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Developing robust distribution networks for future urban planning scenarios

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Abstract

Supply chain planning of consumer goods distribution is a constant process with expanding cities and increasing consumer demand. This project is based in the municipality of Ekurhuleni, Gauteng, South Africa. The aim of the project is to develop a model that will use data of the predicted population distribution of Ekurhuleni in 2030 to develop a robust supply chain for consumer goods.

Three possible development and population layout scenarios that the future of the municipality could embody were investigated. A model was developed to locate a distribution centre (DC) and develop a distribution network, that will be compatible with all three of these scenarios. A literature review was conducted to determine the best practices in the fields of facility location modelling, distribution network development, robust networks and optimisation models. An algorithm was developed based on the best practices and the data of the *UrbanSim* model to solve the problem. The municipality was divided into 1058 zones and based on the algorithm the best zone to locate the DC is zone 538.

This zone placement passes with a logical test, since the total cost is lower if the DC is located near the center of the municipality rather than on the outskirts of the municipality. Further verification and validation was done on the model. Sensitivity analysis on the model was done by changing certain parameters such as the number of trucks, the capacity of the trucks, and the operating cost per truck. The operating cost per truck has the most influence on the robustness of the distribution network. A maximum total saving of R 63 279 could made by using this approach to place a DC and develop a distribution network for consumer goods. Thus if the impact on a small scale problem is already this significant, the impact on a full scale distribution operation could be tremendous. Future work should consider determining the demand per zone more accurately and in categories since it will impact the given solution.

Declaration of originality

I, Carike Karsten, u15012396, hereby declare that the work in this document is my own original work and that the list of references provides a complete list of the sources cited in this document.

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Chapter 1

Introduction

1.1 Background

South Africa is a developing country at the southern tip of Africa. In 2011 the South African population was 51.7 million and it grew to 55.6 million in the subsequent 5 years. The current average population growth per year in South Africa is 2.207% [2].

The population growth in urban areas and the expansion of cities to surrounding areas is known as urban growth. This is a result of both population growth and people relocating from rural areas to urban areas mainly for work opportunities. Urban growth leads to an increase in economic development for both the city and the country [40].

A wide variety of people live in these urban areas. These people can be classified into household types. Each of the different household types have specific attributes. The households types have a certain demand level range for consumer products. Population and urban growth leads to an increase in this demand for consumer products, especially in urban areas for all household types. The continuous change in both demand and the city form makes it more difficult to develop robust distribution networks for these consumer products. Supply chains have to be designed and implemented to continuously keep up with the demand.

A supply chain is a series of activities that converge raw materials into finished products, as is illustrated in Figure 1.1. A supply chain of consumer products can be simply explained for example by the process that is followed to transform cocoa beans into a chocolate. The supply chain process starts at the farmer who plants and harvests the cocoa beans. The cocoa beans are then transported to a refinery, where the beans are processed. The refined cocoa is transported to the chocolate factory, where the chocolate is manufactured. The chocolate is then transported to a distribution centre (DC), where it is stored. From the DC, the chocolate is delivered to the retailers where the consumer can buy a chocolate.

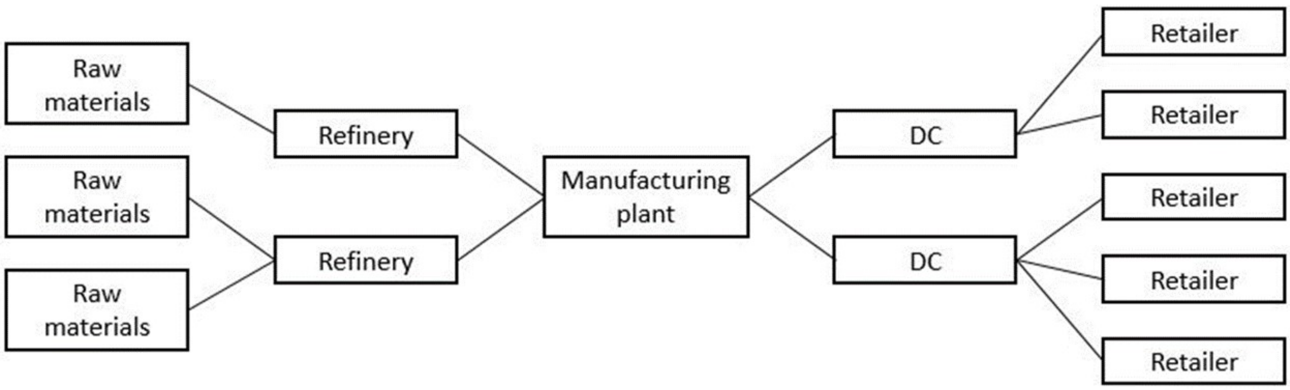

Figure 1.1: Simple supply chain

Supply chains and distribution networks have to expand continuously as a result of population growth and expanding cities. To develop a long term supply chain strategy, the estimated demand of the consumer products for the next couple of decades must be taken into account.

The role of urban supply chain planning has increased due to rapid advances in smart city design where the cities are designed for robustness and sustainability in the long run [15]. In order for a supply chain to be robust in the long run, the supply chain configuration should ensure that it remains at the desired performance level for multiple possible future scenarios.

It is important to evaluate both logistics and urban planning simultaneously when developing a new distribution network. Urban planning is needed to understand the current and future environment in which the distribution network will be deployed in, while logistics is required to develop the distribution network. Thus both are crucial parts of the process of developing a distribution network.

A supply chain is the combination of distribution networks to move goods from point A to point B. Facility location models place the DCs in the best strategic locations [9].

This distribution network and facility location project is based in the Ekurhuleni municipality in Gauteng, South Africa. The location of Ekurhuleni is show in Figure 1.2. This municipality is chosen due to the development potential in the area. There is a great deal of freight movement in the area around the O.R. Tambo international airport and this will increase more with the planned expansions in the area.

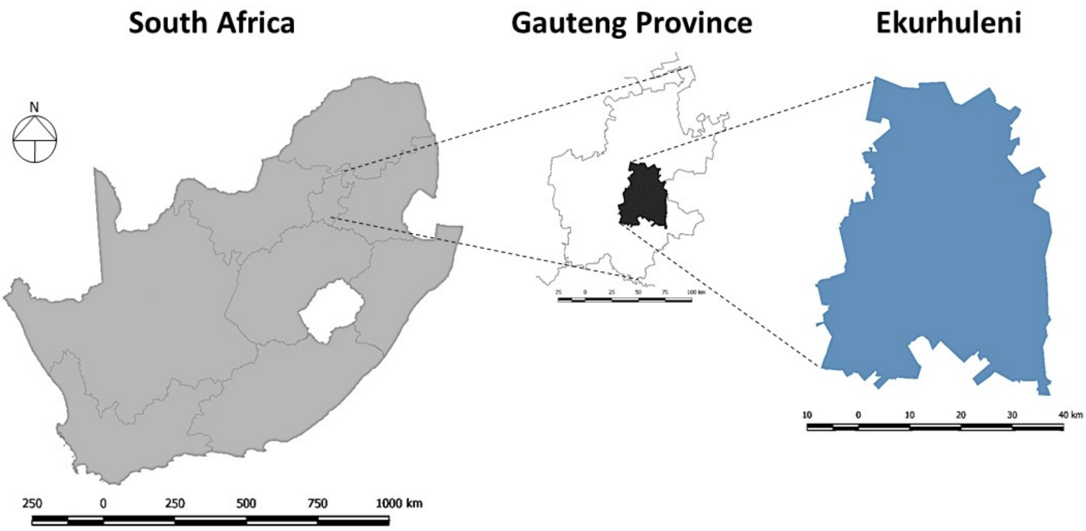

Figure 1.2: Ekurhuleni with regards to South Africa

Due to the planned expansions and the implementation of these projects the population of the municipality as well as the industries in the area will drastically increase. The demand is based the population size and distribution in the given area and period. The population size and distribution is an output of *UrbanSim* models. *UrbanSim* is an urban development simulation software package that supports the planning and analysis of development in urban areas [44]. *UrbanSim* uses data of interaction between various role players and parameters such as the current population, land use, the economy, and transportation to ultimately make decisions with regards to the city form in the couple of years [43].

1.2 Rationale and problem statement

The growth and expansion of cities lead to an increase in consumer product demand and an increase in the distribution network area. These factors increase the difficulty to develop a robust supply chain for the future.

Long term distribution network decisions of today will have a big impact on the future logistics of the company [9]. The design of the distribution network of a company is of utmost importance in order to keep a competitive advantage and to be able to easily adapt to the changes occurring in the supply chain during the next 30 years. Having to regularly alter a distribution network is very costly for a company because it affects the cost, time and quality of the customer service [20].

Logistics cost consumes a large part of a company's budget. These costs can be reduced by carefully designing the supply chain, but especially the last mile distribution of consumer goods [34]. In 2014 the logistics cost of a product was 11.2% of the Gross Domestic Product which is the market value of a given product. These logistics costs are set to increase at a rate of just under 1% per year. There are four main contributors to logistics costs namely transportation (57%), warehousing (15.2%), inventory carrying cost (14.6%) and management and administration cost (13.2%) [18]. Thus especially transportation costs have a huge impact on the supply chain cost. A saving of R 63 279 in logistics costs was seen in the small facility location and distribution network project, thus the savings can become even grater on a large project.

Another important aspect to consider in logistics is the location of DCs. Currently there is a lack of models that investigate the location of DCs and the distribution network of consumer goods to customers, based on how a city will expand in the future.

1.3 Objective

The objective of the project is to design a distribution network model that will be compatible with any of the multiple scenarios for the Ekurhuleni municipality in 2030, while also catering for the current demand.

Using the output data of *UrbanSim* the predicted population distribution of 2030 will be used for supply chain planning of consumer goods. The model should locate a DC on the best strategic place, consider the fleet size of each DC and develop a distribution network for the last mile delivery of consumer goods to the customers. During the project the link between urban planning and supply chain design will be investigated for the last mile transportation of consumer goods.

1.4 Project Approach

The project started by identifying an improvement opportunity. Once the opportunity was identified a detailed problem investigation was done. An in-depth literature review was conducted in order to become familiar with the best practices of robust distribution network design, facility location modelling and optimisation models. Once the best practices have been identified the model formulation was done. The formulation ensured that all aspects of the problem was considered before developing the algorithm.

The problem was solved using a local search optimisation technique. The model and the solution was evaluated and verified to ensure that the model leads a robust solution.

1.5 Document structure

The remaining chapters of the document are organised as follows: Chapter 2 is an in-depth investigation of the problem. Chapter 3 is the critical literature review of the best practices and solution techniques. Chapter 4 is the conceptual design in which the data preparation is described and mathematical formulation is done. Chapter 5 is the discussion and interpretation of the solution. Chapter 6 is the discussion of the model verification and validation. Lastly, Chapter 7 is a conclusion on the work done thus far and a description of future work that can be done with regards to the project.

Chapter 2

Problem investigation

With cities expanding rapidly, it is difficult to determine what a city would look like in a few decades' time and, in turn, what the demand for a product would be. Urban growth modelling is often used as a tool to predict what the future spatial distributions of households and jobs would be in a city. To this extent, the CSIR has implemented UrbanSim® in multiple cities, of which Ekurhuleni is one. The output of the simulation models were made available as a base to work from in this project.

Ekurhuleni had a population of 3 118 574 in 2011 and it is expected to grow to 4 852 896 in 2030, which translates to a yearly growth of almost 2% [43]. A synthetic population was created based on this data for simulation purposes. A synthetic population is a representation of the actual population with only the crucial attributes for modelling purposes [40]. The synthetic population is segmented into categories by attributes such as income class, job type and their living arrangement (the type of house and the number of people in their household).

Furthermore, to assist with data allocation the entire municipality is divided into 1058 zones, as seen in Figure 2.1, to assist with the data allocation. These zones are all approximately $3m^2$. Each zone consists of a number of parcels, where parcels refer to cadastral parcels — a representation of the individual erven. Parcels are classified according to their underlying land-use and a parcel could either be built-up (has one or more buildings present) or vacant (has no buildings). Vacant parcels are areas that can still be developed and for the purposes of this project, only these will be considered when placing the DC. the difference between vacant and built-up parcels can be seen in Figure 2.2.

