COORDINATED BUDGET ALLOCATION IN MULTI-DISTRICT HIGHWAY AGENCIES

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This research work is dedicated to

my parents

and

family members

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SUMMARY

In an area-wide road network involving a central administration and multiple highway agencies, the allocation of annual operation budget among the regional agencies is a major management task that has a far-reaching effect on the state of health of the entire road network. Ideally, funds should be allocated to areas where maintenance is needed most in order to achieve the best results. In reality, this cannot be easily handled as the highway development and maintenance needs for one region would differ from another. This thesis tries to overcome this difficulty in an attempt that spans into three phases of research work.

The first phase of the research employs a two-step genetic algorithm optimization approach to account for the different goals of the central administration and the regional agencies in the budget allocation process. The first step analysis considers the needs and funds requirements of the regional agencies, while the second step analysis imposes the constraints and requirements of the central administration to arrive at the final allocation strategy. The two-step GA approach is shown to produce better allocation results under various road network characteristics and conditions compared to traditional formula-based and needs-based allocation procedures. The two-step GA approach is further used to perform a sensitivity study on the effect of different regional objective functions on the final central allocation strategy.

In the second phase, the concept of multi-agent systems is employed to provide greater integration of information between the upper and lower management levels, thus producing an allocation strategy that is more likely to give a better overall benefit. Each decision-maker is modeled as an autonomous agent that strives for its own objectives and constrained by its own resources. Regional agents are linked by a central budget and interact vertically and recursively with the central administration to 'negotiate' the fund allocation strategy that best meets their needs. Genetic algorithms are used by regional agents for the optimization of allocated funds for the programming of regional-level pavement maintenance activities. The approach, named multi-agent vertically integrated optimization approach, is shown to consistently produce budget allocation strategies that results in significant savings in overall maintenance cost compared to the two-step optimization and traditional allocation methods.

Phase three is concerned with the horizontal integration in the multi-agent optimization approach developed in phase two. Horizontal integration refers to the integration of information among regional highway agencies where they interact to coordinate the sharing of idle resources in any of the regions. A tournament-like resource-sharing protocol was developed in this research to coordinate the sharing of resources among regional agents. It was found that the vertically and horizontally integrated approach consistently produce budget allocation strategies that results in savings in overall maintenance cost compared to other approaches. The results also confirm earlier observations that commonly used highway fund allocation approaches, the formula- and needs-based approaches, are unsatisfactory fund allocation tools for certain network-level pavement management.

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LIST OF SYMBOLS

C_{jr} = maintenance cost incurred in road segment j of region r

C_r = total maintenance cost needed to repair all distresses in region r

B_r = budget allocated to region r

D_d = distress value for distress type d

F_j = weighting factor equal to the sum of all priority weights

f_{Dj} = priority weight for distress type

f_{Sj} = priority weight for distress severity

f_{Cj} = priority weight for road class

L_{jr} = length of road segment j in region r

M_p = total manpower (in man-days) available for manpower type p

m_{pj} = number of man-days required of manpower type p for road segment j

N = total number of road segments in a region

PDI = Pavement Damage Index

P_r = percentage of funds to be allocated to region r

Q_e = available work-days of equipment type e in a region

q_{ej} = number of work-days required of equipment type e for road segment j

x_j = binary decision variable that indicates whether or not road segment j is selected for maintenance

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

In the past 30 years pavement management has evolved from a mere concept into an active process at federal, state or provincial, regional, and local levels (Haas and Hudson 1987, Haas 1998). Today, pavement management systems (PMS) are widely used at all levels of government at varying degrees of details and sophistication. Pavement management was originally defined by RTAC (1977) as thus:

"A pavement management system encompasses a wide spectrum of activities including the planning or programming of investments, design, construction, maintenance and the periodic evaluation of performance. The function of management at all levels involves comparing alternatives, coordinating activities, making decisions and seeing that they are implemented in an efficient and economical manner".

The two main concerns for PMS were clearly stated in the definition, which are to improve *efficiency* and ensure *economic* return. Almost twenty years later, Haas et al. (1994) described PMS as "a set of analytical tools or methods that assist decision makers in finding optimum strategies for maintaining pavements in a serviceable condition over a given period of time." Evidently, the interest for an efficient and economical PMS has not changed after twenty years of progress and development.

Given that, the issue of an efficient and optimal budget allocation strategy has become an integral part of PMS. For the past twenty years, much research effort has focused on ensuring an efficient manner by which available funds could be allocated to the activities that can give the highest return to the agency as well as road users. As a result, numerous optimization and decision-making methods and approaches have been tested and implemented by highway agencies, with many more being proposed and refined. The advent of powerful computing technologies with exceptional computation capabilities, too, has added much spice to the field of pavement management. In the course of this rising excitement, expertise in pavement engineering has been coupled with knowledge from other domains such as management science, operations research, and artificial intelligence for increased effectiveness. In a similar vein, this research is part of the attempt to bring the science of optimal decision-making in pavement management to a higher level by tapping relevant concepts from the field of artificial intelligence and multi-agent systems.

1.2 ISSUES OF OPTIMAL BUDGET ALLOCATION IN PMS

Although there exists a very large body of work on optimization in pavement management, a number of simplifying assumptions are always used in previous approaches in order to handle the high complexity and large search spaces involved. One of these assumptions pertains to the relationship between allocations of budget and scheduling of pavement maintenance activities, where it was always implicitly assumed that a certain amount of budget is readily allocated for a road network *before* maintenance activities within that network are programmed. In such an optimization model, a maintenance programme that gives the highest benefits subject to a given funding level is derived. This approach, while able to give an optimal program of maintenance activities within a single network subject to the allocated budget, could not guarantee optimality where the global budget is concerned. In fact, the optimization problem should *simultaneously* optimize the overall budget allocation and network-level programming of maintenance activities, a problem previously considered too hard to tackle. It is the objective of this research to propose several solution approaches with respect to this issue.

The issue of budgeting and activities programming as described above is relevant in the allocation of highway funds between several regional agencies. In practice, road funds are allocated by a central administration to regional agencies based on predetermined criteria or formulas with some consultation with regional agencies. Such practice, though convenient and easy to apply as far as the central administration is concerned, would not lead to an optimal usage of funds and resources because applying a common fund allocation formula to all cannot meet the differing needs and goals of different regions. The fund-allocation problem is complicated by the following two issues:

(a) The overall network-wide development needs and emphases may not be in the interest of some or all of the sub-networks at the regional level. For example, the central administration's intention to promote development along selected road corridors may not be in line with the development or management emphases of all the regional agencies.

(b) The regional agencies are more likely than not to differ in their budget needs and network management considerations or objectives. This is so due to the following reasons:

   i) the states of development of the regional road networks are unlikely to be the same, and hence their respective emphases for subsequent development would be different;

   ii) the operational characteristics and composition of road classes are likely to be different in different regions;

iii) the available resources and capability of different regional agencies are likely to be different; and

iv) the road network development and management strategies of the regional agencies might not be the same.

The problem thus involves multiple-goal and multiple-level considerations, which must be solved simultaneously in order to preserve the underlying parallel nature of the problem. In this research, genetic algorithms, a robust search technique which has been successfully applied to pavement management (Chan et al. 1994, Fwa et al. 1994a, 1994b, 1996, 2000, Hoque 1999), is used for network-level pavement maintenance programming, while multi-agent systems is used to allow interactions and coordination to take place among the decision makers.

1.3 SIGNIFICANCE OF RESEARCH

This research has much economic values. Studies by World Bank showed that spending on roads can absorb as much as 5 to 10 percent of a government's recurrent expenses and 10 to 20 percent of its development budget (Heggie and Vickers, 1998). This amounts to billions of dollars every year. With such huge spending demand, there is a need to ensure that every dollar spent on roads returns the highest possible benefit to the decision makers. Indeed, the process of budget allocation is one of the areas in pavement management where an optimal solution can bring about significant financial savings.

In solving for an efficient and optimal allocation of funds between regions, several issues will need to be addressed. These include the system goal of the central administration, network management objectives of all the regional agencies, current state of conditions of the road network, development and maintenance needs of the regional networks, budget and administrative constraints of the central administration, and resource and operational constraints of the regional agencies. The interplay of these issues will naturally affect the way funds are allocated to each region. The research will give significant insight into these issues in relation to the allocation strategies adopted.

Apart from the economic and engineering values, the proposed research also contributes to the body of knowledge spanning the fields of pavement management, genetic algorithms, and multi-agent systems. While the research is not focused on creating new breakthroughs in the areas of genetic algorithms and multi-agent systems research, the application and implementation of these new technologies in budget allocation for pavement management is a new attempt in itself. It is the hope of this research to add the latest technological advances in computing and optimization to benefit the field of pavement management.

1.4 ORGANIZATION OF THESIS

This thesis consists of six chapters. ***Chapter 1*** is the introductory chapter where the background of the problem that led to this research is laid out. The objectives, scope and significance of this research are also discussed in this chapter.

Chapter 2, the literature review, presents past research works related to the major components of this research – budget allocation, pavement maintenance programming, genetic algorithms and multi-agent systems. Relevant past research is also summarized here.

Chapter 3 describes a two-step optimization approach developed to solve the budget allocation problem in multi-regional highway agencies using sequential genetic algorithms. The practicality and applicability of the solution procedure is analysed on a hypothetical example problem. The method of solution, together with the results from the analysis, is presented in this chapter. An application of the method to study the sensitivity of regional objective functions to the final budget allocation is also demonstrated.

Chapter 4 presents a distributed vertically integrated fund allocation approach based on multi-agent systems. The motivation for a multi-agent approach is first discussed, followed by detailed description of the multi-agent system developed to handle the fund allocation among regional highway agencies. The distributed approach is applied to the hypothetical example used earlier in Chapter 3 and comparisons of the results are made.

Chapter 5 describes an enhancement to the distributed vertically and horizontally integrated fund allocation approach to enable the sharing of idle resources among regions. The agent architecture is described, followed by a demonstration of the benefits of the approach based on results obtained using the hypothetical example problem from the earlier chapters.

Chapter 6 concludes and summarizes the major findings of this research. The significance of the research and its findings are outlined. Some future works for further research into this area is also proposed in this Chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

In this chapter, the background of the multi-regional budget allocation problem in pavement management is laid out. The various levels of budget-related decision-making in pavement management are described, with a review of current practices in budget allocation in pavement management. A basic formulation of the budget allocation problem in multi-regional pavement management as a bi-level programming problem is also discussed. Following that, network-level pavement maintenance programming, which is the main component of any pavement management system, is given an extensive review. This constitutes the main component of the lower-level problem in the bi-level formulation of the problem. A review of the various approaches available in the literature for pavement maintenance programming leads to an extensive treatment on the mechanisms of genetic algorithms, which will be used extensively as an optimization tool in this research. Next, multi-agent systems, which will feature mainly in Chapters 4 and 5 as a tool for inter-network and intra-network coordination, are reviewed. Here, the background, definitions and terminologies, and the different types of agents and agent architectures available in the literature are reviewed.

This chapter also gives a review of relevant past research and solutions to problems similar to the budget allocation problem in multi-regional highway agencies. The reviews are categorized into several sub-sections based on the tool and technique used. Finally, the chapter closes with a summary of the research needed in this area and also the scope of the research which will be presented in this thesis.

2.2 BUDGET ALLOCATION IN PAVEMENT MANAGEMENT

2.2.1 Successive Levels of Budgeting Decisions

The budgeting process occurs at various levels of decision-making in pavement management. Typically, pavement management has been identified to comprise two operational levels, the project level and network level. A third level, the planning level is referred to in order to distinguish the highest level in the pavement management hierarchy. OECD (1994) gives a different name for the three levels of decision-making, but the main roles and functions are the same. In this thesis, the three levels are referred to as project, network, and planning levels respectively. Each of these levels is explained in the following sub-sections.

a) Project Level

Project-level pavement management is considered the bottom-most level in the management structure. It is concerned with the technical and engineering aspects of a single pavement section or project. At this level, the pavements are considered individually and on a project-by-project basis. The major activities at the project level are primarily associated with the planning, design, and construction of individual pavement sections. Examples of these activities, among others, include planning and coordination of pre-construction activities, detailed engineering design, economic analysis, and the actual physical implementation of road works (Collura et al 1994, Haas 1998). Budgeting decisions at project level is usually associated with cost-benefit analysis of different construction or maintenance alternatives, budget leveling for the entire project duration, and scheduling of activities in accordance to budget availability. An optimization model for project-level pavement management has been reported by Mamlouk et al (2000).

b) Network Level

Pavement management at network level is concerned with the entire system of pavement network. At this level, questions pertaining to *which* pavement sections should be maintained, and *how* and *when* they should be maintained, are tackled, taking into consideration the state of the whole pavement network, available resources and operational constraints. The main concerns at this level of management include the current and future network pavement condition as well as level of service, priority setting of maintenance and rehabilitation, and programming of maintenance and improvement activities. Very often the maintenance of a group of pavements within a network (or sub-network) is put under the charge of an agency. For very large networks such as that in countrywide, regional or municipal road networks, pavements are usually further divided into several sub-networks, with each taken care of by one highway agency.

Budget allocation at network level pavement management normally refers to the distribution of available budget to different projects under consideration in a particular network. To ensure the optimal use of available funds at network level, maintenance and rehabilitation activities (conveniently called projects) for the whole network are selected and scheduled in such a way that will give the highest return for a given funding level. This is usually referred to as pavement maintenance programming at network level. A large part of the previous research has focused mainly on this aspect of pavement management, with a wide variety of methods and approaches available in the literature.

c) Planning level

Apart from the project and network level, a third level, variably known as planning level, policy level or central office level is sometimes identified to highlight the budgeting process, general allocation of funds, and decision-making at the highest level of the management structure. This level is primarily concerned with policy-making and planning of long-term objectives taking into consideration political, social, environmental and economic factors. The allocation of budget for highway agencies responsible for different sub-networks is performed at this level of the management hierarchy.

All three levels of pavement management, in their own ways, are complex management tasks that are influenced by a variety of factors – technical, economic, social, political, and environmental – at varying degrees. Each level can be viewed as a precedent setting for lower levels of planning. The central office level will therefore produce a set of policies considering all networks in its jurisdiction, which provide a framework within which each network level pavement management takes place. Network level management, in turn, will constrain the options to be considered at the project level. Thus, another way of viewing the process is one of successive optimization whereby higher levels of management (and associated decision making) provide the constraints for sub-system optimization. These constraints provide the links that inter-relate each level of management. Therefore, two important levels of decision-making in pavement management will be of utmost importance in this research: network level and planning level.

The network- and planning-level optimizations can be combined into a global optimization that simultaneously considers the different objective functions and constraints at the two levels. A usual approach to solve this type of problem is to formulate it as a bi-level programming problem. This will be discussed in the next section.

2.2.2 Pavement Management as a Bi-level Programming Problem

Pavement management can be viewed as a bi-level programming problem with the upper level decision-making being the budgeting decisions of the planning level while the lower level involves the network-level pavement maintenance programming. A bi-level programming problem is a sequence of two optimization problems where the constraint region of the upper level problem is determined implicitly by the solution set of the lower level problem.

Mathematically, the bi-level programming problem is to find $(x^*, y^*) \in X \times Y$ such that (x^*, y^*) solves

$$\min_{x \in X} F(x, y) \tag{2.1}$$

subject to $$G(x, y) \leq 0 \tag{2.2}$$

And y is a solution of the following optimization problem for any fixed $x \in X$:

$$\min_{y \in Y} f(x, y) \tag{2.3}$$

subject to $$g(x, y) \leq 0 \tag{2.4}$$

The objective function $\min_{x \in X} F(x, y)$ is referred to as the upper-level problem, and $\min_{y \in Y} f(x, y)$ for any fixed x as the lower-level problem. In this study, the variables x in the upper level refer to the network-level pavement management decisions, while the lower level variables y are the amount of budget allocated to each region.

Bi-level programming problem leads to problem complexities not generally encountered in familiar single-level mathematical programming problems (Anandalingam and Friesz 1992). Bialas and Karwan (1984) showed that even a simple two-level resource control problem is non-convex, while Ben-Ayed and Blair (1990) showed that the bi-level linear programming problem is NP-hard, making it unlikely that there would be exact algorithms for it. A problem is said to be NP-hard if it can be polynomially reduced to a selection problem. Several types of optimality conditions and generalizations have been proposed based on different equivalent formulations. Various algorithms for the bi-level programming problem have been developed, such as the extreme point algorithm for bi-level linear programming, branch and bound methods for bi-level convex programming problem, complementary pivot algorithms, descent methods and penalty function methods. Chen (1992) and Vicente and Calamai (1994) gave a comprehensive review of these algorithms.

The non-convex and NP-hard properties of the bi-level programming problem make it one of the hardest optimization problems to solve. Even though various mathematical algorithms have been proposed to solve bi-level programming problems, the formulation and solution procedures are tedious and time-consuming. These mathematical programming approaches are also rigid, making it difficult to modify the constraints and objective function in the formulation of these algorithms.

Due to the above weaknesses, a non-traditional genetic algorithms approach will be proposed in this study to solve the bi-level optimization problem involving the network-level and planning-level optimizations. The solution technique and procedures will be given in Chapter 3. In the next section, current approaches used in allocating a global budget to several regional, provincial, or district road networks, which is the upper-level problem, are reviewed. The lower-level problem, which is the network-level pavement maintenance programming, is reviewed in Section 2.3.

2.2.3 Current Practices in Budget Allocation at Planning Level

The allocation of budget at the planning level is associated with the distribution of certain global resources to sub-network jurisdictions and road systems. In most countries, the allocation of budget is usually carried out by elected officials and their trusted civil servants, and the resources for allocations usually come from the State budget. The procedure and method for the allocation of budget in different countries highly depends on the administration/organization structures set up by the respective countries (OECD 1994).

In a typical pavement management situation, a network of pavements is usually sub-divided into several other sub-networks according to one or more factors, such as region, functional classes, administration boundaries, traffic demand, or types of pavement (Heggie and Vickers 1998, Saarinen et al. 1998). OECD (1994) defines two types of classification most commonly used by OECD countries – functional and administrative road classifications. The functional road classification divides the roads into motorways, main roads, collector roads, local roads, urban roads and private roads. The administrative road classification classifies roads into federal/national roads, state/provincial roads, county roads, city roads, rural community roads, and other roads. Usually, one or more classes of road networks are administered by an appointed highway agency. A majority of the funds for road works are allocated by the central administration, which could be the Ministry of Transport or relevant federal or state highway authorities. In some countries, local roads have the means to combine local and central funding.

The procedures for the allocation of funds to different road classes vary in different countries, with different authoritative structures, funding sources, and spending objectives. However, these approaches can be generalized into two basic approaches. The road fund can either allocate the funds using formulas or base the allocations on a direct assessment of need (Heggie and Vickers 1998). Apart from these two approaches, an analytical approach to budget distribution between regions and road classes based on shadow prices have been proposed by OECD (1994). The following sub-sections describe these approaches.

2.2.3.1 Formula-based Allocation System

A formula-based system usually starts by allocating the funds among the main, urban, and rural road agencies and then goes on to subdivide each allocation among the individual road agencies within each group. The road fund will therefore allocate a certain percentage of its revenues to urban roads and a certain percentage to rural roads, with the remainder going to the main road network. For example, Zambia allocates 25 percent of its road funds revenues for rural roads and 15 percent for urban roads (Heggie and Vickers 1998). After allocating the funds according to road type, each allocation is then distributed among the road agencies in each group.

There are two main ways of further distributing the funds to each agency in each group. Either each group agency must compete for the available resources or the resources are allocated on the basis of network and traffic characteristics. Under the first system the road agencies bid for the funds, which are evaluated by a panel. The panel will then decide the appropriate amount of funds each road agency should get. In this system, the bids cover both maintenance and investment programs. Hungary and Zambia use this system (Heggie and Vickers 1998).

Under the second system, revenues are allocated separately for investment and for maintenance. Investment funds are usually allocated using benefit-cost analysis. The road fund usually issues guidelines on how the investment programs are to be prepared, offers advice on how to compute the benefit-cost ratios, may specify the minimum acceptable benefit-cost ratio, and audits the calculations to ensure they have been carried out correctly. Revenues for maintenance, on the other hand, are allocated based on certain formulas that take into account network and traffic characteristics. Parameters such as length of the road network, volume of traffic, and ability to pay are often used. The formulas generally include road length (or lane-km), which may be for different types of roads as in Latvia (Heggie and Vickers 1998). They may also include vehicle-km or the vehicle population and will often include resident population. Some countries include a term to reflect ability to pay, such as in Korea. The U.S. Federal Highway Trust Fund includes a predetermined minimum maintenance allocation (Heggie and Vickers 1998).

Formula-based allocation systems, though simple and easy to use, does not address the maintenance needs of the pavement network. Parameters such as length of the road network, volume of traffic, and ability to pay are not indicative of the actual maintenance needs, since one region may have a large network of roads but only requires minimal maintenance due to low traffic volume. Similarly, the region with a large road network may be better off financially and does not require much assistance from the available central funds. Therefore, by allocating funds based on network characteristics alone is unlikely to achieve an optimal use of available funds.

2.2.3.2 Needs-based Allocation System

A needs-based approach commonly practiced relies on funds needed to repair all existing pavement distresses or deficiencies. In the needs-based allocation system, funds for maintenance and investments are allocated separately. For investments, evaluations are again based on benefit-cost analysis. Maintenance funds, though still allocated based on certain formulas, are administered according to a more careful assessment of network needs. The level of complexity of the methods depends on the technical capacity of the road agencies involved. The simplest way to estimate needs is by using standard unit rates for each routine and periodic maintenance activity according to type of road surface. Each rate is multiplied by each road agency's total length of road that requires maintenance in each road class to arrive at the total required maintenance budget. Adjustments may then be made for climatic variations and other factors. South Africa uses this method to estimate multiyear allocations for rural roads in her nine provinces (Heggie and Vickers 1998).

Another way to assess maintenance needs is by basing requirements on the output of a standardized road management system. Gáspár (1994) and Bakó et al. (1995) reported a compilation of the first Hungarian PMS that is capable of allocating funds to the regions. The allocation starts by first carrying out the countrywide distribution of available financial means according to intervention categories, pavement types, condition variants, and traffic sizes. This countrywide distribution is accomplished using an optimization routine in the PMS. The appropriate funds for each region are then determined based on a simple proportioning according to the shares of the total area of each regional highway sections among the entire national area with given parameters. These parameters are the average annual daily traffic, pavement type and condition variant.

The needs-based allocation system is a better reflection of the maintenance needs of the road network. However, this allocation procedure is unable to effectively recognize the differences in maintenance strategies that are likely to be adopted by different regions. Even though more sophisticated method and models enable these financial needs to be optimized taking into account system objectives such as long-term pavement performance, safety or societal impact, the level of financial need varies according to the system objective addressed. Different regions may have different system objectives. Allocation of budget to different regions in proportion to the level of their financial needs without addressing their respective system objectives would not arrive at an optimal solution system-wide.

2.2.3.3 Fund Allocation Approach by OECD

OECD (1994) proposed an analytical approach for the allocation and distribution of highway funds among regions or road classes. The method is based on the equalization of the shadow price, which aims to find the best use of agency cost for user benefits. The approach is illustrated in Fig. 2.1. First, a graph of user versus agency cost is plotted for each region/road class. Starting from the highest budget in each region/road class, the slope or shadow price of lowering the agency cost by one step is calculated. The region/road class with the least negative shadow price is chosen, and its agency cost is lowered one step further. The shadow prices are compared again, and this is repeated until the final budget level for all region/road classes has been reached.

The technique above is based on economic analysis rather than optimization. As such, it is designed for the management objective of minimizing the increase in user cost for every unit reduction in agency cost. It is not possible to customize and formulate the approach to reflect changes in the management objective, which is to be expected in an optimization problem.

2.3 Pavement Maintenance Programming at Network Level

Network level planning is described by Cook and Lytton (1987) as "a problem of many projects". As such, inter-project tradeoffs and budget limitations become of paramount importance in network level analysis. The greater complexity inherent in network level analysis (as compared to project level) is in fact attributable to these two features. Following Cook and Lytton's (1987) arguments, network level decision-making involves two types of planning, namely program planning and financial planning. Program planning is the what, when and how of maintenance alternatives, while financial planning is generally concerned with determining the level of funding needed in order to maintain the health of pavement network at some desired level. These two types of planning constitute the programming of pavement management activities.

Traditionally, the two most basic techniques for network level decision-making are the priority ranking approach (also known as prioritization) and optimization (Cook and Lytton 1987, Haas et al. 1994). In addition, decision-making capitalizing on artificial intelligence techniques has recently been employed in the field of pavement engineering, with several key applications in network level pavement management programming (Sundin and Braban-Ledoux 2001).

2.3.1 Priority Ranking Approach

Priority ranking approach is the most widely used programming method in pavement management systems. In a survey conducted in the United States, 77 percent of the state highway agencies adopted a prioritization model of some kind in their pavement management systems (Irrgang and Maze 1993).

Priority ranking is essentially a program planning tool, which rank projects according to their relative importance. The importance of each project is determined by how well the particular project could meet the needs specified by the pavement manager. The ranking of each project will help determine which projects to consider first and which to defer when financial situation does not permit all projects to be carried out in that financial year, which unfortunately, is always the case. This approach to priority ranking has the effect of maximizing benefits for a specified budget level.

An alternative approach to priority ranking is to determine the funding required to achieve a certain network pavement quality specified by the pavement manager. In this approach, projects are usually ranked according to the costs required for carrying out the projects, with higher priority given to the lower cost projects. This way, the resulting network level maintenance strategy will have the effect of minimizing maintenance costs subject to a specified level of quality. Several pavement management systems have the capability of developing priority programs in either the cost minimization or effectiveness maximization mode (Haas et al. 1994).

The simplest form of priority ranking is based on subjective judgment, which is a quick and simple method that is subject to bias and inconsistency, and thus, the results can be far from optimal. Better ways to priority rank projects is to base it on parameters associated with maintenance needs such as serviceability and deflection, or parameters associated with economic analysis. Various works that prioritize road sections according to their maintenance needs has been reported by Schoenberger (1984), Mercier (1986), and Fwa et al. (1989). In addition, Sharaf and Mandeel (1998) gave an analysis of the impact of different priority setting techniques on network pavement condition.

In the priority ranking approach, program planning and financial planning are considered separately and sequentially (Cook and Lytton 1987). As such, all decisions are actually project level decisions, with network decisions being the sum of several project decisions. Priority ranking approach could not effectively evaluate inter-project tradeoffs and select appropriate strategies that satisfy budget constraints. Consequently, truly optimal maintenance strategies could not be obtained using priority ranking. This shortcoming led to the use of the optimization approach, which simultaneously schedules, budgets and evaluates intra- as well as inter-project trade-offs.

2.3.2 Optimization Approach

A survey conducted in 1991 reported that only 28 percent of the state highway agencies in the United States used optimization models for their PMS (Irrgang and Maze 1993). The unpopularity of the optimization approach could be due to the large computation capacity required and a general lack of understanding on the role of optimization in PMS (Thompson 1994). However, a promising 19 percent of the state highway agencies surveyed indicated their intention to have an optimization model in their PMS in the future.

Optimization primarily deals with problems of minimizing or maximizing a function of several variables usually subject to equality and/or inequality constraints.

In pavement management, however, the role of optimization is not restricted to the quantitative analysis of a given mathematical equation, but also involves the analysis of political, engineering, and economic judgments of several decision makers (Thompson 1994). A number of factors are usually considered for optimization in pavement management systems, such as policy, program and resource allocation for various maintenance strategies. In order to perform optimization, it is necessary to express the desired objective mathematically in the form of an objective function. At the network level pavement management system, probable objectives include, among others, preservation of pavement condition, maximizing user comfort, maximizing network pavement condition, minimizing agency and/or user costs, and maximizing the utilization of equipment and/or manpower. Similar to the priority ranking approach, network optimization systems can also be used either to minimize cost given a set of one or more performance standards, or to maximize benefits for a given budget level, or a combination of the two.

One of the first pavement management systems that successfully employ network level optimization was developed for use in Arizona (Golabi et al. 1982). The Arizona PMS was considered a real breakthrough in the optimization approach to pavement management as it successfully reduced the size of the problem, which was the main barrier in earlier attempts. This is achieved by dividing the road networks into classes, which are further sub-divided into discrete condition levels or states. This classification eliminates the need for exhaustive project-level analyses to be incorporated into the network level optimization. Since then, subsequent optimization methods have assumed a similar approach (Kher and Cook 1985, Hajek and Phang 1989).

Optimization models can be grouped into static models and dynamic models (Cook and Lytton 1987). The static models are those where system parameters such as pavement performance as well as planning for rehabilitation and maintenance are static i.e., remain unchanged with time. On the other hand, dynamic models consider variable pavement conditions at different state or time, which is more realistic. In the domain of static optimization models are integer programming (Fwa et al. 1988) and linear programming (Davis and Dine 1988). Dynamic models, on the other hand, include probabilistic dynamic programming (Thompson et al. 1987) and dynamic programming with the Markov process (Butt et al. 1994, Takeyama and Hoque 1995, Li et al. 1995).

Traditional optimization methods, which include integer programming, linear programming, and dynamic programming, have several limitations that restrict their attractiveness. One of these limitations is the difficulty in problem formulation, where changes in the objective function and addition/reduction in the number of constraints would require extensive reprogramming. This difficulty severely restricts the flexibility of traditional optimization methods in solving real-world problems, where changes to the problem characteristics are often inevitable. In addition, traditional optimization methods require large computation capacity, which in turn result in long computation time. The artificial intelligence approach to network level programming is able to overcome these limitations and will be discussed in the next subsection.

2.3.3 Artificial Intelligence Approach

Recent advances in artificial intelligence have made their impact on pavement management systems, with applications in almost all levels of decision-making. Basically, artificial intelligence (AI) is the method of imitating the thought processes of humans and natural processes to solve specific problems. AI is comprised of expert systems, artificial neural networks (ANNs), fuzzy logic, and genetic algorithms (GAs). The following is a brief review of these expert systems and their applications in network level pavement management.

a) Expert Systems

Expert systems are designed to perform as an expert human in a particular field. An expert system is composed of two components, the knowledge base and the inference engine. The first component is the power of the expert system where all empirical and factual information are contained. The second component, the inference engine, searches through the knowledge base to find the optima for each sub-goal and thus, the entire problem. The major differences between the expert system and traditional computer programs are described by Ritchie (1987) as: i) the domain knowledge is separated from the inference mechanism; ii) the manipulation of knowledge is primarily symbolic rather than numerical; iii) and the more transparent representation of process and knowledge, which is manifested in a transparent knowledge and an explanation facility. The applications of expert systems to PMS have been reported, among others, by Antoine et al. (1989), Sinha et al. (1990), and Wang et al. (1994).

Expert systems are knowledge-oriented systems that are better suited for empirical and factual data. As such, it is not an appropriate tool for network level optimization tasks, where most computations are performed on numerical data.

b) Artificial Neural Network

Artificial neural networks were originally developed to imitate the decision-making process of the human brains. Just as humans apply knowledge from past experiences to solve new problems, a neural network has the ability to learn from past experiences and apply them in a new problem situation (Zurada 1992). A neural network consists of an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the animal neuron. Usually, a few layers of nodes are used. By providing an initial training data set, which consists of both input and the desired output, the nodes are made to learn the relationship between input and desired output through a series of error correction. Hence, the neural network will be able to deduce an expected output from any given input in a new problem situation. Fwa and Chan (1993) described an application of artificial neural networks to the priority rating of pavement maintenance needs. Zhang et al. (2001) also presented a study based on neural network coupled with genetic algorithms to analyze the implications of prioritization in pavement maintenance management.

Due to its learning capability, neural network is a powerful tool for pattern recognition and prediction applications, particularly when noisy data is involved. However, neural network is not meant as a tool for optimization purposes, as there is no functionality in neural network for searching and evaluating the search space in an optimization problem.

c) Fuzzy Logic

Fuzzy set theory was first introduced by Zadeh (1965) to mathematically represent uncertainty and vagueness, and provide formalized tools for dealing with the imprecision intrinsic to many problems. The decision-making process of fuzzy logic resembles human reasoning in its use of approximate information and uncertainty to generate decisions. By contrast, traditional computing demands precision down to each bit. Since knowledge can be expressed in a more natural way by using fuzzy sets, many engineering and decision problems, which are highly subjective, can be greatly simplified. Fuzzy set theory implements classes or groupings of data with boundaries that are not sharply defined (i.e., fuzzy). Any methodology or theory implementing *crisp* definitions such as classical set theory, arithmetic, and programming, may be fuzzified by generalizing the concept of a crisp set to a fuzzy set with blurred boundaries. The benefit of extending crisp theory and analysis methods to fuzzy techniques is the strength in solving real-world problems, which inevitably entail some degree of imprecision and noise in the variables and parameters measured and processed for the application. The application of fuzzy logic to pavement condition rating and maintenance needs assessment was described by Fwa and Shanmugam (1994).

d) Genetic Algorithms

Genetic algorithm is a powerful AI optimization technique that has been applied to pavement management. The GA is a stochastic global search method that is formulated based on the principles of natural selection (Holland 1975). GAs operate by cycling a random pool of feasible solutions through a number of generations so that better and better solutions are hoped to be evolved through each generation. This way, a pool containing the best solutions is hoped to be obtained at the end of the cycle. The method of moving from one generation to another is based on ideas borrowed from Darwin's principle of evolution.

Genetic algorithms are powerful tools widely used for optimization problems. They do not have the rigidity and computational complexities of traditional optimization methods. The robust search characteristic and multiple-solution handling capability of genetic algorithms are additional advantages of this optimization approach. The application of genetic algorithms to network level programming of maintenance activities has been extensively studied by Chan et al. (1994) and Fwa et al. (1994a, 1994b, 1996). Hoque (1999) and Fwa et al. (2000) extended the use of GA for the programming of pavement maintenance activities to include multiobjective optimization. A more extensive review of genetic algorithms will be given in the following section.

2.4 GENETIC ALGORITHMS IN PAVEMENT MANAGEMENT

2.4.1 Background of GAs

The desire to create systems and computers that mimics natural processes has led to biologically inspired research that, over the years, have developed into several fields known collectively as artificial intelligence. Genetic algorithms are one of these powerful tools that have been widely used to solve many real-world problems.

Holland (1975) was recognized as the first person to put computational evolution on a firm theoretical footing. In his 1975 book "Adaptation in Natural and Artificial Systems", Holland presented the genetic algorithm as an abstraction of biological evolution and gave a theoretical framework for adaptation under the GA. The traditional theory of GAs as introduced by Holland (1975) is based on the notion that good chromosomes (i.e. good genetic strings) tend to be made up of good building blocks, termed as schemas (or schemata). By discovering, emphasizing and recombining good schemas through such genetic operators as mutation, crossover, and inversion, better chromosomes are hoped to be produced as the population mature from one generation to another. The whole cycle of searching, modifying and recombining the better solutions through each generation is based on the basic principle of survival of the fittest in the theory of evolution.

Unlike other evolutionary computation research such as evolution strategies and evolutionary programming, Holland's (1975) original idea of genetic algorithms was not meant to solve specific problems, but rather to formally study the phenomenon of adaptation as it occurs in nature and to model such adaptation mechanisms using computer systems. The mathematical framework that Holland (1975) formulated was first experimentally proven by DeJong (1975). Since then, much work has been done on the theoretical foundation of GAs (see Goldberg, 1989; Rawlins, 1991; Whitley, 1993; Whitley and Vose, 1995).

As the science of genetic algorithms matures over the years, variations of genetic algorithms have been applied to a diverse range of scientific and engineering problems and models. Successful application of GAs in these and other areas has fuelled growing interest among researchers in many disciplines.

2.4.2 GAs versus Traditional Methods

GAs differ substantially from more traditional search and optimization methods in several aspects. The following is a brief outline on the differences that sets GAs apart from traditional methods:

- GAs search a population of points simultaneously, not a single point.
- GAs use probabilistic transition rules, not deterministic ones.
- GAs work on an encoding of the parameter set rather than the parameter set itself (except in cases where real-valued individuals are used).

- GAs do not require derivative information or other auxiliary knowledge; only the objective function and corresponding fitness levels influence the directions of search.

2.4.3 Basic Terminologies and Mechanics of GAs

GAs borrowed the vocabulary from the natural genetics. In GAs the most important genetic structure is the *chromosome*, which is essentially a candidate solution to a problem. The chromosome can be conceptualized as a string made up of blocks of cells called the genes. Each gene encodes a particular character of the candidate solution (e.g. the color of the eye) while the possible value of a gene is termed as the *allele* (e.g. brown, black, green, etc.). Each gene is located at a particular *locus* (position) on the chromosome. A complete set of chromosomes is called the *genotype*.

A group of chromosomes forms a *population* of candidate solutions. The quality of each candidate solution is evaluated based on how well it satisfies a predefined objective function. The evaluation value of each candidate solution is then mapped to a fitness value, which represents how “fit” the candidate is in relation to other solutions in the population. From this population, only the fitter of the candidate solutions will survive to the next generation. In every generation, new solutions (*offspring*) are generated from the fitter solutions (*parents*) using such genetic operators as mutation, crossover, and inversion. More on these operators will be discussed in the next section. As the population moves from one generation to another, better and better solutions are hoped to be evolved until the cycle stops on reaching a certain stopping criterion.

An important step in the GA process is in encoding the problem parameters to represent the problem as a string of chromosome. There is no universal encoding technique for all sorts of problems. Koza (1990) noted that: "Representation is the key issue in genetic algorithm work because the representation scheme can severely limit the window by which the system observes the world". The chromosomal representation must ensure that all necessary parameters are completely represented by the genotype.

Generally, after chromosomal representation and evaluation function formulation, the GA machinery proceeds step-wise as follows (Davis 1991, Freeman 1994):

1. Initialize a pool of solutions, known as parent pool.
2. Determine the fitness of each of the solutions in the parent pool by means of the evaluation function.
3. Select parent solutions for the creation of the next generation with a probability relative to their fitness.
4. Create new solutions (offspring) by means of genetic operators on the selected parent solutions.
5. Use a selection scheme to form a new parent pool for the new generation.
6. Check whether stopping criteria are met. If not, go back to step (2). Otherwise, stop the search and print the best solution.

2.4.4 Genetic Operators

In GAs, genetic operators are employed to establish a bridge through which good properties from the good parents can be transferred to their offspring and hopefully the new offspring will possess better properties than their parents. A large number of genetic operators have been used in GAs. Three of the most commonly used operators: crossover, mutation and inversion will be described here.

a) Crossover

The most commonly used genetic operator is known as the crossover operator. Crossover does not generate new alleles. It only exchanges some of the existing alleles between two chromosomes. The role of crossover in producing new offspring is two-fold, one is called *idea*, and the other, *mechanics* of crossover (Jones 1995). The idea of crossover is the hope that building blocks from two individuals may be combined into an offspring whose fitness exceeds either parent. The mechanics of crossover is the process by which an attempt is made to implement this idea. All forms of crossover share similar idea, but the mechanics may vary considerably. Such variations occur particularly when strings do not have fixed length.

b) Mutation

The mutation operator is another most commonly used genetic operator. Mutation does not create any new structure. Its role is to find bits lost by crossover. Therefore, crossover is the driving force, while it is mutation's responsibility is to keep the pool well stocked. Mutation is an important operator in genetic algorithms as it helps push the search effort into different search spaces by introducing new (and unexpected) allele values into the string structure, thus creating new possibilities that might not have been created in the initial pool of solutions. This is an important feature that provides the global search characteristic inherent in genetic algorithms.

c) Inversion

Another operator is known as the inversion operator. The inversion operator chooses two points on a genotype, and the operation is performed by cutting the genotype at those two points and swapping the end points at the cut section. Similar to crossover, inversion does not generate new, unexpected alleles, but only reshuffles some of the existing alleles. Unlike crossover, however, inversion only reshuffles alleles from within a single chromosome. Thus, its effect is not so much as to direct the search in a *coarse* manner as mutation and crossover, but rather, to further *refine* the search within a more confined space. Therefore, the inversion operato r could not be used entirely on its own without the other operators (crossover and mutation) to obtain good solutions. The roles of these operators are more complementary than autonomous.

2.4.5 Selection Scheme

In each generation of GA, only certain strings will be selected for reproduction. The manner in which the strings are selected for reproduction in the next generation is called the *selection scheme*. In any GA, the selection scheme employed will determine the quality of the population in the subsequent generations. Thus, a proper selection scheme plays an important role in GA by improving the average quality of the population (Blickle and Thiele 1995). To prevent any premature convergence, an efficient selection scheme that provides accurate, consistent and efficient sampling needs to be applied (Baker 1985, 1987).

In order to increase the quality of the population in the next generation, better individuals are given a higher chance to be selected and copied into the next generation. These better individuals are determined based on a comparison of their fitness values. In simple selection schemes, the parent genotypes would be assigned a probability number (of being selected) based on the ratio of its fitness value and the aggregate fitness of the parent pool. One form of such simple selection schemes is the roulette selection, where all genotypes are fitted onto a biased roulette wheel, with the fitter genotypes occupying a bigger portion of the wheel. This way, the fitter genotype would always dominate the selection process, though less fit genotypes still stand a chance to be selected nonetheless. This ensures that highly fit genotypes always get more chances to transfer their properties to the next generation.

Various other selection schemes have been reported in the literature. DeJong (1975) explored some interesting selection schemes that include the elitist model. In the elitist model, the best genotype is always preserved into the next generation to ensure the best individual is always brought forward as the evolution proceeds. Brindle (1981) also explored other variations of selection schemes. These variations include: (i) deterministic sampling, (ii) remainder stochastic sampling without replacement, (iii) stochastic sampling without replacement, (iv) remainder stochastic sampling with replacement, (v) stochastic sampling with replacement, and (vi) stochastic tournament or Wetzel ranking. Booker (1982) suggested that variation (ii) was superior to variation (iii). Variation (ii) has also been used by Goldberg (1989) and Michalewicz (1992). The study by Baker (1985) showed that the ranking method performed relatively well as a means to prevent premature convergence. Baker (1987) proposed another selection scheme known as the Stochastic Universal Sampling (SUS) algorithm to reduce bias and increase efficiency as he found the “remainder stochastic sampling without replacement” model to be severely biased.

2.5 MULTI-AGENT SYSTEMS (MAS)

2.5.1 Background of MAS

Multi-agent systems or MAS is a very new field of study with only around 20 years of history. Multi-agent systems research is concerned with coordinating intelligent behavior among a collection of autonomous intelligent *agents* aiming at solving a given problem (Bond and Gasser 1988). While still being categorized as a part of *distributed artificial intelligence* (DAI) more than 10 years ago (Bond and Gasser 1988), MAS is increasingly being recognized as a discipline of its own in recent years. According to Ferber (1999), the multi-agent approach lies at the crossroads of several disciplines, of which the two most important ones are *distributed artificial intelligence* and *artificial life* (AL).

Notions of Distributed Artificial Intelligence (DAI) can be said to begin with the inception of AI in the 1950s, when the conceptual basis for concurrent processes based on artificial intelligence was developed (Bond and Gasser 1988). At that time, there were two main approaches to AI – heuristic search using list processing methods, and neural net modelling. These two approaches were the earliest research that point in the direction of concurrent models of intelligent behavior. By the late 1970s, the first phase of research into DAI came into full swing with works by Lenat (1975) and Hewitt (1977). Since then, several important systems have made great impact on future multi-agent systems. These include the Distributed Vehicle Monitoring Test (DVMT) by Lesser and Corkill (1983), the Mace system by Gasser et al. (1987), and the Contract Net by Smith (1979). These systems became the foundations on which many future works are based on. A very good summary of DAI research and development can be found in Bond and Gasser (1988) and Moulin and Chaib-Draa (1996).

In contrast to the cognitive approach that is characteristic of DAI, artificial life puts the emphasis on behavior, autonomy and, above all, the issue of viability (Ferber 1999). The field of artificial life extends over several topics, including that of cellular automata, evolutionary algorithms, and the study of collective phenomena based on the interaction of several reactive agents. Research works in artificial life attempts to obtain complex collective behavior through very basic communications that consist of simple propagations of signals with no intrinsic significance or representations. The agents in artificial life are reactive rather than cognitive, which means the agents are not individually intelligent but respond to stimulus based on simple conditions and rules. It is the collective reaction to events that lead to intelligent behavior overall. Examples of work on artificial life include the study of anthill by Corbara et al. (1993) where a colony of ants coordinate among themselves to solve complex problems without any one ant having authority or planning power over the rest.

Other research fields that have influenced the development of MAS include distributed systems and models of concurrency, and automation and robotics. Today, research in MAS has expanded in many different directions with many applications in a diverse range of disciplines such as computer science, speech acts, game theory, economics, social sciences, and the manufacturing domains, among others. Ferber (1999) provides a good summary of the current trends in MAS research and of certain school of thoughts which are developing in this area.

2.5.2 Definitions and Terminologies

A multi-agent system can be defined as "a loosely-coupled network of problem solvers that work together to solve problems that are beyond their individual capabilities" (Durfee et al. 1989). These problem solvers, often called *agents*, are autonomous and may be heterogeneous in nature, where different agents may have varying degrees of problem solving capabilities. A central theme in MAS is the coordination among agents, particularly concerning how they can coordinate their knowledge, goals, skills and plans jointly to take action or to solve problems.

Ferber (1999) defines MAS as a system that comprises an environment, a set of objects, an assembly of agents, an assembly of relations which link objects and agents to each other as well as among themselves, an assembly of operations for the agents to operate on the objects, and operators. The set of objects are situated and passive, i.e. they can be perceived, created, destroyed and modified by the agents, while the agents themselves are specific objects representing active entities of the system. *Purely communicating MAS* is a special case where all objects are agents and there is no environment. In purely communicating MAS, the agents do nothing except communicate, as can be found in software modules. Another special case exists when agents are situated (having a position in the environment) but do not communicate by sending messages but only by the propagation of signals. These are called *purely situated MAS*.

The term *agent* has been used vaguely in the literature. To date, there is no formalized definition of agent that is globally accepted, but the characterization by Wooldridge (1997) has been widely referred to among researchers: *"An agent is an encapsulated computer system that is situated in some environment and that is capable of flexible, autonomous action in that environment in order to meet its design objectives"*.

A more elaborate description was given by Wooldridge and Jennings (1995). According to this description, agents are: (i) clearly identifiable problem solving entities with well-defined boundaries and interfaces; (ii) situated (embedded) in a particular environment – they receive inputs related to the state of their environment through sensors and they act on the environment through effectors; (iii) designed to fulfill a specific purpose – they have particular objectives (goals) to achieve; (iv) autonomous – they have control both over their internal state and over their own behavior; (v) capable of exhibiting flexible problem solving behavior in pursuit of their design objectives – they need to be both reactive (able to respond in a timely fashion to changes that occur in their environment) and proactive (able to act in anticipation of future goals).

