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911 Safety Emergency Response System Call Center Staffing Characterization using Stochastic Simulation

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ABSTRACT *Based on ENVIPE 2021 national poll, public insecurity perception in México represents the number one topic of concern according to 68.2 and 58.9% of people 18 years old and older for the years 2020 and 2021 respectively. These are clearly alarming statistics and represent a challenge for public administration. Although public safety Emergency Response Systems (ERS) represent a corrective and contention resource, they are certainly one of the institutions that people rely on to guarantee a peaceful environment to conduct their lives with freedom and trust. Response time is recognized in the literature as the key performance parameter in an ERS since people´s lives and integrity depend on immediate assistance. This time is traditionally measured from the time a call is answered to the time a patrol arrives at the location of interest. However, ringdown time, which is the length of time that a phone rings before it is answered, is also considered a waiting response time and it depends on the ERS´s communications infrastructure and the number of agents answering incoming calls. Our research considers a representative public safety ERS in México and characterizes adequate or ideal staffing allocation to meet international reference ringdown times established by state and professional association.*

KEY WORDS *Emergency Response System, Response Time, Ringdown Time, Police Call Center, Staffing Allocation, Public Insecurity*

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I. INTRODUCTION

For over three decades, insecurity levels in Mexico have been increasing substantially to become a generalized condition, which is derived from multiple national and international complex factors. According to the Perception and Victimization National Poll (ENVIPE) 2021 (INEGI, 2021), public insecurity perception in Mexico, represents the number one area of concern based on 68.2% and 58.9% of population at least 18 years old for the years 2020 and 2021 respectively. Furthermore, the average percent perception of insecurity of the same population base and source, ranges from the minimum value of 72.3% in the year 2013, to a maximum of 79.4% in the year 2018, and 75.6% in the year 2021 considering only data from 2013 to present.

Public safety Emergency Response Systems (ERS) are accountable to prevent and control potential and real criminal actions within society and require ideal allocation of resources and strict operating procedures to be effective in their mission. The key performance parameter for all ERS including safety, is *response time* (Piyadasun et al., 2017; van Barneveld et al., 2018). This parameter is measured from the time a call is received, to the time a support unit arrives to the location of the event needing assistance (D'Amico et al., 2002; Stevens, 1980). However, "received" is generally understood as "answered". Nevertheless, according to the U.S.A. Department of Justice, Bureau of Justice Statistics (Yung and Dayharsh, 1980), *ringdown time*, which is the time a phone rings before it is answered, represents part of the caller´s waiting time while the call is answered at the Public Safety Answering Point (PSAP), and consequently it is part of the *response time* offered by the safety ERS. *Ringdown time* is a design parameter for ERSs in order to configure an adequate allocation of resources including the number of phone lines and the number of agents answering calls at the PSAP. This configuration is subject to design parameters that include a maximum or ideal *response time*, a maximum or ideal *ringdown time*, and a quality or level of service in terms of the percent of calls that comply with the *response time* and *ringdown time* (Yung and Dayharsh, 1980).

According to the U.S.A. Department of Justice, Bureau of Justice Statistics (Yung and Dayharsh, 1980), the *ringdown time* used for design purposes in 911 ERS, is managed by state standards. The authors also establish that a commonly used *ringdown time* is the time that two or three rings of the telephone take, which is approximately 10 seconds. The same source establishes that several states in the U.S.A. have 911 standards that require a given percentage of the incoming calls to be answered within a defined number of seconds. The source explains that typically, the requirement specifies that 90% of the calls must be answered within 10 seconds.

There are other and very similar references concerning the *ringdown time* in the United States of America. Chin and Sprecher (1990) model a customer service center to optimize the level of service to the customers which considers answering 95% of the calls within the first three rings. Robbins (2007) makes emphasis on efficient scheduling of agents in call centers, especially when they are subject to strict service levels agreements to meet predefined goals such as answering incoming calls in 15 or 20 seconds. Additionally, the National Emergency number Association (NENA, 2020) in the United States of America, refers to the standard of answering all 9-1-1 calls where 90% of all calls arriving at the PSAP shall be answered within 15 seconds, and 95% within 20 seconds.

