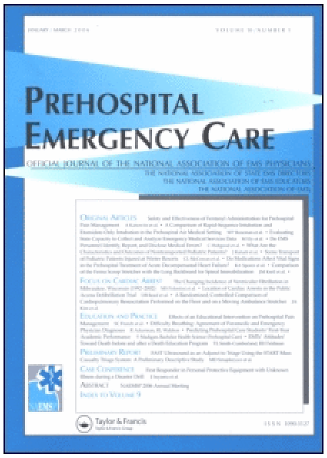

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Are EMS Call Volume Predictions Based on Demand Pattern Analysis Accurate?

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Abstract

Most EMS systems determine the number of crews they will deploy in their communities and when those crews will be scheduled based on anticipated call volumes. Many systems use historical data to calculate their anticipated call volumes, a method of prediction known as demand pattern analysis. **Objective.** To evaluate the accuracy of call volume predictions calculated using demand pattern analysis. **Methods.** Seven EMS systems provided 73 consecutive weeks of hourly call volume data. The first 20 weeks of data were used to calculate three common demand pattern analysis constructs for call volume prediction: average peak demand (AP), smoothed average peak demand (SAP), and 90th percentile rank (90%R). The 21st week served as a buffer. Actual call volumes in the last 52 weeks were then compared to the predicted call volumes by using descriptive statistics. **Results.** There were 61,152 hourly observations in the test period. All three constructs accurately predicted peaks and troughs in call volume but not exact call volume. Predictions were accurate (±1 call) 13% of the time using AP, 10% using SAP, and 19% using 90%R. Call volumes were overestimated 83% of the time using AP, 86% using SAP, and 74% using 90%R. When call volumes were overestimated, predictions exceeded actual call volume by a median (Interquartile range) of 4 (2–6) calls for AP, 4 (2–6) for SAP, and 3 (2–5) for 90%R. Call volumes were underestimated 4% of time using AP, 4% using SAP, and 7% using 90%R predictions. When call volumes were underestimated, call volumes exceeded predictions by a median (Interquartile range; maximum under estimation) of 1 (1–2; 18) call for AP, 1 (1–2; 18) for SAP, and 2 (1–3; 20) for 90%R. Results did not vary between systems. **Conclusion.** Generally, demand pattern analysis estimated or overestimated call volume, making it a reasonable predictor for ambulance staffing patterns. However, it did underestimate call volume between 4% and 7% of the time. Communities need to determine if these rates of over- and underestimation are acceptable given their resources and local priorities.
Key words: emergency medical services; health services needs and demand; health resources.

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Introduction

In 1983 Stout first described the concept of System Status Mangement.[1] This term was intended to describe any system used by a community to determine where available ambulances should be placed while they await the next request for emergency aid. In general, EMS systems strive to achieve the shortest possible time interval between a request for emergency medical assistance and arrival of emergency personnel at the patient's side. This is because for some disease processes, decreased time to emergency care may improve patient outcome. However, minimizing prehospital response time is a balance between having sufficient numbers of staffed ambulances available to respond to requests for aid, while not wasting community resources by having too many providers waiting idly for requests.[2]

One method of analyzing data for System Status Management is through demand pattern analysis. This type of analysis is intended to provide adequate emergency response capacity for typical peak demands, with excess capacity during nonpeak times kept to a minimum or used for nonemergency responses. Demand pattern analysis is usually calculated by using 20 weeks of baseline data and one of three mathematical constructs. These include average peak demand (AP) (Figure 1), smoothed average peak demand (SAP) (Figure 2), and the 90th percentile for ranked demand (90%R) (Figure 3). Individual systems choose the construct that best meets their individual needs.

Although System Status Management is widely used, there have been no published analytic studies evaluating the process.[3] This study is the first to begin the process of scientifically evaluating demand pattern analysis and its ability to forecast calls. The purpose of this study is to determine whether demand pattern analysis calculations based on 20-week historical data accurately predict EMS call volume over the subsequent year.

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$$\text{Average Peak Demand (AP) for hour j} = \{[\mathrm{Max}(WK_1HR_j \text{ to } WK_{10}HR_j)] + [\mathrm{Max}(WK_{11}HR_j \text{ to } WK_{20}HR_j)]\}/2$$

where Max is the highest observed number of calls during the selected hour over the baseline period, and j can be equal to 1 to 168. A separate calculation is made for each hour of each day; thus, a total of 168 (24 hours times 7 days) separate calculations should be made. Further, a baseline period of 20 weeks is required where WK_{1-10} is equal to the first 10 weeks in the base period and WK_{11-20} is equal to the last 10 weeks in the base period.

