Green Supply Chain Design:

A Lagrangian Approach

by

Ryan J. Merrick

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Ryan Merrick

Abstract

The expansion of supply chains into global networks has drastically increased the distance travelled along shipping lanes in a logistics system. Inherently, the increase in travel distances produces increased carbon emissions from transport vehicles. When increased emissions are combined with a carbon tax or emissions trading system, the result is a supply chain with increased costs attributable to the emission generated on the transportation routes. Most traditional supply chain design models do not take emissions and carbon costs into account. Hence, there is a need to incorporate emission costs into a supply chain optimization model to see how the optimal supply chain configuration may be affected by the additional expenses.

This thesis presents a mathematical programming model for the design of green supply chains. The costs of carbon dioxide (CO_2) emissions were incorporated in the objective function, along with the fixed and transportation costs that are typically modeled in traditional facility location models. The model also determined the unit flows between the various nodes of the supply chain, with the objective of minimizing the total cost of the system by strategically locating warehouses throughout the network.

The literature shows that CO_2 emissions produced by a truck are dependent on the weight of the vehicle and can be modeled using a concave function. Hence, the carbon emissions produced along a shipping lane are dependent upon the number of units and the weight of each unit travelling between the two nodes. Due to the concave nature of the emissions, the addition of the emission costs to the problem formulation created a nonlinear mixed integer programming (MIP) model.

A solution algorithm was developed to evaluate the new problem formulation. Lagrangian relaxation was used to decompose the problem by echelon and by potential warehouse site, resulting in a problem that required less computational effort to solve and allowed for much larger problems to be evaluated. A method was then suggested to exploit a property of the relaxed formulation and transform the problem into a linear MIP problem. The solution method computed the minimum cost for a complete network that would satisfy all the needs of the customers.

A primal heuristic was introduced into the Lagrangian algorithm to generate feasible solutions. The heuristic utilized data from the Lagrangian subproblems to produce good feasible solutions. Due to the many characteristics of the original problem that were carried through to the subproblems, the heuristic produced very good feasible solutions that were typically within 1% of the Lagrangian bound.

The proposed algorithm was evaluated through a number of tests. The rigidity of the problem and cost breakdown were varied to assess the performance of the solution method in many situations. The test results indicated that the addition of emission costs to a network can change the optimal configuration of the supply chain. As such, this study concluded that emission costs should be considered when designing supply chains in jurisdictions with carbon costs. Furthermore, the tests revealed that in regions without carbon costs it may be possible to significantly reduce the emissions produced by the supply chain with only a small increase in the cost to operate the system.

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Chapter 1:

Introduction

Transportation provides the link between firms in a supply chain. With the globalization of supply chains, the distance between nodes in the distribution network has grown considerably. Consequently, longer travel distances produce increased vehicle emissions on the transportation routes, resulting in an inflated carbon footprint. With the growing public concern around global warming, organizations are being called to review their current practices and shift towards green and sustainable policies (Seuring & Muller, 2008; Mohanty & Mohanty, 2009). The implementation of sustainable practices, while having a profound impact on the environment, can also enhance the reputation of the firm as a green organization. Hence, there is a need to effectively and efficiently design eco-friendly supply chains, to both improve environmental conditions and the bottom line of the organization.

The economics of logistics frequently conflict with sustainable design and environmental responsibility. Alternative fuel vehicles, such as electric or hybrid means of transportation, are often not fiscally viable without vast subsidies or substantial fringe benefits (i.e. marketing or public relations benefits). As such, decisions to improve the productivity at a logistics firm often come at the expense of the environment. The need for corporate sustainability was identified over a decade ago, although it has just recently gained traction throughout the business world (Hesse, 1995; Greene & Wegener, 1997).

Network design is a logical place to start when looking to green a supply chain. Wu and Dunn (1995) cite transportation as the largest source of environmental hazards in the logistics system. This claim is supported by the fact that transportation via combustion engine vehicles accounted for 27% of the Canadian greenhouse gas (GHG) inventory in 2007 (Environment Canada, 2009). And while heavy duty diesel vehicles, such as diesel tractors commonly used in logistics, account for only 4.2% of vehicles on the road, they also accounted for 29.2% of Canadian GHG emissions from transportation in 2007. Thus, reducing the number of vehicle kilometers travelled (VKT) through the strategic placement of nodes could play a significant role in reducing the carbon footprint of the nation.

In the past, network location models have focused on minimizing the operating cost of the system. Works by Cornuejols et al. (1991), Pirkul & Jayaraman (1998) and Elhedhli & Gzara (2008) all proposed solution methods for three-echelon facility location models, focusing on the transportation cost between nodes and fixed cost of opening a facility. However, these traditional models do not account for the environmental implications of the logistics network. With carbon tax or cap-and-trade systems in place in many jurisdictions, and on the horizon in many more, the cost of carbon emissions in supply chain design models is becoming increasingly relevant.

This thesis extends on the aforementioned publications and develops a green supply chain design model that incorporates the cost of carbon emissions into the objective function. The goal of the model is to simultaneously minimize logistics costs and the environmental cost of CO_2 emissions by strategically locating warehouses within the distribution network. A three echelon, discrete facility location model is proposed. The model is extended beyond previous research through the inclusion of a nonlinear term to account for CO_2 emissions in the objective function. This paper uses published experimental data to derive nonlinear concave expressions relating vehicle weight to CO_2 emissions. The resulting nonlinear mixed integer programming (MIP) model can be used to minimize the total cost (logistics cost plus emissions cost) of the network. A method is proposed to exploit the structure of the problem to reduce it to a linear MIP problem. Lagrangian relaxation is used to decompose the problem by echelon and by warehouse site. This decomposition results in subproblems that require less computational effort than the initial problem. The lower bound for the initial problem is determined by the subproblems, while the upper bound is computed via the Lagrangian dual master problem. By keeping most of the features of the original problem in the subproblems, a strong Lagrangian bound was achieved in a relatively small number of iterations. A primal heuristic was proposed to generate a feasible solution in each iteration using information from the subproblems. The quality of the heuristic was measured against the Lagrangian bound. Test results indicated that the proposed method was effective in finding good solutions.

The remainder of the thesis is organized as follows. The next section has a comprehensive literature review, followed by the problem formulation and motivating examples in Chapter 3. Chapter 4 details the solution method, with a primal heuristic for generating feasible solutions proposed in Chapter 5. Finally, the solution algorithm is tested in Chapter 6, and Chapter 7 contains our conclusions.

Chapter 2:

Literature Review

Strategic supply chain management involves the both the location of facilities throughout the supply chain and the allocation of products across the network. This scenario has been referred to as the strategic supply chain design problem (Vidal & Goetschalckx, 1997). A great deal of research has been done analyzing supply chain design models, as reviewed by Goetschalckx et al. (2002). However, the incorporation of environmental attributes into supply chain design models is a relatively novel concept. Supply chain design literature, as well as articles identifying a need for sustainable supply chains, is identified in this chapter. Green supply chain design models that have incorporated the cost of carbon emissions into the objective function are also identified. Lagrangian relaxation is also discussed briefly in this section, as it is imperative to the solution method discussed later in this thesis.

The model developed in this thesis incorporates the cost of emissions into the objective function of a supply chain design model. As such, a review of emissions and carbon equivalents is in order. The method of converting emissions into a cost, such as a carbon tax or cap-and-trade system, is also discussed. Finally, gaseous emissions from heavy-duty diesel vehicles (i.e. tractors-trailers commonly used in logistics) are examined.

2.1 Supply Chain Design Models

The facility location literature provides a variety of models for supply chain design. These models range from simple uncapacitated facility location models to complicated multi-echelon, multi-product, capacitated facility location models. When considering facility location in the sense of a supply chain, the objective is to locate facilities throughout the network while minimizing production and transportation costs throughout the supply chain. A review by Sarmiento & Nagi (1999) depicts how supply chain location models can be broken down and classified. This thesis concentrates on multi-echelon deterministic models with direct trips and no transshipment points, with the objective to minimize the cost. This is arguably the most popular objective in supply chain design (Melo, Nickel, & Saldanha-da-Gama, 2009). A review of modeling design methods in the sense of global logistics systems was compiled by Goetschalckx et al. (2002). Sahin & Sural (2007) present a recent comprehensive review of multi-echelon facility location models. Production and distribution systems, as well as unit flow formulations and solution methods, which are of particular interest to this thesis, are discussed in depth in this review.

2.1.1 Lagrangian Relaxation in Location Models

The Lagrangian relaxation technique has been used for various applications in operations research. Applications include location models and strategic supply chain design models, to name a few. Many facility location problems can be view as relatively simple problems with a complex set of constraints that makes the problems difficult to solve.

Lagrangian relaxation attempts to simplify the problem by dualizing the complicating constraints and inserting them into the objective function with a penalty term. The result is a problem with a simpler evaluation procedure where the optimal solution is a lower bound to the original problem (for minimization problems). See Geoffrion (1974) and Fisher (1981) for details on the use of Lagrangian relaxation in integer programming.

The unique attribute of the Lagrangian relaxation procedure is the ability to decompose a problem into smaller subproblems after dualizing specific constraints. An example of how Lagrangian relaxation can be used to decompose a strategic supply chain design problem was presented by Wu & Golbasi (2004). They considered a multi-commodity supply chain design model that attempted to locate facilities and compute unit flows. The original problem was decomposed by relaxing certain constraints into two subproblems: one subproblem computed the unit balance throughout the network with the setup constraints relaxed; and, a second subproblem relaxed the multi-product constraints while keeping intact the mass balance and setup constraints. The subproblems required considerably less computational effort to solve than the original problem and allowed for larger problems to be tackled.

Pirkul and Jayaraman (1998) also demonstrated how Lagrangian relaxation could be used to break the down a facility location problem into smaller subproblems. This study considered a three-echelon facility location model, with the first echelon being manufacturing plants, the second being warehouses or distribution centres, and the third echelon being retailers. Constraints were imposed to ensure the unit flows into and out of the warehouses in the second tier are exactly equal. Coincidently, these constraints also linked the top two echelons of the problem to the bottom two tiers. The authors relaxed these linking constraints, which allowed for the problem to be separated into two subproblems: one that solves for locations and unit flows in the top two tiers of the model, and a second subproblem that solves for the bottom two echelons. The ability to decompose the initial problem into smaller subproblems decreased the computational demand and allowed for larger problems to be evaluated.

2.1.2 Heuristics in Supply Chain Design Models

The previous section detailed how Lagrangian relaxation can be utilized to find a lower bound to a strategic supply chain problem. However, Lagrangian relaxation does not reveal the combination of product flows, customer assignments and open facilities that will produce the optimal result. Hence, heuristics are commonly used in conjunction with Lagrangian algorithms to generate feasible solutions, which are in essence an upper bound (for a minimization problem).

Several Lagrangian heuristics for locations models are proposed and evaluated by Beasley (1993). The paper presented a framework for developing robust interchange Lagrangian heuristics by using methods that range from simple methods that require little computational effort and are computed every iteration to difficult techniques are only executed once per test run. The framework was evaluated on both capacitated and uncapacitated warehouse location problems and benchmarked against other proposed Lagrangian heuristics. It was noted that while Lagrangian heuristics presented by Cornuejols et al. (1991) and Pirkul (1987) produced better solutions, the interchange heuristic proposed by Beasley was able to generate optimal or near-optimal solutions at a reasonable computational cost.

Agar & Salhi (1998) proposed a Lagrangian heuristic to generate feasible solutions in large scale capacitated plant location problems. The method starts by producing a list of illegal plant location combinations for the original problem. The problem formulation is then relaxed and solutions are generated. The relaxed solution is compared against the illegal combination list to see if it is a feasible solution. If it is not, then alterations are strategically made to the solution until it becomes feasible. This method improved the efficiency of the Lagrangian algorithm when introduced.

The shortest path algorithm was tested in a Lagrangian supply chain design algorithm by Wu & Golbasi (2004). The heuristic seeks to generate feasible solutions that minimize the transportation distance in the network. Thus, a feasible solution is reached by linking with the closest open source facility that has the available capacity to accommodate the customer. The authors showed that in certain situations the algorithm could produce high quality solutions in a fraction (roughly 2%) of the computational time.

Of particular interest to this thesis is the use of primal heuristics in strategic supply chain design models that also use Lagrangian relaxation to decompose the problem by echelon. The solution from the subproblems can be substituted into the original problem formulation, which is then solved to yield a feasible solution and an upper bound (for a minimization problem). The primal heuristic is activated in each iteration of the Lagrangian algorithm to find a feasible solution. Since the subproblems will retain at least some of the characteristics of the original problem, this heuristic has the ability to produce good feasible solutions. Examples of this procedure are provided by Jayaraman and Pirkul (2001) and Elhedhli and Gzara (2008).

Several meta-heuristics have also been used to generate feasible solutions in supply chain design models. Meta-heuristics are traditionally search algorithms that strategically exploit the nature of the problem to search for the optimal feasible solution. Syam (2002) used simulated annealing in combination with a facility location problem to produce feasible solutions. Altiparmak & Karaoglan (2008) presented an adaptive heuristic that combined tabu-search and simulated annealing methods to find a feasible solution in a transportation problem constructed with a concave cost structure. Another commonly used meta-heuristic is the genetic algorithm. This procedure attempts to strategically combine pairs of feasible solutions in the hopes that the positive attributes of each individual will come together in the offspring. The genetic algorithm approach is applied to a multi-echelon supply chain network by Syarif, Yun & Gen (2002).

2.1.3 Test Problems

In order to test the Lagrangian solution approach developed in this thesis, a procedure for generating sample problems was required. Several procedures have been suggested in the literature, each with its own advantages and drawbacks. For this thesis, test problems were generated in accordance with the procedure for capacitated facility location problems as suggested by Cornuejols et al. (1991). The procedure calls for problems to be generated randomly while keeping the parameters similar those experienced in practice.

The coordinates of the all facilities are generated uniformly over a defined region. Transportation and handling costs between nodes in the model were set at ten times the distance between nodes and then adjusted using a scalar during sensitivity analyses. The demand of each customer was also generated randomly in the testing process. The difficulty of the problem was defined by a user input scalar. The storage capacity of a warehouse facility was generated randomly, and then scaled so that the ratio of total warehouse capacity to customer demand is equal to a predetermined value. The cost of opening a warehouse was based on the storage capacity of the facility and reflected increasing economies of scale.

This testing procedure suggested by Cornuejols et al. (1991) has been used in subsequent studies, such as Elhedhli and Goffin (2005) and Elhedhli and Gzara (2008).

2.2 Green Logistics

Green logistics and sustainable supply chains are relatively novel concepts. The movement towards corporate sustainability started gaining momentum in the 1990's, when a variety of articles were published identifying the need for green supply chains (McKinnon, 1995; Black, 1997; Greene & Wegener, 1997). Nearly twenty years later, many organizations have taken notice of the benefits of green practices and have incorporated sustainability into their corporate culture. A recent survey identified popular green strategies employed by North American and European firms (Murphy and Poist 2000, 2003) and highlighted the willingness of companies to implement sustainable practices. Wu and Dunn (1995) demonstrated that several aspects of the supply chain are impacted by environmental issues, including the acquisition of raw materials, inbound logistics and outbound logistics. Accounting for the economics of sustainability has become so prevalent that many academics have suggested the idea of a corporate triple bottom, which includes financial, social and environmental impacts (Forana, Lenzenb, Deyb, & Bilek, 2005). However, the financial leg of the triple bottom line is still the clear driver, with the social and environmental pillars being secondary (Norman & MacDonald, 2004).

With the advent of government imposed emissions costs in certain jurisdictions, the environmental and financial legs of the triple bottom have become linked. As such, increasingly more attention has been paid to the environmental pillar. A recent review showed that the number of publications in the field of sustainable supply chains has risen steadily over the past decade (Linton, Klassen, & Jayaraman, 2007). However, the majority of the papers offer only conceptual framework and are lacking theoretical background (Seuring & Muller, 2008). The desire of firms to implement green strategies is apparent, and the need from an environmental standpoint is obvious, but the green supply chain design tools provided by the literature are still developing, and a comprehensive toolbox is not yet available.

Extensive reviews of the sustainable supply chain literature are provided by Seuring and Muller (2008) and Carter and Rogers (2008). Still, only a small selection of the work cited in these reviews focus on optimization tools for sustainable supply chain design. The next chapter takes a looks a look at the green logistics models available and their advantages and shortfalls.

2.2.1 Green Logistics Models

Both consumers and legislation have urged organizations to consider environmental impact when designing their logistics network. While reducing the carbon footprint of a supply chain is an important part of green logistics, cost minimization must also be considered simultaneously. The literature does offer select multi-criteria supply chain design models that incorporate environmental considerations into the decision criteria. Cruz and Matsypura (2009) consider multi-criteria decision-making behaviour in the design of supply chain networks. The objective of the model is to maximize profits, while minimizing both emissions and risk. Manufacturing costs are modeled similarly to traditional facility location models, with a fixed and per unit component. However, emissions and risk are modeled as convex and continuously differentiable functions that increase exponentially with demand. The variational inequality formulation is used to develop a solution method to compute the equilibrium flows and price patterns.

Nagurney et al. (2007) demonstrated how sustainable supply chains can be transformed and studied as transportation networks. This publication studied a multi-echelon problem with multiple manufacturers each operating multiple plants and competing for retailers. A range of transportation modes were available between the plants and retailers. Again, the solution model was multi-objective, focusing on both profit maximization and emissions minimization. The weighting of these decision parameters were weighted distinctly by the different decision makers. Emissions produced on the transportation routes were modeled linearly. The paper concludes by proposing a solution algorithm and proving that a sustainable supply chain model can be reformulated and solved as an elastic demand transportation network equilibrium problem.

A green supply chain simulation model was examined by Merrick and Bookbinder (2010). Their simulation model investigated the effect of various shipment consolidation policies on the amount of pollutants emitted during the movement of goods. Nonlinear concave expressions relating carbon dioxide emissions to vehicle weight were derived from published experimental data and used to evaluate the performance of each shipment release policy. The simulation studied particular situations and presented general conclusions based on the results. The results showed that for short holding times, the quantity policy performed best, both in terms of logistics cost and pollution reduction. In the case of low order arrival rates and long holding times, the time policy was best at reducing emissions and logistics costs. However, the best dispatch policy conflicts in terms of pollution reduction and logistics cost minimization for the following cases: (i) moderate holding times; and (ii) long holding times combined with high order arrival rates. In these cases, it is necessary to consider the speed of travel, trip length and unit cost of emissions when selecting the optimal shipment release policy.

