Planning of Oil Distribution Network with Artificial Intelligence Techniques

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Abstract

This paper addresses a regional oil distribution network in Sri Lanka. Linear programming fundamentals have been used to develop a mathematical model to cater the preliminary requirements of the network. The intended objective is to minimize the total distribution cost, subjected to the constraints of vehicle availability.Manual computations are impractical and AI techniques have been used to generate cost effective routes. In two stages of the methodology, Ant Colony Optimization was incorporated to determine the best from the all feasible options based on the demand at each dealer point and the corresponding distance. The decision factors are weighted according to the relative importance of each criterion. At the second stage, initial routes are optimized by local (swap and exchange) and global (Simulated Annealing) optimization techniques. Numbers of simulations revealed the proposed approach is highly endorsed in planning of routes in oil distribution.

Keywords
Local Optimization Techniques, Global Optimization Techniques, Ant Colony Optimization, Simulated Annealing

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1. Introduction
Distribution refers to moving and storing a product from the supplier doorstep to the customer doorstep (S. Chopra 2002). Each organization has set their goals at different phases according to their own mission and vision. For instance, achieving the higher responsiveness with minimum lead time becomes the target of one party whereas others want to minimize their logistics cost. However, it is contradictory to achieve both objectives simultaneously and many organizations have a kind of compromised objectives which give higher priority to the company vision.

Comparatively distribution plays critical role due to the higher cost. Therefore, necessity arises to optimize distribution operations in order to alleviate the burning condition of the industrial sector.Planning of distribution operations of a particular distribution network is different from one to another. The planning is done based on the product, nature of the customer etc. However, when a product like petroleum is considered, due to the rising price and the flammable nature of the product, it is important to plan and coordinate the distribution operations carefully and efficiently. However, manual scheduling techniques will not help to fully utilize the resources and to achieve above objectives. Therefore, necessity arises to see the applicability of mathematical approach. Apparently, many researchers have studied about the applicability of various mathematical models for different distribution networks optimization (Verderame et al. 2009, Bilgen 2010). However, it is hard to find studies related to petroleum distribution.

This study considered the petroleum distribution of Sri Lanka. The current practice of the system is to deliver the ordered quantity in full amount within 48 hours. The study pays more attention on current distribution routes, order quantities and order frequency patterns of dealer points.Efficient planning/scheduling of the petroleum distribution operation means generating sets of routes which consists of retailers in an order in such a way that minimizing total travel distance while using the fleet optimally.
In addition, catering the customer demand with the given hours is also a primary objective. Therefore, the intended objectives of this research would be improving the customer service level and minimizing the total distribution cost with the means of optimum route selection and optimum vehicle allocation.

Developing a routing system for petroleum distribution with minimum cost is practically challengeable due to the existence of number of customer which leads to number of alternative solutions. Mathematically, this type of problem belongs to combinatorial optimization problem category. However, for this kind of problems, the manual computations are inefficient due to higher number of computations which consumes considerable time. Previously, numbers of researches have been conducted in oil refinery process scheduling (Cao et al. 2010) and storage capacity planning (GhateeandHasheni 2009). However, no evidence found in the literature which were tested the applicability of mathematical models towards the petroleum distribution(Creazza et al. 2010,CanelandKhumawala 1996). However, though many differences appears in the study of Sherali and Al – Yakoob(2006) that can be considered as one of the most closet study to our one. They have developed a mixed integer method for optimal fleet mix and scheduling for single source – single destination distribution problem. They have studied the ocenic transportation of petroleum from one source (refinery) to one destination (storage facility with known demand structure) using both self – owned and chartered vessels. In their proposed model, researchers have focused on satisfying customer demands with the minimum resource usage and minimum penalties. However, this model basically deviates from our study with respect to the nature of the distribution network, the mode of transportation and computational technique. The model developed in the above study applied for a single source – single destination with vessels as transportation mode whereas our research focuses on single source – multiple destinations with tanker lorries as transportation mode.

