KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY
DEPARTMENT OF MATHEMATICS

TOPIC

APPLICATION OF KNAPSACK TO SITE SELECTION PROBLEM FOR SOLID WASTE DISPOSAL
A CASE STUDY OF LEKZOKUKU-KROWOR MUNICIPAL ASSEMBLY (LEKMA)

A Thesis Submitted to the Department of Mathematics, Kwame Nkrumah University of Science and Technology in Partial fulfilment of the requirement for the degree of

Master of Science (Industrial Mathematics)

By

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DECLARATION

I hereby declare that this submission is my own work towards the Master of Science degree and that, to the best of my knowledge, it contains no material previously published by another person nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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DEDICATION

To the Almighty God, for him everything is possible

To the entire Sefah family for their support they gave me.

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To God be the glory, for seeing me through this course.

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ABSTRACT

The knapsack problem is a Classical combinational problem used to model many industrial situations. In this thesis, we modeled landfill sites selection and management challenges in Lekma as binary integer programming problem. The general objective is to determine how the landfill sites in Lekma municipal are selected. Since the problem was modeled as a binary integer programming problem, the branch-and-bound algorithm of the Horowitz-Sahni was used to solve our proposed problem. First, the algorithm was presented along with relevant examples. Data on site, from LEKMA was analyzed from the perspective of the said algorithm. It was observed that the solution that gave optimum achievable value was (1, 1, 0, 0, 0, 1, and 1). This means that the Metropolitan Assembly should spend a total cost of fifty thousand Ghana Cedis (GH¢50,000) to obtain an optimal site development of one hundred and five thousand (GH¢105,000) tones per week, consisting of selecting Site 1, Site 2, Site 6, and Site 7. The use of a well-structured procedure in computation gives a systematic and transparent solution as compared with an arbitrary method. Using the more scientific Knapsack problem model for the landfill site development of LEKMA refuse disposal management gives a better result. We therefore recommend our proposed solution to LEKMA.

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CHAPTER ONE

1.0 INTRODUCTION

There has been increased concern over municipal solid waste management in recent years in the country. This expression of increased concern stems from the alarming rate at which, municipal solid waste is generated mostly in the large urban areas. In the year 2002, Ghana's population was estimated to be twenty (20) million and at the same period the country produced a daily per capita waste of approximately 0.45kg and an annual solid waste generation of about 3.3 million tons (EPA, 2002). Much as solid waste management has been privatized, the country is still bedevilled with serious solid waste management challenges, which are threatening the potential outbreak of some communicable diseases with its attendant negative effect on human resources (Menel, 1994).

The daily solid waste generation in Accra, with an estimated population of about 3.3 million is 1500 tons. The quantities of waste generated have been increasing rapidly and is projected to reach double figures in the not too distant future (EPA, 2002). As in most cities, solid waste in Accra has a high putrescible organic content. The organic fraction is made up of kitchen waste including food leftovers, rotten fruits, vegetables, leaves, crop residues, animal excreta and bones (Asomani-Boateng and Haight, 1999). Plastics, glass, metals and paper account for less than 15% of total waste. High organic and moisture contents coupled with prevailing high temperatures necessitate frequent removals, which place additional burden on an overstrained collection system.

When the waste is not disposed at a distant from the city it emits a foul smell especially in low income areas where the solid waste is often mixed with human waste due to inadequate sanitation facilities (Boadi and Kuitunen, 2003).

The District Assemblies are unable to cope with the quantities of waste generated. The Accra Metropolitan Authority, for instance, is only able to collect about 55% of solid waste generated within the city. In the face of increasing costs of waste collection, transportation and disposal in addition to the long distant location of new disposal sites, the already poor collection performance may deteriorate even further.

Moreover, municipal solid waste disposal practices in Ghana in the past have not been environmentally friendly (EPA, 2002). The recent edition of the United Nations' Human Development Report (2007) for Ghana indicated that both solid and liquid waste disposal have been a source of concern as they contribute to a great deal of unsanitary conditions in cities in Ghana. Nationally, about 58 percent of households dispose of their refuse at public dump sites. About a quarter of households dispose of their solid waste elsewhere into valleys, pits, bushes, streams or river side's, open gutters or on undeveloped plots of land. About 8 percent burn, 4 percent bury, while only about 5 percent of households have their solid waste collected in an organized way (United Nations' Human Development Report 2007).

The statistics seem to suggest that our waste management system as a nation leaves very much to be desired and hence there is an urgent need to find pragmatic measures to ensure effective management of the landfill sites.

1.1.1 CHALLENGES OF LANDFILL SITES MANAGEMENT AND EFFECTS OF THEIR MISMANAGEMENT AND IMPROVEMENT

The insufficient landfill sites capacity and lack of internal resources are the greatest problems for the Waste Management Department. Even with the privatization of garbage collection there is still a severe waste management crisis throughout many parts of Accra. Throughout the city numerous central waste containers can be seen brimming over with trash from several days of no collection. This situation is further compounded by case base; individuals dispose of this remaining volume of waste wherever they can because it cannot be handled by the existing waste management system (Sam, 2002). The lack of waste collection capacity has resulted in direct and indirect dumping by individuals who are not being served by the current waste management system. Direct dumping occurs when persons dump solid waste directly into water sources or drain structures; indirect dumping occurs when solid waste is left alongside water sources such as streams and drains with the expectation that rains will eventually carry it away (Sam 2002).

Both dumping methods are hazardous to the citizens in these communities. Water sources and drains are then contaminated and silted by waste materials, thereby creating blockages, which results in exacerbating the flood conditions (Sam, 2002). This chapter focuses on solid waste management challenges in general (thus Global and Africa perspective), waste management practices in Ghana, population of people living in an area and the waste they generate, the problems of landfill site management, effects of uncontrolled landfill sites and the willing on the part the people to contribute to solving the problem without Government intervention using contingent valuation method.

1.1.2 POPULATION AND WASTE GENERATION IN LEKMA

Population dynamics have significant influence on the amount of waste generated and its proper handling in the municipality. The population of LEKMA is rapidly increasing because of the rural-urban migration among other factors in Accra. The population of Accra has grown from a mere 450,000 in 1960 to 1,600,000 in 1990 (Leitman, 1993), and in 2002 population stands at 3 million with a floating population of 300,000 (Ghana Statistical Services, 2002). The statistical service observed that approximately 50,000 economic migrants come to Accra daily and about 5,000 stay behind after close of business for weeks or months. Whiles the national population growth rate as at the year 2000 stood at 2.7 per cent that of Accra stood at 3.5 per cent.

This population growth has not been accompanied by increase in housing and basic sanitation facilities. The implications of these are increases in population density with low income settlements, large waste generation and increased pressure on waste management facilities (Ghana Statistical Service 2002). The UN-habitat (2003) observes that today's true builders and planners of cities in developing countries are the urban poor who build houses and establish legal or illegal settlements where they can to make life comfortable no matter what. "Slums have been the only large-scale solution to providing housing for low-income people. It is the only type of housing that is affordable and accessible to the poor in these cities" (UN-habitat, 2003). People in the slum most often do not pay for waste services and the nature of these settlements make no room for access roads for effective waste collection.

Associated with the increasing population are rising levels of affluence, shorter product cycles, and the large number of packaging, consumption and the demand for portable products that have brought increases in the waste stream. Ehrlich and Holdren (1971) established a relationship between the human environmental impact (I) (solid waste generation in this case under review), sub-national population size, growth, and concentration (*P*), people's affluence (*A*), and the methods (*T*) it employs to obtain its livelihood and dispose of its consumed products. This relationship they expressed through a mathematical model, I = PAT. Translating this into real life situation, this means that greater waste generation and its environmental impact would accompany a large, rapidly growing, and high density population and this is what has been the situation in Accra.

According to the Waste Management Department (WMD) of Accra Metropolitan Assembly, about 1800 tons of municipal solid wastes are generated per day in the metropolis and the average waste generated per capita per day is estimated at 0.5kg. Holding change in production and consumption patterns constant, future projections are subject to population growth, taking into account the present population of about 3million and growth rate of 3.5 per cent as sited in Anomanyo (2004).

The high proportion of food and plant waste is due to the fact that Ghana's economy largely depends on agricultural products for export and domestic consumption. Apart from the food waste from consumption and food processing factories, post harvest losses due to inadequate storage facilities and ready market for the farm produce contribute the greater percentage of the food and plant waste (Ministry of Food and Agriculture, 2000). Inert waste including rubbles from demolition and construction works are rarely disposed of as waste in Ghana since they are used on site roads in areas of housing and road construction.

According to EPA (2002), hazardous solid wastes generally occur in small quantities, except in the case of specific industrial operations for which the industry concerned takes responsibility and is assisted to put in place management plans guided by standards on effluent and discharges set by the EPA. These wastes though important, are not included in this discussion. The waste generated per day in the metropolis are however, not totally collected from their sites of generation.

1.1.3 AN OVERVIEW OF LANDFILL SITES MANAGEMENT IN LEKMA

In the LEKMA metropolitan area, solid waste collection and disposal is the responsibility of LEKMA Metropolitan Assembly's Waste Management Department (WMD). The department therefore sees to the collection, transport, treatment and disposal of solid waste. The WMD is thus responsible for the management of the solid waste disposal sites and waste landfill sites in LEKMA. Solid Waste Management all over the world is a complex one. The municipality spent about 0.17 percent of its Gross Nation Product (GNP) on solid waste management service in 1994 (World Bank, 1999).