Environmental issues have on occasion been combined with city logistics. City logistics involve the transportation of a high volume of goods in a geographically concentrated area. Queuing theory and congestion models are frequently used in city logistics to simulate urban traffic patterns. Taniguchi et al. (1999) developed a mathematical model for determining the optimal size and location of public logistics terminals and conclusions are drawn about the environmental impacts. Later work by

Taniguchi and van der Heijden (2000) evaluated city logistics initiatives in terms of carbon dioxide (CO_2) emissions using a vehicle routing model. Similarly, carbon monoxide (CO) emissions were studied by Sugawara and Niemeier (2002) in an attempt to find an upper bound on the benefit that can be gained by optimizing trip assignments via city logistics. Ando and Taniguchi (2006) provided a vehicle routing model with time windows that simultaneously reduces costs and emissions of various pollutants creating an environmentally friendly delivery system for an urban area.

2.3 Cap-and-Trade vs. Carbon Tax

With the growing awareness of environmental issues, many governments have passed legislation to implement programs where citizens must pay for the emissions they produce. The two most common types of emissions tariffs are a cap-and-trade system or a carbon tax. This chapter will first look at carbon dioxide equivalents (CO_2e) and then discuss the cap-and-trade systems in the European Union and Alberta, along with the British Columbia carbon tax.

Carbon dioxide equivalents are measurement systems used in carbon markets. They account for the global warming potential (GWP) of the gas emitted. The six gaseous compounds that make up CO_2e are: CO_2, methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFC), perfluorocarbons (PFC), and sulphur hexafluoride (SF_6). The GWP of each of these gases, as determined by the Intergovernmental Panel on Climate Change, are shown in Table 2.1 (Intergovernmental Panel on Climate Change, 2003).

Table 2.1: Global warming potential of gases.

Compound	GWP
carbon dioxide	1
methane	23
nitrous oxide	300
hydrofluorocarbons	120 - 12,000
perfluorocarbons	5,700 - 11,900
sulphur hexafluoride	22200

To determine the amount of CO_2e, the weight of a particular gaseous emission is multiplied by the respective GWP (from Table 2.1) and then summed. Emission allowances, the currency in cap-and-trade systems, are typically issued for the emission of one tonne of CO_2e.

Cap-and-trade systems attempt to set a limit on the CO_2e emissions from a particular region. A maximum allowable emission quantity is defined for the region and divided among the constituents. If a constituent emits over their allowance, a penalty or fine is imposed. The most prolific cap-and-trade system in the world is the European Union emissions trading scheme (EU ETS). The EU ETS is the world's largest emissions permit market and encompasses nearly half of the EU's total greenhouse gas emissions (Hintermann, 2010).

The EU ETS program operates in phases, with phase 1 spanning 2005-2007 and phase 2 from 2008-2012. At the beginning of a phase, emission allowances (one-time rights to emit 1 tonne of CO_2e) are issued to participating parties for use over the duration of the phase. The number of emission allowances issued is intended to decrease with each consecutive phase in accordance with the Kyoto Protocol targets. Firms can trade allowances freely throughout the EU, but must turn in permits on April 30 of each year to account for emissions produced in the previous calendar year. The penalty for non-compliance is €40 during phase 1 and €100 in phase 2 for every tonne of CO_2e for which an allowance is not surrendered by a firm. During phase 1, the price of an allowance ranged from less than €1 to just over €30. In phase 2, the price of an emissions allowance has stabilized between €10 and €20.

In 2007, Alberta became the first province in Canada to pass legislation to reduce greenhouse gas emissions intensity generated by large industrial constituents. The cap-and-trade system created applies to firms that emit more that 100,000 tonnes of carbon dioxide equivalents, and requires them to reduce their greenhouse gas emission intensity by 12% annually (Province of Alberta, 2006). The program applies to approximately 100 companies, which account for roughly 70% of the provinces industrial emissions. The involved companies have three means to reduce their environmental impact: (i) by making operational improvements to reduce GHG emissions, (ii) by purchasing Alberta based emissions offsets from firms that emit less than the 100,000 tonne threshold, or (iii) by contributing to the government administered technology fund. The technology fund contribution carries a price tag of $15 per tonne CO_2e. Revenue generated by the technology fund is intended to be reinvested into the province to develop GHG reducing technologies, such as carbon capture and storage.

In 2008, the government of British Columbia imposed carbon tax legislation in an effort to curb GHG emissions. The carbon tax is a consumption tax applied to all fuels and combustibles, which is applied at the point of sale (Ministry of Finance, 2010). The tax rate for each fuel is based upon the CO_2e emissions produced from the combustion of the respective fuel. Thus, cleaner fuel, such as natural gas, would have a lower tax rate than a dirty fuel, such as gasoline or diesel. The tax rates prior to July 1, 2010 were based on $15 per tonne CO_2e, although after July 1, 2010, the rates will be increased and based on $20 per tonne CO_2e.

2.4 Vehicle Emission Data

Few comprehensive data sets exist that show the relationship between vehicle weights and exhaust emissions. While the exact emission levels will depend on the engine type, terrain driven and the driver tendencies, the general relationship between vehicle weight and emissions will not change (i.e. linear, concave or convex relationship). This section reviews the available emissions data and draws conclusions about the relationship between emissions and the vehicle operating weight.

The most comprehensive data set of vehicular GHG emissions for is that contained in the Mobile6 computer program (Environmental Protection Agency, 2006). Mobile6 contains an extensive database of carbon dioxide (CO_2) emissions for heavy heavy-duty diesel vehicles (HHDDV) obtained from full scale experiments. The database contains emissions factors for various vehicle weights, ranging from class 2 trucks up to class 8b. Speed correction factors, outlined by the California Air Resources Board (Zhou, 2006) for use with the Mobile6 program, can also be applied to relate CO_2 emission levels with vehicle weight and speed of travel. Figure 2.1 displays the relationship between vehicle weight and CO_2 emissions for various speeds of travel. The units for

CO_2 emissions are grams (g) per vehicle kilometer travelled (VKT) and the vehicle weight is in pounds (Note that "vehicle weight" represents the empty weight plus the cargo). The concave expressions are clearly nonlinear and can be well approximated by polynomial functions.

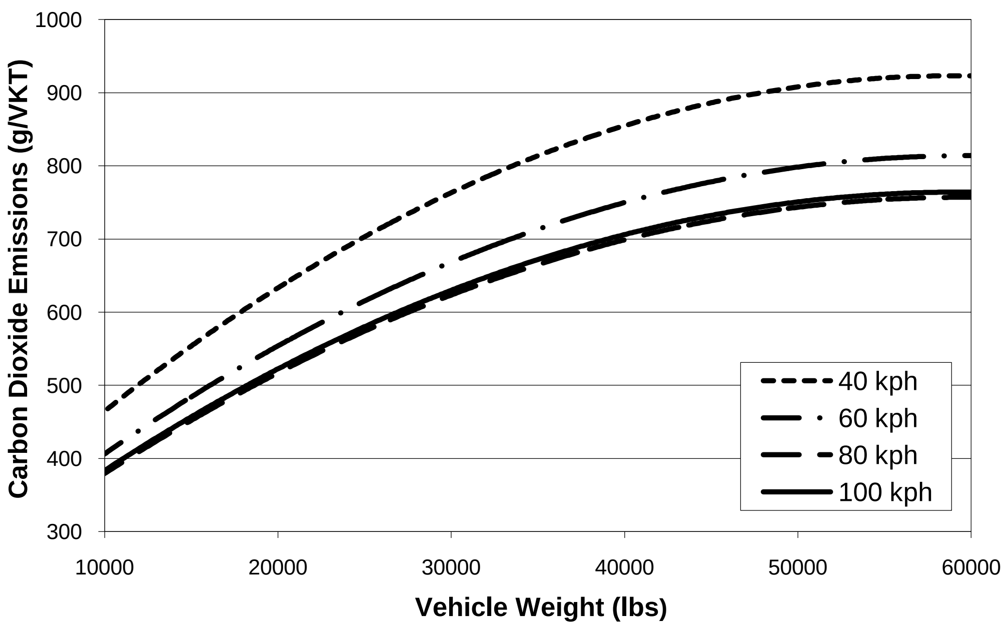

Figure 2.1: Vehicle weight vs. CO_2 emissions at various travel speeds (Environmental Protection Agency, 2006).

Figure 2.1 shows that, for any given speed, the quantity of emissions is a concave increasing function of vehicle weight. In addition, for a given weight, as vehicle speed increases from 40 kph to 60 kph to 80 kph, the CO_2 emissions decrease. Note that the two curves for 80 kph and 100 kph are virtually indistinguishable.

While the Mobile6 data set is comprised of emissions from a number of fully-loaded vehicles of varying weight classes, the data are still useful in determining the emissions from a logistics network. In the case of large carriers (either private or common) with a diverse fleet of vehicles, it would be optimal in terms of fuel consumption, economics and emissions to choose the smallest vehicle possible that could accommodate the required payload (i.e a vehicle at or near its capacity). Thus, in this case of large carriers with diverse vehicles fleets, the carrier would select an optimally sized vehicle and the Mobile 6 data presented in Figure 2.1 would accurately represent the emissions along the respective shipping lane.

For carriers with smaller fleets, it is unlikely that they will be able to assign an optimally sized vehicle to meet the needs of the shipper in every circumstance. Thus, the emission characteristics of a single vehicle (i.e. a class 8 tractor-trailer) with varying payload levels must be considered. The published data available in this scenario is lacking. While it would be expected that the emissions versus operating weight relationship would follow a similar pattern to that shown in Figure 2.1, it is important to verify this assumption.

As previously mentioned, there is a relatively small number of data sets available that provide CO_2 emission levels at a number of vehicle weights. Researchers have commonly measured emission rates at two operating weights. However, this practice will always demonstrate a linear association between emissions and vehicle weight. Several publications confirm that CO_2 emission rates increase as the operating weight of the truck is increased (Gajendran & Clark, 2003; Brodrick, Laca, Burke, Farshchi, Li, & Deaton, 2004; Strimer, Clark, Carder, Gautam, & Thompson, 2005). However, only the former two publications provide adequate data (three or more data points) to establish a concave expression relating. Figure 2.2 presents the emissions data from Gajendran & Clark (2003) and Strimer et al. (2005) for an HHDDV operating at a variety of vehicle weights.

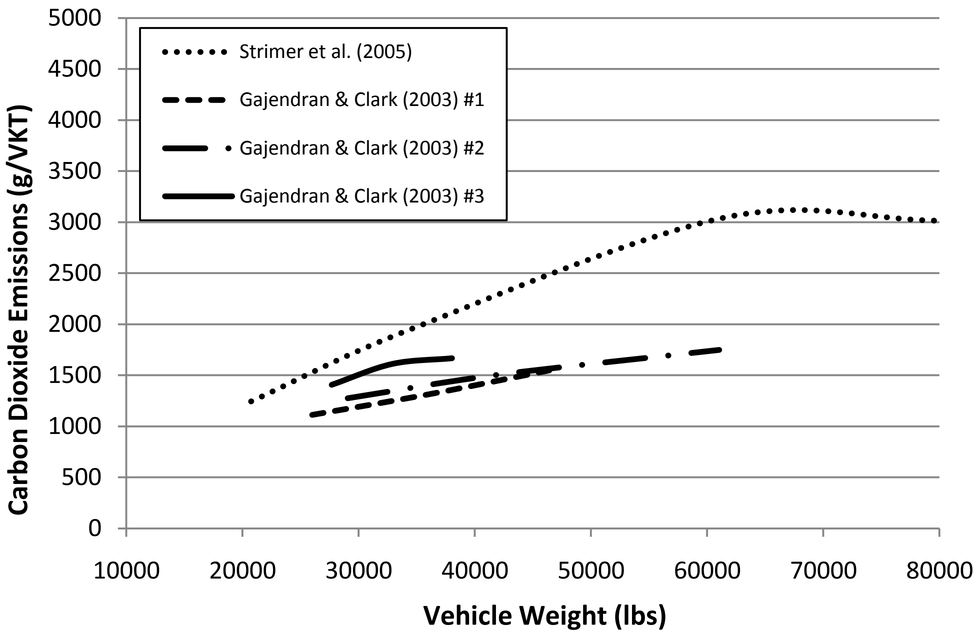

Figure 2.2: Vehicle weight vs. CO_2 emissions.

The data shown in Figure 2.2 indicate a concave relationship between CO_2 emission rates and vehicle operating weights. This conclusion is consistent with that reached through examination of the Mobile6 data.

Clark et al. (2002) also concluded that emissions are nonlinear concave as grade is increased. If it is assumed that both grade and vehicle weights affect the work done by the engine, the statement by Clark et al. (2002) can be expanded to conclude that an increase in vehicle weight results in a nonlinear concave increase in CO_2 emissions.

The data presented in this section show a concave relationship between vehicle weight and CO_2 emissions, both in the case of fully-loaded vehicles at differing weight classes and in the case of a single vehicle with varying payload weights. By incorporating the carbon emissions, and later the carbon costs, into the cost function for the logistics network, the network can be optimized both fiscally and environmentally. Since the objective of this work is to develop a solution method to a set of network problems with a concave cost function, rather than an exact solution to a particular emissions data set, the shape of the relating curve is more important than the specific values. Thus, with the concave relationship established, the solution method can be adapted to represent the emissions of a particular vehicle fleet.

2.5 Positioning

The current research extends beyond traditional facility location models by incorporating emission costs into the decision criteria. Traditional facility location models, such as those reviewed by Melo, Nickel and Saldanha-da-Gama (2009), have focused only on minimizing production, transportation and fixed costs. By incorporating the cost of carbon emissions into the objective function, the present study minimizes both the logistics cost of the network and the environmental cost. The relationship between vehicle weight and carbon emissions has been modeled as linear (Nagurney, Liu, & Woolley, 2007), convex (Cruz & Matsypura, 2009) and concave (Merrick & Bookbinder, 2010) in the past. This thesis uses emissions data from laboratory tests (Environmental Protection Agency, 2006) that show a concave relationship between vehicle weight and emissions, i.e. emissions per unit vehicle weight decrease as vehicle weight is increased. These concave emissions are combined with a carbon cost and added to the objective function of a strategic supply chain design model to create a nonlinear MIP. This extension creates a unique *green* strategic supply chain design model that has not been previously studied.

Chapter 3:

Problem Formulation and Motivation

The introduction of emission taxes and cap-and-trade systems mean that governments are now realizing the cost that industrial operations impose on the environment. The financial outlook of a firm can now be impacted by carbon costs, and thus, operational decisions should incorporate methods to reduce the environmental impact of the supply chain. The ultimate solution for the organization can be derived through a combination of traditional facility location analysis and modern green supply chain methods. The objective function for the hybrid model will then seek to minimize the sum of the logistics and carbon costs of the resulting network.

This chapter outlines the operational problems that have produced a need for this research. First, a problem formulation is developed that captures carbon costs into the objective function of the model. Then, examples of real-world situations where the model could be used are discussed.

3.1 Problem Formulation

This thesis extends on traditional facility location models by incorporating emission costs into the objective function of a network design problem. The goal of the model in this thesis is to strategically locate distribution centres and compute the unit flows between plants, distribution centres (also denoted as warehouses or DCs) and retailers (also referred to as customers) in a distribution network. These variables are calculated while trying to minimize both the logistics cost and the emissions produced by the resulting supply chain. The logistics cost of the system is comprised of the fixed cost to establish a distribution centre and the variable per unit cost to handle and transport each unit throughout the supply chain. The emissions cost of the supply chain is made up of the carbon dioxide emissions produced by the network, multiplied by an assumed per volume cost to emit greenhouse gases.

The research conducted in this thesis is made unique by the addition of carbon cost into the objective function of the model. The emission costs produced by the supply chain are a result of the carbon dioxide emissions along the transportation routes. The carbon emissions, and thus the carbon costs as well, are a variable per unit quantity that is related to the weight of the vehicle transporting the goods. As more units are shipped on a single vehicle, the vehicle weight is increased and the per unit emissions resulting from the transportation is reduced. Thus, a concave relationship between the number of units on a vehicle (or the weight of the vehicle) and the resulting emissions (and emission costs) is established. For this research, experimental data from the U.S. EPA was used to correlate vehicle weight to carbon dioxide emissions, shown in Figure 2.1 (Environmental Protection Agency, 2006). The resulting emissions from the supply chain can then be multiplied by the market cost of carbon emissions to get the emission costs, which are combined with the logistics cost of the system in the objective function to minimize the total cost of the network.

The network was designed as a three-echelon supply chain, with plants at the first level, distribution centres at the second and retailers at the third level. Figure 3.1 illustrates the three-echelon model.

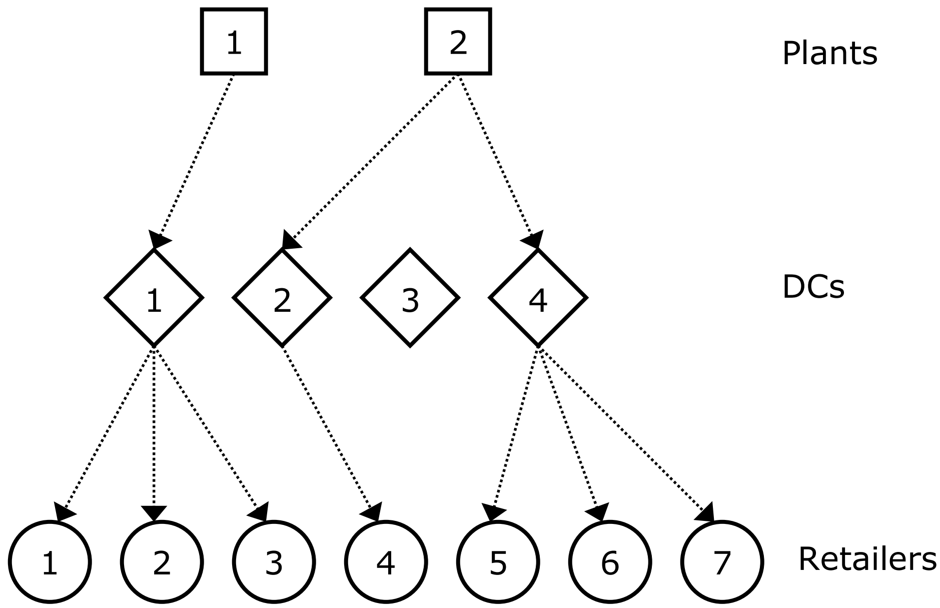

Figure 3.1: Three echelon supply chain.

