Designing the Emergency Medical Operations System Structure:
A Case Study

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Abstract

This study describes the efforts of the Mexican Red Cross institution located in the metropolitan area of Monterrey, México to reduce ambulance response time. The major focus for improving the performance of emergency medical systems has been the reduction of ambulance response time by determining the optimal number and locations through the use of mathematical modeling. A general two-stage scheme consisting of a geospatial - time statistical analysis and a mathematical modelling stage is applied based on an emergency call database generated from during 2016 and the beginning of 2017. The mathematical modelling stage includes the application of the Double Standard Model (DSM). Scenario analysis for the resulting demand levels per day and various combinations of fixed and mobile ambulance bases are evaluated. Results of a pilot program are provided.

Keywords:
Emergency medical service; hot spot analysis; platinum ten; response time; mathematical model.

1. Introduction

The fundamental responsibilities of Emergency Medical Service (EMS) systems are to provide urgent medical care, such as pre-hospital care, and to transport the patient to the hospital if needed (Fitch, et al., 2016). The emergence of Mexican EMS institutions has taken place since the beginning of the current century. According to Fraga-Sastrías et al., (2010), in Mexico, 33% of the institutions that offer emergency medical services are private organizations; 31% are non-governmental organizations financed through donations; and 26% of the institutions receive government financing. Pinet (2005) stated that in Mexico, the institutions and organizations that offer prehospital services are not being overseen in terms of coordination, regulation and performance evaluation. One of the main private institutions that provide emergency medical services is the Mexican Red Cross which was founded in 1910.

This study recommends the application of mathematical programming modeling to determine the optimal Emergency Medical Operations System Structure to Decrease Response Time for the Red Cross operations located in the metropolitan Monterrey area. The system structure consists of the definition of the number and location of ambulance bases.

The paper consists of four sections. The following section provides a review of relevant research on the topic and a description of the general scheme applied to define the optimal EMS structure and of the main concepts used. Section three describes the application to the EMS operations for the metropolitan Monterrey Red Cross. Section four provides a discussion of the results and the main conclusions of the study.

2. Review of literature for determining the optimal EMS operations structure

As previously described, the structure of the EMS operations system consists of defining the number and location of ambulance bases such that an objective function is satisfied. The configuration of the EMS structure determines the patient flow through the Healthcare System (HS). According to Saghafian et al., (2015), patient flow in healthcare systems can be viewed from two perspectives: operational and clinical (Coté, 2000; Coté et al., 2000; and Marshall et al., 2005). The first perspective refers to the physical movement of patients through a set of locations, and the latter refers to the progression of their health status. In this paper, we use the term patient flow to mean the first perspective. Patient flow can be classified as patient flow into, in, and out of the HS. Even though, the EMS structure impacts very significantly total physical patient flow through the overall system, its structure is mostly defined by increasing patient flow into the HS. This is done by minimizing ambulance response time.

When an accident happens, an ambulance is sent to the location of the accident to provide first aid and to transport the patient to the hospital. To limit the risk of medical complications, the patient should arrive at the hospital as soon as possible. Because the locations of hospitals are fixed, the time until a patient arrives at the hospital can only be influenced by the time it takes for an ambulance to arrive at the patient's location as the treatment time needed at the scene cannot be influenced. In addition, the sooner an ambulance arrives at the accident location, the sooner the medical treatment can start.

Ambulance response time is a key metric used to evaluate prehospital emergency medical services (Peleg et al., 2004). This coupled with the understanding that shaving minutes off of response time has a great potential to save lives (Mayer, 1979), has led to a focus on optimizing this first step in the patient flow process. Policies regarding ambulance deployment and location have become commonplace. The EMS Act of 1973 mandates that 95% of requests be served within 10 minutes in rural areas, and 30 minutes in urban areas (Ball et al., 1993). Such stipulations on service times are not exclusive to the United States (Gendreau et al., 2001; Galvao et al., 2005). A survey of more than 3000 calls in Ireland showed that only 81% of calls had a response within 15 minutes (Breen et al., 2000), and England and Australia struggle with response benchmarks as well (Kelly et al., 2002; Stoykova et al., 2004). Ambulance deployment and location represents some of the earliest OR/OM work not only in emergency response services, but in healthcare.

