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Ni Wang

Jye-Chyi Lu

Paul H. Kvam

University of Richmond, pkvam@richmond.edu

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# Reliability Modeling in Spatially Distributed Logistics System

Ni Wang, Jye-Chyi Lu and Paul Kvam

The School of Industrial and Systems Engineering,  
Georgia Institute of Technology, GA 30332-0205

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**Abstract:** This article proposes methods of modeling reliability of delivering products to meet demands in supply-chain's logistics system. The system usually consists of thousands of retail stores and many distribution centers (DCs) at various locations. Products are transported through numerous routes between DCs and stores. The service reliability depends on layout of DC locations, distance between DCs to stores, product-replenish time requirement at stores, DCs' capability for supporting store demands and probability of routes being smoothly operated. Contingency events such as labor dispute, bad weather, road condition and traffic situation and terrorist threats have great impact to system's reliability. Because the large number of store locations and many combinations of routing schemes, this article applies an approximation technique for developing first-cut reliability analysis models. The approximation relies on multi-level spatial models to describe patterns of store locations and demands. These models support several types of reliability evaluation of the logistics system under different probability scenarios and contingency situations. Examples with data taken from a large-size logistics system of an automobile company illustrate the importance of studying supply-chain system reliability.

**Keywords:** Contingency, Degradation, Distribution Centers, Service Reliability, Supply-chain Systems.

## Acronyms

CA            Continuum Approximation

DC	Distribution Center
GDC	Global Distribution Center
LDC	Local Distribution Center
SC	Supply-Chain

## Notation

$\lambda(\mathbf{x})$	Spatial density function at location $\mathbf{x}$
$d(\mathbf{x})$	Distance between a DC and the store at location $\mathbf{x}$
$r(\mathbf{x})$	Service reliability of a DC to a store for meeting time requirement
$p_i$	Failure probability for GDC <sub><i>i</i></sub> due to some contingency

## 1 Introduction

Logistics systems are designed to move goods, energy (e.g., electricity and gas), water, sewage, money or information from origins to destinations in a timely manner. A typical logistics system in large-size supply-chains has thousands of stores, many global or regional level distribution centers (DCs) and even local transshipment points. The service reliability of such logistics system depends on the strategy of how stores are supported by DCs and capabilities of these DCs in replenishing materials in a timely fashion for meeting demands. The probability of smooth operations in transportation routes to support time-guaranteed supplies also plays an important role. Moreover, there are cases that uncertainties may disrupt logistics operations significantly. For example, the labor dispute at Long Beach in 2002 shut down the port for 10 days, and the estimated cost was in the range of \$2 billion - \$20 billion [9]. However, there are very few analytical models for supply chain reliability, despite the calling for designing and operating supply chains that are resilient to disruptions [15].

Many studies examine problems in network reliability [1], system performance degradation and workload re-routing for telecommunication, power and transportation networks [13], [14]. Most of these concentrated on evaluating network reliability based on probability of functioning in network links. Meeting the delivering time requirement is seldom the focus. Past studies [4] on road-transportation reliability did address the travel time issues for trucks routing through connected links of stops. However, the size of the network in these studies is much smaller than the logistics systems

considered in this article. Thus, their detailed probability-based reliability models have limited use in our supply-chain logistics systems.

Reliability studies in the logistics service system is also different from reliability research of product designs [11], where there is no DCs and stores and no connectivity problems exist between them. The characteristics of supply-chain's system reliability are discussed in a few literature. For example, Bundschuh *et al.* [3] considered an integrated inbound supply chain with many potential suppliers for products. Their concern is to choose proper suppliers such that the supply-system is reliable with a low failure probability in getting needed supplies. Focusing on logistics cost but not service reliability, Snyder and Daskin [15] studied situations where logistics facilities (e.g., DCs) fail at times, and they used mixed integer programming method to find a solution such that the increase of transportation costs under failure scenarios is minimized. Thomas [16] proposed probability models for quantifying reliability of supply chains under contingency situations. However, he only considered simple probability models of supply meeting demand,  $Pr(\text{supply} > \text{demand})$ , based on assumed parametric distributions of supply and demand quantities. The complicated network issues between DCs and stores were not discussed.

This article focuses on developing "first-cut" reliability models for very large-size logistics systems to support strategic planning decisions (e.g., DC location allocation and serving area optimization ([6])). Our key contribution is to bring statistical spatial modeling techniques to approximate store location and demand data. Then, system reliability models can be built on these approximations for entertaining various scenarios of DC location designs and DC capacity constraints, and for evaluating impact of contingency causing DC partially or fully shut down. Some of these issues are touched in the above literature, but none of them integrates spatial models with network reliability calculations together. The following provides more details of introducing our multi-level modeling and reliability evaluation procedures in handling very large-size networks.

Continuum approximation (CA) [7] is the usual tool for modeling logistics systems for supporting strategic decisions in transportation and supply-chain management [8]. The CA approach first simplifies logistics network by assuming that spatial locations (of stores, facilities, etc.) are modeled via a density function  $\lambda(\mathbf{x})$  which describes the number of points per unit area as a function of position  $\mathbf{x}$ . This article extends their homogeneous Poisson intensity function to the nonhomogeneous case capable of handling variations in store counts and demands at different locations such that DC allocation and serving area can be decided more realistically. In our system reliability evaluation, distance between store and the nearest DC is the key factor for meeting product's time-guaranteed

replenish requirement. Given a set of DC locations and capacities, reliability of the entire SC-logistics system is then an average of reliability over all store locations and demands based on approximation models. Our illustration example has eight DCs serving stores in the entire U.S. continent. Section 4.1 shows that when one of the DCs breaks down, the entire system reliability could drop 10.2%. We also provide reliability degradation paths as a function of demand growth in DC's serving area.

For the tactical level decisions in choosing most reliable and cost-effective routes, a similar approximation model is built on regional store locations and demands. The reliability of regional logistics system is more concerned with whether certain routes are functioning or not. Thus, the experience learned from telecommunication network reliability is utilized to develop reliability evaluation procedures at this level. Section 4.2 provides examples with stores in Texas.

