AMBULANCE REDEPLOYMENT: FACT OR FICTION

Hari K. Rajagopalan, hrajagopalan@fmarion.edu, Francis Marion University, SC
Elizabeth Sharer, esharer@fmarion.edu, Francis Marion University, SC
Kay Lawrimore-Belanger, KLawrimore@fmarion.edu, Francis Marion University, SC
Cem Saydam, saydam@uncc.edu, UNC Charlotte, NC

ABSTRACT

Demand for ambulances is known to fluctuate spatially and temporally by day of the week, and time of day. Faced with fluctuating demand during the day, EMS managers have the option of redeploying their fleet to compensate for such varying demand. We conducted a small survey, with a random sample of counties from North and South Carolina, in order to explore the impact of fleet redeployment on day-to-day operations. Survey results suggest that EMS managers are aware of the benefits and drawbacks of redeployments. Such shifting of personnel, while better able to cover a region with fluctuating demand, can cause fatigue and loss of morale amongst ambulance crewmembers.

Keywords: Location problems; Emergency Response Systems; Ambulance Deployment.

INTRODUCTION AND MOTIVATION

Historically, ambulances have been located at fire stations, hospitals, and/or ambulance-specific stations [1]. As communities realize population growth, demand for ambulance services has grown in parallel [2], typically requiring the establishment of additional bases. In an effort to assist/inform the making of strategic-level ambulance location (base) decisions, researchers developed a variety of static ambulance location models [3]. Since demand for ambulances fluctuates spatially and temporally by both day-of-the-week, and time-of-the-day, the building of permanent (fixed) bases to cover such varying forms of demand is indeed costly and may, in fact, be ineffective.

Recent advances in computing, geographic information systems (GIS), and commercially available software tools (e.g., MARVLIS [4]), as well as the availability of geographic positioning system (GPS) signals, have enabled emergency medical systems (EMS) managers to implement redeployment plans [5, 6]. Redeployment is defined as moving ambulances from one part of a city to another when faced with a fluctuating demand scenario. There are generally two types of redeployment plans: (1) Multi-period and (2) real-time. The former are created *a priori* and utilize call volume forecasts for various sectors of a city, and for a few hour-blocks, in order to redeploy a fleet in anticipation of demand shifts in space and magnitude. Under a real-time redeployment plan, when one or more vehicles are dispatched, the remaining available ambulances are relocated to ensure that the region is covered to the greatest extent possible. Although this strategy is expected to improve coverage statistics there is some evidence that it can have counterproductive effects also. Therefore, we conducted a small survey, based on a random sample of counties from North and South Carolina, in order to explore the impact of fleet redeployment on day-to-day operations. Survey results suggest that EMS managers are aware of the benefits and drawbacks of redeployments. Such shifting of personnel, while better able to cover a region with fluctuating demand, can cause fatigue and loss of morale amongst ambulance crewmembers.

The remainder of this paper is organized as follows. In the next section, we review the relevant literature and show some gaps in the literature. In the following section we present and discuss the results of our survey and conclusions and directions for future research are discussed in the last section.

BACKGROUND AND LITERATURE REVIEW

The literature on location models in general and ambulance location problems in particular, is rich and diverse. In this regard, we refer the reader to ReVelle et al. [7] for a comprehensive review of location modeling, and to Brotcorne et al.'s [3] review of recent developments in ambulance location problems. The readers can trace earlier developments in Shilling et al. [8] and Owen and Daskin [9].

Recent Developments in Coverage Models

The first wave of published location models were deterministic in nature [10, 11], and, thus, did not account for the probability that a particular ambulance might be busy at a given time. This uncertainty of availability was subsequently addressed by probabilistic location models. Early such models [12, 13] used simplifying assumptions, e.g., all vehicles have the same busy probability while operating independently. In general, these earlier assumptions were not reflective of "real world" conditions where servers cooperate through centralized dispatching, and have varying busy probabilities. Batta et al. [14] and Rajagopalan [15] showed that using such assumptions in location models may lead to an overestimation of coverage, and an underestimation of the number of servers required.

More recently, in an effort to increase the realism of prescriptive models by reducing/eliminating simplifying assumptions, researchers have begun utilizing the descriptive hypercube model. Larson's hypercube model [16, 17] represents an important milestone in that it introduces a *spatially distributed queuing framework* for facility location problems [9]. This structure, and its various extensions, has been found particularly useful in determining performance of EMS systems [1, 14, 16, 18-23]. Erkut et al. [24] challenged the typical use of coverage metrics in both deterministic and probabilistic models. In doing so, they proposed a novel approach to incorporating survival functions by developing a maximal expected survival location model and extending it to include probabilistic response times. Rajagopalan and Saydam [25] subsequently developed the *minimum* expected response location model. This work was motivated by the fact that shorter response distances (equivalently, times) increase the likelihood of saving additional lives. Their model is based on Hakimi's *p*-median [26], and ReVelle and Hogan's α-reliable *p*-center, problem [27].

