Sufficiency Analysis of Ambulances for Traffic Accidents in Metro Manila Using Facility Location Models

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ABSTRACT

In this paper, we analyze the sufficiency of ambulances that attend to the victims of traffic accidents in Metro Manila using facility location models. Since there was an increase of traffic accidents for the past years as reported by the Philippine National Police–Highway Patrol Group, we want to know the location of facilities and the sufficient number of ambulances to provide an effective and reliable response system that will significantly reduce the fatalities brought by traffic accidents. In our analysis, we used some facility location models, particularly the maximum expected coverage location problem (MEXCLP), to evaluate if the number of ambulances is sufficient to serve the demands in Metro Manila for the year 2016. The study shows how facility location models can be applied to determine if the number of ambulances are sufficient at any given time.

Keywords: maximum expected coverage location problem, facility location services, ambulance services, traffic accidents

INTRODUCTION

Emergency medical services (EMS) is a system that provides emergency medical care. It involves multiple people and agencies. A comprehensive EMS system is ready every day for every kind of emergency, one of which is road accidents. Locally, EMS is commonly referred to as ambulance services. Having to decide where to locate the facilities that will provide the best coverage of service to concerned people within the coverage area becomes a common problem to both the public and private sectors (Basar et. al, 2011). It is important to know the location and total number of needed facilities to provide an effective plan of facility locations in order to significantly reduce the fatalities and disabilities brought by accidents, natural disasters, illnesses, and crime-related injuries.

The Philippine National Police–Highway Patrol Group (PNP-HPG) reported an increase in traffic accidents for the years 2014 to 2016 (Ager, 2016). A total of 95,615 vehicle accidents were recorded, which caused 519 fatalities in Metro Manila, Philippines (Francisco, 2015). Due to the alarming number of traffic accidents in Metro Manila, this study aims to determine if there are a sufficient number of ambulances to serve the demands in Metro Manila and where these ambulances must be located.

A method used to find the optimal sites for the locations of the facilities is the facility location model, also known as the location allocation model. It simultaneously selects a set of location for facilities and assigns spatially distributed sets of demands to the facilities to optimize the measurements needed. Facility location provides a framework for investigating service accessibility problems, comparing the quality and efficiency of previous locational decisions, and generating alternatives such as suggestions to have more efficient service systems or to improve existing systems of the EMS (Meskarian et. al, 2017).

In a study by Daskin and Stern (1981), they used hierarchical programming, one type of facility location model, to minimize the number of ambulances needed to satisfy a service requirement and to maximize the extent of multiple coverage zones. A hierarchical programming is the process where we classify the data according to the features of the system being studied based on how pattern, service availability at each level of hierarchy, and spatial configuration of services to locate facilities. A hierarchical objective set covering model for EMS vehicle deployment tells us to define specifically the importance of the interdistrict responses. Other studies also apply hierarchical programming to address location problems such as location of the stations (Plane & Hendrick, 1977; Kolesar & Walker, 1972). They minimized the number of vehicles required to cover all zones with at least one vehicle based on the set covering problem. As a result, they have shown that the number of vehicles identified is always equal to the number found by the set covering formulation. To optimize the use of medical units such as ambulances, Daskin and Stern (1981) showed that it can be analyzed by using maximum expected covering location model.

For our study, we are going to apply the maximum expected coverage location problem (MEXCLP) on the 2016 road vehicle accidents report provided by the road safety unit of the Metro Manila Development Authority system. The model will be used to identify the optimum facility locations to station the EMS.

Materials and Methodology

The Metro Manila Accident Recording and Analysis System, which is operated by the road safety unit of the MMDA, provided us the records of traffic accidents starting from January 2016 until December 2016 communicated through email. The MMDA were informed about the data cleansing that we will do. The data they provided covered the 17 cities of Metro Manila. In the data given, the classified accidents are listed according to the date, time, and location of occurrence. We also classified the data according to the days of the week when it happened. The accidents considered in this paper are the traffic accidents reported and availed ambulance services that resulted to fatal and nonfatal injuries. Fatal injuries mean that the injury or accident caused the death of the injured person; injuries other than these are nonfatal. We assumed that all the ambulances are equipped with the same resources and personnel so that anyone can respond to any emergency, which is consistent with the operating fleet. We have gathered 16,841 records after the data cleansing phase, where we eliminated accidents with inaccurate information and accidents that did not require ambulances.

