Ashenafi Aregawi Weldemichael

OPTIMIZATION BASED APPROACH FOR LAND-USE / TRANSPORTATION POLICY MAKING

PhD Thesis in Doctoral Program in Transport Systems, supervised by Professor António Pais Antunes and Professor P. Christopher Zegras, submitted to the Department of Civil Engineering of the Faculty of Sciences and Technology of the University of Coimbra

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FCTUC FACULDADE DE CIÊNCIAS E TECNOLOGIA UNIVERSIDADE DE COIMBRA

Optimization based approach for land-use/transportation policy making

By

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Submitted to the Department of Civil Engineering of the University of Coimbra in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Transportation Systems jointly offered by

Faculty of Sciences and Technology of the University of Coimbra
Faculty of Engineering of the University of Porto
Instituto Superior Técnico – Technical University of Lisbon
And with the support of the Massachusetts Institute of Technology through the MIT Portugal Program

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Coimbra, August, 2015

Financial support

This thesis was financed by "Fundação para a Ciência e a Tecnologia" (FCT, Portugal) through the PhD grant for MIT Portugal program with grant reference number SFRH / BD / 33742 / 2009. This PhD is also co-financed by the project "EMSURE (Energy and Mobility for sustainable regions)" with project ID: CENTRO – 07 – 0224 – FEDER – 002004.

MIT Portugal

FCT Fundação para a Ciência e a Tecnologia

MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E ENSINO SUPERIOR Portugal

Acknowledgements

I am thankful to many people who have contributed to my thesis in various ways.

First and foremost I would like to thank my supervisors Professor António Pais Antunes and Professor P. Christopher Zegras for their extraordinary guidance in my thesis process. I thank them for being wonderful mentors.

For the past six years, Professor Antunes guided me through my academic journey at University of Coimbra and provided me with all the necessary facilities for my research. He has always provided me with quick support in all scientific and administrative matters. I am truly privileged to have had learned from him and worked with him.

I would like to express my gratitude to Professor Christopher Zegras for providing insightful discussions regarding my research. I especially thank him for his great support during my visit time at the Department of Urban Studies and Planning at the MIT.

I would also like to thank all colleagues from the Spatial Planning and Transportation Engineering Group (DEC, University of Coimbra) and from the Ethiopian Institute of Technology – Mekelle (EiT – M) for their professional and moral support.

I am grateful to my friends at University of Coimbra. Their support has always been important source of power for me to move forward. To name just a few, Miguel Santos, Silvia Carvalho, Merkebe Getachew, and Rui Santos (IST). Special Thanks to Nuno Ribeiro who helped me with preparation of case stud data.

Last, but not least, I like to thank my family. Without their love and patience, this thesis would not have been possible. This thesis is dedicated to them.

Abstract

This thesis explores the potentials of optimization for land-use/transportation policy-making purposes. Fundamentally, the research aimed to design an approach that generates efficient maps (solutions) to respond to specific land-use/transportation policy objectives. In this context, unlike simulation based land-use/transportation models which vastly employ trial and error, the purpose was to design an optimization approach which directly guarantees the efficiency of solutions.

The mixed-integer optimization model upon which the approach is based has multiple objectives and is aimed at determining land use allocations and transportation infrastructure developments taking into account current form and future demographic changes at municipality level. The objectives of the optimization model are defined to address issues such as accessibility of population to jobs and services, suitability of land units to particular land-use types, compatibility of adjacent land-use types and utilization of existing infrastructure. The model makes special emphasis to the interactions between transportation and land-use.

In addition to the development of the model, this thesis explores potential solution methods. Initially, the optimization model is solved using a branch and bound method. In general, the computational effort requirement for this method is high. For that reason, a heuristic method, genetic algorithm, is developed. The quality of algorithm parameters and that of solutions are assessed. The heuristic method provides optimum and near optimum solutions with much smaller computational efforts.

The proposed approach was tested for hypothetical cities as well as for the municipality of Coimbra (Portugal). Results suggest that the approach can be of great practical utility as planning support tool in land-use/transportation policy-making processes, in the search for efficient solutions that also care for equity concerns in spatial development.

Keywords: *Land-use; transportation; policy-making; modeling; optimization; genetic algorithms.*

Resumo

Esta tese explora as possibilidades da otimização para ajudar no estabelecimento de planos integrados de usos de solos e transportes. Fundamentalmente, a investigação em que se apoia teve por propósito definir soluções (mapas) eficientes para responder a objetivos específicos em matéria de usos de solo e transportes. Ao contrário do que acontece com abordagens de simulação, cuja aplicação envolve processos de tentativa e erro, a otimização permite obter diretamente as referidas soluções para as hipóteses adotadas.

A abordagem proposta tem por base um modelo otimização inteiro-misto que permite determinar a utilização a dar aos solos de uma cidade e as evoluções da respetiva rede de transportes que mais bem permitem responder as crescimento demográfico esperado tendo em conta três objetivos: a adequação dos usos do solo às características físicas dos terrenos; a compatibilidade do uso dado a cada parcela de terreno com o das parcelas adjacentes; e a acessibilidade agregada aos empregos e serviços disponíveis na cidade.

Para resolver o modelo, que é do tipo inteiro linear, recorreu-se inicialmente ao método de branch-and-bound. No entanto, verificou-se que o esforço computacional correspondente seria muito elevado, tornando impossível a utilização do modelo em muitas situações reais. Assim, para estas situações, foi desenvolvido um algoritmo genético. O algoritmo e os respectivos parâmetros foram avaliados, concluindo-se que através da respectiva aplicação é possível encontrar soluções ótimas ou quase-ótimas com um esforço computacional muito mais reduzido.

A abordagem desenvolvida foi testada em cidades hipotéticas e no município de Coimbra (Portugal). Os resultados obtidos sugerem claramente que ela pode ser de grande utilidade como instrumento de apoio em processos de planeamento de usos de solo e transportes, na procura de soluções eficientes que também tenham em conta preocupações de equidade no desenvolvimento do território.

Table of contents

List of figures

List of tables

1 Introduction

1.1 Research framework

Decisions pertaining to the uses of land are among the most important that local authorities (decision-makers) have to make because of their multiple consequences on urban life and, in particular, their implications with respect to the transportation systems. Owing to this importance and given the complex nature of urban phenomenon, there has always been a strong desire to develop urban models, and more specifically, urban land-use/transportation models and utilize them as decision support tools.

Land-use/transportation models are mathematical models that are used to elucidate and forecast spatial outcomes in the form of land-uses, activities, traffic flows and transportation infrastructures. The purpose of land-use/transportation models is to serve as tools for planning; and serve as tools by which our understandings of the principles of urban organization can be enhanced (Batty 1976).

Since the time the first mathematical urban models were developed in the mid 50s – the Chicago Area Transportation Study in 1955 is considered to be the first study where such model were applied urban model (Plummer 2007) –, they have gone through lots of evolutionary changes. Two forces have contributed for this evolution. The first one is changes in urban phenomenon which call for the need of continuous development and utilization of urban models and the second one is the advances in theory and computational power which led to significantly improving model application.

Among the forces that called for the need for continuous development and utilization of models are changes in demographic and economic conditions, and their underlying effects on the mobility and environmental statuses of urban areas. For instance, a report from the United Nations Population Fund indicates that more than half of the world's population is currently living in urban areas (UNFPA 2007). This slow but steady growth of urban population coupled with other developments such as the presence of women in the workforce has led to economic growth, increased car ownership and increased investments in transportation infrastructure. At the same time these changes have raised concerns, in particular, the negative contributions of increased road infrastructure and mobility to environmental and living quality have been scrutinized. This is due to the fact that changes in land-use and transportation have been linked with increased space and energy consumptions and high emissions of greenhouse gases (Newman and Kenworthy 1999, Price et al. 2006). Besides, trends in urban development like sprawl, fast open space development at the outskirts (rather than re-development of declining inner cities) as well as large patches of single land-use types have become dominant urban forms. It has been long observed that these urban forms are at the center of increasing ethical and economical separation, deterioration of the environment, loss of agricultural land, economic inefficiency and the erosion of society's architectural heritage (Newman and Kenworthy 1999, Ligmann-Zielinska et al. 2008). In response to the challenges and motivated by the desire to capture the essence of these changing phenomenon, urban decision-makers have been resorting to the development and utilization of urban models.

Among the forces behind the improvement of model capabilities are the theoretical and computational advancements achieved over the past couple of decades. For instance, the process of urban land-use transportation modeling has passed at least through three generations. First generation models regarded as spatial-interaction/gravity models were based on Newton's law of gravity and its variations (see for example: Model of

Metropolis, Lowry 1964; ITLUP, Putman 1983; LILT, Mackett 1983; and IRPUD, Wegener 1982). Second generation models were aggregate models based on random utility theory (see for example: CATLAS, Anas 1982; TRANUS, de la Barra 1989; MUSSA, Martinez 1992; DELTA, Simmonds 1999; and PECAS, Hunt and Abraham 2005). Third generation models are dynamic and disaggregate models based on micro-data and activity-travel patterns. Activity-based models of travel behavior; multi-agent models of land use and transportation, and cell based models of urban land use are the emerging models within the third generation (see for example: ILUTE, Miller et al. 2004; ILUMASS, (Moeckel et al. 2002, Strauch et al. 2005); RAMBLAS, (Veldhuisen et al. 2000, 2001, 2005), MATISM-T, (www.matsim.org); and UrbanSim, (www.urbansim.org, Waddell, 2002; Waddell et al. 2003)). These evolutionary changes in land-use/transportation modeling are attributed to the gains on computational capability and to the development of discrete choice, cellular automata and multi-agent simulation. These forces, in turn, contributed to the further development of models and help cement the importance of models in the decision making processes.

These two evolutionary changes have complemented each other in that changes in urban phenomenon have continuously motivated model developers to look for innovative ways of modeling the systems and incite the development of new ideas, objectives and goals by which urban areas must be governed. Similarly, advances in modeling capabilities have influenced decisions and policies though perhaps not as much as anticipated by the initial purposes of models (see for example Hatzopoulou and Miller 2009, for the role of models in Canadian practice).

The result of the two evolutionary changes is an urban land-use/transportation decision making process that relies on models for clear perceptions of would be outputs and understanding of existing situations. The trend in urban modeling further signifies the reliance of urban decision-makers on models and the growing influence of these models in the decision making process.

Over the years, the progresses in the urban modeling arena have been tremendous. Large scale models such as ILUTE, ILUMASS, RAMBLAS, MATSIM-T and UrbanSim have transformed the way we perceive and analyze changes in urban phenomenon and are actively contributing towards planning applications. The latest models are, however, simulation based and rely on trial and error approaches when applied to land-use/transportation policy design. This raises some questions when these models are viewed from policy analysis perspective, specifically in terms of assessing the efficiency of policy measures. This is because simulation based models employ trial-and-error approaches, and, since the number of alternative actions is very high, they may fall short of identifying optimum strategies thereby unable to fully test the performance of policy measures.

To overcome the shortcomings of simulation based models, it is possible to resort to optimization approaches. Optimization, which involves maximizing or minimizing a quantified objective function subjected to certain constraints, has the purpose of making a system work in its most efficient way. In fact optimization based approaches have been used as land-use planning support systems for a considerably long period of time (for example see Gilbert et al. 1985, Diamond and Wright 1990, Ward et al. 2003).

Thanks to progresses made in the process of formulating objectives; and advancements in solution techniques, applications of optimization for land-use/transportation planning purposes are becoming common. With respect to application in planning the majority of previous applications of optimization have been for the purposes of land use allocation.

Land use allocation is a process used for determining locations of sites for uses such as residential, agricultural and recreational uses. Examples of land use allocation models are presented in Aerts and Heuvelink (2002), Aerts et al. (2003a), Ward et al. (2003), Datta et al. (2008), Stewart et al. (2004), Ligman-Zielinska et al. (2005), Jassen et al. (2008), and Ligmann-Zielinska and Jankowski (2010). In these applications, transportation systems are represented in a very simplistic way.

1.2 Thesis objectives

The objective of this thesis is to design an optimization approach for the assessment of the efficiency of urban land-use/transportation policy measures. The approach constitutes the developments of a mathematical model and solution methods. The objective is also to illustrate the usefulness of the approach as a tool for assessing efficiency of land-use/transportation policy measures considering number of application problems in hypothetical as well as real world settings.

For the first objective, we develop an optimization based land-use/transportation model. The model is formulated by focusing on three key elements which are defined considering site, neighborhood and network characteristics of a particular urban area. Specifically, the key elements are land-use suitability, land-use compatibility and accessibility to services and jobs. With these key elements, the model represents the overarching goals of urban areas in providing environmentally suitable and livable neighborhoods, accessible opportunities and encouraging efficient utilization of public funds – in terms of transportation investments.

Furthermore, for the first objective, we develop solution methods to solve the optimization model. Two solution methods are explored: a branch and bound and a heuristic algorithm. The main difference between these two methods is that in branch and bound, the optimality of a solution is guaranteed but it is computationally demanding. Whereas in heuristic solution methods, computational efforts are less but quality of solutions must be assessed. i.e. optimality of a solution is not guaranteed. The purpose of the heuristic solution method is, therefore, to capitalize on the computational efforts while maintaining the optimality of solutions (in this case solutions refer to land-use/transportation maps). For the heuristic method we developed, we have assessed the performances of algorithm parameters and quality of solutions.

For the second objective, we illustrate the usefulness of the approach considering number of hypothetical and real world application settings. In both settings, resulting efficient land-use/transportation maps are analyzed with specific emphasis on local and global fulfillments of suitability, compatibility and accessibility objectives. For the real world application, the capability of the approach is further tested considering sensitivity and scenario analyses. For the sensitivity analysis, the weights for individual objectives are systematically altered and for the scenario analysis, the variability of the efficient land-use/transportation map is assessed considering changes in land-use demand, transportation investment and development equity issues. The applications case is the municipality of Coimbra in Portugal.

In the process of developing the optimization approach, special emphasis is bestowed to the quality of solutions, computational efforts and to land-use/transportation interaction. By determining good quality solutions, in terms of land-use/transportation arrangements, the approach intends to show the potential of the optimization based model for the assessment of the efficiency of key land-use/transportation related policy measures. By capitalizing on computational efforts, in terms of lower computation times, the approach intends to show the potential of this optimization model as part of spatial decision support system. And by focusing on the two way interactions between land-use and transportation, the approach intends to exploit the complementary nature of land-use and transportation related policies.

In the future, the approach can be applied and be a valuable planning support tool for cities in the developing countries. With high urbanization rate, lack of sufficient data and lack of modeling experiences in those countries, the approach can serve as an initial starting point for the process of land-use/transportation planning. In addition to serving as planning support tool, it can serve as learning platform.

1.3 Text structure

This thesis has seven chapters. Following this introduction, Chapter II presents review of recent applications of optimization for land-use/transportation planning. The review starts by explaining the key methodological issues which are significant in the design of optimization models. From the land-use/transportation planning point of view, the key methodological issues are spatial scale, model parameters, policy implications and handling of the transportation system in the models. The same methodological issues are used to review the optimization models. For each of the optimization models, detailed presentation of model formulations, objectives and constraints are presented. Then a comparative assessment of the models is provided in reference to the key methodological issues. Finally, in this chapter our proposed optimization based model is introduced followed by discussion on where it stands in the state of the art/practice of optimization based models for land-use/transportation planning.

Chapter III presents the basic version of the optimization based model we are proposing. The model assigns land use types and transportation connection change options to an urban area taking into account the existing form and future expansions. It has three objectives that correspond to site, neighborhood and network characteristics of a study area. The objectives are maximizations of land-use suitability, land-use compatibility and accessibility. This chapter also reports on the computational effort requirements of the basic model when applied to number of problems with varying sizes. In this chapter, the branch and bound solution method is used.

Chapter IV presents about possibilities that are explored to improve the computational efforts involved with using the branch and bound method. Specifically, this chapter presents a heuristic solution method – genetic algorithm. A detailed explanation of the algorithm is provided including design procedure and algorithm elements. This chapter also reports on the strategies we follow in order to assess the quality of algorithm parameters (calibration), and to assess quality of solutions (validation). The genetic algorithm is used to solve same problems which are solved using the branch and bound method in Chapter III. A detailed comparison of results from the genetic algorithm and the exact branch and bound solution methods are explained in this chapter.

Chapter V presents the advanced version of the basic model presented in Chapter III. The basic model is modified to include additional components of urban systems such as additional transportation modes, additional land-use definitions and considerations of the effects of congestion on transportation links. A four step transportation demand model is incorporated.

Chapter VI presents an application of the optimization approach for a case study in Coimbra, Portugal. The purpose of this case study is to generate municipal land-use/transportation maps (or communitywide land-use design maps as classified in Berke et al. 2006) taking into account the existing urban form and future changes. The approach will produce efficient land-use/transportation maps which give particular attention to spatial organization of residential, commercial, industrial, open space, schools, parks and transportation at the municipal level. In applying the approach for the case study, census counts, historic land-use maps and travel survey data are used as main inputs. In this chapter, the applicability of the approach is furthered explored by considering number of sensitivity and scenario analyses.

Chapter VII provides concluding remarks, research and policy implications, limitations and possible future works of the thesis.

2 Review of optimization based land-use/transportation models

2.1 Introduction

Optimization is an approach that looks for a possible way of designing a system that makes it work at its best or in its most efficient manner. An optimization approach involves mathematical representation of a problem (modeling); specifications objective functions, decision variables and constraints; and determination of solution methods. In general, optimization seeks to find values of decision variables that maximize/minimize a quantified objective function subjected to set of constraints.

There are number of approaches that are commonly used for the process of modeling and solving a problem in a system. The approaches include, but not limited to, simulation, gaming and optimization. The choice of type of approach influences the degree of abstraction and the solution procedure. For instance in gaming human decision maker is part of the approach whereas in simulation and optimization the human decision maker is external to the approach (Bradley et al. 1997). When viewed from the perspective of representing a real world system, optimization has highest degree of abstraction. In optimization, a problem is fully represented by mathematical terms. The mathematical representation is in terms of objective functions to be maximized or minimized subject to set of constraints. Constraints depict the necessary conditions under which the decisions have to be made.

In using optimization approach, objectives are represented using objective functions and the decisions to be made are represented using decision variables. Objective functions are the measures of performances expressed as function of the decision variables. Objective functions can be usually seen as representations of cost. Constraints are any restrictions on the values the decision variables can take. These restrictions, for instance in the case of land-use allocation, can be on the amount of land available or on the amount of land required. Also there can be logical constraints or simply non negativity constraints which restrict the ranges of the decision variables and the relationships among them.

In optimization, objective functions can be formulated as having a single objective or multiple objectives. The single objective optimization model has one objective. And a multiple objective optimization model has multiple objectives and multiple decision variables. In this section, our main focus is multiple objective optimization models.

The general multi-objective optimization model with *n* decision variables, *m* constraints and *p* objectives is: (after Cohen 1970)

$$\begin{aligned} \textit{mixim}&\textit{ize } Z\left(x_1, x_2, ..., x_n\right) \\ &= [Z_1(x_1, x_2, ..., x_n), \\ &\quad Z_2(x_1, x_2, ..., x_n), \\ &\quad ..., Z_p(x_1, x_2, ..., x_n)] \end{aligned} \tag{2.1}$$

$$\begin{aligned} s.t. \quad & g_i(x_1, x_2, ..., x_n) \leq 0, \quad i = 1, 2, ..., m \\ & x_j \geq 0, \quad j = 1, 2, ..., n \end{aligned} \tag{2.2}$$

Where $\boldsymbol{Z}$ $(x_1, x_2,...,x_n)$ is the objective function with $Z_1(\ )$, $Z_2(\ )$,…, $Z_p(\ )$ are the *p* individual objective functions; $x_1, x_2, ..., x_n$ are the decision variables; $g_1(\ )$, $g_2(\ )$, …,$g_m(\ )$ are the *m* individual constraints. Model parameters are implicit in the symbol for function.

The general form of a multi-objective optimization model can further be explained by considering specific land-use allocation problem as an example. Land-use allocation is defined as the problem of determining a land-use map that identifies locations for specific land-use types. The objectives can be minimization of cost and/or minimization of environmental impacts. The decision variables will, therefore, be the determination of whether a particular land-use type is applied to particular location or not. Parameters include values that characterize the land-use unit (such as area, population, slope, etc.) or can be the amount of land demanded, and supplied, the distance among land-use units, and so forth. And the constraints can be demand constraints that limit allocation amounts and variable type constraints, which define the type of the decision variable, or budget constraints. The final solution of these kinds of optimization models is a land use map with every land-use type allocated to the best possible land-use unit within the study area.

It is important to note in equation 2.1 that the objective functions are only listed. There is no mathematical operation (addition, multiplication) applied to combine them. Combining multiple objectives in optimization models is a vast area of study. In land-use/transportation planning, two of the widely reported approaches used to combine multiple objectives are weighted sum and goal programming (reference point approach). Both methods have their own advantages and drawbacks. The weighted sum method of formulating objectives is most commonly used and relatively simple. However, this method has drawbacks in that it can lead to highly biased results with a tendency to extremes (some objectives being very well satisfied, while others perform very poorly). On the other hand the goal programming approach has the advantage of being able to produce balanced optimal results but since it relies on the initial definitions of what is ideal and what is the goal for each objective, it might yield to biased results. Both the weighted sum and the goal programming approaches allow for evaluations of tradeoffs among competing objectives. They also provide allowances for involvement of decision makers in the model.

There are number of application cases where optimization approach is used for land-use/transportation planning purposes. The approach is used to determine optimal allocations of land for various uses considering, for instance, the minimization of allocation and acquisition costs as an objective.

In the sections following this introduction, we present a review of some of the noted applications of optimization in land-use/transportation planning. Before the reviews, however, some important practical issues are briefly explained. These issues are important design elements of optimization based models for land-use/transportation applications. These issues are spatial scale, model parameters, policy implications and transportation system. The issues are significant in the definition of scope of a model as well as in the process of preparation of data. They are used as bases for evaluating the optimization based land-use/transportation models reviewed in this chapter.

2.2 Key design elements

Spatial scale

In optimization models that are used for land-use/transportation planning, spatial scale is one of the most significant design elements. Defining spatial scale has implications on computational efforts and on the scope of a model, i.e. in terms of the level and type of policy issues the model can address.

In most studies spatial scale is represented using a parcel or a cell of various sizes. A cell can have varying dimensions in different applications and it can have regular or irregular shapes. In most cases a cell is characterized as having only one land-use type. The differences in spatial scale among different models are related to the types of questions the planner intends to address using the optimization approach.

Data input (model parameters)

The most common data inputs for land-use and/or transportation optimization models are size and location of land-use types, available budget, allocation (or acquisition) costs, and land-use demand (reflecting demographic changes).

Role of transportation in land-use optimization models

When dealing with urban land-use planning issues, there are reasons to why a more thorough representation of the transportation system is justified. First, land use and transportation are highly interrelated systems. An essential two way land use-transportation interaction exists, i.e. transportation affects land use and land use affects transportation. The fundamental purpose of transportation is to offer mobility to individuals and businesses located at different points. In doing so, the transportation system confers locational advantage to sites with good accessibilities while sites without good accessibilities are in relative disadvantage. Second, transportation related decisions are usually public sector responsibilities and involve large amount of investments. Thus in land-use/transportation planning, a thorough representation of transportation will not only promote efficient use of public funds but also serves as a tool to influence land-use planning.

Policy implications

Optimization models are designed to determine efficient land-use and transportation arrangements for the area of study. These models have been used for land-use and/or transportation planning purposes. In most applications, optimization models are used for the assessment of locational (where to develop), environmental (what to preserve), and economical (how much to spend) policy options. The purpose of optimization based models for land-use/transportation planning should not be seen as only to look for the efficient solution, it is also to find feasible alternatives that provide insight and enhance understanding. For instance, optimal solutions can help us avoid the least favorable measures or alternatively they can provide starting solutions that stimulate discussions. Also they can provide us with solutions that we have never thought would be good alternatives.

The remainder of the chapter presents a review of selected land-use/transportation optimization models. Most of these models are recent developments and are applied for case studies in various places. First each model is briefly introduced and then a summary is provided highlighting the key design elements. We will also introduce our optimization based approach and define its placement in the modeling arena.

2.3 Land-use/transportation optimization models

There are number of applications of optimization for land-use/transportation planning. However, most applications have been for the purposes of land-use allocation. Land use allocation is the process of allocating land uses among a set of geographic units. The process is used for planning of new towns, design of suburbs, and location of sites for residential, manufacturing, shopping, recreational and major facility uses (Diamond and Wright 1990; Stewart et al. 2004). Examples of land use allocation models are available in Gilbert et al. (1985), Aerts and Heuvelink (2002), Ward et al. (2003), Datta et al. (2008), and Ligman-Zielinska et al. (2005).

Land-use allocation models can deal with single land use allocation (alternatively referred to site selection) and multiple land use allocation. Models by Gilbert et al. (1985) and Diamond and Wright (1990) are examples of single land use allocation models, and models by Ward et al. (2003), Aerts and Heuvelink (2002), Ligmann-Zielinska et al. (2005), and Datta et al. (2008) are examples of multiple land-use allocation models. These single and multiple land-use allocation models, which can have any number of objectives, are concerned with determining efficient arrangements of land use types in a geographic unit.

Even though many of the optimization models in land-use/transportation planning applications have been in the form of land-use allocation, there are a few studies which included transportation. For example, models by Los (1979), Feng and Lin (1999), and Lowry and Balling (2009) can be regarded as land-use/transportation optimization models.

In this section, we present a review of land-use and land-use/transportation optimization models. This review starts with land-use optimization models then continues with land-use/transportation optimization models.

2.3.1 Land-use optimization models

Some of the earlier applications of optimization to land-use allocation are single land-use allocation models. A model by Wright et al. (1983) is one of the single land-use allocation models. The main issue addressed on this model is the problem of land acquisition for the construction of any structure such as real state, parks etc. This model has three objectives: maximization of acquired area, maximization of compactness and minimization of cost. It uses grid cells as spatial units.

The objective functions are formulated as:

$$minimize \; -w_a \sum_{z \in Z} a_z x_z + w_b \sum_{z \in Z} c_z x_z + w_c \sum_{z \in Z} \sum_{z \in T_z} s_{zj} (p_{zj} + n_{zj}) \qquad (2.3)$$

Where:

a_z – area of parcel z;

c_z – cost of acquiring cell z;

n_{zj} = 1 if x_j = 1 and x_z = 0; otherwise n_{zj} = 0;

p_{zj} = 1 if x_z=1 and x_j = 0; otherwise p_{zj} = 0;

s_{zj} – the length of the border between cells z and j;

w_a – the weight on the area objective;

w_b – the weight on the cost objective;

w_c – the weight on the compactness objective;

$x_z = 1$ if cell z is acquired; x_z = 0 otherwise;

T_z – the set of cells adjacent to cell z;

Z – set of zones/cells.

The first two objectives in equation 2.3 represent the maximization of acquired area and minimization of acquisition cost. The third objective represents the maximization of compactness. The first two objectives are straight forward, a brief explanation of the third objective is necessary. The target of the third objective is to minimize external border of a cell. A border is referred as external if it is separating acquired cells from those that are not acquired. A logical constraint is introduced that forces the p_{zj} and n_{zj} to be as low as possible so that the third objective is optimized. The p_{zj} and n_{zj} sum up to 1 if the border separating cell z from cell j in the final solution is an external border (when either x_z or x_j is equal to 1).

A model by Gilbert et al. (1985) is another multi-objective single land-use allocation model. The objectives are cost, proximity (distance from desirable and undesirable land features) and the shape of the area. The cost minimization objective includes acquisition and development. For the proximity objective the amenity and detractor cells are assumed to be known and are designated in advance. Proximity is calculated using Euclidean distances between the designated cells and new allocations. The shape objective deals with the compactness of the selected cells for development. It is calculated as the product of the perimeter (number of outside edges) and diameter (the maximum distance between any two cells in the shape) of the set of allocated cells – the smaller the quotient the better. In addition to these objectives, this model has a contiguity constraint.

An iterative algorithm is developed to solve the optimization model by Gilbert et al. (1985). It was applied for the allocation of residential developments in Norris, Tennessee, United States. The zones for the whole study area were classified as amenity, commercial/industrial, roads and public lands (unavailable for development).

Another single land-use allocation model is by Diamond and Wright (1990). This site acquisition model forms a sub-region by choosing and adding cells of land units until the required amount is acquired. This model is different in that it uses irregular shaped cells. It has two objectives: minimization of acquisition and development costs; and minimization of disruption to the natural environment i.e. impact of the allocated land-use type (facility) to the surrounding land.

The minimization of disruption of the natural environment objective determines the potential impact of the proposed land-use development on the study area. This is done by analyzing the suitability of cells for a target land-use type. The overall sub-regional suitability is determined as a function of individual cell suitability. Suitability is determined using the weakest link principle. That is, the suitability of a sub-region is determined by the suitability value of the least suitable cell within the sub-region. The objective, therefore, is defined as maximization of the minimum suitability of a given sub-region for the proposed land use.

The objective functions are formulated as:

$$minimize \sum_{z \in Z} c_z x_z \tag{2.4a}$$

$$maximize \min_{(z \mid x_z = 1)} (s_z x_z) \tag{2.4b}$$

Where:

c_z – cost of acquiring cell z;

s_z – suitability of cell z for the target land-use to be acquired;

$x_z = 1$ if cell z is acquired; $x_z = 0$ otherwise;

Z – set of zones/cells.

The objective functions in equation 2.4a-2.4b have area, compactness and contiguity constraints. The area constraint limits the amount of land acquired within a higher and a lower bound. The compactness is used to describe the shape of the sub-region. It is calculated by taking the ratio of the square of diameter by the area of the sub-region.

Diameter is measured as the distance between two most distant points. The contiguity constraint has the purpose of maintaining continuity of a feasible sub-region, i.e. it is possible to travel from one point to any other point within the sub-region without leaving the sub-region.

A model by William and Revelle (1996) is another single land-use allocation (acquisition) model. This is a reserve selection model with two objectives: minimization of reserve cost and maximization of the amount of land protected. It identifies land-use units as core or buffer zones, while encouraging spatial attributes of contiguity and compactness.

The objective function is formulated as:

$$minimize \sum_{z \in Z} c_z x_z \tag{2.5}$$

Where:

c_z – cost of acquiring cell z;

$x_z = 1$ if cell z is selected for a reserve; $x_z = 0$ otherwise;

Z – set of zones/cells.

The objective function is formulated as having a single objective with minimization of cost of cells selected for a reserve (equation 2.5). The other objectives are considered as constraints. The area of the core reserve is specified in advance and for every core cell selected all the neighboring cells should also be selected at least as a buffer (or they can be selected as core). Core cells refer to the main reserve whereas buffer cells refer to areas separating reserve from the rest of the study area. This model was applied for the search of space for new reserve location for a hypothetical case. An exact method and a heuristic method are used to solve the model.

The optimization model by Xiao et al. (2002) is another single land-use allocation model. This is a multi objective site search model. It uses a genetic algorithm to generate alternative (optimal or close to optimal) solutions. The purpose of this site search model is to find group of contiguous places (e.g. grid cells) that meet specific objectives. This model additively determines tracts of land for single land-use purposes.

The objective functions are formulated as:

$$minimize \sum_{z \in Z} c_z x_z \tag{2.6a}$$

$$\sum_{z \in Z} [(x''_z - x')^2 + (y_z - y')^2]^{1/2} x_z \tag{2.6b}$$

c_z – cost for cell z;

x_z = 1 if cell z is selected; otherwise x_z = 0;

x''_z – the *x-coordinate* of cell z;

y_z – the *y-coordinate* of cell z;

x' – the *x-coordinate* of the facility;

y' – the *y-coordinate* of the facility.

It is assumed that the cost for each cell is known in advance. Besides the location of the facility (this can be shopping center, hospital, etc.) is fixed and known beforehand. The goal is, therefore, to determine a patch of land for specific use considering the minimization of cost and distance between the site and the facility.

In addition to single land-use allocation models discussed earlier, optimization models have been used for multiple land-use allocation purposes. A model by Benabdallah and Wright (1992) is a multiple sub-region allocation model. It aims at grouping basic geographical units into sub-regions. This model was formulated as an extension of the single land-use allocation model proposed by Wright et al. (1983). It has cost minimization, area maximization and compactness maximization as objectives. The solution procedure is similar to the one used in Wright et al. (1983) and the model uses regular grid cells.

The main decision in the model by Benabdallah and Wright (1992) is to choose a cell that should belong to a sub-region. The decision variable x_{zk} equals 1 if parcel z is assigned to sub-region k and 0 otherwise. This model was applied for districting problem with range of sizes. The problem was to divide a region into five contiguous districts.

Another multi-site land-use allocation model is due to Ward et al. (2003). This model integrates spatial optimization with cellular automata applied for possible growth scenarios in south east Queensland, Australia.

The model by Ward et al. (2003) constitutes of two parts. First it applies a regional optimization model that allocates specified land-use classes to defined planning units, and then a cellular automata model of urban growth is applied at the planning unit level in order to represent local realizations of growth scenarios. The two main objectives of the whole model are minimization of the total deviation from specified zoning targets and minimization of disturbances of natural areas. The zoning options (land-use types) considered are rural residential, urban residential, commercial, industrial, special use and recreational (or open space).

The objective functions are formulated as:

$$minimize\ w_1 \sum_{j\in J} \sum_{t\in T} (u^{+}_{jt} + u^{-}_{jt}) + w_2 \sum_{i\in N} \sum_{j\in D} \sum_{t\in T} x_{ijt} \tag{2.7}$$

Where:

w_1 – target deviation weight;

w_2 – preserved/natural area disturbance weight;

u^{+}_{jt} - target shortfall for zoning option j in time t;

u^{-}_{jt} - target surplus for zoning option j in time t;

x_{ijt} - fraction of area i (planning unit) assigned zoning option j in time t;

I – set of planning units (zones);

J – set of zoning options (land-use types);

T – set of planning periods;

N – set of natural state areas;

D – set of environmentally altering zoning options.

This model is applied to allocate land-use types to regions in order to address economic, social and environmental issues associated with population growth in Queensland, Australia. The optimization approach determines which residential units should change their densities considering two possible scenarios low density, diffuse growth (no restrictions on the area of growth; allocation of large development projects is allowed) and high density compact growth (with no change in high density and 20% increase in low density required).

A different kind of multi-site land-use allocation model was the studied by Datta et al. (2008). This is an optimization model for achieving multiple objectives simultaneously by allocating suitable land use types to different units of a landscape. The objectives are maximization of economic return, maximization of carbon sequestration and minimization of soil erosion as a result of particular land-use allocations. The spatial units used are grid cells of equal size.

The objective functions are formulated as:

$$maximize \sum_{z \in Z} \sum_{e \in E} \sum_{t \in T} m_{ezt} x_{ze} \tag{2.8a}$$

$$\sum_{z \in Z} \sum_{e \in E} \sum_{t \in T} c_{ezt} x_{ze} \tag{2.8b}$$

$$minimize \sum_{z \in Z} \sum_{e \in E} \sum_{t \in T} n_{ezt} x_{ze} \tag{2.8c}$$

Where:

c_{ezt} – the net amount of carbon sequestered in year t from event e applied to cell z;

m_{ezt} – the discounted net present economic return from event e, harvested from cell z in year t;

n_{ezt} – the net amount of soil eroded in year t from cell z under event e;

x_{ez} = 1 if event e (land-use type change) is applied to cell z; x_{ez} = 0 otherwise;

E – set of events (land-use developments);

T – set of periods of times;

Z- set of cells/zones;

The first objective, equation 2.8a, maximizes the economic return from a proposed land-use change (or as a result of allocating land-use type to a cell). It is calculated as a discounted net present economic return from event *e*, harvested from cell *z* in year *t*. The second objective, equation 2.8b, maximizes the carbon sequestration rate as result of land-use change. And the third objective, equation 2.8c, minimizes the net amount of soil eroded in year *t* from cell *z* under event *e*.

In this model by Datta et al. (2008), the land-use types considered are: annual agriculture, permanent agriculture, mixed agriculture, forest and shrubs. Their application uses genetic algorithm to solve the model and involves a case study in Southern of Portugal. The quality of their solution was not verified since no exact solution exists for the landscape.

Another widely reported multi-objective land-use optimization model is the multi-site land-use allocation initially developed by Aerts and Heuvelink (2002). This model has been used in number of applications with little changes to the representation of the objective function and the way the multiple objectives are combined. Two methods have been used to combine the objective function of this multi-site land-use allocation model in separate occasions. The first one is weighted sum and the second is goal programming (reference point approach). Changes also have been made to the solution techniques. Exact linear programming techniques and heuristics (simulated annealing and genetic algorithm) have been used as solution techniques.

In this multi-site land-use optimization model initially proposed by Aerts and Heuvenlink (2002), land-use allocation, x_{zl}, is defined as the assignment of land-use type l to a geographic unit z. The geographic units used are rectangular grid cells. The amount of land-use per single allocation is equal to the size of the cell.

The two main objectives of Arets and Heuvenlik (2002)'s model are minimization of cost and maximization of spatial compactness. Cost, which is evaluated for each land-use type, mainly refers to acquisition and development. Compactness, which is a spatial-pattern objective, seeks to encourage the assignments of similar land-use types near to or in proximity to one another.

The objective functions are formulated as:

$$minimize \sum_{z\in Z}\sum_{l\in L} c_{zl}x_{zl} - \beta\sum_{z\in Z}\sum_{l\in L} b_{zl}x_{zl} \tag{2.9a}$$

Where:

b_{zl} – the number of cells neighboring cell z that have land-use l

$$\begin{aligned} b_{zl} &= x_{(-j)l} + x_{(+j)l} + x_{(j-)l} + x_{(j+)l} \\ x_{(-j)l} &= \text{cell to the left of } j \text{ with land use } l \\ x_{(+j)l} &= \text{cell to the right of } j \text{ with land use } l \\ x_{(j+)l} &= \text{cell to the top of } j \text{ with land use } l \\ x_{(j-)l} &= \text{cell to the bottom of } j \text{ with land use } l \end{aligned} \tag{2.9b}$$

β – weight for compactness objective relative to the cost objective;

c_{zl} – cost of allocation of land-use l to cell z;

x_{zl} = 1 if land-use l is allocated to cell z; x_{zl} = 0 otherwise;

L – set of land-use types;

Z – set of zones;

The first part of equation 2.9a is the cost minimization objective and the second part is the spatial compactness maximization objective.

The constraints of this model are demand constraints which restrict the amount assigned to each land-use type; and homogeneity constraint that ensures a single land-use type per grid-cell. Moreover the model has a constraint that is used to evaluate the spatial compactness term, b_{zl}. This constraint is evaluated as the summation of land-use assignments (x_{zl}) in cells surrounding a target cell. The ideal value for this term is 4 i.e. all the neighbors (top, down, right and left) are assigned with the same land use type as the target cell. This adds non linearity to the model (equation 2.9b).

One of the early applications of the previously introduced optimization model is in the restoration of a mining site in Spain by Aerts and Heuvenlink (2002). They solved the basic optimization model using simulated annealing (SA). The spatial scale used was a grid cell of equal sizes. In total they considered three land-use types – forest, shrub and water. Development costs were calculated for each potential land use type considering the elevation and slope of the cells.

A similar application is presented in Aerts and et al. (2003a). This time the goal was to examine the suitability of mathematical programming techniques to solve the multi-site optimization model. This work compares four different integer programming models (three linear and one nonlinear) by solving same basic problem using two criteria: efficacy (in terms of solution time for small and large data sets, while encouraging spatial compactness) and their ability to yield a mathematically optimal allocation alternative. These applications use the weighted sum method to allow evaluation of preferences.

The same basic model has also its objective function represented in different ways and applied for some case studies (Aerts et al. 2003b, 2005, Stewart et al. 2004, and Jassen et al. 2008). These studies choose different formulations of the objective function. Instead of using weighted sum, they use an alternative goal programming. The goal programming method works by first defining an ideal value for each objective (computed or heuristically assessed). Then it specifies a goal value that indicates a satisfactory level of performance. These goals serve as ways of modeling preferences of decision makers. This formulation is expected to generate land-use maps which are as close as possible to the ideal values. The goal programming based model is formulated as (equation 2.10):

$$maximize \sum_{p \in P} \left[\frac{f_p(u) - I_p}{\gamma_p - I_p} \right]^{\rho} + \sum_{k \in K} \sum_{q \in Q} \left[\frac{s_{kq}(u) - I_{kq}}{\lambda_{kq} - I_{kq}} \right]^{\rho} \tag{2.10}$$

Where:

$f_p(u)$ – the total value for all cost attributes p of the cost objective for land-use map u

$s_{kq}(u)$ – the total of spatial measures q, which in this application are number, size and perimeter of clusters

I_p, I_{kq} – the best possible value for each objective p if optimized on its own (taken as ideal values)

γ_p, λ_{kq} – are goal values for the cost and compactness objectives, respectively

ρ – power factor (preferably large, value equal to 4 is used in this application)

P- set of cost attributes

Q – set of spatial measures

K – set of land-use types

This particular formulation expands the cost and compactness objectives to be summation of objectives which together are expected to result in low cost and compact final land-use map. The objectives are to minimize allocation cost; minimize cost of changing land-use types; minimize fragmentation; maximize the largest cluster and maximize overall compactness. The first two objectives are straight forward, the last three objectives which are all variations of the spatial compactness objective are briefly explained below.

The first one of the spatial compactness objectives, minimizing fragmentation, deals with minimizing the number of clusters per land use type. That is less number of clusters of a particular land-use type are encouraged. The second objective, maximizing the largest cluster relies on the concept that, when it comes to spatial compactness, having one large cluster (of similar land-use types) is preferable than many small clusters. The third spatial objective, maximizing overall compactness, deals with minimizing the perimeter of a cluster. It is evaluated by dividing the perimeter of a cluster by the square root of its area.

There are multiple applications of these goal programming based models. Aerts et al. (2003b) solved the model using simulated annealing; Aerts et al. (2005) solved the model using simulated annealing and genetic algorithm, and Stewart et al. (2004) solved the model using genetic algorithm. This model was applied for a case study in Jisperveld, Netherlands. The case study considers nine land-use types. The plan of the case study was to find the optimal location of two land use types, which are not present in the case study area. The land-use types in demand are extensive agriculture and water (limited access for recreational purposes).

A follow up to the optimization model by Stewart et al. (2004), equation 2.10, was used as part of a spatial decision support system (SDSS) in the study by Janssen et al. (2008). In this work, an interface is built to facilitate interactive planning process. First a land-use plan is presented to a planner and he/she is asked for feedback. The planner can give feedback on the weights of the six objectives, areal limits for the land-use types demanded and land-use allocations that the planner want unchanged. Using the feedback from the planner, the model is run again. This back and forth process may have to be done a number of times before an acceptable land-use plan is achieved. The model, which is solved through a genetic algorithm, was applied in future land-use development of Jisperveld, Netherlands.

Another multi objective optimization model was development by Ligmann-Zielinska et al. (2005, 2008, and 2010). The model is specifically designed for sustainable urban land-use allocation. The model has four objectives: minimization of open space development that encourages efficient urban land-utilization; minimization of redevelopment that ensures economically defensible spatial change; minimization of incompatibility of adjacent land-uses that might prevent environmental deterioration; and minimization of distance of new development to already developed areas.

The objective functions are formulated as:

$$\textit{minimize} \sum_{z \in Z} \sum_{l \in L} (1 - a_z) x_{zl} \tag{2.11a}$$

$$\sum_{n \in Z} \sum_{l \in L} r_z x_{nl} \tag{2.11b}$$

$$\sum_{z \in Z} \sum_{l \in L} (1 - c_{zl}) x_{zl} + \sum_{n \in Z} \sum_{l \in z, n \in z | l \neq n} (1 - c_{nl}) x_{nl} \tag{2.1c}$$

$$\sum_{z \in Z} \sum_{l \in L} d_z x_{zl} \tag{2.11d}$$

Where:

a_z – attractiveness of undeveloped location z, defined by the planner;

r_z – resistance to change of location z with existing land-use type of n;

c_{ln} –compatibility index between land-use l and land-use m;

d_z – distance of location z to its nearest developed area;

x_{zl} =1 if undeveloped land at location z is changed to land-use type l; x_{zl} = 0 otherwise;

x_{nl} = 1 if current land-use n at location z is changed to l, x_{nl} = 0 otherwise;

Z – set of zones;

L – set of land-use types.

In addition to the objectives mentioned above, this model has a specifically developed density based design constraint (DBDC). The constraint has the purpose of maximizing spatial compactness by promoting user-specified neighborhood infill development.

Compactness is defined as an allocation of same land use types to cells that are in direct proximity of one another.

This model was applied in Chelan City, Washington, USA. The application considers five land-use types: residential, commercial, industrial, undeveloped and restricted. Attractiveness of undeveloped location was derived based on planned development; and attributes of buildable areas such as slope, distance to water, distance to parks, forests and other recreational areas. The resistance to change of an existing land-use type was obtained considering the building value and occupation levels. Distance to developed cells was calculated using ArcGIS Euclidean distance function.

A recent land-use optimization study by Cao et al. (2011) considers three objectives: minimization of cost of land-use conversion, maximization of compatibility of adjacent land-use types, and maximization of accessibility. This model is land-use optimization because it only handles land-use types. Accessibility is included as a parameter that remains the same for the study area irrespective of the land-use changes.

The objective functions are formulated as:

$$minimize \ -\sum_{z\in Z}\sum_{l\in L} b_{zl}x_{zl} \tag{2.12}$$

Where:

b_{zl} – a parameter of the three objective which depends on the objectives and the attributes of the area;

L – set of land-use types;

Z – set of cells;

$x_{zl} = 1$ if land-use type is allocated to cell z; $x_{zl} = 0$ otherwise.

In this study, the accessibility objective is determined using an influence index for every class of urban roads. The roads are classified based on the land-use type (neighborhoods) they serve. Based on this, a study area can have roads that primarily serve residential neighborhoods, major routes for all transportation, and routes that serve commercial and mixed use. For each class of road, an influence index is obtained. The influence index is a matrix value of the road class and land-use types (adapted from the standard national table in China). The influence index, e_{ij}^{r}, is the influence value of the i_{th} road to j_{th} point, and r is the suitably normalized distance between the i_{th} road and j_{th} point. A compatibility matrix is also used for the compatibility objective. The model is applied for a case study in Tongzhou in Southeast of Beijing China. In this study five land-use types are considered: residential, industrial, commercial, green space and undeveloped land.

The single and multiple land-use allocation optimization models discussed so far are applied specifically for land use planning purposes. In those applications transportation is represented in a very simplified way (at most). In the application of optimization to spatial planning, only a few studies tried to use optimization for land-use/transportation policy purposes.

For example, Los (1979) simultaneously solves two optimization algorithms, one for determining an optimal transportation network and another for determining an optimal land use plan. The model assigns activities (regarded as demand-activities and facility-activities) to locations and chooses the practical capabilities of the arcs of the network, so as to minimize a total cost composed of site costs, capital costs for the links of the network, and transportation user costs. This model is more a facility location and network design model than a land-use transportation optimization model. Similar studies can be found in Melkote and Daskin (2001) and Bigotte et al. (2010), the latter with real world application – Centro Region, Portugal.

A sketch layout model by Feng and Lin (1999) is another example of land-use/transportation optimization model. Their model has environmental harmony and development efficiency as objectives. Environmental harmony, which was alternatively called comfortable life, is measured by relative distance between dissimilar land use types. Development efficiency is to maximize the benefit/cost ratio of public investment. The model has a constraint that requires the provision of at least one transportation path for any two different cells in the planned area. Transportation here is represented by the shortest path distance. The solution method used to solve the partially provided model formulation is genetic algorithm. During the application of genetic algorithm, model developers have assessed the qualities of the parameters but not the quality of the solution.

A study by Lowry and Balling (2009) is another example of an optimization based model for land-use/transportation planning. Their model is a hierarchical, optimization based, model for land-use and transportation planning. The model is run twice, first at the regional level and then at city level. In the first planning stage, the model specifies the class for each existing primary street and the percentage of land-uses in a district (groups of zones). These specifications are then sent down to the cities where the city planners use same approach and specify the classes of the existing and proposed secondary streets (given the prescribed primary street specifications) and land-use types for each zone. City planners include minimization of deviation from specifications sent down from regional planners as an objective. The model has objectives of minimization of total travel time (evaluated using the four step transportation model) and minimization of opposition towards change from the existing land-use/transportation conditions. The objectives are optimized considering the housing potentials, employment potentials and green space provision requirements. The solution method is genetic algorithm but quality of the solutions is not assessed.

2.4 Summary of literature review

In this chapter, we have provided reviews of studies that have used optimization for land-use/transportation planning purposes. In most of the studies, the approach was used more often for land-use allocation (land-use planning) than for land-use/transportation planning. In general, the goals of these studies have been to find optimal locations for land-use types or alternatively to acquire tracts of land for specific use. The objective functions were formulated considering the target land-use type and the location and neighborhood characteristics of the spatial units. Most of the studies involve case study applications and in most of the applications, the location characteristics are collectively represented in terms of cost. In determining the cost of a spatial unit, most models consider cell attributes such as slope, soil type, and attractiveness – which all together determine the price of a land use unit. In addition development costs are determined based on the type of land-use to be developed. Besides to cost, some of the studies consider additional location based objectives such as suitability. This objective determines the ability of the cell to carry the land-use type as well as the suitability of the land-use type for the land (in the cell). This objective has environmental significance.

Another widely represented objective is one that focuses on neighborhood characteristics of a study area. This objective can be compatibility, compactness, contiguity, and proximity. The compatibility objective has the purpose of increasing harmony among neighboring land-use types. Compactness is the most widely addressed objective. This objective has the purpose of maximizing the possibility of allocating the same (or similar) land-use types in a close nearness to one another. The proximity objective addresses the issues of allocating land-use types closer to more desirable sites (parks, recreations) and farther from undesirable sites (highways, industrial sites etc.). Contiguity is another neighborhood characteristic used as an objective. This objective represents the significance of allocating land-use types in continuous and unbroken fashion. Contiguity has great significance in selecting sites for reserve location. It allows the possibility of moving from one cell to another cell without living the land-use type (reserve).

Similarly, another represented objective is the minimization of distance between different land-use types. For example this objective was used in Los (1979) with the purpose of minimizing distance between facilities and demand land-use types. In other studies the distance objective is used as coarse representation of accessibility and has the purpose of minimizing the distance from new allocations to already developed areas (Ligmann-Zielinska et al. 2008).

There are few applications which specifically target for sustainable land-use allocation (Ward et al. 2003, Ligmann-Zielinska et al. 2008). They define sustainable allocation as a land use arrangement that minimizes re-development and open space development while encouraging infill development. These models also extend the notion of using optimization approach to allocate land-uses in undeveloped areas to brown-field allocation that allows the assignment of additional land-uses to already developed areas (i.e. promote infill development).

