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OPTIMIZATION OF A BARGE TRANSPORTATION SYSTEM FOR PETROLEUM DELIVERY

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ABSTRACT

This paper describes a simulation model of a liquid fuel supplier operating on the Ohio River. Each day, orders arrive for six different fuel types at six different locations. The goal of this study was to determine the appropriate number of tow boats required to meet the demand for fuels. The system was analyzed using Arena and OptQuest.

1 INTRODUCTION

The objective of this model was to determine the best configuration and schedule of dedicated tows to deliver volumes of six liquid fuel products to six distinct locations. To accomplish this goal, we had to determine the number of dedicated boats required to meet the demand for fuel, including having a pool of available barges vs. dedicated tows made up of dedicated barges and boats. The six liquid petroleum commodities and their respective code used in the model are shown in Table 1.

Table 1: Petroleum Product Codes

Product	Code
Oxygenated Unleaded Regular	O_ULR
Oxygenated Unleaded Premium	O_ULP
Conventional Unleaded Regular	C_ULR
Conventional Unleaded Premium	C_ULP
Low Sulfur #2	LS_2
High Sulfur #2	HS_2

The fuels are delivered to six locations on the river system. All trips begin and end at Mt. Vernon. The specific demands, in barrels per day, for the six products at the six locations are shown in Table 2. Owensboro, Louisville, and Cincinnati are upriver of Mt. Vernon, while Paducah is downriver.

The configuration of a tow is as follows; a tow is made up of four barges, a barge is made up of 10 tanks (two each of five different sizes). A barge can be loaded with either all diesel or all non-diesel fuel. This means a barge can have any number of tanks of LS_2 and HS_2 but diesel and non-diesel cannot be mixed within a barge. However, diesel and non-diesel can be mixed within a tow.

Initial modeling assumptions included:

1. The supply location, Mt. Vernon, never runs out of fuel.
2. Barges are loaded at a rate of 5000 bbls/hr, 1 barge at a time.
3. Barges are unloaded at a rate of 2800 bbls/hr, 1 barge at a time.

2 DESCRIPTION OF THE SIMULATION MODEL

The Arena model works as follows. Each fuel level at each location is represented by a variable. 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. Figure 1 shows an example of the create submodels. For example, the demand for C_ULR at the Node 4 location is 1114 bbls./day, so following the logic in Figure 1, the create node generates one entity every 24 hours. That entity reduces the level of the on-hand inventory of C_ULR Owensboro(4) by 1114 bbls then is assigned two attributes called Fuel_Type and Destination_ID. These attributes are later used for decisions, batching, etc. The entity then arrives at the decision node where it can either be disposed or sent on to batch an order to replenish the on-hand inventory of C_ULR Owensboro(4). If the level of the on hand inventory is below a set reorder point, the entity can now be thought of as an order to replenish inventory. If the level of inventory is above the reorder point, we've already decremented the level of the inventory, so the entity is disposed. The assign node is used to increment the total

Table 2: Petroleum Demand Quantities by Location

Destination	C_ULP	C_ULR	HS_2	LS_2	O_ULP	O_ULR
Cincinnati(1)	2732	10764	2236	1262	470	2539
Louisville(2)	758	2990				
Louisville(3)	1183	5962	1623		700	3787
Owensboro(4)	205	1144				
Owensboro(5)	58	699	264	449		
Paducah(7)	1115	5886				