Section 2 presents a general framework for modeling reliability of global-level logistics networks and evaluates effect of degradation in GDC's capacity. Section 3 defines regional-level logistics reliability measures. In both sections, well-known spatial smoothing methods with software available commercially are utilized to obtain spatial intensity function for supporting CA approximation and reliability evaluation. Numerical illustrations with real-life data are provided in Section 4. Conclusion and future work are offered in Section 5.

## 2 Reliability Modeling for Global SC-Logistics Systems

Uncertainty is of main concern in many logistics planning activities. Often, safety stocks are utilized to accommodate uncertain demand or shipping delay. The logistics facilities such as DCs are also subject to many types of risk. Snyder and Daskin [15] considered a situation where facilities fail time to time due to poor weather, labor dispute or other factors, and applied the mixed integer programming method to find a contingent logistics solution. The focus of this article is to develop procedures for evaluating whether a large-size SC-logistics system is capable of handling certain contingency for meeting deadlines of product replenishment. Hereafter, the "stores" refer to stores in retail chains or dealers in automobile distribution networks.

This paragraph rigorously defines the logistics service reliability. Consider a store located at  $\mathbf{x}$ , and assume it is served by a GDC  $d(\mathbf{x})$  miles away. Model speed of trucks transporting goods on routes from GDC to surrounding stores as a random variable  $V$  with a distribution function  $F_V(\cdot)$ .

Figure 1: The service reliability  $r(\mathbf{x})$  as a function of  $d(\mathbf{x})$ , where  $d(\mathbf{x})$  is the distance of  $\mathbf{x}$  from the serving DC

Then, the service reliability at  $\mathbf{x}$  for meeting the deadline  $t_0$  is defined and calculated as

$$\begin{aligned} r(\mathbf{x}) &= P(T \leq t_0) = P[d(\mathbf{x})/V \leq t_0] \\ &= P[V \geq d(\mathbf{x})/t_0] = 1 - F_V[d(\mathbf{x})/t_0], \end{aligned} \tag{1}$$

where  $T$  is the traveling time. Many distributions are suitable for  $V$ . The next example shows that the normal distribution with a reasonable choice of mean and variance produces a nice reliability function. Figure 1 shows that the service reliability of a GDC to stores within a certain distance (e.g., 400 miles) is near one, i.e., the logistics system can meet the deadline without much troubles. Then, for those stores beyond the certain distance, the reliability starts to drop in a reversed-S shape gradually and reach zero for stores very far away. These stores should be served by other GDCs.

**Example 1:** Suppose  $V$  is normal distributed with mean 40 and standard deviation 10 miles per hour. Because the routes between GDC to stores could include highways and local streets, this article sets the mean and standard deviation conservatively for accommodating possible varying factors such as road congestions, bad weather and so on. Then the service reliability can be calculated as a function of distance  $d(\mathbf{x})$  as shown in Figure 1. Notice that within 400-mile distance, the reliability is very close to one. It drops to 80% when the distance is around 650 miles. The reliability is close to zero when the distance reaches 1300 miles from GDC. One can image that when the deadline is more loose (e.g., 24 hours), the system is more reliable. In this case, the region of near 100% service reliability can be larger than the current region (about 400 mile radius distance) with  $t_0 = 20$  hours.

## 2.1 Service Reliability for Large-size Logistics Systems

If one assigns specific stores to specific DCs, there will be tremendous number of combinations in store-to-DC assignments. This makes the calculation of system reliability very complicated. This section extends the reliability defined in Eq. (1) to many stores at locations  $\mathbf{x} = (x_1, x_2)$  modeled by a smooth density function  $\lambda(\mathbf{x})$ . The demand for stores is also assumed to be a spatial function with mean  $\mu(\mathbf{x})$ . This makes the system-reliability calculation easier and allows flexibility of handling many variations in the logistics system with stores and DCs organized differently. Our procedure explained in Eq. (2) below integrates the reliability of Eq. (1) over the serving region of a DC for

assessing the service reliability in that region. Then, extend this idea to all DCs' serving regions. The reliability for the entire system with many DCs is then obtained.

$$r_{system} = \int_A \lambda(\mathbf{u})\mu(\mathbf{u})r(\mathbf{u})d\mathbf{u} / \int_A \lambda(\mathbf{u})\mu(\mathbf{u})d\mathbf{u}. \quad (2)$$

Section 2.2 shows that this procedure allows us to easily handle problems with limited capacities in certain DCs. If there are more DCs added into the system (or some DCs dropped) to handle certain demand growth or contingency, the system reliability can always be evaluated in the same method as long as the serving regions are designated. It is possible to include reliability or other measures in the objective function (e.g., [6]) for deciding the serving region and then calculate the resulted system reliability. However, up to this point, practitioners usually decide the serving region for a DC based on logistics and facility cost concerns (e.g., [7]) and other “political” reasons. Thus, the scope of this article will be limited to evaluating the reliability based on a given set of serving regions for DCs provided by practitioners. That is, we do not discuss how to optimize DC locations and serving regions.

It is common that in strategic planning of supply chain networks, exact store-location and demand information is often not available or is projected based on aggregate planning or forecasting (see Eq. (9) and its description in Section 2.3 for details). Thus, this section follows the idea used in the Continuous Approximation (CA) approach for large-scale facility design problems by modeling store locations with a spatial Nonhomogeneous Poisson Process [5]. Its intensity function at the location  $\mathbf{x} = (x_1, x_2)$  is  $\lambda(\mathbf{x})$ , which can be interpreted as an expected number of stores within unit area around  $\mathbf{x}$ . By using the CA approach, facility-location (e.g., DC location) allocation problems can be transformed to problems of finding the optimal size of DC's service regions supporting the demands of stores in the regions. Managers can change the intensity function (or the expected store counts (in Eq. (9)) for projecting future situations when demand grows (or diminishes) in certain regions. Then, the system reliability will be changed according to the change of the intensity function. This allows managers to evaluate if more DCs are needed to improve its system reliability.