The spatial scale used in the reviewed models is mostly grid cells of equal size. This is computationally advantageous but falls short in representing the reality. In practice, land-use units are available in the form of irregular shapes and with varying areas. One of the models developed by Diamond and Wright (1999) uses irregular shaped grid cells with different areas.

In addition to spatial scale, the number of spatial units per study has tremendous effect on computational efforts. The decision on the number of cells has been a key factor for choosing a solution method. In so many instances, it was shown that heuristic algorithms have the potential of handling large size problems with in relatively smaller amount of time. The issue is to find ways of calibrating/validating the algorithm parameters as well as algorithm solutions.

As it was mentioned earlier, most of the reviewed optimization models are applied for land-use allocation purposes. Transportation is not represented in most of these studies. Indeed, some land-use allocations are applied for specific purposes as for site restoration (Aearts et al. 2005) or reserve selection (Diamond and Wright 1999) or environmental protection (Ditta et al. 2008). These specific purpose models have neither the purpose nor the scope to in include the transportation system. They are presented in the review as land-use optimization models that will help us understand key elements of land-use allocation design. But even in the case where the optimization models are developed for urban planning, the representation of the transportation system was not adequate. In most cases, the closest the models get to representing transportation were in terms of distance values. That is, in some of the applications distance from/to two land-use type locations are used as coarse representation of the transportation system (Ligmann-Zielinska et al. 2008). Among the land-use allocation models, there is one application that has maximization of accessibility as an objective (Cao et al. 2011). However, the accessibility in this study is not as a result of changes in the land-use/transportation system. It is taken as fixed parameter that depends on the classifications of roads depending on the type of spatial units they connect.

Land-use/transportation optimization models are very limited. Indeed, the models by Feng and Lin (1999), and Lowry and Balling (2009), can be regarded as the only true land-use/transportation optimization models. The hierarchic model by Lowry and Balling (2009) used a four step transportation model whereas Feng and Lin (1999) applied the shortest path algorithm to model the transportation system.

The models reviewed in this chapter were applied in a number of case studies. Most applications were in site selection, i.e. in the selection of areas of land for nature reserves, or specific land-use types such as residential, facility, agriculture and so on. Similarly, there are applications in site restoration and resource conservation. Besides, the models were applied for urban land-use/transportation planning purposes such as in redevelopment, providing additional residential and service areas to growing population. In some cases, optimization models have been included within spatial decision support systems (SDSS) framework. The key requirement for a model to be included in SDSS is that it has to be able to provide alternative solutions within reasonable computation times.

The optimization based land-use/transportation model we are proposing in this thesis shares basic similarities with the optimization models reviewed in this chapter. In terms of objectives, our model focuses maximization of suitability, maximization of land-use compatibility among neighboring land-uses, and maximization of accessibility to services and jobs. These objectives represent the site characteristics, neighborhood characteristics and network characteristics of a study area respectively. The suitability objective has the purpose of verifying the appropriateness of a zone for a particular land-use type. It has also the purpose of verifying the appropriateness of land-use type to a land unit. The compatibility objective minimizes disturbances, discomforts and pollutions resulted from allocating one land-use type in proximity to another. The third objective, which we believe is a significant contribution of this study – in terms of using optimization for integrated land-use/transportation planning, maximizes accessibility to services and jobs. In designing our model we put special emphasis in the integration of land-use and transportation related decisions.

In our model, spatial scale is represented using cells with different shapes and sizes. This is a significant shift from the grid-based equal sized cells. Representing the spatial units using different areas is more realistic as we are seeking for municipal level decision support tool where the lowest spatial units tend to have different sizes.

The model we are proposing can be used for many purposes. The model can be used as a decision support tool for land-use/transportation planning at municipality level. For instance, our model can be used to generate municipal land-use/transportation plans (or communitywide land-use design plans as classified in Berke et al. 2006). These plans give particular attention to spatial organization of housing, commerce, manufacturing, open space, schools, parks and transportation at the municipal level. These municipal level maps have the purpose of defining spatial arrangements that promote day to day functions of a city involving interactions among land-uses, livability, environmental quality, economic development, and equitable distribution of opportunities and investments (Berke et al. 2006).

3 Optimization model for land-use/transportation policy making: Basic model

3.1 Introduction

The theory regarding the two way interaction between land-use and transportation is well-developed. In most of the literature, the interaction theory is discussed in terms of a two way relationship that exists in the form of current land-use impacting travel behavior and transportation impacting land-use development patterns; see for instance Stead and Marshall (2001), van Wee (2002), Timmermans (2003), Handy (2005) and Maat and et al. (2005) for some recent reviews. At the core of this land-use and transportation interaction is the notion of accessibility. Accessibility, which can be defined as the ease with which potential employment and service opportunities are reached, serves as the kernel of land-use and transportation interaction. From the land-use viewpoint, accessibility of activities dictates travel decisions whilst from the transportation system viewpoint, relative accessibility of locations drives land-use changes.

Land-use and transportation systems constitute significant part of an urban system. Particularly, decisions related to land-use/transportation influence the form and function of an urban area and they are among the most important local municipal authorities have to make. In many instances, the decisions have significantly contributed to creating well organized and attractive urban areas.

Over the years, the significance of land-use/transportation decisions is highlighted by the great deal of attention bestowed to the systems and the decision making processes. The significances are also highlighted by the amount of budget allocated, the institutional structure & capacity built around the systems, decision effects and the non-reversible nature of some of the decisions.

The significances and complementary nature of land-use/transportation decisions coupled with the two way interaction have led to the development of numerous integrated decision support tools (models). In many applications, the role of these decision support tools has been tremendous. For instance see simulation modeling efforts and applications such as ILUTE (Miller et al 2004), ILUMASS (Moeckel et al. 2002, Strauch et al. 2005), MATSIM-T (www.matsim.org), RAMBLAS (Veldhuisen et al. 2000, 2001, 2005), and UrbanSim (www.urbansim.org, Waddell 2002, Waddell et al. 2003). Even though the progresses are significant, some questions remain when these models are viewed from the policy analysis point of view. Indeed, simulation models utilize trial-and-error approaches for land-use/transportation policy analysis, and, since the number of alternative actions is very high, they may fall short of identifying optimum strategies. To avoid this, it is possible to resort to optimization approaches.

Optimization based models have been applied to land use allocation in several studies. Land use allocation is the process of allocating land use(s) among a set of geographic units. The process is used for planning of new towns, design of suburbs, and location of sites for residential, manufacturing, shopping, recreational and major facility uses (Diamond and Wright. 1990; Stewart et al. 2004). Examples of land use allocation models are presented in Gilbert et al. (1985), Diamond and Wright (1990), Aerts and Heuvelink (2002), Aerts et al. (2003), Ward et al. (2003), Datta et al. (2008), Stewart et al. (2004), Ligman-Zielinska et al. (2005), Jassen et al. (2008), and Ligmann-Zielinska and Jankowski (2010). Detailed reviews of optimization models for land-use/transportation planning are presented in the second chapter of this dissertation.

These allocation models are mostly concerned with determining optimal arrangements of land use types in a geographic unit considering economic and spatial characteristics of the allocations as an objective. They assume no or in some cases simplified transportation representations.

This chapter contains detailed descriptions and application examples of the basic optimization based land-use/transportation model we have developed. The chapter is organized into five sections. The next section presents the basic optimization based model, its formulations and assumptions. An application example, solved using a multi-objective integer programming solver – branch and bound, is presented in section 3. Information on the model solving techniques, computation times and comparison of different sized problems is provided in section 4. The chapter concludes with some observations about model implementation and further works.

3.2 Basic model

In this section we present an optimization model that allocates land use types and transportation connection upgrade options to an urban area taking into account the existing form and future demands. The optimization model proposed in this chapter has the purpose of generating efficient land-use/transportation maps considering multiple objectives. The maps are reflections of the applications of different land-use and transportation policies on an existing urban area. The policies are represented through the definition of decision variables and constraints.

The basic model considers various land-use/transportation policies and their combinations in determining the efficient land-use/transportation arrangements. In land-use, the model can consider policies related to zoning, location, growth boundary, land preservation, infill/brown field development and concurrency regulations. In transportation, the model can consider policies related to highway investments (expansion and improvement) and fast transit investments. These policies are found to have effects of change in density, sprawl, mixed use and environmental protection.

Location policies are used to direct land-use developments to designated areas while discouraging development, for instance, in peripheral areas. Zoning policies are used to implement high density and create mixed use developments. And concurrency policies are used to define locations to build public service facilities (universities, hospitals and so on). In this basic model, transportation investment related policies are designed in terms of allocating public funds appropriately; the transportation investment policies are laid out in terms of the amount of budget available and how to allocate them efficiently. Planners define number of feasible transportation programs.

The policies mentioned above have been commonly tested and applied for urban land-use/transportation planning purposes. For instance see, among others, Kavage et al. (2005) for zoning; Pucher (1998) for land-preservation; Song (2005) for concurrency regulations; Bengston et al. (2004) for growth boundaries; Ligman-Zielinska et al. (2005) for infill/brown filled development; Schwanen et al. (2004) for location polices; and Antunes et al. (2003) for highway expansion policies.

Given the land-use/transportation policies, the key decisions of the model are what type of land-use should be allocated to which zone, and which transportation program should be implemented. These decisions are implemented in a way to maximize the defined objectives.

The optimization based model has two major components: a land-use allocation model and a transportation model. It is, however, designed as an integrated model i.e. for land-use/transportation policies that require strong institutional/regulatory coordination, the model imposes a logical constraint that guarantees decisions regarding one of the systems is conditional up on (subjected to) decisions on the other system. The logical constraint is in addition to the accessibility objective which acts as a linkage between land-use and transportation.

The land-use component allocates various land-use types, as residential, industrial, manufacturing and commercial business district (CBD); and the transportation component implements transportation upgrade programs such as deciding the segment of the highway to upgrade and part of the network where fast transit mode is introduced. The changes are based on the future demands and the amount of budget available for transportation improvement projects. The changes are also considering the form and function of the existing urban area.

The model is sought for application by a municipal authority that has control over the land use and transportation for a given urban area. This area consists of urban zones, each one characterized with a given land use type (residential, shopping, manufacturing, etc.), and of nearby vacant zones that can be transformed into urban. The various zones are connected with a given transportation network. With respect to the future, the demand for various types of land uses is known. Also, possible transportation improvement actions are known. The model can provide insights – what is the efficient land-use/transportation arrangement, what can be done in terms of managing urban growth, and how to allocate and spend available budget for transportation programs. It can also increase understanding – what would happen if certain changes occur in the land-use/transportation system and how the changes would affect the existing urban area and how the changes play out in defining the future of the urban area. Urban planners and/or decision makers are potential users of the model.

The optimization based model has three objectives: maximization of land use suitability; maximization of the compatibility between neighboring land uses; and maximization of accessibility to jobs and services.

For formulating the model consider the following notation:

<u>Sets</u>

$\boldsymbol{J} = \{1, 2\ldots, J\}$ - set of zones (urban and vacant);

$\boldsymbol{J_V}$ - set of vacant zones;

$\boldsymbol{M} = \{1, 2\ldots, M\}$ - set of land use types;

$\boldsymbol{R} = \{1, 2\ldots, R\}$ - set of possible transportation improvement programs (each program comprises highway improvement and fast transit investment projects);

$\boldsymbol{Y} = \{y_{jmknr}, j \in \boldsymbol{J}, k \in \boldsymbol{J}, m \in \boldsymbol{M}, n \in \boldsymbol{M}, r \in \boldsymbol{R}\}$.

<u>Parameters</u>

s_{jm} - suitability index for land use m in zone j;

c_{jmkn} - compatibility index for zone j with land use m and zone k with land use n (the higher this index, the more compatible land use types are);

a_j – measure of accessibility in zone j to all opportunities D_k in zones k;

h_j - area of zone *j;*

$f(t_{jk})$ – generalized function for travel time between zones *j* and *k*; with an impedance parameter β;

l_m - demand for land use type *m.*

Decision variables

x_{jm} - equals 1 if land use type *m* is assigned to zone *j* and 0 otherwise;

y_{jmknr} - equals 1 if the connections between zones *j* and *k* with land use types *m* and *n*, respectively, are improved through transportation improvement program *r* and 0 otherwise;

p_r - equals 1 if transportation improvement program *r* is chosen and 0 otherwise;

z_{jmkn} - equals 1 if land use *m* is assigned to zone *j* and land use *n* is assigned to zone *k*; and 0 otherwise.

Given the notations above, the optimization based land-use/transportation model can be formulated as follows:

$$maximize \quad \sum_{j\in J}\sum_{m\in M} s_{jm}x_{jm} \tag{3.1}$$

$$\sum_{j\in J}\sum_{m\in M}\sum_{k\in J}\sum_{n\in M} c_{jmkn}\,z_{jmkn} \tag{3.2}$$

$$\sum_{j\in J} a_j$$

$$a_j = \sum_{k\in J}\frac{D_k}{f(t_{jk})}(\boldsymbol{Y}) \tag{3.3}$$

Subject to:

$$\sum_{m\in M} x_{jm} = 1;\ \forall j\in J \tag{3.4}$$

$$y_{jmknr} \le p_r;\ \forall j,k\in J,\ m,n\in M,\ r\in R \tag{3.5}$$

$$\sum_{r\in R} p_r = 1 \tag{3.6}$$

$$\sum_{j\in J} h_j x_{jm} = l_m;\ \forall m\in M \tag{3.7}$$

$$2z_{jmkn} \le x_{jm} + x_{kn};\ \forall j,k\in J,\ m,n\in M \tag{3.8}$$

$$z_{jmkn} \ge y_{j,m,k,n,r};\ \forall j,k\in J,\ m,n\in M,\ r\in R \tag{3.9}$$

$$x_{jm};\ y_{jmknr};\ z_{jmknr};\ p_r \in \{0,1\} \tag{3.10}$$

The objective functions in (3.1), (3.2) and (3.3) of the multi-objective integer optimization model maximize land-use suitability, maximize compatibility of adjacent land-use types and maximize aggregate accessibility to services and jobs respectively. The three objectives are normalized using min-max method and can be weighted as desired. More on the normalization and weight process on later sections of this chapter.

The first objective (3.1), suitability, assesses the fitness between the land use that is allocated to a zone and the physical and environmental attributes of the zone (e.g. slope, solar exposure, soil/geology, and hazard exposure). This objective also assesses the fitness between the allocated land use and current use (e.g. good agricultural land must be preserved, heritage must be protected, etc.) This objective was also retained in related land-use optimization studies, e.g. Diamond and Wright (1990) and Wang et al. (2004).

The second objective (3.2) maximizes compatibility between neighboring land uses. For example, residential uses are not compatible with heavy manufacturing activities, thus these land use types should be allocated far from each other. This objective is in line with the spatial compactness concerns of Aerts and Heuvelink (2002), Aerts et al. (2003a), and Ligmann-Zielinska et al. (2005), when they encourage the assignments similar land use types close to one another. In our optimization based model, compatibility is described by an index that is evaluated for every zone and all its neighbors considering every possible land use types. The compatibility between two land use types, for example, is evaluated based on how far zones are located and its importance decays with distance.

The third objective (3.3) seeks for land-use/transportation arrangements that maximize aggregate accessibility to jobs and services. Here accessibility is computed using the gravity based accessibility measure. It evaluates the accessibility of a zone as function of service and employment potentials of surrounding zones and considering how far (in terms of travel cost) these potentials are located. The gravity based accessibility measure (also referred to as potential accessibility measure) has been widely used in urban land-use/transportation studies see for example Ingram (1971), Vickerman (1974), Antunes et al. (2003), Geurs and van Wee (2004).

In our model we chose to use the gravity based accessibility measure because such measures are easy to compute using available (easily determined) land-use/transportation data. These measures are also capable of assessing the combined effects of land-use/transportation elements.

In evaluating the accessibility measure, since the land-use types of the zones and transportation link types are not deterministically known (that is the purpose of the allocation); the measure is tied to a decision variable and is written as function of ***Y*.** The accessibility measure is calculated depending on the land-use types allocated and transportation improvement programs implemented for the particular urban area. The size of an allocation and population are used as potential opportunity measures for accessibility to jobs and services respectively.

Constraint (3.4) restricts the maximum land use type allocated to a zone to be one. Similarly, constraints (3.5) and (3.6) make sure that only one transportation program is implemented.

Constraint (3.7) guarantees demand for land is satisfied, constraints (3.8) and (3.9) are logical constraints. In 3.8, the decision variable z_{jmkn} will only be 1 if both x_{jm} and x_{kn} are equal to 1. That means the compatibility objective is considered between two zones to which a land-use is allocated. Expression (3.9) ensures the integration of land-use/transportation decisions. Constraint (3.9) complemented by (3.8) indicates if land use m is allocated to zone j (x_{jm} = 1) and no land use n is allocated to zone k (x_{kn} = 0), a transportation program that consists a project for the improvement of link connecting zone

j to k is not recommended ($y_{jmknr} = 0$). However, if land use m is allocated to zone j ($x_{jm} = 1$) and land use n is allocated to zone k ($x_{kn} = 1$), a transportation program that consists a project for the improvement of link connecting zones j and k is recommended provided that such improvement contributes to the overall accessibility maximization. Conversely, if y_{jmknr} is to be equal to 1, both zones j and k need to have land use allocations m and n respectively. Finally (3.10) guarantee that the decision variables are binary.

3.3 Model applications

In his section, we present series of application examples of the basic model to number of partially randomly generated case studies. The purpose of these examples is to check whether the basic model is behaving the way we intended it to i.e. allocate the land-use types and assign transportation programs in a way to maximize suitability, compatibility and accessibility. The purpose is also to understand the computation efforts involved in solving the basic model when applied to various sizes of problems. There are three application examples. The first one is an application for an urban area with 10 zones; the second one is an application for 17 zones; and the third is application for an urban area with 26 zones.

The first example has simplified transportation program definition. Only highway improvement projects are considered, and only five programs are defined. Specifically, the first example is designed to show the resulting land-use/transportation maps when each objective is optimized individually. It also shows resulting efficient maps from when the objectives are normalized and differently weighed. The next two examples consider bigger urban areas (17 zone and 26 zones) and introduced the option of fast transit project to their transportation programs. These two examples show resulting efficient land-use/transportation maps when the objectives are normalized and equally weighted.

The model is solved with exact branch and bound method of linear integer solver in Xpress MP developed by Dash Optimization™ (FICO, 2012).

3.3.1 Example 1

The first example is the application of the model to an urban area with 10 zones. The zones are placed on a grid cell of size 3X3. The ten zones are arranged as shown in Figure 3.1. The zones can have maximum area of four units and minimum area of 1 unit. The urban area is characterized by having five zones with existing land-use and five other zones available for further development. The existing development has land use types of residential (RS), manufacturing (MN), commercial business district (CBD). Besides, the urban area has sparsely populated, almost vacant, zones (VN). In addition to the land-use types, the existing urban area is well connected with highways.

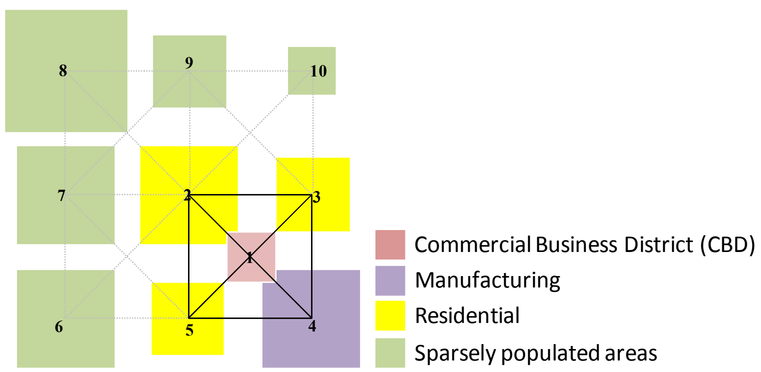


Figure 3.1 - Initial land-use/transportation map (10 zones)

Zones one to five represent the initial form of the urban area. The existing development is composed of land use types of residential (zones 2, 3, and 5), manufacturing (zone 4) and

CBD (zone 1). The remaining zones are potential development sites and are sparsely populated.

Model data

Two types of data are required to run the land-use/transportation model: land use related and transportation related. With respect to land-use, the area and land use suitability index values are randomly generated (Table 3.1). Area values are between 1 and 4 units whereas suitability values are between 0 and 1. The suitability index values are given for each land use types (RS and MN). This is because the land use types in demand, for this example, are residential and manufacturing. A higher value of suitability index indicates that a zone is more suitable for corresponding land use type. Table 3.1 presents sample values of areas and land-use suitability indexes. Since zones 1 to 5 are occupied, the table presents values for zones available for future development (zones 6-10).

Table 3.1 - Area and land-use suitability (10 zones)

Zone	6		7		8		9		10	
Area	3		3		4		2		1	
Land-use type	RS	MN	RS	MN	RS	MN	RS	MN	RS	MN
Suitability index	0.67	0.15	0.98	0.54	0.87	0.49	0.26	0.46	0.52	0.92

The land use compatibility index is evaluated for each zone and possible land-use type based on the principle that compatible land-use types can be allocated in adjacent zones where as incompatible land-use types are recommended to be allocated as far from each other as possible. Straight line distance among each zone is used to represent proximity.

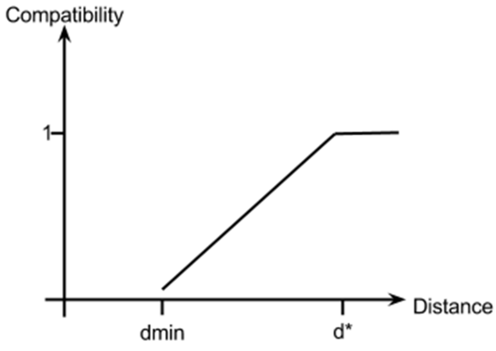


Figure 3.2 - Compatibility indexes of land-uses m and n

For two different land-use types ($m \neq n$), if the distance in between is less than a specified minimum value (d_{min}=1km), compatibility is zero. And if the distance is larger than maximum specified value (d_{max} = 1.5km), compatibility is one (the highest), see Figure 3.2. For different land-use types located at a distance value between the maximum and the minimum, the compatibility index is computed using a linear interpolation (equation 3.11).

$$c_{jmkn} = (dt_{jk} - d_{min}) / (d_{max} - d_{min}) \tag{3.11}$$

d_{min} – minimum distance below which the compatibility of neighboring land uses will be zero;

d_{max} – maximum distance beyond which the compatibility of neighboring land uses will be one (compatible);

dt_{jk} – straight line distance between zones *j* and *k*.

The demand for residential and manufacturing uses is given in Table 3.2. The land use assignment should satisfy demand. Based on the amount of area demanded for each land use type, there can be number of residential and manufacturing assignments.

Table 3.2 - Land use demand (10 zones)

Land-use type	Demand (Area)
RS	7
MN	3

With respect to transportation, the developed part of the city is very well connected using highways. For the remaining zones, there exists a slow highway connection. The transportation problem is, therefore, to determine which one of the slow highway links should be upgraded to fast highway so that aggregate accessibility is maximized. In this example it is considered that there is a limited budget for highway improvements and using this budget five transportation programs can be proposed. Each program is comprised of the upgrade of five slow highway links into fast highways.

Given the available budget, five transportation programs are randomly generated. The five possible programs for this example are shown in Figure 3.3.

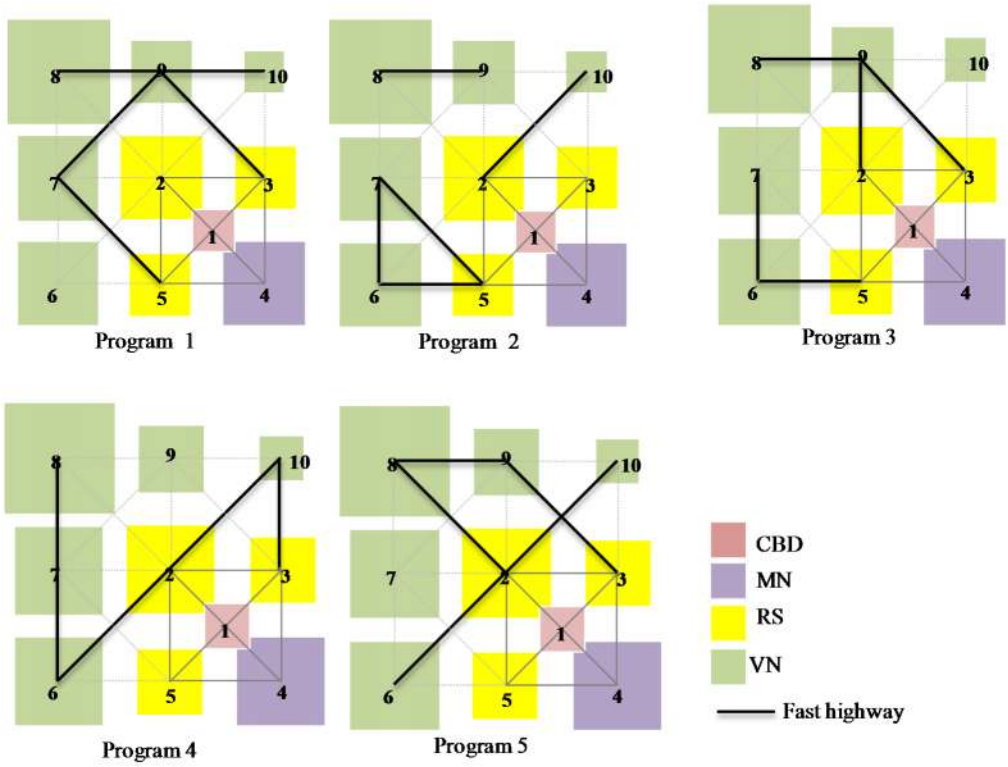


Figure 3.3 - Transportation programs (10 zones)

These are the type of transportation programs available for selection during the optimization process. While generating the programs, it is with the assumption that transportation planners will first layout possible transportation changes based on the amount of budget available and feasibilities of projects.

In this application, measure of accessibility is evaluated using gravity based accessibility measure. The opportunities are evaluated using the amounts of land-use types allocated (e.g. area for job opportunities and population for service opportunities). For instance, a zone with large area, if allocated with manufacturing land-use type has greater employment potential. Similarly a large zone allocated with residential land-use type has greater service potential. For evaluating the generalized function for travel time, we used a negative exponential form (considering β =0.5, for this application). This is because this function form is most commonly used and is found to have better representation of travel behavior theory (Handy and Niemeier 1997).

In order to evaluate the travel times, first we determine the shortest distance among pair of zones using Djikstra algorithm. Then, for each project, travel times among every pair of zones are calculated using speed-distance relationships. Different speed values are used for link types identified as fast highway, slow highways and existing highways. Depending on the type of project implemented, the algorithm updates the shortest paths automatically.

Model Results

Figure 3.4 (a-c) shows the land-use/transportation arrangements resulted from the first three runs of the optimization model using three sets of preference weights. These three figures show the land use/transportation arrangements when the objectives are optimized considering a weighting factors of {1, 0, 0}, {0, 1, 0} and {0, 0, 1} respectively. The weighting factors indicate the emphasis provided to particular objective. For instance the first weighting factor indicates that the model is solved considering the land use suitability objective only.

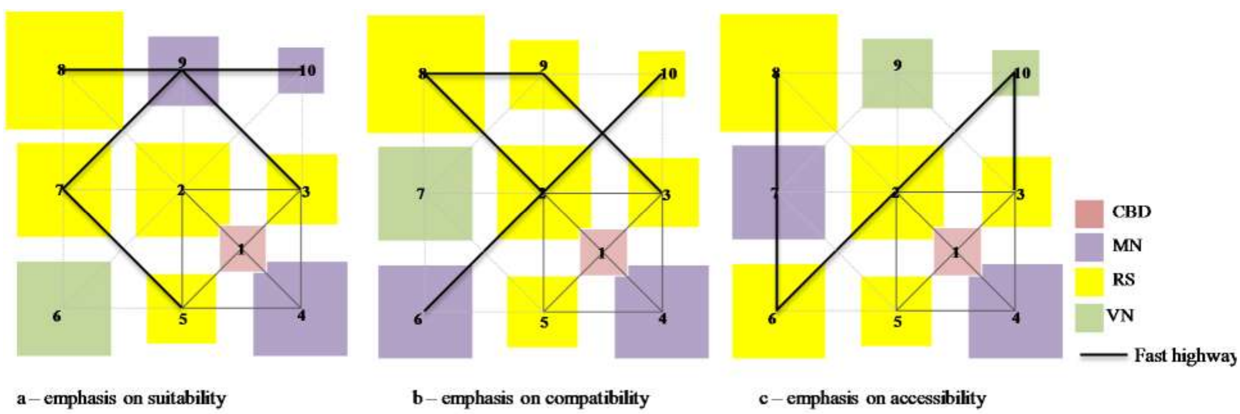


Figure 3.4 - Efficient maps for three weighing combinations

Figure 3.4(a) shows land-use/transportation arrangement if land-use suitability objective is maximized. It can be seen that the land-uses are assigned to their respective suitable locations. For instance zones 7 and 8 are suitable for residential whereas zone 10 is suitable for manufacturing uses. In comparison with Zones 7 and 8, Zone 6 is less suitable for residential land-use type.

Figure 3.4(b) shows land-use/transportation arrangement when compatibility is considered as the only objective. It can be seen that incompatible land use types are allocated far from each other. Residential zones 8, 9, and 10 are separated by rural area, zone 7, from the manufacturing zone in 6. Figure 3.4(b) also shows that zone 6 is the least suitable for manufacturing but it is more convenient when compatibility is considered. That is the fact that residential locations are assigned in zones 8, 9, and 10 makes zone 6 ideal location for the purpose of compatibility requirements.

Since accessibility objective is not considered in these two runs, the transportation programs shown in Figure 3.4(a) and 3.4(b) are just random picks by the model but the programs are in accordance to the logical constraint requirements.

Figure 3.4(c) shows land-use/transportation arrangement when the objective is to maximize accessibility. The figure shows that the newly assigned land has to be arranged in such a way that the manufacturing zone is placed in between the residential zones. An upgrade to the link that directly connects zones 6, 7 and 8 will result in shorter travel times between zones with large potentials i.e. higher accessibility. It is also important to note the land-use allocations in zone 7. Despite it being the most suitable location for residential use, zone 7 is allocated with manufacturing. This is due to the important transport interactions that would result from such land-use/transportation arrangements are more significant when it comes to improving accessibility.

The transportation program selected here has additional benefits as it provides upgraded connection to sparsely populated areas.

Following these single-objective maximizing cases, a min-max approach is used to normalize the objectives. In order to apply the approach first individual objectives are optimized. In doing so values of objectives, other than the one being optimized are computed. For instance while optimizing the first objective (maximizing suitability of land uses) the values of the second (compatibility) and the third (accessibility) objectives are computed. Let f_1, f_2 and f_3 be the three objective functions to be optimized individually. While maximizing the first objective, for example, values for second and the third objectives are computed and so forth as shown in Table 3.3.

Table 3.3 - Normalization of Objectives

Maximize	f_1		f_2		f_3	
Compute	f_2	f_3	f_1	f_3	f_1	f_2

For the computed objectives, the minimum, $f_{o,min}$, and maximum, $f_{o,max}$, values are identified. After identifying the maximum and minimum values of the objectives, the objective functions were normalized as shown in equation 3.12.

$$F = \sum_{0=1}^{3} \frac{f_o - f_{o,min}}{f_{o,max} - f_{o,min}} \tag{3.12}$$

Where:

F – value of the objective function (sum of the three objectives);

f_o – value of individual objective, o, being optimized (o = 1…3);

$f_{o,min}$ – minimum value of objective o computed while the other two objectives are optimized;

$f_{o,max}$ - maximum value of objective o computed while the other two objectives are optimized.

Figure 3.5 shows the efficient land-use/transportation arrangement after the objectives are normalized and equally weighted. Zones 6 and 8 are assigned with residential land uses while zones 9 and 10 are assigned with manufacturing. The land-use/transportation allocation result shows combinations of the effects of the three objectives.

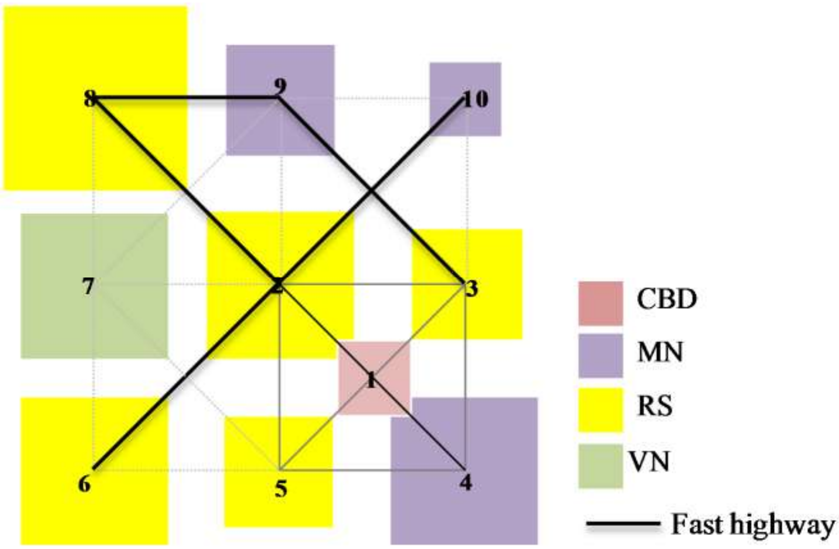


Figure 3.5 - Efficient map; equally weighted objectives

To observe the effects of changing importance in objectives, it is possible to assign weight values on the normalized objectives. For instance, if equal emphasis is given to the suitability and accessibility objectives where as no emphasis on the land-use compatibility objective (weighted by 0.5; 0; 0.5), the resulting land-use/transportation allocation looks like in Figure 3.6.

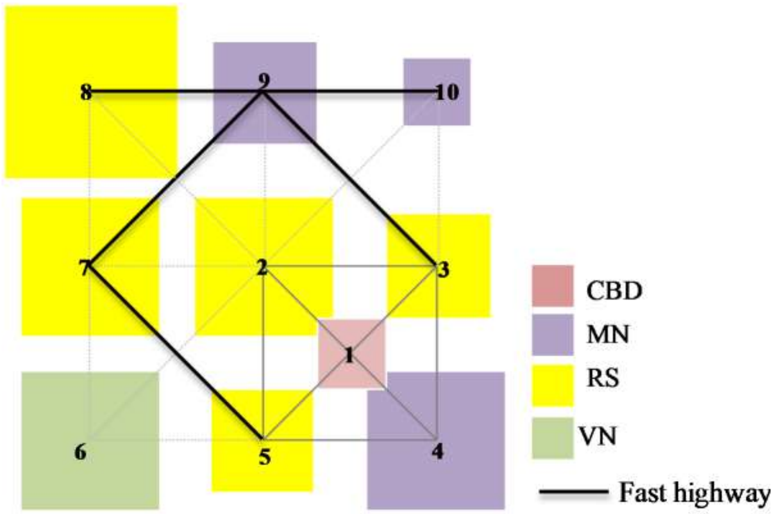


Figure 3.6 - Efficient map: emphasis on suitability and accessibility

The efficient land-use/transportation map in Figure 3.6 shows the emphasis given to the land-use suitability objective. It also shows the changes in transportation program to accommodate the change in land-use allocation while maintaining good level of access.

3.3.2 Example 2

In order to further test and understand the basic model, we examined more application examples. The second example is the application of the model to an urban area with 17 zones.

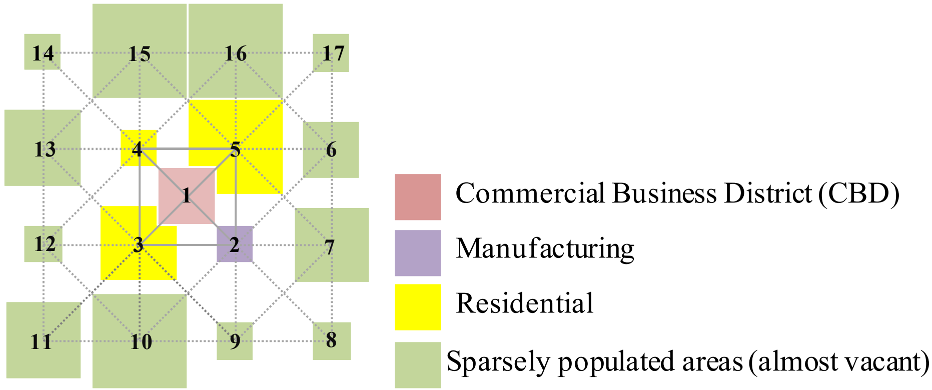


Figure 3.7 - Initial land-use/transportation map (17 zones)

The zones are placed on a grid cell of size 4X4. The seventeen zones are arranged as shown in Figure 3.7. This urban area is characterized by having five zones with existing land-use and twelve zones available for future development. Like in the first example, the existing development has land use types of residential (RS), manufacturing (MN), commercial business district (CBD). Zones 6 to 17 are potential development sites which are currently sparsely populated.

Model data

The land-use data for this example are mostly the same as the land-use data from the previous example. Except now the demand for land is larger and arrangement of the whole urban area is different. Area and land-use suitability index values are randomly generated and the land-use compatibility index is evaluated applying the same concept as in example 1.

The demand for residential and manufacturing uses is given in Table 3.4.

Table 3.4 - Land use demand (17 zones)

Land-use type	Demand (Area)
RS	22
MN	7

In regard to transportation, this example tests more choices in terms of the definition of programs and projects. The number transportation programs are now up to twenty five and each program is comprised of two possible projects: a highway upgrade/improvement project and a project that introduces fast transit. The highway project allows for the improvement of ten links and the transit project allows for the construction of five links for fast transit. The programs and projects are randomly generated.

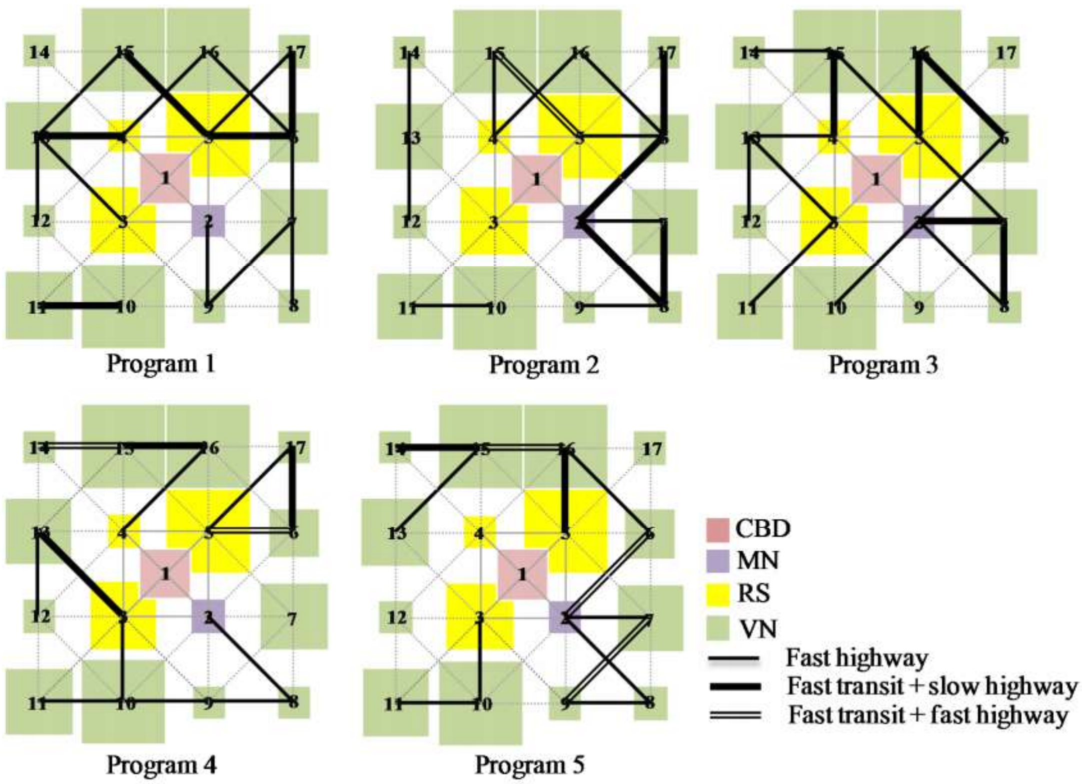


Figure 3.8 - Sample transportation programs (17 zones)

Figure 3.8, shows sample of transportation programs. Any number of such programs can be defined in the model but for this application example we defined twenty five programs. As can be seen from the figure, each program is comprised of highway improvement (ten links) and introduction of fast transit mode (five links).

Model results

The three objectives are first normalized and equally weighted. Result for one problem setting is shown in Figure 3.9.

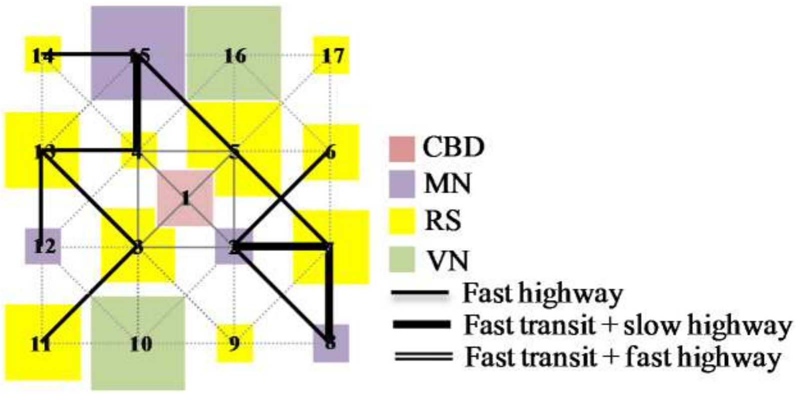


Figure 3.9 – Efficient map: equally weighted objectives

Figure 3.9 is the efficient land-use/transportation map when equal significance is given to all objectives. The land-use arrangements have satisfied the demand and a transportation program that best maximizes the aggregate accessibility is chosen. The map shows the transportation projects that directly connect major population and employment centers, for example zones 7, 5 and 15. For the 17 zone problem, we made additional model runs and all the resulting efficient land-use/transportation maps are presented in Appendix A.

Example 3

The third example is application of the basic model to an urban area with 26 zones. The zones are placed in grid cell size of 5X5 arranged as in Figure 3.10. In terms of the existing urban area form, this example is the same as to the previous two examples. Zones 6 to 26 are available for future development.

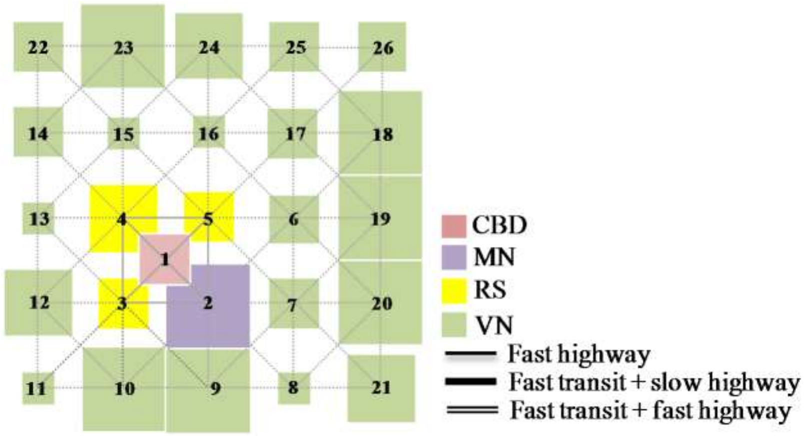


Figure 3.10 - Initial land-use/transportation map (26 zones)

Model data

The only change between land-use data of this example and the previous examples is that now the demand for land is bigger. The demand for land is given in Table 3.5.

Table 3.5 - Land use demand (26 zones)

Land-use type	Demand (Area)
RS	33
MN	14

The number of transportation programs for this case is twenty five. But unlike the previous example, each program consists of upgrade of sixteen links to fast highway and the addition of fast transit in eight links. The programs and projects are randomly generated (see Figure 3.11 for sample programs).

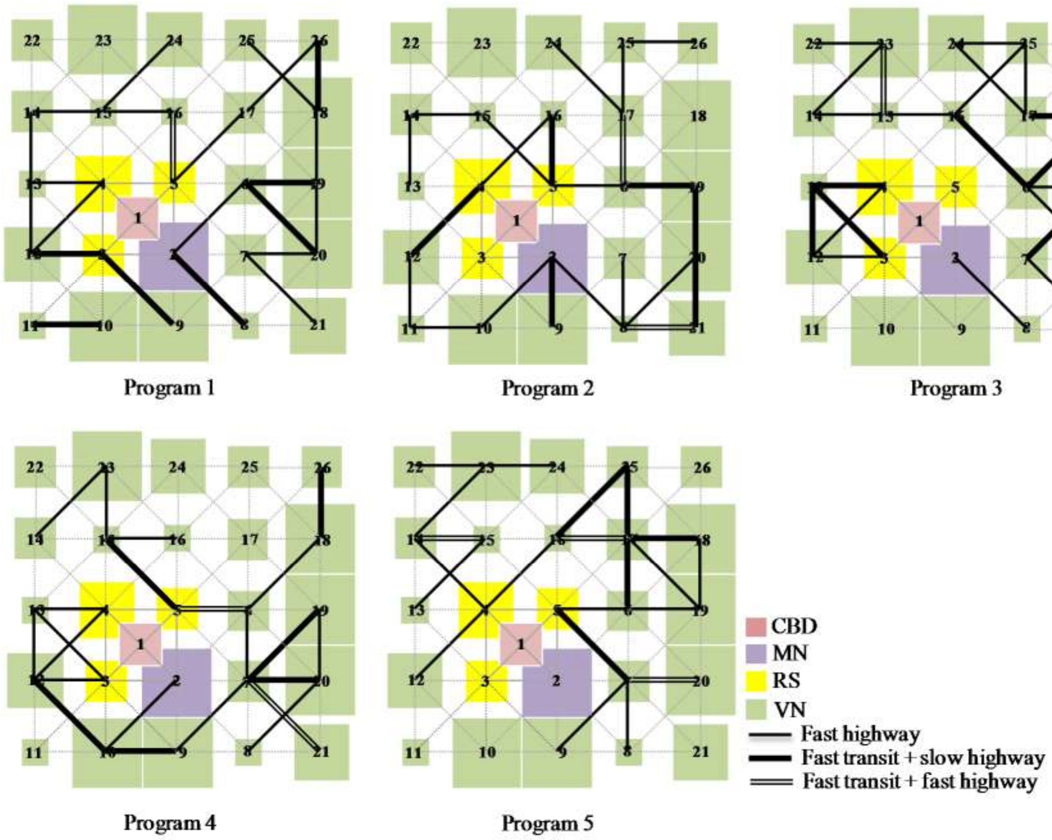


Figure 3.11 - Sample transportation programs (26 zones)

In Figure 3.11 sample transportation programs for the twenty six zone problem are shown. Each program is comprised of highway improvement (16 links) and introduction of fast transit mode (8 links).

Model results

As in the second example, the three objectives are first normalized and then equally weighted. Results are shown in Figure 3.12.

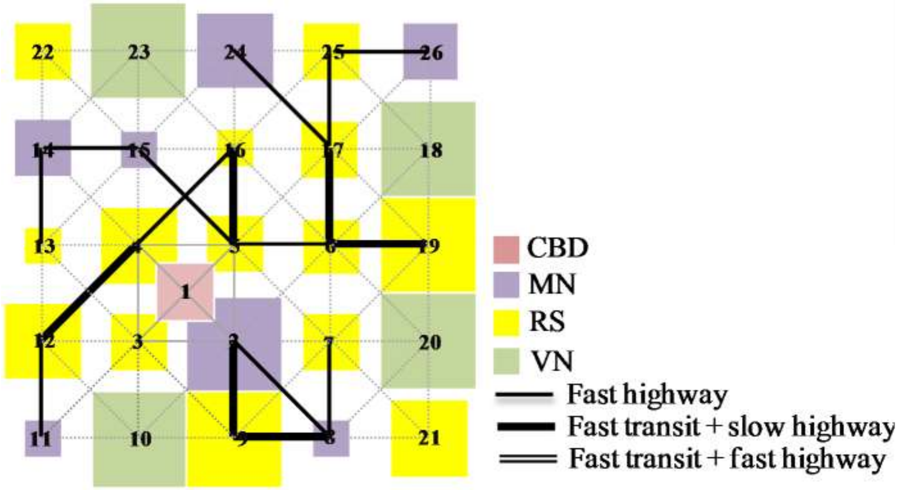


Figure 3.12 – Efficient map: equally weighted objectives

In the optimal land-use/transportation arrangement in Figure 3.12, all the objectives are equally weighted. Given the three objectives, the demand and logical constraint the map is an indication of the best urban form that can be achieved. There were twenty five transportation programs with each consisting sets of highway improvement and fast transit construction projects. The program that best maximizes the aggregate accessibility is shown in the figure. The program chosen has highway improvement, fast transit and occasional fast transit and fast highway improvements on a single link. Additional results for different urban settings are shown in Annex A.

In summary, the efficient land-use/transportation maps presented in examples 1, 2 and 3 indicate what can be achieved by applying the basic model. The basic model showed that the three objectives and constraints are combined to inform a decision maker what an efficient urban form would look like given existing conditions and future demands. It also showed that number of transportation programs and projects can be defined based on the amount of available budget and based on the feasibility of individual project. The basic model has integrated land-use and transportation decisions and this integration effect is shown in the resulting maps.

3.4 Model solving

This section reports on the technical and computational efforts involved in solving the basic model. For purposes of fair comparison, all computational times were based on solving of the model, as mixed integer programming (MIP), using a built-in optimizer in Xpress. All model runs were made using Windows XP on a computer with Intel(R) Core™ Quad CPU at 2.83 GHz, and 4GB RAM.

For this purpose, we defined three problem sets with ten, seventeen and twenty six zones. For the ten zone problems, twenty five transportation programs are defined with each composed of four highway upgrades and two fast transit lines projects. For the seventeen zone problems, twenty five transportation programs are defined with each containing ten links for highway upgrade and five fast transit line projects. Finally for the twenty six zone problems, the number of transportation programs is kept at twenty five but each program has sixteen highway upgrade projects and eight fast transit line projects.

The first thing we are looking for in these exercises is the computation time. For the ten zone problems, the time the models took to reach at the efficient solution was less than a minute. Computation time results for the seventeen zone problems are shown in Table 3.6.

