MINIMIZATION OF TOTAL TRANSPORTATION COSTS IN A DELIVERY NETWORK WITH A SINGLE ORIGIN AND SINGLE TRIP DISTRIBUTION SYSTEM

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Signature of the supervisor: .... Date: ....
Dr. Mahinda Bandara

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ABSTRACT

Invention of contemporary solutions in transport and logistics sector is significantly important with the growth in the volume of freight transportation in any local and international context. Most transport problems are related to the cost incurred through congestion, shortage of labour and the fuel price hike. Each vehicle fleet of individual organizations should be improved and managed to its optimum level to eliminate waste and costing transportation. Transportation management systems (TMS) are used to minimize aggregate operational costs in many companies worldwide. TMS is a subset of supply chain management concerning transportation operations and may be part of an enterprise resource planning system. A TMS usually "sits" between an ERP or legacy order processing and warehouse/distribution module. A typical scenario would include both inbound (procurement) and outbound (shipping) orders to be evaluated by the TMS Planning Module offering the user various suggested routing solutions. These solutions are evaluated by the user for reasonableness and are passed along to the transportation provider analysis module to select the best mode and least cost provider. Once the best provider is selected, the solution typically generates a schedule of loading the vehicles in order to dispatch shipments with the selected carrier, and later to support freight audit and payment (settlement process). Links back to ERP systems (after orders turned into optimal shipments), and sometimes secondarily to warehouse management system (WMS) programs also linked to ERP are also common. Estimating the total cost of an ERP software solution requires a careful assessment of an array of variables which can vary wildly from one company to the next. The size of a business, its unique requirements and the scope of use all play a critical role in determining the cost of system.

Understanding the factors that influence the cost of ERP will help give you a better idea of how much a business can expect to pay. Moreover, it gives the enterprise the knowledge to carefully evaluate estimates that fall significantly below or above industry standards. Most ERP systems are priced on a per-user basis. Specifically, the number of users that will be using the system at the same time and the level of access they require. The number of users and the functions which are included are factors that affect the price and the price in most cases is exorbitant.

The main objective of the research is to introduce a simplified and low-cost method of minimizing the transport costs by minimizing the number of truck movements or vehicles in the fleet, maximizing the quantity volume per kilometre, minimizing the mileage of each vehicle in the fleet and finally generate a rational but easy to use dispatching schedule for start-ups, small and medium scale companies who are yet to implement a sophisticated and integrated transport scheduling system. This research was carried out considering, outbound logistics of companies which are having the spoke-hub distribution system.

Analysis will be carried using randomly generated data which include vehicle fleet data (trucks) and customer (Agent) demands. To minimize the total transportation cost, the optimum number of truck movements with different capacities was selected for each agent by applying the Simplex Method in Linear Programming. The results will give a proper insight to prepare a vehicle schedule to dispatch each shipment by considering the agent's available safety stocks. This study assists the company to reduce its carbon footprint by eliminating unnecessary truck movements. Human errors were also reduced by using this systematic way of scheduling vehicles. Outcome of the research demonstrates that the application of the proposed model for truck scheduling system in transport operation to increases the efficiency of outbound logistics thereby maximising the profit of the company. This paper therefore brings a solution to the vehicle scheduling problem and overcomes the bottlenecks in transportation at such companies.

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Keywords: Transportation Optimization, Fleet Optimization and Management, Outsourcing, Cost minimization, Enterprise Resource Planning, Simplex Method

CHAPTER ONE

INTRODUCTION AND BACKGROUND

1.1. Introduction

Emerging rise of incidences corresponding to increasing volumes in freight transport should be answered by innovative solutions. The invention of contemporary solutions in transport and logistics sector is significantly important with the growth in the volume of freight transportation in any country. Most transport problems are related to the cost incurred through congestion, shortage of labour and the fuel price hike. Considering all global and local difficulties in transportation each vehicle fleet of individual organizations should be improved to its optimum level to eliminate problems. Implementation of mitigation measures for negative impacts of natural and social habits is another challenge that lies on the logisticians in world context and, due to tropical climate conditions such as flood, the same applies to Sri Lanka context.

Transportation cost is a very major part of a business's overall logistics spend. When the fuel price is increased, the share assigned to transportation can be increased significantly. That cost is transferred on to the end consumer and the price of products continues to rise. Transportation cost is one of main financial component for a business to reduce and there are several ways of which transportation costs can be minimized and also there are a several transportation strategies that can be implemented by management to help minimize overall costs. In the scenario of transportation costs being so high, management must introduce methods that will detect inefficiencies in transportation section in the supply chain and come up with solutions to solve those problems.

Generally, logistics managers are given the task to deliver the best quality efficient transport. Same time the distributors, agents streamline their systems to make lower cost for higher volumes, and the logistics manager must adopt strategic and systematic strategies when it comes to the number of carriers used. One of duties of logistics managers are to find systems to select the best fit carrier, at the lowest cost. When the fleets have multiple carriers with different types the logistics managers have negotiated the best arrangement for each route, but may not considered at the big picture. There are so many scenarios have to be looked at when processing this task and also, so many variables can be identified such as when reducing the number of carriers, the number of work offered to the remaining carriers will increase. By serving distributors, agents a larger volume of goods, the carrier should be able to offer lower rates across all routes by using full truck loads. When calculating separately on some routes the rate is not as lowest as was used with another type of carrier, but aggregate transport costs across all routes need to be the lowest.

To guarantee to have an optimized supply chain, customer satisfaction must be achieved by delivering what the customers want, when they want it. And it must achieve by at the lowest cost possible. Minimizing company's transportation costs can be a significant method to bring down the overall spend of the company, without reducing customer service.

Transport Management Systems (TMS) are introduced to the industry as a solution to the criticalness of transportation in the business. TMS may be part of an enterprise resource planning system. Mostly TMS software modules consist with route planning and optimization, capacity optimization, scheduling, freights and payments, yard planning, sales orders of agent and carrier management. The value of the business upgrade through minimizing the costs by effective route planning, efficient capacity optimization, obtaining the best carrier mix and mode selection, improve accountability and visibility based on a systematic way in the transport process, ability of getting greater flexibility to make changes to the delivery plans according to any scenarios by using TMS.

Setting up costs of TMS are a significantly high. Companies have more concerns when it's come to purchase by occurring such amount of expense. The implementing cost of TMS varies greatly depending on the type of business, country and other several factors. As examples the estimation cost by business size (Ray Collazo, 2016):

- Small businesses: $10,000 - $150,000
- Mid-sized businesses: $150,000 - $500,000
- Large enterprises: $1 million - $10+ million

The cost of the ERP software is only one part of the setup cost. Many other costs go to internal and external human resources. Furthermore, an annual recurrent fee to be paid that are not included in the initial implementation.

Normally, cost of the software is between from 15% to 30% of the total cost of implementation. Software vendors have different pricing models, most of time the software costs generally determined with the number of users IDs request to access the ERP. When the number of users increase that need to access the ERP, the cost coming to high with the licensing costs. If the company is in a more specialized industry, it is problematic to select an ERP that will sufficiently address and fully support its needs. Therefore, the implementation may require heavy customization and third-party add-ons, which will increase costs significantly. Moreover, if the company operates in multiple locations, the software vendor may charge more.

1.2. Significance of the Study

The area of this study confirms the increase in the efficiency of the logistic processes by eliminating human errors and unnecessary cost occurrences. More over using this system can control the cost, affiliated with operating and upholding a group of vehicles in the fleets and increase the flexibility of companies' supply chains. This system facilitates for pre-preparation of the other upcoming industrial software such as ERP, TMS etc.

1.3. Research Objectives

The main objective of the research is to introduce a simplified and low-cost method of minimizing transport costs by minimizing the number of truck movements, maximizing the quantity volume per kilo-meter and minimizing the mileage of each vehicle in the fleet. Other objectives of the research were to provide a platform for developing transport scheduling software which can be utilized by companies engaged in transporting the similar kind of goods, to increase the customer satisfaction by elimination stock outs, to minimize human errors, and to reduce company carbon footprint by eliminating unnecessary truck movements. For the model development purpose, the main objectives were sub-divided;

- Minimize the Number of vehicles in the fleet.

Use of this application, will help to understand the minimum number of vehicles which are wanted to utilize truly to fulfil the demand of the agent.

- Minimize the mileage of running by each vehicle in the fleet.

Eliminating unnecessary trips and full filling agent's demand by using minimum number of trucks help to reduce miles of running by each vehicle in the fleet.

- Minimize use of labour.

Reduction of usage of vehicle miles directly deducts the companies' labour costs.