The problem we addressed in this research is identified in the literature as a staffing problem to determine the ideal number of call answering agents in call centers that meet performance restrictions including ringdown time (Yung and Dayharsh, 1980; Pichitlamken et al., 2003; Robbins, 2007; Buist et al., 2008; Liao et al., 2009; Ibrahim et al., 2012; Yu et al., 2013; Passmore and Zhan, 2013; Zhang et al., 2014; Seada and Eltawil, 2015; Yu et al., 2018; Li et al., 2019; Champanit and Udomsakdigool, 2020). According to Robbins (2007), uncertainty of incoming calls for service and productivity of agents answering calls, originates that efficient staffing and scheduling be very difficult and a cost relevant factor, since labor costs of operating a call center usually account for 60% to 70%.

Our research evaluates performance of an ERS in a large city in México that is integrated by nine police districts. The scope of the research considered data from one police district with demand for service above average. The city´s ERS forms part of the 911 National Emergency Response System and integrates several organizations providing assistance within the geographical area covering highways and roads. Historical data was obtained from the ERS of the city corresponding to 552 consecutive hours of operation.

II. LITERATURE REVIEW

According to the National Emergency Number Association (NENA, 2020) and the U.S.A. Department of Justice, Bureau of Justice Statistics (Yung and Dayharsh, 1980), the concept of rundown time as the time interval that a phone rings before being answered exists, with a small time difference in the standards for its acceptable or required values given identified customer service levels for incoming calls for service. In Figure 1, a logic flow diagram is presented of an incoming call for service in a 911 Emergency Response System according to National Emergency Number Association (NENA). In this figure we can observe that the concept of the rundown time is measured from process No. 2 identified as "Call Rings at PSAP" and process No. 3 identified as "Call Answered." As observed in this figure, the operating standards for the National Emergency Number Association (NENA) and the National Fire Protection Association (NFPA) related to the rundown time are the same. For NENA and NFPA, the call answer interval is: 90% of calls RT <= 15 seconds, and 95% of calls RT<= 20 seconds. However, as presented before, the U.S.A. Department of Justice, Bureau of Justice

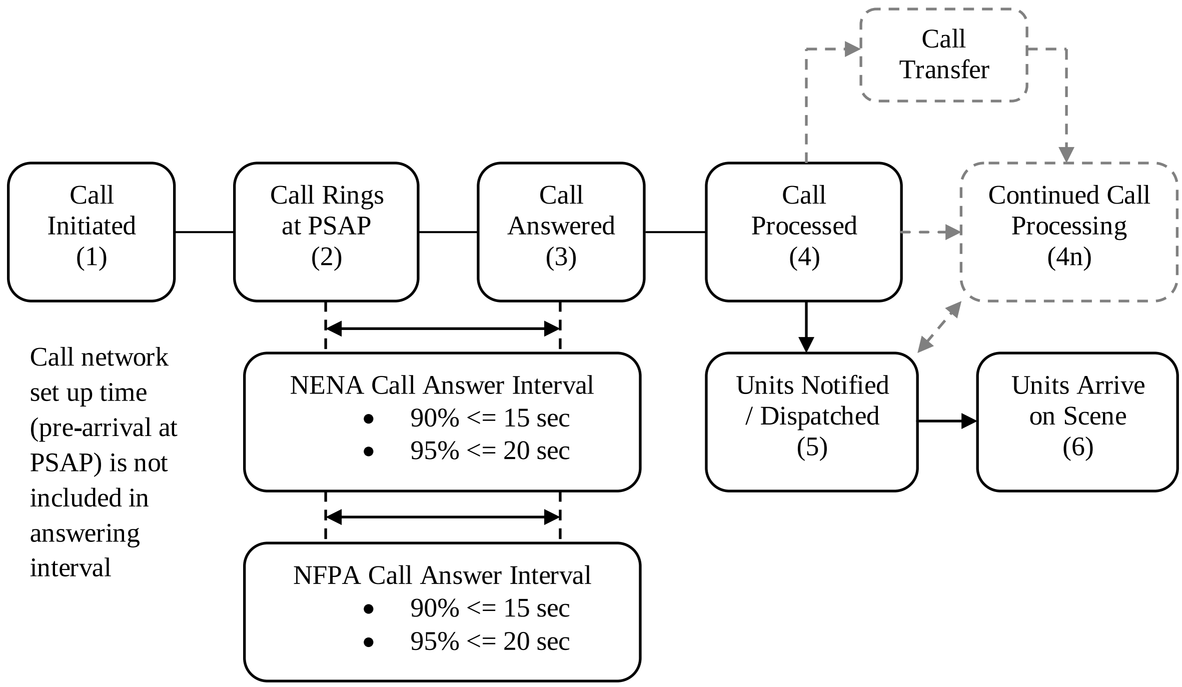

Figure 1: NENA call answering interval for 9-1-1 calls (NENA-STA-020.1-2020, 2020)