An agent can be characterized by its *architecture* and by its *behavior*. The architecture of an agent refers to its physical structure which gives it certain capability to accomplish its designated actions. The agent's architecture characterizes its internal structure, that is, the principle of organization which subtends the arrangement of its various components. The behavior of the agent is characterized by the actions that the agent manifests in its environment and in response to particular situations. It is akin to the function that an agent is capable of. The behavior of an agent is actually largely determined by its architecture. The behavior is seen as an external specification for the agent, with the architecture defining the internal relationships making it possible to arrive at this specification (Ferber 1999).

2.5.3 Cognitive versus Reactive Agents

An agent can be designed to be cognitive or reactive. Cognitivity and reactivity are important properties of an agent which directly defines its behaviors. *Cognitive agents* are agents that are 'intelligent' and have a knowledge base, allowing them to solve complicated problems in a relatively individual manner. These agents are capable of carrying out tasks and handling interactions with the other agents and their environment. Cognitive agents have goals and explicit plans that allow them to achieve their goals (Ferber 1999).

Reactive agents, on the other hand, have no representation of the universe in which it is operating and cannot carry out *a priori* reasoning by itself (Ferber 1999, Müeller 1998). These agents merely react to the situation, having no individual sophistication. Their strength comes from their capacities for adaptation and evolution which emerge from the interactions between their members. Reactive agents are part of the artificial life school of thoughts described in Section 2.3.1.

The cognitive/reactive distinction is not a categorical opposition but rather represents two extremities of a straight line segment. Fig. 2.2 shows the two extremes between purely cognitive agents and purely reactive agents and the distinctions in between. Both extremes do not give rise to the best performing systems, and current interest lies in trying to balance between the two. Balance can be achieved by constructing cognitive agents based in reactive organizations, or by creating agents which have both cognitive and reactive capacities at the same time.

2.5.4 Types of Agent Architecture

Many different agent architectures have been reported in the literature. These can be categorized into several types, of which the most common ones will be described here.

The *modular horizontal architecture* is one of the most widespread architectures (Ferber 1999). Most architecture proposed for cognitive agents are based on the overall concept of horizontal modules linked by pre-established connection. This architecture is conceived as being an assembly of modules, each carrying out a specific horizontal function. The most widespread modules include, among others, perceptive and motor functions, sending and interpretation of communications, beliefs base, management of obligations, expertise of skill domain, management of goals and decision making, and planning of actions. Fig. 2.3 shows a typical example of the horizontal module architecture. In the ascending phase, signals coming from the environment through sensors are filtered to obtain information of a more and more abstract nature, until it can be integrated into the modellings of the agent. The highest function is carried out by the decision-making module, which decides to act on the basis of the data it receives and in accordance with its own objectives. In the descending phase, the planning module determines the actions that need to be carried out to attain the selected objective. These are then transmitted to the execution module.

The *blackboard architecture* (Nii 1986a, 1986b, Corkill et al. 1986) is another one of the most common architectures used for cognitive multi-agent systems. A blackboard system is usually partitioned into several levels of abstraction, and agents working at a particular level of abstraction have access to the corresponding blackboard level along with the adjacent levels. In that way, data that have been synthesized at any level can be communicated to higher levels, while higher-level goals can be filtered down to drive the expectations of lower-level agents (Moulin and Chaib-Draa 1996).

The blackboard model is based on a division into independent modules which do not communicate any data directly but which interact indirectly by sharing data, in a way similar to a blackboard. A blackboard-based system comprises three subsystems – the knowledge sources, the shared base (the 'board'), and a control device for managing conflicts of access to the shared base among the knowledge sources. Blackboard architecture has numerous advantages, including great flexibility in describing modules and articulating their functioning (Ferber 1999). It was one of the earliest systems conceived in the distributed artificial intelligence domain in the Hearsay II system (Erman et al. 1980) and later the DVMT system (Lesser and Corkill 1983). In the DVMT system, a collection of identical blackboard-based systems were used to solve problems of monitoring and interpreting data from a set of sensors at spatially distributed locations which covers a region (Lesser and Corkill, 1983).

The subsumption architecture is first proposed by Brooks and Connell (1986). In contrast to modular horizontal architecture which divides an agent into horizontal modules, subsumption architecture breaks an agent down into vertical modules, each of them being responsible for a very limited type of behavior. This architecture is used to describe reactive agents (Müeller 1998).

Other architectures include the competitive tasks structure (Drogoul and Ferber 1992), production systems, classifier-based systems, connectionist architectures, dynamic systems, and multi-agent systems based architectures. A comprehensive survey of existing agent architectures can be found in Müeller (1998). In this thesis, multi-agent system will be used as a research tool rather than a research subject. Therefore, an existing multi-agent system architecture, named Cougaar (BBN Technologies 2002a, 2002b, Brinn et al. 2001), will be used for the purpose of this research. Cougaar is a component-based agent architecture that describes cognitive agents. The architecture of this system is described in detail in Chapter 4.

2.5.5 Distributed Problem Solving and Planning

Distributed problem solving and planning is a subfield of distributed artificial intelligence. It considers how the work of solving a particular problem can be divided among a number of modules, or "nodes" that cooperate at the level of dividing and sharing knowledge about the problem and about the developing solution (Lesser and

Corkill 1987, Smith and Davis 1981). Due to an inherent distribution of resources such as knowledge, capability, information, and expertise among the agents, an agent in a distributed problem-solving system is unable to accomplish its own tasks alone, or at least can accomplish its tasks better when working together (Durfee 1999). A task is said to be accomplished better if it is accomplished more quickly, completely, precisely, or certainly. In a pure distributed problem solving system, all interaction (cooperation and coordination) strategies are incorporated as an integral part of the system.

In distributed problem solving, agents need to *want* to work together, that is, a fair degree of group coherence needs to be present either by specifically designing the agents to work collectively, or by instilling a motivation among agents to work together by giving them payoffs that can only be accrued through collective efforts. Another important element in distributed problem solving is *group competence*, that is, agents need to know how to work together well (Durfee 1999).

Two classes of distributed problem-solving strategies are used widely in the literature: task sharing and result sharing strategies. In task sharing, a task is decomposed and shared among a group of agents to be collectively accomplished. The main idea of a task sharing system is to break down a complex problem into smaller, less complicated sub-problems which can be simultaneously solved by multiple agents with different abilities, skills or expertise. In result sharing, multiple agents perform the same tasks on the same problem to arrive at independent results which are shared and compared to achieve a high level of confidence, completeness, precision and timeliness.

The multi-agent system approach which will be presented in this thesis is relevant to the distributed problem solving and planning domain where the agents are specifically designed to function as a group rather than be fully autonomous. A task sharing strategy is used to decompose and distribute the main problem into several network-level pavement management optimization problems. The multi-agent system approaches are explained in Chapters 4 and 5 of the thesis.

2.6 RELEVANT PAST RESEARCH

2.6.1 Multi-Network Budget Optimization in PMS

In existing literatures, optimization (decision-making) at different levels of management is often considered separately. Therefore, constraints imposed by higher management, such as budget availability and quality requirements, are often treated as fixed variables for lower management optimization problems. Such approaches, though valid for within-network optimization of maintenance activities, could not guarantee optimality (or near-optimality) when several networks linked by a global fund are concerned. Several attempts have been made to overcome this problem.

One notable attempt was reported by Wang and Zaniewski (1994). They used Dantzig-Wolfe decomposition algorithm (Dantzig and Wolfe 1960) to hierarchically solve a global optimization problem for 15 road categories linked by an annual statewide budget. Each sub-problem as well as the master problem has its own constraints, but they all share a common objective of minimizing agency costs. The procedure involves an iteration of feasible solutions between the master program and sub-programs, which can be interpreted as a coordination of sub-problem actions by the master problem using prices set on available resources. This study can be considered as an attempt to integrate pavement optimization at the planning level (allocation of funds between different road categories) with that at the network level (optimization within each road category). However, the solution procedure can only solve for a single objective function which is shared by all sub-problems. In a real-world situation, the sub-problems are more likely to have different goals and needs which should be reflected in the optimization process. The use of linear programming also makes the solution procedure rigid and difficult to adapt to changing problems.

Alviti et al. (1994) reported an enhancement to the original network optimization system (NOS) that has the capability to allocate funds for maximum benefit across the entire road network. The enhanced NOS, called the linked model, uses Dantzig-Wolfe decomposition algorithm to obtain the optimal allocation of statewide budget for different road categories. The solution involves a finite number of iteration between a master coordinator (top-level manager who allocates the budgets) and independent sub-problems (maintenance activities for different road categories) where a certain negotiation process takes place until a compromise (state of stability) is reached. The enhanced NOS, however, does not consider the different objective functions that may be adopted by the different sub-problems. As a result, the different needs and goals of the sub-problems are not considered effectively.

Another work on the use of decomposition algorithm for hierarchical maintenance programming was reported by Worm (1994) in his doctoral dissertation and again by Worm and van Harten (1996). Their work, however, does not involve the allocation of funds between different pavement sub-networks. Here, decomposition algorithm is used to handle the complexities that arise from the attempt to integrate several elements into the objective function. Thus, even though the procedure solves the fund allocation problem hierarchically, the problem of multi-objective multi-regional highway allocation of fund is not considered here.

In a more recent work, Bonyuet et al. (2002) presented a methodology that simultaneously investigates both pavement and bridge management systems under limited budget resource. The research focused on the design of highway management systems (HMS) that would integrate a pavement and a bridge management system into a single system. It determines how much should be invested in the rehabilitation of each road section, and which bridges should be replaced or rehabilitated, in order to minimize total user travel costs without violating budgetary constraints. The main focus of this work is on the integration between pavement and bridge management systems and does not tackle the problem of multi-regional pavement management. Nevertheless, it provides a good reference on the use of mixed non-linear programming approach to solve hierarchical optimization problems.

The budget allocation problem, being an age-old issue, has also been extensively studied outside the realm of pavement management. One work in particular, which deals with regional allocation of budget, is worth noting here. In their work, Corbett et al. (1995) developed a hierarchical budget allocation procedure to allocate funds for site decontamination projects in different regions. Two major concerns were addressed: i) decentralization of responsibilities, where each region is responsible for selection and execution of projects within their own regions, while the central level allocates funds for each region; and ii) minimum information flow between regions and central government. A two-stage heuristic procedure using integer and dynamic programming was used to solve the hierarchical budget allocation. The first stage analysis is the optimization of regional strategies for a given number of budget levels, while in the second stage, the central level divides the total available budget based on summary information produced by each region in stage one, such that the overall environmental effects are maximized. This approach, in contrast to the traditional price- or resource-directed procedure where a true tandem of repeated optimization between region and central levels would emerge, involves only one iteration of information exchange between central and regional levels per planning period. The solution procedure, however, is formulated based on the premise that all regions assume the same objective function that is in line with the central objective. This may not be true in a situation where greater decision-making responsibility is given to the regional authorities. The procedure is also limited by the rigidity of mathematical programming approaches used in formulating the problem.

2.6.2 Genetic Algorithms in Pavement Management

The application of genetic algorithms in pavement management was first reported by Chan et al. (1994), Tan (1995) and Fwa et al. (1994a, 1994b, 1996). These works at the National University of Singapore studied the application of natural evolutionary algorithms for pavement management activities optimization. It was found that GA can handle the network optimization problem of pavement management activities effectively.

Hoque (1999) studied the constraint-handling aspect of genetic algorithms for network-level highway maintenance optimization. A new constraint-handling method called the Prioritized Resource Allocation Method (PRAM) was introduced to handle the complex and highly constrained problems commonly found in network programming in pavement management. PRAM differs from traditional GAs in that the chromosome string encodes more than the number of decision variables, and the GA in PRAM does not work on the value of the decision variable directly. The performance of PRAM was tested on an example problem, and compared with common constraint-handling methods. In his paper, Hoque (1998) explained the concept of the penalty method as a constraint-handling technique in the application of GA to network-level pavement maintenance programming. A practical example problem consisting of planning maintenance activities for four highway types over a 45-day planning period was solved to demonstrate the use of the penalty method in a genetic-algorithms application to network-level highway optimization problem.

Fwa et al. (2000) later extended the application of genetic algorithms in pavement management to include multiobjective optimization. The concepts of Pareto optimal solution set and rank-based fitness evaluation were adopted and a numerical example problem was solved for two- and three-objective optimization respectively. The proposed algorithm was able to produce a set of optimal solutions that were well spread on the Pareto frontier. Other works on the application of GAs on network-level pavement management include Yuge et al. (1998) and Chou and Tack (2002).

2.6.3 Related works in Multi-Agent Systems

Multi-agent systems are increasingly becoming an essential tool for distributed decision-making. At the time of writing, no references have been found on the use of multi-agent systems in budget allocation for pavement management. There are, however, numerous applications of multi-agent systems in similar budget allocation problems encountered in other research domains. The references given here are not meant to be exhaustive but to show a precedent on the use of multi-agent systems on similar type of problems and also to give some insights into how this is achieved.

Arbib and Rossi (2000) discussed a methodology for the optimal allocation of resources to a manufacturing system in a multi-agent environment. They showed that quantitative decision-making can be implemented by the agents using a new spur system based on dual pricing to stimulate agents to propose alternative service configurations in order to improve the current resource allocation established at the supervisor level. Their proposed approach is claimed to be different from existing literature in that it uses mathematical properties of the model to guarantee or approximate an optimal behavior of the agents with respect to both local and global objectives. A basic negotiation protocol is defined, which involves both resource bidding and agents cooperation. They concluded that the multi-agent systems approach turns out to be more profitable than conventional centralized approach, with global improvement noted in both computational efficiency and solution.

In a more recent paper, Gorodetski et al. (2003) considered a multi-agent approach for resource allocation and scheduling of shipping logistics benchmark problem known as Vehicle Routing Problem with Time Windows (VRPTW). The solution algorithm proposed includes auction-based resource allocation and scheduling, distributed reallocation algorithm and distributed version of the "look ahead" algorithm. The VRPTW MAS was carried out with the use of a multi-agent platform called Multi-agent System Development Kit, MASDK, developed by the author(s). Two conclusions were drawn from this research. The first is that the reallocation procedure improves the results approximately from 10 to 15%. Secondly, great time-saving is achieved for one of the problem sets using the multi-agent systems compared to conventional branch-and-bound method, even though the optimal solution obtained from MAS is slightly inferior to that of the latter.

Cicirello and Smith (2002) applied two models inspired by the natural self-organization of the wasp colony for the coordination of factory operations in a decentralized manner. The “routing wasp model” was used for the allocation of tasks or jobs in product flows, while the “scheduling wasp model” was used for dynamic scheduling of jobs for a specified objective function. In the models, the multi-agent coordination mechanisms are modelled as an adaptive process based on two aspects of wasp behavior: 1) self-coordinated task allocation and 2) self-organized social hierarchies. The performances of the models were found to be superior compared to state-of-the-art for the problems examined.

There have also been applications of genetic algorithms in multi-agent systems. Cardon et al. (2000) presented the application of genetic algorithms in multi-agent systems for a job-shop scheduling problem. Their problem considers the goal of minimizing the delays and advances for all jobs according to the “due dates” given by the manager according to their (jobs’) objectives. While the scheduling is achieved using genetic algorithms to optimize for multiple objective functions, the agent is modelled based on the contract-net protocol to improve a solution corresponding to a Gantt diagram. In their approach, each agent represents a genetic entity, or a solution string, in the genetic algorithm, which is used to drive the physical evolution of the agents through reproduction between agents. A three dimensional graph was plotted showing the value of the economic function (their objective functions) according to the number of agents and the number of genetic operations used by agents. Cardon et al. (2000) concluded that the modelling of an agent as a completely autonomous genetic entity is the beginning of what can be an interesting research area in the field of artificial life.

Drezewski (2003) presented a co-evolutionary multi-agent system (CoEMAS) where two or more species co-evolve in order to solve a given problem. In CoEMAS, there exists two different species: niches and solutions. All agents live in 2D space, which has the structure of discrete torus, with each node connected to its four neighbors. Agents that represent niches are located in nodes and cannot change their locations, while agents representing solutions are also located in nodes but they can change their locations by migrating from node to node. A concept called ‘*life energy*’ was introduced as a resource for which individuals compete to guide the migration of agents from one node to another. Agent starts reproduction, searches its neighborhood for partner and then new agent is created via mutation and crossover, all of which requires *life energy*. The application of the CoEMAS has been demonstrated on multi-modal function optimization using four test functions. Results showed that the system is able to properly detect and stably maintain the peaks of these test functions.

2.7 RESEARCH NEEDED AND SCOPE OF PROPOSED RESEARCH

2.7.1 Summary of Review

Budgeting decisions in pavement management involves several levels of inter-related decision-making, which can be seen as a hierarchical optimization problem. In this study, the planning and network levels have been identified as the two important levels of decision-making in pavement management that will be considered. The problem can thus be formulated as a bi-level programming problem where the upper-level problem is the budget allocation problem of the planning level and the lower-level problem is the network-level pavement maintenance programming problem.

A review of the current practices in budget allocation at the planning level of a pavement management system has been given in this chapter. These approaches can be generalized into two main approaches, the formula-based and the needs-based allocation system. The formula-based approach uses formula and percentages to determine the funds to be distributed while the needs-based approach proportions fund based on financial needs of the different pavement sub-networks. Both these approaches do not arrive at the optimal usage of central fund. A third analytical approach was proposed by OECD (1994). The method is based on microeconomic principles and recognizes the hierarchical nature of decision-making at the different management levels. However, the method is not based on optimization analysis and it is not designed to handle other objective functions than minimization of user costs, which may not be the main concern for some highway agencies.

The network-level pavement maintenance programming, which is the lower-level problem in the bi-level formulation of the multi-network pavement management problem, is the programming of pavement management activities pertaining to the what, when, and how of maintenance alternatives. The two most basic approaches used for network level pavement maintenance programming are the priority ranking approach and optimization approaches. Recently, artificial intelligence techniques have also been used for pavement management programming at the network level.

Genetic algorithms are a stochastic optimization technique that are first used by Chan et al. (1994) and Fwa et al. (1994) in the pavement management programming at the network level. The ease-of-use and robustness of the technique makes it an attractive alternative to mathematical programming to solve NP-hard optimization problems. Better results are reported by researchers who studied the use of genetic algorithms for network-level pavement management programming. As a result, more and more applications of genetic algorithms in pavement management have been found in the literature recently. Multi-objective analysis of pavement management has also been successfully performed using genetic algorithms (Fwa et al. 2000). The simplicity, robustness and ability to solve NP-hard multi-objective problems make genetic algorithms a highly suitable tool for the multiple objectives, multi-agency problem considered in this research.

Multi-agent system is a new field of study that offers a coordinated approach to solving distributed problems. Multi-agent systems are a group of problem solvers that work collectively to solve problems that are beyond their individual capabilities. The application of multi-agent systems for optimal resource allocation has been given a lot of attention due to recent technological advances. In many cases, automated negotiation has been a main issue with resource optimization using multi-agent systems. A negotiation protocol is usually applied to guide the bargaining and negotiation process towards equilibrium or mutually acceptable agreement. This provides an elegant solution to the multi-level decision-making scenario inherent in pavement management, where interactions among decision-makers are essential in simulating the 'negotiation' process between the different levels of management to arrive at a globally optimal budget allocation strategy.

2.7.2 Further Research Needed

Budget allocation in pavement management is a hierarchical optimization problem where the higher levels of management provide the constraints for sub-system optimization. These constraints become the links that inter-relate each level of management. In existing literatures, optimization (decision-making) in pavement management has often been considered separately for the different levels involved. Therefore, constraints imposed by higher management, such as budget availability and quality requirements, are often treated as fixed constraints for lower management optimization problems. Such approaches, though valid for within-network optimization, could not guarantee optimality (or near-optimality) when several networks linked by a global fund are concerned.

Solving the above calls for a global optimization approach that simultaneously optimize the global fund based on the objective functions and constraints of both upper- and lower-level managements. While several good attempts have been made in the literature to accomplish this, they do not effectively consider the needs of the pavement sub-networks. Regional highway agencies, for example, are more likely than not to have different needs and priorities due to differences in various aspects, which may include states of development, operational characteristics, availability of resources, and development and management strategies of each region. Ideally, the optimization process needs to recognize the lower-level objectives of each regional highway agency along with the higher-level objectives of the central administration.

Hierarchical optimization problems as described above are often treated as a bi-level optimization problem where decomposition algorithms based on mathematical programming approaches are used. However, the main drawback of such approaches is that they could not exemplify the inherent cooperation and negotiation process that takes place among decision-makers in arriving at the mutually agreeable (and supposedly optimal) solution. Solving the bi-level optimization problem through mathematical approaches is also a tedious process, and the approach is rigid – the problem formulation is not easily modifiable to solve for different problem sets. A better and more elegant approach to solving bi-level optimization problem in pavement management is sought.

Recent advances in the science of distributed artificial intelligence have enabled the concept of agency to be applied in the study of resource optimization. In this arena, great efforts have been put into the study of coordination and negotiation among autonomous agents. This notion of agency fits well into the hierarchical and distributed nature of pavement management where highway agencies in both central and regional levels strive to achieve independent goals but are bound by the same global fund. Each agency has its own agenda, resources and constraints, and they need to coordinate among themselves in order to make the best use of the available global fund. Multi-agent systems offer an attractive alternative for tackling the problem of multi-objectives, multi-level, and multi-agency pavement management without compromising the interaction process that takes place. However, no attempt has been made in this direction.

This thesis is an effort aimed at studying the global optimization of pavement maintenance fund using advanced artificial intelligence techniques. The scope and methodology used in this thesis is described in the next section.

2.7.3 Scope of Proposed Research and Methodology

The primary objective of this research is to study the optimization of a global central budget to several regional highway agencies for pavement maintenance purposes. The main considerations in this study are:

- The objectives and management goals of the various decision makers at the upper and lower management levels are different. The fund allocation strategy derived should best meet regional and central goals subject to various operational and resource constraints.
- The distributed nature of the problem. In a typical setting, regional highway agencies are geographically distributed. Therefore, data pertaining to the pavement and network-level specific information are likely to be stored in separate databases in the respective regional highway agencies. The fund allocation procedure should take this into consideration.
- Integration of information among decision-makers. The effect of information integration will be studied in this thesis. This is achieved using multi-agent concepts to enhance the optimization process by allowing interactions among the lower-level decision-makers.

In this study, the budget allocation problem for highway agencies is divided into three classes according to level of complexities:

a) *Class 1: Sequential two-step optimization approach*. In the first phase of the research, a simple two-step allocation procedure will be formulated using sequential genetic algorithms. In this approach, there will only be a single passing of information from regional agencies to the central authority. This approach is well-suited for situations where limited interaction between decision makers is desired. The procedure formulated here will set the stage for subsequent allocation approaches.

b) *Class 2: Distributed multi-agent vertically integrated optimization approach*. Here, the fund allocation procedure is modelled using multi-agent technology. An agent is used to represent each decision-maker at each management level. An iterative approach is adopted to simulate the actual interactive coordination process between the central authority and regional agencies to arrive at a satisfactory proportion of budget for each agency.

c) *Class 3: Distributed multi-agent vertically and horizontally integrated optimization approach*. A more comprehensive approach incorporating vertical as well as horizontal interaction is formulated. The multi-agent approach from the previous phase of study is further improvised to handle a more complex fund allocation that includes horizontal sharing of resources. This approach will incorporate cooperation among regional agencies to share idle resources among them in order to attain greater benefits for all.

This research will focus on the fund allocation methodology. A simple two-level road management organization consisting of three regions is used as hypothetical example problem. At this stage of the research, the scope will be limited to the allocation of maintenance fund only and a planning period of one-year.

Genetic algorithms are chosen as the optimization tool for this research for its flexibility in handling variations in the objective function and constraints, which are useful to accommodate the variety of goals and constraints adopted by the different decision-makers. Moreover, at any iteration genetic algorithms contain a population of possible solutions, which might be more important than obtaining an isolated optimum in view of possible political, social or other restrictions that might render the best solution unpractical. Multi-agent system is used in the later part of this research to incorporate interaction and coordination capabilities into the fund allocation process among spatially-distributed decision-makers. It is able to provide the means for automated coordination among decision makers situated in different geographical locations.

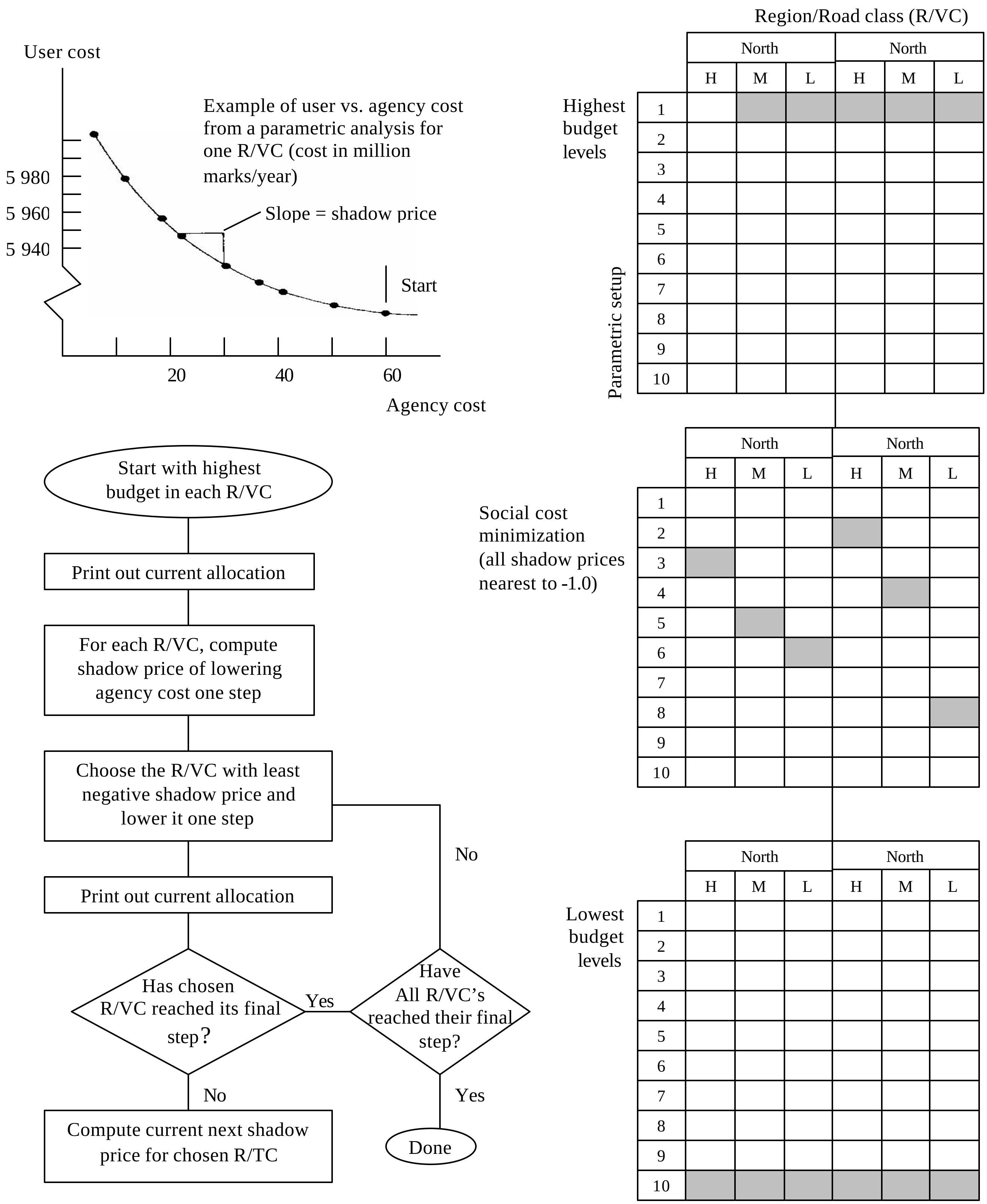


Fig. 2.1 Budget distribution between regions and road classes according to OEEC (1994)

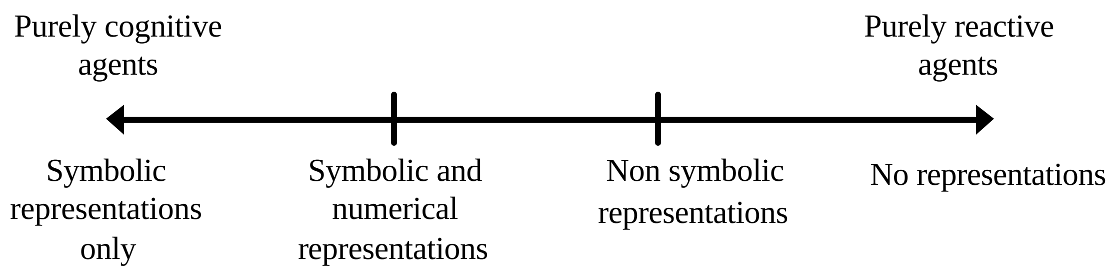


Fig. 2.2 The cognitive/reactive distinction as two extremities of a straight-line segment (Ferber 1999)

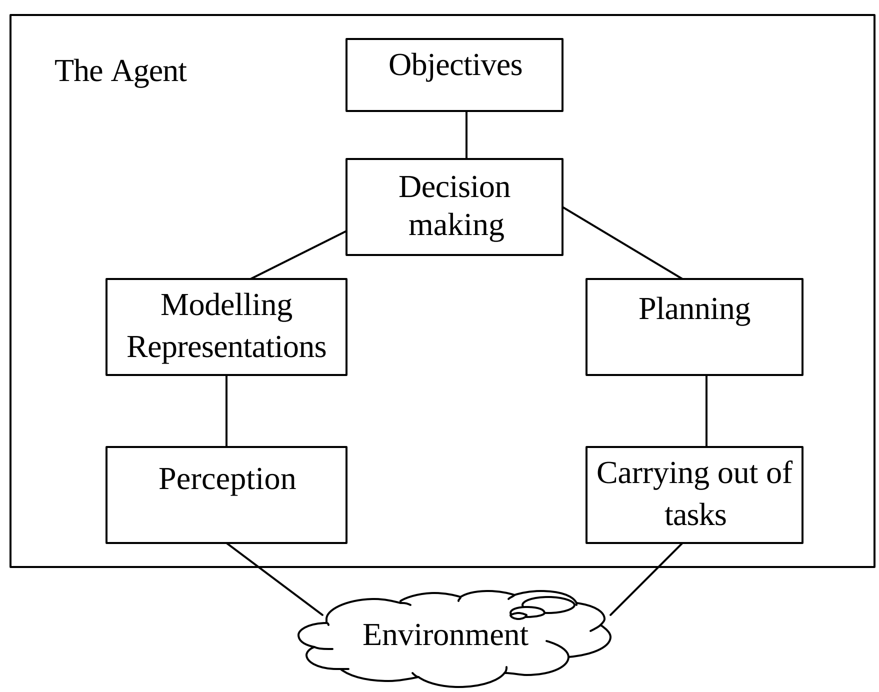


Fig. 2.3 Characteristic representation of an agent with horizontal modular architecture (Ferber 1999)

CHAPTER 3

TWO-STEP GENETIC ALGORITHMS OPTIMIZATION APPROACH

3.1 INTRODUCTION

In practice, the basis for pavement maintenance fund allocation among different road sub-networks has been mainly empirical and subjective. Conventional fund allocation approaches usually allocate funds based on the proportion of road length in each road sub-network or the proportion of funds needed by each road sub-network.

A two-step optimization approach for budget allocation in multi-regional highway agencies using two-step genetic algorithms is presented in this chapter. The proposed method allocates pavement maintenance fund from a central authority to regional highway agencies with the central and regional objectives considered in the evaluation function of the optimization routines. Based on hypothetical example problems, the solution procedure of the proposed approach is given and its performance compared with that of typical conventional allocation procedures.

3.2 DESCRIPTION OF TWO-STEP GA OPTIMIZATION APPROACH

The two-step analysis technique takes into account the different goals of the central administration and the regional agencies. The first step analysis considers the needs and funds requirements of the regional agencies. Given the state of network pavement conditions, the desired objective function, and operational and resource constraints of a particular region, a genetic algorithm optimization computer program is developed to derive the optimal pavement maintenance strategy for a specified maintenance budget. This analysis is repeated to obtain the corresponding optimal maintenance strategies for different budget levels over the range of possible maintenance budgets. By this process, a database that relates the optimal maintenance strategy with the level of maintenance budget for all the regions concerned can be established.

The second step analysis considers different fund allocation strategies by the central administration. The input to this step of the analysis includes the available total budget, objective function, constraints and requirements of the central administration, as well as the budget-maintenance strategy database established in the first step analysis for the regions. Fig. 3.1 shows the main steps of the analysis. For a trial allocation strategy, the allocated funds for each region can be computed. Using the allocated funds as input, the maintenance strategy for each region is obtained from the budget-maintenance strategy database. From the maintenance strategies of all the regions, the system objective function value of the central administration for the entire system-wide road network can be derived. This analysis process can be coded as another genetic algorithm optimization computer program to arrive at the final optimal fund allocation strategy. The formulation and working of the genetic algorithm optimization processes for the first and second step analysis respectively are explained in the next section using a numerical example.

3.3 APPLICATION OF THE TWO-STEP GA OPTIMIZATION APPROACH

3.3.1 The Hypothetical Example Problem

To study the performance of the two-step optimization approach, a hypothetical pavement management problem described by Fwa et al. (1998) is considered. The original problem is modified to include a two-level road management organization structure consisting of a central highway administration and three regional road agencies. The analysis deals with allocation of the available pavement maintenance budget at the central administration to the three regional agencies. It addresses the global network level pavement management goal of the central administration, as well as pavement maintenance budget needs, constraints of resources (including manpower and equipment) and pavement distress conditions at the regional level. The regional highway agencies are responsible for the selection and execution of pavement maintenance programmers, for which a budget is allocated to each by the central authority.

For comparison with other allocation approaches, three cases of different regional road data are generated in this study. The three cases use separate data sets with different network characteristics and varying road conditions, as described in the following:

Case 1: Regions having comparable total road length and network pavement condition.

Case 2: Regions having similar total road length but vastly different network pavement condition.

Case 3: Regions having vastly different total road length and network pavement condition.

Case 1 is intended as the baseline case for "normal" circumstances where all regional road networks are of about the same size and condition. The other cases are used to portray the circumstances under which the conventional approaches could be "deceived" into suboptimal funds allocation policy. The maintenance costs required are calculated based on road conditions in each region. A summary of the three cases is given in Table 3.1.

The pavement maintenance management objectives of the three regional agencies are given as follows:

Region 1 -- Maximizing the number of distressed road segments repaired

Region 2 -- Maximizing the performance level of regional road network pavements

Region 3 -- Maximizing the usage of the available manpower

At the central level, the overall available budget and the overall pavement conditions of the entire road network are the main concerns. The objective function of the central administration in this example problem is to maximize the overall performance level of the entire road network covering the three regional networks.

3.3.2 Planning Data for Regional Networks

The hypothetical problem considers a planning period of one year. Road segments in each region comprise two classes of road, namely expressway and arterial roads. For easy presentation, each segment is assumed to have only one distress type. Three distress types (namely cracks, ruts and potholes), and three levels of distress severity (namely low, medium and high) are considered. All road segments have the same length of 1 km and two lanes per traffic direction. Table 3.2 lists the distribution of distress types and distress severity levels in the three regions for the three cases.

There are four types of manpower (supervisors, laborers, equipment operators and drivers) and six types of equipment (dump trucks, pickup trucks, crew cabs, distributors, rollers and pavers). Table 3.3(a) and 3.3(b) list the manpower and equipment required for each repair activity while the maintenance costs and production rates are given in Tables 3.3(c) and 3.3(d) respectively. The manpower and equipment available in each region were about 80% of the required resources.

3.4 GENETIC ALGORITHM FORMULATION

3.4.1 GA String Structures

The decision variables of a problem are represented in GAs by a string structure similar to the chromosomes in natural evolution. At the regional level for the example problem, the decision variables pertain to the choice of road segments selected for maintenance. An appropriate string structure is one that consists of one cell for each road segment as shown in Fig. 3.2(a). The total length of the string structure (i.e. the number of cells) is therefore equal to the number of road segments of the region concerned. The value of each cell gives the maintenance decision taken for the road segment that the cell represents. A value of 1 for the k^{th} cell means that the k^{th} road segment is selected for maintenance, while a value of zero indicates that the road segment is not selected for maintenance.

At the central level, the decision variables are simply the percentage shares of budget allocation for the three regions. As shown in Fig. 3.2(b), there are only 3 cells. The values of the genes represent the shares of budget that will be allocated for each region.

3.4.2 Objective Functions and Constraints for Step 1 Analysis

As the objective functions and constraints of the three regions are different, the GA formulation and optimization analysis are performed independently. This section presents the mathematical expressions of objective function and constraints for each region. For Region 1, the objective function is to maximize the number of distressed road segments repaired, that is,

$$\text{Maximize } \sum_{j=1}^{N} x_j \qquad (3.1)$$

where x is either 0 or 1, depending on whether or not road segment j is selected for maintenance. The objective function is subject to the following constraints,

- The manpower needed for the maintenance program must not exceed the available number in each manpower category. The following constraint is checked for every manpower type:

$$\sum_{j=1}^{N} m_{pj} x_j \leq M_p \tag{3.2}$$

  where m_{pj} denotes the number of man-days required of manpower type p for road segment j, and M_p denotes the total available man-days for manpower type p. N is the total number of segments in the region considered while x_j is the binary decision variable that indicates whether or not segment j is selected for maintenance.

- The equipment required for the maintenance program must not exceed the available number in each equipment category.

$$\sum_{j=1}^{N} q_{ej} x_j \leq Q_e \tag{3.3}$$

  where q_{ej} denotes the work-days required of equipment type e for road segment j, and Q_e the available work-days of equipment type e in the region considered.

- The total maintenance expenditure must not exceed the total budget allocated, as given by,

$$\sum_{j}^{N} C_{jr} x_j \leq B_r \tag{3.4}$$

where C_{jr} is the maintenance cost incurred in road segment j of region r, N the total number of road segments in the region, and B_r the budget allocated to region r.

For Region 2, the objective function is to maximize the performance level of regional road network pavements given by,

Minimize (Regional network PDI after maintenance)

where PDI is the Pavement Damage Index. To compute the regional network PDI or the total weighted PDI, the PDI for individual road segments must first be calculated. The pavement damage index PDI_{jd} of road segment j for distress type d with distress value D_d is given by the following expression:

$$PDI_{jd} = \frac{D_d}{(\text{Terminal Value})_d} \times 100\% \tag{3.5}$$

The value of PDI lies within the range of 0 and 100. The higher the PDI value, the worse is the distress condition. Table 3.4 gives the distress values for different distress conditions and their respective terminal values. The regional network PDI is calculated as follows:

$$\text{Network PDI} = \frac{\sum_{j}^{N} (PDI)_j F_j}{\sum_{j}^{N} F_j} \tag{3.6}$$

where N is the total number of road segments in the region considered, and F_j the weighting factor equal to the sum of ($f_{Dj} + f_{Sj} + f_{Cj}$) as defined in Table 3.5. Thus, the objective function for Region 2 can be expressed as

$$\text{Minimize } \frac{\sum_{j}^{N} PDI_{jd}F_j - \sum_{j}^{N} PDI_{jd}F_j x_j}{\sum_{j}^{N} F} \times 100 \tag{3.7}$$

The objective function of Region 3 is to maximize the usage of the available manpower. This is achieved by maximizing the total man-days assigned in the maintenance program as follows, assuming that different manpower categories carry equal weights:

$$\text{Maximize } \sum_{j}^{N}\sum_{p}^{P} m_{pj}x_j \tag{3.8}$$

where P is the total number of manpower types considered.

The constraints for Regions 2 and 3 are also given by Eqs. (3.2) to (3.4), except that the value of the total number of road segments N, and the limits of the available resources M_p, Q_e, and B_r would change accordingly.

3.4.3 Objective Functions and Constraints for Step 2 Analysis

In the Step 2 analysis, the aim is to identify the best fund allocation proportions for the three regions such that the overall network pavement performance level covering the three regions would be raised as much as possible with the available budget. Expressing the performance level in terms of network PDI as defined by Eq. (3.7), where N' represents the total sum of road segments of the three regions, the objective function is

$$\text{Minimize } \frac{\sum_{j}^{N'} PDI_{jd}F_j - \sum_{j}^{N'} PDI_{jd}F_j x_j}{\sum_{j}^{N'} F} \times 100 \tag{3.9}$$

The only constraint in this step of analysis is that the sum of the funds allocated to the three regions cannot be more than the total budget available to the central authority.

3.5 GA PARAMETERS AND METHOD OF ANALYSIS

The general steps involved in the steps 1 and 2 GA optimization analyses are shown in the flow chart in Figs. 3.3(a)–(b). The optimization analyses for the three regions were conducted independently. The results from the optimization of regional networks (Step 1 analysis) are used to perform the central optimization (Step 2 analysis). The GA optimization program was developed using a GA library *PGAPack* (Levine 1996). PGAPack allows different settings of the parameters to enhance the performance of the search algorithm.

3.5.1 Sensitivity Study of GA Parameters

In order to determine the set of GA parameters that will produce good solution sets for this example problem, a sensitivity study was carried out. Parameters that were studied include population size, offspring size, mutation rate and crossover rate. An experiment was also conducted to determine whether the mutation and crossover operators should be used simultaneously, or only either operator should be used at a time. For the purpose of this sensitivity study, the data set of road network characteristics and road conditions of Region 3 from Case 1 was selected for experimentation. Similar parameters are then adopted for all three regions for all three cases. The objective of maximizing the utilization of manpower is adopted, with the budget level set at S$140,000. This amount was selected such that budget will not be the limiting constraint in the search for solution. The idea was to stretch the solution space with respect to the other constraints so that the number of feasible solutions is as large as possible, and hence greater search difficulty.

A total of ten pool sizes were studied to determine the appropriate population size for the example problem. For this purpose, the offspring size was maintained at 80% of the population size, while mutation and crossover rates were left at the default values set by PGAPack. The default value for mutation rate is the reciprocal of the string length (in this case 2%) while the default crossover rate is 85%. Crossover was only performed on strings that did not undergo mutation. The pool sizes ranged from 100 to 1000 in increments of 100. The results are shown in Fig. 3.4, where it can be observed that slower convergence was obtained for population sizes of 300 and less. For pool sizes of 400 and above, increase in performance can still be seen, albeit less significantly. The best performance occurred when the population size is maintained at 900. Hence, a population size of 900 is adopted for the example problem.

The effect of offspring size was studied next. This was done by keeping the population size at 900, mutation rate at 2%, and crossover rate at 85%. Mutation and crossover were again applied exclusively of each other. A total of seven offspring sizes were tested. Fig. 3.5 showed that the GA performance increases with an increase in offspring size up till it is 90% of the population size. At 100% where all parent strings are replaced by offspring, the GA performance decreased. This could be due to the fact that none of the good parents are retained in the next generation when a 100% replacement strategy was adopted. Therefore, a replacement strategy of 90% of population size is adopted.

The experiment on whether mutation and crossover should be applied simultaneously or exclusively of one another were done based a population size of 1000 and replacement strategy of 90% from the population size. Mutation and crossover rates were maintained as before. The results are shown in Fig. 3.6. Apparently, the GA performed best when both mutation and crossover were applied simultaneously. This is because the application of both operators at the same time induces the search mechanism to cover a wider range of solutions.

With the appropriate population size and offspring pool size determined, and both mutation and crossover operators identified for simultaneous use, the next parameter to be set is the mutation operator. The effect of mutation rate on the GA convergence is shown in Fig. 3.7. From the plot, it was obvious that a higher mutation rate actually helped the GA to converge faster. However, the experiment also showed that high mutation rates result in sub-optimal results, where a 100% convergence could not be reached when the GA terminated. This is because high mutation rates reduce the ability of the GA to refine its search even though a wider range of solution is explored more quickly. The only mutation rate that could give a 100% convergence is the default value, i.e. 2% in this case. Thus, it was decided that a mutation rate of 2% be used for the example problem. In this case, the lost in convergence rate is deemed insignificant compared to sub-optimal results.

The final parameter to be determined is the crossover rate. Four crossover rates were tried, and the results shown in Fig. 3.8. It was found that crossover rates of 85% and 95% produced almost comparable rates of convergence, whereas 75% and 65% crossover rates gave slightly slower convergence. In choosing the appropriate crossover rate, a smaller value is deemed a better choice than a higher one, since a higher crossover rate, similar to high mutation rate, contains higher possibility of producing sub-optimal results. Hence, the crossover rate of 85% is chosen for the example problem.

Thus, the final GA optimization for step 1 analysis was run with the number of population maintained at 900, where 90% of these (810 strings) were replaced at each generation. The initial pool of solutions was randomly generated, including a do-nothing solution with all decision variables set to zero. The GA crossover and mutation operators were employed simultaneously to generate offspring solutions. The mutation rate was the reciprocal of the string length (2%) while the crossover rate adopted was 85%. Trial runs have shown that convergence could be achieved within about 100 iterations. The stopping criterion was chosen to be 100 iterations for each budget level. Budget levels were increased in steps of $1000 until 10 consecutive increases had produced no improvement in the evaluation value.

The Step 2 analysis involved shorter string structures, and it was found that satisfactory solutions could be obtained with a population size of 800, with 500 solutions replaced by new offspring every iteration The same crossover rate, mutation rate, and stopping criteria as those adopted for the first step of the analysis were found applicable. For both Steps 1 and 2 of the optimization, infeasible solutions were penalized by setting their fitness values as zero.

3.5.2 Initialization of GA Strings

The initialization routine in GA optimization is useful in starting the search on the right direction. In this research involving repeated analysis for different budget levels, a proper initialization was adopted to achieve efficient optimization analysis.

The initialization routine used in this research makes use of the best result from the immediate previous optimization run for the last budget level. In this case, the *most* *probable values* refer to the number of maintenance projects activated. Before the optimization iterates for the next budget level, the number of maintenance activation from the previous optimization (previous budget level) is recorded. This number is used as the probability function of the number of maintenance activation for the next budget level. Almost all (90% probability) of the GA strings will be initialized to contain this probability of maintenance activation. The rest of the GA strings (approximately 10%) are direct copies of the previous best solutions. This approach is most suitable for this problem since the starting point of all regional optimizations is at budget level S$1000, which is the lowest budget level with the probability of maintenance activation virtually zero. Thus, all strings are always initialized to zero at the beginning of all optimization runs.

