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# WORKING PAPER

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# Heterogeneous truck routing policies with tour routing time restriction

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**TITLE:** **Heterogeneous truck routing policies with tour routing time restriction**

**ABSTRACT:** We study a heterogeneous full-truckload vehicle routing problem based on the case of a trucking company in Malaysia, where trucks originate from a depot and are dispatched to various parts of the service area. Each order defines an origin-destination pair for pickup and delivery locations. Goods have to be picked up or delivered within the pre-specified pickup and delivery time windows. Besides, we consider a restriction on tour routing time, i.e. the total time taken from the time each truck leaves the depot, servicing a number of orders, to the time it returns to the depot. Our objective is to minimize total deadhead costs. Four integer programming solution policies are proposed. Three of the policies identify the set of home-bound trucks before assigning jobs to trucks, while the last policy is a one-off algorithm that assigns job routes to all the trucks and makes sure that each truck will not exceed the total route time limit when it returns to the depot. Cross-sectional computation results show that the one-off policy is the best amongst the four. Cumulative analysis results show that all four policies do better than the company's original assignment in terms of deadhead costs and truck utilization.

**KEY WORDS:** ***Vehicle routing; full-truck-load; pickup and delivery; tour routing time***

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# 1. Introduction

In this paper, we consider a specific type of vehicle routing problem (VRP), known as the pickup and delivery problem (PDP). In the PDP, transportation requests are received to move goods from an origin location to a destination location. In other words, each request forms an origin-destination pair. The PDP has been widely studied over the past decades, due to its significant contribution and relevant application in the logistics and transportation industry. Many variants of the PDP have been applied to suit real-life applications, such as dial-a-ride transportation services for the elderly and disabled, parcel transportation, pickup and delivery of soft drinks and empty bottles, and demand-responsive freight transportation systems, amongst others.

Generally, the PDP can be categorized into two types, i.e. those concerning Less-than-Truckload problems, and Full-Truckload problems. This paper considers problems which fall into the second category. As such, each vehicle can serve only one request at a time, and a delivery must be completed before the next pickup. In addition to the Full-Truckload problem, we consider the case of having a heterogeneous fleet of vehicles servicing requests, where each vehicle is differentiated in terms of load capacity.

In essence, the majority of applications for the PDP include restrictions on time windows. This slight variant to the generic PDP, also known as the Pickup and Delivery Problem with Time Windows (PDPTW), considers time window restrictions on pickup and delivery. In addition, we also consider a restriction on the tour routing time for each vehicle. This is the total time taken from the time the vehicle leaves the depot, servicing a number of requests, to the time the vehicle returns to the depot.

The study presented in this paper is based on the case of a company, who maintains a heterogeneous fleet of trucks of different capacities, providing long-haul trucking services to various customers across the country. The company manages a depot located in the Northern region, serving as its headquarters. Trucks are dispatched from the depot for the first job request, while requests for subsequent days are spread across the Southern region. Each schedule day assumes that trucks depart either from their previous delivery locations or from the depot. Job requests are received for the pickup and delivery of full-truckload goods on a daily basis. Each job specifies its load capacity requirements, origin and destination locations. Generally, goods are picked up on the day requested, and delivered the next day. As most jobs are known either the day before, or on the day of pickup, it is difficult to plan the entire route beforehand, with the long planning horizon of approximately one week. Since a truck driver has to be away from home for a long time, turnover rate is high. Therefore, a total route time limit is imposed in this paper to make sure that drivers will return home within the total route time limit.

In this study, we develop four re-optimization policies which can be used to determine strategically the assignments of customer orders or job requests to available vehicles. Three of the policies identify the set of home-bound trucks, i.e. trucks that are at the end of their routing trip and have to be sent back to the depot in this decision cycle. A matching algorithm is used to assign jobs to these home-bound trucks. For the remaining trucks, job routes are assigned by using a routing integer programming formulation. The last policy is a one-off algorithm that assigns job routes to all the trucks and makes sure that each truck will not exceed the total route time limit when it returns to the depot. By using sample data from the trucking company, we then compare the policies by running a cross-sectional performance test using the same input data on each test run. We also conduct a cumulative analysis by updating the results of each test run as an input to the following test run's data.

The rest of the paper is organized as follows. Section 2 gives a literature review on previous works related to the Pickup and Delivery Problem. Section 3 provides a description of the problem studied in this paper. In Section 4, four different re-optimization policies are proposed as solution approaches to the problem studied. In Section 5, we present results and analyses comparing the performance of the four policies and the company's original assignment. Finally, Section 6 concludes the paper.

# 2. Literature review

A wide array of studies has been conducted in the area of the Pickup and Delivery Problem. In their paper, Savelsbergh and Sol (1995) presented a general model of the Pickup and Delivery Problem and discussed some of the different characteristics or variations of the PDP in literature. Savelsbergh and Sol further categorized the General Pickup and Delivery Problem (GPDP) into three special cases, i.e. the Pickup and Delivery Problem (PDP), the Dial-a-Ride Problem (DARP) and the Vehicle Routing Problem (VRP). In essence, the full-truckload pickup and delivery problem considered in this study is a special case of the GPDP which falls under the category of the PDP. Descrochers et al. (1988) describes the pickup and delivery problem with time windows (PDPTW) as determining the routes of a number of vehicles in order to service customer demands. Each customer specifies a pickup location (origin) and a delivery location (destination) for the transportation of goods or items. In addition, a time window is commonly used to determine the time frame within which goods must be picked up or delivered. In their review, Desrochers et al. gave a mathematical programming formulation of the PDPTW which minimizes the total traveling costs between origins and destinations. Several methods were reviewed to solve the problem.

Many heuristics and exact algorithms have been developed to solve the PDPTW. Van der Bruggen et al. (1993) developed a two-phase local search method based on a variable-depth search. This was applied to the case of a single-vehicle PDPTW. For the multiple-vehicle PDPTW, Nanry and Barnes (2000) developed a reactive tabu search heuristic for solving a set of transportation requests by a fleet of homogeneous vehicles, while Lao and Liang (2002) developed a two-phase method, incorporating a hybrid heuristic consisting of an insertion procedure and a sweep procedure in the first phase to construct an initial solution, and a tabu search heuristic to improve on the solution in the second phase. More recently, Lu and Dessouky (2006) proposed an insertion-based construction heuristic for solving the PDPTW. Their solution considers not only the minimal increase in travel time when determining which location to insert next, but also the reduction in the slack in time windows.

In general, two main approaches have been used to develop exact algorithms for the PDPTW. The first approach uses branch-and-price methods, while the second approach uses branch-and-cut methods. Dumas et al. (1991) first considered using a branch-and-price algorithm for solving a set partitioning formulation of the problem, using column generation techniques to solve linear relaxations of the problem. Savelsbergh and Sol (1998) further extended the work for larger-scale instances using more advanced column management mechanisms. Lu and Dessouky (2004) proposed an exact algorithm to solve an integer-programming formulation of the multiple-heterogeneous-vehicle PDP. Their solution allows for flexibility by not setting tight constraints on time windows and capacity constraints. Their solution uses a branch-and-cut algorithm as an approach to the problem. Ropke et al. (2007) improved on a branch-and-cut algorithm first developed for the DARP, initially proposed by Cordeau (2006). Ropke et al. presented new families of valid inequalities to further improve the column generation techniques. More recent reviews of the PDPTW can be found in Desrosiers et al. (1995), Savelsbergh and Sol (1995) and Cordeau et al. (2007).

In terms of applying practical issues experienced in real-world logistics operations, Xu et al. (2003) considered a Practical Pickup and Delivery Problem (PPDP) which considered not only multiple time window constraints, but also other types of constraints more typically found in practice. Xu et al. looked at the case of having multiple carriers and vehicle types carrying out customers orders which could have more than one pickup and/or delivery time windows. In addition to various cost structures, they considered driving time and working time rules specified by the U.S. Department of Transportation, compatibility constraints in terms of goods carried, and nested precedence constraints, which followed a “last-in-first-out” rule for goods carried. The solution proposed used column generation techniques to solve the master problem, and fast heuristics to solve the sub-problems.

In terms of full truckload problems, Bodin et al. (1983) presented two procedures using route-first-cluster-second approximations. Both procedures constructed one giant route, before sub-dividing the route into smaller feasible routes. The first procedure applied a solution to a rural postman problem, while the second procedure applied a solution to an asymmetric Traveling Salesman Problem (TSP).

Desrosiers et al. (1988) proposed an optimization algorithm for the multiple-depot full truckload pickup and delivery problem. They transformed the problem into an asymmetric TSP, and eliminated subtours which did not include depots. They also applied distance constraints by prohibiting illegal sub-paths. Yang et al. (2004) presented online algorithms to solve the case of a generic real-time multiple-vehicle truckload pickup and delivery problem. Their solution caters for a homogeneous fleet of vehicles, and forms the inspiration for part of the solution approach proposed in this paper.

Another variation to the VRP which specifies the pickup and delivery locations of customer demands is the Rollon-Rolloff Vehicle Routing Problem (RRVRP). In their paper, Bodin et al. (2000) and Baldacci et al. (2006) applied the RRVRP to the application of sanitation collection, where the demands for service are large trailers used for collecting waste material at various locations. Trailers are moved by tractors between their specified locations and dedicated disposal facilities. Each demand for service specifies an origin-destination pair. Each tractor can only move one trailer at a time, and the objective is to determine efficient routes for the tractors in order to minimize deadhead routes. A similar work is the skip problem (SP), which models a routing problem for the collection and delivery of skips used on construction sites to collect debris (see De Meulemeester et al.,1997). Here, the RRVRP and the SP are similar to a full truckload pickup and delivery problem, since only one trailer (or skip) can be moved at one time.