Table 3.6 - Computation times, 17 zones

Problem	Time (mins)
1	82.77
2	47.7
3	76.27
4	94.37
5	46.45
6	66.48
7	168.3
8	152.45
9	118.61
10	201.23

For the seventeen zone problems, the smallest computation time was 48 minutes and the largest 3 hours and 20 minutes. The corresponding land-use/transportation maps for five of the ten problems are presented in Figure 3.13.

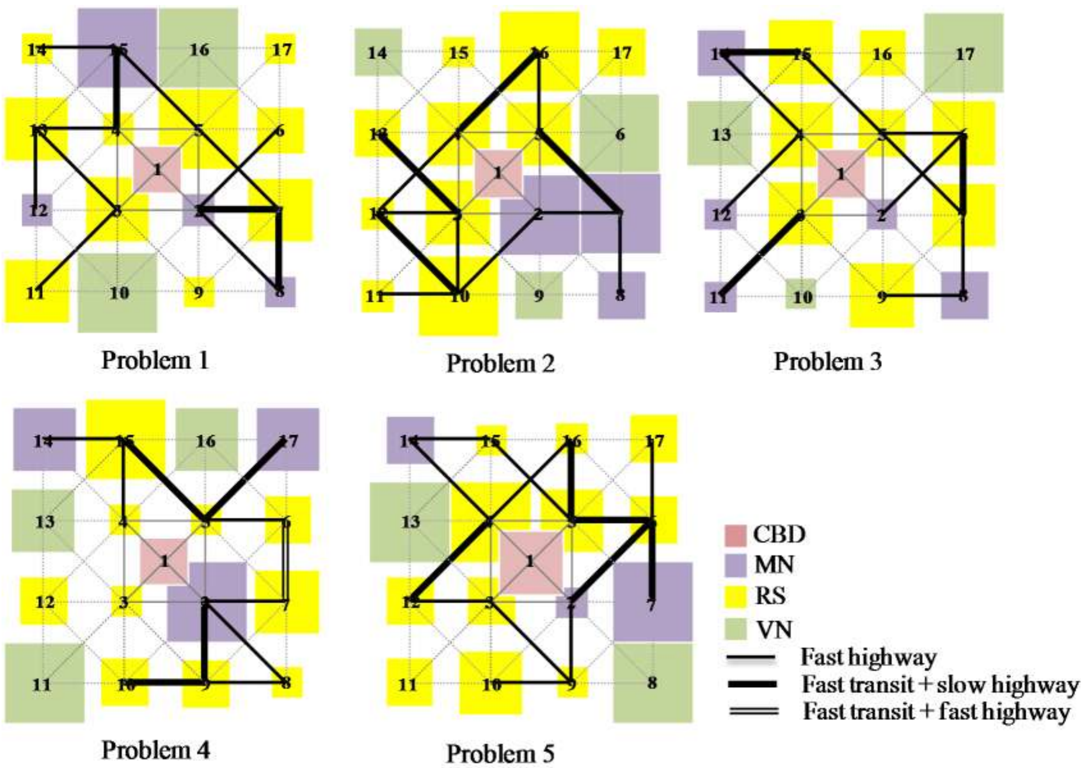


Figure 3.13 – Efficient maps: equally weighted objectives (17 zones)

The average computation time for the 17 zone problems is around 1.5hrs. This is not large computation time particularly considering the purpose of such model for proposing long term land-use/transportation arrangements. The computation times for three 26 zone problems is shown in Table 3.7.

Table 3.7 - Computation times, 26 zones

Problem	Time (mins)
1	7620.51
2	8081.54
3	6053.98

The computation times increase very much when the problem size is increased from 17 to 26 zones. This is expected development. Much of the increment can be attributed to the combinatorial nature of the problem and large number of decision variables. As can be seen on Table 3.7, the average computation time is 5 days. This is significantly large computation time specially considering the size of the problem is only 26 zones. For real world applications, the number of zones in an urban area can be easily larger than 26.

The resulting efficient land-use/transportation maps from the three problem runs are presented in Figure 3.14.

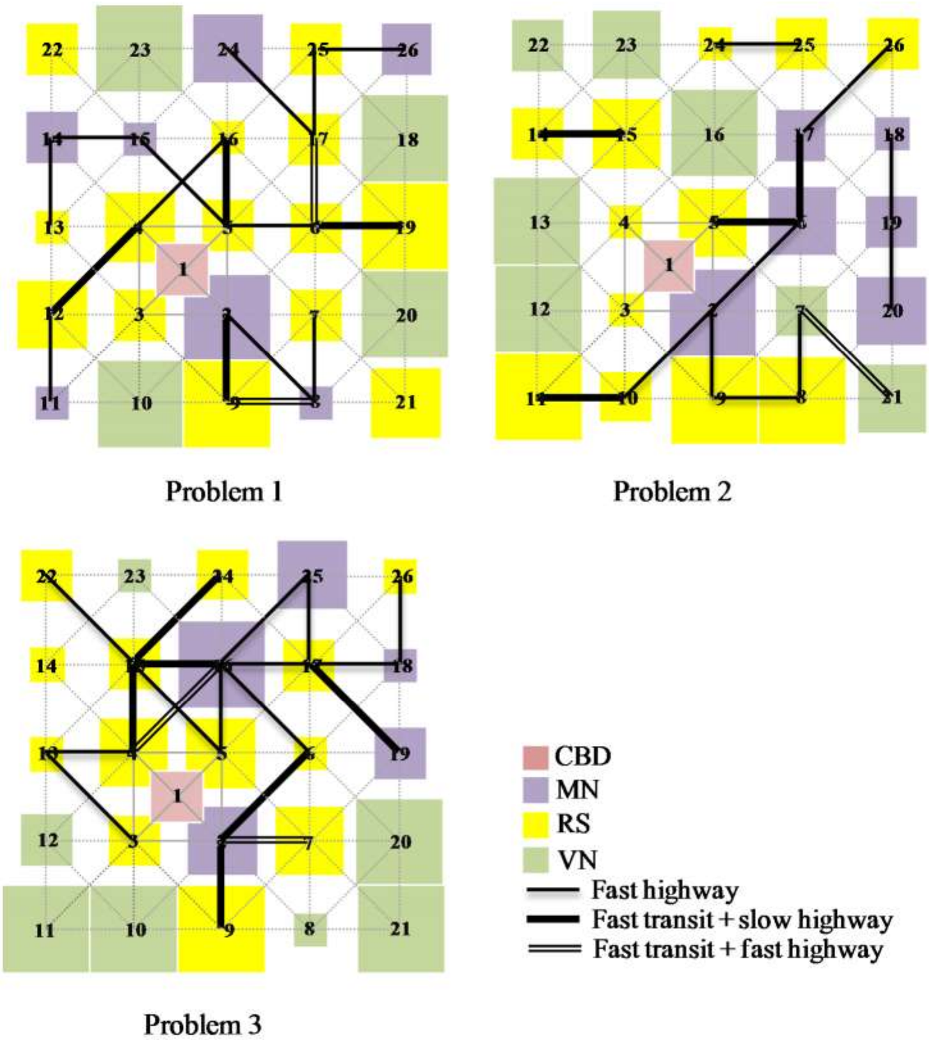


Figure 3.14 – Efficient map: equally weighted objectives (26 zones)

In order to further understand the computational efforts, we carefully observe the evolution of the efficient solutions and the way the gap between the best upper bound and the best solution is closing.

For one of the twenty six zone problems the gap between the best bound and the best solution is 83% after 19 hours of running. As it is summarized on Table 3.8, the model even took long to find a solution which is better than the current solution – the percentage of total time in reference to the time for best current solution is 38% and counting. The twenty six zone problem displays a behavior such that if an efficient heuristic algorithm is applied to solve the basic model, the solution time may be improved considerably while maintaining the goodness of the solution.

Table 3.8 - Summary of model solving

Item	Problem	
	17-Zones	26-Zones
No. of integer solutions	16	16
Best Solution	11750	50917
Best Upper Bound	11750	93286
Difference to Best (%)	0	83.2
Total Computing Time (mins)	94	1189
Best Solution Computing Time (mins)	46	446
Percentage of Total (%)	49	38

In general, it is observed that the computing time is growing considerably with increasing the size of the problem. This makes a case for the possibility of looking for and applying heuristic technique which is capable of solving the basic model at considerably short time.

In the next chapter, we explore a heuristic algorithm that can be used to solve the basic model for similar problem sizes and types as were solved in this chapter.

3.5 Summary of basic model

The main objective of this chapter was to introduce a new optimization model for urban land-use/transportation policy design. The objective was also to test the performance of the model in various application settings.

A multi-objective land-use/transportation optimization is developed considering the maximization of the normalized weighted sum of land-use suitability, land use compatibility, and accessibility objectives. These objectives have been selected based on the current practices in land use and transportation planning. Land-use suitability objective quantifies the physical, institutional and locational characteristics of a zone in reference to particular land use type. Land-use compatibility is a spatial objective which has been commonly used by many land-use optimization models. It is based on the principle of allocating the similar land uses in proximity to one another. This objective reduces the environmental discomfort that might arise from placing incompatible land use types next to one another. Considering accessibility as an objective has so many implications. First accessibility, as a concept, is at the center of land-use/transportation interaction and it should constitute part of any integrated model. Second accessibility has, in so many instances, used an indicator for socio-economic development. And an efficient land-use/transportation map resulting from an optimization model that has maximization of accessibility as an objective can be considered as fulfilling social and economic development objectives.

The three objectives were combined after being normalized and weighted. The normalization was made using a min-max normalization method. Then the model was solved using built-in linear programming solver in Xpress. The usefulness of the model in generating efficient land-use/transportation arrangements was evaluated using several examples, all of them having different problem settings. In all problem settings, the model generates land-use/transportation arrangements that maximize the normalized weighted sum of suitability, compatibility and accessibility.

The first problem setting was an urban area with 10 zones. For this problem setting, the three objectives were first optimized individually. Then the objectives are normalized and weighted. Results from each model runs reflected the importance attached to the objective. Computation effort for this problem setting was very small. The subsequent problem settings were urban areas with 17 and 26 zones. For these problem settings the objectives were normalized and equally weighted. Also for these problem settings more transportation program and project options were considered. The number of programs was increased up to 25 and in addition to the highway improvement; a fast transit project was included. Efficient results from these problem settings show land-use/transportation maps that maximized the three objectives, satisfy demand and comply with demand and integration constraints. Computational efforts for the 17 zone problems were acceptable, whereas the 26 zone problems required considerably high computation effort.

The issue of computing time becomes evident as the problem size grows. This is due to the combinatorial nature of the problem and the fact that the model has large number of decision variables and constraints. This large computation effort makes a case for the development of more efficient heuristic algorithms, if the model is going to be applied for case studies with larger urban areas.

This optimization model has shown it can be a valuable decision support tool. It also showed that there is a lot of space for improvement. First improvement would be refining the parameters such as areas, suitability index and transportation inputs. Besides refinement of parameters, the transportation component of the model will be made to include modal split and effects of congestion on the transportation links. A new solution method (heuristic algorithm) will be developed and integrated into this basic model. The model will finally be applied to a real world case study application.

4 Computational efforts

4.1 Introduction

In the previous chapter, we have introduced the basic version of the optimization based model we developed for urban land-use/transportation planning purposes. The basic model was solved using an exact brunch and bound method built in Xpress MP developed by Dash Optimization™ (FICO, 2012). In that chapter, we have also mentioned that the exact solution method, while guaranteeing efficiency of solutions, is characterized by large computational requirements. Specifically, the method takes considerably large amount of computation time to solve medium to large sized problems.

In operations research (management science) there are well established procedures for developing heuristic solution methods. These heuristic methods, compared with the exact solution methods, are characterized by lower computational requirements. This is, of course, at the expense of quality of solutions i.e. when developing a heuristic solution method, there is a tradeoff between solution quality and computation effort. The tradeoff can be designed to be in favor of quality of solutions once the nature and behavior of the heuristic method is understood.

There are number of heuristic solution methods but simulated annealing (SA), add interchange (AI) and genetic algorithms (GA) are the most commonly applied for land use optimization applications. In the land-use allocation models, discussed in Chapter 2 of this thesis, most commonly used heuristic methods are simulated annealing and genetic algorithms (see for e.g. Aerts and Heuvelink 2002, Aerts et al. 2003– for simulated annealing applications; and Feng and Lin 1999, Stewart et al. 2004, Datta et al. 2008, and

Janssen et al. 2008 – for genetic algorithm applications). In some applications, model developers have solved an optimization model using both methods simulated annealing and genetic algorithm. For example study by Aerts et al. (2005) has solved their multi objective optimization using simulated annealing and genetic algorithm.

Numbers of previous studies have reported that genetic algorithms are superior solution methods for multi-objective combinatorial problems (see for example studies by Fonseca and Fleming 1995, Jaszkiewicz 2002, and Stewart et al. 2004). Moreover, study by Aerts et al. (2005) have tested simulated annealing and genetic algorithm to solve a multi objective land allocation model and concluded that genetic algorithm is slightly superior in terms of computation times and solution qualities, in reference to solution values of one of their objectives. The observations from these previous studies regarding genetic algorithm are that the method is favorable solution method for discrete problems with large design spaces, such as the type of multi-objective land-use/transportation model we have introduced in previous chapter.

The purpose of this chapter is to explore the potentials of possible heuristic solution method, genetic algorithm, for the purpose of solving the optimization based land-use/transportation model introduced in the previous chapter. The current chapter will introduce the basic concepts and design procedures of genetic algorithms. The purpose is also to report on the calibration and validation procedures of a genetic algorithm specifically developed to solve the optimization based land-use/transportation problem.

Following this introduction, the chapter presents the solution method of our choice, genetic algorithm and its design procedure. Then it goes on to present algorithm calibration (assessment of quality of algorithm parameters) and validation (assessment of quality of solutions) procedures. Finally the chapter presents discussions and recommendations on the solution method.

4.2 Genetic algorithms

Genetic algorithms are heuristic problem solving methods which are based on the principle of evolving population of candidate solutions using genetic operators such as variation and natural selection adopted from biology (Mitchell 1999). Genetic algorithms belong to class of stochastic search methods that work on population of candidate solutions, hence are population search methods.

In the context of design of genetic algorithm, it is necessary to explain some of the biological terminologies that are analogously used. A chromosome refers to candidate solution to a problem. The particular elements of the candidate solution are encoded by a gene. Roughly, an allele is type of bit a gene can take, see Figure 4.1.

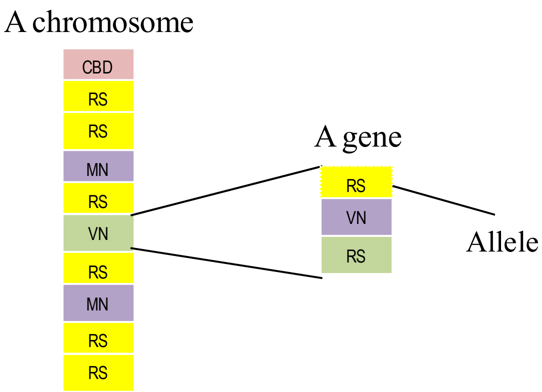


Figure 4.1 - Components of GA

In the application of genetic algorithm to land-use allocation, a chromosome refers to one out of number of possible solutions. A solution here is particular allocation of land-uses in an area. A gene may refer to a zone with the possibility of accommodating a land-use type.

The location and land-use type in the zone are very significant in determining the nature of the solution (chromosome). The specific land-use type allocated to a zone can be referred to as an allele (Figure 4.1).

Genetic algorithm has applications in land-use/transportation studies (for example: Stewart et al. 2004, Feng and Lin 1999, Xiao et al. 2002, Aerts and Herwijnen 2005, Datta et al. 2008). The algorithm has the advantage of being fast and it is considered efficient in solving discrete problems with large design space (Stewart et al. 2004). The issue with using heuristic algorithm such as genetic algorithm is that efficiency of solutions is not always guaranteed. Quality of solutions should be verified either against solutions from exact solution method or from using other heuristic algorithms, considering similar problem.

In the application of genetic algorithm for land-use/transportation systems, the solution coding can be briefly summarized as in Figure 4.2. A solution is comprised of land-use allocation plus a transportation program connecting the zones. Every solution has its own fitness value (F_i) that is computed from the normalized and weighted objective functions. A population (N) of candidate solutions from single run of the algorithm constitutes a generation (G).

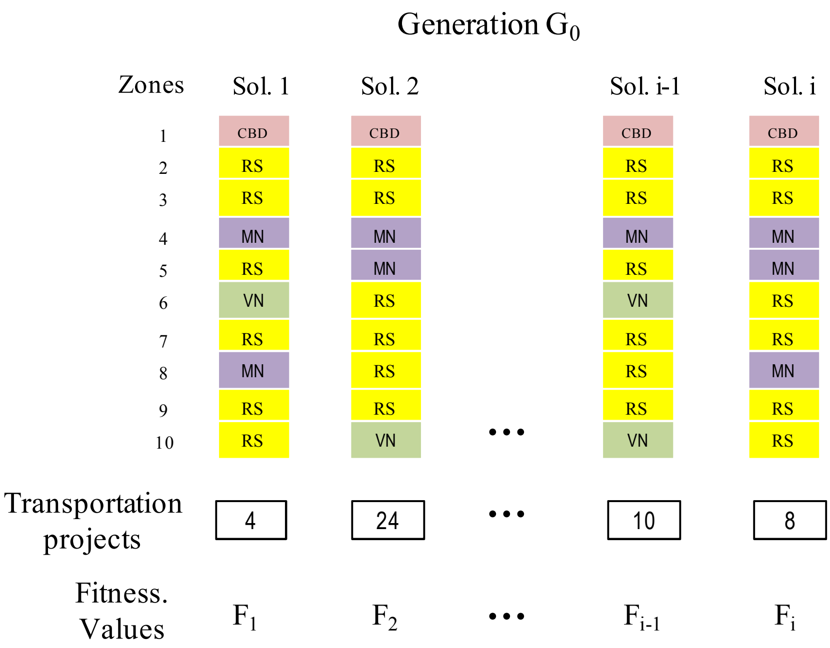


Figure 4.2 - Solution coding

4.3 Design of genetic algorithm

The design of genetic algorithm has number of steps. Flow chart in Figure 4.3 shows the key steps in the design of genetic algorithm. The steps involved are formulation of the problem and preparation of data, initialization of candidate solutions, evaluation of fitness of solutions, updating of solutions and selection process. Each of the key steps involved in the design of genetic algorithm are discussed in the following sub sections.

4.3.1 Initialization

The initialization step of genetic algorithm design generates population of candidate solutions. This process is partially randomly generated. The number of these candidate solutions is referred to as the size of the population. It is possible to have any size of population, but the size may affect the computation time of the algorithm. In the process of initiating candidate solutions, it is necessary to check for their feasibilities.

In the application for land-use/transportation optimization, the random initial solutions are in relation to arrangements of land-use types as well as transportation projects. And the feasibilities are related to the conditions that only one land-use type per zone; and one transportation program for every solution. Moreover, initial solutions should take the form of the existing urban area in to consideration.

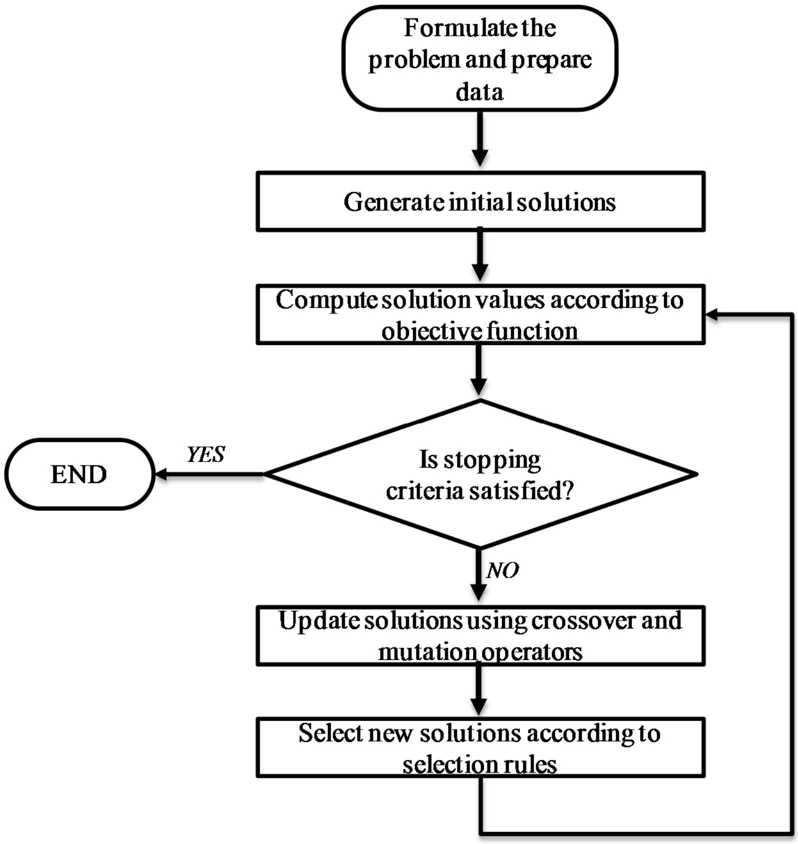


Figure 4.3 - Genetic algorithm design procedure

4.3.2 Evaluation

For the initially generated candidate solutions, values of the fitness function are computed. Since our optimization based model has three objectives, the fitness function must normalize and combine the three objectives. A min-max normalization method is used.

For all individual solutions i in the population N:

F_i – value of fitness function for solution i (i=1…N);

f_{io} –value of individual objective, o, that belongs to solution i (o=1…3).

$$F_i = \sum_{0=1}^{3} \frac{f_{io} - min\, f_{io}}{max\, f_{io} - min\, f_{io}}; \forall i \in N \tag{4.1}$$

Considering the best value of the fitness function from the population of candidate solutions, the fulfillment of the stoppage criteria is checked. However, since genetic algorithm depends on the refinement of solutions using genetic operators, it is less likely that good solutions will be obtained during this initial stage. The solution with the highest fitness value in the initial stage is saved and candidate solutions are passed on to the updating step.

Depending on the size of the population, there are now N candidate solutions. These candidate solutions will be passed through genetic operators with the expectation of finding improved solutions in the process. Updating population of candidate solutions is done using three genetic operators: crossover, mutation and selection.

4.3.3 Updating of solutions using genetic operators

Crossover

Crossover is analogous to the process in biology where the building blocks of two parents are mixed to produce an offspring. The crossover operation in genetic algorithm is performed between two candidate solutions (parents). It involves the exchange of part or parts from each parent, depending on the type of crossover operator used.

There are three commonly used crossover operators in genetic algorithm. These are single point, two-point and uniform crossover operators. The difference among these operators is on the number and location of crossover points (Mitchell 1999). The choice on the type of crossover operator to use depends on the problem type as well as the amount of exchanges required. The figure below exemplifies the three crossover operators (Figure 4.4).

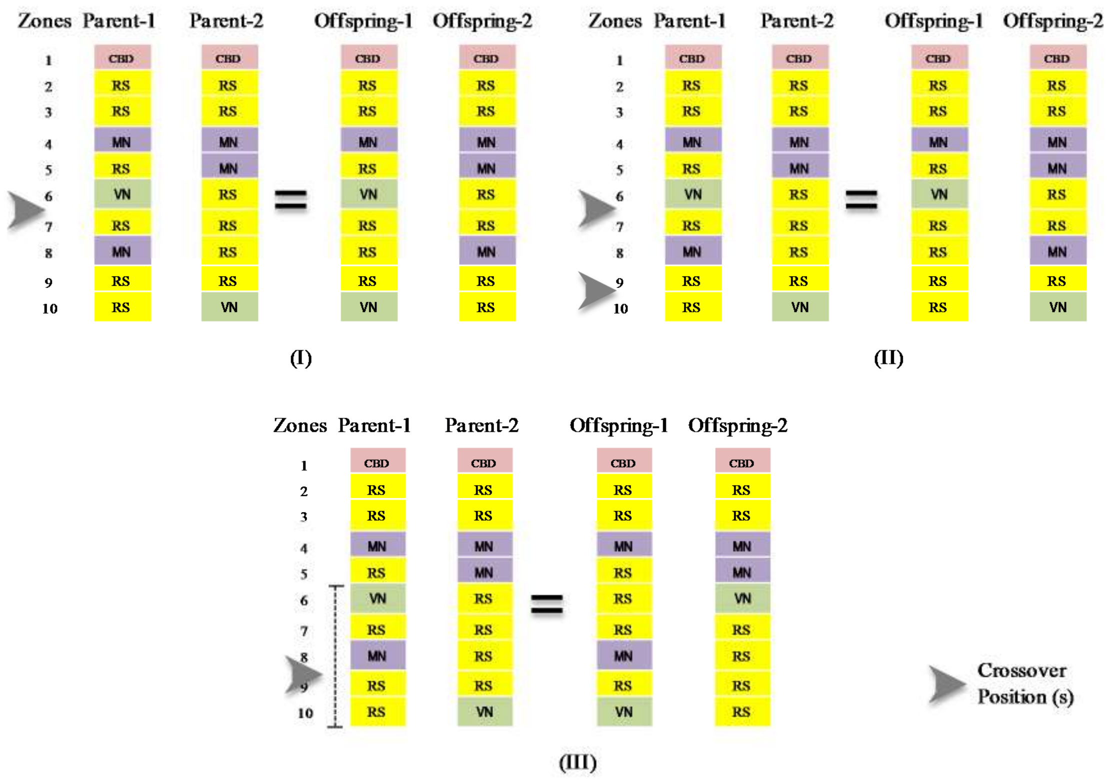


Figure 4.4 - Crossover operators: single point (I), two point (II) and Uniform (III)

Single point crossover involves choosing single fixed position in the candidate solution (chromosome) and exchange parts of parents to produce two offspring with traits from both parents. Owing to its nature, the single point crossover will not be able to check all possible cases of exchanges. Since the structure of the offspring depends on the location of crossover position, this operator is subjected to positional bias. Moreover depending on the position, this operator might destroy the structure of parent solutions.

Two-point crossover involves choosing two fixed points in each parent solution and exchange parts. The two-point crossover, though it is less likely to destroy the structure of parent solutions, is still less likely to check all the possible cases of exchanges.

Uniform crossover is a parameterized operator that involves the possibility of exchanging parts at any location within the two parent solutions. Uniform crossover has no positional bias and is less likely to disturb the structure of parent solutions. Even though these characteristics of uniform crossover operator are not necessarily desirable all the time, it is a better operator nevertheless. In this application we use the uniform crossover operator.

In applying the uniform crossover operator, the first step is parent selection. In order to do so, all candidate solutions are placed in a pool. We developed an algorithm that randomly chooses two parents from the pool considering two conditions: one, the two parents must be unique and two, no repetition i.e. once parent solutions are crossed-over they will be removed from the pool.

Once the two parent solutions that will be subjected for instant crossover are selected from the pool of solutions, the uniform crossover involves determining the location of crossover. This process is random and probabilistic. That is, a parameter in the form of probability of crossover (PC) is first defined. And depending on the probability of crossover and value of a random number, parts from one parent solution are exchanged with parts from the other parent solution (Figure 4.4 –III). The crossover is carried out until all the pairs of parents in the pool are exhausted.

For our land-use/transportation application, a parent solution constitutes land-use allocations and transportation project arrangements. For the land-use allocations, for example, the locations of crossover (crossover points) are the zones and the parts to be exchanged are the land use types. The crossover is also done for transportation programs.

Mutation

Mutation operator is analogous to the process in biology where permanent changes occur to the material that transfers genetic characteristics. In genetic algorithm, this operator is usually carried out within a solution and it involves the alteration of part of a solution. Mutation is a random and probabilistic process. That is, a parameter in the form of probability of mutation (PM) is first defined. And depending on the probability of mutation and value of a random number, part from a solution is randomly altered (Figure 4.5).

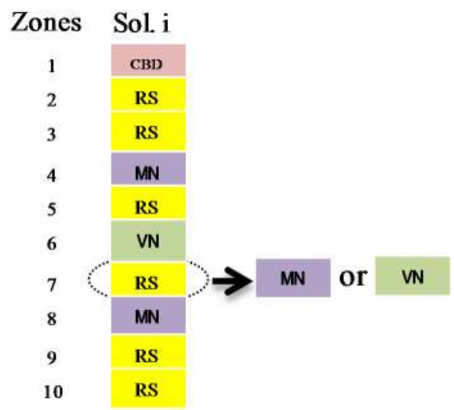


Figure 4.5 - Mutation operator

For our land-use/transportation application, mutation is carried out on a solution that constitutes land-use allocations and transportation project arrangements. For land use map, for example, the mutation operator is executed at zone level of a particular solution. For a zone that is allocated with a land-use, first the type is identified. And based on the probability of mutation and value of a random number, the land-use type of that zone will be changed from the existing to another randomly picked use. The changes involve, for example, converting residential to manufacturing or vice versa; also changes from developed to vacant and vice versa.

Feasibilities of candidate solutions

Following the crossover and mutation, the next step in the genetic algorithm is the application of the selection operator. Before proceeding to the selection operator however, we have to verify the feasibilities of the population of solutions obtained so far. This feasibility verification specifically targets the amount of land area allocated i.e. in principle amount of land allocated in a solution should be equal to the amount of land demanded. Owing to the nature of the problem (zones have different areas) such infeasible solutions are ubiquitous. Of course it is possible to fix or eliminate the infeasible solutions but such actions will affect the size of the population and will also limit the flexibility of the solution method. Instead, we opt for the option of keeping but penalizing infeasible solutions. We introduced a penalty function in the form of equation 4.2. Solution values are penalized in proportion to their violations of area requirements. Penalty π is deducted from the fitness value.

$$\pi = \pi' \Delta | h_m | \tag{4.2}$$

π' –is multiplying factor for the penalty term (usually between 0.5 to 0.8);

h_m –amount of land (area) allocated for land use type *m;*

$\Delta|h_m|$–is the difference between the amount of area allocated and the amount of area demanded for land-use type *m*.

The penalty term has a multiplying coefficient that can be varied. This means solutions that digress from the area demand are penalized accordingly. The penalty coefficient, π', has the possibility of taking any values. But we found values from 0.5 – 0.8 to be large enough to guarantee feasibility and small enough to allow for keeping some infeasible solutions that, after genetic variations, might become good feasible solutions.

Selection

After passing through the crossover and mutation operators, the new offspring solutions have to be carried onto the next generation. This is performed by the selection operator. Similar to the biological phenomenon survival of the fittest, this selection operator is based on the principle that fitter solutions have higher chances of being carried into the next generation than less fit ones. For this operator, first a probability value is determined based on the value of the fitness of each candidate solution. This probability is evaluated in such a way that the best candidate solution has a probability of selection equal to 1 (100% chance of being chosen for the next generation) whereas the worst candidate solution has a probability of selection equal to 0.

By using the selection operator, a definite number of candidate solutions are carried to the next generation. Here it is possible for a candidate solution to be chosen more than once. And the first among the population of candidate solutions, in terms of fitness value, is always chosen.

The process of updating of population of solutions using genetic operators is carried out number of times. The algorithm parameter that controls the numbers of cycles of population update is the number generation, *G*. Every update cycle produces generation of candidate solutions. Indeed, it is possible to define any number of generations. However, this parameter is directly proportional to computational effort i.e. defining large number of generations may lead to higher computation times.

After finishing the process of updating populations of solutions, the final output is a best solution in the form of land-use/transportation map. This final solution is the best the algorithm could yield given the population size, probability of crossover and mutation, and number of generations. This best solution, however, might not be the optimal solution. In order to verify the optimality of the best solution, the algorithm parameters must go through certain calibration stages and the solution itself must be validated. Following sections will present calibration and validation procedures.

4.4 Calibration of algorithm parameters

Genetic algorithms have certain unique characterizing parameters. These parameters have great influence on the evolution and quality of solutions as well as on the computation times. These algorithm parameters are population size (*N*), probability of crossover (*PC*), probability of mutation (*PM*) and number of generations (*G*).

Calibrating these parameters, meaning determining parameter values that yield with good solutions in relatively short computation times, is a rigorous process. This is because the algorithm parameters typically interact with one another and their interaction behavior can't be easily modeled. There is a great deal of discussion on parameter calibration in genetic algorithm literature. Previous efforts to define right approaches to parameter calibration and determine the right parameter settings (values) are not conclusive. Most previous applications use algorithm parameter values that had worked well in preceding studies (Mitchell 1999).

The land-use transportation optimization model proposed in this thesis is typically complex. Its complexity partially arises from the fact that there is fixed demand for land that should be satisfied and the land-use units (zones) have varying areas. Besides, the model has logical constraints that add difficulty to the solution process. In order to deal with the demand constraint, we implemented a penalty function that penalizes infeasible solutions accordingly. The presence of penalty function, the fact that the zones have widely different sizes and considering the fact that demand is strictly fixed make the calibration process uneasy. This is because any changes due to crossover or mutation have the potential of distorting solution quality significantly. This leads to the conclusion that care must be taken when choosing the algorithm parameters (calibration).

In calibrating algorithm parameters, we opted for rigorous process that involves number of algorithm runs for different problem types and sizes. The calibration process we applied for our study is presented in the subsequent sections. Before proceeding with the algorithm calibration procedures we have employed, however, we explain the terms we are going to use throughout the remaining sections of this chapter. The terms are problem, instance and case (Figure 4.6).

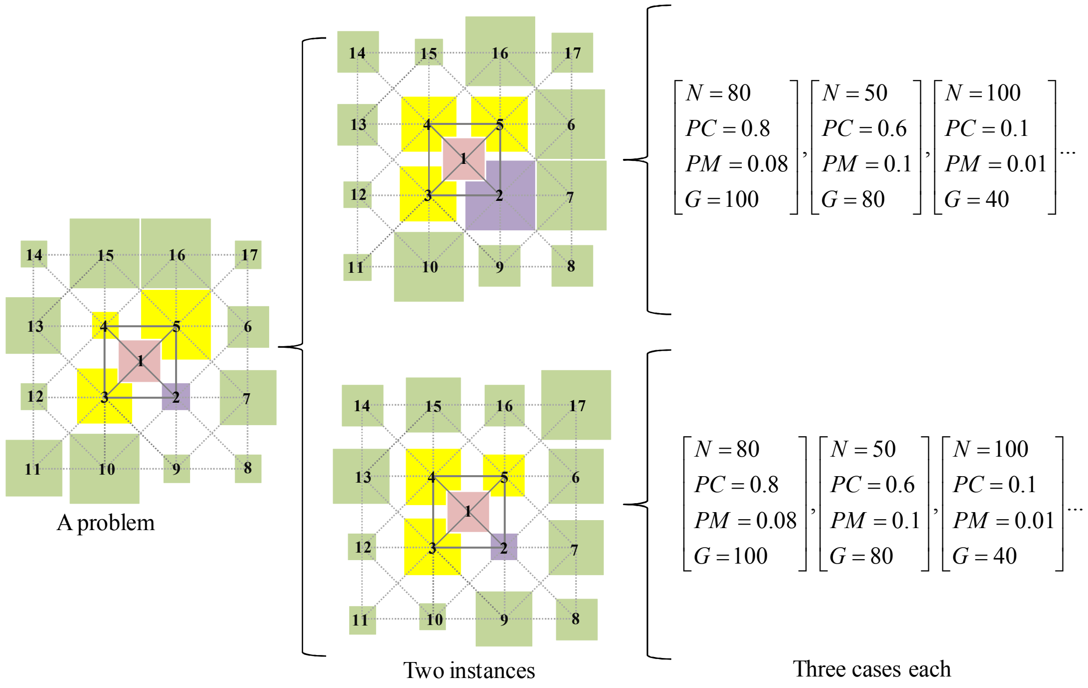


Figure 4.6 - Parameter calibration terminologies, example

A problem is defined as a particular urban area with existing land-use/transportation arrangements and vacant land for future development. Problem types are differentiated based on the number available zones for future development and based on the number of possible transportation programs that could be implemented. For instance, in the calibration process we defined two problem types: a 26-zone and 17-zone problems.

An instance refers to a problem that has zones with particular area values and particular transportation project combinations. We can define several instances for a problem.

A case refers to an instance with particular values of algorithm parameters. We can have several cases for a single instance. For example, in the calibration process presented in this chapter more than fifty cases are randomly defined for particular instance.

In this thesis we approach the calibration process by performing numerous model runs with different combinations of parameter values. We made test runs for various problem sizes and instances. We applied a three stage process. The first stage is to decide on the range of values the algorithm parameters have to take. The second stage is to further narrow the ranges by analyzing values of fitness functions and focusing on parameters that yield with good solution values. The third stage is to use these parameter values and make further systematic model runs.

For the calibration process, we solved the basic optimization based model for two problem sizes—the 17 and 26 zones. For both problem types we made runs of numerous instances and cases, depending on the stage of calibration. For each model run we considered random variations of the algorithm parameters. The processes involved and the results obtained from the three calibration stages are briefly presented in the following sub sections.

4.4.1 Calibration stage – 1

The purpose of the first calibration stage is to observe the evolution of candidate solutions across all generations and determine starting values for algorithm parameters. The purpose is also to make a pre-analysis on the solution method and gain better understanding of its parameters and define parameter ranges that will be tested on the next calibration stages. In this first calibration stage we used the algorithm parameter ranges shown in Table 4.1 i.e. a parameter can assume any value within the specified range. In the course of model runs, we carefully observe the changes in solution values from one generation to the next. Besides we analyzed fitness function values for the two problem sizes and various problem instances.

In this calibration stage we tested several instances of the two problem sizes, 17 & 26 zones. For the 17 zone problem we tested 10 instances and for the 26 zone problem we tested three instances. For each problem type and for every instance, the algorithm was tested for fifty cases. For each case, the algorithm parameters are randomly varied within the range of values in Table 4.1.

Table 4.1 - Range of parameters (stage – 1)

Algorithm Parameters	Ranges 17-Zone	26-Zone
N	10 - 170	10 - 260
PC	0.1 - 1	0.1 - 1
PM	0.1 - 1	0.1 - 1
G	10 - 100	10 - 100

Based on results obtained from the first calibration stage, it became clear that relatively higher values for population size (*N*), generations (*G*) and probability of crossover (*PC*) will be sufficient to add the required changes and contribute to the upward evolutions of candidate solutions in subsequent generations. The results also indicate that lower mutation probability (*PM*) values have high chances of maintaining the goodness of a solution while allowing for the occasional alterations that will lead to better fit solutions. Considering this preliminary observation, we defined new algorithm parameter ranges for the second calibration stage. We defined a mutation range of 0.01 to 0.1 and kept other parameter ranges the same as in Table 4.1.

4.4.2 Calibration stage – 2

The purpose of the second calibration stage is to further refine the values for algorithm parameters. Based on the new parameter ranges obtained from the first calibration stage, the second calibration tested the algorithm for two problem sizes, 17 and 26 zones. For the 17 zone problem we tested five instances and for the 26 zone problem we tested two instances. For each instances, the algorithm was run for fifty cases.

The figures shown in Figures 4.7 and 4.8 are examples of the kinds of results from model runs after the second calibration stage.

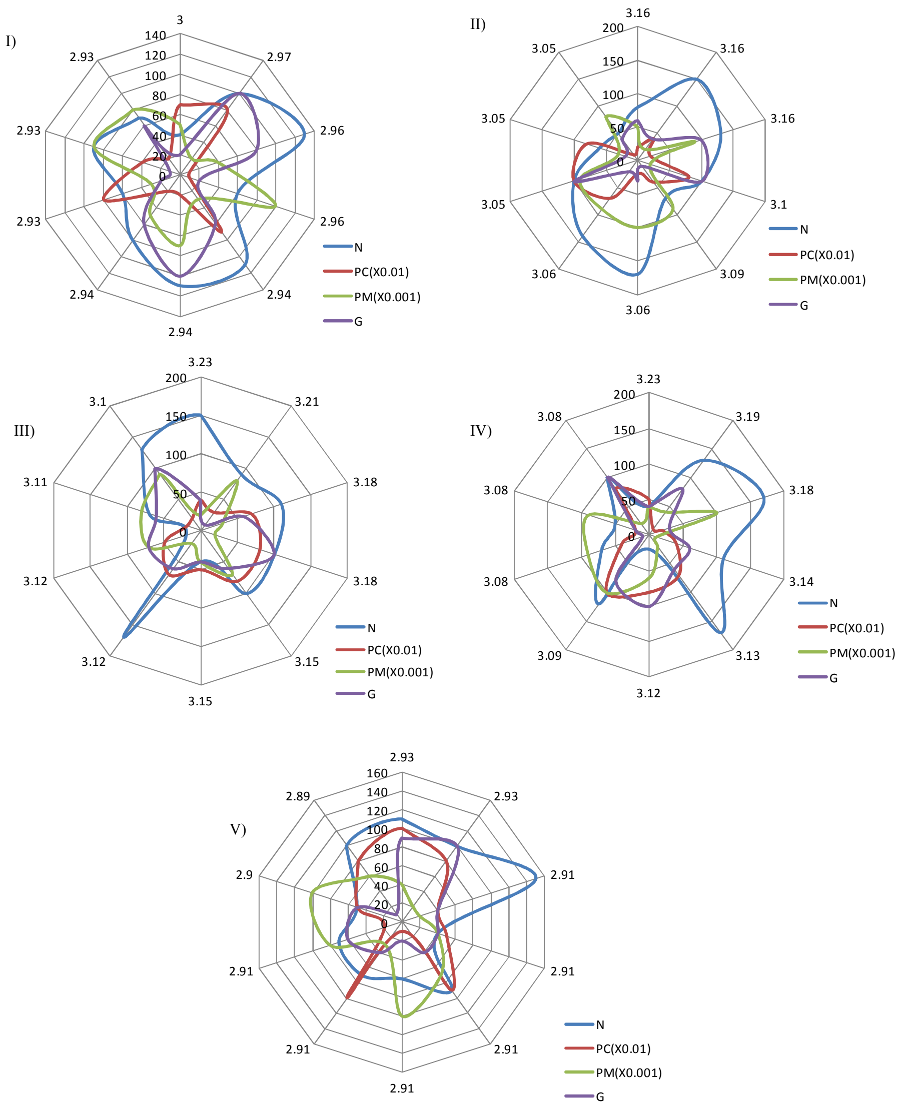


Figure 4.7 - Fitness Vs algorithm parameters 17-zone problem five instances

For the purpose of clarity, we plot in Figure 4.7 few problem cases (mainly the top 10 in terms of solution values). The figure shows plots of values of the fitness function versus the values of algorithm parameters population (*N*), probability of crossover (*PC*), probability of mutation (*PM*) and number of generations (*G*). Each figure represents an instance of 17-zone problem which is run for fifty cases but only results from top ten cases are plotted. In each plot, circular lines show the value of algorithm parameters and the value of the fitness function is shown at the tip of the radial lines. For instance in Figure 4.7(I), the fitness value 2.97 is resulted from a model run that uses an *N* value of 100; *PC* value of 0.8; *PM* value of 0.02 and 100 generations (*G*).

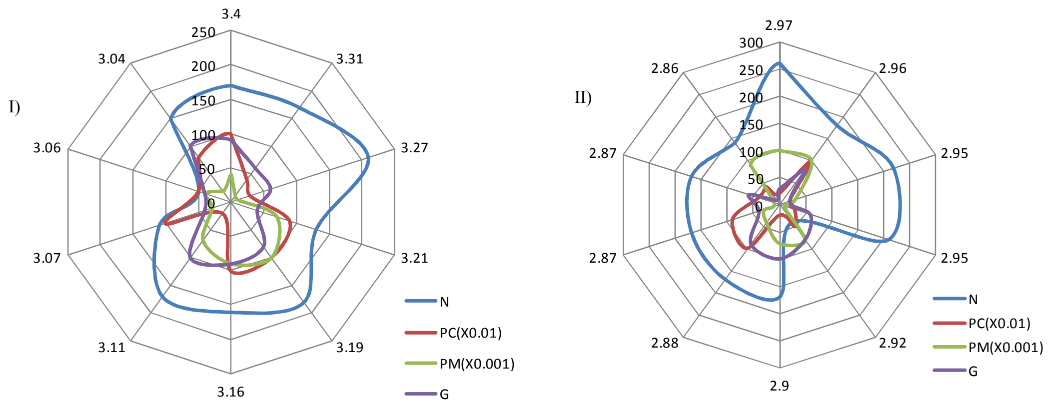


Figure 4.8 - Fitness Vs algorithm parameters 26-zone problem two instances

Similarly, for the 26- zone problem solutions from two instances are shown in Figure 4.8. The plots in Figure 4.8 are sample results from the 26 zone problem and first two instances. As it was mentioned earlier, each instance is tested for fifty cases by varying the algorithm parameters. As an example, top ten results for the two instances are plotted in Figure 4.8.

Each of these solutions, Figures 4.7 and 4.8, represents a particular land-use/transportation arrangement. For each problem size, the best solutions (maps) of the first instances are shown in Figures 4.9 and 4.10 as an example.

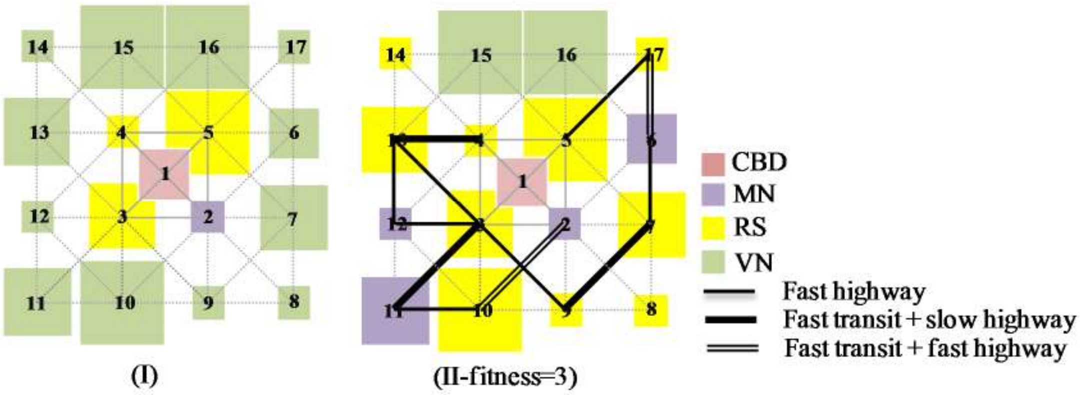


Figure 4.9 - Example problem (I) and solution (II) 17-zone

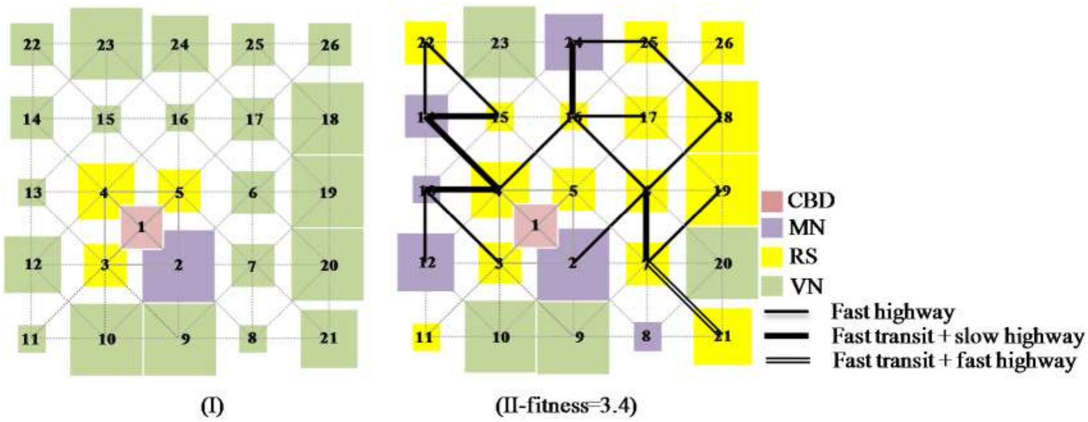


Figure 4.10 - Example problem (I) and solution (II) 26-zone

Figures 4.9(I) and 4.10(I) show the urban area with initial land-use and transportation arrangements. Results in Figure 4.9(II) and 4.10(II) show the final land-use/transportation arrangements for 17 zone and the 26 zone problems respectively. Note that these are sample results for the two problem sizes, first instances and best cases.

By carefully examining the resulting land-use/transportation arrangements and analyzing the solution values from the newly defined algorithm parameters we have observed that changes in parameters have improved quality of the solutions. The newly defined mutation range has managed to improve the overall fitness of the solutions as well as it managed to narrow the differences among consecutive solutions. This is a significant improvement as it raises the confidence level on the algorithm. Results also indicate that population size is significant in determining the quality of the solution but higher population size doesn't always guarantee good solutions. The value for number of generations (*G*) is another significant parameter. We observed that higher values of *G* have positive effect on the quality of a solution. However, higher *G* values result in longer computation times.

In general, the key towards good solutions heavily lies on the *PC* and *PM* values and how these two parameters interact. At this analysis stage, there are signs that indicate these two parameters are inversely related. i.e. in the cases where the solutions are good and the mutation probabilities are higher, the crossover probability turned out to be low.

As it is mentioned earlier and shown in Table 4.1, the algorithm parameters are defined within range of values. That means there are number of possibilities from which a particular algorithm parameter can take its value. In order to help us understand the nature of the algorithm more, it was necessary to narrow the ranges. Based on the analysis from the second calibration stage, we defined new parameter ranges shown in Table 4.2.

Table 4.2 - Range of parameters 17 and 26 zones

Algorithm Parameters	Ranges 17-Zone	26-Zone
N	100 - 130	100 - 150
PC	0.8 - 1	0.8 - 1
PM	0.01 - 0.03	0.01 - 0.03
G	80 - 100	80 - 100

4.4.3 Calibration stage – 3

The purpose of this third calibration stage is to make further model runs using the algorithm parameters obtained from the second calibration stage. The purpose is also to refine the algorithm parameters and determine right values that will yield with good quality solutions.

In this calibration stage, instead of making number of runs for random cases, we based our analysis on the results from the second calibration stage. That is, in this stage the focus was mainly on the extreme cases (worst and best) in terms of solution values. Using the newly defined parameters (Table 4.2); first the cases that perform poorly in the second stage are identified and tested. The principle behind choosing the worst performing cases is that we would like to check how far we can improve quality of solutions using new algorithm parameters. Based on the results i.e. observing how the new algorithm parameters have managed to improve the worst ones, the parameter values will be accepted or subject to further changes. Moreover, by rerunning the best performing cases using the newly defined algorithm parameters we planned to verify the goodness of the parameters.