The idea behind this approach is that the best solution for a particular budget level will also always be one of the better solutions, if not still the best, for the next budget level. By starting the search here, the search efficiency is greatly amplified. Results showed that the GA almost always found the best solution within about 10 generations when this initialization routine was used. Without this initialization routine, convergence was hard to achieve, usually resulting in premature convergence.

3.6 COMPARISON WITH CONVENTIONAL ALLOCATION APPROACHES

Two typical conventional allocation procedures, based on formula- and needs-based approaches respectively, is used as a basis for comparison with the proposed two-step GA approach. The formula-based approach considered employs a simple and yet frequently used formula calculated according to the proportion of the regional road length to the total road length of all regions. According to this formula, the percentage of funds P_r to be allocated to region r, can be expressed as follows:

$$P_r = \frac{\sum_{j}^{N} L_{jr}}{\sum_{r}^{R}\left(\sum_{j}^{N} L_{jr}\right)} \times 100\% \tag{3.10}$$

where L_{jr} denotes the length of road segment j in region r, N is the total number of road segments in the region considered, and R is the total number of regions involved.

The needs-based approach allocates central funds according to the proportion of funds needed by each region to repair all distresses in the region. The formula is expressed as follows:

$$P_r = \frac{C_r}{\sum_{r}^{R} C_r} \times 100\% \tag{3.11}$$

where C_r is the total maintenance cost needed to repair all distresses in region r.

The above two allocation formulas are applied for the three cases of example problems described.

3.7 RESULTS OF ANALYSIS

3.7.1 Results of Step 1 of the Optimization Analysis

In the first step, the procedure outlined in Fig. 3.1 was applied to each of the three regions independently to establish the relationship between budget and optimal maintenance strategy. These relationships for the three regions for Case 1 are shown in Figs. 3.9(a)–(c) respectively. Fig. 3.9(a) shows that, for Region 1, the number of distressed road segments increased rather rapidly as the allocated budget increased from near zero to about S$7,000. Thereafter the rate of increase tended to level off. This is because the objective of maximizing the number of roads repaired had pushed for the lowest cost maintenance to be performed first. This means that when the budget was at a low level, a given quantum of increase in funds would repair more road segments than when the budget was at a higher level. The steps in the curve of Fig. 3.9(a) were caused by the fact that increments of the objective function value were always in whole numbers.

Fig. 3.9(b) gives the trend of optimal network damage index (PDI) of Region 2 with increasing budget. A steady fall in the network PDI occurred initially, and leveled off when budget becomes abundant. The optimization process picked the most severely distressed road segments for maintenance first. At high budget levels, any additional budget would be spent on repairing the low-severity road distresses that contributed little improvement in the PDI, hence the leveling off of the network PDI for high-allocated budgets. For Region 3, Fig. 3.9(c) shows that there was a steady increase in manpower employment until a certain budget level where all available manpower were committed.

The budget versus optimal maintenance strategy relationships for the other two cases are shown in Figs. 3.10 and 3.11 respectively. The trends of these relationships are the same with that of Case 1 with some differences only in the values.

3.7.2 Results of Step 2 of the Optimization Analysis

The relationship of maintenance strategy and allocated budget for each of the regions established in the preceding section offers a convenient database for the Step 2 analysis. Following the steps in Fig. 3.1 and the algorithm depicted in Fig. 3.3(a) and (b), the optimal shares of budget for the three regions are computed and they are presented in Fig. 3.12 (a)–(c).

In all three cases, Region 2 always gets a bigger portion of maintenance funds at extremely low total budget level. At this budget level, where the total fund ranges from S$10,000 to about S$30,000, spending the available fund in Region 2 would achieve the most improvement in PDI, since the objective function of Region 2 is the same as that of the central administration. This resulted in a highly unbalanced (but presumed optimal) allocation of budget where Region 2 received more than 70% of the funds in all cases. As the available budget increased, the bulk of the fund began to shift to either Region 1 or Region 3, depending on which region is able to contribute more towards PDI improvement. The total percentage of budget used began to taper off at S$140,000 for Cases 1 and 2, and at S$300,000 for Case 3 because the central budget has been increased to a point where constraints other than budget become binding, and any further increase in central budget could no longer improve the regional objectives. When this occurs, the proportion of budget allocated to each region becomes synonymous with the proportion of the sub-network size of each region, because the available manpower and equipment resources of each region were set to 80% of that required.

3.7.3 PDI Improvements from the Allocation Strategies

With the maintenance program from Step 1 and the allocation strategy from Step 2, the overall PDI improvements resulting from the funds allocation exercise at the central level can be determined. The overall network PDI is calculated by using equation 3.6 on all three regions. For each of the three cases considered, the PDI improvement achieved from the two-step GA fund allocation approach is compared against that from conventional approaches. These are shown in Fig. 3.13 (a)–(c). While Fig. 3.13(a) shows that the two-step GA and conventional approaches do not give rise to much differences in PDI improvements under "normal" circumstances (Case 1), Fig. 3.13 (b)–(c) indicate otherwise for the other cases.

In Case 2, the formula-based solution was "fooled" into allocating equal proportions of funds to all regions, even though the maintenance needs of each region is highly dissimilar as indicated by the network PDI values. Clearly, the formula-based solution is unsuitable for situations where the size of the road network is not proportionate to the road condition. The distribution of the different types and severity of distresses results in the maintenance costs required to repair all pavement distresses in each region being at a comparable level. Thus, the needs-based solution, which is based on the proportion of funds needed by each region, will also tend to allocate equal proportions to all regions. This results in a poor overall road condition as indicated by the overall network PDI values (after maintenance) shown in Fig. 3.13(b).

Case 3 is a unique case where the total weighted PDI of each region is almost equivalent, although the network size of each varies greatly. This results in the smallest region (Region 1) having the highest network PDI (worst pavement condition), and vice versa. The maintenance needs is proportionate to the network size. In this case, both the needs- and formula-based solutions will distribute the smallest portion of funds to Region 1 and the largest portion to Region 3. Fig. 3.13(c) shows that this may not be the best allocation strategy, since all the conventional funds allocation approaches result in poorer road conditions than the two-step GA at most levels of available funds.

In all three cases, the two-step GA approach consistently performed better than the two conventional allocation procedures. In Case 1, the maximum percentage of improvement on overall network PDI by the two-step GA approach is 5.15% and 4.81% more than that by the needs- and formula-based solutions respectively. The maximum difference in percent improvements achieved by the two-step GA in Case 2 are significantly higher: up to 17.83% and 17.23% higher than needs- and formula-based solutions respectively, while for Case 3, the two-step GA out-performed the needs- and formula-based solutions by a maximum of 19.73% and 19.13% respectively. The three cases also show that all the three allocation procedures perform comparatively well at high budget levels, because by then the funding level to each region will be sufficiently high to achieve high improvements in PDI, irrespective of the proportion each region received.

3.8 SENSITIVITY STUDY OF OBJECTIVE FUNCTIONS

The preceding sections have laid out the procedures of the two-step optimization analysis for highway funds allocation among regions based on a hypothetical example. The usefulness of the two-step optimization approach, however, is not limited to the allocation of fund only. The two step approach can also be used to study the effect on the allocation due to different strategies adopted by regional highway agencies. This is further illustrated in this section, with a sensitivity study on the effect of different regional objective functions on the final central allocation strategy. The problem similar to that described earlier in this chapter is used for this analysis.

3.8.1 Regional Pavement and Resource Data

As in the previous example, a two-level road management organization structure consisting of a central highway administration and three regional road agencies is considered. For the purpose of this analysis, however, all three regions will be assumed to have exactly the same characteristics in terms of the total number of road segments, distribution pattern of road distresses in the region, as well as manpower and equipment availability. This assumption is made to eliminate the effects of these characteristics on regional maintenance requirements and subsequent central budget allocation decision. The planning data of Case 1 Region 1 in the previous analysis will be used for all regions. The distributions of distress type and distress severity levels for all regions were given in Table 3.2 (for Case 1 Region 1). All other data including resource requirements, repair cost, production rate, distress severity and terminal values, and priority weights are the same as in the previous analysis (Tables 3.3 – 3.5).

3.8.2 Objective Function Considerations

Three objective functions as used in the previous analysis will be considered. These objective functions and their corresponding constraints were described in Section 3.4.2. In this analysis, different combinations of objective functions for different regions are analyzed. It must be noted here that since all regions have the same pavement and resource characteristics, a given set of 3 regional agency objectives, regardless of the pairing of region and objective, will have no effect on the analysis. For example, if objective functions a, b, and c are adopted by regions 1, 2, and 3 in that order, it makes no difference to the analysis whether the sequence is *abc*, *acb*, *cba*, *cab*, *bac*, or *bca*. Hence, there are altogether 10 different possible combinations of objective functions, as given in Table 3.6.

The objective function of the central administration is to maximize the overall performance level of the entire road network covering the three regional networks.

3.8.3 Genetic Algorithm Formulation

The analysis performed here used the same GA string structure as in the previous analysis as described in Section 3.4.1. All GA parameters such as population size, offspring size, mutation rate and crossover rate are also maintained at the values identified from the sensitivity study presented in Section 3.5.1. The problem is analyzed for a range of budget level and the initialization routine as described in Section 3.5.2 is used in this analysis.

3.8.4 Results of Objective Function Sensitivity Study

The first step of the analysis establishes the relationship between budget and optimal maintenance strategy of the three regions. These relationships are shown in Figs. 3.14(a)-(c). Since all three regions have similar network and resource characteristics, differentiations are made with regard to objective functions rather than regions. These curves exhibit the same characteristics as that observed in the first analysis, and explanations for the trends of the curves were given in Section 3.6.1. The relationships as shown in Figs. 3.14(a)-(c) are used for all 10 cases studied in this analysis.

The 10 cases of different combination of objective functions yield different allocation strategies as depicted in Figs. 3.15–3.24. From all the plots, it can be seen that the maximum consumption of budget for all three regions is around S$120,000 – S$130,000. From thereon, the total percentage of consumed budget tapered off even though the central budget increases. This occurs because the overall central budget has been increased to a point where constraints other than budget become binding, and any further increase in central budget could no longer improve the regional objectives. When this happens, all regions receive an equitable proportion of budget, irrespective of what objective they represent. It should be noted that the diminishing percentages of allocation do not mean that the amount of allocated budget has been reduced. Rather, the amount has been maintained at the maximum while the central budget increased, thus resulting in the diminishing percentage seen in the figures. The following sections present the results from these case studies.

3.8.4.1 All Regions Having Different Objectives

The case where all regions adopt different objectives from one another is illustrated by Case A (see Table 3.6 for description). Figs. 3.15(a) and 3.15(b) show the allocation strategy and network PDI of each region when all regions have different objective functions defined. This case is the same as that used in the earlier analysis, and the allocation strategies have similar characteristics. There are three distinct patterns of allocation over the range of central budgets considered. The first pattern occurs for total budget up to S$20,000, the second pattern occurs in zone 2 for total budget ranging from S$20,000 to S$50,000, and the third is in zone 3 for total budget beyond S$50,000.

In zone 1, the total budget is very low. Thus, the best strategy is to spend most of the funds on Region 2 where improvement in PDI is most rapid. At this low budget level, contributions by Region 1 and Region 3 are not competitive compared to Region 2 due to the objective functions adopted. As a result, a highly unbalanced allocation is effected, with Region 2 receiving more than 80% of the total funds. In zone 2, Region 3 begins to pick up momentum, giving more competition to Region 2 in terms of contribution to PDI improvement. Thus, the proportion of funds for Region 3 increased considerably. Region 1 only begins to receive increased share of the funds when the total budget reached S$50,000 in zone 3. The slower boost in the shares of allocation for Region 1 compared to Region 3 is in contrast with the previous analysis in Chapter 3, where Region 1 became competitive earlier than Region 3. With the objective function for each region in both these analyses being the same, the implication is that the network as well as resource characteristics actually play an important part in tipping the final allocation strategy.

The corresponding network PDI as shown in Fig. 3.15(b) follows closely the pattern of funds allocation. In this case, Region 2, which received the bulk of the funds in zone 1, has the lowest network PDI in the beginning. The network PDI for Region 3 began to drop when higher shares of the budget are given to it. Region 1 shows similar behavior for total budget of S$50,000 and beyond. Here, it is observed that when the maximum allocation for each region is reached, Region 2 always give the lowest network PDI, followed by Region 3 and then Region 1. Similar results were obtained in the previous analysis described in Section 3.7. This implies that all things being equal, the choice of objective function is the main factor to achieve the lowest possible network PDI.

3.8.4.2 All Regions Having Similar Objectives

Figs. 3.16(a), 3.17(a) and 3.18(a) show the analyses of the central allocation strategy when all three regions declared similar objective functions in their optimization routines (Cases B, C and D in Table 3.6). From these plots, it is clear that having regions with the same objective functions will result in an equitable budget allocation strategy in times of fiscal scarcity.

It should be noted here, however, that the plots are obtained as an average of several optimization runs. In actuality, the allocation tends to be biased to an arbitrary region, with an excessive amount of budget allocated to it, while other regions receive only small portions of the funds. This occurs because the central objective is always better achieved by investing most, if not all, of its available budget into one single region to achieve the best result, rather than relying on average results from several regions. Over several runs, all regions have equal opportunities to be chosen for the limited funds, thus resulting in equitable allocation after averaging off from these runs.

The corresponding network PDIs obtained from these plots are shown in 3.16(b), 3.17(b) and 3.18(b). As expected, the equitable allocation strategy resulted in all three regions achieving comparable network PDI. When the maximum allocation for each region has been reached (at around S$120,000), all regions show similar values for their network PDI.

3.8.4.3 Two Regions Sharing the Same Objective

This situation involves six cases, which can be further broken down into 3 each for each objective function being shared by any two regions. When two regions are sharing one objective function, i.e. having the same objective function, the study points towards the sensitivity of the objective function adopted by the other region.

Two Regions With Objective 1

Figs. 3.19 and 3.20 show the plots for the case where Region 1 and Region 2 adopt the objective of maximizing the number of road segments repaired, while Region 3 adopts the objective of minimizing network PDI (Case E, shown in Fig. 3.19) and maximizing the utilization of manpower, respectively (Case F, shown in Fig. 3.20). In both these plots, Region 3 is always given the highest portion of the funds when the central budget is very limited. The implication is that both the objective functions of minimizing network PDI and maximizing the utilization of manpower are more superior than maximizing the number of road segments repaired.

The corresponding network PDI plots in Figs. 3.19(b) and 3.20(b) shows that Region 3 always has the lowest network PDI among the three regions, even after the maximum allocation amount has been reached. The network PDI of Regions 1 and 2 understandably does not differ much. They also have the same lowest network PDI value after the maximum allocation amount has been reached. The big jump in the proportion of allocation to Region 3 at central budget S$30,000, as shown in Fig. 3.20(a) shows that the capability of Region 3 in improving the overall network PDI is outstanding at that budget level. This is reflected by the PDI plot in Fig. 3.20(b), where Region 3 achieved an outstandingly low PDI value, with minimal decline in PDI to Regions 1 and 2. The budget to Region 3 is maintained thereafter in order to channel additional funds for the improvement of the other two regions.

<u>Two Regions With Objective 2</u>

Here, Regions 1 and 2 adopt the objective of minimizing network PDI, while Region 3 adopts the alternate objective of maximizing the number of road segments repaired (Case G) and maximizing the utilization of manpower (Case H). In both the plots given in Figs. 3.21(a) and 3.22(a), Region 3 is given the lowest portion of the funds for low total budget levels (S$10,000 to S$40,000). Additional shares are only given to Region 3 when a certain level of total budget has been reached. Hence, we can say that the objective function adopted by Region 3 is inferior to the one adopted by Regions 1 and 2. The PDI plots in Figs. 3.21(b) and 3.22(b) reconfirm this conclusion.

Two Regions With Objective 3

Regions 1 and 2 again adopt a similar objective, which is to maximize the utilization of manpower, while Region 3 adopts the other two objectives in two separate cases. These are represented by Cases I and J. The plots for the final allocation strategy are shown in Figs. 3.23(a) and 3.24(a).

In Fig. 3.23(a) where Region 3 maximizes the number of road segments repaired, lower percentage of funds are allocated to Region 3 compared to the other two regions at total budget levels of S$20,000 to S$60,000. However, a high percentage of funds, which are actually more than the other two regions, are given to Region 3 at the lowest central budget level of S$10,000. This could be due to the more rapid improvements to network PDI at low budget levels for Objective 1 compared to Objective 3, as shown in Figs 3.14(a) and (c) respectively. Fig. 3.23(b) shows the corresponding attainable network PDI.

The plot in Fig. 3.24(a) is rather straightforward, with larger portion of funds initially given to Region 3, as the objective of minimizing total network PDI is able to contribute more to the central objective. As such, the network PDI of Region 3 for low central budget is lower than the other two regions. Comparison of both these strategies (Fig. 3.23(a)-(b) and Fig. 3.24(a)-(b)) reconfirms earlier observations that maximizing the number of roads repaired is an inferior objective to maximizing the utilization of manpower, and minimizing network PDI is superior to maximizing manpower utilization.

3.9 CHAPTER SUMMARY

In this study, conventional allocation approaches that are based on road network characteristics and maintenance needs are shown to be ineffective and inadequate in certain funds allocation situations resulting in under-performance of the overall maintenance strategy with respect to the central government's objective. These situations arise due to certain regional road network characteristics and conditions that "deceive" the formula- and needs-based allocation approaches into allocating funds to areas where it cannot be best utilized.

A two-step optimization approach has been proposed for the regional allocation of central highway funds. The significance of the proposed method includes:

- Objectives of regional agencies are considered in the budget allocation process. Thus, the funds allocation is in line with the goals and considerations of regional agencies. The allocation procedure optimizes the central budget according to the needs and interests of regional agencies.
- The objective of the central highway authority is considered in the final allocation. Therefore, the final allocation is also optimized with respect to the overall system goal set by the central authority.
- The method allows for analysis of scenarios for different budget levels at the central level with relative ease. This is an important advantage in the strategic planning for different scenarios.
- The two-step approach requires only one iteration of information exchange per planning period between regional and central levels. This saves significant negotiation and consultation time between the two levels of decision makers.

The major findings from experiments carried out using the proposed two-step optimization method include:

- The computational capacity required for the optimization routine is minimal.
- Under tight budget constraints, a highly unbalanced allocation of funds is likely to occur. This will result in unequal pavement conditions in the respective regions. This can be avoided by placing a higher level of constraint on the allowable network PDI of each region.
- The proposed method allows for flexibility in defining the objective functions and constraints in the optimization routine. This is a result of using GAs as the optimization tools for both central as well as regional optimizations. This flexibility is demonstrated by the ease with which the central level can adjust the maximum allowable network PDI of each region.

An application of the proposed two-step optimization approach has also been demonstrated to study the sensitivity of objective functions adopted by regions towards the central allocation strategy. A total of 10 cases of different combination of regional objective functions are analyzed. For all cases, the central objective of minimizing the total network PDI of the whole road network is maintained. Network and resource characteristics of each region are standardized. The major findings and conclusions obtained from this analysis are summarized as follows:

- It is found that the region that is better able to complement the central objective will always benefit in the funds allocation process. This region can be said to have a superior objective function compared to the other regions. In this case, the order of superiority of the objective functions is Objective 2, Objective 3 and Objective 1, in that order.

- In this analysis, the relative superiority of objective functions is rather distinct due to the simplistic nature of the objectives considered. In a real-world application, the superiority of objective functions will be less discernable due to the different performance measures adopted by each highway agency. For example, the central administration might consider a certain set of parameters such as pavement surface roughness, skid resistance, and distress conditions as performance measures of the road network, while region agencies might take into consideration other sets of parameters. In these circumstances, the two-step optimization approach will become more useful for funds allocation.
- Apart from the objective function, network and resource characteristics of each region are identified as other factors that affect the decision made with regard to funds allocation. A sensitivity study on these characteristics can be conducted in order to investigate the effect of the different roads and management features in each region towards the shares of budget that they will receive.
- By the two-step optimization approach, an inequitable allocation strategy is bound to occur due to the lack of compromise/consultation between central and regional agencies. This issue will be addressed in subsequent work, which will be further elaborated on in the next chapter.

Table 3.1 Summary of the three case studies and their attributes

	Case 1		
	Region 1	Region 2	Region 3
Number of road segments	30	40	50
Network PDI	32.53	24.74	32.78
Maintenance Needs (S$)	44 937.60	59 767.36	69 074.56
	Case 2		
	Region 1	Region 2	Region 3
Number of road segments	40	40	40
Network PDI	10.82	21.07	41.19
Maintenance Needs (S$)	63 453.76	60 616.96	63 825.28
	Case 3		
	Region 1	Region 2	Region 3
Number of road segments	30	80	150
Network PDI	50.45	22.05	12.83
Maintenance Needs (S$)	59 392.96	126 652.80	217 744.00

Table 3.2 Pavement conditions of regional road networks

Case 1

Region	Road Type	Crack H	Crack M	Crack L	Rut H	Rut M	Rut L	Pothole H	Pothole M	Pothole L
1	Expressway	2	4	1	1	0	3	1	0	0
	Arterial Road	1	0	1	3	2	4	3	1	3
2	Expressway	1	2	7	1	5	6	1	2	2
	Arterial Road	3	0	4	0	1	1	2	1	1
3	Expressway	2	1	1	2	3	3	1	0	4
	Arterial Road	2	2	3	6	4	9	3	2	2

Case 2

Region	Road Type	Crack H	Crack M	Crack L	Rut H	Rut M	Rut L	Pothole H	Pothole M	Pothole L
1	Expressway	0	2	13	0	0	4	0	0	0
	Arterial Road	1	1	12	0	0	1	0	1	5
2	Expressway	1	0	6	0	0	3	0	0	1
	Arterial Road	4	4	8	2	2	5	1	0	3
3	Expressway	1	1	1	3	5	1	1	0	0
	Arterial Road	3	1	1	9	5	4	0	2	2

Case 3

Region	Road Type	Crack H	Crack M	Crack L	Rut H	Rut M	Rut L	Pothole H	Pothole M	Pothole L
1	Expressway	2	1	0	5	1	0	2	1	0
	Arterial Road	1	1	0	9	2	1	3	0	1
2	Expressway	5	3	11	2	4	4	1	3	4
	Arterial Road	2	2	22	1	2	4	1	5	4
3	Expressway	1	2	28	0	2	14	0	0	9
	Arterial Road	2	3	53	3	0	20	2	3	8

Note: H = High Severity, M = Medium Severity, L = Low Severity

Table 3.3 Resources and system information for the example problem

(a) Manpower requirements for each repair activity (man-days/production day)

Repair Activity	Supervisors	Laborers	Operators	Drivers
Crack Sealing	1	2	4	2
Premix Levelling (Rutting)	1	5	1	1
Patching (Pothole)	0	4	0	2

(b) Equipment requirements for each repair activity (equipment-days/production day)

Repair Activity	Dump Trucks	Pickup Trucks	Crew Cabs	Distri-butors	Rollers	Pavers
Crack Sealing	2	1	0	1	0	0
Premix Levelling (Rutting)	1	1	0	0	1	0
Patching (Pothole)	1	0	1	0	0	0

(c) Road segment repair costs (S$)

Distress Type	High Severity	Medium Severity	Low Severity
Crack	2000.00	2000.00	2000.00
Rut	2208.00	1324.80	441.60
Pothole	2472.96	1313.76	386.40

(d) Production rate data

Maintenance Activities	Production Rate
Crack Sealing	1.0 (km/day)
Premix Leveling	30.0 (tonnes of mix/day)
Patching with premix	30.0 (tonnes/day)

Table 3.4 Distress values and terminal values for different distress types

Distress Severity	Crack Area (m^2/km)	Rut Depth (mm)	Pothole Percentage (% road surface)
Low	0.1	2.5	2.5
Medium	0.3	7.5	8.5
High	0.6	12.5	16.0
Terminal Value	1.4	20.0	30.0

Table 3.5 Priority weights used in Equations (3.6) and (3.7)

Item	Priority Weight
Distress Type (f_{Dj})	100 for crack
	80 for rut
	60 for pothole
Distress Severity (f_{Sj})	30 for low severity
	70 for medium severity
	100 for high severity
Road Class (f_{Cj})	100 for expressway
	10 for arterial road

Note: subscript j pertains to road segment

Table 3.6 Ten cases of different combinations of regional objective functions

Case	Objective Functions		
	Region 1	Region 2	Region 3
A	Obj. 1	Obj. 2	Obj. 3
B	Obj. 1	Obj. 1	Obj. 1
C	Obj. 2	Obj. 2	Obj. 2
D	Obj. 3	Obj. 3	Obj. 3
E	Obj. 1	Obj. 1	Obj. 2
F	Obj. 1	Obj. 1	Obj. 3
G	Obj. 2	Obj. 2	Obj. 1
H	Obj. 2	Obj. 2	Obj. 3
I	Obj. 3	Obj. 3	Obj. 1
J	Obj. 3	Obj. 3	Obj. 2

Note: Obj. 1: Maximise number of distress road segments repaired

Obj. 2: Maximise the performance level of regional road network pavements

Obj. 3: Maximise the utilisation of available manpower

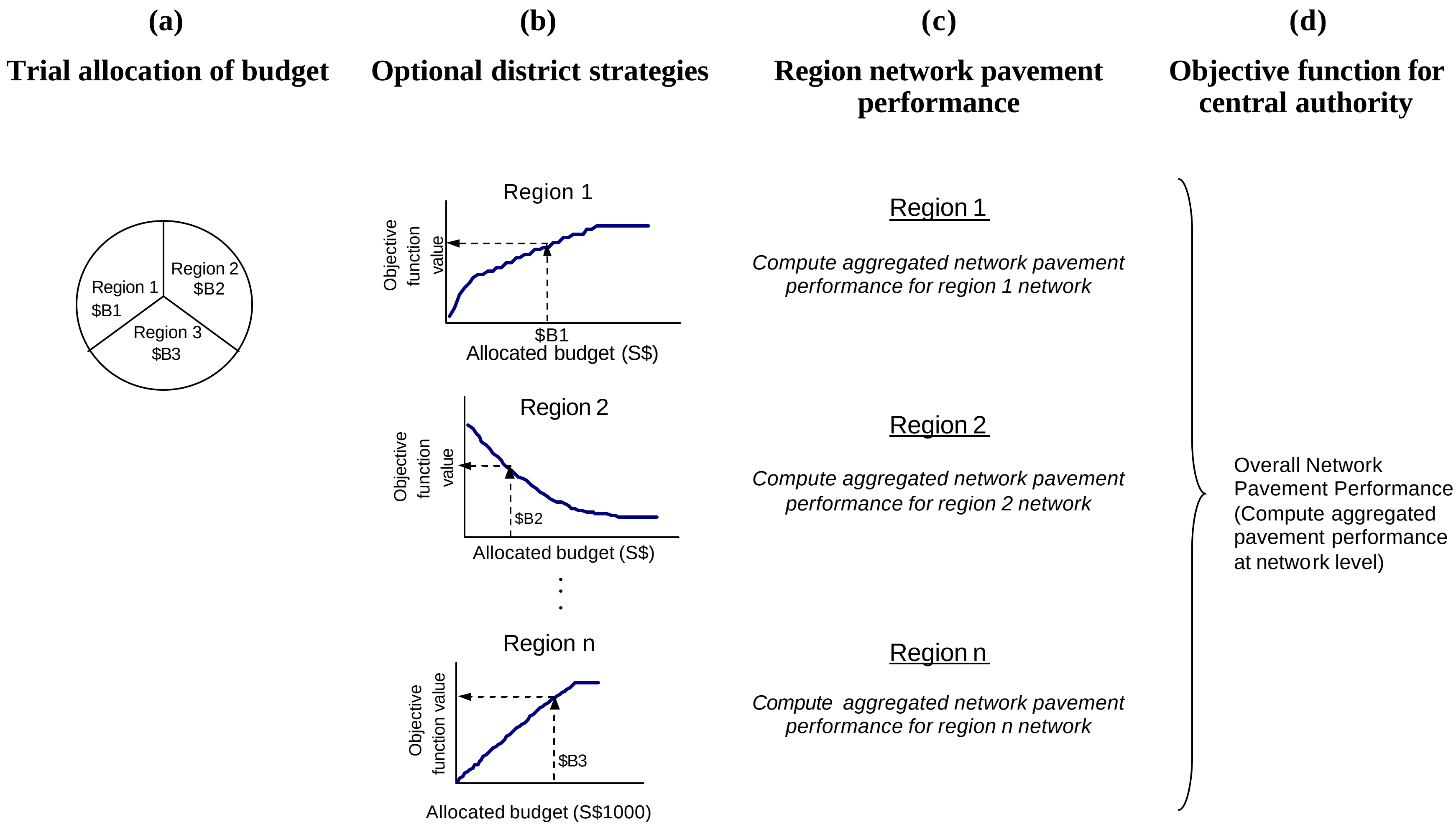
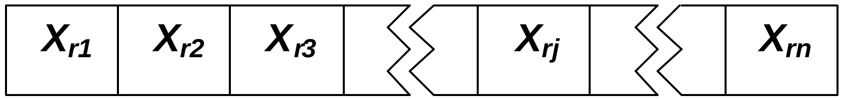


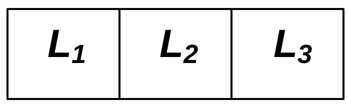
Fig. 3.1 Sequence of analysis for budget allocation for multi-regional highway agencies



$$X_{rj} = \begin{cases} 0 \text{ for segments not selected for maintenance} \\ 1 \text{ for segments selected for maintenance} \end{cases}$$

n = number of road segments in region r

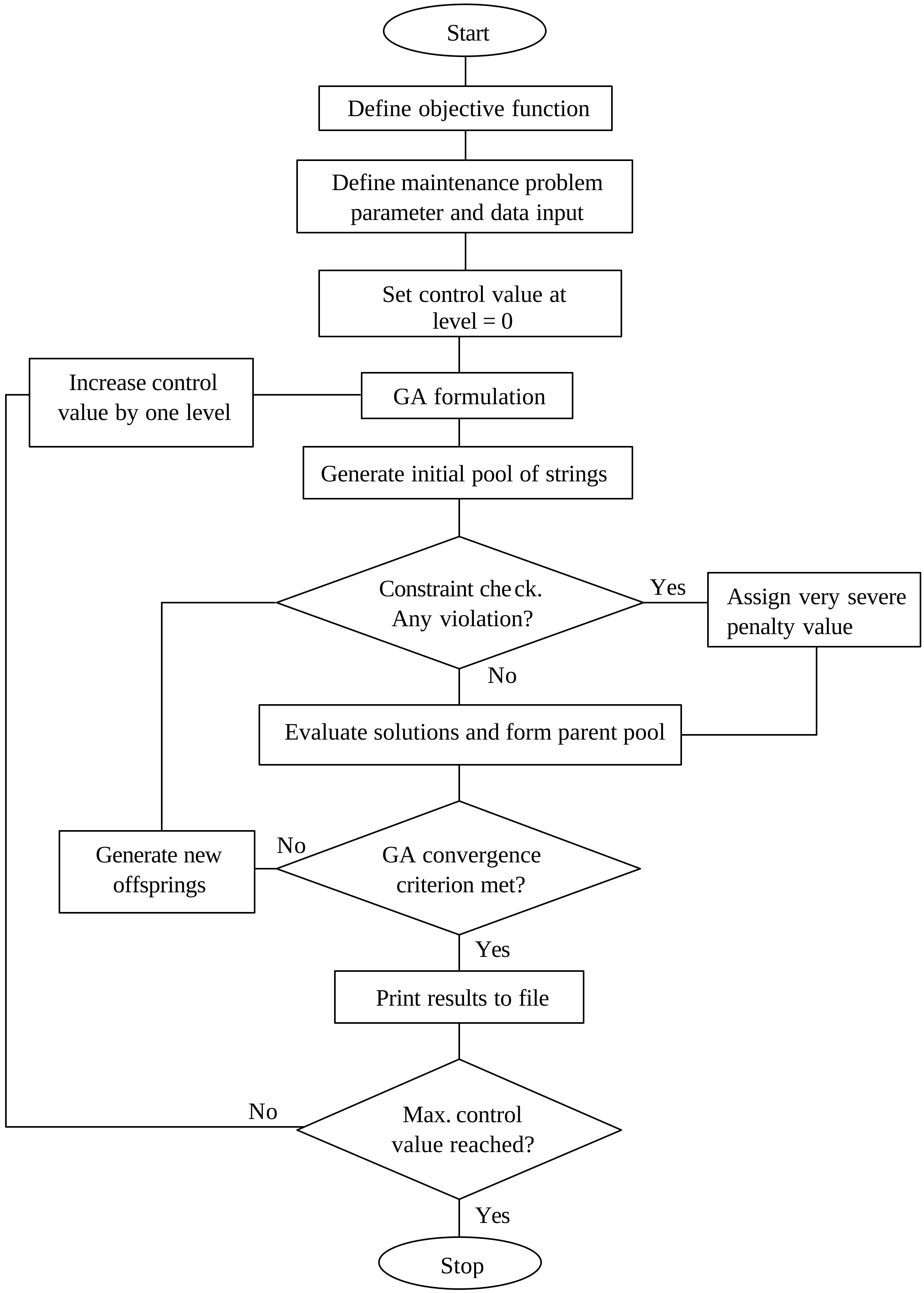
(a) String of genes for regional level GA



L_1, L_2, L_3 = levels of budget allocated to the regions 1, 2 and 3

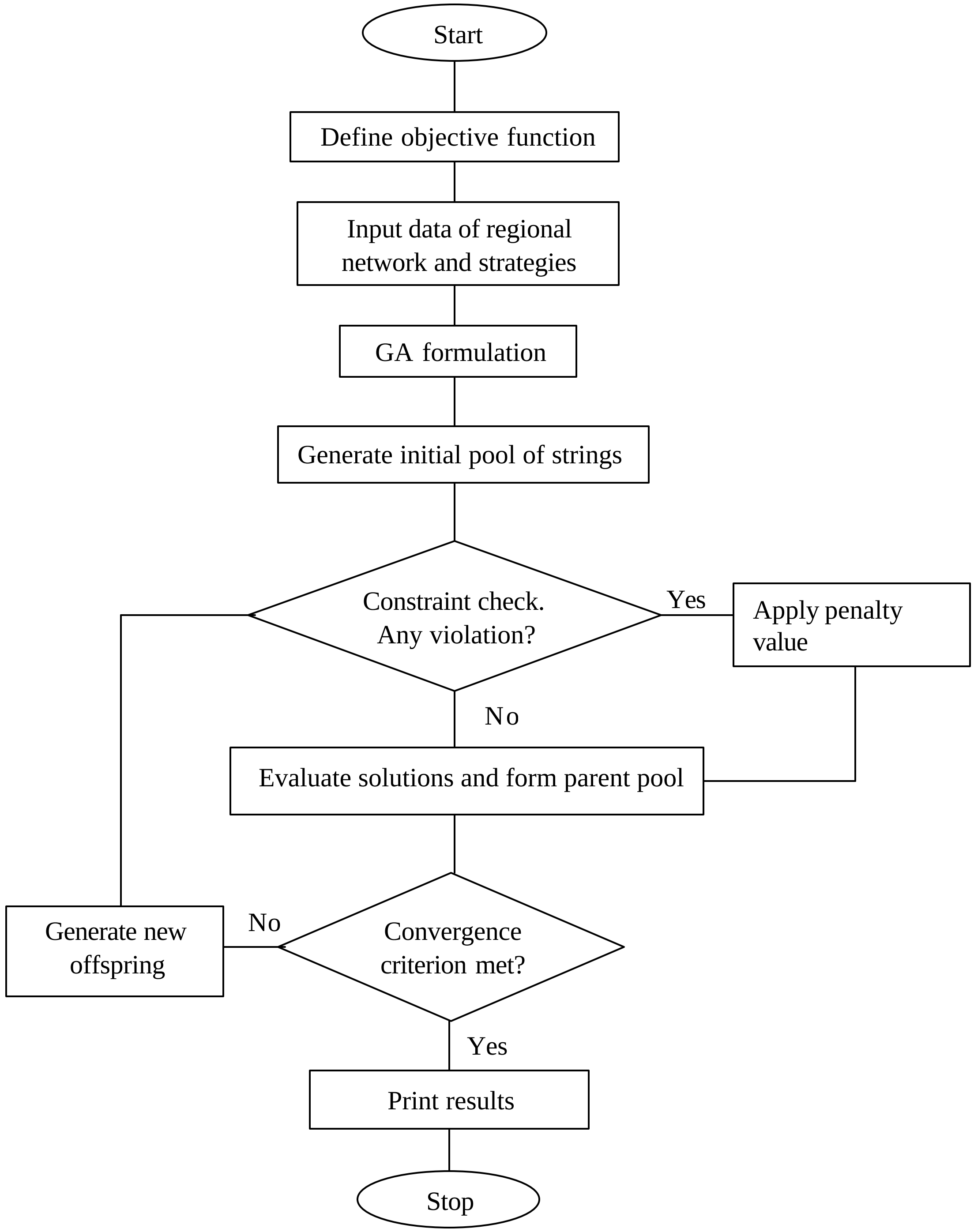
(b) String of genes for central level GA

Fig. 3.2 String structures of the genetic algorithm formulation



(a) Regional level optimization process

Fig. 3.3 Flow chart for genetic algorithm optimization process (to be continued)



(b) Central level optimization process

Fig. 3.3 Flow chart for genetic algorithm optimization process (continued)

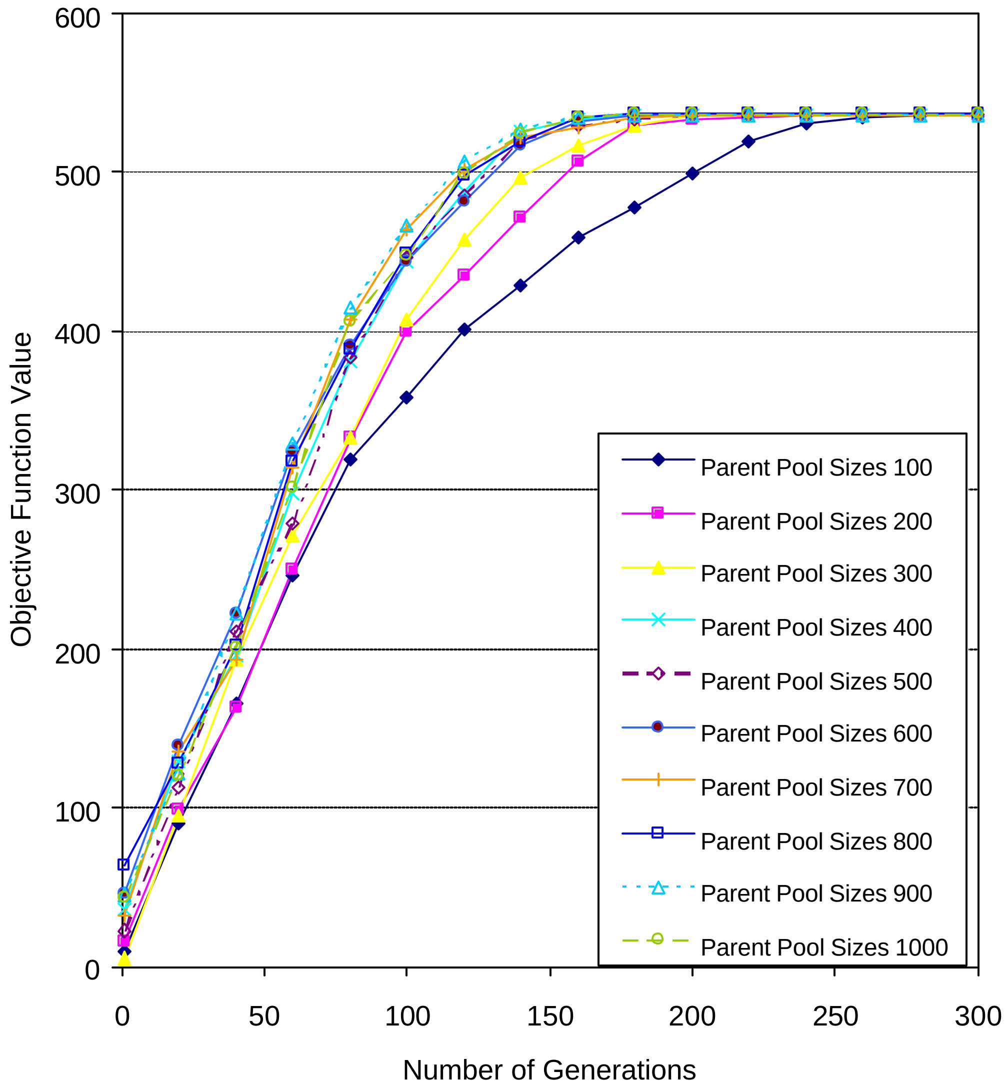


Fig. 3.4 Effect of Parent Pool Sizes on GA Convergence in Analysis of Region 3

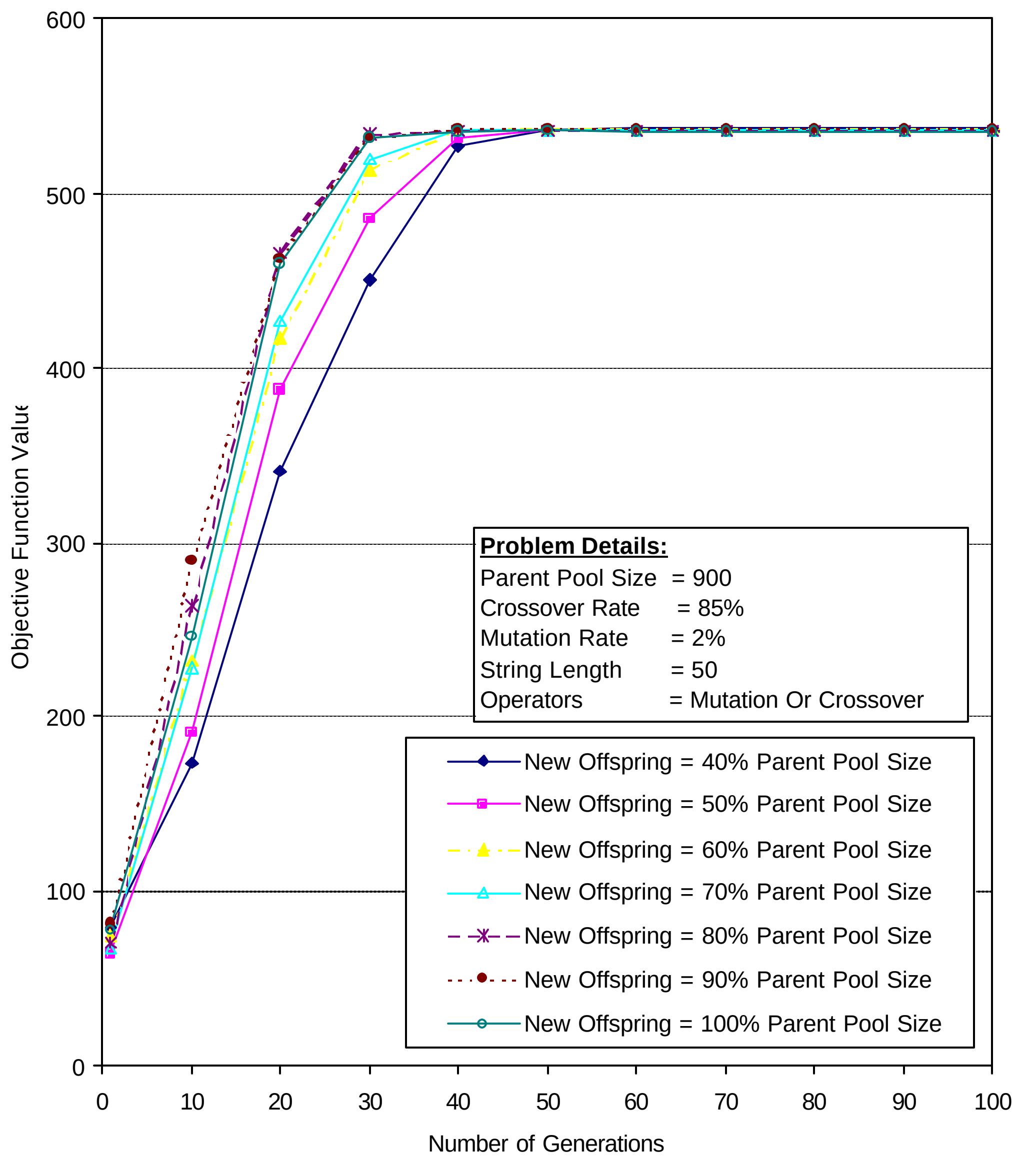


Fig. 3.5 Convergence of GA Solutions with Different New Offspring Sizes in Analysis of Region 3