FIGURE 1. Formula for average peak demand.

METHODS

Design

This study was a retrospective analysis of call volume data from seven EMS agencies maintained by a single syndromic surveillance service. The study was determined to be exempt from review by the Institutional Review Boards at the University of California at Los Angeles, State University of New York, Upstate Medical University, and the University of Rochester, School of Medicine.

Setting and Subjects

Seven EMS systems who are members of the Coalition of Advanced Emergency Medical Services (CAEMS) agreed to participate and make their data available for this study. Each of these agencies provides call volume data to FIRSTWATCH, a syndromic surveillance and data intelligence service. Call volume data are maintained in a centralized data warehouse and are updated electronically via downloads from each EMS agency's computer aided dispatch system.

The seven participating EMS systems are geographically dispersed throughout the continental United States, serve urban, rural, and mixed areas with populations ranging from 197,790 to 930,000 people, covering land areas ranging from 78 to 3,000 square miles, and requesting emergency aid between 16,972 and 144,859 times per year.

$$\text{Smoothed Average Peak Demand (SAP) for hour j} = [(0.2 \times AP_{j-1}) + (0.6XAP_j) + (0.2 \times AP_{j+1})]$$

where AP is the average peak demand calculated by using the formula in Figure 1, where j can be equal to 1 to 168. A separate calculation is made for each hour; thus, a total of 168 (24 hours times 7 days) separate calculations should be made. A weight is assigned to average peak demand for the hour of interest and for the hour before and after the hour of interest. These weighted numbers are then added to estimate the demand for the hour of interest.

FIGURE 2. Formula for smoothed average peak demand.

$$\text{90th percentile ranked } (WK_{1-20}HRj)$$

where the demand for hour j over the 20-week baseline period is ranked according to the number of requests made for the hour of interest. The hour of interest ranges from 1 to 168; thus, 168 calculations are made. The value at the 90th percentile from the ranked list for each hour j is the value for the 90th Percentile for ranked demand for that hour.

FIGURE 3. Formula for 90th percentile for ranked demand (90%R).

Experimental Protocol

For each participating EMS system, 73 consecutive weeks of call volume data, beginning April 12, 2004, were extracted from the data warehouse. These data included the number of requests for EMS response by 1-hour or 15-minute periods for the entire 73-week period. For the purpose of comparison, all data were consolidated into hourly periods. Therefore, for any week there were 168 unique hourly periods with demand data for each system.

The first 20 weeks of data were used as the baseline period for conducting the demand pattern analysis. For each hourly period within each system's dataset, the baseline period data were used to calculate the three-demand pattern analysis constructs: AP, SAP, and 90%R. The formulas are shown in Figures 1, 2, and 3.

The 21st week of the dataset served as a buffer period; data from that week were not used in any part of the analysis. The final 52 weeks of data (weeks 22–73) served as the test period. For each system, the actual call volume for every observed hour during the test period was compared to the call volume predicted for that hour by each of the three-demand pattern analysis constructs.

Measurements

We determined estimated, actual, average, and maximum call volume for each hourly period within each system per week. We also determined the proportion of accurate estimations, overestimations (fewer calls than predicted), and underestimations (more calls than predicted), as well as the magnitude when over- and underestimations occurred.

Demand pattern analysis predictions may predict fractions of calls. For example, the analysis might predict 7.5 calls for a particular hour. In our analysis, we used the actual prediction for the number of calls and did not round the prediction to full numbers. Therefore, the difference between the estimation and the actual number of calls could be a fraction. For the purposes of this analysis, we only considered differences that were ± 1 call or greater to be inaccurate. That is, if the analysis predicted 7.5 calls and there were actually 8 calls during that period, that was considered an accurate prediction.

When the estimations were inaccurate, we rounded to the nearest whole number by using standard methodology to summarize the number of aid requests over or under the predicted number of requests during any hourly interval.

Analysis

This is an observational study reporting all of the events over the study period; therefore, descriptive statistics were used. We report the percent of time that the predictions were accurate, overestimated, and underestimated; as well as the magnitude of any over- or underestimations.