Like most developing cities, the municipality allocates a greater proportion of its solid waste management budget to collection and transporting services than development of proper disposal sites, equipment acquisition, and maintenance (Cointreau-Levine, 2000). Also in most developing cities, collection fees are usually based on communities' wealth, ability to pay and the quality of services desired. This system places low social class areas at a disadvantage since the quality of their primary collection service suffers (World Bank, 1999). Poor mental quality or amenities, due to income elasticity of environmental services only 31 percent, out of 82 percent of the population that relied on communal waste disposal site, pay a levy (Benneh et al., 1993).

1.1.4 LANDFILL SITE MANAGEMENT

The majority of wastes are dumps on open plots, wetlands, and lands with water near the surface (Johannessen and Boyer 1999). They are usually not provided with liners, fences, compactors or soil cover. Waste pickers use this advantage to visit the site and sort valuables for themselves (Adeyemi et al, 2001, Yhdego 1995). According to Korfmacher (1997), South Africa, Uganda, Ghana and Egypt are upgrading their landfills to sanitary ones. One great concern is that in Africa, the landfills are owned and operated by the very body that is supposed to enforce standards. The philosophy of getting waste out of sight and consequently out of mind seems to be the overriding consideration of these authorities. Hence removing the waste is considered paramount giving their limited resources.

This neglect starts from the way aid donor see waste matters. According to Johannessen and Boyer, (1999), 'of all the regions, Africa has the lowest level of investment of World Bank funds in solid waste sector'. This author also notes that even though, African governments spend much on solid waste management the investment on this waste sector, as a fraction of total project costs is very low compared to other regions (Johnnessen and Boyer 1999).

1.1.5 REGULATORY FRAMEWORK FOR WASTE MANAGEMENT IN GHANA

There had been no comprehensive legislation on environment in Ghana until the late 1990s. What was happening was that a number of laws that concerned exploitation of natural resources sometimes had specific aspects of the environment. Even then, issues such as industrial effluents and waste were virtually left uncovered. The environmental protection agency (EPA) was established in 1994, under an Act of parliament Act 490 which replaced the EPC. The EPA is empowered to besides advising the Minister of the Environment, enforce, monitor, and control environmental standards and regulations including the following means: coordinates the activities of bodies concerned with the technical or practical aspects of the environment and serves as a channel of communication between such bodies and the ministry.

The EPA is responsible for; secure in collaboration with such persons as it may determine the control and prevention of discharge of waste into the environment and the protection and improvement of the quality of the environment; issues environmental permits and pollution abatement notices for controlling the volume, types, constituents and effects of waste discharges, emissions, deposits or other sources of pollutants and of substances which are hazardous or potentially dangerous to the quality of the environment or any segment of the environment; issues notices in the form of directives, procedures or warnings to such bodies as it may determine for the purpose of controlling the volume, intensity and quality of noise in the environment; prescribes standards and guidelines relating to the pollution air, water, land and other forms of environmental pollution including the discharge of waste and the control of toxic substances (Ministry of Local Government and Rural Development 2003).

1.1.6 POLICIES AND REGULATIONS OF LANDFILL SITE MANAGEMENT

Solid waste regulations in Ghana are normally coming from the Ministry of Local Government and Rural Development, the Ministry of Environment, and the EPA. In 1999, the Ministry of Local Government Rural Development came out with the national environmental sanitation plan that seeks to develop and maintain a clean, safe and pleasant physical environment for human settlements. Along this policy, local governments have been enjoined to develop strategic environmental plans to implement the programmes proposed in the policy. AMA enforces these policies.

The EPA has designed solid waste management guidelines for municipalities, and has equally established standards for design, construction and management of waste disposal system to protect health and the environment. The purpose of the guidelines is to assist the district assemblies and other relevant stakeholders in the planning and management of waste. The EPA makes sure the District Waste Management Plan (DWMP) addresses all aspects of solid waste management in the district.

1.2 STATEMENT OF THE PROBLEM

There are several methods to treat waste, but for collected waste in developing countries the most common method is disposal at an open dump site. In most cases, the wastes at the dump sites are never collected for recycling of any form. They are allowed to develop into heaps or burnt locally causing serious pollution to the environment. According to the Ministry of Local Government (1992) this is mainly due to lack of education, low environmental consciousness, long distance from containers and poor enforcement of the law against indiscriminate offenders. The environmental and health hazards associated with this improper disposal of waste are immeasurable.

Nonetheless, Kendie (1999) argues that, the recent upsurge in waste disposal problems stems from the fact that, the procedure for selecting the site where the wastes are disposed is done anyhow.

In the wake of the mounting challenges of landfill sites management and the inability of the local authorities to deal efficiently with the menace ranging from their limited expertise as well as improper model for site selection that this study has been necessitated. This study seeks to model landfill sites selection and management challenges in the LEKMA Municipal Assemblies mathematically as a binary integer programming problem and solve the problem.

1.3 OBJECTIVES OF THE STUDY

The general objective of this study is to determine how the landfill sites in LEKMA Municipal are selected.

Specific objectives:

(i) To assess the landfill site management problems in the LEKMA Municipality.

(ii) To examine the capacity of the selected dump sites in the area.

(iii) To assess the cost involve in developing and managing these sites and the willingness on the part of the people in the municipalities-to-pay to deal with the situation without government intervention.

1.4 METHODOLOGY

Since the problem would be modeled as a binary integer programming problem, we shall propose the branch-and-bound algorithm for solving our proposed problem. First, the algorithm is presented along with relevant examples. Data from LEKMA would be analyzed from the perspective of the above algorithm.

1.5 JUSTIFICATION

The importance of the study cannot be under-estimated. It will serve as a useful guide to policy makers to map out efficient and effective ways of financing waste management in the country as a whole. This study will be very significant in providing policy makers with concrete recommendations to deal with the solid waste management crisis. It will also provide the city authorities with information about how landfill sites are and the cost involve in developing and managing these sites.

1.6 SCOPE OF THE STUDY

Solid Waste Management all over the world is a complex one. The scope of the study was LEKMA Municipalities in the Greater Accra Region of Ghana. However, the main focus of this research work was the problem of landfill sites selection and management in the Municipality and also the effect of the landfill sites in the Municipality on the people living in these areas.

1.7 LIMITATION OF THE STUDY

The study is limited to selection of landfill sites for solid waste management challenge, thus other types of waste such as liquid, industrial, health care and radioactive waste and their management will not be covered in this study. This is a deliberate effort on the researcher's part to make the study manageable given the time and resources available to the researcher to complete the study. The study was limited to the perceived effect of landfill site selection and management challenge on the people living in the municipality, the effects of the landfill sites in some communities in the Municipality.

1.8 ORGANIZATION OF THE THESIS

In chapter one, we presented a background study of waste management problem in Accra. In chapter two, pertinent literature in the field binary integer programming problems, to be specific, Knapsack problems would be discussed.

In chapter three, the branch-and-bound algorithm will be introduced and explained.

Chapter four will provide a computational study the branch-and-bound algorithm applied to our problem instances.

Chapter five will conclude this thesis with additional comments on branch-an-bound algorithm.

1.9 SUMMARY

In this chapter, we discussed increased concern that stems from the alarming rate at which, municipal solid waste is generated mostly in the large urban areas.

Challenges of landfill sites management and effects of their mismanagement and improvement, population and waste generation in LEKMA, an overview of landfill sites management in LEKMA, landfill site management, regulatory framework for waste management, policies and regulations of landfill site management, were also put forward. We also discussed our problem statement, objectives of the study, methodology, justification, and the scope of the study.

In the next chapter, we shall put forward pertinent literature on Knapsack Problems.

CHAPTER TWO

LITERATURE REVIEW

The knapsack problem is a classical combinatorial problem used to model many industrial situations. Faced with uncertainty on the model parameters, robustness analysis is an appropriate approach to find reliable solutions. Kalai and Vanderpooten (2006) studied the robust knapsack problem using a max-min criterion, and proposed a new robustness approach, called lexicographic α-robustness. The authors showed that the complexity of the lexicographic α-robust problem does not increase compared with the max-min version and presented a pseudo-polynomial algorithm in the case of a bounded number of scenarios.

Knapsack problems with setups find their application in many concrete industrial and financial problems. Moreover, they also arise as sub-problems in a Dantzig-Wolfe decomposition approach to more complex combinatorial optimization problems, where they need to be solved repeatedly and therefore efficiently. Micheal et al., (2009) considered the multiple-class integer knapsack problem with setups. Items are partitioned into classes whose use imply a setup cost and associated capacity consumption. Item weights are assumed to be a multiple of their class weight. The total weight of selected items and setups is bounded. The objective is to maximize the difference between the profits of selected items and the fixed costs incurred for setting-up classes. A special case is the bounded integer knapsack problem with setups where each class holds a single item and its continuous version where a fraction of an item can be selected while incurring a full setup. The authors showed the extent to which classical results for the knapsack problem can be generalized to these variants with setups. In particular, an extension of the branch-and-bound algorithm of Horowitz and Sahni (1974) is developed for problems with positive setup costs.

The multidimensional knapsack problem (MKP) is a well-known, strongly NP-hard problem and one of the most challenging problems in the class of the knapsack problems. In the last few years, it has been a favorite playground for meta-heuristics, but very few contributions have appeared on exact methods. Renata and Grazia (2009) presented an exact approach based on the optimal solution of sub-problems limited to a subset of variables. Each sub-problem is faced through a recursive variable-fixing process that continues until the number of variables decreases below a given threshold (restricted core problem). The solution space of the restricted core problem is split into subspaces, each containing solutions of a given cardinality. Each subspace is then explored with a branch-and-bound algorithm. Pruning conditions are introduced to improve the efficiency of the branch-and-bound routine.

