A METAHEURISTIC APPROACH TO THE ASSIGNMENT, SCHEDULING AND ROUTING OF CARE WORKERS IN THE HOME AND COMMUNITY-BASED SCENARIO IN SOUTH AFRICA

by

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Executive Summary

The HIV/AIDS pandemic has reached an unprecedented scale in South Africa. The burden this has placed on the country's already restricted health care resources has lead to a greater emphasis on the value of home-based care. Home-based care is a service model appropriate to a number of contexts from palliative and elderly care to support of orphaned and vulnerable children.

Home-based care not only relieves the burden on hospitals and community clinics, but is an affordable alternative to institutional care. In order to recognise home-based care as an equal, rather than an inferior alternative to institutional care, good service delivery is imperative.

The numerous restrictions encapsulated by the home-based care problem, such as adhering to time windows and efficient skill and need matching contributes to the complexity of the problem. The wide geographical dispersion of households in South Africa exacerbates this problem. As far as possible the assignment of beneficiaries to care workers should be done in such a way that the travelling time of the care workers will be minimised.

Through an extensive literature study, the home-based care problem has been identified as a combination of the Nurse Rostering Problem and the Vehicle Routing Problem with Time Windows. Both of these are optimisation problems that determines the optimal assignment of beneficiaries to care workers and minimise the time spent travelling, while adhering to constraints.

A hybrid approach is proposed to address this problem. A conceptual solution algorithm that combines the Variable Neighbourhood Search and Tabu Search metaheuristics is considered in this document. The algorithm will be enhanced by adding a heuristic ordering algorithm which will construct an initial solution.

The complete hybrid algorithm was evaluated by applying it to test data from home care visits to orphaned and vulnerable children in Hearbeat's Nellmapius Community Project.

The solution algorithm provided sufficient results with care worker schedules not exceeding four hours a day and an equal workload between care workers.

The results indicate that the algorithm does have the ability to improve service delivery of home-based care by improved assignment, routing and scheduling of care workers. However, to ensure feasibility of this algorithm, careful implementation and monitoring is imperative.

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List of Acronyms

AIDS	Acquired Immune Deficiency Syndrome
AMP	Adaptive Memory Procedure
CP	Constraint Programming
CVI	Child Vulnerability Index
GA	Genetic Algorithm
GUI	Graphical User Interface
HIV	Human Immunodeficiency Virus
IP	Integer Programming
ISP	Iterated Swap Procedure
LIP	Linear Integer Programming
LP	Linear Programming
LS	Local Search
MDVRP	Multi-depot Vehicle Routing Problem
MDVRPTW	Multi-depot Vehicle Routing Problem with Time Windows
MIP	Mixed Integer Programming
MP	Mathematical Programming
MTSP	Multiple Travelling Salesman Problem

NP	Non-Deterministic Polynomial-Time
NRP	Nurse Rostering Problem
OVC	Orphaned and Vulnerable Children
OVRP	Open Vehicle Routing Problem
PSO	Particle Swarm Optimisation
PVRP	Periodic Vehicle Routing Problem
SA	Simulated Annealing
TS	Tabu Search
TSP	Travelling Salesman Problem
VNS	Variable Neighbourhood Search
VRP	Vehicle Routing Problem
VRPHE	Vehicle Routing Problem with Hetergeneous Fleet
VRPTW	Vehicle Routing Problem with Time Windows

Chapter 1

Introduction and Background

1.1 Rationale for home-based care in South Africa

With a total of 5.7 million people living with HIV, South Africa is home to the largest population of HIV/AIDS affected people in the world (UNAIDS, 2009). The HIV/AIDS pandemic, other communicable diseases such as tuberculosis, infectious diseases, non-communicable diseases and various other health problems have reached an unprecedented scale, having an impact on all South Africans (Department Of Health, 2001).

South Africa is a country with limited health care resources, an increasing demand for health care and an unequal distribution of income. As a result it is the impoverished communities which are most affected by HIV/AIDS due to their restricted access to health care (Department Of Health, 2001).

The effects of AIDS are not only reflected by the country's health statistics, but also by the number of orphans in the country. Nearly 3.8 million children, 21% of South Africa's 18 million children, have lost one or both their parents. This number is expected to increase to 5.7 million over the next five years due to AIDS (Pendlebury et al., 2009).

According to Peu et al. (2008), the value of home and community-based care [1] services in South Africa became apparent as a result of the rapid growth of the HIV/AIDS pandemic.

Home-based care can be aimed at any of the following:

- Assisting frail, elderly people with everyday activities.
- Assisting people during convalescence .
- Providing support to orphans or other healthy people in need.
- Supporting persons living with HIV/AIDS or any other debilitating disease.
- Providing palliative care for terminally ill patients.

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[1] For the remainder of the document, the term home and community-based care will only be referred to as home-based care

- Supporting people with mental illnesses and other mental and physical disabilities.

Home-based care not only relieves the burden on hospitals and community clinics, but is also an affordable alternative to institutional care. Home-based care is also addressing the problem of the increase in children left orphaned and vulnerable due to HIV, by assigning some of the care responsibilities to trained care workers in the community.

1.2 Examination of the problem

Home-based care is an increasing trend in the South African health sector. To justify home-based care as an alternative to institutional care, good service delivery is of the utmost importance. Restrictions that hamper good service delivery such as unreliable public transport, legal occupational restrictions and care worker incompetence should be addressed. An overview of typical constraints relevant to home-based care can be viewed in Figure 1.1.

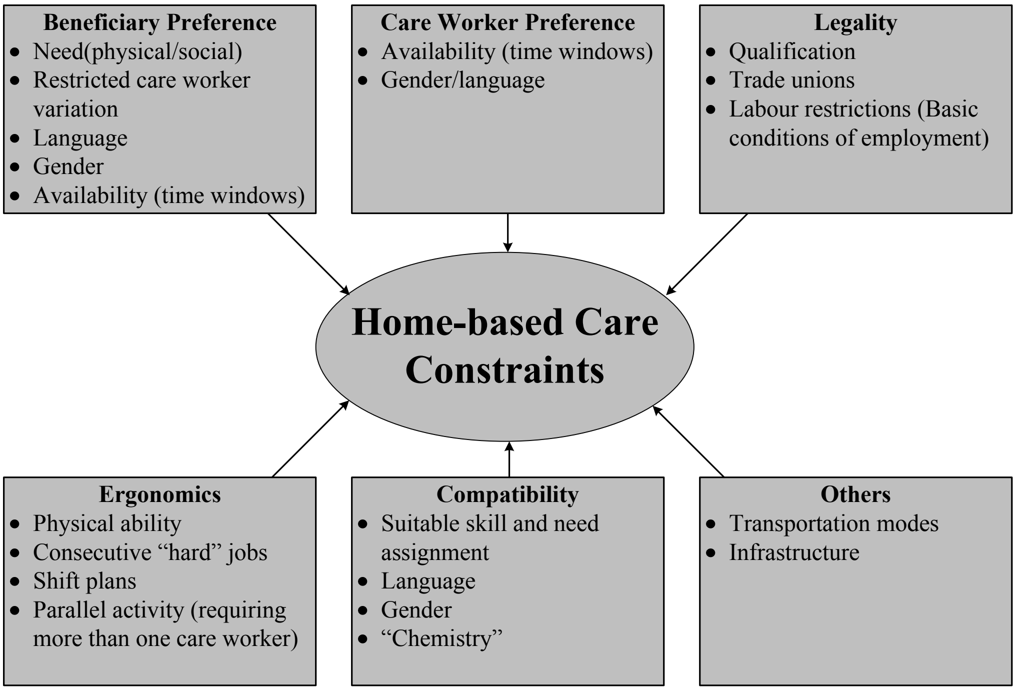

Figure 1.1: Overview of constraints relevant to the home-based care problem

In the typical home-based care scenario, the needs of the beneficiary are determined by an assessor. The care duties are then assigned to care workers, according to the care worker's skill, ability, knowledge and expertise (Peu et al., 2008). When planning home visits, it should also be taken into consideration that the beneficiaries have preferential time windows in which they would like to be visited, and as far as possible the beneficiaries should be visited by the same care worker. The rationale behind this is to provide a sense of safety and continuity for the beneficiaries. The beneficiaries should not be exposed to a new face with each visit, enabling them to build a trusting relationship with the care worker (Eveborn et al., 2006; Peu et al., 2008). It becomes clear that even just assigning care workers to beneficiaries according to time window preferences requires a lot of coordination to ensure good service delivery.

The service delivery of care workers is further constrained by transport availability and travel time. Since most care workers make use of public transport or travel by foot, the distance to be travelled in a day is often too far and some visits cannot be made. It would be ideal if the daily travel time of each care worker can be minimised, while at the same time dividing the care duties equally between the workers and meeting the other home care requirements.

After analysing this problem the question is:

> *"How can the assignment, routing and scheduling of care workers be improved in order to advance service delivery in the Home Based Care sector in South Africa?"*

1.3 Heartbeat—A real world case

Heartbeat is a non-profit and public benefit organisation, founded as a response to the orphan challenges in South Africa. Heartbeat endeavours to empower orphaned and vulnerable children (OVC) to reach their full potential by addressing the needs of the children through basic service provision. Key programmes provided in Heartbeat communities include care and academic support at after school centres, food provision and community food garden development, educational and recreational extracurricular activities and home care.

Of the 3.1 million orphaned children a few are fortunate enough to be cared for by a grandparent or other relative. Numerous children are, however, forced to take on the role of caregiver and provider. These children, who live without adequate care and protection, are more susceptible to exploitation and child labour.

Through regular home visits to OVC families, Heartbeat attempts to provide a sense of stability, protection and care by assuming the role of caregiver or parent. Trained home care workers provide counselling, homework and chore assistance and mediation of disputes, to name a few. The frequency of the home visits vary depending on the type of households with child-headed household visited most frequently and relative-headed households visited the least.

Limited staff capacity and an overload of destitute OVC are two major challenges faced by Heartbeat. This problem is amplified by the geographical spread of households, resulting in long travelling distances required to reach OVC. Consequently, the quality of the home care services suffers greatly.

Minimising the travel time of each care worker while simultaneously matching beneficiary needs to care worker skills will drastically improve the quality of home-care services. Not only will this improved assignment, scheduling and routing of home care workers reduce the hassles a home-care worker experience, but it will also enhance service delivery.

Heartbeat's Nellmapius community project, one of 14 community projects, will be used as a research subject during the development of a home-based care assignment, scheduling and routing algorithm. Nellmapius is a semi-urban settlement east of Pretoria with an estimated population size of 65 000. Despite the availability of basic amenities, government services such as health care are limited. Unemployment, crime and drug abuse are prevalent in this area. Health statistics also indicates a high HIV prevalence which is reflected in the large number of OVC in Nellmapius. Nellmapius is a typical example of a community with a great need for home-based care, but very little resources. Therefore, it is an ideal setting for the development of such an algorithm.

1.4 Research Design and Methodology

The main focus of this project will be the development of a generic computerised solution algorithm. This algorithm will assist in solving the home-based care problem by developing daily assignment, routing and scheduling solutions. The solution will be based on the following user inputs:

- Care worker profile: Skill, availability time window (working hours), geographical location and transportation mode.

- Beneficiary profile: Requirements and needs, availability time windows, geographical location and care worker preference.

The development of a *generic* algorithm is paramount in order to provide flexibility for algorithm application. This will ensure that the algorithm can be applied to all the different variations of home based care in South Africa.

The first step towards the development of this algorithm is to review cases similar to the home-based care problem. This will aid in the identification of solution approaches for this type of problem. Comparing these solution approaches, the most applicable algorithms should be adapted and integrated and then refined to fit the home-based care problem. The main objective of this new algorithm will be to minimise the travel time of care workers while still meeting beneficiary requirements. For implementation purposes the algorithm will then be coded in the *GNU Octave*® development environment, an open source programming language.

The robustness and flexibility of the algorithm will be tested using data from Heartbeat's Nellmapius project. Results will enable verification and validation of the algorithm which will pinpoint necessary model refinements and customisation.

To ensure the maximum utility of this algorithm, a user-friendly and accessible graphical user interface (GUI) should be developed to accompany the algorithm. The purpose of this interface will be to allow the organisations, who wish to use the algorithm for routing and scheduling, to input the required data in a familiar environment (not using a specific programming language). The development and coding of the GUI falls outside the scope of the project. However, information system design specifications will be developed to assist with this work.

1.5 Document Structure

Chapter 2 presents a critical review of the home-based care problem as well as the two sub problems - Nurse Rostering Problem (NRP) and the Vehicle Routing Problem (VRP). Applicable variants of the VRP are also introduced. A study of the exact and approximation solution methods for the problem is also presented in this chapter. Chapter 3 continues the discussion of the chosen solution approaches as well as their adaptation for the problem at hand. Chapter 4 presents the computational results obtained from applying the algorithm to the Heartbeat Nellmapius project. The analysis of the results as well as algorithm performance will also be discussed in Chapter 4. Chapter 5 will conclude the report with further research suggestions and specification requirements for the development of a user interface for the algorithm.

Chapter 2

Literature review

2.1 Problem Identification

The home-based care problem encapsulates two distinct sub-problems: The assignment of beneficiaries to suitable care workers, identified as the Nurse Rostering Problem (NRP), and the optimal scheduling and routing of care workers, identified as an extension of the Vehicle Routing Problem (VRP).