2.1 A brief relevant literature on EMS structure

The EMS structure definition problem has been studied for several years as the ambulance location problem, with a variety of solution methods and approaches proposed over the years. Excellent reviews of the models and procedures developed for solving this problem are provided by Belanger et al., (2015), Rais et al., (2010) and Brotcorne et al., (2003). In particular, models can be classified based on the decision level considered; strategic, tactical and operational. According to Belanger et al., (2015) strategic decisions deal with the definition of the location of the ambulance stations and fleet size. At the tactical level, it is important to determine potential stanby sites and crew scheduling decisions. The operational decisions refer to real-time aspects such as ambulance relocation and dispatching rules. Other common classification takes into account the level of stochasticity of the parameters of the model and how the model represents the dynamics of the situation modeled.

The initial works developed consisted of deterministic and static simple approaches, such as the set covering model of Toregas et al., (1971) and the maximal covering location problem proposed by Church et al., (1974). In any of these models, emergency coverage may become insufficient when vehicles become busy. This aspect is improved by the model suggested by Gendreau et al., (1997). This model is called as the Double Standard Model (DSM). It uses two coverage standards that seek to maximize the demand covered twice within a time standard of r1, using p ambulances, at most pj ambulances at site j, and subject to the double covering constraints. This model has been used to optimize the location of ambulance services in Belgium (Thirion, 2006), Canada (Gendreau et al., 1997), Austria (Doerner et al., 2005), and Tijuana (Dibene et al., 2017) proving to be one of the most widely accepted and used models of the ambulance location problem (Laporte et al., 2009). The issue of the possibility of having ambulances not available for service due to emergency call congestion is treated by the maximum expected covering location model (MEXCLP) developed by Daskin (1983) and the maximal availability location model (MALP) suggested by Revelle et al., (1989). Both models include the concept of ambulance busy fraction which represents the probability that an ambulance is not available to answer an emergency call. These two models incorporate the probabilistic nature of the EMS process. Finally, the dynamic nature of the EMS process may require the relocation of ambulances periodically to maintain an adequate service level. For example, the work of Schmid et al., (2010) recommends the application of the DSM over successive time periods to account for varying travel times across the day. Two interesting works comparing several ambulance location models are Van Der Berg et al., (2016) and Morohosi (2008).

2.2 Description of the Double Standard Model (DSM).

The main objective of standard DSM is to maximize the demand covered at least twice within a given time standard $r_1 > 0$ with the constraints that: All demand be covered at least once within a second time standard $r_2 > r_1$; A fraction $\alpha \in [0; 1]$ of the demand must be covered within r_1; All this must be accomplished using a total of $p > 0$ ambulances, and; At most $0 \leq p_j \leq p$ ambulances at site $j \in$ W. The set of sites that cover point i within r_1 is $W_i^1 = \{j \in W : t_{ij} \leq r_1\}$ and within r_2 is $W_i^2 = \{j \in W : t_{ij} \leq r_2\}$. Figure 1 shows the structure of the DSM.

$$\text{Maximize} \qquad \sum_{i \in V} d_i y_i^2 \qquad\qquad (1)$$

$$\text{Subject to}$$

$$\sum_{j \in W_i^2} x_j \geq 1 \ (i \in V) \qquad\qquad (2)$$

$$(3)$$

$$\sum_{i \in V} d_i y_i^1 \geq \alpha \sum_{i \in V} d_i$$

$$\sum_{j \in W_i^1} x_j \geq y_i^1 + y_i^2 \ (i \in V) \tag{4}$$

$$y_i^2 \leq y_i^1 \ (i \in V) \tag{5}$$

$$\sum_{j \in W} x_j = p \tag{6}$$

$$x_j \leq p_j \ (j \in W) \tag{7}$$

$$y_i^1, y_i^2 \in \{0,1\} \ (i \in V)$$

$$x_j \ integer \ (j \in W)$$

Figure 1 DSM model structure

Where d_i is the weight of demand point i, x_j is the number of ambulances at site j and the binary variable y_{ki} is equal to 1 if and only if demand point i is covered at least k times within r_1. The objective function (1) computes the sum of the weights of the demand points covered at least twice within r_1. Constraint (2) enforces that all demand is covered within r_2 and (3) ensures that a fraction α of all demand is covered within r_1. Constraint (4) states that at least two ambulances are required for double coverage while (5) asserts that a demand point cannot be covered twice if it is not covered at least once. Constraints (6) and (7) ensure that p ambulances are used and at most p_j ambulances are located at site j respectively.

