KEEPING TRUCKING IN-HOUSE: A DYNAMIC MULTI-ITEM SHIPMENT CONSOLIDATION MODEL FOR A MANUFACTURER-DISTRIBUTOR

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Introduction

From the perspective of a manufacturer-distributor (MD) such as Procter & Gamble, who manufactures a variety of products (item types) and who employs its own fleet of trucks to convey freight to its Distribution Centre (DC) from where individual orders are paddled to the retailers (R1, R2 etc.), what is the best consolidation and dispatch policy, and under which conditions? We aim to shed light on these practical questions from a dynamic modeling approach. Figure 1 displays of the problem setting at hand.

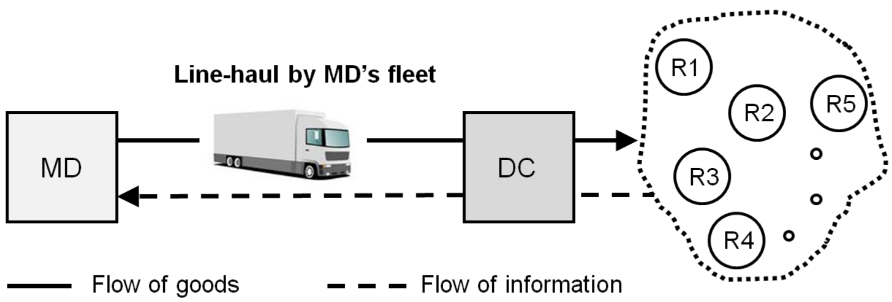

Figure 1. Pictorialization the problem setting

Shipment ConsoLidation (SCL) is a commonly used logistics strategy that combines two or more small orders or shipments so that a larger quantity can be dispatched on the same vehicle, to the same delivery zone. A good implementation of SCL may yield truckloads of savings by lowered unit transportation cost, and may reduce the carbon foot print of the freight. In so doing, shippers and carriers may benefit line-hauling at lower rates, thereby enabling discount economies to consignees. SCL can also enhance logistics customer service by allowing for faster and consistent transit times and fewer stop-offs (e.g., Hall, 1987; Buffa, 1988; Ülkü, 2012). The fundamental decision in developing an SCL policy is "when to dispatch" a consolidated load. Figure 2 shows the constraints that are most prevalent in implementing an SCL program. The appropriate SCL policy for inbound or outbound logistics essentially depends on the operating environment of the customer order characteristics, such as product type and due dates as well as the cost and transportation capabilities of the consolidating party. For example, a shipper (or consignor) can consolidate its orders going to a specific destination and ship them to the consignee (or receiver) using its own fleet. Alternatively, a carrier can consolidate orders from different shippers at a make-bulk terminal, line-haul a particular lane, and then break-bulk the consolidated load at the destination terminal for local deliveries to individual customers. The latter operation uses what is termed "common carriage," i.e., a for-hire trucking company. SCL primarily favors the carrier's pickup, delivery, and dock-handling costs (e.g., Crainic, 2003). We also note that trucking, in most parts of the world, is the major mode of transportation. For example, in 2002, trucks moved almost 60% U.S. commercial by weight. Although it is more expensive than rail, trucking industry, be it truckload (TL) or less than truckload (LTL), provides the benefits of door-to-door shipments with a shorter delivery time (Chopra and Meindl, 2016).

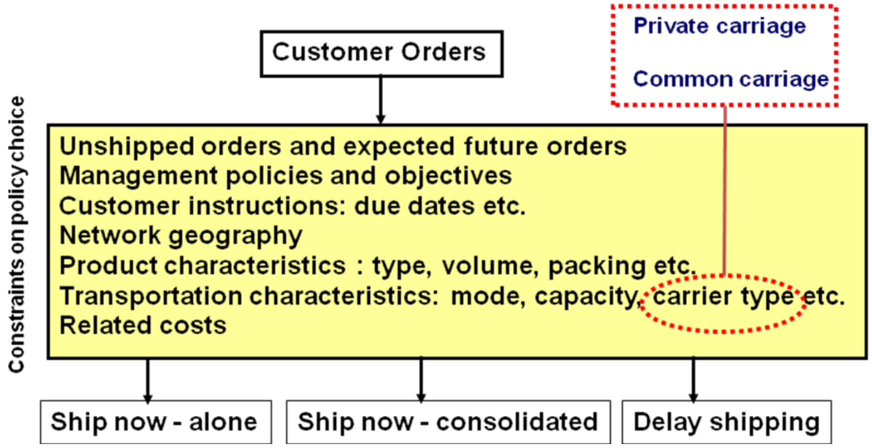

Figure 2. Policy variables for SCL programs (Adapted from Higginson and Bookbinder, 1994)