2.1.1 The Nurse Rostering Problem

The NRP is described by Burke et al. (1999) as: "The assignment of duties to a set of people with different qualifications, work regulations and preferences." The similarities between the NRP and the assignment of care workers are clear. Solving this problem will ensure that the skills of care workers and requirements of beneficiaries are matched and that the time availability of care workers will be taken into consideration.

The complexity of the NRP is mainly as a result of the vast number of hard and soft constraints encountered in this type of problem. Hard constraints have to be met under any circumstances in order for the schedule to be considered feasible (Burke et al., 2010; Akjiratikarl et al., 2007). Typical examples are:

- Qualification requirements.
- Working hours.
- Worker requirements for shifts.

Alternately, soft constraints allow unavoidable constraint violations without rendering a solution infeasible. Soft constraints include:

- Leave applications.
- Shift type preferences (i.e. night or weekend shifts).
- Avoiding unfavourable shift successions (i.e. a night shift followed by an early day shift).

2.1.2 The Vehicle Routing Problem

In the classical Vehicle Routing Problem (VRP) a sequence of deliveries are generated for a set of K identical vehicles in a fleet with a carrying capacity Q. This fleet, which is based at a single depot, must deliver order quantities q_i with $i \in (i = 1, ..., n)$ to n customers without exceeding the capacity of a vehicle, Q. This should be done in such a way that all customer demands are met, without exceeding the maximum route length D (Taillard, 1999; Li et al., 2007). The mathematical formulation of the VRP, as adapted from Joubert (2006), is presented as:

$$x_{ij}^k = \begin{cases} 1 & \text{if vehicle } k \text{ travels from node } i \text{ to } j\text{, where} \\ & i, j \in \{1, 2, ..., N\} | i \neq j, \text{ and } k \in \{1, 2, ..., K\} \\ 0 & \text{otherwise} \end{cases} \tag{2.1}$$

$$\min z = \sum_{i=0}^{N} \sum_{\substack{j=0 \\ j \neq i}}^{N} \sum_{k=1}^{K} c_{ij} x_{ij}^k \tag{2.2}$$

subject to

$$\sum_{i=0}^{N} \sum_{k=1}^{K} x_{ij}^k = 1 \qquad \forall j \in \{1, 2, ..., N\} \tag{2.3}$$

$$\sum_{j=0}^{N} \sum_{k=1}^{K} x_{ij}^k = 1 \qquad \forall i \in \{1, 2, ..., N\} \tag{2.4}$$

$$\sum_{i=0}^{N} x_{ip}^k - \sum_{j=0}^{N} x_{pj}^k = 0 \qquad \forall p \in \{1, 2, ..., N\}, k \in \{1, 2, ..., K\} \tag{2.5}$$

$$\sum_{j=0}^{N} q_j \left(\sum_{i=0}^{N} x_{ij}^k \right) \leq Q \qquad \forall k \in \{1, 2, ..., K\} \tag{2.6}$$

$$\sum_{i=0}^{N} \sum_{j=0}^{N} t_{ij} x_{ij}^k \leq D \qquad \forall k \in \{1, 2, ..., K\} \tag{2.7}$$

$$\sum_{j=1}^{N} x_{0j}^k \leq 1 \qquad \forall k \in \{1, 2, ..., K\} \tag{2.8}$$

$$\sum_{i=1}^{N} x_{i0}^k \leq 1 \qquad \forall k \in \{1, 2, ..., K\} \tag{2.9}$$

$$x_{ij}^k \in \{0, 1\} \qquad \forall i, j \in \{1, 2, ..., N\}, k \in \{1, 2, ..., K\} \tag{2.10}$$

The term c_{ij} in (2.2) can be used interchangeably for travel cost, travel distance or travel time, depending on the objective of the specific problem. In this specific problem the objective is to minimise the total travelling cost while constraints (2.3) and (2.4) ensure that only one vehicle handles deliveries to a given customer. Constraint (2.5) ensures that a vehicle will leave a node it has arrived at. The total capacity that a single vehicle can deliver cannot exceed Q in (2.6) and (2.7) limits the maximum travel distance, D (t_{ij} may also be defined as the travel time in which case (2.7) will limit the maximum route duration of each vehicle). Constraints (2.8) and (2.9) ensure that a vehicle is not scheduled on more than one route.

2.2 Variants of the Vehicle Routing Problem

The VRP is a very practical and challenging problem often encountered in the logistics sector. However, the rigid assumptions that the classic VRP makes often restricts its applicability to real-life problems (Ho et al., 2008). These assumptions include utilisation of a homogenous fleet, servicing from a single depot and that each vehicle can only serve one route (Joubert, 2006). By adding additional constraints to this problem, these assumptions can be corrected, but this will increase the complexity of a problem formulation that is already difficult to solve in itself. Several variants of the VRP exist which is also applicable to the home-based care problem.

2.2.1 The Vehicle Routing Problem with Time Windows

Dondo and Cerdá (2007) describes a time window as a time period during which a service can be done. This time is usually defined by an earliest time and latest time at which service may commence at a specific node (Joubert, 2006). Time windows can be further characterised as *hard* or *soft*. In the case of a *hard* time window, the arrival time at a node must fall within the specified time window, else the arrival will not be allowed. A time window may be considered as *soft* when a delivery is permitted outside the specified time window, but usually a penalty cost is incurred (Akjiratikarl et al., 2007; Joubert, 2006).

The routing of home care workers has been identified as an extension of the Vehicle Routing Problem with Time Windows (VRPTW) by Akjiratikarl et al. (2007), Eveborn et al. (2006), Bertels and Fahle (2006) and Cheng and Rich (1998). In the home-based care problem it is the availability of beneficiaries and care workers that typically give rise to time windows.

2.2.2 The Multi-Depot Vehicle Routing Problem

As a variant of the VRP, the multi-depot VRP (MDVRP) is applied to cases where a company has more than one depot to consider. Hence, the single homogeneous fleet will be dispersed between the multiple depots. This results in an additional problem of assigning depots to customers prior to scheduling the fleet (Ho et al., 2008).

Another variant which relates to the MDVRP is the open vehicle routing problem (OVRP). In the OVRP a vehicle does not return to a central depot after servicing the last customer on the route. This problem is most often encountered when contracted delivery men make use of their own transport.

Cheng and Rich (1998) identified the home-based care problem as a VRPTW with many depots (MDVRPTW). In this approach each care worker's home serves as a depot housing a single vehicle (i.e. the care worker). This method eliminates the travelling of the care worker to and from a central depot, since the routes start and end at the care worker's home.

2.2.3 The Vehicle Routing Problem with Heterogeneous Fleet

The VRP with a heterogeneous fleet (VRPHE) is applied to problems where the fleet of vehicles vary with regard to capacity or cost. Bertels and Fahle (2006) states the importance of incorporating this variant of the VRP into the home-based care problem. In many home care scenarios the care workers make use of different transportation modes resulting in varying travelling velocities and time. The home-based care problem will however not be treated a as VRPHE, since the travelling speed between nodes will be predetermined.

2.3 Solution Approaches

There are very limited publications which examine the solution approaches of the home-based care problem defined in Chapter 1. That is, the solution which combines the NRP and the VRP. Separately, these problems have attracted much more research. The solution approaches for the two separate problems as well as the limited solution approaches that have been applied to the home-based care problem will be discussed.

Steeg and Schröder (2007) identified both the NRP and the VRPTW as two well known non-deterministic polynomial-time hard (NP-hard) problems. As a result, the home-based care problem can also be classified as NP-hard, since it combines the NP-hard NRP and VRPTW.

NP-hard problems are most often difficult to solve optimally (Steeg and Schröder, 2007) or unpractical to solve optimally due to the vast amount of computational time required for all but the smallest problem instances. Such problems are rather solved by applying approximation or heuristic algorithms (Winston and Venkataramanan, 2003). Due to the extensive application of heuristics and metaheuristics found in the literature, a brief overview of these approaches will be given:

Heuristics are approximation solution algorithms which construct initial solutions and then apply search methods to improve this feasible initial solution (Winston and Venkataramanan, 2003). Although optimality is not guaranteed, this usually results in good, feasible solutions. Heuristics do, however, have the tendency to get trapped in the first local optimum found. This is a result of the initial solution upon which the improvement search was based (Winston and Venkataramanan, 2003; Joubert, 2006).

Metaheuristics are solution techniques which orchestrate decision making techniques to search for an improved solution in the solution space (Glover and Kochenberger, 2003; Joubert, 2006). This method differs from heuristic techniques since the robust searches also allow non-improving feasible moves. According to Rardin

(1998), this characteristic of metaheuristics reduces the probability of getting stuck at local optima.

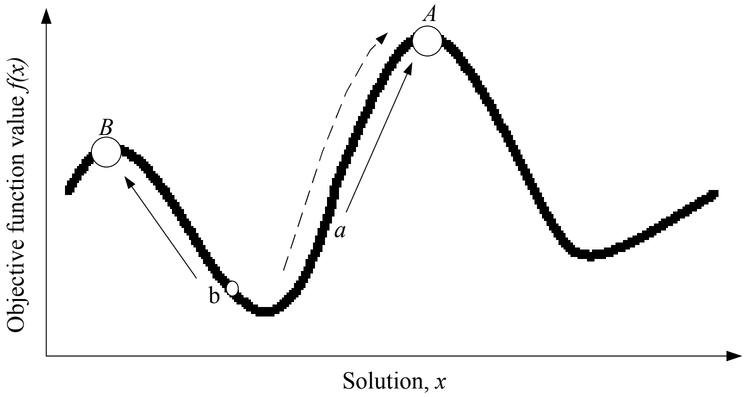

Figure 2.1: Comparison of global and local optima (Joubert, 2006)

Figure 2.1 illustrates the difference between the solution approaches of heuristics and metaheuristics. If a heuristic starts with initial solution a, it can only improve until its local optimum A is reached. Although the local optimum A also happens to be the global optimum, the same approach follows for initial solution b, which can only improve until B is reached. This is a result of the restriction of heuristics which only allows improving moves. The ability of metaheuristics, which prevent getting stuck at local optima (B) by allowing non-improving moves, is illustrated by the dotted line. The solution starts at b, but first worsens while moving in the direction of a, before it improves towards A (Joubert, 2006).

2.3.1 Nurse Rostering Problem

Bertels and Fahle (2006) comment on the importance of solving the NRP in the home-based care problem as efficiently as possible, in order to obtain feasible and applicable solutions. This is necessary due to the high interdependencies between the rostering constraints and optimised routes.

In their paper *Nurse Rostering Problems - A bibliographic survey*, Cheang et al. (2003) state that the two methodologies commonly used to solve the NRP are mathematical programming (MP) and heuristics. Although exact algorithms exist for the NRP, little research has been done on applications because in the field of nurse rostering, problems are usually very large and the application of metaheuristic approaches seems to dominate.

Very recently, Burke et al. (2010) proposed a hybrid model for highly-constrained NRP's. An integer programme (IP) is used to solve the sub-problem which contains only the hard constraints. The hard constraints are the constraints that have to be met in order to consider the solution as acceptable and feasible. A variable neighbourhood search (VNS) is then applied which focuses on enforcing the excluded soft constraints while attempting to improve the initial results of the IP. Curtois et al. (2008) follow a very similar approach to Burke et al. (2010), by also developing a hybrid VNS algorithm. The algorithm uses a repeating and iterative VNS which is followed by a disruption and repair process and is further improved through backtracking.

Hansen and Mlandenović (2001) describe the VNS as a metaheuristic which exploits the idea of a systematic neighbourhood change within a search algorithm. In contrast with general metaheuristics which only apply a local search in the neighbouring search space, the VNS explore increasingly distant neighbourhoods and moves from one neighbourhood to the next only if an improvement will be made by the move. This allows the search to avoid a descent to a local minimum and to escape the valley which contains them (Hansen and Mlandenović, 1997).

Bai et al. (2000) examine a stochastic ranking method for solving constrained optimisation problems such as the NRP. This method is combined with a genetic algorithm (GA) and simmulated annealing (SA) metaheuristic.

GA's are search techniques inspired by the biological evolution of species, which is associated with the aim of continuous improvement to always search for the better solution (Dréo et al., 2003). The core focus of this algorithm is based on the development of new solutions through the mutation or random selection and change of old solutions (Cheang et al., 2003). According to Rardin (1998), GA's search for globally optimal solutions through the intellectual exploitation of random search methods, emulating biological evolution, will ensure that the current best optimum is always in the solution.

Despite the interest observed in applying GA to rostering problems, Aickelin and Dowsland (2000) comment that the classic GA metaheuristic is not well equipped to handle the conflicting objectives and constraints which are often encountered in the NRP. They approach the problem by decomposing it into two stages which are formulated as IP's. Stage one is a standard knapsack problem which assures that there are sufficient personnel to meet the constraints and stage two is concerned with the allocation of shifts. The adapted GA is implemented in the second stage.

Another acclaimed approach that has been used to solve the NRP is the MP-based near-optimal method. Cheang et al. (2003) mention the work of Valouxis and Housos who used this specific method. An initial solution is obtained by solving an IP which is further improved using a Tabu Search (TS).