In terms of the RRVRP and the SP, both problems consider all vehicles starting from the depot at the same time, and ending at the depot at the end of the planning horizon. This would mean that all vehicles share the same time window. In the problem considered in this paper, all vehicles may not be starting from the depot at the same time, and since there is no clear-cut planning horizon, vehicles may not end at the depot at the same time.

Several other works considered the dynamic characteristics of the problem. One such work is the dynamic vehicle allocation (DVA) problem. In the DVA problem, a fleet of vehicles are assigned to locations where customer demands occur in a dynamic manner. Powell (1988) and Dejax and Crainic (1987) provided reviews for this class of problems. Powell (1996) and Frantzeskakis and Powell (1990) provided an approximation solution to the problem, and applied it to a truckload trucking application. They made use of stochastic programming formulations to arrive at approximation solutions. Powell et al. (2000a) further developed two optimization-based heuristics to solve the dynamic assignment problem, which provided dual information for producing alternative solutions in addition to the recommended solution. In a related work, Powell et al. (2000b) considered user noncompliance as a factor to compare myopic optimal solutions with greedy suboptimal solutions. The use of adaptive dynamic programming algorithms using nonlinear functional approximations was studied by Godfrey and Powell (2002a, 2002b). More recently, Spivey and Powell (2004) investigated the use of linear value function approximations that focus on assigning one resource to one task, without considering assigning a sequence of two or more tasks at the same time.

Mitrovic-Minic and Laporte (2004a) investigated the dynamic PDPTW in an application of a courier service, considering the starting point of routes at several initial locations, rather than a single depot. Each vehicle is allowed to wait at its initial location, or a customer’s pickup or delivery location. The study considers several waiting strategies, to investigate the ways of effectively distributing waiting time, which can affect the overall solution. Mitrovic-Minic and Laporte (2004b) proposed double-horizon based heuristics to investigate both short-term and long-term impacts of a decision made. Hvattum et al. (2006) considered a sample scenario hedging heuristic procedure to solve the case of a dynamic and stochastic routing problem. Although their study only focused on the pickup part of the problem, the deterministic formulation proposed considers constraints similar to those in this study. Apart from time window constraints, the formulation allows for a unique identification of each vehicle in service, although a homogeneous fleet is considered. As such, capacity constraints are considered.

Yang et al. (2004) looks into the dynamic truckload pickup and delivery problem. They proposed a mixed-integer programming formulation for the offline version. To consider the dynamic version of the problem, Yang et al. proposed five rolling horizon strategies and compared their solutions and performances. They found that re-optimization policies consistently outperform other simpler local (heuristic) rules. However, their work was limited to the application of a homogeneous fleet in the model. Several works have considered the case of a heterogeneous fleet of vehicles for the pickup and delivery problem. For instance, the works of Xu et al. (2003), Lu and Dessouky (2004), Ropke and Pisinger (2006) and Prive et al. (2006) considered heterogeneous vehicles for pickups and deliveries of non-truckload requests, whereas Currie and Salhi (2003) considered the case of heterogeneous vehicles delivering full truckload products between different depots and customers. However, although the works considered returning vehicles to depot within a certain time horizon, all job requests are assumed known prior to formulating the total route or tour for the vehicles. In our case, in addition to a heterogeneous set of vehicles, we consider the case where not all job requests are known prior to formulating the entire tour, but rather allowing re-optimization policies to construct the tour of vehicles while job requests are received each day, and ensuring that the total time covered by the tour does not exceed a pre-specified limit.

# 3. Problem description

The problem studied in this paper is based on a real-world case of a company maintaining a fleet of heterogeneous trucks of different capacities, servicing job requests from customers across the country. Customers served originate from different industries, and generally require pickup and delivery services from the company. Each job requires full-truckload service, and can only be served by one truck at any one time. This means that a delivery has to be completed before the pickup of the next job. Job queues are non-preemptive; meaning that once a job is picked up, it must be delivered to its destination without disruption. Customer pickup and delivery locations are spread across the country. Due to the distance traveled for most jobs, delivery can only be completed one day after pickup. This is especially so for outstation job requests, where pickup and delivery locations are located in different states in the country. Current company policy practices pickups in the afternoon of the job request, and deliveries the next morning. It is common practice for trucks to travel overnight. In some cases, jobs could be delivered within the same day if travel time permits.

Here, our objective is to assign jobs to trucks, such that as far as possible, all jobs for the day are to be catered for. We aim to minimize the costs incurred through “empty movements”, or movements where trucks are not carrying loads. These empty movements are considered as “deadhead” trips and are non-revenue generating trips. The cost of an empty movement is considered as the time required traveling the Euclidean distance between two locations, where all trucks are assumed to move at a constant speed. In addition to the above costs, we also aim to minimize delays in deliveries. A job can be rejected temporarily for the day if certain constraints cannot be met. However, it will be put back into the pool as a new job for the next day and a penalty is incurred, measured by the number of days the job is postponed. For each day that a job is postponed, the penalty is increased. This penalty is a non-tangible cost, but can be used according to the service level provided by the company. As such, the weight of this cost in relation to the cost of deadhead trips can be adjusted in deciding costs which are considered of a larger impact to the company’s policy.

Job-truck assignments are subject to several constraints which are governed by the size of trucks, working hours of the customers, and also total tour length of each truck. For each tour, a truck starts its journey from the depot, services a number of job requests, and returns to the depot within the time limit specified for total tour length. Each truck is also differentiated by its size or capacity. Naturally, trucks can be used to service jobs which are equal in size or smaller. The pickup and delivery times of the jobs must also fit into the working hours of the customers. This depends not only on truck and job locations, but also on each job’s length. The length of a job is defined as the time it takes to complete a job, from the start of pickup time to the end of delivery time. This includes the time it takes to travel the distance between pickup and delivery locations, plus loading and unloading times.

# 4. Solution approach

In this section, four solution policies are proposed to solve the problem described in the previous section. The first three policies, Large-Job-First (LJF), Small-Truck-First (STF) and Load-Capacity-Constrained (LCC), are two-stage solution policies. In common practice, a decision maker identifies trucks that have to return to the depot before assigning any job to a truck. In these three policies, trucks that are approaching the end of their tour length are identified before the truck-job assignment. They are labeled as *home-bound* trucks. A classical matching formulation is used to assign jobs to these home-bound trucks before returning to the depot. With this matching formulation, at most one job is assigned to each home-bound truck. After that, an integer programming routing formulation, inspired by the formulation developed for the homogeneous truckload pickup and delivery problem by Yang et al.(2004), is used to assign the route of each *non-home-bound* truck with the remaining unassigned jobs. The first two solution policies, LJF and STF, assign routes for non-home-bound trucks iteratively. Since large sized jobs can only be served by large sized trucks, large sized jobs and large sized trucks will first be considered in the routing formulation in the LJF policy. Conversely, small sized trucks will first be considered in the routing formulation for the STF policy. In LCC, load capacity constraints are added to the routing formulation instead of running it iteratively. The last solution policy, Total-Route-Limit (TRL) policy is a one-off policy, which ensures that the total routing time of a truck does not exceed the tour routing time limit by adding additional route time constraints to the routing formulation. Therefore no matching for home-bound trucks is needed. The following sections describe the details of the four policies.

### *4.1 Home-bound truck matching formulation*

In this formulation, we consider trucks that are approaching the end of their tour length, i.e. home-bound trucks. A tour length is defined as the length of time it takes for a truck to depart from the depot, service a number of jobs and return to the depot. Each truck's tour length is subject to a *tour routing time limit, $L$*, which specifies the maximum number of days a truck can be away from the depot. Home-bound trucks are identified as trucks which are away from the depot for ($L$-$c$) days, where $c$ is the upper bound for the travel time of a truck if it returns to the depot after serving a job, regardless of the truck's current location, and the job's pickup and delivery location. Home-bound trucks that are identified will be matched with jobs with the objective of minimizing the deadhead cost. This includes the deadhead between the current location of a truck and the pickup location of an assigned job. In addition, the deadhead from the delivery location of the assigned job to the depot is considered. For home-bound trucks that are not assigned a job, the deadhead cost to depot from the current location of the truck is considered.

In this sub-problem, we use the classical matching formulation to solve the problem. Let $K$ be the number of home-bound trucks, and $N$ be the total number of jobs. Let $T_1 = \{1..K\}$ be the node set representing the set of trucks and $T_2$ be a set of $p = \max(N\text{-}K,0)+\max(K,N)$ nodes representing dummy trucks. Similarly, let $C_1 = \{1..N\}$ be the node set representing the set of jobs and $C_2$ be a set of $q = \max(K\text{-}N,0)+\max(K,N)$ nodes representing dummy jobs, such that $|T| = |C|$, where $T=T_1 \cup T_2$ and $C=C_1 \cup C_2$.

A truck is said to be compatible to a job, if its capacity is at least as large as the job's load size. Each node $i \in T_1$ has an edge to each node $j \in C_1$ if job $j$ is compatible with truck $i$. The weight of its edge, $w_{ij}$, equals the distance from the current location of truck $i$ to the pickup location of job $j$, plus the distance from the delivery location of job $j$ to the depot location. In addition, each node $i \in T_1$ is also connected to each dummy node $j \in C_2$, where $w_{ij}$ equals the distance from the current location of the truck $i$ to the depot. Furthermore, each node $i \in T_2$ has an edge to each node $j \in C$, where $w_{ij}$ equals to a sufficiently large number $M$. Therefore, the North-bound truck-job matching can be formulated as the following one-to-one bipartite matching problem:

$$\min \quad \sum_{i\in T}\sum_{j\in C} w_{ij}\, x_{ij}$$

Subject to

$$\sum_{j\in C} x_{ij} = 1, \quad \forall i \in T \tag{1}$$

$$\sum_{i\in T} x_{ij} = 1, \quad \forall j \in C \tag{2}$$

$$x_{ij} = \{0,1\}, \quad \forall i \in T, j \in C \tag{3}$$

In the optimal solution, if a truck $i$ in $T_1$ is matched with a job $j$ in $C_1$, truck $i$ will serve job $j$ before going back to the depot. If $j$ is in $C_2$, truck $i$ will go back to the depot without serving any job.