Next, let us illustrate the flexibility of the above setup in evaluating system reliability by considering that some DCs might be shut down due to certain contingency. Suppose there are  $n_I$  GDCs serving the whole region  $A$ . Let  $\psi_i = 1$  or  $0$  be indicating parameters for the functioning status of  $GDC_i$ ,  $i = 1, \dots, n_I$ . If the  $GDC_i$  is shut down (i.e.,  $\psi_i = 0$ ), the stores served by  $GDC_i$  will be served by closest DC available. No matter how many  $GDC_i$ s are available, all the stores in the entire region will be served by only one of the GDC. Using the minimal distance concept, the serving

regions of the GDC<sub>*i*</sub>s are then defined. Thus, Eq. (2) can be used to evaluate the system reliability in this situation. See the algorithm presented in the end of this section for details of the calculation steps. See Example 2 in Section 4.1 for a numerical illustration.

To elaborate, denote  $\boldsymbol{\psi} = \{\psi_1, \psi_2, \dots, \psi_{n_I}\}$  as a scenario of the indicating parameters. For example, if  $\boldsymbol{\psi} = (1, 1, 0, 0)$  for four DCs. It means that the first two DCs are functioning and the other two are not. Different contingency will lead to distinct values of these indicating parameters. Notice that this setup allows us to evaluate cases with multiple DCs shut down easily.

Similar to Eq. (1), we define the service reliability  $r^\psi(\mathbf{x})$  as the service reliability for stores at location  $\mathbf{x}$  served by DC<sub>*i*</sub> under the scenario  $\boldsymbol{\psi}$ ,

$$r^\psi(\mathbf{x}; d^\psi(\mathbf{x})) = 1 - F_v[d^\psi(\mathbf{x})/t_0], \quad (3)$$

where  $d^\psi(\mathbf{x})$  is the distance of  $\mathbf{x}$  from the closest functioning GDC under the scenario  $\boldsymbol{\psi}$ . Then, the reliability under this scenario is  $r_{system}^\psi$ , which is the same as Eq. (2), with a replacement of  $r(\mathbf{x})$  by  $r^\psi(\mathbf{x}; d^\psi(\mathbf{x}))$ . Finally, the expected service reliability of the logistics system under many possible scenarios is the weighted average of the reliability  $r_{system}^\psi$  with weights given as the probability of that scenario occurred. That is,

$$E(r_{system}) = \sum_{\boldsymbol{\psi} \in \Psi} r_{system}^\psi p(\boldsymbol{\psi}), \quad (4)$$

where  $\Psi$  is the state space of all the scenarios,  $p(\boldsymbol{\psi}) = \prod_{i=1}^{n_I} (1 - p_i)^{\psi_i} p_i^{1-\psi_i}$  and  $p_i$  is the probability of the GDC<sub>*i*</sub> being shut down.

**Remark on Computing the Expected System Reliability:** Enumerating all the possible scenarios may be cumbersome, however, Eq. (1) can be further simplified by changing the sequence of summation and integration. Thus, one can work on the GDC<sub>*i*</sub>s one at a time. Then,

$$E(r_{system}) = \int_A \lambda(\mathbf{x}) \mu(\mathbf{x}) r_{system}(\mathbf{x}) d\mathbf{x} / \int_A \lambda(\mathbf{u}) \mu(\mathbf{x}) d\mathbf{x}, \quad (5)$$

where the calculation of  $r_{system}(\mathbf{x})$  can be simplified as follows:

- Consider each location  $\mathbf{x}$ . Denote GDC<sub>(1)</sub> as its serving GDC;
- Order other GDCs according to their relative distance from  $\mathbf{x}$ . Denote them as GDC<sub>(2)</sub>, GDC<sub>(3)</sub>, ..., GDC<sub>(*n<sub>I</sub>)*</sub> with relative distances  $d_{(2)}$ ,  $d_{(3)}$ , ...,  $d_{(n_I)}$ ;
- Let  $p_{(i)}$  be the failure probability for GDC<sub>(*i*)</sub>. Denote  $r(\mathbf{x}, d_{(i)})$  as the service reliability at  $\mathbf{x}$  when it is served by GDC<sub>(*i*)</sub>, which means that GDC<sub>(1)</sub>, ..., GDC<sub>(*i*-1)</sub> are all failed;



- The  $r_{system}(\mathbf{x})$  inside the integration can be evaluated as

$$r_{system}(\mathbf{x}) = \sum_{\boldsymbol{\psi} \in \Psi} p(\boldsymbol{\psi}) r^{\boldsymbol{\psi}}(\mathbf{x}) \quad (6)$$

$$= (1 - p_{(1)})r(\mathbf{x}, d_{(1)}) + p_{(1)}(1 - p_{(2)})r(\mathbf{x}, d_{(2)}) + \dots \quad (7)$$

$$+ p_{(1)} \cdots p_{(n_I-1)}(1 - p_{(n_I)})r(\mathbf{x}, d_{(n_I)}),$$

where only one term in Eq. (6) is used. For example, if the nearest GDC, namely  $GDC_{(1)}$ , is available, the reliability is the success probability  $(1 - p_{(1)})$  multiplied by the reliability  $r(\mathbf{x}, d_{(1)})$  based on the distance  $d_{(1)}$  from store location  $\mathbf{x}$  to  $GDC_{(1)}$ . Others are defined similarly.

For practical reasons, a grid can be laid on the focused region such that Eq. (5) can be calculated by replacing integrals with summations as follows:  $r_{system} = \sum_i \sum_j \lambda_{ij} \mu_{ij} r_{system}^{ij}(\mathbf{x}) / \sum_i \sum_j \lambda_{ij} \mu_{ij}$ , where  $\lambda_{ij}$ ,  $\mu_{ij}$  is the total intensity and demand within  $(i, j)$ th block in the grid, and  $r_{system}^{ij}(\mathbf{x})$  is the service reliability evaluated at the center of the grid by Eq.(6).

## 2.2 Service Reliability in Logistics Systems with Capacitated DCs

The reliability models discussed so far dealt with problems of un-capacitated DCs. That is, no matter how large the demand in a region is grown, the responsible DC can still handle its products replenishment, packing and loading tasks without losing any efficiency. This section extends the reliability models described in the previous section to the case where each DC can only handle limited demand. Denote that each  $GDC_i$  serving the region  $A_i$  has a fixed capacity  $\xi_i$ ,  $i = 1, \dots, n_I$ , and the union of all non-overlapped  $A_i$ 's is the whole region  $A$ .