2.3.2 Vehicle Routing Problem

Ho et al. (2008) solved the MDVRP by developing a hybrid GA which consists of a grouping, routing, scheduling and improvement component. The Clark and Wright saving method, VNS and iterated swap procedure (ISP) are hybridised in this solution algorithm. The first two are concerned with the generation of the initial solution while the ISP aims to improve the solution.

Very little research has been done on the development of solution algorithms for the OVRP. Li et al. (2007) found that all the existing algorithms for the OVRP are based on heuristics with good performance by the VNS, TS, and record-to-record travel which is a variant of SA. In their work, Li et al. (2007) specifically refer to the work of Brandão who uses a VNS to generate an initial feasible solution and an improving TS with embedded insertion and swap methods.

Dondo and Cerdá (2007) present a discrete 3-phase cluster-based heuristic approach to solve the multi-depot VRPTW and a heterogeneous fleet. Phase 1 uses a heuristic clustering algorithm which clusters the depots in order to reduce the computational burden of the problem. Phase 2 and 3 are concerned with the scheduling and routing and is done by solving a mixed integer linear problem (MILP) and travelling salesman problem (TSP) respectively.

Joubert (2006) developed an integrated and intelligent metaheuristic for the constrained VRP. This metaheuristic integrates an Artificial Neural Network (ANN), TS, GA and fuzzy c-clustering. The goal of this metaheuristic is to find the best possible solution for any real-life vehicle routing and scheduling problem.

Semet and Taillard (1993) developed a TS based method for solving a VRPHE. Despite using this standard method very satisfactory results were obtained. Semet and Taillard (1993) comment that introducing an iterated constructive process into this TS method may result in further improvement of the solution.

Taillard (1999) approached the VRPHE by developing a heuristic column generation method. For each vehicle type in the fleet the classic VRP (with a homogeneous fleet) are solved with an adaptive memory procedure (AMP). The AMP is based on the TS method of Semet and Taillard (1993). Once all the homogeneous VRP are solved, they are combined to produce a solution to the VRPHE.

The Tabu Search (TS) method, which allows local search (LS) methods to overcome local optima, is based on the properties of human memory. When a local optimum is encountered, LS techniques are employed to search for improved solutions in the neighbouring search space. The LS techniques allow non-improving moves (Winston and Venkataramanan, 2003). The TS algorithm contains a memory-based property, preventing future mistakes based on mistakes made in the past (Dréo et al., 2003). By using this memory, previously visited solutions are stored in a tabu list which prevents this solution being revisited within a predetermined number of iterations. The TS has the ability to start with a single initial solution as well as a population of initial solutions. The latter is obtained through the implementation of a beam search (Winston and Venkataramanan, 2003).

2.3.3 Home-based care

Eveborn et al. (2006) approached the assignment of visits to care workers, using a set partitioning model combined with a repeated matching heuristic to determine the best solution. This heuristic uses the branch-and-bound algorithm in combination with a successive shortest path algorithm (Engquist, 1982; Eveborn et al., 2006). The merit of the solutions obtained was judged by evaluating the travel time of the care workers and the amount of patients not assigned care workers. Both of these had to be minimised. Bertels and Fahle (2006) criticise this approach, as excessive computational time is required for column generation approaches, such as the set partitioning model used by Eveborn et al. (2006). Despite this criticism, this system was successfully implemented in Sweden, showing a reduction in both the planning and travel time for home care visits (Eveborn et al., 2006).

Steeg and Schröder (2007) follows a hybrid approach to solve the periodic home-based care problem. Constraint programming and a guided branch-and-bound search was applied to find an initial feasible solution for the combinatorial NRP and periodic vehicle routing problem with time windows (PVRPTW). The VNS metaheuristic, which is guided by a SA metaheuristic, attempts to improve this initial solution while an underlying constraint programme assures feasibility of the NRP.

The VNS technique follows a different approach to local search techniques by changing the solution significantly. The SA metaheuristic is a non-randomised stochastic search method which simulates the physical process of combining particles in a cooling system (Winston and Venkataramanan, 2003). According to Glover and Kochenberger (2003) the key factor of SA is its ability to escape local optima by allowing moves which worsen the objective function value in the hopes of finding the global optimum. This memory less approach allows any feasible improvement in the objective function value, while the acceptance of inferior solutions are based on the Boltzman function evaluation criterion (Winston and Venkataramanan, 2003).

Another hybrid approach for solving the home-based care problem was applied by Bertels and Fahle (2006) in the development of their PARPAP® software which serves as a planning tool for staff rostering and routing in the home-based care industry. An initial feasible solution was obtained using a combination of constraint programming (CP) and linear programming (LP). The improvement algorithm which was then applied combines CP and the TS metaheuristic. This combinatorial application delivered near optimal results and also performed superior to single paradigm applications of CP, TS, GA or SA.

In the works of Akjiratikarl et al. (2007), the home health care problem was identified as an extension of the multiple depot VRPTW (MDVRPTW).The relatively novel Particle Swarm Optimisation (PSO) metaheuristic was adapted to solve this problem. An initial solution was developed by assigning the home care tasks with the earliest start time priority and minimum distances first. The local improvement procedures (LIP) search algorithm, which is embedded in the PSO, was then applied to obtain the global best solution through insertion and swap procedures. By applying this approach the total distance travelled by the care worker is minimised, while capacity and time window constraints are satisfied.

PSO is a population based search technique which emulates the collective behaviour of animals i.e. birds flocking and fish schooling (Akjiratikarl et al., 2007). The development of this algorithm was inspired by the theory of socio-psychology, which posits that an individual's movement is influenced by their own and their neighbour's last behaviour (Dréo et al., 2003). In PSO, the decision of a particle's adjustment in position is dependent on their current speed and direction of movement as well as the best preceding position of the particle itself and its neighbours (Akjiratikarl et al., 2007; Dréo et al., 2003). This is an indication of memory-based decision making. Hence, the PSO attempts to balance the exploration and exploitation by combining a local search (particle's best position retrieved from memory) with a global search (neighbouring experience retrieved from memory) (Akjiratikarl et al., 2007).

Cheng and Rich (1998) presents the home health care routing and scheduling problem as a mixed integer problem (MIP) based on the multiple travelling salesman problem (MTSP). A two phased algorithm is implemented as solution. The first phase is concerned with a parallel tour building procedure which develops routes simultaneously, while the second phase improves on these developed routes by trying to find the best schedule, based on a set of constraints. This approach yielded good results and had a short computational time, but was only tested with a very small dataset, consisting of four nurses and 10 patients.

2.4 Selection of Solution Techniques

Based on the literature it is clear that there are several solution approaches that have proved successful in solving the home care problem as well as the NRP and VRP. The use of hybrid approaches, combining the strengths of heuristics and metaheuristics, seems to be the norm. In the attempt to develop a robust generic solution algorithm for solving the home-based care assignment, routing and scheduling problem in South Africa, an appropriate combination of metaheuristics should be chosen with the intent of hybridisation.

The solution algorithms for the home-based care problem discussed in the literature have been developed for very problem specific situations. Since the South African home-based care problem also contains problem specific restrictions it is decided to approach the problem as a combinatorial NRP and VRPTW.

From the conducted literature-study the dominant use of two metaheuristics for the NRP became apparent — The GA and the VNS. As stated by Aickelin and Dowsland (2000), the conflicting constraints often encountered in the NRP inhibit the ability of GA's to consistently produce good solutions. Based on this, the VNS will be applied to the nurse rostering component of the problem. The study also indicates that the VNS, SA, TS and GA metaheuristics, or combinations thereof are suited to solve the vehicle routing component of the problem. This part of the problem requires determining a good sequencing of the set of jobs determined by the VNS for a specific care worker. TS presents the advantage of requiring less computational time than SA and GA (mainly as a result of algorithm complexity) while still obtaining good solutions. It is also suitable to be used in conjunction with other metaheuristics. Since a hybrid approach will be used and Li et al. (2007) mention the successful use of a VNS with TS, the TS is chosen to solve the VRP.

Both the VNS and TS are metaheuristics that improve an initial solution received as input to the algorithms. A construction heuristic needs to be developed in order to generate an initial solution. Burke et al. (2010) introduce a heuristic ordering method as construction heuristic to solve the NRP. An adaptation of this algorithm will be developed to serve as construction algorithm.

The solution of the home-based care problem thus entails a hybrid approach which combines the strengths of the VNS and TS metaheuristics as well as a construction heuristic. The VNS will be applied to the NRP and will investigate possible improving shift and care worker switches. Simultaneously, a TS will be used to determine the best sequencing of this proposed change and the resulting travel time.

2.5 Conclusion

This chapter presented a look into the problem of the optimal assignment and routing of care workers in a home-based care scenario. The home-based care problem has been identified as a combination of two NP-hard problems–The Nurse Rostering Problem and the Vehicle Routing Problem. Both these problems are difficult to solve optimally and metaheuristics are most often applied to get a good solution. Several solution approaches exist to solve this problem - each with its own merits. A hybrid approach, combining the Variable Neighbourhood Search and Tabu Search metaheuristics is deemed suitable to solve the home-based care problem. In the following chapter the discussion of the chosen solution approaches will be extended and the adapted conceptual solution algorithm for the home-based care problem presented.

Chapter 3

Solution Algorithm

The home-based care problem is a combination of two well-known NP-hard problems - The Nurse Rostering Problem and the Vehicle Routing Problem with time windows. Due to the complexity associated with the problems, and the vast computational time required to solve them optimally, it is decided to employ a hybridised metaheuristic approach. Although this approach will not be able to guarantee optimality, both the Variable Neighbourhood Search (VNS) and the Tabu Search (TS) have demonstrated their ability to obtain near optimal solutions.

The remainder of this chapter describes the proposed solution algorithm. Firstly, the individual algorithms will be discussed after which the conceptual hybrid algorithm will be presented. Table 3.1 presents a list of the terminology that will be used frequently throughout this chapter:

Table 3.1: Solution Algorithm Terminology

Term	**Description**
J_i	Care activities that need to be performed, $i \in I$
N_n	Set of care workers, $n \in N$
R^n	Roster for care worker n consisting of all jobs assigned to the care worker
M_n^T	Maximum allowed daily schedule duration for care worker n
p_{jn}	Penalty value associated with assigning activity j to care worker n
T^n	Visiting schedule for care worker n
S'	Set containing individual visiting schedules for all care workers
$t_k^{(n)}$	Starting time of job k, for care worker n, $k \in J$
k_{max}	Stopping criteria for VNS
t_{max}	Stopping criteria for TS
T'_{opt}	Incumbent TS duration
S'_{opt}	Incumbent schedule solution
N_k	Neigbourhood structure of VNS

3.1 Solution Algorithm

Due to the complexity of solving the home-based care problem optimally, a hybrid solution algorithm is proposed. The algorithm will combine the VNS and TS metaheuristics. The sequential development of this algorithm will be based on the sequence used by Bertels and Fahle (2006) in their solution approach for the home-based care problem. The steps, discussed in more detail subsequently, include: Pre-processing of data, development of an initial solution, and improvement of the care activity assignment and the sequencing of the individual rosters.

3.1.1 Pre-processing of data

The aim of this step is to reduce the data complexity of a problem. A 0-1 matrix is developed which indicates care worker/care activity compatibility with regard to skill and time windows. A one will be an indication of a care activity with a time window that coincides with the time window of a care worker who possesses the skills necessary to perform the activity. A zero is an indication of incompatibility. In the case where there exist only one care worker who is compatible with a care activity, the care activity, J_i, is fixed in the care worker's roster.

This concept will be explained through the matrix in Table 3.1. As the matrix indicates the only critical compatibility combination exist for care activity J_3, which only care worker N_2 can perform. All the other care activities have more than one care worker that can perform the specific activities, and are therefor not regarded as critical.

Table 3.2: Compatibility Matrix

	N_1	N_2	N_3	N_4	N_5
J_1	1	0	1	1	0
J_2	1	1	0	0	1
J_3	0	1	0	0	0
J_4	1	1	1	1	0
J_5	0	1	1	0	1

3.1.2 Construction of an initial solution

Both the VNS and TS are metaheuristics which find good solutions through the iterative improvement of a feasible solution. It is thus necessary to construct an initial feasible solution as input to the metaheuristics. As stated before, the quality of the final solution is highly dependent on the initial solution of the problem since this will direct the search techniques employed by the metaheuristics. A heuristic ordering method, similar to the one applied to the NRP by Burke et al. (2010), is proposed for the development of an initial feasible solution. This feasible solution $S = \{R^{(1)}, ..., R^{(N)}\}$ consists of N rosters, where $R^{(n)} = \{J_1^{(n)}, ..., J_k^{(n)}\}$ represents the roster for each care-worker. The pseudo-code for the construction heuristic of the initial solution can be viewed in Algorithm 1.

Evaluation criteria for determining the difficulty of a care activity is predetermined and a weight is assigned to each criterion. The weighted sum of the difficulty of assignment for each care activity (except those already assigned during the preprocessing phase) is determined and the care activities are sorted from most to least difficult. The care activities are then, in turn, assigned to the care worker that incurs the least penalty, p_{jn}, in receiving the activity. Maximum allowable working hours for care workers, a constraint which is not considered by Burke et al. (2010), will also be incorporated into the construction heuristic. During the assignment of care activities the maximum allowed work time, M_n^T, of each care worker may not be exceeded. The assignment should also endeavour to equally distribute the workload of each care worker as far as possible.

