OPRE 6366. SCM : 2. SC Design

1 Frequency decomposition of dynamic systems

As we pointed out earlier, integration is the central theme in SCM. Since full integration is difficult to handle, we introduced the concept of integration by decomposition. Along these lines, we will now talk about how to arrange decisions sequentially to obtain a good decomposition which limits the comprimises from the benefits of integration. Our discussion is based on the frequency decomposition concept borrowed from Gershwin [5].

Let us first note that any input to a decision process can be treated as a decision itself by expanding the boundaries of the decision model. For example think of choosing a place to go for a dinner today. One of the key inputs to this decision is the amount of money you are willing to spend. There are two ways to go about this. In the first way, you may fix your budget, say $12 and then choose a place. In the second way, you may fix a range for the budget, say $10-20, and decide on the place in conjunction with how much you exactly spend. Although, the difference between these two approaches seem miniscule for a dinner affair, the difference is quite striking for SCM decisions, such as capacity expansion for a plant. Depending on the company in question, the people who decide on what machines to buy may or may not be deciding on the expansion budget. If they also decide on the budget, expansion decision is a one integrating budgeting and expansion. Clearly, choosing both the budget and machines is more complex than choosing only machines. Also it requires more responsibility. For those reasons, companies generally have different groups working on different decisions and output of one group's decision becomes input to another. As a result, decisions and inputs depend on the model boundaries. A linear programming anology here is helpful; You should consider inputs as capacity constraints in your linear program and decisions as decision variables. Recall from your linear programming class that capacities can also be turned into decision variables by expanding the model boundary.

By now, we must agree that we have the flexibility to specify inputs and decisions at the begining of the decision process. Frequency decomposition outlines how to do this. The first step of frequency decomposition is figuring out the frequency of decisions. For example, I decide on my dinner budget once in a year (say considering my salary) but I have to decide on the restaurant for the dinner every day. Budget decision is made once a year, restaurant decision is made once a day, i.e. 365 times more frequent. Frequency decomposition groups decisions with lower (higher) frequency into a higher (lower) level decision group. Higher level decisions (such as budgeting) are made either ignoring or aggregating lower level decisions (such as daily restaurant selection). Once the higher level decisions are made, those decisions are fixed and become inputs for lower level decisions: budget becomes an input for restaurant selection decision. If there are several decisions that occur at about the same (by an order of 1/4 to 4) frequency, those decisions can be considered in the same group together. For example, quarterly sales targets (produced 4 times a year) can be considered with annual budgeting decisions. This is for convenience, otherwise almost every decision will be considered by itself. Considering several decisions together also improves integration. In short, frequency decomposition groups decisions according to their frequency and imposes a hierarchical decision making process from a higher level decision group down to lower level decision group where higher level decisions become inputs for lower level decisions.

Recall that in an earlier section we talked about differences among strategy, policy and decision. These three are also decision groups hierarchically positioned according to their relative frequencies: Outputs of strategic decisions become inputs to policy decisions, etc.

2 SC design decisions

By design decisions, we mean decisions regarding strategic choices or policies which are done relatively infrequently, i.e. with a frequency of less than twice per annum. Such decisions include: Facilities location (Plants and Warehouses site selection), facility capacities, transportation fleet selection, fleet capacity, allocation of products to facilities, allocation of customers to warehouses, etc. Note that implementing these decisions requires substantial capital investments. Moreover, switching from one decision to another (say closing a warehouse in Atlanta but opening one in Dallas) is very costly. High costs involved in implementing and modifying design decisions are the reason why these decisions are done infrequently. Using the frequency decomposition approach of the previous section, we place SC design decisions at the top level of decisions because of their infrequency. Therefore, we will first come up a with a SC design and use that design as an input to decision processes at lower levels. Note that some authors use the term (logistics) network design as a synonmy of SC design. That is because decisions mentioned above were studied under the title of (logistics) network design before the term SC was born.

$\Re\epsilon\alpha\delta$ Chopra §4.1, 4.2, 5.1, 5.2 and 5.3.

3 Analytical models for SC design

In the previous sections, we learned about qualitative factors affecting the SC design. Many companies naturally consider quantitative factors as well. Actually SC design decisions are made using quantitative models and paying attention to qualitative factors. We now study the quantitative models.