The general scheme considered in this work consists of the following steps:

- Emergency call data collection and analysis. The purpose of this step is to gather a statistically significant quantity of data, analyze its volume and location through every hour and weekday. As a result, the geographical area of possible ambulance locations is delimited by identifying hotspots or high emergency call density points.

- Select operations scenarios and apply selected relevant mathematical model(s) such as the ones described in section 2.1.

- Assess results and select a solution scenario for implementation.

3. Application of the scheme

This work applies the previous scheme to improve the level response time of the organization´s operations in the Monterrey metropolitan area. The operations count with ten fixed locations and seven mobile locations from which ambulances are sent to service pre-hospital events. The organization has 34 ambulances but the financial resources allow to operate only 50% of them during any day. The services considered in the application are those occurring from January to September of year 2016. The actual level of response time was estimated in 19.9 minutes on average.

3.1 Identification of demand size and location

The structure of the optimal EMS operations system depends upon the behavior of service density and its dynamics throughout the day and the ambulance desired response time. Emergency call data analysis includes a volume and a location analysis.

Considering daily service demand requirements behavior, two different patterns are identified; a low demand level in the range of two to three services per hour occurring from the 23:01 hrs of a day to 7: 59 A.M. of the following day and; a high demand level with a range of four to five services per hour occurring the rest of the following day. Therefore, from the demand behavior of emergency calls, three daily ambulance deployment strategies were developed for each day. One high-demand strategy for Monday to Friday, one low-demand strategy for Monday to Saturday, and one low-demand strategy for Sunday.

The location of ambulances depends upon the behavior of service density and its dynamics throughout the day and the ambulance desired response time. Both conditions can be identified using hotspot analysis (Choudhary et al., 2015). This tool is a method of using past incident data to predict future event (crimes, accidents and alike) patterns. These patterns emerge due to the location of the events not being random. Their location is dependent on the geographical layout, social and environmental characteristics of the area (Chainey et al., 2005). Methods of identifying hotspots include point mapping, spatial ellipses, thematic mapping for geographical areas or a grid, kernel density estimation. Kernel density estimation is widely used within

police crime analysis to identify hotspots. Chainey et al., (2008) and LeBeau (1991) illustrate that this methodology has good spatial analysis and visualization properties which have proved useful. A study into the ability of each of the methods mentioned above to predict future crime locations and carried out by Chainey et al., (2008) proved that Kernel density estimation is the best method. For our case, emergency service demand presents a particular locational behavior shown in Figure 4 for the high demand scenario. According to the kernel density maps, emergency service needs are concentrated on specific places of the Monterrey metropolitan suburban area. The most concentrated place includes Monterrey downtown and a corridor that extends towards the northwest of the city close to the Garcia city. The other areas with concentrations of emergency services are Santa Catarina city, the frontier between Escobedo and San Nicolas cities, downtown Guadalupe city and Apodaca city.

In addition to the density analysis, hotspot analysis is performed to delineate the spatial clustering of the emergency calls based on Getis-Ord Gi* statistic (Ord et al., 1995) using fixed distance band in ArcGIS software (Mitchell 2005). The resultant Z score identified the areas having the high or low values of cluster spatially. For statistically significant The positive and larger Z scores indicated the more intense the clustering of high values (hot spot) and negative and the smaller the Z score signified the more intense the clustering of low values (cold spot). A z score near zero indicates no apparent spatial clustering. The Getis-Ord local statistic is given as:

$$G_i^* = \frac{\sum_{j=}^{n} w_{ij} x_j - \overline{X} \sum_{j=1}^{n} w_{ij}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij} \right)^2 \right]}{n-1}}} \qquad (8)$$

Where x_j is the attribute value for feature j, w_{ij} is the spatial weight between feature i and j, n is equal to the total number of features and:

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n} ; \qquad (9)$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\overline{X} \right)^2} \qquad (10)$$

Figure 2 illustrates the existence of an emergency call cluster located in Monterrey downtown with a confidence level of 99%. Manepalli et al., (2011) presents an interesting comparison of the previous two statistical techniques kernel density estimation (K) and Getis-Ord Gi* statistic using a Geographic Information System (GIS) for hotspot identification. These methods identified similar hotspots. These results are similar to the findings from Flahaut et al. (2003).

