SCATTER SEARCH OPTIMIZATION OF AN INLAND WATERWAY TRANSPORTATION SYSTEM

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ABSTRACT

This paper presents an optimization-simulation model for determining inventory operating policies for an inland waterway transportation system involving petroleum delivery. The overall process involves the use of a criterion model, represented as a decision maker's utility function, and an optimization procedure which employs scatter search. Variance reduction techniques are also employed in order to improve the accuracy of the estimates of the performance measures associated with the system. The main purpose of the system is to determine values for inventory policy variables such as the reorder points and reorder quantities at various network locations.

Keywords: Logistics, Simulation, Optimization, Inventory Modeling

1. INTRODUCTION

This paper describes a simulation-based decision support system for determining operating policies for a barge transportation system on an inland river system. In addition to a simulation model, the system relies on the input of a decision maker's utility function over conflicting performance measures, the use of standard variance reduction techniques, and an optimization procedure based on the heuristic optimization procedure, scatter search (Glover and Laguna 2000).

The next section of this paper gives a brief description of the system under study and the associated simulation model. The third section of the paper gives an overview of the decision support system, including a discussion of the utility function, the optimization methodology, and the variance reduction techniques employed. The fourth section of the paper provides an illustrative example of the use of the system. Finally, the fifth section of the paper provides a summary and conclusions.

2. DESCRIPTION OF THE TRANSPORTATION SYSTEM AND MODEL

The application was developed to aid a decision maker in a complex, stochastic environment. The Arena software package (Kelton, Sadowski, and Sturrock 2007) was chosen as a base for the DSS. The flexibility of Arena is demonstrated in this research as the DSS includes Arena modules, SIMAN blocks, imbedded Visual Basic for Applications, and is manipulated by external Visual Basic code.

The objective of this study was to determine the best values for reorder points and reorder quantities for fuel deliveries in an inland waterway system. The fuels are delivered to six locations on the river system. All trips begin and end at a supply location, Location 6. Locations 1 through 5 are upriver of Location 6, while Location 7 is downriver. The fuels are delivered by a tow system. Each tow consists of four barges; a barge is made up of ten tanks. A barge can be loaded with either all diesel or all non-diesel fuel, i.e., diesel and non-diesel cannot be mixed within a barge. However, diesel and non-diesel can be mixed within a tow. The system operated according to a reorder point, order –up-to quantity. That is, the main control variables associated with the inventory policy were the reorder point and the maximum capacity for each storage tank (i.e., demand point).

There is one supply location in the system, and it is assumed that this supply point never runs out of fuel. Barges are loaded at a rate of 5000 barrels per hour, and unloaded at a rate of 2800 barrels per hour.

The simulation model employs respective variables to represent the fuel levels of various types at each location in the system. Each day an entity is created for each fuel at each location. This entity decrements the level of the variable representing the level of that fuel type for that particular location. If the level of the on-hand inventory is below a set reorder point, a check is made to determine if there is a stockout situation. If there is a stockout, a counter is incremented and a mechanism is invoked to record the amount of time associated with the stockout.

The entity can now be thought of as an order to replenish inventory.

Depending on the destination of the fuel, the tow will travel through one or more set(s) of locks. The stochastic nature of the locking process is accounted for in the simulation model. Based on historical data, the locking times are assumed to follow a triangular distribution with a minimum of one hour, a maximum of three hours, and a mode of two hours.

Upon arriving at the lock, the tow attempts to seize a resource representing the lock. If this resource is busy, the tow waits in queue for passage through the lock. The locking time, or time required to traverse the lock, is a source of uncertainty in the model. The tow travels to its destination, seizing and delaying at locks as required. In this way, the tow is delayed for the appropriate travel time to and from its destination. When the tow arrives at its destination, each entity is then routed to the appropriate storage based on its attributes, where it decrements the total number of orders in the system and increments the level of inventory.

3. SCATTER SEARCH OPTIMIZATION, UTILITY FUNCTION, AND VARIANCE REDUCTION

The decision support system consists of several components, including the simulation model, an optimization procedure based on scatter search, a utility function to represent the tradeoffs that the manager is willing to make between the various performance measure associated with the system, and a procedure to allow for variance reduction with respect to the estimates of these performance measure values. The basic simulation model was described in the previous section of the paper. This section will describe the optimization algorithm, the utility function, and the variance reduction techniques employed.

