EVALUATING PETROLEUM DEPOT OPERATIONS WITH SCENARIOS PLANNING AND ECONOMIC SIMULATION-OPTIMIZATION

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ABSTRACT

Oil terminals are widely used to store various liquids and gases. The refinery scheduling problem is one of the most challenging problems in operational research due to the complexity of the refinery scheduling operations and the corresponding process models. In this paper, we present a model by which a decision maker should be able to choose the optimal number of tanks, tank size and truck arrival rate to maximize average total profit per week for an oil terminal operation. One of the refineries procedures is used to determine which combination of levels. Of number of tanks, tank size and truck arrival rate will result in highest average total profit per week.

We started the estimation process, for 180 weeks with 20 weeks of warm-up period with ten replications were conducted for four different scenarios and the total profit week ($) for each run was compiled in spread tables.

Given an oil flow rate into the Terminal, tank and truck fill rate and a cost and revenue structure, the model is able to predict with 99% confidence a set of factor levels that yields the highest average total profit per week.


1. INTRODUCTION

Present day’s competitive market, customer satisfaction is accorded as much attention as profit as a low level results in loss of profit opportunity and eventual loss of customers. The Petrol industry is highly capital-intensive, and mostly high-volume...
and low-margin. The refinery operations have distinctive features which differentiate them from other industries and require special attention, as discussed in the next paragraph. Due to these, identifying the optimal profit for the oil refinery operations and present a model by which decision maker should be able to choose the optimal number of tanks, tank size and truck arrival rate.

Many researchers working in supply chain optimization to preferred way to reduce costs, improve performance, and manage the business amidst various uncertainties. Supply Chain Management is an important element in enterprise management in this era marked by globalization (Srinivasan, 2007). Pitty et al. (2005), evaluate the effect of supply chain policies and investment decision on the supply chain and clearly, decision-making in a supply chain has to be integrated and coordinated among likeminded entities participating in the supply chain so as to maximize benefits. A dynamic simulation can be useful for a variety of other integrated decision-making at the operational, strategic, and tactical levels (Goldsim Technology Group, 2004) if the discrete events and continuous actions, time delays, information asymmetries, nonlinearities, and other complexities are adequately captured. Therefore, schedulers usually base their work on experience, heuristics, and the use of spreadsheets. The scheduling and inventory management levels have a lack of rigorous mathematical approaches to optimize refinery operation. Classical optimization techniques based on mathematical programming, such as continuous time differential equation models, discrete time difference equation models, and operational research techniques, generally work well for small-scale, short-term supply chain problems, about 2–4 weeks in size. However, they have not been shown to be successful in dealing with large-scale, long-term, integrated, stochastic, dynamic, non-linear problems.

This paper introduces petroleum refinery supply chain simulation and tries to optimize the refinery operating policies and capacity investments by using a genetic algorithm. Policy and investment decisions have significant impact on the refinery bottom line. Furthermore, specialized formulations are required for each problem. A general-purpose decision support methodology that works on two cases are desirable and focus on the current work. Transportation times are relatively long; it takes between 4-8 weeks for a Large Crude Carriers (LCC) carrying crude oil from Iraq to reach refineries in Asia. To use the advantages of optimization while managing the complexities at the same time, the current trend is towards synergistic union of simulation and optimization, which is adopted (Tahar and Abduljabbar 2010).

2. RELATED BACKGROUND

Most studies in the literature on oil refinery optimization deals with sub-section of the refinery for example oil scheduling, production planning, gasoline blending etc. The majority are based on mathematical programming.

Neiro and Pinto (2004) and Reddy et al. (2004) give a comprehensive review of works related to optimization in the refinery supply chain. Interestingly, similar trend is observed for refinery supply chain simulation. Most works on refinery supply chain simulation reported in the literature address only a part of the supply chain, such as crude transportation logistics using discrete event simulation and optimal control (Cheng and Duran, 2004), simulation-based short-term scheduling of crude oil from port to refinery tanks and distillation unit (Chryssolouris et al., 2005), agent-based crude procurement (Julka et al., 2002). Outside the refinery context, Banks et al.
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(2002) survey many SCM simulation studies at IBM and Virtual Logistics and discuss issues related to strategic and operational SCM, distributed SCM simulation, and commercial packages for SCM simulation. Kleijnen (2005) distinguish four types of simulation – spreadsheet simulation, system dynamics, discrete-event dynamic simulation, and business games – and provide a literature review of the application of each type in SCM. Jung et al. (2004) propose a simulation-based optimization computational framework for determining safety stock levels for planning and scheduling applications. They combine deterministic planning and scheduling models for optimization and a discrete-event simulation model. Their work is focused only on planning and scheduling. Supply Chain Management (SCM) is an important element in enterprise management in this era marked by globalization (Srinivasan, 2007). Shapiro (2007) discussed the application of modeling in various areas of SCM, such as strategic, tactical, and operational planning, inventory planning, and decision-making under uncertainty. Clearly, decision-making in a Supply Chain (SC) has to be integrated and coordinated among likeminded entities participating in the SC so as to maximize benefits. Geographically distributed exogenous events – occurring in the premises of SC entities or elsewhere in the globe (terrorist attacks, hurricanes, earthquakes, etc.) – can disrupt an efficient SC (Griffy-Brown, 2003; Zsidisin, Ragatz, & Melnyk, 2005).