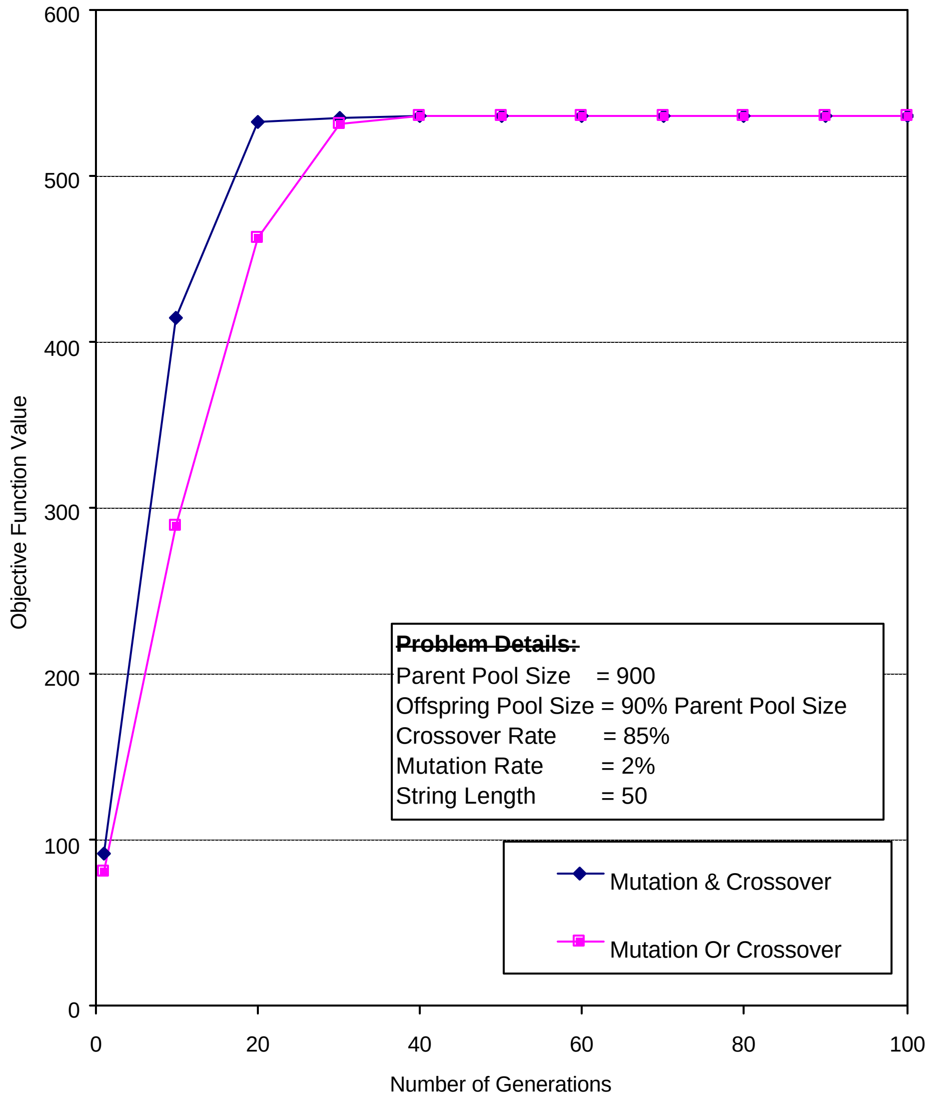


Fig. 3.6 Effect of Choice of Genetic Operators

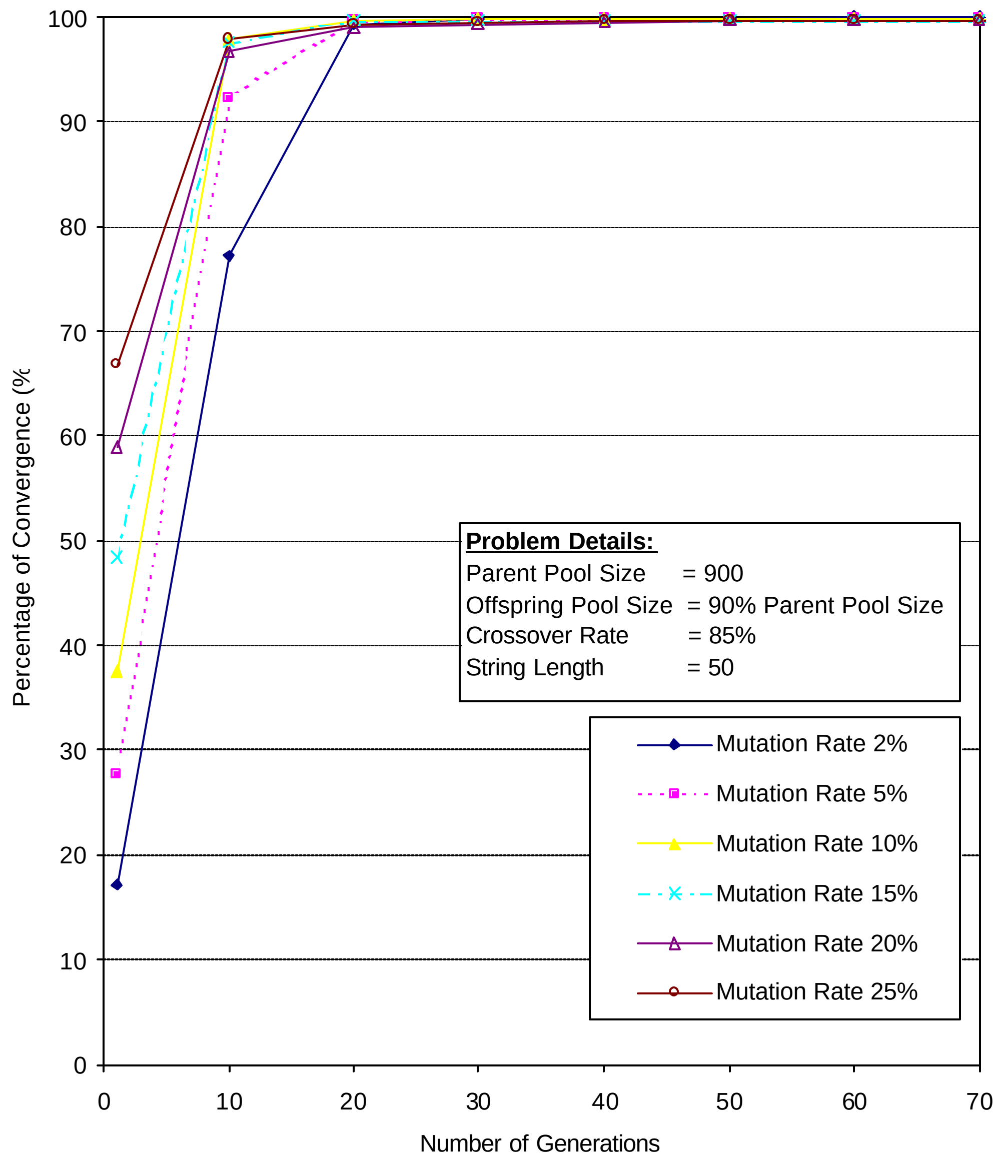


Fig. 3.7 Effect of Mutation Rate on GA Convergence

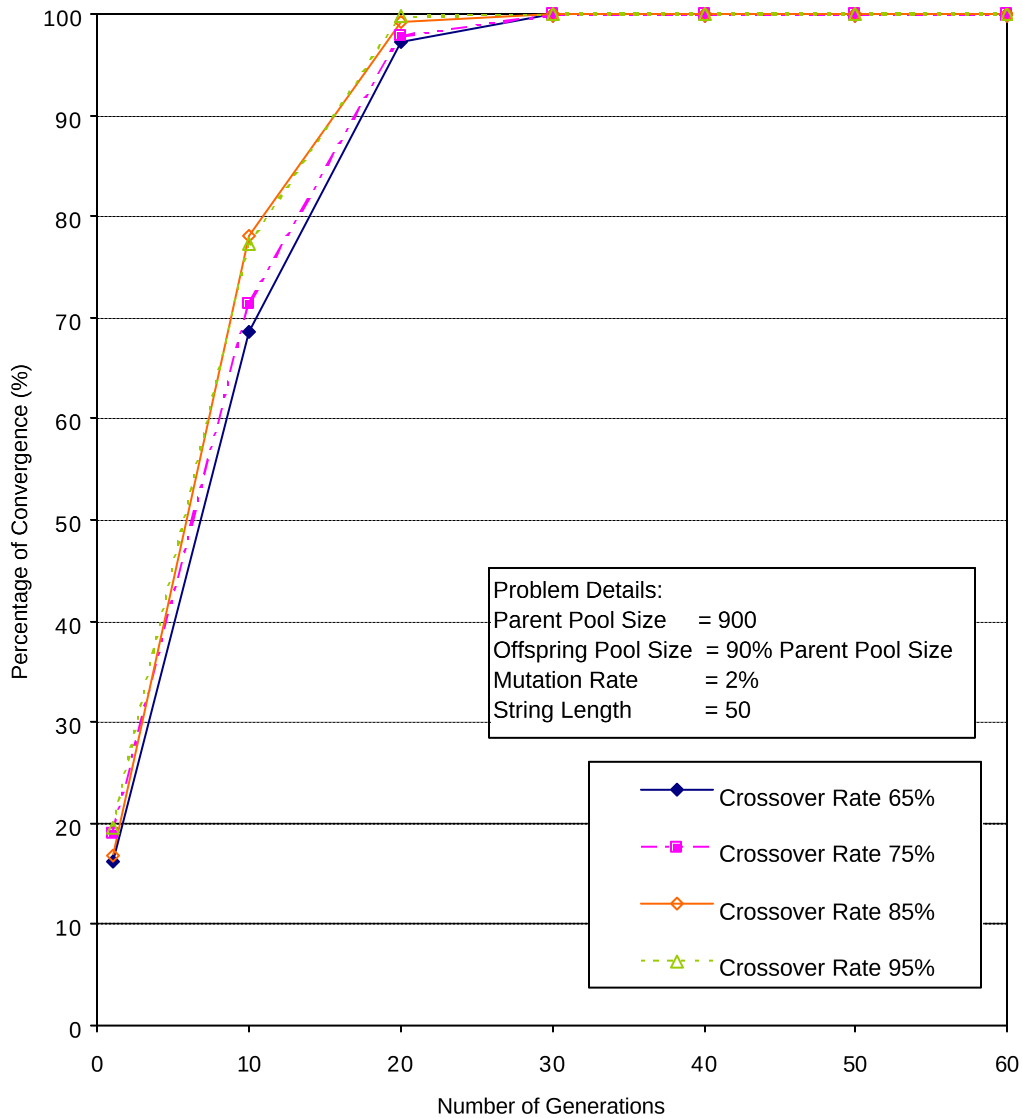
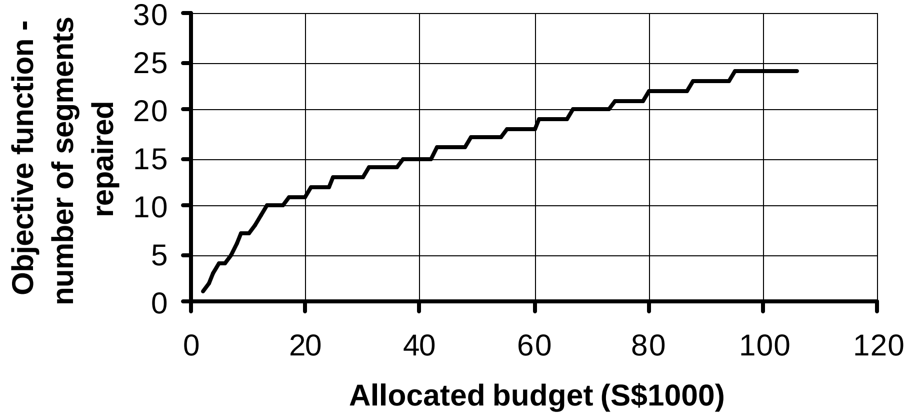
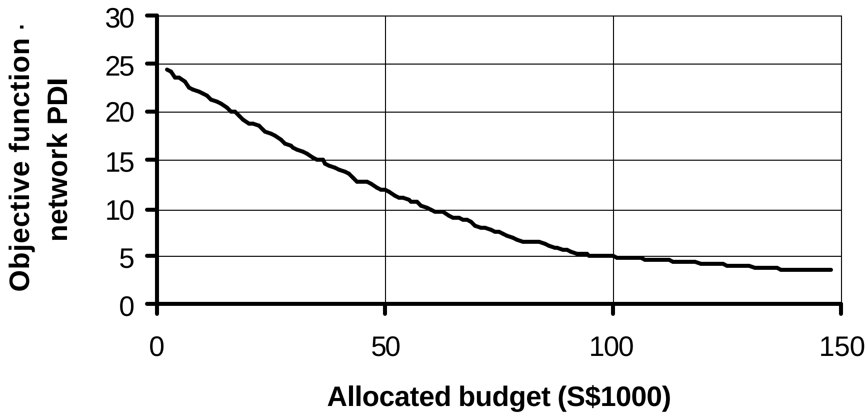


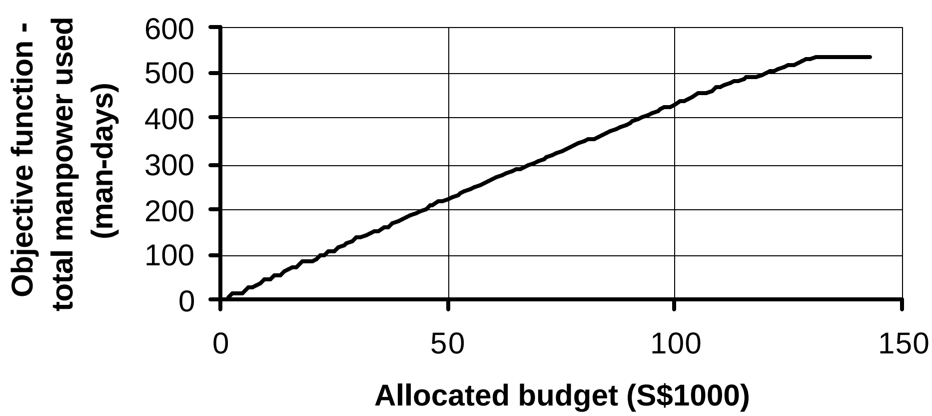
Fig. 3.8 Effect of Crossover Rate on GA Convergence



(a) Region 1

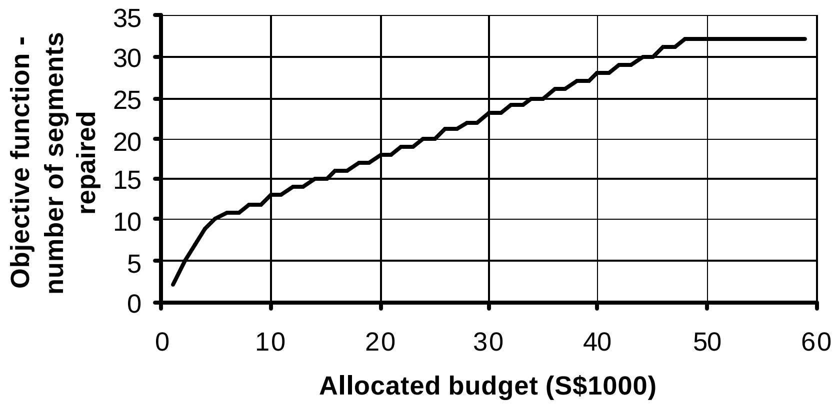


(b) Region 2

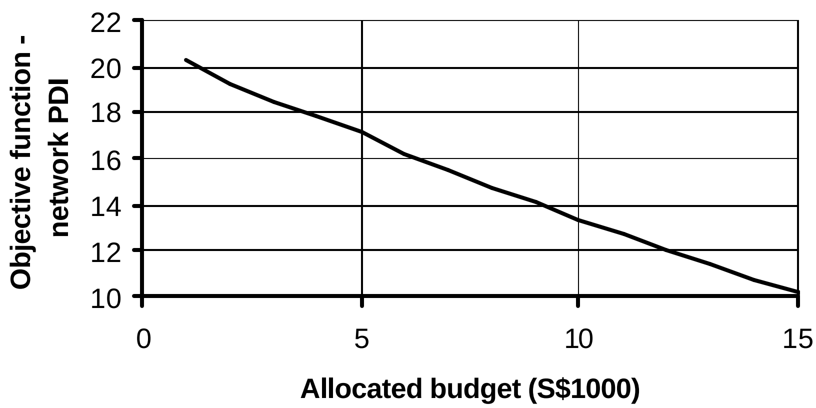


(c) Region 3

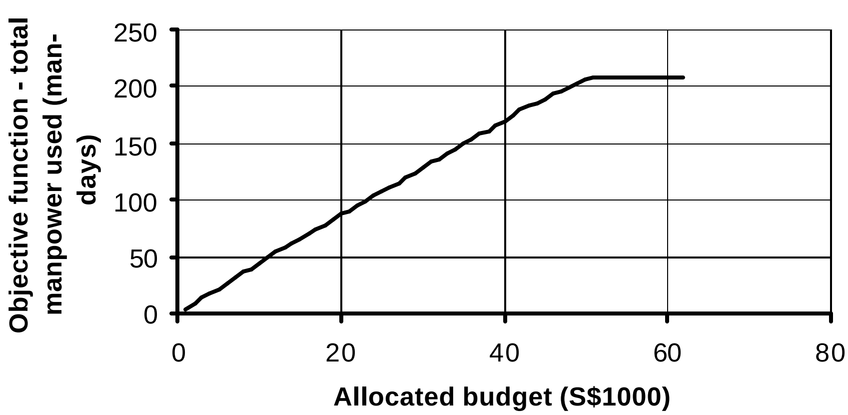
Fig. 3.9 Optimal solutions for regional networks Case 1



(a) Region 1

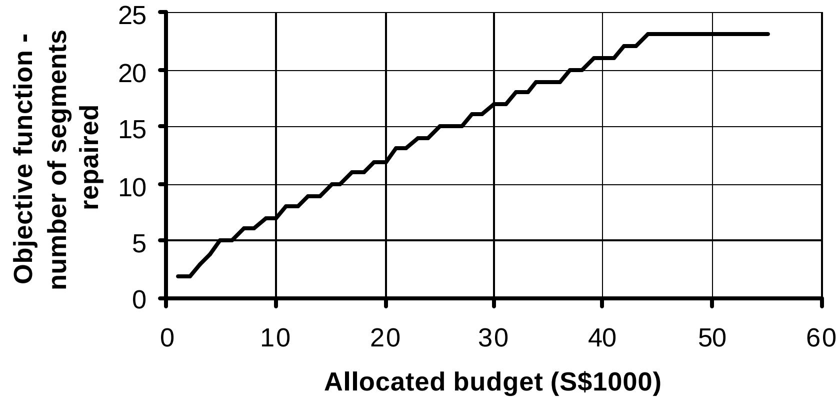


(b) Region 2

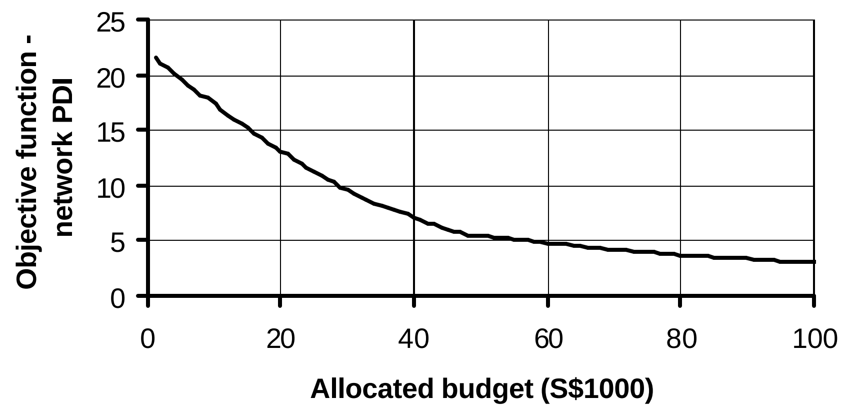


(d) Region 3

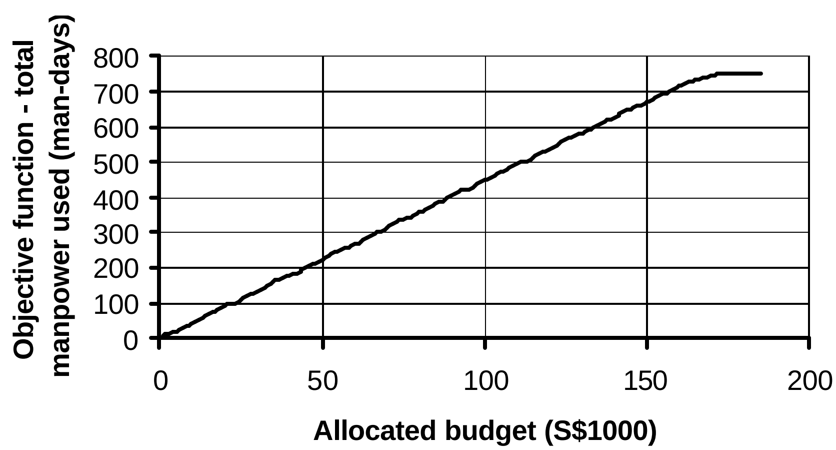
Fig. 3.10 Optimal solutions for regional networks Case 2



(a) Region 1

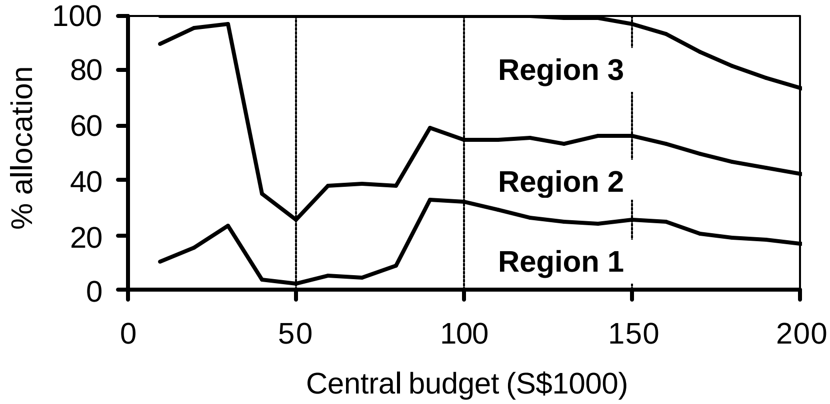


(b) Region 2

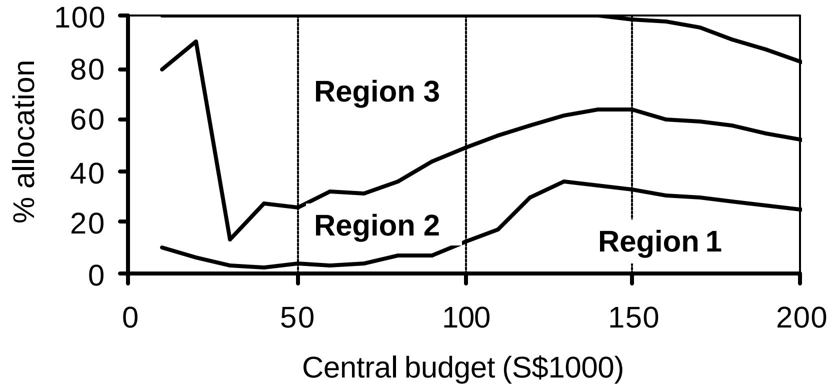


(c) Region 3

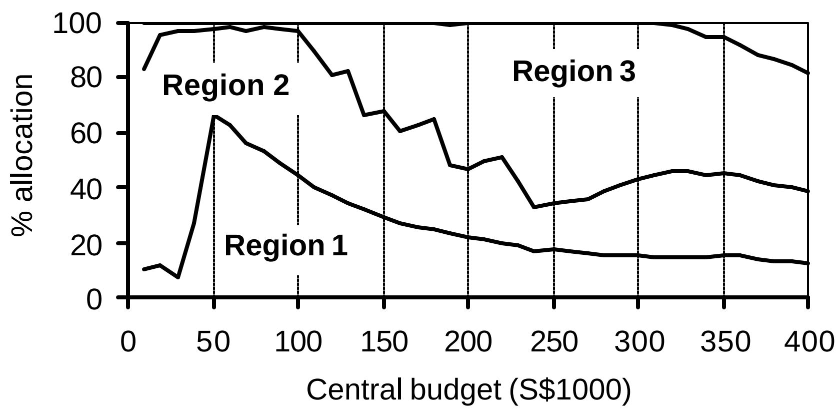
Fig. 3.11 Optimal solutions for regional networks Case 3



(a) CASE 1

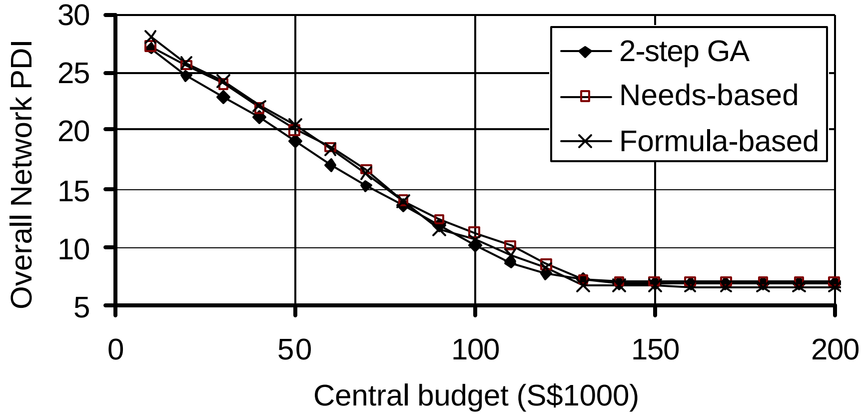


(b) CASE 2

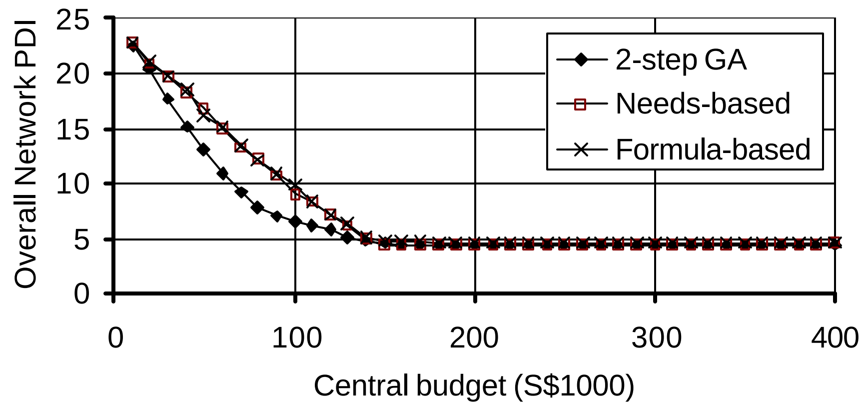


(c) CASE 3

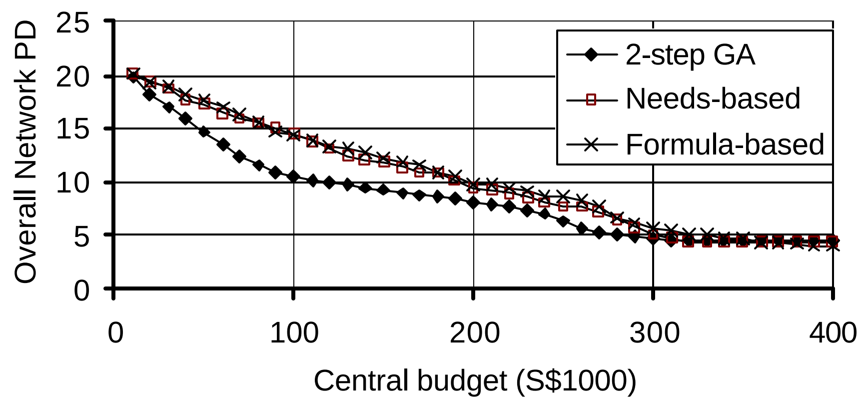
Fig. 3.12 Budget allocation for different total budgets



(a) CASE 1

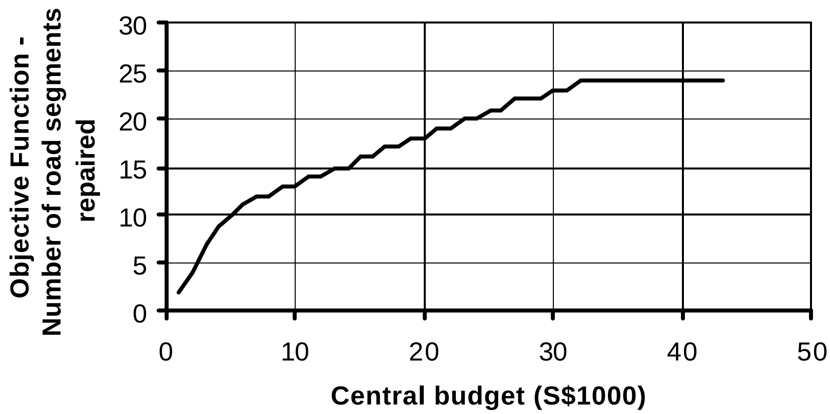


(b) CASE 2

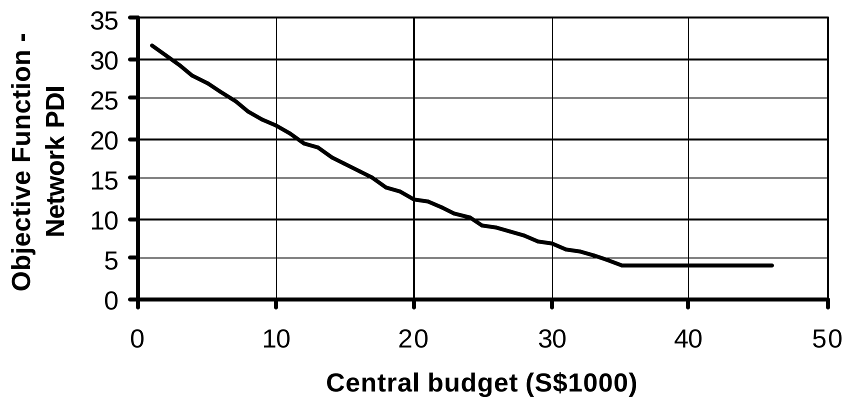


(c) CASE 3

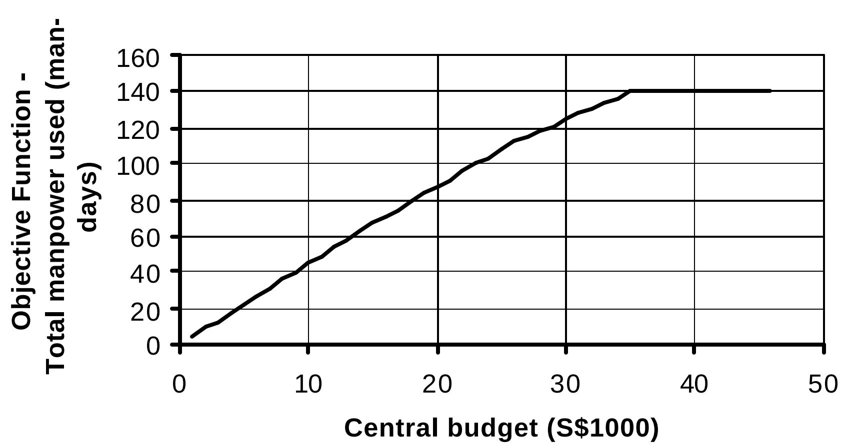
Fig. 3.13 Comparison of overall network PDI with different budget allocation strategies



(a) Objective Function: Maximize the number of road segments repaired

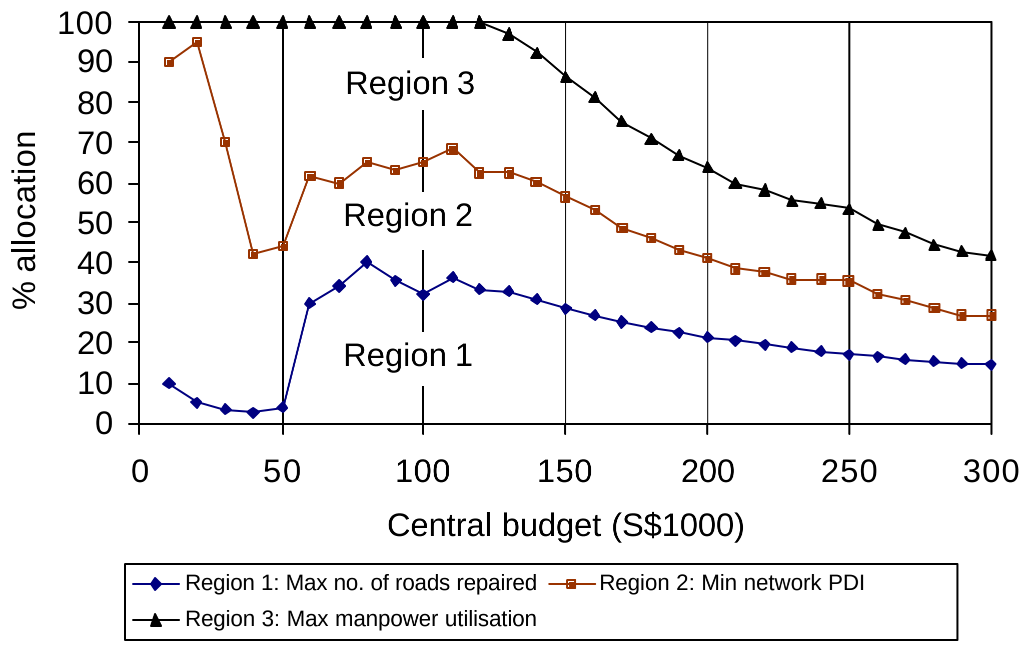


(b) Objective Function: Maximize network PDI

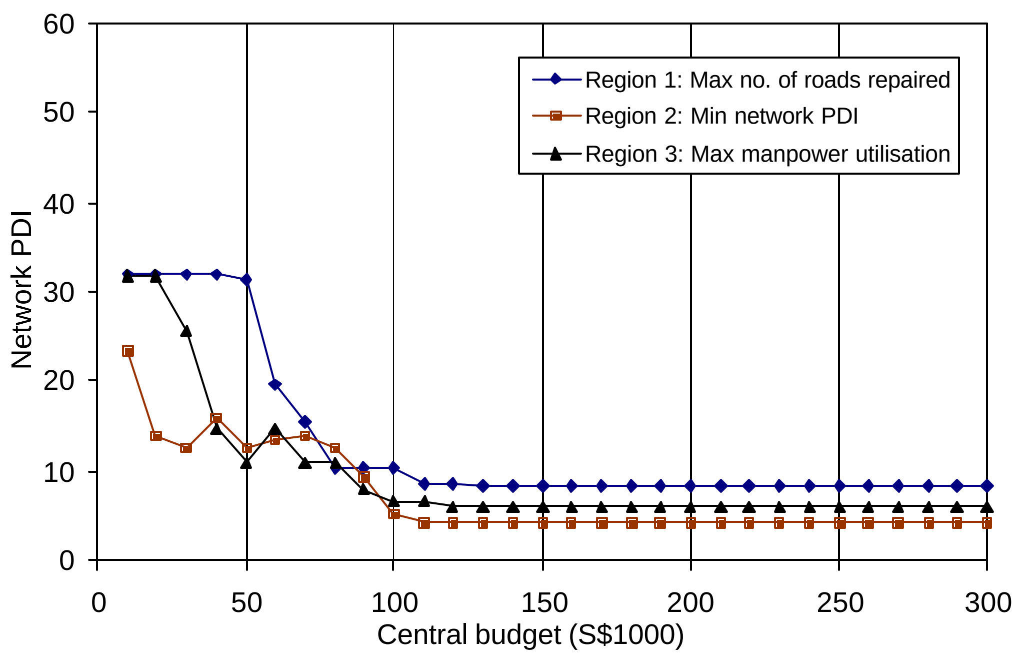


(c) Objective Function: Maximize total utilisation of manpower

Fig. 3.14 Optimal solutions for regional networks

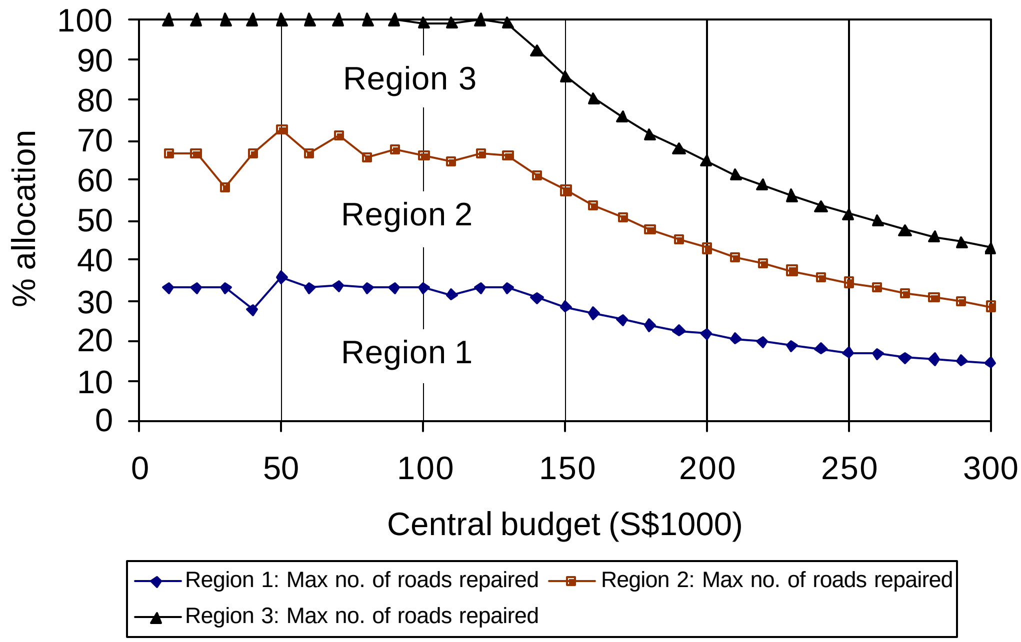


(a) Budget allocation shares of regions for different available total budgets

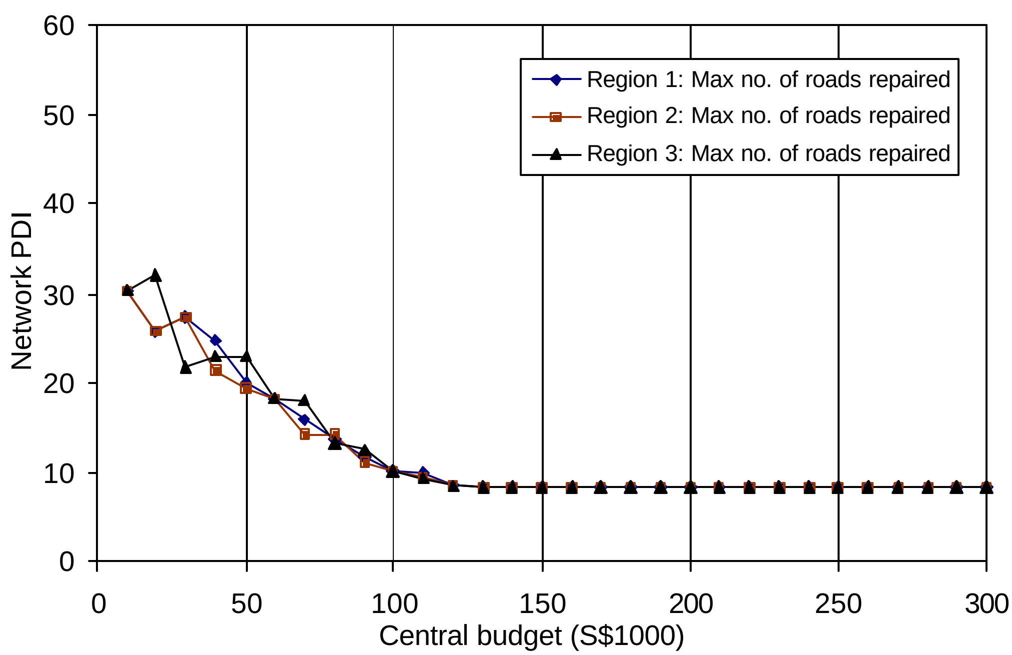


(b) Regional network PDI distributions for different available total budgets

Fig. 3.15 Budget allocation strategy for Case A (see Table 3.6)

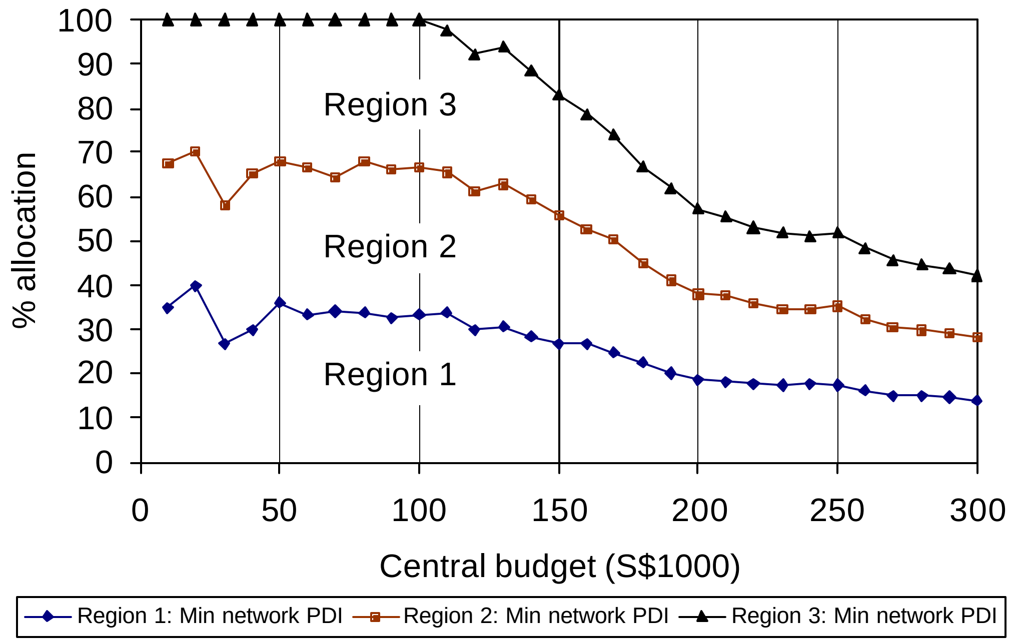


(a) Budget allocation shares of regions for different available total budgets

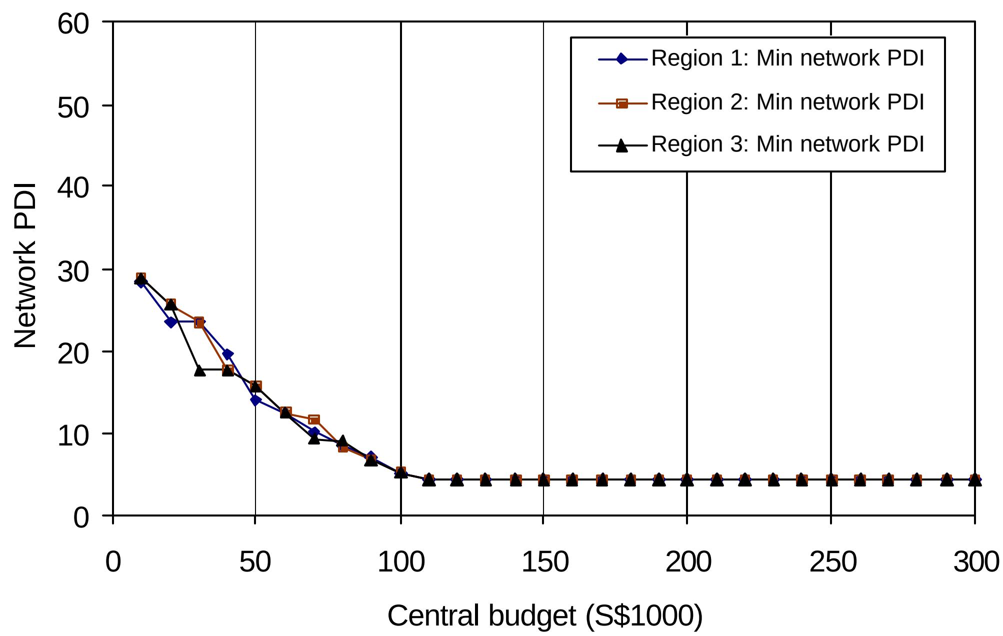


(b) Regional network PDI distributions for different available total budgets

Fig. 3.16 Budget allocation strategy for Case B (see Table 3.6)

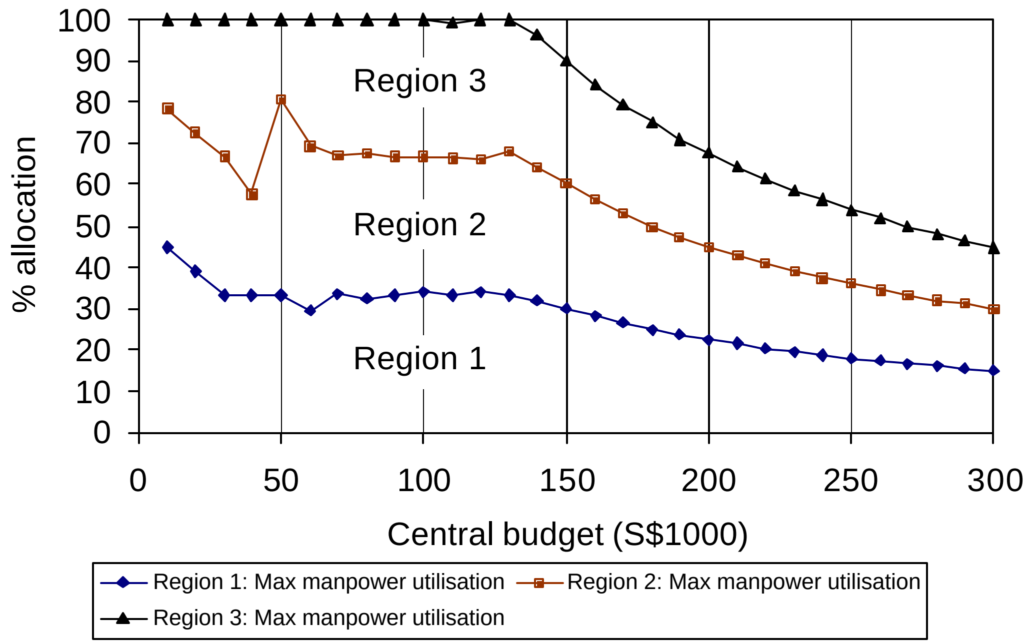


(a) Budget allocation shares of regions for different available total budgets

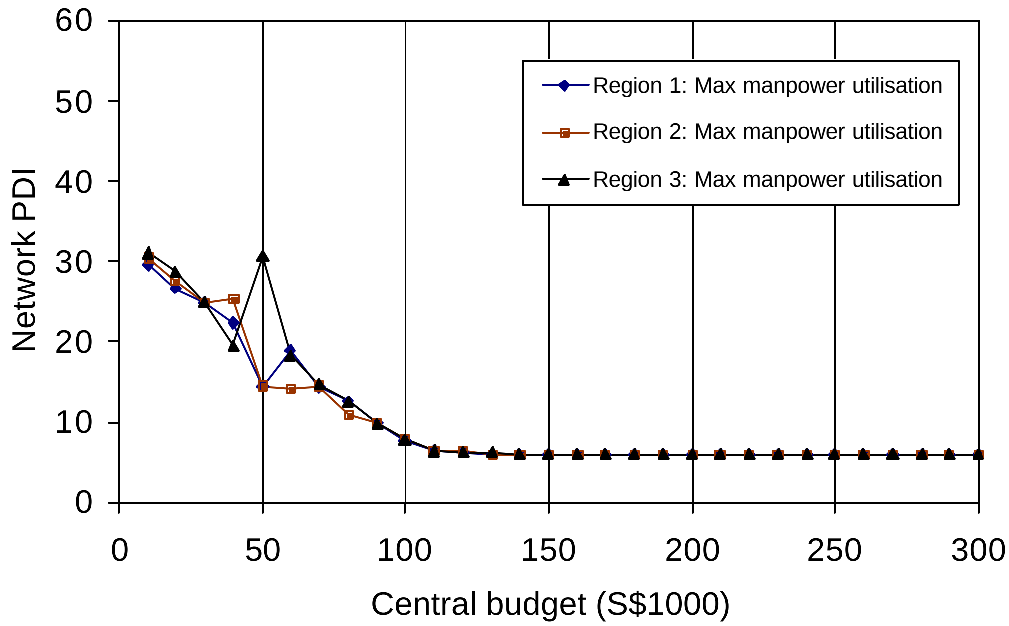


(b) Regional network PDI distributions for different available total budgets

Fig. 3.17 Budget allocation strategy for Case C (see Table 3.6)

