DESIGN OF EFFICIENT FACILITY LOCATION-ALLOCATION SYSTEM IN CASE OF DISRUPTIONS

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ABSTRACT

This paper considers an emergency backup supply (EBS) system from the secondary supplying facility (SSF), when the primal supplying facility (PSF) can't satisfy the demand in case of disruptions. In this context, EBS requires each demand point to be covered by a PSF and an SSF. We consider two performance metrics, the total relevant costs (TRC) and the expected number of demand satisfied (ENDS). Using a multi-objective programming model, we find the option that would generate the most efficient one and investigate the effect of backup supply from the SSFs on the facility location-allocation (FLA) design problem through a case study.

Keywords: Emergency Backup Supply, Primal Supplying Facility, Secondary Supplying Facility, Multi-Objective Programming Model, Facility Location-Allocation

INTRODUCTION

In these days, one of the most critical issues for the facility location-allocation (FLA) design problem is how to deal with various disruptive events, which will affect the performance of the facility. Traditionally, the FLA design problem has considered a single sourcing strategy, assuming the facility is always available, but, in fact, is vulnerable to a wide range of disruptive events (see Peng et al. [29]). Some examples of supply chain disruptions have been very well known. Especially combining the effects of both 2005 Hurricanes Katrina and Rita, 1.3 million barrels/day of refining was shut down. Garcia-Herreros et al. [18] cite that a fire accident caused by a random lightning bolt at the Philips microchip plant in Albuquerque, New Mexico, is one of the emblematic cases of supply chain network resilience. When the fire cut off the supply of a key component for cell phone manufacturers Nokia and Ericsson, Nokia's production lines were able to adapt quickly by using alternative suppliers, whereas Ericsson lost in revenue of $400 million (See Latour [24]). Mitigating the impact of disruptions has become one of the main issues in the area of logistics and supply management.

When the facilities are under the risk of disruptions, the expected number of demands satisfied (ENDS) from the primary supplying facilities (PSFs) would be one of the most important performance measures. Thus, contrary to the conventional total cost minimization approaches, we formulate FLA problem as the multi-objective programming (MOP) model with the objective of simultaneously maximizing the ENDS and minimizing the total relevant cost (TRC). When a specific facility, a PSF assigned to satisfy the demands of the sites, becomes unavailable or shut down due to disruption, emergency backup supplying from secondary supplying facilities (SSFs) to the sites, which are assigned to the PSF, would surely increase ENDS with the increased TRC. Such emergency backup supplying will increase the distribution cost, inventory holding cost, and transportation time in supplying items to the sites. But, increasing ENDS would reduce the penalty cost incurred for unsatisfied demand.

We use the productivity-driven approach, where the productivity is defined to be the ratio of an output, ENDS, to an input, TRC. We generate the input, TRC, and the output, ENDS, directly through formulating and solving the FLA problem as the MOP model.

MOP MODEL WITH BACKGROUND

Basic MOP Model

The following nomenclature is used:

Sets:

M: index set of potential facility sites (*j =1, 2, …, M, for facility j and m = 1, 2…M, for site m*)

Decision Variables:

F_j: binary variable deciding whether a facility is located at site j

y_{jm}*:* binary variable deciding whether site m is covered by facility j

Let us consider the case (Case I) where only PSFs satisfy the demand. Let the nonnegative deviation variables, $\delta^{+}_{TRC_I}$ and $\delta^{-}_{ENDS_I}$, denote the amounts by which each value of TRC_I and $ENDS_I$ deviates from the minimum value of TRC_I, TRC_I^{Min}, and maximum values of *ENDS*, $ENDS_I^{Max}$, respectively. Then, the deviation variables are given by

$$\delta^{+}_{TRC_I} = TRC_I - TRC_I^{Min}, \tag{1}$$

$$\delta^{-}_{ENDS_I} = ENDS_I^{Max} - ENDS_I. \tag{2}$$

For the expressions of TRC_I and $ENDS_I$, see Hong [21]. The formulation for multi-objective FLA model with the minimax objective is given as follows:

$$Minimize\ Q = Max\left\{\alpha_1^{+}\frac{\delta^{+}_{TRC_I}}{TRC_I^{Min}},\ \alpha_2^{-}\frac{\delta^{-}_{ENDS_I}}{ENDS_I^{Max}}\right\} \tag{3}$$

subject to

$$\alpha_1^{+}\frac{\delta^{+}_{TRC_I}}{TRC_I^{Min}} \le Q, \tag{4}$$

$$\alpha_2^{-}\frac{\delta^{-}_{ENDS_I}}{ENDS_I^{Max}} \le Q, \tag{5}$$

Constraints (1) and (2) and normal FLA constraints (See Hong [21])

The productivity score (PS) is defined to be the ratio of the output(s) that the system produces to the inputs that it uses. From the above MOP model, the PE for the ω^{th} option generated by solving the MOPs would be defined to be

$$PS_I^{\omega} = \frac{ENDS_I^{\omega}}{TLC_I^{\omega} + TPC_I^{\omega}}, \tag{6}$$

where TPC_I denotes the total penalty cost for demand unsatisfied. Another important performance measure is the percentage of satisfied/covered demand to total demand (PSDT), where PSDT for the ω^{th} option is given by

$$PSDT_I^{\omega} = \frac{ENDS_I^{\omega}}{\sum_{m \in M} D_m}. \tag{7}$$

For the maximum productivity score to be equal to one (1.000), we use normalized productivity score (NPS) as follows:

$$NPS_I^{\omega} = \frac{PS_I^{\omega}}{Max_{\kappa \in \{1,\dots\Omega\}} PS_I^{\kappa}}. \tag{8}$$

MOP Model with EBS System

Now, let us consider the second case (Case II) where an emergency backup supply (EBS) system allows SSFs to cover the DPs when the PSF is disrupted. We introduce a new decision variable, x_{jm}, which is a binary variable deciding whether site m is backed up by the facility j. We add two new constraints, $\sum_{j \in M} x_{jm} = 1, \forall m \in M$and $(y_{jm} + x_{jm}) \leq 1, \ \forall m \ and \ \forall j.$ For the expressions of TRC_{II} and $ENDS_{II}$, see Hong [21].

CASE STUDY AND OBSERVATIONS

To demonstrate the applicability of the mathematical models and the frameworks presented, we conduct a case study using major disaster declaration records in South Carolina (SC) that Hong [21] uses. Historic flooding tore through SC in October 2015 when numerous rivers burst their banks, washing away roads, bridges, vehicles, and homes. Hundreds of people required rescue and the state's emergency management department urged everyone in the state not to travel. The Federal Emergency Management Agency (FEMA) opened disaster recovery centers (DRCs) in several SC counties to help SC flood survivors. We use the problem of locating DRCs in SC as our case study. Forty-six (46) counties are clustered based on proximity and populations into twenty counties. Then, one city from each clustered county based on a centroid approach was chosen. We assume that all population within the clustered county exists in that city. The distance between these cities is considered to be the distance between counties. We assume that when a major disaster is declared, the DRC in that county can't function due to the damaged facility and supply items and closed or unsafe roads and highways. Based on the historical record from FEMA database and the assumption, the risk probability for each site (a county or a clustered county) is calculated. For the case study, we hypothetically pre-determine the input parameters.