RESULTS

The demand pattern analysis using the initial 20 weeks of data predicted hourly call volumes ranging from 2 to 28 calls, and actual demand in the 61,152 test period hourly observations ranged from 0 to 31 calls. The predictions were accurate between 10% and 19% of the time, depending which calculation method was used. When demand pattern analysis underestimated call volume, the median number of calls underestimated was between 3 and 4, and the maximum underestimation was between 19 and 24 calls. Overestimation, predicting more calls then there actually were, was much more common than underestimation. The median number of calls that was overestimated was between 1 and 2, and the maximum number was between 18 and 20 calls. Table 1 shows the frequency of under- and overestimation by the type of demand pattern analysis calculation used. Figure 4 shows the magnitude of the over- and under estimations.

TABLE 1. Accuracy of Demand Pattern Analysis Predictions

	Average Peak Demand	Smoothed Average Peak Demand	90th percentile for Ranked Demand
Estimation accurate	13%	10%	19%
Over estimated	83%	86%	75%
Median (IQR)	4 (2–6) calls	4 (2–6) calls	3 (2–5) calls
Maximum	24 calls	22 calls	19 calls
Underestimated	4%	**4%**	7%
Median (IQR)	1 (1–2) call	1 (1–2) call	2 (1–3) calls
Maximum	18 calls	18 calls	20 calls

IQR–Interquartile Range.

Although absolute accuracy in estimation occurred, depending on the construct used, between 10% and 19% of the time during the yearlong study period, the demand pattern analyses did appear to reliably predict the timing of peaks and troughs in demand. Demand pattern analysis performance did not appear to vary significantly from system to system (data not shown).

DISCUSSION

System Status Management is the process of matching the supply of EMS resources with the demand for EMS services. Some of the objectives of System Status Management are to reduce response intervals while improving fiscal and operational efficiencies.[4] However, there have been no previously reported scientific studies that evaluated the effect of System Status Management on response intervals.[3] This study represents a first attempt at scientifically evaluating System Status Management by looking at a key component, the accuracy of the demand pattern analysis predictions.

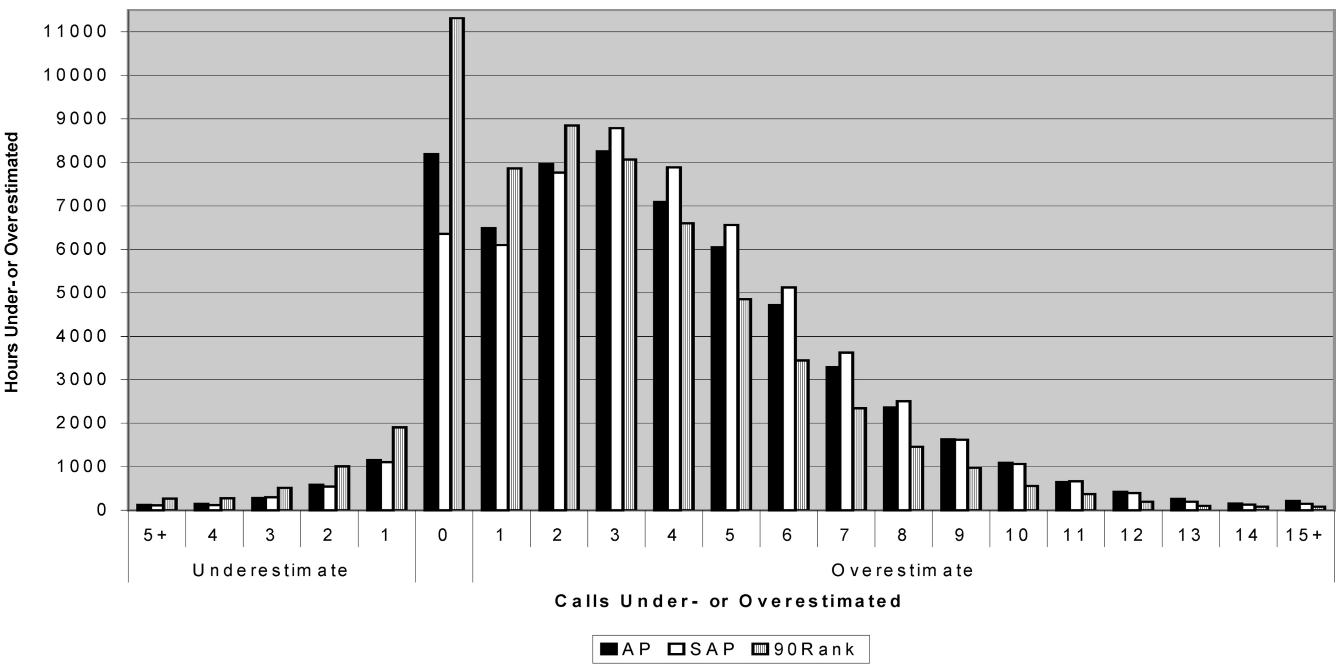

FIGURE 4. Magnitude of over- and underestimates by prediction type.