This study tries to optimize the petroleum distribution operation optimally with the help of linear programming and heuristics techniques. Initially a mathematical model was developed to cater the preliminary requirements of the network using fundamentals of linear programming. The intended objective of the model was to minimize the total distribution cost within the constraints of vehicle availability, capacity restrictions and sub – tour elimination. Due to the complexities in computations, heuristics and meta heuristics techniques have been used to generate optimal routes with minimum total distance. The program was folded into two stages, initial route generation and optimizing the initially generated routes. The initial solution is generated by Ant Colony Optimization (ACO), simultaneously considering the both distance and demand which is modeled as multi objective optimization problem. The initial solution further investigated with the Simulated Annealing in order to go for the global optimum. The developed model and the algorithm have been applied to petroleum distribution network of Gampaha district in Sri Lanka which is governed by Ceylon Petroleum Storage Terminals Limited (CPSTL).

2. Problem Formulation

The petroleum distribution network considered in this study comprises of a single distribution centre (storage terminal), set of dealer points (fuel stations) with reasonable lead time (48 hours) and fleet of heterogeneous capacity tanker lorries. All the dealer points are going to be catered by a single distribution centre. The travel time is proportional to the distances in between and assumed that the road condition and traffic will not affect on it. Loading and unloading time is also neglected.

Customers: the distribution network consists of number of dealer points i = {1, 2, …n: index of filling stations} located at different locations. Distribution center also considered as a dealer point i = 0 where the origin and destination of a route. Distance between any two dealer points (including distribution centre) is denoted by d_{ij}

Vehicle: the fleet consists of tanker lorries with different capacities (c = 1, 2,…n : indices of vehicle capacities) and different types (t = 1, 2, ….n). Number of lorries in type ***t***andcapacity **c** is denoted by $\boldsymbol{n_{t,c}}$

$i = 1, 2, 3 \dots \dots \dots N : index of filling statons$
$t = 1, \dots \dots, T : types of vehicles$

$c = 1,2,3 \ldots\ldots\ldots c : indices of capacities of vehicles$

$c_t = capacity of a vehicle of type t\ (in litres)$

$M_t = number of vehicle of type t$

$D_i = demand of filling station i$

$d_{ij} = distance between filling station i and j$

$C_{ij} = cost of transportation between node i and j$

$r_{t,c} = rate of delivery of one liter per kilometer by using a bowser of type t of cap\ city c$

$n_{t,c} = number of vehicles used in distribution process of type t and capacity c$

V_c = capacity of vehicle type c

$$x_{i,j}^{t,c} = \begin{cases} 1, & if\ vehicle\ travels\ between\ customer\ i\ and\ j\ by\ bowser of type t of capacity c \\ 0, & otherwise \end{cases}$$

$$transport cost between any node i and j = distance * delivered quantity * rate$$

$$C_{ij} = d_{ij} * (V_c - \textstyle\sum_{i=1}^{N} D_i) * r_{t,c} \quad (1)$$

$$Min(Z) = \textstyle\sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{t=0}^{T} \sum_{c=1}^{c} C_{i,j} x_{i,j}^{t,c} \quad (2)$$

Subjected to:

1. $$\frac{\sum_{i=0}^{N} D_i}{\left(\frac{\sum_{t=1}^{T}\sum_{c=1}^{c} c_t n_{t,c}}{\sum_{t=1}^{T}\sum_{c=1}^{c} n_{t,c}}\right)} \leq k \quad (3)$$

2. $$\textstyle\sum_{i=1}^{N} D_i = \sum_{t=1}^{T} \sum_{c=1}^{c} c_t\, n_{t,c} \quad (4)$$

