Performance-based strategic resource allocation in supply networks

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Abstract

One driving force behind continued logistics planning research is firms’ need to maintain competitive performance and efficient resource allocation. Operations research has been instrumental in advancing logistics planning research particularly in the petroleum industry. The impact and potential of incorporating performance imperatives however, have been largely unaddressed while the problem’s general complexity has grown. This paper focuses on performance planning through resource allocation in supply networks by developing a profit-maximizing network model for distribution planning, and explicitly incorporating order performance criteria for distribution centers and delivery vehicles. The approach has been tested on forty realistic-sized problems, and tradeoff models provide insight and guidelines for assessing the interaction among expected profits, customer service, and operational efficiency for resource acquisition and redistribution. Managerial implications are also provided. © 2000 Elsevier Science B.V. All rights reserved.

Keywords: Supply networks; Resource allocation; Performance measurement

1. Introduction and background

This paper makes three primary contributions. First, a supply network planning model is developed for resource allocation in the downstream petroleum industry. Second, the structural model is generalized into a performance-based framework where performance on the distribution resources is considered. Forty realistic-sized problems are tested based on actual data provided by a large sample firm in this industry. While much research exists for optimizing the location of facilities or competitive interaction, no empirical results exist which document the tradeoffs among resource efficiency, profit-maximization and key service performance metrics. Finally, the approach integrates DEA efficiency results into a resource allocation model which, can provide managers with methods for comparing productivity either internally or externally against ‘best practices’, and improving efficiency of low-performing operating centers.

The downstream petroleum industry produces and markets refined petroleum. Crude oil is processed into several classes of petroleum products and distributed to retail outlets for consumption. In the agricultural segment of this industry, distributors receive such products from refinery operations to supply farmers with fuel to operate...
heavy equipment. Customers (farmers) require large quantities and various grades of commodity petroleum to operate their farms. A typical customer often requires one or more types of power fuels, during a planning horizon. Petroleum products account for 60–70% of revenues, and operational distribution centers must provide at least one type of petroleum to its market zone. Customers are sensitive to reliable delivery service and also expect stable prices. In commodity markets such as this, switching can occur quite easily but farmers typically value and honor the long term relationships with their distributors if the service is reliable. The supply network might span a region within a state or even across several contiguous states. Products flow from supply sources in various quantities and mixes to intermediate warehouses or distribution centers. Distribution centers (DC) within the network serve well-defined areas. From the DC level, break-bulking occurs, and product orders are filled for delivery to specific demand zones. Thus the customer assignments to DCs generate distribution resource allocation requirements. Supply sources such as refinery operations process crude oil into various grades of petroleum. Primary transport modes to distribution centers can be pipeline, railcar, barge or by truck depending on the infrastructure (location, capacity and facility type) in place at the receiving location. Some DCs may specialize in non-petroleum products such as fertilizer and seed products required by customers. These products are generally for in-store pickup only, and not delivered. For managers, these product variety issues, if they exist must not be overlooked when evaluating current and future operations. Secondary transport supplies the end customer usually via truck. Ownership of these assets (DCs, primary and secondary transport) may be shared (as in COOP environments or strategic alliances), or outright (for vertically integrated firms). Flat oil prices and rapid cost increases since 1989, declining profit margins, and technological advancements have changed the operations environment facing this industry. In consequence, both strategic and operational decisions are needed to help firms take a proactive, rather than reactive, posture to marketplace challenges to plan for efficient resource use in supply networks. We address the strategic nature of defining service areas and allocating resources to them. Although the strategic approach considered in this paper may be related to vehicle routing issues, we assume methods for routing vehicles already exist.

The next section discusses relevant literature and summarizes the point from which this paper embarks. Section 3 formulates the allocation model and explicitly illustrates where and how decision makers can incorporate resource performance goals. Supplemental analyses are offered to further illustrate the approach and form the basis for discussing strategic some issues relevant to performance-based resource allocation.