In order to proceed with the third calibration stage, first we ranked the solutions from the second calibration stage based on their fitness values. For each problem size, we picked the least five solution values and the instances that correspond to them. Using the newly defined algorithm parameters, we run these least performing instances. Results are presented in Table 4.3:

Table 4.3 - Calibration results, 17-zone five instances

	Instance	No.	Value	N	PC	PM	G
After the 2nd stage	9	1	2.68	80	0.9	0.04	30
	33	2	2.68	50	0.2	0.09	20
	44	3	2.67	10	0.7	0.04	40
	19	4	2.6	20	0.4	0.1	90
	24	5	2.56	40	0.7	0.03	20
After the 3rd stage	9	1	2.88	110	1	0.03	80
	33	2	2.92	100	0.8	0.01	80
	44	3	2.99	100	0.8	0.01	100
	19	4	2.96	110	0.9	0.02	90
	24	5	2.99	100	0.8	0.01	100

(I)

	Case	No.	Value	N	PC	PM	G
After the 2nd stage	1	1	2.76	20	0.8	0.06	100
	43	2	2.76	30	0.2	0.03	10
	3	3	2.72	100	0.8	0.06	10
	8	4	2.66	10	1	0.1	50
	41	5	2.25	20	0.1	0.1	20
After the 3rd stage	1	1	3.16	130	0.8	0.02	90
	43	2	3.06	120	0.9	0.02	100
	3	3	3.16	100	0.9	0.02	100
	8	4	3.04	120	0.9	0.02	80
	41	5	3.16	100	0.8	0.01	100

(II)

	Case	No.	Value	N	PC	PM	G
After the 2nd stage	33	1	2.85	50	0.2	0.09	20
	2	2	2.82	70	0.4	0.09	10
	8	3	2.8	10	1	0.1	50
	29	4	2.79	60	0.1	0.1	20
	38	5	2.78	90	0.4	0.09	10
After the 3rd stage	33	1	3.14	100	0.9	0.03	90
	2	2	3.14	120	0.9	0.02	100
	8	3	3.15	110	0.8	0.01	90
	29	4	3.18	120	0.8	0.01	100
	38	5	3.09	100	1	0.03	80

(III)

	Case	No.	Value	N	PC	PM	G
After the 2nd stage	37	1	2.78	70	0.2	0.08	60
	44	2	2.7	10	0.7	0.04	40
	19	3	2.67	20	0.4	0.1	90
	40	4	2.67	60	0.5	0.07	40
	18	5	2.53	90	0.3	0.08	10
After the 3rd stage	37	1	3.12	100	0.8	0.01	90
	44	2	3.19	130	0.9	0.02	100
	19	3	3.12	100	0.8	0.01	80
	40	4	3.09	100	1	0.02	80
	18	5	3.23	110	0.8	0.02	100

(IV)

	Case	No.	Value	N	PC	PM	G
After the 2nd stage	22	1	2.55	30	0.2	0.01	50
	41	2	2.52	20	0.1	0.1	20
	33	3	2.51	50	0.2	0.09	20
	38	4	2.46	90	0.4	0.09	10
	8	5	2.35	10	1	0.1	50
After the 3rd stage	22	1	2.89	100	1	0.03	100
	41	2	2.95	100	0.8	0.01	80
	33	3	2.93	110	0.8	0.01	100
	38	4	2.91	110	0.9	0.02	100
	8	5	2.81	100	1	0.03	90

For 17 zone problem, results from five instances are presented in Table 4.3. For each instances, the tables present case number, rank (descending order), algorithm parameters and fitness values. The tables also present results from the two calibration stages. The values after the second stage represent the worst performing solutions prior to the third calibration stage. And values after the third calibration stage represent values that are obtained using the newly defined algorithm parameters. As it can be seen from the case numbers, the results in both calibration stages represent the same problem, the same instances and corresponding cases.

Results in Table 4.3 show clear indication that the newly defined algorithm parameters have managed to improve quality of solutions. When viewed in reference to the qualities of the worst performing solutions, the improvements in average are more than 13%.

Table 4.4 - Calibration results, 26-zone two instances

(I)

	Instance	No.	Value	N	PC	PM	G
After the 2nd stage	13	1	2.66	60	0.7	0.06	20
	18	2	2.65	130	0.3	0.08	10
	46	3	2.65	70	0.1	0.08	40
	19	4	2.59	20	0.4	0.1	90
	8	5	2.15	20	1	0.1	50
After the 3rd stage	13	1	3.41	150	0.8	0.01	100
	18	2	3.41	140	1	0.02	100
	46	3	3.47	120	0.8	0.01	80
	19	4	3.41	150	0.9	0.02	80
	8	5	3.44	110	0.8	0.02	100

(II)

	Case	No.	Value	N	PC	PM	G
After the 2nd stage	31	1	2.54	210	0.7	0.09	20
	43	2	2.53	40	0.2	0.03	10
	16	3	2.5	150	1	0.09	100
	46	4	2.46	70	0.1	0.08	40
	45	5	2.45	100	0.8	0.03	20
After the 3rd stage	31	1	2.95	100	0.8	0.02	80
	43	2	3.02	100	0.9	0.01	90
	16	3	3.08	140	0.8	0.01	90
	46	4	2.96	150	1	0.03	100
	45	5	2.93	100	0.8	0.02	90

For the 26 zone problem, results for two instances are shown in Table 4.4. For each instance solution values after second stage represent results from the second calibration stage (the five least performing cases). And solution values after the third stage represent results after the third calibration stage in which the algorithm parameters from Table 4.2 are used. Similar to the results in Table 4.3, results in Table 4.4 contain the case number, rank, algorithm parameters and solution values of a particular instance.

Results in Table 4.4 show significant improvements in terms of solution values after the problems, instances and cases are run using the newly defined algorithm parameters at the third calibration stage. In reference to the value of a solution after the second stage, the improvements have averaged at more than 21%.

By observing the results for the numerous instances and the two problem types, we can deduce that the newly defined algorithm parameters have improved solution quality. This is a significant observation as it indicates the direction we should follow in the next steps of the algorithm calibration process.

In order to support our claim that the new algorithm parameters have improved quality of solutions, we made further model tests. This time the target cases were those who have performed well in the second calibration stage. Note that our purpose is still to verify the goodness of algorithm parameters in Table 4.2.

For the 17 zone problem we made model rerun tests for the same five instances. For these five instances, we rely upon the solutions obtained from the second calibration stage. As we have mentioned earlier solutions from the second calibration stage were ranked based on their fitness values. From the best five solutions, we randomly pick three cases and made the model run using the newly defined algorithm parameters.

Results in Table 4.5 show solutions for the three randomly chosen cases of a 17-zone problem, five instances. The tables show case number, rank of solution, algorithm parameter and value of fitness function.

Table 4.5 - Calibration results, 17-zone five instances

	Case	No.	Value	N	PC	PM	G
After 2nd stage	11	1	2.96	130	0.1	0.04	80
	29	2	2.96	60	0.1	0.1	20
	39	3	2.94	110	0.7	0.03	60
After 3rd stage	11	1	2.9	100	0.8	0.01	100
	29	2	2.97	130	0.9	0.03	90
	39	3	2.93	100	0.8	0.01	80

(I)

	Case	No.	Value	N	PC	PM	G
After 2nd stage	6	1	3.16	80	0.2	0.05	60
	30	2	3.16	130	0.2	0.09	100
	2	3	3.09	70	0.4	0.09	10
After 3rd stage	6	1	3.16	100	0.8	0.01	100
	30	2	3.16	110	0.9	0.02	100
	2	3	3.16	110	0.8	0.02	90

(II)

	Case	No.	Value	N	PC	PM	G
After 2nd stage	10	1	3.23	150	0.4	0.02	40
	18	2	3.21	90	0.3	0.08	10
	39	3	3.18	110	0.7	0.03	60
After 3rd stage	10	1	3.18	130	0.9	0.03	100
	18	2	3.18	100	0.8	0.02	100
	39	3	3.14	120	0.8	0.02	100

(III)

	Case	No.	Value	N	PC	PM	G
After 2nd stage	11	1	3.19	130	0.1	0.04	80
	50	2	3.14	110	0.4	0.01	60
	20	3	3.13	170	0.7	0.02	60
After 3rd stage	11	1	3.23	100	0.9	0.01	90
	50	2	3.09	130	0.8	0.02	80
	20	3	3.08	120	1	0.03	100

(IV)

	Case	No.	Value	N	PC	PM	G
After 2nd stage	14	1	2.93	110	1	0.04	90
	42	2	2.93	100	0.8	0.02	100
	25	3	2.91	40	0.5	0.04	40
After 3rd stage	14	1	2.91	100	0.8	0.02	90
	42	2	2.89	120	0.9	0.03	80
	25	3	2.91	110	0.8	0.01	80

(V)

Results in Table 4.5 show that, the newly defined algorithm parameters have performed very well. In many instances, the parameters have resulted in solution values that are at least as good as the top ranked solution values from the second stage.

Similarly for the 26-zone problem we made rerun of the two instances mentioned earlier. This time the algorithm tests were made for four randomly chosen cases from the top ranked solutions from the second stage.

Table 4.6 - Calibration results, 26-zone two instances

Stage	Case	No.	Value	N	PC	PM	G
After 2nd stage	50	1	3.31	170	0.4	0.01	60
	23	2	3.27	210	0.3	0.01	60
	27	3	3.21	130	0.9	0.07	40
	5	4	3.19	180	1	0.1	80
After 3rd stage	50	1	3.47	100	0.8	0.01	90
	23	2	3.43	100	0.8	0.01	90
	27	3	3.43	150	1	0.02	100
	5	4	3.38	100	0.9	0.03	100

(I)

Stage	Case	No.	Value	N	PC	PM	G
After 2nd stage	12	1	2.97	260	0.2	0.1	30
	5	2	2.96	180	1	0.1	80
	21	3	2.95	220	0.2	0.03	20
	15	4	2.92	40	0.5	0.08	80
After 3rd stage	12	1	3.01	100	0.9	0.02	80
	5	2	3.02	120	0.8	0.01	100
	21	3	2.99	110	1	0.03	100
	15	4	3.09	100	0.8	0.01	90

(II)

Fitness values from Table 4.6 indicate that the qualities of solutions have improved after the third calibration stage. For the 26 zone problem, in both instances, solution values after the third calibration stage are higher than after the second calibration stage. This is to say that by using the newly defined algorithm parameters we didn't only get good solutions but we get solutions which are even better than the top solutions from the second calibration stage.

In the process of calibrating algorithm parameters, we are now in the third stage. Results so far have shown clear indication that the improvements on the quality of parameters. This was displayed in terms of improvements of solution values considering two different circumstances. The first one was to test the worst performing cases and the second one was the best performing cases from the second calibration stage. Irrespective of the standings of the cases, the newly defined algorithm parameters have managed to improve solution values in many occasions. In some instances, these parameters have shown that they have the potential of producing solutions that are as good as their previous counterparts.

Even though, at this stage of calibration we couldn't conclude that these parameters are the right ones but we can say that these parameters and the way we changed them in the subsequent calibration stages is a right way. It is important to note here that we are talking in relative terms. That is till now we have no indication that the good solutions obtained are optimal solutions. We are simply making relative comparisons among candidate good solutions in different calibration stages.

To further verify the quality of the newly determined algorithm parameters, we made more tests for both problem types. For these tests, we defined additional five instances for the 17 zone problem and one instance for the 26 zone problem. For each instance, five random cases were tested using the algorithm parameters from the second and third calibration stages. Results after the third calibration stage are presented on Tables 4.7 and 4.8 for 17 zone and 26 zone problems respectively. Results from the second calibration stage were much inferior to results from the third calibration stage.

Table 4.7 - Calibration results, 17-zone five instances

	Case	No.	Value	N	PC	PM	G
After the 3rd stage	1	1	3.24	120	0.8	0.01	90
	2	2	3.17	100	0.9	0.03	90
	3	3	3.3	130	0.8	0.02	100
	4	4	3.24	100	0.8	0.02	80
	5	5	3.3	110	1	0.01	100

(VI)

	Case	No.	Value	N	PC	PM	G
After the 3rd stage	1	1	2.93	110	1	0.02	100
	2	2	2.97	100	0.8	0.01	90
	3	3	2.92	100	1	0.03	80
	4	4	2.96	100	0.8	0.01	80
	5	5	2.97	120	0.9	0.02	100

(VII)

	Case	No.	Value	N	PC	PM	G
After the 3rd stage	1	1	3.13	130	0.9	0.03	100
	2	2	3.13	120	0.8	0.03	90
	3	3	2.99	130	1	0.01	100
	4	4	2.95	100	0.9	0.02	80
	5	5	3.05	100	0.8	0.01	90

(VIII)

	Case	No.	Value	N	PC	PM	G
After the 3rd stage	1	1	2.92	120	0.9	0.03	80
	2	2	2.81	100	0.8	0.01	90
	3	3	2.9	130	1	0.03	100
	4	4	2.89	130	0.8	0.02	100
	5	5	2.86	100	0.9	0.01	90

(IX)

	Case	No.	Value	N	PC	PM	G
After the 3rd stage	1	1	3.17	120	0.9	0.02	100
	2	2	3.21	130	0.8	0.02	100
	3	3	3.08	110	1	0.01	90
	4	4	3.15	100	0.8	0.03	80
	5	5	3.12	100	0.8	0.02	80

(X)

Table 4.8 - Calibration results, 26-zone one instance

	Case	No.	Value	N	PC	PM	G
After the 3rd stage	1	1	3.24	100	0.8	0.01	90
	2	2	3.27	120	1	0.02	100
	3	3	3.41	150	0.8	0.03	100
	4	4	3.29	150	0.9	0.01	100
	5	5	3.27	110	1	0.03	80

(III)

These additional tests have strengthened our conclusion that the algorithm parameters used for the third calibration stage have produced better quality solutions. Much discussion on these comparisons will be presented on section 4.5 of this chapter.

4.4.4 Dealing with the issues of random component

Genetic algorithms, by their nature, have a random component. The random component controls the order by which the probabilities of crossover and mutation are evaluated. Even though the orders by which the probabilities are evaluated does not significantly affect the goodness of the final solutions, it may sometimes happen that the limit on the number of generations might be reached before the candidate solutions attain the required number of changes. This change in random component is the reason for difference in fitness values for the same cases and same instances (see results on Table 4.6-I, for example).

In order to verify if the changes in random component or lack of it, thereby changes in the order of execution of the probabilities, have a significant influence on the quality of solution values; we tested more model runs by randomly fixing the random component of the algorithm. This means, for the same case, every probability on every generation is executed in the same order.

Table 4.9 - Calibration results, 17-zone four instances, fixed random component

	Case	No.	Value	N	PC	PM	G
After the 3rd stage	9	1	2.88	110	1	0.03	80
	33	2	2.92	100	0.8	0.01	80
	11	3	2.9	100	0.8	0.01	100
	39	4	2.93	100	0.8	0.01	80
After random fix	9	1	2.88	110	1	0.03	80
	33	2	2.89	100	0.8	0.01	80
	11	3	2.96	100	0.8	0.01	100
	39	4	2.99	100	0.8	0.01	80

(I)

	Case	No.	Value	N	PC	PM	G
After the 3rd stage	43	1	3.06	120	0.9	0.02	100
	8	2	3.04	120	0.9	0.02	80
	6	3	3.16	100	0.8	0.01	100
	2	4	3.16	110	0.8	0.02	90
After random fix	43	1	3.16	120	0.9	0.02	100
	8	2	3.16	120	0.9	0.02	80
	6	3	3.16	100	0.8	0.01	100
	2	4	3.16	110	0.8	0.02	90

(II)

	Case	No.	Value	N	PC	PM	G
After the 3rd stage	2	1	3.14	120	0.9	0.02	100
	8	2	3.15	110	0.8	0.01	90
	38	3	3.09	100	1	0.03	80
	39	4	3.14	120	0.8	0.02	100
After random fix	2	1	3.23	120	0.9	0.02	100
	8	2	3.23	110	0.8	0.01	90
	38	3	3.23	100	1	0.03	80
	39	4	3.18	120	0.8	0.02	100

(III)

	Case	No.	Value	N	PC	PM	G
After the 3rd stage	19	1	3.12	100	0.8	0.01	80
	40	2	3.09	100	1	0.02	80
	50	3	3.09	130	0.8	0.02	80
	20	4	3.08	120	1	0.03	100
After random fix	19	1	3.23	100	0.8	0.01	80
	40	2	3.19	100	1	0.02	80
	50	3	3.08	130	0.8	0.02	80
	20	4	3.08	120	1	0.03	100

(IV)

Results in Table 4.9 are obtained after the random component of the algorithm is systematically fixed to have the same order of change for every generations and every case. This means results from an instance are expected to have the same results provided that the values for algorithm parameters are the same. This is because the order of change is made to be the same by fixing the random component. By looking at the kind of results obtained from Figure 4.9, we can conclude that the newly defined algorithm parameter have performed very well in that the solution values even after fixing the random component of the algorithm can be regarded as very good. This comparison, as mentioned earlier, is in reference to the best results obtained during the second calibration stage.

Similarly for 26 zone problems, results after fixing the random component are shown in Table 4.10.

Table 4.10 - Calibration results, 26-zone three instances, fixed random component

	Case	No.	Value	N	PC	PM	G
After the 3rd stage	8	1	3.44	110	0.8	0.02	100
	19	2	3.41	150	0.9	0.02	80
	23	3	3.43	100	0.8	0.01	90
	5	4	3.38	100	0.9	0.03	100
After random fix	8	1	3.47	110	0.8	0.02	100
	19	2	3.47	150	0.9	0.02	80
	23	3	3.47	100	0.8	0.01	90
	5	4	3.47	100	0.9	0.03	100

(I)

	Case	No.	Value	N	PC	PM	G
After the 3rd stage	31	1	2.95	100	0.8	0.02	80
	16	2	3.08	140	0.8	0.01	90
	12	3	3.01	100	0.9	0.02	80
	15	4	3.09	100	0.8	0.01	90
After random fix	31	1	2.93	100	0.8	0.02	80
	16	2	2.99	140	0.8	0.01	90
	12	3	2.99	100	0.9	0.02	80
	15	4	3.05	100	0.8	0.01	90

(II)

	Case	No.	Value	N	PC	PM	G
After the 3rd stage	1	1	3.24	100	0.8	0.01	90
	2	2	3.17	120	1	0.02	100
	4	3	3.24	150	0.9	0.01	100
	5	4	3.3	110	1	0.03	80
After random fix	1	1	3.27	100	0.8	0.01	90
	2	2	3.26	120	1	0.02	100
	4	3	3.27	150	0.9	0.01	100
	5	4	3.27	110	1	0.03	80

(III)

Results for the three instances of the 26 zone problem, Table 4.10 show that even after the random component is fixed, the new algorithm parameters have performed very well. This is in reference to the best results after the second calibration stage. The whole exercise of dealing with the random component has improved our confidence level on the calibration procedure and rule out any possibility luck might have in the generation of good solutions.

So far in this chapter, we have seen the design procedures of genetic algorithms and its application for solving a land-use/transportation problem. We mentioned that the algorithm has certain characterizing parameters in the form of population size (*N*), probability of crossover (*PC*), probabilities of mutation (*PM*) and number of generations (*G*). These algorithm parameters are determinant in the process of evolution of populations of solutions and on the quality of final solution. We have introduced a calibration procedure with three stages. At first calibration stage a systematic observation scheme was designed to observe the evolution of candidate solutions across generations. This calibration stage had the purpose of defining ranges for algorithm parameters as an output. After making number of model runs, varying the problem size, instances and cases, we have come up with initial range values for algorithm parameters.

In the second calibration stage the purpose was to conduct number of model runs using the algorithm ranges from the first calibration stage. The purpose of this calibration stage was also to observe the goodness of solution values and record the corresponding algorithm parameters that lead to the results. In the second calibration stage, for example, we have made model tests for two problem sizes. And for each problem size we defined number of instances, for example five instances for the 17-zone problem and two instances for the 26 zone problems. Each instance was tested for fifty cases by randomly varying algorithm parameters. This calibration stage had the purpose of defining new ranges for algorithm parameters as an output. After making number of model runs, varying the problem size, instances and cases, we have come up with new ranges (narrower) of algorithm parameters.

In the third calibration stage, we designed a calibration procedure that is based on solution values from second calibration stage and using the newly defined algorithm parameters. In this calibration stage, first we ranked solutions from the second calibration stage for each instance in descending order. For the five worst performing cases of an instance, we made reruns of the problems by changing only the algorithm parameters (ranges). Similarly from the five best performing cases of an instance, we made reruns on four random cases of the problems by changing algorithm parameters (ranges). These reruns were made for five instances of the 17-zone problem and two instances of the 26 zone problem.

In this third calibration stage, we also made further tests. For the 17 zone problem we defined five additional instances and rerun five cases of each instance randomly. Similarly we defined one additional instance for the 26 zone problem. We made reruns using the newly defined algorithm parameters by randomly picking five cases from an instance.

Results after the third calibration stage, after passing the tests and reruns, show conclusive evidence that solution values have improved significantly when compared with results from the second calibration stage. Results also show that the solution values for the same instance but different cases are very close to each other thereby indicating the algorithm parameters have proven to be consistent and stable.

In order to increase the confidence level on the newly defined parameters and rule out any possibility luck might have on the goodness of solutions, we have randomly fixed the random component of the algorithm. In this respect we tested five instances of 17 zone problem and three instances of the 26 zone problem. For every instance, this particular rerun was made for four cases. Results from this process of fixing random algorithm component have also shown that the newly defined algorithm parameters have performed well in determining good final solution values.

Based on our three stage calibration process, we can conclude that the algorithm parameters in Table 4.2 have managed to yield with good solution values that show the tendency of converging within the same instances.

4.5 Validating algorithm results

Due to their very nature, heuristic algorithms don't guarantee optimality of solutions. Genetic algorithm is no different. The solution values obtained after the three calibration stages are good but we can not be sure that they are optimal. This is to say that by solving a problem using a heuristic method only, one cannot say the solution is optimal. The best thing one can conclude is that the solutions are the best the algorithm could possibly yield. This is why we need to validate or assess quality of solution of our genetic algorithm. There are two possible ways of verifying the optimality of results from heuristic algorithm, such as genetic algorithm. Either use exact methods or develop another heuristic to solve the same problem and make the comparisons. One might ask if there are exact solution methods that guarantee optimality, why bother with heuristics. Well, there are exact methods but they usually take quite a long computation time to arrive at optimality. It would be difficult to use exact methods for large problems, which is the case in our application.

For the 17 zone and 26 zone size problems it was possible to run the problem using branch and bound (B&B) method to optimality. Results from the branch and bound method are discussed in chapter three of this thesis. In there, it has been mentioned that for the 17 zone it was quiet manageable to run the branch and bound method for 10 instances, but for the 26 zone problem the computation effort has grown so much that it was only viable to get optimal result for three instances. These same results will be used here for the validation purpose of the genetic algorithm.

The purpose of this validation process is to assess the quality of solutions obtained from genetic algorithm solution method. The purpose is also to determine the gap in terms of differences in fitness values from both solution methods and device possible ways of improving algorithm results, if necessary. For this validation purpose, we have tested two exactly the same problem types using the brunch & bound and genetic algorithm solution methods. The comparison criteria are solution quality and computation time.

Table 4.11 - Validation results, 17-zone five instances

Instance	Case	Genetic Algorithm	Exact B&B	Gap (%)
(I)	9	2.88	3	***4.17***
	11	2.9	3	***3.45***
	19	2.96	3	***1.35***
	24	2.99	3	***0.33***
	29	2.97	3	***1.01***
	33	2.92	3	***2.74***
	39	2.93	3	***2.39***
	44	2.99	3	***0.33***
(II)	1	3.16	3.16	***0***
	2	3.16	3.16	***0***
	3	3.16	3.16	***0***
	6	3.16	3.16	***0***
	8	3.04	3.16	***3.95***
	30	3.16	3.16	***0***
	41	3.16	3.16	***0***
	43	3.06	3.16	***3.27***
(III)	2	3.14	3.23	***2.87***
	8	3.15	3.23	***2.54***
	10	3.18	3.23	***1.57***
	18	3.18	3.23	***1.57***
	29	3.18	3.23	***1.57***
	33	3.18	3.23	***1.57***
	38	3.09	3.23	***4.53***
	39	3.14	3.23	***2.87***
(IV)	11	3.23	3.23	***0***
	18	3.23	3.23	***0***
	19	3.12	3.23	***3.53***
	20	3.08	3.23	***4.87***
	37	3.12	3.23	***3.53***
	40	3.09	3.23	***4.53***
	44	3.19	3.23	***1.25***
	50	3.09	3.23	***4.53***
(V)	8	2.81	2.95	***4.98***
	14	2.91	2.95	***1.37***
	22	2.89	2.95	***2.08***
	25	2.91	2.95	***1.37***
	33	2.93	2.95	***0.68***
	38	2.91	2.95	***1.37***
	41	2.95	2.95	***0***
	42	2.89	2.95	***2.08***

The first validation tests were made for the 17 zone problem. As it can be recalled, the 17 zone problem was run ten times using both B&B and genetic algorithms. Results from exact B&B were discussed on chapter three and results from the genetic algorithm were discussed on the current chapter. Results on Table 4.11 present fitness values from both solution methods and the corresponding gap for the first five instances of the problem. The gap here is a representation of the differences in solution values obtained from the exact and heuristic solution methods. Since the exact methods always guarantee optimality, smaller gaps are indications of the good quality of heuristic solutions.

The validation results on Table 4.11 indicate that, for the 17-zone problem, in terms of fitness (solution value), the genetic algorithm has managed to arrive at solutions that are close to the optimal solutions. As can be seen from the gap values, the largest gap is less than 5%.

Table 4.12 - Validation results, 26-zone three instances

Instance	Case	Genetic Algorithm	Exact B&B	Gap (%)
(I)	5	3.38	3.57	***5.62***
	8	3.44	3.57	***3.78***
	13	3.41	3.57	***4.69***
	18	3.41	3.57	***4.69***
	19	3.41	3.57	***4.69***
	23	3.43	3.57	***4.08***
	27	3.43	3.57	***4.08***
	46	3.47	3.57	***2.88***
	50	3.47	3.57	***2.88***
(III)	1	3.24	3.43	***5.86***
	2	3.27	3.43	***4.89***
	3	3.41	3.43	***0.59***
	4	3.29	3.43	***4.26***
	5	3.27	3.43	***4.89***

Instance	Case	Genetic Algorithm	Exact B&B	Gap (%)
(II)	5	3.02	3.1	***2.65***
	12	3.01	3.1	***2.99***
	15	3.09	3.1	***0.32***
	16	3.08	3.1	***0.65***
	21	2.99	3.1	***3.68***
	31	2.95	3.1	***5.08***
	43	3.02	3.1	***2.65***
	45	2.93	3.1	***5.80***
	46	2.96	3.1	***4.73***

Similarly for the 26 zone problem, the validation tests were carried out for three instances. Results on Table 4.12 present instance and gaps in solution values obtained from the exact and heuristic methods. As can be seen from the gap values, the genetic algorithm has yielded with solutions that are close to those from B&B. The maximum gap between the two solution-values is slightly more than 5%.

Based on the observation of validation results from the two problem types it became evident that the genetic algorithm we have developed has the potential of being a good solution method. It also became evident that the gap between the two solutions seems bigger and should be smaller than the current 5%. In such circumstances, one can resort to local search routines that can be effective in finding better solutions in short computation times. The local searches will be implemented on the current best solutions from the genetic algorithm and involve mere controlled adjustments of land-use allocations and transportation program arrangements. More calibration and validation results are presented in Appendix B.

4.6 Local search routines

Once the algorithm parameters are defined and the runs are made, it is still possible to implement some specific local search algorithms to make certain that the good solutions that are obtained are indeed close to optimal. In our case, the first local search routine fixes the final land-use allocation and checks for all possible transportation projects changing one by one and evaluating value of the fitness function. This will rule out any possibility that a transportation program has not been checked. The second local search routine fixes the final transportation project and locally changes land-use types in selected zones. This can be done few times in selected zones. The changes in the land-use for the second local search routine are made in such a way that the area demands are exactly satisfied.

4.6.1 Local Search – 1

The purpose of this local search routine is to check whether the value of the fitness function can be improved further by making changes on the transportation program. As it was discussed in earlier sections, the final solution from the algorithm run is a land-use/transportation map. The first local search routine is implemented on this map by keeping the land-use allocations constant and varying the transportation programs one by one until all of them are exhausted. The need for this kind of local search routine is to make up for the randomness of the whole process and verify if there is a transportation program that hasn't been checked by the genetic algorithm. When the land-use map is kept fixed, the values for suitability and compatibility objectives will remain the same. By changing the transportation program, this local search routine alters the value of the accessibility objective.

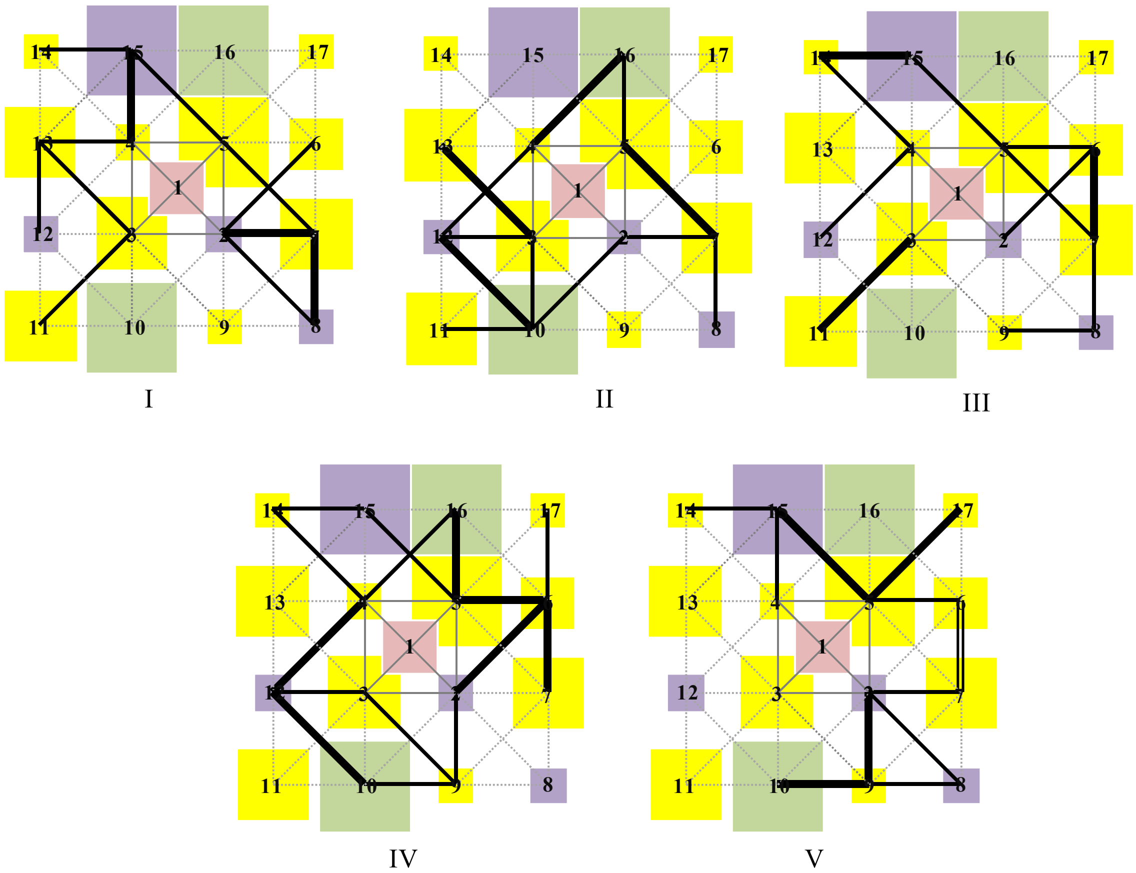


Figure 4.11 - Example for Local serch-1

As an illustrative example, let's consider a particular solution in Figure 4.11 (I-V). The first map, I, is the best solution from a particular algorithm run. The local search routine is conducted based on this land-use/transportation map. In every iteration of this routine, a transportation program is changed, choosing from the stock of predefined transportation programs which in this case are 25. For every change in transportation program, a value of the accessibility objective is evaluated. In this example, performances of four additional transportation programs are checked against the accessibility objective (Figure 4.12, maps II – IV). In the process of checking the performance of all transportation programs, if the value for accessibility objective is improved, the new map leading to this solution value improvement is saved.

4.6.2 Local search – 2

The purpose of this second local search is to find out the possibilities, if any, of improving the fitness of the solution by tweaking the land-use allocations locally. This routine, as in the first one, is done on the final best land-use/transportation map. The difference between the local search-1 and local search-2 is that the first one prescribes changes on the transportation programs whereas the second one prescribes changes on the land-use allocations. In this second local search routine, changes in land-use allocation brings changes in the values of all three objectives.

There are so many ways of executing this routine, but for sake of verification the following example is provided. The key requirement for this local search routine is that feasibilities of final solutions must be verified. This feasibility is in terms of the demand-supply relations of the land i.e. demand must be satisfied and allocations should not be in excess of the demand.

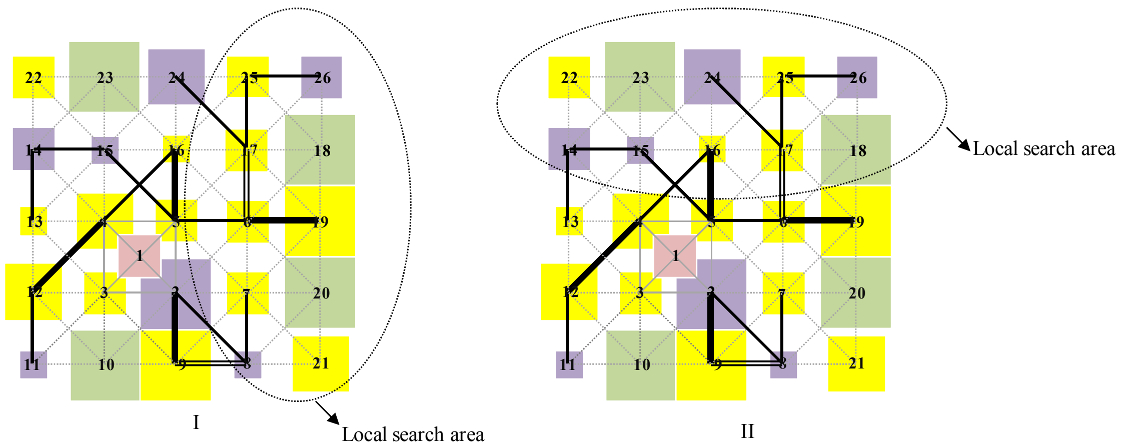


Figure 4.12 - Example for Local search-2

The main principle of this local search routine is to define a local area where possible land-use exchanges can be conducted and make land-use changes. For example in the land-use/transportation map shown in Figure 4.12-I, the local search area is defined and the algorithm can automatically identify zones whose land-use types can be changed. For example, in map I of Figure 4.12, zone 25 is allocated residential and zone 26 is allocated with industrial land-use types. Bothe zones have the same area, hence the local search routine can change zone 25 to industrial and zone 26 to residential. The local search routine we have developed tries to exhaustively check possible land-use changes in possible local search areas.

After implementing the two local search routines, results for both problem sizes have improved. Results are presented in Tables 4.13. For the smaller, 17 zone problems, the two local search routines have resulted in solution values that are equal to those obtained from exact solution methods. This was particularly tractable problem as the numbers of possible local searches are smaller, attributed to the smaller number zones. For the 26 zone problem and the three instances, the local search routines have managed to limit the gap within 0.56%, 0.32 and 0.59% for the three instances respectively.

Table 4.13 - Validation results, 26-zones three instances, after local search

Instance	Case	Genetic Algorithm	Exact B&B	Gap (%)
I	5	3.55	3.57	***0.56***
II	45	3.09	3.1	***0.32***
III	1	3.41	3.43	***0.59***

Results on Table 4.13 show the gap between genetic algorithm and branch and bound results after the two local search routines are implemented. Results indicate that the local search routines have given the genetic algorithm method more competitive edge with the B&B method. The gaps now stand at less than 0.6%.

4.7 Computation time

One of the main reasons to use heuristic solution methods is in order to reduce computational efforts (usually in terms computation times) involved with using branch and bound method.

Table 4.14 - Computation time values-B&B Vs GA

			Value		Time(mins)		
Problem	**Instance**	**Case**	**B&B**	**GA**	**B&B**	**GA**	**Gap (%)**
17 zones	I	29	3	3	82.77	75.307	-
	II	2	3.16	3.16	47.7	58.99	-
	III	18	3.23	3.23	76.27	81.973	-
	IV	44	3.23	3.23	94.37	100.49	-
	V	38	2.95	2.95	46.45	53.172	-
	VI	5	3.3	3.3	66.48	57.483	-
	VII	5	3.05	3.05	168.3	67.403	-
	VIII	1	3.14	3.14	152.45	109.75	-
	IV	4	2.94	2.94	118.61	119.96	-
	X	2	3.23	3.23	201.23	135.1	-
26 zones	I	27	3.57	3.55	7620.51	296.55	0.56
	II	46	3.1	3.09	8081.54	308.05	0.32
	III	4	3.43	3.41	6053.98	317.05	0.59

Result on Table 4.14 presents the solution values and computation times for ten instances of the 17 zone problem and three instances of the 26 zone problem. The computation times and solution values include the processes of local search routines.

For the 17 zone problem, the improvements in computation time are minimal at best, even in some instances the algorithm has taken longer time than the exact method. However, there is no discernible difference in computation times i.e. considering the purpose of the model for aiding land-use/transportation decisions.

For the 26 zone problem, however, the differences in computation times between both methods are tremendously high. The computation times for the heuristic method are very much less than the computation times for the exact method. For example an instance from a 26-zone problem, could take up to more than four days. This, compared with the maximum five hours taken by the GA, is significantly large computation time. Considering the gap of 0.6%, the gain in computation time becomes even more important.

4.8 Summary of computational efforts

The purpose of this chapter was to find alternative solution method for the optimization based model for land-use/transportation decision making proposed in this dissertation. Owing to its lower computation efforts, capability of determining solutions for problems with large spaces and based on experiences from applications of similar nature, we opt for genetic algorithms.

Genetic algorithms are population based search heuristics that are based on the principle of evolving candidate solutions using genetic operators such as crossover, mutation and selection. These algorithms are heuristics meaning the optimality of their solutions isn't always guaranteed.

Two important processes are mandatory prerequisites before applying genetic algorithms. The first one is a process that assesses the quality of parameters (calibration) and the second one is process that assesses quality of solutions (validation). In our study we designed a rigorous three stage procedure for calibrating algorithm parameters such as population size (*N*), probability of crossover (*PC*), probability of mutation (*PM*) and number of generations (*G*). In all the three stages, the calibration procedures have the target of identifying algorithm parameters that yield with good solutions – in terms of fitness value. For this process we defined two problem types each with number of possible instances and cases. After testing the problem types, instances and cases for number of times, we have come up with algorithm parameter ranges that yield with good solution values. The algorithm parameters were accepted after additional tests by changing the cases and instances as well as altering the random component of the algorithm.

In addition to assessing the quality of parameters, we have also made algorithm validation. This was carried out by making comparisons for the same set of problems between algorithm results and B&B results. The comparisons were made considering the gap between two solutions resulted from the two solution methods. Initial validation results indicate that the algorithm has performed in acceptable way and that the maximum gaps were within 5%. However, we felt this is not small gap for optimization solutions. We implemented two local search routines in an effort to narrow down the gap and increase value of the fitness function. The local search routines have improved the solution value to the point that the maximum gap is less than 0.6%.

The whole exercise of developing a heuristic algorithm was to capitalize on the weak performance of exact methods in relation to computation times i.e. the B&B methods while guaranteeing optimality are characterized by long computation times. As it was the case in our optimization based model, the genetic algorithm has reduced the computation time significantly specially for the large problem types.

5 Advanced model

5.1 Introduction

The purpose of this chapter is to introduce the advanced version of the basic model explained in Chapter 3 of this dissertation. In principle, the advanced model is similar to the basic model in that it assigns land-use types and transportation improvement programs considering socio-economic changes, budget constraints and existing urban form. The most significant change made to the basic model is the upgrades in the transportation component. These improvements are in terms of modeling the transportation demand, transportation modes and transportation externalities, in the form of congestion.

Following this introduction, this chapter presents modeling transportation with detailed explanations on each of the four stages: generation, distribution, modal split and assignment. Then it goes on to present on transit related issues. Finally the chapter presents some practical modeling considerations.

5.2 Modeling transportation

The transportation model is one of the most important improvements made to the basic optimization model. This upgrade includes the implementation of the four step transportation model taking into account the effects of congestion. The classic four step method has trip generation, trip distribution, modal split and trip assignment steps. Each of these steps is briefly explained on the next sections.

5.2.1 Trip generation

Trip generation is a step that refers to the determination of total number of trips generated from a zone. It has two components in the form of trip production and trip attraction. Trip production represents the number of trips leaving from a zone whereas trip attraction represents the number of trips entering to a zone. Factors that influence trip production are income, car ownership, family size, household structure, value of land, and residential density. Factors that influence trip attraction include office and retail space and employment levels (Ortuzar and Willumsen 2011).

There are number of ways to modeling trip generation. The most common generation models are growth factor modeling, regression models, cross-classification models and discrete choice models. In this study since we are interested we choose to use simpler method that requires less data. We used a method suggested by the Institute for Transportation Engineers (ITE, 2012). The ITE method proposes that trips can be estimated by considering the land-use type and a trip generation factor. The generation factors are determined by rigorously studying trips for many years in North America. These rates are given for any possible land-use type (residential, commercial, shopping malls, stadiums, prisons and so on). The units for these rates differ based on the type of land-use to which they are referring. For example, for residential area, rates are given in terms of values per dwelling units, whereas for the case of commercial uses trips are given in terms of values per unit area (square foot) occupied. Based on the type of use one is referring, the trips can therefore be determined as the product of the rate multiplied by the area (or equivalently by number of dwelling units for case of residential neighborhoods).

The ITE tables are designed based on the experiences from North America but with adjustments to the units and making some adaptations to the rates, we believe they can be applied to our case. In our model since a zone is assumed to be occupied by a single land-use type, area of the zones represents the amount of a land use type allocated. The trips here are therefore product of modified ITE rates and the area (or equivalently the number of dwelling units) of a zone. Results from trip generation step are amounts of trips produced (O_j) and amounts of trips attracted (D_k) from/to a zone. See Appendix A for vaues.

5.2.2 Trip distribution

Given the number of trips produced (O_j) from a zone and trips attracted (D_k) to a zone, the distribution step determines the number of trips from each zone to all other zones.

There are some established methods that can be applied for trip distribution modeling. But the most commonly used methods are those that are based on gravity model. The gravity based distribution methods have their basis on the principle of gravitational attraction. Same as in physics, gravity based distribution methods use two key components of zones: the size and distance separating them. The core concept is trips are inversely proportional to distance and directly proportional to size of zones. That is larger zones have the tendency of producing too many interactions and these interactions/flows decrease with distance.

Since we know the production and attractions (we have values of O_j and D_k from the generation step), we used the doubly constrained gravity model.

$$T_{jk} = A_j O_j B_k D_k f(c_{jk}) \tag{5.1}$$

T_{jk} – number of trips from zone j to zone k

A_j, B_k – balancing factors

O_j – productions of zone j

D_k – attractions of zone k

$f\,(c_{jk})$ – generalized travel cost function between zones j and k

The generalized cost function can be exponential, power or a mixture of both. In this application we chose to use the exponential cost function. The double constrained gravity model then becomes

$$T_{jk} = A_j O_j B_k D_k exp(-\beta c_{jk}) \tag{5.2}$$

β –impedance (distance deterrence) parameter

$$A_j = 1/(\sum_k B_k D_k exp(-\beta c_{jk})) \tag{5.3}$$

$$B_k = 1/(\sum_j A_j O_j exp(-\beta c_{jk})) \tag{5.4}$$

The expression in equation 5.2 has unknown β, A_j and B_k. The balancing factors can be determined using simple iterative methods but the impedance parameter β has to be calibrated using observed trip rates. One of the calibration techniques widely reported is the method originally proposed by Hyman (1969). Some earlier studies have reported that the Hyman's calibration method is efficient compared to another methods (Williams 1976, Ortuzar and Willumsen 2011).

Hyman's calibration method

This method which is initially proposed by Hyman (1969) aims at determining a value for the impedance factor β such that the modeled set of trips, T_{jk}, is a correct representation of the observed set of trips, t_{jk}. The main concept of the Hyman's calibration method is to make series of approximations for β values. Every new approximation is linearly interpolated from preceding two approximations (Williams 1976). This is done until the β values converge. Once the value of β is fixed, then the balancing factors A_j and B_k can be calculated iteratively using equations 4.3 and 4.4.

As it is evident from equation 5.2, the trip matrix at any stage of the calibration process is unique and it is a function of the estimate of β at that stage, $T_{jk}(\beta)$. The mean trip cost, c, therefore can be defined as (equation 5.5)

$$c = c(\beta) = \sum_{jk} T_{jk}(\beta) c_{jk} / T \qquad (5.5)$$

$$T = \sum_{jk} T_{jk}(\beta)$$

Similarly, let c^* be the observed mean trip cost. It can be defined as

$$c^* = \sum_{jk} (t_{jk} c_{jk}) / \sum_{jk} t_{jk} \qquad (5.6)$$

Where

c^* - mean cost from observed trips

t_{jk} – observed number of trips

c_{jk} –cost of traveling between j and k

The criterion to adapt for calibrating β is to choose the value of β such that the mean modeled and observed trip costs are equal, i.e.

$$c = c(\beta) = \sum_{jk} [T_{jk}(\beta) c_{jk}] / T = c^* = \sum_{jk} (t_{jk} c_{jk}) / \sum_{jk} t_{jk} \quad (5.7)$$

The difficulty here is the balancing factors A_j and B_k are unknown. Values of the balancing factors can be determined simultaneously while calibrating the β.

The steps for calibrating β are as follows (Ortuzar and Willumsen 2011, Williams 1976)

1. Initiate the first iteration by setting n=0 and estimating initial β_0 value using: $\beta_0 = 1/c*$
    a. Using this value for β_0 and setting B_k = 1 find a solution for A_j in equation 5.3;
    b. Using this new value for A_j, re-evaluate B_k from equation 5.4;
    c. Using the new values of B_k, re-evaluate A_j;
    d. This process continues until the changes in A_j's and B_k's between iterations is below some defined limits;
2. Calculate a trip matrix using β_0 and the standard gravity model (equation 5.2). By using equation 5.7 obtain the mean modeled trip cost c_0. And estimate a better value for β using equation 5.8.

$$\beta_n = \beta_0 c_0 / c^* \quad (5.8)$$

3. Continue the iteration by setting n = n+1. Using the latest value for β (i.e. β_{n-1}) calculate a trip matrix using equation 5.2. Calculate the new mean modeled cost c_{n-1} and compare it with $c*$. If they are satisfactorily close, stop and accept β_{n-1} as the best estimate for the parameter; otherwise go to step 4
4. Obtain a better estimate β as:

$$\beta_{n+1} = \frac{(c^* - c_{n-1})\beta_n - (c^* - c_n)\beta_{n-1}}{c_n - c_{n-1}} \quad (5.9)$$

5. Repeat steps 3 and 4 until the last mean modeled cost c_{n-1} is satisfactorily close to the observed value $c*$

Note: steps (a) to (d) are repeated whenever a new value of β is estimated.

5.2.3 Modal split

The modal split step is used to determine the share of trips for each mode. There are number of modal split models. But in this study owing to the availability of data and purpose of the modeling process we opt for synthetic models. The gravity based model introduced in trip distribution step can be made to include the modal split. There are advantages to simultaneously modeling distribution and modal splits. One advantage is that this approach represents the process of making travel choices realistically. i.e. Most of the time people choose destinations and modes simultaneously. Besides the target here is to model aggregate urban area trips where there may always not be multiple modes to get to ones destination. We have used a joint distribution/modal split model proposed by Wilson (1974) shown in Equation 5.10.

$$T_{jk}^{m} = A_j O_j B_k D_k exp(-\beta K_{jk}) \frac{exp(-\lambda c_{jk}^{m})}{\sum_m exp(-\lambda c_{jk}^{m'})} \qquad (5.10)$$

Where

T_{jk}^{m} – is the amount of trip between j and k using mode m;

c_{jk}^{m} – travel cost between j and k using mode m;

K_{jk} – is the composite cost of travelling between j and k;

λ – parameter controlling dispersion in mode choice.

There are different ways of specifying the K_{jk}. Some studies suggested that the composite cost can be the minimum of the cost of available modes while others suggested it should be the weighted average cost of available modes. However, we use a specification proposed by Williams (1976). This specification is found to be consistent with the popular theory of rational choice behavior.

$$K_{jk} = \frac{-1}{\lambda} log \sum_{m} exp(-\lambda c_{jk}^{m}) \tag{5.11}$$

In the process of modeling the modal split, we have verified the theoretical soundness of the parameters λ and β. That is the significance of cost is more critical in the choice of mode than in the choice of destination and the average composite cost should always reduce (or at least stay equal) with the increase of modes.

5.2.4 Assignment

Given the number of trips between pairs of zones and transportation network elements, this step determines travel times and congestion on the transportation links and the network.

We used the method of successive averages (MSA) for congested assignment. The method requires cost-flow relations that consider type of connection, speed and capacity of connection. In this application we use cost-flow relations recommended by the United Kingdom Department of Transportation (UK-DOT) as shown in Appendix A.

The method of successive averages is an iterative algorithm which is specifically designed to tackle the issue of congestion i.e. the issue of assigning too much traffic to low capacity links. The method iteratively determines current link flows as linear combinations of flow on the previous iteration and an auxiliary flow resulting from an all or nothing assignment in the present iteration.

The algorithm can be described as follows (Ortuzar and Willumsen 2011):

Given

V_l – is the flow in link l in vehicles per hour (VPh), or passenger car units (PCU) per hour;

F_l – is auxiliary flows;

1. Selection of set of current link costs using free flow travel times; and initialization of all flows by setting $V_l = 0$; make n=0;
2. Determination of the set of minimum cost trees in the network using the current costs; and make $n = n$+1;
3. Loading the whole of the matrix T all-or-nothing to these minimum cost trees obtaining a set of auxiliary flows F_l;
4. Calculation of the current flows using:

$$V_l^n = (1-f)V_l^{n-1} + fF_l \tag{5.12}$$

$with\ 0 \leq \phi \leq 1$, for better convergence take $\phi = 1/n$

5. Calculation of a new set of current link costs based on the flows V_l^n. If the flows (or current link costs) have not changed significantly in two consecutive iterations, stop; otherwise proceed to step 2.