$\Re\epsilon\alpha\delta$ Chopra §5.4

Previous models do not explicitly state how the distances are computed. We now provide some more detail on distance types and computations. The euclidean distance is the shortest distance between any two points. Let x, y be the coordinates of a point. Consider the distance between two points A and B,

$$\text{Euclidean distance:} \quad d_{A,B} = \sqrt{(x_A - x_B)^2 + (y_A - y_B)^2}.$$

If A and B are further away from each other, the curvature of the world must be taken into account. Let lon, lat stand for the longitude and lattitude of a point. For long distances in the continental US, distance $d_{A,B}$ between two points A (lon_A, lat_A) and B (lon_B, lat_B) is given approximately by

$$\text{Euclidean distance with world's curvature:} \quad d_{A,B} = 69\sqrt{(lon_A - lon_B)^2 + (lat_A - lat_B)^2}$$

where 69 is the number of miles per degree of latitude in the continental US (see Simchi-Levi et al. [7]). Note that d_{AB} is the direct distance (plane ride) between A and B. Since highways are not straight between locations, d_{AB} is inflated by a circuity factor ρ when computing surface distances. In metropolitan US, take $\rho = 1.3$. In rural US, take $\rho = 1.14$.

The second measure resembles driving along perpendicular city blocks (called city-block or rectilinear distance). The city-block distance between A and B is given by

$$\text{Rectilinear distance:} \quad d_{A,B} = |x_A - x_B| + |y_A - y_B|.$$

An intuitive property that may simplify the solution procedures for location-transportation problems is the triangular property of the distances: For three demand points A, B and C,

$$d_{A,B} + d_{B,C} \geq d_{A,C}.$$

If you imagine A, B and C as the corners of a triangle, the triangle property says that sum of the lengths of two sides of a triangle (AB and BC sides in the formula above) is longer than the length of the third side (AC in the formula above).

We now provide a classification for location models. A more detailed classification and discussion is given in Drezner [4]. Here are the list of criteria used in our classification:

1. Objective function: This is the criterion to be optimized while choosing facility locations. There are two main variations: private sector objective and the public sector objective. The private sector objective minimizes the sum of distances from a demand point to the closest service facility. Private sector objectives strive for overall efficiency whereas public sector objectives also deal with the equity among demand points. The public sector objective minimize the maximum distance between a demand point and the closest service facility. For example, hospitals and fire stations are located in this manner so that everybody can access to these services within a maximum allowable time period. Some service facilities are not desirable and people want to be away from them, then the objective turns out to be maximizing distances rather than minimizing them. This case is examined under the term obnoxious location models.

2. Demand allocation: This criterion examines how consumers choose which facility they will go. Many analytical models assume that consumers prefer the closest facility. This may be true for convenience stores, however in general demand allocation is more complex. Consumers may be making up their mind considering cost, congestion, service quality, etc.

3. Demand pattern: Typically demand is represented by demand points, each of which may represent several hundreds (or thousand) of consumers whitin the same geographic area. Depending on the corresponding population, purchasing power and amount of material flow, demand points are assigned weights. Higher weights pull service centers closer to demand points during optimization. Note that Hotelling's model of market splitting does not use demand points but considers demand as continuously distributed over the line segment $[0, 1]$

4. Feasible sites: Two approaches are common. In the first approach, all feasible sites are identified and passed to the location problem as an input. Problem is constrained to pick one (or more) of only feasible sites. In the second approach, the optimal location is found as if all sites are feasible. But then the feasible site closest to the optimal location is chosen.

5. Distances: This refers to the distance between the demand point and its service center. Generally travel times are assumed to be proportional to distances so objective functions are given in terms of distances. Two measures of distances are the most common: Euclidean and Rectilinear; see above.

3.1 p-Median Model

This model has private sector objective, demand allocation by the closest facility, demand concentrated at demand points, only feasible sites are taken as input. Distances can be either euclidean or rectilinear but the model formulation looks the same in both cases. The p-median problem deals with locating p service facilities. The objective is the minimization of the sum of the amount of material flowing (among demand points and service centers) multiplied by the distance it flows over.