In this research, we introduce *Dynamic Multi-Item* Shipment Consolidation (DMISCL). Being a better representation of logistics industry practices, DMISCL arises when the orders (package, or LTL shipments) come for varying types of product, and it requires the decisions of continuing to consolidate a load (hold), versus shipping it now (dispatch) to be made at the *arrival* time of each order. DMISCL is a better representation of industrial practices.

The literature pertinent to DMISCL is scant. Close to our study, Higginson (1995) utilizes a recurrent-decision approach in the case of a "single item" with simpler costing mechanisms. Again for a single item, Bookbinder and Higginson (2002) obtain practical decision rules for temporal freight consolidation for a private carrier by employing results from stochastic-clearing systems. Brandimarte (2006) considers the stochastic version of the classical multi-item capacitated lot-sizing problem, where demand uncertainty is modeled by scenario trees. Also, a multi-product stochastic dispatch problem is studied by Papadaki and Powell (2003). As opposed to myopic policy we devise for DMISCL, they apply an approximate dynamic programming algorithm to minimize the total cost, over a finite horizon of discrete periods. On the other hand, Anily and Tzur (2005) study the deterministic version of the problem of shipping multiple items on vehicles, using dynamic programming. Another recent work on deterministic multi-item dispatch problem is that of Dror and Hartman (2007) in which they examine by using game theory the cost allocations for multiple items that are to be consolidated and shipped together.

The DMISCL model

The DMISCL, using myopic analysis, finds the optimal decision rules that yield the cost-minimizing dispatch time or quantity. (Table 1 displays model nomenclature.) We model this problem at its tractable generality. Then, we focus on numeric examples so as to reveal some managerial insights.

The *realized* total cost of dispatching a load accumulated by time *t*, denoted by $TC_d(t)$, can be found as

(1) $$TC_d(t) = D + \sum_{i=1}^{N}\left[h_i q_i(t) + \delta_{q_i(t)} \sum_{j=1}^{q_i(t)} c_i k_i (t - t_i^j)\right] \text{ where } \delta_{q_i(t)} = \begin{cases} 1 & \text{, if } q_i(t) \in \{1,\dots,m_i\} \\ 0 & \text{, otherwise} \end{cases}.$$

In Eq. (1), the SCL holding cost includes both a temporal and a fixed portion that is item-specific. A consolidated order of type-*i* accrues a cost over time until it is dispatched, i.e. $c_i k_i (t - t_i^j)$, plus a fixed cost of handling h_i. This formulation flexibility enables aggregation of individual costs of N item types. Also, the indicator function $\delta_{q_i(t)}$ zeroes the cost of an item if it is not included in the consolidated load.

Discounting of costs is plausibly not accounted for. The uncertainty in our DMISCL model comes from three sources: the arrival times, weights, and volumes of the randomly-arriving orders. First, we devise the probability that the weight of an order will conform to the residual "weight" capacity of the truck.