- Maximize volume quantity per Km.

The possibility of selecting the optimum capacity truck to fulfil the relevant agent's demand will maximize the volume quantity per Km.

- Develop a systematic way of scheduling the fleet of vehicle.

The human errors will be reduced by using a systematic way of scheduling vehicle.

- Facilitate the consignment agent to arrange their daily redistribution plan.

Convenience of calculating the estimated time of arrival (ETA) of the trucks to the premises of consignment agent will help them to arrange their daily redistribution plan.

Other objectives,

- Show the reduction in carbon footprint by eliminating unnecessary truck movements.

Achieving above major objectives this research project will lead to eliminate operational bottle necks of the companies' supply chain, through smooth running of operations in the outbound logistics divisions.

1.4. Methodology

A major issue faced by managers is how to allocate scarce resources among various company activities and projects. Linear programming, or LP, is an effective method of allocating limited resources in an optimal and effective way. It is one of the most widely used operation research tools and has been a decision-making aid in almost all transport, manufacturing industries and in financial and service organizations in the today's world.

Targeting to minimize the cost of the Transport system in the outbound logistic section, the linear programming model was carried out. A set of randomly generated data was used as transportation statistics to carry out the calculation. Assumed the fleet is consisted with 50 trucks which have three different capacities (1000, 950, 850, 800, 750 units) to meet the daily demands of 20 distributors established in different parts of the country. The developed model assumed a single trip is done by a truck in one delivery. If the truck is return to the origin, it can be added to the fleet as available for the next trip.

1.5. Structure of the Dissertation

The dissertation consisted of five chapters. First Chapter consists of the introduction and background of the research. Second Chapter is the literature review. and the discussion of the theoretical back ground. Third Chapter is the methodology of the study. Fourth Chapter explains the analyses of the findings and the final Chapter concludes conclusions and recommendations and future research on the research. The references and Annexures are attached subsequently.

CHAPTER TWO

LITERATURE REVIEW

2.1. Research on transportation problem

To understand the researches already exist with respect to transport optimization and management; a literature review in this industry was carried out. Furthermore, it provides the details about the comprehensive mathematical models which have been used to optimize transport costs in many industries.

Bartling & Muhlenbein (1997) have described a large-scale vehicle scheduling and routing issue which is greatly significant to parcel distribution companies. They have developed a Breeder Genetic linear algorithm with the capability to deal with up to 10,000 transportation requests to be serviced by an inhomogeneous fleet of vehicles within a 24-hour time interval. A transportation request is defined as the task to move a loaded container from one depot to another. Since the depots do not send out the same number of containers as they receive, the number of empty containers available at the depots must be balanced. The optimization task, thus, is twofold: determine suitable balance trips and find a low-cost schedule for the fleet of vehicles.

As per Lee et al, (2006) one of the most significant factors in implementing supply chain management is to efficiently control the physical flow of the supply chain. Due to its importance, many companies are trying to imitate those efficient methods to increase customer satisfaction and reduce costs. Cross-docking is considered a good method to reduce inventory and improve responsiveness to different customer demands. It is also necessary, when considering cross-docking from an operational viewpoint, to find the optimal vehicle routing schedule. Thus, an integrated model considering both cross-docking and vehicle routing scheduling was treated in their study. Linear programming algorithm based on a Tabu search algorithm was proposed.

Foster & Ryan (1976) described an integer programming formulation of the vehicle scheduling problem and illustrated how such a formulation can be extended to incorporate restrictions on work load, coverage and service that occur in real world vehicle scheduling problems. The integer programme was solved by using the Revised Simplex method and by introducing an additional constraint to retain integrity during convergence. The method was demonstrated on fifteen problems ranging in size from 21 to 100 locations and the results generally show an improvement from previously published results.

Löbel (1998) investigated the solution of the Linear Programming (LP) relaxation of the multi-commodity flow formulation of the multiple-depot vehicle scheduling problems arising in mass public transit. He developed a column generation technique that makes it possible to solve the significant linear programs that arise. He proposed Lagrangean pricing as one of the basic ingredients of an effective method to solve multiple-depot vehicle scheduling problems to proven optimality.

Komenda & Pechoucek (2010) described about a multi-agent VRP solver method. It utilizes the contract-net protocol based allocation and several improvement strategies. It provides the solution with the quality of 81% compared to the optimal solution on 115 benchmark instances in polynomial time. The self-organizing capability of the system successfully minimizes the number of vehicles used. The presented solver architecture supports great runtime parallelization with incremental increase of solution quality. The presented solver demonstrates applicability to the VRP problem and easy adaptation to problem variants.

Giaglis & Zeimpekis (2004) says that vehicle routing (VR) is critical in successful logistics execution. The emergence of technologies and information systems allowing for seamless mobile and wireless connectivity between delivery vehicles and distribution facilities is paving the way for innovative approaches to real-time VR and distribution management. This paper shows avenues for building upon recent trends in VR-related research towards an integrated approach to real-time distribution management. A review of the advances to-date in both fields, i.e. the relevant research in the VR problem and the advances in mobile technologies, forms the basis of this investigation. Further to setting requirements, we propose a system architecture for urban distribution and real-time event-driven vehicle management.

Ghiani & Guerriero (2003) have described vehicle routing problems (VRPs) are central to logistics management both in the private and public sectors. They consist of determining opti- mal vehicle routes through a set of users, subject to side constraints. The most common operational constraints impose that the total demand carried by a vehicle at any time does not exceed a given capacity, the total duration of any route is not greater than a prescribed bound, and service time windows set by customers are respected. In long- haul routing, vehicles are typically assigned one task at a time while in short-haul routing, tasks are of short duration (much shorter than a work shift) and a tour is to be built through a sequence of tasks.

Slater (2002) explains the recent developments in e-commerce for marketing and selling physical products will change the role of logistics management, who need to adopt suitable order fulfilment practices to meet the growing demands and expectations of customers. One significant new customer expectation of the e-commerce fulfilment process is the customer's ability to select, at the time they specify on their order, a specific delivery time and date (often within a 30-minute Time Window) so that they receive their delivery. The order fulfilment process must be designed and planned to be able to guarantee such timed deliveries with a substantial degree of certainty at the time the customer places their order. The real value offered to the e-commerce customer in such a fulfilment process is created through a combination of the simplicity of placing orders at a time convenient to themselves, visibility of product availability at the time of placing the order, and the offer of a selection of Time Windows for delivery of the order. Such an offer is supported by the reliability that the delivery will arrive ''in full, on time and with the correct documentation''. One of the most difficult problems for logistics management in such a fulfilment process is to solve how to plan and implement a cost-effective delivery operation, in a dynamic environment, where commitments to customers must be given while orders are being received. Traditional vehicle routing and scheduling methods as described by the National Computing Centre (1969) rely on all orders being received before operational planning takes place and are, therefore, inappropriate when delivery commitments need to be given as each customer order is placed. E-commerce solutions imply a new approach is required to solve the Dynamic Vehicle Routing and Scheduling Problem (DVRSP).

2.2. Theoretical Background

Linear Programming was developed in 1947 by G.B. Dantzig and has become a valuable tool in the field of operations research. Linear programming is a mathematical method to obtain solutions for optimizing problems. The word (linear) indicates that the relations involved in are linear, while the term programming in the context means planning and scheduling of activities. The objective of this process is to maximize or minimize a single objective function related to a set of constraints. Linear programming models mathematically represent constrained optimization problems. Certain characteristics are common in these models. It has two categories of characteristics which are components and assumptions. Four components which provide the structure of a linear programming model:

a) Objective Function.
b) Decision variables.
c) Constraints.
d) Parameters.

Single goal or objective should be there, to formulate Linear programming algorithms such as the maximization of profits, Minimization of cost etc. Maximization and minimization are the two general types of objectives. A maximization objective might involve the profits, revenues, efficiency, or rate of return. Contrariwise, a minimization objective might involve the cost, time, distance travelled, or scrap. To determine the total profit (or cost, etc., depending on the objective) for a given problem, the objective function represents the mathematical expression.

Choices available to the decision maker in terms of amounts of either inputs or outputs are represented by the Decision variables. Some problems require choosing a combination of inputs to minimize the total cost, while others require selecting a combination of outputs to maximize profits or revenues.