The 109,322 reported traffic accidents in Metro Manila in the year 2016, which are provided by MMDA, led to the following three accident classifications: fatal injury, nonfatal injury, and damage to property. However, for our study, we will only take the first two classifications since we will be only considering accidents that required an ambulance. This helped us trim down our data to 16,841.

To process the data we obtained, we will use two facility location models: the set covering location problem (SCLP) and the maximum expected coverage location problem (MEXCLP). The SCLP was among the first approaches to facility location model proposed by Torregas in 1971 while the MEXCLP was developed by Daskin in 1983.

The SCLP will be used to find the minimum number of dispatching stations r. The model is given below (Castaneda & Villegas, 2017):

$$\min r = \sum_{j \in J} w_j$$
$$\text{subject to: } \sum_{j \in N_i} w_j \geq 1$$
$$w_j \in \{0,1\} \quad \forall j \in J$$

In this model J, is the set of locations of the dispatching stations, and I is the set of demand zones. The decision variable w_j $(j \in J)$ represents the location of the station, while N_i is the set of covering stations for each district i, i, $\in I$.

The objective function minimizes the number of dispatching stations of ambulances needed to operate the emergency response system. The first constraint makes sure that each district will have at least one dispatching station. The next constraint limits the values of w_j to be only 0 or 1.

The next model is the MEXCLP, which will determine the number of ambulances p to cover the locations in Metro Manila where the accidents happen. The model from the same source is as follows:

$$\max z(p) = \sum_{i \in I} \sum_{k=1}^{p} d_i\, q_k y_{jk}$$
$$\text{subject to: } \sum_{j \in N_i} x_j \geq \sum_{k=1}^{p} k y_{ik} \quad \forall i \in I$$
$$\sum_{k=1}^{p} y_{ik} \leq 1 \quad \forall i \in I$$
$$\sum_{j \in J} x_j = p$$
$$x_j \in Z^+ \quad \forall j \in J.$$
$$y_{ik} \in \{0,1\} \quad \forall i \in I, k = 1, \dots, p$$

The decision variable xj represents the number of ambulances in location $j \in J$ while di represents the number of traffic accidents, $i \in I$. In addition qk, indicates the availability of the service in a district and y_{ik}, indicates the coverage offered to each district i when there are k ambulances located in the set of covering stations .

The objective function maximizes the coverage of ambulances for the demand of traffic accidents per city. The first constraint determines if district is covered by ambulances while the second constraint ensure that there would only be one available service in a district. The third constraint guarantees that p ambulances will be deployed in operating stations while the fourth constraint requires the values of the decision variables to be integers greater than zero. The last constraint, on the other hand, indicates if district i is covered by k ambulances or it is not.

To measure a quality index qk that indicates the availability of the service in a district when there are k ambulances located in the set of covering stations , the value of qk is calculated for each possible value of as follows (Castaneda & Villegas, 2017):

$$q_k = 1 - b^k \text{ for } k = 1, \dots, p$$

where

$$b = \frac{t \sum_{i \in I} d_i}{l \times p}$$

based on the shift length (given in minutes), the standard service attention time t (also in minutes) for each incident, and the aggregate demand di.

With the data on hand, we used the IBM ILOG CPLEX Optimization Studio Version 12.7.1 to find the minimum dispatching stations r and the required ambulances p needed for Metro Manila. The IBM ILOG CPLEX Optimization Studio 12.7.1 is an analytical decision support toolkit that combines an integrated development environment (IDE) with the powerful Optimization Programming Language (OPL) and high-performance CPLEX and CP Optimizer solvers that enable a rapid development and deployment of optimization models using mathematical and constraint programming. It could also be used to optimize business decisions with high-performance optimization engines and create real-world applications that can improve the outcomes of business (https://www.ibm.com/ph-en/products/ilog-cplex-optimization-studio). This was used to find and optimize the solutions for all the models in the study.