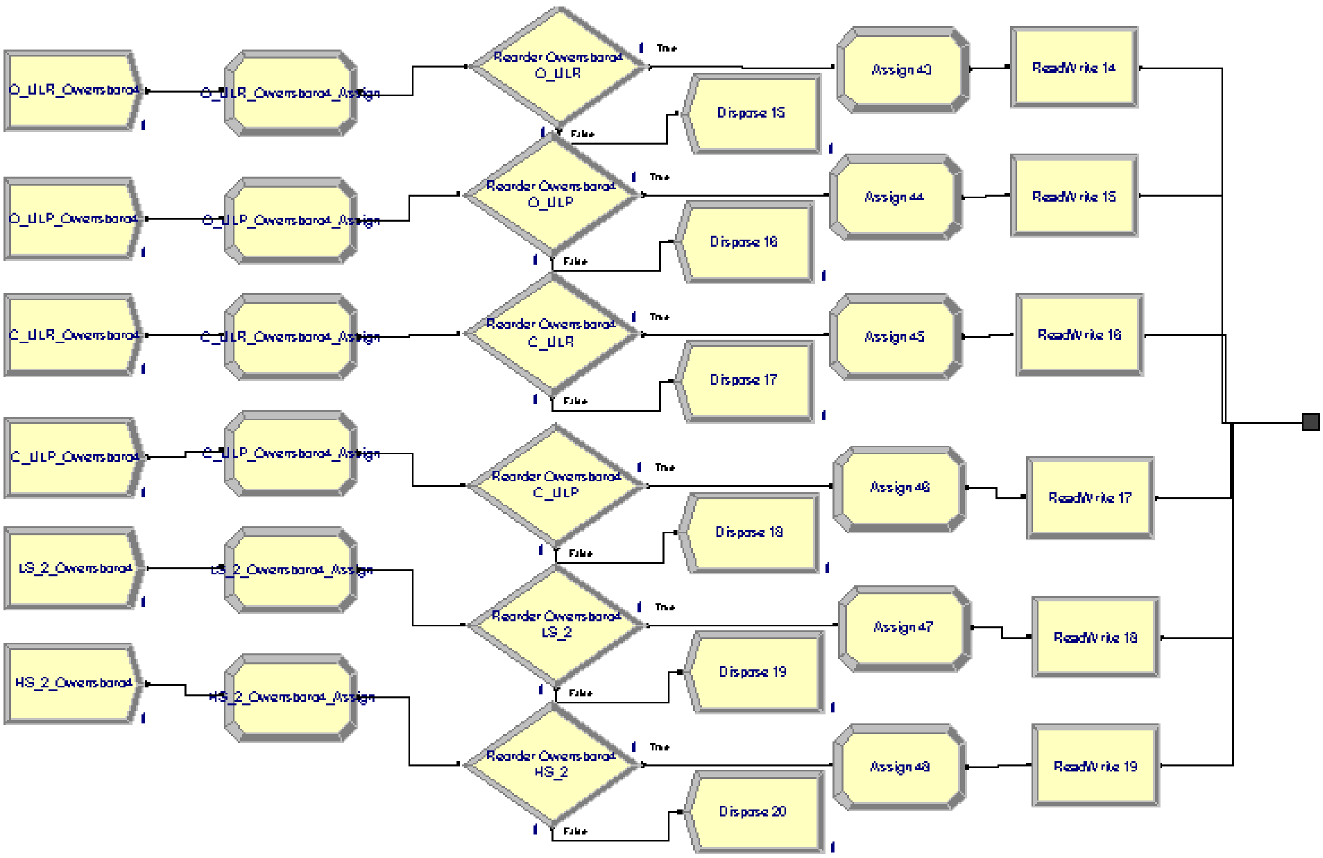

Figure 1: Example of Create Submodel

orders in the system and manipulate other statistics. The entity reads the size of the tank it will be seizing from "strapping tables" in space delimited text format. Each barge has either 8 or 10 tanks of varying sizes.

Figure 2 shows an example of the further logic in the model. The first Decide Module is used to separate the diesel fuel from the non-diesel fuel. Recall that a barge can be loaded with either all diesel or all non-diesel fuel; this means that we are not allowed to mix diesel and non-diesel within a barge. We can, however, mix diesel and non-diesel within a tow. When the two main categories of fuel are separated, the entities are batched in sizes of 10 to form barges. Four barges are then batched together to form a tow. The tow is now a complete shipment ready for loading and transport. The batch seizes a boat and is delayed for loading for 20 hrs. The tows, made up of four barges, have a capacity of 100,000 bbls. The tow is then delayed for the appropriate travel time to its destination. The delay for unloading at the destination is next. The tow is unbatched into the four barges, next the four barges are unbatched into the forty entities. Each entity is then routed to the appropriate Assign Module based on its attributes, where it decrements the total number of orders in the system and increments the level of inventory. The forty entities are batched back together and delayed for the travel time back to Node 6, where the boat is released.

