

Optimizing Fleet Composition and Size under Uncertainty in Urban Transit Systems

Final Report
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16. Abstract The goal of this project was to study the fleet sizing problem in the context of an urban transit system with several unique features: (1) a fleet with a heterogeneous mixture of vehicles; (2) integrated decision support, including acquisition, retirement, and allocation decisions over multiple time periods; and (3) various uncertainties regarding demand for origin-destination (OD) pairs and vehicle efficiency. Over the course of a one-year grant effort, the researchers first developed a deterministic optimization model to minimize the total fleet acquisition and operation costs for all time periods within the planning horizon. Then, a two-stage stochastic programming (SP) model was devised to explicitly cope with uncertainty. The model minimizes the expected total costs by optimizing (1) the here-and-now fleet acquisition and retirement decisions in the first stage and (2) the allocation recourse decisions in the second stage after the random parameters are realized. The research team collaborated with a local third-party logistics (3PL) company in St. Louis, Missouri, who provided real-world data for this project. Computational studies were conducted to show the benefit of the two-stage SP model by comparing it to the deterministic model using point estimates of random parameters.			
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**Final Report
March 2018**

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INTRODUCTION AND BACKGROUND

A transportation fleet is a capital-intensive asset for a logistics/transportation company or manufacturer. Optimizing the composition (types of vehicles) and size of a fleet is crucial for efficient and cost-effective operations (Mourafetis and Kamat 2014). Fleet optimization in urban transit systems faces additional complexities due to heterogeneous demand/customer types and uncertain demand, travel time, and vehicle productivity. It is not uncommon for a logistics company to oversize its fleet, which can result in a low utilization rate. Additionally, all too often in paratransit and regular bus services, larger vehicles than necessary are used in anticipation of few occasions when they might be needed. An agency may also need to tradeoff between the cost per trip versus the seating capacity. All of these situations reflect the need for proper methods to determine and optimize the fleet size and composition.

Earlier work on fleet optimization, such as Powell (1986) and Powell (1987), developed stochastic optimization approaches for dynamically allocating truck fleets under uncertain demand. These models did not explicitly address the fleet sizing decision, but rather focused on optimal use of an existing fleet. Turnquist and Jordan (1986) proposed a model for container fleet sizing under uncertain travel and service times. Sherali and Tuncbilek (1997) proposed a dynamic time-space model for rail-car fleet management. Their approach included a sensitivity analysis for addressing “what-if” types of questions but did not explicitly optimize fleet sizing under uncertainty. More recent research efforts have attempted to optimize fleet sizing under explicit uncertainty. Notably, List et al. (2003) presented a robust optimization approach for fleet sizing and planning under demand uncertainty. Papier and Thonemann (2008) applied queuing models for sizing and structuring rental fleets. Hsu and Chen (2014) developed an integrated approach to optimize fleet size and delivery scheduling for perishable food distribution.

This research project addressed the problems of fleet sizing and composition optimization in the context of urban transit systems with unique features. First, a complex transportation network and heterogeneous demand call for the effective management of a fleet with a mixture of different sizes and types of vehicles. Second, the typical urban business environment makes it possible to source/acquire vehicles at a reasonable cost and frequency through purchasing, renting, and/or outsourcing to a carrier. Therefore, it is beneficial for a logistics/transportation provider or manufacturer with its own fleet to simultaneously optimize the fleet sizing and deployment decisions. Third, various uncertainties of origin-destination (OD) demand and vehicle productivity may significantly impact the fleet sizing decision and should be adequately addressed.

LITERATURE REVIEW

The researchers reviewed the existing literature on fleet sizing optimization pertaining to the trucking, rail, rental, public transportation, marine transportation, and health care.

Trucking

Beaujon and Turnquist (1991) proposed a nonlinear programming model for optimizing fleet size and utilization simultaneously with stochastic demand and vehicle travel times. The objective was to maximize total profit as the difference between the revenue and the direct transportation costs, ownership costs for vehicles en route, holding costs for idle equipment, and closed-form expected penalty costs for unmet demand.

List et al. (2003) studied a fleet sizing problem with two types of uncertainty: the future demand to be served by the fleet and the productivity of individual vehicles. They implemented a robust optimization approach to simultaneously optimize fleet acquisition, retirement, and allocation decisions.

Pascual et al. (2013) proposed an integrated decision support framework that allows fleet size and maintenance capacity requirements to be jointly estimated under several criteria. Using a business-centered life-cycle perspective, they considered global cost, availability, and throughput as performance measures. Their methodology was based on a queueing network model, which can be evaluated via analytical methods.