Since the main objective of the solution is to determine the optimal routing which will result in the shortest schedule duration for each care worker, the duration of the care worker schedule should now be determined. For the initial solution, the current ordering of jobs, as determined through the preceding assignments will be used. This will result in a solution $S' = \{T^1, ..., T^N\}$ where $T^{(n)} = \{(j_0^{(n)}, t_0^{(n)}), ..., (j_k^{(n)}, t_k^{(n)}), (j_{k+1}^{(n)}, t_{k+1}^{(n)})\}$, and t is the starting time for each corresponding job. The starting time t for each job is calculated by adding the duration of the previous job and the travelling time, d_{ij}, between two nodes to the starting time of the previous job. The nodes j_0 and j_{k+1} are also included in this schedule to incorporate the travelling time to and from the care worker's home or the central depot as well.

3.1.3 Variable Neighbourhood Search

The Variable Neighbourhood Search (VNS) is a simple and effective metaheuristic for combinatorial problems which applies the systematic change of neighbourhoods within a local search algorithm with the aim to find an improved solution (Hansen and Mlandenović, 2001). This is a relatively novel approach and differs from other metaheuristics with regard to search space (Burke et al., 2010). Although the larger search space is mostly the attractive feature of this metaheuristic, constructing the correct neighbourhood structures is of vital importance for the success of the metaheuristic (Hansen and Mlandenović, 2001). The basic structure of the VNS, as adapted from Curtois et al. (2008), is presented in Algorithm 2.

The algorithm starts by determining an initial feasible solution within the defined neighbourhood structures (Step 0). A local search technique then allows the search for possible improved solutions within increasingly distant neighbourhoods (Step 2). An incumbent solution tracks the best solution found and is updated only when an improved solution is found (Step 3). Once all the neighbourhoods have been searched and an improved solution found the algorithm terminates (Step 1).

The VNS will be applied to the nurse rostering component of the home-based care problem. The proposed VNS algorithm is developed combining aspects identified in the work of Curtois et al. (2008) and Burke et al. (2010).

The initial solution $S = \{R^{(1)}, ..., R^{(N)}\}$, as obtained from the heuristic ordering

Algorithm 1: Pseudo-code of the construction heuristic

```
Input : Penalty value $p_{nj}$ for assigning care worker $n$ to job $j$.
        Criteria for difficulty of job assignment.
        Weight factor for each criterion.
        Distance matrix.
Output: Roster set $S = \{R^{(1)}, ..., R^{(N)}\}$.
        Schedule set $S' = \{T^{(1)}, ..., T^{(N)}\}$.
Step 1: Compute difficulty of shift assignment. Determine the weighted sum of the difficulty of assignment for each care activity $j \in J$.
Step 2: Determine $order_j$. Sort the care activities in a descending order according to difficulty of assignment.
Step 3: Assign. According to $order_j$, assign the care activity to the care worker who will incur the smallest penalty, $p_{jn}$, without violating the $max\_time_n$ constraint of the care worker. Once a care activity has been assigned remove it from the list. Repeat this step until all care activities have been assigned.
Step 4: Compute total schedule duration. For each roster $R^{(n)}$, determine the corresponding schedule $T^{(n)}$ and total schedule duration for each schedule.
```

Algorithm 2: High Level Variable Neighbourhood Search Algorithm

```
Step 0: Initialisation. Define a set of neighbourhood structures $N_k$, where $k = 1, ..., k_{max}$ and determine a feasible initial solution $x$. Set the best solution to the current solution $x_{opt} \leftarrow x$ and set $k \leftarrow 1$.
Step 1: Stopping. If $k = k_{max}$ then stop. The algorithm only terminates after all neighbourhoods have been explored.
Step 2: Explore. Explore the neighbourhood $N_k$ of $x$ until the best solution $x'$ in $N_k$ is found.
Step 3: Incumbent Solution. If $x'$ is better than $x_{opt}$, replace $x_{opt} \leftarrow x'$.
Step 4: Increment. If $x_{opt} \leftarrow x'$ set $k \leftarrow 1$ and return to step 1, else set $k \leftarrow k + 1$ and return to step 1.
```

method described in Section 3.1.2, will be used as the initial solution. A VNS is then applied to the solution. The following adjustments to neighbourhood structure define the neighbourhoods of the VNS:

1. Swapping a care activity assigned to a care worker, with an assigned care

activity of another care worker.

2. Swapping two care activities of the same care worker between different days in the schedule.

The TS, which will be discussed in the next section, is embedded in the VNS. The purpose of the TS is to determine the best routing for each proposed move of the VNS in order to determine the total time of the proposed roster. The total schedule time will be an indication of the quality of the proposed move.

From the initial solution, the search within the first neighbourhood commences. This search induces a single swap of a care-activity from a pair of care-workers. The quality of the proposed swap is then evaluated by calculating the total schedule time of the new proposed roster with the TS. If the best solution (shortest schedule) obtained in the current neighbourhood is not an improvement of the solution in the previous neighbourhood, the algorithm extends its search to search for another move that will result in an improvement. Otherwise, the solution is updated as the incumbent solution and the algorithm returns to the first neighbourhood of the new solution. When there are no more improving moves left within the first neighbourhood, or the stopping criteria is met, the search extends to the second neighbourhood.

The search within the second neighbourhood proposes an exchange between care activities in a specific care worker's schedule. This search is conducted for each of the care workers. If the proposed move results in an improved solution, the incumbent solution is updated to the current result. This process is repeated until the stopping criteria is met.

The process is illustrated by the pseudo-code in Algorithm 3.

3.1.4 Tabu Search

The TS is an established metaheuristic and has proved successful in numerous applications to the VRPTW. It prevents the tendency of getting stuck at local optima by also allowing non-improving moves in the improving search (Rardin, 1998).

Algorithm 4 illustrates the high-level structure of the TS as adapted from Rardin (1998). This algorithm will be adapted and applied to the scheduling component of the home-based care problem. As can be seen from the high level algorithm, the first step of the TS is to determine an initial feasible solution. Although any feasible solution will be sufficient, the solution quality of the TS is notorious for its sensitivity to the initial solution. Since the TS is embedded within both neighbourhoods of the VNS, the proposed swap of the VNS will supply the initial solution to the TS. The search space of the TS is confined to only the jobs within the specific roster under examination in the VNS. The main purpose of this algorithm is to generate solutions with improved schedule ordering and resultantly shorter duration. Every allowable, non-tabu move should be evaluated. If the resulting schedule time from the proposed move is shorter than the current best solution, the incumbent solution has to be updated. For each swap within the roster, the activity with which another activity is replaced has to be moved to the tabu list for a specific duration. This will prevent subsequent searches from proposing the same move. This is an iterative

Algorithm 3: Pseudo-code for Variable Neighbourhood Search Algorithm

```
Input  : Initial Solution Roster set $S = \{R^{(1)}, ..., R^{(N)}\}$.
         Initial Solution Schedule set $S' = \{T^{(1)}, ..., T^{(N)}\}$.
Output: Improved Roster set $S_{opt} = \{R^{(1)}, ..., R^{(N)}\}$.
         Improved Schedule set $S'_{opt} = \{T^{(1)}, ..., T^{(N)}\}$.
Neighbourhood 1: Assigning a care activity to a different care worker
Set $k \leftarrow 1$
while $k \leq k_{max}$ do
    Explore the neighbourhood $N_k$. For each proposed move calculate duration of $S'$.
if $S' \leq S'_{opt}$ then
    $S'_{opt} \leftarrow S'$
    set $k \leftarrow 1$
else
    set $k \leftarrow k + 1$
Neighbourhood 2: Swapping care workers of roster sets
for care workers=1:n do
Set $k \leftarrow 1$
while $k \leq k_{max}$ do
    Explore the neighbourhood $N_k$. For each proposed move calculate duration of $S'$.
if $S' \leq S'_{opt}$ then
    $S'_{opt} \leftarrow S'$
else
    set $k \leftarrow k + 1$
```

Algorithm 4: High Level Tabu Search Algorithm

Step 0: Initialisation. Determine a feasible initial solution $\boldsymbol{T}^{(0)}$ as well as an iteration limit t_{max}. Set the current best solution $\boldsymbol{T}_{opt} \leftarrow \boldsymbol{T}^{(0)}$ and the iteration count $t \leftarrow 0$. Currently the tabu list is empty.

Step 1: Stopping. If $t = t_{max}$, or if no move can be made to a feasible neighbour of $\boldsymbol{T}^{(t)}$, then stop.$\boldsymbol{T}_{opt}$ is then used as the approximate optimum.

Step 2: Move. Pick an allowable feasible non-tabu move $\triangle \boldsymbol{T}^{(t+1)}$.Update $\boldsymbol{T}^{(t+1)} \leftarrow \boldsymbol{T}^{(t)} + \triangle \boldsymbol{T}^{(t+1)}$.

Step 3: Step. Update $\boldsymbol{T}^{(t+1)} \leftarrow \boldsymbol{T}^{(t)} + \triangle \boldsymbol{T}^{(t+1)}$.

Step 4: Incumbent Solution. If $z(\boldsymbol{T}^{(t+1)})$ is better than $z(\boldsymbol{T}_{opt})$, replace $\boldsymbol{T}_{opt} \leftarrow \boldsymbol{T}^{(t+1)}$.

Step 5: Tabu List. Remove any tabu moves that have been on the tabu list long enough. Also, add new moves including any that would immediately return from $\boldsymbol{T}^{(t+1)}$ to$\boldsymbol{T}^{(t)}$.

Step 6: Increment. Increase $t \leftarrow t + 1$ and go to step 1.

---

process and should be repeated until the stopping criterion, t_{max}, is met. The stopping criteria and the tenure duration of a value in the tabu list will determine solution quality. The incumbent solution, T'_{opt}, recorded upon termination of the algorithm, is regarded as the approximate optimum solution.

3.2 Hybrid algorithm

The solution algorithm presented in this paper represents an iterative process in which a TS is embedded within a VNS. This is preceded by a heuristic ordering algorithm which constructs an initial feasible solution as input to the VNS. This overall process is illustrated by the Pseudo-code in Algorithm 5.

3.3 Conclusion

This chapter presented the conceptual hybrid solution algorithm that is proposed to solve the home-based care problem in South Africa. This proposed algorithm combines the strengths of the VNS and TS metaheuristics. It also includes a heuristic ordering algorithm which is employed to construct an initial feasible solution.

The remainder of the report will consist of the computational results obtained by applying this solution algorithm to a real-world case. This will allow further

Algorithm 5: Pseudo-code for overall hybrid algorithm

```
Create initial solution with heuristic ordering method
REPEAT : For Neighbourhood 1
    Variable Neighbourhood Search
    For each proposed move apply Tabu Search
        if $current\ duration \leq best\ duration$ then
            set best schedule ← current schedule
            set best duration ← current duration
        else
            set current schedule ← best schedule
UNTIL : Search Terminated - Proceed to Neighbourhood 2
REPEAT : For Neighbourhood 2
    Variable Neighbourhood Search
    For each proposed move apply Tabu Search
        if $current\ duration \leq best\ duration$ then
            set best schedule ← current schedule
            set best duration ← current duration
        else
            set current schedule ← best schedule
UNTIL : Search Terminated
```

analysis and improvement of the algorithm. The concluding chapter will discuss further improvements and relating research that can still be done.

Chapter 4

Model Execution

In this chapter the proposed solution algorithm is verified and tested. This is done by applying data from Heartbeat's Nellmapius project site, and comparing the results.

4.1 Heartbeat

The Nellmapius project currently serves 132 households. The home visits are conducted by five care workers with the purpose of assessing the need of the children, addressing problems within the household, and providing assistance with everyday activities.

The recommended frequency of visits per target group is illustrated in the table below:

Table 4.1: Recommended frequency of home-visits (UNAIDS, 2009)

Target Group	**Frequency**
Child-Headed Household	Three times per week
Potential Child-Headed Household	Three times per week
Relative-Headed Household (without grant)	Once a week
Relative-Headed Household (with grant)	Once a month

The purpose of the high frequency contact between care workers and child-headed households as well as potential child-headed households (children living with terminally ill parents), is to provide stability to these homes by means of assigning the responsibilities of parents to the care workers. For this reason it is highly recommended that a specific care worker should be assigned to each of these households, to ensure stability. Due to the large need in Nellmapius, Heartbeat's ideal ratio of 1 care worker for every 10 households is exceeded by far (1:26), and this is severely impairing the quality of the care. This also often leads to variation of care workers with the critical visits.

A complete map of Nellmapius, with the locations of the care workers and the various households, is presented in Figure 4.1.