Limitations for the decision makers that restrict the alternatives available are referred as constraints. The three types of constraints are,

i. Less than or equal to (≤)
ii. Greater than or equal to (≥)
iii. Simply equal to (=)

An upper limit on the amount of some scarce resource available for use is implied by the less than or equal (≤) constraint. A minimum that must be achieved in the final solution is specified by the greater than or equal (≥) constraint. To specify exactly what a decision variable should equal is represented by the = constraint. One or more constraints can be consisted in a linear programming model. The set of all feasible combinations of decision variables are defined by the constraints of a given problem. This set is referred to as the feasible solution space. In terms of the objective function, the linear programming algorithms are assigned to find the feasible solution space for the combination of decision variables that will yield an optimum. A LP model contains a mathematical statement of the objective and mathematical statement of each constraint. The symbols which are used to represent the decision variables and numerical values are called parameters

LP model as a research tool has been used in different applications in transport and logistics give examples referring the lit.

Iraschko (1996) explains Linear Programming (LP) or, more specifically, Integer Programing (IP), has been applied to the problem of optimal spare capacity planning in a span restorable network. The number of constraints required by an integer program to find the optimal capacity placement in a network of practical size is often prohibitively large. To function effectively, the constraint system for formulating the IP must be defined carefully.

Sitek & Wilkarek (2013) have described the problem of outsourcing logistics management in supply chain with multimodal network environment and a mathematical model of supply chain optimization in multimodal environment as an integer linear programming problem. This model can be the basis for the decision support in the supply chain management. The application of the model will allow answering many decision questions such as: How to realize customers' orders at the best price? How will they look at the time of delivery? Which distributors will take part in the supply? Do distributors have sufficient capacity to carry out the orders? What is the level of utilization of capacity distributors? There can be many more of such questions. As you can see, the results of the optimization of the presented model can be the basis for the decision support (both offline and online). The complexity and flexibility of the presented model as well as the manner of its implementation are the main achievements and contributions of the article. An additional achievement is the formulation of the model in the form of integer linear programming, which facilitates its use in the practical aspects.

Martin et al. (1993) presented a linear programming model for planning production, distribution and inventory operations in the glass sector industry. Chen and Wang (1997) proposed a linear programming model to solve integrated supply, production and distribution planning in a supply chain of the steel sector. Ryu et al. (2004) suggested a bi-level modeling approach comprising two linear programming models, one for production planning and one for distribution planning. These models subsequently consider demand uncertainty, resources and capacities when they are reformulated by multi-parametric linear programming. Kanyalkar and Adil (2005) proposed a linear programming model for aggregated and detailed production and dynamic distribution planning in a multiproduct and multiplant supply chain. Oh and Karimi (2006) put forward a linear programming model that integrates production and distribution planning for a multinational firm in the chemical sector in a multi-plant, multi-period and multi-product environment. This model also works with tax and financial data, such as taxes related with the firm’s business activity or amortizations. Jung et al. (2008) compared linear programming models for centralized and decentralized production and transport planning environments.

Mcdonald and Karimi (1997) presented a mixed deterministic integer linear programming model to solve a production and transport planning problem in the chemical industry in a multi-plant, multi-product and multi-period environment. Barbarosogˇlu and Ozgur (1999) developed a mixed integer linear programming model which is solved by Lagrangian and heuristic relaxation techniques to become a decentralized two-stage model: one for production planning and another for transport planning. On the other hand, Dogan and Goetschalckx

(1999) proposed a mixed integer linear programming model for designing supply chain production and distribution planning. Goetschalckx et al. (2002) presented two mixed integer linear programming models, one for the supply chain design phase and the other for production planning, inventory planning and national supply chain transport planning with seasonal demand. Timpe and Kallrath (2000) and Kallrath (2002) presented a mixed integer linear programming model for production, distribution and sales planning with different time scales for business and production aspects. Dhaenens-flipo and Finke (2001) developed a mixed integer linear programming-based planning model in a multi-firm, multi-product and multi-period environment. Jayaraman and Pirkul (2001) put forward an integrated model for supply chain design and planning by means of mixed integer linear programming. Sakawa et al. (2001) elaborated a mixed integer linear programming model for production and transport planning in a Japanese firm that produces construction elements. On the other hand, Bredstrom and Ronnqvist (2002) considered two independent mixed integer linear programming models, one for production planning which considers transport costs, and the other for distribution planning in a multi-period and multi-product environment. Jang et al. (2002) developed a system with four modules for supply chain management, these being supply chain design, production and distribution planning, the model management module and the data processing module. The supply chain design and the production planning models, which have several supply tiers in relation to the list of materials, and transport, are formulated by mixed integer linear programming. Perea-lopez et al. (2003) developed a multi-period mixed integer linear programming model for supply chain dynamical characterization. The use of a predictive control model complements this model. Gen and Syarif (2005) elaborated a mixed integer linear programming model for production and transport planning solved by genetic algorithms and fuzzy techniques. Park (2005) suggested an integrated transport and production planning model that uses mixed integer linear programming in a multi-site, multi-retailer, multi-product and multi-period environment. Likewise, the author also presented a production planning submodel whose outputs act as the input in another submodel with a transport planning purpose and an overall objective of maximizing overall profits with the same technique. Eksiog˘lu et al. (2006) showed an integrated transport and production planning model in a multi-period, multi-site, mono-product environment as a flow or graph network to which the authors added a mixed integer linear programming formulation. Later, Eksiog˘lu et al. (2007) extended this model to become a multi-product model solved by Lagrangian decomposition. Rizk et al. (2006) suggested a mixed integer linear programming model for the production process along with three different piecewise linear functions used to develop three equivalent mixed integer linear programming models for the distribution process in which scale economies are contemplated. Bilgen and Ozkarahan (2007) considered a model that integrates mixes, loads and transport between various sea ports used in the cereal industry by means of mixed integer lineal programming in a multi-period environment. Meijboom and Obel (2007) developed a mixed integer linear programming model for midterm planning. The authors also studied the coordination between the various stages of a supply chain. Rizk et al. (2008) suggested a mixed integer linear programming model for production and distribution planning in a production environment with a single production plant and several distribution centers. Romo et al. (2009) implemented a model for optimizing Norwegian natural gas production and transport in a mixed-integer linear programming context.