2. Literature review

This section briefly examines literature related to: (1) objective function approach, (2) resource utilization efficiency, (3) recent performance-based implementation studies. Expected profit is generally accepted as a useful objective for modeling strategic alternatives. The objective function of related studies have modeled slack and system efficiency, resource utilization, travel distance (or time), market share allocation, customer service level, noise pollution, and accident rates. The measurement of these phenomena in commensurate units, as objective functions, makes the general modeling problem inherently more complex. These objectives have been used in several single- and multi-objective approaches to supply network planning across many scenarios. Multi-objective approaches to distribution system design, generally help decision makers interactively solve the underlying model constraints [1,2], but have not addressed resource performance. Instead, resource performance is determined as a by-product of the model's best solution outcome. The performance goals of supply network resources, which are sometimes modeled as multiple objectives, are transformed into constraints for a novel single-objective, profit-maximizing approach in this paper. Typically some set of metrics (e.g., volume of sales, revenue or earnings per operating unit) captures operational performance. The set should represent best practice standards (BPS) in the industry, or the
‘internal’ practices of the firm; by ‘internal’ the focus is on the exemplary internal operating units [3]. These units can be identified using operational and market-oriented data commonly available to typical decision makers in this industry.

Performance-based models were not generally considered until Truscott [4] proposed an early supply network design model. This model incorporated market penetration goals for existing and potential new facilities in the system. Channel design and multiplicative competitive interaction (MCI) models estimate market share and integrate this data into quantitative models based on Truscott’s work [5,6]. Ghosh and Craig [7,8] also incorporate competitive information into modeling. Limitations of these approaches for characterizing ‘good performance’ include (1) upward biases in market share estimates derived from surveys, (2) the general assumption that survey respondents have perfect information, (3) the complex task of objectively assessing operations across different geographic regions, and (4) decision maker skill set. Several studies have demonstrated the veracity of DEA [9] for measuring resource efficiency in many different environments [10–15]. Papavasiliou [16], Ross et al. [17], and Turner [18] also present performance frameworks for reconfiguring supply networks in service settings.

Resource performance criteria used in a single-objective formulation to emphasize resource efficiency, and sensitivity analysis of profit and efficiency offer a new research dimension for measuring logistics performance. Such an approach to planning may be warranted particularly when reconfiguring resource allocations in supply networks, or scaling back operations; these shifts in strategy are often influenced by market shrinkage, low resource utilization efficiency, a decision to re-focus on core competencies or products at the enterprise level, constrained resources or excess inventories [19]. Researchers have proposed many methods for evaluating resource efficiency and allocation, and used a variety of objective function structures [20,21]. It is not our purpose to review them or conjecture on their limitations. Our purpose, rather, is to present a planning model which demonstrates an approach to integrating performance goals into strategic resource allocation. We use the downstream petroleum sector as our back-drop. Our use of DEA is purposeful, but other quantitative techniques such as regression analysis or forecasting may be just as robust. The allocation of resource capacities at supply sources, DCs, and in vehicles, the flows of products to customers, and the optimal re-allocation of customers to delivery zones must be determined subject to operational and economic constraints. Solving models of such supply chain issues often requires analysis of the competing tradeoffs.

Section 3 presents a profit-maximizing model containing such resource performance criteria. It is not the specific criteria, but their integration into planning models that this research offers. The complexities associated with multiple criteria approaches are avoided by specifying as constraints what prior research has sometimes modeled as multiple objectives. This enables a sensitivity analysis of the performance criteria and resource efficiency.

3. Model formulation

The following model proposes a performance-based approach to planning supply networks. It is adaptable to the multi-commodity scenario, and it contains interval and side constraints on product-related flows within the supply network. These side constraints are performance imperatives. Supply network planning remains a complex transportation planning problem, often described with many objectives. The single-objective formulation presented in this research considers a subset of those objectives simultaneously by specifically transforming them into output expectations for key operational resources such as vehicles, facilities, and personnel, at the strategic level and unique to this industry. There are several immediate benefits: (1) the comparison of competing objectives (efficient frontiers) is reduced to a single objective, (2) the impact of operations resources on the objective function is measurable in common units, although the resources themselves may be measured in different units as constraints of the model, and (3) the level of these constraints can be readily varied to assess their impact on the objective function, and more generally the reconfigured supply network.
These benefits are extensions to those cited earlier and are especially important in the petroleum industry [22].