The Quadratic Knapsack Problem (QKP) calls for maximizing a quadratic objective function subject to a knapsack constraint, where all coefficients are assumed to be nonnegative and all variables are binary. The problem has applications in location and hydrology, and generalizes the problem of checking whether a graph contains a clique of a given size.

Alberto et al., (2007) proposed an exact branch-and-bound algorithm for QKP, where upper bounds are computed by considering a Lagrangian relaxation that is solvable through a number of (continuous) knapsack problems. Suboptimal Lagrangian multipliers are derived by using sub-gradient optimization and provide a convenient reformulation of the problem. The authors also discussed the relationship between our relaxation and other relaxations. Heuristics, reductions, and branching schemes were described. In particular, the processing of each node of the branching tree is quite fast: Their approach does not update the Lagrangian multipliers, and use suitable data structures to compute an upper bound in linear expected time in the number of variables. The authors approach report exact solution of instances with up to 400 binary variables, i.e., significantly larger than those solvable by the previous approaches. The key point of this improvement is that the upper bounds we obtain are typically within 1% of the optimum, but can still be derived effectively. They also showed that their algorithm is capable of solving reasonable-size Max Clique instances.

The Knapsack Problems are among the simplest integer programs which are NP-hard. Problems in this class are typically concerned with selecting from a set of given items, each with a specified weight and value, a subset of items whose weight sum does not exceed a prescribed capacity and whose value is maximum. The specific problem that arises depends on the number of knapsacks (single or multiple) to be filled and on the number of available items of each type (bounded or unbounded). Because of their wide range of applicability, knapsack problems have known a large number of variations such as: single and multiple-constrained knapsacks, knapsacks with disjunctive constraints, multidimensional knapsacks, multiple choice knapsacks, single and multiple objective knapsacks, integer, linear, non-linear knapsacks, deterministic and stochastic knapsacks, knapsacks with convex / concave objective functions, etc. The classical 0-1 Knapsack Problem arises when there is one knapsack and one item of each type. Knapsack

Problems have been intensively studied over the past forty (40) years because of their direct application to problems arising in industry (for example, cargo loading, cutting stock, and budgeting) and also for their contribution to the solution methods for integer programming problems. Several exact algorithms based on branch and bound, dynamic programming and heuristics have been proposed to solve the Knapsack Problems.

Oppong (2009) presented the application of classical 0-1 knapsack problem with a single constraint to selection of television advertisements at critical periods such as Prime time News, news adjacencies, Break in News and peak times. The Television (TV) stations have to schedule programmes interspersed with adverts or commercials which are the main sources of income of broadcasting stations. The goal in scheduling commercials is to achieve wider audience satisfaction and making maximum income from the commercials or adverts. The author approach is flexible and can incorporate the use of the knapsack for Profit maximization in the TV adverts selection problem, and focused on using a simple heuristic scheme (Simple flip) for the solution of knapsack problems.

The collapsing knapsack problem is a generalization of the ordinary knapsack problem, where the knapsack capacity is a non-increasing function of the number of items included. Whereas previous methods on the topic have applied quite involved techniques, Ulrich et al., (1995) presented and analyze two rather simple approaches: One approach that was based on the reduction to a standard knapsack problem, and another approach that was based on a simple dynamic programming recursion. Both algorithms have pseudo-polynomial solution times, guaranteeing reasonable solution times for moderate coefficient sizes. Computational experiments are provided to expose the efficiency of the two approaches compared to previous algorithms

Kosuch and Lisser (2009) studied a particular version of the stochastic knapsack problem with normally distributed weights: the two-stage stochastic knapsack problem. Contrary to the single-stage knapsack problem, items can be added to or removed from the knapsack at the moment the actual weights become known (second stage). In addition, a chance-constraint is introduced in the first stage in order to restrict the percentage of cases where the items chosen lead to an overload in the second stage. According to the authors, there is no method known to exactly evaluate the objective function for a given first-stage solution, and therefore proposed methods to calculate the upper and lower bounds. These bounds are used in a branch-and-bound framework in order to search the first-stage solution space. Special interest was given to the case where the items have similar weight means. Numerical results are presented and analyzed.

Stefanie (2010) presented an Ant Colony Optimization algorithm for the Two-Stage Knapsack problem with discretely distributed weights and capacity, using a meta-heuristic approach. Two heuristic utility measures were proposed and compared. Moreover, the author introduced the novel idea of non-utility measures in order to obtain a criterion for the construction termination. The author argued why for the proposed measures it is more efficient to place pheromone on arcs instead of vertices or edges of the complete search graph. Numerical tests show that the author's algorithm is able to produce, in much shorter computing time, solutions of similar quality than CPLEX after 2h. Moreover, with increasing number of scenarios the percentage of runs where his algorithm is able to produce better solutions than CPLEX (after 2h) increases.

Mattfeld and Kopfer (2003) described terminal operations for the vehicle transshipment hub in Bremerhaven as a knapsack and have derived an integral decision model for manpower planning and inventory control. The authors proposed a hierarchical separation of the integral model into sub models and can develop integer programming algorithm to solve the arising sub problems.

In bus transit operations planning process, the important components are network route design, setting timetables, scheduling vehicles, assignment of drivers, and maintenance scheduling. Haghani and Shafahi (2002) presented integer programming model to design daily inspection and maintenance schedules for the buses that are due for inspection so as to minimize the interruptions in the daily bus operating schedule, and maximize the utilization of the maintenance facilities.

The setting of timetables and bus routing or scheduling are essential to an intercity bus carrier's profitability, its level of service, and its competitive capacity in the market. Yan and Chen (2002) developed a model that help Taiwanese intercity bus carriers in timetable settings and bus routing or scheduling. The model employs multiple time-space networks that can formulate bus movements and passenger flows and manage the interrelationships between passenger trip demands and bus trip suppliers to produce the best timetables and bus routes or schedules.

Higgins et al., (1996) described the development and use of integer programming model to optimize train schedules on single-line rail corridors. The model has been developed with two major applications in mind: as a decision support tool for train dispatchers to schedule trains in real time in an optimal way and as a planning tool to evaluate the impact of timetable changes, as well as railroad infrastructure changes. The model was developed based on a real-life problem.

Ghoseiri et al., (2004) developed an optimization model for the passenger train-scheduling problem on a railroad network, which includes single, and multiple tracks, as well as multiple platforms with defferent train capacities.

Claessens et al., (1998) considered the problem of cost optimal railway line allocation for passenger trains for the Dutch railway system. A mathematical programming model was developed, which minimized the operating costs subject to service constraints and capacity requirements. The model optimized on lines, line types, routes, frequencies, and train lengths. First, the line allocation model was formulated as an integer nonlinear programming model. The model was then transformed into an integer linear programming model with binary decision variables. The model was solved and applied to a sub network of the Dutch railway system for which it showed a substantial cost reduction.

The deterministic knapsack problem is a well known and well studied NP-hard combinatorial optimization problem. It consists in filling a knapsack with items out of a given set such that the weight capacity of the knapsack is respected and the total reward maximized. In the deterministic problem, all parameters (item weights, rewards, knapsack capacity) are known (deterministic). In the stochastic counterpart, some (or all) of these parameters are assumed to be random, i.e. not known at the moment the decision has to be made. Stefanie et al., (2010) studied the stochastic knapsack problem with expectation constraint. The item weights are assumed to be independently normally distributed. The authors solved the relaxed version of this problem using a stochastic gradient algorithm in order to provide upper bounds for a branch-and-bound framework. Two approaches to estimate the needed gradients are applied, one based on Integration by Parts and one using Finite Differences. Finite Differences is a robust and simple approach with efficient results despite the fact that the estimated gradients are biased; meanwhile Integration by Parts is based upon a more theoretical analysis and permits to enlarge the field of applications.

Stefanie et al., (2009) proposed a mixed integer bi-level problem having a probabilistic knapsack constraint in the first level. The problem formulation is mainly motivated by practical pricing and service provision problems as it can be interpreted as a model for the interaction between a service provider and clients. The authors assumed the probability space to be discrete which allows us to reformulate the problem as a deterministic equivalent bi-level problem. Via a reformulation as linear bi-level problem, we obtain a quadratic optimization problem, the so called Global Linear Complementarity Problem. Based on this quadratic problem, the authors finally proposed a procedure to compute upper bounds on the initial problem by using a Lagrangian relaxation and an iterative linear min-max scheme.

The Knapsack Problem (KP) and its Multidimensional version (MKP) are basic problems in combinatorial optimization. Thibaut and Jacques (2010) presented the multiobjective extension (MOKP and MOMKP), for which the aim is to obtain or to approximate the set of efficient solutions. In a first step, the authors classified and described briefly the existing works that are essentially based on the use of meta-heuristics. In a second step, the authors proposed the adaptation of the two-phase Pareto local search (2PPLS) to the resolution of the MOMKP. With this aim, the authors used a very-large scale neighborhood (VLSN) in the second phase of the method that is the Pareto local search. They compared their results to state-of-the-art results and showed that they obtained results never reached before by heuristics, for the biobjective instances. Finally they considered the extension to three-objective instances.

