
29	0.75	0.95	0.71	0.75	0.20	0.49	3.85
30	0.75	0.94	0.86	0.75	0.15	0.47	3.93
31	0.75	0.94	0.88	0.96	0.17	0.47	4.17
32	0.75	0.95	0.74	0.91	0.32	0.48	4.15
33	0.75	0.95	0.80	0.94	0.23	0.48	4.15
34	0.75	0.95	0.75	0.95	0.26	0.49	4.14
35	0.75	0.94	1.00	0.88	0.12	0.45	4.15
36	0.75	0.95	0.61	0.88	0.17	0.51	3.87
37	0.75	0.94	0.93	0.85	0.13	0.46	4.06
38	0.75	0.94	0.90	0.84	0.13	0.47	4.03
39	0.75	0.95	0.68	0.90	0.25	0.49	4.02
40	0.75	0.94	0.88	0.93	0.19	0.43	4.12
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
128	0.87	0.96	0.54	0.75	0.14	0.09	3.35

* Nor : Normalize

Table I4 An example list of SNOV of optimized plans for case area 2 in 2019.

Ranking from Fitness value	Nor_Value of Obj. 1	Nor_Value of Obj. 2	Nor_Value of Obj. 3	Nor_Value of Obj. 4	Nor_Value of Obj. 5	Nor_Value of Obj. 6	Sum of all Objective
predicted urban LU 2019	**0.86**	**1.00**	**0.00**	**0.83**	**0.10**	**0.29**	**3.08**
1	0.84	0.96	0.87	0.83	0.29	0.28	4.08
2	0.84	0.96	0.79	0.94	0.28	0.30	4.12
3	0.83	0.92	0.85	0.85	0.27	0.31	4.03
4	0.83	0.92	0.78	0.86	0.32	0.32	4.03
5	0.88	0.99	0.74	0.83	0.31	0.12	3.88
6	0.86	0.97	0.76	0.93	0.33	0.27	4.11
7	0.83	0.93	0.67	0.83	0.39	0.33	3.97
8	0.84	0.96	0.70	0.83	0.35	0.25	3.93
9	0.83	0.92	1.00	0.87	0.26	0.23	4.11
10	0.83	0.92	0.79	0.94	0.34	0.32	4.14
11	0.83	0.93	0.73	0.84	0.39	0.27	3.97
12	0.83	0.93	0.66	0.87	0.37	0.28	3.93
13	0.87	0.99	0.88	0.94	0.25	0.24	4.17
14	0.84	0.96	0.68	0.84	0.35	0.31	3.98
15	0.86	0.97	0.69	0.93	0.33	0.28	4.06
16	0.87	0.99	0.64	0.85	0.30	0.21	3.85
17	0.83	0.92	0.83	0.89	0.32	0.32	4.10
18	0.84	0.95	0.93	0.94	0.28	0.28	4.22
19	0.86	0.98	0.63	0.83	0.38	0.21	3.89
20	0.83	0.93	0.70	0.82	0.39	0.32	3.99
21	0.84	0.96	0.65	0.88	0.34	0.31	3.98
22	0.83	0.93	0.65	0.87	0.35	0.33	3.96
23	0.86	0.95	0.63	0.70	0.36	0.28	3.78
24	0.83	0.92	0.79	0.93	0.30	0.32	4.10
25	0.85	0.97	0.63	0.86	0.33	0.29	3.93
26	0.83	0.92	0.93	0.95	0.29	0.30	4.21
27	0.83	0.92	0.83	0.93	0.31	0.32	4.14
28	0.85	0.96	0.71	0.92	0.20	0.30	3.94
29	0.94	0.96	0.49	0.68	0.37	0.12	3.56
30	0.85	0.96	0.85	0.87	0.29	0.26	4.09
31	0.84	0.96	0.65	0.81	0.39	0.26	3.91
32	0.87	0.99	0.85	0.92	0.21	0.16	4.00
33	0.89	0.97	0.49	0.76	0.30	0.24	3.65
34	0.85	0.94	0.78	0.89	0.25	0.28	4.00
35	0.86	0.97	0.65	0.93	0.35	0.29	4.05
36	0.83	0.92	0.77	0.93	0.30	0.32	4.08
37	0.83	0.92	0.88	0.98	0.29	0.31	4.20
38	0.85	0.95	0.86	0.85	0.28	0.26	4.05
39	0.93	0.97	0.63	0.71	0.32	0.18	3.74
40	0.86	0.97	0.95	0.95	0.28	0.23	4.24
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
74	1.00	0.98	0.33	0.87	0.32	0.09	3.58

* Nor : Normalize

Table I5 An example list of SNOV of optimized plans for case area 3 in 2016.