N	Total number of item types
i	Item-type index, $i = 1,..., N$
T	Length of a SCL period
t	Current time-marker since the last dispatch $(0 \le t \le T)$
L	Total loading and transportations time for the consolidated load
T_{max}	Maximum holding time for the first-arriving order
T^f	Forced dispatch time
T^*	Optimal dispatch time
C_V	Volume capacity of the vehicle
C_W	Weight capacity of the vehicle
D	Fixed cost of dispatching a vehicle
c_i	Consolidation cost per unit volume of per unit time of item type-*i*
h_i	Handling cost for item type-*i*
A_i	Random variable representing the interarrival time of item type-*i*
U_i	Random variable representing the weight of a unit-volume of item type-*i*
F_X, and f_X	Cumulative, and probability density function of a random variable *X*
λ_i	Poisson arrival rate for item type-*i*
t_i^j	Arrival time of the j^{th} order of type-*i*
k_i	Volume multiplier for item type-*i*, $(k_i \in \{1,..., C_V\})$
m_i	Maximum number of items of type-i that can fit the vehicle $(m_i = C_V / k_i)$
V_i	Volume of order type-*i* $(V_i = k_i \le C_V)$
W_i	Random variable representing the weight of order type-i $(W_i = k_i U_i)$
V_i^j	Realized volume of the j^{th} order of type-*i*
W_i^j	Realized weight of the j^{th} order of type-*i*
$q_i(t)$	Total number or type-*i* orders accumulated by time *t* $(q_i(t) \le m_i)$
$Q_S(t)$	System state vector by time *t* $(Q_S(t) = [q_1(t),..., q_N(t)])$
$Q(t)$	Total number of orders accumulated by time *t*
$R_V(t)$	Residual volume at time *t*
$R_W(t)$	Residual weight at time *t*
P_i	Probability that the next order arrival is of type-*i*
P_d	Probability that a new order arrives before the forced dispatch time
$P^{V_i}(t)$	Probability at time *t* that a type-*i* order fits the residual volume
$P^{W_i}(t)$	Probability at time *t* that a type-*i* order fits the residual weight
$P_f(t)$	Probability at time *t* that an arriving order can be included in the current load

Table 1. Model nomenclature and specifics used in DMISCL

Our model includes temporal probability computations. The weight constraint is especially important for heavy shipments that may "weigh out" the transport capacity. There might be plenty of room in the vehicle, yet the weight constraint might impede the loading of an additional shipment to achieve higher capacity utilization. This is generally the case when the items are dense (e.g., heavy metal). The probability that an arriving item type-*i* conforms to remaining weight capacity, $P^{W_i}(t)$, necessitates calculating the residual weight capacity by time *t*, $W_R(t)$ by $R_W(t) = C_W - \sum_{i=1}^{N}\sum_{j=1}^{m_i} W_i^{\,j}$. Recall that W_i denotes the random weight of item type-*i*. Then, we find $P^{W_i}(t) = \Pr\{W_i \le W_r(t)\}$. In our setting, it is assumed that orders are being weighed as they arrive. Data are recorded on the type of the item, arrival time and weight. (Weight is a single dimension, and thus is easier to measure than volume. Hence, upon arrival of each item, we have the realized value of its weight.

We emphasize that the order (shipment) of type-*i* itself is a *multiple* of the generic, unit volume weight of that type (U_i). This is a deliberate choice of modeling, so as to analyze the effects of packaging variability of the shipper on the vehicle packing efficiency of the carrier (the consolidating party). For example, the shipper may wish to pack his products in dozens. We model the total weight W_i of an order of type-*i* as the unit volume weight U_i (a random variable) multiplied by a scalar, a positive integer k_i. The shipment type can then easily be calibrated by industrial data: A light but bulky shipment type, for example, can be modeled by a high value of k_i and a low mean (and narrower support) of U_i. Then, $P^{W_i}(t) = \Pr\{k_i U_i \le R_W(t)\} = F_i(R_W(t)/k_i)$, and $P^{W_i}(t) \ge P^{W_i}(s+t)$ for $s \ge 0, t \ge 0$, and $s+t \le T$. That is the probability of fitting in the volume is non-increasing in time.

What is the probability that an arriving shipment (of random size) will fit to a truck? This is not an easy-to-answer question, for the following reasons. First, even if the weight constraint were not violated, the shape of the arriving shipment may not be known. The dispatch might be unnecessarily delayed in an attempt to include that order to include in the current consolidated load, and hence leading to extra cost. Second, even in the case of regularly shaped or modular packages, the exercise of fitting a shipment into the truck depends not only on the composition of the accumulated load, but also on how the pallets would be stacked in the vehicle.

The vehicle loading problem becomes prevalent when there are loading restrictions, or if the items or vehicles do not always have regular shapes. For example, pallets of some items can be stacked on top of other shipments but not underneath. Efficient packaging needs to account for loading rules and box orientations such as fixed, horizontal turn, and all-way (e.g., Hall, 1989). These patterns are also affected by questions of unit load, i.e. the use of pallets or boxes vs. loose freight. Attanasio et al. (2007) investigate, by a case study, the issues in joint dispatching and packing problem. Lim et al. (2005) give a recent survey of three-dimensional packing heuristics.