The available plants, warehouse sites and retailers are indexed by $i = 1, \ldots, m$, $j = 1, \ldots, n$, $k = 1, \ldots, p$, respectively. The cost of emissions are a function of the weight of the payload being transported and are captured by the concave function, *f*. A distribution centre at location *j* has a maximum capacity V_j and a fixed cost of g_j. Each customer has a demand of d_k. The variable cost of handling and shipping a production unit from a plant at location *i* to distribution centre *j* is designated as c_{ij}. Similarly, h_{jk} denotes the average handling and shipping cost to move a production unit from distribution centre *j* to customer *k*. One continuous flow variable and two binary location variables are introduced: x_{ij} is the flow of units from plant *i* to warehouse *j*; y_{jk} takes a value of one if customer k is assigned to distribution centre j and zero otherwise; and, z_j is given a value of one if distribution centre j was opened and zero otherwise. The capacity of the plants is assumed to be unlimited, which models a situation where the manufacturer has the capacity to increase production to meet all customer demands (i.e. additional overtime or weekend production capabilities). The resulting MIP is:

$$\text{[FLM]:} \quad \min \sum_{i=1}^{m}\sum_{j=1}^{n} f(x_{ij}) + \sum_{j=1}^{n}\sum_{k=1}^{p} f(d_k y_{jk}) + \sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}x_{ij} + \sum_{j=1}^{n}\sum_{k=1}^{p} h_{jk}d_k y_{jk} + \sum_{j=1}^{n} g_j z_j$$

s.t.

$$\sum_{j=1}^{n} y_{jk} = 1 \qquad \forall k \qquad (1)$$

$$\sum_{i=1}^{m} x_{ij} = \sum_{k=1}^{p} d_k y_{jk} \qquad \forall j \qquad (2)$$

$$\sum_{i=1}^{m} x_{ij} \leq V_j z_j \qquad \forall j \qquad (3)$$

$$\sum_{k=1}^{p} d_k y_{jk} \leq V_j z_j \qquad \forall j \qquad (4)$$

$$y_{jk},\ z_j \in \{0,1\};\ x_{ij} \geq 0 \qquad \forall i,j,k \qquad (5)$$

The objective function in [FLM] minimizes the handling and transportation cost of goods between all nodes, the fixed cost of opening warehouses, and the pollution cost to the environment. The cost of all carbon dioxide emissions is accounted for in the first two terms of [FLM], which are a function of the product flows between nodes. Constraints (1) guarantee that each customer is assigned to exactly one distribution centre. Constraints (2) balance the flow of goods into and out of the warehouse, thus linking the decisions between echelons in the network. Constraints (3) and (4) force capacity restrictions on the distribution centres, as well as ensured that only open facilities are utilized.

[FLM] was formulated with a few unique attributes. Foremost, it was designed to strategically select distribution centre sites, thus it was plausible that several potential DC sites would not be used in the optimal solution. Furthermore, the binary variable y_{jk} ensured that each retailer was single-sourced by only one distribution centre. Finally, the problem formulation allowed for distribution centres to be served by more than one plant. However, since the plants were assumed to have limitless production capacity, it is later proven that the optimal solution will always result in each distribution centre being served by a single plant.

3.2 Motivating Examples

Recent legislation in certain jurisdictions has imposed emission costs on logistics firms. The problem studied in this thesis has been formulated to design a supply chain network where carbon costs are incurred. In addition, the problem formulation has been arranged to deal with firms who operate the following types of logistics networks:

1) Free on board manufacturer (FOB-M) delivery system
2) Networks with large and diverse vehicle fleets

These situations are discussed in the forthcoming sections and their applicability to the problem formulation is reviewed.

3.2.1 Free On Board Manufacturer Delivery

The problem formulated in this thesis was designed to support certain types of real world problems. This first motivating example to consider is the case where a manufacturer controls the delivery of a product from the plant through to the retailer, thus operating all transportation vehicles throughout the supply chain. In this scenario, the products are typically shipped via tractor-trailer from the plant to the distribution centre. The goods are then cross-loaded, mixed, and placed onto smaller local delivery vehicles for transport to the retailers.

The FOB-M delivery model fits well within the problem formulation for several reasons. Foremost, the structure of the problem means that there will be a higher unit flow on the shipping lanes between the plants and distribution centres than there will be on the routes between the DCs and retailers. This scenario fits the FOB-M distribution model well since this system typically has larger vehicles to transport the additional units between the first two echelons and smaller vehicles to transport the lesser quantity of units between the last two echelons. A manufacturer in control of product delivery from the DC to the customer can select an appropriately sized vehicle to meet the demand of the retailer and create a situation where the vehicles are nearly full on each trip.

Secondly, the concept of selecting a vehicle appropriately sized for the unit demand of the customer (whether internal or external) fits well with the emissions data used in this research. The most comprehensive carbon dioxide emissions data set is that published by the U.S. EPA (Environmental Protection Agency, 2006). While this data set is comprised of emissions from a number of vehicles of varying weight classes, the data works perfectly when considering a fleet of vehicles, varying in class, that are loaded at or near their maximum payload. This synergy between the problem structure and the emissions data creates an accurate model to tackle a real world issue.

3.2.2 Networks with Large and Diverse Fleets

The problem presented in this thesis is well suited for solving a network design problem for a firm with a large and diverse vehicle fleet. An organization with large and diverse fleet can select vehicles that are appropriately sized to meet the demand of the customer being served. Since the emissions data used in this thesis were derived from experiments on a number of vehicles of varying weight classes, the data is most applicable when dealing with trucks that are loaded at or near their maximum payload. Again, a synergy is produced where the problem structure and the emissions data produce a precise model to tackle a real world supply chain and logistics matter.

Chapter 4:

Solution Methodology

4.1 Lagrangian Relaxation

Lagrangian relaxation was used to decompose the initial problem, [FLM], into a set of simpler problems that could be solved more easily. Lagrangian relaxation is a commonly used technique for solving mixed integer programming problems, as outlined by Geoffrion (1974) and Fisher (1981). The method involves the strategic elimination of select constraints, which are transformed and incorporated into the objective function, to obtain a set of subproblems that are easier to solve than the original problem. The Lagrangian relaxation technique yields a bound on the objective function value, and is usually combined with a heuristic to produce good solution sets.

We can exploit the echelon structure of the current problem using the Lagrangian relaxation technique. Relaxing constraints must be done strategically as the relaxation of certain constraints can deteriorate the quality of the bound and heuristics. In this thesis, constraints (2) are relaxed since they link the echelons of the supply chain, as done in Pirkul & Jayaraman (1998) and Elhedhli & Gzara (2008). To decompose [FLM], Lagrangian multipliers, μ_j, are associated with constraints (2), which led to the following problem:

$$\text{[LR-FLM]:} \quad \min \sum_{i=1}^{m}\sum_{j=1}^{n} f(x_{ij}) + \sum_{j=1}^{n}\sum_{k=1}^{p} f(d_k y_{jk}) + \sum_{i=1}^{m}\sum_{j=1}^{n}(c_{ij} - \mu_j)x_{ij}$$

$$+ \sum_{j=1}^{n}\sum_{k=1}^{p}(h_{jk}d_k + d_k\mu_j)y_{jk} + \sum_{j=1}^{n} g_j z_j$$

s.t. Constraints (1), (3), (4) and (5)

With the relaxation of Constraints (2), the problem is then separable by echelon. Compiling all terms and constraints containing the decision variables y_{jk}, along with the fixed cost term from the objective function, lead to:

$$\text{[SP1]:} \quad \min \sum_{j=1}^{n}\sum_{k=1}^{p} f(d_k y_{jk}) + \sum_{j=1}^{n}\sum_{k=1}^{p}(h_{jk}d_k + d_k\mu_j)y_{jk} + \sum_{j=1}^{n} g_j z_j$$

$$\text{s.t} \quad \sum_{j=1}^{n} y_{jk} = 1 \qquad \forall k$$

$$\sum_{k=1}^{p} d_k y_{jk} \le V_j z_j \qquad \forall j$$

$$y_{jk},\ z_j \in \{0,1\} \qquad \forall j,k$$

The remaining terms and constraints were combined as:

$$\text{[SP2]:} \quad \min \sum_{i=1}^{m}\sum_{j=1}^{n} f(x_{ij}) + \sum_{i=1}^{m}\sum_{j=1}^{n}(c_{ij} - \mu_j)x_{ij} \qquad \forall j$$

$$\text{s.t.} \quad \sum_{i=1}^{m} x_{ij} \le V_j z_j$$

$$x_{ij} \ge 0 \qquad \forall i,j$$

Note that [SP2] can also be decomposed by potential warehouse site, resulting in *n* subproblems. [SP1] determines the assignment of customers to a distribution centre, while [SP2] determines the flow of goods from a plant to a distribution centre.

Examination of [SP1] reveals that it is simply a capacitated facility location problem with single sourcing:

$$\text{[SP1]:} \quad \min \sum_{j=1}^{n} \sum_{k=1}^{p} \big(f(d_k) + h_{jk} d_k + d_k \mu_j\big) y_{jk} + \sum_{j=1}^{n} g_j z_j$$

$$\text{s.t.} \quad \sum_{j=1}^{n} y_{jk} = 1 \qquad \forall k$$

$$\sum_{k=1}^{p} d_k y_{jk} \le V_j z_j \qquad \forall j$$

$$y_{jk},\ z_j \in \{0,1\} \qquad \forall j,k$$

Now consider the formulation of [SP2].

$$\text{[SP2]:} \quad \min \sum_{i=1}^{m} \sum_{j=1}^{n} f\big(x_{ij}\big) + \big(c_{ij} - \mu_j\big) x_{ij} \qquad \forall j$$

$$\text{s.t.} \quad \sum_{i=1}^{m} x_{ij} \le V_j z_j \qquad (3)$$

$$x_{ij} \ge 0 \qquad \forall i,j$$

Since z_j is a binary variable, we can consider the following two cases for [SP2]:

1) $z_j = 0$
2) $z_j = 1$

In case (1), the right-hand side of Constraints (3) is zero and thus x_{ij} is equal to zero for all values of *ij*. When considering case (2), [SP2] reduces to a concave minimization problem in the following form:

$$[\text{SP2}]: \quad \min \sum_{i=1}^{m} \sum_{j=1}^{n} \left[f(x_{ij}) + (c_{ij} - \mu_j) x_{ij} \right] \qquad \forall j$$

$$\text{s.t.} \quad \sum_{i=1}^{m} x_{ij} \leq V_j \qquad (3)$$

$$x_{ij} \geq 0 \qquad \forall i, j$$

An important property of a concave minimization problem is that every local and global solution is achieved at an extreme point (Pardalos & Rosen, 1986). In the particular case of [SP2], it has an optimal solution at an extreme point of $\{x_{ij} \geq 0, \sum_{i=1}^{m} x_{ij} \leq V_j\}$. This implies that at optimality at most one x_{ij} will take the value of V_j and the remaining x_{ij} will be equal to 0.

We can visualize this property by looking at concave curve of the cost of the network, shown in Figure 4.1.

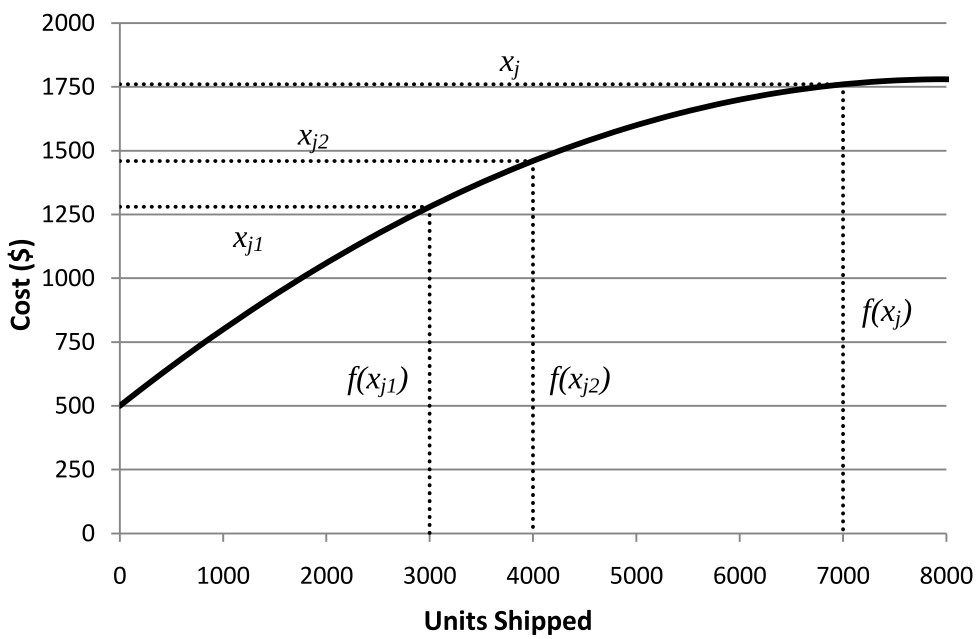

Figure 4.1: Concave cost curve.

Figure 4.1 has three unit quantities denoted, x_j, x_{j1} and x_{j2}, where $x_j = x_{j1} + x_{j2}$. If the DC requires x_j units, we have the option to ship x_j on a single truck, or to ship x_{j1} on one truck from plant 1and x_{j2} on a subsequent truck from plant 2. Due to the shape of the curve, it can be declared that cost to ship one truck is less than the cost to ship an equal number of units on multiple vehicles from multiple plants, or:

$$f(x_{j1}) + f(x_{j2}) \geq f(x_j) = f(x_{j1} + x_{j2})$$

Knowing that at most one x_{ij} will take the value of V_j and the remaining x_{ij} will be equal to 0, allows us to reformulate [SP2] as:

$$\text{[SP2-}j\text{]:} \quad \min \sum_{i=1}^{m} \left(f(V_j) + c_{ij} - \mu_j\right) x_{ij}$$

$$\text{s.t.} \quad \sum_{i=1}^{m} x_{ij} \leq V_j$$

$$x_{ij} \geq 0 \qquad \forall i$$

This formulation of [SP2] is now broken into n subproblems, each corresponding to a particular j. The Lagrangian multipliers will determine if the DC is open at site j. The Lagrangian multipliers, μ_j,will vary for iteration through the Lagrangian algorithm. When μ_j is such that $\left(f(V_j) + c_{ij} - \mu_j\right) > 0$, then all x_{ij} will equal to zero in order to minimize the objective function. This situation also signals that the distribution centre will not receive any product from the plants, and thus the site isclosed and z_j is equal to zero for the corresponding j. When μ_j is such that $\left(f(V_j) + c_{ij} - \mu_j\right) < 0$, then x_{ij} is equal to V_j for $i = i^*$ and x_{ij} is equal to zero for $i \neq i^*$. This signals that product is flowing from the plant (i^*) to the respective distribution centre, which is open, and thus z_j equal to one for the corresponding j.

[SP2-j] now has emissions cost terms that are deterministic. Since $f(V_j)$ takes a single value (the cost of emissions produced by transporting V_j), the nonlinearity is removed from the problem and it can be solved using linear MIP methods.

The advantage of this relaxation procedure is that [SP1] retains several important characteristics of the initial problem, such as the assignment of all customers to a single warehouse and the condition that the demand of all customers is satisfied. In addition, [SP2] reduces to n subproblems, which can be solved with little computational effort relative to the original problem. The drawback of this formulation is that [SP1] does not decompose further into a set of smaller subproblems, and instead remains a capacitated facility location problem with $[(n \times p) + n]$ assignment variables. Thus, the solution to [SP1] requires significantly more computational effort than [SP2]. However, [SP1] is still easier to solve than [FLM] and by retaining the critical characteristics of the [FLM] in [SP1], the Lagrangian bound can be achieved in a relatively small number of iterations and reduce the overall solution time while still obtaining a high quality bound (Elhedhli & Gzara, 2008).

The solution to the subproblems can be obtained by inserting an initial set of Lagrangian multipliers, μ_j, into each subproblem. The solutions to the subproblems yield a lower bound, *LB*, to the overall problem according to the following:

$$LB = \left[v[SP1] + \sum_{j=1}^{n} v[SP2 - j] \right]$$

LB is calculated in each iteration, with the best Lagrangian lower bound, *LB**, being:

$$LB^* = \max_{\mu}\left[v[SP1] + \sum_{j=1}^{n} v[SP2 - j]\right]$$

LB^* is a concave non-differentiable problem, which is equivalent to:

$$\max_{\mu}\left\{\min_{h\in I_x}\sum_{j=1}^{n}\sum_{k=1}^{p}\left(f(d_k) + h_{jk}d_k + d_k\mu_j\right)y_{jk} + \sum_{j=1}^{n} g_j z_j + \sum_{j=1}^{n}\min_{h_j\in I_{yj}}\sum_{i=1}^{m}\left(f(V_j) + c_{ij} - \mu_j\right)x_{ij}\right\} \tag{6}$$

where I_x is the index set of feasible integer points of the set:

$$\left\{\left(y_{jk}^h, z_j^h\right): \sum_{j=1}^{n} y_{jk}^h = 1\,; \sum_{k=1}^{p} d_k y_{jk}^h \le V_j z_j^h; y_{jk}^h \in \{0,1\};\ z_j^h \in \{0,1\}, \quad \forall j,k\right\}$$

and I_{yj} is the index set of extreme points of the set:

$$\left\{\left(x_{ij}^{h_j}\right): \sum_{i=1}^{m} x_{ij}^{h_j} \le V_j;\ x_{ij}^{h_j} \ge 0, \quad \forall i\right\}$$

We can then reformulate (6) in the Lagrangian master problem:

$$\text{[LMP]:} \quad \max \theta_0 + \sum_{j=1}^{n}\theta_j$$

$$\text{s.t.} \quad \theta_0 + \sum_{j=1}^{n}\left(\sum_{k=1}^{p} d_k y_{jk}^h\right)\mu_j \le \sum_{j=1}^{n}\sum_{k=1}^{p}\left(f(d_k) + h_{jk}d_k\right)y_{jk}^h + \sum_{j=1}^{n} g_j z_j^h \qquad h \in I_x$$

$$\theta_j - \sum_{i=1}^{m} x_{ij}^{h_j}\mu_j \le \sum_{i=1}^{m}\left(f\left(x_{ij}^{h_j}\right)\right) + \sum_{i=1}^{m} c_{ij}x_{ij}^{h_j} \qquad h_j \in I_{yj},\ \forall j$$

[LMP] can be solved as a linear programming problem. $\overline{I_x} \subset I_x$ and $\overline{I_{yj}} \subset I_{yj}$ define the relaxation of [LMP]. An initial set of Lagrangian multipliers, $\bar{\mu}$, is used to solve [SP1] and [SP2] and generate $n+1$ cuts of the form:

$$\theta_1 + \sum_{j=1}^{n}\left(\sum_{k=1}^{p} d_k y_{jk}^{\bar{a}}\right)\mu_j \leq \sum_{j=1}^{n}\sum_{k=1}^{p}\big(f(d_k) + h_{jk}d_k\big)y_{jk}^{\bar{a}} + \sum_{j=1}^{n} g_j z_j^{\bar{a}}$$

$$\theta_j - \sum_{i=1}^{m} x_{ij}^{\bar{b}}\mu_j \leq \sum_{i=1}^{m}\left(f\left(x_{ij}^{\bar{b}}\right)\right) + \sum_{i=1}^{m} c_{ij}x_{ij}^{\bar{b}} \qquad \forall j$$

The index sets $\overline{I_x}$ and $\overline{I_{yJ}}$ are updated at each iteration as $\overline{I_x} \cup \{\bar{a}\}$ and $\overline{I_{yJ}} \cup \{\bar{b}\}$, respectively.