Suppose that some contingent event (or demand growth) cause a ‘‘degradation’’ of  $GDC_i$ 's capacity from  $\xi_i$  to  $\xi'_i$  that the  $GDC_i$  can only handle the demands from stores in a subregion of  $A_i$ . The unserved stores need to go to other nearby GDCs for service (if those GDCs have available capacity to serve them). In implementing this idea, we start with each GDC and revise its serving region based on its capacity to meet demands in nearest stores grid by grid as described in the above computing remarks. When all the stores in the original region assigned to a particular GDC are all served, and if this GDC still has extra capacity to serve other stores, the reliability computing algorithm will pick up the unserved stores in grids nearest to this GDC. Finally, all the capacities at all GDCs are all used. If there are still some stores unserved, the system reliability will drop. In this case, the managers might consider adding capacity to certain GDCs or adding some temporary GDCs. See Example 3 in Section 4.1 for numerical illustrations.

**Remark:**

The above idea is simple, but might not be optimal in the sense of maximizing the system reliability. For example, consider two neighboring DCs, where DC<sub>1</sub> has available capacity for handling the demands from one unserved store at location  $a$  responsible by DC<sub>2</sub> originally. Suppose that the distance from this store to DC<sub>2</sub> is  $d_{2a} = 5$  miles and to DC<sub>1</sub> is  $d_{1a} = 8$  miles. According to the idea described above, this store should be served by DC<sub>1</sub>. However, suppose that there is another store (at location  $b$ ) responsible by DC<sub>2</sub> with equal demands, and its distance to DC<sub>2</sub> is  $d_{2b} = d_{2a} + 1 = 6$  miles and to DC<sub>1</sub> is  $d_{1b} = d_{1a} + 10 = 18$  miles. Although the store at location  $b$  is slightly farther away from DC<sub>2</sub>, its distance to DC<sub>1</sub> is much farther away than that from the store at location  $a$ . Thus, if we let DC<sub>2</sub> serve the store  $b$ , the “saved” traveling distance (9 miles) gained by using DC<sub>1</sub> to serve the store  $a$  will increase the system reliability, which is a monotone function of traveling distance. That is, we should look for the case that the store gains the most saving in traveling distance for keeping it in the original DC’s serving responsibility, but not the nearest store. Thus, the algorithm should first calculate the differences for stores traveling to two DCs. Then, choose the most saving case for deciding the service responsibility. For example, the difference for the store  $a$  to DC<sub>1</sub> and DC<sub>2</sub> is  $\text{diff}_a = 8 - 5 = 3$  miles. Similarly, this difference for the store  $b$  is  $18 - 6 = 12$ , which is much larger than  $\text{diff}_a$ . Thus, the store  $b$  should be served by DC<sub>2</sub> and the store  $a$  should be served by DC<sub>1</sub>.

This modified idea only works for equal demands in these two stores. The issue for the unequal demands becomes very complicated, especially in pooling demands from a few stores together to match the demand for another store to calculate the total distance saved. Because this article develops beginning work to introduce service-reliability in large-size supply-chain logistics systems, the scope of such an in-depth study is beyond the mission of this article. We will leave it to future research.

### 2.3 Global-level Spatial Density Modeling

In logistics planning at corporate level, many strategic plans utilize data projected in aggregated forms. For example, the manager who handles marketing departments might forecast a total demand for many stores in a region, e.g., Georgia State or South Eastern region. This section employs a commonly used smoothing technique for estimating the intensity function  $\lambda(\mathbf{x})$  described in Section 2.1 based on constraints of from the total store counts in a region set by the marketing manager. This technique can be applied to both store intensity or mean demand functions.

Figure 2: The counts  $w(B_j)$  of stores for each  $B_j$  in USA

As an example, consider the state,  $B_j$  ( $j = 1, \dots, n_J$ ), as a region that the marketing manager has some aggregated store counts. Figure 2 illustrates these aggregated counts for states in the continental U.S. (region  $A$ ), where darker colors indicate larger counts. Because Texas State has the largest number of stores in this data set, its color is the darkest. See Table 2 for details of the data. Tobler [17] constructed an estimator  $\hat{\lambda}(\mathbf{x})$  to minimize the following smoothness function (in second derivatives),

$$\iint_A \left[ \left( \frac{\partial^2 \lambda(\mathbf{x})}{\partial x_1^2} \right) + \left( \frac{\partial^2 \lambda(\mathbf{x})}{\partial x_2^2} \right) \right]^2 dx_1 dx_2 \quad (8)$$

subject to constraints:  $\lambda(\mathbf{x}) \geq 0$  and

$$\int_{B_j} \lambda(\mathbf{x}) d\mathbf{x} = E(W(B_j)), \text{ for } j = 1, \dots, n_J, \quad (9)$$

where  $E(W(B_j))$ 's are the expectation of projected store counts in each subregion  $B_j$  and  $\mathbf{x} = (x_1, x_2)$  is the two-dimensional coordinate for the region  $A$ . Because the procedure is a nonparametric smoothing method making interpolations of given data. The assumption needed is that there exists a density function, which is non-negative and has a finite value for every location in the domain. For the logistics data we are working on (see Section 4), this assumption is hold. Moreover, Since we only consider stores within continental U.S., the spatial density at the boundary is fixed at zero. See Tobler [17] for showing the existence and uniqueness for this constrained optimization problem. See Figure 4 in Section 4.1 for the fitted smooth intensity function.

### 3 Reliability Evaluation of Regional Logistics Systems

In regional logistics operations, one needs to conduct more detailed decision analyses such as which local DC and which routes to use for serving what stores. The time constraints become more stringent. In this situation, local distribution centers (LDCs) or transit points are closer to stores, and thus being able to provide more timely service. In strategic decision, failure of GDCs is a primary concern. However, at the regional-level, one is more concerned about weather conditions, road traffic or other factors that might affect tactical decisions on truck-routing and product-inventory. Thus, in this section we assume that the transportation links are subject to failure, and contingent events may disrupt a specific route connecting the GDC to LDCs and between LDCs and stores. To keep the study focused, we do not discuss inventory issues. See Dandamudi and Lu [6] for such studies.