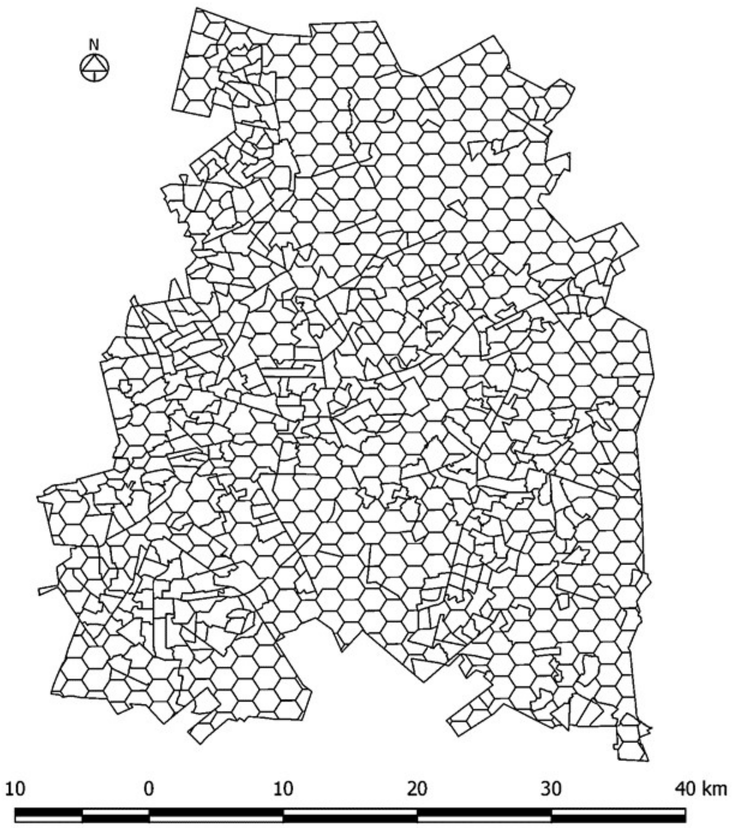

Figure 2.1: Ekurhuleni divided into 1058 zones

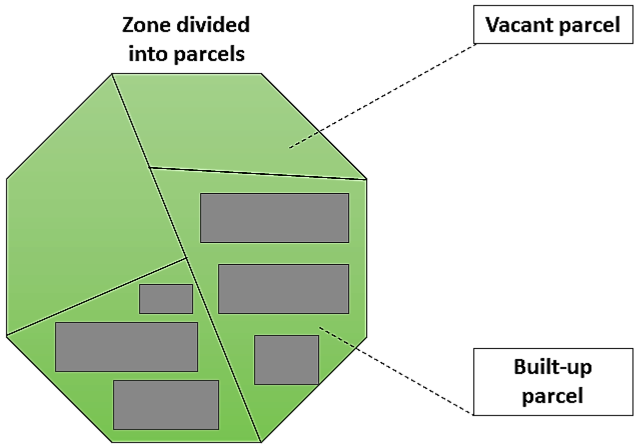

Figure 2.2: Schematic illustration of different land utilisation parcels constructing a zone

The municipality has identified 21 projects that they would like to implement in the next 20 years to stimulate the economy and ensure growth. Most of these projects are planned in or close to the priority areas, which are earmarked as areas in which development is prioritised through higher densities and focused investment in infrastructure projects.

Data related to the 21 projects and priority areas were included in the CSIR's *UrbanSim* simulation model together with a base synthetic population and job opportunities in the city.

Three scenarios were developed between the CSIR and the municipality to see what the possible future spatial distribution would be for different city futures. The scenarios reflect differences in household and economic growth in the city, which would influence where households and jobs are located in future. These three scenarios are: *Trend*, *Aerotropolis* and *Human Settlements Project* (HSP), and will be described in more detail in the rest of this chapter.

2.1 Scenarios

2.1.1 Trend

In the **trend scenario**, 11 of the 21 planned projects of the municipality will be completed; these are the projects in the priority zones as previously mentioned. This scenario leads to an increase in both residential and industrial activity. This scenario is more or less a continuation of the current development rate in Ekurhuleni. The number of the households and location of these households of this scenario's simulation are illustrated in Figure 2.3. The total households in 2030 in this scenario is 1 756 631.

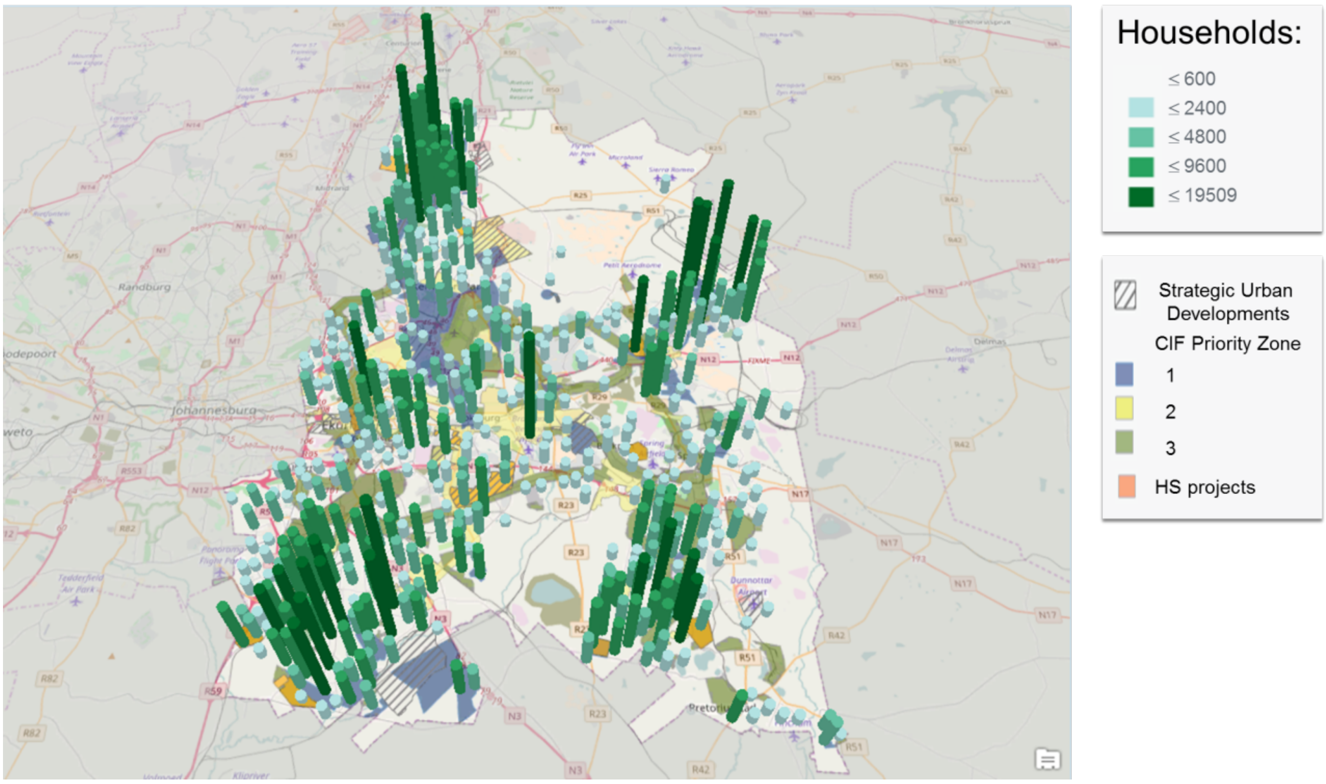

Figure 2.3: Total number of households in each zone in 2030 given the trend scenario [43].

2.1.2 Aerotropolis

The **aerotropolis scenario** is an aggressive scenario where all 21 of the projects of the municipality will be completed. This will lead to a significant increase in industrial activity making it an economic hub and leading to a large increase in the number of jobs available. Many of these projects are located around the O.R.Tambo international airport in Johannesburg. This scenario will lead to significant economic development. The number of the households and location of these households of this scenario's simulation is illustrated in Figure 2.4. The total households in 2030 in this scenario is 1 786 766.

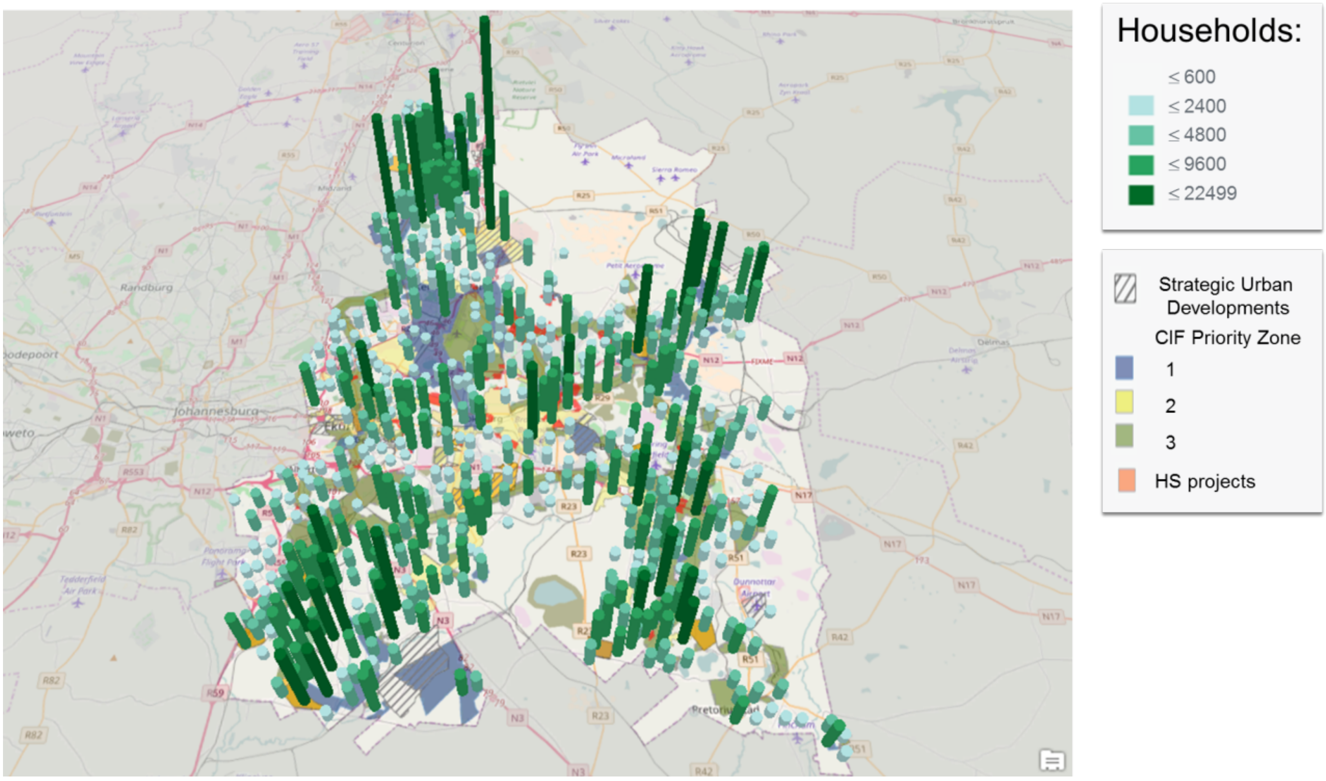

Figure 2.4: Total number of households in each zone in 2030 given the aerotropolis scenario [43].

2.1.3 Human Settlements Project

The **HSP scenario** is mainly focused on housing projects. Most of the larger housing projects are broken up into small projects in strategically located areas closer to transportation and jobs. This will lead to densification of already built-up areas. The number of the households and location of these households of this scenario's simulation is illustrated Figure 2.5. The total households in 2030 in this scenario is 1 783 283.

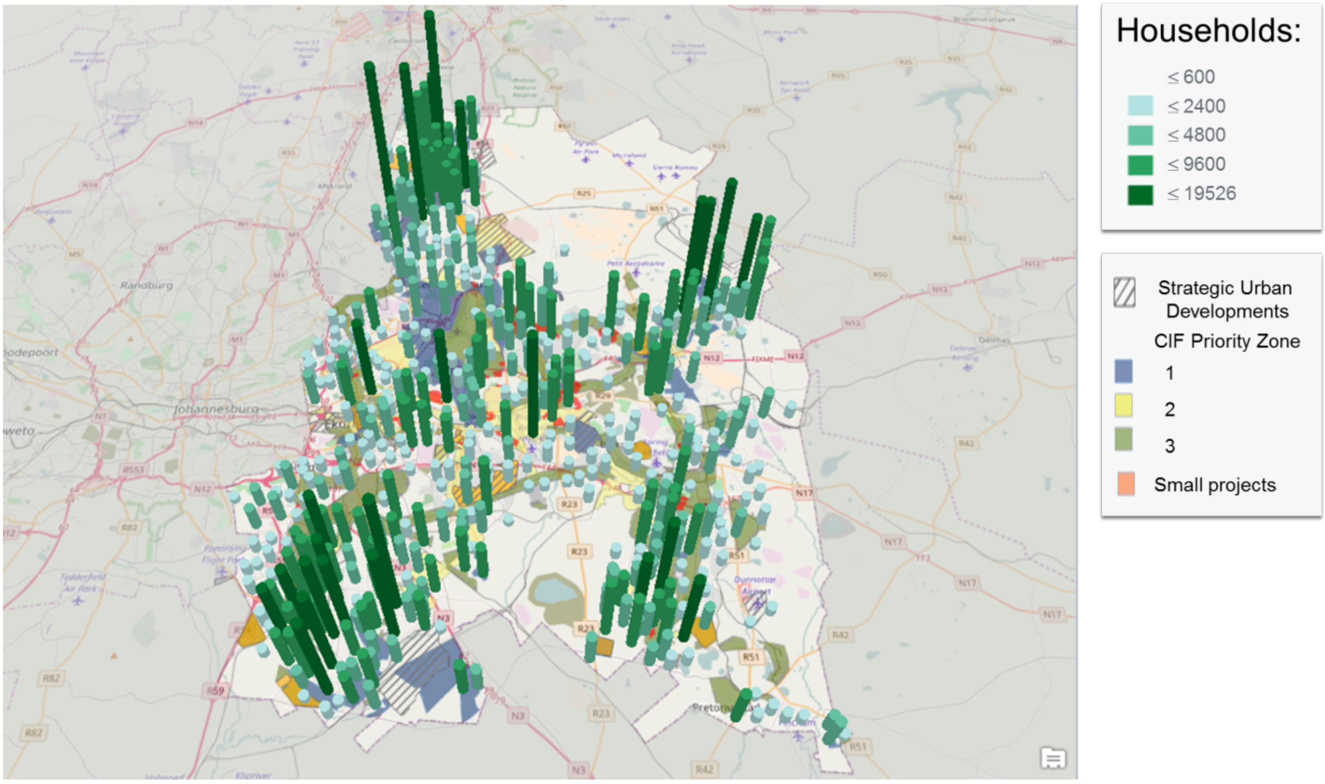

Figure 2.5: Total number of households in each zone in 2030 given the HSP scenario [43].