The solution to the [LMP] produces an upper bound, *UB*, to the full master problem and a new set of Lagrangian multipliers. The new set of Lagrangian multipliers is input to [SP1] and [SP2] to generate a new solution to the subproblems and an additional set of cuts to the [LMP]. The procedure of iterating through subproblems and master problem solutions is terminated when the best lower bound is equal to the upper bound, at which point the Lagrangian bound is achieved. A flow chart outlining the proposed Lagrangian solution method is shown in Figure 4.2. Note that the heuristic procedure designed to generate a feasible solution is outlined and discussed in the next chapter.

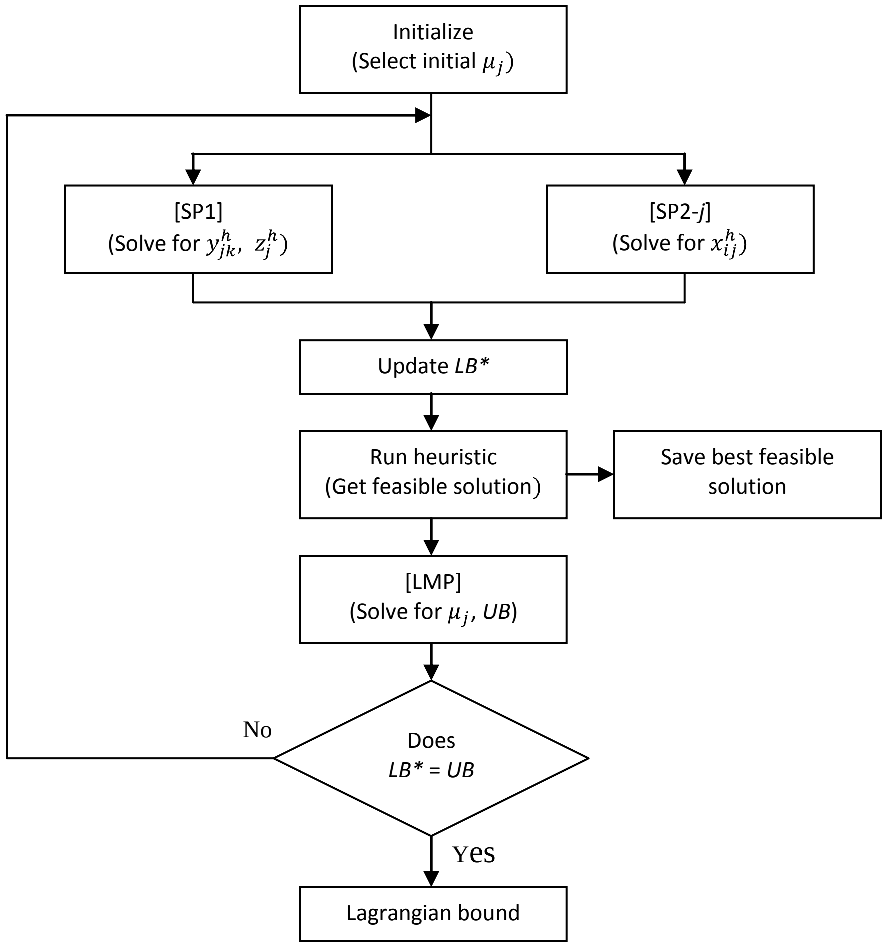

Figure 4.2: The Lagrangian algorithm

Chapter 5:

A Primal Heuristic for Generating Feasible Solutions

While the Lagrangian algorithm provides the optimal objective function value, it does not reveal the combination of product flows, customer assignments and open facilities that will produce this result. Hence, heuristics are commonly used in conjunction with Lagrangian relaxation algorithms to generate feasible solutions, see for example Jayaraman & Pirkul (2001) and Elhedhli & Gzara (2008). Several meta-heuristics have also been used to generate feasible solutions in location models, such as simulated annealing (Syam, 2002), genetic algorithm (Syarif, Yun, & Gen, 2002) and hybrid method termed as tabu-simulated annealing (Altiparmak & Karaoglan, 2008).

An efficient heuristic was extremely important for the Lagrangian relaxation of the formulation proposed in this thesis. Due the strength of [SP1], the Lagrangian bound will be achieved in a relatively small number of iterations. Since the Lagrangian algorithm only attempts to produce one feasible solution per iteration, a quality primal heuristic must produce a good feasible solution in a relatively small number of attempts. To generate feasible solutions, a primal heuristic was introduced that was based on the solution obtained from the subproblems. Subproblem [SP1] generated the assignments of customers to distribution centres and determined if a distribution centre was open or closed. The optimal solution produced by subproblem [SP1] for iteration h was denoted as y_{jk}^h and z_j^h. Using y_{jk}^h and z_j^h from [SP1], the units demanded by the retailers at each distribution centre can be determined. With the demand at each distribution centre being deterministic, the original problem could be reduced to a simple continuous flow transportation problem, [TP], which will always have a feasible solution.

$$\text{[TP]:} \quad \min \sum_{j=1}^{n}\sum_{k=1}^{p}\left(f(d_k) + h_{jk}d_k\right)y_{jk}^h + \sum_{i=1}^{m}\sum_{j=1}^{n} f\left(x_{ij}\right) + \sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}x_{ij} + \sum_{j=1}^{n} g_j z_j^h$$

$$\text{s.t.} \quad \sum_{i=1}^{m} x_{ij} = \sum_{k=1}^{n} d_k y_{jk}^h \qquad \forall j$$

$$x_{ij} \geq 0 \qquad \forall i,j$$

The first and fourth terms in [TP] are simply constants, thus leaving only two terms in the objective function. The first and fourth terms in [TP] are grouped together and denoted as C in future formulations. The problem formulation stipulated that the each warehouse will be single-sourced by one plant and that the goods will be transported on a single truck, as opposed to being spread over multiple vehicles (see proof in section 4.1). Therefore, the optimal flow of units from a plant to warehouse will be equal to the quantity demanded by the warehouse or zero. [TP] can then be formulated as an assignment problem of the following form:

$$\text{[TP]:} \quad \min \sum_{i=1}^{m}\left(f\left(\sum_{k=1}^{p} d_k y_{jk}^h\right) + c_{ij}\left(\sum_{k=1}^{p} d_k y_{jk}^h\right)\right)x_{ij} + C$$

$$\text{s.t.} \quad \sum_{i=1}^{m}\left(\sum_{k=1}^{p} d_k y_{jk}^h\right)x_{ij} = \sum_{k=1}^{p} d_k y_{jk}^h \qquad \forall j$$

$$x_{ij} \in \{0,1\} \qquad \forall i,j$$

where x_{ij} takes a value of one if warehouse j is supplied by plant i and zero otherwise. In numerical testing of the algorithm, the heuristic was activated at each iteration to find a feasible solution. The quality of the heuristic solution was evaluated through a comparison of the heuristic objective function value with the Lagrangian bound.

Chapter 6:

Numerical Testing

The Lagrangian solution algorithm, outlined in section 4.2, was tested on a number of sample problems. The test problems varied in size, cost structure and difficulty to provide a robust proving ground for the model. This Chapter first outlines the problem generation procedure, which is then followed by the definition of evaluation statistics and the numerical testing results and analysis.

6.1 Problem Generation

The solution algorithm was implemented in Matlab 7 and utilized Cplex 11 to solve the subproblems, heuristic problem and the master problem. The test problems were generated in accordance with the procedure for capacitated facility location problems as suggested by Cornuejols et al. (1991), and later used by Elhedhli and Goffin (2005). The procedure calls for problems to be generated randomly while keeping the parameters realistic. The coordinates of the plants, distribution centres and customers were generated uniformly over a unit square of dimension 190, or U[10,200]. From the coordinates, the Euclidean distance between each set nodes, d_{ij} and d_{jk}, was computed. The transportation and handling costs between nodes were then set using the following relationship, where β was simply a scaling parameter to exploit different scenarios in numerical testing:

$$c_{ij} = \beta_1 \times \lceil 10 \times d_{ij} \rceil \qquad\qquad h_{jk} = \beta_2 \times \lceil 10 \times d_{jk} \rceil$$

The demand of each customer, d_k, was generated uniformly on U[10,50]. The capacities of the distribution centres, V_j, were also created randomly using the following form, where κ was used to scale the ratio of warehouse capacity to demand:

$$V_j = \kappa \times [U[10{,}160]]$$

In essence, κ dictates the rigidity or tightness of the problem and has a large impact on the time required to solve the problem. The capacities of the distribution centres were scaled so as to satisfy

$$\kappa = \left(\frac{\sum_{j=1}^{n} V_j}{\sum_{k=1}^{p} d_k}\right) = 3, 5, 10$$

The fixed costs of the DCs were designed to reflect economies of scale. The fixed cost to open a distribution centre, g_j, was calculated using the following equation:

$$g_j = \alpha \times \left[U[0{,}90] + U[100{,}110] \times \sqrt{V_j}\right]$$

Again, α is a scaling parameters used to test different scenarios in the numerical testing phase.

The research in this thesis differs from traditional facilities location models due to the addition of emission costs into the objective function. Just as the problem formulation was extended, the testing model must also be extended. In order to compute the emission costs, the distance travelled, vehicle weight and emission rate must be known. The distance travelled can easily be determined from the randomly generated coordinates of the sites. The vehicle weight is determined by the number of units loaded on the truck (x_{ij} or $d_k y_{jk}$). To compute the weight of the vehicle, an empty vehicle weight of 15,000 pounds was assumed and the weight of a single production unit was assumed to be 75 pounds. The payload was calculated as the number of units on the truck multiplied by the weight of a single unit, which resulted in loads between 0 and 45,000 pounds. The sum of the empty tractor-trailer weight and the payload results in a loaded vehicle weight range of 15,000 pounds to 60,000 pounds. It was assumed that single vehicle trips would be made between nodes, thus the vehicle weights were reasonable and the emissions curve for a single truck was used. However, the emissions curve could be substituted with a best fit concave line that would represent a number of vehicle trips, if so desired. Finally, the emission rate, *e*, was determined using the U.S. EPA lab data, shown in Figure 2.1 (Environmental Protection Agency, 2006). Using these parameters, the emission cost of the network, *f*, can be determined using the following equation:

$$\sum_{i=1}^{m}\sum_{j=1}^{n} f(x_{ij}) = \Omega \times \left[\sum_{i=1}^{m}\sum_{j=1}^{n} [0.2 \times e(x_{ij}) \times d_{ij}]\right]$$

$$\sum_{j=1}^{n}\sum_{k=1}^{p} f(d_k y_{jk}) = \Omega \times \left[\sum_{j=1}^{n}\sum_{k=1}^{p} [0.2 \times e(d_k y_{jk}) \times d_{jk}]\right]$$

Ω is used as a scaling parameter to test various network scenarios. The constants on the right-hand sides of the above equations are used for unit conversions and to associate a dollar value to the emission quantity. For all test cases, a travel speed of 80 kph was used to compute emission levels, which was assumed to be representative of highway transportation.

6.2 Test Statistics

The solution algorithm underwent rigorous testing to measure its effectiveness. Each test case investigated a unique combination of facilities. The test problems ranged in size for a small problems, with 3 plants, 5 warehouses and 15 customers, to large scale problems, 10 plants, 20 distribution centres and 150 customers.

Several statistics were tracked throughout the computation procedure for later evaluation. Upon completion of the Lagrangian algorithm, the Lagrangian bound and best feasible solution were used to calculate more statistical indicators. This section describes how the test statistics were computed using information collected during the solution procedure.

Foremost, the load ratio of the open distribution centres was calculated. The DC load ratio, *DCLR*, relates the total capacity of all open DCs to the total units demanded by the customers, and was computed as:

$$DCLR = \frac{\sum_{j=1}^{n}(V_j \cdot z_j)}{\sum_{k=1}^{p}(d_k)}$$

The cost breakdown of the best feasible network resulting from the solution algorithm was also evaluated. Three primary cost groups were considered: the fixed costs to open the distribution centres (*FCR_DC*), the variable logistics costs (*VCR*) and the emissions costs (*ECR*). These categories were computed as a percentage of the total system expense, denoted as *Z*, using the following formulas:

$$FCR\_DC = \frac{\sum_{j=1}^{n}(g_j \cdot z_j)}{Z}$$

$$VCR = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}x_{ij} + \sum_{j=1}^{n}\sum_{k=1}^{p} h_{jk}d_k y_{jk}}{Z}$$

$$ECR = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} f(x_{ij}) + \sum_{j=1}^{n}\sum_{k=1}^{p} f(d_k y_{jk})}{Z}$$

The Lagrangian algorithm employed in this research leveraged a primal heuristic to generate a feasible solution at each iteration. The quality of the heuristic was measured by comparing the cost of the feasible solution versus the Lagrangian bound, denoted as LR, as follows:

$$Heuristic\ Quality = 100 \times \left(\frac{heuristic\ solution - LR}{LR}\right)$$

Data on the evaluation times required to solve each section of the Lagrangian algorithm were also collected. The computation time was computed as a percentage of the total solution time in each of the following sections: subproblems 1, subproblems 2, generating a feasible solution via the primal heuristic, and the Lagrangian master problem. The solution times can be used to give insight as to the relative difficult of the particular problem.

Finally, the number of iterations required to achieve the Lagrangian bound was tallied and recorded for each test case.

6.3 Base Scenario

The solution algorithm was tested using a variety of cases. The first test case considered was the base scenario, which serves as baseline for comparison. In the base case the scaling parameters were set as follows:

$$\beta_1 = \beta_2 = 1$$

$$\alpha = 100$$

$$\Omega = 1$$

The base case was tested with varying DC capacity ratios: tight capacities ($\kappa = 3$), moderate capacities ($\kappa = 5$), and excess capacities ($\kappa = 10$). The results for the base scenario testing are provided in Tables 6.1, 6.2 and 6.3, corresponding to tight, moderate and excess capacities, respectively.

The test statistics lead to several insights about the problem formulation and solution algorithm. First, consider the distribution centre load ratio (DCLR). The data show that the rigidity of the problem (dictated by κ) had a large impact on the DCLR, both in terms of the average and range of the ratio. Tables 6.1 to 6.3 show that as the tightness of the problem is decreased (or as κ is increased), the DCLR is also lessened. This is evident by the decreasing trend in the mean DCLR, which reduces from 0.919, to 0.869, to 0.709, for tight, moderate and excess capacities, respectively. Furthermore, the results show that the range of the DCLRs increase as κ increases. For tight capacities, the range of load ratios produced was relatively small (from 0.825 to 0.981), whereas the excess capacities base scenario produced a range in excess of 50% of the DCLR (from 0.409 to 0.997). Thus, it can be said that the tightness of the problem has an adverse effect on the load ratio of the distribution centre.

The cost breakdowns for the base scenario test cases are also presented in Tables 6.1 to 6.3. In contrast to the DCLR, the distribution of costs is fairly stable across the varying DC capacity levels. For the base test case, the FCR_DC range was between 0.35 and 0.40, the VCR ranged from 0.50 to 0.55, and the ECR was between 0.10 and 0.15, for tight, moderate and excess capacities. Hence, the value of κ had little impact of the cost distribution of the network.

Table 6.1a: Base test scenario – Tight capacities.

Problem						
m.n.p	Vars.	DCLR	FCR_DC	VCR	ECR	Iters.
3.5.15	95	0.828	0.387	0.496	0.117	3
3.5.25	145	0.827	0.304	0.567	0.129	3
4.8.20	200	0.903	0.378	0.512	0.110	4
4.8.30	280	0.825	0.398	0.484	0.118	4
5.10.20	260	0.917	0.404	0.489	0.107	4
5.10.40	460	0.886	0.371	0.522	0.107	4
5.10.60	660	0.858	0.343	0.537	0.120	4
8.15.25	510	0.947	0.486	0.423	0.091	4
8.15.50	885	0.952	0.380	0.509	0.111	4
8.15.75	1260	0.980	0.339	0.539	0.122	5
10.20.50	1220	0.978	0.454	0.444	0.102	4
10.20.75	1720	0.944	0.398	0.498	0.105	4
10.20.100	2220	0.972	0.409	0.485	0.106	4
10.20.125	2720	0.981	0.363	0.519	0.117	4
10.20.150	3220	0.980	0.365	0.527	0.108	5
Min	-	0.825	0.304	0.423	0.091	3
Mean	-	0.919	0.385	0.503	0.111	4.0
Max	-	0.981	0.486	0.567	0.129	5

Table 6.1b: Base test scenario – Tight capacities.