We now give a mixed integer linear programming formulation. Let D_i be the demand at the demand point i. Let F be the set of feasible service sites and let $d_{i,j}$ be the distance between demand point i and the service facility site j. We assume that each service facility has infinite capacity so we can assign as many demand points to a single site as we would like. Binary decision variables $x_{i,j}$ and y_j are defined as,

$$x_{i,j} = \left\{ \begin{array}{ll} 1 & \text{if the demand point } i \text{ is asigned to the service facility at site} j \\ 0 & \text{otherwise} \end{array} \right\}.$$

$$y_j = \left\{ \begin{array}{ll} 1 & \text{if the facility at site } j \text{ is opened} \\ 0 & \text{otherwise} \end{array} \right\}.$$

$$\begin{array}{ll} \text{Minimize} & \sum_i D_i \sum_{j \in F} d_{i,j} x_{i,j} \\ \text{Subject to:} & \end{array}$$

$$\begin{array}{rcll} \sum_{j \in F} y_j & = & p & \\ x_{i,j} & \leq & y_j & \text{for all } i, j \\ \sum_{j \in F} x_{i,j} & = & 1 & \text{for all } i \\ x_{i,j} \ , \ y_j & \in & \{0, 1\} & \text{for all } i, j \end{array}$$

The first constraint sets the number of service facilities to p. The second constraint says that demand point i can be assigned to the service facility j only if service facility j is open. The third constraint enforces that exactly one service facility is assigned to each demand point. For a certain instance of this problem, input data p, D_i, F and $d_{i,j}$ take numerical values which are used to build and solve the formulation with Excel, Lindo or AMPL softwares.

3.2 p-Center Model

This model differs from the p-Median problem only in its objective: it uses a public sector objective function, i.e. minimizes the maximum distances between service facilities and demand points. Note that if $d_{i,j}x_{i,j}$ is positive, it is the distance between the demand point i and its service facility. Define the objective function rigoursly: The maximum distance is $d = \max\{d_{i,j}x_{i,j} : i \text{ is a demand point}\}$. The p-Center model minimizes this distance d.

3.3 p-Covering Model

In this problem the objective is to cover (meet) as much demand as possible with given number of service centers. The distances are not relevant in this problem. As in the p-median problem we have demands given as D_i. In addition, we have a set (called N_i) of service centers associated with each demand point i.

If service center j is in set N_i, then j is accesible by i, or i can be served from j. Once more we suppose that there are p service facilities to locate. Binary decision variables are as follows,

$$x_i = \left\{ \begin{array}{ll} 1 & \text{if demand point } i \text{ is covered} \\ 0 & \text{otherwise} \end{array} \right\}.$$

$$y_j = \left\{ \begin{array}{ll} 1 & \text{if the facility at site } j \text{ is opened} \\ 0 & \text{otherwise} \end{array} \right\}.$$

Note that the definition of y_j is the same both in p-Median and p-Covering problems.

$$\begin{array}{llcll} \text{Maximize} & \sum_i D_i x_i & & & \\ \text{Subject to:} & & & & \\ & \sum_{j \in N_i} y_j & \geq & x_i & \text{for all } i \\ & \sum_j y_j & = & p & \\ & x_i \ , \ y_j & \in & \{0,1\} & \text{for all } i,j \end{array}$$

The first constraint enforces that if the demand point i is covered there must be a service facility j (that can cover i, so $j \in N_i$) open. The second constraint sets the number of facilities to p.

3.4 p-Choice Model

This model is an extension of p-Median model. It allows demand point i to pick the facility j with probability $p_{i,j}$. Generally $p_{i,j}$ is computed by taking distance $d_{i,j}$ and attractiveness of j into account. Therefore, in p-Choice model a demand point does not necessarily choose the service facility closest to it.

3.5 Models with Multiple Decision Makers

Until now, we have reviewed location problems from only one decision maker's perspective. That decision maker aims to minimize the sum of overall location related costs. While locating franchises, there are at least two decision makers: franchisor (the parent company giving the franchise) and the franchisee (the company/person seeking/taking the franchise). The parent company may sell its products through franchises (e.g. Volkswagen and its US dealers), and may also receive royalty and trademark fees. On the other hand, franchisee uses the name recognition of the franchise to boost its sales. Then, the franchisor wants to give many franchises to increase its royalty fees. However, existing franchisees do not want to have a competing franchise next door, so they want to limit the number / locations of new franchises. As a result, locations of new franchises are decided upon by sometimes three parties; franchisor, existing franchisees and new franchisees. One way to overcome conflicting interests is locating new franchises away from the existing ones by some prespecified (in franchise contract) distance. In a way, new franchises become undesirable facilities for the existing ones so one should expect similarities in these models and obnoxious facility location models.