3. $$D_i = c_t (t \in t = 1 \ldots T) \quad (5)$$

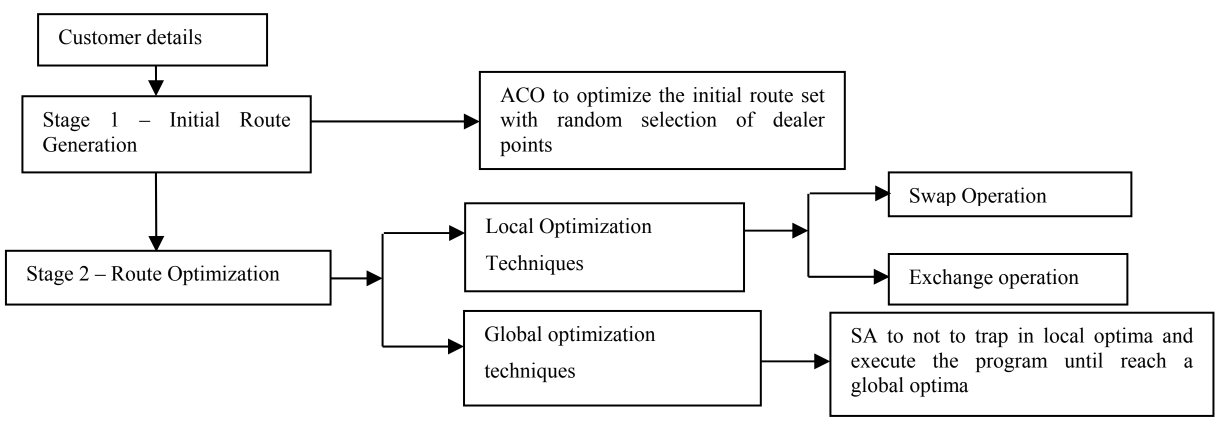

Figure1: Steps of the methodology

Equation (3) emphasizes that the available tanker lorries are able to satisfy actual demand. From equation (4), it is ensured that the total quantities ordered by dealer points are delivered in their full quantities. According to equation (5), demand quantity of any dealer point should not exceed the capacity of any tanker lorry.

2.1 Program Development

- Stage – 1 - Initial Route Generation

Initial sets of routes are generated with the help of ACO which are compatible with vehicle capacities and available customer points. ACO is developed based on thenatural behaviour of ants in finding food and it has been used to solve combinatorial optimisation problems. An ant represents a vehilce in VRP and the first task is randomly selected and allocate to a vehicle. Initial route is contructed by filtering all the possible candidates by considering the remaining capacity of the vehicle and the demand of the considered point. The visibility (η_{ij}) which is (1/d_{ij}) is calculated for the filtered customers where d_{ij} is distance between customeri and j. Selecting the next customer with maximum visibility will give route with minimum distance. Demand point with the maximum visibility is selected as the next delivery point and update the route. However, with the intension of unloading the carriage τ_{ij} is incorporated with some modifications. The general usage of $\tau_{ij}$is the intensity of pheramone trail is not suitable for this type of distribution network which lead to a biased solution. As there are dealer points located in different locations (regions or areas), the route should take to reach that point may vary and selecting a previously selected route may lead to a completely different region or location with respect to the intended region or location. Therefore,τ_{ij} is related to demand of respectivecustomer as selecting a dealer point with very less demand quantity than the availablecapacity of the tanker lorry, may lead to increase the number of dealer points. Finally that may generate a route set with higher number of dealer points and higher total route distances. Therefore obviously it is favourable to select a dealer point with higher demand quantity. So the probability of selecting the j^{th} dealer point after i^{th} dealer point is defined as below,

$$P_{ij} = \frac{(D_j)^{\alpha}\left(1/d_{ij}\right)^{\beta}}{\sum_{u\in TL}(D_j)^{\alpha}\left(1/d_{ij}\right)^{\beta}} \quad (6)$$

$$\alpha + \beta = 1 \quad (7)$$

$P_{ij} = probabilityofselectingj^{th}dealerpointimmediatelyafteri^{th}dealerpoint$
$D_j = demandquantityofj^{th}dealerpoint$
$d_{ij} = distancebetweeni^{th}dealerpointandj^{th}dealerpoint$

- Stage 2 - Route Optimization

The route set that was initially generated are further optimized by using different local (Swap and Exchange operators) and global optimization (SA) methods.

Exchange operator: Elements are exchanged between two routes when the feasibility exists.

Swap Operator: Elements are changed within the route without checking the feasibility as the delivered quantity of the vehicle is not changed.

o Simulated Annealing (SA):

SA technique is mainly used in optimization problems of large scale, especially suitable for situations where desired global optimum is hidden among many poor local optimums. At higher temperatures, molecules of a liquid move freely with respect to another molecule due to the high energy state of the molecule and if the liquid is slowly cool the thermal mobility of the molecules are lost and atoms are able to line up themselves and form a pure crystal which is having the minimum energy state.