**Notation of the IP**

- \( j = 1, \ldots, J \) number of potential DC locations (new and existing)
- \( k = 1, \ldots, K \) number of customers to be serviced
- \( i = 1, \ldots, I \) number of vehicles in service
- \( \text{RCAP}_i \) targeted total aggregate capacity for vehicle \( i \)
- \( \text{MNDPS}_i \) targeted total number of drops for vehicle \( i \)
- \( \text{VCAP}_i \) maximum capacity for vehicle \( i \)
- \( \text{DCAP}_j \) maximum storage capacity for DC \( j \)
- \( \text{DIST}_{kj} \) travel distance from customer \( k \) to DC \( j \)
- \( \text{DVYCST}_j \) trip cost per mile for deliveries originating in DC \( j \)
- \( \text{DPS}_k \) number of deliveries required by customer \( k \)
- \( \text{VOL}_k \) average order size per drop for customer \( k \)
- \( \text{OPC}_j \) cost of operating DC \( j \)
- \( \text{CV}_{ij} \) operating cost of vehicle \( i \) at DC \( j \)
- \( \text{R}_j \) revenue per unit volume of product sold at DC \( j \)
- \( \text{PC}_j \) purchase cost per unit volume of product at DC \( j \)

**Variables of the model**

- \( V_{ij} \) 1 if delivery vehicle \( i \) is assigned to DC \( j \), 0 if not
- \( D_j \) 1 if DC \( j \) is operating, 0 if not
- \( \text{CUS}_{kij} \) 1 if customer \( k \) is allocated to vehicle \( i \) from DC \( j \), 0 if not

**0–1 PROGRAM FORMULATION (PROF_MAX):**

\[
\text{MAX PROF\_MAX} = \left( \sum_{j=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \text{CUS}_{kij} D_j R_j \text{VOL}_k \text{DPS}_k \right)
\]

\(- \left( \sum_{j=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \text{OPC}_j D_j + \sum_{j=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \text{CV}_{ij} \right) \]

\(+ \left( \sum_{j=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \text{CUS}_{kij} D_j \text{PC}_j \text{VOL}_k \text{DPS}_k \right) \]

\(+ \left( \sum_{j=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \text{CUS}_{kij} \text{DIST}_{kj} \text{DVYCST}_j \text{DPS}_k \right) \)  

s.t.

\( \sum_{i=1}^{I} V_{ij} \leq \text{ID}_j \) for \( j = 1, 2, \ldots, J \), \( \text{(2)} \)

\( \sum_{j=1}^{J} V_{ij} \leq 1 \) for \( i = 1, 2, \ldots, I \), \( \text{(3)} \)

\( \sum_{i=1}^{I} \sum_{j=1}^{J} \text{CUS}_{kij} = 1 \) for \( k = 1, 2, \ldots, K \), \( \text{(4)} \)

\( \text{CUS}_{kij} \leq V_{ij} \) for \( k = 1, 2, \ldots, K \), \( \text{(5a)} \)

\( j = 1, 2, \ldots, J \)

\( \sum_{i=1}^{I} V_{ij} \text{VCAP}_i \leq \text{DCAP}_j \text{D}_j \) for \( j = 1, 2, \ldots, J \), \( \text{(6)} \)

\( \text{D}_j \text{RCAP}_i \leq \sum_{k=1}^{K} \sum_{j=1}^{J} \text{VOL}_k \text{CUS}_{kij} \leq \text{VCAP}_i \) for \( i = 1, 2, \ldots, I \), \( \text{(7)} \)