$\Re\epsilon\alpha\delta$ Chopra §5.5.

4 SC Design in an Uncertain Environment. $\Re\epsilon\alpha\delta$ Chopra §6.1-6.6

5 Transportation Networks. $\Re\epsilon\alpha\delta$ §14.1-14.4 of Chopra

6 Trade off between Transportation Cost and Customer Responsiveness

$\Re\epsilon\alpha\delta$ the associated part of §14.5 of Chopra. Skip the subsection: Transportation and Inventory Cost Trade off. We will return to this section after learning more about inventory.

7 Distribution Networks. $\Re\epsilon\alpha\delta$ §4.3-4.5

8 Routing and Scheduling in Transportation

In this section two important decisions will be made: Assignment of trucks to demand points (clustering demand points) and the sequence in which each truck visits demand points assigned to it (routing trucks). These two decisions together are refered to as Vehicle Routing Problem (VRP) in operations management literature. The problem of sequencing the demand points to create the shortest route is known as the Travelling Salesman Problem (TSP). Note that TSP deals only with the second decision of VRP. In the special case of only one truck, all demand points are trivially assigned to the same truck. Then, the first decision of VRP is trivial or nonexistent, so VRP reduces to TSP. Although TSP is very intuitive and comes up in various contexts (other than transportation), finding the optimal solution is very hard if there are more than couple thousand demand points to sequence. From a practical point of view, real-life size TSP problems can be solved with heuristics to almost optimality within couple minutes.

Since we will not specify exactly when trucks pick up the materials or when they deliver them. Thus, we will deal with only sequencing but not with scheduling. However, we keep the word ”scheduling” in the title to keep consistency with the textbook.

8.1 VRP classification

Next we examine a list of criteria to classify VRP problems (see Chen [3] for details):

1. Demand uncertainty: In most VRP models, the amount of material demanded at each demand point is known with certainty at the time of routing. However, this may not always be the case. For example, Xerox employs repairmen who drive to customers with their vans carrying some repair parts inventory. When repairmen are routed to customers who has failed Xerox machines, repairmen do not know possible failures and customer calls that might happen while they are on the route. Basically demand for repair parts is uncertain and is updated continuously. VRP with uncertain demand is called stochastic vehicle routing problem.

2. The nature of operations: Trucks can do deliveries, pick ups or both at a single customer point. In retail networks, trucks are generally assumed to be doing deliveries. In a repair network such as Xerox's, repairmen might have to pick up a failed machine for service. Depending on the nature of operations, the specification of demand (pick up/delivery/both) and the time it takes to serve that demand must be specified.

3. Planning periods: Most VRP models concern only with a single planning period or assume that every period looks exactly the same at the start of the period. For example, all Webvan trucks might be returning to their home base at night and the planning period can be taken as a single day. However, Ryder trucks may spend 5-6 days away from their home base so they cannot be assigned to a new route at the start of every day; The location of trucks at the start of the first day is different than those at the start of the second. Ryder's problem can be thought as a VRP with multiple periods where each period is a day. When the problem has multiple periods, the amount of inventory held at DCs also become relevant. The version of VRP that also accounts for inventory costs is called Inventory Routing Problem.

4. Static vs. Dynamic VRP: In static VRP's, the real time information regarding demands cannot alter already fixed routes. On the contrary, this information can be used to improve routes in dynamic VRP's. Naturally dynamic VRP's are more efficient but difficult to manage.

5. Fleet capacity: The number of trucks in the fleet are fixed in most operational decision making situations. However, when decisions are of strategic nature, the number of trucks (fleet capacity) can become a decision variable itself. With extra trucks, a better servivce can be provided to customers at the expense of buying / operating extra trucks.

6. Delivery time window: Sometimes customers specify not only what they want but also when they want it. This puts a restriction on acceptable delivery times. Sometimes companies can impose such a restriction on themselves as a competitive strategy, as in the case of Webvan's 30 mins. or cable companies' 2-hour-delivery windows. A delivery window is specified by the earliest acceptable delivery time and the latest acceptable delivery time. In some cases, customers impose only delivery due dates, i.e. the latest acceptable delivery time.