While lean SCs with low inventories are generally considered efficient because of less locked-in capital, the minimal buffers make them more vulnerable to disruptions (Zsidisin et al., 2005). Perea-L´opez, Grossmann, and Ydstie (2001) developed a control-theoretic model focusing on inventory and proposed decentralized control strategies. In the refinery domain, models have been developed for various sub-parts such as crude procurement (Julka, Karimi, & Srinivasan, 2002), crude transportation logistics (Cheng & Duran, 2004), and short-term scheduling of crude oil supply from port to refinery tanks and distillation units (Paolucci, Saclie, & Bocalatte, 2002; Chryssolouris, Papakostas, & Mourtzis, 2005). The effects of such exogenous events can be foreseen only if the complex dynamics originating from these perturbations are understood. The best remedial actions can be identified and their adequacy determined if the dynamics of the SC are modeled and simulated. A dynamic simulation can be useful for a variety of other integrated decision-making at the operational, strategic, and tactical levels (Goldsim Technology Group, 2004) if the discrete events and continuous actions, time delays, information asymmetries, nonlinearities, and other complexities are adequately captured. At present, simulation remains the predominant methodology for tackling the inherent complexities in these problems. Simulation is appropriate for supply chain studies as it is able to model uncertainties and complex dynamics in a scale-free fashion (Ding, Benyoucef, & Xie, 2006).

3. THEORETICAL BACKGROUND

3.1. System Model Description

If oil is not required for immediate use, it may be stored in large tanks, owned by the oil and gas companies, or rented at a transport refineries oil terminal. From a major pipeline as shown in fig.1, the oil terminal tanks receive regular oil. Oil arrives in batches from the pipeline. It then enters into one of several tanks, each holding up to a maximum capacity. Trucks, each with a fixed capacity, arrive at a certain average rate at the terminal. After arrival to the terminal, trucks will then wait in a central queue.
until a tank is available for loading oil. Tank availability is defined as having oil, equal to truck capacity, available in the tank and currently, no truck is queued in front of the tank for refuelling. If a truck arrives at the terminal and the number of trucks currently queued at the central queue is equal to the queue capacity then the arriving truck balks back to the truck depot.

Figure 1 The process model flowchart

After loading oil, trucks then depart for their destination customer location. In the event the terminal, will pass downstream and is sold as a lower grade, less profitable product, that will be referred to as discount oil. The difference between regular oil and discount oil is that a quality check is not made on the discount oil. The total cost of maintaining oil in the terminal and the associated truck costs is $C$ per week. The contribution margins derived from sale of regular and discount oil is $R$ per week.
3.2. Proposed model
Using a discrete-event simulation modelling approach, a model of the oil terminal was created in ARENA. Figure 1 shows the simplified flowchart of the model. In the model, an entity of oil is represented as a blue dot, whereas truck entities are identified by truck symbols. Both entities follow a stationary poison arrival process as depicted by the nature of the process, number of events that occur in an interval of time when the events are occurring at a constant rate. All inter-arrival times are independently and identically distributed exponential random variables with parameter as the average time between arrivals.

The simulation model has ten distinct blocks and each block is discussed separately below. The model consists of tow arrival nodes to create oil and truck arrivals. Decide nodes help determine whether or not oil should enter the terminal as regular oil or be sent downstream to be converted into a lower grade fuel, discount oil. Decide nodes are also used to determine to which tank the trucks should be sent for refuelling. Find J node helps send oil entity to a tank with the smallest number of truck batches waiting to be loaded. A truck batch equals 2,000 m$^3$ of oil. Process node executes the time required to fill oil into tanks. Assign nodes assign batch sizes to incoming oil entities and increase or decrease the oil work in process in the terminal to maintain a paper count of oil within the system. Hold node represents tanks and hold oil until a signal node sends a message to release oil into trucks. Signal nodes also send message to the removes node, which removes queued truck from the Queue node on a first-come-first-serve (FCFS). A Queue node with queue capacity holds arriving trucks in a central queue. Match nodes help match a truck to a batch of oil before sending it to the process node, which executes the time required to fill oil into trucks. Batch nodes are used to batch oil equal to the truck capacity. Several animated counters are used to help debug the model.