Eleni and Nicos (2010) presented a new exact tree-search procedure for solving two-dimensional knapsack problems in which a number of small rectangular pieces, each of a given size and value, are required to be cut from a large rectangular stock plate. The objective is to maximize the value of pieces cut or minimize the wastage. The authors considered the case where there are a maximum number of times that a piece may be used in a cutting pattern. The algorithm limits the size of the tree search by using a bound derived from a Langrangean relaxation of a 0–1 integer programming formulation of the problem. Sub-gradient optimization is used to optimize this bound. Reduction tests derived from both the original problem and the Lagrangean relaxation produce substantial computational gains. The computational performance of the algorithm indicates that it is an effective procedure capable of solving optimally practical two-dimensional cutting problems of medium size.

Lawler (1997) presented fully polynomial approximation algorithms for knapsack problems are presented. These algorithms are based on ideas of Ibarra and Kim, with modifications which yield better time and space bounds, and also tend to improve the practicality of the procedures. Among the principal improvements are the introduction of a more efficient method of scaling and the use of a median-finding routine to eliminate sorting. The 0-1 knapsack problem, for n items and accuracy $\varepsilon > 0$, is solved in (n log

(1/ε) + 1/ε4) time and 0(n + 1/ε3) space. The time bound is reduced to 0(n + 1/ε3) for the "unbounded" knapsack problem. For the "subset-sum" problem, 0 (n + 1/ε3) times and 0 (n + 1/ε2) spaces, or 0(n + 1/ε2 log (1/ε)) time and space, are achieved. The "multiple choice" problem, with m equivalence classes, is solved in 0(nm2/ε) time and space.

The 0-1 knapsack problem is a linear integer-programming problem with a single constraint and binary variables. The knapsack problem with an inequality constraint has been widely studied, and several efficient algorithms have been published. Balasubramanian and Sanjiv (1988) considered the equality-constraint knapsack problem, which has received relatively little attention. The authors described a branch-and-bound algorithm for this problem, and present computational experience with up to 10,000 variables. An important feature of this algorithm is a least-lower-bound discipline for candidate problem selection.

Esther et al., (1993) studied a variety of geometric versions of the classical knapsack problem. In particular, the authors considered the following "fence enclosure" problem: given a set S of n points in the plane with values $v_i > 0$, we wish to enclose a subset of the points with a fence (a simple closed curve) in order to maximize the "value" of the enclosure. The value of the enclosure is defined to be the sum of the values of the enclosed points minus the cost of the fence. They also considered various versions of the problem, such as allowing S to consist of points and/or simple polygons. Other versions of the problems are obtained by restricting the total amount of fence available and also allowing the enclosure to consist of at most M connected components. When there is an upper bound on the length of fence available, we show that the problem is NP-complete. We also provide polynomial-time algorithms for many versions of the fence problem when an unrestricted amount of fence is available.

Volgenant and Zoon (1990) presented a multidimensional 0-1 knapsack problem using heuristic, based on Lagrange multipliers, that also enables the determination of an upper bound to the optimal criterion value. This heuristic is extended in two ways: (1) in each step, not one, but more multiplier values are computed simultaneously, and (2) at the end the upper bound is sharpened by changing some multiplier values. From a comparison using a large series of different test problems, the extensions appear to yield an improvement, on average, at the cost of only a modest amount of extra computing time.

The binary knapsack problem is a combinatorial optimization problem in which a subset of a given set of elements needs to be chosen in order to maximize profit, given a budget constraint. Das and Ghosh (2003) studied a stochastic version of the problem in which the budget is random. The authors proposed two different formulations of this problem, based on different ways of handling infeasibility, and propose an exact algorithm and a local search-based heuristic to solve the problems represented by these formulations. The authors also presented the results from some computational experiments.

Goyal and Ravi (2009) presented a stochastic knapsack problem where each item has a known profit but a random size. The goal is to select a profit maximizing set of items such that the probability of the total size of selected items exceeding the knapsack size is at most a given threshold. The authors presented PTAS for the case when each item size is normally distributed and independent of other items. They also presented a parametric LP formulation and show that it is a good approximation of the chance-constrained stochastic knapsack problem. Furthermore, they gave a polynomial time algorithm to round any fractional solution of the parametric LP to obtain an integral solution whose profit is within $(1 + \in)$-factor of the objective value of the fractional solution for any $\in > 0$.

The dominant traffic on the Internet has changed from text and graphics based Web content to more information-rich streaming media content, such as audio and video. With the dramatic increase of network bandwidth and the advancement of technologies on media authoring, encoding, and distribution, media traffic on the Internet has increased explosively and now accounts for the majority of traffic volume. Modern Internet streaming services have utilized various techniques to improve the quality of streaming media delivery. Proxy server is one of the main solutions used to improve Internet QoS, especially for the QoS of streaming media. Replacement algorithm optimization is the core of caching model research. However, existing techniques for caching text and image resources are not appropriate for the rapidly growing number of continuous media streams. Based on the concept of hit ratio, Lei Shi et al., (2010) presented a 0-1 knapsack problem that set up a hit ratio model of proxy cache, by use of which a proxy cache policy is presented. As compared with the classical dynamic streaming scheduling strategies, the proposed algorithm is shown that it can make full use of space of proxy cache, and also get a higher hit ratio.

The knapsack problem is known to be a typical NP-complete problem, which has 2^n possible solutions to search over. Thus a task for solving the knapsack problem can be accomplished in 2^n trials if an exhaustive search is applied. In the past decade, much effort has been devoted in order to reduce the computation time of this problem instead of exhaustive search. In 1984, Karnin proposed a brilliant parallel algorithm, which needs $O(2^{n/6})$ processors to solve the knapsack problem in $O(2^{n/2})$ time; that is, the cost of Karnin's parallel algorithm is $O(2^{2n/3})$. Der-Chyuan Lou and Chin-Chen Chang (1997) proposed a fast search technique to improve Karnin's parallel algorithm by reducing the search time complexity of Karnin's parallel algorithm to be $O(2^{n/3})$ under the same $O(2^{n/6})$ processors available. Thus, the cost of the proposed parallel algorithm is $O(2^{n/2})$. Furthermore, the authors extended their technique to the case that the number of available processors is $P = O(2^x)$, where $x \geq 1$. From the analytical results, the saw that their search technique is indeed superior to the previously proposed methods. They do believe their proposed parallel algorithm is pragmatically feasible at the moment when multiprocessor systems become more and more popular.

Knapsack problem is a typical NP complete problem. During last few decades, Knapsack problem has been studied through different approaches, according to the theoretical development of combinatorial optimization. Garg and Sunanda (2009) studied the evolutionary algorithm for 0/1 knapsack problem. A new objective function evaluation operator was proposed which employed adaptive repair function named as repair and elitism operator to achieve optimal results in place of problem specific knowledge or domain specific operator like penalty operator (which are still being used). Additional features had also been incorporated which allowed the algorithm to perform more consistently on a larger set of problem instances. Their study also focused on the change in behavior of outputs generated on varying the crossover and mutation rates. New algorithm exhibited a significant reduction in number of function evaluations required for problems investigated.

Srisuwannapa and Charnsethikul (2007) presented a variant of the unbounded knapsack problem (UKP) into which the processing time of each item is also put and considered, referred as MMPTUKP. The MMPTUKP is a decision problem of allocating amount of n items, such that the maximum processing time of the selected items is minimized and the total profit is gained as at least as determined without exceeding capacity of knapsack. In this study, we proposed a new exact algorithm for this problem, called MMPTUKP algorithm. This pseudo polynomial time algorithm solves the bounded knapsack problem (BKP) sequentially with the updated bounds until reaching an optimal solution. The authors presented computational experience with various data instances randomly generated to validate their ideas and demonstrate the efficiency of the proposed algorithm.

Ronghua et al., (2006) presented a new multiobjective optimization (MO) algorithm to solve 0/1 knapsack problems using the immune Clonal principle. This algorithm is termed Immune Clonal MO Algorithm (ICMOA). In ICMOA, the antibody population is split into the population of the non-dominated antibodies and that of the dominated anti-bodied. Meanwhile, the non-dominated antibodies are allowed to survive and to clone. A metric of Coverage of Two Sets is adopted for the problems. This quantitative metric is used for testing the convergence to the Pareto-optimal front. Simulation results on the 0/1 knapsack problems show that ICMOA, in most problems, is able to find much better spread of solutions and better convergence near the true Pareto-optimal front compared with SPEA, NSGA, NPGA and VEGA.

Deniz et al., (2010) studied maximization of revenue in the dynamic and stochastic knapsack problem where a given capacity needs to be allocated by a given deadline to sequentially arriving agents. Each agent is described by a two-dimensional type that reflects his capacity requirement and his willingness to pay per unit of capacity. Types are private information. The authors first characterize implementable policies. Then they solved the revenue maximization problem for the special case where there is private information about per-unit values, but capacity needs are observable. After that they derived two sets of additional conditions on the joint distribution of values and weights under which the revenue maximizing policy for the case with observable weights is implementable, and thus optimal also for the case with two-dimensional private information. In particular, they investigated the role of concave continuation revenues for implementation. They also constructed a simple policy for which per-unit prices vary with requested weight but not with time, and prove that it is asymptotically revenue maximizing when available capacity/ time to the deadline both go to infinity. This highlights the importance of nonlinear as opposed to dynamic pricing.

Computational grids are distributed systems composed of heterogeneous computing resources which are distributed geographically and administratively. These highly scalable systems are designed to meet the large computational demands of many users from scientific and business orientations. However, there are problems related to the allocation of the computing resources which compose of a grid. Van dester et al., (2008) studied the design of a Pan-Canadian grid. The design exploits the maturing stability of grid deployment toolkits, and introduces novel services for efficiently allocating the grid resources. The changes faced by this grid deployment motivate further exploration in optimizing grid resource allocations. By applying this model to the grid allocation option, it is possible to quantify the relative merits of the various possible scheduling decisions. Using this model, the allocation problem was formulated as a knapsack problem. Formulation in this manner allows for rapid solution times and results in nearly optimal allocations.