\( \sum_{k=1}^{K} \text{DPS}_k \sum_{j=1}^{J} \text{DIST}_{kj} \text{CUS}_{kij} \leq \text{RCM}_i \) for \( i = 1, 2, \ldots, I \), \( \text{(8)} \)

\( \sum_{k=1}^{K} \text{DPS}_k \text{CUS}_{kij} \geq \text{MNDPS}_i \) for \( i = 1, 2, \ldots, I, j = 1, 2, \ldots, J \), \( \text{(9)} \)

\( D_j = 0, 1 \) for all \( k \), \( \text{(10a)} \)

\( V_{ij} = 0, 1 \) for all \( i, j \), \( \text{(10b)} \)

\( \text{CUS}_{kij} = 0, 1 \) for all \( k, i, j \), \( \text{(10c)} \)

The profit-maximizing objective function (1) states the expected system profits which includes:
Expected revenues are based on forecasted order sizes and frequencies for each customer. \( R_j \) varies among DC regions.

The fixed operating costs (construction, overhead, etc.) for a DC in \( \text{OPC}_j \).

The variable operating costs (utilities, maintenance, purchase, direct labor) for vehicle \( i \) assigned to DC \( j \) is \( CV_{ij} \). These can vary across market regions.

Expected product purchase cost from supplier. This includes conversion and transportation costs.

The delivery cost is determined using average delivery costs in each geographic zone, \( DIVYCST \), order frequency, and travel distance to each customer: This includes direct labor and fuel costs. These kinds of data are often available from internal databases or accounting systems, or other easily accessible internal data sources.

The constraints of the model are:

1. (2 & 3) Vehicles are assigned only to opened DCs, and not shared among DCs.
2. (4 & 5) All customers must be assigned to a DC. Demand may be split among vehicles assigned the same DC.
3. (6) Total vehicle capacity must not exceed DC storage capacity.
4. (7) Portion of market zone demand allocated to vehicle \( i \) must meet some minimum target, \( RCAP_i \) (LHS constraint), and not exceed maximum capacity (RHS constraint).
5. (8) Aggregate travel distance is constrained by an upper bound on expected accumulated mileage for each vehicle.
6. (9) Each vehicle in operation must complete a minimum number of deliveries in its zone. Some minimum number of drops (deliveries) are required of all operational resources.
7. (10) zero–one restrictions are imposed on the model variables.

The bounds RCM, RCAP, and MNDPS are performance measures. They represent the performance goals of a potential final configuration. In the model, customer performance is not a by-product of the model. Rather it is determined by the decision makers’ specification of the values for RCM, RCAP, and MNDPS as summarized below:

The variable RCM in (8), is the recommended total mileage accumulated on vehicles during the planning horizon. Its target level can be determined based on replacement costs, depreciation schedules, and operational guidelines of the vehicle itself. As a limit on the distance vehicles may travel, RCM is important because it defines the spatial market area for vehicles in concert with (7) and (9).

The variable RCAP, is the minimum volume load size for delivery vehicles at the beginning of a delivery trip. For example, a 10,000 gallon capacity delivery vehicle must begin its delivery cycle with orders totaling 75–80% of its storage capacity to be ideally profitable and efficient. This variable is also important for planning because it controls vehicle load capacities for a route. As shown in (7), actual or forecast demand must be known.

The variable MNDPS, is the minimum number of deliveries required during a trip for each vehicle. This represents the expected number of deliveries required to maintain the route service and also delivery timeliness. This may be influenced by the average inter-customer delivery distance. As shown in (9) and coupled with (8), customers’ forecast or actual order frequencies within each market area must meet some minimum threshold value. This variable specifies what that minimum should be for each vehicle placed in service at an opened facility.