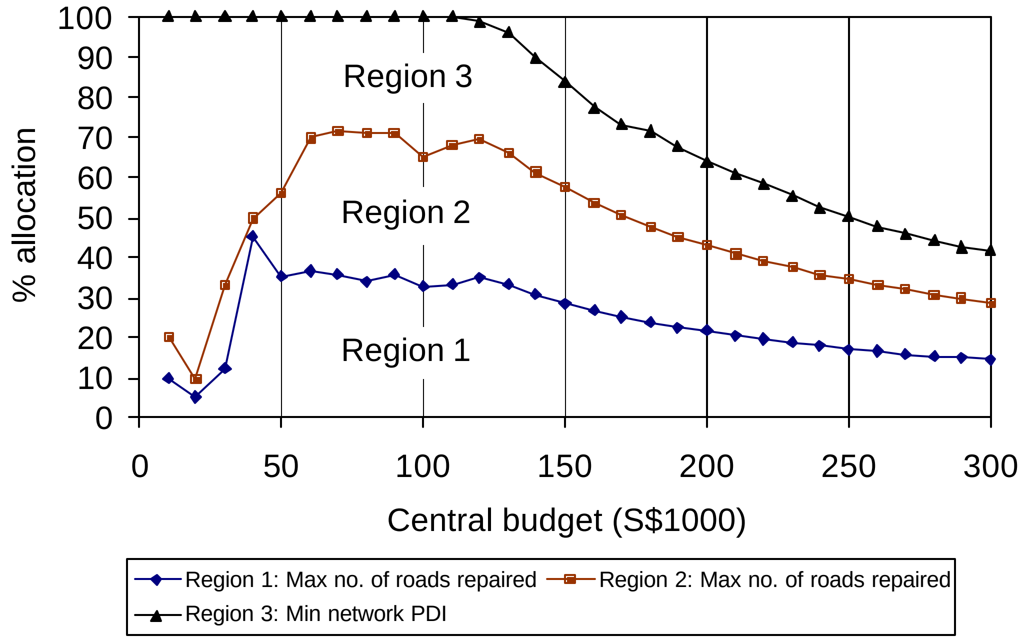


(a) Budget allocation shares of regions for different available total budgets

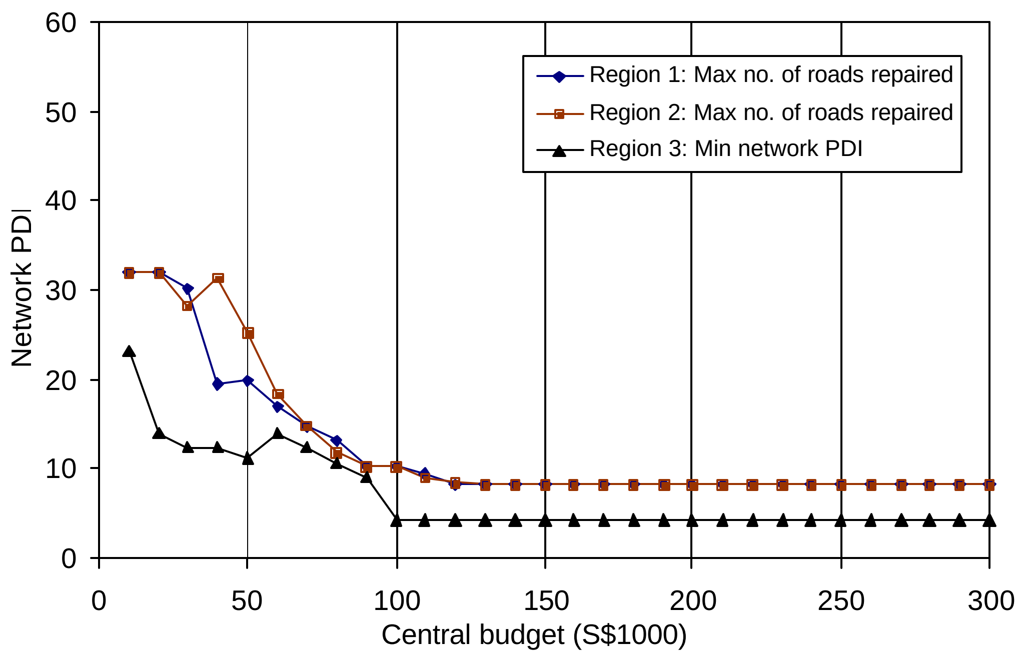


(b) Regional network PDI distributions for different available total budgets

Fig. 3.18 Budget allocation strategy for Case D (see Table 3.6)

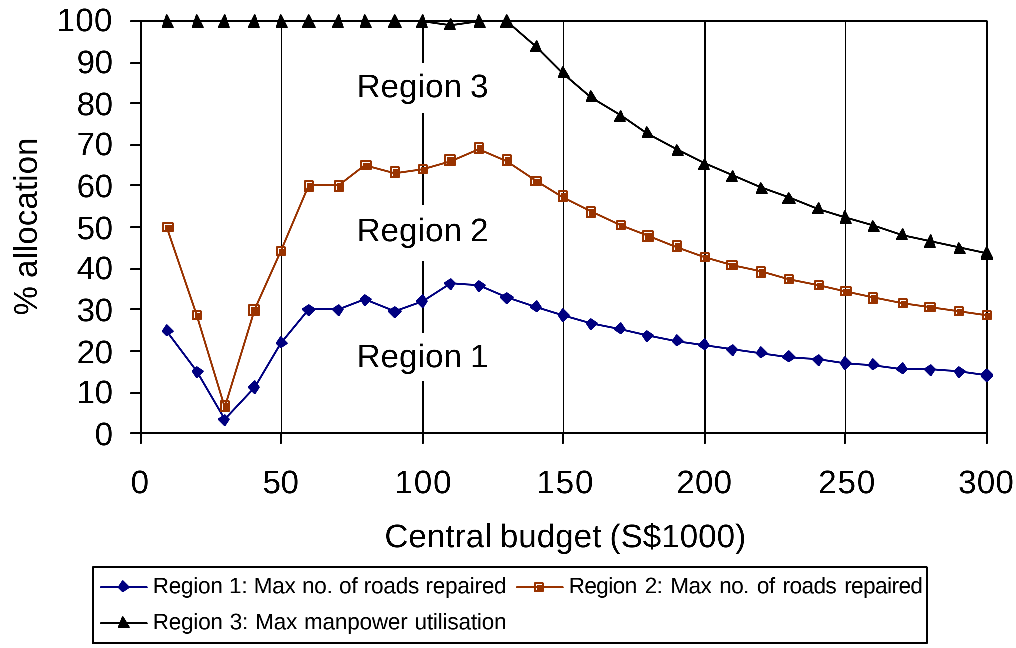


(a) Budget allocation shares of regions for different available total budgets

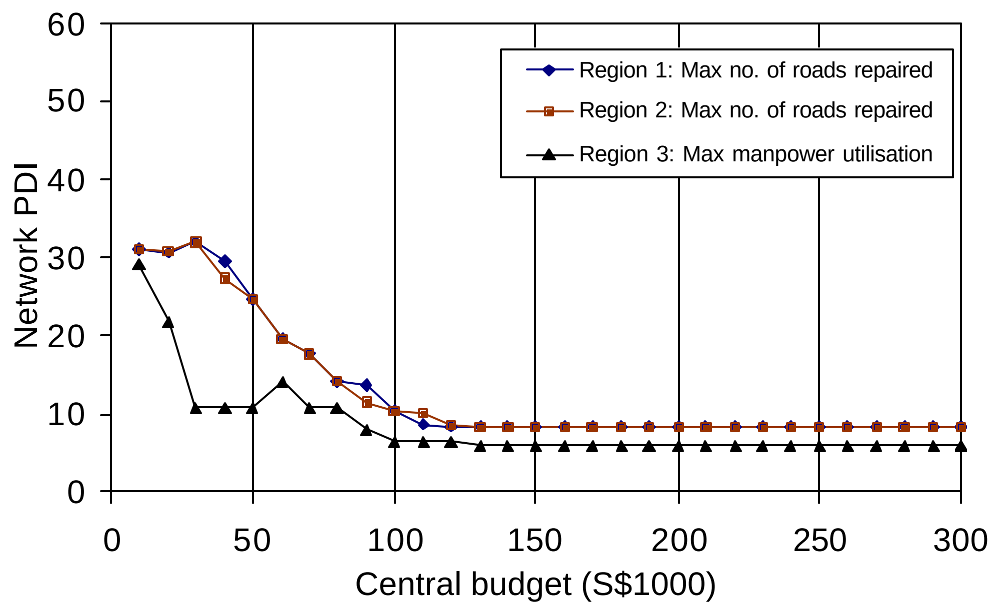


(b) Regional network PDI distributions for different available total budgets

Fig. 3.19 Budget allocation strategy for Case E (see Table 3.6)

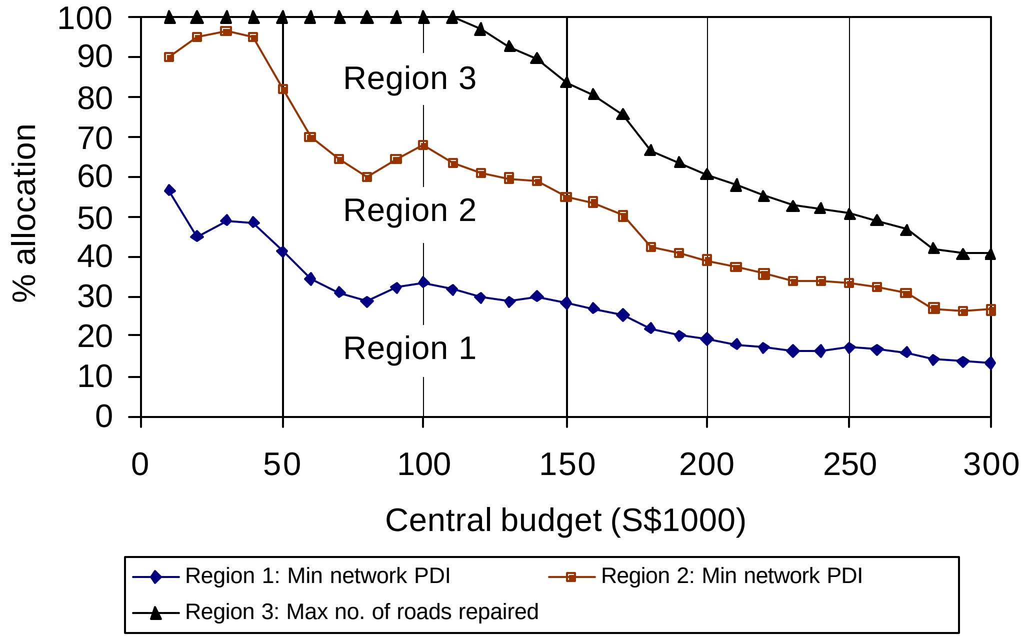


(a) Budget allocation shares of regions for different available total budgets

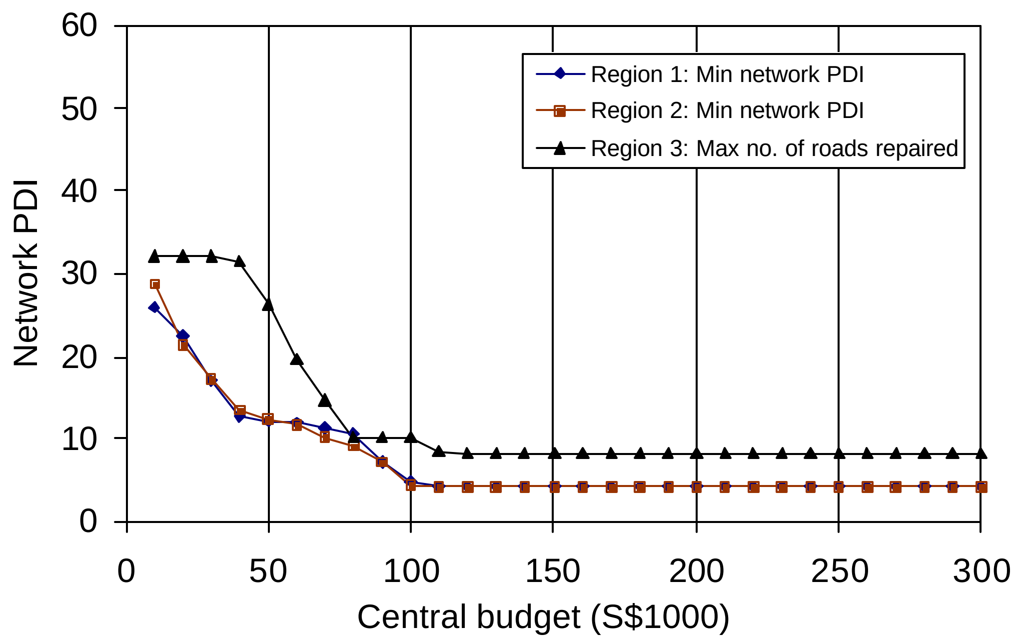


(b) Regional network PDI distributions for different available total budgets

Fig. 3.20 Budget allocation strategy for Case F (see Table 3.6)

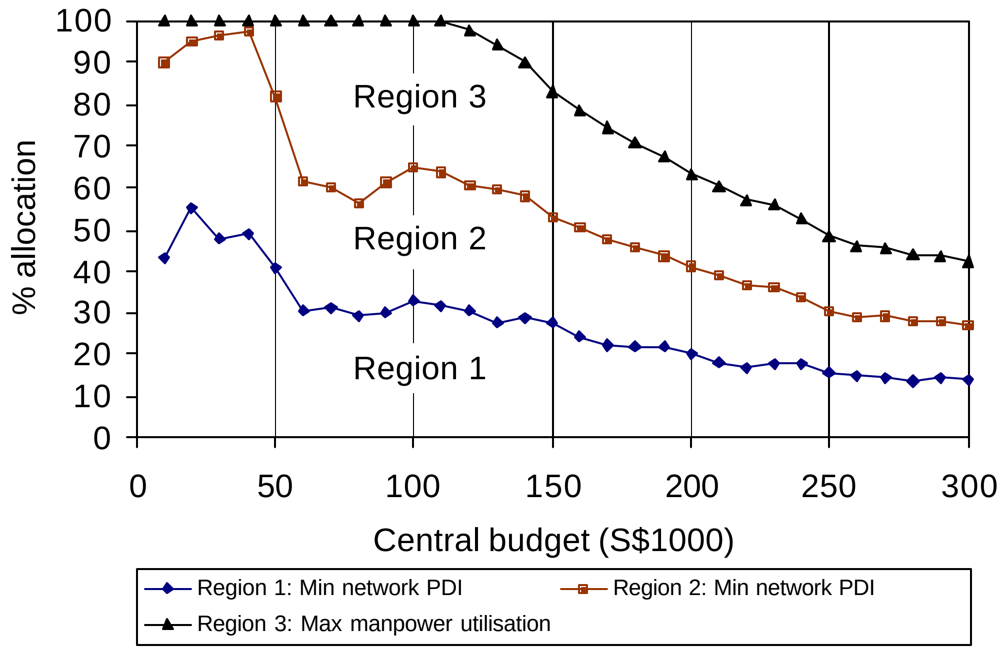


(a) Budget allocation shares of regions for different available total budgets

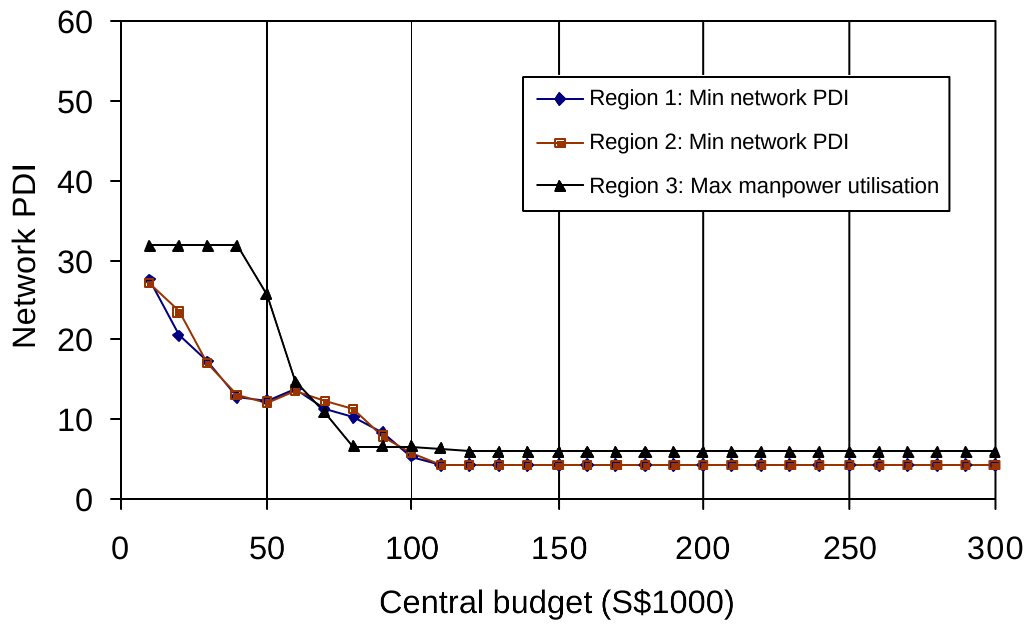


(b) Regional network PDI distributions for different available total budgets

Fig. 3.21 Budget allocation strategy for Case G (see Table 3.6)

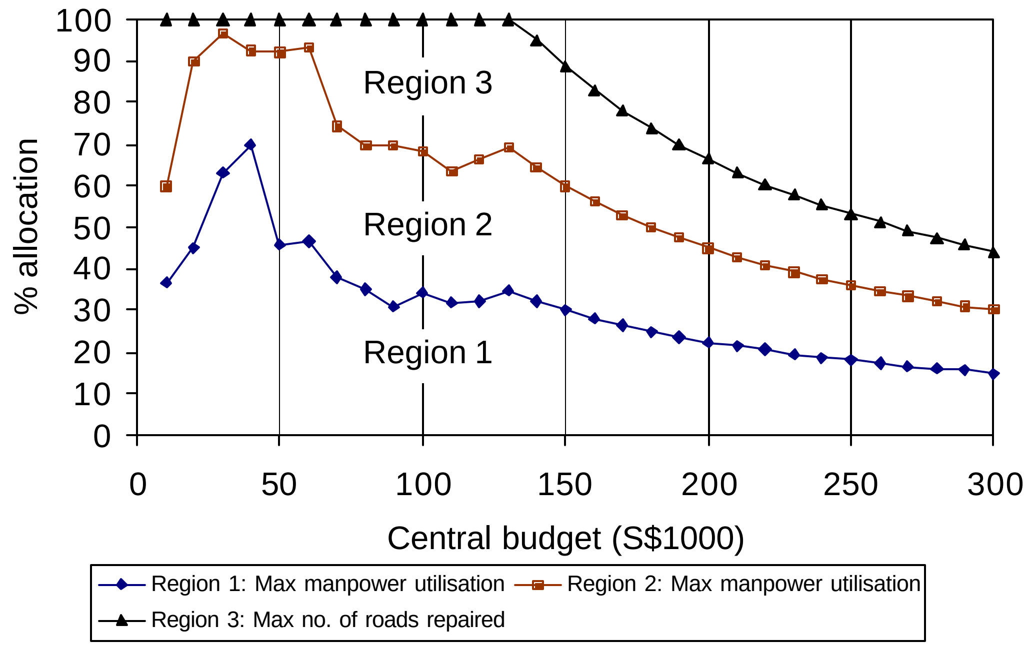


(a) Budget allocation shares of regions for different available total budgets

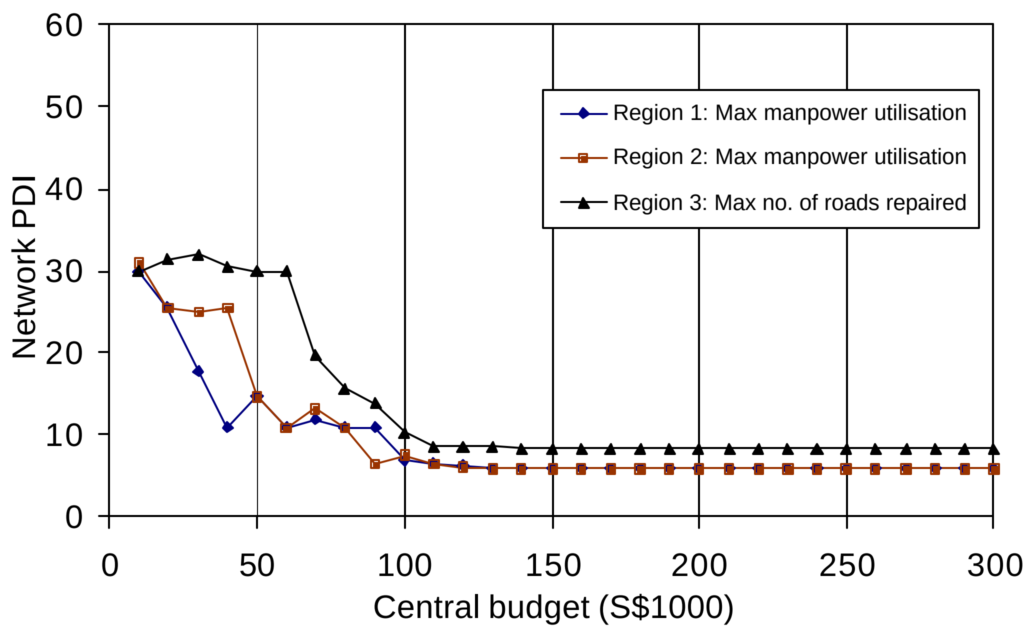


(b) Regional network PDI distributions for different available total budgets

Fig. 3.22 Budget allocation strategy for Case H (see Table 3.6)

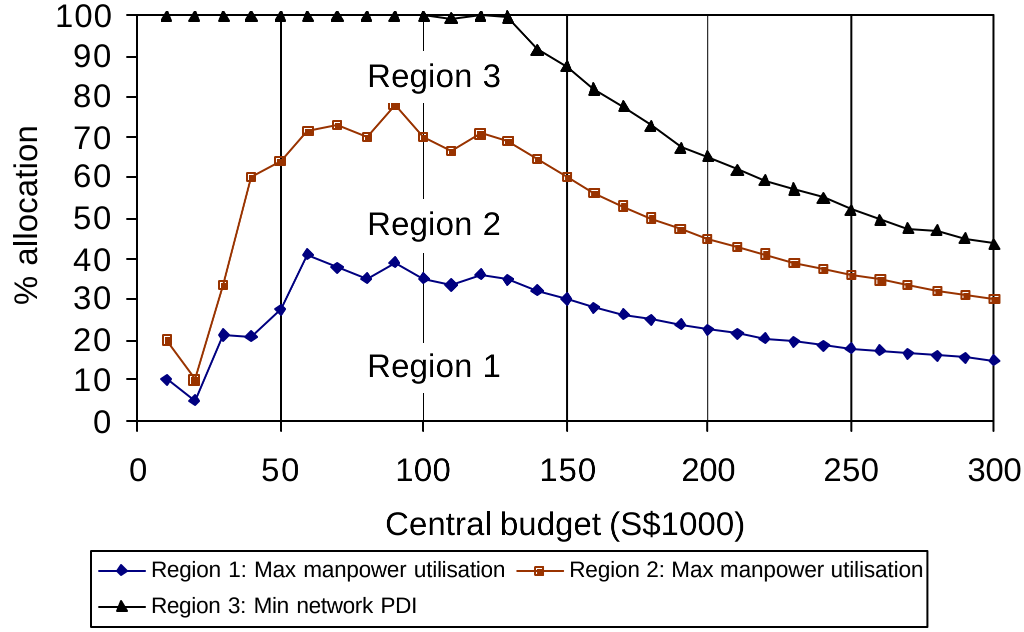


(a) Budget allocation shares of regions for different available total budgets

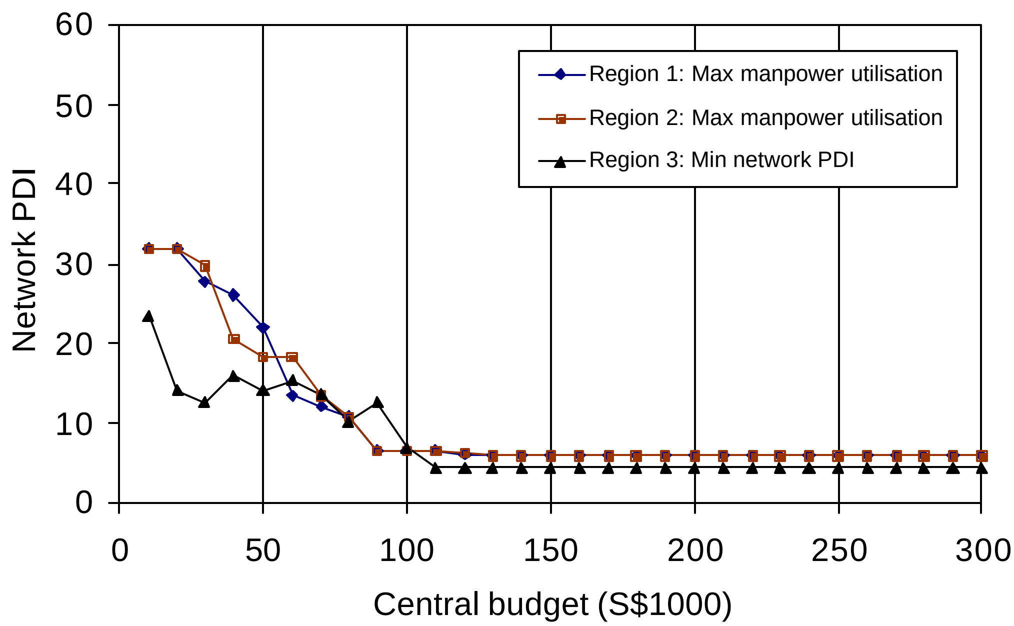


(b) Regional network PDI distributions for different available total budgets

Fig. 3.23 Budget allocation strategy for Case I (see Table 3.6)



(a) Budget allocation shares of regions for different available total budgets



(b) Regional network PDI distributions for different available total budgets

Fig. 3.24 Budget allocation strategy for Case J (see Table 3.6)

CHAPTER 4

MULTI-AGENT VERTICALLY INTEGRATED OPTIMIZATION APPROACH

4.1 INTRODUCTION

In the previous chapter, a two-step optimization analysis for highway fund allocation among regions has been described. The procedure is based on a two-step genetic algorithm with a single passing of information between the upper- and lower-level managements. In this chapter, a distributed fund allocation approach based on multi-agent systems is proposed. The earlier hypothetical example problem is solved using the proposed approach and the results are compared against that obtained using traditional as well as the two-step optimization approach.

4.2 MOTIVATION FOR DISTRIBUTED OPTIMIZATION IN MULTI-NETWORK PAVEMENT MANAGEMENT

The following are the main drives and motivation for a distributed fund allocation approach in multi-level pavement management:

- *'Negotiation' between central and regional agencies.* In the real-world budget allocation process, higher- and lower-level managements interact with one another through a series of directives and feedbacks before arriving at the final allocation strategy. This negotiation process is essential for a compromise to be reached. Multi-agent systems provide a more realistic representation of the 'negotiation' process that takes place between the central administration and regional highway agencies.

- *Complexity of problem.* The multiple-network pavement management problem, when considered globally, is a highly complex problem involving large number of parameters, objective functions and constraints which need to be taken into account. When the number of pavement networks becomes very large, or when considerations are expanded onto other related systems than pavement, the problem can be too extensive to be analyzed as a whole. While centralized approaches could still be possible, solutions based on independent local approaches allow the problem to be better understood and solved more elegantly.
- *Spatially distributed problem.* The fund allocation problem among pavement sub-networks, by its very nature, is a physically distributed problem. The various provincial, regional or district highway agencies reside in different locations, with each looking after the pavement networks in their respective geographical boundaries. The central administration would also be separately situated from the other highway agencies. This makes it highly suitable for the multi-agent systems approach.
- *Distributed data and processing.* Being situated in different geographical locations means that the data are also distributed over the topology, with each regional agency overseeing the data and processing of information in its own jurisdiction. Merging these large and distributed data into a single database for a centralized optimization would require significant amount of resources and efforts. Further, the database merging process can be made complicated if the data from the various highway agencies are not in a standardized format. A distributed approach would allow the processing of the data to be carried out in

a distributed manner, and only the most essential information is transmitted to the relevant party.

4.3 DESCRIPTION OF MULTI-AGENT VERTICALLY INTEGRATED OPTIMIZATION APPROACH

4.3.1 The Model

The funds allocation process in multiple agency pavement management can be modelled using MAS approach. Studies on similar problems from the group perspective in MAS research have been widely reported in the literature. Malone (1990) proposes a comprehensive study of group organization. "A group of agents is an organization if they are connected in some ways (arranged systematically) and their combined activities result in something better (more harmonious) than if they were not connected. An organization consists of: a group of agents; a set of activities performed by agents; a set of connections among agents; and a set of goals or evaluation criteria by which the combined activities of the agents are evaluated." Hence, group organization depends upon the capacity of agents to coordinate their activities.

In this context, each decision-maker can be modelled by an agent - the central authority is represented by a central agent while the regional highway agencies are represented by one regional agent each. Each agent has decision-making capabilities and specific roles to perform. The central agent is the authority over-looking the entire budgeting process, while regional agents receive directives from the central agent, work on the directives, and return a feedback to the central agent. A two-way communication is thus established and based on this communication, the needs and emphasis of each decision-maker is negotiated. The activities performed by regional agents would essentially be the scheduling of maintenance activities and reporting to the central agent. The scheduling task is carried out based on certain constraints (e.g. budget) set by the central agent as well as local manpower and equipment constraints. The central agent will evaluate the overall system benefit derived from the combined feedback from regional agents. Based on this evaluation, the central agent will then provide further directives (another budget allocation) to regional agents, informing them if any changes or improvements to the original plan are required. A series of interaction between central and region agents will continue until satisfactory solutions are achieved or the maximum number of iterations is reached.

4.3.2 Overview of Cognitive Agent Architecture (Cougaar)

The Cognitive Agent Architecture or Cougaar (BBN Technologies 2002a, 2002b, Brinn et al. 2001) is used as the underlying multi-agent system in this research. Cougaar is a Java-based architecture for the construction of large-scale distributed agent-based applications. It is the product of a multi-year research project by the Defense Advanced Research Projects Agency (DARPA) in the United States which looks into large scale agent systems for military transportation scheduling (Montana et al. 2000). The agent system has been made available to the general public through open source licensing and has enjoyed worldwide user community in a wide variety of application domains.

Cougaar provides a code baseline that provides developers with a framework to implement large-scale distributed agent applications with minimal consideration for the underlying architecture and infrastructure. This is essential as focus can be maintained on the optimization problem at hand rather than inventing a new agent architecture for the purpose of this research. Cougaar allows its agents to cooperate with one another to solve a particular problem, storing the shared solution in a distributed fashion across the agents. Cougaar agents are composed of related functional modules, which have the capability to dynamically and continuously rework the solution as the problem parameters, constraints, or execution environment change. Other advantages of Cougaar include its scalability for large systems, ability to schedule over the internet and dynamic replanning and execution monitoring capabilities.

Cougaar is built on component-based, distributed agent architecture based on the blackboard concept. The agents communicate with one another by a built-in asynchronous message-passing protocol. A Cougaar agent consists of two major components: a partitioned blackboard, and plugins (Fig. 4.1). Plugins are software components that provide behaviors and business logic to the agent's operations. Each plugin provide unique capabilities, knowledge and behavior that allow the plugin to specify how to complete a given task. Therefore, an agent that requires certain functionality will load the plugin or plugins designed to accomplish this functionality. The plugins of an agent interact with the agent and with each other by publishing and subscribing to objects on the blackboard. The Cougaar blackboard is a partitioned data structure that contains a collection of objects that is being communicated between an agent and its plugins. By design, plugins have no direct interaction with other plugins (other than through publishing and subscribing to objects in the blackboard) and for a given message do not know which plugin will process it or if that plugin is in the same agent or in another agent. This is where the agent is reactive, i.e. it reacts to subscribed objects added to its blackboard.

A Cougaar *agent* is an agent that has been given behaviors to model a particular organization, business process or algorithm. It can be programmed to have both cognitive and reactive capabilities. A Cougaar *society* is a collection of agents that interact to collectively solve a particular problem or class of problems, which are typically associated with planning. A Cougaar *community* is a notional concept, referring to a group of agents with some common functional purpose or organizational commonality. Thus, a Cougaar society can be made of one or more logical communities, with some agents associated with more than one community.

By default, Cougaar agents do not know of the existence of other agents in their society, nor do they know how to communicate or take advantage of them. For proper interactions within a society to be established, relationships among agents must be established. Relationships between Cougaar agents represent a role or capability that a given agent can perform for another agent. Some standard roles and relationships include superior-subordinate and customer-provider relationships. Each relationship is mutual, for example if A is the superior of B, then B is the subordinate of A. Cougaar allows a given agent to be in many different roles and relationships simultaneously, and these roles and relationships can be dynamic, i.e. they can be modified, enhanced, deleted, and extended in the course of the processing of the society.

4.3.3 Cougaar in the Multi-Agent Vertically Integrated Optimization Approach

4.3.3.1 The Agents

In Cougaar, the names of the agents are listed in a node initialization (*.ini) file. This file contains the name of all agents that will be created by the system at startup. Each agent is defined by another separate agent initialization file. The name of the file must be the same as the name of the agent, for example, *Central.ini* defines the agent named "Central". Regional agents are named as *Region1*, *Region2* and so on. The agent initialization file contains the list of java classes that make up the agent object, the uic (agent name), the names of the plugin classes that will be implemented by the agent, and whether or not the agent is cloned. All agents are set as not cloned.

4.3.3.2 The Community

In the system implemented, the agent initialization file also defines a community domain so that all agents are related to each other as a community. The entities (each agent) in the community – their names, member types, and roles – are defined in an XML file. The central agent has the role of "administrator", while the regional agents have the role of "region". The role names are important to categorize the agents into different groups according to their roles. These are used during the message passing.

4.3.3.3 Agent Relationships

The central agent is the "*superior*" to other region agents, while the region agents are "*subordinates*" to the central agent. The relationship that each agent has with regard to another agent is defined in a *<region-name>-prototype-ini.dat* file. In this implementation, however, the agent relationships are not important because their roles are used as the main criteria for message passing. The roles have been defined in the community XML file (Section 4.3.3.2).

4.3.3.4 Objects

The system consists of many objects, some of which are manipulated only by the regional agents, while some are used solely by the central agents. While not all objects will be exhaustively accounted for in this section, the important ones are described in the following:

Road – Road is an object that represents each road segment. Each Road contains all data pertaining to the road segment, including its ID, road type, length, number of lanes, distress type, distress severity, the pavement condition, and the cost and resources required for its repair activity. This object is only used by region agents.

RoadCollection – RoadCollection is a container that holds together the Road objects in a regional pavement network. This object also functions as the interface between the database and Cougaar in that it retrieves the pavement network information from the database and creates the Road objects for use in the multi-agent system.

SimplePMS – This object is the pavement management system of the region agents. It defines all constants and variables pertaining to the pavement management system, including unit maintenance costs, production rates, premix density, resource requirements, terminal severity values, weights, warning levels, network size, allocated budget, manpower availability, and system objectives of a region. SimplePMS also provides all the methods for the calculation of required maintenance costs, resources, network pavement condition index, and activities scheduling and optimization.

Optimizer – This object works and interfaces with SimplePMS to perform the optimization routine. It stores all information that is calculated during an optimization run, and provides methods for analyzing the genetic strings of each individual solution during the optimization, assigning evaluation values, checking constraints, and assigning penalty values.

Budget – Budget is an object created by the central agent and broadcasted to the region agents. The Budget contains two vital information, the total number of regions, and the amount of fund to be allocated to each region.

RegionalReport – This is the feedback report created and modified by region agents after each network-level optimization is performed. It is sent to the central agent for evaluation purposes. This report contains summary information on network characteristics, cost of maintenance for the particular maintenance program, the budget assigned to it, the pavement performance after maintenance, and the resources used.

RankReport – This is a copy of the RegionalReport kept by the central agent. It is created each time a RegionalReport is received by the central and ranked according to the criteria set by the central. Ranking can be based on the improvement in pavement performance, amount of budget allocated, or the region number. The purpose of the ranking is for the central to sort the reports for housekeeping and other computational purposes. For example, the reports may be received in a random order, and the central would need to sort them according to amount of budget allocated for further processing.

CentralRecord – This is a list of RankReports kept by the central agent. This record is used to store a *complete* set of RankReports for any one budget allocation strategy. 'Complete' means all regions have submitted a report for any particular budget allocation strategy, which can be determined by checking the number of RankReports in the CentralRecord. The CentralRecord also sums and stores the total network

Pavement Damage Index as well as cost and sum of weights information as each RankReport is added into it.

CentralSystem – The main purpose of this object is to store all CentralRecords that are still being used by the central agent. It enables a neat and clean housekeeping of CentralRecords, as well as defining system constants such as the available central fund, and temporary variables such as the best objective value achieved and the iteration number at which it is achieved.

4.3.3.5 Plugins

The plugins are the main components that define the behaviors of the agents. All the actions and reactions of an agent are defined by its plugins. Only two plugins are required for this implementation – region agents use RegionPlugin, while the central agent implements CentralPlugin. Both plugins subscribe to two objects on the agent's blackboard, Budget and RegionalReport. RegionPlugin subscribes to RegionalReport as a way to keep the latest copy of its RegionalReport available to itself, since the RegionalReport is being continuously updated. Similarly, CentralPlugin subscribes to Budget as a way to keep its copy of Budget object up-to-date.

Subscriptions enable the agent to react according to certain rules when the object/objects it subscribes to is/are detected on the blackboard. An object that is subscribed is identified by using *predicates* that are defined in the subscription. In Cougaar, it is possible for a plugin to identify if an object is newly added or changed in the blackboard. For example, the RegionPlugin creates a new RegionalReport when it detects a new Budget object on the blackboard. However, when the Budget object is detected to have changed, the RegionPlugin will retrieve a copy of its own RegionalReport from the blackboard and publish changes to it instead of creating a new report. This helps to save computer memory by reducing the number of objects in the Java Virtual Machine (JVM) at any one time.

4.3.3.6 Message Passing

Message passing, or the sending of objects among agents is accomplished using a RelayObject. The RelayObject is an object that is used to encapsulate another object that is desired to be added to an agent's blackboard. RelayObject contains information regarding the message source, target, a UID (message identity), and the message object. The target can be consists of one agent or a list of other agents, which can be queried to from their roles in the community. Thus, if a Budget object is to be broadcasted to all regions, a query is first made for all agents who have the role of 'region' in the community. The list of agents that fits the query is defined into the RelayObject. Next, the Budget object that is to be sent is attached to the RelayObject, and the sender's identity is included in the message source. This way, the message can be received by all other region agents, and they will know that the message is sent by the central agent based on the source information.

The communications in Cougaar have been modelled in an asynchronous manner, that is, the messages are transmitted in any order and the length of time taken for an agent to respond to a message is of no concern to the agents. The system, therefore, needs to be programmed in such a way that all possibilities of delayed communication is taken into account before certain types of processing which requires specific messages to be received prior to processing is carried out. Coordination also needs to be taken care of explicitly to avoid circumstances of infinite loop where agents wait for certain messages from each other in order to continue processing, but because none of the agents has received any messages, the system is caused to go into an infinite loop. This is an undesirable situation but is very common if coordination among the agents is not in the correct order. Most of the actions undertaken by an agent include checks on various parameters and indicators of received messages.

4.3.4 The Solution Procedure

Fig. 4.2 shows the flow chart for the interactions and decision-making process of the central and regional agents. At start-up, each agent identifies their pre-defined identity specified in the system. This is necessary so that each agent knows the role they are going to play in the system. The central agent, in addition, performs a query to the system to identify the number of regional agents registered. Subscriptions are then set up to enable the agents to subscribe to communications from other agents.

The grey areas of Fig. 4.2 represent the genetic-algorithm steps involved in the proposed budget allocation methodology. The central agent uses genetic algorithms to search for an optimal budget allocation strategy, while region agents use genetic algorithms for regional network-level pavement maintenance optimization. Fig. 4.3 shows the distributed optimal budget allocation process using multi-agent systems and genetic algorithms. At each generation, budget communications from the central agent relay a genetic solution string which represents a random allocation strategy to be evaluated by the regional agents. Evaluation is performed by regional agents using another set of regional-level genetic algorithms. Thus, the whole process can be viewed as two successive genetic algorithms that work interactively to reach the central goal while also still optimizing the regional goals. After each evaluation, regional agents generate a report that is communicated back to the central giving the optimal solution from regional-level optimization for the funds specified. The RegionalReport informs the central agent of the regional road network information, total PDI repaired and cost required for such repair. Upon receiving reports from all regions, the central agent will then perform an evaluation as to the effectiveness of the current budget allocation strategy in question with respect to its system goal. The evaluation value is fed into the central-level genetic-algorithms and the whole process repeats for the next solution string. Iterations will stop once the central agent reaches a specified number of generations. The best funds allocation strategy that has been found will then be relayed to the regional agents for implementation.

4.4 APPLICATION OF MULTI-AGENT VERTICALLY INTEGRATED APPROACH

A hypothetical example problem involving a two-level pavement management structure as described in Chapter 3 (Section 3.3) is solved using the distributed optimization approach to demonstrate its technique in an actual pavement management application as well as to gauge its performance. The three cases that are used as case studies for the distributed multi-agent approach are re-summarized in Table 4.1(a) while the pavement conditions of the regional road network for the cases are given again in Table 4.1(b). Similar pavement network characteristics, resource availability, and objective functions and constraints as that in the earlier example problem are assumed. The objective functions of each regional highway agency and central administration are re-summarized here:

Region 1 -- Maximizing the number of distressed road segments repaired

Region 2 -- Maximizing the performance level of regional road network pavements

Region 3 -- Maximizing the usage of the available manpower

The only things that will differ from the earlier problem solved in Chapter 3 will be the genetic string structures and solution methodology.

4.4.1 GA String Structures

Different GA string structures are used in the optimization analysis by the central and region agents. At the regional level optimization, the GA string structure is similar to the one used in Chapter 3. The decision variables pertain to the choice of road segments selected for maintenance. Thus, an appropriate string structure for each region agent is one that consists of one cell for each road segment as shown in Fig. 4.4(a). The total length of the string structure (i.e. the number of cells) is therefore equal to the number of road segments in the region concerned. The value of each cell gives the maintenance decision taken for the road segment that the cell represents. A value of 1 for the k-th cell means that the k-th road segment is selected for maintenance, while a value of zero indicates that the road segment is not selected for maintenance. The GA package used for the optimization process in the region agents is PGAPACK (Levine 1996).

At the central level optimization, the decision variables are the binary representations of the shares of budget allocation for the three regions. The total length of the string structure depends on the maximum number of bits that may be involved. Since one region can at most be allocated the maximum available central funds, the maximum number of bits is therefore the number of bits in the binary representation of the total available central funds multiplied by the number of regions.

$$\text{Total length of GA String} = \begin{pmatrix} \text{Maximum number of bits} \\ \text{in binary representation of} \\ \text{total available central funds} \end{pmatrix} \times \begin{pmatrix} \text{Total number of regions} \\ \text{involved} \end{pmatrix} \qquad (9)$$

The GA string structure for the central agent is shown in Fig. 4.4(b). A Java-based genetic-algorithm package ECJ (Luke 2002) is used at the central level

4.4.2 Constraint Handling of Central GA

At the central level, a small GA population size is desirable because the evaluation of each central individual requires a genetic algorithm optimization run to be performed by each regional agent. A small increase in the central GA population size will significantly increase the total number of function evaluations to complete each cycle of central GA generation. Therefore, it is desirable to enable the GA to converge using a small population size, and to reduce the amount of function evaluations required at each generational run. This can be achieved using a decoder and repair algorithm method (DRAM) (Hoque 1999) to handle constraint violations at the central GA.

The DRAM algorithm is used before each central GA is evaluated. This ensures that the central budget availability constraint is not violated before it is sent to the regional agents for regional-level optimizations. To preserve the regional budget allocation as much as possible, the DRAM algorithm first search for the regional share of budget that exceeds the central budget constraint and randomly mutates the budget share of this region until it is within the central budget limit. Next, the sum of all regional budget shares is checked against the total budget availability. If a violation is detected, the individual is randomly reinitialized.

Fig. 4.5 shows a comparison of the central GA run with and without using the DRAM algorithm described above. A marked improvement in the convergence of the GA can be seen when the DRAM algorithm is used. It shows that the DRAM algorithm is able to guide the GA to start the search with much fitter individuals. Good convergence is achieved with a small population size of 10 and within 100 generations.

4.4.3 Sensitivity Analysis of Central GA Parameters

The problem at the regional level remains the same as in Chapter 3. Therefore, the same GA parameters in the regional agents are used here. Sensitivity analysis is conducted for the central GA.

The sensitivity analysis is conducted using Case 2 as the test case. The best of three runs is reported for a particular GA parameter value analyzed. Fig. 4.6 shows the effect of different population sizes on the GA convergence of the central agent. To study the effect of population size, the offspring size is fixed at 80% of the population size, while the crossover and mutation rates are 85% and 5% respectively. Mutation and crossover are simultaneously applied as the genetic operators. Results show that the population size of 40 gives faster convergence compared to the other population sizes. However, smaller population sizes such as 10 and 20 gives comparable performance as population size 40 where the final convergence value is concerned. Smaller population size is preferable as explained in Section 4.4.2. Therefore, population size of 10 is used for the central agent.

The offspring size is determined as shown in Fig. 4.7. The percentage of parent pool size refers to the newly generated individuals in the offspring population. For example, an offspring size of 90% of the parent pool size means that 10% of the individuals in the parent population will be retained into the offspring population and the remaining 90% are newly generated individuals. Results show that the final convergence value decreases as the offspring size increases up to 50% of the parent pool size. Therefore, offspring size of 60% of the parent pool size is found to be the most suitable. The convergence value obtained from offspring size of 60% is also the same as that obtained in the analysis for the population size. This value is expected to be the true convergence value.