Figure 3: DC Locations and Service Regions

For the illustration purpose consider the LDCs shown in Figure 3, where the “Origin” could be a GDC or some supply-source of products. There are four LDCs,  $LDC_k$ ,  $k = 1, 2, 3, 4$ , located in populated areas. These LDCs are transportation “stop-points” for aggregating and mixing products from different sources. Stores at location  $\mathbf{x}$  will be served by these LDCs. Denote the “long-haul” transportation lines (called “links”) between GDCs and LDCs as  $e_l$ ,  $l = 1, \dots, n_l$  as illustrated in Figure 3 with  $n_l = 5$ . Thus, we model the regional logistics system as a stochastic network  $G$ , where the links  $e_l$ s have independent failure probability  $p_{e_l}$ ,  $l = 1, \dots, n_l$ . A scenario  $s$  of the network indicates availability for each links  $e_l$ , where  $s = (1, \dots, 0_l, \dots, 1)$  if  $l$ th link fails. Denote  $\mathcal{S}$  as the space of the logistics network  $G$  for all possible scenarios. Let  $Pr(s) = Pr(S = s)$  be the probability of the scenario  $s$ , where  $s \in \mathcal{S}$ .

After products being transported to  $LDC_k$  in a speed  $V_{DC}$  through long-haul links (e.g., regional highways or railways), local trucks will deliver the products to stores at  $\mathbf{x}$  at a speed  $V_s$ . Compared with transportation speed  $V_s$ , the long-haul transportation speed  $V_{DC}$  usually has less variation due to more stable traffic and road conditions. For simplicity, we assume that the travel speed  $V_{DC}$  is deterministic, and  $V_s$  is a random variable with distribution function  $F_s(\cdot)$ , which has similar form as  $F_V(\cdot)$  described in Eq. (1), but with possible different mean and variance. Section 4.2’s example sets  $V_{DC}$  as 60 miles per hour and uses 40 and 10 miles/hour as the mean and standard deviation, respectively, for the normal distribution of  $F_s(\cdot)$ . Because in this article both  $V$  described in Example 1 and  $V_s$  defined here are set at the same speed, we use the same distributions to keep our presentation brief. Thus, to the end of this article, we set  $V_s$  as  $V$ .

Before defining the regional-level service reliability  $r_{system,R}$ , we need to state several assumptions for bringing telecommunication’s network-reliability definitions and procedures here. First, a *minimal path* [10] is a minimal set of links whose simultaneous functioning ensures the functionality of a regional logistics network. Define *shortest path* between origin (GDC) and destination (store) to be the available minimal path which takes the least amount of time to pass for minimizing the transportation cost. In our model, unless some routes have failed, we assume the flow of products will always go through the shortest path to maximize the service reliability of a region. Let us use the following example to illustrate these concepts and prepare for the latter applications (e.g., Section 4.2).

**Example 2:** Focus on the region of Texas State with four LDCs receiving products from a GDC

Figure 4: Minimal Path Sets for Node Pairs

and shipping them to surrounding stores as shown in Figure 3. From these LDC locations, the lengths of links (in miles) are calculated as:  $(l_{e_1}, l_{e_2}, l_{e_3}, l_{e_4}, l_{e_5}) = (500, 296, 300, 350, 356)$ . For simplicity, assume every store has the same demand ( $\mu_0$ ) during the unit time studies.

Denote  $MP_{i_1}, \dots, MP_{i_{g_i}}$  the ordered minimum paths (MPs) from the origin (GDC) to the LDC,  $LDC_i$ , according to the total link transportation cost and link mean transportation time. See Figure 4 for a summary of all minimum paths in the four LDCs. To make it clear, consider  $LDC_1$ , there is only one minimal path,  $e_1$ , which is also the shortest path. Consider  $LDC_2$ , it has two minimum paths,  $(e_1, e_2)$  and  $(e_1, e_4, e_3)$ . In this case,  $g_2 = 2$ . According to the distance calculation, the minimum path  $MP_{2(1)} = (e_1, e_2)$  is the shortest path. The other path  $MP_{2(2)} = (e_1, e_4, e_3)$  will be used when the critical link such as  $e_2$  is failed. Similarly,  $LDC_3$  has two minimum paths,  $MP_{3(1)} = (e_1, e_4)$  and  $MP_{3(2)} = (e_1, e_2, e_3)$ , where  $MP_{3(1)}$  is the shortest path here. Finally,  $LDC_4$  has one minimum path,  $MP_{4(1)} = (e_1, e_5)$ .

Denote  $s_{i(k)}$  the scenario that  $MP_{i(k)}$  is the shortest minimum path from origin to  $DC_i$ . For example, when the link  $e_2$  is failed,  $MP_{2(2)} = (e_1, e_4, e_3)$  is the shortest path only under this scenario  $s_{2(2)}$ .

Let  $p_{e_j}$  be the failure reliability of link  $e_j$ . Then we can calculate the system reliability for a given scenario  $s_{i(k)}$ . When the system reliabilities under all possible scenarios are evaluated, an expected system reliability can be obtained as a weighted average of these reliabilities with the weight set as the probability of scenario occurred. For example, the scenario  $s_{1(1)}$  is for the route  $e_1$  to be functioning for products moving from GDC to  $LDC_1$ . Thus, the probability of this scenario is  $Pr(s_{1(1)}) = (1 - p_{e_1})$ . Follow this idea. The probability of routing from  $MP_{3(1)} = (e_1, e_4)$  is  $Pr(s_{3(1)}) = (1 - p_{e_1})(1 - p_{e_4})$  for both routes  $e_1$  and  $e_4$  to function simultaneously. On the other hand, for another minimum path of  $LDC_3$ ,  $MP_{3(2)} = (e_1, e_2, e_3)$ , for the trucks to take this longer route than the shortest path  $MP_{3(1)}$ ,  $e_4$  must have been failed. Thus, the probability in this special scenario  $s_{3(2)}$  with a failure of  $e_4$  and functioning of  $e_1, e_2$  and  $e_3$  is  $Pr(s_{3(2)}) = (1 - p_{e_1})(1 - p_{e_2})(1 - p_{e_3})p_{e_4}$ . By applying this idea, we can calculate all the other scenario-probabilities as follows:  $Pr(s_{2(1)}) = (1 - p_{e_1})(1 - p_{e_2})$ ,  $Pr(s_{2(2)}) = (1 - p_{e_1})(1 - p_{e_3})(1 - p_{e_4})p_{e_2}$ ,  $Pr(s_{4(1)}) = (1 - p_{e_1})(1 - p_{e_5})$ . These probabilities will be used in Section 4.2 for evaluating the system reliability.