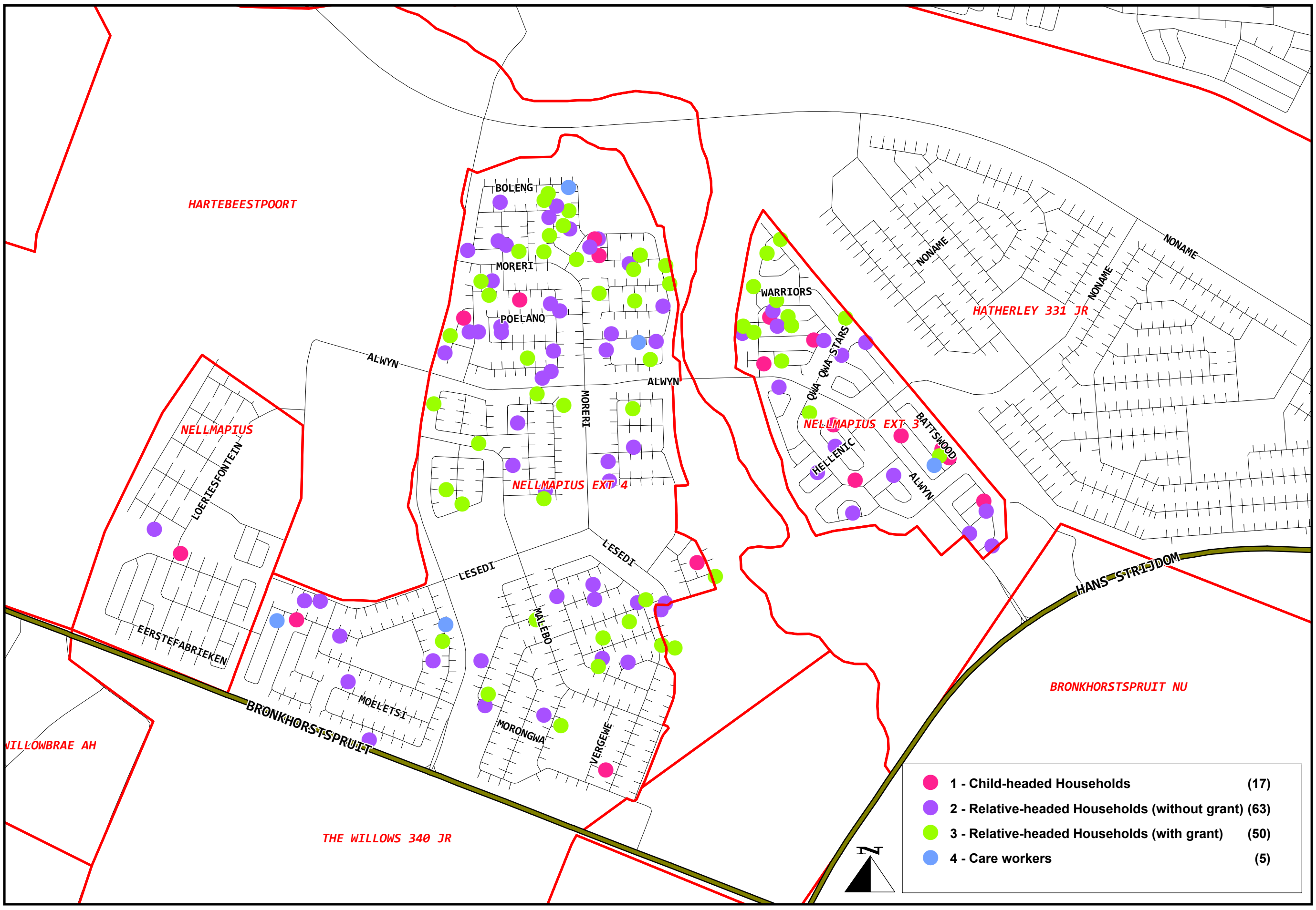

Figure 4.1: Geographical representation of Heartbeat care worker and household location in Nellmapius, Gauteng

Currently no structured approach is being followed for the assignment of visits to care workers—resulting in unfulfilled demand of visits. This is mainly a result from OVC not being at home when a care worker wants to conduct a home visit, because no prior arrangements were made. These visits are seldom followed up, due to a lack of time and poor monitoring of performed visits. The geographical dispersal of the households also contribute to this problem. The households located on the outskirts of the settlement, furthest from the care workers, are often neglected because of the extra effort required to perform visits at these households.

The following sections will examine the results of the solution algorithm for solving the home-based care problem of OVC for Heartbeart's Nellmapius project.

4.2 Route and Schedule construction

4.2.1 Data gathering and Preparation

Applicable data, to be used as input for the algorithms described in Chapter 3, is a critical component of the solution algorithm. For this reason it was necessary to follow an approach that would transform the raw data received from Heartbeat, into processable input data for the solution algorithm.

Heartbeat is currently in the process of conducting a census to collect information to update their data basis. A list of the households in Nellmapius served by Heartbeat, containing addresses, type of household and the number of beneficiaries, collected during this census, was provided by Heartbeat.

The data was cleaned and standardised, and through the process of geocoding the geographic coordinates of the addresses, expressed as latitude and longitude, were obtained. The geographic coordinates allow the data to be mapped and entered into geographical information systems (GIS). The data pertaining to the household information is contained in Appendix A.

The most critical data set for the solution algorithm is the internodal distances. The GIS programme, MapInfo, was used to determine the road distances between all the households and care workers, and an internodal distance matrix was constructed. The distance matrix contains 18,084 combinations, and therefor requires ample space. A partial distance matrix can be viewed in Appendix B, and the complete distance matrix is included on the compact disc accompanying the document.

Of the 132 households served by Heartbeat in Nellmapius, 17 are child-headed or potential child-headed households, 64 are relative-headed households not receiving grants, and 51 are relative-headed households receiving grants. In order to meet the frequencies of visits prescribed in Table 4.1, for the 132 households, a total of 511 visits need to be conducted during a four-week period.

As discussed in Chapter 3, the development of care worker schedules to perform these 511 visits was done through the following stages:

- Pre-processing of data.
- Construction of an initial solution.
- Improvement of initial solution.

4.2.2 Pre-processing of data

The care workers employed by Heartbeat are all community members who received the same informal training from Heartbeat. Since no skill variation exist between the care workers, it is proposed that the critical visits–the child-headed households and potential child-headed households–are permanently assigned to a specific care worker. These assignments should preferably be made to a care worker within a close proximity. This will ensure that a trusted adult is nearby in case of an emergency, prevent care worker variation and as a result add to the sense of stability that is provided.

The following table depicts the assignment of the critical visits to care workers, where Household ID refers to the unique identification Heartbeat uses for the specific household.

These visits are fixed to the schedule of the applicable care worker and won't be adjusted in the following steps.

Table 4.2: Pre-processing: Assignment of critical visits to care workers

	Worker 1	**Worker 2**	**Worker 3**	**Worker 4**	**Worker 5**
Household ID	28, 46, 116, 124	48, 107	19, 53, 90	25, 32	2, 8, 9, 16, 55

4.2.3 Initial Solution

The construction heuristic, elucidated in Algorithm 1, was used for the construction of the initial solution.

The remaining visits, not assigned during the pre-processing phase, were ordered in a descending order form the most difficult to least difficult to assign. The criteria used was the type of visit, with relative-headed households not receiving grants regarded more critical than relative-headed households receiving grants.

The visits were then assigned to the care worker who will incur the smallest penalty for conducting the visit. The penalty is calculated taking into consideration the distance between the care worker and the household, as well as the number of visits already performed by the care worker.

This assigned visits were then ordered into a schedule, to serve as an initial solution.

The results obtained from the construction heuristic are presented in Appendix C. For each worker a five day schedule, over a four week period is constructed. The numbers indicate the specific Heartbeat identification for the household, as defined by Visit ID in Appendix A.

Although the solution algorithm focuses on the effective assignment of visits to care workers, and the improved routing and scheduling of the assigned visits, it was necessary to include visit duration for computation purposes. The total schedule duration includes the travelling time between the nodes as well as the visit duration, and highlights the trade-off between the travelling distance of the care worker and the number of visits conducted by the care worker.

Because the visits conducted by care workers usually takes approximately 30 minutes, it was decided use a normal distribution for visit durations , with a mean of 30 minutes and standard deviation of 2 minutes.

4.2.4 Improved Solution

The hybrid solution algorithm was applied to the results obtained from the initial solution with the intent of improving this solution.

The first variable neighbourhood search (VNS) of the solution algorithm was performed in the extended neighbourhood of the schedules of all the care workers. Visits, assigned to the care workers through the construction heuristic, were exchanged between the care workers in order to reduce the total schedule duration and to achieve more equal schedule durations between the care workers. This resulted in a fair assignment of care activities where a trade-off was made between travelling distance and duration, and the number of visits, so that the care worker of whom it is required to travel further distances, will perform less visits.

Once this search was completed, the algorithm advanced to the second neighbourhood structure. During this search the effect of exchanging visits in an existing schedule of a care worker was evaluated for each care worker.

For each of these searches a VNS was executed for 200 iterations, with an embedded tabu search (TS) performing 200 iterations within each iteration of the VNS to determine the optimal routing for each proposed swap of the VNS.

4.3 Results

The improved care worker schedules, as obtained from the solution algorithm are included in Appendix D.

For illustration purposes Figure 4.2 provides a typical representation of an approximated optimal daily route for care workers in Nellmapius as obtained from the solution algorithm.

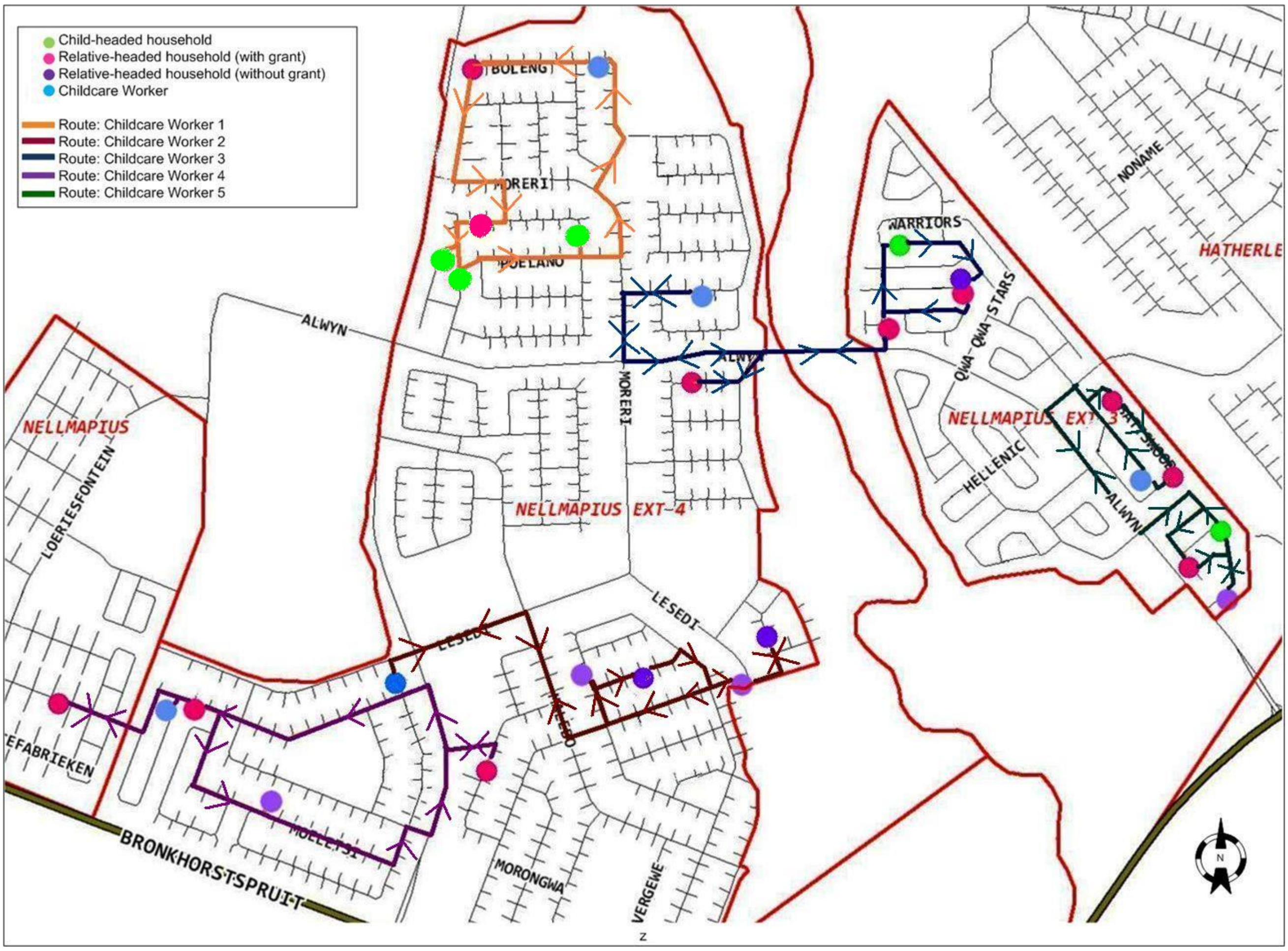

Figure 4.2: Geographical representation of an approximated optimal route for care workers (Week 4, Day1)

Figure 4.3 presents a detailed representation of the approximated daily route for care worker 1 presented in Figure 4.2. Care workers depart from their own