Therefore, in general, we will assume that the optimal loading of a given capacity (cargo loading problem) can be done *a priori*, and will be tabulated for various shipment types. The state space of the system will be bounded because the number of the item types is finite, and there are only a few variations in truck capacity as well.

We denote by $P^{V_i}(t)$ the probability that an item of type-*i* will fit in the residual space on the truck. Conditioning on the current load make-up, we can derive $P^{V_i}(t) = \Pr\{V_\mathrm{i} \le R_V(t) | Q_S(\mathrm{t})\}$, $\mathrm{i} = 1,\ldots,\mathrm{N}\}$

where $R_V(t) = C_V - \sum_{i=1}^{N}\sum_{j=1}^{m_i} V_i^j$. Naturally, this probability is defined only for $q_i(t) \le m_i$. Also, we devise the following structural property: $P^{V_i}(t) \ge P^{V_i}(s+t)$ for $s \ge 0, t \ge 0,$ and $s + t \le T$.

In our analysis, T^f denotes the "forced" dispatch time. That is, the vehicle has to be dispatched at or before T^f, regardless of the amount and the composition of the consolidated load at hand. T^f is related to the service level of the SCL policy. Though it might be more economical, even optimal in the sense of cost, to wait longer and consolidate a larger load that enables greater utilization of the truck, service to the first-arriving order might suffer. Hence, we apply a uniform maximum holding time ($T_{\max}$) initiated by the arrival of the first order. We note that $T_{\max}$ is an important managerial parameter, and define the forced dispatch time by $T^f = T_{\max} - L$, where L is the time it takes to load, line-haul, and unload a vehicle. In what follows, we regard L, as well as the costs associated with it, to be deterministic. $T_{\max}$ may be shorter or longer than the optimal SCL cycle time T^*. For a particular consolidation period, if $T_{\max}$ is larger than the optimal dispatch time, then we guarantee a cost-minimizing and timely delivery. If it is shorter, we trade-off between the service level (delivery lead time) and the cost that could have been reduced by waiting longer. In our formulation $T^* \le T^f$. Hence, any improvement in loading or unloading will be reflected as a reduction in L. Note also that L may be a function of the composition of the load; certain types of items might be less time consuming to load than others. Yet, we will assume L to be a constant value, determined by the dispatch practices of the MD.

Optimal dispatch rules for DMISCL

We have derived the *realized* cost of dispatching a consolidated load by time *t* in Equation (1). However, upon arrival of the shipment at time *t*, we could have decided not to dispatch but to hold the consolidated load until another shipment arrives, and then dispatch all together. Recall that the total number of shipments that have arrived by time *t* is defined as $Q(t) = \sum_{i=1}^{N} q_i(t)$. The realized total cost of dispatching $Q(t)$ shipments together is $TC_d(t)$. Suppose instead that this load is held until another shipment arrives at a later time *s*, $s > t$. Now, denote the expected interarrival time for type-*i* orders by $\overline{A}_i$. Conditioning on the type of the next-arriving item, the expected waiting time $\bar{s}$ before a state transition can be obtained by $\bar{s} = \sum_{i=1}^{N} P_i \overline{A}_i$. Again, conditioning on the type of item, the expected handling cost $\bar{h}$ for the next arriving shipment is simply $\bar{h} = \sum_{i=1}^{N} P_i h_i$. Let P_d be an upper bound for the probability that a new item arrives before T^f. Then, we find $P_d = \Pr\{\min(A_1,..., A_N) \le T^f\}$. Let now the probability that the arriving item will conform to the time, volume and weight constraints (i.e. *fitting* probability) by time *t* to be. Then, $P_f(t) = P_d \sum_{i=1}^{N} P_i P^{V_i}(t) P^{W_i}(t)$. The explicit inclusion of $P_f(t)$ in our DMISCL model possibly enables extra expected savings. For example, this happens when the rule implies to dispatch earlier than the forced dispatch time if the likelihood of a new item arriving within that limited time is almost nil.