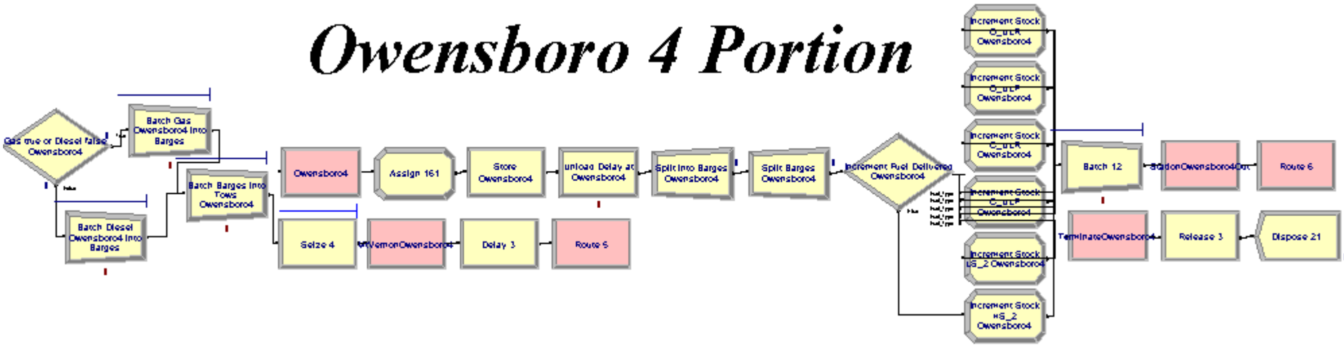

Figure 2: Further Model Logic Example

3 DEVELOPMENT OF A CRITERION MODEL

One purpose of this paper is to illustrate how a variety of criterion models can be interfaced with a simulation model of a system.

Optimization of a system through the use of a simulation model is difficult for several reasons, including:

1. Typically a simulation model can output a large number of conflicting performance measures for a system. It is a rare situation for a design to yield a good set of values for all of the performance measures; i.e., tradeoffs must be made among the performance measures in choosing a particular design. A criterion model can be used to implicitly represent the tradeoffs that a decision maker is willing to make among the performance measures.
2. Since a simulation model is used to implicitly represent the relationships between the control variables and the performance measures of the relevant system, one does not have access to a closed-form algebraic representation of this relationship, unless one is willing to use the simulation model to develop some type of "metamodel". This fact limits the choice of optimization techniques available.
3. In addition to not being of a closed form, the relationship referred to above is typically of an uncertain nature. That is, one can only obtain <u>estimates</u> of parameter values associated with random variables, along with associated confidence intervals. Hence, in developing a criterion model for a particular design situation, one must account for the inherent risk/uncertainty.

In the petroleum transportation model discussed above, potential decision variables would include 36 reorder point values (one for each combination of the six products and the six destinations), along with the number of tows. Potential performance measures would include:

1. The number of lost sales due to a "stock-out".
2. Variable transportation costs (related to total distance traveled by the tows).
3. Fixed transportation costs (related to the number of tows used in the system).
4. The carrying charges associated with the inventories of petroleum.

As with all inventory design problems involving uncertain demand and lead times for inventory delivery, there is an inherent conflict between minimizing the costs associated with maintaining inventory and maximizing the level of customer service.

Any one of several different criterion models could be used to address the tradeoffs that the decision maker is willing to make among the objectives. For example, one might use a model that minimizes the expected costs associated with categories two, three and four above subject to constraints on lost sales and on the width of the confidence interval associated with expected cost. Another criterion model might involve the maximization of expected utility, where utility would be a function of two performance measures, or attributes: expected cost, and number of lost sales. One advantage of using a utility function is that it would implicitly account for the uncertainty in the performance measure values (for a particular set of values for the control variables) and the resulting risk that the decision maker is willing to take.

Our initial experimentation with OptQuest, described below, involved a relatively simple criterion model in which the number of lost sales was to be minimized.

4 EXPERIMENTATION WITH OPTQUEST

With very little modification to the Arena model, we were able to create a scheduling tool that could be used to aid to company in their order fulfillment and scheduling operations. The main drawback of this scheduling tool is that it takes the input of the user and forecasts how the system will behave based on those inputs. As a result, we can be quite confident that we are failing to find a very good solution. For example, we set the reorder points based on experimentation with different levels and the effects of said levels. This meant that our solution may have been good, but not necessarily optimal. The model was further enhanced to enable the use of OptQuest to determine the appropriate levels for the reorder points. The objective of the example considered in this paper is to determine the optimal reorder points for six different types of liquid fuels at six different locations on the Ohio River. The upper bound on each reorder point was set at 150,000 bbls. An example of the Control Selection screen of OptQuest is shown in Figure 3.

The model was also modified to include an additional variable, called penalty. Whenever any of the fuel inventories drops below zero at any location, the value of penalty is incremented by 1. Our objective was to minimize the value of penalty, thus minimizing the number of stock outs experienced. The Objective and Requirements Selection screen is shown below in Figure 4.