Problem	Heur.	Time (%, %, %, %, sec)				
m.n.p	Quality	SP1	SP2	Heur	MP	Total
3.5.15	0.135	67.5	17.1	7.8	7.6	0.19
3.5.25	0.160	83.5	9.2	3.9	3.4	1.1
4.8.20	0.072	89.0	6.8	2.2	1.9	1.6
4.8.30	0.127	96.1	2.4	0.8	0.7	2.3
5.10.20	0.102	91.7	5.3	1.7	1.3	2.5
5.10.40	0.092	98.6	0.9	0.2	0.2	14.0
5.10.60	0.099	98.8	0.8	0.2	0.2	22.0
8.15.25	0.053	94.1	3.6	1.5	0.8	189
8.15.50	0.025	99.6	0.2	0.1	0.1	358
8.15.75	0.008	99.6	0.2	0.1	0.1	276
10.20.50	0.024	99.6	0.3	0.1	0.0	986
10.20.75	0.060	99.9	0.1	0.0	0.0	765
10.20.100	0.010	99.9	0.1	0.0	0.0	1543
10.20.125	0.013	99.9	0.0	0.0	0.0	1328
10.20.150	0.019	99.8	0.1	0.0	0.0	2194
Min	0.008	67.5	0.0	0.0	0.0	0.19
Mean	0.067	94.5	3.1	1.2	1.1	512
Max	0.160	99.9	17.1	7.8	7.6	2194

Table 6.2a: Base test scenario – Moderate capacities.

Problem						
m.n.p	Vars.	DCLR	FCR_DC	VCR	ECR	Iters.
3.5.15	95	0.770	0.331	0.540	0.129	4
3.5.25	145	0.708	0.330	0.550	0.121	3
4.8.20	200	0.823	0.341	0.540	0.119	4
4.8.30	280	0.750	0.345	0.538	0.117	4
5.10.20	260	0.849	0.402	0.489	0.109	4
5.10.40	460	0.818	0.331	0.552	0.117	4
5.10.60	660	0.917	0.280	0.595	0.124	4
8.15.25	510	0.917	0.428	0.461	0.111	5
8.15.50	885	0.887	0.402	0.473	0.125	4
8.15.75	1260	0.939	0.352	0.531	0.116	4
10.20.50	1220	0.970	0.371	0.506	0.123	4
10.20.75	1720	0.937	0.344	0.532	0.124	4
10.20.100	2220	0.935	0.343	0.531	0.127	4
10.20.125	2720	0.897	0.310	0.563	0.127	4
10.20.150	3220	0.916	0.298	0.578	0.125	4
Min	-	0.708	0.280	0.461	0.109	3
Mean	-	0.869	0.347	0.532	0.121	4.0
Max	-	0.970	0.428	0.595	0.129	5

Table 6.2b: Base test scenario – Moderate capacities.

Problem	Heur.	Time (%, %, %, %, sec)				
m.n.p	Quality	SP1	SP2	Heur	MP	Total
3.5.15	0.124	64.1	18.7	9.1	8.1	0.31
3.5.25	0.179	78.2	12.2	5.1	4.5	4.4
4.8.20	0.069	91.3	5.1	2.1	1.6	51.7
4.8.30	0.126	81.5	11.2	4.1	3.2	0.66
5.10.20	0.063	85.0	9.6	3.1	2.4	1.00
5.10.40	0.077	97.5	1.5	0.5	0.4	7.5
5.10.60	0.041	97.9	1.2	0.5	0.3	17.0
8.15.25	0.039	92.7	4.7	1.6	1.0	147
8.15.50	0.036	94.3	3.0	1.3	1.4	180
8.15.75	0.030	99.3	0.4	0.2	0.1	592
10.20.50	0.009	95.6	2.6	0.9	0.9	583
10.20.75	0.023	99.9	0.0	0.0	0.0	883
10.20.100	0.014	99.6	0.3	0.1	0.1	1061
10.20.125	0.041	99.8	0.1	0.0	0.0	1242
10.20.150	0.041	98.8	0.8	0.3	0.2	1548
Min	0.009	64.1	0.0	0.0	0.0	0.31
Mean	0.061	91.7	4.8	1.9	1.6	421
Max	0.179	99.9	18.7	9.1	8.1	1548

Table 6.3a: Base test scenario – Excess capacities.

Problem						
m.n.p	Vars.	DCLR	FCR_DC	VCR	ECR	Iters.
3.5.15	95	0.580	0.334	0.550	0.116	3
3.5.25	145	0.560	0.270	0.590	0.140	4
4.8.20	200	0.409	0.496	0.401	0.103	4
4.8.30	280	0.505	0.401	0.470	0.129	3
5.10.20	260	0.623	0.483	0.399	0.118	4
5.10.40	460	0.655	0.259	0.580	0.161	4
5.10.60	660	0.640	0.273	0.611	0.116	3
8.15.25	510	0.904	0.356	0.533	0.111	4
8.15.50	885	0.772	0.326	0.523	0.151	4
8.15.75	1260	0.826	0.315	0.558	0.127	6
10.20.50	1220	0.902	0.450	0.434	0.116	4
10.20.75	1720	0.997	0.307	0.564	0.129	4
10.20.100	2220	0.646	0.327	0.538	0.135	4
10.20.125	2720	0.927	0.298	0.577	0.125	5
10.20.150	3220	0.693	0.297	0.562	0.141	4
Min	-	0.409	0.259	0.399	0.103	3
Mean	-	0.709	0.346	0.526	0.128	4.0
Max	-	0.997	0.496	0.611	0.161	6

Table 6.3b: Base test scenario – Excess capacities.

Problem	Heur.	Time (%, %, %, %, sec)				
m.n.p	Quality	SP1	SP2	Heur	MP	Total
3.5.15	0.174	45.9	22.3	20.8	11.0	0.13
3.5.25	0.079	60.8	18.5	12.7	8.0	0.56
4.8.20	0.097	86.6	7.0	4.1	2.4	0.74
4.8.30	0.061	62.7	18.2	12.6	6.6	0.21
5.10.20	0.204	99.9	0.1	0.0	0.0	96.1
5.10.40	0.039	94.8	2.9	1.4	0.9	2.4
5.10.60	0.083	95.5	2.9	0.9	0.7	1.4
8.15.25	0.040	99.1	0.5	0.2	0.1	16.8
8.15.50	0.118	92.7	5.0	1.3	1.0	1.8
8.15.75	0.049	95.7	2.9	0.7	0.6	4.5
10.20.50	0.050	99.8	0.1	0.0	0.0	106
10.20.75	0.001	96.8	1.8	0.7	0.7	6.6
10.20.100	0.034	99.7	0.2	0.1	0.0	59.2
10.20.125	0.008	99.9	0.1	0.0	0.0	199
10.20.150	0.035	98.6	1.0	0.2	0.2	173
Min	0.001	45.9	0.1	0.0	0.0	0.13
Mean	0.071	88.6	5.6	3.7	2.2	45
Max	0.204	99.9	22.3	20.8	11.0	199

Time data was also collected in the numerical testing procedure. The results showed that as the numbers of decision variables in the problem increased, the computation time required to complete the solution algorithm also increased. Additionally, the average solution time increased as the tightness of the problem increased. Data was also collected regarding the percentage of time spent computing each step in the algorithm. The data showed that the majority of the solution time was spent solving [SP1], accounting for roughly 90% of the total time. The next largest time consumer was [SP2], although it required considerably less time than [SP1] due to the fact that [SP2] was decomposed by DC site into many smaller problems that were easier to solve. Making up the remainder of the processing time were, in decreasing order, the heuristic solution and the Lagrangian master problem. It was also observed that as the number of variables increased, an increasing percentage of the solution time was spent solving [SP1].

The primal heuristic proposed in this research is critical to the Lagrangian algorithm, since it selects the DCs to be opened and computes the unit flow between nodes. To evaluate the quality of the heuristic, the objective function value produced best feasible heuristic solution is compared against the Lagrangian bound. The data collected from the base scenario test runs showed that the primal heuristic produced very good feasible solutions that were in all cases less than 1% away from the optimum. Contributing to the strength of the heuristic was the fact that the information used to construct the heuristic solution was taken from [SP1]. Furthermore, [SP1] retained many attributes of the original problem and was already a very strong formulation, which was evident by the large amount of time spent solving [SP1]. As such, the heuristic quality was much improved and allowed for a very good feasible solution to be achieved in a small number of iterations.

6.4 Dominant Fixed Cost Scenario

The second test scenario for the solution algorithm is the dominant fixed cost case. This scenario enlarges the scaling parameter on the fixed costs to establish the distribution centres, which causes the total fixed cost of the network to represent a large portion of the total system expense. For the dominant fixed cost scenario the scaling parameters were set as follows:

$$\beta_1 = \beta_2 = 1$$

$$\alpha = 1000$$

$$\Omega = 1$$

The dominant fixed cost scenario was also tested with varying DC capacity ratios: tight capacities ($\kappa = 3$), moderate capacities ($\kappa = 5$), and excess capacities ($\kappa = 10$). The solution statistics from the dominant fixed cost scenario are present in Tables 6.4, 6.5 and 6.6, which correspond to tight, moderate and excess capacities, respectively.

Table 6.4a: Fixed cost dominant scenario – Tight capacities.

Problem						
m.n.p	Vars.	DCLR	FCR_DC	VCR	ECR	Iters.
3.5.15	95	0.631	0.885	0.094	0.022	4
3.5.25	145	0.983	0.756	0.204	0.039	4
4.8.20	200	0.952	0.858	0.119	0.023	4
4.8.30	280	0.954	0.868	0.105	0.027	4
5.10.20	260	0.991	0.855	0.121	0.024	4
5.10.20	260	0.923	0.836	0.136	0.028	4
5.10.60	660	0.994	0.733	0.208	0.059	4
8.15.25	510	0.995	0.902	0.079	0.019	4
8.15.50	885	0.963	0.871	0.118	0.011	5
8.15.75	1260	0.961	0.817	0.147	0.037	6
10.20.50	1220	0.980	0.853	0.110	0.037	4
10.20.75	1720	0.953	0.856	0.097	0.047	4
10.20.100	2220	0.932	0.844	0.102	0.054	4
10.20.125	2720	0.978	0.786	0.191	0.023	5
10.20.150	3220	0.978	0.820	0.159	0.021	4
Min	-	0.631	0.733	0.079	0.011	4
Mean	-	0.944	0.836	0.133	0.031	4.3
Max	-	0.995	0.902	0.208	0.059	6

Table 6.4b: Fixed cost dominant scenario – Tight capacities.

Problem	Heur.	Time (%, %, %, %, sec)				
m.n.p	Quality	SP1	SP2	Heur	MP	Total
3.5.15	0.081	73.0	10.6	10.6	5.8	0.28
3.5.25	0.007	99.0	0.4	0.4	0.2	7.5
4.8.20	0.017	99.9	0.1	0.0	0.0	80.4
4.8.30	0.006	98.0	0.9	0.7	0.4	4.6
5.10.20	0.002	98.5	0.7	0.5	0.3	6.7
5.10.20	0.017	99.9	0.0	0.1	0.0	311
5.10.60	0.001	100.0	0.0	0.0	0.0	1586
8.15.25	0.001	100.0	0.0	0.0	0.0	705
8.15.50	0.001	99.9	0.1	0.0	0.0	2100
8.15.75	0.014	99.9	0.1	0.0	0.0	3151
10.20.50	0.002	99.9	0.1	0.0	0.0	3051
10.20.75	0.003	98.9	0.4	0.4	0.3	601
10.20.100	0.005	100.0	0.0	0.0	0.0	5550
10.20.125	0.012	100.0	0.0	0.0	0.0	6800
10.20.150	0.009	100.0	0.0	0.0	0.0	8050
Min	0.001	73.0	0.0	0.0	0.0	0.28
Mean	0.012	97.8	0.9	0.8	0.5	2134
Max	0.081	100.0	10.6	10.6	5.8	8050

Table 6.5a: Fixed cost dominant scenario – Moderate capacities.

Problem						
m.n.p	Vars.	DCLR	FCR_DC	VCR	ECR	Iters.
3.5.15	95	0.865	0.799	0.161	0.040	4
3.5.25	145	0.689	0.766	0.183	0.051	4
4.8.20	200	0.916	0.722	0.226	0.052	4
4.8.30	280	0.905	0.650	0.286	0.063	4
5.10.20	260	0.960	0.824	0.149	0.028	4
5.10.40	460	0.983	0.744	0.213	0.042	4
5.10.60	660	0.997	0.716	0.237	0.047	4
8.15.25	510	0.953	0.846	0.123	0.030	5
8.15.50	885	0.944	0.811	0.150	0.039	5
8.15.75	1260	0.994	0.808	0.155	0.037	5
10.20.50	1220	0.999	0.828	0.142	0.030	5
10.20.75	1720	0.972	0.791	0.178	0.032	5
10.20.100	2220	0.983	0.768	0.190	0.042	5
10.20.125	2720	0.999	0.745	0.216	0.039	5
10.20.150	3220	0.991	0.715	0.235	0.050	5
Min	-	0.689	0.650	0.123	0.028	4
Mean	-	0.943	0.769	0.190	0.041	4.5
Max	-	0.999	0.846	0.286	0.063	5

Table 6.5b: Fixed cost dominant scenario – Moderate capacities.

Problem	Heur.	Time (%, %, %, %, sec)				
m.n.p	Quality	SP1	SP2	Heur	MP	Total
3.5.15	0.015	80.6	6.0	6.0	7.4	0.61
3.5.25	0.025	73.1	14.9	6.3	5.7	0.20
4.8.20	0.011	99.9	0.1	0.0	0.0	116
4.8.30	0.016	93.7	3.9	1.3	1.2	1.1
5.10.20	0.010	91.8	5.5	1.5	1.3	1.00
5.10.40	0.003	100.0	0.0	0.0	0.0	295
5.10.60	0.000	99.1	0.5	0.3	0.1	12.5
8.15.25	0.005	83.5	9.2	3.5	3.8	1.2
8.15.50	0.006	100.0	0.0	0.0	0.0	3263
8.15.75	0.001	98.2	1.0	0.4	0.4	34.0
10.20.50	0.000	100.0	0.0	0.0	0.0	2410
10.20.75	0.004	100.0	0.0	0.0	0.0	1478
10.20.100	0.002	99.5	0.3	0.1	0.1	49.3
10.20.125	0.000	99.9	0.1	0.0	0.0	248
10.20.150	0.002	99.9	0.1	0.0	0.0	194
Min	0.000	73.1	0.0	0.0	0.0	0.20
Mean	0.007	94.6	2.8	1.3	1.3	540
Max	0.025	100.0	14.9	6.3	7.4	3263

Table 6.6a: Fixed cost dominant scenario – Excess capacities.

Problem						
m.n.p	Vars.	DCLR	FCR_DC	VCR	ECR	Iters.
3.5.15	95	0.587	0.789	0.171	0.040	4
3.5.25	145	0.417	0.785	0.176	0.038	3
4.8.20	200	0.718	0.774	0.190	0.037	7
4.8.30	280	0.695	0.772	0.179	0.050	5
5.10.20	260	0.914	0.738	0.213	0.048	4
5.10.40	460	0.875	0.712	0.234	0.055	5
5.10.60	660	0.825	0.637	0.293	0.070	6
8.15.25	510	0.948	0.736	0.217	0.048	5
8.15.50	885	0.924	0.607	0.328	0.064	7
8.15.75	1260	0.905	0.615	0.319	0.065	5
10.20.50	1220	0.998	0.811	0.152	0.036	6
10.20.75	1720	0.949	0.788	0.168	0.044	6
10.20.100	2220	0.949	0.725	0.218	0.057	6
10.20.125	2720	0.973	0.689	0.255	0.056	6
10.20.150	3220	0.968	0.714	0.226	0.060	5
Min	-	0.417	0.607	0.152	0.036	3
Mean	-	0.843	0.726	0.223	0.051	5.3
Max	-	0.998	0.811	0.328	0.070	7

Table 6.6b: Fixed cost dominant scenario – Excess capacities.

Problem	Heur.	Time (%, %, %, %, sec)				
m.n.p	Quality	SP1	SP2	Heur	MP	Total
3.5.15	0.045	46.4	16.7	16.9	20.0	0.18
3.5.25	0.088	56.1	16.5	18.5	8.9	0.14
4.8.20	0.034	83.7	8.2	5.1	3.1	0.83
4.8.30	0.011	84.6	7.6	5.0	2.7	0.68
5.10.20	0.015	99.9	0.1	0.0	0.0	58.2
5.10.40	0.005	99.9	0.1	0.0	0.0	100
5.10.60	0.013	92.4	4.1	2.2	1.3	1.8
8.15.25	0.005	90.8	5.4	2.4	1.4	1.6
8.15.50	0.009	98.1	1.2	0.4	0.3	10.1
8.15.75	0.011	98.4	0.9	0.4	0.2	51.9
10.20.50	0.000	99.8	0.2	0.1	0.0	88.6
10.20.75	0.001	98.2	1.1	0.4	0.3	67.0
10.20.100	0.001	98.7	0.7	0.3	0.3	60.3
10.20.125	0.001	99.6	0.2	0.1	0.1	99.6
10.20.150	0.002	99.8	0.1	0.0	0.0	193
Min	0.000	46.4	0.1	0.0	0.0	0.14
Mean	0.016	89.7	4.2	3.5	2.6	49
Max	0.088	99.9	16.7	18.5	20.0	193

The test statistics from the fixed cost dominant scenario have many similarities, as well as differences, to the results from the base test case. Looking at the warehouse load ratio, a decrease in the average DCLR was observed as κ was increased. Also, the range of the computed load ratios increased as the DC capacities were increased. These trends were the same as observed in the base case. However, the average DCLR in the tight, moderate and excess capacities cases was noticeably higher in the dominant fixed cost scenario than in the base case. This is due to the increased cost incurred to open a DC, which increases the importance of utilizing the DC space available before opening a new facility.

As would be expected, the cost breakdowns for the fixed cost dominant test cases were drastically different than those observed in the base case. The inflated fixed cost to open a warehouse meant that the fixed cost of the network was substantially higher than in the base scenario. Around 80% of the network costs were observed in the fixed costs, with the remaining amount distributed to the variable and emission costs. As observed in the base case, the distribution of costs is fairly stable across the varying DC capacity levels.

On average, the solution time for the fixed cost dominant case was greater than that required in the base scenario. The increased fixed cost seemingly created a tighter problem to be solved and in turn increased the computational difficulty and the solution time. Again, the majority of the time was spent in the solution of [SP1], with the remainder of the time attributed to [SP2], heuristic solution and the master problem, in decreasing order. It was also observed that as the number of variables increased a greater percentage of the solution time was spent solving [SP1].

The primal heuristic produced very good feasible solutions in the dominant fixed cost cases. In all cases, the heuristic produced a solution that was within 1% of the optimal solution.