Chang et al. (2014) proposed a simulation sequential metamodeling (SSM) approach for a vehicle fleet sizing problem. The SSM approach answers “what-if” type questions in real time. They evaluated the performance of SSM under various scenarios and applied SSM in an empirical study based on real data from a semiconductor company.

Rahimi-Vahed et al. (2015) proposed a new modular heuristic algorithm (MHA) to address the problem of determining the optimal fleet size for three vehicle routing problems (VRPs): a multi-depot VRP, a periodic VRP, and a multi-depot periodic VRP. The proposed heuristic algorithms incorporated different exploration and exploitation strategies to produce good results.

Lei et al. (2016) developed a two-stage robust optimization model for the mobile facility fleet sizing and routing problem with demand uncertainty and no information about the underlying probability distribution function. A two-level cutting plane-based method was developed, which included a procedure to generate customized lower bound inequalities in the outer level and a hybrid algorithm in the inner level that combines heuristic and exact methods to solve the recourse problem.

Rail

Sherali and Tuncbilek (1997) proposed a dynamic time-space network framework, where each origin and destination location on each day is represented by a distinct node, for the multilevel-car fleet management problem faced by RELOAD, a branch of the Association of American Railroads (AAR). They developed methods to compile required data and to solve the problem effectively by decomposing the solution process into a sequence of time-space network subproblems.

Bojovic (2002) presented an optimal control model to determine the optimal number of homogeneous rail freight cars. The state space concept was employed to estimate uncertainty in loaded and empty car arrival times.

Godwin et al. (2008) proposed a simulation-based approach to determine the locomotive fleet size and associated deadheading policy in a rail network where freight trains do not operate according to a fixed schedule. A heuristic method based on a Petri net model was developed for assigning locomotives to tracks at a tactical level and for deadheading them.

Sayarshad and Ghoseiri (2009) developed a new multi-period mathematical optimization formulation and a simulated annealing (SA) approach for optimizing the fleet size and homogeneous freight car allocation where car demand and travel times are assumed to be deterministic and unmet demands are backordered. Their methodology provided decision support regarding yard capacity, unmet demand, and number of loaded and empty rail cars in railway networks. Sayarshad et al. (2010) built a mathematical model to optimize their three objectives of profitability, unmet demand, and service quality. They employed Pareto analysis to explore the tradeoffs. Sayarshad and Tavakkoli-Moghaddam (2010) proposed a two-stage stochastic programming model for optimizing the fleet size and freight car allocation in the rail industry under uncertain demand.

Klosterhalfen et al. (2014) developed a two-phase mathematical model to determine the optimal rail car fleet structure and size under uncertainty in demand and travel time. They employed a deterministic mixed integer linear programming (MILP) model in the first phase to optimize the fleet composition, while minimizing the total direct rail car cost under a given rail car availability. Optimal fleet size was determined by a stochastic inventory control model in the second phase.

Milenkovic et al. (2015) proposed a discrete model productive control (MPC) framework to simultaneously optimize the rail freight car fleet size and allocation. Demands and travel time of loaded and empty rail freight cars were considered as stochastic parameters. The authors employed an autoregressive integrated moving average (ARIMA)-Kalman approach to estimate the number of freight cars at a future time period over the prediction horizon. Two rail freight car inventory control models were proposed: a stochastic multi-period economic order quantity (EOQ) model and a single-period random newsboy model.

Rental

Wu et al. (2005) presented a linear programming model to determine the optimal rental truck fleet size and mix. Their model simultaneously considered operational decisions (including empty truck movement and vehicle assignment) and tactical decisions (including asset purchases and sales). Computational studies using simulated data for the truck-rental industry were conducted to show the effectiveness of the approach for solving large-scale problems.

Papier and Thonemann (2008) developed analytical queueing models for rental fleet sizing, fleet structuring (types of cars), and fleet leasing problems. Their model takes into account demand and rental time uncertainty, seasonality, and order batching. They derived an analytical expression for the service level, profit function, and efficient solution methods.

George and Xia (2011) studied the problem of determining the optimal number of vehicles to maintain in the fleet in a general vehicle rental system for profit maximization. The exact solution was obtained via an iterative algorithm.

Public Transportation

Kliewer et al. (2006) proposed a time-space-based network flow model for the multi-depot multi-vehicle-type bus scheduling problem (MDVSP), which minimizes total operational costs, including the costs of unloaded trips and waiting time. They devised procedures to significantly reduce the model size.