The technical definition of annealing is slow cooling with allowing ample time for redistribution of the atoms as they lose mobility. This concept has been used in minimization algorithms to avoid getting trapped in immediate local optimums and allow reaching to a global minimum solution. In any minimization problems, it is gone for quick and nearby solutions from the starting point by going immediately downhill as far as it can practically go. This leads to a local minimum but not for a global minimum.

$$Prob(E) \sim \exp(-E/kT) \quad (8)$$

The above mentioned Boltzmann probability distribution expresses that a system in thermal equilibrium at temperature Thas its energy probabilistically distributed among all different energy states$E$. Correspondingly, there is a chance for the system to get out of a local energy minimum in favour of finding a more global minimum energy level. In equation (8), T uses as a control parameter called *Annealing Schedule* which tells how the energy state is lowered form high to a lower value.

This study is inspired by SA in order to optimize the initial solution with the help of local operators in order to avoid the trapping in local optimal. SA gives a probabilistic chance to accept worse solutions in terms of distance with the thought of having better solution in future steps according to the value of $\exp((-diff)\ /\ T)$ where $diff = currentroutedistance - bestdistance\ ,\ T = temperatureofthesystem.$ SA has been used to avoid trapping in a local optimum solution and ensure that the program is running for a reasonable number of iterations to get a global optimum solution.

3. Simulation Results

The selected problem was a distribution problem which is having one source point and number of delivery points with various demands. The fleet is heterogeneous with the size of 18. The researcher investigates the most suitable value combination for α and β to get minimum total route distance. In the second phase of analysis, the initial solutions were improved by using local optimization methods and global optimization technique (SA) is investigated.

3.1 Setting up α and β

Setting up α and β is done through the numbers of simulations which were based on four different data sets in different sizes varying from 10 to 40 delivery points. To choose the best α and β value combinations, initial distance was calculated for above data sets varying α, β value combinations ranging from 0 to 1. Figure 2 shows the variation of travelled distance with different α, β value combinations. Comparisons were done based on travelled distance which is generated by the initial solution. Optimized travelled distance is not applicable for this simulation since it has the probabilistic influence from SA heuristic and therefore, it doesn't reflect the real influence of α, β over the real problem.

The Table 1 shows the summary of the results taken from the figure 2. The optimal α, β values that give the minimum total distances for the different route sets generated are given in the table.

Table 1: Summary of Best α, β values for each Problem Size

	10 Customers		20 Customers		30 Customers		40 Customers	
	α	β	α	β	α	β	α	β
Problem # 1	0.2	0.8	0.2	0.8	0.3	0.7	0.2	0.8

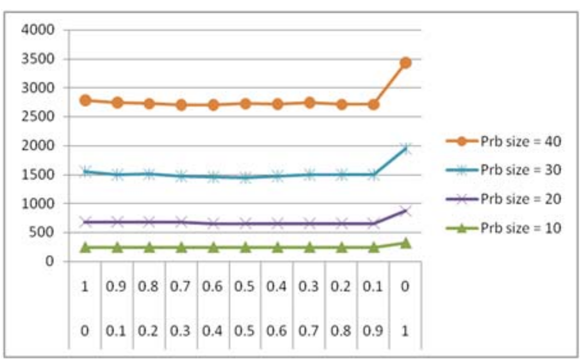

Figure 2:Variation of initial solution with different α,

According to the Table 1, it can be concluded that the average optimal α, β value combination changes in a similar trend regardless of the problem size. It is noticed that α, β value combination lies between 0.2 to 0.3 and 0.7 to 0.8 respectively. This range can be existed due to the differences in the data of the different problems. It is taken the best value combination as α = 0.2and β = 0.8 with the seventy five percent success rate.

3.2 Real Data Analysis

The model was checked for its applicability in solving the distribution in real petroleum distribution network. Five clusters with different sizes were taken for this simulation. Two types of simulations were carried out in order to emphasis the initial solution improvement by SA heuristic and to show the applicability of develop algorithm for real petroleum distribution.