The optimization was run for 1 hour and the best result for the reorder point was obtained. Since this was to be a new contract for ACBL, the model assumed no inventory at the start of simulation, so some stock outs would inevitably occur. The model was then further modified to read in the results of the optimization to set the reorder points for the various fuels. We then ran the model again, generating a schedule to show ACBL not only how to deliver to best meet the demand for fuels, but also how long they could expect the transient period of stock outs to last. Figure 5 shows the best results obtained using OptQuest.

The results from OptQuest were then used to prime the Arena simulation model. The simulation model was modified to write the inventory levels, i.e. the values of the various variables, of each fuel at each location every 12 hours. The time persistent values of theses inventory levels are shown in Figure 6. As shown in Figure 6, we can expect a transient stock-out period to last approximately 3000 hrs. ACBL would probably choose to use more towboats during this time period to minimize the stock outs. The model does show that 3 towboats will handle the demand for fuel once we move past the transient period of building inventories.

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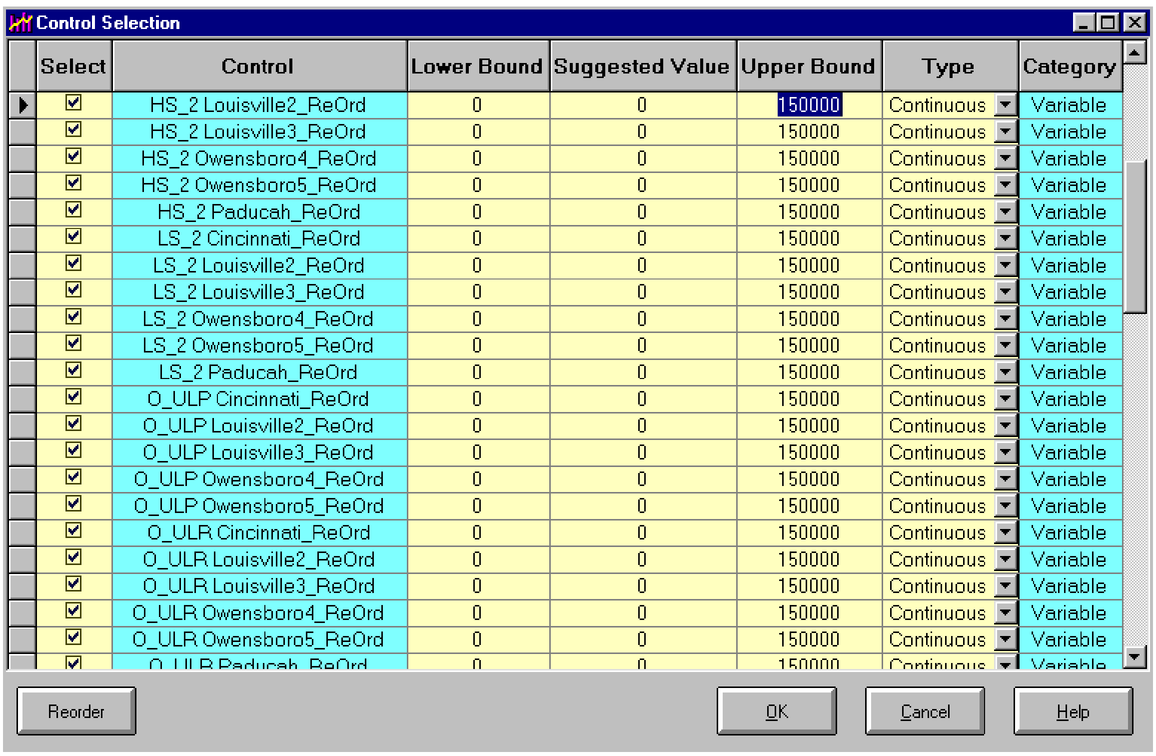
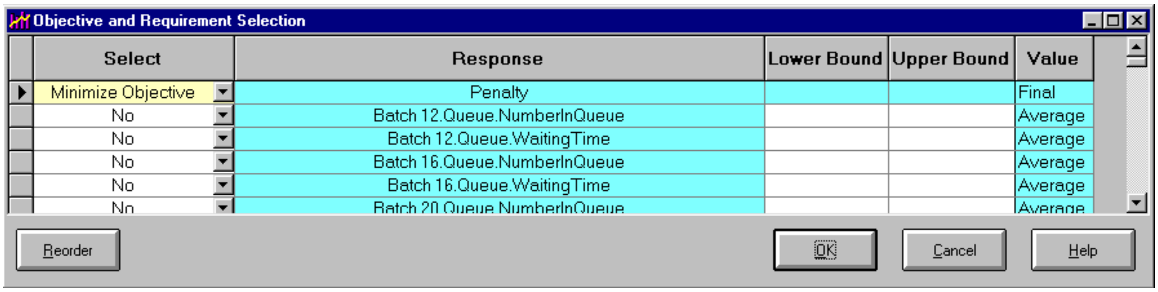