Under scenario  $s$  for some functioning and failed links, define  $r^s(\mathbf{x})$  as the service reliability, which is the probability of delivering products from the GDC to store at  $\mathbf{x}$  before deadline  $t_0$ . That

is,  $r^s(\mathbf{x}) = Pr(T \leq t_0)$ , where  $T$  is the total transportation time calculated below. Denote  $t_{ok}^s$  the minimum long-haul transportation time from the origin  $O$  (GDC) to LDC $_k$  through the shortest path. This  $t_{ok}^s$  is equal to the distance  $d_{O,k}$  between  $O$  to LDC $_k$  divided by the deterministic long-haul traveling speed  $V_{DC}$ . Denote the distance between the LDC $_k$  and its serving store at  $\mathbf{x}$  as  $d_k(\mathbf{x})$ . Then, the transportation time between the LDC and store is  $d_k(\mathbf{x})/V$ . Note that for simplicity, the local and short-distance routes between the LDCs and stores are assumed to be always functioning. This implies that the total transportation time between the origin to the store is  $T = d_k(\mathbf{x})/V + t_{ok}^s$ . Thus, the service reliability for a store at  $\mathbf{x}$  is  $r^s(\mathbf{x}) = Pr(T \leq t_0) = 1 - F_V[d_k(\mathbf{x})/(t_0 - t_{ok}^s)]$ . Apply the store location and demand smoothing idea described in Section 2. The total service reliability under scenario  $s$  for the entire region  $A_0$  (e.g., State of Texas) is

$$r_{system,R}^s = \int_{A_0} \lambda(\mathbf{x})\mu(\mathbf{x})r^s(\mathbf{x})d\mathbf{x} / \int_{A_0} \lambda(\mathbf{x})\mu(\mathbf{x})d\mathbf{x}. \quad (10)$$

Consider all the possible scenarios  $s$  with different occurrence probability  $Pr(s)$ . The expected system reliability for this region is then  $E(r_{system,R}) = \sum_{s \in \mathcal{S}} Pr(s)r_{system,R}^s$ .

For the modeling of  $\lambda(\mathbf{x})$  and  $\mu(\mathbf{x})$  in the local regions, because there is no such constraints as aggregated region store counts given in Eq. (9) for the regional studies here, the following well-known kernel smoothing technique [2] is used.

$$\hat{\lambda}(\mathbf{u}) = \frac{1}{n_M} \sum_{m=1}^{n_M} w(u_1 - x_{1m}; h_1)w(u_2 - x_{2m}; h_2),$$

where  $\mathbf{u} = (u_1, u_2)$  is the evaluation point of the intensity and  $\mathbf{x}_m = (x_{1m}, x_{2m})$ ,  $m = 1, \dots, n_M$  are the available store locations for smoothing.  $w(\cdot)$  is a symmetric univariate density function (Gaussian) with  $\int \mathbf{w}(\mathbf{u})d\mathbf{u} = 1$ . The specification of the bandwidth  $h_i$ s is important for practical implementation; however, it is beyond the scope of this paper to present the details of selection  $h$ . Thus, we will use the following well-known estimate ([18], page 60) in our implementation in Section 4.2.

$$\hat{h}_{opt} = \left\{ 8\pi^{1/2} \int w(u)^2 du / [3n_M (\int u^2 w(u) du)^2] \right\}^{1/5} \hat{\sigma}, \quad (11)$$

where  $\hat{\sigma}$  is an estimate of standard deviation of store locations. This estimator is known as the *optimal* bandwidth estimator to minimize the *mean integrated squared error*, when the store locations are from Normal distributions. See [2] for a discussion on computation issues.

Figure 5: Spatial Density Function from Global-Level Model

Figure 6: The Locations of 8 Regional DCs in US

## 4 Applications of System Reliability Measures

### 4.1 Global-level Modeling and Reliability Analysis

The data used for illustrating the proposed reliability measures are contributed from a major U.S. automobile manufacturing company. The stores in this case represent car dealers. The store counts per state are provided in an aggregated form as shown Table 2 and Figure 2. This company has eight global DCs serving the whole U.S. See Figure 6 for their locations. Based on the count data  $W(B_j)$ , a smooth function  $\hat{\lambda}(\mathbf{x})$  is obtained using the constrained interpolation method discussed in Section 2.3, where a  $100 \times 50$  grid is overlaid on the U.S. continent map. All the computations are implemented using R [12]. Figure 5 presents the intensity function of store density. Note that New York and Boston city areas have the highest intensities contributed from the most amount of stores in the relatively small regions. Texas has the most number of store counts, but the size of the state is relatively large. Thus, its store intensity is not as large as the New York and Boston areas.

**Example 3:** In this example, we calculate system reliability under the scenario of single DC shutdown and possibly multiple DC shutdowns. Follow the assumption of distribution of the speed  $V$  and the product delivery time given in Example 1. When all GDCs are available, i.e.,  $\boldsymbol{\psi}_0 = (1, \dots, 1)$ , the original system reliability is calculated as  $r_{system} = r^{\boldsymbol{\psi}_0} = 0.926$ , using Eq. (2).

When only one GDC is fully shutdown, i.e.,  $\boldsymbol{\psi} = (1, \dots, 0_j, \dots, 1)$  and  $p_j = 1$  for the case of  $GDC_j$  shutdowns, the Eq. (2) and Eq. (6) gives the resulted system reliability as reported in Table 1. Notice that  $GDC_8$  near Boston is the only GDC in the North-Eastern region with a lot of demands. Its shutdown should greatly affect the system reliability. According to our calculation given in Table 1, its shutdown does have the largest impact to the system reliability; a 10.2% drops of the system reliability. The  $GDC_3$  near Atlanta has the second largest impact with about 7.7% drop in the system reliability. On the other hand,  $GDC_7$  near Detroit has the least amount of drop (0.4%) in the system reliability. One might wonder if that GDC is really needed from the system reliability

DC	1	2	3	4	5	6	7	8
$r^\psi$	0.914	0.890	0.855	0.907	0.903	0.917	0.922	0.832

Table 1: The System Reliability after a particular DC fails

point of view.