7. The objective: The objective generally minimizes each of the following measures or some weighhted combination thereof: transportation costs, inventory costs, the number of vehicles, vehicle costs, crew costs, etc.

When studying VRP, decision makers have the flexibility to mold a specific problem into a convenient class of VRP. For example, Ryder truck's VRP can be considered as a single period problem where a period is a week or Xerox VRP can be modelled as a static or dynamic VRP. The decision maker must choose the class that represents reality accurately while keeping an eye on the complexity and the tractability of the model. Both tractability and complexity relate to solution techniques and that is what we will study next.

8.2 VRP Heuristics

There are several classes of algorithms to solve VRPs. The most popular class is the two-phase route construction heuristics where demand points are clustered first and trucks are routed next. Books generally talk about two methods for demand point clustering: Savings Matrix Method and Generalized Assignment Method. These methods cluster the demand points that will be served by the same truck. Once the clustering is done, the demand points must be put into a sequence that will lead to a reasonably short route. Sequencing can be done by two classes of heuristics as well: Route Sequencing Procedures and Route Improvement Procedures. As the name implies the first group constructs the routes from scratch whereas the second group improves upon existing routes.

$\Re\epsilon\alpha\delta$ §14.6-14.7 of Chopra.

Remarks:

1. The farthest insert procedure may appear counterintuitive but it works well in practice. Note that it deals with the significant distances first. Thus, the rough shape of the final route is obtained very early during the implementation.

2. Under the triangular cost property, Rosenkrantz et al. [6] showed that the nearest insert procedure at worst yields a tour twice the length of the optimal tour. Similarly, the length of the nearest neighbor route can at worst be $\{log_2(n+1)+4/9\}/3$ times the length of the optimal tour, where n is the number of demand points in the tour.

3. For approximate solutions to Euclidean Traveling Salesman problem see [1].

$\Re\epsilon\alpha\delta$ §14.8 of Chopra

9 Exercises

1. In a manpower planning study of a Wendy's on Preston & Campbell, the following list of events were recorded:
   A. Counting the money in the cash registers and doing the financial summaries (done daily, requires 4 man-hours)
   B. Counting the inventory (done weekly; requires 3 man-hours)
   C. Placing an order for replenishment of the inventory (done weekly; requires 1 man-hour)
   D. Stocking the incoming incventory (done weekly, exactly 24 hours after the order is placed, requires 3 man-hhours)
   E. Staffing for the rush times that occur in the morning and around the noon
   F. Deciding on the sequence of operations that are performed in serving a client
   G. Advising one of the cashiers assemble 5-10 sandwiches whenever the cooks get more than 45 seconds behind in their work.
   a. Create a hierarchy of events following the frequency decomposition approach. Briefly explain the approach that you are using in constructing your hierarchy.
   b. Suppose that you are currently studying event E, staffing for the two daily rush periods. According to the frequency decomposition approach, briefly describe which of the decisions above will become inputs and which decisions will be ignored?

2. An interesting concept is congestion externality, the extent to which the utility of one customer receiving a service is affected by existence or lack of other customers. Negative congestion externalities are generally due to longer waiting times for service, which happens if there are many customers already waiting for service. For example, you may choose to go to a barber shop further from your home than other shops, in order to avoid long waiting lines at the shops around your home. Other factors causing negative congestion externalities are traffic on roads, noise in residential areas, the student-to-teacher ratio at universities, etc.
   a) Give an example for positive congestion externality?
   b) Do you think that the congestion externality should affect the decision regarding the number of facilities or the capacities of facilities? Everything else being equal, does positive congestion externality lead to more facilities or fewer?

3. While customers would like some service facilities (malls, banks, hospitals, etc) be located close to themselves, they do not want to be close to some others? Give examples of service facilities that customers may want to avoid? These facilities, considered undesirable by the customers, are called "obnoxious". Qualitatively discuss how one may modify the objective functions of the location formulations.