Statistics (Yung and Dayharsh, 1980), establish that several states have 911 standards and usually the requirement for *rundown time*, is that 90% of the calls must be answered within 10 seconds. The Lincoln Emergency Communication Center or LECC (Righter, 2011) could also be used as example of the application of this 911 standard. In its 2011 Annual Report it is established that 10 seconds or less is the expected *ringdown time*, and the expectation of an *average call duration time* of 70 seconds for all calls. According to this source, the real average *ringdown time* for LECC in the year 2011 was 5.58 seconds. The *ringdown time* performance parameter is also applied to non emergency call centers focusing on particular customer service levels requirements expressing them as a % of calls to be served within a given time interval in seconds or number of rings. Examples of these are: 80% of calls answered within 20 seconds (Seada and Eltawil, 2015), 100% of calls answered in 15 to 20 seconds (Robbins, 2007), and 95% of calls answered within the first 3 phone rings (Chin and Sprecher, 1990).

The literature reports several methodological tools in the area of operations research applied to evaluate and solve efficiently and effectively the staffing and scheduling problems found in a call center, which is subject to performance measures, probabilistic parameters such demand for service, service rates, as well as cost and budgets constraints. Green and Kolesar (2004) establish the long history of operations research and emergency servicing such as policing applying deterministic mathematical programming or queueing models. In our literature review for improving call centers in ERS or in the service industry, we also observed the utilization of operational research methodologies to improve operational strategies, which include discrete event stochastic simulation, mathematical programming, queueing mathematical models, and heuristic models. In some cases, more than one of these methodologies, are applied and results are compared (Pichitlamken et al., 2003; Ridley et al., 2003; Seada and Eltawil, 2015).

Among sources utilizing discrete event stochastic simulation in the analysis and improvement of ERS call centers we have van Buuren et al. (2015), Bieger et al. (2009), Brooks et al. (2011), Buist et al. (2008), Conley and Grabau (2013), Ibrahim et al. (2012), L'Ecuyer and Olson (2018), Li et al. (2019), Pichitlamken et al. (2003), Ridley et al. (2003), Seada and Eltawil (2015), and Steinmann and de Freitas Filho (2013). Brooks et al. (2011), propose a simulation model for calls for service given that police administration frequently requires justification to government levels the current or desired size of the police resources. The model is based on probability distributions that characterize call arrivals and service rates as inputs to the simulation model, and statistics are generated as outputs for the response delay, response times, cross-sector calls, and officer utilization. This model was applied in an urban police department.

Concerning findings in the utilization of queueing mathematical models to improve ERS we found sources that include Hashizume et al. (2012), Liang (2015), Nag and Helal (2017), Pichitlamken et al. (2003), Ridley et al. (2003), Yu et al. (2013), and Seada and Eltawil (2015). According to Nag and Helal (2017), call centers are suitable to be modeled with queueing systems where calls arrive, wait in a information technology system queue, and served by agents or persons that take and respond the call. These authors state that the queueing model M/M/N or the Erlang C model, is the simplest representation of a call center. This model assumes Markovian arrival and serving processes, which follows Exponential or Poisson probability distributiosn, and "N" number of servers with a common waiting queue. Nag and Helal (2017) applied their queueing model on an airline call center. Based on Pichitlamken et al. (2003), queueing models are insightful, require less amount of time for computations, and are simpler to construct compared to simulation models.

Other methodologies and developments contributing to minimize the time of any of the processes included in the response time of ERS, are varied and mainly based on different technologies (Cloud, 5G, Edge, Fog, UAV) applied within the processes involved (Holubier et al., 2019; Wenguang and Zhiming, 2021; Mkhwanazi et al., 2020; Singh et al., 2021, Jamil and Khan, 2019; Yang et al., 2021).

III. METHODOLOGY

Our research was focused on creating a stochastic discrete event simulation model of the initial processes in the 911 ERS call center of a large city en Mexico. These processes of interest are represented by stages (1) to (5) in Figure 1, where the NENA call answering interval for 9-1-1 calls (NENA-STA-020.1-2020, 2020) is presented. Data was obtained from 552 hours of continuous operations of the city´s ERS. For every call for service processed associated times for every process were recorded. Based on these data the arriving and servicing (stages 4 and 5 in Figure 1) call processes were probabilistically characterized so they could be used as input in the simulation model as referred by Brooks et al. (2011).