2.2 Demand

The population distribution in the Ekurhuleni municipality will be used to determine the demand for the consumer products in each zone in 2030. This demand for the consumer products will be linked to the number of households in each zone. The demand will be used in the model to determine which is the best zone to place the DC.

2.3 Conclusion

The whole of Ekurhuleni was divided into zones and these zones consist of smaller parcels. Parcels are classified as built-up or vacant. A zone with vacant land of 5000 m^2 will be considered for the placement of the DC. The demand for the consumer products will be linked to the number of households in each zone. Thus the total demand per zone is the sum of the demand from all the households in the zone. Three possible future scenarios for the Ekurhuleni municipality were investigated. The **trend scenario** which is a continuation of the normal. The **aerotropolis**

scenario which is an aggressive scenario where large development projects are implemented. The **HSP scenario** in which large housing projects are broken into smaller projects closer to work opportunities and public transport. A literature study was conducted to find the best practices to solve the robust distribution network and facility location problem with uncertainty.

Chapter 3

Literature review

Based on the scope of the problem, the following best practices were investigated during the literature review. ***Urban distribution centres and city logistics*** since the environment of the problem is in an urban area. ***Demand*** needs to be investigated to gain an understanding of how to convert household attributes into demand. ***Facility location models*** are needed to determine the optimal location for the facilities. ***Vehicle routing models*** will be required to develop the routes that the trucks will follow to minimise the transportation cost. ***Distribution network models*** are a key aspect to investigate since the problem is based on distribution networks in Ekurhuleni. ***Robustness*** is also very important since it is the core of the problem. ***Uncertainty*** also plays a major role in the problem since the future is fairly unknown and thus the demand will also be uncertain. Ways to handle these uncertainties will be investigated. Lastly ***optimisation models*** to solve the problem will be investigated in order to ensure that the most suitable technique is used. The rest of the chapter provides more detail with regards to these topics.

3.1 Urban distribution centre

City logistics is an attempt to understand the flow of goods in urban areas, while taking sustainability into account. City logistics also considers plans that can be set into action to improve the efficiency of the flow as well as reduce the congestion [10].

An urban distribution centre (DC) is a logistics facility that is located relatively close to an urban area or in an urban area. The purpose of these urban distribution centres is to serve the demand of the population in the area. These centres are used to complete the last mile delivery to the consumers. By optimising the distribution networks of these centres, the total cost and the carbon dioxide (CO_2) emissions can be reduced since less unnecessary travel is done [14].

Locating DCs in urban areas has its advantages and disadvantages. Some of the advantages and disadvantages are as follow.

Advantages:

- Environmental and social benefits from efficient and less intrusive transport operations.
- Better inventory control, product availability and customer service.
- Facilitation of a switch from push to pull logistics through better control and visibility of the supply chain.
- Shorter delivery routes from the urban DC to the customers.

Disadvantages:

- Increased delivery costs, though depending on how well the DC is integrated in the supply chain.
- Potential for creation of monopolistic situations.
- Loss of direct interface between suppliers and customers.

Urban DCs and city logistics are important aspects to consider when moving forward, since the Ekurhuleni is an urban area. Although an urban DC has a couple of disadvantages, the advantages outweigh them thus it will still be a good idea to locate the DC in the municipality.

3.2 Demand

Demand is an important aspect for both facility location models and distribution network models. The customers will be located at the centre of the zone to make the modelling easier [30].

Consumers buy goods for different reasons and in different ways. These purchasing behaviours can be categorised in four groups.

- **Routine purchases** are everyday use products that has a relatively low cost.
- **Occasional purchases** are goods like clothes that also has a relatively low cost but there is a significant amount of time going into the purchase.
- **Complex purchases** are buying items such as laptops or cars. These purchases are expensive and a great deal of research goes into the purchase.
- **Impulse purchases** are purchases made on impulse due to advertising [38].

There are many factors that can influence consumer behaviour and thus influence the demand for a certain product. They are:

- **Cultural factors** play a very important role in determining the consumer behaviour. These factors include the culture, sub-culture and the social class of the consumer. The types of products purchased are highly dependent on this factor. The culture of a person has a major impact on the consumer products that they buy based on trend or tradition.
- **Social factors** are important for the quality or class of product purchased. These factors include the consumer's family and status. Consumers are driven by the opinions of their families and of society. Thus this is a very important factor driving the demand for certain status items.
- **Personal factors** are the most important with regards to the type and value of goods purchased. These factors include age, gender, occupation, financial situation, lifestyle and personality. These factors are extremely important for demand forecasting since they influence all aspects of the demand.
- **Psychological factors** are the perceptions of consumers of certain product. This factor includes motivation, perception, research and believes with regards to the product [32].

For the problem addressed in this report, the personal and cultural factors will be most relevant for the demand forecasting. Most of the personal and cultural factors of the synthetic population are available as an output of the *UrbanSim* model. Since it is an urban logistics problem only the cultural and personal factors can be used to determine the demand for each scenario. These factors are attributes of each household and can be used to determine the demand per household.

3.3 Facility location models

Facility location models are used to determine the optimal location for the DCs and when the DC should be opened [4]. Facility location network design problems are concerned with finding the optimal locations for facilities as well as the distribution of consumer goods to the customers [13]. These decisions are crucial for the strategic planning of a company [31].

The selected sites for the facilities should not only be profitable in the current environment but also in several possible future scenarios in the lifetime of the facility [31]. Robust facility location optimisation is used in models when uncertainty exists over multiple periods [5].

Facility location modelling is used in urban and regional planning to locate facilities that provides a service [46]. There are several single period facility location models grouped by objective. These objectives are:

- **Min-sum models** are used for normal proportion median problems where the total cost or travel time is minimised.

- **Uncapacitated facility location problems** are used to minimize the overall operational costs.

- **Min-max models** are used to minimise the largest distance from DC to customer.

All of these models try to find the minimum number of facilities servicing the maximum number of customers [35]. In these models, the total cost to serve is minimised. Both the min-sum model and min-max model assume that the set-up costs for all the possible new facilities are the same [28].

Multi-period facility location problems are used when parameters change in a predictable way over time. The aim is to adapt the facilities configuration to the changing parameters. Stochastic parameters should also be included to account for uncertainty in future customer demands [28].

For this problem, the facility placing will be kept simple and multi-period modelling will not be used. The focus will only be on the placing of the DC in a specific zone and not the timing of the placement. It will be assumed that the set-up costs for all the facilities will be equal. The min-sum model will be used because it minimises the set-up and transportation costs.

3.4 Vehicle routing models

Vehicle routing problems (VRP) are a combination of optimisation problems that allow the modelling of vehicle fleets and their trips which can include multiple stops. These models are a representation of the flow of distribution vehicles through the urban areas. An example of a basic VRP is shown in Figure 3.1. The black dots in the left image are all the customers, the aim is to serve all the customers from the DC with minimum cost or in minimum time. The image on the right illustrates the output of a VRP. The best routes to serve all the customers in minimum time and with minimum cost have been identified.

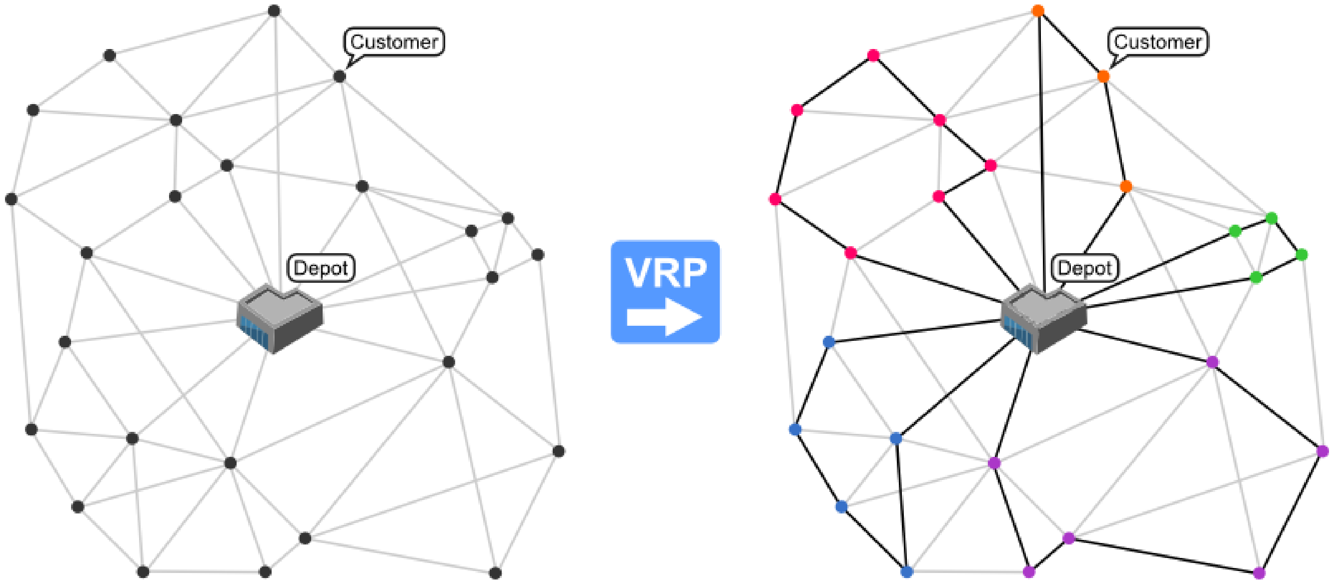

Figure 3.1: An example of a basic vehicle routing problem [6].

There are two main motives for doing vehicle routing optimisation in urban areas. The first is to increase mobility of freight transportation and to reduce the congestion in the urban areas at a minimum cost. The second is related to the environmental and social aspects where the greenhouse gas emissions and noise pollution are reduced. In these ways the quality of life of the people in the urban areas can be improved [7].

An important aspect in urban areas is the time of day. The travel time is highly dependent on the congestion, which in turn, is dependent on the time of day. When using time dependency in a model, every hour of the day has a certain travel speed associated to it based on the congestion in the area at that time. Two sets of solutions can be modelled to determine the impact that the time dependency will have on solution of the model. By taking into account the time dependency time can be reduced by up to 10% and the greenhouse gas emissions will thus also be reduced. Including the time dependency into the model will reduce the variability in the duration of the trips [7].

There are a couple of variations of vehicle routing problems each with its own specifications: The variations are:

- **Capacitated VRP:** The vehicles used to transport the goods has a certain capacity.
- **Pick up and delivery VRP:** Goods need to be collected from one location and delivered to another.
- **Multi-trip VRP:** The vehicles can be assigned more than one route at a time.
- **Vehicle routing with time windows:** The vehicles has a specified time window in which they should complete the delivery [24].

The nearest neighbour technique is a technique used to solve vehicle routing problems. This technique takes the first customer (A) and finds the next closest customer (B). Then it will find the next nearest neighbour (C) to the most recent one (B). This process will be repeated until all the customers have been reached. Next it will start at the second customer to complete the process again. This is then done for all of the customers to determine the best route for the vehicle to travel [45].

For this problem the vehicle routing will be kept simple; the trucks will have a certain capacity and will be assigned more than one customer at a time. There will be no time window for the model since it is not currently the core problem.

3.5 Supply chain and distribution network models

Supply chain networks and distribution networks are supposed to be used for a long period during which many parameters may change. Thus it is important to develop networks that can cope with these changes [28]. Large costs are associated with these network configurations, therefore stability and robustness are desirable features in such networks [37].

Distribution network design is one of the most important strategic decisions because of the competitive nature of the industry these days [41]. The uncertainty of the future is modelled by scenarios with probabilities that are known. A robust supply chain will perform efficiently for all of the given scenarios and time periods [19].

There are four robust distribution network modelling techniques that can be used for this problem.

- **Stochastic programming** uses scenarios with known probabilities in a two-stage model. Where the first stage develops the distribution network configuration and second stage the material flow configuration after the uncertainty has been resolved. The objective of this model is to maximise the expected profits in all of the scenarios. This technique will give a mean based solution [19].

- **Fuzzy or probabilistic linear programming** is used when some parameters cannot be estimated. Fuzzy logic can be used to model their uncertainty [19].

- **Robust optimisation** assumes that the probabilities of each scenario realising is unknown. The aim is to maximise the profit or minimise the cost over all of the given scenarios. [19].