Using Excel Analytical Risk Solver Platform, we solve the MOP models for various values of $\boldsymbol{\alpha}$, where each weight changes between 0 and 1 with an increment of 0.05. There are 21 configurations arising out of the combinations of the setting of $\boldsymbol{\alpha}$. In Table 1, we report these configuration schemes, along with the set of weights, $\boldsymbol{\alpha} = (\alpha_1^+, \alpha_2^-)$ and the values of several performance values explained in the previous section, TRC_I^{ω}, $ENDS_I^{\omega}$, PS_I^{ω}, NPS_P^{ω} and $PSDT_I^{\omega}$ for Case I (without EBS system) and TRC_{II}^{ω}, $ENDS_{II}^{\omega}$, PS_{II}^{ω}, NPS_{II}^{ω} and $PSDT_{II}^{\omega}$ for Cae II (with EBS system). To see the effects of backup supply which allows SSFs to cover the unsatisfied demands due to the disrupted PSFs, we compute the corresponding values of performance measures for Case II. The resulting TRC_{II}^{11}, $ENDS_{II}^{11}$, PS_{II}^{11}, NPS_{II}^{11} and $PSDT_{II}^{11}$ are reported in Table 2. For example, the FLA scheme #11 of Case I for u_P of \$20.00 is generated by solving the MOP model with weight value at $\boldsymbol{\alpha} = (0.50,\ 0.50)$. The resulting TRC_I^{11}, $ENDS_I^{11}$, PS_I^{11}, NPS_I^{11} and $PSDT_I^{11}$ are \$45,254.63, 3838.81, 0.0848, 1.000, and 0.854. Indeed, as $NPS_I^{11}$of 1.000 indicates, this scheme turns out to be the most efficient one with PS_I^{11} of 0.0848 when backup supply is not allowed. To see the effects of backup supply which allows SSFs to cover the unsatisfied demands due to the disrupted PSFs, we compute the corresponding values of performance measures for Case II. The resulting TRC_{II}^{11}, $ENDS_{II}^{11}$, $PS_{II}^{11}, NPS_{II}^{11}$ and $PSDT_{II}^{11}$are \$53,068.92, 4393.11, 0.0828, 0.936, and 0.977. Thus, such a case, the scheme #11 yields a less efficient option if EBS system is allowed. Now, if EBS system is allowed (Case II), the scheme #18 becomes the most efficient one with PS_{II}^{18} of 0.0894, which is greater than PS_I^{11} of 0.0848. It implies, for u_P of \$20.00, that the most productive scheme with EBS system is more efficient than the most productive scheme without EBS system.

In Figure 1, we depict the DRC location-allocation for the efficient schemes for each case when for u_P= \$20.00. In Figure 1, where a solid arrow line represents the distribution from a PSF to a site while a green dashed arrow line represents the distribution from an SSF to a site if the PSF is disrupted. As shown, the efficient scheme selects four DRCs {Anderson, Beaufort, Conway, Greenville}.

SUMMARY AND CONCLUSIONS

In this paper, we introduce the concept of an emergency backup supply (EBS) system for a facility location-allocation (FLA) design problem under the risk of disruptions. An EBS system allows secondary supplying facility (SSF) to cover some sites, when primal supplying facility (PSF) can't satisfy the demands of those sites due to disruptions. Thus, all sites are expected to be covered by a PSF and backed up by an SSF. For FLA design, we consider two major performance metrics: the total relevant cost (TRC) and the expected number of demand satisfied (ENDS) by either PSFs or SSFs in the case of PSF disruptions. The TRC consists of the fixed cost of locating facilities, the transportation cost, cycle stock cost, safe stock cost, and the penalty cost for unsatisfied demand. The productivity score (PS) is defined to be the ratio of ENDS to TRC to find efficient FLA schemes. We develop a multi-objective programming (MOP) model for the FLA problem, taking these two performance metrics into consideration simultaneously.

Through the case study using actual major disaster records in South Carolina, which are available in FEMA databases, we demonstrate the applicability of our proposed an efficiency-driven approach and compare two cases, without EBS system (Case I) and with EBS system (Case II). From the numerical results, we observe that FLA schemes with EBS system perform well regarding increasing ENDS and yielding the higher PS. As the unit penalty cost increases, the FLA schemes with EBS system turn out to be more efficient than the schemes without EBS system. The proposed efficiency-driven FLA model with EBS system would help decision makers design and select the efficient FLA schemes.