6.5 Dominant Variable Cost Scenario

The third solution scenario tested was the dominant variable cost case. This scenario increases the scaling parameter on the variable per unit handling and transportation costs, thus creating a situation where the variable costs represent a significant percentage of the total system expenditure. For the dominant variable cost scenario the scaling parameters were set as follows:

$$\beta_1 = \beta_2 = 5$$

$$\alpha = 100$$

$$\Omega = 1$$

Again, this scenario was tested with varying DC capacity ratios: tight capacities ($\kappa = 3$), moderate capacities ($\kappa = 5$), and excess capacities ($\kappa = 10$). The results from the variable cost dominant case are shown in Tables 6.7, 6.8 and 6.9, which correspond to tight, moderate and excess capacities, respectively.

Table 6.7a: Variable cost dominant scenario – Tight capacities.

Problem						
m.n.p	Vars.	DCLR	FCR_DC	VCR	ECR	Iters.
3.5.15	3220	0.584	0.165	0.800	0.034	4
3.5.25	145	0.572	0.142	0.825	0.033	4
4.8.20	200	0.666	0.218	0.745	0.037	4
4.8.40	360	0.784	0.126	0.836	0.038	4
5.10.20	260	0.639	0.217	0.745	0.038	4
5.10.40	460	0.718	0.141	0.828	0.031	4
5.10.60	660	0.619	0.125	0.841	0.034	4
8.15.25	510	0.837	0.198	0.770	0.032	4
8.15.25	510	0.874	0.217	0.744	0.038	4
8.15.75	1260	0.830	0.143	0.823	0.034	4
10.20.50	1220	0.780	0.211	0.754	0.034	4
10.20.75	1720	0.864	0.157	0.703	0.141	5
10.20.100	2220	0.804	0.170	0.695	0.135	7
10.20.125	2720	0.797	0.134	0.705	0.160	5
10.20.150	3220	0.664	0.161	0.700	0.139	5
Min	-	0.572	0.125	0.695	0.031	4
Mean	-	0.736	0.168	0.768	0.064	4.4
Max	-	0.874	0.218	0.841	0.160	7

Table 6.7b: Variable cost dominant scenario – Tight capacities.

Problem	Heur.	Time (%, %, %, %, sec)				
m.n.p	Quality	SP1	SP2	Heur	MP	Total
3.5.15	0.054	83.4	4.9	6.7	3.2	0.35
3.5.25	0.150	85.7	5.6	5.6	3.1	0.53
4.8.20	0.162	95.9	2.0	1.4	0.7	2.2
4.8.40	0.030	96.0	1.9	1.4	0.7	2.3
5.10.20	0.110	95.1	2.4	1.6	0.9	2.1
5.10.40	0.091	99.6	0.2	0.1	0.1	27.8
5.10.60	0.073	99.9	0.1	0.0	0.0	91.7
8.15.25	0.051	87.1	7.3	3.6	2.0	0.96
8.15.25	0.071	95.4	3.1	0.8	0.7	2.1
8.15.75	0.055	99.6	0.2	0.1	0.1	29.6
10.20.50	0.062	90.2	5.3	2.2	2.3	1.8
10.20.75	0.156	99.9	0.1	0.0	0.0	141
10.20.100	0.189	99.8	0.1	0.0	0.0	164
10.20.125	0.243	99.9	0.1	0.0	0.0	213
10.20.150	0.370	99.9	0.1	0.0	0.0	199
Min	0.030	83.4	0.1	0.0	0.0	0.35
Mean	0.124	95.2	2.2	1.6	0.9	59
Max	0.370	99.9	7.3	6.7	3.2	213

Table 6.8a: Variable cost dominant scenario – Moderate capacities.

Problem						
m.n.p	Vars.	DCLR	FCR_DC	VCR	ECR	Iters.
3.5.15	95	0.667	0.132	0.825	0.043	3
3.5.25	145	0.522	0.120	0.841	0.040	3
4.8.20	200	0.676	0.143	0.827	0.030	4
4.8.40	360	0.902	0.120	0.843	0.037	5
5.10.20	260	0.584	0.185	0.770	0.045	5
5.10.40	460	0.603	0.127	0.841	0.032	4
5.10.60	660	0.515	0.152	0.818	0.030	4
8.15.25	510	0.780	0.216	0.748	0.036	5
8.15.50	885	0.876	0.166	0.799	0.035	4
8.15.75	1260	0.469	0.202	0.762	0.035	4
10.20.50	1220	0.699	0.229	0.733	0.038	4
10.20.75	1720	0.763	0.196	0.772	0.032	5
10.20.100	2220	0.655	0.148	0.815	0.037	4
10.20.125	2720	0.750	0.144	0.821	0.035	5
10.20.150	3220	0.742	0.136	0.828	0.036	4
Min	-	0.469	0.120	0.733	0.030	3
Mean	-	0.680	0.161	0.803	0.036	4.2
Max	-	0.902	0.229	0.843	0.045	5

Table 6.8b: Variable cost dominant scenario – Moderate capacities.

Problem	Heur.	Time (%, %, %, %, sec)				
m.n.p	Quality	SP1	SP2	Heur	MP	Total
3.5.15	0.040	53.7	17.6	19.5	9.2	0.14
3.5.25	0.073	52.3	17.4	20.6	9.6	0.13
4.8.20	0.078	54.7	21.4	15.6	8.3	0.20
4.8.40	0.020	65.9	16.4	11.4	6.3	0.30
5.10.20	0.130	73.3	14.0	8.2	4.5	0.43
5.10.40	0.051	97.7	1.2	0.7	0.4	4.1
5.10.60	0.089	96.5	1.7	1.1	0.6	2.9
8.15.25	0.053	91.7	4.9	2.1	1.3	1.8
8.15.50	0.050	93.6	3.6	1.8	1.0	2.0
8.15.75	0.079	96.2	2.2	1.1	0.6	3.4
10.20.50	0.057	94.7	3.1	1.4	0.8	3.0
10.20.75	0.020	99.8	0.1	0.1	0.0	87.6
10.20.100	0.040	99.8	0.1	0.0	0.0	107
10.20.125	0.034	99.8	0.1	0.0	0.0	120
10.20.150	0.029	99.8	0.1	0.1	0.2	213
Min	0.020	52.3	0.1	0.0	0.0	0.13
Mean	0.056	84.6	6.9	5.6	2.9	36
Max	0.130	99.8	21.4	20.6	9.6	213

Table 6.9a: Variable cost dominant scenario – Excess capacities.

Problem						
m.n.p	Vars.	DCLR	FCR_DC	VCR	ECR	Iters.
3.5.15	95	0.201	0.354	0.613	0.033	5
3.5.25	145	0.317	0.137	0.821	0.042	4
4.8.20	200	0.973	0.095	0.851	0.054	4
4.8.20	200	0.446	0.150	0.820	0.030	5
5.10.20	260	0.331	0.223	0.741	0.036	4
5.10.20	260	0.330	0.241	0.725	0.034	4
5.10.60	660	0.202	0.191	0.782	0.027	4
8.15.25	510	0.423	0.202	0.766	0.032	5
8.15.50	885	0.430	0.243	0.717	0.039	5
8.15.75	1260	0.400	0.186	0.779	0.035	5
10.20.50	1220	0.579	0.201	0.761	0.038	4
10.20.75	1720	0.579	0.149	0.813	0.038	4
10.20.100	2220	0.402	0.178	0.790	0.032	4
10.20.125	2720	0.437	0.172	0.792	0.036	4
10.20.150	3220	0.345	0.176	0.793	0.030	4
Min	-	0.201	0.095	0.613	0.027	4
Mean	-	0.426	0.193	0.771	0.036	4.3
Max	-	0.973	0.354	0.851	0.054	5

Table 6.9b: Variable cost dominant scenario – Excess capacities.

Problem	Heur.	Time (%, %, %, %, sec)				
m.n.p	Quality	SP1	SP2	Heur	MP	Total
3.5.15	0.335	47.5	21.9	20.1	10.5	0.17
3.5.25	0.065	54.5	18.1	18.3	9.1	0.16
4.8.20	0.001	56.0	21.0	14.8	8.3	0.20
4.8.20	0.088	58.6	24.6	9.3	7.6	0.19
5.10.20	0.106	95.0	2.5	1.6	0.8	2.0
5.10.20	0.190	97.4	1.6	0.5	0.4	2.9
5.10.60	0.127	97.4	1.3	0.8	0.5	3.9
8.15.25	0.085	95.6	2.5	1.2	0.7	3.5
8.15.50	0.031	73.0	15.9	7.0	4.1	0.57
8.15.75	0.056	84.5	9.0	4.1	2.4	0.97
10.20.50	0.040	81.0	11.7	4.7	2.6	0.80
10.20.75	0.036	86.9	6.9	2.9	3.2	1.3
10.20.100	0.071	99.7	0.2	0.1	0.0	57.6
10.20.125	0.047	99.8	0.1	0.0	0.0	88.1
10.20.150	0.077	97.2	1.7	0.7	0.4	5.5
Min	0.001	47.5	0.1	0.0	0.0	0.16
Mean	0.090	81.6	9.3	5.7	3.4	11
Max	0.335	99.8	24.6	20.1	10.5	88

The dominant variable cost cases were drastically different than the base scenario. Again, it was observed that the average DCLR decreased as κ was increased, and the range of the computed load ratios increased as the DC capacities were increased. On the other hand, the average DC load ratio was substantially lower in the variable cost dominant scenario than the baseline situation. The increased cost to transport the units between nodes resulted in more DCs being opened in order to reduce the total travel distance. As a result, the warehouses are under-utilized and a low DCLR is observed.

As anticipated, the cost breakdowns for the variable cost dominant test scenarios were dissimilar to those recorded in the base case. The increased variable transportation costs encourage shorter routes, which leads to more DCs being open. In turn, the system cost was comprised primarily of variable costs, followed by the fixed cost to open a DC. The emission costs were observed to be very low in comparison to the alternatives. Further, as seen in the base case, the distribution of costs is fairly stable across the varying DC capacity levels.

The solution time for the dominant variable cost cases were substantially less than those observed in the base and dominant fixed cost scenarios. The increased variable cost decreased the rigidity of the problem and thus decreased the computational difficulty and the solution time. As seen in the previous cases, the majority of the time was spent in the solution of [SP1]. The balance of the computational effort was spent in [SP2], heuristic solution and the master problem. The percentage of time spent on [SP1] increased as the size of the problem was expanded.

Similar to the base scenario, the primal heuristic produced very good feasible solutions in the variable cost cases. In all cases tested, the heuristic achieved a solution that was within 1% of the Lagrangian bound.

6.6 Dominant Emission Cost Scenario

The fourth test scenario analyzed was the dominant emission cost case. This case amplifies the scaling parameter on the cost of carbon emissions. The quantity of carbon emissions is dependent on the distance travelled, vehicle weight (number of units shipped) and the emissions rate. The increased scale factor on the cost of carbon emissions produces a condition where the emissions costs represent a vast percentage of the total system expenditure. For the dominant emission cost case the scaling parameters were set as follows:

$$\beta_1 = \beta_2 = 1$$

$$\alpha = 100$$

$$\Omega = 5$$

The scenario outlined above was tested with varying DC capacity ratios: tight capacities ($\kappa = 3$), moderate capacities ($\kappa = 5$), and excess capacities ($\kappa = 10$). The results from the emission cost dominant case are shown in Tables 6.10, 6.11 and 6.12, corresponding to tight, moderate and excess capacities, respectively.

Table 6.10a: Emission cost dominant scenario – Tight capacities.

Problem						
m.n.p	Vars.	DCLR	FCR_DC	VCR	ECR	Iters.
3.5.15	95	0.830	0.262	0.332	0.406	3
3.5.25	145	0.655	0.227	0.354	0.419	3
4.8.20	200	0.864	0.288	0.376	0.336	4
4.8.30	280	0.953	0.205	0.361	0.434	4
5.10.20	260	0.822	0.382	0.278	0.340	4
5.10.40	460	0.871	0.279	0.343	0.378	4
5.10.60	660	0.766	0.231	0.353	0.416	4
8.15.25	510	0.912	0.364	0.303	0.333	4
8.15.50	885	0.869	0.313	0.316	0.371	4
8.15.75	1260	0.992	0.255	0.382	0.362	4
10.20.50	1220	0.952	0.355	0.311	0.334	4
10.20.75	1720	0.803	0.332	0.344	0.324	5
10.20.100	2220	0.883	0.306	0.363	0.331	5
10.20.125	2720	0.849	0.315	0.335	0.350	5
10.20.150	3220	0.785	0.270	0.408	0.323	5
Min	-	0.655	0.205	0.278	0.323	3
Mean	-	0.854	0.292	0.344	0.364	4.1
Max	-	0.992	0.382	0.408	0.434	5

Table 6.10a: Emission cost dominant scenario – Tight capacities.

Problem	Heur.	Time (%, %, %, %, sec)				
m.n.p	Quality	SP1	SP2	Heur	MP	Total
3.5.15	0.587	52.1	13.1	15.4	19.4	0.17
3.5.25	1.047	56.7	16.3	17.7	9.3	0.14
4.8.20	0.796	97.2	1.3	1.0	0.5	3.2
4.8.30	0.065	98.9	0.5	0.4	0.2	7.9
5.10.20	0.571	99.3	0.4	0.2	0.1	13.2
5.10.40	0.417	96.4	1.8	1.1	0.6	2.7
5.10.60	0.739	97.4	1.3	0.8	0.4	3.8
8.15.25	0.568	91.2	5.0	2.4	1.3	1.4
8.15.50	0.353	98.9	0.6	0.3	0.2	11.8
8.15.75	0.022	98.9	0.5	0.3	0.3	13.9
10.20.50	0.143	100.0	0.0	0.0	0.0	362
10.20.75	0.625	99.3	0.4	0.2	0.1	27.7
10.20.100	0.136	99.8	0.1	0.0	0.0	112
10.20.125	0.050	99.7	0.2	0.1	0.0	58.4
10.20.150	0.976	99.7	0.2	0.1	0.0	74.0
Min	0.022	52.1	0.0	0.0	0.0	0.14
Mean	0.473	92.4	2.8	2.7	2.2	46
Max	1.047	100.0	16.3	17.7	19.4	362

Table 6.11a: Emission cost dominant scenario – Moderate capacities.

Problem m.n.p	Vars.	DCLR	FCR_DC	VCR	ECR	Iters.
3.5.15	95	0.608	0.287	0.386	0.327	5
3.5.25	145	0.657	0.245	0.415	0.340	4
4.8.20	200	0.676	0.257	0.389	0.354	3
4.8.40	360	0.567	0.269	0.386	0.344	5
5.10.20	260	0.701	0.353	0.315	0.332	5
5.10.40	460	0.557	0.329	0.336	0.335	4
5.10.60	660	0.633	0.230	0.389	0.381	4
8.15.25	510	0.875	0.315	0.314	0.371	4
8.15.50	885	0.856	0.253	0.384	0.363	5
8.15.75	1260	0.678	0.314	0.349	0.337	4
10.20.50	1220	0.814	0.364	0.280	0.355	4
10.20.75	1720	0.706	0.306	0.351	0.342	4
10.20.100	2220	0.709	0.289	0.362	0.349	4
10.20.125	2720	0.788	0.315	0.354	0.331	5
10.20.150	3220	0.690	0.287	0.373	0.340	4
Min	-	0.557	0.230	0.280	0.327	3
Mean	-	0.701	0.294	0.359	0.347	4.3
Max	-	0.875	0.364	0.415	0.381	5

Table 6.11a: Emission cost dominant scenario – Moderate capacities.

Problem	Heur.	Time (%, %, %, %, sec)				
m.n.p	Quality	SP1	SP2	Heur	MP	Total
3.5.15	1.138	57.5	17.2	16.5	8.8	0.20
3.5.25	1.369	87.0	5.1	5.3	2.6	0.55
4.8.20	0.876	62.4	16.9	13.9	6.8	0.19
4.8.40	1.156	96.8	1.5	1.1	0.6	3.2
5.10.20	1.014	94.6	2.8	1.7	1.0	2.1
5.10.40	0.777	87.5	6.3	4.0	2.1	0.77
5.10.60	0.501	99.6	0.2	0.1	0.1	25.2
8.15.25	0.327	100.0	0.0	0.0	0.0	815
8.15.50	0.424	97.6	1.4	0.6	0.4	6.2
8.15.75	0.586	99.6	0.2	0.1	0.1	34.1
10.20.50	0.393	97.3	1.6	0.7	0.4	5.4
10.20.75	0.564	99.9	0.0	0.0	0.0	185
10.20.100	0.469	99.5	0.3	0.1	0.1	31.3
10.20.125	0.411	99.9	0.1	0.0	0.0	207
10.20.150	0.636	99.4	0.3	0.1	0.1	26.6
Min	0.327	57.5	0.0	0.0	0.0	0.19
Mean	0.710	91.9	3.6	3.0	1.5	90
Max	1.369	100.0	17.2	16.5	8.8	815

Table 6.12a: Emission cost dominant scenario – Excess capacities.

Problem						
m.n.p	Vars.	DCLR	FCR_DC	VCR	ECR	Iters.
3.5.15	95	0.414	0.366	0.270	0.364	5
3.5.25	145	0.379	0.263	0.411	0.326	5
4.8.20	200	0.375	0.320	0.347	0.333	5
4.8.40	360	0.513	0.265	0.376	0.359	6
5.10.20	260	0.702	0.365	0.313	0.323	4
5.10.40	460	0.461	0.253	0.366	0.381	5
5.10.60	660	0.364	0.286	0.388	0.326	4
8.15.25	510	0.588	0.310	0.346	0.344	6
8.15.50	885	0.594	0.337	0.338	0.325	5
8.15.75	1260	0.821	0.263	0.371	0.367	5
10.20.50	1220	0.836	0.289	0.355	0.356	4
10.20.75	1720	0.763	0.229	0.391	0.380	4
10.20.100	2220	0.660	0.288	0.332	0.380	4
10.20.125	2720	0.622	0.261	0.354	0.385	5
10.20.150	3220	0.584	0.261	0.359	0.380	4
Min	-	0.364	0.229	0.270	0.323	4
Mean	-	0.578	0.290	0.354	0.355	4.7
Max	-	0.836	0.366	0.411	0.385	6

Table 6.12a: Emission cost dominant scenario – Excess capacities.