Last few years have seen exponential growth in the area of web applications, especially, e-commerce and web-services. One of the most important qualities of service metric for web applications is the response time for the user. Web application normally has a multi-tier architecture and a request might have to traverse through all the tiers before finishing its processing. Request's total response time is the sum of response time at all the tiers. Since the expected response time at any tier depends upon the number of servers allocated to this tier, many different configurations (number of servers allocated to each tier) can give the same quality of service guarantee in terms of total response time. Naturally, one would like to find the configuration which minimizes the total system cost and satisfies the total response time guarantee. Zhang et al., (2004) modeled this problem as integer optimization problem.

The strike-force asset allocation problem consists of grouping strike force assets into packages and assigning these packages to targets and defensive assets in a way that maximizes the strike force potential. Chi-Wei, et al., (2001) modeled this problem as integer programming formulation, and proposed a branch and bound algorithm to solve it.

Sung-Ho (1998) presented techniques for obtaining strategies to allocate rooms to customers belonging to various market segments, considering time dependent demand forecasts and a fixed hotel capacity. This technique explicitly accounts for group and multi-night reservation requests in an efficient and effective manner. This is accomplished by combining an optimal discrete-dynamic model for handling single-night reservation requests, bases on a static integer programming model, developed to handle multi-night reservation requests.

Allocation of resources under uncertainty is a very common problem in many real-life scenarios. Employers have to decide whether or not to hire candidates, not knowing whether future candidates will be stronger or more desirable. Machines need to decide whether to accept jobs without knowledge of the importance or profitability of future jobs. Consulting companies must decide which jobs to take on, not knowing the revenue and resources associated with potential future requests. More recently, online auctions have proved to be a very important resource allocation problem. Advertising auctions in particular provide the main source of monetization for a variety of internet services including search engines, blogs, and social networking sites. Additionally, they are the main source of customer acquisition for a wide array of small online business, of the networked world. In bidding for the right to appear on a web page (such as a search engine), advertisers have to trade off between large numbers of parameters, including keywords and viewer attributes. In this scenario, an advertiser may be able to estimate accurately the bid required to win a particular auction, and benefit either in direct revenue or name recognition to be gained, but may not know about the trade off for future auctions. All of these problems involve an online scenario, where an algorithm has to make decisions on whether to accept an offer, based solely on the required resource investment (or weight) and projected value of the current offer, with the total weight of all selected offer not exceeding a given budget. When the weights are uniform and equal to the weight constraint, the problems above reduces to the famous secretary problem which was first introduced by Dynkin (Dynkin, 1963). Moshe et al., (2008), studied this model as a knapsack problem.

Kleinberg (2009) presented a model for the multiple-choice secretary problem in which k elements need to be selected and the goal is to maximize the combined value (sum) of the selected elements.

Babaioff et al., (2007) studied the matriod secretary problem in which the elements of a weighted matriod arrive in a random order. As each element is observed, the algorithm makes an irrevocable decision to choose it or skip it, with the constraint that the chosen elements must constitute an independent set. The objective is to maximize the combined weight of the chosen elements. The authors proposed an integer programming algorithm for this problem.

Aggarwal and Hartline (2006) designed truthful auctions which are revenue competitive when the auctioneer is constrained to choose agents with private values and publicly known weights that fit into a knapsack. Boryczka (2006) presented a new optimization algorithm based on ant colony metaphor and a new approach for the Multiple Knapsack Problem. The MKP is the problem of assigning a subset of n items to m distinct knapsacks, such that the total profit sum of the selected items is maxi mized, without exceeding the capacity of each of the knap sacks. The problem has several difficulties in adaptation as well as the trail representation of the solutions of

MKP or a dynamically changed heuristic function applied in this approach. Presented results showed the power of the ACO approach for solving this type of subset problems.

The Multiple-Choice Multi-Dimension Knapsack Problem (MMKP) is a variant of the 0-1 knapsack problem, an NP-Hard problem. Due to its high computational complexity, algorithms for exact solution of the MMKPs are not suitable for most real-time decision-making applications, such as quality adaptation and admission control for interactive multimedia systems, or service level agreement (SLA) management in telecommunication networks. Shahadat et al., (2002) presented a heuristic for finding near-optimal solutions of the MMKP, with reduced computational complexity, and is suitable for real-time applications. Based on Toyoda's concept of aggregate resource, the heuristic employs an iterative improvement procedure using savings in aggregate resource and value per unit of extra aggregate resource. Experimental results suggest that this heuristic finds solutions which are close to the optimal (within 6% of the optimal value), and that it out-performs Moser's heuristic for the MMKP in both solution quality and execution time.

Speeding up knapsack problem, one of the NP complete problems, which could be used to design public-key cryptosystems, was presented by Lu and Feng (2004) using quantum algorithm. How to use Grover's quantum searching algorithm to speed up the knapsack problem was presented based on computational complexity theory. Comparisons of quantum searching algorithm with Shor's factoring algorithm were delivered and the factors that affected the performance of quantum algorithms were discussed from group theory point of view. The future of the quantum algorithms was also augmented in the later.

An instance of the geometric knapsack problem occurs in air lift loading where a set of cargo must be chosen to pack in a given fleet of aircraft. Chocolaad (1998) presented a new heuristic to solve this problem in a reasonable amount of time with a higher quality solution then previously reported in literature. The author also reported a new tabu search heuristic to solve geometric knapsack problems. He then employed a novel heuristics in a Master and slave relationship, where the knapsack heuristic selects a set of cargo and the packing heuristic determines if that set is feasible. The search incorporates learning mechanisms that react to cycles and thus is robust over a large set of problem sizes. The new knapsack and packing heuristics compare favorably with the best reported efforts in the literature. Additionally, the author proposed the JAVA language to be an effective language for implementing the heuristics. The search is then used in a real world problem of determining how much cargo can be packed with a given fleet of aircraft.

Knapsack problem has been widely studied in computer science for years. There exist several variants of the problem, with zero-one maximum knapsack in one dimension being the simplest one. Islam 2009) studied several existing approximation algorithms for the minimization version of the problem and propose a scaling based fully polynomial time approximation scheme for the minimum knapsack problem. The author compared the performance of this algorithm with existing algorithms. His experiments show that, the proposed algorithm runs fast and has a good performance ratio in practice. He also conducts extensive experiments on the data provided by

Canadian Pacific Logistics Solutions during the MITACS internship program. The author proposed a scaling based varepsilon-approximation scheme for the multidimensional (d -dimensional) minimum knapsack problem and compares its performance with a generalization of a greedy algorithm for minimum knapsack in d dimensions. His experiments show that the varepsilon-approximation scheme exhibits good performance ratio in practice.

Maya and Dipti (2011) presented a research project on using Genetic Algorithms (GAs) to solve the 0-1 Knapsack Problem (KP). The Knapsack Problem is an example of a combinatorial optimization problem, which seeks to maximize the benefit of objects in a knapsack without exceeding its capacity. The author’s research contains three sections: brief description of the basic idea and elements of the GAs, definition of the Knapsack Problem, and implementation of the 0-1 Knapsack Problem using GAs. The main focus of the research was on the implementation of the algorithm for solving the problem. In the program, he implemented two selection functions, roulette-wheel and group selection. The results from both of them differed depending on whether to use elitism or not. Elitism significantly improved the performance of the roulette-wheel function. Moreover, the author tested the program with different crossover ratios and single and double crossover points but the results given were not that different.

Maya and Dipti (2005) studied several algorithm design paradigms applied to a single problem – the 0/1 Knapsack Problem. The Knapsack problem is a combinatorial optimization problem where one has to maximize the benefit of objects in a knapsack without exceeding its capacity. It is an NP-complete problem and as such an exact solution for a large input is practically impossible to obtain. The main goal of the studies was to present a comparative study of the brute force, dynamic programming, memory functions, branch and bound, greedy, and genetic algorithms. The study discussed the complexity of each algorithm in terms of time and memory requirements, and in terms of required programming efforts. The author's experimental results showed that the most promising approaches are dynamic programming and genetic algorithms. The study examines in more details the specifics and the limitations of these two paradigms.

Yunhong and Victor (2008) modeled a budget constrained keyword bidding in sponsored search auctions as a stochastic multiple-choice knapsack problem (S-MCKP) and proposed a new algorithm to solve SMCKP and the corresponding bidding optimization problem. the authors algorithm selects items online based on a threshold function which can be built/updated using historical data. Their algorithm achieved about 99% performance compared to the offline optimum when applied to a real bidding dataset. With synthetic dataset, its performance ratio against the offline optimum converges to one empirically with increasing number of periods.

Rajeev and Ramesh (1992) presented a new greedy heuristic for the integer knapsack problem. The proposed heuristic selects items in non-increasing order of their maximum possible contribution to the solution value given the available knapsack capacity at each step. The lower bound on the performance ratio for this "total-value" greedy heuristic is shown to dominate the corresponding lower bound for the density-ordered greedy heuristic.

George (1995) studied the average-case behavior of the Zero–One Knapsack problem, as well as an on-line version. The authors allowed the capacity of the knapsack to grow proportionally to the number of items, so that the optimum solution tends to be Θ (n). Under fairly general conditions on the distribution, they obtained a description of the expected value of the optimum offline solution which is accurate up to terms which are o (1). The authors then considered a simple greedy method for the on-line problem, which is called Online Greedy and is allowed to use knowledge of the distribution, and shown that the solution obtained by this algorithm differs from the true optimum by an average of Θ(log *n*); in fact, and can determine the multiplicative constant hidden by the Θ-notation. Thus on average the cost of being forced to give answers on-line is quite small compared to the optimum solution.