### *4.2 Truck routing formulation*

In the second sub-problem, we consider trucks and jobs that have not been assigned using the home-bound truck matching formulation in the first sub-problem. In this formulation, the objective is to minimize the deadhead of all non-home-bound trucks assigned to all jobs (excluding jobs previously assigned). Here, the deadhead cost considered is the deadhead from the current location of a truck to the pickup location of a job assigned, and the deadhead from the delivery location of a job to the pickup location of a subsequent job.

Let $C'=\{1..N'\}$ denote all $N'$ unassigned jobs and $T'=\{1..K'\}$ denote all $K'$ remaining trucks. Let $D^k_{0i}$ be the deadhead distance from the location of truck $k\in T'$ to the pickup location of job $i\in C'$, and $D_{ij}$ be the deadhead distance from the delivery location of job $i\in C'$ to the pickup location of job $j\in C'$. Let $r_i$ be the cost of rejecting job $i$ for the day. $W_i$ specifies job $i$'s work length. $\tau^0_k$ denotes the current available time of truck $k$. $\tau^{AVL}_i$ and $\tau^{ALN}_i$ denote the earliest available time and the latest time for pickup of job $i$. $\tau^{PICK}_i$ is a decision variable denotes the actual pickup time of job $i$. Besides, we define $x^k_{0i}$ =1, if truck $k\in T'$ is assigned job $i\in C'$ as its first job from its current location. $x^k_{ij}$ =1 if truck $k\in T'$ is assigned to job $i$ followed by job $j$, where $i,j\in C'$. Also, we set $x^k_{ii}$ =0, for all job $i\in C'$ and for all truck $k\in T'$. In this paper, job rejection is allowed for the day, and will be re-considered for the next day's schedule. If a job is rejected for the day, then $y_i$ =1 and a rejection cost is incurred. The formulation is presented as follows:

$$\text{Min} \qquad \sum_{k\in T'}\sum_{i\in C'} D^k_{0i} x^k_{0i} + \sum_{k\in T'}\sum_{i\in C'}\sum_{j\in C'} D_{ij} x^k_{ij} + \sum_{i\in C'} r_i y_i$$

Subject to

$$\sum_{k\in T'} x^k_{0i} + \sum_{k\in T'}\sum_{j\in C'} x^k_{ji} + y_i = 1 \qquad \forall i \in C' \tag{4}$$

$$\sum_{i\in C'} x^k_{0i} \le 1 \qquad \forall k \in T' \tag{5}$$

$$\sum_{k\in T'}\sum_{j\in C'\cup\{0\}} x_{ji}^{k} \leq 1 \qquad \forall i\in C' \tag{6}$$

$$\sum_{k\in T'}\sum_{j\in C'} x_{ij}^{k} \leq \sum_{k\in T'}\sum_{j\in C'\cup\{0\}} x_{ji}^{k} \qquad \forall i\in C' \tag{7}$$

$$\sum_{j\in C'} x_{ij}^{k} \leq \sum_{j\in C'\cup\{0\}} x_{ji}^{k} \qquad \forall i\in C', \forall k\in T' \tag{8}$$

$$-\sum_{k\in T'}(D_{0i}^{k}+\tau_{k}^{0})x_{0i}^{k}+\tau_{i}^{PICK} \geq 0 \qquad \forall i\in C' \tag{9}$$

$$-Mx_{ij}^{k}+\tau_{j}^{PICK} \geq \tau_{i}^{PICK}+W_{i}+D_{ij}-M \quad \forall i,j\in C', \forall k\in T' \tag{10}$$

$$\tau_{i}^{AVL} \leq \tau_{i}^{PICK} \leq \tau_{i}^{ALN} \quad \forall i\in C' \tag{11}$$

$$x_{ij}^{k}=\{0,1\}, \quad \forall i\in C'\cup\{0\}, j\in C', \forall k\in T' \tag{12}$$

$$y_{i}=\{0,1\}, \quad \forall i\in C' \tag{13}$$

The first and second terms of the objective function represent the sum of deadhead cost from the current location of each truck $k \in T'$ to its first job and deadhead cost in between jobs, respectively. The last term of the objective function represents the total rejection cost of the day. Constraint (4) ensures that each job is either served by a truck or rejected. Constraint (5) ensures that no truck travels to pickup more than one job from its current location. Constraint (6), (7) and (8) are network flow balance constraints that ensure that each job can be followed by at most one other job. Constraint (8) ensures that each job and truck combination is unique. Constraints (9) and (10) define the pickup time of each job, and ensure that no job is left without a truck if it is not rejected. *M* in constraint (10) represents a sufficiently large positive number. Constraint (11) ensures that each job's pickup time falls within a time window specified. Jobs that cannot meet this time window are rejected, and considered for next day's schedule. Constraints (12) and (13) are binary variable constraints.

## 4.3 Solution policies

The four solution policies proposed in this paper are discussed here in detail. In all policies, trucks are assumed to remain at the destination location of their most recent job assignment, if they are not positioned at the depot.

### 4.3.1 Large-job-first policy

Since only trucks with sizes bigger than the size of the job can be used to serve the job, LJF considers jobs with the largest size first. Jobs and trucks are categorized by size. In the first iteration, only jobs and trucks in the category of the largest size are considered. Starting from the second iteration onwards, any jobs from the previous iterations left unassigned, after running the truck-routing formulation, will be rejected because no trucks can serve them, even if it is re-considered in subsequent iterations. Those trucks left unassigned with a job in the previous iteration together with the trucks in the category of next largest size, will be considered with the jobs in the category of the next largest size. This procedure will run until each job is either assigned with a truck or rejected.

Consider the case of four size categories; 40-foot, 36-foot, 33-foot and 30-foot. Since 40-foot jobs can only be served by 40-foot trucks, we begin by applying the formulation to this group of trucks and jobs in the first iteration. Any 40-footer truck not assigned in this iteration is considered for the second iteration. In the second iteration, any 40-footer truck not assigned previously, and all 36-footer trucks are considered with 36-footer jobs. In the third iteration, previously un-assigned 40-footer and 36-footer trucks are considered, together with all 33-footer trucks. These are applied with 33-footer jobs. In the last iteration, previously unassigned 40-footer, 36-footer, and 33-footer trucks, plus all 30-footer trucks are considered with 30-footer jobs. At the end of each iteration, jobs that are not assigned are rejected, and rescheduled for the next day scheduled run. However, rejected jobs incur a penalty cost, and this cost increases according to the number of days a job has been delayed.

*4.3.2 Small-truck-first policy*

The Small-Truck-First (STF) policy also applies the truck-routing formulation in an iterative manner. However, it differs with the LJF policy in terms of the categories considered in each iteration. In this policy, the first iteration begins by looking at the smallest truck and job categories. A truck with the smallest size can only serve a job with the same size. In the first iteration, only jobs and trucks in the category of the smallest size are considered. Starting from the second iteration onwards, any trucks from the previous iterations left unassigned, after running the truck-routing formulation, will not be considered again in the subsequent iterations. Those jobs left unassigned in the previous iteration together with the jobs in the category of the next smallest size, will be considered with the trucks in the category of the next smallest size. Again, this procedure will run until each job is either assigned with a truck or rejected. For the above case of four size categories, all 30-foot trucks can only serve 30-foot jobs, and no larger jobs. In the first iteration, this group of smallest trucks is assigned with 30-foot jobs. In the second iteration, only 33-foot trucks are considered, and all 33-foot jobs are considered with previously un-assigned 30-foot jobs. In the third iteration, only 36-foot trucks will be considered, with 36-foot jobs and previously un-assigned 33-foot and 30-foot jobs. In the last iteration, only 40-foot trucks are considered, with 40-foot jobs and previously unassigned 36-foot, 33-foot, and 30-foot trucks. In terms of job rejection, this policy differs with the LJF policy. At the end of the first iteration, 30-footer jobs that are not assigned are considered in subsequent iterations. This means that each job that is not assigned in an iteration need not be rejected for the day, only jobs that are rejected in the last iteration are considered delayed by this policy.

*4.3.3 Load-capacity-constrainted policy*

In the Load-Capacity-Constrained (LCC) Policy, the truck-routing formulation is not applied in an iterative manner, as opposed to the LJF and the STF policies. Here, the truck-routing formulation presented in Section 4.2 is considered with an additional constraint. This constraint checks that each truck's capacity size can cater for the job's load size that it is assigned to. $d_i$ defines the load size of job $i$ while $q_k$ is the load capacity for truck $k$. Constraint (14) ensures that this capacity constraint is met for each combination of truck and job.

$$d_j \sum_{i \in C' \cup \{0\}} x_{ij}^k \quad \leq \quad q_k, \quad \forall k \in T', \forall j \in C' \tag{14}$$