3.2 Determining structure of EMS operations

An excellent review of Operations Research contributions for optimizing patient flow in emergency operations is provided by Saghafian et al, (2015). The authors identify ambulance location as an important issue for the improvement of flow into part of the operations. As previously described, the ambulance location problem has been exhaustively treated in the Operations Research area. Brotcorne et al, (2003) present an excellent review of ambulance location and relocation models. Leigh et al, (2016) illustrate a scheme in which a variation of the double standard model used for ambulance dispatching by Gendreau et al., (1997) is included. We will use this model to develop ambulance deployment strategies for our case. Over the period of the study, ambulances were redeployed at proposed posts or bases according to geographic location and spread out to cover a wider area in a time ≤ 10 minutes. Two deployment scenarios were considered according to the service demand behavior exhibited by the emergency data.
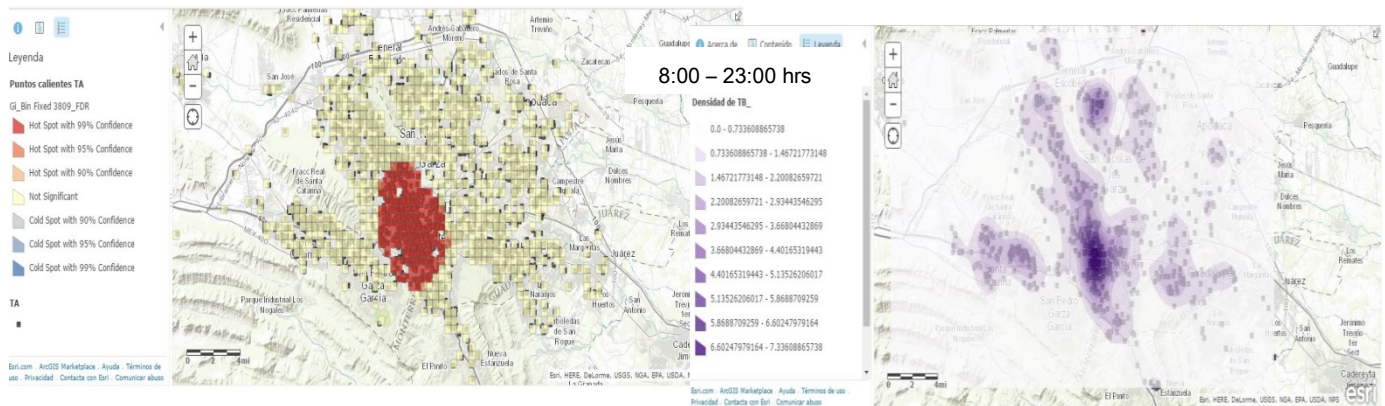
Figure 2 Density and spatial cluster analysis of emergency calls of the Red Cross operations in high demand scenario

The demand points considered for the study are those obtained during the period of January to September of 2016. We selected a total of 1125 potential location sites in the metropolitan area of Monterrey that were located according to the geographical limits delineated by the hotspots identified and illustrated in Figure 2. Shopping malls, schools, government offices and parking areas are selected as potential sites including the locations corresponding to those currently used as bases by the company. The geographic coordinates of these points are obtained from the Google Places API (Google 2014). The solutions obtained from the model are computed using MOSEK as the integer program solver called from MATLAB MOSEK ApS (Mosek 2016). In order to optimize the location of ambulances for our case, we modified slightly the standards set by the United States EMS Act (Ball et al., 1993). The value prescribed for r_1 of 10 minutes is unchanged. The value for α of 0.95 is reduced to 0.90. The value for r_2 was set at 25 minutes. Furthermore, we set the number of ambulances, p, according to the scenario required to analyze.