Next, consider the case with possible multiple GDC shutdowns. For an illustration, suppose  $GDC_1$  and  $GDC_4$  shutdown simultaneously, which means that there is no GDCs in the West including the highly populated California regions. Our calculation shows that the system reliability reduces to 0.834, which is about 9.9%, slightly small than the drop of GDC near Boston area. Consider another extreme case, where three GDCs in the North,  $GDC_6$ ,  $GDC_7$  and  $GDC_8$ , are all shutdown simultaneously. Then, the system reliability reduces to 0.698, which is about 24.6% drop from the original system reliability.

Our procedure allows one to entertain probability of being shut down for many GDCs simultaneously to evaluate the impact of certain contingency. For example, if we assign the probability of every GDCs being shutdown as 0.1 ( $= p_j$ ), the system reliability is 0.896, which is about 3.2% drop from the original system reliability.

**Remark:** Most of the existing CA application in logistics-planning literature assumes constant intensity function (e.g., [7]), and thus the spatial density issues addressed in this article are not considered. Then, the evaluation of service reliability may not be accurate due to the mis-representation of store information. For a comparison purpose, the following provides a few reliability calculations based on this constant intensity model. First, the service reliability for the whole region becomes  $r_{system} = 0.750$ , which is much lower than the 0.926 system reliability calculated from the spatial model. One can image that when there are clusters of stores near DCs, the reliability will be higher. This is what the spatial model represent. When the stores are assumed to be uniformly distributed, the distance from stores to DCs will be larger, and thus, the system reliability will be lower.

When only the  $i$ th GDC fails,  $i = 1, 2, \dots, 8$ , the service reliabilities presented in Table 1 in the constant intensity case become lower and their values are 0.711, 0.699, 0.708, 0.715, 0.708, 0.745, 0.749, 0.720. More importantly, the “ranks” of these reliabilities are changed. For example, shutting down  $GDC_1$  has a larger impact to the system reliability than shutting down  $GDC_8$ . Their reliabilities are 0.914 and 0.832, respectively, as shown in Table 1. However, when the constant intensity model is used, their values become 0.711 and 0.720, and shutting down  $GDC_1$  has a smaller impact to the system reliability then. A wrong reliability evaluation could result to less attention



Figure 7: The Reliability degradation Paths for each DC when its capacity decreases.  $x$ -axis is the available capacity

Figure 8: A snapshot of store Locations in Texas

in maintaining GDC<sub>1</sub>'s functionality. That is, resource could be wrongly allocated to maintain high system reliability.

**Example 4:** This example considers the capacitated GDCs and evaluate the deterioration of system reliability when one GDC's capacity is degraded gradually due to demand growth or certain type of contingency, e.g., labor dispute. For keeping our presentation simple, assume all stores has homogeneous expected demand  $\mu_0$ , and total expected stores demand  $\mu_j$  served by GDC <sub>$j$</sub>  is then,  $\mu_j = \int_{A_j} \mu_0 \lambda(\mathbf{x}) d\mathbf{x}$ . Suppose each GDC is built with capacity  $\xi_j = 1.2 \times \mu_j$ . Thus, neighboring GDCs can share the load to counteract the degradation of one GDC's capacity. Figure 7 shows the reliability degradation path for each GDC when its capacity decreases from zero (no capacity change) to one (complete shutdown of the GDC).

According to these path patterns, the service reliability in GDC<sub>8</sub> and GDC<sub>3</sub> degrade the most; much larger than the others, especially after about a 50-60% capacity degradation in these two GDCs. The reason is that those DCs are further away from neighboring DCs and have relative larger store demands. On the other hand, the capacity degradation of RDC<sub>6</sub> and RDC<sub>7</sub> serving Chicago and Detroit regions have little impact on the system reliability due to their closer distance from each other.

## 4.2 Regional-level Modeling and Reliability Analysis

Figure 8 shows store locations in Texas. Using normal kernel spatial smoothing method described in Section 3, the bandwidth estimator is calculated as  $\mathbf{h} = (h_1, h_2) = (0.604, 0.522)$ . In this article, we lay a  $50 \times 50$  grid on this region and obtain the estimated smooth spatial density of store locations as illustrated in Figure 9.

**Example 5:** By using the minimum and shortest paths and many scenarios described in Example

Figure 9: DC Locations and Service Regions

2, we can calculate the probability of routing through each minimal path, and its corresponding service reliability for stores. For example, consider a grid block of stores represented by the block center (34, 10), its distance to LDC<sub>3</sub> and LDC<sub>5</sub> are 186.3 and 253.36 miles, respectively. Thus, based on transportation cost and reliability concerns, stores located at this block will be served by LDC<sub>3</sub>. Assume all the links have same failure probability  $p_{e_j} = 0.05$ . The probability of the scenario for routing through the first minimal path  $MP_{3(1)} = (e_1, e_4)$  from GDC to LDC<sub>3</sub> is  $Pr(s_{3(1)}) = 0.90$ . Consider a grid block (34, 10) in the spatial density at the region served by LDC<sub>3</sub>, and its distance from LDC<sub>3</sub> is  $d_3(\mathbf{x}) = 186.3$  miles.

Next, we use Eq. (10) to calculate the service reliability. Consider the deadline  $t_0 = 24$  hours from GDC to a store in the block (34, 10) (represented by a triangle pointing upward in Figure 3). The transportation time on the  $MP_{3(1)}$  with link distances  $e_1 = 500$  and  $e_4 = 350$  miles is  $t_{o3}^{s3(1)} = (l_{e_1} + l_{e_4})/v_{DC} \approx 14.17$  hours, where  $v_{DC} = 60$  miles per hour is the deterministic transportation speed between GDC and LDCs. Then, the service reliability is

$$r^{s3(1)}(\mathbf{x}) = Pr(d_3(\mathbf{x})/V + 14.17 \leq 24) = 1 - F_V(d_3(\mathbf{x})/9.83) = 0.98$$

, where the location in this example is  $\mathbf{x} = (34, 10)$  and the distribution of  $V$  is normal with mean and standard deviation equal to 40 and 10 miles per hour, respectively.