*4.3.4 Total-route-limit policy*

This policy does not apply the truck-matching formulation in the solution approach. Instead, the truck-routing formulation is extended to cater for constraints that ensure that trucks adhere to the tour routing time limit, L. In this policy, each truck has a choice either to return to the depot, remain at its current location, or remain at the delivery location of its most recent job. For those that remain at the delivery locations, the time since it first left the depot should not be greater than L-c', where c' is the maximum time for a truck to go back to the depot (without servicing any job). Therefore, additional notations {d} and {s}, are used to denote the depot and a stationary node, respectively. The stationary node signifies if a truck remains at its current location without serving any job, or at the delivery location of the latest job assigned. In addition to the definitions specified in Section 4.2, the following definitions are added. Let $D_{0d}^k$ be the deadhead distance from the current location of truck $k \in T'$ to the depot, and $D_{id}$ be the deadhead distance from the delivery location of job $i \in C'$ to the depot. Also, define $x_{0d}^k = 1$, if truck $k \in T'$ is assigned not to serve any job, but to go back to the depot directly from its current location. $x_{id}^{k}$ =1, if truck k∈T' is assigned to go back to the depot after serving job i∈C'. $x_{0s}^{k}$ =1, if truck k∈T' is to remain in its current location without serving any jobs or going back to the depot. Also, $x_{is}^{k}$ =1, if truck k∈T' is to remain at the delivery location of job i∈C' after serving job *i*. Lastly, let $t_k$ be the time truck $k\in T'$ first left the depot. In addition to the capacity constraint (14) presented in Section 4.3.1, four additional constraints, (24), (25), (26) and (27) are added to ensure the limit on tour routing time is adhered to. The truck-routing formulation is presented here again, with the additional notation for the depot. We define the formulation for the TRL policy is as follows:

$$\text{Min } \sum_{k\in T'}\sum_{i\in C'\cup\{d\}} D_{0i}^{k} x_{0i}^{k} + \sum_{k\in T'}\sum_{i\in C'}\sum_{j\in C'\cup\{d\}} D_{ij} x_{ij}^{k} + \sum_{i\in C'} r_i y_i$$

Subject to

$$\sum_{k\in T'} x_{0i}^{k} + \sum_{k\in T'}\sum_{j\in C'} x_{ji}^{k} + y_i = 1 \qquad \forall i\in C' \tag{15}$$

$$\sum_{i\in C'\cup\{d\}\cup\{s\}} x_{0i}^{k} = 1 \qquad \forall k\in T' \tag{16}$$

$$\sum_{k\in T'}\sum_{j\in C'\cup\{0\}} x_{ji}^{k} \le 1 \qquad \forall i\in C' \tag{17}$$

$$\sum_{k\in T'}\sum_{j\in C'\cup\{d\}\cup\{s\}} x_{ij}^{k} = \sum_{k\in T'}\sum_{j\in C'\cup\{0\}} x_{ji}^{k} \qquad \forall i\in C' \tag{18}$$

$$\sum_{j\in C'\cup\{d\}\cup\{s\}} x_{ij}^{k} = \sum_{j\in C'\cup\{0\}} x_{ji}^{k} \qquad \forall i\in C', \forall k\in T' \tag{19}$$

$$-\sum_{k\in T'} (D_{0i}^{k} + \tau_{k}^{0}) x_{0i}^{k} + \tau_{i}^{PICK} \ge 0 \qquad \forall i\in C' \tag{20}$$

$$-M x_{ij}^{k} + \tau_{j}^{PICK} \ge \tau_{i}^{PICK} + W_i + D_{ij} - M \qquad \forall i,j\in C', \forall k\in T' \tag{21}$$

$$\tau_{i}^{AVL} \le \tau_{i}^{PICK} \le \tau_{i}^{ALN} \qquad \forall i\in C' \tag{22}$$

$$d_i \sum_{j\in C'\cup\{d\}\cup\{s\}} x_{ij}^{k} \le q_k, \quad \forall k\in T', \forall i\in C' \tag{23}$$

$$M(x_{0d}^{k} - 1) + \tau_{k}^{0} + D_{0d}^{k} - t_k \le L, \quad \forall k\in T' \tag{24}$$

$$M(x_{id}^{k} - 1) + \tau_{i}^{PICK} + W_i + D_{id}^{k} - t_k \le L, \quad \forall i\in C', \forall k\in T' \tag{25}$$

$$M(x_{0s}^{k} - 1) + \tau_{k}^{0} - t_k \le L - c, \quad \forall k\in T' \tag{26}$$

$$M(x_{is}^{k} - 1) + \tau_{i}^{PICK} + W_i - t_k \le L - c, \quad \forall i\in C', \forall k\in T' \tag{27}$$

$$x_{ij}^{k} = \{0,1\}, \quad \forall i,j\in C', \forall k\in T' \tag{28}$$

$$y_i = \{0,1\}, \quad \forall i\in C' \tag{29}$$

Constraint (15) ensures that each job is either served by a truck or rejected. Constraint (16) ensures that no truck travels to pickup more than one job from its current location. When compared with constraint (5), constraint (16) allows for an equality constraint, because trucks that are not assigned any jobs are assumed to either return to the depot or remain at the current location. Similar to constraints (6) to (8) in Section 4.2, constraints (17) to (19) are network flow balance constraints that ensure each job can be followed by at most one other job. Constraints (20) and (21) define the pickup time of each job, and ensure that no job is left without a truck if it is not rejected. Constraint (22) ensures that each job's pickup time falls within a time window specified. Jobs that cannot meet this time window are rejected, and considered for next day's schedule. Constraint (23) is the capacity constraint, and makes sure that a job is assigned with a truck with a size that is at least the same as the size of the job. Constraint (24) ensures that a truck which is not assigned a job can travel back to the depot within the total route time limit. Constraint (25) ensures that a truck which is assigned jobs can travel back to the depot, after finishing its last job assignment, within the total route time limit. Constraints (26) and (27) ensure that trucks which remain stationary are within the time limit of *L-c'* days, and this makes sure that the truck will not exceed the route time limit in the next day assignment. Constraints (28) and (29) are binary variable constraints.

# 5. Computational results

Historical data of the trucking company was collected based on the jobs received and the truck assignment each day. In the data considered, the majority of trucks and jobs fall into the category of the larger capacities. Figure 1 shows the number of jobs received per day for the set of 18 days, while Figure 2 shows the distribution of job locations, based on their latitude and longitude values.

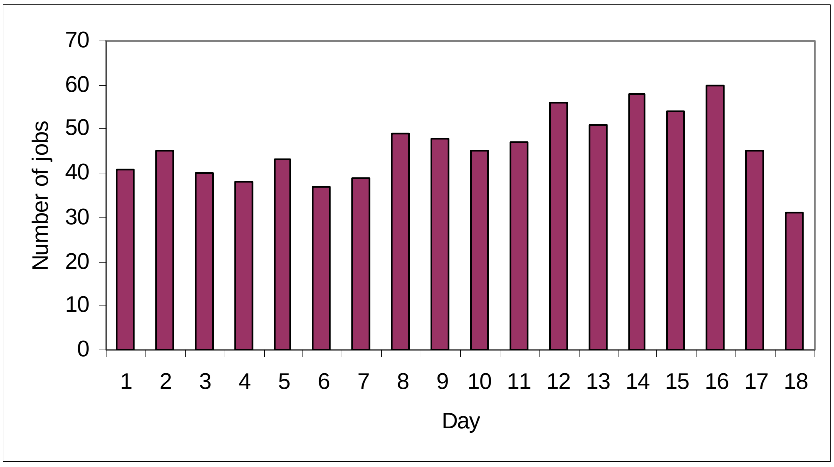


***Fig 1: Number of jobs per day***

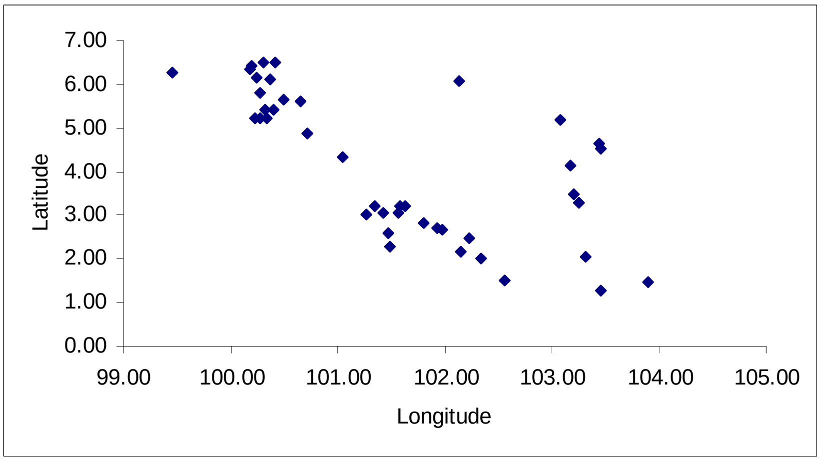


***Fig 2: Job locations***

Each job is characterized by its pickup location, delivery location, and quantity of load to be carried (or type of truck required). Although data concerning the time when the job was first received was not available, it is assumed that all job requests for the day are received by 12:00 each day. In terms of time windows, customers generally operate between the hours of 8:00 to 18:00 daily. In this study, we assume an earliest pickup time of 12:00 and a latest pickup time of 18:00. Jobs that cannot meet the time window for pickup will be rejected and considered for the next day, with a delay cost incurred. The delay cost is weighted based on the number of days the job has been delayed.

All policies were coded in XpressMP Mosel language and tested on PCs with Pentium (4) 2.66GHz processor. Policies LJF and STF were tested on a PC with 256MB memory, while policies LCC and TRL were tested on a PC with 1 GB memory. All tests ran in the Xpress-IVE environment using Xpress Optimizer Version 17.10.04.

In this study, two types of analyses were conducted based on the 18 sets of historical data containing information on jobs and trucks types and locations. The first set of analysis provides a cross-sectional view of the policies, while the second set looks at the cumulative performance of the policies.

### *5.1 Cross-sectional analysis*

In this analysis, each of the four policies was tested against the same input data, which includes considering the same current locations for each truck, for each set. This is to test the cross-sectional performance of the policies, with relation to each other. L is chosen to be 7 days. For the three two-stage policies LJF, STF and LCC, we choose c to be 2 days. This is because the maximum time for performing a job and returning to depot is 2 days. However, for the case of TRL, we use c’ to be 1 day because it is the maximum time for going back directly to the depot regardless of the truck’s current location.

Two types of deadhead costs are considered here. The ‘deadhead-between-location’ cost represents the cost of travel between the current location of a truck to the pickup location of its first job, and between the delivery location of a job to the pickup location of a subsequent job. The ‘deadhead-to-depot’ cost represents the cost of travel for a home-bound truck to the depot, either from the delivery location of a job assigned, or from its current location, if it is not assigned a job. All deadhead costs are measured in terms of travel time hours.