RESULTS AND DISCUSSION

To find the distribution of the events during the week, we sorted out the occurrence of the accidents per day. As shown in Figure 1, the median of the occurrence of accidents on a weekly basis ranges from 40 to 50 accidents. We can also see that the plots differ from each other in terms of variability. This tells us that the accidents per day have a wide range in the values of data, which means that the data are more dispersed. Moreover, the outliers in Monday and Tuesday represent the accidents that are numerically distant from the rest of the data. With this, the pattern of the occurrence of the accidents depends on the day of the week. We then clustered the days of the week into groups using the number of events per hour as multivariate observations to know which days appeared to have a higher occurrence of accidents (see Fig. 2). Based from the clustering analysis, we have shown that the days can be grouped into two: G1 = {Sunday, Saturday} and G2 = {Monday, Tuesday, Wednesday, Thursday, Friday}.

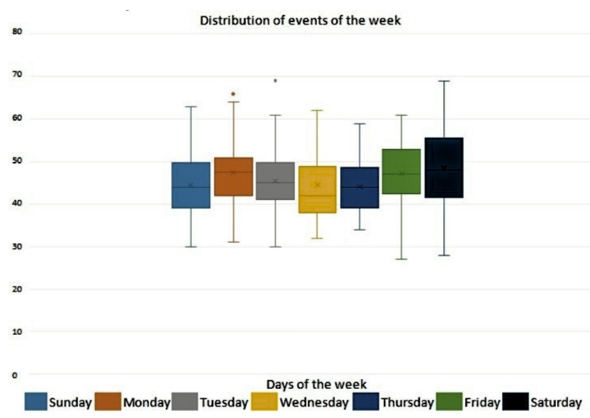

Figure 1. Distribution of traffic accidents in the week.

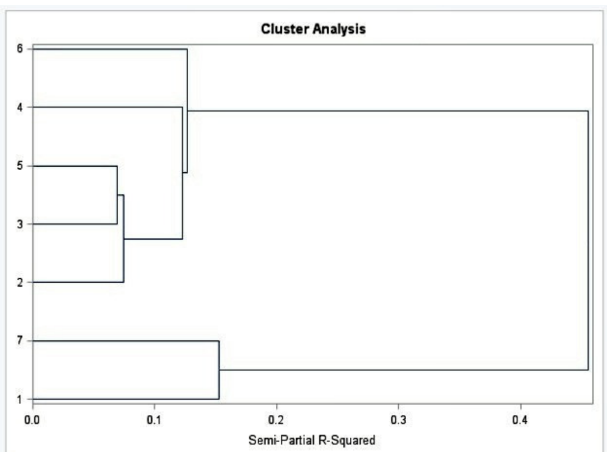

Figure 2. Clustering the distribution of traffic accidents in the week to groups.

To further investigate the distribution of accidents occurring in every hour of a day, we show in Figure 3 the frequency of accidents of G1 and G2 per hour. From the figure, it can be observed that there is a high frequency of accidents at three peaks, namely 5:00 pm, 8:00 pm, and 2:00 am. Moreover, it can be observed that the frequency of the accidents is relatively higher in G2 than in G1. We then divided the days into two shifts in terms of the number of accidents to know which has the higher or lower demand of ambulance services. As a result, the day shift 7:00 am to 7:00pm has the higher demands while the night shift 7:00 pm to 7:00 am has lower demands where both shifts have a total of 720 minutes.