Cost-flow curves

The department of transport in the UK has produced a large number of cost-flow curves for a variety of link types in urban, sub-urban and inter-urban roads. Speed-flow coefficient values used for application are adapted from these cost flow curves (Appendix A).

5.3 Public transport assignment

During the modal split stage of the four step transportation model, trips are divided into their respective modes considering the availability and cost. Trips that belong to public transit mode are assigned to transit lines. Unlike to road traffic, congestion is not a real concern in public transit (except is the cases of metro assignments in large cities). The assignment of public transit trips is therefore made by identifying the available transit paths between pairs of zones and allocating the traffic accordingly. A new transit network, which is a subset of the general transportation network, is first defined. This is done in a way that maintains consistency with previous transit related considerations.

As mentioned in the basic model, a particular transportation program has number of links identified as to having public transit line. The number of these links is dependent on the size of the problem but their arrangement is random. An example below shows how we define the transit sub-network.

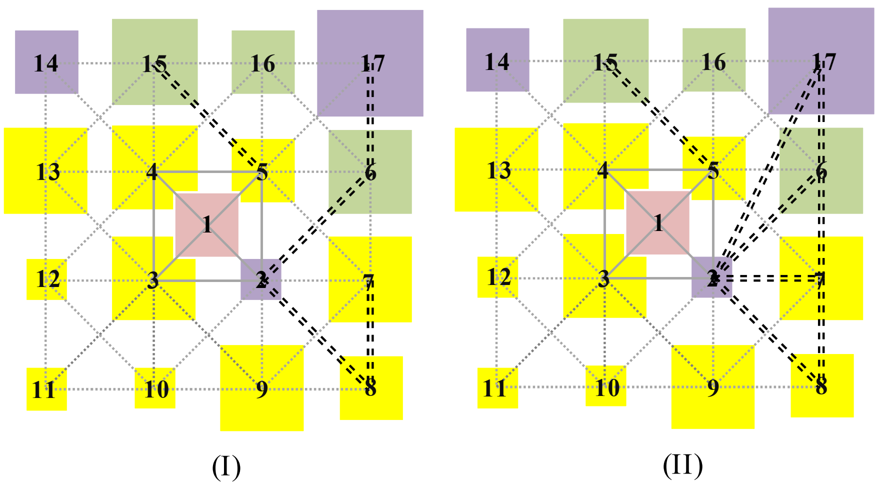


Figure 5.1 - Transit network before (I) and after (II) route selection

The left part of Figure 5.1 shows a particular program with five links designated as public transit. For residents of zone 2, the available transit options are to zones 6, 7, 8 and 17. In the right part of figure 1, the modified transit network is shown. There it can be seen that all the possibilities of going from origin zone to destination zone are represented. Transit trips from a zone will be assigned to links which are present in the modified network. For example, transit trips originating from zone 2 will be assigned to links originating from the zone (Figure 5.1 (II)). In the process of assignment of transit trips, we made provisions to account time lost in interchanges. We consider interchanges at zone locations only.

5.4 Practical issues in the advanced model

Since this is a land-use/transportation optimization model that allocates land-uses to vacant zones and the land-use types are not certainly known, decision variables are included in every stage of the transportation model. The modeling process is represented in Figure 5.2. After the initialization stage, the land-use/transportation layouts of the urban area are known. For particular layout, a transportation model is run to determine the congested travel times within the network. Using these travel times and the current land-use arrangements a measure of accessibility is evaluated. And finally using this accessibility measure, we evaluate the value of the fitness function.

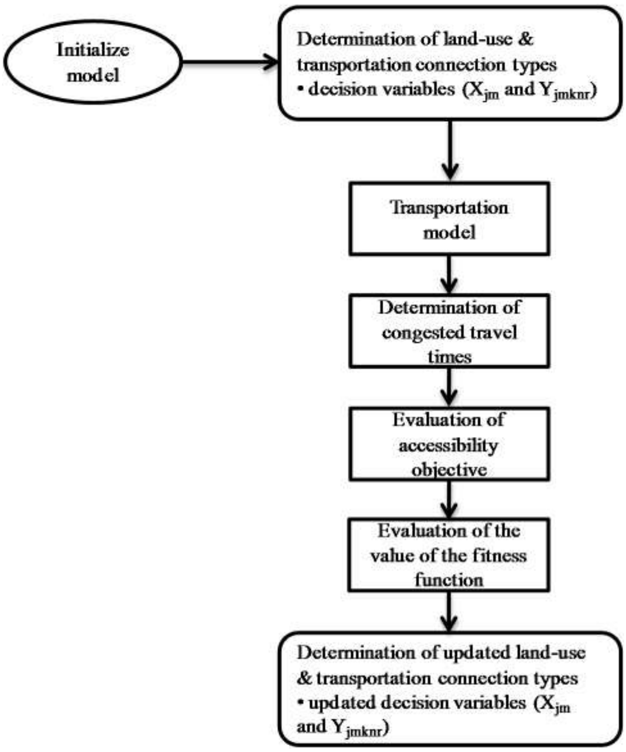


Figure 5.2 - Practical considerations

The advanced optimization based model has a mode choice sub-model. The sub-model can handle two modes of transportation. In the case study application in the following chapter, however, a simplified version of the model is used. That is, transit issues were not dealt with in Chapter 6.

6 Case study: municipality of Coimbra

6.1 Introduction

It is to be recalled from previous chapters of this thesis that an optimization based approach was developed and tested in partially randomly generated applications. Results show that, given the specifications of objectives and constraints, the approach can be used to generate efficient maps that help in discussions regarding an urban area's population, environment, economy, land-use, transportation and infrastructure. Moreover, it was shown that the optimization approach can be used to analyze the effects of adding new transportation facilities on future land use patterns and also it can be used to show the impact of changes in land-uses on flows on transportation network. In order to further test the usefulness of the optimization approach and further explore its significance in real world land-use/transportation planning applications, a case study is designed. In this chapter we report on a case study application of the optimization approach.

The purpose of this case study is, therefore, to test the performance of the optimization based land-use transportation approach on a real world setting. The case study is focused on municipality of Coimbra. Possible outputs from the case study include efficient land-use/transportation maps. For the purpose of the case study, numbers of expansion zones are defined together with possible transportation investment possibilities. The case study will also emphasize on sensitivity and scenario analyses.

This chapter has two major parts. The first part of the chapter characterizes the case study area which is the municipality of Coimbra. The second part of the chapter discusses the description, result and analysis of the case study. The chapter is structured as follows.

After this introduction the municipality of Coimbra is briefly characterized. Then the case study problem is described focusing on the preparation of the input data related to land-use and transportation, and the definitions of sensitivity and scenario analyses. Finally the results section discusses the outputs.

6.2 Municipality of Coimbra

The municipality of Coimbra is located at the Centro region of Portugal. According to the Nomenclature of Territorial Units for Statistics (NUTS) classification, the municipality is part of a NUTS-III sub region called Baixo Mondego. The sub region comprises eight municipalities, including Coimbra (Figure 6.1c).

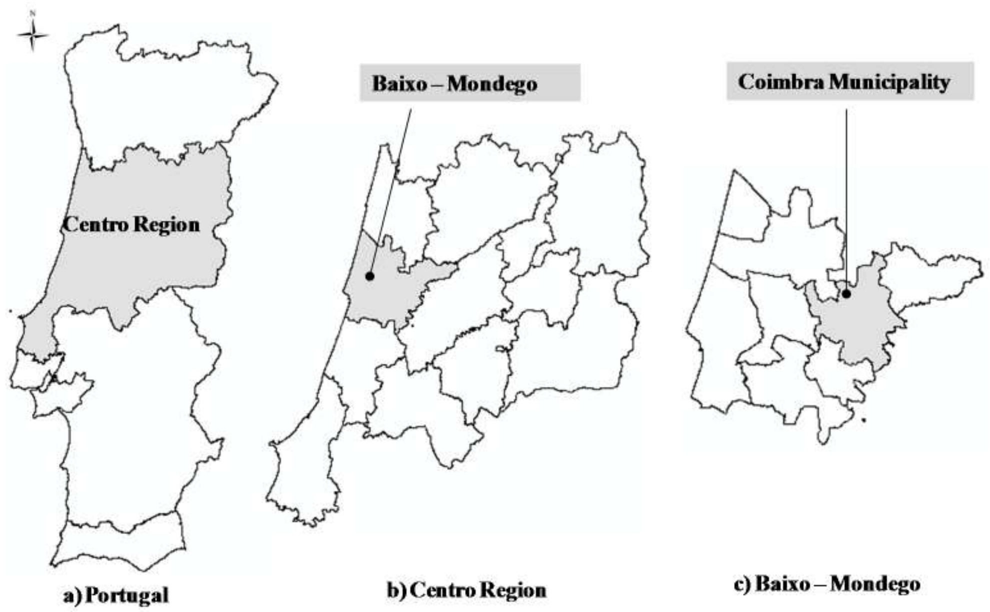


Figure 6.1 - Geographic location of Coimbra municipality

The municipality of Coimbra is bordered to the north by the municipalities of Cantanhede, Penacova and sub-region Baixo Vouga; to the east by the sub-region Pinhal Interior Norte; to the south by the municipality of Condeixa-a-Nova; and to the west by the municipality of Montemor-o-Velho.

It is beyond the scope of this chapter to provide the time line and detailed historical perspective of the municipality of Coimbra. It is however important to mention that Coimbra has been an important city of Portugal. The city was once the capital of Portugal and remained as such for over one hundred and twenty years (1139 – 1260). In those days, Coimbra was not only a political capital, but also an important trade center. The Mondego river served as major connections between the inland regions and the city of Figueira da Foz and its seaport on the Atlantic coast. Furthermore, for so many more years, Coimbra has served as the human resource capital of Portugal and that of the Portuguese speaking countries around the world thanks to its university, which is one of the oldest and most prestigious institutions across the Portuguese speaking countries.

The municipality is located between two major urban centers, about 200 km north of Lisbon and 100 km south of Porto. Currently, the major motorway and rail transportation axes running from/to north/south of Portugal pass through Coimbra. It has also direct motorway and rail connection to the nearby seaport of Figueira da Foz and several other urban centers such as Leiria, and Aveiro, among others. The municipality is also well connected to Spain and other European countries through the E 80 motorway system and the railway line Beira Alta.

Table 6.1 - Municipality of Coimbra in numbers (INE, 2013)

	Unit	Portugal	Baixo Mondego	Coimbra	% National	% Sub-regional	Year
Area	ha	9221202	206280	31940	0.35	15.48	2012
Population	No.	10487289	326364	139151	1.3	42.6	2012
Population (0-14 year)	No.	1550201	41648	17574	1.1	42.2	2012
Population (15 - 24 years)	No.	1123090	30651	12807	1.1	41.8	2012
Population (25- 64 years)	No.	5781392	180319	78948	1.4	43.8	2012
Population older than 65 years	No.	3026563	110609	44319	1.5	40.1	2012
Land-Use (Urban)	ha	X	23078.1	7021.6	X	30.43	1994
Land-use (Main facilities & green area)	ha	X	1403.7	851.7	X	60.68	1994
Land-use (Industrial)	ha	X	3098.3	989.5	X	31.94	1994
Land-use (Tourism)	ha	X	723.8	4.6	X	0.64	1994
Buildings for conventional family housing	No.	3571066	129448	41182	1.2	31.81	2012
Conventional family dwellings	No.	5910006	196208	80790	1.4	41.18	2012
Educational Institutions	No.	298	20	20	6.7	100.00	2012
Hospitals	No.	226	18	12	5.3	66.67	2012

As it can be seen from Table 6.1, the municipality of Coimbra has a total area of 31940 ha and a total population of 139,151 which accounts for 1.3% of the national population of Portugal (INE, 2013). The municipality is the most populous in the Centro region of Portugal. In terms of area, the municipality of Coimbra is the third largest municipality in the Baixo Mondego region. It is a territory that spans 28 km from North to South and 24 km East to West (extreme points). As of 2012, the municipality of Coimbra has 20 higher education institutions and 12 hospitals.

The territory

The sub-region that contains the municipality of Coimbra, Baixo Mondego, can be classified as predominantly urban. Among the usable area of land, the Planos Municipais do Ordenamento do Territorio (PMOT) have in 1994 classified 81.5% of the area as urban, 5% as facilities and urban green areas, 10.9% as industrial and 2.6% as tourism (INE, 2013).

Table 6.2 - Sub-regional land use classifications (Baixo Mondego)

	Urban	Main green area and facilities	Industrial	Tourism
	Area (ha)			
Baixo Mondego	**23 078.1**	**1 403.7**	**3 098.3**	**723.8**
Cantanhede	4 068.3	119.4	344.7	14.3
Coimbra	7 021.6	851.7	989.5	4.6
Condeixa-a-Nova	1 489.5	31.7	263.1	0.0
Figueira da Foz	2 537.0	165.2	1 170.9	379.7
Mira	1 072.3	62.8	103.5	34.4
Montemor-o-Velho	2 239.8	45.2	79.6	0.0
Penacova	2 227.6	52.7	13.6	51.8
Soure	2 422.0	75.0	133.3	239.1

Among the total designated usable land in the Baixo Mondego area, the municipality of Coimbra has 7,021.6 ha of it for urban, 851.7 ha for facilities & main green area 989.5 ha of land for industrial and 4.6 ha for tourism (Table 6.2).

Compared with the sub regional land-use distribution, the municipality is composed of 30.4% urban, 60.8% facilities and main green areas, 32% industrial and 0.64% tourism. This makes Coimbra a municipality with the largest urban and facilities & urban green areas within the sub region. Besides, Coimbra has the second largest industrial land-use type next to the municipality of Figueira da Foz (Figure 6.2).

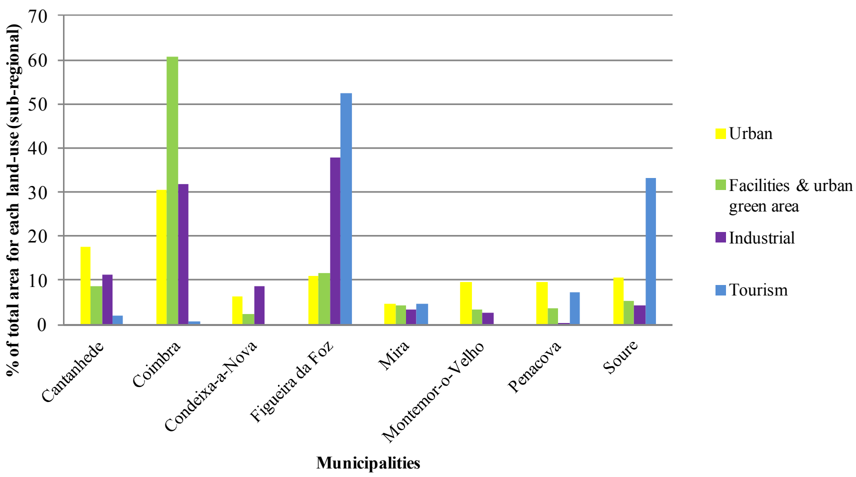


Figure 6.2 - Sub regional land-use classifications

Population and housing

In 1860, the population of Coimbra was merely 12,500 inhabitants. In the next half century the population grew to 18, 000. The population keeps growing steadily and by the end of 1950s, Coimbra had 45,000 inhabitants. In 2012, the total population of Coimbra municipality was 139, 151 inhabitants (INE, 2013).

Table 6.3 - Demographic indicators

	Pop. density	Growth Rates		
		Natural	immigration	Total
	No./km^2	%		
Baixo Mondego	158.2	- 0.40	- 0.63	- 1.03
Cantanhede	93.1	- 0.63	0.13	- 0.50
Coimbra	435.7	- 0.19	- 1.38	- 1.57
Condeixa-a-Nova	124.9	- 0.15	0.65	0.50
Figueira da Foz	162.3	- 0.59	- 0.08	- 0.67
Mira	99.4	- 0.51	- 0.19	- 0.70
Montemor-o-Velho	113.8	- 0.34	0.00	- 0.34
Penacova	68.7	- 0.68	- 0.68	- 1.36
Soure	70.7	- 0.96	- 0.59	- 1.55

Coimbra municipality is one of the most densely populated urban centers in Portugal. Specifically, the municipality has the highest population density in the Baixo Mondego sub region with density value of 435.7 inhabitants per km^2 (see Table 6.3).

Over the past decade, the population of Coimbra has been declining. This change is attributed to the combined effects of declining natural and net immigration rates. As it can be seen in Table 6.3, the decline in population of the municipality of Coimbra is largely attributed to the high out-migration rate. Besides, the decrease in natural growth rate has also contributed to the overall decline of population in the municipality.

Despite the trends in population evolution, the municipality of Coimbra in 2012 has issued a total of 177 building permits of which 136 were for family housing. This permit constitutes for the construction of 185 new dwellings for family housing. The building permits are larger in Coimbra than in any other municipalities in Baixo Mondego sub region (INE, 2012). As of 2012, constructions of 362 buildings of which 313 are for family housing were completed. Of these newly completed constructions 330 were new constructions and the remaining 32 were modifications of existing buildings. In those new constructions 805 dwelling units can be accommodated.

6.3 Case study description

For this case study, we divided the municipality of Coimbra into various zones considering the intuitively perceived neighborhood concepts and considering the census units classifications. For instance, traditionally the downtown Coimbra is a place near the city municipally building; hence this area is classified as downtown zone or ‘Baixa’. Besides the types of land-use in existence contributes to the zoning classification.

The main data required for the case study are population, area, location and neighborhood characteristics of zones, transportation network, trip characteristics, existing land use types and future demands (both in terms of land-use and transportation). The demographic data are obtained from census. The locations, sizes, and existing land use types of the zones are consolidated, using ArcGis, from existing records. The class and type of transportation links are determined from available public records. Trip characteristics are also obtained from travel survey data.

For this case study application, the municipality of Coimbra is divided into 102 zones. Among these zones, 65 represent the developed portion of the municipality whereas the remaining 37 zones represent vacant areas, part of which hold the prospects of accommodating further land-use developments. Among the developed zones 46 zones are classified as residential; 12 are classified as non-residential, commercial district types of uses with large public facilities falling in to this category (or CBD as designated in this chapter); and 5 zones are classified as manufacturing and/or industrial (I). Among the 46 residential zones 9 of them are classified as having high density (HDR), 21 as medium density (MDR) and 16 as low density (LDR). Population, area and land-use related data of all the zones are presented in Figure 6.3, and Tables 6.4 and 6.5.

In addition to land-uses, we have identified four classes of transportation links each with specific speed and capacity characteristics. The transportation links considered are arterial, outer and inner distributors and local streets. Besides, a class of road is defined taking into account the possible future expansions of the city. According to this classification, the transportation network in the municipality of Coimbra consists of 207 links of which 113 are existing links and 59 links are considered to be potential links. The potential links are either existing links that can be upgraded or new links to be built. Among the existing links, 24 are classified as arterials (class 4), 16 inner distributors (class 3), 18 outer distributors (class 2) and 57 local streets (class 1). Tables 6.4 and 6.5 present the area, population, density and land-use types of developed zones of Coimbra.

Table 6.4 - Population and land-use types

ID	Zone	Area (ha)	Population (hab)	Density (hab/ha)	Land Use
1	Ademia	94.5	3413	36.1	MDR
2	Afonso Henriques/Dias da Silva	31.5	1483	47.0	MDR
3	Almalagues	54.8	549	10.0	LDR
4	Alta	27.4	885	32.3	CBD
5	Alto de Sao Joao	25.0	1431	57.3	MDR
6	Antanhol	218.4	2341	10.7	LDR
7	Antuzede	80.5	944	11.7	LDR
8	Areeiro	45.1	1677	37.2	MDR
9	Assafarge	99.4	757	7.6	LDR
10	Av.Elisio de Moura/Sao Sebastiao	38.2	2383	62.4	MDR
11	Bairro Norton Matos	39.9	4342	108.7	HDR
12	Baixa - Camara	14.4	721	50.0	CBD
13	Baixa - Portagem	2.5	122	48.4	CBD
14	Boavista	9.5	839	88.0	HDR
15	Botanico	33.1	84	2.5	G
16	Calhabe	14.1	674	47.9	HDR
17	Carlos Seixas/Verde Pinho	23.5	1343	57.1	MDR
18	Casa Branca	42.1	1489	35.3	MDR
19	Casais	98.7	2126	21.5	LDR
20	Ceira	160.3	1834	11.4	LDR
21	Celas	19.4	1055	54.5	MDR
22	Cernache	284.4	2365	8.3	LDR
23	Cernache Industrial	39.4	50	1.3	I
24	Chao do Bispo	78.8	2343	29.7	MDR
25	Combatentes	20.1	1206	59.9	MDR
26	Conchada	32.1	1735	54.0	MDR
27	Eiras	25.7	888	34.6	MDR
28	Eiras Industrial	248.7	233	0.9	I
29	Fala	107.2	3162	29.5	MDR
30	Fernao Magalhaes	25.3	749	29.6	CBD
31	Forum Coimbra	16.0	10	0.6	CBD
32	Hospital Covoes	16.5	0	0.0	CBD
33	HUC	47.6	217	4.6	CBD
34	Ingote	51.1	3452	67.5	MDR

Table 6.5 - Population and land use types (Continued)

ID	Zone	Area (ha)	Population (hab)	Density (hab/ha)	Land Use
35	Loios/Cidral	30.2	1607	53.2	MDR
36	Lordemao/Corrente	96.5	1346	13.9	LDR
37	Loreto	69.9	3272	46.8	MDR
38	Monte Formoso	11.9	1098	92.6	HDR
39	Montes Claros	34.5	2693	78.1	HDR
40	Oilvais	82.6	3082	37.3	MDR
41	Padre Manuel Nobrega	8.5	1133	134.0	HDR
42	Parque	55.2	302	5.5	G
43	Pedrulha	27.7	1322	47.7	MDR
44	Penedo	5.2	175	33.9	MDR
45	Polo II	30.0	21	0.7	CBD
46	Portela	13.1	756	57.6	MDR
47	Praca	23.6	679	28.8	CBD
48	Quinta da Maia	15.2	1664	109.6	HDR
49	Quinta das Lagrimas	70.4	1190	16.9	LDR
50	Rossio de Santa Clara	135.5	845	6.2	LDR
51	Rua do Brasil	17.7	1321	74.6	HDR
52	Sa da Bandeira	12.7	413	32.5	CBD
53	Santa Clara	166.4	5986	36.0	MDR
54	Sao Joao do Campo	96.7	1533	15.9	LDR
55	Sao Martinho de Arvore/Lamarosa	126.4	1140	9.0	LDR
56	Sao Martinho do Bispo	221.6	4592	20.7	LDR
57	Sao Silvestre	92.2	2016	21.9	LDR
58	Solum	34.1	2918	85.5	HDR
59	Solum Equipamentos	24.1	275	11.4	CBD
60	Sousela s	121.8	680	5.6	I
61	Taveiro	186.1	2435	13.1	LDR
62	Taveiro Industrial	65.0	97	1.5	I
63	Tovim	74.3	1824	24.5	LDR
64	Trouxemil/Fornos	168.9	499	3.0	I
65	Vale das Flores	59.9	3114	52.0	CBD [1]

[1] CBD = Commercial District and Large Public Facilities

HDR = High Density Residential

MDR = Medium Density Residential

LDR = Low Density Residential

I = Industrial, Manufacturing/Large Warehouses

G = Urban green area

VN = Available zones for further development

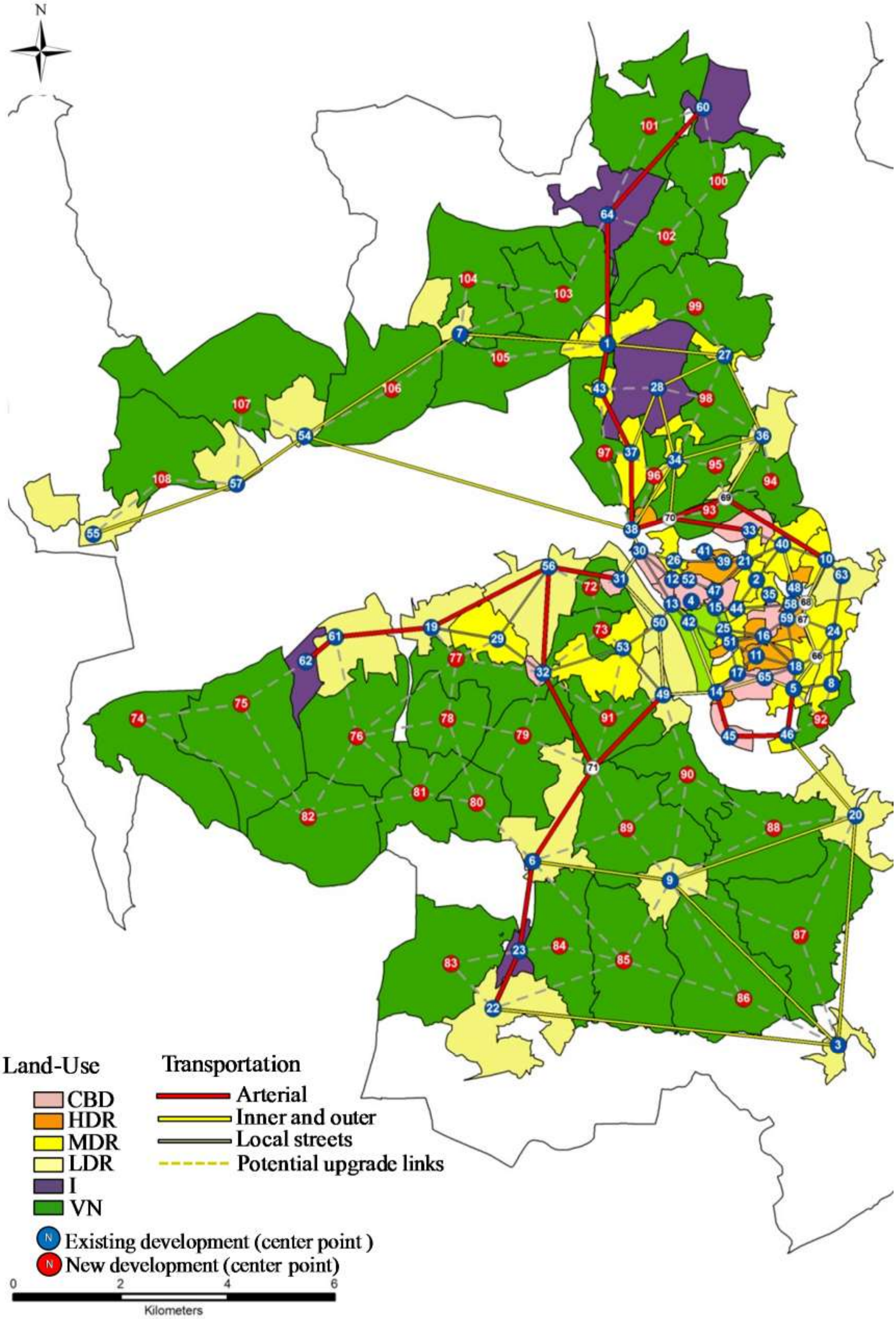


Figure 6.3 - Initial conditions, land-use and transportation

In addition to population and land-use data, the optimization approach requires suitability, compatibility and accessibility parameters as key inputs for the objectives (i.e. maximizing the suitability, compatibility and accessibility).

In order to determine the suitability parameter of every zone for each land-use type, the 37 zones identified as available for further development were classified based on their topographic and terrain conditions and their suitability for the various land-use types were assessed. Accordingly, the proposed development sites were classified as having terrain characteristics such as hilly, rolling and flat land. Depending on the topography of a particular zone, its suitability index for a particular land-use type is evaluated. The suitability index values of all zones for each land-use types are provided in Appendix C.

In addition to suitability, the optimization approach requires compatibility index values as parameter. This compatibility index characterizes neighborhood characteristics in the form of relative locations of land use types. Compatibility index values are computed using similar procedure described in Chapter 3 of this thesis.

Similarly, the optimization based approach requires the determination accessibility of individuals to services and to jobs. This parameter is evaluated considering the land-use types and travel costs taking the effects of congestion in to account. In evaluating the accessibility parameter, we have tried to look at employment records, land-use type distributions and job/service generating potentials of existing and future land-use types. More information on evaluation of accessibility measure is presented in Chapters 3 of this thesis.

As part of the accessibility objective, the approach requires the definitions of transportation programs that involve upgrade of links. The improvements are in terms of building a new link of a given hierarchic level or improve an existing link to a higher hierarchic level. The issue of selecting transport programs is detailed in the following section.

Definitions of transportation programs

For this case study, we have defined 25 possible transportation programs that will involve number of transportation projects in the form of building or upgrading transportation link. In defining the programs, we have assumed that there is a fixed budget allocated for the upgrade of limited number of road transportation links. Considering the budget, taking into account the structure of existing transportation network and considering the form of existing land-use development we have identified 25 programs. In terms of budget requirement, all of these programs are equal. And in terms of geographic distribution, the programs are equitably distributed across all development axes of the municipality.

By taking the city of Coimbra as a reference, the transportation programs are defined along the North, South and West development axes. Combinations of transportation programs in the North-South, North-West and South-West axes are also considered. A sketch of the transportation programs is shown in Figure 6.4.

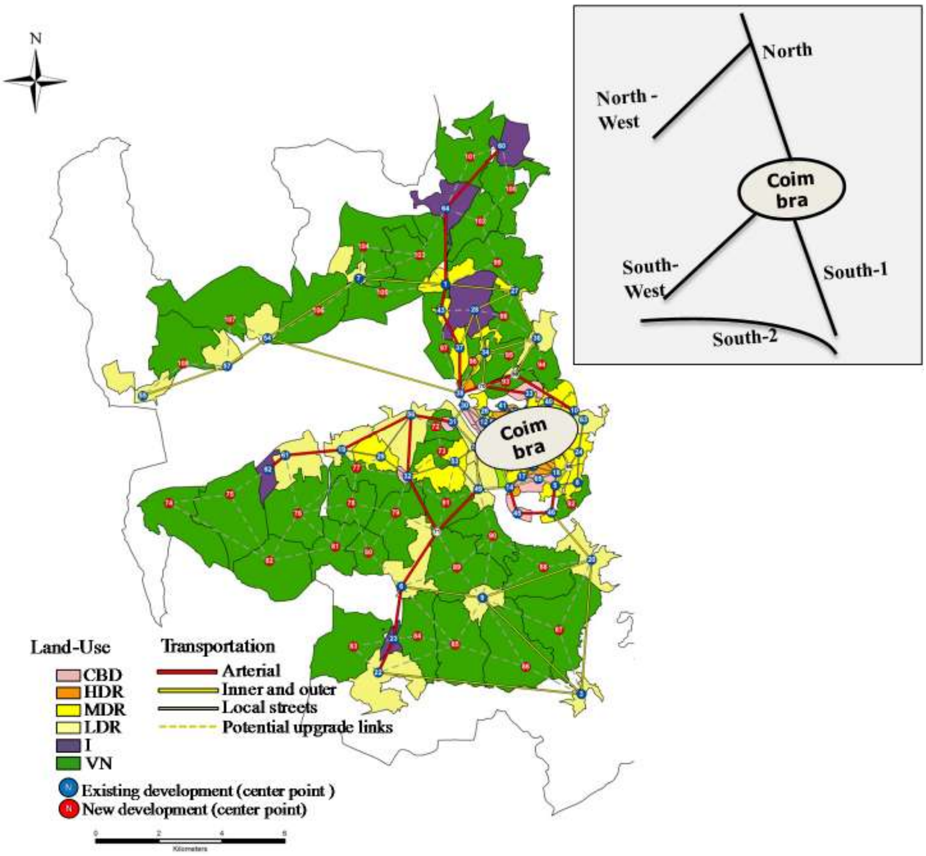


Figure 6.4 - Transportation programs (sketch)

The transportation programs are distributed across all the development axes. According to the sketch in Figure 6.4, the transportation programs are defined in the North, South-1, South-2, North-West and South-West directions.

In reference to Coimbra, 8 of the programs were defined towards the North (which includes North-West); 8 programs defined towards South (which includes South-West) and 9 transportation programs that are combinations. Two sample of the transportation programs are shown in Figure 6.5 and the remaining programs are presented in Appendix C.

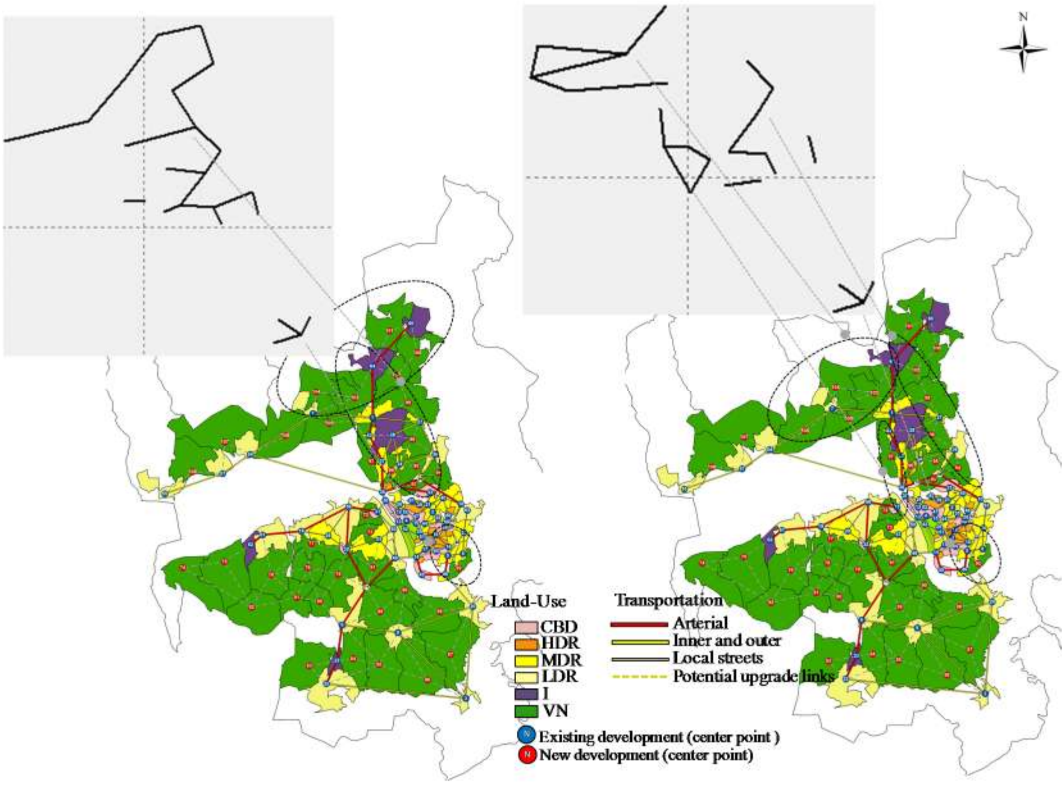


Figure 6.5 - Sample transportation programs

Given the input data provided earlier, we define a base case for which an efficient land-use/transportation map is determined and used it as reference for sensitivity and scenario analyses. For the base case, demand for future land-uses is determined in terms of area requirements for the different land-use types. Considering land-use and population distributions in Tables 6.4 and 6.5, we consider a land-use demand of 30% of the total occupied area. That is, keeping the proportions of land-use types as they are presented in Table 6.4 and 6.5, the development requirements are 30%. The approach determines an efficient solution in terms of the distributions of land-use types and the propositions of the new transportation programs. Moreover, for the base case we assumed a transport investment amounting to the construction or upgrade of 22 km long links. All three objectives are equally weighted for the base case. Additional information regarding the sizes of new development zones are provided in Appendix C.

6.4 Definitions of sensitivity and scenario analysis

For the case study application of the optimization approach, we considered number of scenarios and sensitivities analyses. All comparisons and analyses of resulting map from the scenarios and sensitivity analyses will be made in reference to the map from the base case. In comparing the maps, specific emphasis will be made on the relative variations (performances of) of the suitability, compatibility and accessibility objectives.

The sensitivity analysis is carried out considering three sets of weight values each of which stresses on the significance of suitability, compatibility and accessibility objectives sequentially. In addition to the sensitivity analysis, a scenario analysis is carried out. Three scenario categories are considered: demand, investment and development equity.

Sensitivity analysis

For the sensitivity analysis four combinations of weight values and their effects on the resulting solutions are analyzed. The weight combinations are shown in Table 6.6.

Table 6.6 - Weight combinations for sensitivity analysis

	Sensitivity analysis			
	Base	**Suitable**	**Compatible**	**Accesible**
Weights (W_1; W_2; W_3)	1/3; 1/3; 1/3	1/2; 1/4; 1/4	1/4; 1/2; 1/4	1/4; 1/4; 1/2

This sensitivity analysis has the purpose of analyzing resulting land-use/transportation maps when the importance attached to each objective varies. In reference to the base case (i.e. all objectives are equally weighted), the sensitivity analysis compares the variability of efficient land-use/transportation results when more emphasis is bestowed to suitability, compatibility and accessibility objectives respectively. The weight values in Table 6.6

should be interpreted as some of the possible combinations whose sum should be equal to 1. They signify the importance, in terms of percentage, that should be used as multiplying factor for an objective.

Scenario analysis

In addition to sensitivity tests, scenario analysis has been carried out considering demand, investment and development equity variations. The demand and investment scenarios considered are shown in Table 6.7 and discussed below.

Table 6.7 - Demand and Investment Scenarios

	Scenarios		
	Base	**Growth**	**Decline**
Demand (D)	D_1	$(1+0.5)*D_1$	$D_1/(1+0.5)$
Investment (I)	I_1	-	$I_1/(1+0.2)$

Scenario – 1

The first scenario is regarding the possible growth patterns. Considering the base case, this scenario analyzes the resulting land-use/transportation map given a growth and decline of demand for land-use types. That is in this first scenario, three efficient land-use/transportation maps are compared considering base case, growth and decline scenarios. The decline and growth scenarios consider a demand level of 20% and 45% respectively. The decline and growth are in reference to the 30% demand considered for the base case. This means the change in demand levels among the decline, base-case and growth scenarios varies by 50%.

Scenario – 2

The second scenario is regarding the possible investment choices. In reference to the base case, this scenario analyzes the resulting efficient land-use/transportation maps as a result of decrease in investment values (amounts). The decrease amounts are set to be 20% in reference to the base case.

Scenario – 3

The third scenario is about management of investment and growth with respect to the equitable distribution across various geographic regions of the municipality. In reference to the existing development (i.e. Coimbra) these scenarios compare efficient land-use/transportation maps which are resulted from developments that favored particular geographic regions. Specifically, this development equity scenario compares developments to the north plus south west, north plus south – 1, and north plus south – 2 shown in Table 6.8 and Figure 6.6 (a –c).

Table 6.8 - Development equity scenarios

	Scenarios			
Equity (E)	**Base**	**North plus south west**	**North plus south - 1**	**North plus south - 2**

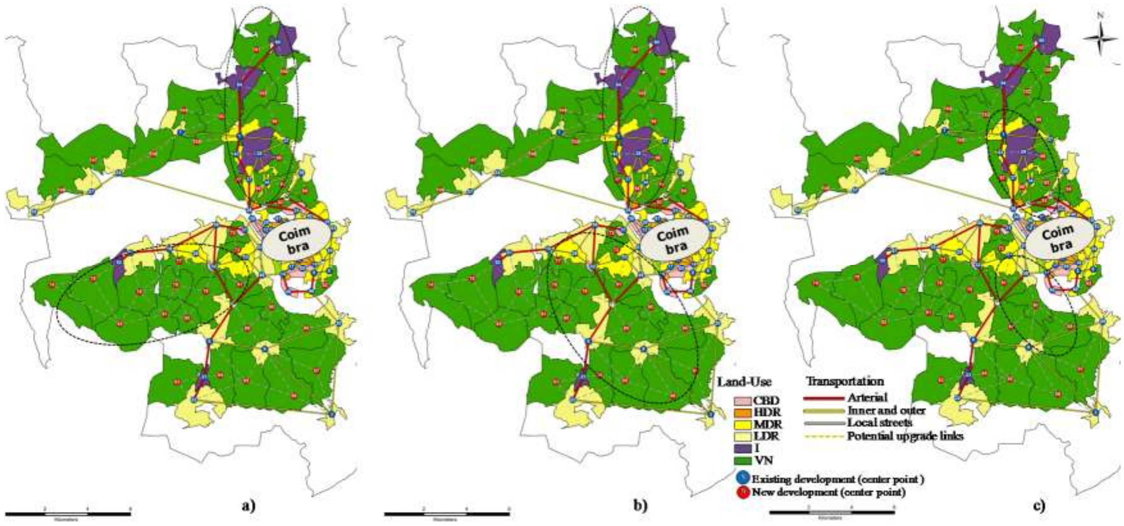


Figure 6.6 - Development equity scenarios

The regions included in each development equity scenario are encircled in the Figure 6.6. The zones and transportation links considered for the north plus south west, north plus south – 1 and north plus south – 2 are shown in Figures 6.6a, 6.6b and 6.6c respectively.

6.5 Problem solving

The optimization approach is solved using genetic algorithm coded with Mosel programming language. The quality of parameters and solutions of the genetic algorithm are assessed in Chapter 4 of this thesis. Those parameters are determined after rigorous calibration and validation process involving number of different size urban areas. The same values for algorithm parameters determined in Chapter 4 are used for this case study application. We believe these algorithm parameters will yield with quality solutions that are efficient.

6.6 Results and discussion for the base case

For the base case, values for the three objectives which are suitability (Objective 1), compatibility (Objective 2) and accessibility (Objective 3) are shown in Table 6.9. The normalized values are determined using the min-max normalization method detailed in Chapter 3 of this thesis. The entries for the Value column of Table 6.9 represent the overall individual objective performances and the entries for the Normalized column represent the normalized values of individual objectives.

Table 6.9 - Objective values for base case

	Objective Values			
	Values	Normalizing		Normalized
		Max.	Min.	
Objective 1	**63.6**	64.2	59.0	**0.9**
Objective 2	**5954.9**	5809.0	5101.7	**1.2**
Objective 3	**1720946.7**	1799323.0	660431.0	**0.9**

The resulting efficient land-use/transportation map, Figure 6.7, has allocated land-uses to suitable locations that maximize the overall compatibility and overall accessibility of users to services and jobs. The figure also shows list of zones with their respective land-use types.

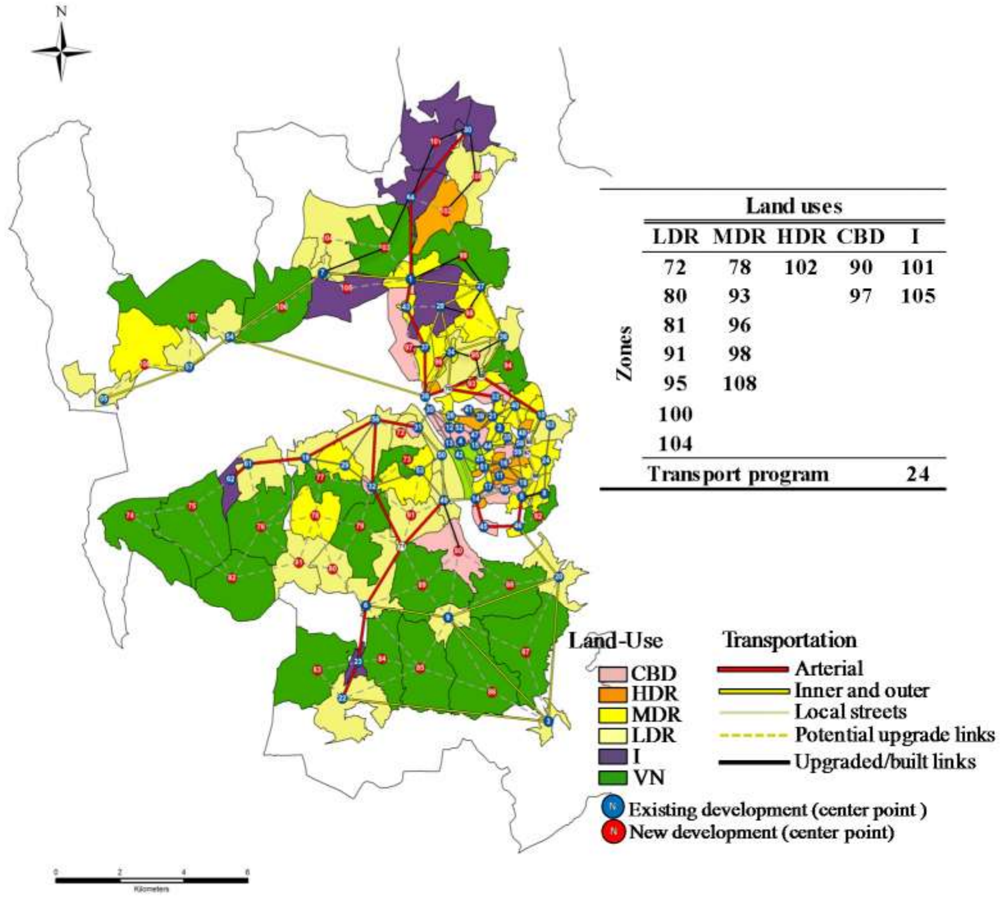


Figure 6.7 - Efficient land-use/transportation map (base case)

Result in Figure 6.7 shows that in terms of the first objective, that is land-use suitability, the land-use types are allocated to suitable zones. For example zone 105 is assigned with industrial type of use and, according to the suitability index, this zone has been identified as suitable for this type of land-use. Similarly the land-use type CBD is allocated to zone 97 which is very suitable for such land-use type. Moreover, with respect to allocations in zones 80, 81, 91, 93 and 98 are suitable for residential uses (most of which are located beyond the hilly zones of 76, 77, 78 and 79). Indeed, in this base case, there are few land-uses which are assigned to least suitable locations this is due to the fact that there are two more objectives that are equally important for the final allocation.

In terms of the second objective, the land-use compatibility, the efficient land-use/transportation map produced good results. For instance, the residential allocation for zones 93, 95, 96, and 98 are located in a neighborhood occupied by similar land-use types such as medium and high density residential in Ingote, Loreto, Monte Formoso, Eiras, Pedrulha and Padre Manuel Nobrega. Moreover, the new industrial use allocations are in zones 105 and 101 which are located in the neighborhood that is close to other existing industrial zones such as Souselas and Trouxemil/Fornos. Similarly a land-use type of CBD is allocated to zones 97 and 90. Zone 97, for instance, is located adjacent to predominantly residential neighborhoods of Eiras, Ignote and Lordemao.

With respect to the third objective, that is accessibility, the efficient land-use/transportation map indicates that new land-use developments tend to follow the existing and/or newly improved arterials. The distributions of land-uses also indicate the accessibility implications of the efficient land-use/transportation map. For example, the CBD type allocated in zone 97 provides additional job and service opportunities to residential areas in zones 37, 38, 34, 43 and 27. These residential areas are not only located closer but are connected with good transportation links. Similarly, the high density residential in zone 102 is located in neighborhoods where there are number of accessible job opportunities from the industrial locations. In the northern part, new land-use developments follow existing arterial. The new transportation link improvements have provided improved connectivity of new residential and industrial areas to the existing residential and industrial areas. For example, connections between zones 102 and 100 as well as zones 100 and 60 are some of the interactions with improved connectivity. A close observation on the distribution of new land-uses indicates the improved accessibility to jobs and services for the existing land-uses and new developments. For example the relative locations of medium density residential in zone 98 at the middle of predominantly residential and an industrial use in Eiras Industrial creates more job opportunities and improves accessibility to services. Furthermore the relative locations of new industrial zones, in addition to maximizing location characteristics, indicate the creation of job opportunities to satisfy the growing population. There is another significant land-use development at zone 90 in the form of CBD. This allocation provides with improved accessibility benefits to sparse locations in Ceira, Assafarge, and Antanhol which are low-density residential neighborhoods. Besides, the new allocation of medium density residential in zone 91 is in proximity to zone 90. This indicates improvements in accessibility to services to zone 91 and to the neighborhood.

The accessibility objective in the efficient land-use/transportation map has performed very well not only locally but also when it is viewed globally i.e. considering the form of the existing developments. The new developments are allocated in a way that improves accessibility without causing considerable strain on the level of service of transportation infrastructure. This is proved by the fact new land-use types are allocated to less congested areas and following existing arterial and taking the advantage of the newly improved links. In the efficient land-use/transportation map, most of the new links provide improved connectivity to high interest areas (high density residential to CBD and/or industrial; industrial to industrial zones).

An observation from the result in Figure 6.7, the efficient land-use/transportation map, most of the significant developments such as CBD, high density residential and industrial uses are to the north of Coimbra. Indeed there are some new land-use developments to the south of the city but they are only in the form of low and some medium density residential uses and one CBD. This might raise the issue of lack of equitable distribution of investments and opportunities.

6.7 Results and discussion for sensitivity analysis

In previous section we have looked at the efficient land-use/transportation map resulted from the base case which among other things considered equal importance of all the three objectives. In this sensitivity analysis, the relative importance of each objective is systematically altered and the resulting land-use/transportation maps are analyzed.

For the sensitivity analysis, three combinations of weights are used. In each combination, the weight for one of the objectives is made to be greater than the weight for the other two objectives. Refer to Table 6.6 for the weight combinations.

This first of the sensitivity results analyses the efficient map when the emphasis to the land-use suitability objective is increased from 33% to 50%. This gain in weight for suitability objective is at the expense of loss of weight values for the compatibility and accessibility objectives, from 33% to 25% each. Result is shown in Figure 6.8.