3.3. Model test procedures
In this section we will explains the test procedures involved in the model such as model validation and verification, calculating the number of runs required and setting up variance reduction methods to achieve a certain confidence interval and finally, addressing the initial transient problem in the non-terminating simulation model.

4. SIMULATION VALIDATION AND VERIFICATION

4.1. Verification
Verification is a technique used to determine if the simulation model performs according to design intent, more colloquially known as debugging of the model. The actual mechanics of model verification were carried out as follow:

4.2. Verification experiment
Set oil and truck arrival rate to constants. Run the simulation for 20 weeks with 10 weeks for warm up period. Factor-levels used are: 4 tanks, tank size of 20,000 m$^3$ and truck_TBA of 75 minutes. Set up trace and highlight module option to follow along simulation steps.

- At time 0, one truck arrived and Truck_In time was set to 0. The next arrival time was set at 106.9 minutes. Truck, with rank 1, was sent to Queue. Message was sent to Message Decision point to verify if there is enough oil in a tank for this truck.
At time 15, one oil entity is sent from the process node to the FindJ node. J is set to 1, indicating that tank 1 should be filled.

At time 30, another entity is released from the process node and is sent to FindJ node. J is set to 1 because there is one truck waiting in the queue and it will be more efficient to send this oil entity to tank 1 even though, other tanks have the least amount of oil.

At time 35.11, oil arrives at terminal and next arrival time is set to 134.26 minutes. With 33.34% probability, batch size is set to 10. Each entity within the batch is evaluated to see if Oil WIP ≥ (Number of Tanks * Tank Capacity).

At time 45, a third entity is released from the process node and is sent to tank 2, which has the least amount of oil.

In summary, using the above experimentation method, the model was verified to meet design intent.

4.3. Validation
Validation is an exercise to ensure that the model behaves as the real system by comparing the results obtained from the simulation runs to that of the actual or observed data from the real system. Unfortunately, for the purpose of this thesis, there is no exact actual or real system to which the model results can be compared. However, it is possible to comment on whether or not the model output represents reality.

4.4. Estimating the number of runs required
Using the methods described by Kelton, W.D. and Law (1991), the number of runs required to estimate the average profit with a specified error or precision, we would like to choose a level of confidence, 100(1-α) %, then an approximate expression for the number of replications is given as:

\[
N(\gamma) = \min \left\{ i \geq N : \frac{t_{1-\alpha/2} \sqrt{\frac{\sigma^2}{i}}}{\bar{X}} \leq \hat{\gamma} \right\}
\]

(1)

Where \( \bar{X} \) is sample of average; \( \gamma \) is the relative error and \( \hat{\gamma} = \gamma(1 + \gamma) \) is the adjusted relative error required to get an actual relative of \( \gamma = 0.05 \), we have:

\[ \hat{\gamma} = \frac{0.05}{1 + 0.05} = 0.047 \]

To start the estimation process, an initial run of 180 weeks with 20 weeks of warm-up period with ten replications were conducted for four different scenarios and the total profit week ($) for each run was compiled in table 1.

Scenario 1
Highest terminal capacity (four tanks, each with capacity of 42,000 m3, for a total of 168,000 m3) and highest truck arrival rate (truck_TBA = 55 minutes).

Using \( \gamma = 0.05 \), \( \gamma = 0.0476 \), \( \bar{X} = 1.054 \), \( S = 0.0274 \) and \( t_{10-1}, 1-0.99 = 3.25 \) for a 99% confidence level, equation (1) for scenario 1 becomes,

\[ 3.25 \times \frac{\sqrt{(0.0274)^2 \times 2}}{10} / 1.054 = 0.0268 < 0.0476 \]

Scenario 2
Highest terminal capacity (four tanks, each with capacity of 42,000 m3, for a total of 168,000 m3 and lowest truck arrival rate (truck_TBA = 115 minutes).
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Using \( \gamma = 0.05, \hat{\gamma} = 0.0476, \bar{X} = 3.0554, S = 0.1266 \) and \( t_{0.05, 1-0.99} = 3.25 \) for a 99% confidence level, equation (1) for scenario 2 becomes,

\[
3.25 \times \frac{\sqrt{((0.1266)^2) / 10}}{3.0554} = 0.0426 < 0.0476
\]

**Scenario 3**

Lowest terminal capacity (one tank, each with capacity of 18,000 m\(^3\), for a total of 18,000 m\(^3\)) and highest truck arrival rate (truck\_TBA = 55 minutes).