Table 1 shows the deadhead costs incurred for each of the policies. Table 2 includes the calculation of the total costs incurred, which considers the sum of the total deadhead costs and delay costs. The delay cost is the cost of delaying jobs, and is measured by the number of days the jobs are delayed, or postponed. It is calculated based on the number of jobs delayed, multiplied by the cost of delay per day. The cost of delay is calculated on a per day basis because the truck-routing formulation has a higher tendency to delay jobs which have a lower delay cost. As such, every job which is delayed for a longer period has a higher delay cost, and would have a lesser chance of being delayed. The cost of delay per day is taken as a value larger than the maximum deadhead cost that can be incurred by any job that is to be served. This is to ensure that a job is not delayed simply because it has a high deadhead cost. However, jobs that cannot be served within its time window may be delayed. For the purpose of this study, the cost of delay per day is set to 100.

***Table 1: Total deadhead cost for cross-sectional analysis***

| | Deadhead between locations | | | | Deadhead to Depot | | | | Total Deadhead | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Policy | | | | Policy | | | | Policy | | | |
| Day | LJF | STF | LCC | TRL | LJF | STF | LCC | TRL | LJF | STF | LCC | TRL |
| 1 | 32.18 | 32.18 | 32.18 | 29.53 | 25.64 | 25.64 | 25.64 | 11.5 | 57.82 | 57.82 | 57.82 | 41.03 |
| 2 | 41.23 | 36.22 | 36.22 | 27.32 | 33.02 | 33.02 | 33.02 | 0 | 74.25 | 69.24 | 69.24 | 27.32 |
| 3 | 44.32 | 44.32 | 44.32 | 20.11 | 4.84 | 4.84 | 4.84 | 0 | 49.16 | 49.16 | 49.16 | 20.11 |
| 4 | 22.49 | 16.58 | 16.58 | 16.28 | 2.08 | 2.08 | 2.08 | 0 | 24.57 | 18.66 | 18.66 | 16.28 |
| 5 | 50.41 | 49.09 | 45.91 | 45.06 | 0 | 0 | 0 | 0 | 50.41 | 49.09 | 45.91 | 45.06 |
| 6 | 31.57 | 30.55 | 24.49 | 18.89 | 15.06 | 15.06 | 15.06 | 0 | 46.63 | 45.61 | 39.55 | 18.89 |
| 7 | 15.73 | 12.69 | 12.37 | 11.85 | 60.05 | 60.05 | 60.05 | 0 | 75.78 | 72.74 | 72.42 | 11.85 |
| 8 | 52.93 | 52.75 | 52.75 | 44.43 | 12.18 | 12.18 | 12.18 | 0 | 65.11 | 64.93 | 64.93 | 44.43 |
| 9 | 47.22 | 65.72 | 65.72 | 56.23 | 0 | 0 | 0 | 0 | 47.22 | 65.72 | 65.72 | 56.23 |
| 10 | 38.5 | 26.73 | 26.73 | 11 | 5.92 | 5.92 | 5.92 | 0 | 44.42 | 32.65 | 32.65 | 11 |
| 11 | 32.58 | 26.55 | 26.55 | 26.55 | 0 | 0 | 0 | 0 | 32.58 | 26.55 | 26.55 | 26.55 |
| 12 | 38.24 | 33.82 | 33.82 | 22.76 | 37.22 | 37.22 | 37.22 | 0 | 75.46 | 71.04 | 71.04 | 22.76 |
| 13 | 55.96 | 53.11 | 53.11 | 46.69 | 58.15 | 58.15 | 58.15 | 0 | 114.1 | 111.3 | 111.26 | 46.69 |
| 14 | 40.09 | 40.09 | 40.09 | 37.2 | 33.15 | 33.15 | 33.15 | 0 | 73.24 | 73.24 | 73.24 | 37.2 |
| 15 | 50.67 | 33.23 | 33.23 | 35.09 | 9.04 | 9.04 | 9.04 | 0 | 59.71 | 42.27 | 42.27 | 35.09 |
| 16 | 54.71 | 59.91 | 59.19 | 58.47 | 0 | 0 | 0 | 0 | 54.71 | 59.91 | 59.19 | 58.47 |
| 17 | 9.42 | 11.96 | 7.01 | 7.01 | 0 | 0 | 0 | 0 | 9.42 | 11.96 | 7.01 | 7.01 |
| 18 | 40.82 | 38.08 | 35.23 | 20.38 | 32.02 | 32.02 | 32.02 | 0 | 72.84 | 70.1 | 67.25 | 20.38 |

***Table 2: Total cost for cross-sectional analysis***

| | Total Deadhead | | | | Delay Cost | | | | Total Cost | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Policy | | | | Policy | | | | Policy | | | |
| Day | LJF | STF | LCC | TRL | LJF | STF | LCC | TRL | LJF | STF | LCC | TRL |
| 1 | 57.82 | 57.82 | 57.82 | 41.03 | 0 | 0 | 0 | 0 | 57.82 | 57.82 | 57.82 | 41.03 |
| 2 | 74.25 | 69.24 | 69.24 | 27.32 | 100 | 0 | 0 | 0 | 174.25 | 69.24 | 69.24 | 27.32 |
| 3 | 49.16 | 49.16 | 49.16 | 20.11 | 0 | 0 | 0 | 0 | 49.16 | 49.16 | 49.16 | 20.11 |
| 4 | 24.57 | 18.66 | 18.66 | 16.28 | 0 | 0 | 0 | 0 | 24.57 | 18.66 | 18.66 | 16.28 |
| 5 | 50.41 | 49.09 | 45.91 | 45.06 | 0 | 0 | 0 | 0 | 50.41 | 49.09 | 45.91 | 45.06 |
| 6 | 46.63 | 45.61 | 39.55 | 18.89 | 0 | 0 | 0 | 0 | 46.63 | 45.61 | 39.55 | 18.89 |
| 7 | 75.78 | 72.74 | 72.42 | 11.85 | 0 | 0 | 0 | 0 | 75.78 | 72.74 | 72.42 | 11.85 |
| 8 | 65.11 | 64.93 | 64.93 | 44.43 | 0 | 0 | 0 | 0 | 65.11 | 64.93 | 64.93 | 44.43 |
| 9 | 47.22 | 65.72 | 65.72 | 56.23 | 300 | 0 | 0 | 0 | 347.22 | 65.72 | 65.72 | 56.23 |
| 10 | 44.42 | 32.65 | 32.65 | 11 | 0 | 0 | 0 | 0 | 44.42 | 32.65 | 32.65 | 11 |
| 11 | 32.58 | 26.55 | 26.55 | 26.55 | 0 | 0 | 0 | 0 | 32.58 | 26.55 | 26.55 | 26.55 |
| 12 | 75.46 | 71.04 | 71.04 | 22.76 | 0 | 0 | 0 | 0 | 75.46 | 71.04 | 71.04 | 22.76 |
| 13 | 114.11 | 111.26 | 111.26 | 46.69 | 700 | 500 | 500 | 0 | 814.11 | 611.26 | 611.26 | 46.69 |
| 14 | 73.24 | 73.24 | 73.24 | 37.2 | 500 | 500 | 500 | 500 | 573.24 | 573.24 | 573.24 | 537.2 |
| 15 | 59.71 | 42.27 | 42.27 | 35.09 | 400 | 400 | 400 | 400 | 459.71 | 442.27 | 442.27 | 435.09 |
| 16 | 54.71 | 59.91 | 59.19 | 58.47 | 200 | 100 | 0 | 0 | 254.71 | 159.91 | 59.19 | 58.47 |
| 17 | 9.42 | 11.96 | 7.01 | 7.01 | 0 | 0 | 0 | 0 | 9.42 | 11.96 | 7.01 | 7.01 |
| 18 | 72.84 | 70.1 | 67.25 | 20.38 | 0 | 0 | 0 | 0 | 72.84 | 70.1 | 67.25 | 20.38 |