- The **variance technique** takes the known probabilities of the scenarios and finds a balance between their expected values, the solution robustness and other factors such as environmental factors. The solution robustness is evaluated on the absolute deviation or the variance[19].

By defining the strategic robust supply chain as a set of Pareto-optimal configurations the problem can be modelled as a mean-standard deviation robust design problem. These configurations can be used to assist with choosing between the alternative solutions based on the trade-offs and what they deem most important [19].

Distribution network design incorporates both facility location models and vehicle routing models at strategic and tactical levels. Studies have shown that these two models are interdependent and if treated otherwise it could lead to excessive costs for the company [34].

For this problem, the robust optimisation technique is most suitable technique to use since the probabilities of each of the scenarios is unknown and the solution should be robust.

3.6 Robustness

A robust optimisation problem is a contradictory problem. Robustness seeks a solution that is capable of still performing relatively well even when conditions change while the optimisation of a supply chain seeks to make the current solution as good as possible. For this reason stochastic problem solving methods will give a much better answer than deterministic methods [17].

Robust networks ensure that the service is at the desired level with minimum service cost to the company in the long run. Robustness also enables the network to cope with the uncertainty that the future holds [3].

For the problem, robustness is extremely important. The solutions for each scenario alone will be treated as the non-flexible solutions. The solution of the combined model where the possibility of all the scenarios are incorporated will be treated as the flexible scenarios. If the network is robust, it will have minimum variation between the flexible and non-flexible solutions [26]. The robustness of the network will be determined by finding the minimum variation between the flexible scenario and each of the non-flexible scenarios.

3.7 Uncertainty

Two of the biggest uncertainties in supply chains are the uncertainty in the supply and demand. The uncertainty in supply is caused by delays or problems at the supplier. Uncertainty in the demand can be as a result of difficulties in forecasting and fluctuation in demands [4]. These future uncertainties are usually a result of changes in the economic environment or in the business [33]. The main uncertainty contributor is the demand, since the demand levels and the household distributions of the future is unknown.

Sensitivity analysis of the demand can be done to test the influence of the uncertainty by determining a base case scenario and then changing the demand in a couple of scenarios. A deviation of 10% from the base case will be sufficient if it is done in both directions. With a good solution it is impossible to improve an objective value without sacrificing at least one other parameter [4]. In this case the demand of each scenario will be altered with the 10% deviation to determine the impact of these changes.

Uncertainty plays a major role in the problem since the future is unknown with regards to the demand and the specific scenario that will realise. Thus sensitivity analysis will be done to test the impact of the uncertainty on the model.

Scenario planning is a way of thinking about the future for companies. The company executives develope a few scenarios and discuss how these scenarios will affect the company. The company can then develop plans the handle each of the scenarios the best of their capabilities. These scenarios are based on a few uncertain paraters that are changed to determine the impact of the parameters on solutions [27].

In this case, scenario planning is used for alternatives of what the future Ekurhuleni municipality might embody. Thus the scenarios will be used to develop a distribution network that will perform well in all of the possible scenarios.

With the uncertainty of which scenario will realise, a method to cope with the uncertainty had to be investigated. The deviations between the objective functions are minimised [39]. This approach is ideal to use when different future scenarios are possible, as is the case in the investigated problem.

3.8 Optimisation algorithms

Optimisation algorithms can either be exact or approximate methods. When using exact methods, a global optimal solution can be identified. When using approximate methods, there is no guarantee that a global optimal solution can be reached [39].

- **Exact methods** determine a specific solution for the given problem using mathematical constructs. These methods focus on discrete events in which branch and bound models are used [22].
- **Approximate methods** can be divided into two types of algorithms. The approximate algorithms and heuristic algorithms. *Approximate algorithms* focus on giving quality solutions in the given time bounds. *Heuristic algorithms* focus on finding a reasonably good solution in an acceptable amount of time. These algorithms assist to find reasonably good solutions for large problems at a reasonable cost. *Metaheuristics* can find better solutions for larger problems than any of the other mentioned methods. Metaheuristics can be used as the starting point to solve any optimisation problem [39]. Metaheuristics include techniques such as tabu search, simulated annealing, genetic algorithms, ant colony optimisation, particle swarm optimisation and differential evolution. A number of different metaheuristics are shown in Figure 3.2. From these different metaheuristics, genetic algorithms and differential evolution algorithms were investigated further. Metaheuristics serve three main purposes: solving problems faster, solving large problems, and obtaining robust algorithms.

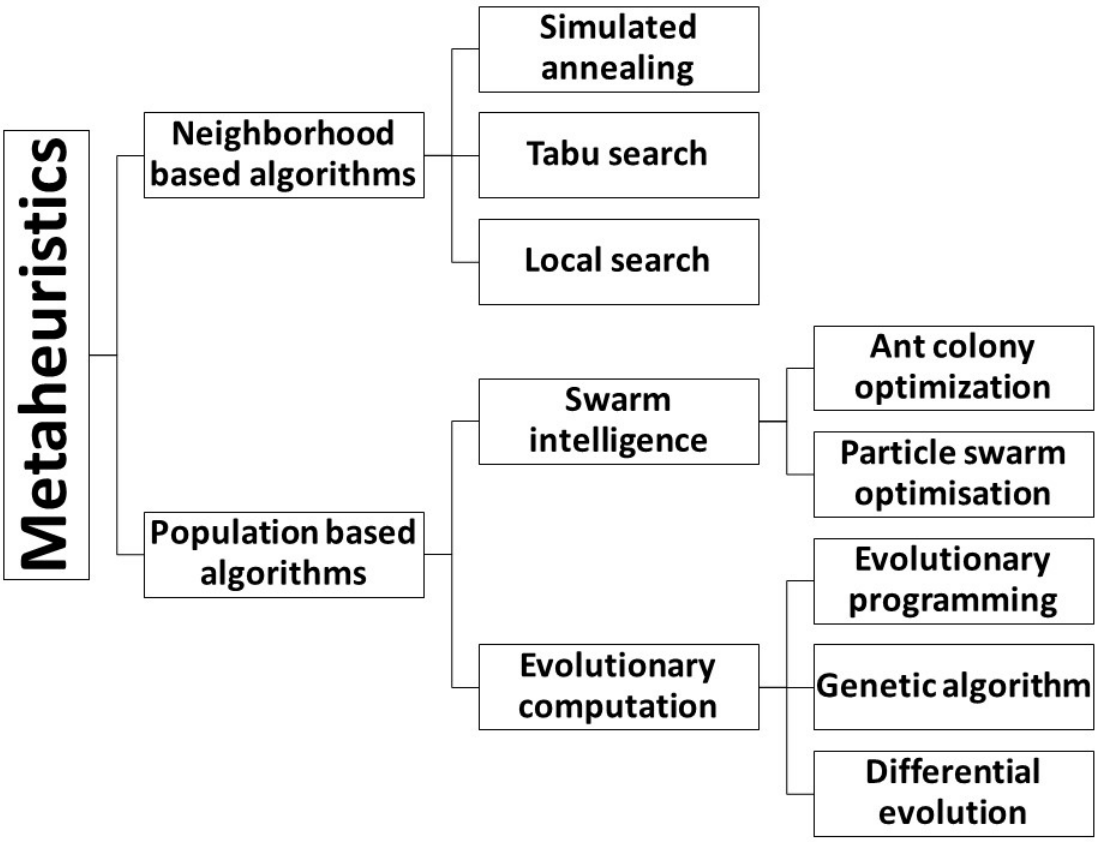

Figure 3.2: Common metaheuristics [16].

3.8.1 Local search

Local search is an optimisation method for solving hard computational problems. This method finds the best solution given a wide range of possible solutions. Local search is commonly used in VRPs and travelling salesman problems. This optimisation method is based on the neighbourhood based algorithms where the nearest neighbour is selected to determine where to travel next.

A local search starts from a given or random candidate solution and iteratively moves to the next neighbour after the candidate solution has been evaluated. This process continues until a satisfactory solution is found [36].

3.8.2 Genetic algorithms

A genetic algorithm is an evolutionary algorithm which is based on the adaptive process in nature. Genetic algorithms take two possible solutions and change aspects of the solutions to develop two new possible solutions. This process is done randomly to diversify the solutions space. As the algorithm evolves, the better solutions have a higher chance of being selected again [45]. The cross-over and mutation process of the genetic algorithm care illustrated in Figure 3.3.

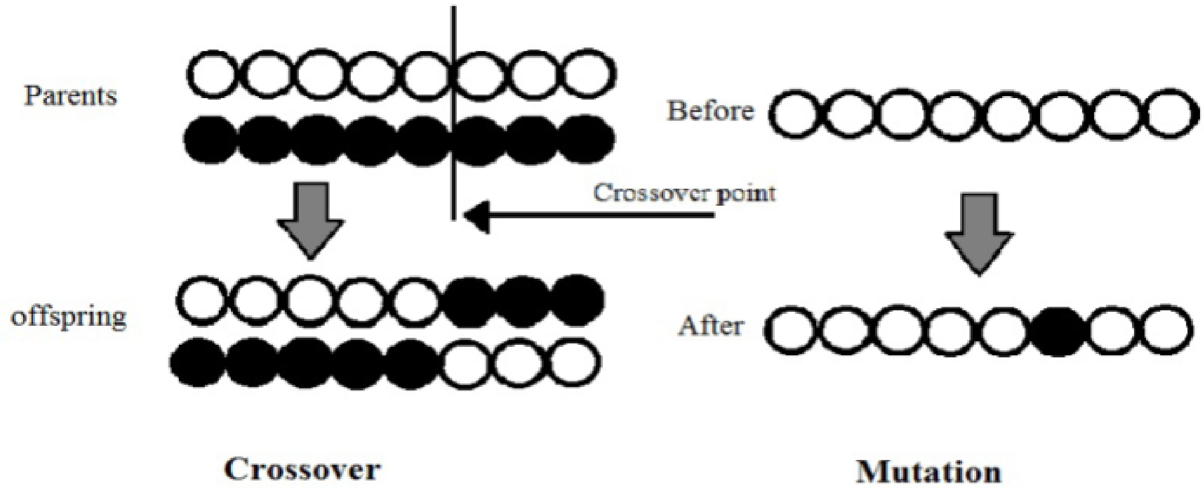

Figure 3.3: A diagram of the crossover and mutation process of genetic algorithms [29].

The process of developing a genetic algorithm is as follow:

1. Create a population of P solutions by randomly generating starting solutions.
2. Randomly select two individuals in the population as parents and produce offspring. If the offspring's fitness function value is the same or less desirable than any individual in the population, it is eliminated. If the offspring is better than at least one member of the population, the worst individual in the population is replaced with the offspring. This process is repeated for G generations.
3. The best individual in the population is the solution [11].

3.8.3 Differential evolution

Differential evolution is an evolutionary population based strategy [12]. This strategy is a robust, effective and simple goal optimisation algorithm. Each individual in the population is treated as a vector. Instead of classical crossover operators of most evolutionary algorithms, the recombination of differential evolution individuals is based on a linear combination.

Differential evolution algorithms have control parameters such as population size, crossover probability and scaling factor. The parameter values have to be selected carefully since they will influence the quality of the solution [47].

The process of developing a differential evolution algorithm is as follows:

1. Create an initial randomly distributed population (P_0) of size k.
2. Set the parameters and termination criteria.
3. The weight difference between two individuals in the population is added to another individual in the population.
4. Crossover and mutation generates new individuals in the population.
5. Selection determines which individuals are suitable with regard to the fitness values to eliminate bad solutions.
6. This process continuous until the termination criteria is reached [47].

3.9 Conclusion

Based on the above analysis of the literature, the following can be concluded. Urban DCs have a couple of disadvantages but the advantages outweigh these disadvantages. There are many aspects that influence the demand for products. In this problem personal and cultural factors will be used to infer the demand. These attributes can be identified for each household to determine the demand per household and aggregate it to demand per zone. The facility location planning model will be kept relatively simple where a min-sum model will be used to determine the location of the facilities at a minimum cost. The vehicle routing problem will also be kept relatively simple. A capacitated vehicle routing problem will be used since the trucks will have specified capacities. For the distribution network development, the robust optimisation technique will be used to determine the optimum configuration. The robustness of the solution will be determined by finding the minimum variation between the flexible and non-flexible scenarios. Local search will be used to solve the problem since it is not as computationally expensive as the other alternatives and it is commonly used in VRPs.

Chapter 4

Conceptual design and formulation

The problem has been defined in Chapter 2 and best practices to solve the problem have been investigated in Chapter 3. With these best practices in mind, the data preparation, conceptual design and model formulation was done in this chapter. During this chapter alternative solution methods were investigated to find the most suitable method.

4.1 Data preparation

The output data of the *UrbanSim* models were analysed and filtered for the purpose of the problem. The data was visualised in *Qgis* to gain a greater understanding.

The current input data of the Ekurhuleni municipality was filtered to show the vacant land in each zone. This reduction was used to determine whether or not there is space for a DC in that zone. The reduction was done by taking the cumulative sum of the area of all the empty, vacant and unknown parcels in each zone.

The latitude and longitude coordinates of the centroids of each zone were identified. These coordinates were used to determine the distances between the zones. The DC as well as the customers were located at these coordinates.