Ranking from Fitness value	Nor_Value of Obj. 1	Nor_Value of Obj. 2	Nor_Value of Obj. 3	Nor_Value of Obj. 4	Nor_Value of Obj. 5	Nor_Value of Obj. 6	Sum of all Objective
existing urban LU 2016	**0.78**	**0.82**	**0.00**	**0.96**	**0.03**	**0.70**	**3.30**
1	1.00	0.97	0.53	0.96	0.08	0.08	3.61
2	0.98	0.93	0.61	0.97	0.18	0.09	3.76
3	0.99	0.95	0.50	0.97	0.22	0.10	3.72
4	1.00	0.94	0.33	0.96	0.18	0.10	3.51
5	0.99	0.95	0.62	0.97	0.20	0.02	3.75
6	0.99	0.94	0.61	0.99	0.17	0.10	3.80
7	1.00	0.95	0.64	0.98	0.13	0.08	3.78
8	0.99	0.93	0.46	0.96	0.14	0.11	3.58
9	0.99	0.93	0.47	0.97	0.08	0.10	3.54
10	1.00	0.98	0.23	0.95	0.13	0.08	3.37
11	0.96	0.89	0.50	0.97	0.21	0.14	3.67
12	0.99	0.94	0.51	0.98	0.17	0.08	3.65
13	1.00	0.94	0.58	0.98	0.08	0.07	3.64
14	1.00	0.96	0.67	0.99	0.17	0.03	3.81
15	0.98	0.96	0.60	0.96	0.12	0.11	3.73
16	1.00	0.96	0.47	0.96	0.08	0.08	3.55
17	1.00	0.94	0.69	0.97	0.13	0.05	3.78
18	1.00	0.97	0.32	0.97	0.15	0.07	3.47
19	1.00	0.96	0.71	0.97	0.09	0.08	3.81
20	0.98	0.96	0.59	0.97	0.16	0.11	3.76
21	0.99	0.96	0.47	0.97	0.10	0.10	3.58
22	1.00	0.97	0.76	0.98	0.09	0.05	3.86
23	1.00	0.94	0.48	0.97	0.13	0.05	3.58
24	0.98	0.93	0.52	0.95	0.20	0.11	3.68
25	0.97	0.98	0.61	0.96	0.14	0.12	3.79
26	0.95	0.96	0.27	0.95	0.09	0.15	3.38
27	0.98	0.97	0.40	0.97	0.13	0.12	3.59
28	0.98	0.92	0.57	0.97	0.16	0.10	3.71
29	1.00	0.93	0.59	0.99	0.19	0.07	3.76
30	0.97	0.91	0.70	0.97	0.09	0.12	3.76
31	1.00	0.98	0.51	0.96	0.13	0.06	3.64
32	0.99	0.97	0.40	0.97	0.08	0.11	3.51
33	0.98	0.94	0.71	0.95	0.15	0.07	3.81
34	1.00	0.97	0.58	0.97	0.13	0.06	3.70
35	0.99	0.94	0.72	0.98	0.07	0.08	3.78
36	0.99	0.96	0.70	0.96	0.10	0.09	3.81
37	1.00	0.96	0.62	0.98	0.17	0.09	3.82
38	0.97	0.94	0.35	0.96	0.17	0.14	3.52
39	1.00	0.93	0.25	0.95	0.11	0.08	3.33
40	0.99	0.97	0.45	0.96	0.12	0.09	3.58
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
370	0.98	0.89	1.00	0.98	0.07	0.07	3.99

* Nor : Normalize

Table I6 An example list of SNOV of optimized plans for case area 3 in 2019.