We found that the predictions were accurate between 10% and 19% of the time. At face value, this does not seem very impressive. However, because the objective is to match the supply or resources with the demand for those resources, the communities served by these systems would have been adequately staffed 93%–96% of the time. The vast majority of patients had EMS resources available to respond when they called for help. Overstaffing with unused response vehicles would be the likely result of systems using demand pattern analysis to determine the amount and scheduling of EMS resources. From a financial standpoint, it may be of concern that systems would have been overstaffed between 75% and 86% of the time. However, they would have been overstaffed by only two to four ambulances; this seems like a reasonable level of excess capacity when considering the need to provide breaks for crews, variability in call duration, and the potential for disasters requiring more EMS resources.

Emergency medical services systems need some method for predicting community ambulance demand to make staffing decisions.[5] Use of historical data is the most obvious method for predicting community need, but it is not the only—and may not be the best—possible method. For example, there is some evidence that economic and demographic variables are related to ambulance demand.[5]

No method of predicting call volume will result in completely accurate demand predictions 100% of the time. Therefore, communities will need to determine what rate of overstaffing is acceptable and affordable given the risk of understaffing, because in all locations health care resources are finite. This study shows that using demand pattern analysis to predict need based on historical data will rarely result in not having enough ambulances to meet demand but will frequently result in having more ambulances available than there is demand. It is likely that in most communities this small amount of overstaffing may be desirable to ensure that all citizens have access to timely care.

LIMITATIONS AND FUTURE QUESTIONS

This study is limited by its retrospective design, because we are unable to determine if there are factors that might explain the under- or overestimations. For example, we have no way to know if the cause of an underestimation was a mass casualty incident. Although EMS systems should generally be prepared for mass casualty incidents, it can be debated whether this is reason enough to maintain high levels of excess capacity.

This study included both 9-1-1 requests for aid as well as other requests that did not come through the 9-1-1 system. Some might question the inclusion of both emergency and nonemergency calls in demand pattern analysis predictions. However, the core purpose of demand pattern analysis is to serve as a guide in determining how many EMS resources are needed to meet a community's demand for ambulance service. Therefore, the data included in this study represented all of the demand for ambulance service in the study communities both emergent and nonemergent.

The predictions made in this study were made by using the first 20 weeks of data that were provided. No attempt was made to account for changes in call volume due to seasonality or changes related to fluctuations in the local population. However, it might be challenging for EMS agencies to change staffing patterns often. It would be up to a given agency to determine how often demand pattern analysis should be conducted, but analysis once a year seems like a reasonable interval for evaluating staffing patterns.

Future studies are needed to evaluate patterns in EMS call volumes. These analyses would inform agencies as to how often they should evaluate their data and their staffing patterns. There may be better models and/or formulas for predicting future call volume, and this should be explored. In addition, while showing that demand pattern analysis accurately predicts call volume is important, System Status Management also has a geographic component. That is, it must be determined where it is most effective to place ambulances as they await the next call to minimize response time. Although many EMS systems use System Status Management to make such decisions, the practice and the methods of making such decisions have not been scientifically evaluated. Studies are needed to look at the geographic patterns of calls and the ability of system status management to address those patterns. Further, agencies typically incorporate anecdotal experience and local knowledge into demand pattern analysis estimations when establishing their staffing patterns. Although this might be more difficult to scientifically evaluate, it is important to determine if these anecdotal data improve predictions. Finally, it must be determined if demand pattern analysis, the process of changing staffing levels, System Status Management, and the practice of moving staff throughout a region actually improve response times, decrease system costs, or affect patient outcomes.

CONCLUSION

Generally, Demand Pattern Analysis estimated or overestimated call volume, making it a reasonable predictor for ambulance staffing patterns. However, it did underestimate call volume between 4% and 7% of the time. Communities need to determine if these rates of over- and underestimation are acceptable given their resources and local priorities.

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