CHAPTER THREE

METHODOLOGY

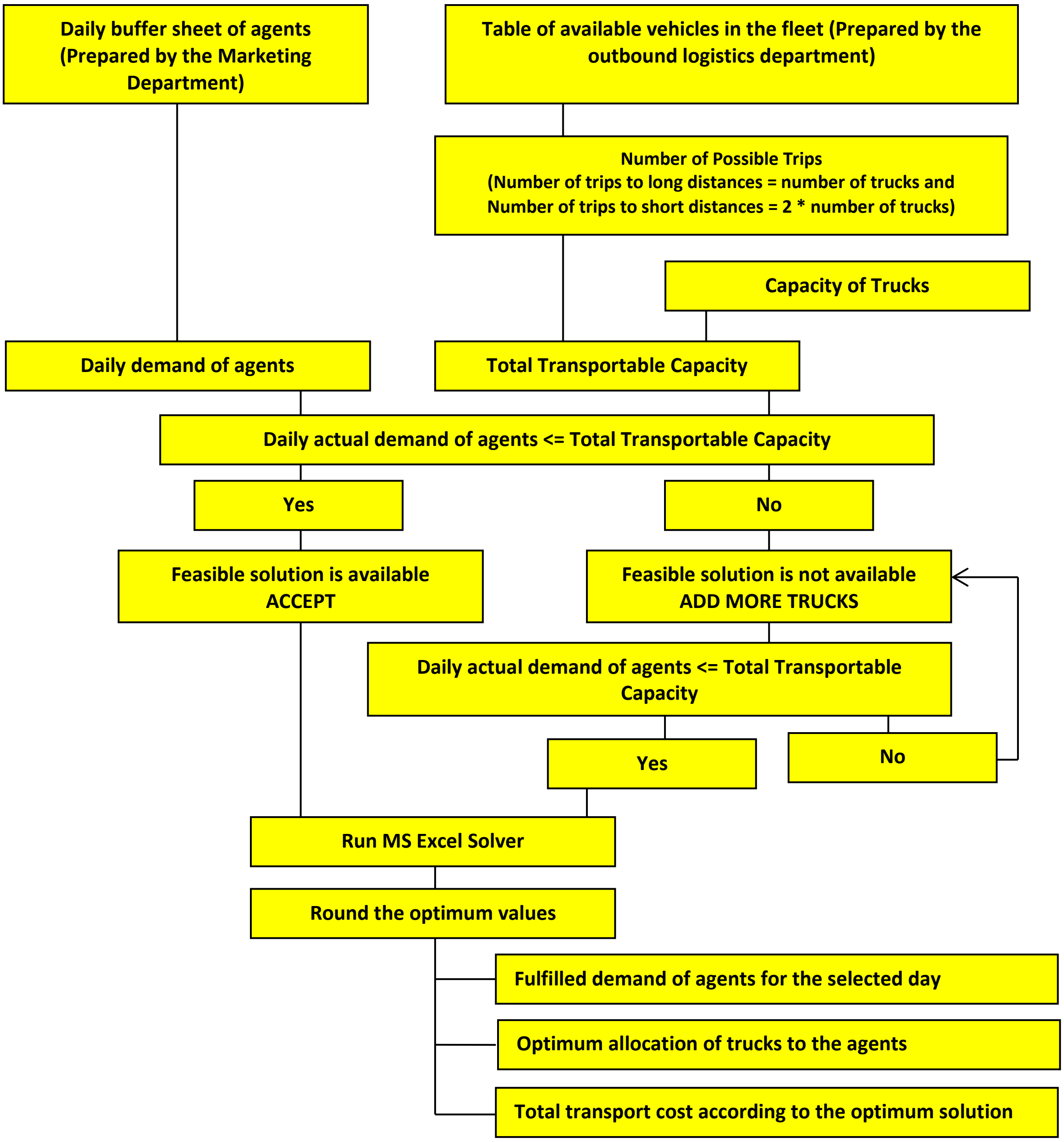
3.1. Introduction

To develop the linear programming model hypotheses randomly generated data was used. Since the realistic field data not available due to company data privacy policy, the research is used simulation method of two different scenarios which are low and high demand. For that two-different data set is randomly generated.

3.2. Model buildings

Randomly generated data was used as transportation data for the analysis. Assuming fifty prime movers with five different capacities (1000, 950, 850, 800, 750 units) and randomly generated demand data which is represented seven scenarios (including low, average, high demand changes) were utilized for the analysis. To minimize the total transportation cost per day, the optimum number of truck movements with different capacities was selected for each agent by applying the Simplex Method in Linear Programming. The proposed vehicle scheduling system is exhibited in Figure 1.

Figure 1: First phase of the proposed vehicle scheduling system



Source: Constructed by the author

Based on the above model the following objective function and constraints were formulated.

The equation of the transportation cost of serving individual agents using different capacity type vehicle can be denoted as follows,

$\boldsymbol{Transport\ cost = min \sum (Kc_i) \times (f_j) \times (c_i)}$ **--------------Objective function**

K_i = Unit cost of transportation of capacity, (**c**) of truck type **i**

i = a, b, c, d

f_j = Frequency of node **j**

j = 1,2,…..n

c_i = Capacity of truck type i

i = a, b, c, d

Subject to

$\sum c_i f_{j,ci}$ >= daily demand node j

$\sum f_{j,ci}$ + <= Number of trip with vehicle capacity i

After allocating the optimum number of trips with the minimum transport cost for each consignment agents by using MS Excel Solver, the truck schedule and the departure time for each truck should be arranged according to the priority of the agents. Generally, the operational team of the company calculates the buffer-days by using average redistribution data and the existing buffer level of each agent. The term buffer-days refers to the number of days that a consignment agent can survive in the market without creating a stock out situation. Agents have been prioritized by ascending order based on their buffer days to avoid stock out situation in a particular market area.

3.3. Testing the Application of the model to a hypothetical scenario

The following data were hypothetically assigned to test the model.

Table 1: Vehicle types and their capacities

Vehicle type	Capacity	Per Km rate	Per unit cost (Rs.)
Type ‘a’ (15 trucks)	1000	52	0.05200
Type ‘b’ (12 trucks)	950	50	0.05263
Type ‘c’ (10 trucks)	850	48	0.05647
Type ‘d’ (07 trucks)	800	46	0.05750
Type ‘e’ (06 trucks)	750	44	0.05867

Source: Constructed by the authors

Table 1 shows the standard vehicle fleet that will use to test the model. Practically the hiring rates of higher capacity vehicles are more expensive than the smaller vehicles. But the benefit from the economies of scale of using bigger vehicles are higher than the smaller vehicles. The forth column (Per unit cost (Rs.)) of the table 01 depicts per unit costs that incur to the company when using each vehicle. The higher capacity vehicles have the lower cost per unit than the smaller vehicles. Thus, the number of higher capacity vehicle are used more in the fleet to gain the cost benefits. As in the table transporting a unit in a full truck load of a higher capacity vehicle is cheaper than a smaller vehicle.

To develop the model and the linear equations the below unit has been introduced and the model is developed based on the assumption of transporting full truck load (FCL) to serve every agent in the network. The Quantity of freight and the capacity of vehicles can be measured in terms of units. Cost per units varies as per the capacity of the selected vehicle and the travel distance between the company and the agent. Cost per unit can be calculated as follows:

$$Transport\ cost = \frac{\text{Distance between company and particular consignment agent } \boldsymbol{X} \text{ Rate per Kilometre}}{\text{Total units carried by the selected vehicle}}$$

This equation shows the total transport payment (cost) based on distance (agent wise). To get the best match vehicle based on the total units to be transported to the destination, total transport cost was brought down to the unit cost per km. Hence, transport cost of transportation to any agent is fully reflected in the above equation.

According to the above formula the cost per unit per Km for each agent has been calculated against the vehicle type in the Table 2.

Table 2: Transport costs per unit per km of each agents against the type of vehicles

Ref. No.	Name of the agent	Distance (Two way)(KM)	Cost per unit (Agent wise)				
			1000	*950*	*850*	*800*	*750*
1	Node 1	160	8.32	8.42	9.04	9.20	9.39
2	Node 2	500	26.00	26.32	28.24	28.75	29.33
3	Node 3	600	31.20	31.58	33.88	34.50	35.20
4	Node 4	50	2.60	2.63	2.82	2.88	2.93
5	Node 5	350	18.20	18.42	19.76	20.13	20.53
6	Node 6	580	30.16	30.53	32.75	33.35	34.03
7	Node 7	960	49.92	50.53	54.21	55.20	56.32
8	Node 8	820	42.64	43.16	46.31	47.15	48.11
9	Node 9	1200	62.40	63.16	67.76	69.00	70.40
10	Node 10	690	35.88	36.32	38.96	39.68	40.48
11	Node 11	1700	88.40	89.47	96.00	97.75	99.73
12	Node 12	1960	101.92	103.16	110.68	112.70	114.99
13	Node 13	1300	67.60	68.42	73.41	74.75	76.27
14	Node 14	1420	73.84	74.74	80.19	81.65	83.31
15	Node 15	1640	85.28	86.32	92.61	94.30	96.21
16	Node 16	1344	69.89	70.74	75.90	77.28	78.85
17	Node 17	1040	54.08	54.74	58.73	59.80	61.01

18	Node 18	284	14.77	14.95	16.04	16.33	16.66
19	Node 19	472	24.54	24.84	26.65	27.14	27.69
20	Node 20	280	14.56	14.74	15.81	16.10	16.43

Source: Constructed by the authors

To develop the objective function; the above unit cost per km is introduced for each agent when serving by each type of vehicles. Then the model is sensitive for both the variables of distance and the transported units to fulfil that agent.

Frequencies of sending vehicles to the agents to fulfil the required demands are denoted in Table 3.

Table 3: Frequencies of trips to agents from the company

Assigned name	Frequency of trips per day
Node 1	f_1
Node 2	f_2
Node 3	f_3
Node 4	f_4
Node 5	f_5
Node 6	f_6
Node 7	f_7
Node 8	f_8
Node 9	f_9
Node 10	f_{10}
Node 11	f_{11}
Node 12	f_{12}
Node 13	f_{13}
Node 14	f_{14}
Node 15	f_{15}
Node 16	f_{16}
Node 17	f_{17}
Node 18	f_{18}
Node 19	f_{19}
Node 20	f_{20}

Source: Constructed by the authors

Optimum frequencies will be derived by the LP model. Agent wise total transportation costs are calculated to form the objective function in the Table 4.

Transportation costs of each vehicles for each agent (unit cost X frequency of delivery (f_n) X capacity of the vehicle [a,b,c,d,e]) are shown in Table 4.