Common to these models is the assumption of a long-term perspective. Further, hourly and daily fluctuations in demand are generally not considered; instead, peak demand periods are used as an estimate of overall demand. Coverage, rather than number of redeployments, is considered the critical issue.

Redeployment Models

As shown by Channouf et al. [28] and Setzler et al. [29], EMS demand is not static, but, rather, fluctuates throughout the week; day of the week; and hour by hour within a given day. When decision models assume a longer-term perspective, hourly and daily fluctuations in demand are generally overlooked and, as noted above, select peak demand periods are used as an estimate for overall demand.

Redeployment models, on the other hand, consider operational -level decisions that managers make on a daily, or hour-by-hour, basis, in an attempt to relocate ambulances in response to demand fluctuations over *both time and space.* The few redeployment models currently found in the literature are of two forms: (1) Real time, where ambulance redeployment is considered with every call, and (2) multi-period, where an ambulance redeployment plan considers an entire day or week based on demand forecasts.

Real Time Redeployment Models

Real time redeployment models typically relocate ambulances every time one is dispatched, or becomes available for dispatch, with the goal of providing maximum coverage at all times. One of the earliest examples of real time redeployment is that presented by Gendreau et al. [5]. The objective of their dynamic double standard formulation at time t ($DDSM^t$) is to maximize backup coverage while minimizing relocation costs. In order to solve the resulting, rather complex model, particularly for short time intervals, the authors developed a fast tabu search meta-heuristic implemented on eight parallel Sun Ultra workstations. To test the quality of solutions found by the tabu search, they solved 33 random problems with a commercially available integer linear programming solver, CPLEX [30], and showed that the worst case departure from optimality was merely 2%. Using real data from the Island of Montreal, their tests indicated that the algorithm was able to generate new redeployment strategies for 95% of all cases.

More recently, Schmid and Doerner [31] extended Gendreau et al.'s [32] double standard model (DSM) from a single to a multi-period model. They also explicitly accounted for time-dependent variations in speed, and resulting changes to coverage. Further, vehicles may be relocated with such changes considered in the objective function. Note that neither model accounts for the probability that an ambulance will be unavailable.

One drawback with real-time redeployment algorithms is the need to compute a new solution whenever a vehicle is dispatched to a call. This can be time consuming, or even infeasible, when calls arrive in quick succession throughout the day [33]. By design, these models are not useful for scheduling, or day-to-day operational plans. Regarding the latter, EMS managers must know (be able to accurately predict) the number of ambulances, and their locations (posts) during different time intervals. This can be accomplished by multi-period redeployment models.

Multi-period Redeployment Models

The earliest multi-period redeployment model was developed by Repede and Bernado [34] who extended Daskin's maximum expected coverage location model (MEXCLP) [12] to multiple time intervals. In doing so, the authors sought to capture the temporal variations in demand; hence, they termed their model TIMEXCLP. This model was incorporated into a decision support system (DSS) developed for EMS in Louisville, Kentucky. A recent and important strategic redeployment model is the dynamic available coverage location model (DACL) of Rajagopalan et al. [6]. This structure seeks to minimize fleet size while meeting specified coverage requirements. Its approach incorporates the uncertainty of vehicle availability using Marianov and ReVelle's available coverage concept [35]. Unlike the previous models discussed here, DACL specifically uses the Jarvis hypercube approximation [25] to calculate vehicle-specific busy probabilities, thus removing the simplifying assumptions made in earlier models. DACL is solved using tabu search and the solution validated via simulation. Importantly, the model allows for relocations but does not account for relocations in the objective. A comparison of redeployment models are show in Table 1.

In an effort to investigate the prevalence and importance of redeployment practices, we conducted a survey of executive leaders of EMS agencies in North and South Carolina. Results of the survey are presented in the next section.