The constrained compartmentalized knapsack problem is an extension of the classical integer constrained knapsack problem which can be stated as the following hypothetical situation: a climber must load his/her knapsack with a number of items. For each item a weight, a utility value and an upper bound are given. However, the items are of different classes (food, medicine, utensils, etc.) and they have to be loaded in separate compartments inside the knapsack (each compartment is itself a knapsack to be loaded by items from the same class). The compartments have flexible capacities which are lower and upper bounded. Each compartment has a fixed cost to be included inside the knapsack that depends on the class of items chosen to load it and, in addition, each new compartment introduces a fixed loss of capacity of the original knapsack. The constrained compartmentalized knapsack problem consists of determining suitable capacities of each compartment and how these compartments should be loaded, such that the total items inside all compartments does not exceed the upper bound given. The objective is to maximize the total utility value minus the cost of the compartments. This kind of problem arises in practice, such as in the cutting of steel or paper reels. Doprado and Nereu (2007) modeled the problem as an integer non-linear optimization problem for which some heuristic methods are designed. Finally, computational experiments were given to analyze the methods.

The Multiple Knapsack Problem (MKP) is a NP-hard combinatorial optimization problem in many real-word applications. An algorithm with the behaviors of preying, following and swarming of artificial fish for searching optimal solution was proposed by Ma Xuan (2009). With regard to the problem that infeasible solutions are largely produced in the process of initializing individuals and implementing the behaviors of artificial fish due to the multiple constraints, which undermines the algorithm performance, an adjusting operator based on heuristic rule was designed to ensure all the individuals in the feasible solution areas. Computational results show that the algorithm can quickly find optimal solution. The proposed algorithm can also be applied to other constrained combinatorial optimization problems

CHAPTER THREE

METHODOLOGY

3.0 INTRODUCTION

This chapter provides an explanation of the branch-and-bound algorithm for solving our problem. In order to understand the value of branch-and-bound for knapsack problems, it is necessary to have a good understanding of the general overview of the branch-and-bound for general integer programming.

Formally, an integer programming problem is formulated as

$$\text{Maximize } c^T x$$

$$\text{Subject to: } Ax \leq b$$

$$x \geq 0 \text{ and integer.}$$

Where; $A \in R^n$, $x \in Z^n$, $b \in R^{1xm}$.

The only difference between this form and the common form of linear programming problem is the integrality restriction. The problem with integer programming problems are the time and resources needed to solve such problems. Integer programming problems are NP-Complete Karp (1972), meaning that all known algorithms require exponential time to solve. Although, many small integer programming problems can be solved quickly, more complex integer programming problems can take extraordinary amount of time to solve and frequently use the entire memory of a computer without obtaining an optimal or even a feasible solution.

Solving integer programming problem is difficult but beneficial, considerable effort has been made to develop methods that can decrease solution times for integer programming problems. The two most common algorithms use a linear relaxation. Linear relaxation is the solution to the integer programming problem without the integer constraint. Linear programming problems can be solved faster than an integer programming, so the integer programming is reformulated as a linear programming problem. The optimal value in the linear programming problem (called the linear relaxation point) is found using the methods available to solve linear programming problem. Once the linear relaxation point is found, either branch and bound or cutting planes can be used to find the solution to the integer programming problem.

Branch and bound uses the linear relaxation as starting point to search for the optimal integer solution. Every linear relaxation solution that is found during the branch and bound process is given a corresponding node on the branching tree. Once a node's relaxations point has been found, any variable with a fractional value may be chosen as the branching variable. Two child nodes with corresponding branches are created from this parent node. One branch requires the branching variable to be greater than or equal to its relaxation value rounded up to the nearest integer. The other branch requires the branching variable to be less than or equal to the relaxation solution rounded down to the nearest integer. Using these values, two new relaxation points are found and two more nodes are created in the tree. This process is repeated until all nodes have been fathomed.

A fathomed node is finished, and no more nodes or branches are created below any fathomed nodes. Fathoming a node in a branch and bound algorithm occurs under three circumstances. If a node is found that: (i) cannot produce a feasible solution to the linear relaxation, then that node is fathomed. (ii) returns an integer solution, then that node is fathomed. Although other feasible solutions may exist below that node, none will be better than that node's solution. (iii) has a linear relaxation solution with a value lower than the value of a previously discovered integer solution, then that node is fathomed.

An alternative to the branch and bound method is to use cutting planes to reduce the linear relaxation space. The basic idea of the cutting plane method is to cut off parts of the feasible region of the corresponding linear program, so that the optimal integer solution becomes an extreme point and can be found by the simplex algorithm. This method attempts to find a hyper plane that intersects the solution space below the current linear relaxation point without eliminating any integer solutions. Once such a hyper plane has been put in place, a new linear relaxation point is found, and branch and bound can be implemented or additional cutting planes can be added until an integer solution is returned as the solution to the linear programming problem.

3.1 BRANCH-AND-BOUND ALGORITHMS FOR KNAPSACKS

The first branch-and-bound approach to the exact solution of KP was presented by Kolesar (1967). His algorithm consists of a highest-first binary branching scheme with:

(a) at each mode, selects the not-yet-fixed item j having the maximum profit per unit weight and generates two descendent nodes by fixing x_j, respectively, to 1 and 0;

(b) continues the search from the feasible node for which the value of upper bound U_1 is a maximum

The large computer memory and time requirements of the Kolesar algorithm were greatly reduced by the Greenberg and Hegerich (1970) approach, differing in two main respects:

(a) at each mode, the continuous relaxation of the induced sub problem is solved and the corresponding critical items ŝ is selected to generate the two descendent nodes (by imposing $X\hat{s} = 0$ on ($X\hat{s} = 1$);

(b) the search continues from the node associated with the exclusion of item ŝ (condition $X\hat{s} = 0$).

When the continuous relaxation has an all-integer solution, the search is resumed from the last node generated by imposing $X\hat{s} = 1$, i.e. the algorithm is of depth – first type.

Horowitz and Sahni (1997) (and independently, Ahrens and Finke (1975)) derived from the previous scheme on depth-first algorithm in which;

(a) selection of the branching variable X_j is the same as in Kolesar;

(b) the search continues from the node associated with the insertion of item j (condition $X_j = 1$), i.e. following a greedy strategy

Other algorithms have been derived from the Greenberg – Hegerich approach (Barr and Ross (1975), Lauriere (1978)] and from different techniques (Lageireg and Lenstra (1972), Guignard and Spielberg (1972), Fayard and Plateau (1975), Veliev and Mamedov (1981). The Horowitz – Sahni one is, however, the most effective, structured and easy to implement and has constituted the basis for several improvements, including that of Martello – Toth algorithm (Martello and Toth, 1977), which is generally considered highly effective. Hence, we will also restrict our research work to that of the Horowitz and Sahni algorithm ad Martello and Toth algorithm.

3.2 THE HOROWITZ – SAHNI ALGORITHM

Assume that the items are sorted. A forward move consists of inserting the largest possible set of new consecutive items into the current solution. A backtracking move consists of removing the last inserted item from the current solution. Whenever a forward move is exhausted, the upper bound U_1 corresponding to the current solution is computed and compared with the best solution so far, in order to check whether further forward moves could lead to a better one; if so, a new forward move is performed, otherwise a backtracking follows. When the last item has been considered, the current solution is complete and possible updating of the best solution so far occurs. The algorithm stops when no further backtracking can be performed. In the following description of the algorithm we use the notations.

$\hat{x}_j$ = current solution;

$\hat{Z}$ = current solution value $(= \sum_{j=1}^{n} p_j \hat{x}_j)$

$\hat{C}$ = current residual capacity $(= C - \sum_{j=1}^{n} w_j \hat{x}_j)$

x_j = best solution so far;

Z = value of the best solution so far $(= \sum_{j=1}^{n} p_j \hat{x}_j)$

THE ALGORITHM

Input: n, C, (P_j), (w_j);

Output: Z; (x_j);

Begin

1. [Initialize]

   Z: = 0;

   $\hat{Z}$: = 0;

   $\hat{C}$: = C;

   p_{n+1}: = 0;

   w_{n+1}:= + ∞;

   j: = 1

2. [Compute upper bound U_1]

   find $r = \min\{i: \sum_{k=j}^{i} w_k > \hat{C}\}$;

   $U: = \sum_{k=j}^{r-1} p_k + \left[\left(\hat{C} - \sum_{k=j}^{r-1} w_k\right)\frac{p_r}{w_r}\right]$;

   If $Z \geq \hat{Z} + U$ then go to 5;

3. [Perform a forward step]

   while $w_j \leq \hat{C}$ do

   begin

   $\hat{C} := \hat{C} - w_j$;

   $\hat{Z} := \hat{Z} + P_j$

   $\hat{x_j} := 1$

   $j := j + 2$

   end

   if $j \leq n$ then

   begin

   $\hat{x_j} = 0$

   $j = j + 1$

   end

   if $j < n$ then go to 2;

if j = n then go to 3;

4. [Update the best solution so far]

    if $\hat{Z} > z$ then

    begin

    Z: = $\hat{Z}$;

    for K: = 1 to n do $x_k := \widehat{x_k}$

    end

j: = n;

if $\widehat{x_n} = 1$ then

begin

$\hat{C} := \hat{C} + w_n$;

$\hat{Z} := \hat{Z} - p_n$;

$\widehat{x_n} := 0$

end

5. [Backtracking]

find i= max {k < j: $\widehat{x_k} = 1$};

if no such i then return;

$\hat{c} := \hat{c} + w_i$;

$\hat{Z} := \hat{Z} - p_i$;

$\widehat{x_i} := 0$;

$j := i + 1$;

go to 2

end

THE MARTELLOW – TOTH ALGORITHM

Their method differs from that of Horowitz and Sahni (1974) in the following main respect (we use the notations introduced in the previous method).