Marine Transportation

Depuy et al. (2004) proposed an integer programming model to address the optimization problem of layout design for a barge fleet. Their model assigned tow breakdown and building activities to various fleet locations. In addition, the model determined the minimum cost location for barge cleaning activities based on both fixed costs and travel costs to and from the cleaning locations.

Dong and Song (2012) proposed a mathematical model to address the container fleet sizing problem in liner services with uncertain customer demand and stochastic inland transport times. Constraints included meeting customer demand, adhering to the distribution requirements of laden containers, and repositioning empty containers. Three simulation-based optimization approaches were applied to solve the model.

Laake and Zhang (2016) proposed a deterministic mixed-integer programming model to jointly optimize strategic fleet planning and the selection of long-term spot contracts while maximizing total profit in tramp shipping. Their model can be used to provide decision support for rental renewal programs, specifically, when to sell, whether to buy old or new ships, and when to charter in or out vessels.

Healthcare

McCormack and Coates (2015) studied the optimization of vehicle fleet allocation and base station location for emergency medical services (EMS). The objective was to maximize the overall expected survival probability across multiple patient classes. An integrated genetic algorithm (GA) and simulation approach was developed to obtain quality solutions efficiently.

Summary

There is clear gap in the tactical-level fleet sizing optimization literature in terms of simultaneously optimizing fleet size, composition, and allocation under uncertainty.

The research described in this report addressed the following decisions: (1) how many vehicles of each type to acquire and retire, and thus the fleet size; (2) how many vehicles of each type to move between an OD pair to satisfy the estimated demand; and (3) the total shipments made and delayed (if necessary). The objective is to minimize the total fleet operation costs, which include the costs of owning, acquiring, and retiring a type of vehicle; the operating costs for a given type of vehicle to make a trip for an OD pair; and the penalty costs of delaying shipment. Uncertainties may be attributed to random customer demand, travel time, and vehicle productivity (especially for aging vehicles).

DETERMINISTIC OPTIMIZATION MODEL

We start with a deterministic fleet sizing optimization problem, which can be formally described as follows.

Consider a set I of sources to satisfy demand at a set of J destinations during a planning horizon of T time periods. The number of shipments to be satisfied at destination j in time period t is $Q_j(t)$. A set of K types of vehicles are available to deliver the shipments. The line-haul cost of the OD pair (i, j) covered by vehicle type k is C_{ijk} . The decision-maker needs to determine the number of different types of vehicles to acquire and retire in each time period, as well as the allocation of shipments to the available mixture of fleet vehicles. The objective is to minimize the total fleet costs. The model formulation can be written as shown below.

Sets

I : set of sources

J : set of destinations

A : set of OD pairs

K : set of vehicle types

T : set of time periods

Parameters

θ_k : cost of owning one vehicle of type k for one time period

λ_k : cost of acquiring one vehicle of type k

δ_k : cost of retiring one vehicle of type k

C_{ijk} : line-haul cost of OD pair $(i, j) \in A$ for a vehicle type k

γ : penalty for delaying one shipment per period

$Q_j(t)$: number of shipments to be satisfied at destination j in time period t

π_k : the percent of time that a vehicle of type k is available

$\Gamma(t)$: the duration of time period t

d_{ij} : travel time of OD pair $(i, j) \in A$

Decision Variables

$q_{ijk}(t)$: number of shipments carried by vehicle type k moved from i to j in time period t

$Q_j^{dly}(t)$: number of shipments delayed at destination j in time period t

$x_{ijk}(t)$: number of vehicles of type k moved from i to j in time period t

$v_{ik}(t)$: fleet size for type k vehicles at origin i in time period t

$\alpha_{ik}(t)$: acquisitions of vehicle type k at origin i in time period t

$r_{ik}(t)$: retirements for vehicle type k at origin i in time period t

Objective Function

Minimize:

$$\sum_{k,t,i} \theta_k v_{i,k}(t) + \sum_{k,t,i} \lambda_k \alpha_{i,k}(t) + \sum_{k,t,i} \delta_k r_{i,k}(t) + \sum_{i,j,k,t} C_{ijk} x_{ijk}(t) + \sum_{j,t} \gamma Q_j^{dly}(t) \quad (1)$$