Model	***Type***	***Objective***	***Coverage Constraint***	***Server Availability***
Gendreau et. al [5]	Real Time	Maximize the total demand covered at least twice within a radius (r_1) minus the a penalty term to reflect the change from the current state of the system	All demand is covered within radius (r_2) and proportion of all demand covered within (r_1)	Assumed to be always available. Deterministic
Schmid and Doerner [39]	Real Time	Maximize the total demand covered at least twice within a radius	All demand is covered within radius (r_2) and proportion of all demand covered within (r_1)	Assumed to be always available. Deterministic
Repede and Bernado [40]	Multi Period	Maximize the total demand covered over multiple time intervals	A proportion of demand is covered	All servers are assumed to be busy with the same probability and they are assumed to operate independently
Rajagopalan et. al [6]	Multi Period	Minimize the number of servers over multiple time intervals	A proportion of demand is covered	Each individual server busy probability calculated and server co-operations taken into consideration

Table 1: Comparison of Redeployment Models

SURVEY OF REDEPLOYMENT PRACTICES IN NORTH AND SOUTH CAROLINA

In order to better understand current EMS operations, and ascertain whether the negative employee impact reported in the initial interview is widespread or unique to the one situation, a questionnaire was developed. The instrument utilized a Likert scale to measure attitude concerning redeployment. Respondents were requested to indicate degree of agreement/disagreement with the following statements:

- Multiple redeployments lower ambulance crew morale.
- Multiple redeployments increase crew's dissatisfaction with job.
- Multiple redeployments increase crew's fatigue.
- Multiple redeployments improve coverage of area.
- Multiple redeployments shorten response time.
- Multiple redeployments help to balance workloads.

Additional questions collected data on whether or not the agency redeployed the benefits and limitations of redeployment, and on descriptors of the territory. The latter included square miles, county, and fleet size.

An on-line survey methodology for collecting the data was judged to be an effective means of collecting the data. Schaefer and Dillman (1998) [38], for example, concluded that e-mail surveys provide more detailed and comprehensive information than do mail surveys. In addition, respondents are more likely to complete and return an e-mail survey.

The sample frame was defined as those experienced in making the redeployment decisions and managing the ambulance crews. Obtaining a list of all EMS executive leaders' email addresses for the two states under study insured that the sample frame could produce data from a planned and known sample of individuals. Clearly, the targeted email messages offered control over those who responded to the survey.
All noted EMS leaders (N = 140) received an email with an appeal to participate in an on-line survey. Given the limited time and scope of the survey, we decided to constrain the sample frame to 140 possible respondents in the North and South Carolina region. In order to encourage the sampled leaders to respond, the email stressed both the importance of the information requested, and the ease of responding. A copy of the results was also offered subsequent to project completion. The realized response rate was 18.57% ($n = 26$). The average response rate for email surveys is 20.7% with a standard deviation of 40.5% [39]. A response rate of 18.57% is thus well within the expected response rate for email surveys.

The small sample size precludes a meaningful statistical analysis of the survey. However, given the survey's principal purpose, which was to determine whether counties other than Charlotte-Mecklenburg practiced redeployment, as well as the perceived or documented advantages and disadvantages of redeployment, we believe frequency counts are sufficient.

Survey Results

We now briefly describe those results of the survey that pertain to the current paper. Ten of the 26 respondents do not use redeployment. The reasons given for keeping ambulances at fixed stations, or their post, were either related to coverage or perception that redeployment negatively impacts upon staff. In the words of one of the respondents: "*Street corner deployment is a morale breaker for employees and affects recruitment/retention.*" Since each of the remaining 16 of 26 respondents represents a different county in North and South Carolina, we are able to conclude that these 16 counties do, indeed, practice redeployment. Figure 1 shows the perceptions EMS managers have regarding the advantages and disadvantages of redeployment.