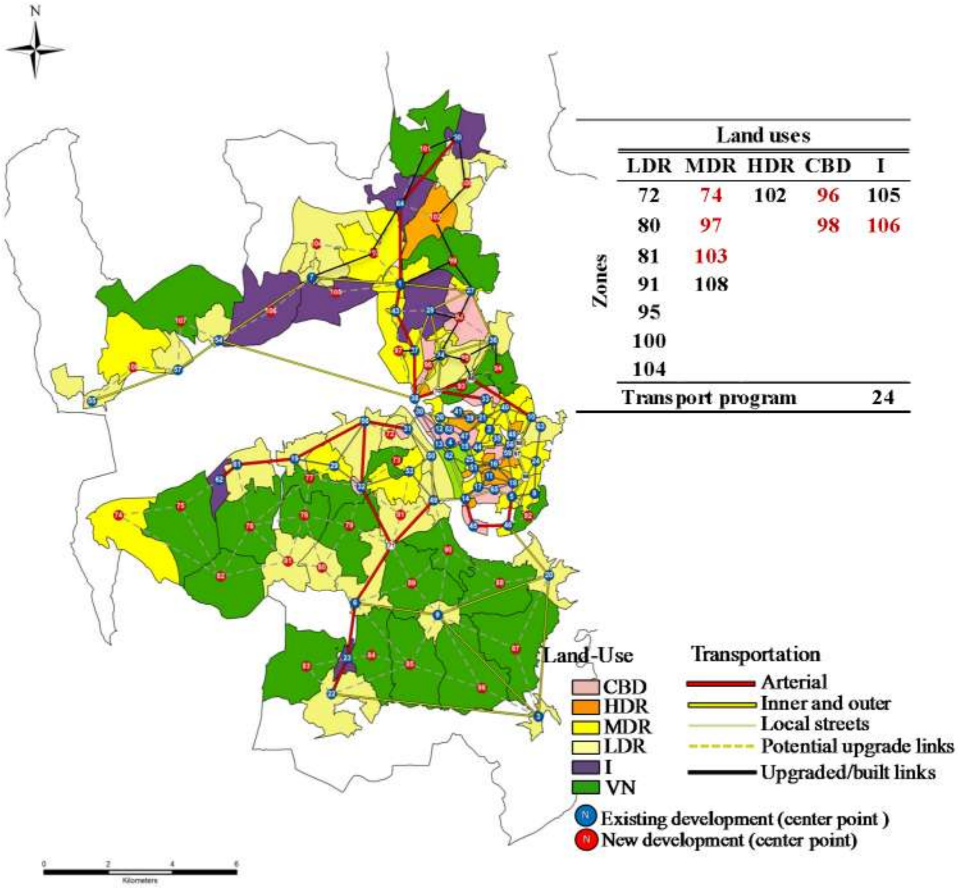


Figure 6.8 - Efficient land-use/transportation map (emphasis on land use suitability)

In comparison with the base case, the map in Figure 6.8 indicates changes in land-use allocations. The changes in land-use types are indicated by the red font entries on the top right of Figure 6.8. Land –use changes reflect an improvement in the value of the suitability objective. This means, in this result most of the land-uses are assigned to locations which are suitable the most. For instance zone 74 is preferred for medium density residential instead of zone 78; zone 96 is allocated with CBD instead of the less suitable zone 96. Moreover, there is a new zone allocated with industrial use. In the base case, zone 101 was an industrial location but in Figure 6.8 with the emphasis on suitability zone 106 is the preferred location for industrial use.

The second resulting map from the sensitivity analysis is when the emphasis is on compatibility objective. That is, the weight for the objective increases from 33% to 50% and the weights for the other two objectives are reduced from 33% to 25%.

In comparison with the base case, the map in Figure 6.9 indicates changes in land-use allocations. The changes in land-use types are indicated by the red font entries on the top right of Figure 6.9. Land –use changes reflect an improvement in the value of the compatibility objective.

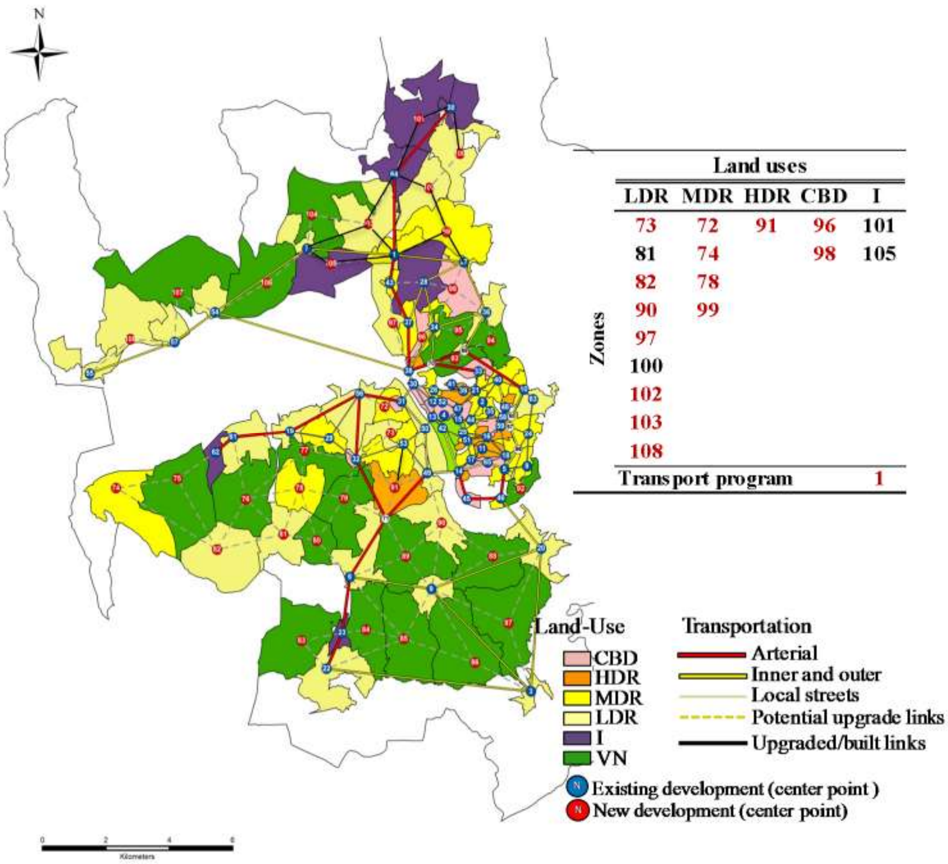


Figure 6.9 - Efficient land-use/transportation map (emphasis on compatibility)

The resulting map on Figure 6.9 shows changes in land-use allocations specifically with the relative locations of residential and industrial uses. In comparison with the result from the base case, the map on Figure 9 has allocated residential uses to zones 97, 103, 102, 99 and 100 which are located close to one another and are continuous. Same goes for the new residential allocations in zones 74, 78, 81 and 82 which are in close proximity to existing residential zones, such as in zones 29 and 19. Moreover, the changes are also observed in the allocation of industrial use, for example in zone 100 which is in close vicinity of zones 50 and 64.

The third resulting map in Figure 6.10 is from the application when the weight for the accessibility objective is increased from 33% to 50% and the weights for the other two objectives reduced from 33% to 25%.

In comparison with the base case, the map in Figure 6.10 indicates changes in land-use allocations. The changes in land-use types are indicated by the red font entries on the top right of Figure 6.10. Land –use changes reflect an improvement in the value of the accessibility objective.

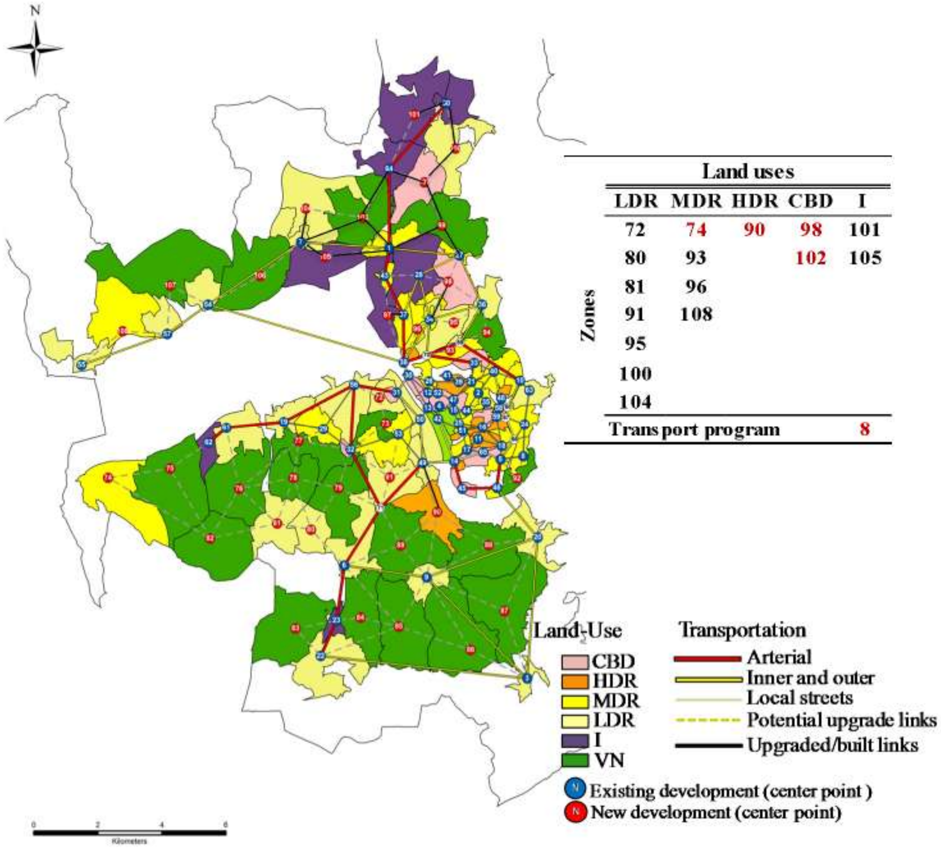


Figure 6.10 - Efficient land-use/transportation map (emphasis on accessibility)

The efficient land-use/transportation map in Figure 6.10 indicates the arrangements of land-uses that increase job and service opportunities. The resulting map also shows the ease with which the jobs and services are accessed i.e. in terms of travel conditions. For instance, an industrial use at zone 97 and CBD use in zone 98 are close proximity to the existing predominantly developed area of Coimbra. In addition to creating opportunities, they are also easily reachable due to high speed high capacity highway and the existence of the newly developed transportation infrastructure. Similarly, the resulting accessibility maximizing map has changes in residential use allocations. For example, the high density residential allocation in zone 90 in neighborhood which is not far from the existing developed area. Besides this new high density residential is also close to the new medium and low density residential uses located to the south. The existence of high density residential provides new service opportunities to the neighborhood. The accessibility objective should be viewed in terms of land-use, transportation and their interactions. When we talk about gains or improvements in the accessibility objective it means there are changes in terms of land-use distributions (specifically in the form of mix of uses) and changes in terms of travel costs which in this case are represented in the form of travel times that took the effects of congestion in to account. This, for instance, can be observed from the new transportation investment that provides improved connectivity of the major generators.

Results from the sensitivity analysis shown in Figures 6.8 – 6.10 show the efficient maps when the emphasis on each objective changes. In order to understand variability of each objective with respect to changing weights, we made a comparative analysis of the results.

The observation from sensitivity analysis is that when the emphasis is on one of the objectives, the increase in objective value comes at the expense of decrease in one or both of the other objectives. For example, the increase in suitability objective comes at the expense of loosing values in the compatibility objective and the increase in the value of the compatibility objective comes at the expense of decrease in land-use suitability and accessibility objectives (Table 6.10). The table shows the weights and the normalized objective values. Except for the base case, the normalized values of the objectives are given in terms of percentages. For the base case, the normalized objective values are shown.

Table 6.10 - Comparative objective values, sensitivity analysis

	Normalized Values		
Sensitivity (W_1; W_2; W_3)	**Objective 1**	**Objective 2**	**Objective 3**
Base (0.33; 0.33; 0.33)	0.9	1.2	0.9
Suitability (0.5; 0.25; 0.25)	17%	-17%	7%
Compatibility (0.25; 0.5; 0.25)	-9%	19%	-8%
Accessibility (0.25; 0.25; 0.5)	4%	-11%	18%

Table 6.10 shows the relative gains/losses in the normalized values of objectives in reference to the base case. As it can be seen from the table, there are no possibilities of increasing one objective without incurring a reduction on the other. For instance, an increase in the suitability objective comes at the expense of decrease in compatibility objective; and an increase in the compatibility objective comes at the expense of decrease in suitability objective. The observation also leads to the fact the accessibility objective also changes when change in the two objectives takes place.

It is important to notice that the changes in weight values are relative i.e. for example when one of the objectives is weighted by 50%; the others are weighted 25% each. That means, in every of the solutions there is at least 25% of contribution from each objective to the final solution. From the results in table 10 and figure 15, two observations are worth discussing. The first one is when the emphasis is on land-use compatibility, the increase in the objective value of 19% is attained at the expense of 8% loss on the accessibility objective. This might be explained by the fact that making the land-use allocations more compatible, that is allocating similar land-use types in proximity to one another, could have negative consequences on the accessibility objective. The second observation is that when the emphasis is on the accessibility objective, the 18% increase is countered by 11% loss on the compatibility objective. This reduction indicates the contribution of mixing uses (hence reducing compatibilities) on the accessibility objective.

The land-use/transportation changes as a result of the sensitivity analysis are shown in Table 6.11 (a-d) and Figure 6.11 (a-d).

Table 6.11 - Land use changes: base (a), suitability (b), compatibility (c), accessibility (d)

	Land uses																			
	(a)					(b)					(c)					(d)				
	LDR	MDR	HDR	CBD	I	LDR	MDR	HDR	CBD	I	LDR	MDR	HDR	CBD	I	LDR	MDR	HDR	CBD	I
Zones	72	78	102	90	101	72	74	102	96	105	73	72	91	96	101	72	74	90	98	101
	80	93		97	105	80	97		98	106	81	74		98	105	80	93		102	105
	81	96				81	103				82	78				81	96			
	91	98				91	108				90	99				91	108			
	95	108				95					97					95				
	100					100					100					100				
						104					102					104				
											103									
											108									
Transport program					24					24					1					8

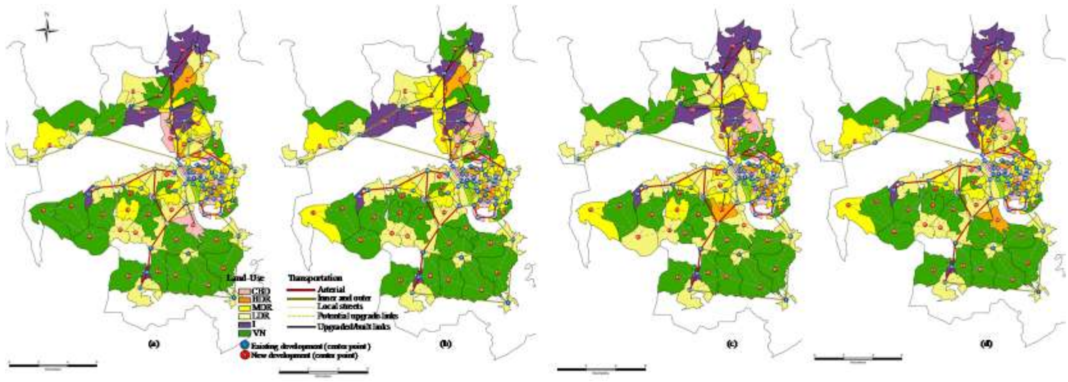


Figure 6.11 - Efficient maps: base (a), suitability (b), compatibility (c), and accessibility (d)

Table 6.11 (a-d) shows land-use allocations for the base case, emphasis on suitability, emphasis on compatibility and emphasis on accessibility respectively. The red font entries on Table 6.11 (b-d) indicate the land-use type changes in reference to the base case. Figure 6.11 (a-d) shows efficient land-use/transportation maps for the base case, emphasis on suitability, emphasis on compatibility and emphasis on accessibility objectives respectively.

In general, the sensitivity analysis which showed the types of results the approach could yield when the emphasis on each objective varies have indicated that it is impossible to gain on one of the objectives without incurring loss in one of (or both of) the other two objectives (Table 6.10).

6.8 Results and discussion for scenario analysis

In general, six scenarios are considered. The first three are related to demand and investment scenarios where as the remaining three are related to development equity scenarios. The first scenario deals with demand growth of 20% and the second scenario deals with demand increase of 45% (both as opposed to the 30% increase considered for the base case). Results for these two scenarios are shown in Figures 6.12 and 6.13.

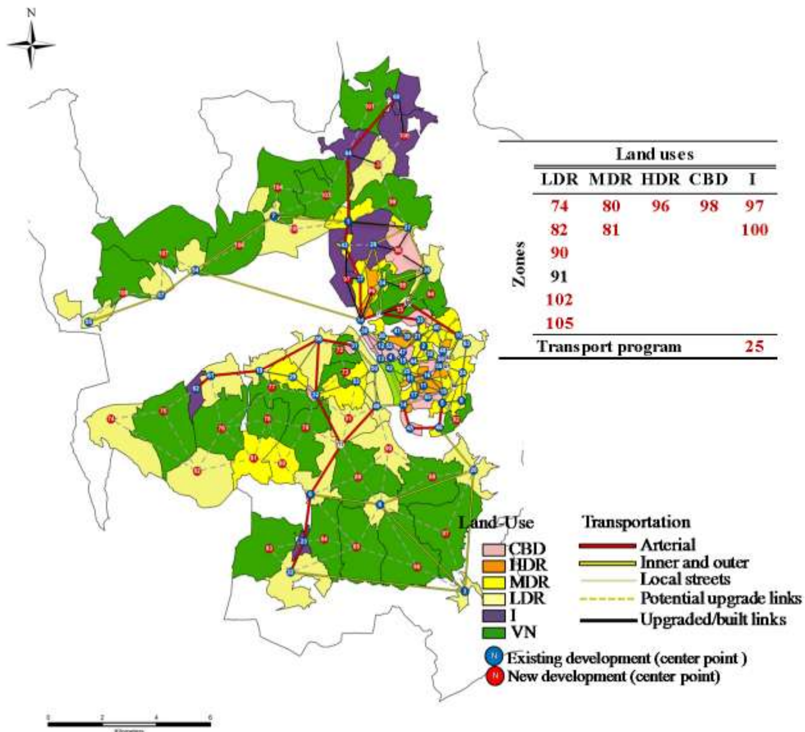


Figure 6.12 - Efficient map:demand scenario, 20% growth

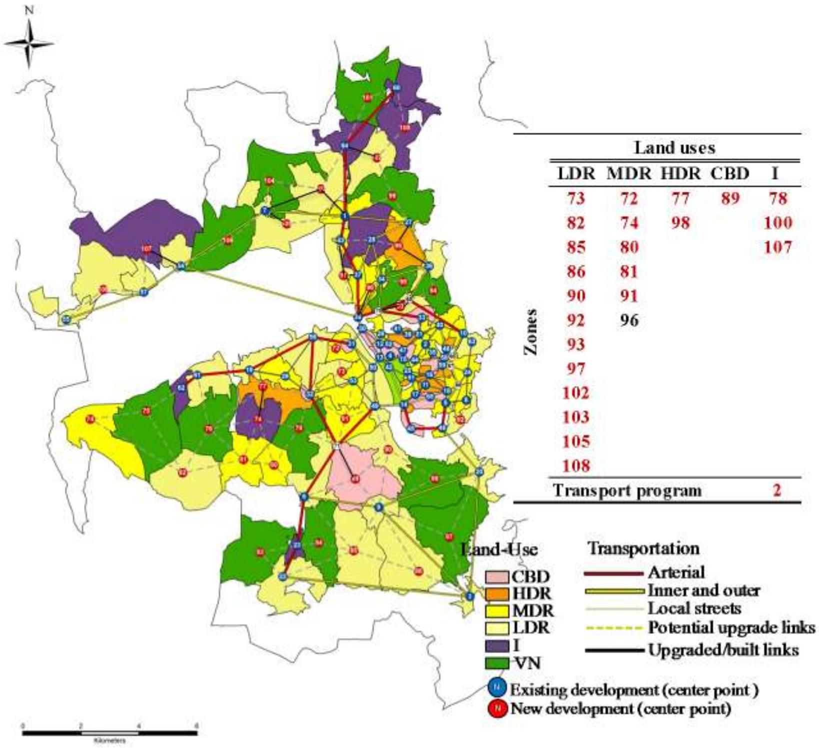


Figure 6.13 - Efficient map: demand scenario, 45% growth

In these two scenarios, it is evident that there will be changes in land-use maps since the demand is varying. But in both scenarios, the transportation programs remained the same as in the base case. That means the results from these two scenarios can be compared in terms of changes in the accessibility objective. In other words, since the investment for transportation is fixed in the base case, first, and second scenarios, these comparisons could give us perspectives on the utilization of investments.

The third scenario is regarding the decrease in investment levels of the transportation programs. The demand for land-use is the same as in the base case so the changes in results should be interpreted in terms of changes in the three objectives when the available funds are very limited. It is important to note here that the transportation programs for the investment scenario are different from the base case in that the total upgrade/construction length is 20 km. Using the sketch in Figure 6.4 as guidance, 25 transport programs are defined. In principle, these programs share similar structure to the programs from base case but shorter in length.

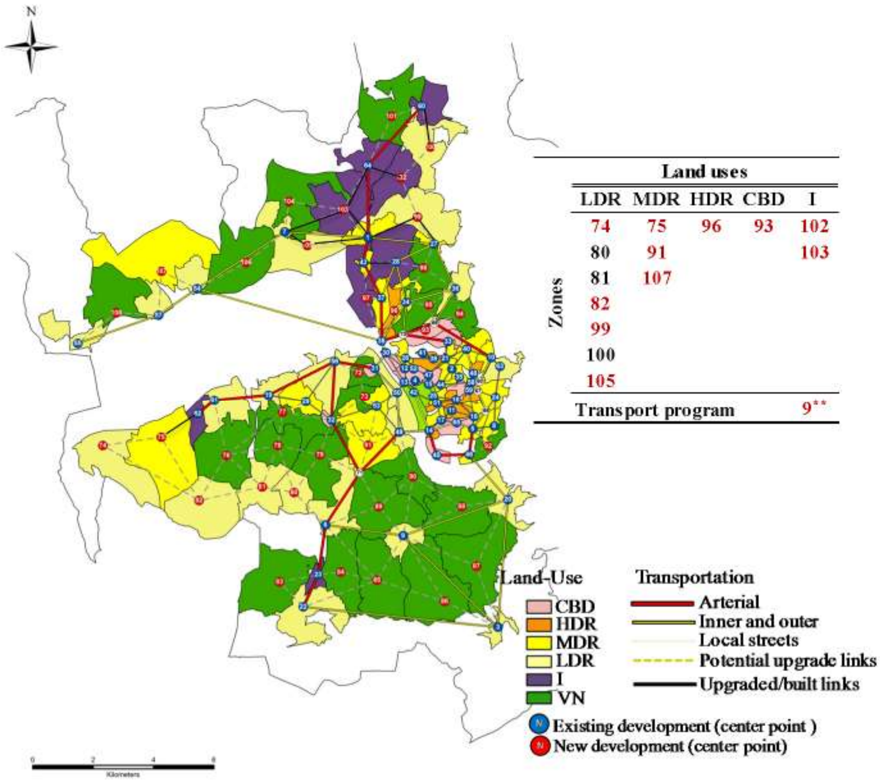


Figure 6.14 - Investment scenario

The results in Figure 6.14 indicate the re-arrangements of land-use types in order to maximize the total benefits of the limited transportation investment. For instance observe the assignment of industrial to zone 103 and 102 (instead of zones 101 and 105) which are closer to the existing and newly improved high speed facilities. Similarly the high density residential in zone 96 and CBD in zone 93 are in proximity to the existing development.

Table 6.12 - Scenario comparison: demand and investment

	Normalized Values		
Scenarios	**Objective 1**	**Objective 2**	**Objective 3**
Base	0.9	1.2	0.9
Low Demand			-26.4%
High Demand			12.9%
Low Investment	9%	-32%	-2.5%

From the resulting Figures 6.13 - 6.14 and Table 6.12, it can be observed that changes in accessibilities are not due to transportation investment changes but also due to changes in land-use. For the first scenario, the accessibility objective has reduced by 26% and for the second scenario it has increased by 13%. The decrease in accessibility objective value is attributed to the reduction in opportunities (less industrial and commercial uses). On the other hand the increase in accessibility is attributed to the development of new land-uses in the southern zones. For instance new industrial locations in zones 107 and 78; commercial use in zone 89; and high density residential in zone 77. The improvement in accessibility in the third scenario indicates the potential of exploiting the full benefits of the proposed transportation investment.

The results in Table 6.12 indicate significant reduction in compatibility objective which can be attributed to the rearrangement of land-use types in order to maintain high levels of accessibility. As we can see from the table the reduction in accessibility is not that significant considering the drop in investment for transportation projects.

The last scenario deals with the equitable distribution of investments and opportunities. In this regard, three additional scenarios have been discussed. The scenarios are north plus south-west based development; north plus south based development – 1; and north plus south based development refer to Table 6.8.

The reason for these equity based scenarios is to see if the investments and opportunities could be distributed towards various geographic regions. This is partly because in the base scenario, most of the industrial, commercial as well as majority of residential developments occurred in the zones to the north of Coimbra.

The first equity scenario is about distribution of developments to the north and south -west of Coimbra. The resulting map is shown in Figure 6.15.

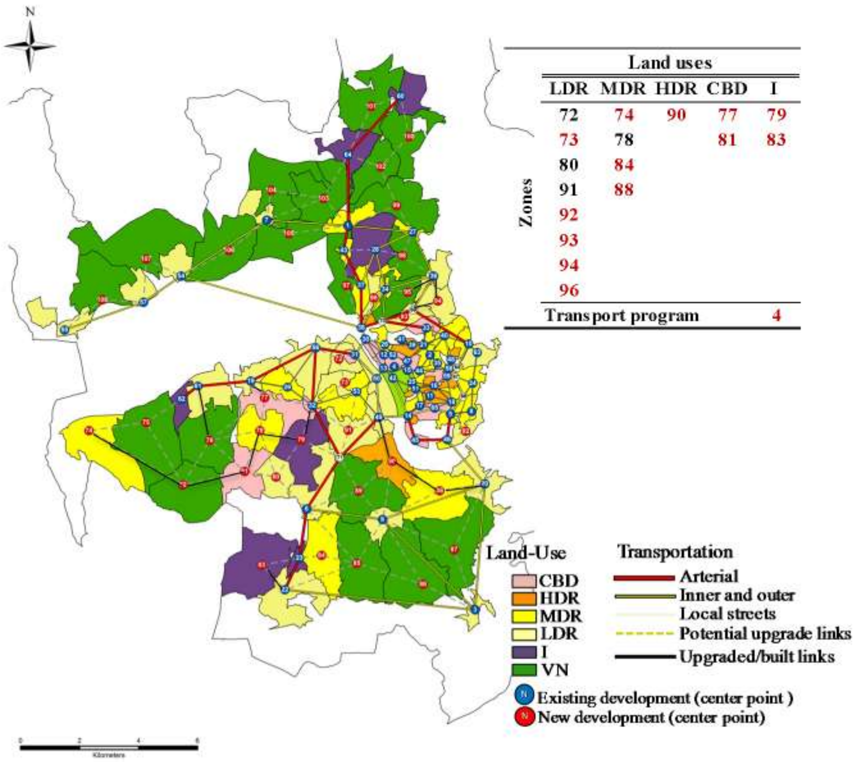


Figure 6.15 - Efficient map: north plus south-west

The second equity scenario deals with distribution of investment and opportunities to the north plus south regions of Coimbra. Result is shown in Figure 6.16.

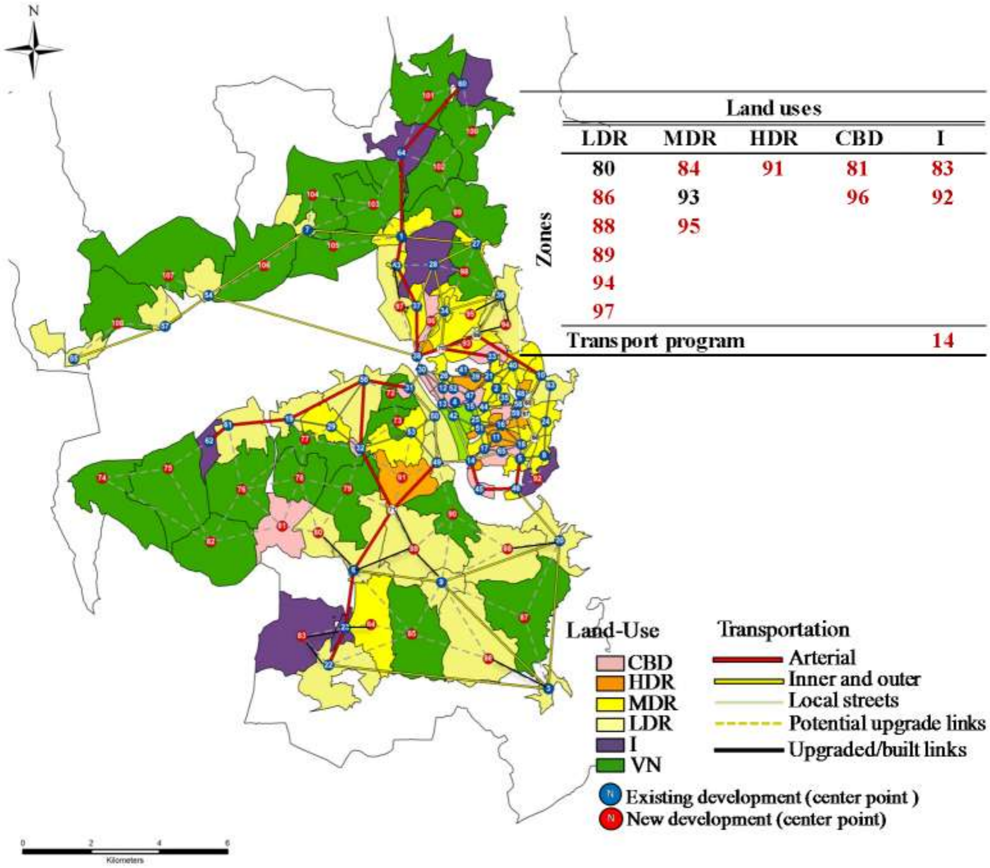


Figure 6.16 - Efficient map: north plus south – 1

The third equity scenario deals with distribution of development to zones which are located north and south of Coimbra. Result is shown in the following Figure 6.17.

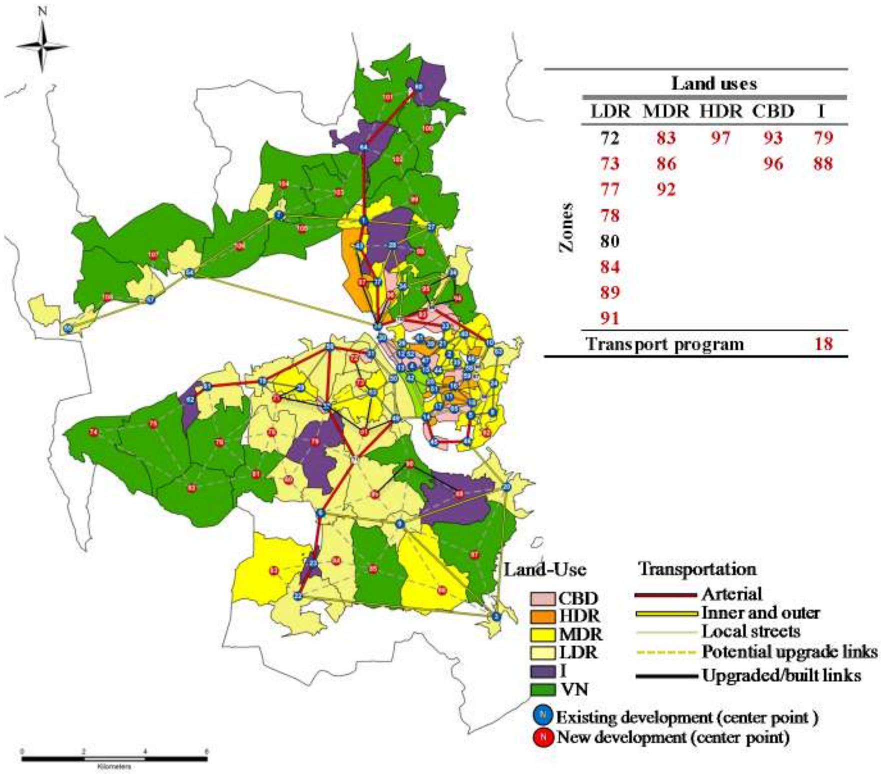


Figure 6.17 - Efficient map: north plus south – 2

Results for the three different equity scenarios are shown in maps (Figures 6.15 to 6.17). The resulting comparison between the values in each objective is illustrated in Table 6.13. The table shows the scenarios and the normalized objective values. Except for the base case, the normalized values of the objectives are given in terms of percentages. For the base case, the normalized objective values are shown.

In general, for all the scenarios there is a reduction in objective values. Specifically the north plus south – 1 and north plus south – 2 have resulted in significant reduction of the suitability objective. This might be attributed to the fact that the zones south of the existing Coimbra are hilly and less suitable for land-use development. For example land uses in 73, 76, 77, 78, 87 and 90 are allocated to less suitable zones.

Table 6.13 - Comparative analysis of development equity scenarios

	Normalized Values		
Scenarios	**Objective 1**	**Objective 2**	**Objective 3**
Base	0.9	1.2	0.9
North plus South West	-35%	-2%	-3.5%
North plus South - 1	-52%	-54%	-6.5%
North plus South - 2	-52%	-16%	10.4%

Similarly, for the second objective, highest reduction in value is observed for the north plus south – 1 scenario. This might be attributed to the fact that the allocations have to be assigned to relatively suitable zones and this might constrain the ability of the model to assign compatible land-use types. For the third objective, the reductions in objective value are relatively small. In fact for the just north and just south equity scenario, the accessibility objective has increased.

The results can be used as investment choice making tools in that decision-makers could understand the value of development equity and costs associated with equitable distribution of costs and investments.

6.9 Summary of case study

This chapter was about the application of the optimization based approach for a real world application in the municipality of Coimbra, Portugal. The chapter analyzes resulting solutions considering number of cases and scenarios. A sensitivity analysis was carried out to test the performance of the approach in response to changing weighting values (importance factor) of each objective. Moreover numbers of scenarios have been defined and analyzed. Results from the sensitivity and scenario analysis are compared with the efficient land-use/transportation map from the base case. The results from base case, scenario analysis and sensitivity analysis have shown that the optimization based approach can be used as planning support tool. That is, given the specifications of objectives, the approach can be used to generate efficient maps that help in discussions regarding changes in urban area's population, environment, land-use, transportation and infrastructure. Results have also shown that the approach can be used to assess the impacts of various growth, investment and development equity choices.

7 Conclusion

Urban centers currently accommodate the majority of the world population and greatly contribute to national and global economies (UNFPA 2007). Changes in structure and function of urban centers have significant ramifications on the livelihoods of individuals and major effects on the environment. These changes are mostly attributed to the changes in land-use and transportation systems. For example, there are studies which relate observed changes in land-use and transportation to the increase in space and energy consumption and high emissions of greenhouse gases (see Newman and Kenworthy 1999, Price et al. 2006). These ongoing changes in form and function of urban areas have been subject of debate for planners, researchers and policy makers. Consequently, there have been continuous efforts to understand land-use/transportation changes which resulted in the development (need for) of decision support tools. Driven by the constant changes in urban phenomenon such as changes in demography, mobility characteristics, income distribution and so forth, and owing to the advancements in theoretical and computational capabilities, there has been a continuous and growing interest in urban land-use/transport models.

This thesis was set out to explore the potentials of optimization approach for identifying efficient land-use/transportation policy measures and assess potentials of the approach for use as spatial planning support tool. The thesis was also set out to find alternative solution methods that have low computational effort requirements to solve land-use/transportation optimization models. To address these research issues, the thesis was organized around four main sections which focus on state of the art/practice, optimization based land-use/transport model, solution methods (computational efforts), and a case study respectively. Results from this thesis indicate that there is significant potential for the optimization approach to be used as decision support tool for urban land-use/transportation planning.

In the first main section, a thorough review of the state of art/practice in optimization in general, and in its application to land-use/transportation planning in particular, has indicated that the approach is prevalent for land-use (activity) allocations but its application for land-use/transportation systems has been limited. Even whenever transportation system was represented it was in simplistic way. This further shows the limitations of previous applications. The review also indicated that the key elements for defining objectives for a land-use/transportation planning purpose should take into account the site, neighborhood and network attributes.

In the second main section, we developed an optimization based land-use/transportation model that incorporates a four step transportation demand model. The optimization model was formulated as multiple objective linear programming. The three objectives are land-use suitability, land-use compatibility and accessibility. These objectives have been selected based on our study of the state of the art and current practices in land-use and transportation planning. Land-use suitability objective quantifies the physical and locational characteristics of a zone in reference to particular land use type, land use compatibility quantifies the environmental harmony and living quality, and accessibility measures the easiness of reaching service and job opportunities. The performance of the model, in terms of producing quality solutions at reasonable computational effort, was assessed considering number of application settings.

The results from the initial runs, using the exact branch and bound solution method, clearly indicated that the approach has indeed generated efficient land-use/transportation maps that maximize a normalized weighted sum of the three objectives. The approach was applied for different types of urban forms leading to solutions where accessibility, compatibility and suitability issues are properly dealt with. The results from the initial runs, using the branch and bound method, have also indicated the challenges associated with computational efforts. Given the complexity of the land-use/transportation model and considering the combinatorial nature of the decision variables, the computation time have increased considerably with increase in number of the zones (size of urban area). For example, in one of the applications it was found that an increase of 50% in the size of the urban area (i.e. in terms of number of zones and transportation links) has on average resulted in 70 fold increase on computation time. This indicates that the branch and bound method, though guaranteeing optimality, requires very high computational efforts. When we look at the purpose of the model as potential tool for urban land-use/transportation planning which in reality contain large number of zones and transportation links, the large computation time observed can be challenging.

The third main section of the thesis was dedicated for the process of determining and evaluating an efficient heuristic algorithm to solve the optimization land-use transportation model. After a systematic review of the most commonly used heuristic algorithms for solving models of similar nature, we came up with the conclusion that the genetic algorithm was an appropriate choice. This is because it has previously been applied for solving models of similar nature with commendable results. Moreover, genetic algorithm are characterized by its population search routine which is a desired property for solving problems with large solution spaces such as the land-use/transportation problem presented here.

In developing and applying the genetic algorithm, the challenge was twofold. The first one was to be able to determine the right parameters for the algorithm and the second one was to determine whether the solutions obtained from the algorithm have the desired quality, in terms of solution (fitness) value. To address the first challenge, the genetic algorithm was used to solve number of problem types considering number of combinations of algorithm parameters. Results from these various runs have provided us with a good understanding of the behavior of the algorithm. For a land-use/transportation problem with non-uniform areas and shapes of zones like the one we addressed, like the one solved here, it can be concluded that relatively larger population size, larger number of generations and smaller probability of mutation yield a steady evolution of solutions towards the optimum. Specifically, the appropriate values for the algorithm parameters were found to be 100, 100, 0.8, and 0.01 for population size (N), number of generations (G), probability of crossover (PC), and probability of mutation (PM) respectively.

For the second challenge, the solution values from the genetic algorithm were compared with the solution values from the branch and bound method. For this, we solved the same set of problems using the exact and heuristic solution methods. Results concluded that the algorithm parameters were good in determining efficient land-use/transportation maps. For the entire comparison test runs, the gaps between solutions from the branch and bound and solutions from the genetic algorithm were evaluated. In most cases the gaps were 0%. For the worst one it was merely 0.59%. The gap in solution value is more appreciated when observing the gains in computational efforts (in terms of running times).

The test runs have concluded the power of the genetic algorithm over the branch and bound method. For all the problem sizes, the computational effort for the genetic algorithm was significantly smaller than the computational effort for the branch and bound method. For the smaller size problems, on average the genetic algorithm has reduced the computational effort requirements of the branch and bound by 23%. For the larger size problems, the gain in computational efforts was tremendous. On average, the computation times required by the heuristic were 22 times lower than the computation time required by the branch and bound method. Considering the maximum gap in the solution values was merely 0.59%, the benefits of gaining on computational efforts greatly outweighs the small gaps in solution values.

Moreover, the tests to compare computational efforts have also indicated that, in case of the genetic algorithm, the change in running time for two different problem sizes is not as large as the change in computation time between problems of similar sizes using the branch and bound method. The test runs have indicated that a 50% increase in the size of a problem results in increase in computation time by 3.5 times (in comparison to the 22 times increment in branch and bound method). This means, in the genetic algorithm, the increment in problem size does not increase the computation time by large factors as it was the case for the branch and bound method.

The fourth main part of the thesis was to illustrate the usefulness of the optimization approach using an application to the city of Coimbra, Portugal. The case study was structured into three main parts. The first one was the determination of efficient land-use/transportation map, the second one was a sensitivity analysis and the third one was a scenario analysis. From the resulting efficient map, it was observed that land-use developments and transportation investments were allocated to maximize the normalized and equally weighted sum of suitability, compatibility and accessibility objectives. Resulting map from the sensitivity analysis indicated the usefulness of the approach in determining tradeoffs among individual objectives. The sensitivity analysis has also showed that there is particularly strong relationship between the compatibility and accessibility objectives. In all the results from sensitivity and scenario analysis, it is consistently shown that increase in land-use compatibility objective brings decrease in accessibility objective. And increase in accessibility objective was partly resulted from the decrease in compatibility objective. This relationship is an indication of the accessibility gains and compatibility losses due to the encouragement of mixed land-use development.

The scenario analysis has particular emphasis on demand, investment and equity issues. Results from the scenario analysis indicate that the approach can be used to evaluate the implications of changes in land-use demand, changes in investment levels and implications of distributing investments and opportunities among different geographic regions of the municipality. The results have also indicated that the approach can be used to quantify the degree of utilization of existing and/or new transportation infrastructure, and to quantify the costs of equitable distribution of opportunities and investments.

The thesis major aim was to design an optimization based approach for land-use/transportation policy making and test its performance (in terms of solution quality, computational effort and applicability) using different application settings. The research and policy implications of its findings should be viewed in terms of quality of solutions and computational efforts associated with them.

The research implication of this thesis is that optimization can be used as approach for land-use/transportation planning purposes. The approach we developed has generated efficient land-use/transportation maps given the objectives and constraints. That means the optimization approach is used to assess the performance of various land-use/transportation measures (policies). The efficient solutions are indicators of the best possible combinations of the policy measures considered in the model formulation.

Another research implication of this thesis is the solution method developed and the process we have followed in calibrating algorithm parameters. The genetic algorithm calibrated and validated in this thesis has clearly shown the potentials of such heuristic algorithm in reducing computational efforts while maintaining the quality of solutions. Moreover, the development of genetic algorithm in this thesis contributes to the research in the form of provision of the right value for algorithm parameters that will lead to a steady evolution of solutions towards the optimum.

The policy implication of the thesis is that the approach is applicable for land-use/transportation planning purposes. The optimization model can be used to evaluate and/or propose policy measures related with land-use and transportation. Specifically, the approach is useful tool to assess impacts of land-use policies such as zoning, location, growth boundary, land preservation and transportation policies such as highway investments and accessibility issues such as land-use distributions (mixed use), travel costs and trip forecasts.

For future, there are two directions that merit further research: model development and application. In terms of model development, the approach can be improved to include mode choice model, hence to consider transit issues for the case study application. In terms of application, more applications have to be done to further verify quality of solutions. The model's applicability (potential for policy support) is appreciated more for applications in growing urban areas. As future research, it would be interesting to see the application of the model in a growing urban area such cities in developing countries. Another direction for future research is that the optimization model should be applied and used in parallel with another integrated land-use/transportation models. These will provide additional insights regarding the capability of our model.

The optimization approach though it serves as important decision support tool, has some limitations. The biggest limitations would be the combinatorial nature of its decision variables, specially the land use ones. Due to this, the assumption that a zone should be characterized as having one land-use type is the biggest limitation. This in turn presents a limit on the size a particular zone can have. Moreover, another limitation of the approach arises from the nature of administrative structures of municipalities. In most cases land-use and transportation decisions are handled by different administrative entities. Considering the structure and priorities of each entity, integrating land-use and transportation decisions might be challenging prospect. This makes the use of optimization approach for decision making difficult. This is because the approach requires the presence of a decision making entity that is in charge of land-use as well as transportation related decisions. Finally, the optimization approach is not dynamic in nature, i.e. it provides an efficient solution (land-use/transportation map) at certain period of time. Perhaps, it would be necessary to explore the possibility of using dynamic optimization approach specifying the evolution of land-use/transportation over time considering for instance short term, medium term and long term decisions.

In summary, we believe this thesis shows the significant contribution to urban land-use/transportation planning process from an optimization approach. The approach is shown to support real world decisions and consequently contribute to the overall goals of improving environmental quality, harmony and efficiency in resource utilization. The findings of this thesis indicate that: (1) the optimization approach developed here has the potential of serving as a tool for proposing land-use/transportation policy measures; (2) a genetic algorithm with the lower mutation and higher crossover probabilities is found to be the right algorithm parameters for solving complex optimization based land-use/transportation models; and (3) optimization approach can serve as spatial planning tool and can also be used to evaluate transport investment and equitable distribution choices.

References

Aerts, J.C.J.H., Herwijnen, M., Van, Jasson, R. and Stewart, T.J. (2005), "Evaluating Spatial Design Techniques for Solving Land-use Allocation Problems," *Journal of Environmental Planning and Management*, 48: 1, 121-142.

Aerts, J., Eisinger, E., Heuvelink, G., and Stewart, T.J. (2003a), "Using linear integer programming for multi-site land-use allocation," *Geographic Analysis*, 35(2), pp. 148-169.

Aerts, J.C.J.H., Herwijnen, M., Van and Stewart, T.J. (2003b), "Using Simulated Annealing and Spatial Goal Programming for Solving a Multi Site Land Use Allocation Problem," *Springer-Verlag*, Berlin, Heidelberg , pp.448–463.

Aerts J., and Heuvelink, G. (2002), "Using simulated annealing for resource allocation," *International Journal Geographical Information Science*, 16(6), pp. 571-587.

Anas, A. (1982), *Residential location markets and urban transportation: Economic theory, econometrics and policy analysis with discrete choice models,* Academic Press, New York, NY.

Antunes, A., Seco, A., and Pinto, N. (2003), "An Accessibility-Maximization Approach to Road Network Planning," *Computer-Aided Civil and Infrastructure Engineering*, 18(3), pp.224–240. Available at: http://doi.wiley.com/10.1111/1467-8667.00312.

Batty, M. (1976), *Urban Modeling: Algorithms, Calibrations and Predictions*, Cambridge University press, UK.

Benabdallah, S., and Wright, J.R. (1992), "Multiple Subregion Allocation Models." *Journal of urban planning and development*, 118(1), pp.24–40.

Bengston, D.N., Fletcher, J.O., and Nelson, K.C. (2004), "Public policies for managing urban growth and protecting open space: policy instruments and lessons learned in the United States," *Landscape and Urban Planning*, Vol. 69, No. 2-3, pp. 271-286.

Berke, P.R., Godshalk, D.R, and Kaiser, E.J. (2006), *Urban Land Use Planning,* University of Illinois Press; 5th edition

Bigotte, J.M.F, Antunes A.P., and Berman O. (2010), *Towards a location modeling approach to urban hierarchy planning*, Doctoral dissertation submitted to the Univesity of Coimra, Portugal.

Bradley, S.P., Hax, A.C., and Magnanti, T.L. (1977), *Applied Mathematical Programming*, Addison-Wesley, Boston, MA.

Cao, K., Batty M., Huang, B., Liu Y., Yu, L. and Chen, J. (2011), "Spatial multi-objective land use optimization: extensions to the non-dominated sorting genetic algorithm-II," *International Journal of Geographical Information Science*, 25(12), pp.1949–1969. Available at: http://www.tandfonline.com/doi/abs/10.1080/13658816.2011.570269.

Cohon J.L. (1970), *Multiobjective Programming and Planning*, Dover Publications, Mineola, NY.

Datta, D., Deb, k., Fonseca, C. M, Lobo, F., Condado, P., and Seixas, J. (2008), "Multi-Objective Evolutionary Algorithm for Land-Use Management Problem".

De la Barra, T. (1989), *Integrated transport and land use modeling: Decision chains and hierarchies*, Cambridge University Press, Cambridge, UK.

Diamond, J.T., and Wright, J.R. (1990), "Efficient land use allocation," *Journal of Urban Planning and Development*, 115(2), pp. 81-96.

Feng, Cheng-Min, and Lin, Jen-Jia (1999), "Using a genetic algorithm to generate alternative sketch maps for urban planning," *Computers Environment and Urban System*s, 23(1999), pp.91-108.

FICO, (2012), FICO ® Xpress Optimization Suite.

Fonseca C.M., and Fleming P.J. (1995), "An overview of evolutionary algorithms in multiobjective optimization," *Evolutionary Computation*, pp. 1–16.

Geurs, K.T., and Wee, B. Van. (2004), "Accessibility evaluation of land-use and transport strategies : review and research directions," *Journal of Transport Geography*, 12, pp.127–140.

Gilbert, K.C., Holmes, D.D., and Rosenthal, R.E. (1985), "A multi-objective discrete Optimization model for land allocation", *Management Science*, 31(12), pp.1509-1522.

Handy, S. (2005), "Smart growth and the transportation-land use connection: what does the research tell us?," *International Regional Science Review*, Vol. 28, No. 2, pp. 146-167.

Handy, S.L., and Niemeier, D.A. (1997), "Measuring accessibility: an exploration of issues and alternatives," *Environment and Planning A* 29, 1175-1194.

Hatzopoulou, M., and Miller, E. J. (2009), "Transport policy evaluation in metropolitan areas: The role of modeling in decision-making," *Transportation Research Part A: policy and practice, 43(4),* pp. 323-38.

Hunt, J. D., and Abraham J. E. (2005), "Design and implementation of PECAS: A generalized system for allocating economic production, exchange and consumption quantities" In

Integrated land-use and transportation models: Behavioral foundations, ed. Martin Lee-Gosselin and Sean Doherty, pp.253-74, Elsevier, Amsterdam.

Hyman, G.M. (1969), "The calibration of trip distribution models," *Environment and Planning* 1, 105–112.

ITE, (2012), *Trip Generation Manual*, 9th Edition.

INE, (2013), Instituto Nacional de Estatística, Portugal (www.ine.pt).

Ingram, D.R. (1971), "The concept of accessibility: a search for an operational form," *Regional Studies* 5, 101‑107.

Janssen, Ron., Herwijnen, M. Van, Theodor J. Stewart, and Jeroen C.J.H. Aerts. (2008), "Multiobjective Decision Support for Land-use Planning," *Environment and Planning B: Planning and Design* 35 (4): 740–756. doi:10.1068/b33071. http://www.envplan.com/abstract.cgi?id=b33071.

Jaszkiewicz A., (2002), "Genetic local search for multi-objective combinatorial optimization," *European Journal of Operational Research,*137:50–71.

Kavage, S.E., Moudon, A.V., Mabry, J.E., Pergakes, N. (2005), "Transportation-efficient land use regulations and their application in the Puget Sound Region, Washington," *Transportation Research Record*, Vol. 1902, pp. 44-54.

Ligmann-Zielinska, A. and Jankowski, P. (2010), "Exploring normative scenarios of land use development decisions with an agent-based simulation laboratory," *Computer, environment and urban systems*, 34 (5), pp. 409–423.

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

Ligmann-Zielinska, A., Church, R.L., and Jankowski, P. (2005), Sustainable Urban Land Use Allocation with Spatial Optimization, In Conference Proceedings, the 8th International Conference on Geocomputation, August 1-3, 2005, University of Michigan, Eastern Michigan University, USA.