We denote by $\overline{TC}_h(t)$ the *expected* cost of dispatching $Q(s) = Q(t) + 1$ shipments together at time $s > t$. This is the expected cost of holding the load until the next arrival of an item. Noting that this cost figure is calculated at time *t*, we then obtain

(2) $\overline{TC}_h(t) = TC_d(t) + \overline{C}(t)$ where $\overline{C}(t) = \overline{h} + \overline{s}\sum_{i=1}^{N} h_i k_i q_i(t)$.

Finally, the optimal DMISCL dispatch rules are summarized in Table 2. (Further details of the derivations and optimality proofs of these rules can be requested from the author.) Note that the structure of the decision rules differ with respect to the most commonly used logistics cost objectives.

Objective	Dispatch Rule
Cost per order	Dispatch if, $Q(t) \geq P_f(t)TC_d(t)/\overline{C}(t)$; otherwise, Hold.
Cost per volume	Dispatch if, $R_V(t) \leq C_V - [\sum_{i=1}^{N} P_i k_i] P_f(t)TC_d(t)/\overline{C}(t)$; otherwise, Hold.
Cost per weight	Dispatch if, $R_W(t) \leq C_W - [\sum_{i=1}^{N} P_i \int dF_i] P_f(t)TC_d(t)/\overline{C}(t)$; otherwise, Hold.
Cost per time	Dispatch if, $t \geq \overline{s}P_f(t)TC_d(t)/\overline{C}(t)$; otherwise, Hold.

Table 2. Summary of DMISCL optimal dispatch rules

Numeric Examples

In this section, to show the utility of the models developed herein, numerical examples are studied. MATLAB r8 is used to simulate the data and to obtain the results of the MDISCL dispatch rules. There are two types of items, type-*I* and type-*II*, whose interarrival time distributions are exponential and for which the unit-volume weights follow a uniform distribution; $A_I \sim \text{Expo}(1)$, $A_{II} \sim \text{Expo}(0.5)$, $W_I \sim \text{Uni}(1,2)$, and $W_{II} \sim \text{Uni}(3,4)$. Other parameters chosen are: $C_V = 30$, $C_W = 60$, $T_{\max} = 14$, $L = 2$, $D = 200$, $(k_I, k_{II}) = (1,2)$, $(c_I, c_{II}) = (1,1)$, and $(h_I, h_{II}) = (2,4)$. These parameter values are used as the "base case" values. To enable reasonable comparisons, the technique of *common random numbers* is employed (cf., Bratley et al., 2011).

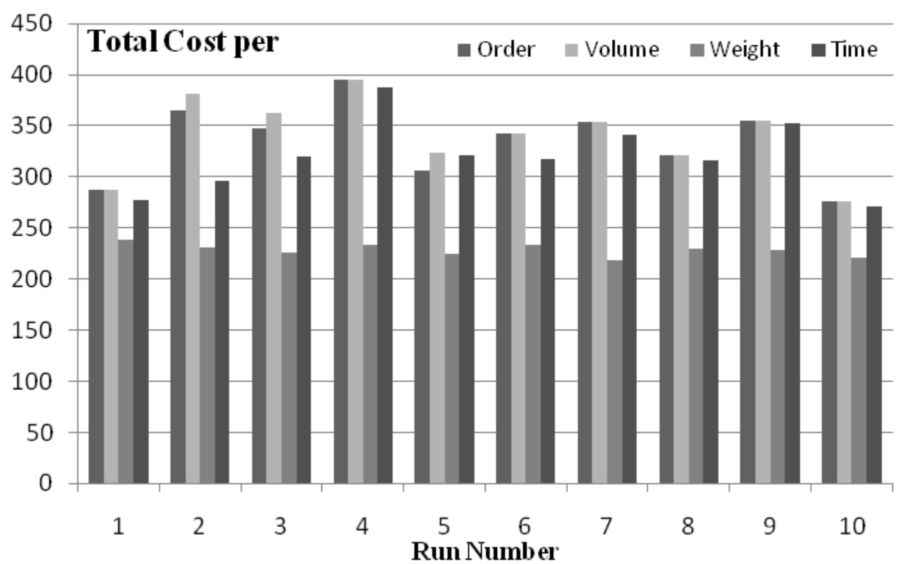

Figure 3. Cost-per-dispatch variability in decision objectives

A challenge in DMISCL is the appropriate determination of an objective function. Figure 3 displays the variabilities on the cost-per-dispatch for each objective considered. In our model, cost per dispatch for a particular objective, say cost per unit volume, is found by multiplying the realized (optimal) cost per unit volume by the volume accumulated in that SCL cycle. Similarly, we obtain other total cost variabilities.