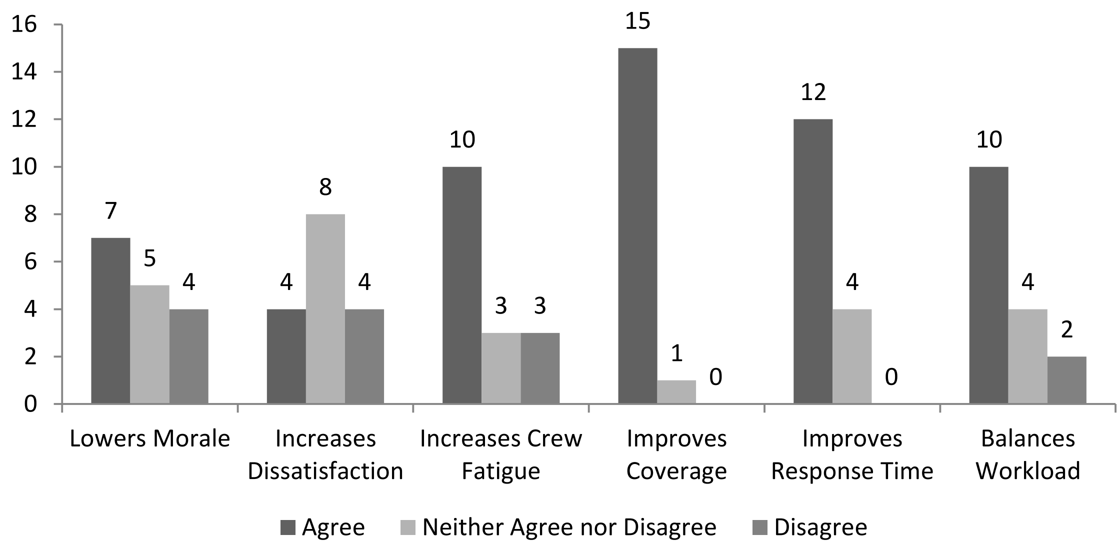

Figure 1: Responses regarding on the impact of redeployment

From these results, we found strong agreement of the positive impact resulting from redeployment (improving coverage, response time and balancing workloads). With respect to its negative aspects, there is some disagreement on whether redeployment increases dissatisfaction and reduces morale of the crew. However, the majority of respondents agree that it does indeed increase crew fatigue. Fatigue-related problems cost America an estimated $18 billion a year in terms of lost productivity [40], while fatigue-related drowsiness on the highways contributes to more than 1500 fatalities, 100,000 accidents, , and 76,000 injuries annually [40]. If we can reduce the number of redeployments without sacrificing coverage, we would be able, at least to some extent, address the problem of ambulance crew fatigue.

SUMMARY AND CONCLUSIONS

"*Cities and counties that locate their ambulances in street corners and parking lots and redeploy them when the demand changes achieve greater coverage but at a certain cost*" [41]. In this paper, we have studied the phenomenon of ambulance redeployment, including a brief survey that sought to understand the perceived advantages and disadvantages of such redeployment. There was broad general agreement on the potential advantages (improved coverage, improved response time, balanced workload); but, at the same time, a significant concern about fatigue within the ambulance crew due to the frequency of redeployments. We believe it is important that future location models take into account this aspect of redeployment when locating their ambulances. Presently, we are conducting experiments with a prototype Dynamic Redeployment Coverage Location (DRCL) model which addresses this issue by jointly minimizing both the number of servers and redeployments while maintaining adequate coverage.

REFERENCES

[1] Goldberg JB. Operations Research Models for the Deployment of Emergency Services Vehicles. EMS Management Journal. 2004;1(1):20-39.
[2] Setzler H. Developing an accurate forecasting model for temporal and spatial ambulance demand via artificial neural networks: A comparative study of existing forecasting techniques vs. an artificial neural network [Ph.D. Thesis]. Charlotte: University of North Carolina at Charlotte; 2007.
[3] Brotcorne L, Laporte G, Semet F. Ambulance location and relocation models. European Journal of Operational Research. 2003;147(3):451-63.
[4] Bradshaw Consulting Services. MARVLIS Deployment Planner. Aiken, SC 2008.
[5] Gendreau M, Laporte G, Semet F. A dynamic model and parallel tabu search heuristic for real time ambulance relocation. Parallel Computing. 2001;27(12):1641-53.
[6] Rajagopalan HK, Saydam C, Xiao J. A multiperiod set covering location model for dynamic redeployment of ambulances. Computers & Operations Research. 2008;35(3):814-26.
[7] ReVelle C, Eiselt HA, Daskin MS. A bibliography for some fundamental problem categories in discrete location science. European Journal of Operational Research. 2008;184(3):817-48.
[8] Schilling DA, Jayaraman V, Barkhi R. A review of covering problems in facility location. Location Science. 1993;1(1):25-55.
[9] Owen SH, Daskin MS. Strategic Facility Location: A Review. European Journal of Operational Research. 1998;111(3):423-47.
[10] Church RL, ReVelle C. The maximal covering location problem. Papers of Regional Science Association. 1974;32:101-18.
[11] Toregas C, Swain R, ReVelle C, Bergman L. The location of emergency service facilities. Operations Research. 1971;19:1363-73.
[12] Daskin MS. A maximal expected covering location model: Formulation, properties, and heuristic solution. Transportation Science. 1983;17(1):48-69.
[13] ReVelle C, Hogan K. The maximum availability location problem. Transportation Science. 1989;23(3):192-200.
[14] Batta R, Dolan JM, Krishnamurthy NN. The maximal expected covering location problem: revisited. Transportation Science. 1989;23(4):277-87.