Using \( \gamma = 0.05, \hat{\gamma} = 0.0476, \bar{X} = 6.3928, S = 0.1293 \) and \( t_{0.05, 1-0.99} = 3.25 \) for a 99% confidence level, equation (1) for scenario 3 becomes,

\[
3.25 \times \frac{\sqrt{((0.1293)^2) / 10}}{6.3928} = 0.0208 < 0.0476
\]

**Scenario 4**

Lowest terminal capacity (one tank, each with capacity of 18,000 m\(^3\), for a total of 18,000 m\(^3\)) and lowest truck arrival rate (truck TBA = 115 minutes).

Using \( \gamma = 0.05, \hat{\gamma} = 0.0476, \bar{X} = 12.1173, S = 0.0838 \) and \( t_{0.05, 1-0.99} = 3.25 \) for a 99% confidence level, equation (1) for scenario 4 becomes,

\[
3.25 \times \frac{\sqrt{((0.0838)^2) / 10}}{12.1173} = 0.0071 < 0.0476
\]

Therefore and from all these scenarios, 10 replications do meet the 99% confidence level and relative error of 0.05 requirements.

Table 2 provides more insight into the solution set. For the solution set, it appears that the percentage of regular oil shipped is between 79.5% and 85.2%. Consequently, the percentage of discount oil shipped is between 14.8% and 20.5%. The truck balk rate ranges from as low as 1.7% to as high as 8.1%.

The truck balk cost as a percent of total cost varies between 0.69% and 4.12%. The truck cost is the major cost item when compared to the lease cost and ranges from 77.43% to 88.54%. The majority of the truck cost is due to truck trips and truck time spent within the system. Truck trip costs as a percentage of total costs range from 45.29% to 47.27%. Truck in system costs as a percentage of total costs varies between 31.11% and 37.57%.

Truck trips are necessary costs and cannot be avoided. However, truck wait cost in system (other than the time spent refuelling) is an avoidable cost and occurs due to variability in the system. The average truck time in system is between 81.8 minutes and 96.24 minutes. Idealy the truck should spend 75 minutes for refuelling and 0 minutes for waiting to be refuelled. For example, in the case of 2 tanks with capacity of 34,000 m\(^3\) and with truck TBA of 75 minutes, the average truck time in system is 87.42 minutes, which is 12.42 (= 87.42 — 75) minutes higher than the time required to refuel. The average total trucks shipped (carrying regular oil) from the system is 20,722.1. Therefore, the additional cost ($) due to truck wait time = (12.42) x (20,722.1)/ (160 weeks x 1,000) = $ 1.6086K.
Table 1 Number of runs analysis- scenarios 1, 2, 3 and 4

<table>
<thead>
<tr>
<th>No. of Runs Calculation</th>
<th>Highest terminal capacity and truck arrival rate</th>
<th>Lowest terminal capacity and truck arrival rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>scenario 1</td>
<td>scenario 2</td>
</tr>
<tr>
<td></td>
<td>Truck TBA=55, Tank size=42 and No. of tanks=4</td>
<td>Truck TBA=115, Tank size=42 and No. of tanks=4</td>
</tr>
<tr>
<td>Relative Error, R=0.05</td>
<td>Total Profit/wk($)</td>
<td>Total Profit/wk($)</td>
</tr>
<tr>
<td>10 replications</td>
<td>Total Profit/wk($)</td>
<td>Total Profit/wk($)</td>
</tr>
<tr>
<td></td>
<td>12.1683</td>
<td>3.1758</td>
</tr>
<tr>
<td></td>
<td>12.1293</td>
<td>3.1410</td>
</tr>
<tr>
<td></td>
<td>12.0740</td>
<td>2.9498</td>
</tr>
<tr>
<td></td>
<td>12.1198</td>
<td>2.9351</td>
</tr>
<tr>
<td></td>
<td>12.0921</td>
<td>3.1388</td>
</tr>
<tr>
<td></td>
<td>12.2533</td>
<td>3.2214</td>
</tr>
<tr>
<td></td>
<td>12.0548</td>
<td>2.8242</td>
</tr>
<tr>
<td></td>
<td>12.0899</td>
<td>2.9939</td>
</tr>
<tr>
<td></td>
<td>12.2236</td>
<td>3.0471</td>
</tr>
<tr>
<td></td>
<td>11.9658</td>
<td>3.1266</td>
</tr>
<tr>
<td></td>
<td>12.1173</td>
<td>3.0554</td>
</tr>
<tr>
<td></td>
<td>0.0838</td>
<td>0.1266</td>
</tr>
<tr>
<td>Student T Statistics</td>
<td>3.2498</td>
<td>3.2498</td>
</tr>
<tr>
<td>( t_{0.95,1-10} )</td>
<td>0.0268 &lt; 0.0476</td>
<td>0.0426 &lt; 0.0477</td>
</tr>
</tbody>
</table>