Similarly, the probability of routing through the second minimal path  $MP_{3(2)} = (e_1, e_2, e_3)$  is  $Pr(s_{3(2)}) = 0.95 \times 0.95 \times 0.95 \times 0.05 = 0.04$ , and it will take  $(l_{e_1} + l_{e_2} + l_{e_3})/v_{DC} \approx 18.27$  hours to pass the long-haul distance. Under this scenario, the service reliability is then

$$r^{s3(2)}(\mathbf{x}) = Pr(d_3(\mathbf{x})/V + 18.27 \leq 24) = 1 - F_V(d_3(\mathbf{x})/5.73) \approx 0.77.$$

Thus, the service reliability for serving the store at  $\mathbf{x} = (34, 10)$  is  $r(\mathbf{x}) \approx 0.98 \cdot 0.90 + 0.04 \cdot 0.77 = 0.92$ .

Consider another grid block  $\mathbf{x}' = (32, 5)$ , which is shown as a triangle pointing downward in Figure 3. Its distance (283 miles) to LDC<sub>3</sub> is shorter than distances from other LDCs. Thus, LDC<sub>3</sub> will serve this block of stores. Because the distance from LDC<sub>3</sub> to this location is much larger than the distance (186.3 miles) from the same LDC to location  $\mathbf{x} = (34, 10)$ , the following shows that the service reliability to this location is lower (0.79 versus 0.92) due to the larger distance here. Using the same procedure as illustrated in the paragraph above, we can calculate the service reliability routing through its first and second minimal paths as 0.87 and 0.17, respectively. Thus, the service reliability evaluated at this block  $\mathbf{x}'$  is  $r(\mathbf{x}') = 0.90 \cdot 0.87 + 0.04 \cdot 0.17 = 0.79$ .

After enumerating all the store at grid-locations within service region of LDC<sub>3</sub>, we can calculate the regional-level system reliability using Eq. (10) as  $r_{system, R3} \approx 0.87$ . By going through all detailed

calculations for all LDCs and minimum paths, the total regional service reliability can be calculated as  $r_{system,R} = \int_{A_0} r(\mathbf{x})\lambda(\mathbf{x})\mu(\mathbf{x})d\mathbf{x} / \int_{A_0} \lambda(\mathbf{x})\mu(\mathbf{x})d\mathbf{x} = 0.90$ .

Now, let's consider a few other examples with different link failure probabilities. Choose  $p_{e_1} = 0.15$  while keeping other probabilities the same as above. Then, the total system reliability drops to 0.80. If  $p_{e_5} = 0.15$  and keep others the same, the service reliability will drop to 0.87. Similarly, we change  $p_{e_3}$  to 0.15, then  $r_{system,R}$  becomes 0.89. This example shows the relative importance of these links in affecting regional system service reliability. The link  $e_1$  is involved in all the LDC service-regions, so it is most critical. Thus, its failure will lead to a larger drop of the system reliability. The link  $e_5$  is slightly more important than the link  $e_3$ , which can be regarded as a backup links between  $LDC_2$  and  $LDC_3$ .

## 5 Conclusion and Future Work

This article employs a spatial approximation method to characterize patterns of store locations (and demands) in a large-size supply-chain logistics system. Based on the approximation models, different reliability evaluation schemes are proposed for logistics planning at global and regional levels. Service degradation patterns are examined to understand their relationship with DCs' capacity limitation.

When we consider the transportation costs, facility, labor and other costs of DC operations, the optimal locations of DCs and the re-routing strategy would be more complicated. How to design a system with minimal cost and robust against possible capability degradations (or fully shut down) under unexpected contingency is a challenging problem. In addition, if the connectivity between DCs and stores is not fully guaranteed, the system reliability evaluation and robust system design issues become even more interesting. This article sets the foundation of research in these directions and shows the potential of research in the service sector focusing on logistics-network reliability evaluation issues.

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## Author Information

**Ni Wang** is a Ph.D. candidate in the School of Industrial and Systems Engineering at Georgia Institute of Technology. He received his Master (2003) in Statistics from Georgia Institute of Technology and B.S. (2001) from University of Science and Technology of China. His research areas are reliability, spatial models and logistics systems.

**Jye-Chyi Lu** is a Professor in the School of Industrial and Systems Engineering at Georgia Institute of Technology. He was a Professor in the Department of Statistics at North Carolina State University, Raleigh. Dr. Lu received his Ph.D. (1988) in statistics from University of Wisconsin-Madison, and B.S. (1979) from National Chiao-Tung University at Taiwan. His 50+ publications appeared in theoretical and applied statistics, reliability and manufacturing journals. Dr. Lu led many project teams working with various companies and university centers on engineering research and education projects. He is a current associate editor for *IEEE Transactions on Reliability*, *Technometrics* and *Journal of Quality Technology*.

**Paul Kvam** is an Associate Professor in the School of Industrial and Systems Engineering at Georgia Institute of Technology. He joined ISyE in 1995 after working for four years as a scientific staff at the Los Alamos National Laboratory. Dr. Kvam received his B.S. in mathematics from Iowa State University in 1984, M.S. in statistics from the University of Florida in 1986 and Ph.D. in statistics from the University of California, Davis in 1991. His research interests focus on statistical reliability with applications to engineering, nonparametric estimation and analysis of complex and dependent systems. Dr. Kvam has served as associate editor for *IEEE Transactions on Reliability* (1992-2000), *Technometrics* (1999-2005), *Journal of the American Statistical Association* (2002-present) and *American Statistician* (2005-present). He is a member of the American Statistical Association, Institute of Mathematical Statistics, Institute for Operations Research and Management Science and IEEE.

Acronym	Counts	Acronym	Counts
AL	85	AZ	46
AR	78	CA	306
CO	61	CT	63
DE	14	FL	166
GA	159	IA	150
ID	31	IL	275
IN	143	KS	94
KY	86	LA	87
MA	99	MD	74
ME	40	MI	210
MN	150	MO	154
MS	76	MT	48
NC	158	ND	43
NE	75	NH	33
NJ	125	NM	30
NV	18	NY	273
OH	238	OK	101
OR	62	PA	279
RI	11	SC	72
SD	48	TN	100
TX	349	UT	36
VA	126	VT	24
WA	80	WI	161
WV	55	WY	24

Table 2: Store Counts for the 48 States in the Continental United States