As identified previously with the demand analysis, two scenarios were evaluated. The optimal number of ambulances required for achieving an average transport time of less than 10 minutes is 23 for the low demand option and 29 for the high demand alternative. These new ambulance requirements represent increases from the initial operating status of 77% for the low demand shift and 71% for the rest of the day. Figure 3 illustrates the location and number of ambulances for both scenarios.
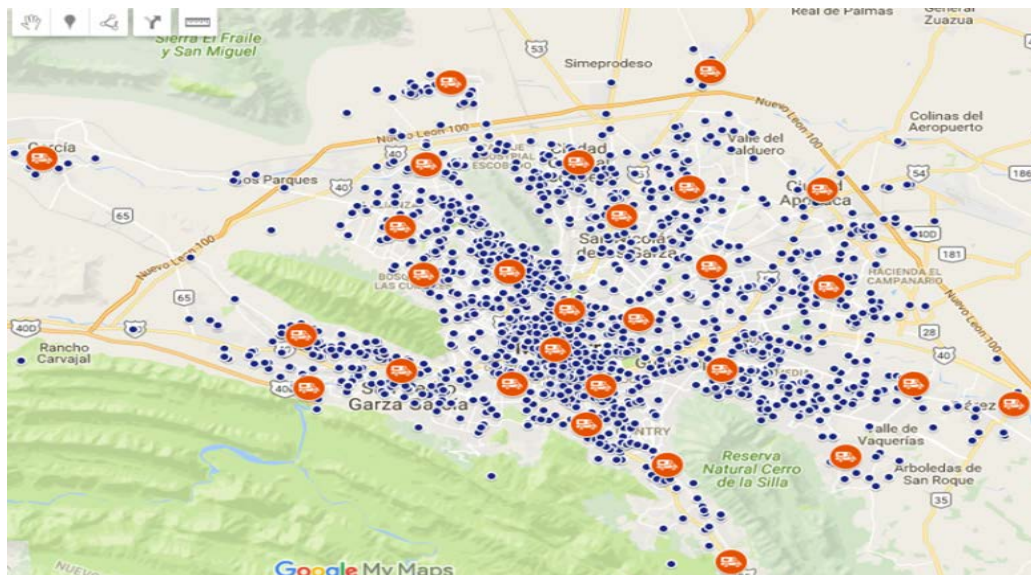

Figure 3 Summary of the optimal location and number of ambulances for the high demand scenario

3.3. Description of Implementation Results

Previously to carrying out full implementation of the selected strategy, the operations management of the institution decided to carry out a modified pilot program. The amount of ambulances in the pilot project was constrained by the shortage of well-trained crew members available at that moment and budgetary constraints. The management decided to increase the number of ambulances during the high demand shifts from 17 to 21. This implies an increase of 23.5% in the number of ambulances. In order to support this pilot program, it was necessary to determine new optimal locations generated by applying the mathematical model for $p = 11$ and 21 ambulances during the low and high demand shifts respectively. Figure 4 illustrates the number and position of the new bases for the high demand scenario. Under this scenario, it was possible to reach 92.2% of the demand with transport times lower than ten minutes. This program was setup for running during November and December of year 2016.

Figure 4 Number and location of ambulance bases for pilot program with high demand
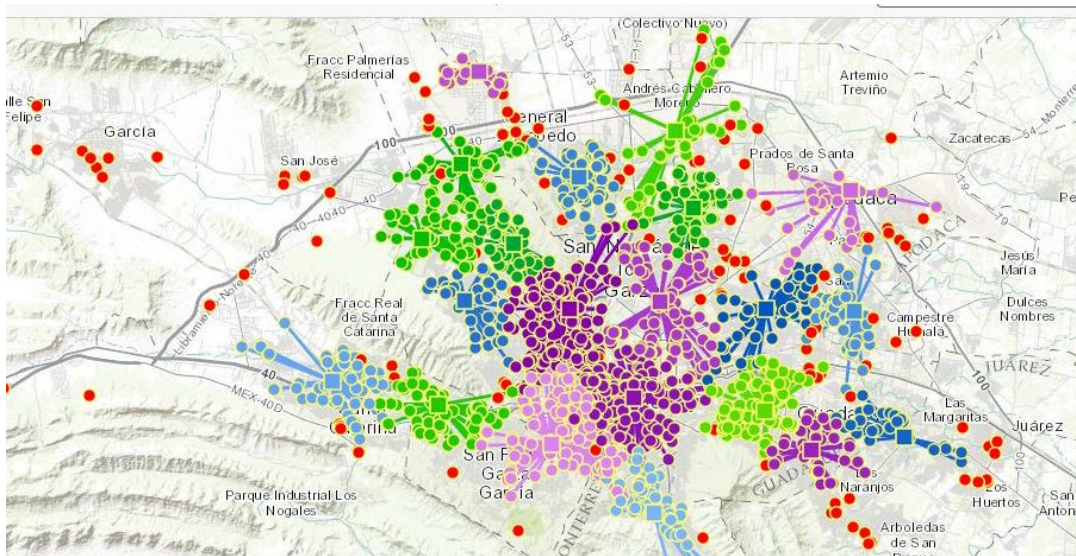
After a month of operating the new base location structure, the average transport time from the ambulance bases to the patient decreased 17.6% from 13.6 minutes to 11.2 minutes. It is expected that, after implementing the optimal ambulance solution, the average transport time will be further reduced to a level lower than 10 minutes.