Control Selection

Select	Control	Lower Bound	Suggested Value	Upper Bound	Type	Category
☑	HS_2 Louisville2_ReOrd	0	0	150000	Continuous	Variable
☑	HS_2 Louisville3_ReOrd	0	0	150000	Continuous	Variable
☑	HS_2 Owensboro4_ReOrd	0	0	150000	Continuous	Variable
☑	HS_2 Owensboro5_ReOrd	0	0	150000	Continuous	Variable
☑	HS_2 Paducah_ReOrd	0	0	150000	Continuous	Variable
☑	LS_2 Cincinnati_ReOrd	0	0	150000	Continuous	Variable
☑	LS_2 Louisville2_ReOrd	0	0	150000	Continuous	Variable
☑	LS_2 Louisville3_ReOrd	0	0	150000	Continuous	Variable
☑	LS_2 Owensboro4_ReOrd	0	0	150000	Continuous	Variable
☑	LS_2 Owensboro5_ReOrd	0	0	150000	Continuous	Variable
☑	LS_2 Paducah_ReOrd	0	0	150000	Continuous	Variable
☑	O_ULP Cincinnati_ReOrd	0	0	150000	Continuous	Variable
☑	O_ULP Louisville2_ReOrd	0	0	150000	Continuous	Variable
☑	O_ULP Louisville3_ReOrd	0	0	150000	Continuous	Variable
☑	O_ULP Owensboro4_ReOrd	0	0	150000	Continuous	Variable
☑	O_ULP Owensboro5_ReOrd	0	0	150000	Continuous	Variable
☑	O_ULR Cincinnati_ReOrd	0	0	150000	Continuous	Variable
☑	O_ULR Louisville2_ReOrd	0	0	150000	Continuous	Variable
☑	O_ULR Louisville3_ReOrd	0	0	150000	Continuous	Variable
☑	O_ULR Owensboro4_ReOrd	0	0	150000	Continuous	Variable
☑	O_ULR Owensboro5_ReOrd	0	0	150000	Continuous	Variable
☑	O_ULR Paducah_ReOrd	0	0	150000	Continuous	Variable

Reorder OK Cancel Help

Figure 3: Control Selection Screen from OptQuest

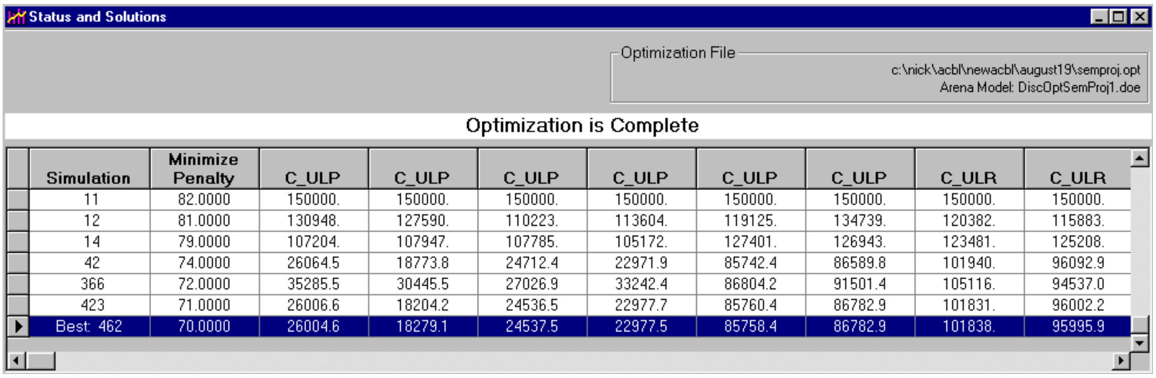


Objective and Requirement Selection

Select	Response	Lower Bound	Upper Bound	Value
Minimize Objective	Penalty			Final
No	Batch 12.Queue.NumberInQueue			Average
No	Batch 12.Queue.WaitingTime			Average
No	Batch 16.Queue.NumberInQueue			Average
No	Batch 16.Queue.WaitingTime			Average
No	Batch 20.Queue.NumberInQueue			Average