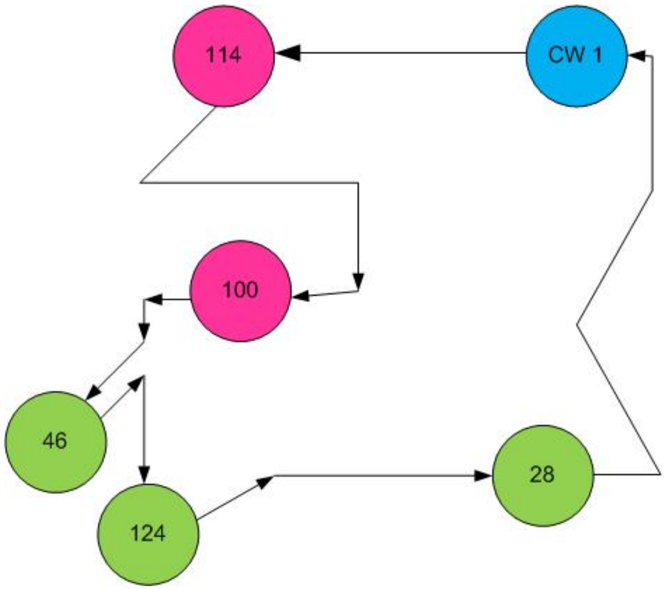

Figure 4.3: Detailed route: Care Worker 1 (Week 4, day1)

residences (light blue nodes) and then perform home visits in the order proposed by the improved schedule. When travelling between nodes, it is assumed that the care worker will follow the shortest route, which is predetermined by the GIS programme. The estimated travelling durations, service times, arrival and departure times for the route presented in Figure 4.3 are presented in Table 4.3:

Table 4.3: Arrival and departure times for an approximated optimal route for care worker 1

Location	Arrival Time	Service Time (minutes)	Departure Time
Care Worker 1	N/A	N/A	14:00
Household 114	14:05	31	14:36
Household 100	14:40	30	15:10
Household 46	15:12	29	15:41
Household 124	15:42	30	16:12
Household 28	16:17	28	16:45
Care Worker 1	16:49	N/A	N/A

A summary of the results of the final improved worker schedules, included in Appendix D, which resulted from the solution algorithm is presented in Table 4.4. From this results it becomes evident that the solutions obtained from the algorithm address the problems currently experienced by Heartbeat, in the following ways:

Fair work distribution The number of visits assigned to each care worker varies between four and six per day. Taking into consideration both the travelling duration of the care worker and the number of visits performed the total schedule duration of each care worker compares favourably the other care workers'.

Table 4.4: Summary of algorithm results

Objective Function	**Worker 1**	**Worker 2**	**Worker 3**	**Worker 4**	**Worker 5**
Total solution duration (min)	3671.45	3594.39	3651.22	3602.66	3670.38
Duration Week 1	941.23	902.18	909.06	879.71	913.50
Duration Week 2	912.52	900.81	918.78	900.29	919.38
Duration Week 3	908.94	894.47	916.14	908.80	919.64
Duration Week 4	908.76	896.93	907.24	913.86	917.86
Total Visits	109	92	107	91	111
Max Daily visits	6	5	6	5	6
Min Daily visits	5	4	5	4	5

Effective routing and scheduling The improved routing and scheduling of the initial solution resulted in care worker schedules not exceeding 3.5 hours on any day. This allows care workers to perform the visits in the afternoon, after school, between 2pm and 6pm.

Limited care worker variation By fixing the visits of child-headed households to specific care workers' schedules, it is ensured that these visits will always be conducted by the same care worker. This will limit the variation of care workers for these critical visits, and enable the children to develop a trusting relationship with the specific care worker. By assigning these visits to the care worker living closest to the family will also add to the security of the child-headed households by ensuring that an adult with whom the children have developed a trusting relationship is close by in case of an emergency.

Visit planning A big advantage of the assignment, scheduling and routing algorithm is that the entire monthly schedule can be determined in a short duration and enable the care workers to make appointments with the children in advance, which allows the children to plan to be at home when the visit is to be conducted.

4.4 Algorithm Performance

Because Heartbeat's current home visit process is extremely ineffective, there are no results that can be used as benchmark for evaluating the performance of the solution algorithm.

As discussed in chapter 2 and chapter 3, using an exact algorithm to solve a problem with this complexity and magnitude optimally, is usually either impossible, or very ineffective due to the vast amount of computation time required.

For the purpose of evaluating the algorithm performance it was decided to replace the final routing component of the algorithm with an exact algorithm. An integer linear programme was designed and solved using LINGO®, an optimisation modelling software. The LINGO®model that was used can be viewed in Appendix E.

The solution was also compared to the preferred constraint of limiting the daily schedule duration to four hours, in order to perform visits during day time, between 2pm and 6 pm.

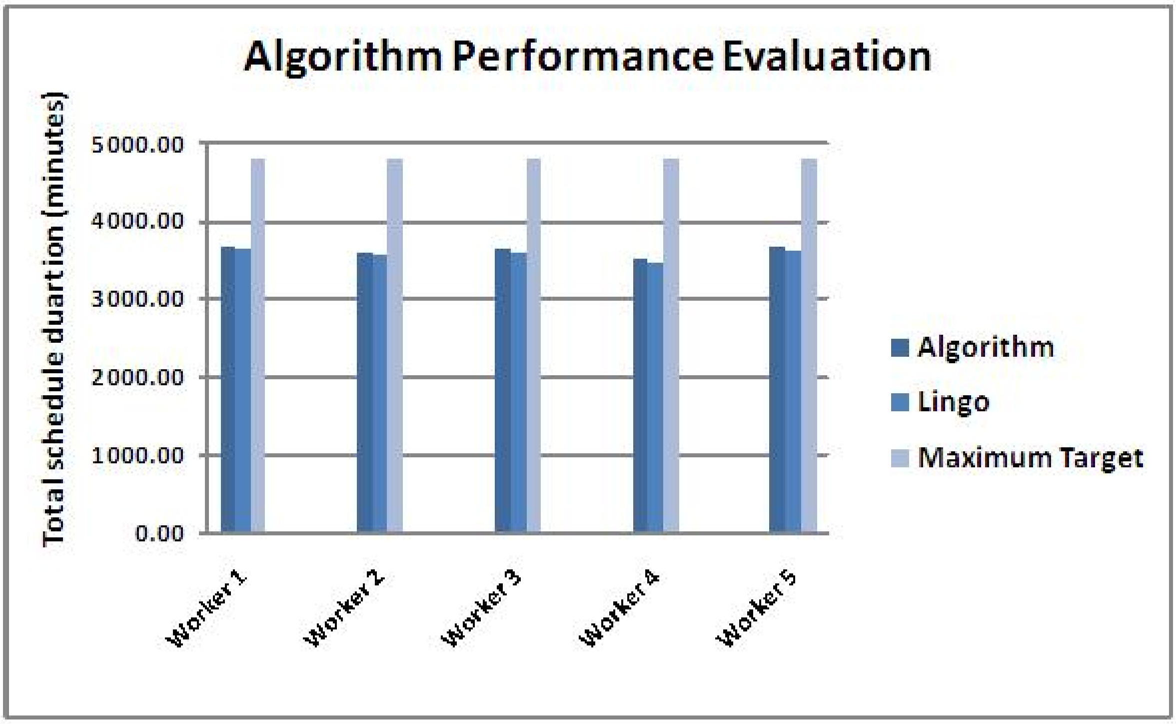

Figure 4.4: Algorithm Performance

Figure 4.4 depicts the results of the performance of the solution algorithm compared to the solution obtained from using LINGO®and the maximum schedule duration constraint,for each worker for the entire four week period. As indicated by the graph, the solution algorithm performs favourably by exceeding the required algorithm performance by an average of 23.51%. The exact solution component included for evaluation purposes also presents an almost insignificant improvement of only 1.81% on average.

Appendix F contains the complete algorithm evaluation results per week, for each of the care workers.

4.5 Conclusion

This chapter presented the process of applying the solution algorithm developed in this project to a real world case, as well as the results obtained from this process.

The improvement of home visits at Heartbeat's Nellmapius project site through the solution algorithm resulted in all the required visits being performed during a four week period, no care worker's daily schedule exceeding 3.5 hours, and all care workers working approximately the same duration over this period.

The evaluation of the algorithm's performance revealed very satisfactory results, with the algorithm performing 23.51% better than the maximum schedule duration constraint. Replacing the final routing component of the approximation algorithm with an exact routing algorithm also only resulted in a mere 1.81% improvement.

The following chapter will discuss the work that can still be done to further improve the results of the algorithm and ensure effective implementation of the algorithm.

Chapter 5

Conclusion

5.1 Future Work

Despite the good results obtained from applying the solution algorithm, there still exist ample opportunities for further improvements. The most prominent and critical of these improvements is the development and implementation of a user interface. This will obviate the need for the user to master the programming language. To mitigate the possibility of human errors, the skill of the user need to be taken into consideration and the minimum amount of data should be entered manually.

The solution algorithm requires an inter-nodal distance matrix as input. The data used for testing, with regard to the inter-nodal distances of Nellmapius, was created with the help of a geographical informations system (GIS) specialist. Applying the solution algorithm to other problems will also require the input data regarding the distances between the applicable nodes. Without the aid of a GIS specialist, one way of obtaining these values is the physical measurement of the distances, but this will be extremely time consuming for larger networks. It is proposed that the implementation of a GIS is investigated. Not only will this produce an accurate inter-nodal distance matrix within a short period of time, but can also provide useful information such as speed limits, obstructions in the road and the infrastructure of the environment.

For implementation purposes the solution algorithm was programmed in *GNU Octave*®, an open source programming language.

5.2 Recommendations for Implementation

The aim of this project states the need to improve the service delivery of home-based care in South Africa. Despite the improvements made by the application of the solution algorithm, it alone will not result in the improvement of home-based care. Implementation and thorough evaluation of this algorithm is critical to the success of this proposed solution.

Strebel (2004) lists several key issues that should be considered and addressed when implementing a programme for OVC, such as the proposed solution algorithm. These include:

- Close monitoring and evaluation, and early intervention and correction is essential to ensure programme viability.
- Necessity of beneficiary involvement in implementation of OVC models to highlight possible pitfalls.
- Due to the large and continually increasing number of OVC, involvement and training of community members as care workers is a good solution to the resource problem.
- For optimal OVC home care the focus should be expanded from physical and developmental needs to include psychosocial needs of OVC as well, making counselling training essential for care workers.
- Model flexibility is crucial in order to adapt to varying community needs.
- Continuous improvements of all applied models is imperative to assure model relevance.

5.3 Conclusion

Home-based care is becoming more prevalent in South Africa, mainly due to the effects of the HIV/AIDS pandemic. The novelty of home-based care as well as inadequate service delivery by care workers has caused reluctance to recognise home-based care as an equal alternative of institutional care.

The aim of this project was to improve the assignment, routing and scheduling of care workers, in order to advance service delivery in the home-based care sector in South Africa.

This problem presented itself as a classical optimisation problem where the travelling duration or distance need to be minimised while adhering to constraints. It combines two well known operations research problems, the Vehicle Routing Problem with Time Windows and the Nurse Rostering Problem.

Both the Vehicle Routing Problem with Time Windows and the the Nurse Rostering Problem are non-deterministic polynomial-time hard problems. Due to the complexity of optimally solving these problems, an approximation solution algorithm was developed which combines a Variable Neighbourhood Search and Tabu Search.

The solution algorithm and a construction heuristic algorithm for initial solution were successfully constructed in the *GNU Octave*® programming environment. Algorithm performance was evaluated by examining the algorithm results from data of Heartbeat's Nellmapius project.

The algorithm can be implemented in its current state, but future projects can be undertaken for further refinement of the algorithm and to develop a user interface to ease utilisation of the algorithm.