The percentage of additional cost due to truck wait time = $1.6086/Average total cost = $1.6086/$34.33 155 = 4.069%. This cost would be avoided if trucks did not have to wait in the system.

Table 2 Simulation Result of for 180 weeks, 20 weeks warm up period and 10 runs

<table>
<thead>
<tr>
<th>Avg profit/week ($)</th>
<th>18.7</th>
<th>18.7</th>
<th>18.9</th>
<th>19</th>
<th>19.06</th>
<th>19.8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truck TBA (min)</td>
<td>75</td>
<td>75</td>
<td>75</td>
<td>75</td>
<td>65</td>
<td>75</td>
</tr>
<tr>
<td>No. of tanks</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Tank size (1,000 m³)</td>
<td>34</td>
<td>18</td>
<td>26</td>
<td>26</td>
<td>18</td>
<td>18</td>
</tr>
<tr>
<td>Terminal capacity (1,000 m³)</td>
<td>68</td>
<td>36</td>
<td>78</td>
<td>52</td>
<td>72</td>
<td>54</td>
</tr>
<tr>
<td>Avg. percentage of total regular oil shipped</td>
<td>83.3</td>
<td>79.5</td>
<td>85.2</td>
<td>82.1</td>
<td>85</td>
<td>83.6</td>
</tr>
<tr>
<td>Avg. percentage of total discount oil shipped</td>
<td>16.7</td>
<td>20.5</td>
<td>14.8</td>
<td>17.9</td>
<td>15</td>
<td>16.4</td>
</tr>
<tr>
<td>Avg. truck balk rate (%)</td>
<td>3.7</td>
<td>8.1</td>
<td>1.5</td>
<td>5.1</td>
<td>1.7</td>
<td>3.2</td>
</tr>
<tr>
<td>Avg. truck trip cost as a percentage of total cost</td>
<td>45.3</td>
<td>46.9</td>
<td>45.6</td>
<td>46.6</td>
<td>45.95</td>
<td>47.3</td>
</tr>
<tr>
<td>Avg. truck in system cost as a percentage of total cost</td>
<td>33</td>
<td>37.6</td>
<td>31.1</td>
<td>35</td>
<td>32.26</td>
<td>34.7</td>
</tr>
<tr>
<td>Avg. truck balk cost as a percentage of total cost</td>
<td>1.74</td>
<td>4.12</td>
<td>0.69</td>
<td>0.49</td>
<td>0.78</td>
<td>1.58</td>
</tr>
<tr>
<td>Avg. truck cost as a percentage of total cost</td>
<td>80</td>
<td>88.5</td>
<td>77.4</td>
<td>84.1</td>
<td>78.99</td>
<td>83.5</td>
</tr>
<tr>
<td>Avg. truck lease cost as a percentage of total cost</td>
<td>20</td>
<td>11.5</td>
<td>22.6</td>
<td>15.9</td>
<td>21.01</td>
<td>16.5</td>
</tr>
<tr>
<td>Avg. truck time in system (min)</td>
<td>87.4</td>
<td>96.2</td>
<td>81.8</td>
<td>90.1</td>
<td>84.26</td>
<td>88</td>
</tr>
</tbody>
</table>
5. CONCLUSION

This paper presents a research project being developed at the Industrial and Systems Engineering Graduate Program at any general oil refinery.

The objective is to develop a system to aid professionals from management and logistics areas to evaluate the profit of the oil through computer simulation and help the decision makers to choose the optimal number of tanks, tank size and truck arrival rate. Among the several possibilities for analysis, simulation can allow one to perform detailed studies on the bullwhip effect in refinery operations. We presented a new way to analyze all of this through simulation models, which break down the system’s complexity on different hierarchical levels.

Oil terminal profitability model is able to 99% predict a group of factor-level mix, which will yield the highest average total profit per week. Management can use this model to predict the combination of (truck_TBA), number of tanks and tank size to yield the highest average profit per week. The model also presents a procedure by which the decision makers can manipulate the input variables to retrieve the most profitable combination.

REFERENCES