Ranking from Fitness value	Nor_Value of Obj. 1	Nor_Value of Obj. 2	Nor_Value of Obj. 3	Nor_Value of Obj. 4	Nor_Value of Obj. 5	Nor_Value of Obj. 6	Sum of all Objective
predicted urban LU 2019	**0.78**	**0.82**	**0.00**	**0.97**	**0.03**	**0.76**	**3.36**
1	0.99	0.96	0.52	0.98	0.14	0.06	3.65
2	0.98	0.98	0.80	0.97	0.11	0.05	3.89
3	0.99	0.97	0.56	0.98	0.09	0.06	3.66
4	0.99	0.97	0.53	0.98	0.04	0.11	3.62
5	0.99	0.96	0.48	0.96	0.12	0.08	3.61
6	1.00	0.96	0.55	0.96	0.10	0.06	3.63
7	0.98	0.97	0.53	0.97	0.09	0.13	3.66
8	0.98	0.93	0.59	0.99	0.10	0.10	3.69
9	0.99	0.96	0.72	0.98	0.12	0.09	3.86
10	0.97	0.97	0.79	0.98	0.11	0.11	3.93
11	0.99	0.94	0.51	0.99	0.12	0.05	3.59
12	0.99	0.98	0.60	0.96	0.07	0.06	3.65
13	0.99	0.98	0.69	0.99	0.16	0.04	3.83
14	0.98	0.97	0.53	0.96	0.05	0.10	3.59
15	0.98	0.94	0.60	0.97	0.15	0.10	3.75
16	1.00	0.96	0.65	0.98	0.08	0.07	3.74
17	0.98	0.95	0.85	1.00	0.08	0.06	3.94
18	0.98	0.97	0.71	0.97	0.17	0.10	3.91
19	0.99	0.93	0.80	0.98	0.12	0.02	3.85
20	0.98	0.97	0.80	0.99	0.04	0.11	3.89
21	0.99	0.96	0.49	0.98	0.09	0.10	3.60
22	0.96	0.96	0.70	0.99	0.19	0.09	3.89
23	0.99	0.98	0.83	0.97	0.10	0.04	3.92
24	0.99	0.99	0.61	0.96	0.14	0.11	3.79
25	1.00	0.96	0.42	0.98	0.02	0.08	3.47
26	1.00	0.96	0.86	0.99	0.02	0.05	3.87
27	0.99	0.94	0.41	0.97	0.11	0.08	3.51
28	1.00	0.96	0.52	0.98	0.19	0.07	3.72
29	0.99	0.97	0.99	0.98	0.08	0.07	4.09
30	0.99	0.97	0.79	0.97	0.08	0.07	3.88
31	0.98	0.94	0.82	1.00	0.09	0.11	3.94
32	1.00	0.96	0.76	0.98	0.07	0.06	3.83
33	0.99	0.97	0.33	0.97	0.14	0.03	3.43
34	1.00	0.98	0.62	0.97	0.07	0.05	3.70
35	0.99	0.94	0.55	0.98	0.06	0.09	3.61
36	1.00	0.96	0.55	0.97	0.08	0.07	3.63
37	0.99	0.95	0.99	0.99	0.03	0.08	4.02
38	0.97	0.92	0.85	0.97	0.15	0.10	3.96
39	1.00	0.97	0.46	0.96	0.02	0.07	3.48
40	0.99	0.96	0.86	0.97	0.13	0.06	3.97
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
115	0.98	0.95	0.47	0.98	0.19	0.12	3.70

* Nor : Normalize

CURRICULUM VITAE

Name Miss. Warunee Aunphoklang

Date of Birth January 14, 1986

Place of Birth Nakhon Ratchasima Province, Thailand

Education 2007 Bachelor Degree in Information Technology (Management Information System) Institute of Social Technology, Suranaree University of Technology

2012 Master Degree in Geoinformatics, School of Remote Sensing, Institute of Science, Suranaree University of Technology

Grant and Fellowships SUT outstanding academic performance scholarship, Suranaree University of Technology.