Operational characteristics (such as customer densities, average travel distances, and order sizes) can vary across demand zones. Variables RCM, RCAP, and MNDPS are used to reconfigure the supply network by balancing the distances, volumes, and frequencies so that the overall efficiency and flow assignment of product are resolved subject to the remaining model constraints and profit maximization. This extension to the basic formulation incorporates transportation planning issues by assigning customers’ demand to specific vehicles with resource capacities in mind. For managers, this can provide strategic insight into managing performance, and for evaluating the implications of allocation decisions. Qualitative issues like customer service, and market share information often are interpreted from interviews or responses to questionnaires. This type of data may often be
susceptible to bias or other subjective assessment, and complicate the modeling and analysis process. However, if used prudently and combined with operations benchmarking, internal best practices can be identified to establish and monitor performance objectively and quantitatively; this minimizes or avoids potential biases.

3.1. Model assumptions and generalizations

Several assumptions and generalizations of the model are now described. First, historical customer data and forecast information remain central to the strategic planning process. Since network re-design is a permanent decision, aggregate trends must be known, or at least forecast in advance. This may require such cross-functional inputs from operations and marketing as the planned market penetration goals for all product classes. Since capacities at the distribution centers are generally known, too, market penetration goals must represent volume estimates for the individual products.

Second, the constraints of model PROF-MAX are classified as Location, Deployment, Flow, or DC Operations type constraints. At the strategic level, the constraint classes define the data input requirements, and identify the model outputs of each constraint class. Table 1 summarizes these attributes using this classification of constraints in PROF-MAX.

Third, product flow constraints in the many related models have sometimes been subject to various upper and lower bounds, or sometimes unrestricted so that the models themselves determine optimal flow levels in both upstream and downstream studies [23–25]. In this model, the bounds are used as measures of future performance standards for operational resources. Using upper and lower limits enhances decision making by supporting the product/service pricing strategies set by management in relation to the identified best-practice standards.

Fourth, customer requirements are explicitly modeled despite their dependence on accurate forecast data or actual data. Since farmers maintain their own fuel storage tanks to be filled by distributors, the geographical market regions are split into serviceable demand zones. Each demand zone is characterized by variable customer densities which are defined by the distances between farms; Travel time may easily be substituted for distance. The zones are also characterized by the average delivery size. Although most orders are less-than-truckload (LTL), some are in fact truckload (TL) for very large-scale farm operations. The nature of this problem scenario does not consider multiple shipment modes at this stage of the supply network. All deliveries are made using trailers, as is standard practice.

Several quantitative methods exist for determining the initial values for the interval and side

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<table>
<thead>
<tr>
<th>Constraint class</th>
<th>Input</th>
<th>Output</th>
<th>Assumptions</th>
<th>Constraint number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>DC and vehicle status</td>
<td>Vehicle allocations; Opened DCs, Meet performance standards</td>
<td>DC and fleet information are current</td>
<td>2, 3, 4, 5, 8</td>
</tr>
<tr>
<td>Deployment</td>
<td>Actual or forecast demands by product Preliminary network layout, service levels or efficiency requirements, etc . . .</td>
<td>Allocation of product mixes at DCs Service frequencies to customers and DCs, allocation of fleet capacity; DC physical supply requirements</td>
<td>Based on aggregate operations data Supply network layout is feasible.</td>
<td>7, 6, 7, 8</td>
</tr>
<tr>
<td>Flow</td>
<td>Supply network layout; product flows, environmental constraints, customer expectations</td>
<td>Meet performance standards</td>
<td>Reliable market data</td>
<td>9</td>
</tr>
</tbody>
</table>
constraint variables (RCM, RCAP, and MNDPS) of this model. For this study, various operational and financial data were available which indicated the input and output levels of all DCs. It was assumed that the data accurately reflected the supply network operations because of the information management infrastructure already in use. Since the data represented heterogeneous DCs operating at different levels, analysis must objectively evaluate the relative efficiencies and help identify best internal practices. In such instances, as documented in research cited earlier, the DEA technique has been ideal; each unit consumed various amounts of each input and produced different levels of identical outputs. It is an objective (unbiased) method for determining and benchmarking operational efficiency of heterogeneous or homogenous decision-making units (DMU). The DCs currently operating are the DMUs for which efficiencies are evaluated. Efficiency is measured for all DMUs in the analysis set. The most efficient DC operations were identified as best internal practices, and used as benchmarks for under-performing facilities or consolidation decisions. It is not the DEA efficiency measures that are used in model PROF\_MAX, but rather the values for the constraint variables, implied by the efficiency measures, which are explicitly modeled in (7)–(9).