Figure 3 shows the initial solution versus optimal solution for five different data sets. It also shows the distance improvement of the initial solution generated by ACO which optimized by SA. Therefore, it can be concluded that SA out perform in solution quality.

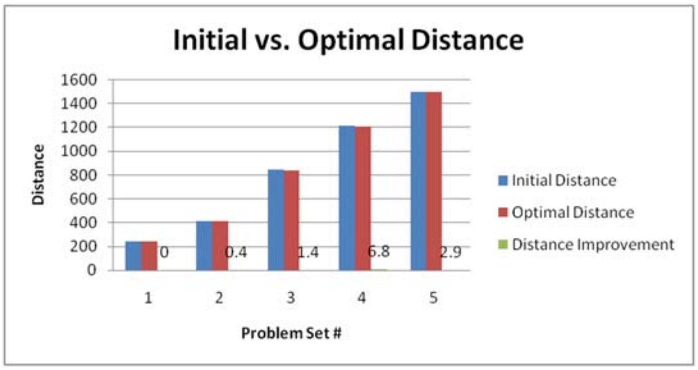

Figure 3: Initial vs. Optimal Distance

Furthermore, a comparisonhas been carried out between the optimal solution generated by the developed algorithm and the actual distribution cost. The real distribution cost was calculated based on the actual route that were followed by the operation's team. Figure 4 shows the actual distances of the routes generated manually and the optimal distances generated by using the algorithm. The table 2 shows the actual travelled distances and optimal distances generated by the developed algorithm.

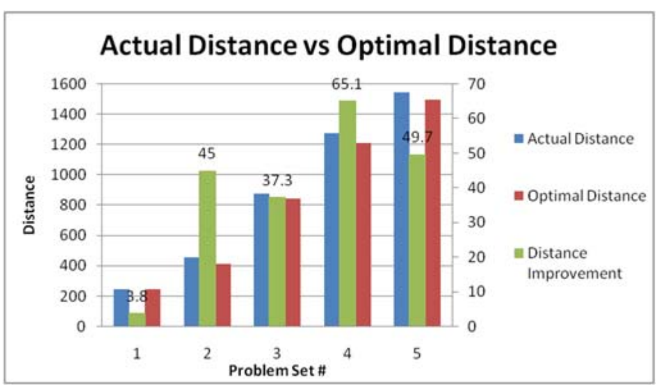

Fig 4: Actual Route Distance vs. Optimal Route Distance

It is obvious that the route generated with the help of the developed algorithm could make the significant saving in terms of travelled distance. Therefore it can be conclude that the developed algorithm is applicable to plan the petroleum distribution operations.

Here it is noted that the distances from each dealer point to every other dealer points are calculated by using "Google Maps" Application. Also all simulations were based on the optimal α, β value concluded by simulations done in section 3.

Table 2: Comparison of Actual Distances and Optimal Distances of different problem sets

No of Dealer Points	Total Demand (1000 liters)	No of Vehicles used	Actual Distance (km)	Optimal Distance (km)	Distance Improvement
10	66	4	247.3	243.5	3.8
20	138.6	7	456.1	411.1	45
30	231	12	878.6	841.3	37.3
40	323.4	18	1276.3	1211.2	65.1
50	402.6	23	1546.7	1497	49.7

4. Conclusion

Distribution is critical logistics function as it directly affects to the customer service level as well as for the cost of the distributor. Among them petroleum distribution needs efficient planning & coordination since it is different from other consumer goods.

In order to minimize the overall transportation / distribution cost, it is highly paramount to have an efficient network planning in such a way that minimizing the travelled distance while fully utilizing the resources.

In this research paper, a mathematical model has been developed to present the petroleum distribution network in mathematical point of view. It is obvious that manual techniques will not help to derive at cost effective solution. Therefore, the researcher has tried with the heuristics techniques in order to yield better solutions. Among the various heuristics techniques, Ant Colony Optimization and Simulated Annealing have been used in this study. The mathematical model and approaches adopted in this study was able to find better solutions for the existing petroleum distribution operations.With the studied data set, it can be concluded that, an average of five percent distance improvement has been achieved comparing the actual distance with the optimal distance.

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