The optimization algorithm used for this application was scatter search. As noted by Glover, Kelly, and Laguna (1999), "Scatter search focuses on generating relevant outcomes without losing the ability to produce diverse solutions, due to the way the generation process is implemented." For example, newly generated points are not convex combinations of the initial points. These new points are extrapolations, containing information not contained in the initial reference points.

Scatter search employs two concepts to guide its search: quality and diversity. The quality of a solution refers to the value of the objective function, while the diversity of a solution set refers to the differences between pairs of solutions in the reference set. Requiring a specified level of diversity helps to assure that the procedure will not get trapped at a local optimum. The basic scatter search design can be described as follows.

The diversification generation method is employed to "generate a starting set of solutions to guarantee a critical level of diversity" (Laguna and Marti 2003). For the purpose of the diversification generation method, the application divides the range of each decision variable value into four subranges of equal size. A solution is then constructed in two steps; a subrange is randomly selected, and then a value is randomly generated from the selected subrange. The diversification generation method focuses on the diversity of the solutions and not the quality. Each solution is then passed to the improvement method.

The improvement method is used to improve the set of diverse solutions, thereby producing a set, denoted by R. The improvement method used for this application is Nelder and Mead's (1965) simplex method. This method is a classical numerical search technique for unconstrained nonlinear optimization problems. The improvement first constructs the current simplex for each diverse solution. The construction of the initial current simplex requires an initial point and a step factor, or distance between two vertices. The initial point is generated by the diversification generation method, while the step factor is input by the decision maker.

The improvement of diverse solutions is repeated until the set R contains the number of unique members specified by the decision maker. The reference set is typically small, made up of no more than 20 solutions. The Reference Set Update Method is then invoked.

The Reference Set Update Method is used to designate a reference set of the best solutions. The best solutions are not based solely on objective function value. A solution may be added to the reference set if it improves the diversity of the set even when the objective function value of the solution is inferior. In this way the reference set includes both high quality and high diversity members from the improved solutions.

The decision maker specifies the size of the reference set, b, at the start of the procedure. The Reference Set Update Method forms two mutually exclusive subsets, b_1 and b_2 such that $b_1 \cup b_2 = b$, so $|b_1| + |b_2| = |b|$, where b_1 represents the subset of high quality solutions and b_2 represents the subset of high diversity solutions. The reference set, *RefSet*, is formed as follows: The set R of improved diverse solutions is sorted in ascending order based on objective function value. The top $|b_1|$ solutions are added to *RefSet* and removed from R. The remaining $|b_2|$ members of *RefSet* are added based on a maximum value of minimum Euclidean distance as follows: For each remaining member of R, we calculate its Euclidean distance from each member of *RefSet*. The minimum Euclidean distance for each member of R is stored. The member of the set R with the maximum minimum Euclidean distance metric is removed from R and added to *RefSet*. We then calculate the Euclidean distance for each remaining member of R to each member of *RefSet* and repeat the process until the size of *RefSet* is that specified by the decision maker.

The Subset Generation Method consists of generating subsets from the reference set that will be used for creating new solutions. The subsets generated in the Subset Generation Method consist of all two element pairs. The number of this type of subset is $(|b|^2 - |b|)/2$. These subsets are then combined using the Solution Combination Method. The Solution Combination Method is used to develop new solutions based on structured combinations of the subsets generated in the Subset Generation Method. These combinations are structured to create points "both inside and outside the convex regions spanned by the reference solutions" (Laguna and Marti 2003).

The individual subset solutions formed by the Solution Combination Method are then improved using the Improvement Method as previously described.

The reference set is then updated as previously described and the stopping criteria are checked. The improved solutions are sent to the Reference Set Update Method and the process iterates until the stopping criteria are met.

The stopping criteria can be based on the decision maker's preferences in terms of the membership of the reference set, the number of iterations, or the elapsed time. For example, when the reference set is updated, it is checked for new members. If all members or a specified number of members are new, the process is repeated. If no new members have been added, the process stops. The decision maker can alternatively specify the number of iterations after which the best solution found thus far will be selected. Finally, the decision maker can specify a time limit on the search. For the purposes of the applications described in this paper, the decision maker is asked to specify a number of iterations as the stopping criteria.