4.2 Conceptual design

The previously defined facility location and distribution network problems were solved using an optimisation algorithm. The formulation and modelling of the problem was divided into four parts as seen in Figure 4.1. The data from the *UrbanSim* model was used to develop potential solutions for all three of the scenarios. The least cost DC placement of each scenario was determined. The cost difference between each possible DC location cost and the least cost DC placement for that scenario was determined for all the possible locations in all three zones. These outputs of the individual scenario models was used in the goal programming approach to find the best robust DC location when taking all three the scenarios into consideration.

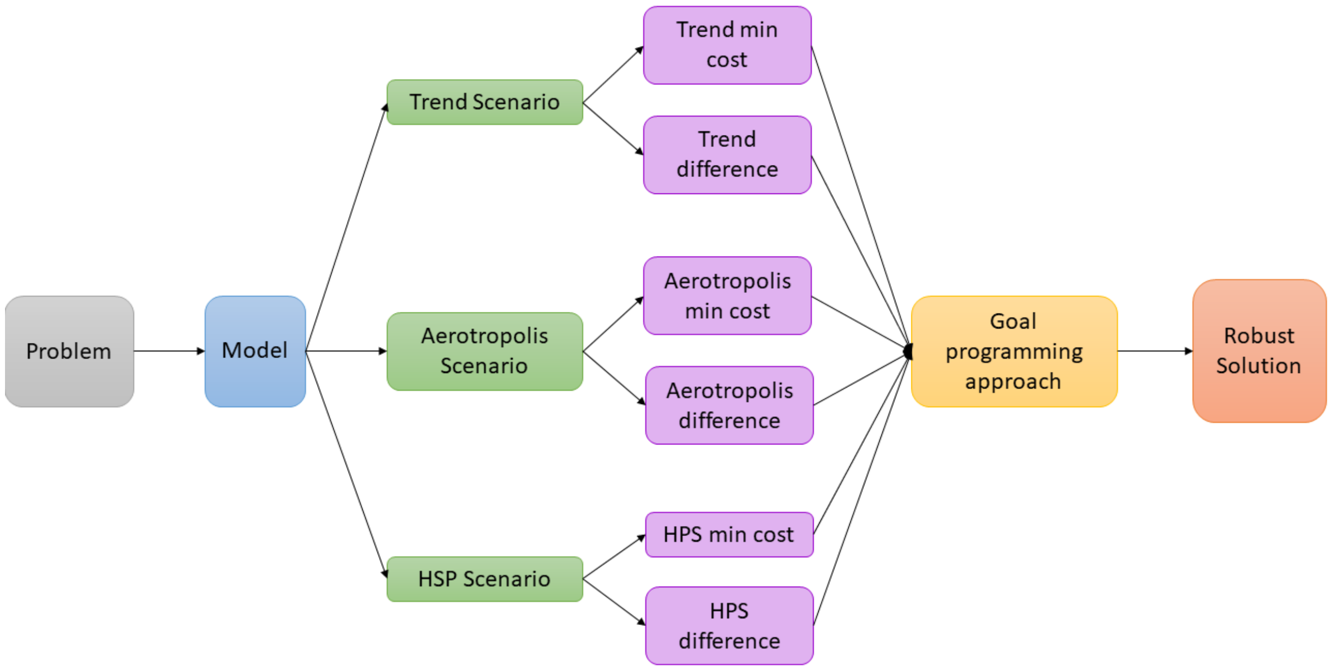

Figure 4.1: The flow from the problem to the solution.

The conceptual design gave a better understanding of how to approach and solve the problem. From the conceptual design a mathematical formulation of the problem was done.

4.3 Formulation

4.3.1 Assumptions made for the model

- The distances between the zones are calculated as the straight line distance between the centroids of the zones.
- The demand per zone is equal to the households per zone.
- It is assumed that a retailer is located at the centroid of each zone, the consumer products are delivered to these retailers.
- A DC cannot be placed in a zone if there is less than $5000\,m^2$ vacant land available in the zone [8].
- If a DC is placed it is placed on the centroid of the zone.
- Only one DC is placed in the model.
- The set-up cost of the DC is is a fixed cost of R29 700 000 [1].
- The product of size $0.2\,m^3$ was selected , which is used to determine the number of units that can fit in a truck.

- The truck can make deliveries to multiple zones in one trip.
- A 3−tonne truck was be used in the model, since the trucks must be mobile in urban areas. The operation cost per km for the truck is $R10.62$. The truck has a cubic space of $10\,m^3$ [42].
- The CO_2 emissions were assumed to be $0.107\,kg/km$ [25].
- The carbon tax is R120 per tonne of CO_2 emitted [23].

4.3.2 Individual models

For each of the three scenarios, the optimal cost and configuration were determined.

Let:
$\boldsymbol{Z}$ be the set of possible DC locations
$\boldsymbol{G}$ be the set of customer locations
$\boldsymbol{J}$ be the set of trucks

4.3.2.1 Parameters

Let:

$$
\begin{aligned}
d_g &\triangleq \textit{Demand per customer } g \in \boldsymbol{G} \\
m_{g_1 g_2} &\triangleq \textit{Distance between customers } g_1 \textit{ and } g_2 \textit{ where } g_1,\ g_2 \in \boldsymbol{G},\ g_1 \neq g_2 \\
o_z &\triangleq \textit{The open space in each zone } z \in \boldsymbol{Z} \\
f &\triangleq Fleet\ size\ of\ the\ DC \\
v &\triangleq The\ capacity\ of\ a\ truck \\
k &\triangleq The\ operating\ cost\ per\ km\ (in\, R) \\
e &\triangleq The\ CO_2\ emissions\ per\ km\ (in\, tonnes) \\
c &\triangleq The\ DC\ capacity\ (in\, units) \\
n &\triangleq The\ cost\ of\ opening\ a\ DC\ (in\, R) \\
s &\triangleq Number\ of\ units\ that\ can\ fit\ in\ a\ truck
\end{aligned}
$$

4.3.2.2 Calculated variables

$$
\begin{aligned}
t_j &\triangleq \textit{The distance travelled by truck } j \in \boldsymbol{J} \\
w_j &\triangleq The\ CO_2\ emissions\ per\ truck\, j \in \boldsymbol{J} \\
b_j &\triangleq The\ cost\ as\ result\ of\ CO_2\ emissions\ per\ truck\, j \in \boldsymbol{J}
\end{aligned}
$$

4.3.2.3 Decision variables

Decision variables are variables that have to be determined by the algorithm [21].

$$x_z = \begin{cases} 1, & \text{if a DC is placed in zone } z \epsilon \boldsymbol{Z} \\ 0, & \text{otherwise} \end{cases}$$

$$a_{jg} = \begin{cases} 1, & \text{if truck } j \in \boldsymbol{J} \text{ delivers to customer } g \in \boldsymbol{G} \\ 0, & \text{otherwise} \end{cases}$$

4.3.2.4 Objective functions

The objective function of a model evaluates a quantitative indicator of importance such as yield, profit or cost [21]. For this problem the total cost which consists of the DC set-up cost and the distribution network cost is minimised. The distribution network costs include the operating cost per truck as well as the CO_2 emissions costs.

$$min \sum_{\mathbf{Z}} n x_z + \sum_{\mathbf{J}} \sum_{\mathbf{G}} a_{jg}(kt_j + b_j) \tag{4.1}$$

The total cost is minimised for each scenario individually to find the optimum solution for each one of the three scenarios.

4.3.2.5 Constraints

$$t_j = \sum_{\mathbf{Z}} \sum_{\mathbf{G}} x_z a_{jg_1} a_{jg_2} m_{g_1 g_2} \quad \forall j \in \boldsymbol{J} \tag{4.2}$$

$$w_j = 0.107 t_j \quad \forall j \in \boldsymbol{J} \tag{4.3}$$

$$b_j = \frac{120}{1000} w_j \quad \forall j \in \boldsymbol{J} \tag{4.4}$$

$$\sum_{\mathbf{Z}} x_z = 1 \tag{4.5}$$

$$x_z \in \{0;1\} \quad \forall z \in \boldsymbol{Z} \tag{4.6}$$

$$\sum_{\mathbf{J}} a_{jg} \in \{0;1\} \quad \forall g \in \boldsymbol{G} \tag{4.7}$$

Equation 4.2 calculates the distance travelled by each truck. Equation 4.3 determines the CO_2 emissions for each truck. Equation 4.4 calculated the cost as a result of CO_2 emissions for each truck. Equation 4.5 ensures that only one DC is placed. Equation 4.6 and 4.7 defines binary variables.

4.3.3 Goal programming approach

The objective of this model is to develop a robust distribution network that is compatible with all three of the original scenarios. Goal programming was used for this approach where all three the original scenarios are taken into account at the same time. Having established the best configuration in terms of minimised costs for the three individual scenarios, a cross-cutting solution was defined through considering all three of the scenarios. This cross-cutting solution was evaluated in all three scenarios. It was expected that the solution will be sub-optimal to all the scenarios but will present the most robust solution capable of addressing most of the uncertainties associated with futuristic modelling.

4.3.3.1 Objective function

This model is a multi-objective model in which the total difference between the optimal cost for each scenario and the total cost of the scenario in the cross-cutting solution is minimised. The standard deviation between these costs were minimised.

$$min\,((y_1 - \theta_1) + (y_2 - \theta_2) + (y_3 - \theta_3) + \sigma(y_1\,y_2\,y_3)) \tag{4.8}$$

Where $\theta_i,\ i\,\epsilon\,\{1,2,3\}$ is the minimum cost solution for each of the original scenarios as calculated in equation 4.1 and $y_i,\ i\,\epsilon\,\{1,2,3\}$ is the robust solution for each original scenario.

Equation 4.8 ensures that the difference between the optimal cost for each scenario and the total cost of the scenario in the cross-cutting solution is minimised. The deviation between these costs were minimised.

4.4 Alternative solution methods

Three software package alternatives for solving the problem were investigated. The first software package that was considered is *AnyLogistix* which is a logistics package from the *AnyLogic* group. This would have been a feasible option if not for the restraints of the student version which limited the number of zones that could be defined. Buying the full version was not an option.

The second alternative that was investigated is programming in *Python*. This option offers the advantage of adding different aspects of the problem together. It is open source thus it would not cost additional money. There is no constraint on the size of the model. Modules can be installed to assist with the solving of the problem.

The last alternative that was investigated for the solving of the problem was *Supply chain guru* from *LlamaSoft*. This was not a feasible option because the student version is very limited and cannot be used to solve the current problem. Thus the only option that was capable of solving the problem given the restraints was programming in *Python*.

Different *Python* packages were investigated to determine which is the best for solving the vehicle routing problem (VRP). The packages that were investigated are: *PyEvolve*, *OR Tools*, and *Inspyred*. A few key criteria were considered and these packages were scored according to a score out of 10, where 1 is very poor and 10 is excellent. These criteria and the scores can be seen in Table 4.1. Based on the total of each package the best package for solving the VRP was selected. Form Table 4.1 it is evident that *OR Tools* has the highest total score and thus *OR Tools* was used to solve the VRP.

Table 4.1: Comparing different *Python* packages to use to solve the VRP

	PyEvolve	***OR Tools***	***Inspyred***
Ease of use	6	7	6
Help documentation	4	8	5
Compatibility with VRP	7	8	8
Total	**17**	**23**	**19**

The conceptual design and mathematical model was developed to assist with the programming that was used to solve the problem. Various alternative methods to solve the problem were investigated and from those alternatives *Python* with the use of *OR Tools* was selected to solve the problem. During the next chapter the solution of the problem will be discussed.

Chapter 5

Solution

In Chapter 4, alternative solution methods for solving the problem were investigated and *Python* programming with the help of *OR Tools* was selected. From the formulation in Chapter 4, a model was developed which consisted of a VRP and a goal programming approach model. The VRP base case for each scenario consisted of 1058 zones and 4 trucks each with a capacity of 50 000 units. Only zones with an open land area of 500 000 m^2 were considered for the placement of the DC.

The demand per zone, the coordinates of the centroid of each zone, the number and capacity of trucks, and a zone in which the DC could be placed, were used as the input parameters for the VRP. A local search, with the help of *OR Tools*, was used to find the best distribution network given the input parameters. During the local search the nearest neighbour zone was determined. The truck delivered the required demand to the next nearest neighbour zone. This nearest neighbour search process continued until the truck was empty, at this point the truck drove back to the DC to reload. This process was completed for all the trucks until the demand of all the zones were met. The distance travelled by all the trucks were received as an output of the VRP.

The VRP was used to determine the total distribution network cost for each zone the DC could be placed in. This cost was calculated by multiplying the cost per km with the total distance travelled by the trucks. The total cost for each zone in the scenario was determined by adding the total distribution network cost and the cost to build a DC. These calculations were done for all the applicable zones of each scenario. From these answers the minimum total cost for each scenario as well as the best zone to place the DC for that scenario could be determined.

The total cost of each applicable zone of each scenario was used in the goal programming approach to determine the best, most robust zone to place the DC given the uncertainty of which scenario will realise in the future. The objective function was minimised to determine the best zone to locate the DC to ensure that the distribution network is as robust as possible.

