Discrete order-splitting for a modal choice problem

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1 Introduction

In this paper, the inventory-theoretic approach is used to determine the optimal mix of transport alternatives when goods are shipped from a supplier (origin) to a receiver (destination). The optimal mix of transport alternatives refers to that particular combination of transport alternatives that results in the lowest total logistics costs for the receiver. It is assumed that only a limited number of different transport alternatives are available to ship the goods, each one having its own specific “logistics characteristics” such as loading capacity, transportation costs and lead time performance.

In the process of determining the optimal mix of transport alternatives, we make the assumption of “fixed order quantities and full capacity utilization”. This means that only those order quantities that are a linear combination of the total capacities of the different transport alternatives are feasible. In other words, if a certain transport alternative is selected to ship the goods from the supplier to the receiver, then its entire capacity is used.

Because of this assumption, the number of possible order quantities is finite and the problem of determining the optimal mix of transport alternatives becomes a combinatorial optimization problem. In a first step to explore the use of metaheuristics for optimization problems like these, we develop a simple Evolutionary Algorithm (EA). In each iteration (generation), the algorithm uses an initial population of solutions (parents), cross-over and mutation operators to generate new solutions (children). These solutions can be improved upon by local search operators.

2. Calculating Total Logistics Costs of a Mix of Transportation Alternatives

The total logistics costs of each combination of TA's consist of five elements, namely total order costs, total transportation costs, total costs of cycle stock, total costs of inventory in-transit and total costs of safety stock.

The total order costs are calculated by multiplying the costs per order by the number of orders placed, i.e. the number of TA's that are used to ship the goods from the supplier to the receiver. Hence, the larger the number of TA's used, the higher the total order costs. To calculate the total transportation costs, the transportation costs per TA are multiplied by the number of TA's used. This is done for each of the five TA's and the five resulting costs are added together. The total costs of cycle stock depend on the total delivery size that is generated by a particular combination of TA's. The larger this delivery size, the higher the costs of cycle stock. The calculation of the total costs of cycle stock is based on the procedure suggested in Moinzadeh and Lee (1989). To calculate the total costs of inventory in-transit, the average lead time per TA is multiplied by the number of TA's used. This, in turn, is multiplied by the value of the product and by the holding
cost. This procedure is repeated for each of the five TA's and the five resulting costs are added together. The final element of the total logistics costs are the total costs of safety stock. The level of safety stock that should be kept by the receiver depends on the pre-defined service level, which is 99% in our problem setting. Under the assumption that demand during lead time is normally distributed\(^1\), a service level of 99% implies that the safety stock should be equal to 2.33 times the standard deviation of demand during lead time (Blauwens et al., 2002). The calculation of this standard deviation involves four parameters, namely the average and variance of daily usage on the one hand, and the average and variance of the lead time of the fastest transport alternative on the other.

The concept of fastest transport alternative deserves some further explanation. We define it as the TA with the shortest average lead time, but we impose the extra condition that the sum of the quantities delivered by it and the quantities delivered by all faster TA's (if any) has to be at least five times the average daily usage. In a final step, the total costs of safety stock are obtained by multiplying the level of safety stock that results from the above analysis by the value of the goods and by the holding cost.

Hence, our method to calculate the safety stock is somewhat different from the approach followed in the traditional “order splitting” literature, which investigates situations where an order is split between several suppliers instead of being placed with one supplier. It has been shown that this supply strategy can reduce the total logistics costs under certain circumstances (see, e.g., Ganeshan et al., 1999). In the order splitting literature it is often implicitly assumed that the first part of the split order that arrives at the destination reduces the probability of stocking out for a sufficient amount of time, without specifying a minimum delivery size. To make sure that the solution generated fulfills this requirement, we make it explicit by requiring a minimum delivery size when determining the fastest transport alternative.

3. Determining the optimal mix of transport alternatives

In order to explore the use of metaheuristics for determining the optimal mix of TA’s, an Evolutionary Algorithm (EA) is developed.

**Constructing the initial population and selecting parents**

A solution to the optimization problem is a vector of integers, one for each transport alternative, indicating the number of times a particular TA is used. Note that the TA’s are sorted on their average lead time. For example \([20 \ 5 \ 0 \ 1 \ 0]\) denotes that the receiver simultaneously orders

\(^1\) This assumption is often made in logistics applications. However, it has been criticized in the literature (see, e.g., Tyworth, ...
twenty small trucks, five large trucks and one medium inland vessel from the supplier. No small or large vessels are used in this particular solution.

To construct the initial population of solutions, we consider two construction algorithms: I1 and I2. Construction algorithm I1 generates the integers in the solution based on the storage capacity of the receiver and the carrying capacity of the TA under consideration, regardless of how much of the storage capacity is already used by the other TA’s.

Because we want to randomly select the first parent proportionately to its fitness (roulette wheel scheme, Goldberg, 1989), the solutions are sorted according to their Annual TLC and a cumulative distribution is constructed to select the first parent based on a random number between 0 and 1. The second parent is not selected from the initial population, but is generated by the construction algorithm (I1 or I2) to maintain genetic diversity.

Cross-over and mutation

The new solutions (children) are generated by performing cross-over and mutation operators. In the current implementation, two simple one-point cross-over operators are used.

For both cross-over operators, the solution (child) with the lowest Annual TLC is selected. With a probability of 0.10 a mutation operator is then applied to the solution. The mutation operator randomly selects a TA, frees the capacity formerly used by that TA and generates a new integer for the solution vector.

Local searches

Two simple local searches, L1 and L2, are suggested to improve upon the new solutions generated after applying the cross-over and mutation operators. The L1 heuristic is based on the well-known 2-Opt improvement heuristic for the Vehicle Routing Problem. The L2 local search increases or reduces the number of times a TA is used in the incumbent solution.