Problem	Heur.	Time (%, %, %, %, sec)				
m.n.p	Quality	SP1	SP2	Heur	MP	Total
3.5.15	1.329	72.8	11.0	10.3	5.8	0.31
3.5.25	2.104	58.1	17.4	16.2	8.3	0.20
4.8.20	0.866	80.7	9.4	6.3	3.6	0.52
4.8.40	0.450	73.5	13.2	8.5	4.9	0.44
5.10.20	0.929	58.0	21.2	13.5	7.3	0.23
5.10.40	0.537	73.9	13.5	8.2	4.4	0.45
5.10.60	0.971	99.5	0.3	0.2	0.1	19.5
8.15.25	0.522	92.5	4.5	1.9	1.1	2.3
8.15.50	0.567	96.5	2.4	0.7	0.4	5.5
8.15.75	0.146	92.9	4.1	1.9	1.1	2.1
10.20.50	0.213	95.2	2.9	1.2	0.7	3.2
10.20.75	0.230	94.5	3.3	1.4	0.8	2.8
10.20.100	0.141	99.3	0.4	0.2	0.1	21.7
10.20.125	0.241	98.2	1.2	0.3	0.2	13.1
10.20.150	0.116	99.4	0.3	0.1	0.1	27.5
Min	0.116	58.0	0.3	0.1	0.1	0.20
Mean	0.624	85.7	7.0	4.7	2.6	7
Max	2.104	99.5	21.2	16.2	8.3	27

The dominant emission cost cases were similar to the variable cost dominant cases, and hence drastically different than the base scenario. It was observed that the average DCLR decreased as κ was increased, and the range of the computed load ratios increased as the DC capacities were increased. Alternatively, the average DCLR was reduced in the emission cost dominant scenario from the base case. This situation arises due to the increased cost of carbon emissions, which are produced on the transportation routes. To minimize the carbon emissions, the travel distance must also be minimized, and thus more DCs are opened in order to reduce the total travel distance. As a result, the DCs are not used to their fullest capacity and a low DCLR is observed.

The cost breakdowns for the emission cost dominant test scenarios were unlike those recorded in the base case. As previously mentioned, the increased emission costs encourage reduced route length, which results in more warehouses being open. In turn, the emissions cost was much higher than in the base case and the overall costs were fairly evenly distributed among the three cost categories. As observed in the base scenario, the distribution of costs is fairly stable across the varying values of κ.

The solution time for the dominant emission cost cases were significantly less than those observed in the base and dominant fixed cost scenarios. As seen with the increased variable cost scenario, the increase emission cost decreased the rigidity of the problem and thus decreased the computational difficulty and the solution time. Once more, the majority of the time was spent in the solution of [SP1], with the remainder attributed to [SP2], heuristic solution and the master problem. It was also observed that as the number of variables increased a greater percentage of the solution time was spent solving [SP1].

In all cases, the heuristic produced good feasible solutions. However, the quality of the heuristic deteriorated slightly in the emission cost dominant scenario versus the base case. The heuristic was shown to be within 3% of the Lagrangian bound in the dominant emissions costs tests.

6.7 Network Design Comparison

Another method used to test the solution algorithm was to visualize the effect that the addition of carbon costs could have on the network design. A relatively small problem with 3 plants, 7 warehouse sites and 15 retailers was considered so that the layout of the network could easily be plotted and visualized. The scaling parameters on the emission costs were varied and the impact on the design of the network was visualized. Three cases were considered: zero emission costs, base scenario and dominant emission cost. The locations of the facilities, fixed costs to open a warehouse, DC capacities and retailer demands were consistent across all three scenarios. This Chapter illustrates how the addition of emission cost can affect the design of a supply chain and discusses the differences between the three problems analyzed.

6.7.1 Design Layout – Zero Emission Costs

The objective of this test was to plot and visualize the best feasible solution generated by the algorithm. The first case considered was zero emission cost scenario, which showed how the network would be designed in the absence of carbon costs. To model this situation, the scaling parameters were set as follows:

$\kappa = 3$ $\beta_1 = \beta_2 = 1$ $\alpha = 100$ $\Omega = 0$

Using these parameters, the evaluation method was run and the best feasible solution was obtained. The objective function value obtained from the heuristic was equal to the Lagrangian bound. Figure 6.1 plots the best feasible solution obtained from the solution method. The plants were denoted with large squares, open distribution centres were represented by circles and retailers were shown with small diamonds. Warehouse sites that were not used were depicted with an "X". The assignment of retailers to warehouses and warehouses to plants are represented by dotted lines, in essence showing the shipping lanes.

The network layout shown in Figure 6.1 highlights three open DCs and four sites that were not selected for a distribution centre, while each plant is serving a single DC. The open warehouses are located close to the plants, and close to the centre of the grid. Each customer is assigned to a DC, as is required by the problem formulation.

Due to the specified customer demands and DC capacities, at least three warehouses must be opened in order to meet the demand of the customers. Hence, this solution contains the minimum possible number of open distribution centres. This arises because the fixed cost of a DC is sufficiently higher than the cost to transport the goods (both the variable costs and the emission cost, which is zero in this instance). In order to minimize the cost of the supply chain, an emphasis is placed on minimizing the number of warehouses in the network and their associated fixed costs.

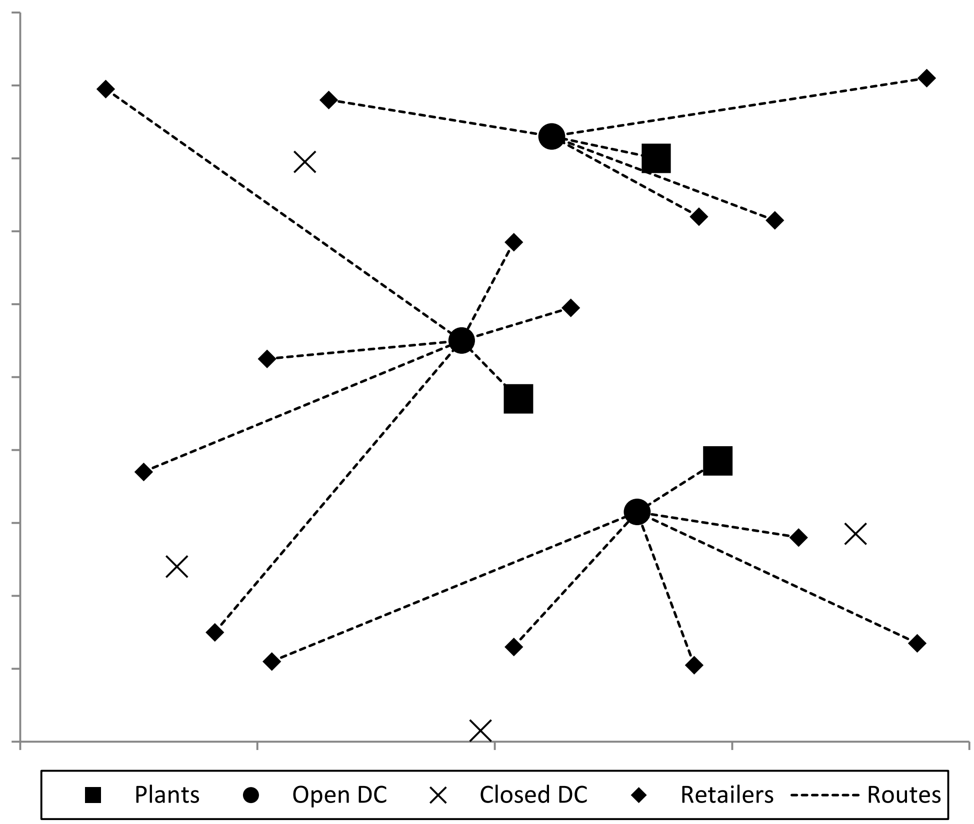

Figure 6.1: Network design – Zero emission costs.

6.7.2 Design Layout – Base Scenario

While the first case considered no cost for carbon emissions, the second situation looked at a system with nominal emission costs, identical to that analyzed in Section 6.3. As such, the scaling parameters were set as follows:

$\kappa = 3$ $\beta_1 = \beta_2 = 1$ $\alpha = 100$ $\Omega = 1$

The values were inserted into the solver and best feasible solution was produced. As seen in section 6.3, the objective function value obtained from the heuristic was within 1% of the Lagrangian bound. Figure 6.2 illustrates resulting supply chain from the best feasible solution generated.

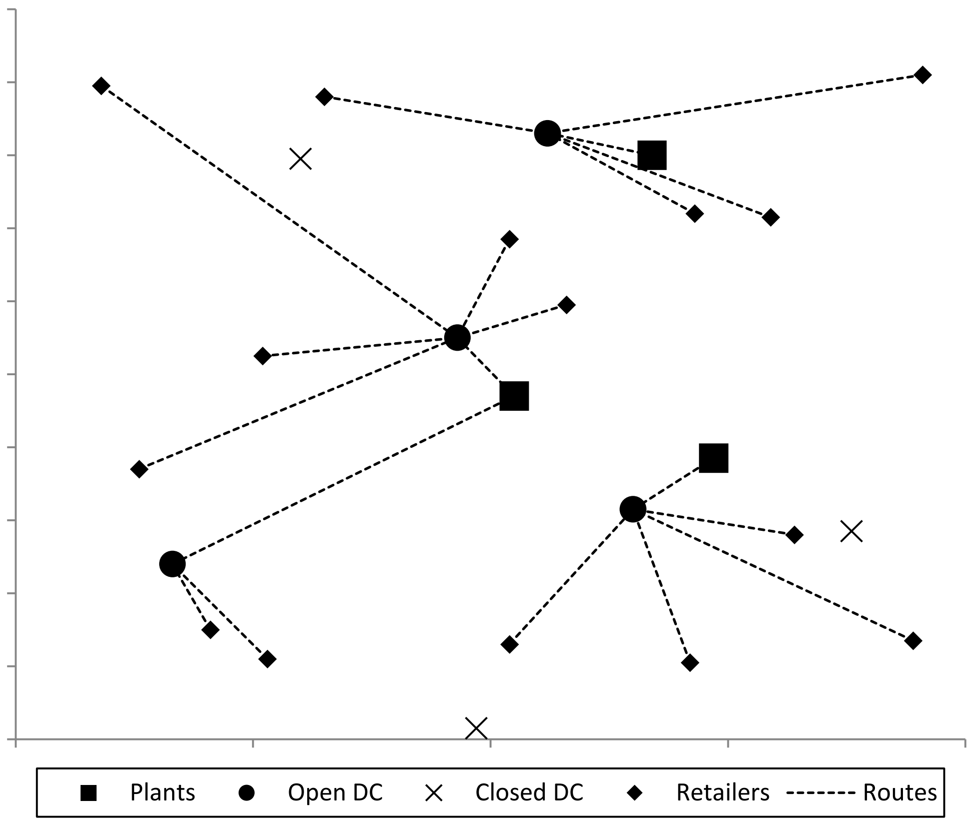

Figure 6.2: Network design – Base scenario.

The resulting network was comprised of four open warehouses and three locations that were not selected for a DC. Only three distribution centres were opened in the zero emissions case, so one additional DC was opened with the inclusion of the emission costs. We know that the total cost of emissions will increase as vehicle kilometers travelled are increased since the emissions cost is dependent on VKT. The opening of a fourth DC indicates that the cost of transporting the units (both the variable and emissions costs) is sufficiently high that a reduction in vehicles kilometers travelled becomes increasingly important. As seen in Figure 6.2, the opening of a distribution centre in the lower left-hand corner of the grid significantly reduces the distance travelled to service the customers in that vicinity, and in turn reduces the emission cost of the network.

6.7.3 Design Layout – High Emission Costs

It was evident that the addition of nominal emission costs can affect the design of a supply chain. This third case analyzes the impact that significant carbon costs would have on the layout of a supply chain. The scaling parameters for the high emission cost scenario were set as:

$\kappa = 3$ $\beta_1 = \beta_2 = 1$ $\alpha = 100$ $\Omega = 5$

The above parameters were entered into the solution procedure to obtain a Lagrangian bound and feasible solution. Similar to cases analyzed throughout this research, the objective function value obtained from the best feasible solution was within 3% of the Lagrangian bound. The best supply chain design from the heuristic problem was obtained and is present as Figure 6.3.

Each plant in this case served two warehouses. In contrast to the three DCs that were opened in the zero emissions case and the four sites opened in the base scenario, the high emission case opens six of the seven potential sites. As seen with the base case, the increased cost to transport units meant increased attention was paid to the reduction of the vehicles kilometers travelled. Thus, more distribution centres were opened to reduce the travel distances and the cost of the system. As Figure 6.3 illustrates, warehouses around the exterior of the grid are now fiscally feasible to minimize the total cost of the system.

An extra DC is opened in the bottom right-hand corner to service local retailers. Additionally, a warehouse is opened in the upper left corner of the grid to serve two local customers. In this case, the cost of transporting the goods extra kilometers is so great that is it feasible to open a facility to serve only a couple customers, if the trip length can be sufficiently reduced.

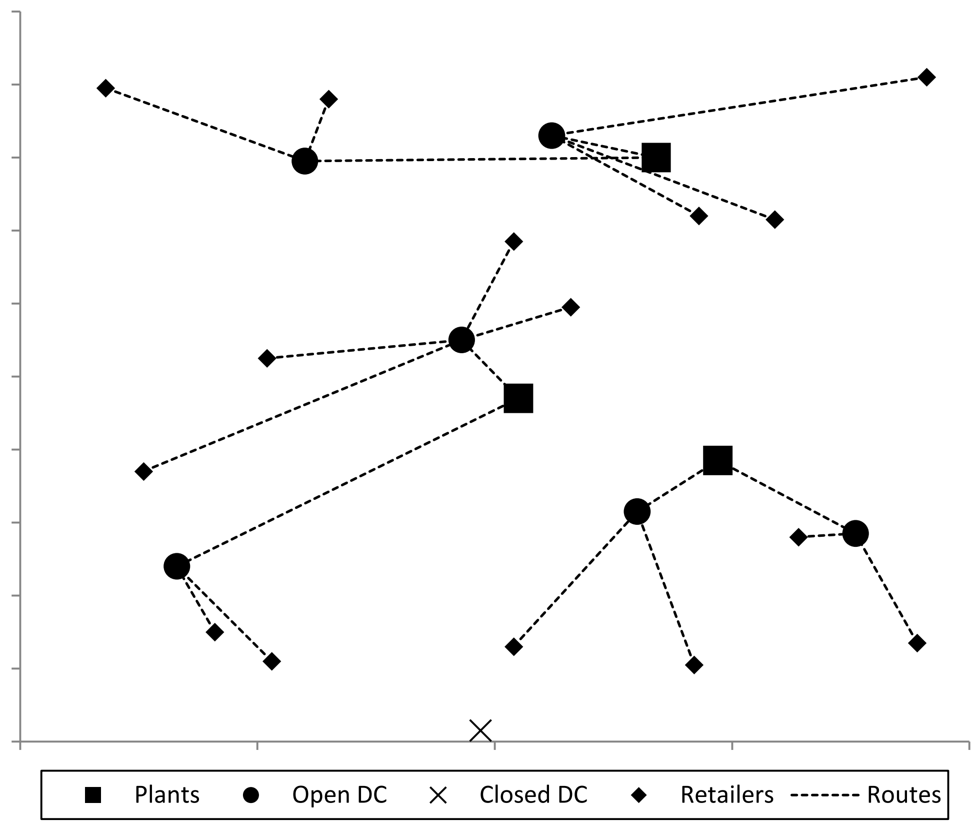

Figure 6.3: Network design – High emission cost.

6.8 Emissions Reductions vs. Cost

The results have shown that as emission costs increase more distribution centres are opened in order to reduce travel distances and minimize the total cost of the system. This section examines the absolute reduction in emissions as emissions costs increase and compares the reductions versus the logistics cost of the system.

In this section, we consider a problem with 5 plants, 15 warehouse sites and 30 retailers. The following scaling parameters were also applied:

$\kappa = 5$ $\beta_1 = \beta_2 = 1$ $\alpha = 100$ $\Omega = 0, \ldots, 10$

The problem was tested several times with the properties of the facilities (location, capacities, demands and costs) remaining constant, but the scaling parameter on the emissions cost was varied. For each test run, the total emissions produced by the network and the logistics cost were recorded. The logistics cost of the network is defined as the sum of the fixed costs plus the variable cost to handle and transport the goods between nodes. Figure 6.4 plots the quantity of emissions versus the logistics cost of the system obtained in the testing.

The results showed that with no emissions costs the system had 3 open distribution centres and produced roughly 780 tonnes of CO_2e (leftmost point on Figure 6.4). As the cost of emissions was increased, the total emissions produced decreased very quickly at first, but then slowed and approached a minimum emissions value. The minimum amount of emissions obtained from this problem was approximately 630 tonnes of CO_2e, which required that 9 DCs be opened (rightmost point in Figure 6.4).

Of particular interest is the fact that a substantial amount of the emissions can be reduced for a nominal incremental cost. For the case considered, a 3.8% increase in the logistics cost of the system (which does not include the emission costs) results in a 17.6% reduction in the total CO_2 emissions produced by the network. We have already seen in previous sections that the introduction of emission costs can alter the optimal design of the supply chain. But, the data presented in Figure 6.4 show that even in jurisdictions without emission costs, for certain cases, a considerable amount of the vehicular emissions can be reduced if a small extra investment is made in the supply chain. While more distribution centres are required in order to reduce the emissions, a large portion of the extra costs to open the warehouses is offset by the reduced handling and transportation costs that arise from the shorter shipping lanes. Thus, considerable environmental benefit can be gained for a nominal extra investment if so desired.

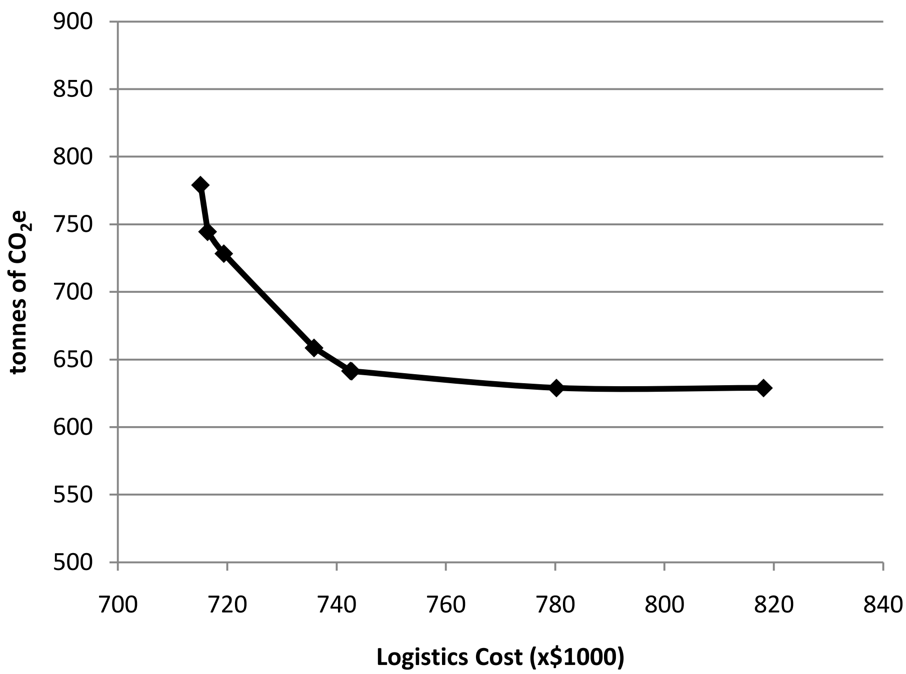

Figure 6.4: Emissions quantity versus logistics cost.