Table4: Transport costs of agents based on frequencies made by each vehicle

Ref. No	Agent	KM	Transport cost (Rs.)				
			a (1000)	*b (950)*	*c (850)*	*d (800)*	*e (750)*
1	Node 1	160	8.32 $f_1 a$	8.42 $f_1 b$	9.04 $f_1 c$	9.20 $f_1 d$	9.39 $f_1 e$
2	Node 2	500	26.00 $f_2 a$	26.32 $f_2 b$	28.24 $f_2 c$	28.75 $f_2 d$	29.33 $f_2 e$
3	Node 3	600	31.20 $f_3 a$	31.58 $f_3 b$	33.88 $f_3 c$	34.50 $f_3 d$	35.20 $f_3 e$
4	Node 4	50	2.60 $f_4 a$	2.63 $f_4 b$	2.82 $f_4 c$	2.88 $f_4 d$	2.93 $f_4 e$
5	Node 5	350	18.20 $f_5 a$	18.42 $f_5 b$	19.76 $f_5 c$	20.13 $f_5 d$	20.53 $f_5 e$
6	Node 6	580	30.16 $f_6 a$	30.53 $f_6 b$	32.75 $f_6 c$	33.35 $f_6 d$	34.03 $f_6 e$
7	Node 7	960	49.92 $f_7 a$	50.53 $f_7 b$	54.21 $f_7 c$	55.20 $f_7 d$	56.32 $f_7 e$
8	Node 8	820	42.64 $f_8 a$	43.16 $f_8 b$	46.31 $f_8 c$	47.15 $f_8 d$	48.11 $f_8 e$
9	Node 9	1200	62.40 $f_9 a$	63.16 $f_9 b$	67.76 $f_9 c$	69.00 $f_9 d$	70.40 $f_9 e$
10	Node 10	690	35.88 $f_{10} a$	36.32 $f_{10} b$	38.96 $f_{10} c$	39.68 $f_{10} d$	40.48 $f_{10} e$
11	Node 11	1700	88.40 $f_{11} a$	89.47 $f_{11} b$	96.00 $f_{11} c$	97.75 $f_{11} d$	99.73 $f_{11} e$
12	Node 12	1960	101.92 $f_{12} a$	103.16 $f_{12} b$	110.68 $f_{12} c$	112.70 $f_{12} d$	114.99 $f_{12} e$
13	Node 13	1300	67.60 $f_{13} a$	68.42 $f_{13} b$	73.41 $f_{13} c$	74.75 $f_{13} d$	76.27 $f_{13} e$
14	Node 14	1420	73.84 $f_{14} a$	74.74 $f_{14} b$	80.19 $f_{14} c$	81.65 $f_{14} d$	83.31 $f_{14} e$
15	Node 15	1640	85.28 $f_{15} a$	86.32 $f_{15} b$	92.61 $f_{15} c$	94.30 $f_{15} d$	96.21 $f_{15} e$
16	Node 16	1344	69.89 $f_{16} a$	70.74 $f_{16} b$	75.90 $f_{16} c$	77.28 $f_{16} d$	78.85 $f_{16} e$
17	Node 17	1040	54.08 $f_{17} a$	54.74 $f_{17} b$	58.73 $f_{17} c$	59.80 $f_{17} d$	61.01 $f_{17} e$
18	Node 18	284	14.77 $f_{18} a$	14.95 $f_{18} b$	16.04 $f_{18} c$	16.33 $f_{18} d$	16.66 $f_{18} e$
19	Node 19	472	24.54 $f_{19} a$	24.84 $f_{19} b$	26.65 $f_{19} c$	27.14 $f_{19} d$	27.69 $f_{19} e$
20	Node 20	280	14.56 $f_{20} a$	14.74 $f_{20} b$	15.81 $f_{20} c$	16.10 $f_{20} d$	16.43 $f_{20} e$

Source: Constructed by the authors

Simplex Method in Linear Programming can be applied to determine the optimum vehicle movements. Based on the above information, the objective function can be derived as follows:

$$
\begin{aligned}
\textit{Aggregate transport cost of the network} = \; & 8.32 f_1 a + 8.42 f_1 b + 9.04 f_1 c + 9.20 f_1 d + 9.39 f_1 e \\
& + 26.00 f_2 a + 26.32 f_2 b + 28.24 f_2 c + 28.75 f_2 d + 29.33 f_2 e \\
& + 31.20 f_3 a + 31.58 f_3 b + 33.88 f_3 c + 34.50 f_3 d + 35.20 f_3 e \\
& + 2.60 f_4 a + 2.63 f_4 b + 2.82 f_4 c + 2.88 f_4 d + 2.93 f_4 e \\
& + 18.20 f_5 a + 18.42 f_5 b + 19.76 f_5 c + 20.13 f_5 d + 20.53 f_5 e \\
& + 30.16 f_6 a + 30.53 f_6 b + 32.75 f_6 c + 33.35 f_6 d + 34.03 f_6 e \\
& + 49.92 f_7 a + 50.53 f_7 b + 54.21 f_7 c + 55.20 f_7 d + 56.32 f_7 e \\
& + 42.64 f_8 a + 43.16 f_8 b + 46.31 f_8 c + 47.15 f_8 d + 48.11 f_8 e \\
& + 62.40 f_9 a + 63.16 f_9 b + 67.76 f_9 c + 69.00 f_9 d + 70.40 f_9 e \\
& + 35.88 f_{10} a + 36.32 f_{10} b + 38.96 f_{10} c + 39.68 f_{10} d + 40.48 f_{10} e \\
& + 88.40 f_{11} a + 89.47 f_{11} b + 96.00 f_{11} c + 97.75 f_{11} d + 99.73 f_{11} e \\
& + 101.92 f_{12} a + 103.16 f_{12} b + 110.68 f_{12} c + 112.70 f_{12} d + 114.99 f_{12} e \\
& + 67.60 f_{13} a + 68.42 f_{13} b + 73.41 f_{13} c + 74.75 f_{13} d + 76.27 f_{13} e \\
& + 73.84 f_{14} a + 74.74 f_{14} b + 80.19 f_{14} c + 81.65 f_{14} d + 83.31 f_{14} e \\
& + 85.28 f_{15} a + 86.32 f_{15} b + 92.61 f_{15} c + 94.30 f_{15} d + 96.21 f_{15} e \\
& + 69.89 f_{16} a + 70.74 f_{16} b + 75.90 f_{16} c + 77.28 f_{16} d + 78.85 f_{16} e \\
& + 54.08 f_{17} a + 54.74 f_{17} b + 58.73 f_{17} c + 59.80 f_{17} d + 61.01 f_{17} e \\
& + 14.77 f_{18} a + 14.95 f_{18} b + 16.04 f_{18} c + 16.33 f_{18} d + 16.66 f_{18} e \\
& + 24.54 f_{19} a + 24.84 f_{19} b + 26.65 f_{19} c + 27.14 f_{19} d + 27.69 f_{19} e \\
& + 14.56 f_{20} a + 14.74 f_{20} b + 15.81 f_{20} c + 16.10 f_{20} d + 16.43 f_{20} e
\end{aligned}
$$

The above objective function should be minimized subject to constraints arising from the daily demand of the agents and number of possible movements available for each type of truck.

Daily demand of an agent =Capacity of the selected vehicle to serve particular agent [a,b,c,d,e] x Frequency of each vehicle visited to that particular agent [$f_{\text{agent, served vehicle}}$]

Constraints arise from the daily demand of agents:

$$a\,f_{1a} + b\,f_{1b} + c\,f_{1c} + d\,f_{1d} + e\,f_{1e} \geq \textit{Daily demand of node 1}$$
$$a\,f_{2a} + b\,f_{2b} + c\,f_{2c} + d\,f_{2d} + e\,f_{2e} \geq \textit{Daily demand of node 2}$$
$$a\,f_{3a} + b\,f_{3b} + c\,f_{3c} + d\,f_{3d} + e\,f_{3e} \geq \textit{Daily demand of node 3}$$
$$a\,f_{4a} + b\,f_{4b} + c\,f_{4c} + d\,f_{4d} + e\,f_{4e} \geq \textit{Daily demand of node 4}$$
$$a\,f_{5a} + b\,f_{5b} + c\,f_{5c} + d\,f_{5d} + e\,f_{5e} \geq \textit{Daily demand of node 5}$$
$$a\,f_{6a} + b\,f_{6b} + c\,f_{6c} + d\,f_{6d} + e\,f_{6e} \geq \textit{Daily demand of node 6}$$
$$a\,f_{7a} + b\,f_{7b} + c\,f_{7c} + d\,f_{7d} + e\,f_{7e} \geq \textit{Daily demand of node 7}$$
$$a\,f_{8a} + b\,f_{8b} + c\,f_{8c} + d\,f_{8d} + e\,f_{8e} \geq \textit{Daily demand of node 8}$$
$$a\,f_{9a} + b\,f_{9b} + c\,f_{9c} + d\,f_{9d} + e\,f_{9e} \geq \textit{Daily demand of node 9}$$
$$a\,f_{10a} + b\,f_{10b} + c\,f_{10c} + d\,f_{10d} + e\,f_{10e} \geq \textit{Daily demand of node 10}$$
$$a\,f_{11a} + b\,f_{11b} + c\,f_{11c} + d\,f_{11d} + e\,f_{11e} \geq \textit{Daily demand of node 11}$$
$$a\,f_{12a} + b\,f_{12b} + c\,f_{12c} + d\,f_{12d} + e\,f_{12e} \geq \textit{Daily demand of node 12}$$
$$a\,f_{13a} + b\,f_{13b} + c\,f_{13c} + d\,f_{13d} + e\,f_{13e} \geq \textit{Daily demand of node 13}$$
$$a\,f_{14a} + b\,f_{14b} + c\,f_{14c} + d\,f_{14d} + e\,f_{14e} \geq \textit{Daily demand of node 14}$$
$$a\,f_{15a} + b\,f_{15b} + c\,f_{15c} + d\,f_{15d} + e\,f_{15e} \geq \textit{Daily demand of node 15}$$
$$a\,f_{16a} + b\,f_{16b} + c\,f_{16c} + d\,f_{16d} + e\,f_{16e} \geq \textit{Daily demand of node 16}$$
$$a\,f_{17a} + b\,f_{17b} + c\,f_{17c} + d\,f_{17d} + e\,f_{17e} \geq \textit{Daily demand of node 17}$$
$$a\,f_{18a} + b\,f_{18b} + c\,f_{18c} + d\,f_{18d} + e\,f_{18e} \geq \textit{Daily demand of node 18}$$
$$a\,f_{19a} + b\,f_{19b} + c\,f_{19c} + d\,f_{19d} + e\,f_{19e} \geq \textit{Daily demand of node 19}$$
$$a\,f_{20a} + b\,f_{20b} + c\,f_{20c} + d\,f_{20d} + e\,f_{20e} \geq \textit{Daily demand of node 20}$$

Constraints arise from number of possible trips for each type of vehicles:

$$f_{1a} + f_{2a} + f_{3a} + f_{4a} + f_{5a} + f_{6a} + f_{7a} + f_{8a} + f_{9a} + f_{10a} + \leq$$ **No of trips vehicle capacity "a"**
$$f_{11a} + f_{12a} + f_{13a} + f_{14a} + f_{15a} + f_{16a} + f_{17a} + f_{18a} + f_{19a} + f_{20a}$$

$$f_{1b} + f_{2b} + f_{3b} + f_{4b} + f_{5b} + f_{6b} + f_{7b} + f_{8b} + f_{9b} + f_{10b} + \leq$$ **No of trips vehicle capacity "b"**
$$f_{11b} + f_{12b} + f_{13b} + f_{14b} + f_{15b} + f_{16b} + f_{17b} + f_{18b} + f_{19b} + f_{20b}$$

$$f_{1c} + f_{2c} + f_{3c} + f_{4c} + f_{5c} + f_{6c} + f_{7c} + f_{8c} + f_{9c} + f_{10c} + \leq$$ **No of trips vehicle capacity "c"**
$$f_{11c} + f_{12c} + f_{13c} + f_{14c} + f_{15c} + f_{16c} + f_{17c} + f_{18c} + f_{19c} + f_{20c}$$

$$f_{1d} + f_{2d} + f_{3d} + f_{4d} + f_{5d} + f_{6d} + f_{7d} + f_{8d} + f_{9d} + f_{10d} + \leq$$ **No of trips vehicle capacity "d"**
$$f_{11d} + f_{12d} + f_{13d} + f_{14d} + f_{15d} + f_{16d} + f_{17d} + f_{18d} + f_{19d} + f_{20d}$$

$$f_{1e} + f_{2e} + f_{3e} + f_{4e} + f_{5e} + f_{6e} + f_{7e} + f_{8e} + f_{9e} + f_{10e} + \leq$$ **No of trips vehicle capacity "e"**
$$f_{11e} + f_{12e} + f_{13e} + f_{14e} + f_{15e} + f_{16e} + f_{17e} + f_{18e} + f_{18e} + f_{20e}$$

And non-negativity constraint:

$$\left.\begin{array}{llllllllll}
f_{1a}, & f_{2a}, & f_{3a}, & f_{4a}, & f_{5a}, & f_{6a}, & f_{7a}, & f_{8a}, & f_{9a}, & f_{10a} \\
f_{11a}, & f_{12a}, & f_{13a}, & f_{14a}, & f_{15a}, & f_{16a}, & f_{17a}, & f_{18a}, & f_{19a}, & f_{20a} \\
f_{1b}, & f_{2b}, & f_{3b}, & f_{4b}, & f_{5b}, & f_{6b}, & f_{7b}, & f_{8b}, & f_{9b}, & f_{10b} \\
f_{11b}, & f_{12b}, & f_{13b}, & f_{14b}, & f_{15b}, & f_{16b}, & f_{17b}, & f_{18b}, & f_{19b}, & f_{20b} \\
f_{1c}, & f_{2c}, & f_{3c}, & f_{4c}, & f_{5c}, & f_{6c}, & f_{7c}, & f_{8c}, & f_{9c}, & f_{10c} \\
f_{11c}, & f_{12c}, & f_{13c}, & f_{14c}, & f_{15c}, & f_{16c}, & f_{17c}, & f_{18c}, & f_{19c}, & f_{20c} \\
f_{1d}, & f_{2d}, & f_{3d}, & f_{4d}, & f_{5d}, & f_{6d}, & f_{7d}, & f_{8d}, & f_{9d}, & f_{10d} \\
f_{11d}, & f_{12d}, & f_{13d}, & f_{14d}, & f_{15d}, & f_{16d}, & f_{17d}, & f_{18d}, & f_{19d}, & f_{20d} \\
f_{1e}, & f_{2e}, & f_{3e}, & f_{4e}, & f_{5e}, & f_{6e}, & f_{7e}, & f_{8e}, & f_{9e}, & f_{10e} \\
f_{11e}, & f_{12e}, & f_{13e}, & f_{14e}, & f_{15e}, & f_{16e}, & f_{17e}, & f_{18e}, & f_{18e}, & f_{20e}
\end{array}\right\} \geq 0$$

Using the simplex method minimize the objective function subject to two constrains of vehicle availability and minimum demand fulfilment of each agents.

This model minimizes the total cost of transportation of all units in the full O-D network subject to any demand variation, fleet variation and demand variation with distance (high demand situation for low distances and high demand situation for longer distances).

Assumptions

Every other cost related to vehicle fleet such as idling costs etc. haven't been applied in the objective function (as in the third party hired fleet of vehicles) and the truck cost per km is fixed irrespective of destination.

Only one trip is assigned per truck per day in the model testing. However, if the truck return it can be included in the fleet for recalculation at any time of the day.

Application

After identifying the objective function and the constraints, data were fed to the Microsoft Excel Solver to find the optimal solutions in the vehicle scheduling system.

CHAPTER FOUR

DATA ANALYSIS

4.1. Introduction

This chapter presents results derived from the developed cost minimization model using a simulation approach. As data related to a realistic transport operation was not available, randomly assigned data on demand, capacity, and fleet number are used to test the application of the model. Several scenarios are also considered to see the flexibility of the model.

Three scenarios are tested by changing the demands of each agents with keeping the same standard number of vehicles in the fleet.

Two scenarios are tested by changing the demands of agents according to their distances factor with keeping the same standard fleet of vehicles.

One scenario is tested by changing the vehicle fleet with keeping the demand factor constant

- ✓ Scenario 1 Low demand situation
- ✓ Scenario 2 Average demand situation
- ✓ Scenario 3 High demand situation
- ✓ Scenario 4 High demand at closer distance agents (less than 300Km one way)
- ✓ Scenario 5 High demand at longer distance agents (more than 300Km one way)
- ✓ Scenario 6 Fleet Change for average demand

Fitness for use of the model will be measured by the results obtain through above scenarios and comparing the outcomes. To compare the out puts; below per unit cost is introduced in term of cost of transportation. This can be calculated as follows:

$$\text{Cost per unit of transportation} = \frac{\text{Total transport cost}}{\text{Total units transferred}} \text{ ----------------------- (45)}$$

Cost per unit is calculated for each scenario. Lower cost per unit is one key performance indicator of many companies. This will help to minimize the total operational cost of the company.

i) Scenario 1 – Low demand situation

In the scenario 1, the developed model is tested in a low demand situation for all agents keeping the vehicle fleet data constant.

Table 5: Vehicle fleet data. (Constant data)

#	Capacity	Rate	No	Per unit cost (Rs.)
1	1000	52	15	0.05200
2	950	50	12	0.05263
3	850	48	10	0.05647
4	800	46	7	0.05750
5	750	44	6	0.05867
			50	

Source: Constructed by the authors

Standard vehicle fleet is used in this scenario as in the table 5. Randomly generated low demand values are used for the test calculation as in the below table 6.