Fig. 4.8 shows the effect of crossover rate on the convergence of the GA of the central agent. Crossover rate of 85% is found to give the best convergence value. The sensitivity of the problem towards mutation rate is studied and shown in Fig. 4.9. The performance of the GA improves as the mutation rate is decreased till 5%. The GA convergence value decreases thereafter. Therefore, the mutation rate of 5% is appropriate for the problem considered.

4.4.4 Method of Analysis

A random initial population of possible individuals (allocation strategies) is generated by the GA in the central agent, and each individual is broadcasted to the regional agents. Regional agents use the budget information as a constraint in their own search for the optimal pavement maintenance schedule in their respective road networks in terms of their respective objective functions. A regional report is generated upon reaching an optimal solution, and this is sent back to the central agent. Upon receiving reports from all regions, the central agent retrieves and processes the information to arrive at the overall network PDI encompassing all regions. This is used as the fitness value of the particular individual in consideration. If there are more unevaluated individuals, the central agent repeats the whole process with the next individual until each and every individual in the population has been evaluated. If all individuals have been evaluated, the algorithm generates a new offspring population using genetic operators such as mutation and crossovers, and the above cycle repeats itself until the maximum number of generation is reached. The whole process is repeated for a range of central available budget.

4.4.5 Comparison with Other Allocation Approaches

The results obtained from the multi-agent vertically integrated optimization approach are compared against those obtained using:

- Two-step optimization approach
- Formula-based allocation approach
- Needs-based allocation approach

These approaches were described in Section 3.6.

4.5 RESULTS OF ANALYSIS

4.5.1 Savings in Total Cost

Each of the allocation method described in the preceding sections was used to obtain the best fund allocation strategy for the three problem cases studied. The percentages of budget allocated to each region according to conventional approaches (needs-based and formula-based approaches) are the same for different total available central funds because they depend on variables that are not sensitive towards the amount of available global funds (Figs. 4.10 and 4.11). In Fig. 4.10, the percentage of central fund that is allocated to each region is directly proportional to the total length of roads in each region. While in Fig. 4.11, the percentage of allocation is directly proportional to the amount of fund needed by each highway agency to repair all distresses in their respective regions.

Figs. 4.12 and 4.13 show the shares of budget allocated to each region according to the two-step optimization and agent-based vertically integrated approaches respectively. In all three problem cases, the general trend of the budget allocation strategies derived from these two approaches is similar. Both the two-step and agent-based approaches allocate the global funds based on its availability, thus providing a more flexible allocation strategy tailored to the needs and constraints of each regional agency as well as the central administration. Each of the cases is discussed in detail below.

(a) Case 1

In Case 1, both allocation procedures allocate the bulk of central funds to Region 2 when the available total budget is at S$30,000 and lower (Figs. 4.12a and 4.13a). However, the multi-agent approach tends to allocate a higher percentage of funds to Region 3 in this budget range. This is in contrast to the allocation strategy of the two-step optimization approach which favors Region 1 to Region 3 for this range of budget. Table 4.2(a) shows that the strategy by the vertically integrated MAS approach results in reduced total maintenance cost by up to 15.59% for this budget range (where PDI limit is 22) compared to the two-step approach. A possible explanation for this is that at low budget levels, allocating more funds to Region 3 instead of Region 1 better serves the central objective because the objective function of Region 1, which pushes to maximize the number of roads repaired, would naturally repair the low severity distresses first to increase the number of roads repaired. Thus, it could not give as high a contribution in reducing the overall network PDI compared to Region 3. This is valid for low central budget availability. From this analysis, the vertically integrated MAS approach is able to find solutions that better serves the central objective function.

Region 2 receives the bulk of the funds when the available central resources are low because its objective function of minimizing network PDI is in line with the central objective. As the central funds increase, the funds being allocated to Region 1 picks up as more funds are now available to include the high severity distresses in that region. The maximum savings achieved with the vertically integrated multi-agent approach compared to the needs-based and formula-based allocation approaches are 28.73% and 36.54% respectively.

(b) Case 2

A similar pattern is observed in Case 2 (Figs. 4.12b and 4.13b). Region 2 is still given the highest priority when the central funds are at very low levels in both the agent-based and two-step allocation methods. After that, the bulk of the fund shifts to Region 3. This is because of the high initial network PDI value in Region 3, which allows for a greater number of high severity distresses to be repaired (and thus significantly reduces the overall network PDI value at the global level) when there are enough central funds. As in Case 1, allocation to Region 1 picks up only when the available central funds are at a level where enough funds are available to include the high severity distresses in the region that could contribute to high reduction in the global network PDI. The maximum savings achieved using the agent-based allocation approach from the 2-step approach is 15.19%, while the maximum savings from the needs-based and formula-based approaches are 37.44% and 36.72% respectively (Table 4.2b).

(c) Case 3

The main difference in the pattern of allocation in Case 3 compared to the first two cases is that Region 1 is given higher priority than Region 3 when the available central fund increases to S$40,000 and above. In Case 3, Region 1 has a significantly higher network PDI than Region 3 where most of the distresses in Region 1 are of high severity. Even though it is more costly to repair these high severity distresses, the algorithm still favors Region 1 to Region 3 for budget levels S$40,000 and above because of the PDI contributions of these segments. Allocating more funds to Region 1 to repair these severely distressed road segments will help to push the overall network PDI down. However, this results in Region 3 receiving very little funding at budget levels S$40,000 to S$100,000. Region 2, as in the previous two cases, continues to receive the most fund when central resources are low (S$30,000 and below). When the central budget reaches S$140,000 and above, the proportion of funding to each region becomes almost equal. This proportion should become synonymous with the proportion of the sub-network size of each region if the analysis is to be continued to more than S$150,000, as was reported in Chapter 3 (Fig. 3.12).

4.5.2 Overall Network PDI

The dual of the problem is to derive the overall network PDI achieved for different available central budget. This is obtained in order to show the differences in the overall network PDI that is achieved using the various fund allocation approaches studied. Fig. 4.14 shows a comparison of the overall network PDI achieved. As expected, the vertically integrated MAS approach gives better overall network PDI for all budget ranges for all three problem cases considered. The differences between the approaches introduced in this thesis (two-step optimization and vertically integrated

MAS approaches) and conventional allocation approaches becomes larger for Case 2 and Case 3. The differences between the two-step optimization and vertically integrated MAS, however, remain small. Nevertheless, the reductions in cost between the two approaches were fairly significant, as reported in the previous section.

4.5.3 Regional Objective Function Values

Fig. 4.15 shows a comparison of the regional objective function values achieved using the two-step optimization and vertically integrated MAS approaches for Case 1. The comparison of regional objective function for Cases 2 and 3 are shown in Fig. 4.16 and 4.17 respectively. A region's objective function value for specific central budget availability obtained using any of the two approaches may rise or drop according to the amount of fund the region gets allocated. It is interesting to note that both approaches do produce strikingly similar curves. Differences in objective function value achieved between the vertically integrated MAS optimization and two-step optimization approaches arise because different funding levels are allocated at specific central budget availability when using different fund allocation approaches. Neither of the two approaches could guarantee a "better" achievement of regional objectives for specific central budget availability. However, a general trend is that the regions will benefit more when the available central budget gets higher.

4.6 CHAPTER SUMMARY

In this chapter, a vertically integrated multi-agent optimization approach to the allocation of multi-regional pavement maintenance fund has been proposed. The approach is well-suited for the problem considered due to the spatially distributed nature of the problem, the distributed data and processing, and the complexity of the multi-network pavement management problem when considered globally. The multi-agent system is implemented using Cougaar, a Java-based code baseline developed by the Defence Advanced Research Projects Agency (DARPA) of the United States for the construction of large-scale distributed agent-based applications. The agent system constructed for the proposed approach has been described.

The solution procedure of the distributed multi-agent optimization approach has been demonstrated using a hypothetical example problem. The example problem of Chapter 3 is solved using the proposed distributed multi-agent optimization approach, and the results compared against that of other allocation procedures, namely the two-step optimization approach introduced in Chapter 3, and the formula- and needs-based allocation approaches. The distributed multi-agent optimization approach has been found to consistently give higher cost savings for a target PDI level. The savings can be as high as 36% compared to formula-based approach for the problem cases considered.

It is obvious both the two-step and agent-based allocation approaches consistently perform better than the conventional needs- and formula-based systems in terms of reduced overall maintenance cost. Both the approaches are able to reduce the spending required for a given target of pavement performance because they fully take into consideration the overall goal of the central administration without compromising local goals. The agent-based approach, however, is better able to save further in maintenance cost compared to the two-step allocation approach due to better interactions through improved information integration between the two management levels made possible using agent technology. The vertical interactions provide a means for information at the two levels to be better integrated, thus resulting in a better overall performance of the budgeting process.

Table 4.1 Planning data for regional road network

(a) Summary of the three cases studied and their attributes

		Region 1	Region 2	Region 3
Case 1	Number of road segments	30	40	50
	Network PDI	32.53	24.74	32.78
	Maintenance Needs (S$)	44 937.60	59 767.36	69 074.56
Case 2	Number of road segments	40	40	40
	Network PDI	10.82	21.07	41.19
	Maintenance Needs (S$)	63 453.76	60 616.96	63 825.28
Case 3	Number of road segments	30	80	150
	Network PDI	50.45	22.05	12.83
	Maintenance Needs (S$)	59 392.96	126 652.80	217 744.00

(b) Pavement conditions of regional road networks

Case 1

Region	Road Type	Crack H	Crack M	Crack L	Rut H	Rut M	Rut L	Pothole H	Pothole M	Pothole L
1	Expressway	2	4	1	1	0	3	1	0	0
	Arterial Road	1	0	1	3	2	4	3	1	3
2	Expressway	1	2	7	1	5	6	1	2	2
	Arterial Road	3	0	4	0	1	1	2	1	1
3	Expressway	2	1	1	2	3	3	1	0	4
	Arterial Road	2	2	3	6	4	9	3	2	2

Case 2

Region	Road Type	Crack H	Crack M	Crack L	Rut H	Rut M	Rut L	Pothole H	Pothole M	Pothole L
1	Expressway	0	2	13	0	0	4	0	0	0
	Arterial Road	1	1	12	0	0	1	0	1	5
2	Expressway	1	0	6	0	0	3	0	0	1
	Arterial Road	4	4	8	2	2	5	1	0	3
3	Expressway	1	1	1	3	5	1	1	0	0
	Arterial Road	3	1	1	9	5	4	0	2	2

Case 3

Region	Road Type	Crack H	Crack M	Crack L	Rut H	Rut M	Rut L	Pothole H	Pothole M	Pothole L
1	Expressway	2	1	0	5	1	0	2	1	0
	Arterial Road	1	1	0	9	2	1	3	0	1
2	Expressway	5	3	11	2	4	4	1	3	4
	Arterial Road	2	2	22	1	2	4	1	5	4
3	Expressway	1	2	28	0	2	14	0	0	9
	Arterial Road	2	3	53	3	0	20	2	3	8

(Column group header in each table: Number of Distressed Segments.)

Note: H = High Severity, M = Medium Severity, L = Low Severity

Table 4.2 Savings obtained from agent-based vertical interaction approach compared to other approaches (to be continued)

(a) Case 1

PDI	Vertically Integrated MAS Approach	2-Step Optimization Approach			Needs-based Approach			Formula-based Approach		
	Total Cost (S$1000)	Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach	
			Amount	%		Amount	%		Amount	%
22	29884.96	35406.12	5521.16	15.59	41933.30	12048.34	28.73	46195.42	16310.46	35.31
21	36657.54	41148.01	4490.46	10.91	45950.08	9292.54	20.22	55414.87	18757.33	33.85
20	42749.68	45669.83	2920.15	6.39	53080.67	10330.99	19.46	62947.58	20197.90	32.09
19	48445.35	50228.03	1782.68	3.55	59655.52	11210.17	18.79	67847.25	19401.90	28.60
18	53326.59	55141.25	1814.66	3.29	64273.33	10946.74	17.03	74190.76	20864.18	28.12
17	58145.95	60081.96	1936.02	3.22	68781.09	10635.14	15.46	82179.21	24033.26	29.24
16	63496.70	65361.09	1864.39	2.85	72526.22	9029.52	12.45	94310.87	30814.16	32.67
15	68772.38	70838.98	2066.60	2.92	76271.36	7498.98	9.83	103539.01	34766.63	33.58
14	72819.93	76880.56	4060.63	5.28	80371.48	7551.55	9.40	111343.30	38523.36	34.60
13	76867.49	83148.90	6281.41	7.55	86432.43	9564.94	11.07	119853.65	42986.16	35.87
12	84475.48	89486.83	5011.35	5.60	95786.43	11310.96	11.81	133119.02	48643.55	36.54
11	90943.46	94934.10	3990.64	4.20	102969.69	12026.23	11.68	144621.42	53677.96	37.12
10	95987.46	100479.63	4492.17	4.47	108899.13	12911.67	11.86	*	*	*
9	101731.47	106395.39	4663.92	4.38	116073.98	14342.51	12.36	*	*	*
8	108333.09	114026.46	5693.37	4.99	125232.85	16899.76	13.49	*	*	*
7	112446.04	126066.98	13620.94	10.80	*	*	*	*	*	*

Note: * The target PDI could not be achieved with the approach indicated in the column.

Table 4.2 Savings obtained from agent-based vertical interaction approach compared to other approaches (continued)

(b) Case 2

PDI	Vertically Integrated MAS Approach	2-Step Optimization Approach			Needs-based Approach			Formula-based Approach		
	Total Cost (S$1000)	Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach	
			Amount	%		Amount	%		Amount	%
22	10,086.29	11,892.22	1,805.93	15.19	15,612.35	5,526.06	35.40	3,493.45	3,407.16	25.25
21	14,152.89	16,646.96	2,494.07	14.98	21,655.12	7,502.22	34.64	18,886.03	4,733.14	25.06
20	18,219.50	20,979.54	2,760.05	13.16	28,094.57	9,875.07	35.15	25,931.04	7,711.54	29.74
19	22,630.49	24,617.21	1,986.72	8.07	34,765.11	12,134.62	34.90	33,646.30	11,015.82	32.74
18	27,158.07	28,254.88	1,096.81	3.88	41,229.31	14,071.24	34.13	40,020.88	12,862.81	32.14
17	31,196.27	32,090.65	894.39	2.79	46,991.23	15,794.96	33.61	44,304.23	13,107.97	29.59
16	34,684.59	36,043.88	1,359.28	3.77	52,909.89	18,225.30	34.45	48,587.58	13,902.99	28.61
15	38,189.02	40,073.21	1,884.19	4.70	58,881.14	20,692.12	35.14	60,350.74	22,161.73	36.72
14	42,414.69	45,075.88	2,661.18	5.90	65,217.01	22,802.32	34.96	64,972.23	22,557.54	34.72
13	46,640.37	50,062.60	3,422.23	6.84	72,989.70	26,349.33	36.10	70,079.71	23,439.34	33.45
12	51,485.65	54,817.35	3,331.70	6.08	82,295.60	30,809.95	37.44	76,105.11	24,619.45	32.35
11	58,071.72	59,572.10	1,500.38	2.52	89,777.47	31,705.76	35.32	84,952.38	26,880.66	31.64
10	63,380.86	65,139.70	1,758.84	2.70	94,970.12	31,589.25	33.26	96,748.68	33,367.82	34.49
9	68,615.02	70,843.29	2,228.27	3.15	100,967.82	32,352.80	32.04	104,540.64	35,925.62	34.37
8	75,300.86	76,993.90	1,693.04	2.20	108,973.67	33,672.80	30.90	111,914.02	36,613.16	32.72
7	83,980.64	88,233.77	4,253.13	4.82	118,116.61	34,135.98	28.90	120,103.44	36,122.81	30.08

Table 4.2 Savings obtained from agent-based vertical interaction approach compared to other approaches (continued)

(c) Case 3

PDI	Vertically Integrated MAS Approach	2-Step Optimization Approach			Needs-based Approach			Formula-based Approach		
	Total Cost (S$1000)	Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach	
			Amount	%		Amount	%		Amount	%
19	13600.93	14080.00	479.07	3.40	27202.68	13601.75	50.00	29330.74	15729.80	53.63
18	20689.97	21912.52	1222.55	5.58	37608.77	16918.80	44.99	44839.32	24149.35	53.86
17	27728.92	29857.95	2129.02	7.13	53999.14	26270.21	48.65	57971.82	30242.90	52.17
16	38699.72	38936.66	236.93	0.61	67571.03	28871.30	42.73	71642.58	32942.86	45.98
15	46096.35	47001.08	904.73	1.92	86322.81	40226.46	46.60	85277.64	39181.29	45.95
14	53981.33	54698.44	717.11	1.31	103574.93	49593.61	47.88	105206.53	51225.21	48.69
13	62329.31	62875.69	546.38	0.87	118436.86	56107.55	47.37	127804.85	65475.54	51.23
12	71803.13	72758.14	955.00	1.31	137054.18	65251.05	47.61	151814.19	80011.06	52.70
11	84377.13	85898.57	1521.44	1.77	157559.19	73182.06	46.45	171709.08	87331.95	50.86
10	107231.45	115820.44	8588.99	7.42	186944.37	79712.93	42.64	210529.28	103297.83	49.07

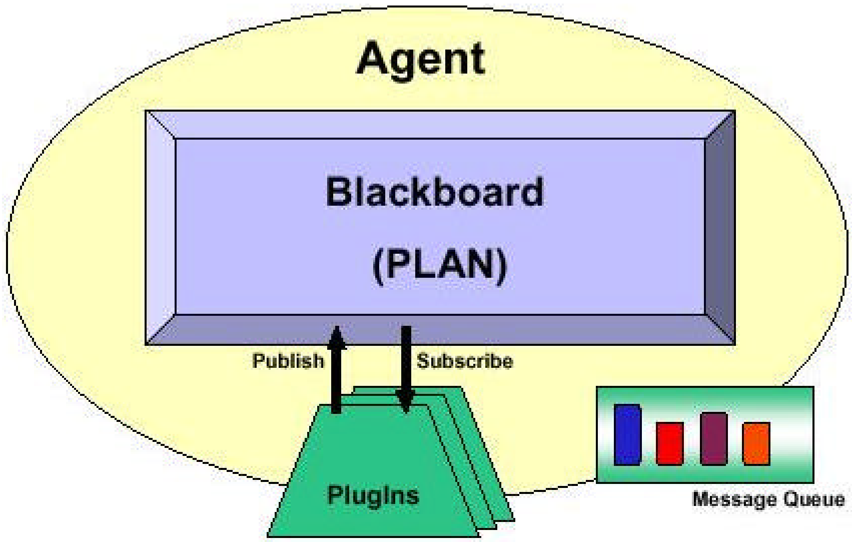


Fig. 4.1 A Cougaar Agent (ALPINE 2002a)

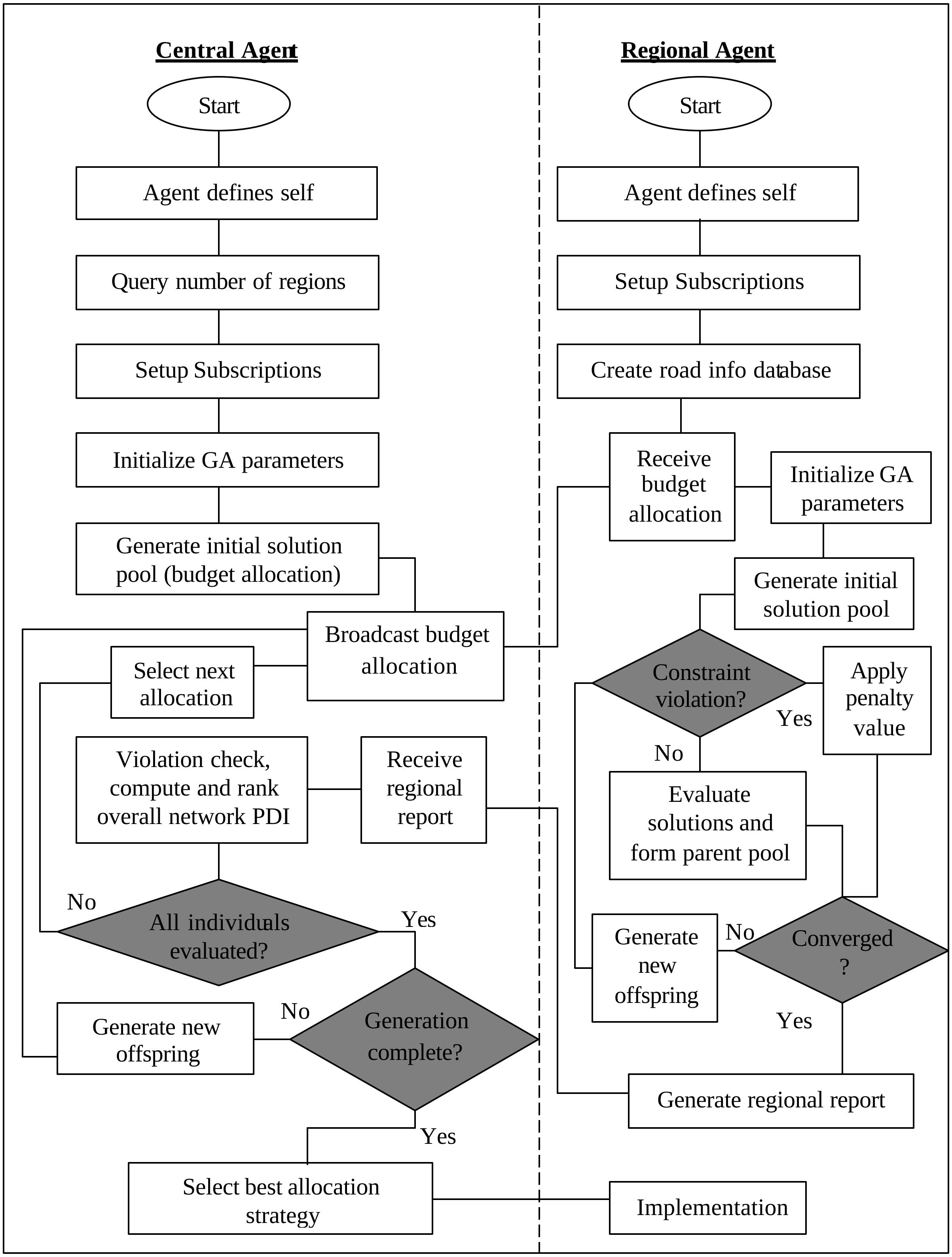


Fig. 4.2 Flow chart for agent interaction and decision-making process

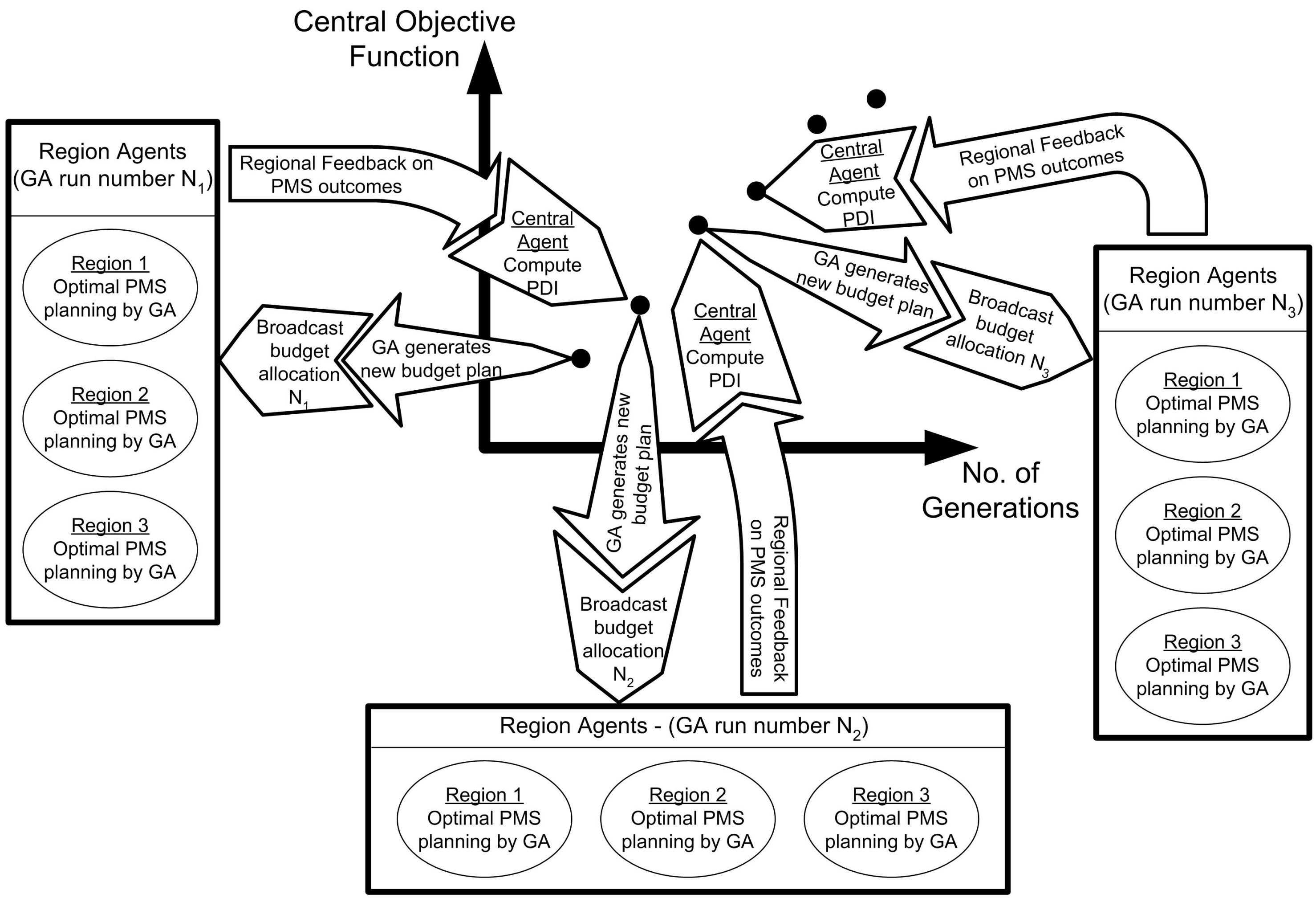
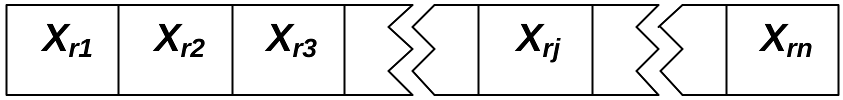


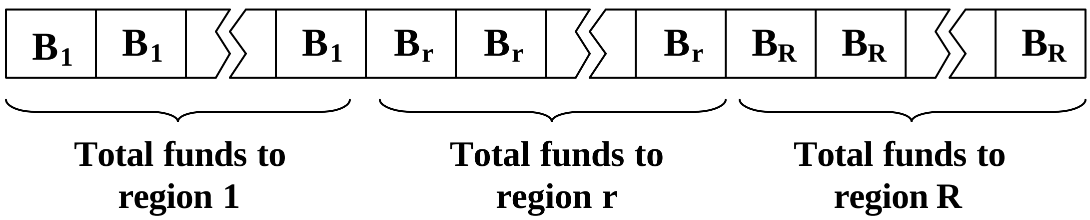
Fig. 4.3 Interactive optimal budget allocation process using Multi-Agent Systems and Genetic Algorithms



$$X_{rj} = \begin{cases} 0 \text{ for segments not selected for maintenance} \\ 1 \text{ for segments selected for maintenance} \end{cases}$$

n = number of road segments in region r

(a) Genetic string structure for region agents



B_r = a single bit of the binary number representing the budget allocated to region r

R = number of regions involved

(b) Genetic string structure for central agents

Fig. 4.4 String structures of the genetic-algorithm formulation in agent-based optimization approach

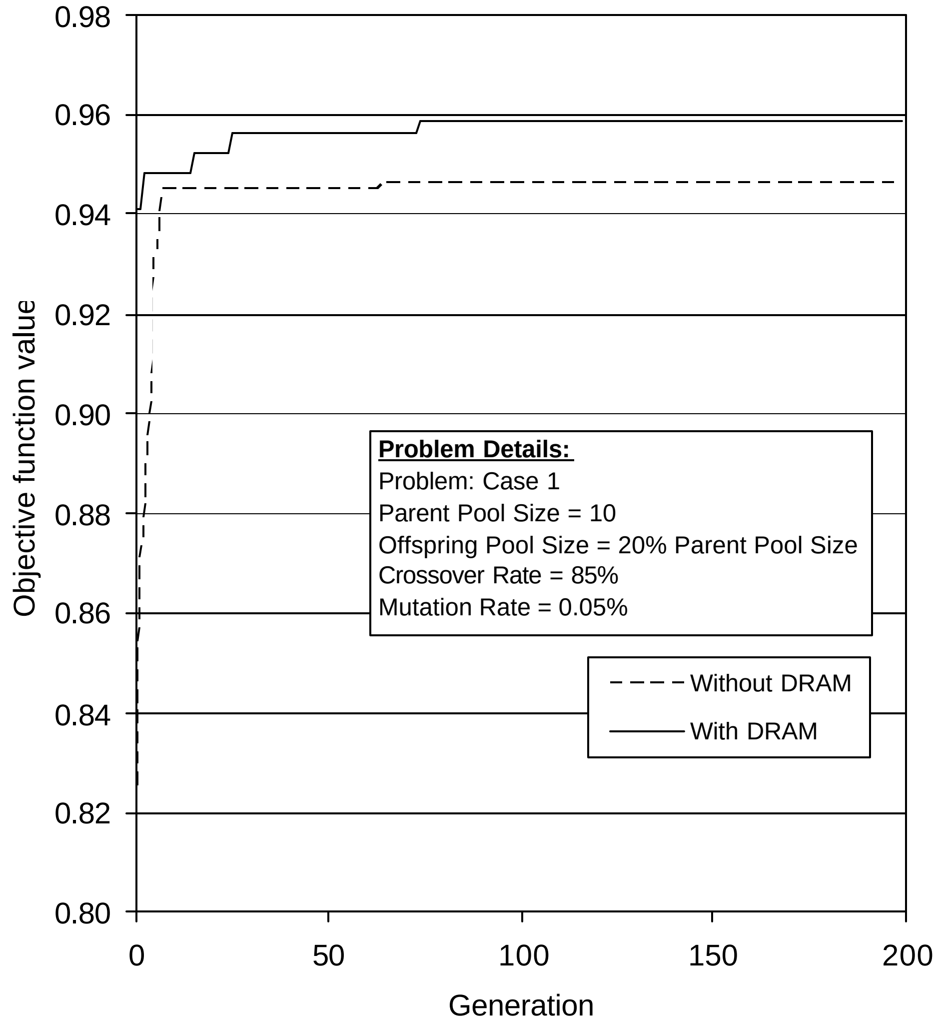


Fig. 4.5 Comparison of the performance of GA of the Central Agent with and without constraint handling method

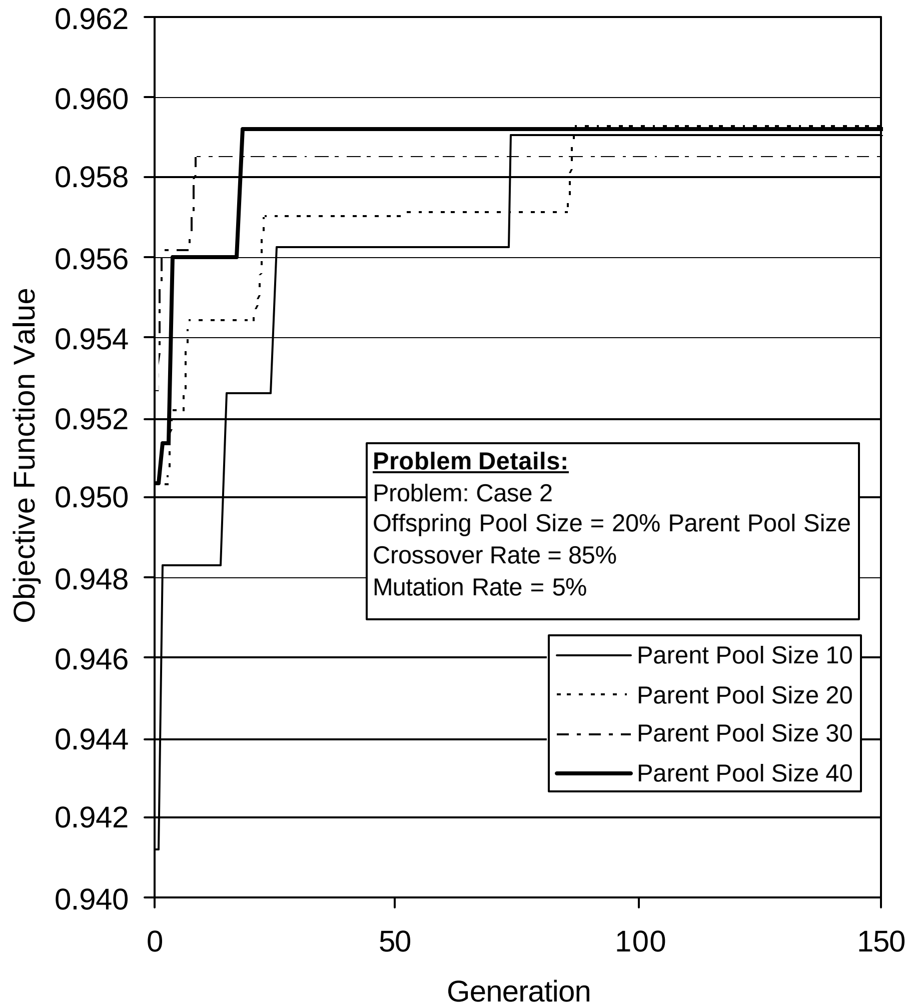


Fig. 4.6 Sensitivity study on the effect of parent pool sizes on GA convergence of the central agent

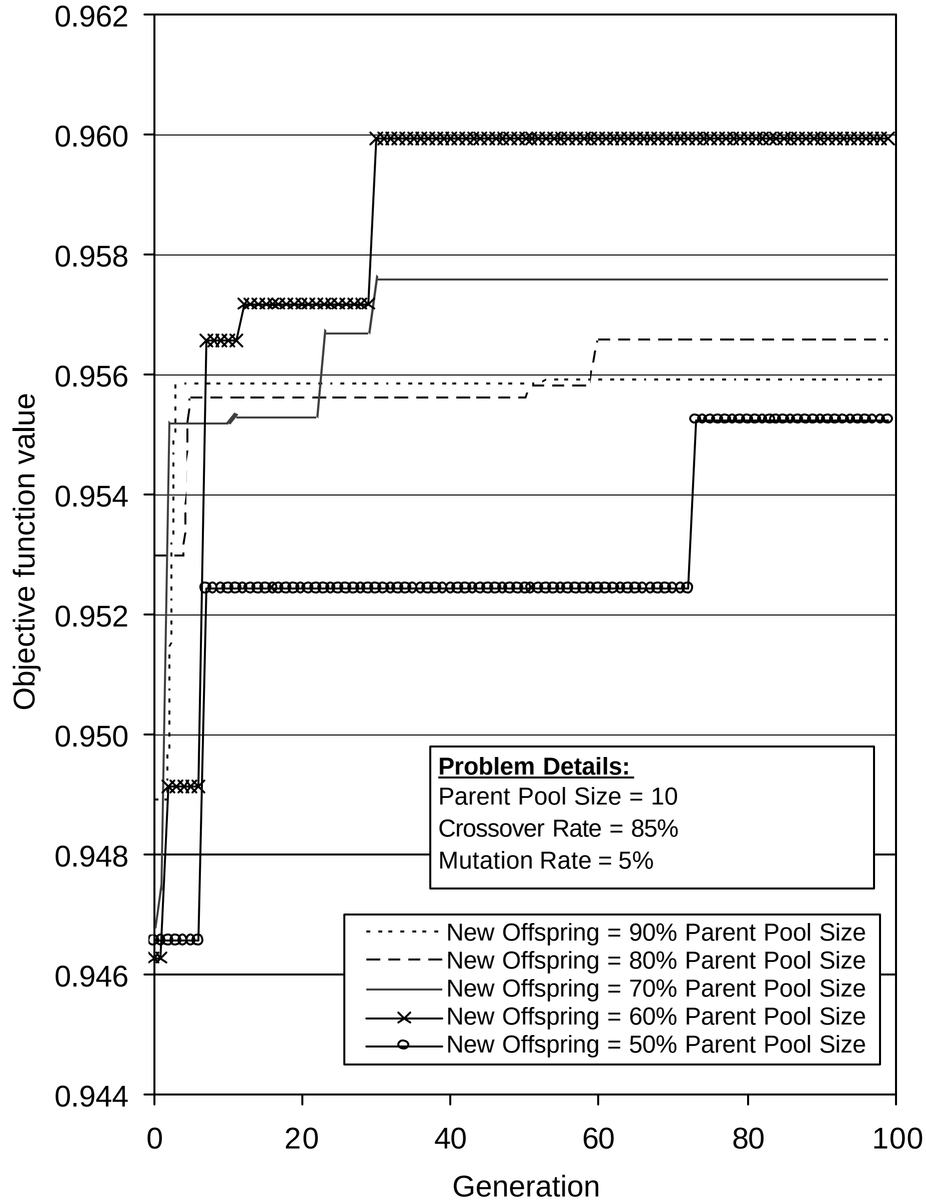


Fig. 4.7 Sensitivity study on the effect of offspring sizes on GA convergence of the central agent

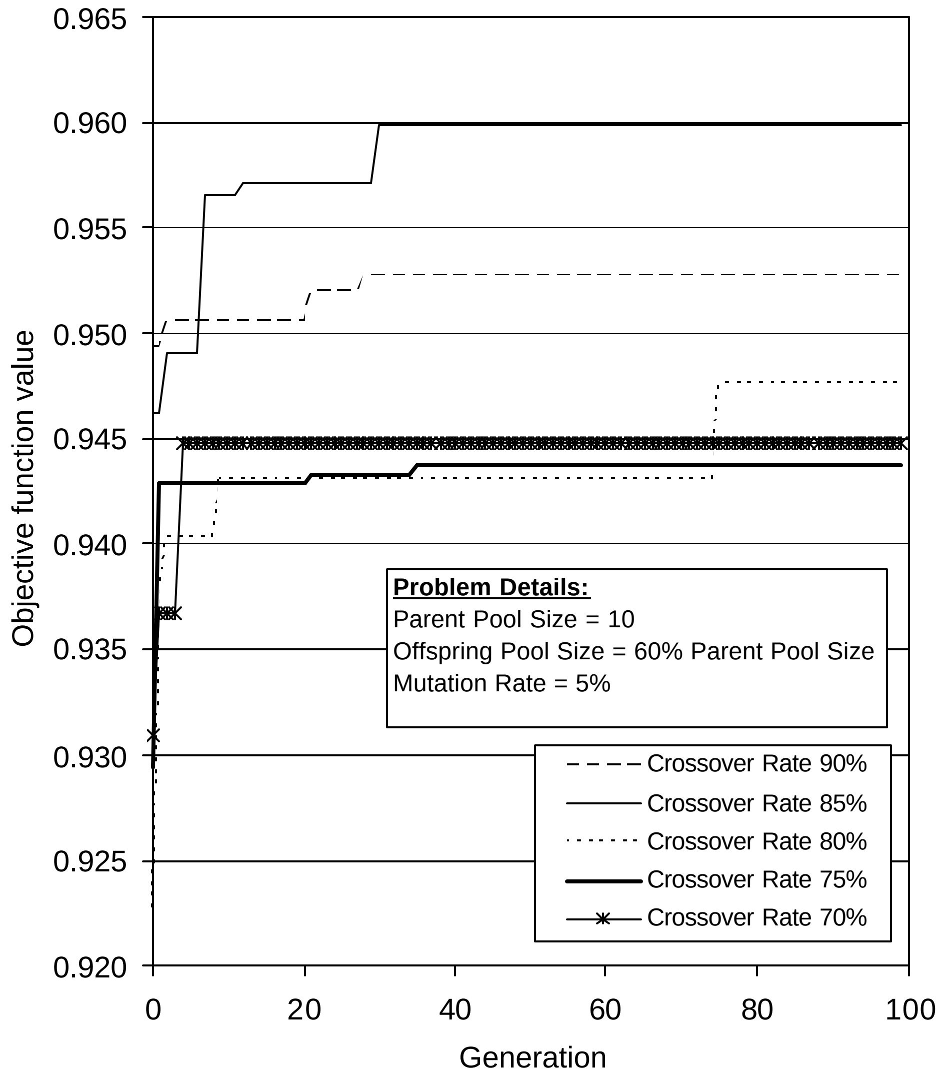


Fig. 4.8 Effect of Crossover Rate on Central GA Convergence

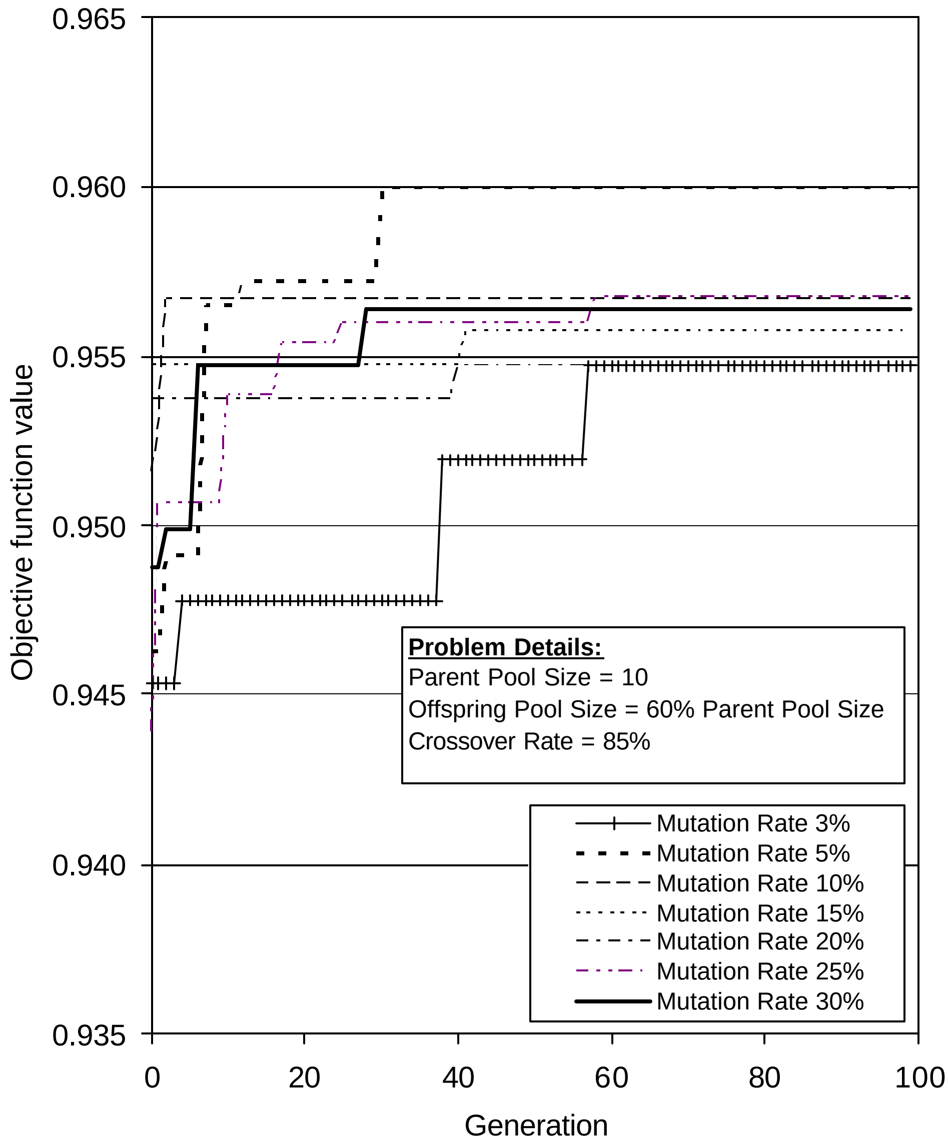
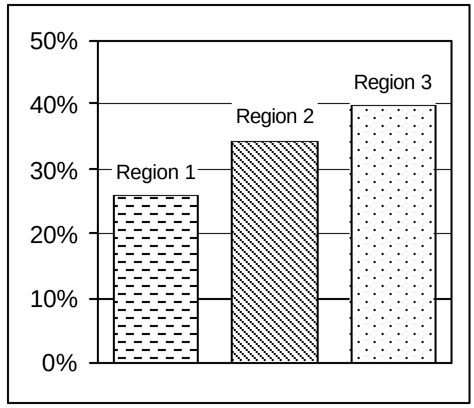
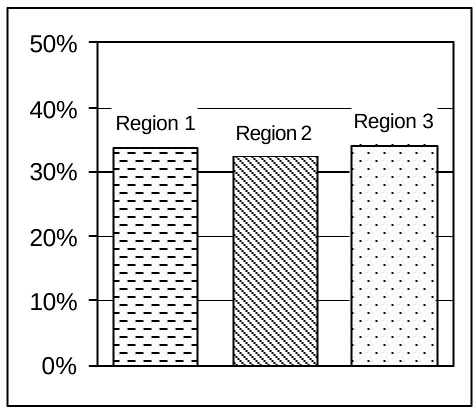


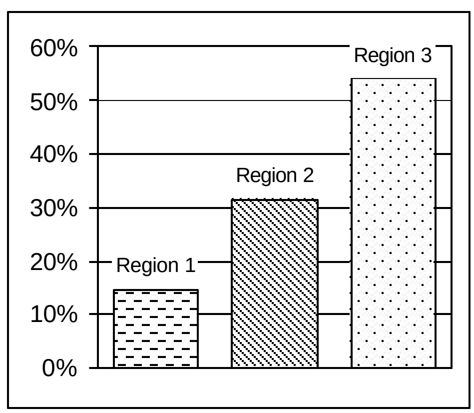
Fig. 4.9 Effect of mutation rate on central GA convergence