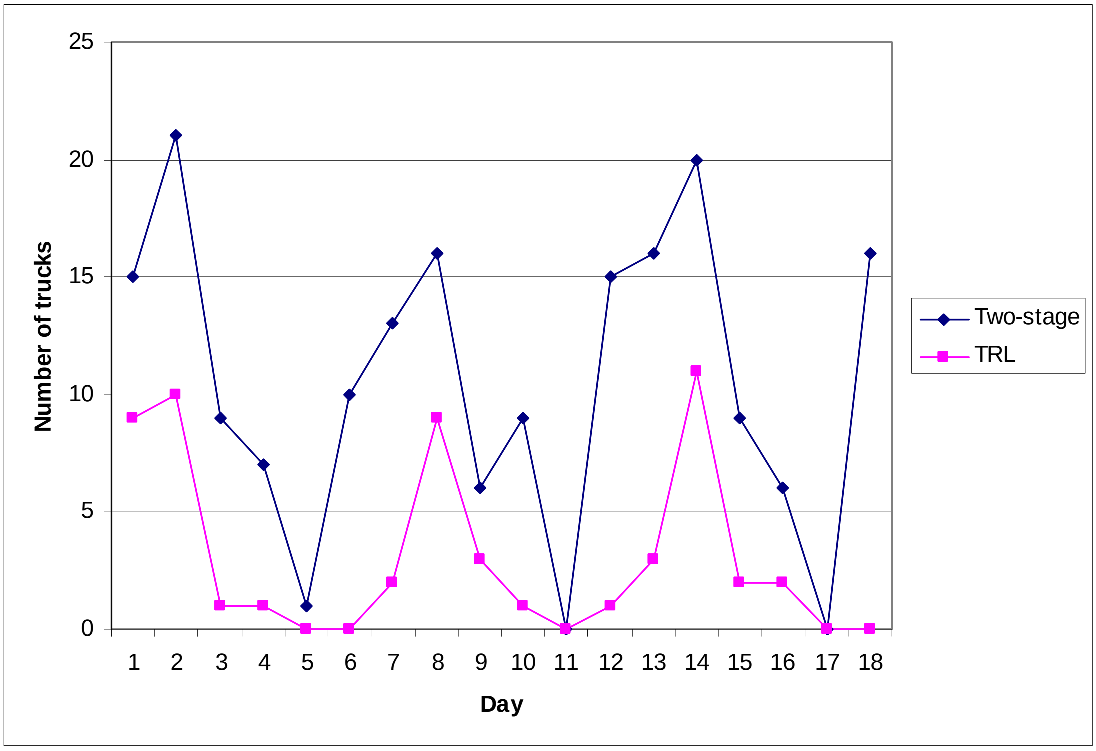


***Fig 3: Number of home-bound trucks for cross-sectional analysis***

For deadhead-between-location, TRL fared the best in most of the cases except day 15, where policies STF and LCC perform better, while LJF does better on day 9 and 16. If we look at the number of jobs delayed on day 9 and 16 in Table 2, we can see that LJF delays more jobs than the other policies. Therefore, the number of jobs that are assigned by LJF in these two days is less than the other policies. This explains why the deadhead-between-location is lower for LJF in these two days. As a result, the total deadhead cost of LJF for these two days are the lowest. For day 15, even though the deadhead-between-location costs are lower for STF and LCC, since the deadhead-to-depot cost for TRL is zero, as a result, the total deadhead cost for TRL is still the lowest. It is to be noted (see Figure 3) that the number of home-bound trucks per day for TRL is actually fewer than those of the two-stage policies, LJF, STF and LCC. Furthermore, in Table 1, all the deadhead-to-depot for TRL is zero except day 1. This means that, in most of the cases, TRL can match a home-bound truck with a job which destines to the depot. This led to better results for the TRL policy in terms of the total deadhead travel.

From the results in Table 2, the TRL policy outperforms all other policies when considering total costs. This is due to the low delay cost of TRL. On the other hand, the LJF policy had the highest tendency to delay jobs. In this case study, we considered a set of data where the trucks and jobs of the larger capacities formed the majority. In the LJF policy, the larger trucks are assigned to larger jobs in the first iteration using the truck-routing formulation. As such, trucks with a smaller proximity to jobs would be assigned first. Trucks in subsequent iterations would then have a larger proximity to the remaining jobs. This leaves a higher chance for smaller jobs to be delayed, as the travel time to pickup the job may not fit into the time window specified. This is also depicted in the deadhead cost for the LJF policy, which is quite high in most instances.

## *5.2 Cumulative analysis*

In this analysis, the same input data is tested on all policies for the first day run. For subsequent days, the locations of the trucks are updated based on the solutions obtained to investigate the cumulative performance on all the policies. For the given truck assignment from the company, 97 trucks, including 15 trucks outsourced from other trucking companies, are used. For our four policies, only 70 trucks are needed for the same demand. Figure 4 shows that none of the policies or the company assignment (CA) dominates in terms of the number of home-bound trucks. However, on average, LJF, STP, LCC and CA identified 10.2, 10.7, 10.5 and 9.9 home-bound trucks, respectively, whereas TRL identified only 8 home-bound trucks. Figure 5 shows the cumulative deadhead cost for all four policies and the company assignment, while Figure 6 shows the cumulative total cost (including cost of delaying jobs) of the four policies. Since data concerning the time when the job was first received was not available, the number of jobs delayed in the company assignment is unknown. Therefore, the total cost of the company assignment is not included in Figure 6.