Table 6: Randomly generated demand values (Low demand)

Distributors	Low demand
Node 01	660
Node 02	1500
Node 03	660
Node 04	900
Node 05	780
Node 06	720
Node 07	1080
Node 08	1140
Node 09	960
Node 10	840
Node 11	780
Node 12	720
Node 13	900
Node 14	660
Node 15	600
Node 16	1080
Node 17	840
Node 18	1020
Node 19	660
Node 20	780

Source: Constructed by the authors

The demand values in the table 6 represent a situation of lower demand of each agent. This data has been generated randomly to perform the model in the scenario 1.

The linear programing model is run through Microsoft excel solver using input details of tables 5 and 6 and derived the results as below. The Tables 7 depicts the output of scenario 1.

Table 7: Outcomes of scenario 1 (Low demand situation)

	Total cost Rs.	No of vehicles used	Total KMs	Required demand	Tot units transferred	Per unit cost Rs.	
Scenario 1	1,118,996.00	18	21538	17280	17850	62.69	**Low demand**

Source: Constructed by the authors based on the output of the model

To fulfil total demand of every agent 18 vehicles have been used out of 50 vehicles in the fleet. Total demand requirement has been achieved. The cost per unit of transportation is Rs.62.69.

ii) Scenario 2 – Average demand situation

In the scenario 2, the developed model is tested in an average demand situation for all agents keeping the vehicle fleet data constant. Since the transport fleet data constant the table 5 is used for the calculation.

Randomly generated average demand values are used for the test calculation as in the below table 8.

Table 8: Randomly generated demand values (Average demand)

Distributors	Average demand
Node 01	1100
Node 02	2500
Node 03	1100
Node 04	1500
Node 05	1300
Node 06	1200
Node 07	1800
Node 08	1900
Node 09	1600
Node 10	1400
Node 11	1300
Node 12	1200
Node 13	1500
Node 14	1100
Node 15	1000
Node 16	1800
Node 17	1400
Node 18	1700
Node 19	1100
Node 20	1300

Source: Constructed by the authors

The demand values in the table 8 represent a situation of average demand of each agent. This data has been generated randomly to perform the model in the scenario 2.

The linear programing model is run through Microsoft excel solver using input details of tables 5 and 8 and derived the results as below,

The Tables 9 depicts the output of scenario 2.

Table 9: Outcomes of scenario 2 (Average demand situation)

	Total cost Rs.	No of vehicles used	Total KMs	Required demand	Tot units transferred	Per unit cost Rs.	
Scenario 2	1,771,296.00	30	34410	28800	28950	61.18	**Average demand**

Source: Constructed by the authors based on the output of the model

To fulfil total demand of every agent 30 vehicles have been used out of 50 vehicles in the fleet. Total demand requirement has been achieved. The cost per unit of transportation is Rs.61.18.

iii) Scenario 3 – High demand situation

In the scenario 3, the developed model is tested in an high demand situation for all agents keeping the vehicle fleet data constant. Since the transport fleet data constant the table 5 is used for the calculation. Randomly generated average demand values are used for the test calculation as in the below table 10.

Table 10: Randomly generated demand values (High demand)

Distributors	Average demand
Node 01	1540
Node 02	3500
Node 03	1540
Node 04	2100
Node 05	1820
Node 06	1680
Node 07	2520
Node 08	2660
Node 09	2240
Node 10	1960
Node 11	1820
Node 12	1680
Node 13	2100
Node 14	1540
Node 15	1400
Node 16	2520
Node 17	1960
Node 18	2380
Node 19	1540
Node 20	1820

Source: Constructed by the authors

The demand values in the table 10 represent a situation of high demand of each agent. This data has been generated randomly to perform the model in the scenario 3.

The linear programing model is run through Microsoft excel solver using input details of tables 5 and 10 and derived the results as below,

The Tables 11 depicts the output of scenario 3.

Table 11: Outcomes of scenario 3 (High demand situation)

	Total cost Rs.	No of vehicles used	Total KMs	Required demand	Tot units transferred	Per unit cost Rs.	
Scenario 3	2,278,512.00	44	44798	40320	40500	56.26	**High demand**

Source: Constructed by the authors based on the output of the model

To fulfil total demand of every agent, 44 vehicles have been used out of 50 vehicles in the fleet. Total demand requirement has been achieved. The cost per unit of transportation is Rs.56.26. The proposed LP model is responded to all demand variation scenarios and formulated different output as in the Table 12.

Table 12: LP solution for different demand levels

	Total cost Rs.	No of vehicles used	Total KMs	Required demand	Tot units transferred	Per unit cost Rs.	
Scenario 1	1,118,996.00	18	21538	17280	17850	62.69	**Low demand**
Scenario 2	1,771,296.00	30	34410	28800	28950	61.18	**Average demand**
Scenario 3	2,278,512.00	44	44798	40320	40500	56.26	**High demand**

Source: Constructed by the authors based on the output of the model

According to the results the totals transport costs, transported capacities and the distances have been increased when the demands increase. But the transport costs per unit have been decreased. This shows the efficiency of allocating the vehicles to each agents to fulfil their demands considering the suitable capacities and transportation costs optimally by the developed LP model.

Demand can be scattered in the network in many ways. Thus the developed LP model is tested to identify the flexibility for such kind of scenarios. Scenario 4 and 5 shows the two different way of demand scatter in the distribution network.

iv) Scenario 4 – High demand at closer distance agents (less than 300Km one way)

In the scenario 4, the developed model is tested in a high demand at closer distance agents. The agents located less than 300km (one way) is considered as a closer agent. Standard vehicle fleet data is used (table 5 is used for the calculation).

Randomly generated demand values are used for the test calculation as in the below table.

Table 13: Randomly generated demand values (High demand at closer distance agents)

Distributors	Distance (one way) (Km)	Daily demands (unit)
Node 04	25	3500
Node 01	80	2660
Node 20	140	2520
Node 18	142	2520
Node 05	175	2380
Node 19	236	2240
Node 02	250	2100
Node 06	290	2100
Node 03	300	1960
Node 10	345	960
Node 08	410	820
Node 07	480	820
Node 17	520	820
Node 09	600	920
Node 13	650	750
Node 16	672	850
Node 14	710	780
Node 15	820	900
Node 11	850	950
Node 12	980	900

Source: Constructed by the authors

The demand values in the table 13 represent a situation of high demand at closer distance agents. This data has been generated randomly to perform the model in the scenario 4.

The linear programing model is run through Microsoft excel solver using input details of tables 5 and 13 and derived the results as below,

The Tables 14 depicts the output of scenario 4.

Table 14: Outcomes of scenario 4 (High demand at closer distance agents situation)

	Total cost Rs.	No of vehicles used	Total KMs	Required demand	Tot units transferred	Per unit cost Rs.	
Scenario 4	1,212,988.00	33	23562	31450	31500	38.51	**High demand closer agents**

Source: Constructed by the authors based on the output of the model

To fulfil total demand of every agent, 33 vehicles have been used out of 50 vehicles in the fleet. Total demand requirement has been achieved. The cost per unit of transportation is Rs.38.51.

v) Scenario 5 – High demand at longer distance agents (more than 300Km one way)

In the scenario 5, the developed model is tested in high demand at longer distance agents. The agents located more than 300km (one way) is considered as a longer distance agent. Standard vehicle fleet data is used (table 5 is used for the calculation).

Randomly generated demand values are used for the test calculation as in the below table.

Table 15: Randomly generated demand values (High demand at longer distance agents)

Distributors	Distance (one way) (Km)	Daily demands (unit)
Node 04	25	960
Node 01	80	820
Node 20	140	820
Node 18	142	820
Node 05	175	920
Node 19	236	750
Node 02	250	850
Node 06	290	780
Node 03	300	900
Node 10	345	950
Node 08	410	900
Node 07	480	3500
Node 17	520	2660
Node 09	600	2520
Node 13	650	2520
Node 16	672	2380
Node 14	710	2240
Node 15	820	2100
Node 11	850	2100
Node 12	980	1960

Source: Constructed by the authors

The demand values in the table 15 represents a situation of high demand at the closer distance agents. This data has been generated randomly to perform the model in the scenario 5.

The linear programing model is run through Microsoft excel solver using input details of tables 5 and 15 and derived the results as below, The Tables 16 depicts the output of scenario 5.