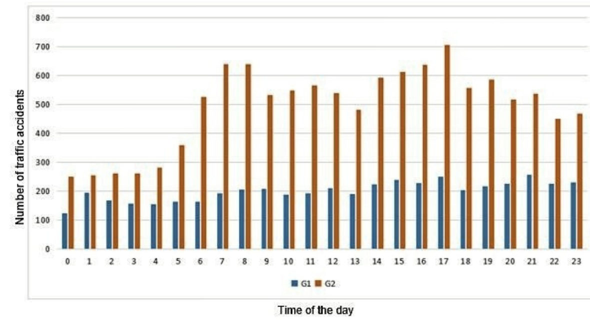

Figure 3. Distribution of the traffic accidents in G1 = Saturday–Sunday and G2 = Monday–Friday.

We computed the distances h_{ij}, where city $i = 1,...,17$, $i \in I$, and $j \in J$ is the possible location of the stations in the 17 cities of Metro Manila through the shortest path method between all pairs of cities using Google Maps. The Manila EMS's desired response time is 10 minutes. The maximum distance h_{max} is computed as the average speed divided by the desired response time per hour. The values of h_{ij} and h_{max} will determine the set N_i for each city where Ni = $\{j \in J : h_{ij} \leq h_{max}\}$.

According to Republic Act No. 4136 Chapter IV Article 1 Section 35, the maximum allowable speed of vehicles does not apply to the driver of an ambulance on the way to and from the place of accidents or other emergency incidents. From this, we consider 60km/h as our maximum average speed considering the traffic conditions in Metro Manila. Furthermore, we consider 20km/hr as our minimum average speed since vehicles can only run up to this speed on crowded streets (Republic Act No. 4136). We then solved the different values of h_{max} calculated from 20km/h to 60km/h. The SCLP model was formulated so that all cities (see Table 2 for the assignment of variables for the cities) are covered by at least one dispatching station depending on the maximum distance . For the objective function, we used all the cities as possible locations of dispatching stations. Given that there are different values for h_{max}, we get different sets of facility sites N_i that can cover city *i*. The SCLP was then processed using IBM ILOG CPLEX Optimization Studio Version 12.7 with different average speed of ambulances used to calculate h_{max}.

Table 1. Assignment of Decision Variables

Variable	City
x_1	Manila
x_2	Mandaluyong
x_3	Marikina
x_4	Pasig
x_5	Quezon City
x_6	San Juan
x_7	Caloocan
x_8	Malabon
x_9	Navotas
x_{10}	Valenzuela
x_{11}	Las Pinas
x_{12}	Makati
x_{13}	Muntinlupa
x_{14}	Paranaque
x_{15}	Pasay
x_{16}	Pateros
x_{17}	Taguig

The output showed different values for the number of dispatching stations. The results are shown in Table 2, where we can observe that as the average speed increases, the needed number of dispatching stations decreases. At the minimum average speed of an ambulance, 16 dispatching stations will be needed, while at the maximum average speed, only 9 dispatching stations are needed. At the minimum average speed, all the cities except Mandaluyong must be designated as dispatching stations. As the speed increased to 22 km/h, the number of dispatching stations decreased. This time, all except San Juan and Makati must be dispatching stations. Mandaluyong, Pasay, and Pateros were excluded as dispatching stations when speed reaches 26 km/h. At 34 km/h, Mandaluyong, Pasig, Valenzuela, and Pasay were the ones excluded. Only 12 dispatching stations are needed at 35 km/h with Navotas added to the previous exclusion. The next decrease in the number of dispatching stations is at 38 km/h. The additional city to the list of exclusion is Taguig. The next added exclusion is Las Piñas at 47 km/h. However, at 50 km/h, there are still 10 dispatching stations needed but a different set of cities excluded. These are Mandaluyong, Pasig, Navotas, Valenzuela, Las Piñas, and Taguig. Interestingly, at 51 km/h, Mandaluyong was replaced by San Juan. For an increase of 1 km/h, the exclusions are Manila, Pasig, San Juan, Navotas, Valenzuela, Las Piñas, and Taguig. At a minimum of 9 dispatching stations from 54 km/h to 60 km/h, the exclusions also vary. First, we have Manila, Caloocan, Navotas, Valenzuela, Muntinlupa, Parañaque, Pasay, and Pateros. When the speed reaches 57 km/h, Pateros was replaced by Pasig. It can be observed that if the excluded city was replaced, the city adjacent to it was added.