The geography of the city´s ERS is integrated by nine police districts and our simulation model only considers one police district. In a police district there are four police quadrants and in every police quadrant there are four patrolling zones. For relevancy, we selected a police district with above average demand for service. The National 911 ERS has three levels of priority of calls for service depending on the urgency of the required assistance. Priority levels 1, 2, and 3 are assigned identification colors to differentiate them graphically as red, yellow and blue respectively, where priority call 1 is the highest level and 3 the lowest level. From previous research projects, extended response times were identified (Holguin-de la Cruz, 2019), and we continue our efforts to minimize partial response times of subprocesses associated.

Our simulation model captures operations of four police quadrants corresponding to one police district of the city´s ERS. It utilizes forty eight call for service arrival probability distributions of patrolling zones (4 police quadrants; 4 patrolling zones per quadrant; 3 call priorities). In the case of the probability characterization of dispatch times, we characterized them by police quadrant and by call priority (4 quadrants; 3 call priorities) to generate twelve probability distributions. Firstly, we generated a simulation model to reproduce actual operating conditions and validated it based on its capacity to reproduce actual behavior, arriving call volumes, and call processing times. We modeled call processing (Stage 4 in Figure 1) and dispatch (Stage 5 in Figure 1) times as one stage as a function of its probability distributions, given availability of data.

The simulation scenarios considered in our research were basically a characterization of incremental capacity in the number of agents answering incoming calls for service, and evaluated how the processing times and the length of waiting queue were affected for calls for service, for a given configuration of the number of agents utilized in each scenario. The simulation model was run for 10 replicates of 552 hours and run these scenarios with and without warm up time of 20 hours.

IV. RESULTS

Arrivals of calls for service to the safety ERS were probabilistically characterized for the selected police district by police quadrant (4), by patrolling zone (4 zones per quadrant), and by call priority (3), generating forty eight probability distributions. Similarly, response times for Stages 4 (Call Processed) and 5 (Units Notified / dispatched) presented in Figure 1, were probabilistically characterized, as one stage process, and twelve probability distributions were obtained corresponding to 4 police quadrants and 3 call priorities. In Table 1, obtained probability distributions are classified according to the probability distribution type for *inter arrival times* of calls and for *Call Processed Time + Dispatch Time*. As it can be observed in this table, *inter arrival times* are mainly characterized by Gamma (43.7%), Lognormal (29.1%), and Weibull (25%) probability distributions. Correspondingly, the total time of *Call Processed Time + Dispatch Time* is essentially characterized by Lognormal (83.3%), and Gamma (16.7%) probability distributions. These findings are similar to results reported by Gualandi and Toscani (2019) where it was established that a Lognormal probability distribution can be used to explain behavior of call centers service times.

Table 1: Probability distributions for calls: *inter arrival time* and *answer + dispatch time*

Parameter	Number of Probability Distributions (95% C.I.)				Total
	Exponential	Gamma	Lognormal	Weibull	
Inter arrival Times: Patrolling Zones: 4 Quadrants, 4 Patrolling Zones / Quadrant, 3 Call Priorities	1	21	14	12	48
Answer Call Time + Dispatch Time: 4 Quadrants and 3 Call Priorities		2	10		12
Total	1	23	24	12	60

Simulation results are presented in Figures 2 and 3. In Figure 2, we present a characterization of the call answering waiting time or *ringdown time* obtained for all incoming calls for one police district. As established before, one police quadrant is integrated by four patrolling zones and one police district by four quadrants. In Figure 2 we have identified four patrolling zones equivalent to a geographic quadrant. These patrolling zones consolidate the calls for service of the four patrolling quadrants divided in four patrolling zones. The capacitated characterization of the serving system consisted, as explain in the methodology, of varying the number of answering agents to serve all incoming calls for service from one to eight agents, and evaluate how the waiting time for the call to be answered or rundown time was modified with different levels of capacitated configuration.