Los, M. (1979), "A discrete-Convex Programming approach to the simultaneous optimization of land use and transportation," *Transport Research B*, 138, pp.33-48.

Lowry, I.S. (1964), *A Model of Metropolis*, RM-4035-RC. Rand Corporation, Santa Monica, Ca.

Lowry M.B., and Balling, R.J. (2009), "An approach to land-use and transportation planning that facilitates city and region cooperation," *Environment and Planning B*, 36, pp. 487-504.

Maat, K., van Wee, B., Stead, D. (2005), "Land use and travel behaviour: expected effects from the perspective of utility theory and activity-based theories," *Environment and Planning B*, Vol. 32, No. 1, pp. 33-46.

Mackett, R.L. (1983), *The Leeds integrated land-use transport (LILT) model report SR 805.* (Crowthorne, UK: Transport and Road Research Laboratory).

Martinez, F. J. (1992), "The bid-choice land use model: an integrated economic framework," *Environment & Planning A,* 24 (6), pp. 871-85.

Melkote, S., and Daskin, M.S. (2001), "An Integrated Model of Facility Location and Transportation Network Design," *Transportation Research*, 35 (6), pp. 515-538.

Miller, E.J, Hunt, J.D, Abraham, J.E., and Salvini, P.A. (2004), "Microsimulating Urban Systems," *Computers, Environment and Urban systems,* Elsevier, 28, pp. 9-44.

Miller, E.J., and Salvini, P.A. (2001), The Integrated Land Use, Transportation, Environment (ILUTE) Microsimulation Modelling system: Description and current status. In: *The Leading Edge in Travel Behaviour Research* (D.A. Henscher, ed.), Selected Papers from *the 9th International Association for Travel Behaviour Research Conference*, Gold Coast, Queensland, Australia.

Minken, H., Jonsson, D., Shepherd, S., Järvi, T., May, T., Page, M., Pearman, A., Pfaffenbichler, P., Timms, P., and Vold, A. (2003), *Developing sustainable urban land use and Transport strategies: A methodological guidebook*, Institute for Transport Economics, Oslo, Norway.

Mitchell M. (1999), *An introduction to genetic algorithms*, A Bradford Book the MIT Press, Cambridge Massachusetts. ISBN: 0−262−13316−4 (HB), 0−262−63185−7 (PB).

Moeckel, R., Schürmann, C., Wegener, M. (2002), "Microsimulation of Urban Land Use," paper presented at *42nd European Congress of the Regional Science Association,* Dortmund, 27-31 August 2002.

Murray, A. T., and Church, R.L. (1995), "Measuring the Efficiency of Adjucency Constraint Structure in Forest Planning Models," *Canadian Journal of Forest Research* 25: 1416–1424.

Newman, P., and Kenworthy, J. (1999), *Sustainability and Cities: Overcoming automobile dependence,* Island Press. Washington, DC.

Ortuzar, J. de D., and Willumsen, L.G. (2011) *Modeling transport*, John Wiley and Sons, The Atrium, Southern Gate, Chichester, West Sussex, PO 018SQ, UK.

Plummer, A.V. (2007). The Chicago area transportation study: Creating the first plan (1955 – 1962): A narrative. Available at http://www.surveyarchive.org/Chicago/cats_1954-62.pdf.

Price, L., S., de la Rue du Can, J. Sinton, E. Worrell, Z. Nan, J. Sathaye, and M. Levine. (2006). *Sectoral Trends in Global Energy Use and Greenhouse Gas Emissions,* LBNL-56144. Ernest Orlando Berkeley National Laboratory, Environmental Energy Technologies Division, Berkeley, CA, July 2006.

Pucher, J. (1998). "Urban transport in Germany: providing feasible alternatives to the car," *Transport Reviews*, Vol. 18, No. 4, pp. 285-310.

Putman, S.H. (1983), *Integrated urban models: Policy analysis of transportation and land use*, Pion London, UK.

Schwanen, T., Dijst, M., Dieleman, F.M. (2004). "Policies for urban form and their impact on travel: the Netherlands experience," *Urban Studies*, Vol. 41, No. 3, pp. 579-603.

Simmonds, D.C. (1999), "The Design of DELTA land-use modeling package," *Environment and Planning B: Planning and Design*, 26, 665-684.

Song, Y., (2005), "Smart growth and urban pattern: a comprehensive study," *International Regional Science Review*, Vol. 28, No. 2, pp. 239-265.

Stead, D., and Marshall, S. (2001), "The relationships between urban form and travel patterns: An international review and evaluation," *European Journal of Transport and Infrastructure Research*, Vol. 1, No. 2, pp. 113-141.

Stewart, T.J., Janssen,R., and Herwijnen, M. Van. (2004), "A genetic algorithm approach to multi-objective land use planning," *Computers & Operations Research*, 31, 2293–2313.

Strauch, D., Moeckel, R., Wegener, M., Gräfe, J., Mühlhans, H., Rindsfüser, G., and Beckmann, K.J. (2005), "Linking Transport and Land Use Planning: The Microscopic Dynamic Simulation Model ILUMASS," Chapter 20 of Atkinson, Peter M., Foody, Giles M., Darby, Steve E., Wu, Fulong (Eds): *Geodynamics*. Boca Raton, Florida: CRC Press, 2005, 295-311.

Timmermans, H. (2003), "The saga of integrated land use – transport modeling: how many more dreams before we wake up?," *10th International Conference on Travel Behavior Reserch, Lucerne*, 10-15 August 2003

UNFPA (2007), *State of world population 2007: Unleashing the potential of urban growth*, United Nations Population Fund, New York, NY

van Wee, B. (2002), "Land use and transport: research and policy challenges," *Journal of Transport Geography*, Vol. 10, No. 4, pp. 259-271.

Veldhuisen, K.J., Timmermans, H.J.P., and Kapoen, L.L. (2005), "Simulating the effects of urban development on activity-travel patterns: an application of Ramblas to the Randstad North Wing," *Environment and Planning B: planning and design* 32, pp.567-80.

Veldhuisen, K.J., Timmermans, H.J.P., and Kapoen, L.L, (2001), "Microsimulation model of activity travel patterns and traffic flows: specification, validation tests, and Monte Carlo error," *Transportation Research Record* 1706, 126–35.

Veldhuisen, K.J., Timmermans, H.J.P., and Kapoen, L.L. (2000), "RAMBLAS: a regional Planning model based on the microsimulation of daily activity travel patterns," *Environment and Planning A* 32, pp.427–43.

Vickerman, R.W., (1974), "Accessibility, attraction, and potential: a review of some concepts and their use in determining mobility," *Environment and Planning A* 6, 675-691.

Waddell, P., Borning,A., Noth, M., Freier, N., Becke, M., and Ulfarsson, G. (2003), "Microsimulation of Urban Development and Location Choices: Design and Implementation of UrbanSim", Preprint of an article that appeared in *Networks and Spatial Economics*, 3, 1, pp. 43-67.

Waddell, P. (2002) "UrbanSim: Modeling Urban Development for Land Use, Transportation and Environmental Planning," *Journal of the American Planning Association*, 68, 3, pp. 297-314.

Wang, X., Yu S., and Huang, G.H. (2004), "Land Allocation Based on Integrated GIS-optimization Modeling at a Watershed Level," *Landscape and Urban Planning* 66 (2) (January): 61–74. doi:10.1016/S0169-2046(03)00095-1. http://linkinghub.elsevier.com/retrieve/pii/S0169204603000951.

Ward, D.P., Murray, A.T., and Phinn, S.R. (2003), "Integrating spatial optimization and cellular automata for evaluating urban change," *The Annals of Regional Science*, 37(1), pp.131–148. Available at: http://www.springerlink.com/openurl.asp?genre=article&id=doi:10.1007/s001680200113.

Wegener, M. (1982), "Modeling urban decline: A multi-level economic- demographic model of the Dortmund region," *International Regional Science Review,* 7(1), pp. 21-41.

Williams, I. (1976), “A comparison of some calibration techniques for doubly constrained models with an exponential cost function,” *Transportation Research* 10, 91–104.

Williams, J.C., and ReVelle, C.S. (1996), “A 0 - 1 programming approach to delineating protected reserves,” *Environment and Planning B: planning and design*, 23, pp.607–624.

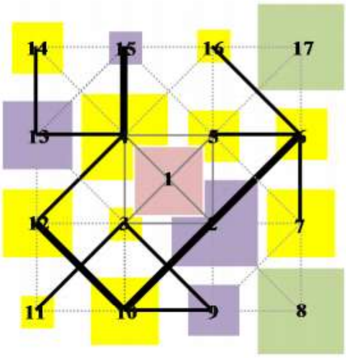
Wilson, A.G. (1974), *Urban and Regional Models in Geography and Planning*, John Wiley & Sons, Ltd Chichester.

Wright, J., ReVelle, C.S., and Cohon, J. (1983), “A multiobjective Integer programming model for the land acquisition problem,” *Regional Science and Urban Economics*, 13, pp.31–53.

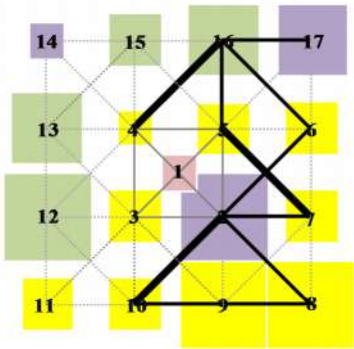
Xiao, N., Bennett, D., and Armstrong, M.P. (2002), “Using evolutionary algorithms to generate alternatives for multiobjective site-search problems,” *Environment and Planning A*, 34(4), pp.639–656. Available at: http://www.envplan.com/abstract.cgi?id=a34109.

Appendix A

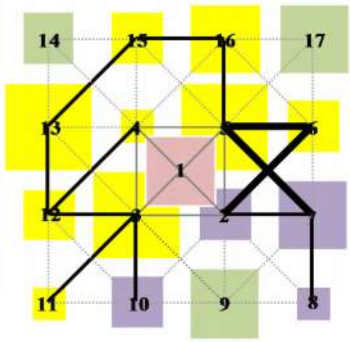
Efficient maps for additional problems: 17 zones



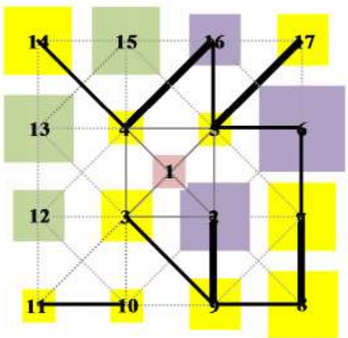
Problem 6



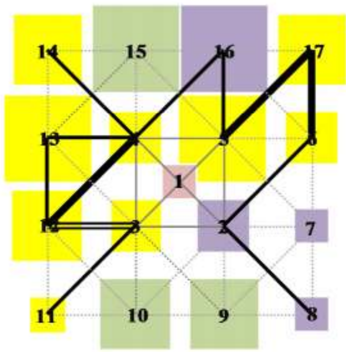
Problem 7



Problem 8



Problem 9



Problem 10

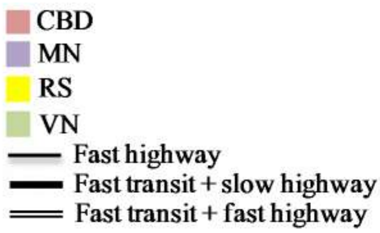


Table A1: Trip generation Values

Trip generation (based on ITE)		
Land-use	Production (trips/pop)	Attraction (trips/Sqkm)
CBD	0.28	19553
HDR	0.3	0.1
MDR	0.34	0.1
LDR	0.56	0.1
I	0.06	5691

Cost flow curve equations

Given

S_0 – free flow speed;

S_1 – the speed at capacity flow F_2;

F_1 – the maximum flow at which free-flow conditions prevail;

d – distance or length of the link;

The time-flow T (V) relationship becomes:

$$T(V) = \begin{cases} d / S_0 & V < F \\ d / S(V) = \dfrac{d}{S_0 + SS_{01} V} & F_1 \le V \le F_2 \\ d / S_1 + (V / F_2 - 1) / 8 & V > F_2 \end{cases} \tag{A.1}$$

$$SS_{01} = \frac{S_0 - S_1}{F_1 - F_2}$$

Table A2: Speed flow curve coefficients

Type	S_0 km/h	S_1 km/h	F_1 pcu/h/lane	F_2 pcu/h/lane
Class 2	30	20	500	900
Class 3	40	25	500	1000
Class 4	60	55	400	1400

Appendix B

Genetic algorithm calibration and validation results

Table B-1 Calibration results after 2nd stage, 17 zone instance I - 50 cases

Case	Value	Time(mins)	N	PC	PM	G
1	2.78	8.27	20	0.8	0.06	100
2	2.8	3.09	70	0.4	0.09	10
3	2.81	11.54	100	0.8	0.06	10
4	2.8	34.62	100	0.8	0.07	60
5	2.77	69.62	120	1	0.1	80
6	2.94	22.24	80	0.2	0.05	60
7	2.75	79.92	80	0.7	0.05	70
8	2.72	2.67	10	1	0.1	50
9	2.68	9.61	80	0.9	0.04	30
10	2.92	55.58	150	0.4	0.02	40
11	2.96	61.68	130	0.1	0.04	80
12	2.89	20.29	170	0.2	0.1	30
13	3	8.86	40	0.7	0.05	20
14	2.89	83.34	110	1	0.04	90
15	2.83	15	20	0.5	0.08	80
16	2.91	39.35	100	1	0.09	100
17	2.91	47.29	160	0.6	0.09	60
18	2.86	3.83	90	0.3	0.08	10
19	2.6	8.07	20	0.4	0.1	90
20	2.81	48.43	170	0.7	0.02	60
21	2.89	22.59	140	0.2	0.03	20
22	2.93	6.97	30	0.2	0.01	50
23	2.92	64.64	140	0.3	0.01	60
24	2.56	5.84	40	0.7	0.03	20
25	2.7	8.74	40	0.5	0.04	40
26	2.75	3.79	90	0.5	0.04	10
27	2.88	19.57	90	0.9	0.07	40
28	2.85	32.45	120	0.9	0.03	40
29	2.96	9.34	60	0.1	0.1	20
30	2.75	65.24	130	0.2	0.09	100
31	2.91	11.26	140	0.7	0.09	20
32	2.73	18.11	70	1	0.03	40
33	2.68	4.33	50	0.2	0.09	20
34	2.74	8.29	30	0.1	0.05	40
35	2.88	12.62	20	0.5	0.07	70
36	2.83	18.04	50	0.5	0.1	50
37	2.93	24.62	70	0.2	0.08	60
38	2.93	6.94	90	0.4	0.09	10
39	2.94	36.54	110	0.7	0.03	60
40	2.75	14.36	60	0.5	0.07	40
41	2.84	1.75	20	0.1	0.1	20
42	2.97	53.61	100	0.8	0.02	100
43	2.93	3.13	30	0.2	0.03	10
44	2.67	2.7	10	0.7	0.04	40
45	2.93	4.92	60	0.8	0.03	20
46	2.87	11.52	50	0.1	0.08	40
47	2.94	105.07	110	0.2	0.07	100
48	2.84	52.84	100	1	0.09	90
49	2.89	11.83	140	0.7	0.04	10
50	2.89	25.91	110	0.4	0.01	60

Table B-2 Calibration results after 2nd stage, 17 zone instance II - 50 cases

Case	Value	Time(mins)	N	PC	PM	G
1	2.76	18.13	20	0.8	0.06	100
2	3.09	3.56	70	0.4	0.09	10
3	2.72	7.68	100	0.8	0.06	10
4	2.92	61.6	100	0.8	0.07	60
5	2.89	70.35	120	1	0.1	80
6	3.16	54.57	80	0.2	0.05	60
7	2.81	26.12	80	0.7	0.05	70
8	2.66	2.13	10	1	0.1	50
9	2.88	14.22	80	0.9	0.04	30
10	3.16	27.19	150	0.4	0.02	40
11	3.04	66.37	130	0.1	0.04	80
12	3.06	23.56	170	0.2	0.1	30
13	2.9	3.33	40	0.7	0.05	20
14	3.02	118.11	110	1	0.04	90
15	2.85	13.35	20	0.5	0.08	80
16	3.05	42.66	100	1	0.09	100
17	3.03	37.63	160	0.6	0.09	60
18	2.78	6.58	90	0.3	0.08	10
19	2.83	21.55	20	0.4	0.1	90
20	2.98	54.33	170	0.7	0.02	60
21	2.96	11.24	140	0.2	0.03	20
22	2.87	6.85	30	0.2	0.01	50
23	2.89	54.38	140	0.3	0.01	60
24	2.94	8.58	40	0.7	0.03	20
25	2.82	6.43	40	0.5	0.04	40
26	2.83	3.82	90	0.5	0.04	10
27	3.01	34.29	90	0.9	0.07	40
28	3	19.4	120	0.9	0.03	40
29	3	9.34	60	0.1	0.1	20
30	3.16	80.26	130	0.2	0.09	100
31	3.06	23.3	140	0.7	0.09	20
32	2.81	11.16	70	1	0.03	40
33	2.86	4.19	50	0.2	0.09	20
34	2.9	11.97	30	0.1	0.05	40
35	2.94	5.71	20	0.5	0.07	70
36	2.91	12.7	50	0.5	0.1	50
37	3.02	35.49	70	0.2	0.08	60
38	2.9	6.59	90	0.4	0.09	10
39	2.87	49.89	110	0.7	0.03	60
40	3	16.79	60	0.5	0.07	40
41	2.25	1.99	20	0.1	0.1	20
42	3.1	52.96	100	0.8	0.02	100
43	2.76	1.84	30	0.2	0.03	10
44	2.91	1.74	10	0.7	0.04	40
45	3.05	6.78	60	0.8	0.03	20
46	3.05	8.38	50	0.1	0.08	40
47	2.93	77.21	110	0.2	0.07	100
48	3	53.77	100	1	0.09	90
49	2.77	5.83	140	0.7	0.04	10
50	2.9	40.65	110	0.4	0.01	60

Table B-3 Calibration results after 2nd stage, 17 zone instance III - 50 cases

Case	Value	Time(mins)	N	PC	PM	G
1	2.89	8.57	20	0.8	0.06	100
2	2.82	2.99	70	0.4	0.09	10
3	2.99	8.49	100	0.8	0.06	10
4	3.15	46.73	100	0.8	0.07	60
5	3.02	119.11	120	1	0.1	80
6	3	40.31	80	0.2	0.05	60
7	3.08	22.94	80	0.7	0.05	70
8	2.8	2.21	10	1	0.1	50
9	3.04	31.38	80	0.9	0.04	30
10	3.23	65.99	150	0.4	0.02	40
11	3.06	65.93	130	0.1	0.04	80
12	3.06	57.08	170	0.2	0.1	30
13	2.87	3.41	40	0.7	0.05	20
14	3.02	52.45	110	1	0.04	50
15	3.03	16.83	20	0.5	0.08	80
16	2.92	56.39	100	1	0.09	100
17	2.97	37.73	160	0.6	0.09	60
18	3.21	7.3	90	0.3	0.08	10
19	3.07	14.48	20	0.4	0.1	90
20	3.12	118.56	170	0.7	0.02	60
21	3.02	29.66	140	0.2	0.03	20
22	2.91	7.41	30	0.2	0.01	50
23	3.04	35.1	140	0.3	0.01	60
24	3.03	6.45	40	0.7	0.03	20
25	3.15	13.63	40	0.5	0.04	40
26	3.01	3.8	90	0.5	0.04	10
27	2.92	19.55	90	0.9	0.07	40
28	3.06	18.59	120	0.9	0.03	40
29	2.79	6.11	60	0.1	0.1	20
30	3.1	188.9	130	0.2	0.09	100
31	2.97	12.36	140	0.7	0.09	20
32	3.08	28.8	70	1	0.03	40
33	2.85	8.01	50	0.2	0.09	20
34	2.99	13.08	30	0.1	0.05	40
35	3.12	5.64	20	0.5	0.07	70
36	2.99	13.1	50	0.5	0.1	50
37	3.11	22.82	70	0.2	0.08	60
38	2.78	7.3	90	0.4	0.09	10
39	3.18	53.23	110	0.7	0.03	60
40	2.98	10.5	60	0.5	0.07	40
41	2.97	4.28	20	0.1	0.1	20
42	3.18	48.54	100	0.8	0.02	100
43	3.05	1.41	30	0.2	0.03	10
44	2.89	1.78	10	0.7	0.04	40
45	2.93	5.02	60	0.8	0.03	20
46	3.03	8.84	50	0.1	0.08	40
47	3.1	115.37	110	0.2	0.07	100
48	3.1	37.81	100	1	0.09	90
49	2.72	7.07	140	0.7	0.04	10
50	2.95	31.31	110	0.4	0.01	60

Table B-4 Calibration results after 2nd stage, 17 zone instance IV - 50 cases

Case	Value	Time(mins)	N	PC	PM	G
1	3.12	19.11	20	0.8	0.06	100
2	3.08	4.79	70	0.4	0.09	10
3	3.06	7.49	100	0.8	0.06	10
4	2.8	24.34	100	0.8	0.07	60
5	3.09	42.6	120	1	0.1	80
6	2.99	24.35	80	0.2	0.05	60
7	3.03	54.82	80	0.7	0.05	70
8	2.78	3.8	10	1	0.1	50
9	2.96	19.59	80	0.9	0.04	30
10	3.01	57.98	150	0.4	0.02	40
11	3.19	142.76	130	0.1	0.04	80
12	3.18	29.05	170	0.2	0.1	30
13	2.9	7.74	40	0.7	0.05	20
14	2.92	95.42	110	1	0.04	90
15	2.83	6.59	20	0.5	0.08	80
16	2.84	63.88	100	1	0.09	100
17	2.88	46	160	0.6	0.09	60
18	2.53	6.09	90	0.3	0.08	10
19	2.67	11.33	20	0.4	0.1	90
20	3.13	92.81	170	0.7	0.02	60
21	3	20.96	140	0.2	0.03	20
22	3	6.18	30	0.2	0.01	50
23	2.97	54.8	140	0.3	0.01	60
24	3.06	6.9	40	0.7	0.03	20
25	3.23	8.21	40	0.5	0.04	40
26	2.93	7.13	90	0.5	0.04	10
27	2.9	31.76	90	0.9	0.07	40
28	2.99	35.52	120	0.9	0.03	40
29	2.9	5.5	60	0.1	0.1	20
30	2.92	66.41	130	0.2	0.09	100
31	2.95	15.33	140	0.7	0.09	20
32	2.91	11.45	70	1	0.03	40
33	3.08	5.02	50	0.2	0.09	20
34	2.8	9.9	30	0.1	0.05	40
35	2.91	12.57	20	0.5	0.07	70
36	2.9	21.29	50	0.5	0.1	50
37	2.78	17.05	70	0.2	0.08	60
38	2.8	3.9	90	0.4	0.09	10
39	2.95	28.03	110	0.7	0.03	60
40	2.67	12.99	60	0.5	0.07	40
41	2.95	2.14	20	0.1	0.1	20
42	3.08	92.04	100	0.8	0.02	100
43	2.95	1.77	30	0.2	0.03	10
44	2.7	4.98	10	0.7	0.04	40
45	3	9.8	60	0.8	0.03	20
46	2.8	8.24	50	0.1	0.08	40
47	2.92	44.1	110	0.2	0.07	100
48	3.08	55.02	100	1	0.09	90
49	2.88	7.06	140	0.7	0.04	10
50	3.14	61.22	110	0.4	0.01	60

Table B-5 Calibration results after 2nd stage, 17 zone instance V - 50 cases

Case	Value	Time(mins)	N	PC	PM	G
1	2.64	15.98	20	0.8	0.06	100
2	2.75	5.57	70	0.4	0.09	10
3	2.89	7.51	100	0.8	0.06	10
4	2.82	44.29	100	0.8	0.07	60
5	2.66	69.14	120	1	0.1	80
6	2.79	21.04	80	0.2	0.05	60
7	2.81	23.43	80	0.7	0.05	70
8	2.35	2.16	10	1	0.1	50
9	2.87	9.83	80	0.9	0.04	30
10	2.91	49.23	150	0.4	0.02	40
11	2.86	41.86	130	0.1	0.04	80
12	2.79	24.12	170	0.2	0.1	30
13	2.66	6.75	40	0.7	0.07	20
14	2.93	99.75	110	1	0.04	90
15	2.65	9.7	20	0.5	0.08	80
16	2.82	43.01	100	1	0.09	100
17	2.77	45.89	160	0.6	0.09	60
18	2.61	5.68	90	0.3	0.08	10
19	2.71	10.16	20	0.4	0.1	90
20	2.83	55.69	170	0.7	0.02	60
21	2.87	11.51	140	0.2	0.03	20
22	2.55	6.2	30	0.2	0.01	50
23	2.86	33.68	140	0.3	0.01	60
24	2.62	9.89	40	0.7	0.03	20
25	2.91	6.56	40	0.5	0.04	40
26	2.89	4.25	90	0.5	0.04	10
27	2.91	14.56	90	0.9	0.07	40
28	2.8	38.88	120	0.9	0.03	40
29	2.91	5.08	60	0.1	0.1	20
30	2.89	52.48	130	0.2	0.09	100
31	2.81	11.62	140	0.7	0.09	20
32	2.91	18.24	70	1	0.03	40
33	2.51	4.24	50	0.2	0.09	20
34	2.8	6.56	30	0.1	0.05	40
35	2.88	6.7	20	0.5	0.07	70
36	2.9	10.31	50	0.5	0.1	50
37	2.91	26.56	70	0.2	0.08	60
38	2.46	3.91	90	0.4	0.09	10
39	2.8	26.61	110	0.7	0.03	60
40	2.7	11.52	60	0.5	0.07	40
41	2.52	1.8	20	0.1	0.1	20
42	2.93	75.03	100	0.8	0.02	100
43	2.88	2.49	30	0.2	0.03	10
44	2.65	3.25	10	0.7	0.04	40
45	2.87	5.28	60	0.8	0.03	20
46	2.73	9.38	50	0.1	0.08	40
47	2.8	76.2	110	0.2	0.07	100
48	2.79	36.27	100	1	0.09	90
49	2.89	7.62	140	0.7	0.04	10
50	2.82	49.42	110	0.4	0.01	60

Table B-6 Calibration results after 2nd stage, 26 zone instance I- 50 cases

Case	Value	Time(mns)	N	PC	PM	G
1	2.68	37.56	30	0.8	0.06	100
2	2.71	11.5	110	0.4	0.09	10
3	2.92	15.13	150	0.8	0.06	10
4	2.93	146.58	140	0.8	0.07	60
5	3.19	189.35	180	1	0.1	80
6	2.78	143.74	130	0.2	0.05	60
7	2.91	331.59	120	0.7	0.05	70
8	2.15	11.25	20	1	0.1	50
9	2.9	35.42	120	0.9	0.04	30
10	2.81	96.41	220	0.4	0.02	40
11	2.93	250.59	190	0.1	0.04	80
12	2.9	74.34	260	0.2	0.1	30
13	2.66	11.83	60	0.7	0.06	20
14	3.4	289.92	170	1	0.04	90
15	2.75	31.18	40	0.5	0.08	80
16	2.77	171.27	150	1	0.09	100
17	3.02	326.08	240	0.6	0.09	60
18	2.65	14.67	130	0.3	0.08	10
19	2.59	17.56	20	0.4	0.1	90
20	2.88	169.31	250	0.7	0.02	60
21	2.99	101.66	220	0.2	0.03	20
22	3.02	53.38	50	0.2	0.01	50
23	3.27	433.98	210	0.3	0.01	60
24	2.74	12.46	50	0.7	0.03	20
25	3.06	42.5	50	0.5	0.04	40
26	2.96	13.08	130	0.5	0.04	10
27	3.21	87.01	130	0.9	0.07	40
28	2.67	66.04	170	0.9	0.03	40
29	2.8	25.28	100	0.1	0.1	20
30	2.87	189.28	200	0.2	0.09	100
31	2.86	54.57	210	0.7	0.09	20
32	3.07	43.12	110	1	0.03	40
33	2.71	16.49	70	0.2	0.09	20
34	2.94	31.02	50	0.1	0.05	40
35	2.91	23.55	30	0.5	0.07	70
36	2.9	33.48	70	0.5	0.1	50
37	2.91	79.05	110	0.2	0.08	60
38	2.88	14.19	140	0.4	0.09	10
39	2.79	97.79	170	0.7	0.03	60
40	2.99	35.2	90	0.5	0.07	40
41	2.68	6.37	20	0.1	0.1	20
42	3.04	320.34	150	0.8	0.02	100
43	2.77	4.31	40	0.2	0.03	10
44	2.75	8.02	20	0.7	0.04	40
45	2.77	28.01	100	0.8	0.03	20
46	2.65	27.63	70	0.1	0.08	40
47	3.11	175.19	170	0.2	0.07	100
48	3.16	139.75	160	1	0.09	90
49	2.87	21.92	220	0.7	0.04	10
50	3.31	237.22	170	0.4	0.01	60

Table B-7 Calibration results after 2nd stage, 26 zone instance II - 50 cases

Case	Value	Time(mins)	N	PC	PM	G
1	2.55	48.7	30	0.8	0.06	100
2	2.84	11.42	110	0.4	0.09	10
3	2.7	15.46	150	0.8	0.06	10
4	2.71	81.33	140	0.8	0.07	60
5	2.96	213.54	180	1	0.1	80
6	2.76	134.06	130	0.2	0.05	60
7	2.82	144.89	120	0.7	0.05	70
8	2.69	16.47	20	1	0.1	50
9	2.54	66.48	120	0.9	0.04	30
10	2.79	270.16	220	0.4	0.02	40
11	2.83	251.69	190	0.1	0.04	80
12	2.97	108.57	260	0.2	0.1	30
13	2.62	12.19	60	0.7	0.05	20
14	2.88	147.93	170	1	0.04	90
15	2.92	31.22	40	0.5	0.08	80
16	2.5	143.75	150	1	0.09	100
17	2.75	203.48	240	0.6	0.09	60
18	2.81	13.34	130	0.3	0.08	10
19	2.55	22.24	20	0.4	0.1	90
20	2.81	325.27	250	0.7	0.02	60
21	2.95	60.25	220	0.2	0.03	20
22	2.77	27.98	50	0.2	0.01	50
23	2.95	166.95	210	0.3	0.01	60
24	2.74	16.49	50	0.7	0.03	20
25	2.54	29.01	50	0.5	0.04	40
26	2.77	13.34	130	0.5	0.04	10
27	2.85	63.15	130	0.9	0.07	40
28	2.87	124.94	170	0.9	0.03	40
29	2.58	21.98	100	0.1	0.1	20
30	2.77	204.79	200	0.2	0.09	100
31	2.54	80.53	210	0.7	0.09	20
32	2.8	118.88	110	1	0.03	40
33	2.85	14.19	70	0.2	0.09	20
34	2.72	26.46	50	0.1	0.05	40
35	2.64	37.55	30	0.5	0.07	70
36	2.74	39.43	70	0.5	0.1	50
37	2.56	118.57	110	0.2	0.08	60
38	2.86	27.13	140	0.4	0.09	10
39	2.85	269.26	170	0.7	0.03	60
40	2.6	41.79	90	0.5	0.07	40
41	2.73	4.31	20	0.1	0.1	20
42	2.85	234.56	150	0.8	0.02	100
43	2.53	4.32	40	0.2	0.03	10
44	2.8	23.55	20	0.7	0.04	40
45	2.45	22.46	100	0.8	0.03	20
46	2.46	27.4	70	0.1	0.08	40
47	2.9	161.84	170	0.2	0.07	100
48	2.73	136.23	160	1	0.09	90
49	2.63	27.99	220	0.7	0.04	10
50	2.87	117.2	170	0.4	0.01	60

Table B-8 Calibration results after 2nd and 3rd stage, 17 zone instance I

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 2nd stage	9	1	2.68	9.61	80	0.9	0.04	30
	33	2	2.68	4.33	50	0.2	0.09	20
	44	3	2.67	2.7	10	0.7	0.04	40
	19	4	2.6	8.07	20	0.4	0.1	90
	24	5	2.56	5.84	40	0.7	0.03	20
	11	1	2.96	61.68	130	0.1	0.04	80
	29	2	2.96	9.34	60	0.1	0.1	20
	39	3	2.94	36.54	110	0.7	0.03	60
After the 3rd stage	9	1	2.88	69.39	110	1	0.03	80
	33	2	2.92	40.22	100	0.8	0.01	80
	44	3	2.99	38.91	100	0.8	0.01	100
	19	4	2.96	55.46	110	0.9	0.02	90
	24	5	2.99	51.3	100	0.8	0.01	100
	11	1	2.9	46.61	100	0.8	0.01	100
	29	2	2.97	74.99	130	0.9	0.03	90
	39	3	2.93	39.07	100	0.8	0.01	80

Table B-9 Calibration results after 2nd and 3rd stage, 17 zone instance II

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 2nd stage	1	1	2.76	18.13	20	0.8	0.06	100
	43	2	2.76	1.84	30	0.2	0.03	10
	3	3	2.72	7.68	100	0.8	0.06	10
	8	4	2.66	2.13	10	1	0.1	50
	41	5	2.25	1.99	20	0.1	0.1	20
	6	1	3.16	54.57	80	0.2	0.05	60
	30	2	3.16	50.26	130	0.2	0.09	100
	2	3	3.09	3.56	70	0.4	0.09	10
After the 3rd stage	1	1	3.16	57.03	130	0.8	0.02	90
	43	2	3.06	56.86	120	0.9	0.02	100
	3	3	3.16	50.62	100	0.9	0.02	100
	8	4	3.04	51.16	120	0.9	0.02	80
	41	5	3.16	54.43	100	0.8	0.01	100
	6	1	3.16	44.18	100	0.8	0.01	100
	30	2	3.16	50.16	110	0.9	0.02	100
	2	3	3.16	58.64	110	0.8	0.02	90

Table B-10 Calibration results after 2nd and 3rd stage, 17 zone instance III

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 2nd stage	33	1	2.85	8.01	50	0.2	0.09	20
	2	2	2.82	2.99	70	0.4	0.09	10
	8	3	2.8	2.21	10	1	0.1	50
	29	4	2.79	6.11	60	0.1	0.1	20
	38	5	2.78	7.3	90	0.4	0.09	10
	10	1	3.23	65.99	150	0.4	0.02	40
	18	2	3.21	7.3	90	0.3	0.08	10
	39	3	3.18	53.23	110	0.7	0.03	60
After the 3rd stage	33	1	3.14	66.75	100	0.9	0.03	90
	2	2	3.14	73.29	120	0.9	0.02	100
	8	3	3.15	71.74	110	0.8	0.01	90
	29	4	3.18	73.11	120	0.8	0.01	100
	38	5	3.09	57.41	100	1	0.03	80
	10	1	3.18	77.73	130	0.9	0.03	100
	18	2	3.18	81.69	100	0.8	0.02	100
	39	3	3.14	73.01	120	0.8	0.02	100

Table B-11 Calibration results after 2nd and 3rd stage, 17 zone instance IV

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 2nd stage	37	1	2.78	17.05	70	0.2	0.08	60
	44	2	2.7	4.98	10	0.7	0.04	40
	19	3	2.67	11.33	20	0.4	0.1	90
	40	4	2.67	12.99	60	0.5	0.07	40
	18	5	2.53	6.09	90	0.3	0.08	10
	11	1	3.19	92.76	130	0.1	0.04	80
	50	2	3.14	61.22	110	0.4	0.01	60
	20	3	3.13	92.81	170	0.7	0.02	60
After the 3rd stage	37	1	3.12	52.9	100	0.8	0.01	90
	44	2	3.19	100.19	130	0.9	0.02	100
	19	3	3.12	46.83	100	0.8	0.01	80
	40	4	3.09	49.81	100	1	0.02	80
	18	5	3.23	79.77	110	0.8	0.02	100
	11	1	3.23	69.86	100	0.9	0.01	90
	50	2	3.09	97.61	130	0.8	0.02	80
	20	3	3.08	87.54	120	1	0.03	100

Table B-12 Calibration results after 2nd and 3rd stage, 17 zone instance V

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 2nd stage	22	1	2.55	6.2	30	0.2	0.01	50
	41	2	2.52	1.8	20	0.1	0.1	20
	33	3	2.51	4.24	50	0.2	0.09	20
	38	4	2.46	3.91	90	0.4	0.09	10
	8	5	2.35	2.16	10	1	0.1	50
	14	1	2.93	49.75	110	1	0.04	90
	42	2	2.93	55.03	100	0.8	0.02	100
	25	3	2.91	6.56	40	0.5	0.04	40
After the 3rd stage	22	1	2.89	44.51	100	1	0.03	100
	41	2	2.95	38.64	100	0.8	0.01	80
	33	3	2.93	51.76	110	0.8	0.01	100
	38	4	2.91	52.83	110	0.9	0.02	100
	8	5	2.81	47.29	100	1	0.03	90
	14	1	2.91	48.07	100	0.8	0.02	90
	42	2	2.89	40.11	120	0.9	0.03	80
	25	3	2.91	39.5	110	0.8	0.01	80

Table B-13 Calibration results after 3rd stage, 17 zone instance VI

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	1	1	3.24	52.71	120	0.8	0.01	90
	2	2	3.17	49.99	100	0.9	0.03	90
	3	3	3.3	78.22	130	0.8	0.02	100
	4	4	3.24	38.43	100	0.8	0.02	80
	5	5	3.3	57.15	110	1	0.01	100

Table B-14 Calibration results after 3rd stage, 17 zone instance VII

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	1	1	2.93	57.51	110	1	0.02	100
	2	2	2.97	54.94	100	0.8	0.01	90
	3	3	2.92	41.32	100	1	0.03	80
	4	4	2.96	48.46	100	0.8	0.01	80
	5	5	2.97	67.72	120	0.9	0.02	100

Table B-15 Calibration results after 3rd stage, 17 zone instance VIII

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	1	1	3.13	109.44	130	0.9	0.03	100
	2	2	3.13	76.43	120	0.8	0.03	90
	3	3	2.99	105.97	130	1	0.01	100
	4	4	2.95	39.85	100	0.9	0.02	80
	5	5	3.05	46.91	100	0.8	0.01	90

Table B-16 Calibration results after 3rd stage, 17 zone instance IX

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	1	1	2.92	83.35	120	0.9	0.03	80
	2	2	2.81	63.54	100	0.8	0.01	90
	3	3	2.9	113.58	130	1	0.03	100
	4	4	2.89	119.64	130	0.8	0.02	100
	5	5	2.86	53.36	100	0.9	0.01	90

Table B-17 Calibration results after 3rd stage, 17 zone instance X

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	1	1	3.17	78.02	120	0.9	0.02	100
	2	2	3.21	134.78	130	0.8	0.02	100
	3	3	3.08	77.49	110	1	0.01	90
	4	4	3.15	42.89	100	0.8	0.03	80
	5	5	3.12	41.81	100	0.8	0.02	80

Table B-18 Calibration results after 2nd and 3rd stage, 26 zone instance I

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 2nd stage	13	1	2.66	11.83	60	0.7	0.06	20
	18	2	2.65	14.67	130	0.3	0.08	10
	46	3	2.65	27.63	70	0.1	0.08	40
	19	4	2.59	17.56	20	0.4	0.1	90
	8	5	2.15	11.25	20	1	0.1	50
	50	1	3.31	237.22	170	0.4	0.01	60
	23	2	3.27	333.98	210	0.3	0.01	60
	27	3	3.21	87.01	130	0.9	0.07	40
	5	4	3.19	189.35	180	1	0.1	80
After the 3rd stage	13	1	3.41	291.54	150	0.8	0.01	100
	18	2	3.41	285.34	140	1	0.02	100
	46	3	3.47	227.33	120	0.8	0.01	80
	19	4	3.41	295.06	150	0.9	0.02	80
	8	5	3.44	282.52	110	0.8	0.02	100
	50	1	3.47	233.23	100	0.8	0.01	90
	23	2	3.43	224.93	100	0.8	0.01	90
	27	3	3.43	295.88	150	1	0.02	100
	5	4	3.38	270.06	100	0.9	0.03	100

Table B-19 Calibration results after 2nd and 3rd stage, 26 zone instance II

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 2nd stage	31	1	2.54	80.53	210	0.7	0.09	20
	43	2	2.53	4.32	40	0.2	0.03	10
	16	3	2.5	143.75	150	1	0.09	100
	46	4	2.46	27.4	70	0.1	0.08	40
	45	5	2.45	22.46	100	0.8	0.03	20
	12	1	2.97	108.57	260	0.2	0.1	30
	5	2	2.96	213.54	180	1	0.1	80
	21	3	2.95	60.25	220	0.2	0.03	20
	15	4	2.92	31.22	40	0.5	0.08	80
After the 3rd stage	31	1	2.95	127.68	100	0.8	0.02	80
	43	2	3.02	185.19	100	0.9	0.01	90
	16	3	3.08	292.66	140	0.8	0.01	90
	46	4	2.96	307.47	150	1	0.03	100
	45	5	2.93	172.13	100	0.8	0.02	90
	12	1	3.01	150.4	100	0.9	0.02	80
	5	2	3.02	291.86	120	0.8	0.01	100
	21	3	2.99	277.66	110	1	0.03	100
	15	4	3.09	258.87	100	0.8	0.01	90

Table B-20 Calibration results after 3rd stage, 26 zone instance III

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	1	1	3.24	207.25	100	0.8	0.01	90
	2	2	3.27	299.08	120	1	0.02	100
	3	3	3.41	315.84	150	0.8	0.03	100
	4	4	3.29	316.5	150	0.9	0.01	100
	5	5	3.27	209.96	110	1	0.03	80

Table B-21 Calibration results after 3rd stage & random component fix, 17 zone instance I

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	9	1	2.88	69.39	110	1	0.03	80
	33	2	2.92	40.22	100	0.8	0.01	80
	11	3	2.9	46.61	100	0.8	0.01	100
	39	4	2.93	39.07	100	0.8	0.01	80
After random fix	9	1	2.88	107.07	110	1	0.03	80
	33	2	2.89	48.1	100	0.8	0.01	80
	11	3	2.96	110.4	100	0.8	0.01	100
	39	4	2.99	59.09	100	0.8	0.01	80

Table B-22 Calibration results after 3rd stage & random component fix, 17 zone instance II

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	43	1	3.06	56.86	120	0.9	0.02	100
	8	2	3.04	51.16	120	0.9	0.02	80
	6	3	3.16	44.18	100	0.8	0.01	100
	2	4	3.16	58.64	110	0.8	0.02	90
After random fix	43	1	3.16	63.44	120	0.9	0.02	100
	8	2	3.16	63.75	120	0.9	0.02	80
	6	3	3.16	81.19	100	0.8	0.01	100
	2	4	3.16	62.35	110	0.8	0.02	90

Table B-23 Calibration results after 3rd stage & random component fix, 17 zone instance III

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	2	1	3.14	73.29	120	0.9	0.02	100
	8	2	3.15	71.74	110	0.8	0.01	90
	38	3	3.09	57.41	100	1	0.03	80
	39	4	3.14	73.01	120	0.8	0.02	100
After random fix	2	1	3.23	71.99	120	0.9	0.02	100
	8	2	3.23	70.03	110	0.8	0.01	90
	38	3	3.23	70.56	100	1	0.03	80
	39	4	3.18	45.74	120	0.8	0.02	100

Table B-24 Calibration results after 3rd stage & random component fix, 17 zone instance IV

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	19	1	3.12	46.83	100	0.8	0.01	80
	40	2	3.09	49.81	100	1	0.02	80
	50	3	3.09	97.61	130	0.8	0.02	80
	20	4	3.08	87.54	120	1	0.03	100
After random fix	19	1	3.23	63.43	100	0.8	0.01	80
	40	2	3.19	125.6	100	1	0.02	80
	50	3	3.08	79.21	130	0.8	0.02	80
	20	4	3.08	96.64	120	1	0.03	100

Table B-25 Calibration results after 3rd stage & random component fix, 17 zone instance V

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	22	1	2.89	44.51	100	1	0.03	100
	38	2	2.91	52.83	110	0.9	0.02	100
	8	3	2.81	47.29	100	1	0.03	90
	42	4	2.89	40.11	120	0.9	0.03	80
After random fix	22	1	2.89	70.48	100	1	0.03	100
	38	2	2.82	42.12	110	0.9	0.02	100
	8	3	2.95	94.38	100	1	0.03	90
	42	4	2.88	43.17	120	0.9	0.03	80

Table B-26 Calibration results after 3rd stage & random component fix, 26 zone instance I

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	8	1	3.44	282.52	110	0.8	0.02	100
	19	2	3.41	295.06	150	0.9	0.02	80
	23	3	3.43	224.93	100	0.8	0.01	90
	5	4	3.38	270.06	100	0.9	0.03	100
After random fix	8	1	3.47	224.7	110	0.8	0.02	100
	19	2	3.47	234.24	150	0.9	0.02	80
	23	3	3.47	231.61	100	0.8	0.01	90
	5	4	3.47	230.72	100	0.9	0.03	100

Table B-27 Calibration results after 3rd stage & random component fix, 26 zone instance II

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	31	1	2.95	127.68	100	0.8	0.02	80
	16	2	3.08	292.66	140	0.8	0.01	90
	12	3	3.01	150.4	100	0.9	0.02	80
	15	4	3.09	258.87	100	0.8	0.01	90
After random fix	31	1	2.93	168.89	100	0.8	0.02	80
	16	2	2.99	126.9	140	0.8	0.01	90
	12	3	2.99	95.7	100	0.9	0.02	80
	15	4	3.05	246.22	100	0.8	0.01	90

Table B-28 Calibration results after 3rd stage & random component fix, 26 zone instance III

	Case	No.	Value	Time(mins)	N	PC	PM	G
After the 3rd stage	1	1	3.24	207.25	100	0.8	0.01	90
	2	2	3.17	299.08	120	1	0.02	100
	4	3	3.24	326.5	150	0.9	0.01	100
	5	4	3.3	209.96	110	1	0.03	80
After random fix	1	1	3.27	213.69	100	0.8	0.01	90
	2	2	3.26	338.59	120	1	0.02	100
	4	3	3.27	303.87	150	0.9	0.01	100
	5	4	3.27	304.33	110	1	0.03	80

Table B-29 Validation results and gap analysis 17 zones, instances (I-X)

Instance	Case	Genetic Algorithm		Exact B&B	Gap (%)	
		After 3rd stage	Fix random component		After 3rd stage	Fix random component
(I)	9	2.88	2.88	3	***4.17***	***4.17***
	11	2.9	2.96	3	***3.45***	***1.35***
	19	2.96		3	***1.35***	
	24	2.99		3	***0.33***	
	29	2.97		3	***1.01***	
	33	2.92	2.89	3	***2.74***	***3.81***
	39	2.93	2.99	3	***2.39***	***0.33***
	44	2.99		3	***0.33***	
(II)	1	3.16		3.16	***0***	
	2	3.16		3.16	***0***	
	3	3.16		3.16	***0***	
	6	3.16		3.16	***0***	
	8	3.04		3.16	***3.95***	
	30	3.16		3.16	***0***	
	41	3.16		3.16	***0***	
	43	3.06		3.16	***3.27***	
(III)	2	3.14		3.23	***2.87***	
	8	3.15		3.23	***2.54***	
	10	3.18		3.23	***1.57***	
	18	3.18		3.23	***1.57***	
	29	3.18		3.23	***1.57***	
	33	3.18		3.23	***1.57***	
	38	3.09		3.23	***4.53***	
	39	3.14		3.23	***2.87***	
(IV)	11	3.23		3.23	***0***	
	18	3.23		3.23	***0***	
	19	3.12		3.23	***3.53***	
	20	3.08		3.23	***4.87***	
	37	3.12		3.23	***3.53***	
	40	3.09		3.23	***4.53***	
	44	3.19		3.23	***1.25***	
	50	3.09		3.23	***4.53***	

Table B-30 Validation results and gap analysis 17 zones, instances (I-X)

Instance	Case	Genetic Algorithm: After 3rd stage	Genetic Algorithm: Fix random component	Exact B&B	Gap (%): After 3rd stage	Gap (%): Fix random component
(V)	8	2.81		2.95	***4.98***	
	14	2.91		2.95	***1.37***	
	22	2.89		2.95	***2.08***	
	25	2.91		2.95	***1.37***	
	33	2.93		2.95	***0.68***	
	38	2.91		2.95	***1.37***	
	41	2.95		2.95	***0***	
	42	2.89		2.95	***2.08***	
(VI)	1	3.24		3.3	***1.85***	
	2	3.17		3.3	***4.10***	
	3	3.3		3.3	***0***	
	4	3.24		3.3	***1.85***	
	5	3.3		3.3	***0***	
(VII)	1	2.93		3.05	***4.10***	
	2	2.97		3.05	***2.69***	
	3	2.92		3.05	***4.45***	
	4	2.96		3.05	***3.04***	
	5	2.97		3.05	***2.69***	
(VIII)	1	3.13		3.14	***0.32***	
	2	3.13		3.14	***0.32***	
	3	2.99		3.14	***5.02***	
	4	2.95		3.14	***6.44***	
	5	3.05		3.14	***2.95***	
(IX)	1	2.92		2.94	***0.68***	
	2	2.81		2.94	***4.63***	
	3	2.9		2.94	***1.38***	
	4	2.89		2.94	***1.73***	
	5	2.86		2.94	***2.80***	
(X)	1	3.17		3.23	***1.89***	
	2	3.21		3.23	***0.62***	
	3	3.08		3.23	***4.87***	
	4	3.15		3.23	***2.54***	
	5	3.12		3.23	***3.53***	

Table B-31 Validation results and gap analysis 26 zones, instances (I-III)

Instance	Case	Genetic Algorithm After 3rd stage	Genetic Algorithm Fix random component	Exact B&B	Gap (%) After 3rd stage	Gap (%) Fix random component
(I)	5	3.38	3.47	3.57	***5.62***	***2.88***
	8	3.44	3.44	3.57	***3.78***	***3.78***
	13	3.41		3.57	***4.69***	
	18	3.41		3.57	***4.69***	
	19	3.41	3.47	3.57	***4.69***	***2.88***
	23	3.43	3.47	3.57	***4.08***	***2.88***
	27	3.43		3.57	***4.08***	
	46	3.47		3.57	***2.88***	
	50	3.47		3.57	***2.88***	
(II)	5	3.02		3.1	***2.65***	
	12	3.01	2.99	3.1	***2.99***	***3.68***
	15	3.09	3.05	3.1	***0.32***	***1.64***
	16	3.08	2.99	3.1	***0.65***	***3.68***
	21	2.99		3.1	***3.68***	
	31	2.95	2.93	3.1	***5.08***	***5.80***
	43	3.02		3.1	***2.65***	
	45	2.93		3.1	***5.80***	
	46	2.96		3.1	***4.73***	
(III)	1	3.24		3.43	***5.86***	
	2	3.27		3.43	***4.89***	
	3	3.41		3.43	***0.59***	
	4	3.29		3.43	***4.26***	
	5	3.27		3.43	***4.89***	