(a) Case 1

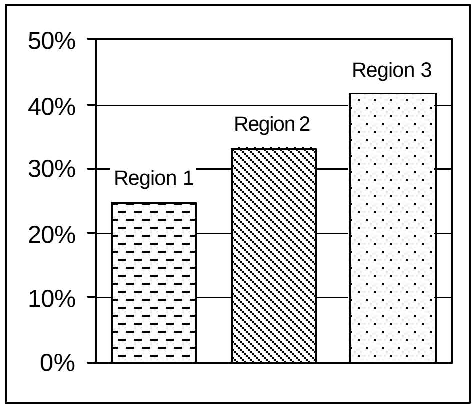


(b) Case 2

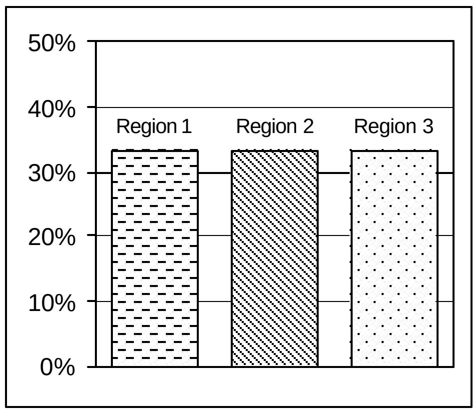


(c) Case 3

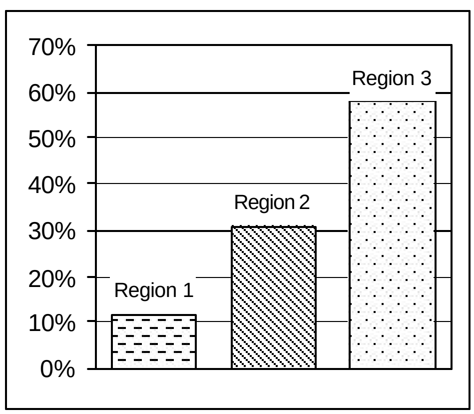
Fig. 4.10 Budget allocation shares of regions derived from needs-based allocation approach



(a) Case 1

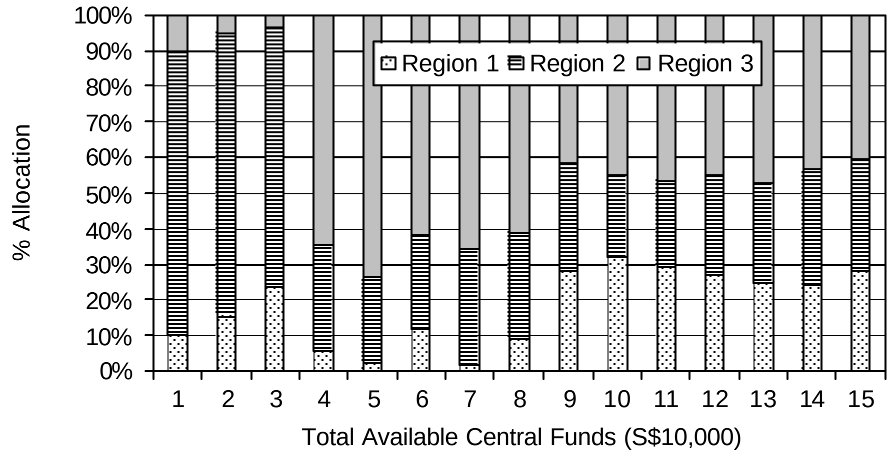


(b) Case 2

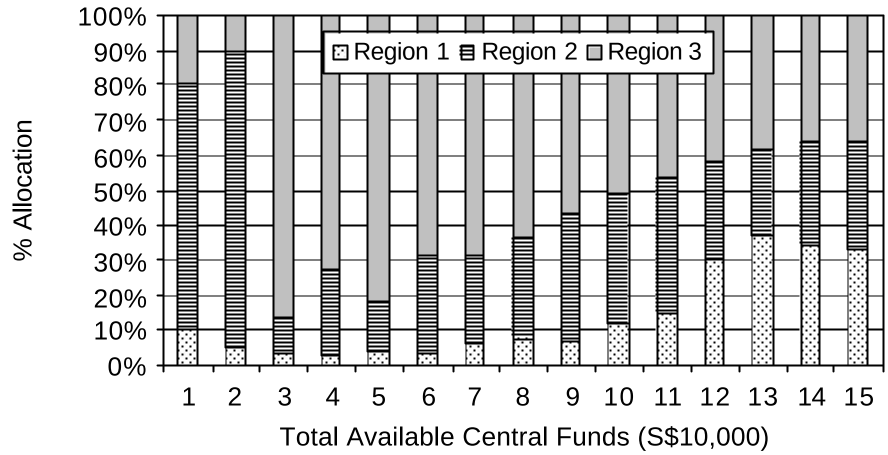


(c) Case 3

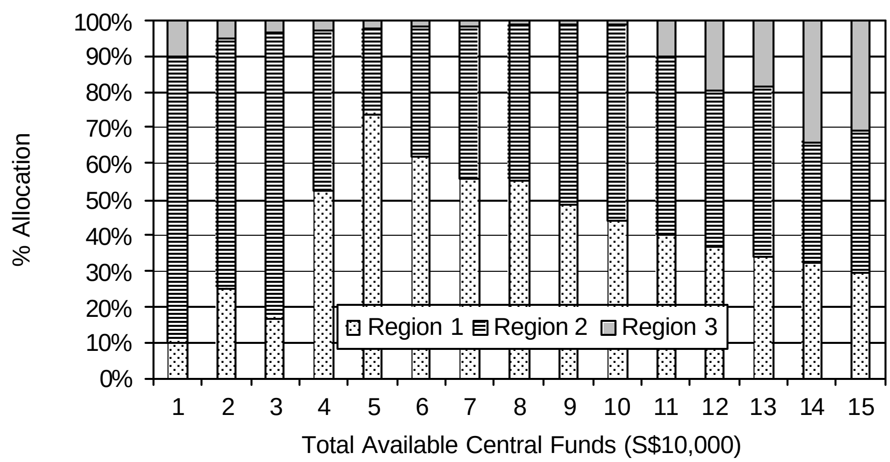
Fig. 4.11 Budget allocation shares of regions derived from formula-based allocation approach



(a) CASE 1

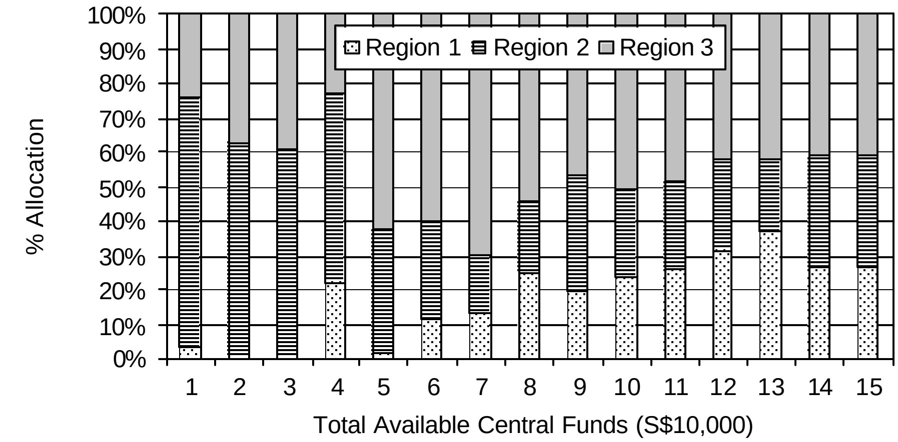


(b) CASE 2

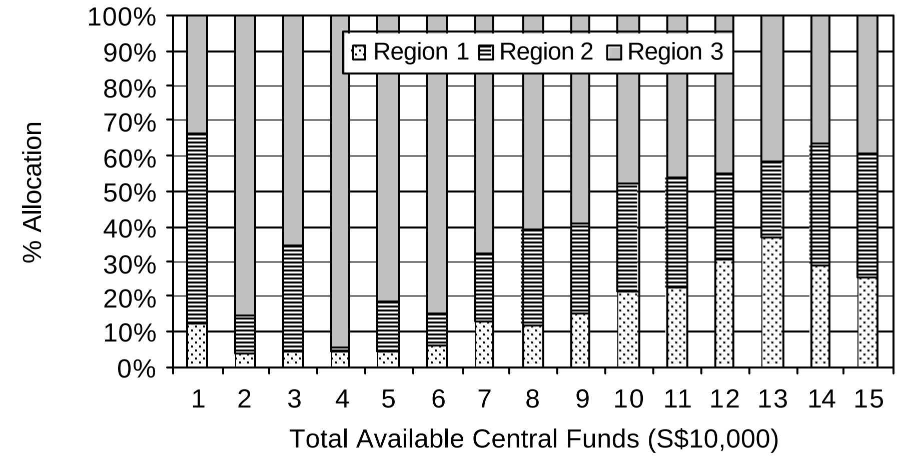


(b) CASE 3

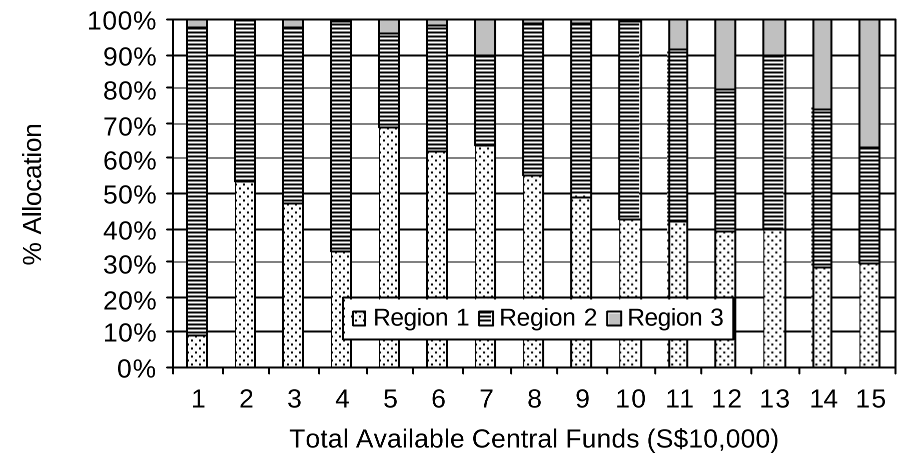
Fig. 4.12 Budget allocation shares of regions for different available central funds derived from 2-step optimization process



(a) CASE 1

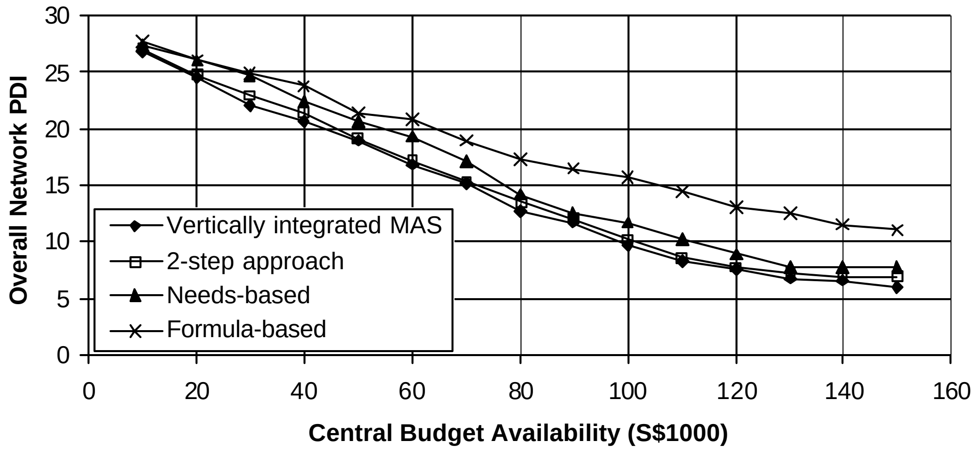


(b) CASE 2

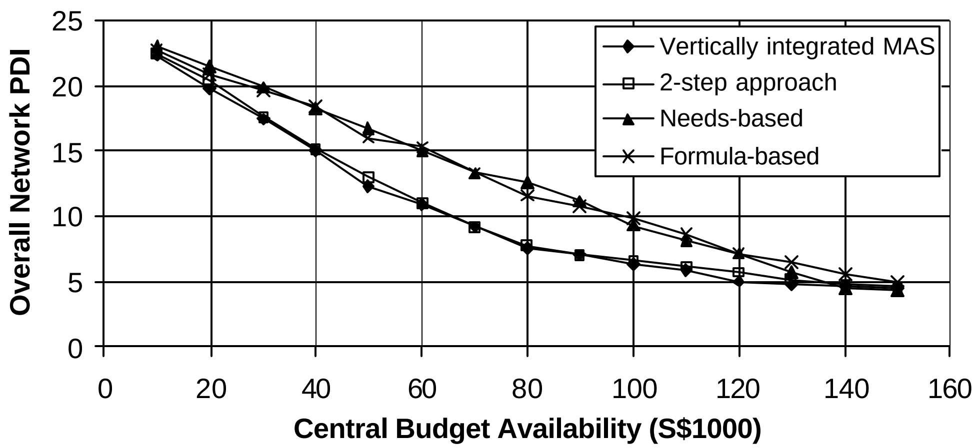


(c) CASE 3

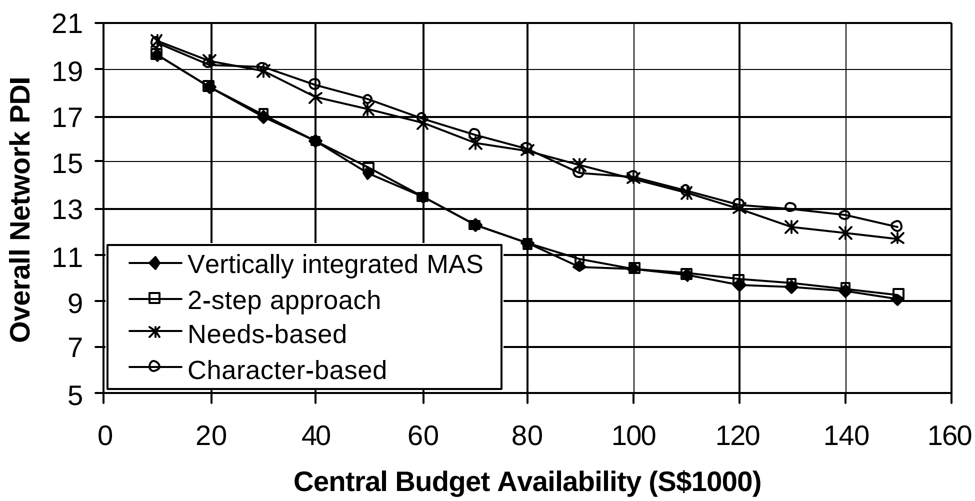
Fig. 4.13 Budget allocation shares of regions for different available central funds derived from vertically integrated multi-agent optimization approach



(a) Case 1

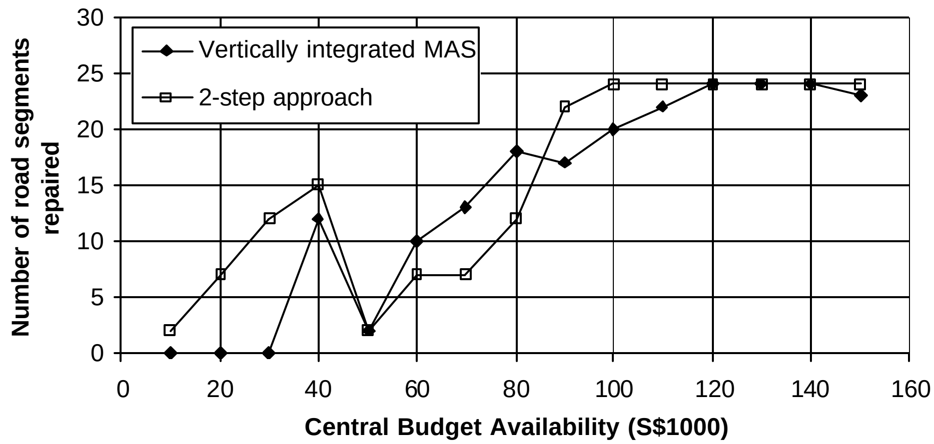


(b) Case 2

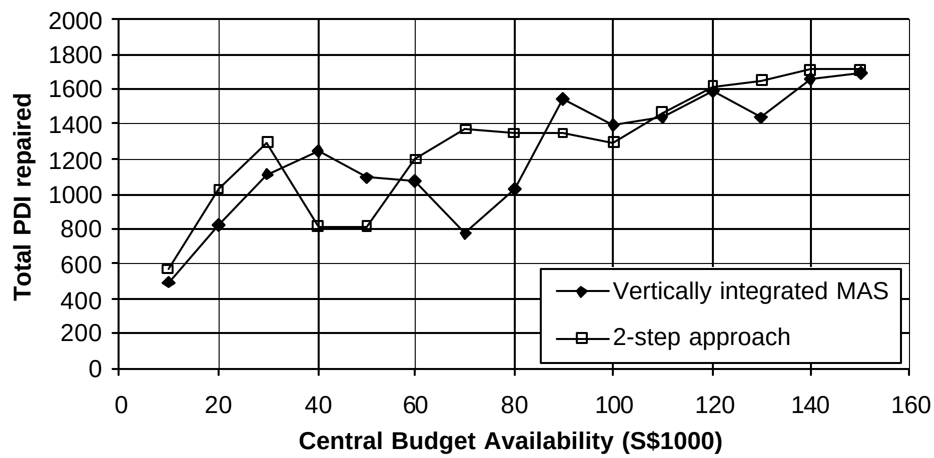


(c) Case 3

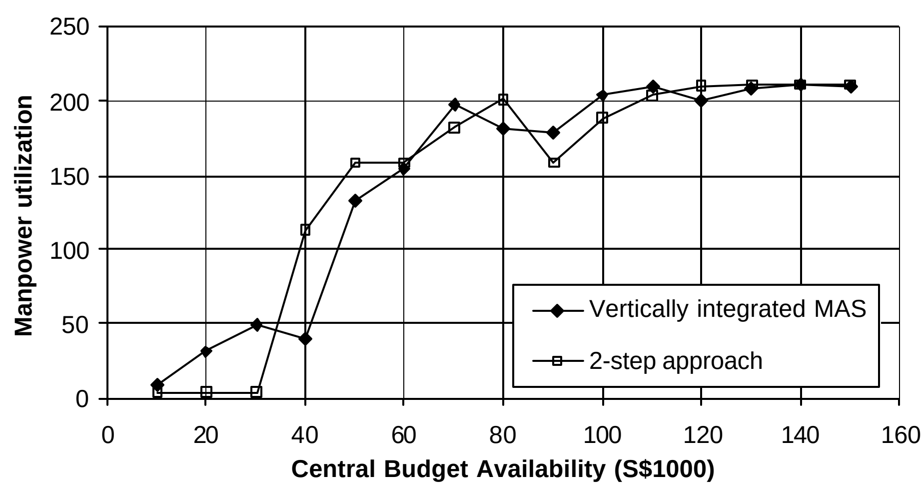
Fig. 4.14 Comparison of overall network PDI achieved with different budget allocation approaches



(a) Region 1

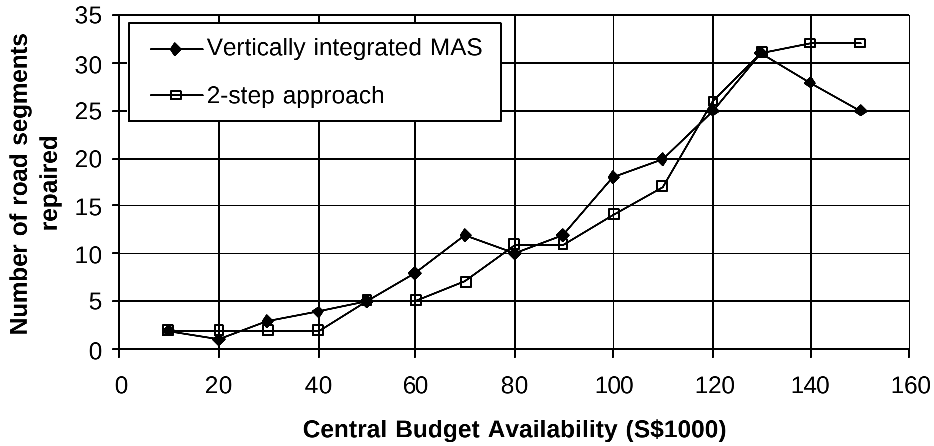


(b) Region 2

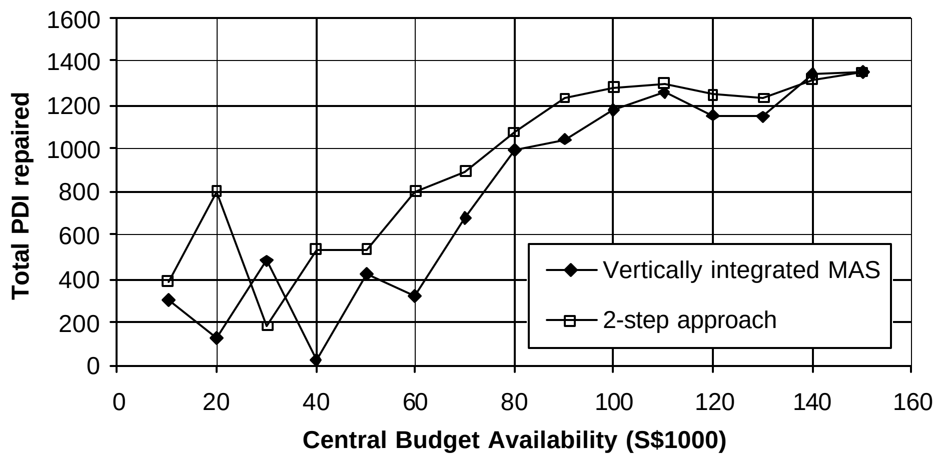


(c) Region 3

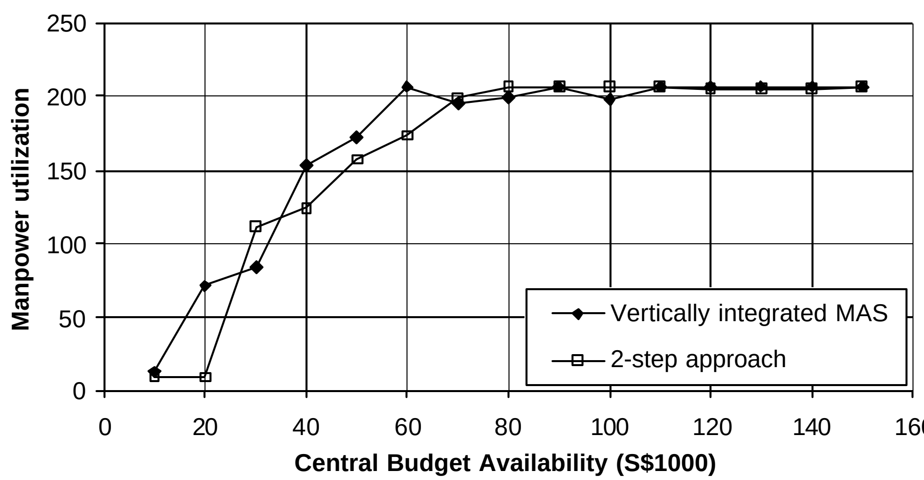
Fig. 4.15 Best regional objective function values achieved at different central budget availability for Case 1



(a) Region 1

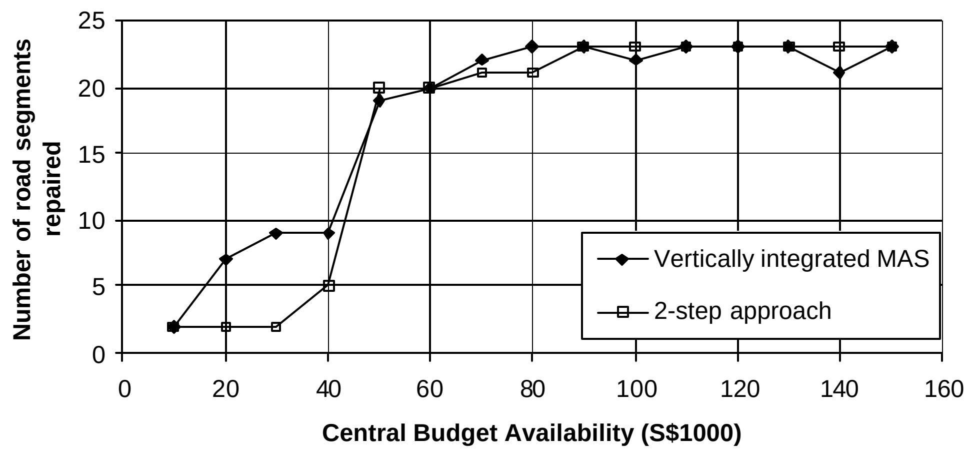


(b) Region 2

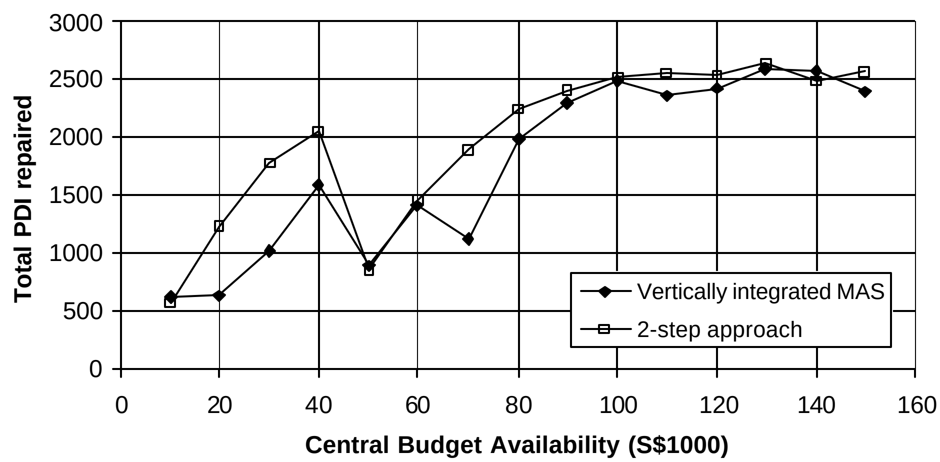


(c) Region 3

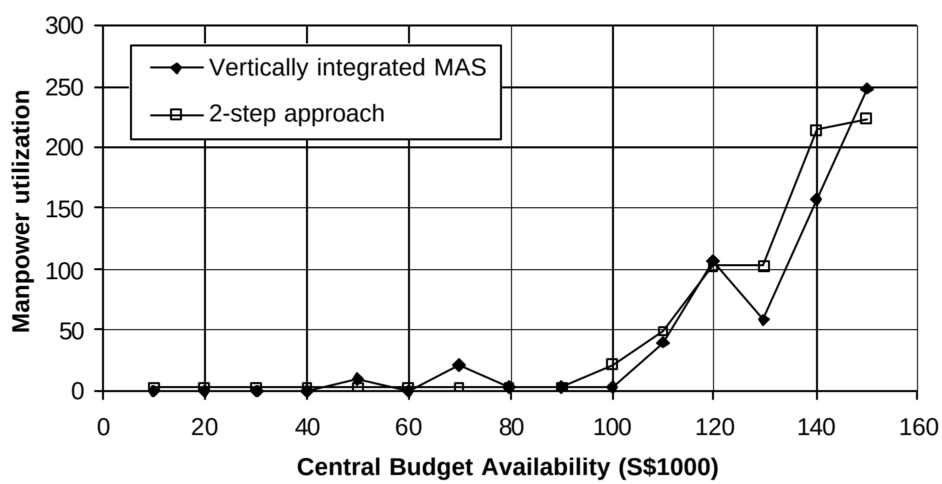
Fig. 4.16 Best regional objective function values achieved at different central budget availability for Case 2



(a) Region 1



(b) Region 2



(c) Region 3

Fig. 4.17 Best regional objective function values achieved at different central budget availability for Case 3

CHAPTER 5

MULTI-AGENT VERTICALLY AND HORIZONTALLY INTEGRATED OPTIMIZATION APPROACH

5.1 INTRODUCTION

In the previous chapter, a distributed multi-agent vertically integrated optimization approach has been proposed to solve the problem of optimal fund allocation among regional highway agencies. In the approach, communications are established only between vertical management hierarchies, i.e. between the central highway authority and the regional agencies. No communication exists among regions. Regions are completely independent of one another, with the only things binding them and affecting their optimization runs being the central available fund and the central objective function, which indirectly affects the amount of fund allocated to each region.

In this chapter, the approach is further improved to include horizontal integration among regional highway agencies in order to arrive at a *better* overall allocation strategy. 'Better' is in terms of the objective function defined by the central agent (which represents the central governing authority). Also, regional agencies benefit from access to additional resources through horizontal integration. Difficulties arise, however, in the programming and negotiation for the idle resources, particularly questions concerning how the idle resources is introduced into the optimization process, which agent should receive the idle resource, and how much should each agent receive, needs to be answered.

This chapter begins with a discussion on the motivation for implementing horizontal integration in the budget allocation process, followed by a description of the modified vertically and horizontally integrated approach. The procedure of the horizontally integrated fund allocation is demonstrated using the hypothetical example problem from the earlier chapters. The results of the allocation is analysed and compared with the earlier approaches analyzed in this study.

5.2 MOTIVATION FOR HORIZONTAL INTEGRATION

The horizontal integration in the budgeting processing allows regional agents to communicate with each other during the negotiation with the central administration. Such communication can be essential to resolve conflicts between regions or to enable cooperation and coordination that can result in greater benefits for all. In the case of pavement management, horizontal integration can be potentially beneficial for several pavement contractors to cooperatively schedule their highway maintenance operations in such a way to avoid time conflicts, to reduce operation time, or to achieve savings in cost. In keeping with the multi-level, multiple-agencies setting as laid out in the thesis, horizontal integration can be used to enable the sharing of leftover resources among regions. This will allow for the full utilization of any resources that are idle in any of the regions. Subsequently, greater overall benefit can be achieved in the regional sub-networks as well as the whole pavement network.

With the capability for regional agents to communicate, automated negotiation can be implemented to resolve many conflicts that may occur, or to solve coordination problems among regions. In this thesis, regional communication is established to enable the sharing of resources among regional highway agencies. The agents share information on which of their resources will be idle for a given allocation strategy, and how much of the resources will be idle. The amount of idle resources will then be added by other agents to their own resources. This has the effect of relaxing the resource constraints and increasing the solution space for the optimal maintenance programming in a particular region, thereby increasing the objective function value of that agent. A resource-sharing protocol is implemented to make this possible.

The sharing of resources can be realistically achieved in countries with a very strong central authority. In such a setting, regions can be made to oblige the central authority to release their idle resources when required. The expense of moving the resources is also negligible if the country or regions are not large. However, a transfer cost may be involved in other cases where regions may not be willing to forego their idle resources without setting a price or if the mobilisation of the resources across a large country incurs high expenses. The approach presented in this chapter does not take into account the transfer cost which may be involved for the sharing of resources to occur. The next section describes the proposed horizontally and vertically integrated fund allocation approach.

5.3 DESCRIPTION OF THE PROPOSED APPROACH

The proposed horizontally and vertically integrated optimization approach is an added modification to the multi-agent vertically integrated approach described in Chapter 4. The solution diagram is shown in Fig. 5.1.

In the horizontally and vertically integrated optimization approach, the architecture of the multi-agent system is the same as that of the vertically integrated approach. The primary difference between this approach and the previous one as presented in Chapter 4 is the added communication among regional agents, which require some additions and modifications to the existing agent infrastructure. The following subsections describe these modifications.

5.3.1 Modifications to the Multi-Agent System

The configurations of the agents and their relationships remain the same as the vertically integrated approach described in Chapter 4. All the objects introduced in the previous approach are also used here, with several additional objects. In this new approach, a new object named Resource is created to store information regarding the leftover resources in a particular region. This object is used in the message passing among regions to convey data on how many idle manpower or equipment that a region has for each manpower and equipment type. Resource is the basic object that is required in the resource-sharing protocol which will be described in the next sub-section. Other objects are also introduced to be used as signals for the regions to inform one another upon completion of certain processes such as the resource-sharing process, or to request for objects such as Resource so that further processing can continue.

The two plugins that specifies the behaviours of the agents, CentralPlugin and RegionPlugin, are modified to give additional functionalities to both central and regional agents. RegionPlugin is modified to allow region agents to subscribe to object Resource and other signal objects. Upon receiving a Budget object from the central agent, region agents immediately start the resource-sharing process. Region agents are also made to react to every changed Resource object, and to respond to different situations that may arise during the resource-sharing process.

CentralPlugin, on the other hand, is modified slightly to enable it to process the additional RegionalReports that are created due to the resource-sharing process. The additional RegionalReports are for different resource-sharing strategies produced for each trial budget allocation and sent to the central agent for consideration. The resource-sharing protocol used is described in detail in the following subsection.

5.3.2 Tournament-based Resource-sharing Protocol

The communication among region agents requires that a certain protocol be implemented in order to resolve the resource-sharing complexities of the problem. The protocol used in this research is based on a tournament type of selection where the region that gains the highest improvement of its objective function will receive the leftover resources under consideration. Improvements are determined by comparing the objective function value that is obtained from a certain strategy with that of a previous strategy. The protocol is shown graphically in Fig. 5.2.

There are two stages in choosing the best resource-sharing strategy, the first stage occurs at the regional level while the second stage occurs at the central level. At the regional level, region agents will compete among themselves in a tournament-style selection. For each budget allocation strategy, a region is picked to be the first to announce its idle resources to all other regions. Each of the other regions will re-run its network-level optimization module, this time with the first region's idle resources added to its own. Improvements on the objective function value of the other regions are expected since the additional resources have an effect of lowering the resource constraints, thus increasing the solution space.

A series of tournaments are held among the remaining agents to decide who among them will receive the idle resources. In each round of the tournament, a region agent is picked as a challenger. The challenger collects reports from all other regions and compares their percentages of improvement from the usage of the leftover resources against its own. The calculated improvement is based on the objective function of each region. If the percentage of improvement of the challenger is higher than the other regions, it will receive the prize of the tournament, which is the leftover resource from the first region. A new optimization run is performed by the winner, and any leftover resource from this new optimization becomes the prize for the next tournament which involves the remaining regions. A new challenger is picked from the remaining regions and the above process is repeated until no challenger is left. In the event that a challenger could not produce the highest improvement, the next challenger is selected and the above process is again repeated until no challenger is left. The last region will be responsible for sending the regional reports of all regions to the central agent at the end of the tournaments.

In the tournament-style selection described above, the region that is picked to be the first to announce its leftover resources does actually make a difference to the end result of the resource-sharing strategy. If the first region has very little resources left, the prize of the first tournament would be less thereby affecting the performance of its participants and subsequent tournaments. On the other hand, if the first region has plenty of resources left, the first tournament would be very competitive, resulting in better performance of the regions. It is highly likely that the region that is picked to start the resource-sharing may not be the most ideal region for the task. Therefore, in order to test for each possibility, each region is given a chance to be the first to share out its idle resources as the initial prize of the tournament. For each of these trials, a complete set of regional reports is sent to the central for evaluation. Thus, the central agent will receive as many sets of reports as there are regions in the multi-agent community, as denoted by n in Fig. 5.2.

At the end of the tournaments, the central agent chooses the best resource-sharing strategy from the n number of strategies. Decision is made based on the objective function of the central agent.

5.3.3 Selection Criteria Used in Tournament

A series of selection criteria is used in the tournament to determine whether or not a challenger wins a tournament. These criteria are used one at a time, in a predefined order. The next criterion in the order is used in the event that the earlier criterion results in a tie. The criteria used in this research, in that order, are:

1. Percentage of improvement of objective function value, and
2. Network PDI, which is the central objective function.

If two regions have the same percentage of improvement in their objective function value, the network PDI achieved is used to determine the winner. In the event that both criteria results in a tie, the challenger is automatically chosen to receive the leftover resources. In the tournament, a challenger competes with all other regions in the community. Thus, as the number of regions increase, the likelihood of ties in both criteria will decrease.

5.4 APPLICATION OF PROPOSED APPROACH

The performance of the proposed horizontally and vertically integrated approach is gauged by comparing the improvement, if any, that is achieved using the approach compared to other budget allocation approaches presented previously in Chapter 3 and 4. An improvement on the overall pavement network is expected since the addition of horizontal integration should increase the number of possible solutions and thus enable a more flexible maintenance strategy to be derived.

5.4.1 Hypothetical Example Problem

The hypothetical example problem described in Chapter 3 is again used here so that the results can be compared. The problem involves two levels of management, the central level and the regional level, where the regional level comprises three regional highway agencies. The two cases studied in Chapter 4 are analyzed here. Details of the two cases are given in Table 4.1. Similar pavement network characteristics and resource availability as that in the earlier example problem are assumed. These were described in detail in Sections 3.3.1 and 3.3.2 respectively.

The objective functions of each regional highway agency and central administration are:

Central Authority – Maximizing the performance level of the whole road network.

Region 1 -- Maximizing the number of distressed road segments repaired

Region 2 -- Maximizing the performance level of regional road network pavements

Region 3 -- Maximizing the usage of the available manpower

Constraints considered include budget, manpower and equipment constraints. The full explanation on the objective functions and constraints was given in Section 3.4.

5.4.2 GA String Structures

The GA string structures used in the optimization analysis are the same as that used in the distributed multi-agent vertically integrated approach. At the regional level optimization, the decision variables pertain to the choice of road segments selected for maintenance and the total length of the string structure is equal to the number of road segments in the region concerned. At the central level optimization, the decision variables are the binary representations of the shares of budget allocation for the three regions. The total length of the string structure depends on the maximum number of bits that may be involved, as was given by the Eq. 4.1.

The GA package used for the optimization process in the region agents is PGAPACK (Levine 1996) while a Java-based genetic-algorithm package, ECJ (Luke 2002) is used at the central level. The string structures were shown in Fig. 4.4. A more detailed description of the string structures were given in Section 4.4.1.

5.4.3 Method of Analysis

The procedures in Fig. 5.2 are used to generate budget allocation strategies for a range of network PDI limits and central budget levels. Random budget allocation is generated by the central GA, and the multi-agent system is used to convey the information to the regional agents. The budget information is used by region agents as a constraint in their own search for the optimal pavement maintenance strategy with respect to their objective functions. The regional optimization is also constrained by the availability of manpower and equipment resources in the respective regions. The resource-sharing protocol as shown in Fig. 5.2 is then used to determine the resource-sharing strategy among the regions. A series of tournaments are held and the winner of each round of tournament will receive the leftover resources considered in that round. The criteria for selection of winners are the percentage of improvement in objective function value followed by the regional network PDI value. If both criteria result in a tie, the current challenger is considered the winner. At the end of each round of tournament, a full report is sent to the central agent. Among the reports, the central agent will choose one that gives the best value with respect to the central objective function. The whole process is repeated for the next budget allocation from the central agent.

The overall optimization process is driven towards the central optimal value by the GA of the central agent. A small population size of 10 is used and the maximum number of generations is set to 10. This gives a total of 100 budget allocation trial at the central level, and it has been found that this is sufficient to produce good results. The crossover probability used is 0.8 and the mutation probability is 0.05. Out of the 10 individuals, one elite individual is selected to proceed to the next generation. At the region agent, the GA population size used was 1000. Only one elite solution is selected to the next generation. The mutation rate was 0.4 while the crossover rate adopted was 0.9. The maximum number of generations is set to 200.

5.4.4 Comparison with Other Allocation Approaches

The results obtained from the horizontally and vertically integrated optimization approach are compared against those obtained using:

- Distributed multi-agent vertically integrated optimization approach
- Two-step optimization approach
- Formula-based allocation approach
- Needs-based allocation approach

The distributed multi-agent vertically integrated optimization approach was presented in Chapter 4, while the two-step optimization approach was presented in Chapter 3. The formula-based and needs-based allocation approaches are conventional allocation approaches that are widely used in practice. These have been described in Section 2.1.2 and the formulations were given in Section 3.6.

5.4.5 Proportion of Fund Allocated to Regions

Fig. 5.3 shows the proportion of budget allocated to each region for a range of central budget levels derived from the horizontally and vertically integrated optimization approach. The general trend of the result obtained here is similar to the results obtained from the vertically integrated approach presented in Chapter 4. For both Case 1 and Case 2 of the example problems, Region 2 initially receives the most of the very low central available fund. As the budget increases, the rise in funding level are seen in Region 3 first, followed by Region 1. This observation is consistent with the findings of the sensitivity study of objective function presented in Section 3.8, where it was observed that for very low central budget availability the fund allocation tends to favour the region that can better complement the central objective function. At high budget levels, the network characteristics and maintenance needs of each region begin to have more weights on the funding strategy.

Interestingly, for Case 1 and Case 2, the horizontally and vertically integrated multi-agent optimization approach produces the same allocation strategy as the horizontally integrated multi-agent optimization approach for budget levels of S$30,000 and lower. This is because the vertically integrated multi-agent approach could not find a better solution in the severely constrained solution space for these budget levels. For Case 2, the budget allocation is more lopsided towards Region 3 for most of the budget levels. This is because in Case 2, Region 3 contains many road segments with high severity distresses. This allows Region 3 to contribute high improvements to the overall network pavement performance for most of the available budget levels. As in Case 1, Region 1 receives less proportion of the central budget initially, and as the central budget increases, the allocation to Region 1 also increases.

A different trend, however, is observed in Case 3. In this case, Region 1 receives the most funds for most of the budget levels. Even for very low budget levels of S$30,000 and below, Region is given the top priority by the algorithm. This is in contrast with the two-step and horizontally integrated approach where Region 2 is favoured when central fund is at very low levels. This is because the sharing of resources, which is made possible in the vertically and horizontally integrated approach, has enabled Region 1 to push for the repair of more high severity road segments. Apparently, Region 1 managed to win the idle resources from the other regions in the tournament-style selection implemented in this approach. This is logical because Region 1 contains the most number of rut distresses of high severity level in Case 3. Rut distresses of high severity contribute significantly to the Pavement Damage Index and are thus more likely to be chosen for repair compared to other types of distresses. Moreover, the cost to repair rut distresses of high severity is competitive compared to the other high severity distresses.

5.4.6 Cost Savings Achieved

The total maintenance cost to achieve a target PDI level for each fund allocation approaches are shown in Table 5.1. The differences in total cost between the various fund allocation approaches are calculated. It is clear that all other budget allocation approaches result in over-spending compared to the horizontally and vertically integrated approach for any target network pavement performance.

For Case 1 (Table 5.1a), the horizontally and vertically integrated approach consistently saves over 30% in maintenance cost for all the range of target network PDI levels compared to formula-based allocation approach. For the example problem considered, this savings amounts to at least S$16,000 depending on the level of target PDI. For a target PDI of 11, the savings achieved compared to the formula-based approach is S$63,000. The savings achieved with the horizontally and vertically integrated approach over the needs-based allocation approach is consistently over 17%, corresponding to saving of over S$14,000. This savings can reach as high as S$23,000 in maintenance cost. From this result, it seems that the needs-based allocation approach outperforms the formula-based approach for the case considered. The minimum savings over the 2-step optimization approach, which was presented in Chapter 3, is at least 10%. The amount of money saved over the 2-step approach can be as high as $18,700. The savings over the vertically integrated approach range from 0.56% (S$168) for a required PDI of 22 to S$9,400 for PDI of 11.

For Case 2 (Table 5.1b), the savings over the formula-based and needs-based allocation approaches are more than 25% and 35% respectively for the range of PDI considered. In contrast to Case 1, the savings over the needs-based approach is higher than the savings over the formula-based approach. This shows that the needs-based approach may perform better than the formula-based approach in some cases, while in other cases, the formula-based approach gives a better fund allocation. In this study, the needs-based approach out-performs the formula-based approach in Case 1, while the formula-based approach does better than needs-based approach in Case 2. These two fund allocation approaches, though widely practised, do not produce good results for every pavement management situation.

In Table 5.1(c), the vertically and horizontally integrated MAS approach saved about 50% in maintenance cost from needs-based and formula-based approaches. This is a significant percentage of savings which can mean a large sum of money. The savings from vertically integrated approach is much less, ranging from 0.58% to 8.99%. For this case, the sharing of resources does not produce much savings in maintenance cost.

For the range of target PDI considered, the savings observed over the 2-step approach range from 6% to 15%. The savings are smaller over the vertically integrated approach. This trend is consistent for all three problem cases. This observation shows that the horizontally and vertically integrated approach performs better than the vertically integrated approach and the 2-step approach in terms of overall results. The savings over the vertically integrated approach is zero for the highest three PDI levels because the maintenance costs needed for these PDI levels are too small to make any difference to the optimization process. At such high PDI levels, the binding constraints are the manpower and equipment availability rather than the budget availability.

5.4.7 Network Pavement Performance

Fig. 5.4 shows the overall network PDI that is achieved using the various fund allocation approaches. As expected, the vertically and horizontally integrated MAS approach gives better network pavement performance for a given central budget availability compared to the other approaches for all three problem cases analysed. The improvement in overall network PDI achieved from the vertically and horizontally integrated approach compared to vertically integrated approach is the highest in Case 1, followed by Case 2 and Case 3. This is in agreement with the earlier results on the savings achieved from using the approach, where greater savings are obtained in Case 1 followed by Case 2 and Case 3.

5.4.8 Regional Objective Function Values

The objective function value of each region is plotted in Figs. 5.5-5.7 for the three problem cases studied. The plots show how the objective function value of each region fares when the central budget is allocated using the different approaches studied in this thesis. Generally, there is no one approach that will always give more benefit to any one region. Since the algorithms are subjective to the changes in budget level, the objective function value of a region may rise or drop when the budget level at the central administration changes. The general trend of the vertically and horizontally integrated approach is still in line with the other two approaches compared in the plots.

5.5 MINIMUM BUDGET CONSTRAINT

In the analyses conducted so far, the fund allocation strategy produced can be highly unequal. In the real world, such unequal allocation of fund is undesirable because it will cause dissatisfaction in the region that receives very little funding. This can be rectified by imposing a minimum budget constraint in the algorithm.

A minimum budget constraint is introduced into the vertically integrated and vertically and horizontally integrated approaches, and the fund allocation is re-analysed for a selected budget level using each of the approaches. The budget constraint used is 10%, which means any of the regions must receive at least 10% of the total available budget. If this condition is not satisfied, a repair algorithm is used to move the solution nearer to the constraint-satisfaction boundary. The repair algorithm sets the budget level of the region with less than 10% of the total budget to 10% of the total budget, and recalculates the rest of the budget allocation repeatedly until the entire budget is allocated and the minimum budget condition is met.

The budget level selected for each approach is one that produced highly unequal fund allocation strategy where one of the regions receives less than 3% of the total fund. For the vertically integrated MAS approach, the budget level chosen is S$100,000 while for the vertically and horizontally integrated MAS approach, S$40,000 is chosen. The results are shown in Table 5.2(a)-(b).

For both approaches, the budget is now more equally allocated to each region. Each region receives more than 10% of the total budget. The minimum budget constraint, however, results in a slightly inferior network pavement performance. This is because the addition of the constraint reduces the original solution space of the problem such that the best solution is no longer within the solution space. In this case, the algorithm chose the second best solution. The small drop in network pavement performance should be acceptable in real world practise for the benefit of obtaining a more equal fund allocation.