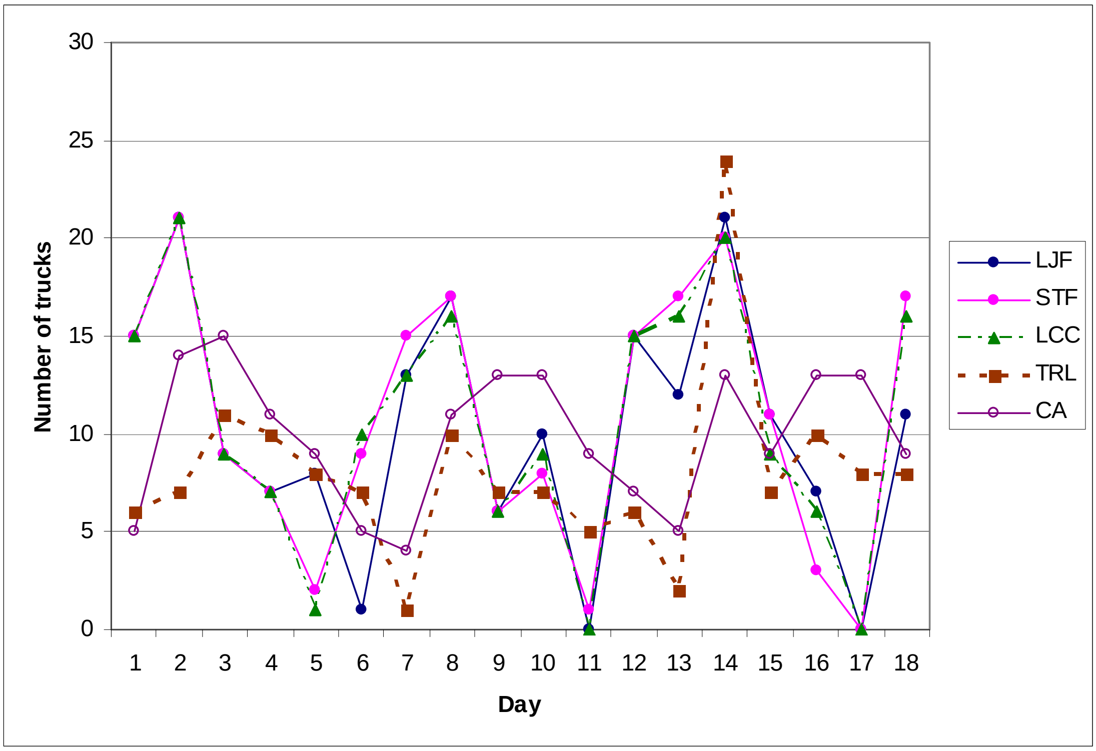


*Fig 4: Number of home-bound trucks for cumulative analysis*

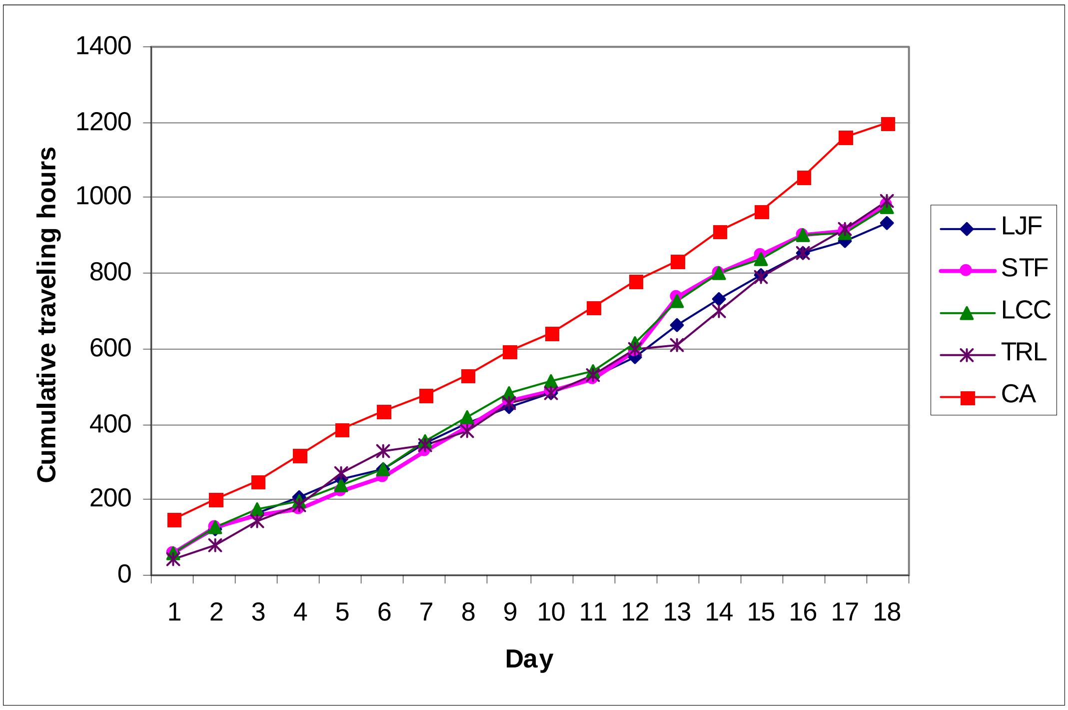


*Fig 5: Cumulative deadhead costs for cumulative analysis*

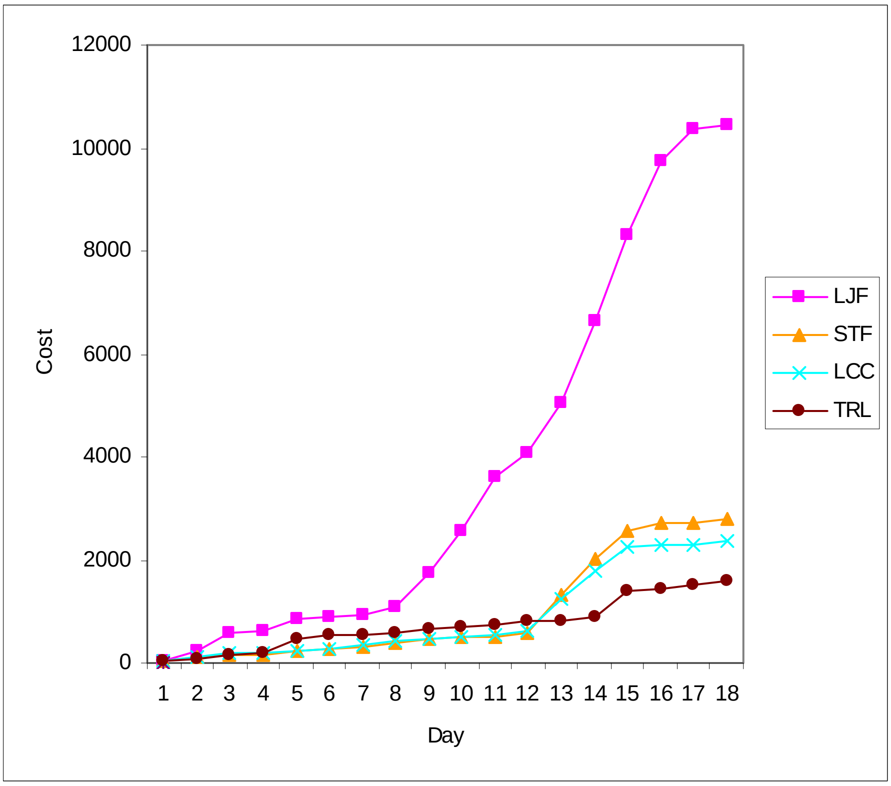


***Fig 6: Total cost for cumulative analysis***

From the results, we can see that, based solely on the cumulative deadhead cost, the four policies are closely competitive at this level of comparison. On the other hand, the cumulative deadhead cost extracted from the original assignment of the company is higher than all policies suggested (**Figure 5)**. However, when we look at the cost comparison for total costs (including the cost of delaying jobs), we find that clearly the TRL policy is the best performer. This is due to the fact that the TRL policy has the least tendency to delay jobs in the long run. On the contrary, the LJF policy is the worst performer as it has the highest tendency to delay jobs.

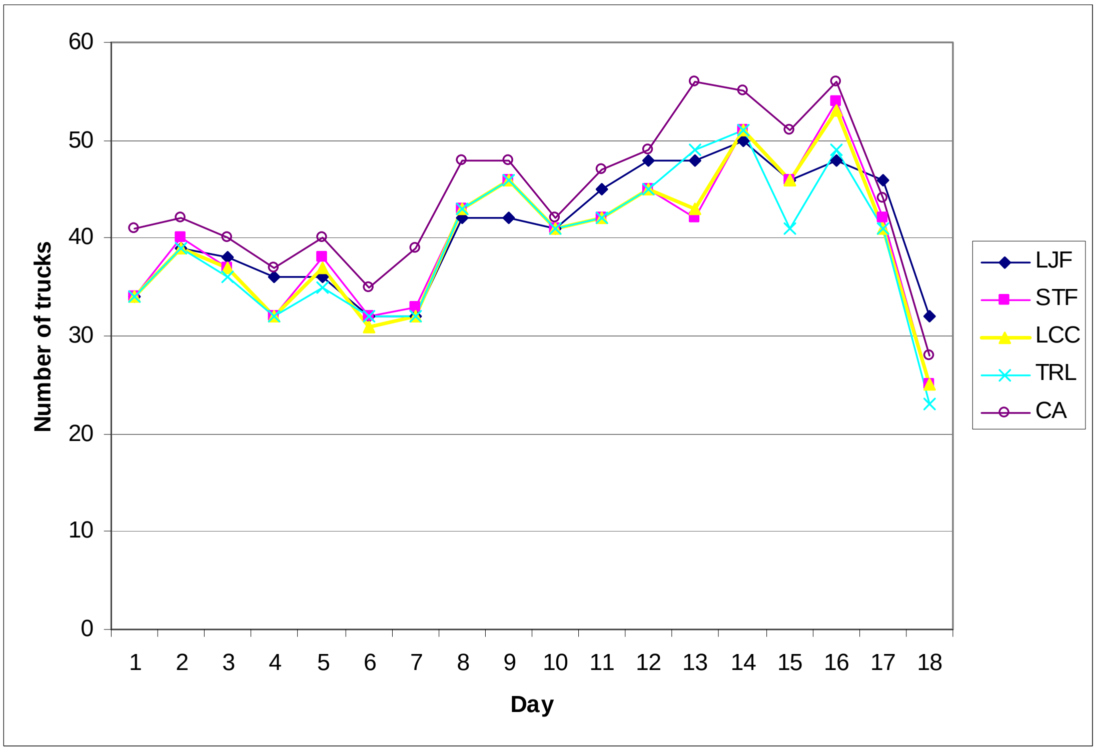


*Fig 7: Number of trucks working*

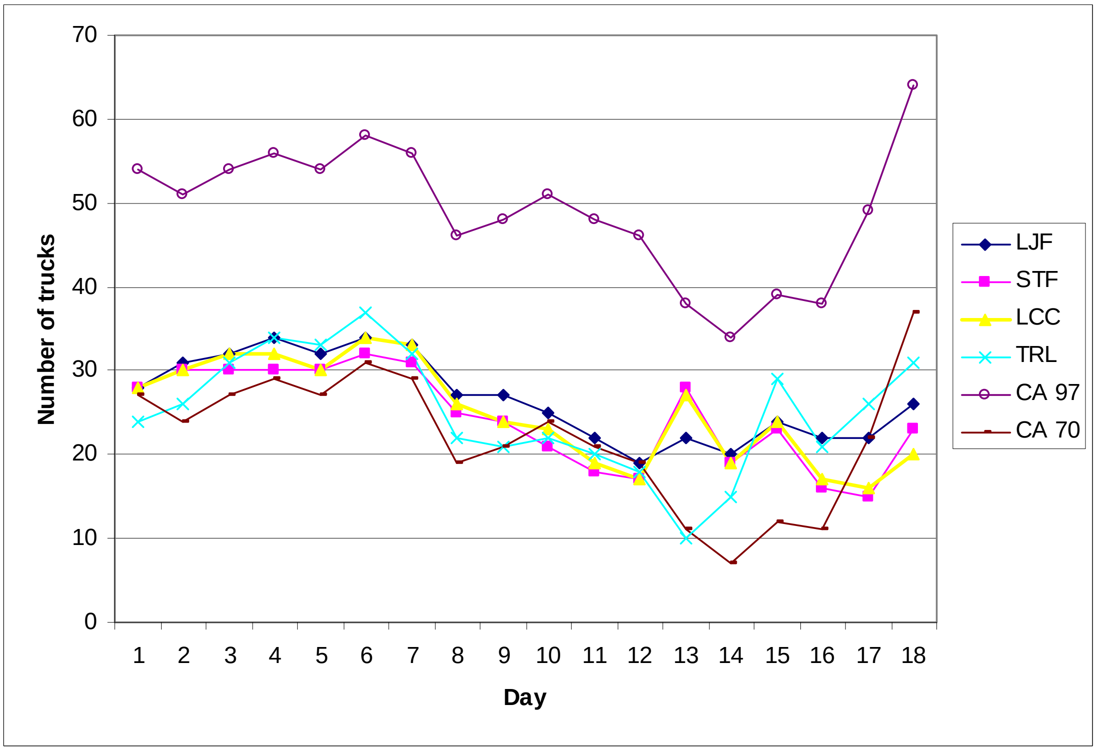


*Fig 8: Number of trucks idled at depot*

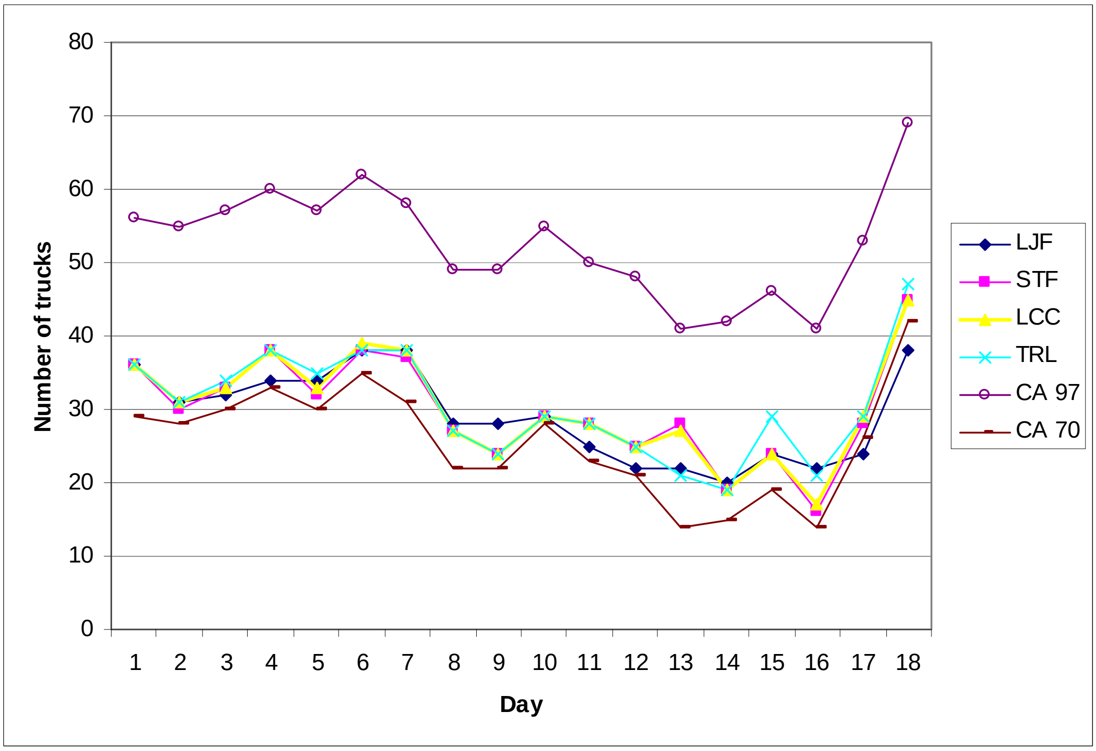


***Fig 9: Total number of trucks idled***

Figure 7 shows number of trucks involved in a working tour each day. We can see that the number of trucks used in working tours of the company's assignment is higher than the four policies. If we look at the number of trucks idle in the depot (see Figure 8), it (CA 97) is much higher than those of the four policies. However, the actual number of trucks that the company used is 97, whereas we only needed 70 trucks in our policies, and some of the truck capacities are wasted in the company assignment. In order to compare the company's assignment with the four policies, we assume that these wasted capacities are located at the depot and deduct those 27 'excess' trucks from the idled trucks at the depot of the company assignment to get the line of CA 70 in Figure 8. Thus, we can see that there are less idled trucks at the depot. In other words, there is more available truck capacity for future demand in our four policies. As such, the utilization of the trucks capacities is better in all four policies than the company's original assignment. The same result can be seen in Figure 9, where the number of idled trucks including those idled at any of the clients' locations is shown.