Appendix C

Data for case study application

Table C-1 Area of new development zones

ID	Area (ha)	Land Use
72	70	VN
73	80	VN
74	100	VN
75	130	VN
76	100	VN
77	50	VN
78	50	VN
79	80	VN
80	130	VN
81	60	VN
82	100	VN
83	110	VN
84	80	VN
85	110	VN
86	130	VN
87	130	VN
88	100	VN
89	110	VN
90	50	VN
91	50	VN
92	60	VN
93	80	VN
94	110	VN
95	150	VN
96	50	VN
97	50	VN
98	50	VN
99	90	VN
100	70	VN
101	100	VN
102	50	VN
103	90	VN
104	100	VN
105	70	VN
106	110	VN
107	150	VN
108	80	VN

Table C-2 Land-use suitability index

Zone	Land Use	Suitability index	Zone	Land Use	Suitability index
65	1	0.8	73	1	1
65	2	0	73	2	1
65	3	0	73	3	1
65	4	0	73	4	1
65	5	0	73	5	0.2
66	1	0	74	1	1
66	2	0	74	2	1
66	3	0	74	3	1
66	4	0	74	4	1
66	5	0	74	5	0.2
67	1	0	75	1	1
67	2	0	75	2	1
67	3	0	75	3	1
67	4	0	75	4	1
67	5	0	75	5	0.2
68	1	0	76	1	0.2
68	2	0	76	2	0.2
68	3	0	76	3	0.2
68	4	0	76	4	0.6
68	5	0	76	5	0
69	1	0	77	1	0.2
69	2	0	77	2	0.2
69	3	0	77	3	0.2
69	4	0	77	4	0.6
69	5	0	77	5	0
70	1	0	78	1	0.2
70	2	0	78	2	0.2
70	3	0	78	3	0.2
70	4	0	78	4	0.6
70	5	0	78	5	0
71	1	0	79	1	0.2
71	2	0	79	2	0.2
71	3	0	79	3	0.2
71	4	0	79	4	0.6
71	5	0	79	5	0
72	1	0.2	80	1	1
72	2	0.2	80	2	1
72	3	0.2	80	3	1
72	4	0.6	80	4	1
72	5	0	80	5	0.2

Table C-2 (continued)

Zone	Land Use	Suitability index	Zone	Land Use	Suitability index
81	1	1	89	1	1
81	2	1	89	2	1
81	3	1	89	3	1
81	4	1	89	4	1
81	5	0.2	89	5	0.2
82	1	0.2	90	1	0.2
82	2	0.2	90	2	0.2
82	3	0.2	90	3	0.2
82	4	0.6	90	4	0.6
82	5	0	90	5	0
83	1	0.8	91	1	1
83	2	0.8	91	2	1
83	3	0.8	91	3	1
83	4	0.8	91	4	1
83	5	1	91	5	0.2
84	1	1	92	1	0.2
84	2	1	92	2	0.2
84	3	1	92	3	0.2
84	4	1	92	4	0.6
84	5	0.2	92	5	0
85	1	1	93	1	1
85	2	1	93	2	1
85	3	1	93	3	1
85	4	1	93	4	1
85	5	0.2	93	5	0.2
86	1	0.2	94	1	0.2
86	2	0.2	94	2	0.2
86	3	0.2	94	3	0.2
86	4	0.6	94	4	0.6
86	5	0	94	5	0
87	1	0.2	95	1	0.2
87	2	0.2	95	2	0.2
87	3	0.2	95	3	0.2
87	4	0.6	95	4	0.6
87	5	0	95	5	0
88	1	0.2	96	1	1
88	2	0.2	96	2	1
88	3	0.2	96	3	1
88	4	0.6	96	4	1
88	5	0	96	5	0.2

Table C-2 (continued)

Zone	Land Use	Suitability index	Zone	Land Use	Suitability index
97	1	0.8	105	1	0.8
97	2	0.8	105	2	0.8
97	3	0.8	105	3	0.8
97	4	0.8	105	4	0.8
97	5	1	105	5	1
98	1	1	106	1	0.8
98	2	1	106	2	0.8
98	3	1	106	3	0.8
98	4	1	106	4	0.8
98	5	0.2	106	5	1
99	1	0.2	107	1	0.8
99	2	0.2	107	2	0.8
99	3	0.2	107	3	0.8
99	4	0.6	107	4	0.8
99	5	0	107	5	1
100	1	0.8	108	1	1
100	2	0.8	108	2	1
100	3	0.8	108	3	1
100	4	0.8	108	4	1
100	5	1	108	5	0.2
101	1	1			
101	2	1			
101	3	1			
101	4	1			
101	5	0.2			
102	1	0.8			
102	2	0.8			
102	3	0.8			
102	4	0.8			
102	5	1			
103	1	0.8			
103	2	0.8			
103	3	0.8			
103	4	0.8			
103	5	1			
104	1	1			
104	2	1			
104	3	1			
104	4	1			
104	5	0.2			

Table C-3 Coordinates of zone centers

Zone	X-co.	Y-co.	Zone	X-co.	Y-co.
Ademia	547300.94	4455739	Padre Manuel Nobrega	549146.6	4451911
Afonso Henriques/Dias da Silva	550118.76	4451389	Parque	548875	4450590
Almalagues	551734.52	4442768	Pedrulha	547168.6	4454902
Alta	548910.33	4450982	Penedo	549760.2	4450851
Alto de Sao Joao	550831.13	4449380	Polo II	549646.7	4448485
Antanhol	545998.29	4446128	Portela	550724.3	4448518
Antuzede	544544.52	4455902	Praca	549347.5	4451173
Areeiro	551545.86	4449481	Quinta da Maia	550838.2	4451239
Assafarge	548572.51	4445794	Quinta das Lagrimas	548404.3	4449244
Av.Elisio de Moura/Sao Sebastiao	551422.07	4451779	Rossio de Santa Clara	548323.6	4450572
Bairro Norton Matos	550125.44	4449986	Rua do Brasil	549643.4	4450230
Baixa - Camara	548561.09	4451379	Sa da Bandeira	548856.6	4451377
Baixa - Portagem	548549.62	4450923	Santa Clara	547644.2	4450107
Boavista	549388.09	4449302	Sao Joao do Campo	541663.5	4453978
Botanico	549354.36	4450866	Sao Martinho de Arvore/Lamarosa	537733.8	4452116
Calhabe	550295.51	4450397	Sao Martinho do Bispo	546245	4451595
Carlos Seixas/Verde Pinho	549780.77	4449658	Sao Silvestre	540393.9	4453079
Casa Branca	550871.44	4449786	Solum	550763.5	4450666
Casais	544063.56	4450450	Solum Equipamentos	550524.8	4450676
Ceira	552018.32	4447035	Souselas	549041.3	4460138
Celas	549895.88	4451729	Taveiro	542271.6	4450256
Cernache	545286.15	4443386	Taveiro Industrial	541723.3	4449798
Cernache Industrial	545762.98	4444462	Tovim	551716.4	4451490
Chao do Bispo	551572.65	4450449	Trouxemil/Fornos	547276.9	4458139
Combatentes	549514.57	4450464	Vale das Flores	550291.5	4449585
Conchada	548581.27	4451730	66	551265.4	4449984
Eiras	549488.85	4455549	67	550997.6	4450656
Eiras Industrial	548240.19	4454941	68	551048.9	4450978
Fala	545303.48	4450245	69	549533.9	4452905
Fernao Magalhaes	548128.19	4451629	70	548504	4452519
Forum Coimbra	547574.93	4451375	71	547110.3	4447878
Hospital Covoes	546155.22	4449629	72	547036.6	4451224
Huc	549979.89	4452299	73	547242.9	4450432
Ingote	548581.17	4453595	74	538596.7	4448702
Loios/Cidral	550365.44	4451117	75	540524.7	4448999
Lordemao/Corrente	550214.91	4454061	76	542689.9	4448413
Loreto	547765.36	4453729	77	544535.9	4449878
Monte Formoso	547787.92	4452292	78	544382.9	4448758
Montes Claros	549509.36	4451716	79	545789.9	4448465
Oilvais	550598.48	4452047	80	544939.8	4447202

Table C-3 Coordinates of zone centers (continued)

Zone	X-co.	Y-co.
81	543883.2	4447377
82	541795.32	4446902
83	544492.06	4444211
84	546514.98	4444557
85	547716.96	4444298
86	549955.98	4443617
87	551004.11	4444805
88	550488.64	4446789
89	547748.77	4446754
90	548874.58	4447767
91	547381.42	4448800
92	551348.1	4448808
93	549233.74	4452669
94	550367.88	4453221
95	549338.49	4453513
96	548196.28	4453304
97	547267.87	4453715
98	549147.5	4454744
99	548932.17	4456444
100	549336.28	4458775
101	548053.95	4459784
102	548383.67	4457745
103	546468.93	4456654
104	544683.31	4456913
105	545300.33	4455454
106	543280.24	4454865
107	540479	4454545
108	539002.58	4453149

Table C-4 Road classes

Zone	Zone	Class	Zone	Zone	Class
Ademia	Antuzede	3	Baixa - Portagem	Rossio de Santa Clara	1
Ademia	Eiras	3	Boavista	Antanhol	4
Ademia	Pedrulha	4	Boavista	Carlos Seixas/Verde Pinho	1
Ademia	Trouxemil/Fornos	4	Boavista	Hospital Covoes	4
Afonso Henriques/Dias da Silva	Celas	1	Boavista	Parque	2
Afonso Henriques/Dias da Silva	Loios/Cidral	1	Boavista	Polo II	4
Afonso Henriques/Dias da Silva	Oilvais	1	Boavista	Quinta das Lagrimas	2
Afonso Henriques/Dias da Silva	Penedo	1	Boavista	Vale das Flores	2
Almalagues	Assafarge	3	Botanico	Alta	1
Almalagues	Ceira	3	Botanico	Combatentes	1
Almalagues	Cernache	4	Botanico	Penedo	1
Alta	Botanico	1	Botanico	Praca	1
Alto de Sao Joao	Areeiro	1	Calhabe	Bairro Norton Matos	1
Alto de Sao Joao	Casa Branca	2	Calhabe	Casa Branca	1
Alto de Sao Joao	Portela	4	Calhabe	Combatentes	1
Alto de Sao Joao	Vale das Flores	2	Calhabe	Rua do Brasil	1
Antanhol	Assafarge	3	Calhabe	Solum	1
Antanhol	Boavista	4	Calhabe	Solum Equipamentos	1
Antanhol	Cernache Industrial	4	Carlos Seixas/Verde Pinho	Bairro Norton Matos	1
Antanhol	Hospital Covoes	4	Carlos Seixas/Verde Pinho	Boavista	1
Antuzede	Ademia	3	Carlos Seixas/Verde Pinho	Rua do Brasil	1
Antuzede	Sao Joao do Campo	3	Carlos Seixas/Verde Pinho	Vale das Flores	1
Areeiro	Alto de Sao Joao	1	Casa Branca	Alto de Sao Joao	2
Areeiro	Chao do Bispo	1	Casa Branca	Bairro Norton Matos	1
Assafarge	Almalagues	3	Casa Branca	Calhabe	1
Assafarge	Antanhol	3	Casa Branca	Solum	2
Assafarge	Ceira	3	Casa Branca	Vale das Flores	1
Av.Elisio de Moura/Sao Sebastiao	Lordemao/Corrente	3	Casais	Fala	1
Av.Elisio de Moura/Sao Sebastiao	Oilvais	1	Casais	Sao Martinho do Bispo	4
Av.Elisio de Moura/Sao Sebastiao	Quinta da Maia	2	Casais	Taveiro	4
Av.Elisio de Moura/Sao Sebastiao	Solum	2	Ceira	Almalagues	3
Av.Elisio de Moura/Sao Sebastiao	Tovim	1	Ceira	Assafarge	3
Bairro Norton Matos	Calhabe	1	Ceira	Portela	3
Bairro Norton Matos	Carlos Seixas/Verde Pinho	1	Celas	Afonso Henriques/Dias da Silva	1
Bairro Norton Matos	Casa Branca	1	Celas	Huc	1
Bairro Norton Matos	Rua do Brasil	1	Celas	Montes Claros	1
Baixa - Camara	Fernao Magalhaes	1	Celas	Oilvais	1
Baixa - Camara	Sa da Bandeira	1	Celas	Praca	1
Baixa - Portagem	Fernao Magalhaes	1	Cernache	Almalagues	4
Baixa - Portagem	Parque	1	Cernache	Cernache Industrial	4

Table C-4 Road classes

Zone	Zone	Class	Zone	Zone	Class
Cernache Industrial	Antanhol	4	Ingote	Monte Formoso	3
Cernache Industrial	Cernache	4	Loios/Cidral	Afonso Henriques/Dias da Silva	1
Chao do Bispo	Areeiro	1	Loios/Cidral	Penedo	1
Chao do Bispo	Solum	1	Loios/Cidral	Quinta da Maia	1
Chao do Bispo	Tovim	1	Lordemao/Corrente	Av.Elisio de Moura/Sao Sebastiao	3
Combatentes	Botanico	1	Lordemao/Corrente	Eiras	3
Combatentes	Calhabe	1	Lordemao/Corrente	Huc	3
Combatentes	Rua do Brasil	1	Lordemao/Corrente	Ingote	3
Conchada	Monte Formoso	1	Loreto	Eiras Industrial	3
Conchada	Montes Claros	1	Loreto	Monte Formoso	4
Conchada	Sa da Bandeira	1	Loreto	Pedrulha	4
Eiras	Ademia	3	Monte Formoso	Conchada	1
Eiras	Eiras Industrial	3	Monte Formoso	Fernao Magalhaes	4
Eiras	Lordemao/Corrente	3	Monte Formoso	Huc	4
Eiras Industrial	Eiras	3	Monte Formoso	Ingote	3
Eiras Industrial	Ingote	3	Monte Formoso	Loreto	4
Eiras Industrial	Loreto	3	Montes Claros	Celas	1
Fala	Casais	1	Montes Claros	Conchada	1
Fala	Hospital Covoes	1	Montes Claros	Padre Manuel Nobrega	1
Fala	Sao Martinho do Bispo	1	Oilvais	Afonso Henriques/Dias da Silva	1
Fernao Magalhaes	Baixa - Camara	1	Oilvais	Av.Elisio de Moura/Sao Sebastiao	1
Fernao Magalhaes	Baixa - Portagem	1	Oilvais	Celas	1
Fernao Magalhaes	Forum Coimbra	4	Oilvais	Quinta da Maia	2
Fernao Magalhaes	Monte Formoso	4	Padre Manuel Nobrega	Montes Claros	1
Fernao Magalhaes	Sao Martinho do Bispo	4	Parque	Baixa - Portagem	1
Forum Coimbra	Fernao Magalhaes	4	Parque	Boavista	2
Forum Coimbra	Rossio de Santa Clara	2	Parque	Rua do Brasil	1
Forum Coimbra	Sao Martinho do Bispo	4	Pedrulha	Ademia	4
Hospital Covoes	Antanhol	4	Pedrulha	Loreto	4
Hospital Covoes	Boavista	4	Penedo	Afonso Henriques/Dias da Silva	1
Hospital Covoes	Fala	1	Penedo	Botanico	1
Hospital Covoes	Santa Clara	1	Penedo	Loios/Cidral	1
Hospital Covoes	Sao Martinho do Bispo	4	Penedo	Solum	1
Huc	Celas	1	Penedo	Solum Equipamentos	1
Huc	Ingote	3	Polo II	Boavista	4
Huc	Lordemao/Corrente	3	Polo II	Portela	4
Huc	Monte Formoso	4	Portela	Alto de Sao Joao	4
Ingote	Eiras Industrial	3	Portela	Ceira	3
Ingote	Huc	3	Portela	Polo II	4
Ingote	Lordemao/Corrente	3	Praca	Botanico	1

Table C-4 Road classes (continued)

Zone	Zone	Class	Zone	Zone	Class
Praca	Celas	1	Solum	Solum Equipamentos	1
Praca	Sa da Bandeira	1	Solum Equipamentos	Calhabe	1
Quinta da Maia	Av.Elisio de Moura/Sao Sebastiao	2	Solum Equipamentos	Penedo	1
Quinta da Maia	Loios/Cidral	1	Solum Equipamentos	Solum	1
Quinta da Maia	Oilvais	2	Souselas	Trouxemil/Fornos	4
Quinta da Maia	Solum	2	Taveiro	Casais	4
Quinta das Lagrimas	Boavista	2	Taveiro	Taveiro Industrial	4
Quinta das Lagrimas	Rossio de Santa Clara	2	Taveiro Industrial	Taveiro	4
Quinta das Lagrimas	Santa Clara	1	Tovim	Av.Elisio de Moura/Sao Sebastiao	1
Rossio de Santa Clara	Baixa - Portagem	1	Tovim	Chao do Bispo	1
Rossio de Santa Clara	Forum Coimbra	2	Trouxemil/Fornos	Ademia	4
Rossio de Santa Clara	Quinta das Lagrimas	2	Trouxemil/Fornos	Souselas	4
Rossio de Santa Clara	Santa Clara	1	Vale das Flores	Alto de Sao Joao	2
Rua do Brasil	Bairro Norton Matos	1	Vale das Flores	Boavista	2
Rua do Brasil	Calhabe	1	Vale das Flores	Carlos Seixas/Verde Pinho	1
Rua do Brasil	Carlos Seixas/Verde Pinho	1	Vale das Flores	Casa Branca	1
Rua do Brasil	Combatentes	1	Ademia	99	5
Rua do Brasil	Parque	1	Ademia	103	5
Sa da Bandeira	Baixa - Camara	1	Ademia	105	5
Sa da Bandeira	Conchada	1	Almalagues	86	5
Sa da Bandeira	Praca	1	Almalagues	87	5
Santa Clara	Hospital Covoes	1	Alto de Sao Joao	92	5
Santa Clara	Quinta das Lagrimas	1	Antanhol	80	5
Santa Clara	Rossio de Santa Clara	1	Antanhol	85	5
Sao Joao do Campo	Antuzede	3	Antanhol	89	5
Sao Joao do Campo	Sao Silvestre	3	Antuzede	103	5
Sao Martinho de Arvore/Lamarosa	Sao Silvestre	3	Antuzede	104	5
Sao Martinho do Bispo	Casais	4	Antuzede	105	5
Sao Martinho do Bispo	Fala	1	Antuzede	106	5
Sao Martinho do Bispo	Fernao Magalhaes	4	Areeiro	92	5
Sao Martinho do Bispo	Forum Coimbra	4	Assafarge	85	5
Sao Martinho do Bispo	Hospital Covoes	4	Assafarge	86	5
Sao Silvestre	Sao Joao do Campo	3	Assafarge	87	5
Sao Silvestre	Sao Martinho de Arvore/Lamarosa	3	Assafarge	88	5
Solum	Av.Elisio de Moura/Sao Sebastiao	2	Assafarge	89	5
Solum	Calhabe	1	Assafarge	90	5
Solum	Casa Branca	2	Casais	77	5
Solum	Chao do Bispo	1	Ceira	87	5
Solum	Penedo	1	Ceira	88	5
Solum	Quinta da Maia	2	Cernache	83	5

Table C-4 Road classes (continued)

Zone	Zone	Class	Zone	Zone	Class
Cernache	85	5	Trouxemil/Fornos	103	5
Cernache Industrial	83	5	69	93	5
Cernache Industrial	84	5	69	94	5
Eiras	98	5	69	95	5
Eiras	99	5	70	93	5
Eiras Industrial	98	5	71	79	5
Fala	77	5	71	89	5
Forum Coimbra	72	5	71	91	5
Hospital Covoes	73	5	72	Forum Coimbra	5
Hospital Covoes	77	5	72	Sao Martinho do Bispo	5
Hospital Covoes	79	5	72	73	5
Hospital Covoes	91	5	73	Hospital Covoes	5
Ingote	95	5	73	Santa Clara	5
Ingote	96	5	73	72	5
Ingote	98	5	74	75	5
Lordemao/Corrente	94	5	74	82	5
Lordemao/Corrente	95	5	75	Taveiro Industrial	5
Lordemao/Corrente	98	5	75	74	5
Loreto	96	5	75	82	5
Loreto	97	5	76	Taveiro	5
Monte Formoso	96	5	76	77	5
Monte Formoso	97	5	76	78	5
Pedrulha	97	5	76	81	5
Portela	92	5	76	82	5
Quinta das Lagrimas	90	5	77	Casais	5
Quinta das Lagrimas	91	5	77	Fala	5
Santa Clara	73	5	77	Hospital Covoes	5
Santa Clara	91	5	77	76	5
Sao Joao do Campo	106	5	77	78	5
Sao Joao do Campo	107	5	78	76	5
Sao Martinho de Arvore/Lamarosa	108	5	78	77	5
Sao Martinho do Bispo	72	5	78	79	5
Sao Silvestre	107	5	78	80	5
Sao Silvestre	108	5	78	81	5
Souselas	100	5	79	Hospital Covoes	5
Souselas	101	5	79	71	5
Taveiro	76	5	79	78	5
Taveiro Industrial	75	5	79	80	5
Trouxemil/Fornos	101	5	80	Antanhol	5
Trouxemil/Fornos	102	5	80	78	5

Table C-4 Road classes (continued)

Zone	Zone	Class	Zone	Zone	Class
80	79	5	92	Alto de Sao Joao	5
80	81	5	92	Areeiro	5
81	76	5	92	Portela	5
81	78	5	93	69	5
81	80	5	93	70	5
81	82	5	94	Lordemao/Corrente	5
82	74	5	94	69	5
82	75	5	95	Ingote	5
82	76	5	95	Lordemao/Corrente	5
82	81	5	95	69	5
83	Cernache	5	96	Ingote	5
83	Cernache Industrial	5	96	Loreto	5
84	Cernache Industrial	5	96	Monte Formoso	5
84	85	5	97	Loreto	5
85	Antanhol	5	97	Monte Formoso	5
85	Assafarge	5	97	Pedrulha	5
85	Cernache	5	98	Eiras	5
85	84	5	98	Eiras Industrial	5
85	86	5	98	Ingote	5
86	Almalagues	5	98	Lordemao/Corrente	5
86	Assafarge	5	99	Ademia	5
86	85	5	99	Eiras	5
87	Almalagues	5	99	102	5
87	Assafarge	5	100	Souselas	5
87	Ceira	5	100	102	5
88	Assafarge	5	101	Souselas	5
88	Ceira	5	101	Trouxemil/Fornos	5
88	90	5	102	Trouxemil/Fornos	5
89	Antanhol	5	102	99	5
89	Assafarge	5	102	100	5
89	71	5	103	Ademia	5
89	90	5	103	Antuzede	5
90	Assafarge	5	103	Trouxemil/Fornos	5
90	Quinta das Lagrimas	5	103	104	5
90	88	5	104	Antuzede	5
90	89	5	104	103	5
91	Hospital Covoes	5	105	Ademia	5
91	Quinta das Lagrimas	5	105	Antuzede	5
91	Santa Clara	5	106	Antuzede	5
91	71	5	106	Sao Joao do Campo	5
			107	Sao Joao do Campo	5
			107	Sao Silvestre	5
			108	Sao Martinho de Arvore/Lamarosa	5
			108	Sao Silvestre	5

Figure C-1 Transportation programs 1 and 2

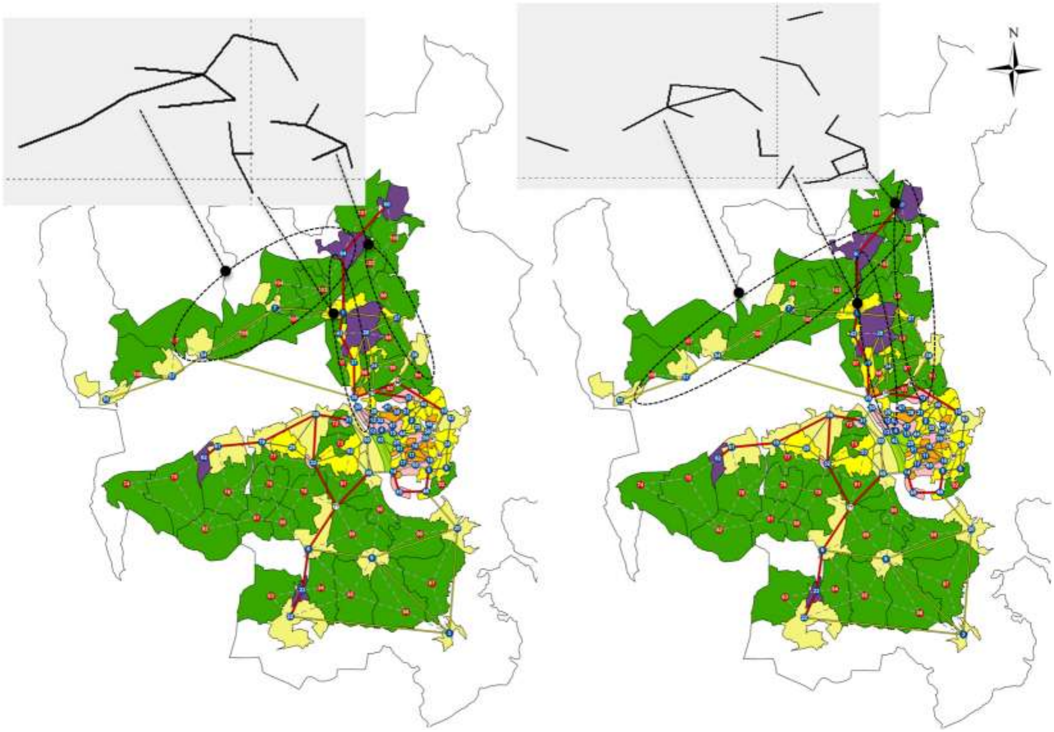


Figure C-2 Transportation programs 3 and 4

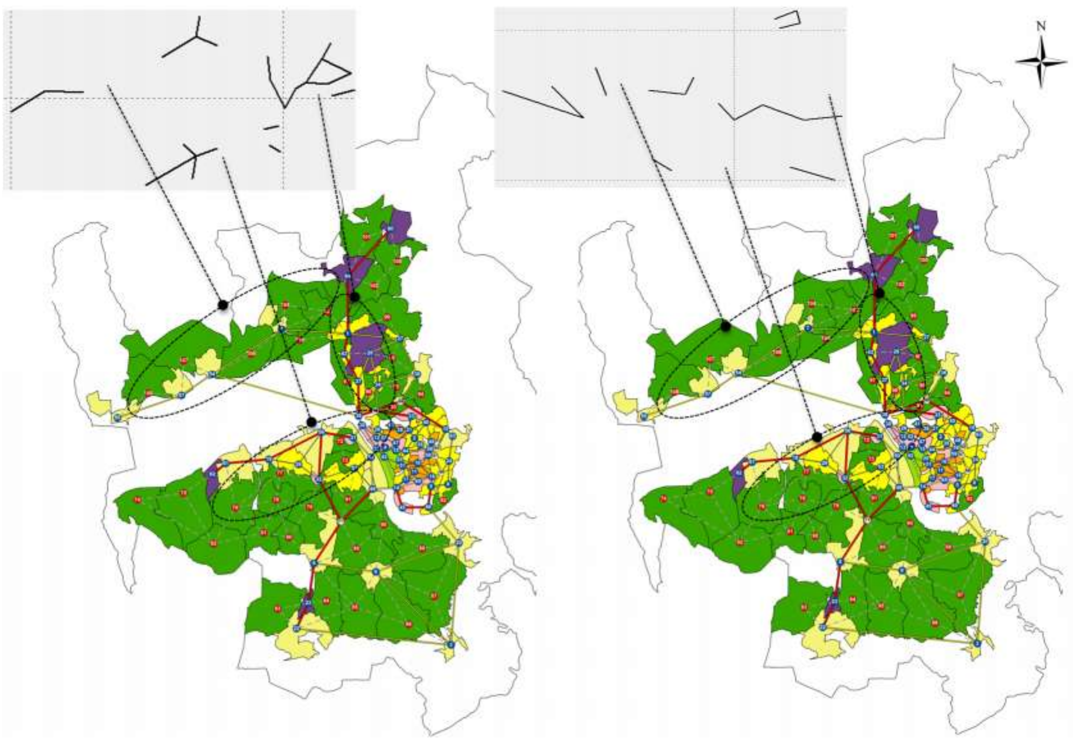


Figure C-3 Transportation programs 5 and 6

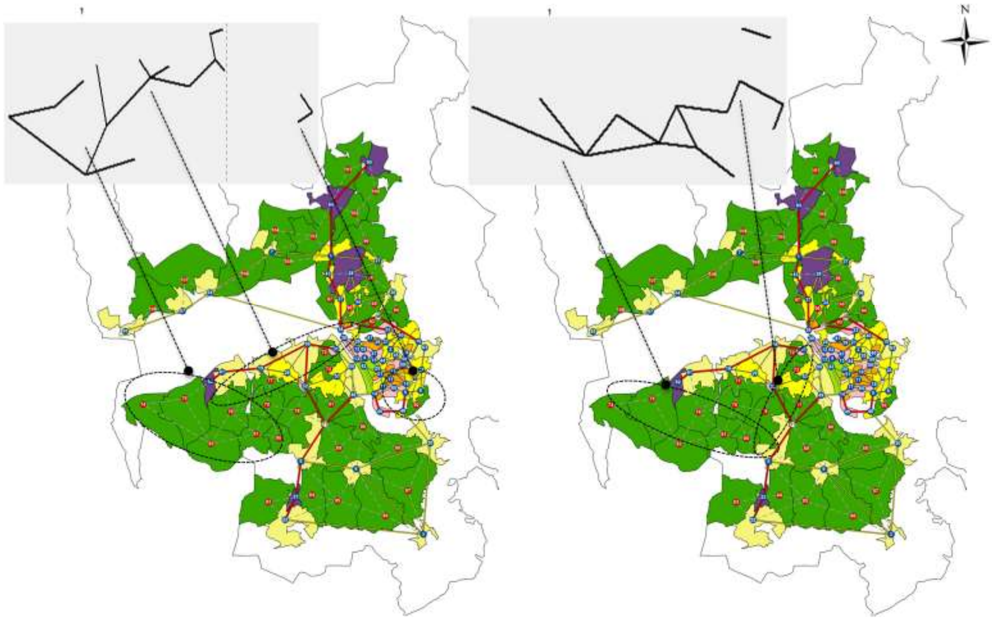


Figure C-4 Transportation programs 7 and 8

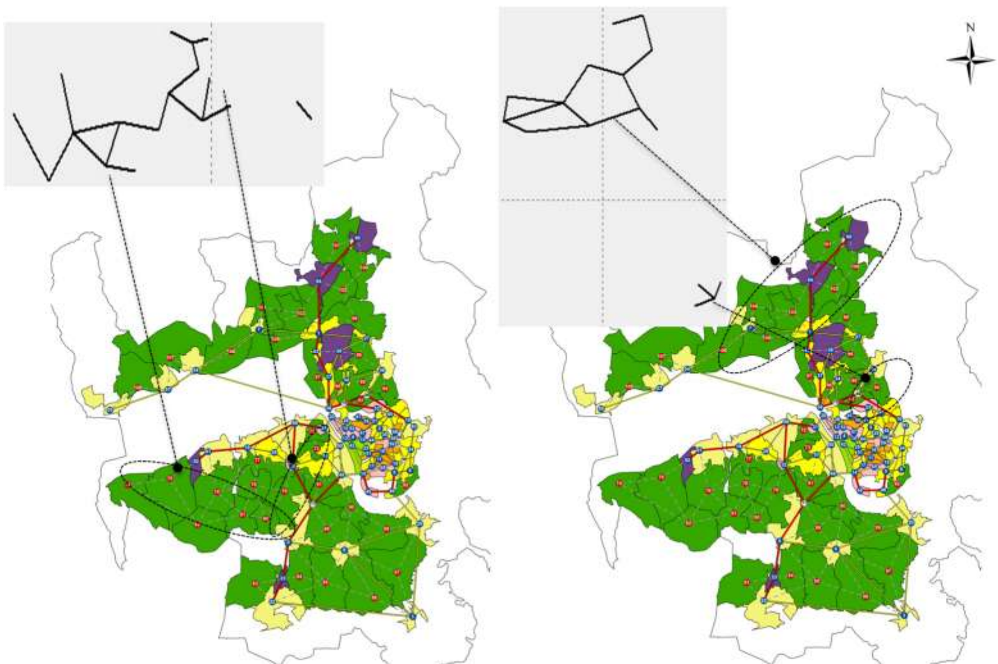


Figure C-5 Transportation programs 9 and 10

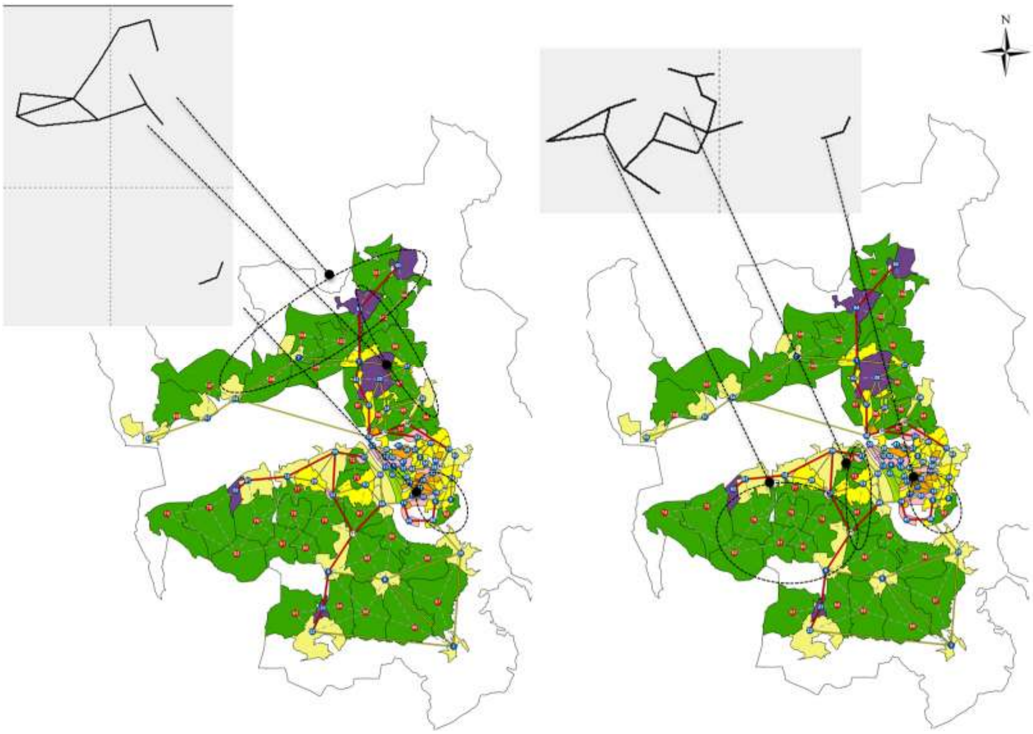


Figure C-6 Transportation programs 11 and 12

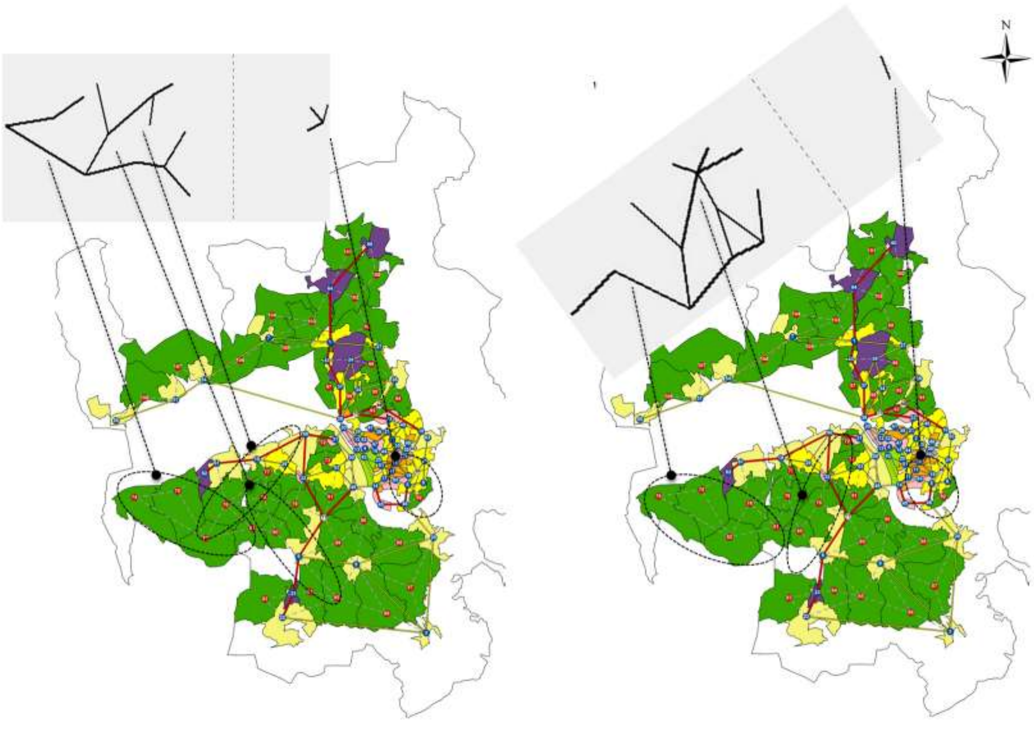


Figure C-6 Transportation programs 13 and 14

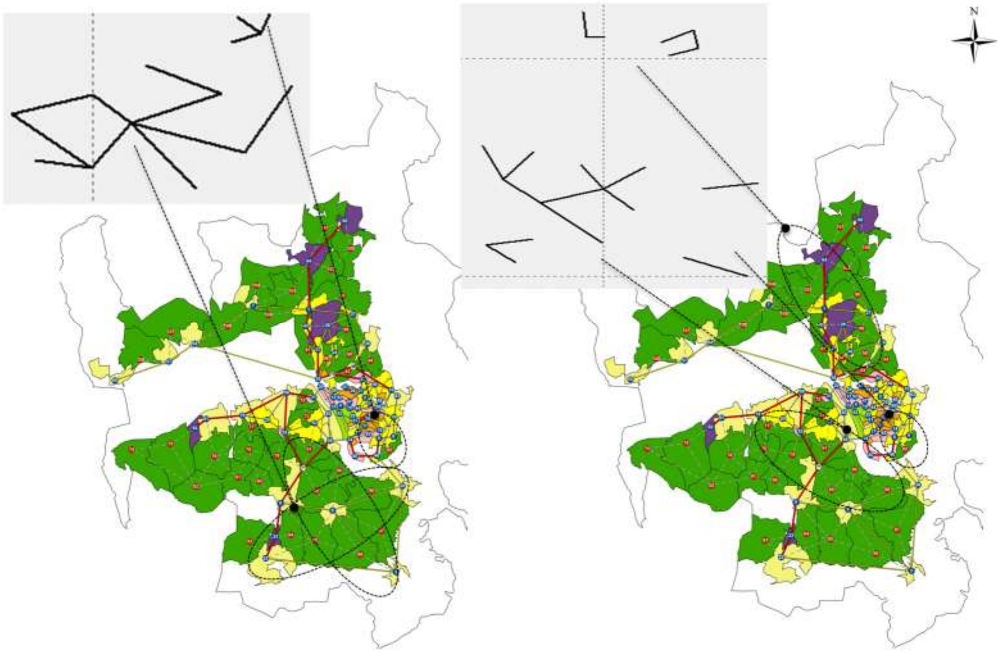


Figure C-7 Transportation programs 15 and 16

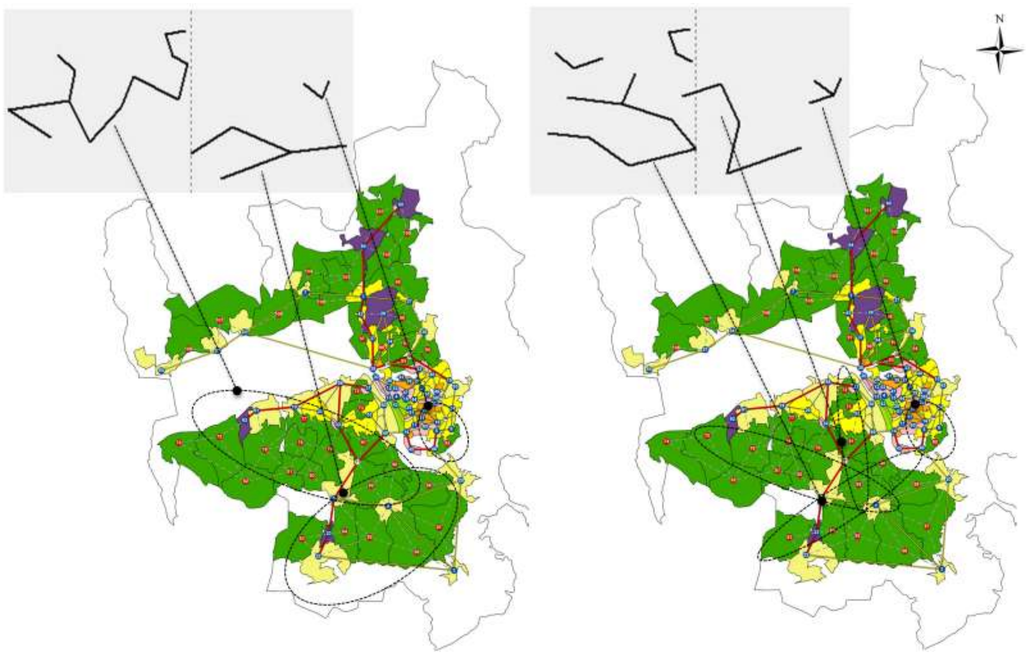


Figure C-8 Transportation programs 17 and 18

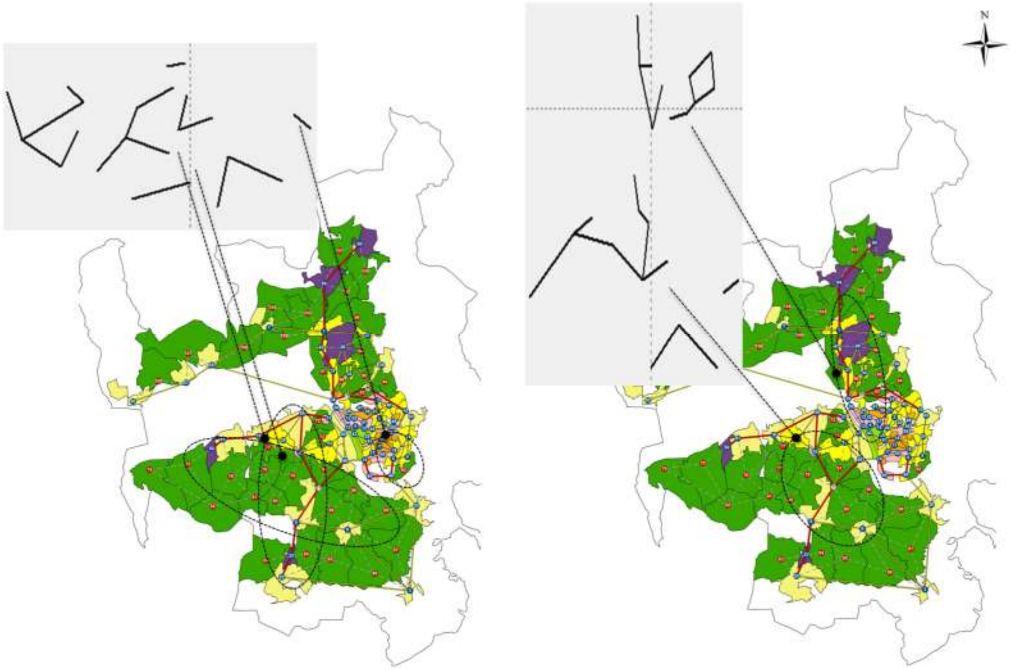


Figure C-9 Transportation programs 19 and 20

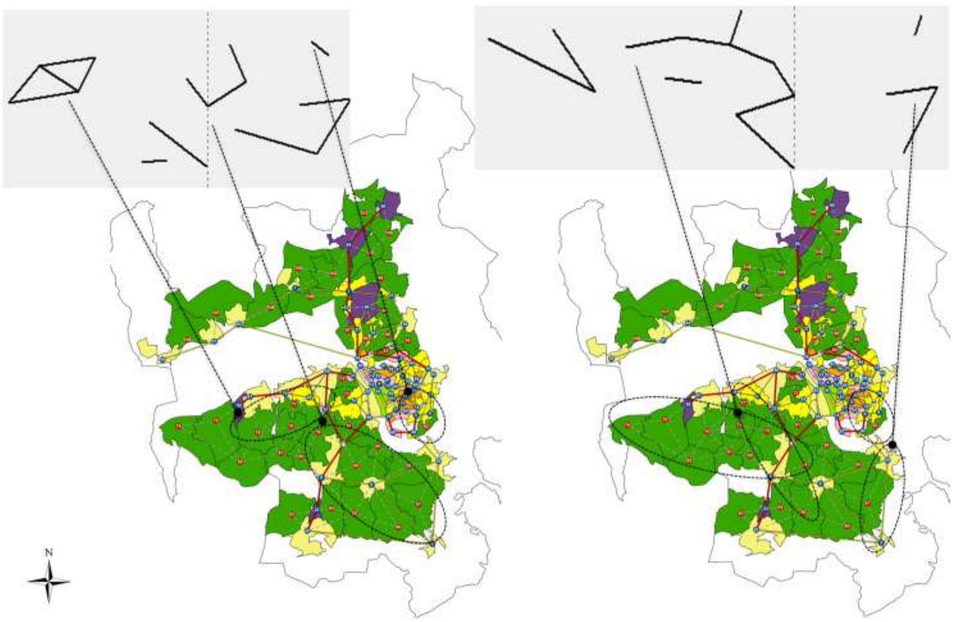


Figure C-10 Transportation programs 21 and 22

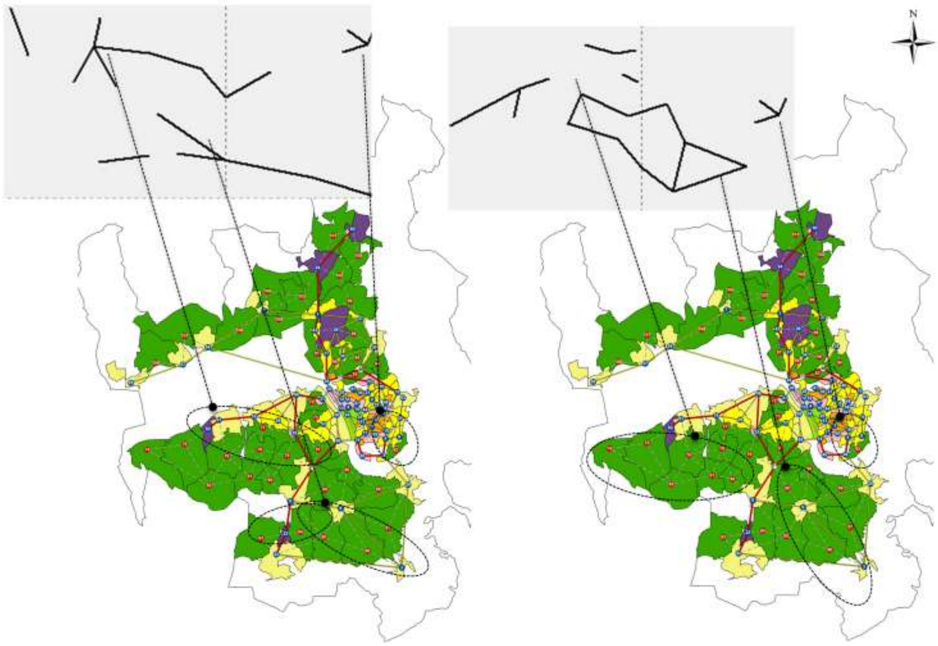


Figure C-11 Transportation programs 24 and 25

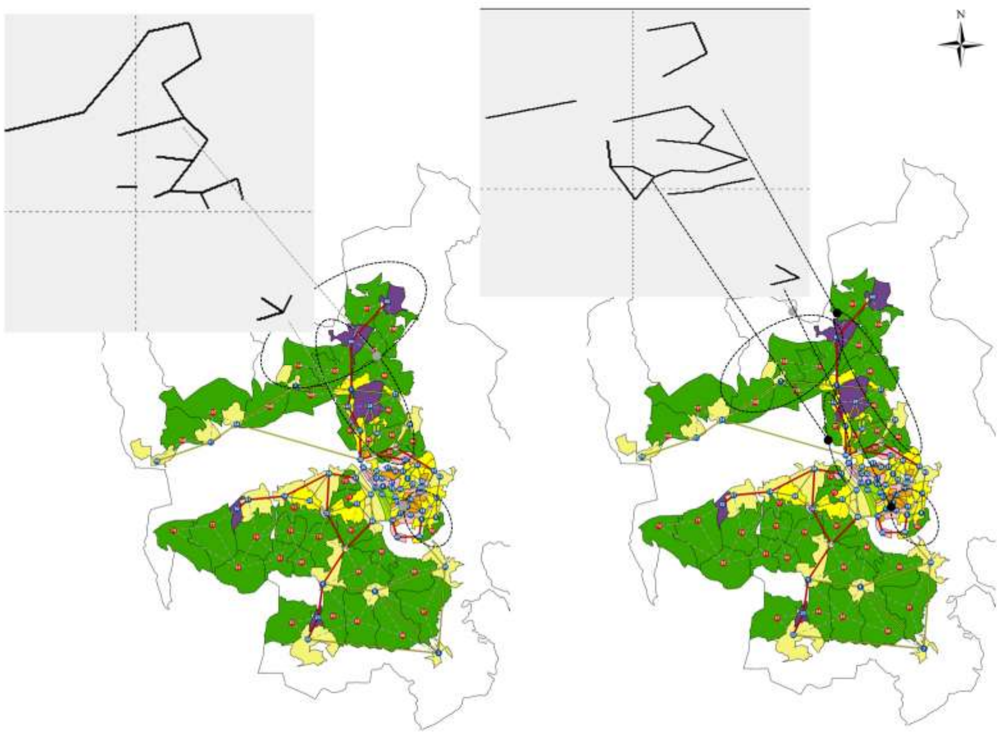


Figure C-12 Transportation program 23