The net result provided decision makers with recommended guidelines for key performance indicators at any DMU which can be explicitly modeled. It is important to acknowledge that with different data sets than those used here, analysis may suggest different strategies for performance attainment; however the process of performance-based planning remains transparent. We also recognize the reality that some recommendations for improving resource efficiency may be impractical for managers to implement. How to accomplish such improvements can be a challenge for individual DC managers.

### 3.2. Supplemental analysis: Service efficiency

Cost-containment strategies, and resource efficiency are used to describe many supply networks. To what extent, however, can they influence the network’s actual allocation of resource? This is an important question for logistics managers and analysts. Using the initial data provided by the sample firm, the current system strategy was compared to the DEA-constrained model in Table 2. To preserve privacy, the data have been altered without loss of generality. In the current layout of the network, there are 210 DCs in operation serving an average local demand zone of 111 farmers with a fleet of five vehicles each. DEA computed the relative efficiency for the system to be 0.763 and actual annual profit was reported at $4,134,238. The best-practice standards (BPS) were then imposed on the model and solved. Now the system would have generated a 3.6% increase in profits (see column 3) using only 190 DCs. Of the original 210 currently opened, model PROF\_MAX suggested 11 DC closures and eight consolidations. The average market size increased to 122 customers per zone with only four vehicles required to service the demand zone; Vehicle operations costs increased under BPS from $1.0M to $2.07M; Delivery costs increased to $3.2M; Total purchase costs were nearly identical. Such increases in components of total cost, however were offset in magnitude by the savings generated from DC closures and consolidations. The net savings from DC operations alone was $2.5M (or 16.7%). Another clear benefit was that system efficiency improved by 13% over the ‘current’ strategy. Thus assets may in fact be strategically placed to improve efficiency and profit contribution.

This approach can be very robust in helping decision makers arrive at ideal market zone sizes,

### Table 2

Preliminary comparison to BPS

<table>
<thead>
<tr>
<th>Descriptor</th>
<th>Current</th>
<th>BPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total # potential DCs</td>
<td>225</td>
<td>225</td>
</tr>
<tr>
<td># DCs in use</td>
<td>210</td>
<td>190</td>
</tr>
<tr>
<td># New DCs</td>
<td>—</td>
<td>1</td>
</tr>
<tr>
<td># DC closures</td>
<td>—</td>
<td>11</td>
</tr>
<tr>
<td># DC consolidations</td>
<td>—</td>
<td>8</td>
</tr>
<tr>
<td>Avg. DC mkt. size</td>
<td>111</td>
<td>122</td>
</tr>
<tr>
<td>Avg. fleet size</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Avg. efficiency</td>
<td>0.763</td>
<td>0.862</td>
</tr>
<tr>
<td>Expected profit($)</td>
<td>$4.13M</td>
<td>$4.28M</td>
</tr>
<tr>
<td>% change from current</td>
<td>—</td>
<td>+ 3.63%</td>
</tr>
</tbody>
</table>

expected product inventory allocations (MND PS), fleet size, and fleet usage restrictions (RCM and RCAP) as shown in model PROF\_MAX, for this and similar strategic scenarios.

3.3. Frontier analysis of profit and efficiency

Alternative designs were developed by relaxing the performance side constraint values in (7)–(9) from BPS. To protect the privacy of the sample firm, forty problems were generated based on the sample data provided (see Table 3). The market regions were divided into low customer-density and high customer-density regions. For low-density problems, the average inter-customer distance was ten percent higher than for high-density problems, and the standard deviation was 40–50% higher. Simultaneous relaxation occurred in 5% increments away from BPS. For each realistic-sized sample problem, PROF\_MAX was generated and solved using Extended LINGO\textsuperscript{TM}. Table 4 summarizes the impact on supply network design alternatives.