Though this example is not statistically conclusive, again we can at least observe that the total cost variability for cost-per-unit weight is the smallest amongst the other objectives.

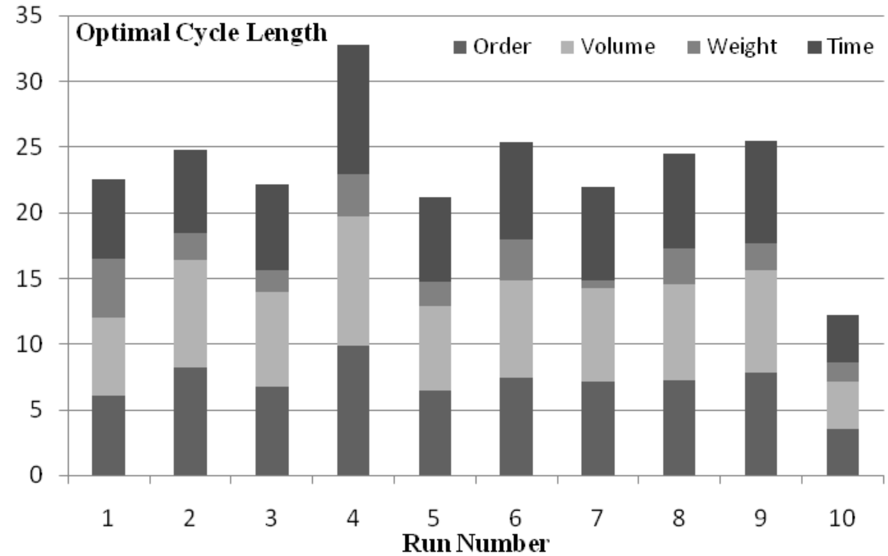

Figure 4. Variability of optimal SCL cycle length with respect to decision objectives

In Figure 4, the length of the optimal SCL cycle length is compared for each objective. This comparison is quite important because the length of a cycle directly affects the delivery times of the consolidated load, and thereby the service level. The variability ranges in the length of the consolidation cycle for the objectives of cost-per-order, cost-per-unit volume, and cost-per-unit time are within 6.25 time units, as opposed to that of 3.9 time units for the objective of cost-per-unit weight. Again, we can observe that cost-per-weight is a more stable objective as justified here.

The results of our other sensitivity analyses (not included here due to space limitation) reveal further insights into the behavior of optimal dispatch decisions: We observe, for example, that larger volume differences increase the chances of earlier dispatch. We note that as the maximum holding time decreases, the optimal SCL cycle time decreases as well. The optimal cycle length is observed to be non-decreasing in both volume and weight capacity, which in turn verifies the use of *modularization* in packaging. That is, if the MD can optimize trucking capacity in such a way that transportation costs are minimized, while vehicle utilization is increased, and a good logistics service is offered.

Final remarks

For the private carriage of a manufacturer-distributor, we investigated the impacts of load make-up and the item-specific order attributes (arrival rates, weights, and volumes) on the dynamic dispatch decisions about the timing and quantity of consolidated orders. We developed a new cost model for DMISCL which, if implemented by the use of transport data analytics, may greatly drive both economic and environmental costs out of the supply chain logistics. In a dynamic setting, we employed a novel concept of time-varying probability to tie the dispatching and load-planning decisions. Managerial implications along with simulation results, are reported. Naturally, due to its versatility, DMISCL model can also be modified to and applied in other modes of transportation, including intermodal. Our model can be also extended to suit the “common carrier” costing systems. Integrating DMISCL optimal dispatch decision rules to enterprise resource planning software would be the next step. Finally, explicitly including in the DMISCL the environmental impact performance metrics manifests itself as an important research venue.

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