Based on the calculations done, the best zone to place the DC is zone 538. Figure 5.1 illustrates where zone 538 is located with regards to Ekurhuleni and all the other zones. The large red dot is the location of the DC, in zone 538 and the other smaller dots are the zones to which the consumer goods must be delivered in Ekurhuleni.

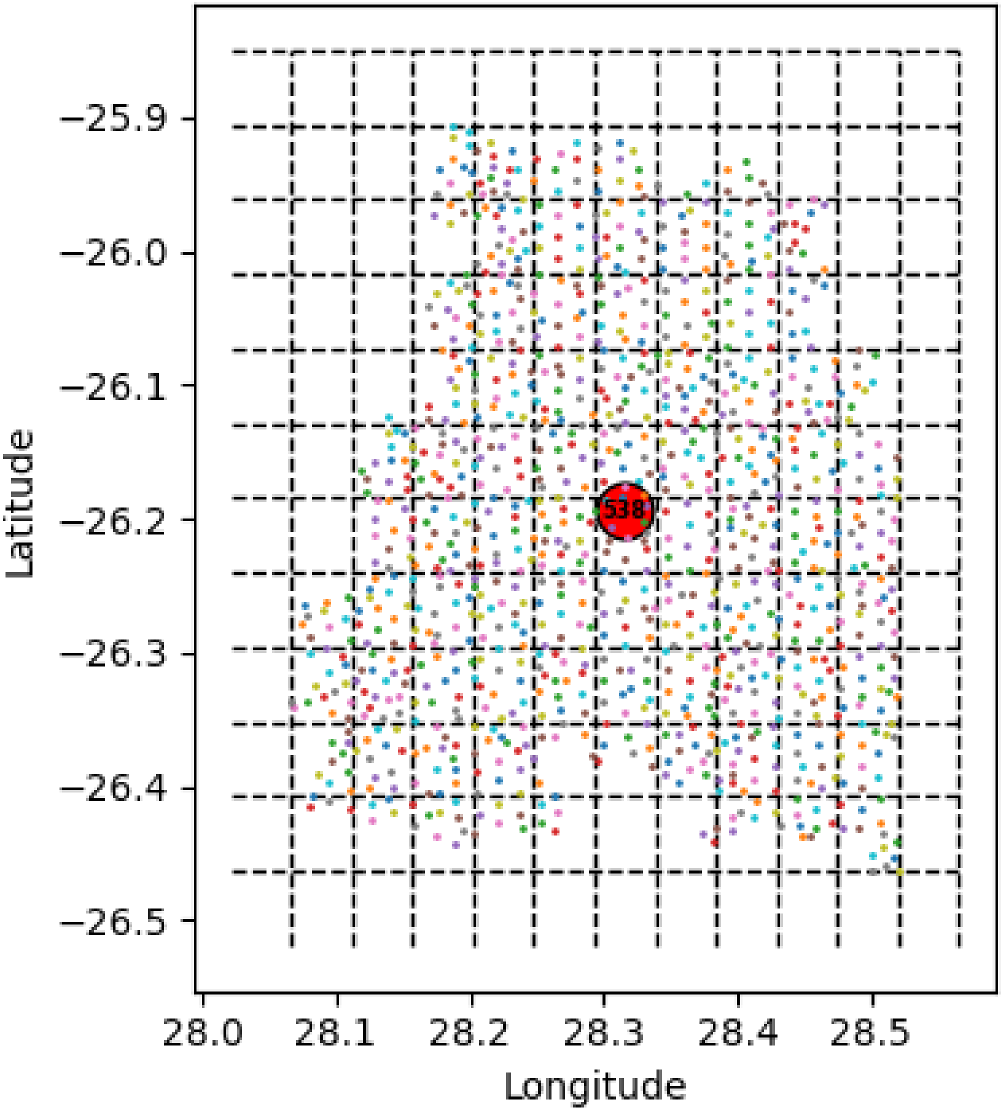

Figure 5.1: The most robust location for the DC is zone 538

The total number of households for the trend scenario by 2030 is 1 756 631. The total number of households for the aerotropolis scenario by 2030 is 1 786 766. The total number of households for the HSP scenario by 2030 is 1 783 283. The total number of households in each zone are very similar and thus the minimum cost location for the different scenarios does not differ significantly.

The minimum total cost for each scenario can be seen in Table 5.1 together with the zone in which the DC should be placed in to obtain this minimum cost. These values are compared to that of the robust solution and the difference between the minimum cost and the cost given the most robust zone to place the DC is given. It is apparent that the difference between the minimum cost for each scenario and the robust cost for each scenario is small which implies the distribution network is indeed robust.

Table 5.1: Comparing the optimal solutions for each scenario with the robust solution.

	Trend	**Aerotropolis**	**HSP**
Minimum total cost DC zone	444	895	538
Minimum total cost	R 29 725 140	R 29 725 400	R 29 725 206
Robust DC zone	538	538	538
Robust total cost	R 29 725 964	R 29 725 611	R 29 725 206
Difference	R 824	R 211	R 0

Figure 5.2 illustrates the minimum cost DC location for each scenario with regards to the locations of the customers. The red dot on each image is the location of the DC with the minimum total cost in the given scenario. For the trend scenario, the DC is located in zone 444. For the aerotropolis scenario, the DC is located in zone 895 and for the HSP scenario, the DC is located in zone 538. For all three the scenarios the DC is located more or less in the same area. This similarity is due to the fact that only one DC is placed per scenario and the number of households in the scenarios does not differ by significantly.

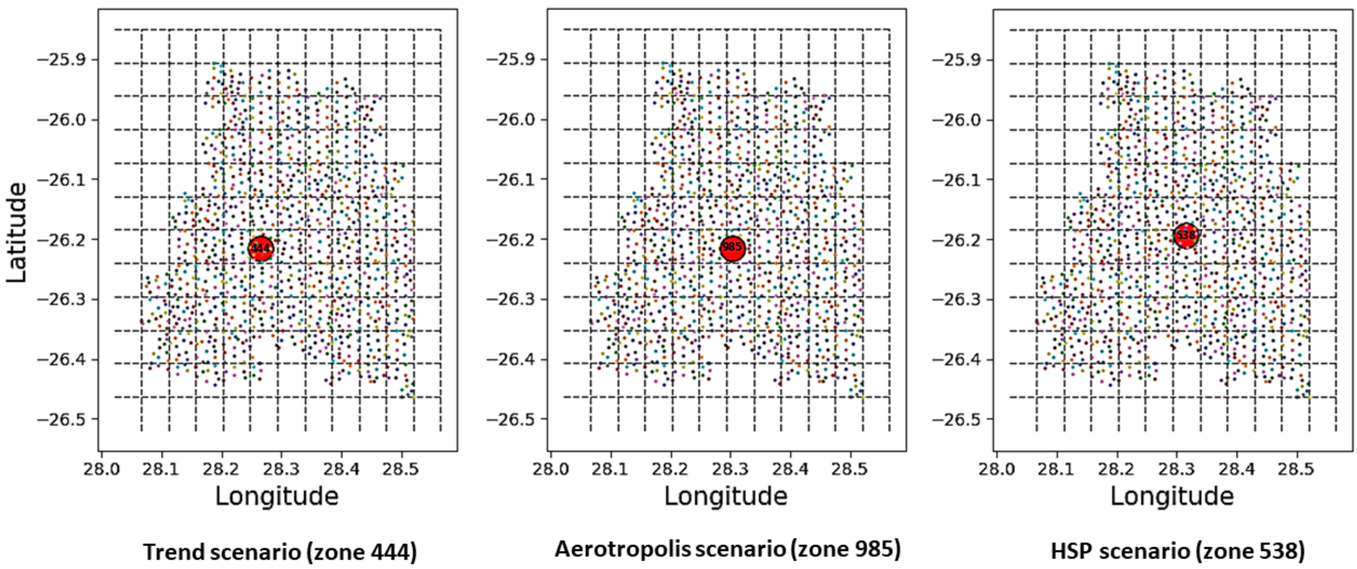

Figure 5.2: The optimal least cost routes for each original scenario

The graphs in Figure 5.3 illustrates the total costs for each scenario. The dot in each graph is the minimum cost for that scenario while the triangle is located on the total cost for the robust supply chain for each original scenario. The minimum cost for the HSP scenario and the total cost for the robust supply chain is the same since in both cases the DC is placed on in zone 538.

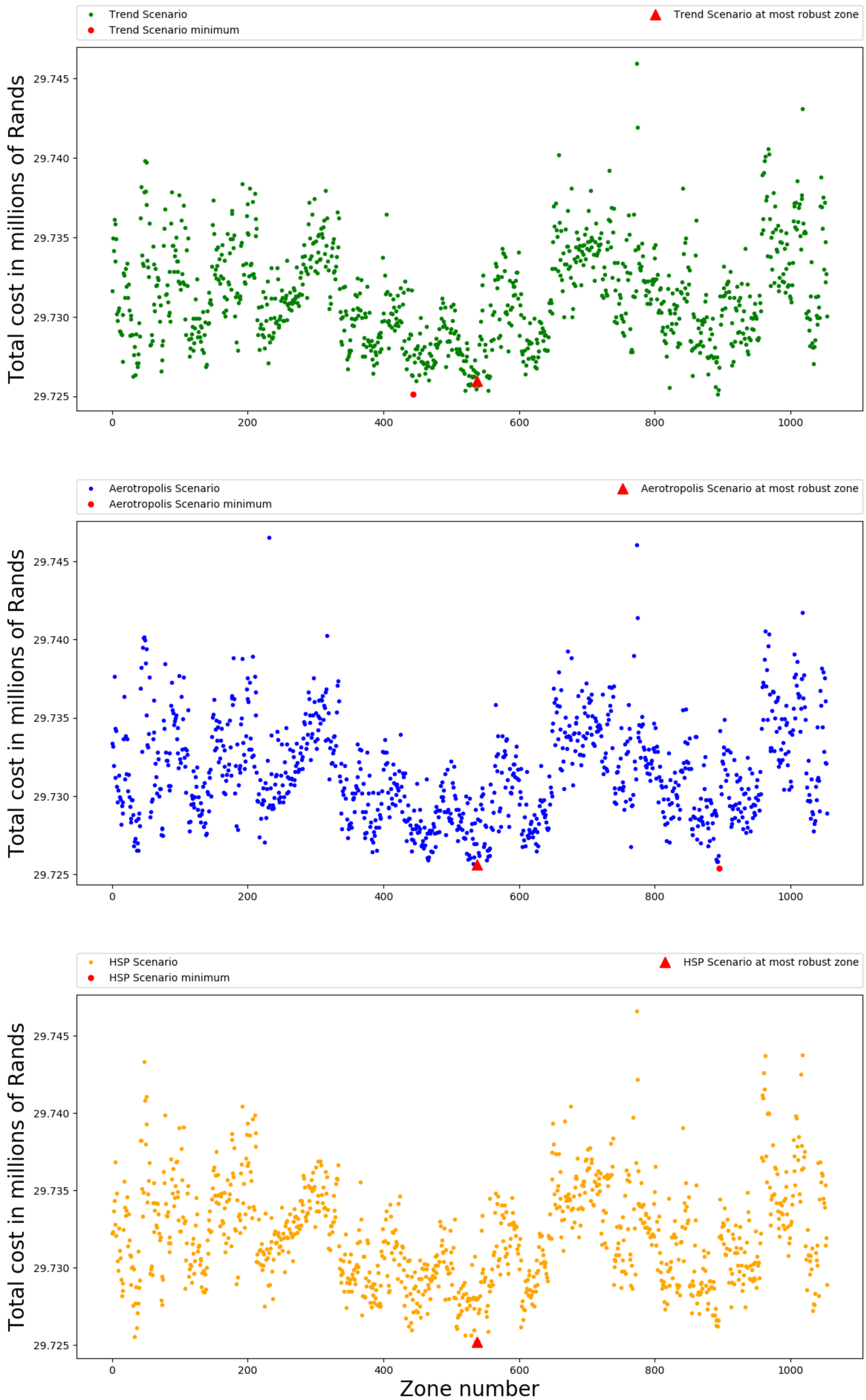

Figure 5.3: Total cost graphs for each scenario

Table 5.2 provides the total cost for the distribution network for a randomly selected zone in which the DC could be placed for the three scenarios. The total cost difference between the minimum cost for each scenario as stated in Table 5.1 and the cost if the DC were placed in the stated zone was determined. The last column of Table 5.2 is the objective function value that was minimised to find the most robust distribution network and the best zone to locate the DC. Zone 538 is indeed the most robust zone to place the DC, since its objective function value is the lowest.

Table 5.2: Evaluating the robustness of the chosen zone for the DC against other possible zones

Zone	**Trend**	**Aerotropolis**	**HSP**	**Total cost difference**	**Standard deviation**	**Objective function**
37	R 29 726 852	R 29 727 026	R 29 727 077	5 208	96	5 304
355	R 29 730 464	R 29 729 823	R 29 729 343	13 884	459	14 343
520	R 29 725 386	R 29 727 316	R 29 725 619	2 574	860	3 434
538	**R 29 725 964**	**R 29 725 611**	**R 29 725 206**	**1 035**	**310**	**1 345**
631	R 29 729 039	R 29 729 760	R 29 732 049	15 102	1 283	16 385
749	R 29 731 215	R 29 732 429	R 29 732 629	20 527	625	21 152
917	R 29 731 231	R 29 732 310	R 29 728 951	16 746	1400	18 146
1000	R 29 731 156	R 29 730 953	R 29 732 779	19 141	817	19 958

From Table 5.2 three of the randomly selected zones were selected to illustrate why their objective functions differ so much from that of the most robust zone, zone 538. Figure 5.4 is an illustration indicating where the DCs of the three randomly selected zones are located. From the figure it can be seen that all these DCs are located relatively on the outskirts of Ekurhuleni, whereas if the DC is located in zone 538 it is close to the center of the municipality. If the DC is located on the outskirts of the municipality the total distance travelled will increase, which will subsequently increase the total cost.