(a) Upper bound U_2 is used instead of U_1

(b) The forward move associated with the selection of the j^{th} item is split into two phases: building of a new current solution and saving of the current solution. In the first phase, the largest set N_j of consecutive items which can be inserted into the current solution starting from the j^{th} is defined, and the upper bound corresponding to the insertion of the jth item is computed. If this bound is less than or equal to the value of the best solution so far, a backtracking move immediately follows. If it is greater, the second phase, that is, insertion of the items of set N_j into the current solution is performed only if the value of such new solution does not represent the maximum which can be obtained by inserting the jth item. Otherwise, the best solution so far is changed, but the current solution is not updated, so that unnecessary backtrackings on the items in N_j are avoided.

(c) A particular forward procedure, based on dominance criteria, is performed whenever, before a backtracking move on the i^{th} item, the residual capacity $\hat{C}$ does not allow insertion into the current solution of any item following the ith. The procedure is based on the following consideration;

The current solution could be improved only if the i^{th} item is replaced by an item having greater profit and a weight small enough to allow its insertion, or by at least two items having global weight not greater than $W_i + \hat{C}$. By this

approach it is generally possible to eliminate most of the unnecessary nodes generated at the lowest levels of the decision – tree.

(d) The upper bounds associated with the nodes of the decision-tree are computed through a parametric technique based on the storing of information related to the current solution. Supposing the current solution has been built by inserting all the items from the j^{th} to the r^{th}: then, when performing a backtracking on one of these items (say the i^{th}, $j \leq i < r$), if no insertion occurred for the items preceding the j^{th}, it is possible to insert at least items $i + 1, \ldots r$ into the new current solution. To this end, we store in $\bar{r}_i$; $\bar{p}_i$ and $\bar{w}_i$ the quantities r+1, $\sum_{k=i}^{r} P_k$ and $\sum_{k=i}^{r} w_k$, respectively, for $i = j, \ldots, r$, and in $\bar{r}$ the value $r - 1$ (used for subsequent updating). Below is the detailed description of the algorithm.

THE ALGORITHM

Input: $n, C, (P_j), (w_j)$;

Output: $Z; (x_j)$;

begin

1. [Initialize]

   $Z: = 0;$

   $\hat{Z} : = 0;$

   $\hat{C}: = C;$

   $P_{n+1}: = 0;$

   $w_{n+1}: = + \infty;$

   for $k: = 1$ to n do $\widehat{x_k} := 0;$

   compute the upper bound $U = U_2$ in the optimal solution value;

   $\bar{w}_1 := 0;$

   $\bar{p}_1 := 0;$

   $\bar{r}_1 := 0;$

   $\bar{r} := n;$

   for $k: = n$ to 1 step $- 1$ do compute $m_k = \min \{w_i: i > k\}$;

j: = 1;

2. [build a new current solution]

while $w_j > \hat{C}$ do

if $Z \geq \widehat{Z} + [\widehat{C}\, P_{j+1/}\, w_{j+1}]$ then go to 5 else j:=j+1;

find r = min $\{i : \bar{w}_j + \sum_{k=\bar{r}_j}^{i} w_k > \hat{C}\}$;

$P^1 := \bar{p}_j + \sum_{k=\bar{r}_j}^{r-1} p_k$;

$w^1 := \bar{w}_j + \sum_{k=\bar{r}_j}^{r-1} w_k$;

If $r \leq n$ then $U := \max\left([\hat{c} - w^1)\frac{p_{r+1}}{w_{r+1}}], [Pr - (p_r - \left(w_r - (\hat{c} - w^1)\frac{p_{r-1}}{w_{r-1}}\right]\right)$,

else U: = 0;

if $Z \geq \widehat{Z} + P^1 + U$ then go to 5;

if U = 0, then go to 4;

3. [save the current solution]

$\hat{C} := \hat{C} - w^1$;

$Z \geq \widehat{Z} + P^1$

for k: = j to r – 1 do $\widehat{x_k} := 1$

$\bar{w}_j := w^1$

$\bar{p}_j := P^1$;

$\bar{r}_j := r$;

for k: = j + 1 to r – 1 do

begin

$\bar{w}_k := \bar{w}_{k-1} - w_{k-1}$;

$\bar{p}_k := \bar{p}_{k-1} - p_{k-1}$

$\bar{r}_k := r$

end

for k: = r to $\bar{r}$ do

begin

$\bar{w}_k := 0;$

$\bar{p}_k := 0$

$\bar{r}_k := k$

end

$\bar{r} := r - 1;$

j: = r + 1;

if $\hat{C} \geq m_{j-1}$ then go to 2;

if Z $\geq \hat{Z} +$ then go to 5;

$P^1 := 0$

4. [Update the best solution so far]

   $Z \geq \hat{Z} + P^1$;

   for k: = 1 to j – 1 do $x_k := \widehat{x_k}$

   for k: = j to r - 1 do $x_k := 1$

   for k: = r to n do $x_k := 0$;

   if $Z = U$ then return;

5. [Backtracking]

   find i = max {k < j: $\widehat{x_k}$=1};

   if no such i then return;

   $\hat{C}$: = $\hat{C}$ + w_j;

   $\hat{Z} = \hat{Z} - p_i$;

   $\widehat{x_i}$:=0

   j: = i + 1;

   if $\hat{C} - w_i \geq m_i$ then go to 2;

   j: = i;

   h: = i;

6. [try to replace item i with item h]

   h: = h + 1

if $Z \geq \hat{Z} + [\hat{C}\frac{p_h}{w_h}]$ then go to 5;

if $w_h = w_i$ then go to 6

if $w_h > w_i$ then

begin

if $w_h > \hat{C}$ or $Z \geq \hat{Z} + p_h$ then go to 6;

$Z := \hat{Z} + p_h$;

for $k := 1$ to n do $x_k := \widehat{x_k}$;

$x_h = 1$;

if $Z = U$ then return;

$i := h$;

go to 6

end

else

begin

if $\hat{C} - w_h < m_h$ then go to 6;

$\hat{C} := \hat{C} - w_h$;

$\hat{Z} := \hat{Z} + p_h$;

$\widehat{x_k} := 1$;

$j := h + 1$;

$\bar{w}_h := w_h$;

$\bar{p}_h := p_h$;

$\bar{r}_h := h + 1$;

for $k := h + 1$ to $\bar{r}$ do

begin

$\bar{w}_k := 0$;

$\bar{p}_k := 0$;

$\bar{r}_k := 0$;

end

$\bar{r} := h$;

go to 2

end

end

For the purpose of our research, we shall employ the branch-and-bound algorithm of The Horowitz – Sahni in solving our model.

CHAPTER FOUR

DATA COLLECTION AND ANALYSIS

4.0 INTRODUCTION

In this chapter, we shall consider a computational study of branch-and-bound algorithm applied to knapsack instance. Consideration is given to the 0-1 knapsack problem where $n \subset N$ such that $\sum_{i=1}^{n} w_i \leq b$. Each item has a profit or cost c_i and a weight w_i. The problem is to select a subset of the items whose total weight does not exceed the knapsack capacity b, and whose total profit is a maximum.

We assume without loss of generality that all input data are positive integers. Introducing the binary decision variable x_i with

$$x_i = \begin{cases} 1 \text{ if item i is selected} \\ 0 \text{ otherwise} \end{cases}$$

we obtain the integer linear programming model:

$$\text{Maximize} \quad Z = \sum_{i=1}^{n} c_i x_i$$

$$\text{Subject to} \quad \sum_{i=1}^{n} w_i x_i \leq b$$

$$x_i \in \{0, 1\}^N,\ i \in Z^+.$$

We may assume that $w_i < b$ for $i \in Z^+$ to ensure that each item considered fits into the knapsack, and that $\sum_{i=1}^{n} c_i > b$ to avoid trivial solutions.

The choice of a knapsack model is a real life problem in municipal assembly waste management problem. The municipality aim at optimizing the land capacity allocated for waste disposal in the metropolis so that the metropolis gets the best usage of land at a minimal cost. The general practice is that the current establishments under consideration do not have a well structured plan on how to allocate land for waste disposal and management. Landfill sites are allocated by the discretion of people or departments in charge. These methods are basically inefficient as landfill sites available are not optimally utilized.

4.1 DATA COLLECTION AND ANALYSIS

LEKMA has a budget of fifty thousand Ghana Cedis (GH₵50,000.00) for the development of new garbage disposal areas. Seven landfill sites are available, whose projected capacities and development costs are given in Table 4.1.

Table 4.1: List of the capacity (tons/week) and the cost (1000/unit) for each site

SITE	1	2	3	4	5	6	7
CAPACITY	70	20	39	37	7	5	10
COST	31	10	20	19	4	3	6

The problem here is to select landfill site in such a way that the optimal capacity would be achieved without over shooting the amount allocated for the land development.

Comparing this to the knapsack model, the holding capacity of the bag is the resource limit, given here as the budget limit. The items to be considered are the different landfill sites that can be developed, the weight of any item is the cost of developing the landfill site, and the value of the item is the capacity of the landfill site.