Constraints

$$v_{i,k}(t) = v_{i,k}(t-1) + \alpha_{i,k}(t) - \gamma_{i,k}(t) \quad \forall i \in I, k \in K, t \in T \quad (2)$$

$$\sum_{i,k} q_{ijk}(t) + Q_j^{dly}(t) = Q_j(t) + Q_j^{dly}(t-1) \quad \forall t \in T, j \in J \quad (3)$$

$$q_{ijk}(t) \leq x_{ijk}(t) \quad \forall (i,j) \in A, k \in K, t \in T \quad (4)$$

$$\sum_j x_{ijk}(t) d_{ij} \leq \pi_k \Gamma(t) v_{ik}(t) \quad \forall i \in I, k \in K, t \in T \quad (5)$$

$$x_{ijk}(t), q_{ijk}(t), Q_j^{dly}(t), v_{ik}(t), \alpha_{ik}(t), r_{ik}(t) \geq 0 \quad (6)$$

The objective function (1) minimizes the total fleet costs, including five cost components: maintenance/operational costs of the existing fleet, acquisition costs, retirement costs, line-haul costs, and shipment delay penalty costs. Constraint (2) maintains the flow balancing relationship

on the fleet size, such that the fleet size of a certain vehicle type in one period equals that in the last period plus the acquisitions and minus the retirements in the current period. Constraint (3) states that the available shipments in one period should either be covered by the available fleet or delayed. Constraint (4) requires that the number of shipments covered by a certain vehicle type for an OD pair cannot exceed the number of same-type vehicles moved on the same OD pair. Constraint (5) ensures that the allocated hours of a type of vehicle at a source cannot exceed the available vehicle hours of the same type. Finally, Constraint (6) specifies that all decision variables are non-negative.

This project's model formulation is a linear program (LP), which does not require the fleet size to be integral. It is suitable for tactical-level planning rather than decision support at the operational level. An additional benefit of an LP model is that it can handle large-scale problems efficiently.

TWO-STAGE STOCHASTIC PROGRAMMING MODEL

To explicitly cope with uncertainty, we devised a two-stage stochastic programming model (Birge and Louveaux 2011). The model considers the number of shipments \tilde{Q}_j at destination j in the current time period to be random. Fleet sizing decisions concerning acquisition and retirement must be made here and now, while allocation and shipment delay decisions can be made after the random parameters are realized. The objective of the model is to minimize the first-stage fleet sizing cost plus the expected second-stage cost. The following new set and parameters are needed for describing the extended formulation of the two-stage stochastic program.

S : set of scenarios of random demand

Q_{js} : number of shipments at destination j in scenario s

p_s : probability for scenario $s \in S$ to occur

First-Stage Decision Variables

v_{ik} : fleet size for type k vehicles at origin i in the current time period

α_{ik} : acquisitions for fleet type k at origin i in the current time period

r_{ik} : retirements for fleet type k at origin i in the current time period

Second-Stage Decision Variables

Q_{js}^{dly} : number of shipments delayed at destination j in the next time period when scenario s occurs

x_{ijk_s} : number of vehicles of type k moved from i to j in the next time period when scenario s occurs

Objective Function

Minimize:

$$\sum_{k,i} \theta_k v_{ik} + \sum_{k,i} \lambda_k \alpha_{ik} + \sum_{k,i} \delta_k r_{i,k} + \sum_{i,j,k,s} p_s C_{ijk} x_{ijk_s} + \sum_{j,s} \gamma p_s Q_{js}^{dly} \quad (7)$$

Constraints

$$v_{ik} = \alpha_{ik} - \gamma_{ik} \quad \forall k \in K, i \in I \quad (8)$$

$$\sum_{i,k} x_{ijks} + Q_{js}^{dly} = Q_{js} \quad \forall j \in J, s \in S \quad (9)$$

$$\sum_j x_{ijks} d_{ij} \leq \pi_k \Gamma v_{ik} \quad \forall i \in I, k \in K, s \in S \quad (10)$$

$$v_{ik}, \alpha_{ik}, r_{ik}, Q_{js}^{dly}, x_{ijks} \geq 0 \quad (11)$$

Real fleet data from a local 3PL company in St. Louis were employed to examine the performance of these optimization models. The data set contained 12 months of data with 10 sources and 50 destinations. Preliminary computational study showed that the two-stage stochastic programming solution was a significant improvement over the deterministic solution based on point estimates of customer demand.

NEXT STEPS

The researchers have developed new optimization models to address the problem of tactical-level fleet sizing optimization in the context of an urban transit system with some unique characteristics.

This work has paved the way for the development of a more advanced solution approach. For instance, there is a need for a rolling horizon framework that embeds the optimization model developed in this project in each time period for real-life decision support. Additionally, the inputs to the two-stage stochastic program require some data-driven mechanisms to estimate the probability distributions of the random parameters. This can be achieved by implementing various forecasting and statistical methods to be integrated into the solution framework.

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