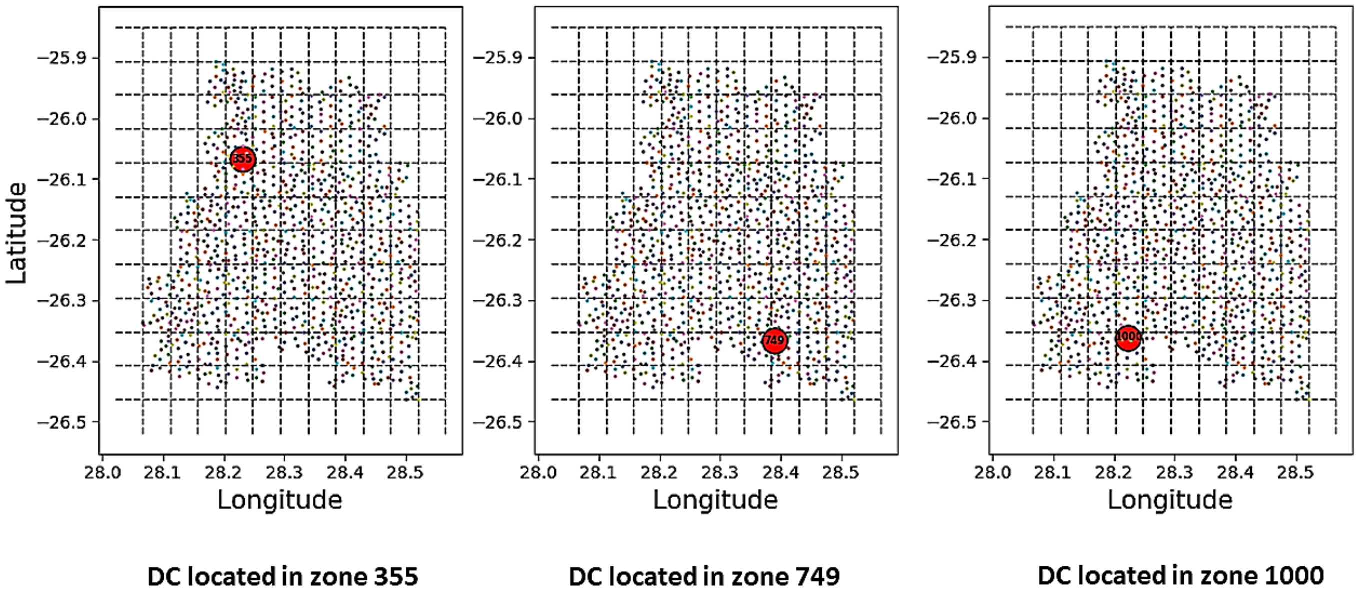

Figure 5.4: The location of the DC in three different zones with regards to Ekurhuleni

For the current problem a maximum total saving of R 63 279 could be made by using this approach to locate a DC and develop a distribution network for consumer goods. Thus if the impact on a small scale problem is already this large, the impact on a full scale distribution operation could be tremendous.

From a logical point of view the solution seemed to be a feasible solution, since the DC is located relatively in the center of the municipality. Further verification, validation and sensitivity analysis was done to determine the validity and sensitivity of the model and the solution.

Chapter 6

Verification and validation

For the model verification, the model was assessed against the aim of the project. If the model was in-line with the objective the model would be deemed valid. The model was verified using a logical test to determine whether or not a reasonable answer was given by the model. A sensitivity analysis was conducted to determine the sensitivity of the model with changing parameters.

The objective of the project was to design a distribution network model that will be compatible with any of the multiple development scenarios for the Ekurhuleni municipality in 2030, while also catering for the current demand. The model should locate the DC on the best strategic place, consider the fleet size of each DC and develop a distribution network for the last mile delivery of consumer goods to the customers. During the project the link between urban planning and supply chain design was investigated for the last mile transportation of consumer goods.

The given solution is a robust solution since it has the lowest cost difference between the scenarios as well as between each scenario's minimum and the cost of the distribution network if that scenario realises. The model found the best zone to place the DC given the uncertainty of which scenario will realise in the future. A link between urban planning and supply chain design was defined since the predictive urban planning data was used to determine the best DC location and distribution network for last mile transportation of consumer goods. This link can thus be used to save money by determining the best supply chain configuration given the uncertainty of how the area will expand in the future. With this project R 63 279 could be saved using this approach. Thus all the objectives of the project were met.

A logical test with regards to the location of the DC was implemented. This test determined whether or not the output of the model was a reasonable solution. The solution is a reasonable solution, since the DC is located relatively in the center of the municipality. The placement of the DC in the center of the municipality will keep the distribution network cost lower than if the DC was located on the outskirts of the municipality, since less distance will be travelled by the trucks.

The CSIR department that developed the *UrbanSim* simulation models were consulted to determine if the solution met their expectations. The department was satisfied that the solution gave an answer which they were seeking for.

6.1 Sensitivity analysis

A sensitivity analysis was conducted to determine if the model is generic and if reasonable answers are given as solutions. The following parameters were altered to determine the sensitivity of the model: the *operating cost per km*, the *truck capacity* and the *number of trucks*. The base case of every scenario has 4 trucks each with a capacity of 50 000 units and an operating cost of R10.27 per km.

6.1.1 Operating cost per km

The operating cost per km for the trucks was altered to investigate its impact, since fuel price is a continuously changing parameter. The operating cost per km is narrowly related to the total cost since if the operating cost increases or decreases the total cost will do the same. Table 6.1 is a summary of the sensitivity analysis done for the operating cost per km. For each case the optimal cost, the robust cost and the cost difference for each scenario is given. Table 6.2 provides the total cost difference between each scenario's optimal and robust solution for each case as well as the objective function value for each case.

Table 6.1: Effect of altering the operating cost per km per truck

	Optimal DC zone	**Optimal total cost**	**Robust DC zone**	**Robust total cost**	**Cost difference**
Trend (R9.27)	440	R29 722 695	533	R29 722 991	296
Trend (base case)	444	R29 725 140	538	R29 725 964	824
Trend (R11.27)	442	R29 727 585	531	R29 728 180	595
Aerotropolis (R9.27)	894	R29 722 930	533	R29 723 582	652
Aerotropolis (base case)	895	R29 725 400	538	R29 725 611	211
Aerotropolis (R11.27)	894	R29 727 870	531	R29 728 171	301
HSP (R9.27)	536	R29 722 755	533	R29 723 439	684
HSP (base case)	538	R29 725 206	538	R29 725 206	0
HSP (R11.27)	536	R29 727 657	531	R29 728 489	832

Table 6.2: The total cost difference and objective function value for each case due to altering the operating cost per km

	Total cost difference	**Objective function value for most robust zone**
R9.27 total difference	R1 632	2 321
Base case total difference	R1 035	1 344
R11.27 total difference	R1 728	4 923

Figure 6.1 illustrates the relationship between the minimum total cost and robust cost for each scenario in each of the cases when altering the operating cost per km. From the graph it can be seen that the relationship between the total operating cost and the operating cost per km is relatively linear. Thus it will be easy to determine the total cost of a scenario for any given operating cost by just plugging the value into the straight line equation.

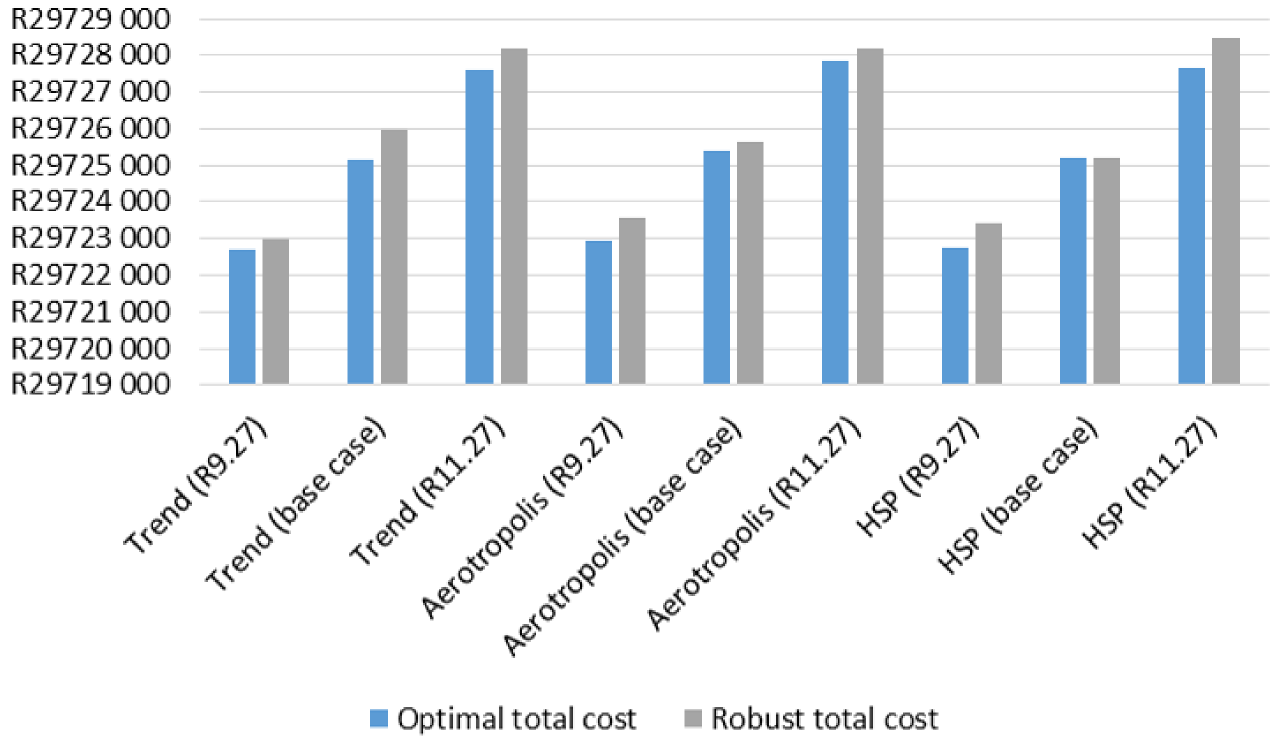

Figure 6.1: The relationship between the minimum total cost and robust cost for each scenario in each of the cases when altering the operating cost per km.

6.1.2 Capacity of trucks

Different truck sizes are available and thus the impact of the capacity of the trucks were investigated to determine the size of the impact. The capacity of the trucks were altered between 40 000 units per truck and 60 000 units per truck. Table 6.3 illustrates the impact of altering the capacity for all the different cases. As seen in Table 6.4 the capacity of the truck has a large impact on the cost as well as the robustness of the solution. The total cost for each scenario for each case increase as the capacity decrease. This relationship is as expected, since the smaller the capacity of the truck the more trips the tucks will have to make to deliver the required number of products to the zones.

Table 6.3: Effect of altering the truck capacity

	Optimal DC zone	Optimal total cost	Robust DC zone	Robust total cost	Cost difference
Trend (40 000 units)	532	R29 728 088	525	R29 728 771	683
Trend (base case)	444	R29 725 140	538	R29 725 964	824
Trend (60 000 units)	547	R29 723 262	552	R29 723 686	424
Aerotropolis (40 000 units)	534	R29 728 768	525	R29 730 551	1783
Aerotropolis (base case)	895	R29 725 400	538	R29 725 611	211
Aerotropolis (60 000 units)	525	R29 723 196	552	R29 724 407	1211
HSP (40 000 units)	517	R29 728 951	525	R29 729 059	108
HSP (base case)	538	R29 725 206	538	R29 725 206	0
HSP (60 000 units)	555	R29 722 798	552	R29 724 088	1290

Table 6.4: The total cost difference and objective function value for each case when altering the truck capacity

	Total cost difference	Objective function value for most robust zone
40 000 Units total difference	R2 574	3 354
Base case total difference	R1 035	1 344
60 000 Units total difference	R2 925	3 219

Figure 6.2 illustrates the relationship between the minimum total cost and robust cost for each scenario in each of the cases when altering the truck capacity. From the graph it can be seen that the relationship between the total operating cost and the operating cost per km is negative linear. Thus it will be easy to determine the total cost of a scenario for any given truck capacity by just plugging the value into the straight line equation. The figure also clearly shows that the robust total cost for each scenario of each case is higher that the minimum cost, which is as expected. The HSP base case minimum total cost and robust cost is the same since the robust zone and minimum cost zone is the same zone.