4. Suppose that you are asked to locate police stations in Richardson. There are five possible locations (A, B, C, D, E) for stations and six districts (1,2,3,4,5,6) to serve. A station in a given location can only serve districts in its vicinity. A station can serve several districts, but every district must be served by at least one station. The table below shows which station can serve which districts:

Possible locations	A	B	C	D	E
Districts served	1,3,5	2,5	3,4	1,3,4	2,6

   Parts a,b and c are independent.
   a) Provide a formulation to minimize the number of police stations required to serve Richardson districts.
   b) Suppose that distiricts 1 and 4 are high crime areas; police can be called for a crime while investigating another crime. Thus, we want to build redundancy by making sure that these distrcits are served by at least two stations. Modify the formulation of (a) accordingly.
   c) Suppose district i has 10,000i population, e.g. district 1 has 10,000, district 2 has 20,000, district 6 has 60,000 people. Provide a formulation to open up exactly two police stations to serve the most of the population.

5. Provide an LP formulation for p-Median Model which minimizes city-block distances. (Hint: There is a slick way to write absolute value constraints in minimization problem; Note that if $|x| = 5$ then $x \geq 5$ and $x \geq -5$.)

6. Provide an LP formulation for p-Center Model. (Hint: There is a slick way to write maximum of several variables in a minimization problem; Note that if $z = \max\{x, y\}$ then $z \geq x$ and $z \geq y$.)

7. Solve the gravity problem if the distances are given as the square of Euclidean distances.

8. Give an example instance for 2-median problem with 3 demand points. That is, make up the necessary numerical data so that p-median formulation provided in the text becomes ready to input to a software.

9. Would you expect that $S(x, y)$ given by equation 10.2 of Chopra and the insertion cost on p. 295 of Chopra are always nonnegative, why? Can you think of a real life situation where they are negative?

10. We will illustrate a different version of Generalized Assignement Problem proposed by Bramel and Simchi-Levi [2]. Their formulation supposes that only demand points can be seeds. Then they assign demand points to seeds (some demand points) while simultanously finding which demand points should serve as seeds. Let $c_{i,j} = Dist(DC, i) + Dist(i, j) - Dist(DC, j)$.

$$y_{i,j} = \left\{ \begin{array}{ll} 1 & \text{if demand point } i \text{ is asigned to a route on which } j \text{ is the seed} \\ 0 & \text{otherwise} \end{array} \right\}.$$

$$z_j = \left\{ \begin{array}{ll} 1 & \text{if demand point } j \text{ is chosen as seed} \\ 0 & \text{otherwise} \end{array} \right\}.$$

Consider the following formulation for N demand points and K trucks :

Minimize $\sum_{j=1}^{N} \sum_{i=1}^{N} c_{i,j} y_{i,j} + 2 \sum_{j=1}^{N} Dist(DC, j) z_j$
Subject to:

$$\begin{aligned}
\sum_{i=1}^{N} a_i y_{i,j} &\leq b_j && \text{for } j = 1..N \\
y_{i,j} &\leq z_j && \text{for } i = 1..N, j = 1..N \\
\sum_{j=1}^{N} y_{i,j} &= 1 && \text{for } i = 1..N \\
\sum_{j=1}^{N} z_j &= K && \\
y_{i,j}\ ,\ z_j &\in \{0,1\} && \text{for } i = 1..N, j = 1..N
\end{aligned}$$

a) How does $c_{i,j}$ differ from the insertion cost defined in the textbook? b) In your words, express the objective function.
c) In your words, explain the second, third and fourth constraints.
d) What is the advantage of this version over the version in the textbook.

11. Consider the simplest transportation problem with two plants and two markets but for two months. All market demands and plant supplies are 20 units. In month 1, transportation costs are $c_{11} = 3$, $c_{12} = 3$,$c_{21} = 3$ and $c_{22} = 4$. Link $(1,1)$ is operated by a truck company, all the other links are operated by another truck company. Suppose that the first company offers a promotional rate of $c_{11} = 1$ in the second month. The market demands, plant supplies and transportation costs are given in the standard transportation tableau format below:

Month 1 :

Plants	**Markets** 1	2	
1	cost 3, 0	cost 3, 20	20
2	cost 3, 20	cost 4, 0	20
	20	20	

Month 2 :