Table 2. Number of Stations and Their Locations According to h_{max}

Speed	h_{max}	No. of *stations*	Locations of *stations*
20	3.33	16	$x_1, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}$
21	3.5	16	$x_1, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}$
22	3.67	15	$x_1, x_2, x_3, x_4, x_5, x_7, x_8, x_9, x_{10}, x_{11}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}$
23	3.83	15	$x_1, x_2, x_3, x_4, x_5, x_7, x_8, x_9, x_{10}, x_{11}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}$
24	4	15	$x_1, x_2, x_3, x_4, x_5, x_7, x_8, x_9, x_{10}, x_{11}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}$
25	4.17	15	$x_1, x_2, x_3, x_4, x_5, x_7, x_8, x_9, x_{10}, x_{11}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}$
26	4.33	14	$x_1, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{17}$
27	4.5	14	$x_1, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{17}$
28	4.67	14	$x_1, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{17}$
29	4.83	14	$x_1, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{17}$
30	5	14	$x_1, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{17}$
31	5.17	14	$x_1, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{17}$
32	5.33	14	$x_1, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{17}$
33	5.5	14	$x_1, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{17}$
34	5.67	13	$x_1, x_3, x_5, x_6, x_7, x_8, x_9, x_{11}, x_{12}, x_{13}, x_{14}, x_{16}, x_{17}$
35	5.83	12	$x_1, x_3, x_5, x_6, x_7, x_8, x_{11}, x_{12}, x_{13}, x_{14}, x_{16}, x_{17}$
36	6	12	$x_1, x_3, x_5, x_6, x_7, x_8, x_{11}, x_{12}, x_{13}, x_{14}, x_{16}, x_{17}$
37	6.17	12	$x_1, x_3, x_5, x_6, x_7, x_8, x_{11}, x_{12}, x_{13}, x_{14}, x_{16}, x_{17}$
38	6.33	11	$x_1, x_3, x_5, x_6, x_7, x_8, x_{11}, x_{12}, x_{13}, x_{14}, x_{16}$
39	6.5	11	$x_1, x_3, x_5, x_6, x_7, x_8, x_{11}, x_{12}, x_{13}, x_{14}, x_{16}$
40	6.67	11	$x_1, x_3, x_5, x_6, x_7, x_8, x_{11}, x_{12}, x_{13}, x_{14}, x_{16}$
41	6.83	11	$x_1, x_3, x_5, x_6, x_7, x_8, x_{11}, x_{12}, x_{13}, x_{14}, x_{16}$
42	7	11	$x_1, x_2, x_3, x_5, x_7, x_8, x_{11}, x_{13}, x_{14}, x_{15}, x_{16}$
43	7.17	11	$x_1, x_2, x_3, x_5, x_7, x_8, x_{11}, x_{13}, x_{14}, x_{15}, x_{16}$
44	7.33	11	$x_1, x_2, x_3, x_5, x_7, x_8, x_{11}, x_{13}, x_{14}, x_{15}, x_{16}$
45	7.5	11	$x_1, x_2, x_3, x_5, x_7, x_8, x_{11}, x_{13}, x_{14}, x_{15}, x_{16}$
46	7.67	11	$x_1, x_2, x_3, x_5, x_7, x_8, x_{11}, x_{13}, x_{14}, x_{15}, x_{16}$
47	7.83	10	$x_1, x_2, x_3, x_5, x_7, x_8, x_{13}, x_{14}, x_{15}, x_{16}$
48	8	10	$x_1, x_2, x_3, x_5, x_7, x_8, x_{13}, x_{14}, x_{15}, x_{16}$
49	8.17	10	$x_1, x_2, x_3, x_5, x_7, x_8, x_{13}, x_{14}, x_{15}, x_{16}$
50	8.33	10	$x_1, x_3, x_5, x_6, x_7, x_8, x_{12}, x_{13}, x_{14}, x_{16}$
51	8.5	10	$x_1, x_2, x_3, x_5, , x_7, x_8, x_{11}, x_{14}, x_{15}, x_{16}$
52	8.67	10	$x_2, x_3, x_5, x_6, x_7, x_8, x_{12}, x_{13}, x_{14}, x_{16}$
53	8.83	10	$x_2, x_3, x_5, x_6, x_7, x_8, x_{12}, x_{13}, x_{14}, x_{16}$
54	9	9	$x_2, x_3, x_4, x_5, x_6, x_8, x_{11}, x_{12}, x_{17}$
55	9.17	9	$x_2, x_3, x_4, x_5, x_6, x_8, x_{11}, x_{12}, x_{17}$
56	9.33	9	$x_2, x_3, x_4, x_5, x_6, x_8, x_{11}, x_{12}, x_{17}$
57	9.5	9	$x_2, x_3, x_5, x_6, x_8, x_{11}, x_{12}, x_{16}, x_{17}$
58	9.67	9	$x_2, x_3, x_5, x_6, x_8, x_{11}, x_{12}, x_{16}, x_{17}$
59	9.83	9	$x_2, x_3, x_5, x_6, x_8, x_{11}, x_{12}, x_{16}, x_{17}$
60	10	9	$x_2, x_3, x_5, x_6, x_8, x_{11}, x_{12}, x_{16}, x_{17}$