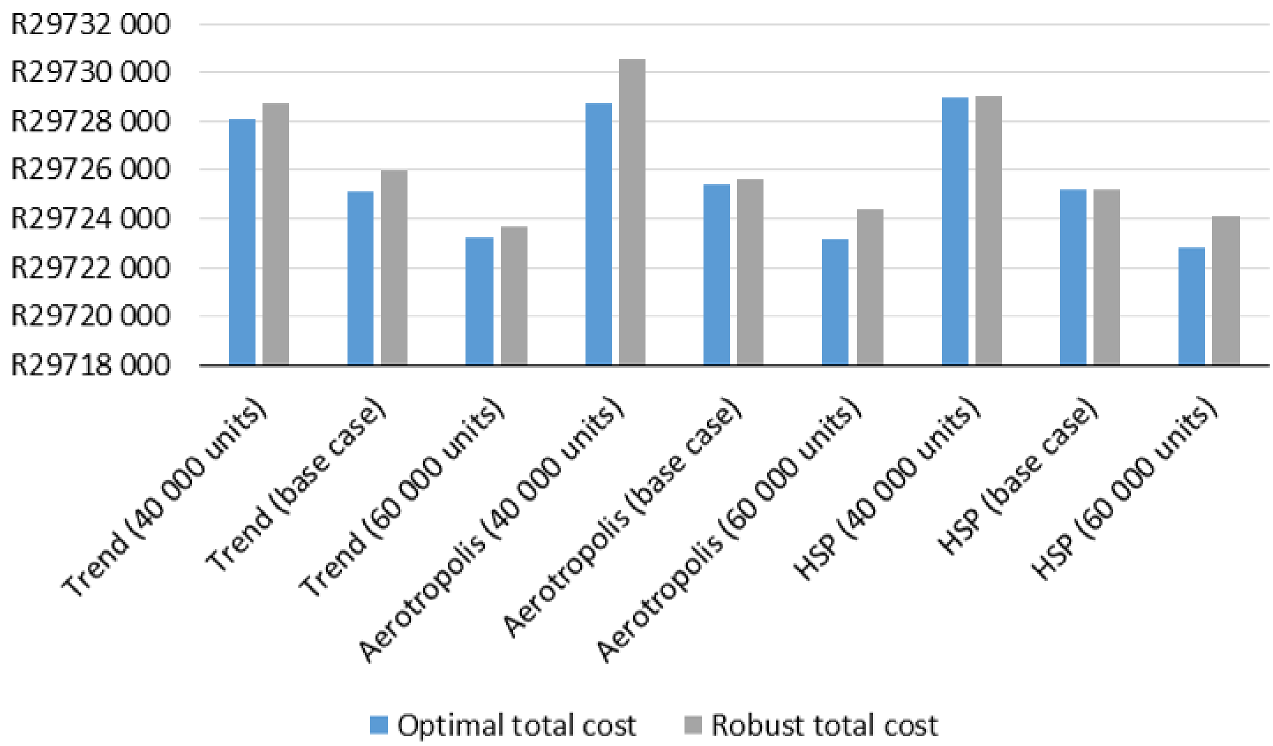

Figure 6.2: The relationship between the minimum total cost and robust cost for each scenario in each of the cases when altering the truck capacity.

6.1.3 Number of trucks

The number of trucks is an uncertain parameter since there is not a fixed number of trucks specification that could be used. Thus the impact of the number of trucks were investigated to determine whether the model is sensitive to these changes. Table 6.5 is a summary of the sensitivity analysis done for the number of trucks, for each case the optimal cost, the robust cost, and the cost difference for each scenario is given. Table 6.6 provides the total cost difference between each scenario's optimal and robust solution for each case. From the data it is clear that the number of trucks have an impact on the solution.

Table 6.5: Effect of altering the number of trucks

	Optimal DC zone	**Optimal total cost**	**Robust DC zone**	**Robust total cost**	**Cost difference**
Trend (3 trucks)	443	R29 725 140	888	R29 725 585	445
Trend (base case)	444	R29 725 140	538	R29 725 964	824
Trend (5 trucks)	442	R29725036	890	R29 725 153	117
Aerotropolis (3 trucks)	891	R29 725 407	888	R29 725 869	462
Aerotropolis (base case)	895	R29 725 400	538	R29 725 611	211
Aerotropolis (5 trucks)	893	R29 725 407	890	R29 725 869	462
HSP (3 trucks)	536	R29 725 244	888	R29 726 651	1407
HSP (base case)	538	R29 725 206	538	R29 725 206	0
HSP (5 truck)	538	R29 725 244	890	R29 726 301	1057

Table 6.6: The total cost difference and objective function value for the change in the number of trucks

	Total cost difference	**Objective function value for most robust zone**
3 Trucks total difference	R2 314	2 764
Base case total difference	R1 035	1 344
5 Trucks total difference	R1 636	2 109

Figure 6.3 illustrates the relationship between the minimum total cost and robust cost for each scenario in each of the cases when altering the number of trucks. In this graph the minimum total cost for each scenario of each case is relativity similar while the robust operating cost for each scenario of each case differs by a large amount. Thus it can be concluded that the number of trucks have a large impact on the robustness of the model. The figure also clearly shows that the robust total cost for each scenario of each case is higher that the minimum cost, which is as expected. The HSP base case minimum total cost and robust cost is the same since the robust zone and minimum cost zone is the same zone.

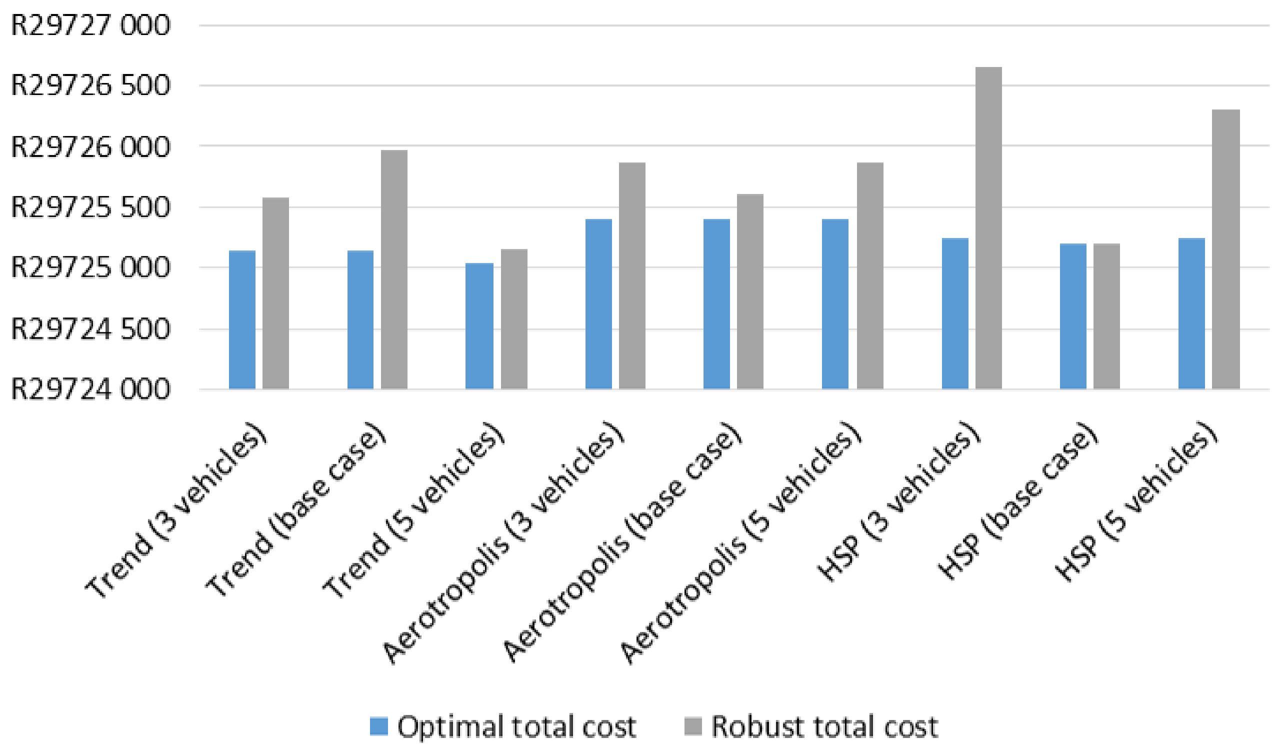

Figure 6.3: The relationship between the minimum total cost and robust cost for each scenario in each of the cases when altering the number of trucks.

For all of the cases tested the DC is placed in more or less the same area although the zone numbers differ by quite significantly they are relatively close to one another. From all of the parameters that were changed the capacity of the trucks has the highest impact on the robustness of the solution.

Chapter 7

Conclusion

This project is based in the Ekurhuleni municipality in Gauteng, South Africa. Presently supply chain models are using the current demand and short term forecasted demands to develop supply chains. This traditional method of forecasting brought about the idea of incorporating urban planning into last mile distribution networks. The urban planing was used to determine the number of households in each zone in the Ekurhuleni municipality. The number of households was converted into a demand per zone located at the centroid of the zone. The data was used to locate a DC and develop a robust distribution network model for 2030.

There are three scenarios of what the municipality could look like in the future. A model was developed that located a distribution centre and developed a distribution network that is compatible with all three of the scenarios. A literature review was conducted to determine the best practices in the fields of facility location modelling, distribution network development, robust networks and optimisation models. An algorithm was developed based on the best practices and the data of the *UrbanSim* model to solve the problem. Based on the algorithm the best zone to locate the DC is zone 538.

This zone placement holds up with a logical test since the DC is located relatively in the center of the municipality, thus it seems feasible. Verification and validation was done to determine the validity of the model and the solution. Sensitivity analysis on the model was done by changing certain parameters such as the number of trucks, the capacity of the trucks, and the operating cost per truck. The operating cost per truck had the most influence on the robustness of the distribution network. A maximum total saving of R 63 279 could be made by using this approach to place a DC and a develop distribution network for consumer goods. Thus if the impact on a small scale problem is already this significant, the impact on a full scale distribution operation could be tremendous.

7.1 Future work

Future work can evaluate the placement of more than one DC when working with a larger area such as a province or country.

The demand of the zones can be divided into different categories based on the household attributes to ensure a higher accuracy in the demand for consumer products. This is an important aspect to consider since the demand will have a great impact on the solution.

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Appendix A

List of symbols

$$
\begin{aligned}
a_{jg} &\triangleq \textit{Which truck } j \in \boldsymbol{J} \textit{ delivers to which zone } g \in \boldsymbol{G} \\
b_j &\triangleq \textit{The cost as result of } CO_2 \textit{ emissions per truck } j \in \boldsymbol{J} \\
c &\triangleq \textit{The DC capacity} \\
d_g &\triangleq \textit{Demand per customer } g \in \boldsymbol{G} \\
e &\triangleq \textit{The } CO_2 \textit{ emissions per km} \\
f &\triangleq \textit{Fleet size of the DC} \\
\boldsymbol{G} &\triangleq \textit{The set of customer locations} \\
\boldsymbol{J} &\triangleq \textit{The set of trucks} \\
k &\triangleq \textit{The operating cost per km} \\
m_{g_1 g_2} &\triangleq \textit{Distance between customers } g_1 \textit{ and } g_2 \textit{ where } g_1,\ g_2 \in \boldsymbol{G},\ g_1 \neq g_2 \\
n &\triangleq \textit{The cost of opening a DC} \\
o_z &\triangleq \textit{The open space in each zone } z \in \boldsymbol{Z} \\
s &= \textit{Number of units that can fit in a truck} \\
t_j &\triangleq \textit{The distance travelled by truck } j \in \boldsymbol{J} \\
u &\triangleq \textit{The cost per square meter to opening a DC} \\
v &\triangleq \textit{The capacity of a truck} \\
w_j &\triangleq \textit{The } CO_2 \textit{ emissions per truck } j \in \boldsymbol{J} \\
x_z &\triangleq \textit{Whether a DC is placed ina zone } z \in \boldsymbol{Z} \\
\boldsymbol{Z} &\triangleq \textit{The set of possible DC locations}
\end{aligned}
$$

Appendix B

Mentor form

Department of Industrial & Systems Engineering
University of Pretoria

Final Year Project Mentorship Form
2018

Introduction
An industry mentor is the key contact person within a company for a final year project student. The mentor should be the person that could provide the best guidance on the project to the student and is most likely to gain from the success of the project.

The project mentor has the following important responsibilities:

1. To select a suitable student/candidate to conduct the project.
2. To confirm his/her role as project mentor, duly authorised by the company by signing this **Project Mentor Form**. Multiple mentors can be appointed, but is not advised.
3. To ensure that the **Project Definition** adequately describes the project.
4. To review and approve the **Project Proposal**, ensuring that it clearly defines the problem to be investigated by the student and that the project aim, scope, deliverables and approach is acceptable.
5. To review and approve all subsequent project reports, particularly the **Final Project Report** at the end of the second semester, thereby ensuring that information is accurate and the solution addresses the problems and/or design requirements of the defined project.
6. Ensure that sensitive confidential information or intellectual property of the company is not disclosed in the document and/or that the necessary arrangements are made with the Department regarding the handling of the reports.

Project Mentor Details

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Project Description:	**Developing robust distribution networks for future urban planning scenarios**
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