[15] Rajagopalan HK. Developing and Validating Realistic Dynamic Relocation Models for Emergency Medical Systems: A Hybrid meta-heuristic approach [Doctoral Dissertation]. Charlotte: University of North Carolina at Charlotte; 2006.
[16] Larson RC. A Hypercube Queuing Model for Facility Location and Redistricting in Urban Emergency Services. Computers & Operations Research. 1974;1(1):67-95.
[17] Larson RC. Approximating the performance of urban emergency service systems. Operations Research. 1975;23(5):845-68.
[18] Burwell T, Jarvis JP, McKnew MA. Modeling co-located servers and dispatch ties in the hypercube model. Computers & Operations Research. 1993;20(2):113-9.
[19] Chan Y. Location Theory and Decision Analysis. Cincinnati: South Western College Publishing; 2001.
[20] Daskin MS. Network and Discrete Location. New York: John Wiley & Sons Inc.; 1995.
[21] Larson RC, Odoni AR. Urban Operations Research. Englewood Cliffs, N.J: Prentice-Hall; 1981.
[22] Saydam C, Aytug H. Accurate estimation of expected coverage: revisited. Socio-Economic Planning Sciences. 2003;37(1):69-80.
[23] Saydam C, Repede J, Burwell T. Accurate Estimation of Expected Coverage: A Comparative Study. Socio-Economic Planning Sciences. 1994;28(2):113-20.
[24] Erkut E, Ingolfsson A, Erdogan G. Ambulance location for maximal survival. Naval Research Logistics. 2008;55(1):42-58.
[25] Rajagopalan HK, Saydam C. A minimum expected response model: formulation, heuristic solution, and application. Socio-Economic Planning Sciences. 2009;43(4):253-62.
[26] Hakimi SL. Optimum Locations of Switching Centers and the Absolute Centers and Medians of a Graph. Operations Research. 1964;12:450-9.
[27] ReVelle C, Hogan K. The Maximum Reliability Location Problem and alpha-reliable p-center problems: derivatives of the probabilistic location set covering problem. Annals of Operations Research. 1989;18(1):155-74.
[28] Channouf N, L'Ecuyer P, Ingolfsson A, Avramidis A. The application of forecasting techniques to modeling emergency medical system calls in Calgary, Alberta. Health Care Management Science. 2007;10(1):25-45.
[29] Setzler H, Saydam C, Park S. EMS call volume predictions: a comparative study. Computers & Operations Research. 2009;36(6):1843-51.
[30] CPLEX. Using the CPLEX Callable Library. Incline Village, NV: CPLEX Optimization, Inc.; 1995.
[31] Schmid V, Doerner KF. Ambulance Location and Relocation Problems with Time-Dependent Travel Times. European Journal of Operational Research. 2010;207(3):1293-303.
[32] Gendreau M, Laporte G, Semet F. Solving an Ambulance Location Model by Tabu Search. Location Science. 1997;5(2):75-88.
[33] Gendreau M, Laporte G, Semet F. The Maximal Expected Coverage Relocation Problem for Emergency Vehicles. The Journal of the Operational Research Society. 2006;57(1):22 - 8.
[34] Repede J, Bernardo J. Developing and validating a decision support system for locating emergency mdeical vehichles in Lousville, Kentucky. European Journal of Operational Research. 1994;75:567-81.
[35] Marianov V, ReVelle C. The Queueing Maximal Availability Location Problem: A model for siting of emergency vehicles. European Journal of Operational Research. 1996;93(1):110-20.
[36] Schmid V, Doerner KF. Ambulance location and relocation problems with time-dependent travel times. European Journal of Operational Research. 2010;207:1293 - 303.
[37] Repede J, Bernardo J. Developing and validating a decision support system for locating emergency medical vehicles in Louisville, Kentucky. European Journal of Operational Research. 1994;75(3):567-81.

[38] Schaefer DR, Dillman DA. Development of a Standard E-Mail Methodology: Results of an Experiment. Public Opinion Quarterly. 1998;62(3):378 - 97.
[39] M.D. K, T.D H, R. L. A Comparison of Web and Mail Survey Response Rates. The Public Opinion Quarterly. 2004;68(1):94 - 101.
[40] Caldwell JA. The impact of fatigue in air medical and other types of operations: A review of fatigue facts and potential countermeasures. Air Medical Journal. 2001;20(1):25 - 32.
[41] Penner J. Interview with the Charlotte MEDIC Director. In: Rajagopalan HK, (Ed.). Charlotte2004.