6.9 Testing Summary

Several trends were noticed in the numerical testing of the solution algorithm. Foremost, the DCLR was greatly impacted by the tightness for the problems generated. In all scenarios, the DCLR decreased as the rigidity of the problem decreased. Furthermore, the range of DCLRs obtained from the best feasible solution increased as the tightness of the problem decreased. As would be expected, the DCLR was also impacted by the cost structure of the problem. Higher fixed facility costs produced higher load ratios, while higher variable and emission costs generated lower DCLRs.

Alternatively, the cost breakdowns observed in the tests were not adversely affected by the tightness of the problem. Rather, the cost compositions of the best solution in the tests were primarily due to the scaling parameters selected for the particular problem.

The time required to process the algorithm increased as the number of variables increased, and also increased as the tightness of the problem increased. The fixed cost dominant scenario appeared to be more difficult to solve than the base case, whereas the variable and emissions cost situations were easier to solve than the base case. Of more importance is the fact the majority of the computation time is spent solving [SP1]. In essence, [SP1] is the bottleneck in the algorithm that prevents larger problems from being tackled. An extension that would alleviate the computational demand of [SP1] could be an area of future research. However, it would be important to do so while maintaining the integrity of the primal heuristic.

The heuristic proposed in this research performed exceptionally, achieving solutions within 1% of the optimum. Even though the algorithm achieved the Lagrangian bound in a small number of iterations, the heuristic still managed to obtain a good solution. The strength of the heuristic was due to the input of variables selected from the solution of [SP1]. Since [SP1] maintained many of the characteristics of the original problem, the solution data passed along to the heuristic aided greatly in producing a high quality feasible solution.

It was visually observed that as the emission costs were increased, the supply chain tended towards shorter transportation routes, and as a result, more distribution centres were opened. This showed that carbon cost schemes can have an impact on network designs, and therefore should be considered when designing or evaluating supply chains in a regulated emissions market.

Finally, the influence of emissions costs on the quantity of emissions produced by the supply chain was analyzed. It was observed that as the emission costs were increased, the carbon emissions produced by the best network design decreased. For the particular case considered, it was shown that a 3.8% increase in the logistics cost of the system resulted in a 17.6% reduction in the total CO_2 emissions produced by the network. Thus, a substantial benefit to the environment can be obtained for a nominal extra investment, even in regions without carbon costs.

Chapter 7:

Conclusion

This thesis attempted to integrate the cost of carbon emissions into a supply chain design model. The new problem formulation minimized the combined expenses associated with the fixed costs to set up a facility, the transportation cost to move goods and the cost of emissions generated on the shipping lanes. A network design model that minimizes both the logistics cost and the emission cost of a supply chain has practical applications for supply chain design, particularly in regions that have a carbon tax or cap-and-trade system.

This thesis offered two primary contributions to supply chain design literature:

1) Foremost, this research proposed a supply chain design model that added the cost of carbon emissions into the objective function. A solution method was then developed to evaluate the new problem formulation. The Lagrangian relaxation technique was used to decompose the problem by echelon and by potential DC site. Then, the problem was linearized and solved to achieve the Lagrangian bound. A primal heuristic that used data from the Lagrangian subproblems was utilized to generate a feasible solution in each iteration.
2) The results from this research confirmed that the addition of carbon costs into the decision process for supply chain can change the optimal configuration of the network. However, rather than using linear or convex functions to express the

emissions costs, this study used experimental data that demonstrated a concave relationship.

Through the application of the solution methodology, this research showed that the addition of carbon costs to a supply chain created a pull to reduce the amount of vehicle kilometers travelled. Since the customer demands must still be met, the solution model suggested that more distribution centres be opened in order to create additional shipping lanes from the plant to the warehouse and reduce the travel distance from warehouse to retailer.

This thesis also demonstrated that substantial environmental benefit may also be able to be obtained for a nominal extra investment in the supply chain. It was shown that for a particular case, a marginal extra investment to open additional distribution centres resulted in a significant decrease in carbon emissions produced by the supply chain. The extra costs to open the warehouses were partially offset by the reduced handling and transportation costs that arise from the shorter shipping lanes, resulting in a greener supply chain with only marginally higher costs.

The practical applications of this research are abundant, especially to organizations with a free on board manufacturer delivery model located in jurisdictions with carbon pricing systems. While only a small number of regions in the world currently operate under a carbon tax system or emissions trading system, the supply chain design in these regions is greatly affected by the additional emission costs. And with the growing awareness of climate change, an increasing number of governments are considering the creation of a carbon pricing system for their constituencies. Thus, the applicability of this research is likely to grow with time, and it is hoped that this study will provide a foundation for future research and model extensions.

Appendix A:

8.1 Problem Generator

```
% Generate random problem
    % Generate Coordinates for each plant, DC, customer
        i_locs = rand(i,2)*190 + 10;
        j_locs = rand(j,2)*190 + 10;
        k_locs = rand(k,2)*190 + 10;

    % Compute i to j distances
        for l=1:i
            for m=1:j
                itoj(l,m) = ((i_locs(l,1)-j_locs(m,1))^2 +
                  (i_locs(l,2)-j_locs(m,2))^2)^0.5;
            end
        end
        c = beta1 * itoj * 10;

    % Compute j to k distances
        for l=1:j
            for m=1:k
                jtok(l,m) = ((j_locs(l,1)-k_locs(m,1))^2 +
                  (j_locs(l,2)-k_locs(m,2))^2)^0.5;
            end
        end
        h = beta2 * jtok * 10;

    % Generate customer demands (between 10 and 50)
        d = rand(k,1)*40 + 10;

    % Generate DC capacities (between 10 and 160)
        V = rand(j,1)*150 + 10;
```

```
    V_sf = kappa1 / (sum(V)/sum(d));
    V = V * V_sf;

% Generate fixed costs for DC's
    g = alpha1 * (rand(j,1)*90 + (rand(j,1)*10 + 100) .*
        V.^0.5);

% Calculate weights of each shipment
    density = 75
    wd = d*density + 6800;
    wV = V*density + 6800;

% Calculate emission values of each route
    fdk = -0.000000814*wd.^2 + 0.0407*wd + 210.45;
    for m=1:j
        for n=1:k
            f_jtok(m,n) = jtok(m,n)*fdk(n,1)*e;
        end
    end
    for m=1:j
        fVj(m,1) = -0.0000008*wV(m,1)^2 + 0.0407*wV(m,1) +
        210.45;
    end
    for l=1:i
        for m=1:j
            f_itoj(l,m) = itoj(l,m)*fVj(m,1)*e;
        end
    end
    dummy3 = [];
    for m=1:i
        dummy3 = [dummy3; V'];
    end
    f_itoj = f_itoj ./ dummy3;
    for m=1:j
        for n=1:k
            hjk_dk(m,n) = h(m,n)*d(n,1);
```

```
        end
    end
```

8.2 Solver Code for Base Scenario

```
% MIP Solver
    solver = 2; % GLPK=1, Cplex=2


% Define Problem - Numerical Testing Parameters
    i = 3; % number of plants
    j = 3; % number of DCs
    k = 15; % number of customers


    % Numerical Testing Scalars
    alpha1 = 100; % multiplier on fixed DC cost
    beta1 = 1; % multiplier on var. trans. cost from i to j
    beta2 = beta1; % multiplier on var. trans cost from j to k
    kappa1 = 3; % ratio of total DC capacity to total demand
    omega1 = 1; % multiplier on emissions cost
    e = 0.2; %
    e = e * omega1; % new emissions cost
    density = 75;
    bound = 10000000 * k;
    initial_mu = -8000;


    % Lagrangian variable and constants
        LB = -inf;
```

```
    UB = inf;

    mu = ones(j,1)*initial_mu;


% GLPK variable and constants

    continuous = 'C';

    integer = 'I';

    if solver == 1

        % GLPK constraints types

        upper = 'U';

        fixed = 'S';

        lower = 'L';

        binary = 'I';

        param.msglev=0;

    end

    if solver == 2

        % Cplex constraint types

        upper = 'L';

        fixed = 'E';

        lower = 'G';

        binary = 'B';

        param.errmsg=0; % For Cplex only

        H = []; % For Cplex only

        save = 0; % For Cplex only

        x0_mp = ones(1+j+j,1)*inf; % For cplex

        x0_sp1 = ones(j*k+j,1)*inf; % For cplex

        x0_sp2 = ones(i,1)*inf; % For cplex

        x0_feas = ones(i*j, 1)*inf; % For cplex
```

```
        end
        senseSP = 1;

% Setup master problem
    tic;
    C_mp = [1, ones(1,j), zeros(1,j)];
    A_mp = [];
    b_mp = [];
    lb_mp = ones(1+j+j,1)*(-bound);
    ub_mp = ones(1+j+j,1)*bound;
    ctype_mp = [];
    vartype_mp = repmat(continuous, 1, j+j+1);
    sense_mp = -1;
    iters = 0;
    time_mp = time_mp + toc;

% Set up [SP1]
    % Constraints
    A_sp1_1 = [repmat(eye(k),1,j) zeros(k,j)];
    A_sp1_2 = [];
    for m=1:j
        for n=1:k
            dummy = zeros(j,1);
            dummy(m,1) = 1*d(n,1);
            A_sp1_2 = [A_sp1_2 dummy];
        end
    end
```

```
    dummy2 = diag(-V);
    A_sp1_2 = [A_sp1_2 dummy2];
    A_sp1 = [A_sp1_1; A_sp1_2];
    % RHS
    b_sp1 = [ones(k,1); zeros(j,1)];
    % bounds
    lb_sp1 = zeros(j*k+j,1);
    ub_sp1 = ones(j*k+j,1);
    % constraints and variable types
    ctype_sp1 = [ repmat(fixed,1,k) repmat(upper,1,j) ];
    vartype_sp1 = repmat(binary, 1, j*k+j) ;

% Set up [SP2]
    A_sp2 = ones(1,i);
    lb_sp2 = zeros(i,1);
    ub_sp2 = ones(i,1)*inf;
    ctype_sp2 = [upper];
    vartype_sp2 = repmat(continuous, 1, i);

% Set up Heuristic Problem
    D = repmat(d',j,1);
    A_feas = repmat(eye(j),1,i);
    b_feas = ones(j,1);
    lb_feas = zeros(i*j, 1);
    ub_feas = ones(i*j, 1);
    ctype_feas = repmat(fixed,1,j);
    vartype_feas = repmat(binary,1,i*j);
```

```
    sense_feas = 1;


% Loop to find Lagrangian Bound
    while UB-LB > 0.01
        % Solve Subproblem [SP1]
            tic;
                % Create GLPK input matrices
                % Update Objective function w/ current mu
                fdk_j = reshape(f_jtok', 1, j*k);
                hjk_dk_row = reshape(hjk_dk',1,j*k);
                dk_mu = reshape( (repmat(mu,1,k) .*
                        repmat(d',j,1))', 1, j*k);
                C_sp1 = [ (fdk_j+hjk_dk_row-dk_mu) g'];


                % Solve IP-SP1 in GLPK/Cplex
                    display 'solving [SP1]'
                    if solver == 1
                        [yz_min,obj_yz_min,status,extra_sp]=gl
                        pkmex(senseSP,C_sp1',A_sp1,b_sp1,ctype
                        _sp1',lb_sp1,ub_sp1,vartype_sp1',param);
                    end
                    if solver == 2
                        [yz_min,obj_yz_min,status,extra_sp]=cp
                        lexmex(senseSP,H,C_sp1,A_sp1,b_sp1,cty
                        pe_sp1',lb_sp1,ub_sp1,vartype_sp1',x0_
                        sp1,param,save);
                    end
```

```
            display '[SP1] solved'

            y = yz_min(1:j*k,1);

            z = yz_min(j*k+1:j*k+j,1);

            SP1_obj = obj_yz_min;

            store_yz = [store_yz; yz_min'];

            z_SP1 = [z_SP1; obj_yz_min];

            time_sp1 = time_sp1 + toc;


% Solve Subproblems [SP2]

    tic;

    for m=1:j

        % Create GLPK input matrices

            C_sp2 = f_itoj(:,m)' + c(:,m)' + mu(m,1);

            b_sp2 = V(m,1);


        % Solve LP-SP2 in GLPK/Cplex

            if solver == 1

                [x_min,obj_x_min,status,extra_sp]=glpk

                mex(senseSP,C_sp2',A_sp2,b_sp2,ctype_sp2',lb_sp

                2,ub_sp2,vartype_sp2',param);

            end

            if solver == 2

                [x_min,obj_x_min,status,extra_sp]=cple

                xmex(senseSP, H, C_sp2, A_sp2, b_sp2,

                ctype_sp2', lb_sp2, ub_sp2,

                vartype_sp2', x0_sp2, param, save);

            end
```

```
        x = [x x_min];
        SP2_obj = [SP2_obj obj_x_min];
    end

    store_x = [store_x; x];
    z_SP2 = [z_SP2; sum(SP2_obj)];
    time_sp2 = time_sp2 + toc;

% Find Lower Bound
    store_LB = [store_LB; SP1_obj + sum(SP2_obj)];
    if LB < SP1_obj + sum(SP2_obj)
        LB = SP1_obj + sum(SP2_obj);
    end

% Find feasible solution
% Create [STP]
    tic;
            % Calc demand at each DC
            y2 = [reshape(y,k,j)]';
            dk_yjk = sum(y2.*D,2);
            dk_yjk2 = repmat(dk_yjk',i,1);

            % Calculate weights of each shipment
            density = density;
            w_dk_yjk = zeros(j,1);
            for m = 1:j
```

```
            if dk_yjk(m,1) == 0
                % do nothing
            else
                w_dk_yjk(m,1) = dk_yjk(m,1) *
                    density + 6800; %
            end
        end
        % Calc emission values of each route
        f_dk_yjk = zeros(j,1);
        for m=1:j
            if w_dk_yjk(m,1) == 0
                % do nothing
            else
                f_dk_yjk(m,1) = -0.0000008*
                w_dk_yjk(m,1)^2 +
                0.0407*w_dk_yjk(m,1) + 210.45;
            end
        end
        for l=1:i
            for m=1:j
                f_itoj_feas(l,m) = itoj(l,m)*
                f_dk_yjk(m,1)*e;
            end
        end

    % Set up problem for [STP]
        c_feas = reshape( ((c.*dk_yjk2) +
```

```
        (f_itoj_feas))', 1, i*j);
    A_feas = repmat(eye(j),1,i) .*
        repmat(dk_yjk,1, i*j);
    b_feas = dk_yjk;

% Solve for feasible solution
    if solver == 1
        [soln_x,obj_x,status_feas,extra_
        heur]=glpkmex(sense_feas,c_feas'
        ,A_feas,b_feas,ctype_feas',lb_fe
        as,ub_feas,vartype_feas',param);
        msg = 171;
    end
    if solver == 2
        [soln_x,obj_x,status_feas,extra_
        heur]=cplexmex(sense_feas,H,c_fe
        as,A_feas,b_feas,ctype_feas',lb_
        feas,ub_feas,vartype_feas',x0_fe
        as, param,save);
        msg = 101;
    end

% Calculate objective function value
    if status_feas == msg
        obj_g = g'*z;
        obj_y = sum(sum((f_jtok +
          hjk_dk).*y2));
```

```
                obj = obj_g + obj_x + obj_y;
                store_feas = [store_feas ; obj];
            end

        % Save solution if minimum optimal
            if status_feas == msg
                if obj < z_feas
                    z_feas = obj;
                    xyz_feas = [soln_x' y' z'];
                end
            end

    time_heur = time_heur + toc;

% Add constraints from SPs to master problem
    tic;
        % constraint from [SP1]
        new_constr1 = [1, zeros(1,j), dk_yjk'];
        fdky = sum(sum(f_jtok.*y2));
        hdky = sum(sum(hjk_dk.*y2));
        gz = sum(g.*z);
        new_rhs1 = fdky+hdky+gz;
        A_mp = [A_mp; new_constr1];
        b_mp = [b_mp; new_rhs1];

        % constraints from [SP2]
```

```
    x_col = sum(x);
    for m=1:j
        dummy = zeros(1,j);
        dummy(1,m) = 1;
        dummy2 = zeros(1,j);
        dummy2(1,m) = x_col(1,m);
        new_constr2 = [0, dummy, dummy2*-1];
        fVjx = sum(sum(f_itoj(:,m).*x(:,m)));
        cx = sum(sum(c(:,m).*x(:,m)));
        new_rhs2 = fVjx+cx;
        A_mp = [A_mp; new_constr2];
        b_mp = [b_mp; new_rhs2];
    end
    ctype_mp = [ctype_mp repmat(upper,1,j+1)];

% Solve [MP] in GLPK
    if solver == 1
      [LMP,new_UB,status,extra_mp]=glpkmex(sense_mp,C_mp',A
      _mp,b_mp,ctype_mp',lb_mp,ub_mp,vartype_mp',param);
    end
    if solver == 2
      [LMP,new_UB,status,extra_mp]=cplexmex(sense_
      mp,H,C_mp,A_mp,b_mp,ctype_mp',lb_mp,ub_mp,va
      rtype_mp',x0_mp,param,save);
    end
    store_LMP = [store_LMP; LMP'];
% Store UB
```

```
            store_UB = [store_UB ; new_UB];
            UB = min(store_UB);


    % Update lambda's and mu's
        store_mu = [store_mu; mu'];
        mu = LMP(1+j+1:1+j+j,1);
        t = toc;
        time_mp = time_mp + t;


    % Iteration Counter
        iters = iters+1
end
```

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