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Appendix A

Household and Care Worker Information

Table A.1: Household and Care Worker Information

ID	Address	X Coordinate	Y Coordinate	Visit Type
1	1284 Aces Street	28.367462	-25.730877	3
2	2127 African Wanders Street	28.374857	-25.738496	1
3	2057 African Wanders Street	28.375145	-25.739865	2
4	2020 African Wanders Street	28.37376	-25.737794	3
5	2129 African Wonders Street	28.374933	-25.7388	2
6	1339 Arsenals Street	28.370004	-25.734004	2
7	1833 Battswood Street	28.371778	-25.7377	2
8	1958 Battswood Street	28.373441	-25.736896	1
9	1961 Battswood Street	28.37368	-25.737156	1
10	1294 Black Leopards Street	28.367928	-25.730447	3
11	2397 Boleng Street	28.357844	-25.729185	2
12	2410 Boleng Street	28.360712	-25.729563	3
13	2292 Boleng Street	28.357255	-25.73078	2
14	2417 Boleng Street	28.36073	-25.730126	2
15	1527 Cape Town Spurs Street	28.367875	-25.734986	2
16	1807 Celtic Street	28.36972	-25.736143	1
17	1814 Celtic Street	28.368919	-25.735781	3
18	1625 Colts Street	28.370383	-25.738866	2
19	1237 Costa Do Sol Street	28.367553	-25.732832	1
20	1048 Costa Do Sol Street	28.366646	-25.733107	3
21	1189 Costa Do Sol Street	28.368307	-25.733089	3
22	1232 Costa Do Sol Street	28.368176	-25.732817	3
23	1185 Costa Do Sol Street	28.367809	-25.733102	2
24	2080 Crusaders Street	28.37437	-25.739485	2
25	602 Delagoa Bay Avenue	28.347463	-25.740112	1
26	3994 Dimakatso Street	28.362885	-25.73566	3
27	3260 Dipuo Street	28.356478	-25.733934	2

Continued on Next Page…

Table A.1 – Continued

ID	Address	X Coordinate	Y Coordinate	Visit Type
28	3301 Dipuo Street	28.357123	-25.732859	1
29	3255 Dipuo Street	28.356654	-25.733393	3
30	3373 Direlago Street	28.36053	-25.73554	3
31	5540 Ditumediso Steet	28.352899	-25.742648	2
32	5762 Ditumediso Street	28.351415	-25.742142	1
33	3771 Emela Street	28.356529	-25.738141	3
34	3737 Emela Street	28.357072	-25.738586	3
35	5586 Gaugela Street	28.356407	-25.742798	3
36	5622 Getrouheid Street	28.35608	-25.743403	2
37	3538 Gontse Street	28.358964	-25.736085	2
38	3386 Gontse Street	28.359627	-25.735189	3
39	2547 Hallelujah Crescant	28.361431	-25.730676	2
40	2552 Hallelujah Crescant	28.361716	-25.73043	2
41	2823 Hallelujah Crescant	28.363686	-25.733587	2
42	2689 Hallelujah Crescent	28.362155	-25.733344	2
43	2214 Hallelujah Crescent	28.364146	-25.731806	3
44	2542 Hallelujah Crescent	28.36096	-25.73106	3
45	2218 Hallelujah Crescent	28.364012	-25.731257	3
46	2551 Hallelujah Crescent	28.361585	-25.730433	1
47	1739 Hellenic Street	28.36979	-25.736801	2
48	4964 Hlagisa Street	28.361971	-25.746759	1
49	5046 Hlompho Street	28.36044	-25.745396	3
50	5093 Hlompho Street	28.35985	-25.745065	2
51	4238 Hulp Street	28.363855	-25.74183	2
52	2515 Itekela Street	28.358998	-25.730817	3
53	1165 Kabylie Street	28.369065	-25.733533	1
54	1055 Kabylie Street	28.366631	-25.73333	2
55	1771 Kaizer Chiefs Road	28.370471	-25.73785	1
56	3610 Kamogelo Street	28.359915	-25.738158	2
57	3328 Kamogelo Street	28.359856	-25.738409	3
58	3100 Karabo Street	28.360176	-25.733872	2
59	3032 Karabo Street	28.360088	-25.732425	2
60	2013 Leeds Street	28.372034	-25.736488	1
61	6149 Lesedi Street	28.35169	-25.741562	2
62	6156 Lesedi Street	28.352235	-25.741566	2
63	5315 Lokile Street	28.357966	-25.744418	3
64	5269 Malebo Road	28.359596	-25.742143	3
65	3691 Malebo Road	28.357629	-25.736714	3
66	3674 Malebo Street	28.3588	-25.737388	2
67	5953 Moeletsi Street	28.353184	-25.744042	2
68	5996 Moeletsi Street	28.353893	-25.745834	2
69	4665 Mogwera	28.361849	-25.743327	2

Continued on Next Page…

Table A.1 – Continued

ID	Address	X Coordinate	Y Coordinate	Visit Type
70	4219 Mokwadi Street	28.363878	-25.742926	3
71	4215 Mokwadi Street	28.364316	-25.743014	3
72	2475 Moreri Street	28.35986	-25.730829	3
73	2388 Moreri Street	28.358367	-25.729295	2
74	4545 Motlotlegi Street	28.361588	-25.741503	2
75	4518 Motlotlegi Street	28.361535	-25.741059	2
76	1326 Ntokozo Street	28.370142	-25.732859	3
77	4619 Odirile Avenue	28.362767	-25.74221	3
78	4648 Odirile Avenue	28.361867	-25.742695	3
79	4368 Odirile Avenue	28.363334	-25.741522	3
80	4244 Odirile Street	28.363997	-25.741625	2
81	4564 Odirile Street	28.363053	-25.741616	2
82	3114 Ofentse Street	28.359298	-25.734097	3
83	2875 Ofentse Street	28.360104	-25.734512	2
84	2872 Ofentse Street	28.3598	-25.734698	2
85	1966 Orlando Pirates Street	28.373351	-25.737111	3
86	4704 Phedisana Street	28.362731	-25.743445	2
87	3148 Poelano Street	28.358395	-25.733131	2
88	2963 Poelano Street	28.360398	-25.732647	2
89	3197 Poelano Street	28.358401	-25.733299	2
90	1080 Qwa Qwa Stars Road	28.367358	-25.734275	1
91	1255 Qwa Qwa Stars Road	28.367783	-25.732326	3
92	1216 Qwa Qwa Stars Road	28.367672	-25.73264	2
93	1052 Qwa Qwa Stars Road	28.36702	-25.733298	3
94	374 Qwa Qwa Stars Road	28.346576	-25.739347	2
95	2438 Raadpleeg Street	28.360521	-25.730019	3
96	2364 Raadpleeg Street	28.360008	-25.72904	3
97	2467 Raadpleeg Street	28.360051	-25.73032	3
98	2446 Raadpleeg Street	28.360291	-25.729423	2
99	2366 Raadpleeg Street	28.359864	-25.729243	3
100	2458 Raadpleeg Street	28.360033	-25.729777	2
101	1349 Ravens Street	28.370833	-25.733612	2
102	4717 Saamroep Street	28.36171	-25.743572	3
103	4418 Saamroep Street	28.360306	-25.741422	2
104	1149 Santos Street	28.367966	-25.734181	3
105	1114 Santos Street	28.369402	-25.733547	2
106	3450 Sebaka Street	28.356106	-25.735497	3
107	4186 Serumola Street	28.365082	-25.740393	1
108	3874 Serumola Street	28.365708	-25.740809	3
109	2798 Setso Street	28.36295	-25.732337	3
110	2787 Setso Street	28.363916	-25.732492	2
111	3230 Somandla Street	28.357716	-25.731728	3

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Table A.1 – Continued

ID	Address	X Coordinate	Y Coordinate	Visit Type
112	3003 Somandla Street	28.357991	-25.732156	3
113	4058 Somandla Street	28.362912	-25.736832	2
114	3225 Somandla Street	28.35809	-25.731718	2
115	4330 Somandla Street	28.357716	-25.743398	2
116	5349 Sterkte Street	28.359034	-25.732319	1
117	2829 Sterkte Street	28.363487	-25.734144	3
118	2160 Sterkte Street	28.361982	-25.733851	2
119	1673 Strikers Street	28.369185	-25.737612	2
120	2585 Thabo Street	28.36291	-25.731357	3
121	2750 Thabo Street	28.363144	-25.730934	3
122	2583 Thabo Street	28.362761	-25.731188	2
123	2527 Thabo Street	28.358575	-25.730613	2
124	2560 Thabo Street	28.361733	-25.730951	1
125	2321 Thereso Street	28.358301	-25.730487	2
126	4118 Tokelo Street	28.362087	-25.737872	2
127	4109 Tokelo Street	28.362049	-25.737281	2
128	4302 Tsebiso Street	28.357848	-25.744776	2
129	3134 Tshepo Street	28.357623	-25.733287	2
130	3289 Tshepo Street	28.357313	-25.733292	2
131	2627 Tumelo Street	28.361731	-25.732102	3
132	1038 Warriors Street	28.367	-25.731894	3
CW1	2399 Boleng Street	28.360688	-25.728847	–
CW2	5425 Gaugela Street	28.356504	-25.742288	–
CW3	2817 Hallelujah Crescent	28.363074	-25.733602	–
CW4	6100 Mapule	28.350754	-25.742166	–
CW5	1996 Orlando Pirates Road	28.37316	-25.737401	–

Appendix B

Internodal Distance Matrix

Table B.1: Partial internodal distance matrix[a]

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	0	1169	1311	1034	1201	448	907	933	972	69	1020	719	1062	706	477	652	586	972	226	271	270	236	260	1227	2339
2	1169	0	161	140	36	724	333	236	197	1177	2072	1798	2037	1760	832	600	693	468	1003	1057	925	956	962	125	2857
3	1311	161	0	279	125	863	430	386	348	1322	2183	1916	2137	1875	943	710	801	509	1133	1180	1058	1090	1092	92	2881
4	1034	140	279	0	169	587	207	109	74	1043	1932	1658	1899	1620	693	462	555	373	864	917	786	817	823	205	2750
5	1201	36	125	169	0	755	352	269	230	1209	2097	1825	2060	1786	857	623	716	474	1032	1085	954	986	991	98	2863
6	448	724	863	587	755	0	465	489	528	464	1383	1095	1378	1064	249	249	234	563	289	365	206	235	251	779	2450
7	907	333	430	207	352	465	0	196	208	929	1752	1487	1710	1445	513	280	371	198	714	753	644	677	673	340	2546
8	933	236	386	109	269	489	196	0	39	940	1852	1572	1827	1537	620	397	488	391	772	832	692	723	732	314	2729
9	972	197	348	74	230	528	208	39	0	979	1888	1610	1861	1573	654	428	520	396	810	869	730	761	770	278	2750
10	69	1177	1322	1043	1209	464	929	940	979	0	1060	758	1111	750	524	684	625	1006	278	335	308	275	307	1241	2405
11	1020	2072	2183	1932	2097	1383	1752	1852	1888	1060	0	312	201	330	1281	1523	1427	1775	1131	1055	1217	1192	1169	2160	1716
12	719	1798	1916	1658	1825	1095	1487	1572	1610	758	312	0	399	67	1006	1246	1153	1521	832	765	918	891	872	1886	1900
13	1062	2037	2137	1899	2060	1378	1710	1827	1861	1111	201	399	0	382	1247	1485	1388	1709	1134	1047	1219	1199	1168	2112	1532
14	706	1760	1875	1620	1786	1064	1445	1537	1573	750	330	67	382	0	962	1204	1109	1471	801	729	888	862	840	1843	1858
15	477	832	943	693	857	249	513	620	654	524	1281	1006	1247	962	0	234	142	519	251	252	224	253	218	853	2205
16	652	600	710	462	623	249	280	397	428	684	1523	1246	1485	1204	234	0	93	322	444	475	382	416	404	619	2361
17	586	693	801	555	716	234	371	488	520	625	1427	1153	1388	1109	142	93	0	388	369	389	317	351	330	711	2288
18	972	468	509	373	474	563	198	391	396	1006	1775	1521	1709	1471	519	322	388	0	757	771	701	736	718	421	2389
19	226	1003	1133	864	1032	289	714	772	810	278	1131	832	1134	801	251	444	369	757	0	100	84	65	41	1046	2253
20	271	1057	1180	917	1085	365	753	832	869	335	1055	765	1047	729	252	475	389	771	100	0	173	163	121	1090	2154
21	270	925	1058	786	954	206	644	692	730	308	1217	918	1219	888	224	382	317	701	84	173	0	34	52	972	2316
22	236	956	1090	817	986	235	677	723	761	275	1192	891	1199	862	253	416	351	736	65	163	34	0	50	1004	2314
23	260	962	1092	823	991	251	673	732	770	307	1169	872	1168	840	218	404	330	718	41	121	52	50	0	1005	2267
24	1227	125	92	205	98	779	340	314	278	1241	2160	1886	2112	1843	853	619	711	421	1046	1090	972	1004	1005	0	2801
25	2339	2857	2881	2750	2863	2450	2546	2729	2750	2405	1716	1900	1532	1858	2205	2361	2288	2389	2253	2154	2316	2314	2267	2801	0
26	730	1288	1365	1158	1305	765	955	1108	1137	799	944	764	840	700	525	713	628	864	585	490	638	641	592	1274	1916
27	1196	1984	2060	1853	2001	1408	1651	1798	1828	1258	585	692	385	644	1192	1401	1312	1555	1160	1062	1235	1224	1183	1969	1340
28	1100	1957	2043	1823	1976	1347	1624	1761	1793	1158	445	551	248	507	1146	1365	1273	1545	1085	991	1164	1150	1112	1951	1488
29	1162	1984	2064	1851	2002	1391	1651	1793	1824	1222	518	632	318	586	1182	1396	1306	1562	1136	1040	1213	1201	1161	1973	1401
30	900	1530	1601	1401	1545	1002	1197	1353	1381	969	811	713	668	646	767	959	873	1095	795	696	857	856	808	1511	1659
31	2036	2335	2337	2242	2336	2041	2046	2239	2254	2105	1692	1773	1491	1715	1792	1905	1846	1871	1900	1806	1947	1954	1904	2264	724
32	2117	2476	2483	2379	2478	2151	2180	2371	2387	2186	1693	1803	1494	1749	1902	2027	1964	2010	1994	1898	2045	2050	2000	2408	538
33	1414	1908	1947	1794	1917	1481	1588	1766	1788	1482	1078	1118	882	1057	1236	1392	1318	1444	1301	1203	1358	1359	1310	1863	1103
34	1401	1851	1887	1739	1859	1446	1534	1715	1736	1470	1125	1145	932	1083	1199	1346	1275	1386	1277	1180	1331	1334	1284	1803	1154
35	1794	1983	1979	1896	1982	1742	1705	1899	1912	1864	1631	1645	1437	1582	1496	1584	1534	1524	1634	1546	1671	1682	1632	1908	1116
36	1870	2035	2026	1951	2033	1811	1761	1957	1969	1939	1707	1725	1511	1661	1566	1649	1600	1578	1708	1620	1743	1755	1705	1956	1107
37	1070	1677	1740	1552	1691	1174	1346	1509	1536	1138	832	800	659	736	936	1119	1037	1231	970	870	1032	1030	983	1651	1460
38	956	1630	1703	1501	1647	1089	1297	1451	1480	1023	742	681	585	616	859	1056	969	1197	869	769	935	931	885	1613	1578
39	628	1664	1779	1524	1690	971	1348	1442	1478	677	425	154	449	100	835	1069	977	1328	684	611	768	744	720	1688	2066
40	596	1652	1770	1512	1679	953	1340	1428	1465	643	445	152	485	116	827	1060	969	1326	665	596	748	723	702	1679	2116
41	502	1293	1396	1156	1316	659	967	1085	1119	571	819	577	768	521	465	694	601	926	412	313	484	476	433	1304	2102
42	621	1450	1548	1313	1472	820	1121	1244	1278	688	679	477	609	413	625	851	758	1068	565	468	641	630	589	1456	1953
43	361	1356	1475	1216	1383	660	1046	1132	1169	424	746	456	751	418	534	766	676	1042	374	300	458	435	410	1385	2255
44	677	1682	1793	1543	1707	1001	1362	1463	1499	729	403	181	400	114	851	1084	992	1332	716	637	800	778	751	1701	1991
45	362	1405	1527	1265	1432	700	1099	1178	1215	418	708	408	728	378	589	819	731	1101	411	348	495	469	449	1437	2278
46	617	1669	1786	1529	1695	972	1356	1445	1482	664	425	137	463	95	843	1076	985	1340	683	614	767	743	721	1695	2096
47	726	562	660	429	583	324	231	380	407	759	1573	1303	1527	1258	289	76	149	246	514	538	456	490	474	569	2677
48	1922	1646	1585	1605	1632	1694	1462	1650	1648	1984	2143	2056	1973	1989	1492	1468	1460	1264	1711	1650	1711	1735	1691	1540	1926
49	1830	1699	1658	1641	1690	1650	1477	1672	1675	1895	1954	1889	1777	1822	1430	1441	1419	1280	1629	1560	1641	1661	1614	1602	1685
50	1820	1736	1701	1674	1728	1658	1505	1700	1705	1886	1907	1852	1727	1785	1433	1455	1429	1309	1625	1552	1640	1659	1611	1643	1604