For each level, the system efficiency and expected profit are reported. For example, with the initial BPS strategy imposed on the model (level = 0%), the expected profit and system efficiency are $4.28M/0.859, and $4.29M/0.864, respectively, for the low- and high-density problems. The percent improvement over current system strategy is also listed. The performance constraints were then simultaneously relaxed by 5%. At this level, there was still a noticeable improvement in expected system efficiency and profit; however the improvement was more pronounced for the high-density problems than for the low-density. Fig. 1 suggests (1) profit may be extremely sensitive to efficiency for low density problems, and (2) profit contribution deteriorates rapidly beyond 5%. In terms of the Flow constraint, one explanation for profit erosion may be that the average cost per mile was greater for low-density problems than for high-density problems (Fig. 3). This seems unusual since the constraint relaxation widens the feasible region of the solution space; however the interaction of customer densities and variable revenue rates per

Table 3

<table>
<thead>
<tr>
<th>Dataset number</th>
<th>Number of problems</th>
<th>Number of DCs</th>
<th>Number of vehicles</th>
<th>Customer density</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5</td>
<td>225</td>
<td>1000</td>
<td>LOW</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>225</td>
<td>1000</td>
<td>LOW</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>225</td>
<td>1000</td>
<td>HIGH</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>225</td>
<td>1000</td>
<td>HIGH</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
<td>225</td>
<td>1100</td>
<td>LOW</td>
</tr>
<tr>
<td>6</td>
<td>5</td>
<td>225</td>
<td>1100</td>
<td>LOW</td>
</tr>
<tr>
<td>7</td>
<td>5</td>
<td>225</td>
<td>1100</td>
<td>HIGH</td>
</tr>
<tr>
<td>8</td>
<td>5</td>
<td>225</td>
<td>1100</td>
<td>HIGH</td>
</tr>
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</table>

Table 4

<table>
<thead>
<tr>
<th>Dataset cust. density</th>
<th>Impact</th>
<th>% Relaxation from best-practice standard (DEA)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0%</td>
</tr>
<tr>
<td>LOW</td>
<td></td>
<td>$4.28M</td>
</tr>
<tr>
<td>Expected profit($)</td>
<td></td>
<td>+ 3.63%</td>
</tr>
<tr>
<td>% change from current</td>
<td></td>
<td>0.86</td>
</tr>
<tr>
<td>System efficiency</td>
<td></td>
<td>+ 12.58%</td>
</tr>
<tr>
<td>HIGH</td>
<td></td>
<td>$4.29M</td>
</tr>
<tr>
<td>Expected profit($)</td>
<td></td>
<td>+ 3.87%</td>
</tr>
<tr>
<td>% change from current</td>
<td></td>
<td>0.864</td>
</tr>
<tr>
<td>System efficiency</td>
<td></td>
<td>+ 13.24%</td>
</tr>
</tbody>
</table>
regions explains the profit erosion. The long-term implication is to serve the customers in these areas using fewer resources; this may improve profitability. For the high density, the rate of decline in expected profits was not as perverse. Shorter average travel distances and higher efficiencies result from serving small, dense market zones (DC Operations constraint and Flow constraint). Costs shifted from delivery to vehicle operations and number of facilities, yet this shift was more than offset by the increased revenue base. At some level, however, high-density zones may adversely affect driver and customer satisfaction, and system efficiency if not properly balanced.

Fig. 2 illustrates the system efficiency tradeoffs as relaxation was increased. It shows that low-density problems are very sensitive to the best practice standard particularly as the 5% threshold
is approached. High-density problems followed the same pattern, but not as dramatically. As the data in Table 4 shows, regions where resource utilization is high may not be as sensitive to BPS because, for example, of simple supply and demand. Fig. 3 suggests that zones which are heavily concentrated and over extended resources can create inefficiencies. For example, efficiency for densities of 0.5–1.5 was less than 0.8, while that for densities between 1.5 and 5.0 was above 0.80; the corresponding profits were relatively equal – an important managerial tradeoff of efficiency versus expected profit.