We then used scatter plot (shown in Fig. 4) to get the summary of the number of dispatching stations needed according to h_{max}.. The same figure can be used to determine where the dispatching stations will be located around Metro Manila. Based on $h_{max} = 6.67$ km, which corresponds to the average speed of 40km/hr, we choose $r = 11$ as the optimal number of dispatching stations of ambulances that will cover all the demands of city as shown in Figure 5.

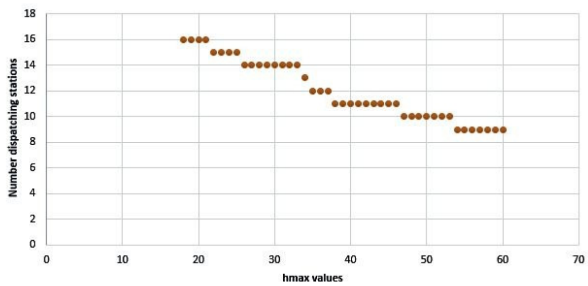

Figure 4. Analysis of the number of dispatching stations according to h_{max}.

Figure 5. Geographical location of bases

Using the maximum expected covering location problem, we will be able to determine if the number of available ambulances will be sufficient to meet the demands in Metro Manila when accidents happen.

We first compute the value of q_k. According to the EMS of Metro Manila, they have 12 ambulances in the year 2016 with a service time of the accidents given at $t = 30$ minutes. With d_i and shift length l = 720 minutes, we have

$$b = \frac{t \sum_{i \in I} d_i}{l \times p} = \frac{30 \times 16{,}841}{720 \times 12} = 57.48$$

This gives us $q_{12} = 1 - 0.5748^{12}. \approx 0.9987$.

We formulated the MEXCLP model such that the objective function contains the total demand of each city and the quality index $q_{12} = 1$. From the output given by the IBM ILOG CPLEX Optimization Studio Version 12.7, the maximum demand that is covered by the minimum number $p = 12$ ambulances is 16,841. This means that the 12 ambulances that EMS had for the year 2016 are sufficient to serve all the demands in Metro Manila.

CONCLUSION

In this paper, we have shown that the use of facility location models can be useful in helping local authorities to determine if there is a need to augment the number of ambulances at any given time at any given place. In our analysis, the SCLP suggests that Metro Manila should have at least 11 dispatching stations that will cover all the cities. By using the MEXCLP model, it shows that Metro Manila needs at least 12 ambulances. This means that some of dispatching stations may have two ambulances like Quezon City, Parañaque and Manila. Thus, the result tells us that the EMS of Metro Manila is sufficient for the year under study.

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