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REFERENCES

References are available upon request from Hong.

Table 1: Numerical Results

Unit Penalty Cost (u_P)=$20.00												
			Case I					Case II				
Scheme	α_1^+	α_2^-	TRC_I^ω	$ENDS_I^\omega$	PS_I^ω	NPS_I^ω	$PSDT_I^\omega$	TRC_{II}^ω	$ENDS_{II}^\omega$	PS_{II}^ω	NPS_{II}^ω	$PSDT_{II}^\omega$
1	0.00	1.00	$71,532.99	4015.93	0.0561	0.662	0.893	$74,713.44	4438.72	0.0594	0.665	0.987
2	0.05	0.95	$49,717.93	3989.43	0.0802	0.946	0.887	$53,385.68	4431.93	0.0830	0.929	0.986
3	0.10	0.90	$49,350.83	3962.64	0.0803	0.947	0.881	$53,034.02	4431.45	0.0836	0.935	0.986
4	0.15	0.85	$48,973.96	3936.62	0.0804	0.948	0.876	$54,990.53	4420.48	0.0804	0.900	0.983
5	0.20	0.80	$48,141.70	3915.11	0.0813	0.959	0.871	$53,118.14	4405.49	0.0829	0.928	0.980
6	0.25	0.75	$47,143.59	3905.95	0.0829	0.977	0.869	$53,775.64	4416.54	0.0821	0.919	0.982
7	0.30	0.70	$46,320.20	3894.52	0.0841	0.991	0.866	$53,303.12	4400.24	0.0826	0.924	0.979
8	0.35	0.65	$46,320.20	3894.52	0.0841	0.991	0.866	$53,303.12	4400.24	0.0826	0.924	0.979
9	0.40	0.60	$45,844.27	3862.81	0.0843	0.993	0.859	$52,778.98	4393.61	0.0832	0.932	0.977
10	0.45	0.55	$45,681.02	3860.20	0.0845	0.996	0.859	$52,473.15	4395.95	0.0838	0.937	0.978
11	0.50	0.50	$45,254.63	3838.81	0.0848	1.000	0.854	$53,068.92	4393.11	0.0828	0.926	0.977
12	0.55	0.45	$45,254.63	3838.81	0.0848	1.000	0.854	$53,068.92	4393.11	0.0828	0.926	0.977
13	0.60	0.40	$45,162.00	3789.83	0.0839	0.989	0.843	$52,959.55	4386.98	0.0828	0.927	0.976
14	0.65	0.35	$44,979.47	3778.21	0.0840	0.990	0.840	$52,067.09	4328.47	0.0831	0.930	0.963
15	0.70	0.30	$44,543.53	3753.75	0.0843	0.993	0.835	$52,619.49	4358.47	0.0828	0.927	0.969
16	0.75	0.25	$44,503.17	3747.21	0.0842	0.993	0.833	$51,716.09	4324.19	0.0836	0.936	0.962
17	0.80	0.20	$44,343.81	3676.54	0.0829	0.977	0.818	$50,934.72	4369.05	0.0858	0.960	0.972
18	0.85	0.15	$44,052.69	3661.11	0.0831	0.980	0.814	$48,500.38	4334.02	0.0894	1.000	0.964
19	0.90	0.10	$43,884.24	3655.15	0.0833	0.982	0.813	$51,714.15	4346.65	0.0841	0.941	0.967
20	0.95	0.05	$43,565.89	3620.56	0.0831	0.980	0.805	$50,928.02	4343.62	0.0853	0.954	0.966
21	1.00	0.00	$43,424.69	3589.81	0.0827	0.975	0.798	$50,115.09	4328.90	0.0864	0.967	0.963

Figure 1: Efficient facility location-allocation networks
(u_P=$20.00)

(Scheme #11/#12 for Case I) (Scheme #11/#12 for Case II)