4. Managerial implications

Without effective policies, inventory stockpiles and stockouts at various DCs can erode profit margins. Inferior resource utilization rates, and inefficiency within supply networks of manufacturing and service firms expose operations to market losses or service degradation. As with any modeling approach, there are critical areas where challenges exist. Managers must assess these challenges and their corresponding tradeoffs when formulating or reformulating policies for supply network configuration. This paper extends an earlier work of Ross et al. [17] by showing how the results of DEA or other performance analyses can be integrated strategically for targeting resource investment or redistribution decisions. This approach and the analytical results are useful not only in identifying practices and investments conducive to improved efficiency and profitability, but also the exemplary operating units most likely to provide sustained returns on such strategic investment decisions.

Infrastructure needs for such analysis may vary, but broadly speaking they include the information needs of modeling, the information needs of constituencies (such as product managers, budgeting and pricing managers, and DC operations managers), and market-based competitive priorities. Effective decision-making is influenced by the quality and the quantity of data inputs available. It is therefore critical that processes or systems be in place to collect, manage, and reliably validate operating and financial data. Specific information requirements cannot be determined without knowing what detailed information is available or accessible through internal systems, and what data is unavai-

![Graph showing expected profit and efficiency as a function of inter-customer travel distance](image)

**Fig. 3.** Efficiency and profit tradeoff.
stages to define goals of the project, determine information needs and assess its availability. Forecast data and historical data from over 200 DCs in the system were accessible and the team exploited this information resource to the benefit of the firm. The volume and type of information available are factors in overall success of the modeling approach selected. For example, product managers integrate and coordinate product decisions at each DC (or service center). They provide economic input to product and resource allocation alternatives. Budgeting managers and Corporate planners oversee regional pricing-volume issues related to inventory efficiencies, price-breaks, and general pricing and transportation costs. Indirectly, several additional internal and industry-level factors impact performance-based planning for operations. Within this industry, upstream firms make profits from direct sales of crude at what are called spot transfer prices. For US distributors in the downstream segment, this decoupling of operations further emphasizes the need to serve core customers (farmers) more efficiently. In retrospect, deregulation in this industry fostered better competition, and this may also have simplified the identification of more appropriate performance indicators for managers.

5. Conclusions

This paper has discussed and briefly illustrated strategies for supply network planning, proposed an example model of petroleum distribution in the downstream segment, coupled performance criteria explicitly, and discussed some of the managerial implications for doing so. It focused on the model structure as proposed in recent implementations, and called for in the logistics planning literature. As stated earlier, there are many studies on heuristic, scenario evaluation and optimal approaches to this class of problems and they are available to practitioners. Such methodologies was not the central focus in this study. This study also offers some useful insights to strategic planning which included sensitivity analysis of the interaction of profit, best practice standards, supply network design. Important factors and issues for performance-based operations planning are numerous between problem scenarios. Generally, as shown in this paper, they may include the need to establish guidelines for quality service, identifying exemplary practices (BPS), resource redistribution and acquisition. Additionally, general support from top management, data collection and analysis systems, knowledge of current industry trends, impact of external regulatory entities, knowledge of markets and products, and the overall needs of the organization are important. This infrastructure and knowledge is assumed already in place.

The results presented in this paper show that operations research tools and key operational data can be used with a minimum degree of sophistication. They help identify performance indicators and use such results for strategic planning of distribution resources to identify inefficiencies and pinpoint shortfalls. Incremental improvements in resource efficiency can generate significant profit potential. The tradeoff models offer insight into the strategic alternatives available to managers on several dimensions. Given the variety of operational settings which exhibit similar characteristics described earlier, research which spans other industries or identifies limitations and benefits of performance-based approaches is important and encouraged.

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References