4. Conclusions and recommendations

As previously mentioned, an important issue in current EMS operations concerns the improvement of ambulance response time. This study recommends the application of Lean Transportation concepts to achieve better ambulance response times. The approach considers the reduction of the time required to travel distance in excess waste by placing ambulances in optimal locations through mathematical modeling. In particular, the DSM model is applied to the Monterrey metropolitan operations of the Mexican Red Cross. The results of the model imply an increase in the number of required ambulances. In addition, it also suggests new locations for them.

After reviewing the recommendations, the management of the institution decided to implement a pilot program considering the limited resources available at the end of year 2016. The idea behind this move was to have further results to justify an increase in the operations budget for improving response time during year 2017. Further work related to this study includes the determination of the number and location of ambulances during holidays and summer. The same scheme is also considered to be used as an aid for strategic medium range planning incorporating the application of other mathematical models that consider ambulance busy periods and capacity and stochastic transport times.

Acknowledgements

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Biography

Bernardo Villarreal is a full professor of the Department of Engineering of the Universidad de Monterrey. He holds a PhD and an MSc of Industrial Engineering from SUNY at Buffalo. He has 20 years of professional experience in strategic planning in several Mexican companies. He has taught for 20 years courses on industrial engineering and logistics in the Universidad de Monterrey, ITESM and Universidad Autónoma de Nuevo León. He has made several publications in journals such as *Mathematical Programming*, *JOTA*, *JMMA*, *European Journal of Industrial Engineering*, *International Journal of Industrial Engineering, Production Planning and Control, Industrial Management and Data Systems* and the *Transportation Journal*. He is currently a member of the IIE, INFORMS, POMS, and the Council of Logistics Management.

Edgar Granda is a full professor of the Department of Engineering of the Universidad de Monterrey. He holds a PhD of Industrial Engineering from ITESM. He has 18 years of professional experience in logistics, operations and supply chain in several Mexican companies. He has taught for 5 years courses on industrial engineering and logistics in the Universidad de Monterrey, ITESM, UMIN and Universidad Autónoma de Nuevo León. As a consultant, he has carried out projects on logistics and supply chain for different companies in México.

Samantha Lankenau Delgado is a CUM LAUDE Industrial Engineer graduated from Universidad de Monterrey (UDEM). She is currently a graduate student at the Master Degree program in Supply Chain Management. Her specialty is strategic planning and the operations and logistics improvement. She has participated on several projects such as The Redesign of the Supply Process of Drugs on a Medical Center and the Improvement of the routing operations of a soft drink bottling firm. Nowadays, she works at FEMSA S.A. de C.V., developing operations strategies for improving quality and productivity. Samantha is a member of the IISE, ASQ and APICS Societies.

Andrea Montalvo is a CUM LAUDE Industrial Engineer just graduated from Universidad de Monterrey (UDEM). She has participated on several projects such as the Improvement of the routing operations of a leading convenience store firm. She also applied Lean Thinking principles for Improving the Productivity of several metal assembly lines for a Mexican metal mechanic company. Currently, she has started to work at a Mexican firm leader in the manufacturing of frozen and refrigerated food as a transportation and traffic analyst. Andrea is a member of the IIE and ASQ Societies.

Ana Cristina Bastidas Lopez is a CUM LAUDE Industrial Engineer just graduated from Universidad de Monterrey (UDEM). She has participated on several projects such as the Improvement of the routing operations of a leading convenience store firm. She also applied Lean Thinking principles for Improving the Productivity of several metal assembly lines for a Mexican metal mechanic company. Currently, she has started to work at a Mexican firm leader in the manufacturing of frozen and refrigerated food as a transportation and traffic analyst. Ana Cristina is a member of the IIE and ASQ Societies.