The problem can be modelled as:

$$\text{Maximize} \quad C = \sum_{i=1}^{n} c_i s_i$$

$$\text{Subject to} \quad \sum_{i=1}^{n} w_i s_i \leq W$$

$$s_i \in \{0, 1\}^N, \qquad i = 1,\dots, n.$$

Where;

C = Total capacity

c_i = Capacity of each site

s_i = Number of sites developed

w_i = Cost of developing a site

W = Total amount available for development (resource limit)

Thus,

$$\text{Maximize } C = 70s_1 + 20s_2 + 39s_3 + 37s_4 + 7s_5 + 5s_6 + 10s_7$$

$$\text{Subject to: } 31s_1 + 10s_2 + 20s_3 + 19s_4 + 4s_5 + 3s_6 + 6s_7 \leq 50.$$

To carry out the computation of the proposed model, we apply the branch-and-bound algorithm by Horowitz – Sahni. As can be seen from Table 4.1, the items are seven, (thus, n = 7) consisting of Sites 1 to 7.

The weights of each item are $w_1 = 31$, $w_2 = 10$, $w_3 = 20$, $w_4 = 19$, $w_5 = 4$, $w_6 = 3$, and $w_7 = 6$. The values of each item are $v_1 = 70$, $v_2 = 20$, $v_3 = 39$, $v_4 = 37$, $v_5 = 7$, $v_6 = 5$, and $v_7 = 10$. The maximum available fund W = 50.

Let $x_j \in$ feasible solutions and Z be the value of the feasible solution.

A step-by-step implementation of the branch-and-bound algorithm of The Horowitz – Sahni with the above model gives the following computational iterative values for the various optimal solutions as shown in Table 4.2.

Table 4.2: Feasible Solutions for the various iterative stages

Iteration	Feasible solution(xj)	Value of the feasible solution(z)	Cost
1	(1,0,0,0,0,0,0)	70	31
2	(1,1,0,0,0,0,0)	90	41
3	(1,1,0,0,0,0,0)	90	41
4	(1,1,0,0,0,0,0)	90	41
5	(1,1,0,0,1,0,0)	97	45
6	(1,1,0,0,1,1,0)	102	48
7	(1,1,0,0,1,1,0)	102	48
8	(1,1,0,0,1,0,0)	97	45
9	(1,1,0,0,1,0,0)	97	45
10	(1,1,0,0,0,0,0)	90	41
11	(1,1,0,0,0,1,0)	95	44
12	(1,1,0,0,0,1,1)	105	50
13	(1,1,0,0,0,0,0)	90	41
14	(1,0,0,0,0,0,0)	70	31
15	(1,0,0,0,0,0,0)	70	31
16	(1,0,0,1,0,0,0)	Not Feasible	51
17	(1,0,0,1,0,0,0)	Not Feasible	51
18	(1,0,0,1,0,0,0)	Not Feasible	51
19	(1,0,0,1,0,0,0)	Not Feasible	51
20	(1,0,0,0,0,0,0)	70	31

RESULTS

From the table above, at the end of the first iteration, the algorithm reported Capacity of 70 at a cost of 31 with {1, 0, 0, 0, 0, 0, 0} site selected. Since Wmax < W, the algorithm will execute the next iteration.

At the end of this iterative stage, capacity is 90, and cost is 41 with {1, 1, 0, 0, 0, 0, 0} site selected. Comparing this solution with the existing solution, this solution is better than the existing solution, hence the algorithm will report C = 90, W_{max} = 41 with {1, 1, 0, 0, 0, 0, 0} site selected as current solution. Since W_{max} < W, the algorithm will execute the next iteration.

At the end of this iterative stage, C_l = 97, and Wcal =45 with {1, 1, 0, 0, 1, 0, 0} site selected. This solution is better than the existing solution, hence the algorithm will report C = 97, W_{max} = 45 with {0, 0, 2, 3} {1, 1, 0, 0, 1, 0, 0} site selected as current best solution. Since W_{max} < W, the algorithm will execute the next iteration.

At the end of this iterative stage, C = 102, and Wcal =48 with {1, 1, 0, 0, 1, 1, 0} site selected. This solution is better than the current best solution. The algorithm will report C = 102, W_{max} = 48 with {1, 1, 0, 0, 1, 1, 0} site selected as current best solution. Since W_{max} < W, the algorithm will execute the next iteration.

At the end of this iterative stage, C = 97, and Wcal =45 with {1, 1, 0, 0, 1, 0, 0} site selected. This solution is not better than the current best solution. The current solution is the maintained as current best solution. Since W_{max} < W, the algorithm will execute the next iteration.

At the end of the twelve iterative stage, C = 105, and Wcal = 50 with {1, 1, 0, 0, 0, 1, 1} site selected. This solution is better than the current best solution; hence the algorithm will report C = 105, W_{max} = 50 with {1, 1, 0, 0, 1, 1, 0} site selected as current best solution. Since $W_{max} < W$, the algorithm will execute the next iteration.

Beyond this iterative stage, the solutions are non-improving one; hence the algorithm will maintain the existing solution.

Hence, the algorithm will report a final solution of (1, 1, 0, 0, 0, 1, and 1) at a cost of (GH₵50,000) to obtain an optimal site development of one hundred and five thousand (105,000) tones per week.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.0 INTRODUCTION

Solid waste is a system of Engineering, involving substantial engineering content, that is particularly set for actions which will best accomplish the overall objectives of the decision makers, within the constraints of law, morality, economics, resources, political and social pressure and which will govern the physical life and other natural sciences Solid waste management is defined as the discipline associated with the control of generation, storage, collection, transfer and transport, processing and disposal of solid waste in a manner that is in accord with the best principles of public health, economic, engineering, conservation, aesthetics and other environment consideration that is also responsive to public attitudes (Tchobanoglous et al., 1993).

In this chapter, we shall present the conclusions and the recommendation of the study.

5.1 CONCLUSIONS

Waste management in the three urban cities of Ghana, is becoming an increasing problem daily and a complex task. The environmental protection agency (EPA) is being considered as the base scenario for development of this waste management model. The State agencies have a major waste management issue and have been noticeable over the last decade. The waste management which in the past times has been addressed with various methods by different administrations in tackling the waste problem yielded nothing.

However, the waste management agencies are charged with the following responsibilities:

1. Removal, collection and disposal of domestic commercial and industrial generated waste.

2. Cleaning and maintenance of Public drainage facilities

3. Cleaning of streets.

4. Removal and disposal of abandoned Scrapped vehicles

In the operational period of the Waste Management Agencies, its activities were initially limited to few urban towns and just recently, due to population growth and progressive urbanization, the service areas are expanded to more Areas.

At all times, human activities have generated waste in various forms in gaseous (abattoirs), liquid and solid. These wastes have often been discarded because they were all considered as negative value goods. The more prevalent method of disposal of these wastes have been to first collect them from their source and then burn them in a landfill site or throw them in the surrounding deep erosion gullies in the state.

However, the steady increase of landfill site, deposition in the gullies, and waste generally has caused a lot of havoc to the potable water being extracted from downstream and ground water. Currently, the emergence and development of new public environmental consciousness have created a strong negative attitude toward landfill and deposition into gullies.

The national and state regulation to protect the environment have increased the cost of developing new landfill and deposition in the gullies, also siting has become increasingly difficult because the public oppose having such facilities nearby. Solid waste management has become a major concern in industrialized developing countries, like Ghana. The ideal way to improve the situation would be, to reduce the generation of waste. But contrarily, this goes against the people's will to preserve their life style and thus to consume more food. Consequently, the society is searching for improved method of waste management and ways to reduce the amount of waste material which can be reused or transformed into useful material (e.g plastic and some cast iron from sites – mechanics) if managed properly.

Many waste management options have been proposed previously by some committees set up by Government but has always been poorly implemented which resulted in failure, unproductiveness and corruption. The most, the implementing Agency, cannot foresee or properly forecast the out-come of such programme, and also properly and well planned scheduling processes were not included in the management system and corruption which has eaten deeply in the system.

Different waste management options must be combined intelligently in a way as to reduce the environmental and social impact at an acceptable cost for the masses in the state. This combined option is called integrated solid waste management and system approach should be used for the assessment of the competing option.

This thesis seeks to solve a real-life problem of a town in Greater Accra Region using the branch-and-bound algorithm of The Horowitz – Sahni. It was observed that the solution that gave optimum achievable value was (1, 1, 0, 0, 0, 1, and 1). This means that the Metropolitan Assembly should spend a total cost of fifty thousand Ghana Cedis (GH₵50,000) to obtain an optimal site development of one hundred and five thousand (105,000) tones per week, consisting of selecting Site 1, Site 2, Site 6, and Site 7.

5.2 RECOMMENDATIONS

The use of a well structured procedure in computation gives a systematic and transparent solution as compared with an arbitrary method. Using the more scientific Knapsack problem model for the landfill site development of LEKMA refuse disposal management gives a better result.

We described the landfill site development problem of LEKMA as a 0-1 knapsack programming problem. We applied the branch-and-bound algorithm of The Horowitz – Sahni to solve the landfill site development problem.

Management may benefit from the proposed approach for landfill site development for refuse disposal to guarantee optimal refuse disposal capacity in tones per week. We therefore recommend that our model should be adopted by LEKMA for refuse disposal management and planning.

Our research focused on the use of the Knapsack problem for landfill site development given a limited available fund for LEKMA in Accra. It can however be applied to any situation that can be modeled as a 0-1 knapsack problem.

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