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[a] The complete internodal distance matrix is included on the compact disc accompanying this document

Appendix C

Initial solution

Table C.1: Schedule: Initial Solution

Worker1	**Week 1**	**Week 2**	**Week 3**	**Week 4**
Day 1	11 28 46 98 116 124	11 28 46 98 116 124	11 28 46 98 116 124	11 28 46 99 116 124
Day 2	12 28 46 100 116 124	13 39 52 100 122 125	13 39 59 100 122 125	13 39 59 100 122 125
Day 3	13 39 59 111 122 125	14 40 59 114 123	14 40 73 114 123	14 40 73 114 123
Day 4	14 40 73 114 123	28 46 73 116 124	28 46 88 116 124	28 46 88 116 124
Day 5	28 46 88 116 124	28 46 88 116 124	28 46 96 116 124	28 46 98 116 124
Worker2	**Week 1**	**Week 2**	**Week 3**	**Week 4**
Day 1	34 50 74 86 113	35 50 74 86 113	36 50 74 86 113	36 51 74 102 113
Day 2	36 51 75 103 126	36 51 75 103 126	48 51 75 103 126	48 56 75 103 126
Day 3	48 56 77 107 127	48 56 78 107 127	48 56 79 107 127	48 57 80 107 127
Day 4	48 63 80 107	48 64 80 107	48 69 80 107	48 69 81 107
Day 5	48 69 81 107	48 69 81 107	49 70 81 107	50 71 86 107
Worker3	**Week 1**	**Week 2**	**Week 3**	**Week 4**
Day 1	1 19 53 82 92 118	6 23 53 83 95 118	6 23 53 83 97 118	6 23 53 83 101 120
Day 2	6 23 53 83 101 121	15 26 53 90 101 131	15 30 53 90 101 132	15 38 53 90 105
Day 3	15 41 53 90 105	19 41 53 90 105	19 41 53 90 105	19 41 54 90 108
Day 4	19 42 54 90 109	19 42 54 90 110	19 42 54 90 110	19 42 58 90 110
Day 5	19 43 58 90 110	19 44 58 92 112	19 45 58 92 117	19 53 72 92 118
Worker4	**Week 1**	**Week 2**	**Week 3**	**Week 4**
Day 1	25 32 62 87 129	25 32 61 84 128	25 32 62 84 128	25 32 62 87 128
Day 2	25 32 66 89 130	25 32 62 87 129	25 32 65 87 129	25 32 66 89 129
Day 3	25 32 67 94	25 32 66 89 130	25 32 66 89 130	25 32 67 94 130
Day 4	27 37 68 115	27 33 67 94	27 37 67 94	27 37 68 106
Day 5	31 61 84 128	31 37 68 115	31 61 68 115	31 61 84 115
Worker5	**Week 1**	**Week 2**	**Week 3**	**Week 4**
Day 1	2 5 9 16 55 60	2 7 9 16 55 60	2 7 9 17 55 76	2 7 9 18 55 85
Day 2	2 7 9 18 55 91	2 8 9 18 55 93	2 8 9 18 55 104	2 8 9 20 55 119
Day 3	2 8 9 21 55 119	2 8 10 22 55 119	2 8 16 24 60 119	2 8 16 24 60
Day 4	3 8 16 24 60	3 8 16 24 60	3 8 16 47 60	3 8 16 47 60
Day 5	4 8 16 47 60	5 9 16 47 60	5 9 16 55 60	5 9 16 55 60

Appendix D

Improved Solution

Table D.1: Improved Solution: Worker 1

Week 1 Schedule	**Duration**	**Week 2 Schedule**	**Duration**
73–11–111–116–114–28	200.2	129–28–114–88–11	172.41
28–88–116–123–46–100	203.52	14–98–13–28–116–46	199.67
12–13–59–124–125	171.5	46–100–116–59–124	166.22
98–28–14–124–46	168.5	116–122–125–73–124–40	206.37
39–46–122–124–116–40	197.51	39–46–124–28–52	167.85
Total Duration	**941.23**	**Total Duration**	**912.52**
Week 3 Schedule	**Duration**	**Week 4 Schedule**	**Duration**
125–46–114–73–13–11	205.05	114–100–46–124–28	169.4
96–116–46–39–122–124	196.92	99–11–125–122–116–28	206.62
123–28–116–40–124	168.51	124–40–46–123–14	162.86
88–59–28–116–98	167.84	116–88–59–39–46	163.69
46–100–28–124–14	170.62	98–28–13–116–73–124	206.19
Total Duration	**908.94**	**Total Duration**	**908.76**

Table D.2: Improved Solution: Worker 2

Week 1 Schedule	**Duration**	**Week 2 Schedule**	**Duration**
103–74–51–48–50	185.26	75–107–48–78	162.7
36–107–113–126	159.73	36–127–113–107–81	191.61
48–63–77–75–56	196.78	51–50–48–69–80	198.68
48–127–107–34	174.2	48–103–74–86	158.71
86–69–81–107–80	186.22	35–107–126–56–64	189.12
Total Duration	**902.18**	**Total Duration**	**900.81**
Week 3 Schedule	**Duration**	**Week 4 Schedule**	**Duration**
48–70–49–50–36	185.26	81–107–74–103	150.37
113–126–127–86–48	197.35	57–113–127–75	152.27
48–107–80–51	160.00	48–80–71–51–107	195.04
75–79–74–81–107	186.75	56–50–86–48–36	197.24
69–103–56–107	162.11	69–48–102–126–107	202.01
Total Duration	**894.47**	**Total Duration**	**896.93**

Table D.3: Improved Solution: Worker 3

Week 1 Schedule	**Duration**	**Week 2 Schedule**	**Duration**
41–110–1–92–105	165.47	26–90–105–53–92	165.45
118–42–58–83–43–19	196.26	19–95–44–112–131	173.62
23–53–90–121–19	173.81	58–90–23–19–83	173.89
109–101–6–15–90–53	201.25	15–53–54–6–101–90	201.38
82–54–53–90–19	172.27	41–53–110–42–118–19	204.45
Total Duration	**909.06**	**Total Duration**	**918.78**
Week 3 Schedule	**Duration**	**Week 4 Schedule**	**Duration**
83–53–101–90–54	173.16	15–90–105–53–19	163.46
30–42–97–23–19	174.8	101–92–23–72–42	176.16
45–19–92–15–90	163.85	38–110–118–6–90–19	209.96
53–132–19–6–90–118	201.62	41–120–90–19–53	167.87
53–105–41–58–117–110	202.71	83–53–54–108–58	189.78
Total Duration	**916.14**	**Total Duration**	**907.24**

Table D.4: Improved Solution: Worker 4

Week 1 Schedule	**Duration**	**Week 2 Schedule**	**Duration**
27–25–94–32	163.89	130–33–128–62	167.88
32–25–31–68–115	190.32	66–129–27–37–84	197.39
32–61–37–129	157.82	25–32–67–61	143.59
25–87–84–89–130	201.96	25–94–68–32–31	186.02
66–67–128–62	165.75	115–87–89–25–32	205.41
Total Duration	**879.71**	**Total Duration**	**900.29**
Week 3 Schedule	**Duration**	**Week 4 Schedule**	**Duration**
115–32–27–87	176.45	32–84–66–94	167.94
84–89–130–37–25	202.62	67–115–32–25	154.28
94–25–31–32–128	193.25	31–25–32–68–128	194.29
25–32–61–62	137.41	61–62–130–106–87	195.63
68–67–65–129–66	199.06	25–37–27–89–129	201.72
Total Duration	**908.80**	**Total Duration**	**913.86**

Table D.5: Improved Solution: Worker 5

Week 1 Schedule	**Duration**	**Week 2 Schedule**	**Duration**
3–2–18–16–55–24	200.8	55–10–93–16–2	175.76
2–7–9–60–55–4	193.1	16–9–5–3–60–8	193.75
2–8–9–60–55–119	191.49	9–55–119–16–2–60	193.22
5–8–16–21–91	171.49	2–54–8–47–22	169.71
9–8–16–47–60	156.61	60–7–9–8–55–18	186.93
Total Duration	**913.5**	**Total Duration**	**919.38**
Week 3 Schedule	**Duration**	**Week 4 Schedule**	**Duration**
16–47–60–8–55	162.59	2–8–24–3–9	166.5
9–2–8–55–18–7	189.44	9–60–8–119–55–2	201.71
9–76–55–16–2–60	205.21	9–20–16–55–7	174.72
119–24–2–9–5–3	198.3	2–18–16–60–55	172.9
60–17–16–104–8	164.1	16–47–5–60–85–8	202.04
Total Duration	**919.64**	**Total Duration**	**917.86**

Appendix E

Exact routing algorithm: LINGO®code

```
Model:

Sets:
Node/1..5/:U;
TimeWindow/2..N/:T;
Link(Node,Node):Dist,X;
Endsets

Data:
Dist=@ole('Distance.xls','distance');
TimeWindow=@ole('Time.xls','timew');

enddata

N=@SIZE(Node);
MIN=@sum(Link:Dist*X);
@For(Node(K):@sum(Node(I):X(I,K))=1;);
@For(Node(K):@sum(Node(J):X(K,J))=1;);
@For(Node(K):@For(Node(J)—J#GT#1#AND#K#GT#1:
U(J)-U(K)+N*X(J,K)¡N-1;));
@For(Link:@Bin(X););

end
```

Appendix F

Algorithm evaluation results

Table F.1: Summary of algorithm evaluation results

Worker 1	**Solution Algorithm Results (min)**	**LINGO Results (min)**	**Maximum Schedule Duration (min)**
Week 1	941.23	925.00	1200
Week 2	912.52	895.26	1200
Week 3	908.94	892.08	1200
Week 4	908.76	892.65	1200
Total	3671.45	3604.99	4800.00
Worker 2	**Solution Algorithm Results (min)**	**LINGO Results (min)**	**Maximum Schedule Duration (min)**
Week 1	879.18	869.23	1200
Week 2	877.81	862.11	1200
Week 3	871.47	858.85	1200
Week 4	873.93	865.46	1200
Total	3502.39	3455.65	4800.00
Worker 3	**Solution Algorithm Results (min)**	**LINGO Results (min)**	**Maximum Schedule Duration (min)**
Week 1	909.06	892.56	1200
Week 2	918.78	905.18	1200
Week 3	916.14	904.96	1200
Week 4	907.24	895.42	1200
Total	3651.22	3598.12	4800.00
Worker 4	**Solution Algorithm Results (min)**	**LINGO Results (min)**	**Maximum Schedule Duration (min)**
Week 1	879.71	866.31	1200
Week 2	900.29	889.33	1200
Week 3	908.80	899.34	1200
Week 4	913.86	906.91	1200
Total	3602.66	3561.89	4800.00
Worker 5	**Solution Algorithm Results (min)**	**LINGO Results (min)**	**Maximum Schedule Duration (min)**
Week 1	913.50	909.92	1200
Week 2	919.38	914.40	1200
Week 3	919.64	912.84	1200
Week 4	917.86	909.62	1200
Total	3670.38	3646.78	4800.00