Plants	**Markets** 1	2	
1	cost 1, 20	cost 3, 0	20
2	cost 3, 0	cost 4, 20	20
	20	20	

a) Check that quantities in the lower right of each cell are the optimal transportation quantities. Compute the transportation costs for each month.
b) Note that the solution for Month 1 differs drastically from that of Month 2. In practical situations, can such a difference cause confusion and problems? Elaborate.
c) Suppose that the second truck company (in charge of links (1,2), (2,1) and (2,2)) charges a contract alteration cost in Month 2 if the total quantity it transports varies. The contract alteration cost is called d and is charged for per unit (positive or negative) change in the total quantity transported by the second compny. If $d = 2$, $2 \cdot (40 - 20)$ is incurred in month 2 to mold the transportation quantities of Month 1 into those of Month 2. Compute the cost in general (in terms of d) of using solutions in the tableaus for Month 1 and 2.
d) What is the smallest value of d such that the solution of the first month remains optimal for the second month, hence for both of the months? Note that if $d = \infty$ you use the same solution for both months. As d decreases, different solutions in different months become more attractive.
e) Let x_{ij}^1 be the transportation quantities in Month 1 and define x_{ij}^2 for Month 2 and set $d = 2$. Provide a formulation that minimizes the total transportation and contract alteration costs in two months.

12. If you are a risk averse person and a friend of Murphy who believes that if there is a possibility of bad things happening, the worst will happen to you. Would you prefer the nearest insert procedure or the nearest neighbor procedure to solve a TSP with 100 demand points, why? How would your answer change if you are risk neutral, why?

13. Wal-Mart is going to redesign its distribution network, which involves assigning retailers to warehouses. Suppose that there are a total of m retailers to be assigned to a total of n warehouses. For ease of operation each retailer is assigned to a single warehouse, this is called single-source sourcing. The distance between retailer i and warehouse j is denoted by c_{ij} and is already known. Retailer i demands a constant d_i amount while each warehouse j can supply only up to s_j amount.
a) Provide an Integer Program formulation to redesign the distribution network to minimize the total distance among assigned retailer and warehouse pairs.
b) For $m = 5$ and $n = 3$, solve the problem to optimality using Excel, Lindo or AMPL with demands as $d = [10;\ 30;\ 50;\ 40;\ 50]$, supplies as $s = [100\ 100\ 10]$ and the distances as

$$\mathbf{c} = \begin{bmatrix} 17 & 22 & 1 \\ 33 & 14 & 20 \\ 8 & 21 & 50 \\ 12 & 17 & 15 \\ 16 & 30 & 50 \end{bmatrix}$$

What are the assignments?
c) In part a), we have designed the network. But during daily operations, demands or supplies may vary resulting in potential demand-supply mismatches. To alleviate the effect of these mismatches dual-sourcing is used, i.e. assigning a retailer to a primary and secondary warehouses. The retailer uses the primary warehouse always except when there is shortage in which case it switches to the secondary source. Explain how dual-sourcing can reduce demand and supply mismatches.
d) Warehouses can be assigned to retailers as secondary sources after ignoring demand and supply data because demands are satisfied by primary sources. Then the assignment is solely based on distances. What are the secondary source assignments for the data in b)?

14. Download the Trucks Game files following the links from the course web page. The data you need is in UTDTrucks.xls file. a) Assume that every day two trucks will be dispatched and use the sweep procedure with the first day orders to find the location of two seeds. If city orders do not fill up a seed's capacity, stop the current sweep at the city whose order pushes the load beyond the capacity and restart another sweep exactly at that city.
b) We now use the generalized assignment method — as described in §14.7 of the textbook. Compute $c_{i,k}$ insertion costs where i is a town and k is a seed. Can $c_{i,k}$ be negative, how?
c) Using the Excel Solver, find the optimal town-seed assignmmets. Print out the piece of the Excel worksheet where you set up Solver, submit this print out.

15. Refer to the previous question. Use somutd.trk as input file to play the Trucks game for 5 full days.
a) Implement the tours found in (c) of the last question for the next five days. Are you using TL or LTL? Print out and submit your Truck Schedule. (To print out, first choose Schedule from the Copy menu, run Microsoft Word or Excel and Paste the Schedule. Now print out from Word or Excel.) What is your total score?
b) Generalized assignment method solves the seed assignment problem only for one period assuming

that trucks are infinitely fast. As you have seen in the Truck game, it may take several days for a truck to complete a single tour. In light of this observation, is it still desirable to fill up trucks as much as possible?

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