The objective used to guide the scatter search optimization procedure is the maximization of expected utility This is a single attribute utility function, in which the attribute is the overall cost, as a function of the reorder point and reorder quantity settings. The costs considered include the total penalty cost (TPC), variable transportation cost (VTC), and the total inventory holding cost (IHCTotal).

The total penalty cost (TPC) is the sum of the product of the number of backorders (BO) and the backorder cost (BOC) and the product of the penalty cost (PC) and the number of days with zero inventory (Penalty) as shown in below.

$$TPC = (BO * BOC) + (PC * Penalty) \quad (1)$$

After decrementing the inventory, the entity checks the level of the inventory versus the reorder point. If the inventory is below the reorder point, the entity then checks whether or not the inventory is negative. If the inventory is negative the entity increments the value of the variable BO by one. The values of BOC and PC are set and do not change during the simulation run.

The Variable Transportation Cost (VTC) is the product of a per mile transportation cost (PMTC) and the distance traveled (DT) as follows:

$$VTC = PMTC * DT \quad (2)$$

The value of PMTC is set and does not change during the simulation run.

The Inventory Holding Cost (IHCTotal) is the sum of the individual inventory holding costs for each of the six fuel types at each of the six locations. The individual IHC's are calculated as the product of three terms: the average level of inventory for a specific fuel at a specific location in units of barrels, a constant h (a holding charge in units of \$/barrel/day), and D (the number of days simulated). The average level of inventory of fuel could be a negative number; therefore the individual holding cost for fuel type i at location j is calculated as shown below.

$$IHC_{ij} = \max(DAVG(fuel_i \text{ at } location_j) * h * D, 0) \quad (3)$$

IHCTotal is then simply the sum of the individual inventory holding costs over all fuel types and locations. Finally, the total solution cost (TSC) is calculated as the sum of TPC, VTC, and IHCTotal. The output from the simulation model is a single value describing the cost for a specific vector of reorder point settings.

Each evaluation performed as part of the optimization procedure discussed above involves the employment of the simulation model. Several replications are made at each design point in order to obtain an estimate of the expected utility for that design point. In order to improve the accuracy of the estimates (i.e., reduce the variances), two common variance reduction techniques are employed.

The variance reduction techniques (VRTs) used in this application are common random numbers and antithetic variates. Common random numbers (CRN) is perhaps the most widely used VRT. Janssens, Deceuninck, and Van Breedam (1995) explain that the CRN methodology is usually used to estimate the difference between the expected performance measures of multiple systems. The CRN method uses the same underlying uniform random numbers to drive the simulation and to make sure that these random numbers are used at exactly the same place for each system. The basic idea is that the random noise will be the same for both systems; therefore the observed differences between the systems will be due to their differences, not random noise.

The concept of antithetic variates (AV) resembles CRN. L'Ecuyer (1994) explains that the idea is that very unlucky events in the first simulation should be compensated by "antithetic" very lucky events in the second one and vice versa, thus reducing the variance on average. So, we run the model using a sequence of underlying IID uniform deviates, *U*'s, to drive the simulation for computing the unbiased estimate of the mean, for example, then we drive the simulation using the antithetic sequence, (1 – *U*)'s, to compute another unbiased estimate of the mean. The average of these two then becomes our new estimate for the mean, which should have a smaller variance.

4. AN ILLUSTRATIVE APPLICATION

Various runs were made for three types of utility functions, involving a "decision maker" who was either risk averse, risk prone, or risk neutral. Note that a risk neutral decision maker is the same as one who wishes to minimize total expected cost.

The decision maker initializes the start of the operation associated with the decision support system by setting values for a series of parameters, including the initial inventory levels and lower and upper bounds for all tanks, the capacities associated with the barge-tow configurations, and the parameter for the scatter search and Nelder and Mead simplex search schemes.

The simulation is set up for a one-year run in real time. For the risk averse case, a total of 142,238 replications at various design points, and expected utility was improved from an initial value of .915 to a final value of .973 through the search process.

5. SUMMARY

This paper has illustrated how various modeling techniques, including heuristic optimization procedures such as scatter search, simulation modeling, variance reduction methods, and utility functions can be merged to solve a complex problem in logistics.

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