Table 16: Outcomes of scenario 5 (High demand at longer distance agents situation)

	Total cost Rs.	No of vehicles used	Total KMs	Required demand	Tot units transferred	Per unit cost Rs.	
Scenario 5	2,170,572.00	33	42350	31450	31500	68.91	**High demand longer agents**

Source: Constructed by the authors based on the output of the model

To fulfil total demand of every agent, 33 vehicles have been used out of 50 vehicles in the fleet. Total demand requirement has been achieved. The cost per unit of transportation is Rs.68.91. The proposed LP model is responded to the demand variations scattered in deferent methods in the distribution network and formulated different output as in the Table 17.

Table 17: LP solution for the different scattered demands in the distribution network

	Total cost Rs.	No of vehicles used	Total KMs	Required demand	Tot units transferred	Per unit cost Rs.	
Scenario 4	1,212,988.00	33	23562	31450	31500	38.51	**High demand at closer distance**
Scenario 5	2,170,572.00	33	42350	31450	31500	68.91	**High demand at longer distance**

According to the results the totals transport costs and the distances have been increased when the high demands locations get far from the company. Demand change for the both scenario is same, thus the transferred units are same in the both scenarios. The cost per unit of transportation also increased when the agents who have higher demand locate far from the company. This shows the sensitivity of the developed LP model for this kind of situations such as variation of distances. This shows that agent/distributor can make a decision on the relocation of the storage of goods to an intermediary location along the all nodes of the network, so that cost savings are possible due to less distance for delivery.

Furthermore there can be variations in the vehicle fleet as well. Thus 7th scenario is carried to show the flexibility of the proposed model with respect to fleet variation.

i) Scenario 7 – Vehicle fleet variation

The vehicle fleet is changed randomly by reducing the number of vehicles as in the Table 18.

Table 18: New fleet to cater the average demand situation

#	Capacity	Rate	No	Reduced by	New fleet
1	1000	52	15	5	10
2	950	50	12	4	8
3	850	48	10	3	7
4	800	46	7	2	5
5	750	44	6	1	5
			50		**35**

Source: Constructed by the authors

Vehicle fleet is reduced as in the table 18. Higher capacity vehicles has been reduced more in order to get a significant impact on the result after running the LP model. The results will be compared with the Scenario 2. The demand data is constant and use the data in the table 8. The linear programing model is run through Microsoft excel solver using input details of tables 8 and 18 and derived the results as below. The Tables 19 depicts the output of scenario 7.

Table 19: Outcomes of scenario 7 (With changing the vehicle fleet)

	Total cost Rs.	No of vehicles used	Total KMs	Required demand	Tot units transferred	Per unit cost Rs.	
Scenario 7	1,721,148.00	35	36894	28800	29050	63.25	**With changed fleet**

Source: Constructed by the authors based on the output of the model

To fulfil total demand of every agent, 35 vehicles have been used out of 50 vehicles in the fleet. Total demand requirement has been achieved. The cost per unit of transportation is Rs.63.25. The results due to vehicle fleet changed is compared with the standard vehicle fleet and constant demand scenario (Scenario 2) in the table 20.

Table 20: Comparison of result with standard and changed vehicle fleet.

	Total cost Rs.	No of vehicles used	Total KMs	Required demand	Tot units transferred	Per unit cost Rs.	
Scenario 2	1,771,296.00	30	34410	28800	28950	61.18	**Average demand**
Scenario 7	1,837,412.50	35	36894	28800	29050	63.25	**Fleet Changed**

Source: Constructed by the authors

According to the results the totals transport costs and the distances have been increased when the vehicle fleet get reduced. Even though the demand is same the transferred capacity has been changed due to less flexibility in the reduced vehicle fleet than the standard vehicle fleet. The cost per unit of transportation also increased due to the same reason. This shows the sensitivity and the flexibility of the developed LP model for this kind of situations.

In the same manner, by changing the constraints and variables in the objective function as per the requirement, the proposed LP model can be used to derive optimal combination of inputs and outputs. This way, a firm can make substantial savings on costs without impacting on the demand. The savings for this model mainly come from payment for fleet and transporting time and sales revenues maximization.

Aggregate cost of transportation incurred after fulfilling total requirement of all the nodes in the network; the cost is distributed over all the units transported to destinations. In this way marginal revenue over each unit, cost contributed to the company's profitability, revenue earn from each unit is above the average unit cost of the product.

CHAPTER FIVE

CONCLUSION

5.1. Conclusion

This thesis attempted to introduce a simplified and low-cost method of minimizing the transport costs by minimizing the number of truck movements or vehicles in the fleet, maximizing the quantity volume per kilometre, minimizing the mileage of each vehicle in the fleet. The study generates easy to use methodology for dispatching vehicles for start-ups, small and medium scale companies who are yet to implement a sophisticated and integrated transport scheduling system. This research was carried out considering, outbound logistics of companies which are having the spoke-hub distribution system.

Analysis was carried out using randomly generated data which include vehicle fleet data (trucks) and customer (Agent) demands. To minimize the total transportation cost, the optimum number of truck movements with different capacities was selected for each agent by applying the Simplex Method in Linear Programming. The spoke-hub distribution paradigm is introduced as the basis of the model and the model shows it as single origins and several destinations. As such, the model estimates the truck delivery costing for a single origin and single trip based distribution system.

It has been clearly mentioned and explain the hub and spoke network. the linear programming which has been used many transportation problems as clearly shown in the literature review; the same has been utilized in order to build the model. This will help to generate the vehicle schedule to dispatch the shipments by considering agents' available safety stocks. This study assists the company to reduce its carbon footprint by eliminating unnecessary truck movements. Human errors were also reduced by using this systematic way of scheduling vehicles. Analysis results demonstrates that the application of the proposed model for truck scheduling system in transport operation to increases the efficiency of outbound logistics thereby minimizing the total transport costs of the company. Minimization of transportation costs come as a priority in operations and the share of transport cost is high and all the mentioned cost elements and other specific inherent elements of any company can be set as constraints when they ready to implement the model. This thesis helps to identify the method to cut down transport related costs systematically; to the companies which do this manually and the impact can be reflected in their profitability.

Analysis results shows that the model is flexible and can accommodate various market changes such as variation in demand level, variation in demand level with respect to geographical proximity to the origin (hub), variation of the fleet used in the transportation. The model shows that at low demand situation average unit cost per km tends to be higher than high demand situation. Further, the average unit cost per km is low when there is a high demand at closer distance over the rate for high demand at longer distance. This indicates that the model accommodates the distance variation and the respective cost variation. Lastly, the model can be used as an effective tool to make fleet allocation decision when there is sudden change in the fleet size. The results generated and presented in this research is based on hypothetical data. The model considers its output based on the data feeding in and generates the best fleet match to the volumes to be transported to a certain destination with a distance. The fleet allocation in the model has been arranged depending on the lowest cost considering each trips' costs.

Outcomes of the study facilitate the consignment agents in arranging their daily redistribution plan by identifying the volume of the freight and the Estimated Time of Arrival (ETA) of the trucks to their premises. This study assists the company to reduce its carbon footprint by eliminating unnecessary truck movements. Human errors are also reduced by using this systematic way of scheduling vehicles. Application of the proposed model for prime movers scheduling system increases the efficiency of outbound logistics thereby maximising the profit of the company. This study therefore brings a solution to the vehicle scheduling problem and overcomes the bottlenecks in transportation subject to the uncontrolled variables of production failures, vehicle breakdowns, bad road and weather conditions, issues of drivers and helpers and physical shape of the product. Further small, medium scale operators may get benefit from this type of a model and be able to save fuel and other operation costs, while sellers will get products in time, and no shortages are possible, and as a result consumer gets benefits.

5.2. Limitation of the research

The study has few limitations. The model is based on constraints related to the demand at the destination and the number of vehicles/trips (limited resources). The limitations are attributed in the develop model as there are few assumptions of model. Storage costs, fleet holding costs, fixed and variable cost impacts on distance and operating time affects the overall cost of the company. The future development of the model can consider the mentioned factors into the system and the validation of the proposed model is left for future research.

Further each run of the model considers only one truck per one trip and it estimates the total transport cost for truck assignment. However, as some truck can return within the day, this model must be re-run any time of the day, when any vehicle come in to the fleet at any time. Then it will give the lowest transportation cost which can be derived at that time.

The proposed system can be generalized by developing a software application which can be handled by staff members at different levels in the company. To automate the proposed scheduling system, sales data of the agents and the service providers should link with the main database of the company.

The model's applicability was tested by simulating 7 common scenarios and comparing them by using universal unit. For future research, this modal can also be used to compare the results of fleet planning systems firms follow in practice and validate against them.

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