Reorder OK Cancel Help

Figure 4: Objective and Requirements Selection Screen from OptQuest



Status and Solutions

Optimization File

c:\nick\acbl\newacbl\august19\semproj.opt

Arena Model: DiscOptSemProj1.doe

Optimization is Complete

Simulation	Minimize Penalty	C_ULP	C_ULP	C_ULP	C_ULP	C_ULP	C_ULP	C_ULR	C_ULR
11	82.0000	150000.	150000.	150000.	150000.	150000.	150000.	150000.	150000.
12	81.0000	130948.	127590.	110223.	113604.	119125.	134739.	120382.	115883.
14	79.0000	107204.	107947.	107785.	105172.	127401.	126943.	123481.	125208.
42	74.0000	26064.5	18773.8	24712.4	22971.9	85742.4	86589.8	101940.	96092.9
366	72.0000	35285.5	30445.5	27026.9	33242.4	86804.2	91501.4	105116.	94537.0
423	71.0000	26006.6	18204.2	24536.5	22977.7	85760.4	86782.9	101831.	96002.2
Best: 462	70.0000	26004.6	18279.1	24537.5	22977.5	85758.4	86782.9	101838.	95995.9

Figure 5: Output from OptQuest

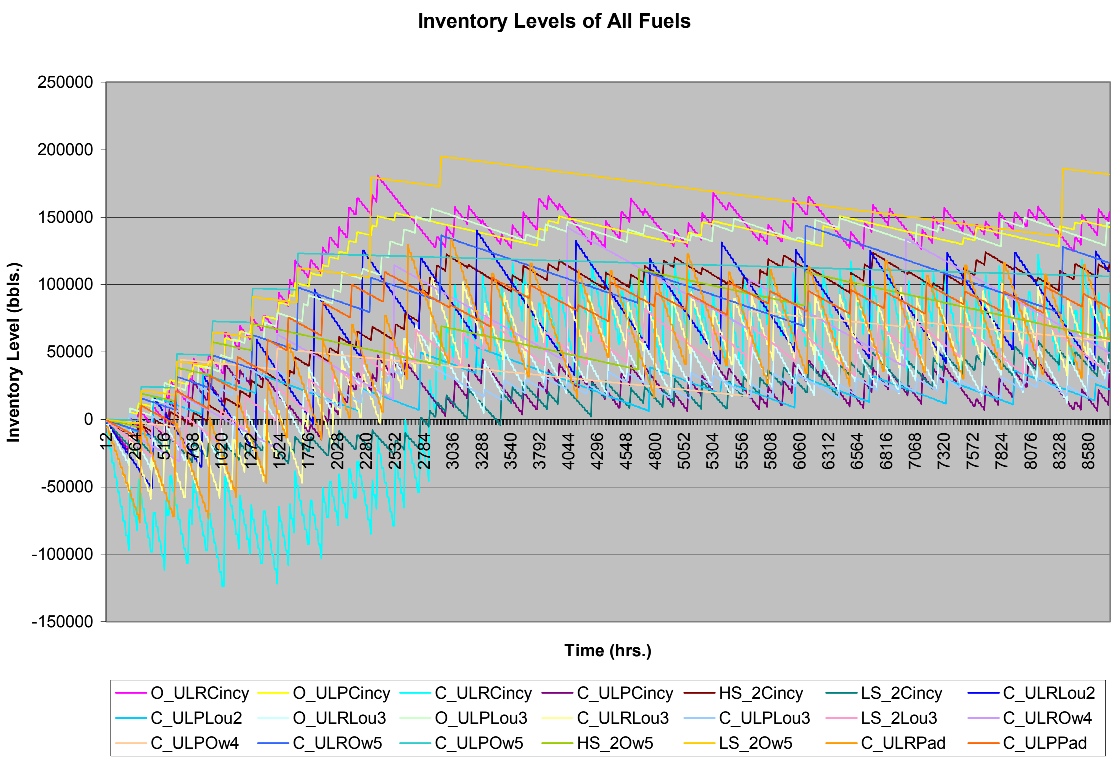


Figure 6: Fuel Inventory Levels

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