5.6 TIME PERFORMANCE

The processing time for the multi-agent optimization approaches are measured to determine the computing cost of performing the analyses. The CPU time taken to complete a single GA generation at the central level is computed. The CPU time analysis is performed only for the vertically integrated and vertically and horizontally integrated approaches as the separated regional and central processing of the two-step approach does not allow a useful comparison with the two-step optimization approach.

Table 5.3 shows the results of the CPU time analysis. The vertically and horizontally integrated multi-agent optimization approach takes significantly more time to run than the vertically integrated approach. The amount of time increases significantly due to the sharing of resources among region agents, of which the operation that consumes the most amount time is the genetic algorithm runs. The number of GA runs at the regional level increases significantly during the resource-sharing operations. For the three-region problem, each resource-sharing operation requires at least twice as many GA runs than without a resource-sharing operation.

The wall clock time for the two approaches is also estimated. The vertically integrated approach takes approximately 2 seconds for each generation of GA at the central level, while the horizontally and vertically integrated approach takes more than 50 seconds for the same. The total amount of time for a typical complete simulation for a single central budget level using the horizontally and vertically integrated approach is approximately 4 hours (240 minutes), compared to the vertically integrated approach that only requires approximately 5 minutes for the same.

The additional cost in processing time, however, should not have much effect in the real-world situation because the budgeting process is not carried out in real-time. And since it is an automated process, the savings in the time required if the budgeting process is to be carried out manually should be able to offset this computer processing time.

5.7 CHAPTER SUMMARY

The distributed multi-agent approach of Chapter 4 has been further improved to include horizontal integration. This allows region agents to interact with one another in order to produce better overall results. In this chapter, the horizontal integration is applied to enable the sharing of idle resources among regional highway agencies in order to arrive at a better overall budget allocation strategy.

The modifications made to the multi-agent system approach to enable horizontal integration have been described. The resource-sharing protocol used is a tournament-type of selection, where region agents enter into tournaments to determine who among them will receive what amount of leftover resources. The workings of the resource-sharing protocol has been presented in detail.

The performance of the horizontally and vertically integrated approach has been studied by comparing the results of the allocation methodology against that of the formula-based, needs-based, 2-step optimization, and distributed multi-agent vertically integrated approaches. Results showed that the horizontally and vertically integrated approach consistently gives better overall results than all the other approaches.

Particularly, high savings for a range of target PDI levels were achieved from the fund allocation strategies derived from this approach compared to the other approaches, for both of the cases studied. It was found that savings in maintenance cost were of significant magnitudes.

The study also confirms the findings made in Chapter 4 on the unsuitability of commonly used highway budget allocation approaches, namely the formula-based and needs-based approaches, for certain pavement management situations. Results showed that these conventional allocation approaches do not always give good allocation strategies in some cases. The fund allocation methodologies introduced in this thesis, on the other hand, are more adaptable to different pavement management situations, and are thus able to produce consistently good allocation strategies for the different cases studied.

Table 5.1 Savings in expenditure achieved by Multi-Agent Vertically and Horizontally Integrated Approach compared to other highway fund allocation approaches (to be continued)

(a) Case 1

PDI	Vertically and Horizontally Integrated MAS Approach	Vertically Integrated MAS Approach			2-Step Optimization Approach			Needs-based Approach			Formula-based Approach		
	Total Cost (S$1000)	Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach	
			Amount	%		Amount	%		Amount	%		Amount	%
22	29716.31	29884.96	168.65	0.56	35406.12	5689.81	16.07	41933.30	12216.99	29.13	46195.42	16479.11	35.67
21	35127.84	36657.54	1529.70	4.17	41148.01	6020.16	14.63	45950.08	10822.24	23.55	55414.87	20287.03	36.61
20	39738.99	42749.68	3010.69	7.04	45669.83	5930.84	12.99	53080.67	13341.67	25.13	62947.58	23208.59	36.87
19	42637.03	48445.35	5808.32	11.99	50228.03	7591.00	15.11	59655.52	17018.49	28.53	67847.25	25210.22	37.16
18	45569.89	53326.59	7756.70	14.55	55141.25	9571.37	17.36	64273.33	18703.45	29.10	74190.76	28620.88	38.58
17	50456.12	58145.95	7689.82	13.23	60081.96	9625.84	16.02	68781.09	18324.97	26.64	82179.21	31723.08	38.60
16	55342.36	63496.70	8154.35	12.84	65361.09	10018.73	15.33	72526.22	17183.87	23.69	94310.87	38968.51	41.32
15	60524.53	68772.38	8247.85	11.99	70838.98	10314.45	14.56	76271.36	15746.83	20.65	103539.01	43014.48	41.54
14	66141.63	72819.93	6678.30	9.17	76880.56	10738.93	13.97	80371.48	14229.85	17.71	111343.30	45201.67	40.60
13	71469.38	76867.49	5398.11	7.02	83148.90	11679.52	14.05	86432.43	14963.05	17.31	119853.65	48384.27	40.37
12	76672.48	84475.48	7802.99	9.24	89486.83	12814.34	14.32	95786.43	19113.95	19.95	133119.02	56446.54	42.40
11	81478.23	90943.46	9465.22	10.41	94934.10	13455.86	14.17	102969.69	21491.46	20.87	144621.42	63143.18	43.66
10	86930.83	95987.46	9056.63	9.44	100479.63	13548.80	13.48	108899.13	21968.30	20.17	*	*	*
9	93833.59	101731.47	7897.88	7.76	106395.39	12561.80	11.81	116073.98	22240.40	19.16	*	*	*
8	101281.20	108333.09	7051.89	6.51	114026.46	12745.26	11.18	125232.85	23951.65	19.13	*	*	*
7	107355.75	112446.04	5090.29	4.53	126066.98	18711.23	14.84	*	*	*	*	*	*

Note: * The target PDI could not be achieved with the approach indicated in the column.

Table 5.1 Savings in expenditure achieved by Multi-Agent Vertically and Horizontally Integrated Approach compared to other highway fund allocation approaches (continued)

(b) Case 2

PDI	Vertically and Horizontally Integrated MAS Approach	Vertically Integrated MAS Approach			2-Step Optimization Approach			Needs-based Approach			Formula-based Approach		
	Total Cost (S$1000)	Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach	
			Amount	%		Amount	%		Amount	%		Amount	%
22	10,086.29	10,086.29	0.00	0.00	11,892.22	1,805.93	15.19	15,612.35	5,526.06	35.40	13,493.45	3,407.16	25.25
21	14,152.89	14,152.89	0.00	0.00	16,646.96	2,494.07	14.98	21,655.12	7,502.22	34.64	18,886.03	4,733.14	25.06
20	18,219.50	18,219.50	0.00	0.00	20,979.54	2,760.05	13.16	28,094.57	9,875.07	35.15	25,931.04	7,711.54	29.74
19	21,936.04	22,630.49	694.44	3.07	24,617.21	2,681.17	10.89	34,765.11	12,829.06	36.90	33,646.30	11,710.26	34.80
18	25,534.09	27,158.07	1623.98	5.98	28,254.88	2,720.79	9.63	41,229.31	15,695.22	38.07	40,020.88	14,486.79	36.20
17	29,092.97	31,196.27	2103.29	6.74	32,090.65	2,997.68	9.34	46,991.23	17,898.26	38.09	44,304.23	15,211.26	34.33
16	32,551.49	34,684.59	2133.11	6.15	36,043.88	3,492.39	9.69	52,909.89	20,358.41	38.48	48,587.58	16,036.09	33.00
15	35,268.17	38,189.02	2920.84	7.65	40,073.21	4,805.04	11.99	58,881.14	23,612.97	40.10	60,350.74	25,082.57	41.56
14	39,627.92	42,414.69	2786.77	6.57	45,075.88	5,447.96	12.09	65,217.01	25,589.09	39.24	64,972.23	25,344.32	39.01
13	43,987.67	46,640.37	2652.70	5.69	50,062.60	6,074.94	12.13	72,989.70	29,002.03	39.73	70,079.71	26,092.04	37.23
12	48,490.47	51,485.65	2995.19	5.82	54,817.35	6,326.88	11.54	82,295.60	33,805.14	41.08	76,105.11	27,614.64	36.28
11	55,584.97	58,071.72	2486.74	4.28	59,572.10	3,987.12	6.69	89,777.47	34,192.50	38.09	84,952.38	29,367.41	34.57
10	61,142.48	63,380.86	2238.39	3.53	65,139.70	3,997.22	6.14	94,970.12	33,827.64	35.62	96,748.68	35,606.20	36.80
9	66,004.24	68,615.02	2610.78	3.80	70,843.29	4,839.05	6.83	100,967.82	34,963.57	34.63	104,540.64	38,536.40	36.86
8	72,142.67	75,300.86	3158.19	4.19	76,993.90	4,851.24	6.30	108,973.67	36,831.00	33.80	111,914.02	39,771.35	35.54
7	79,053.25	83,980.64	4927.39	5.87	88,233.77	9,180.52	10.40	118,116.61	39,063.37	33.07	120,103.44	41,050.20	34.18

Table 5.1 Savings in expenditure achieved by Multi-Agent Vertically and Horizontally Integrated Approach compared to other highway fund allocation approaches (continued)

(c) Case 3

PDI	Vertically and Horizontally Integrated MAS Approach	Vertically Integrated MAS Approach			2-Step Optimization Approach			Needs-based Approach			Formula-based Approach		
	Total Cost (S$1000)	Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach		Total Cost (S$1000)	Savings by proposed approach	
			Amount	%		Amount	%		Amount	%		Amount	%
19	13024.74	13600.93	576.19	4.24	14080.00	1055.26	7.49	27202.68	14177.94	52.12	29330.74	16306.00	55.59
18	18945.00	20689.97	1744.97	8.43	21912.52	2967.52	13.54	37608.77	18663.77	49.63	44839.32	25894.33	57.75
17	27031.96	27728.92	696.97	2.51	29857.95	2825.99	9.46	53999.14	26967.18	49.94	57971.82	30939.86	53.37
16	37398.41	38699.72	1301.32	3.36	38936.66	1538.25	3.95	67571.03	30172.62	44.65	71642.58	34244.18	47.80
15	45108.52	46096.35	987.83	2.14	47001.08	1892.56	4.03	86322.81	41214.29	47.74	85277.64	40169.12	47.10
14	52989.34	53981.33	991.99	1.84	54698.44	1709.10	3.12	103574.93	50585.59	48.84	105206.53	52217.19	49.63
13	61966.58	62329.31	362.72	0.58	62875.69	909.10	1.45	118436.86	56470.27	47.68	127804.85	65838.26	51.51
12	70974.81	71803.13	828.32	1.15	72758.14	1783.32	2.45	137054.18	66079.37	48.21	151814.19	80839.38	53.25
11	81623.40	84377.13	2753.73	3.26	85898.57	4275.17	4.98	157559.19	75935.79	48.20	171709.08	90085.68	52.46
10	97590.30	107231.45	9641.14	8.99	115820.44	18230.13	15.74	186944.37	89354.07	47.80	210529.28	112938.98	53.65

Table 5.2 Results of fund allocation strategy using different approaches with minimum budget constraint imposed

(a) Vertically integrated MAS approach

	Budget allocated (S$)			Overall network PDI
	Region 1	Region 2	Region 3	
Without constraint	41,889	55,876	794	10.45
With constraint	42,286	37,426	20,288	10.48

Note: Total available budget: S$100,000

(b) Vertically and horizontally integrated MAS approach

	Budget allocated (S$)			Overall network PDI
	Region 1	Region 2	Region 3	
Without constraint	26,133	13,033	834	15.66
With constraint	26,320	6,480	7,200	15.81

Total available budget: S$40,000

Table 5.3 CPU time of the multi-agent optimization approaches to complete a single GA generation at the central level

Fund allocation approach	CPU time (seconds)
Vertically integrated MAS	29962.6
Vertically and horizontally integrated MAS	782611.5

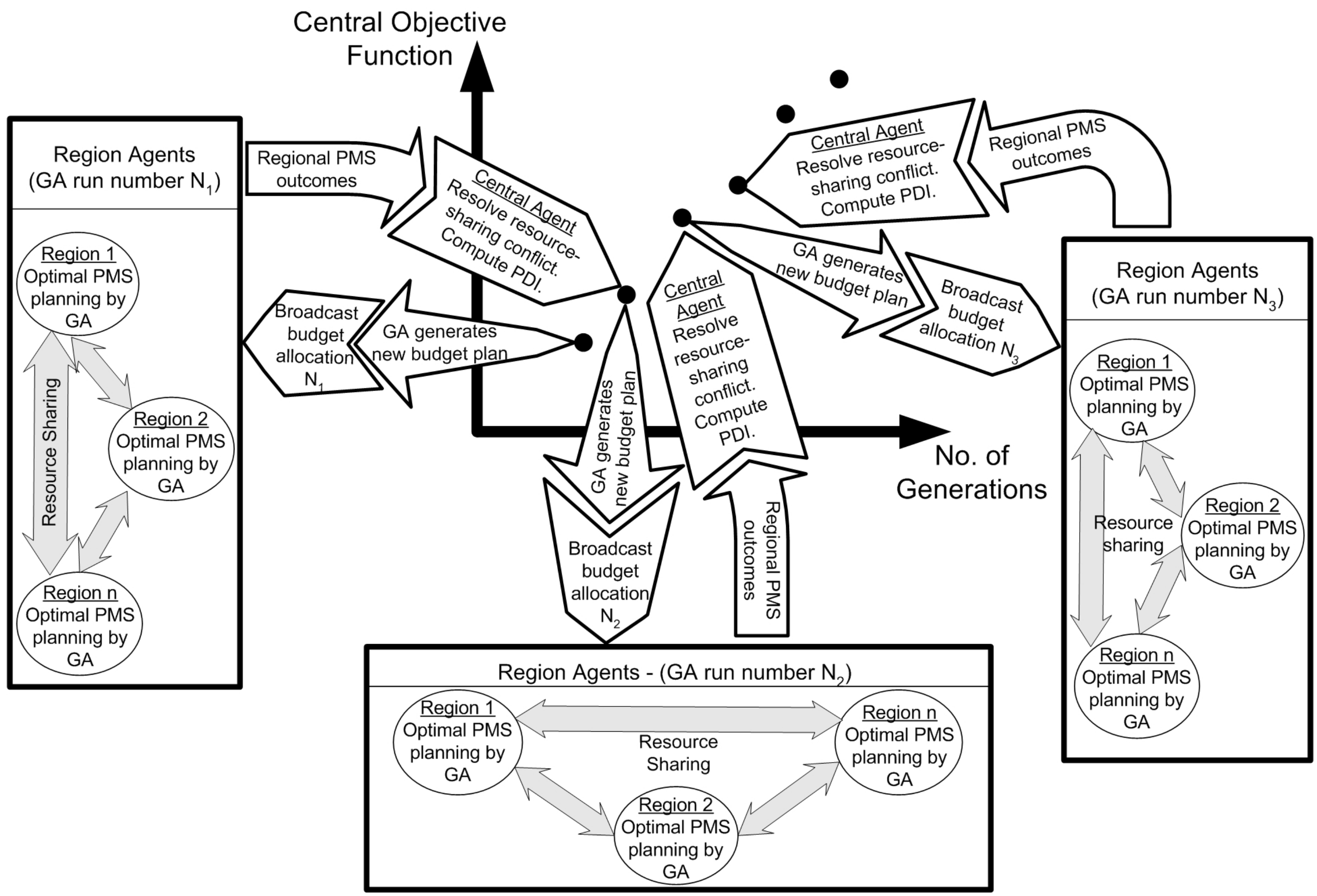


Fig. 5.1 Interactive optimal budget allocation approach with resource -sharing among regions

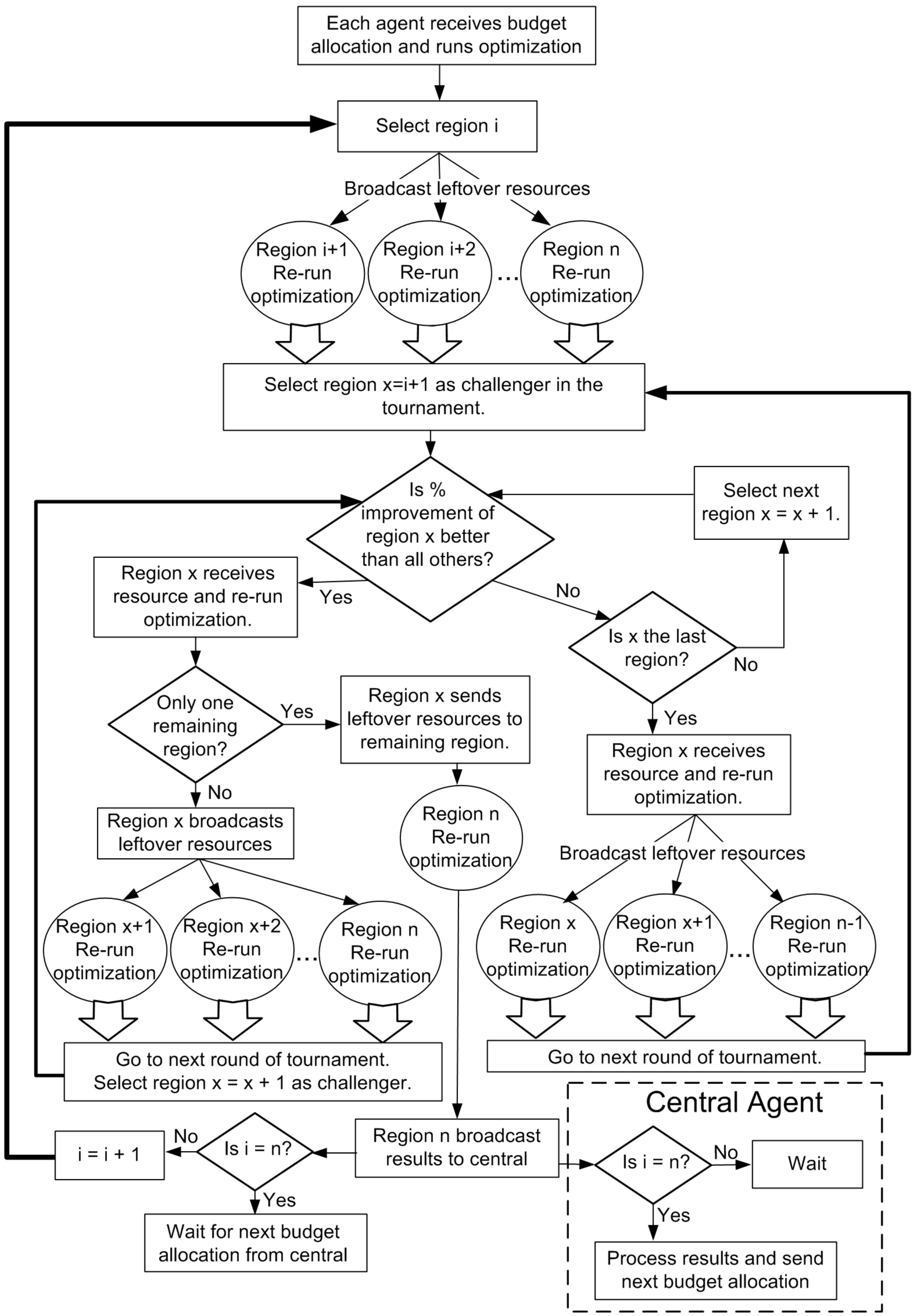
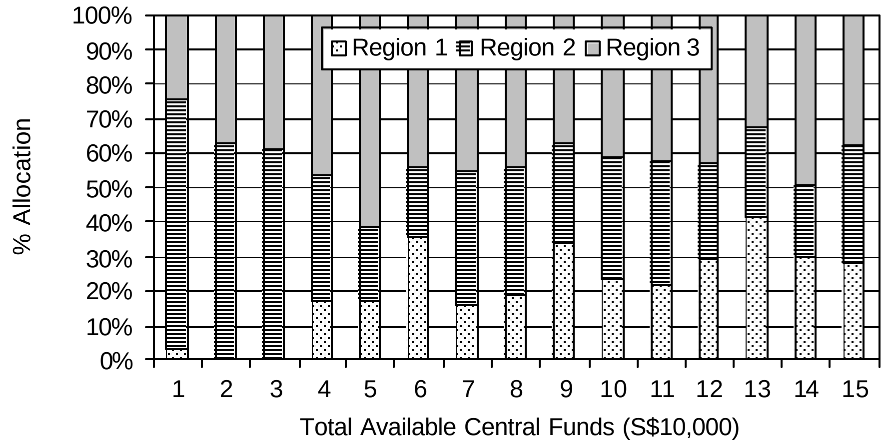
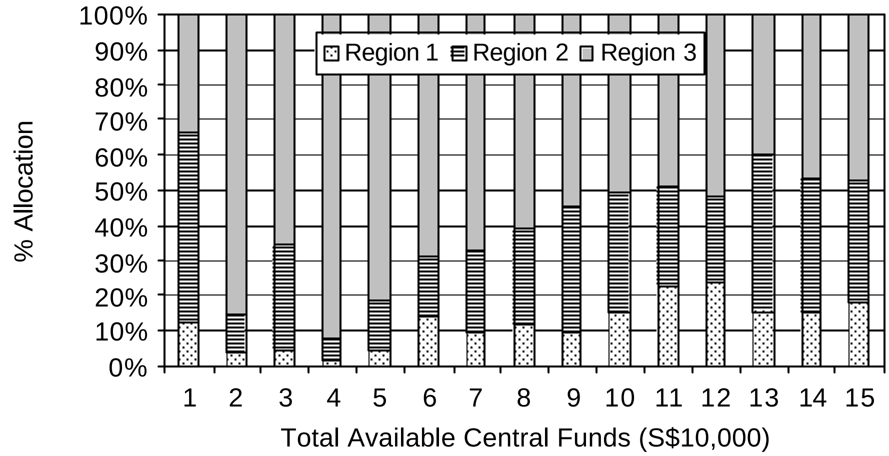


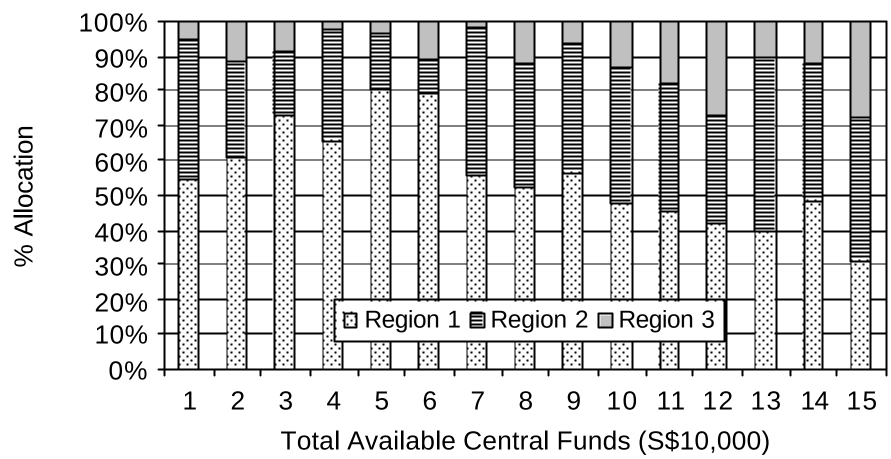
Fig. 5.2 Regional resource-sharing protocol based on a tournament-type selection



(a) CASE 1

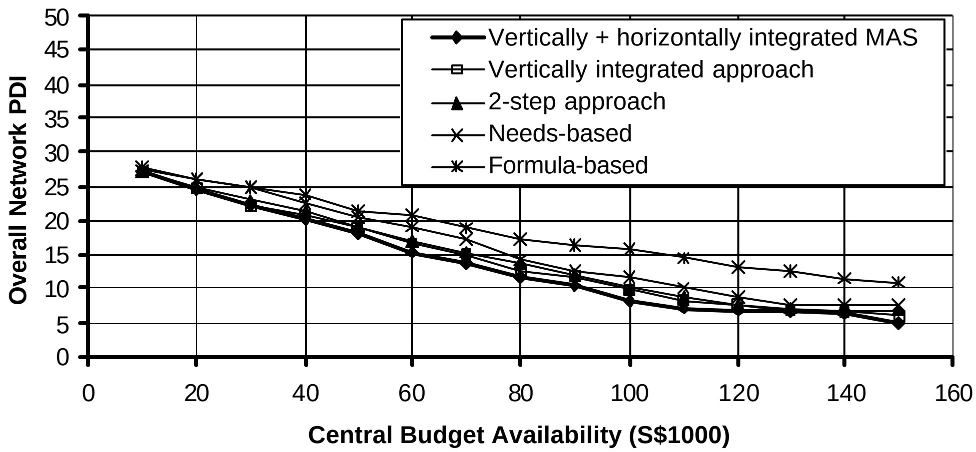


(b) CASE 2

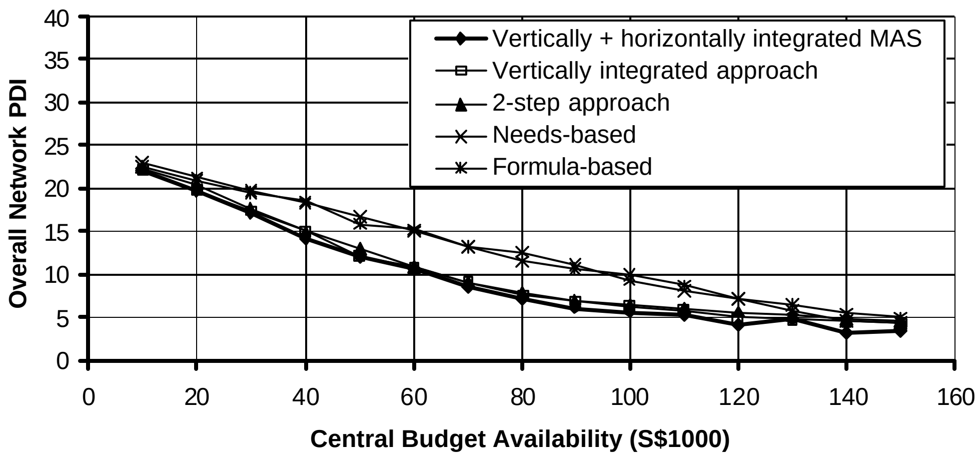


(c) CASE 3

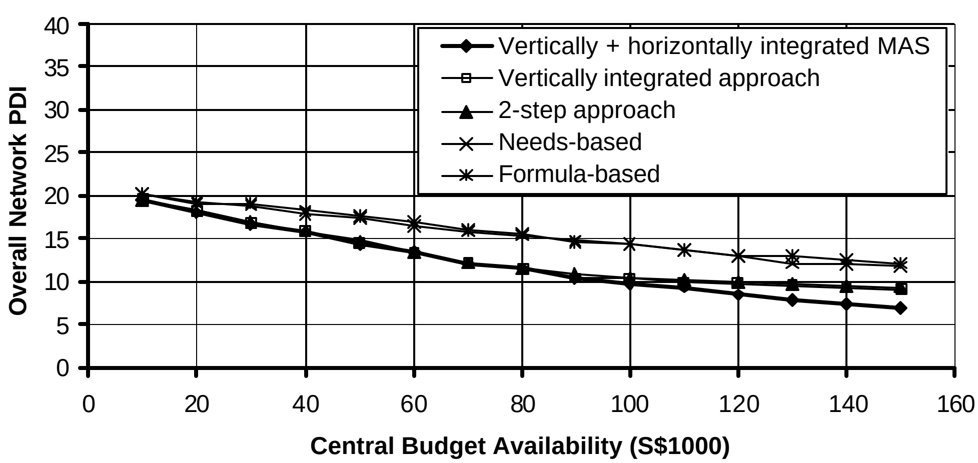
Fig. 5.3 Budget allocation shares of regions for different available central funds derived from multi-agent horizontally and vertically integrated optimization approach



(a) Case 1

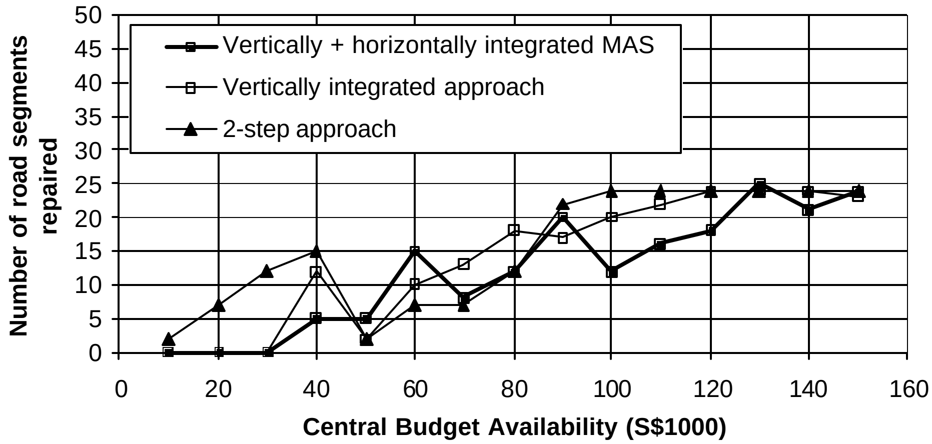


(b) Case 2

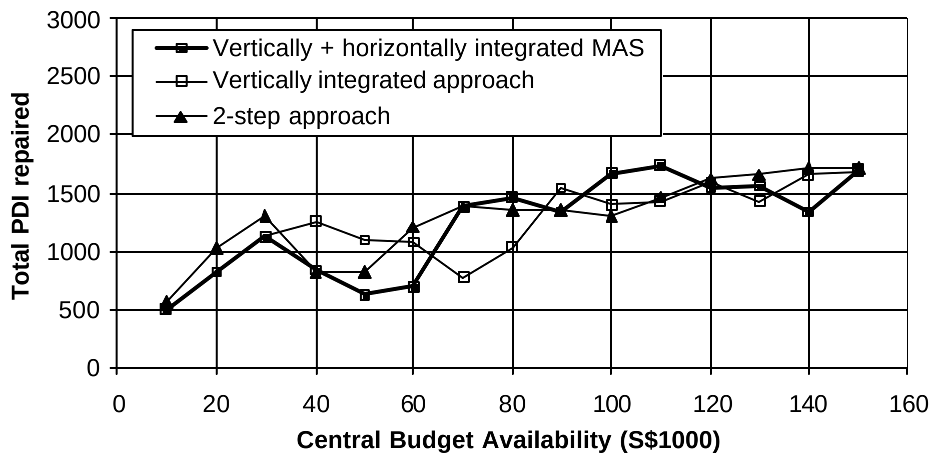


(c) Case 3

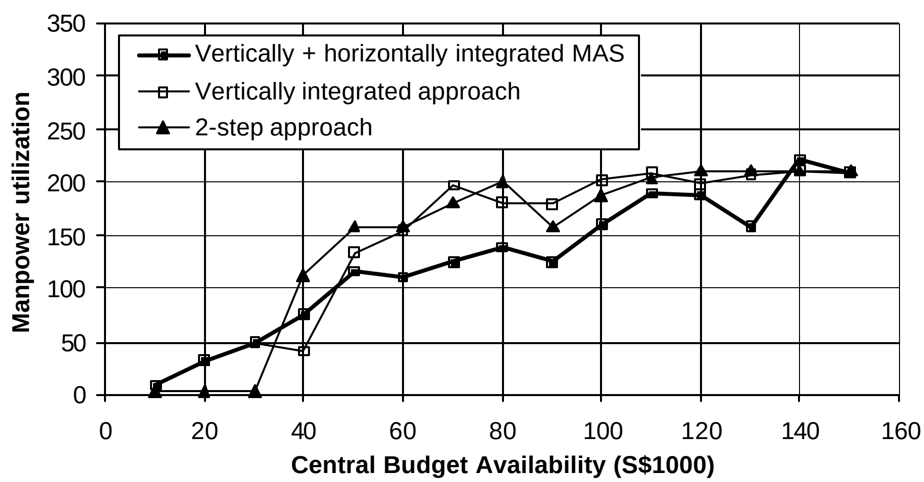
Fig. 5.4 Comparison of overall network PDI achieved with different budget allocation approaches



(a) Region 1

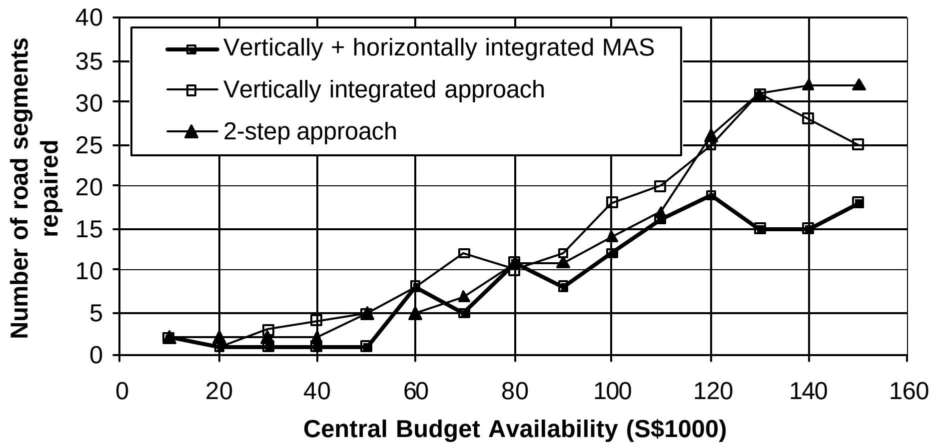


(b) Region 2

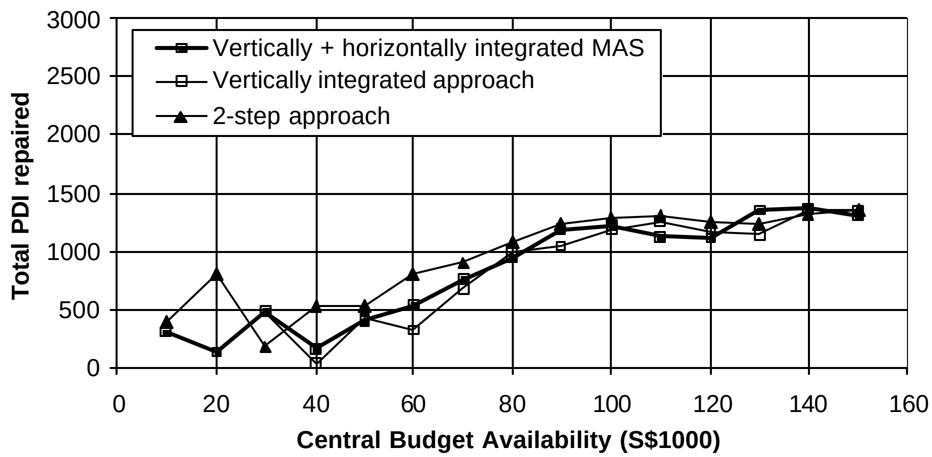


(c) Region 3

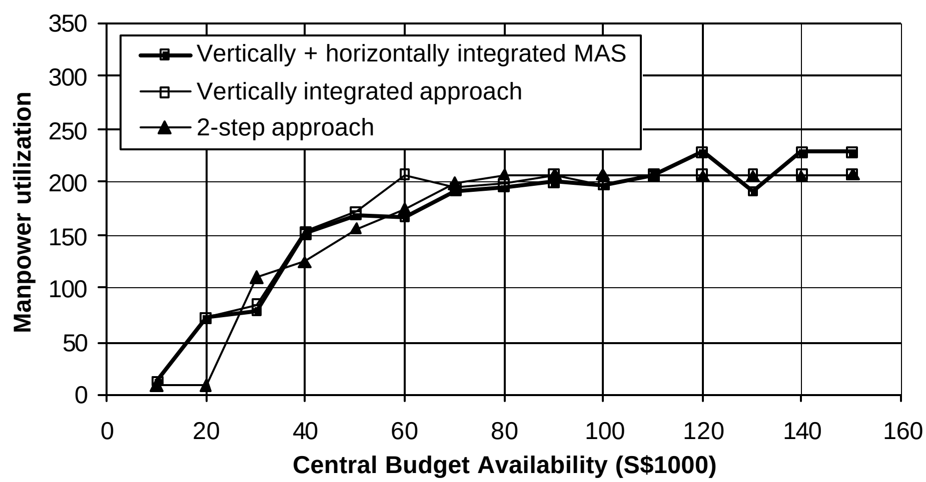
Fig. 5.5 Best regional objective function values achieved at different central budget availability for Case 1



(a) Region 1

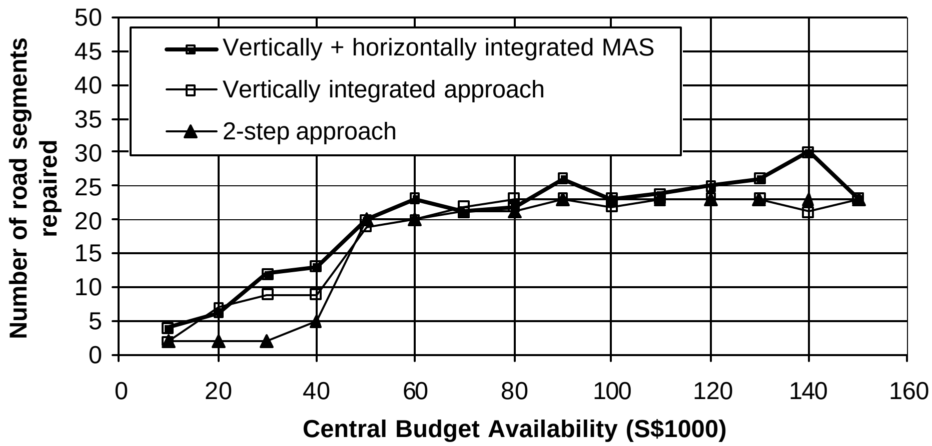


(b) Region 2

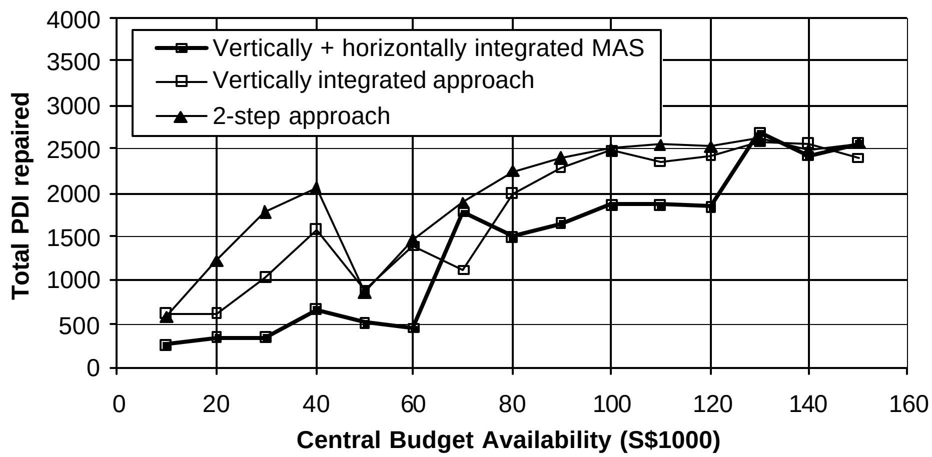


(c) Region 3

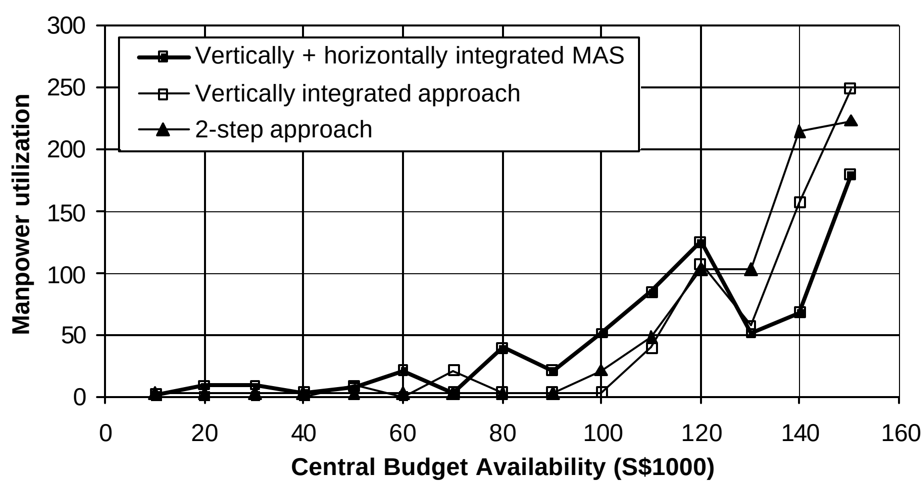
Fig. 5.6 Best regional objective function values achieved at different central budget availability for Case 2



(a) Region 1



(b) Region 2



(c) Region 3

Fig. 5.7 Best regional objective function values achieved at different central budget availability for Case 3

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 SUMMARY AND CONCLUSIONS

The highway fund allocation process can be viewed as a planning task in an organization where several regional highway agencies interact with the central authority in order to obtain a portion of the available funds. As separate entities situated in different geographical locations, inhabited by different communities, and progressing at different developmental rates, each regional agency is bound to have different short and long term interests and objectives. The constraints, technical, social, political, or economic, that are faced by each agency are also likely to be different. In large countries, the climatic condition in one region might also differ from that of another region, giving rise to different pavement performance models. Therefore, the management of each regional pavement network is a unique optimization problem in itself. The link between the different regional pavement networks is provided in the form of a central administration, whose interest lies in the higher-level system goals.

This thesis has presented new methodologies for automated budget allocation for pavement management using new computing technologies. The proposed fund allocation approaches take into account the different needs and objectives of regional highway agencies as well as the central authority. The study of these approaches is summarized below.

6.1.1 Two-step Optimization Approach

The two-step optimization approach to budget allocation has been presented in Chapter 3. This approach involves two optimization steps, one at the central level, and the other at the regional level. The two-step approach requires only one iteration of information exchange between regional and central levels. Genetic algorithms (GA) are used to optimize the selection of pavement maintenance strategies of the regional highway agencies.

The methodology of the solution procedure was demonstrated by solving a budget allocation problem involving a two-level road network management structure consisting of three region agencies and one central authority. The quality of results obtained from this allocation procedure was compared against that of commonly used highway fund allocation approaches, namely the formula-based and needs-based approaches. Sensitivity studies were carried out to determine the appropriate GA parameters for the hypothetical problem. An application of the two-step optimization approach has also been demonstrated to study the sensitivity of objective functions adopted by regions towards the central allocation strategy.

From the analysis of the results, it was shown that the two-step optimization approach is able to provide an objective tool for making budget allocation decisions in multi-region highway agencies. The fund allocation strategy derived from this procedure is able to consistently produce better overall network PDI values for all budget levels considered and for all three cases studied. With this procedure, scenarios for different budget levels can easily be acquired. Unlike mathematical programming methods, the solution method provides a flexible means of control for the central administration, where objective functions and constraints at both central as well as regional optimizations can be modified with ease.

6.1.2 Multi-Agent Vertically Integrated Optimization Approach

The distributed multi-agent vertically integrated optimization approach is described in Chapter 4. It is based on multi-agent systems to enable the interaction among the decision-makers. The approach is well-suited for the problem considered due to the spatially distributed nature of the problem, the distributed data and processing, and complexity of the multi-network pavement management problem. In this research, the agent architecture used is the Cognitive Agent Architecture or Cougaar, an open-source project developed by the Defence Advanced Research Projects Agency (DARPA) of the United States.

The allocation approach involves iterative vertical interaction between the two management levels considered. This allows for information integration between the two levels, thus resulting in better allocation strategy. The approach was tested out using the hypothetical example problem in Chapter 3 and the results compared with the allocation approaches presented earlier. It was found that the vertical integration results in significant savings in maintenance cost for a given target of network PDI level.

6.1.3 Multi-Agent Vertically and Horizontally Integrated Optimization Approach

This approach is an improvement to the multi-agent vertically integrated optimization approach and was described in Chapter 5. Improvement was made to allow for horizontal integration among regional highway agencies. This enables region agents to interact with each other to resolve conflicts or cooperatively solve a given problem. In this study, horizontal integration is employed to enable the sharing of idle resources among regional highway agencies. With the resource-sharing protocol, improvements on the objective function value of the regions and of the central authority are expected since the full utilization of idle resources have the effect of increasing the solution space of the problem.

A tournament-like resource-sharing protocol was introduced in this chapter. Tournaments are held to determine which region will receive how much idle resource from other regions. A region is picked as the challenger at each round of the tournament, and based on predefined selection criteria, the winner of each round of tournament is selected. The workings of the resource-sharing protocol has been presented in detail.

The performance of the distributed multi-agent vertically and horizontally integrated approach is compared with the other approaches using the hypothetical example problem presented in Chapters 3 and 4. It was found that the approach consistently produce budget allocation strategies that results in savings in overall maintenance cost. The results also confirm earlier observations that commonly used highway fund allocation approaches, the formula- and needs-based approaches, are unsatisfactory fund allocation tools for certain network-level pavement management.

6.2 RECOMMENDATIONS FOR FUTURE RESEARCH

In this study, improved budget allocation methods have been proposed to provide an advanced decision-making tool for highway agencies and authorities. The methodologies proposed are able to overcome the weaknesses of existing fund allocation approaches while providing greater control, considerations, and flexibilities for the decision-makers. Nevertheless, there are several improvements which can be made to further enhance the fund allocation approaches:

1) The fund allocation approaches presented in this study consider a one year planning period. A further study would be to improve the approaches to take into account a multi-year planning period. This would involve an inclusion of appropriate pavement deterioration models into the analysis.
2) The methodology presented in this study can be modified for highway asset management, of which PMS is a sub-system. Both problems involve multi-level optimization with different objectives at different levels and bound by a global budget.
3) The processing time required for the distributed vertically and horizontally integrated approach can be reduced. Even though this is not a critical weakness of the approach, it is an interest of research to improve on the efficiency of the multi-agent system.

This can be accomplished by studying the processing time consumed for each operation and reduce the number of operations that require a lot of time to complete.

4) Several resource-sharing protocols in the distributed vertically and horizontally integrated optimization approach can be experimented to determine the protocol that produces the best result. In this research, this study has not been conducted because the resource-sharing protocol is only a small part of the multi-agent system implemented.
5) The sharing of resources may incur a transfer cost in cases where regions may not be willing to forego their idle resources without setting a price or if the mobilisation of the resources across a large country incurs high expenses. This additional cost will have an impact on the solution and the savings for the whole system. This may be addressed in further research.
6) The practicality and effectiveness of the proposed methodology and computer programs presented in this study can be verified by implementation for practical road networks. Practical application may involve, among others, more than three regions, larger road networks, more types of distresses per road section, and consideration for several repair methods per road section. The inclusion of these considerations will further complicate the search space and extensive computing time may be required to achieve convergence. This may be addressed in further research.

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