It is interesting to compare the total routing time of each tour of the company's assignment with the four policies. In the four policies, L is set to be 7, while c and c' are set to be 2 and 1, respectively. After each tour, a day off is scheduled for each truck. On the other hand, the dispatching office is closed every Sunday in the historical data. Therefore we assume the same in all the four proposed policies. From Figure 10, we can see that the company assignment contains 177 completed tours. The mean routing time is 4.85days but the minimum and maximum routing time is 1 and 20, respectively. Therefore there is a wide spread between the minimum and maximum routing time. For the truck with the trip of tour length 20 days, he was away from home for almost a month. This explains the high turnover rate of the driver of the company. If we compare the graph in Figure 10 with Figure 11 (the routing time of the four policies), we can see that the tour routing time is more scattered. There are 188, 197 and 191 completed tours in LJF, STF and LCC, respectively. Most of the tours are 5-day tours for these policies, none of the them has a tour of more than 7 days. In TRL, most of the tours are 6-day or 7-day tours. We can see that there are a few tours with 8 days. This is due to the assumption that the dispatching office is closed on Sunday. If a truck has its seventh day away from the depot on a Sunday, this truck will be schedule back to the depot on Monday instead. Therefore, there are a few tours in TRL that are 8 days away from the depot. All in all, we can conclude that all four policies controlled the number of days away from depot for each tour better than the company's assignment.

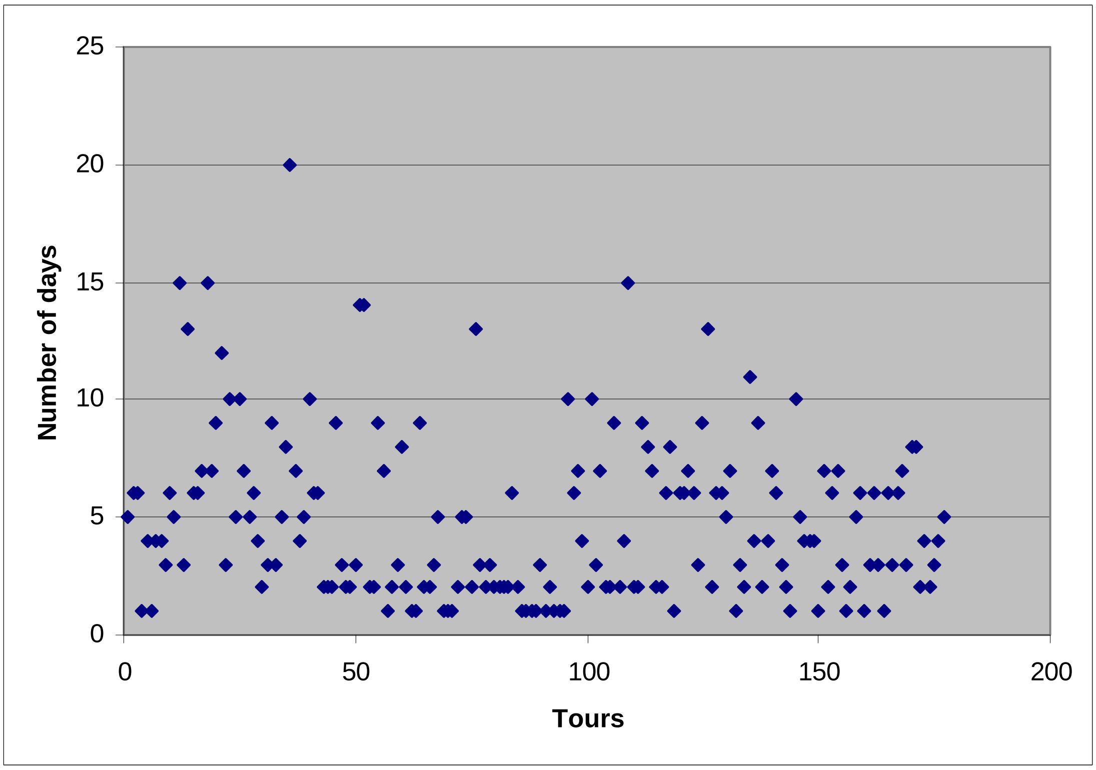


*Fig 10: Number of days away from depot per tour of company assignment*

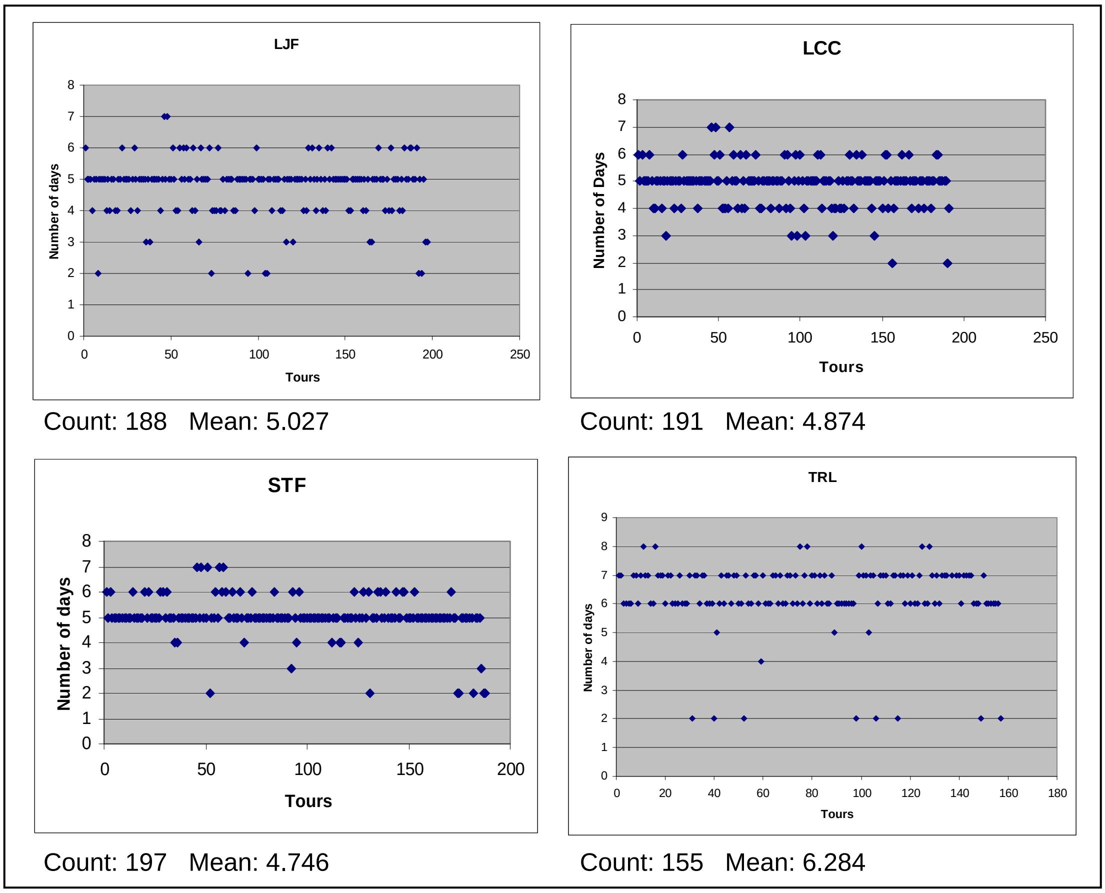


*Fig 11: Number of days away from depot per tour of the four policies*

# 6. Conclusion

In this paper, we considered the case of a dynamic heterogeneous full-truckload pickup and delivery problem, with pickup time windows and tour routing time limit. Four re-optimization policies were proposed, aimed at reducing costs incurred through deadhead travel and delay in deliveries. The policies proposed made use of two integer programming formulations, to optimize the routing of trucks servicing job requests, subject to several constraints.

The policies were tested using historical data obtained from the trucking company. Test results from the cross-sectional analysis showed that in general, the TRL policy fared better than the other policies in this category. The TRL policy gave better results in terms of producing lower deadhead costs, as well as total costs. The TRL policy also had the least tendency to delay jobs. On the contrary, the LJF policy exhibited a strong tendency in delaying jobs, causing higher total costs. Besides, in most cases, the TRL policy assigns home-bound trucks with jobs near the depot. When comparing the cumulative performance of the different policies, all policies exhibited close competition in this scenario. However, when comparing the total costs incurred, the TRL policy outperformed the other policies. In addition, the TRL policy has a mean tour time closer to the tour routing time limit. When compared with the company's original assignment, all four policies are more cost-saving in terms of deadhead cost. Furthermore, all four policies have better truck utilization in terms of the number of trucks working in tours per day and better control in tour routing time.

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