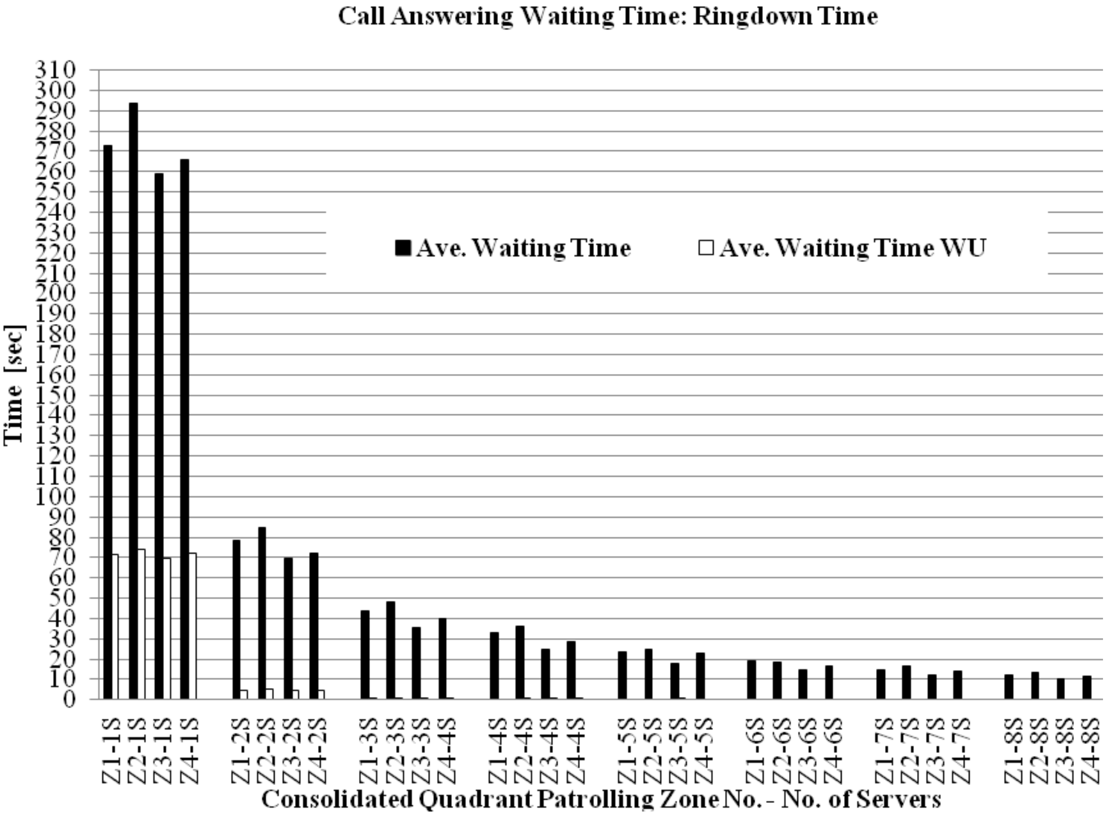

Figure 2: Police district quadrant averages of ten replicates: Estimated call answering waiting time (*ringdown time*) by patrolling zone and by number of servers

In this figure, the series of solid bars in black, represent the scenario where warm up period of 20 hours was not used and series in white, the scenario with warm up (WU) period. As it is observed in the scenario with no warm up period and one answering agent, the *ringdown time* varies from 259.06 seconds to 293.6 seconds. Then, for scenarios with 2 to 8 answering agents its behavior decreases exponentially. When we compare obtained *ringdown times* with referred *ringdown times* by NENA (2020), which states that 90% of calls RT <= 15 seconds, and 95% of calls RT<= 20 seconds, and with referred *ringdown times* by the U.S.A. Department of Justice, Bureau of Justice Statistics (Yung and Dayharsh, 1980), which that 90% of the calls must be answered within 10 seconds, we find that only scenarios with 6, 7, and 8 answering agents only meet NENA (2020) standard of ringdown times <= 20 seconds, although measured for 100% of the calls. We also observe that scenarios with 7 and 8 answering agents meet with 75% and 100% respectively, the NENA standard of *ringdown times* <= 15 seconds. Furthermore, we also observe that the *ringdown time* of 10 seconds standard established by the U.S.A Department of Justice, Bureau of Justice Statistics, was not met by all evaluated scenarios with no WU. However, the scenario with 8 answering agents had *ringdown times* values between 10.19 seconds and 12.12 seconds, which are close to the reference standard.

Nevertheless, for the warm up (WU) scenarios, we can observe that the scenario with one answering agent still generates high *rundown times* with values from 69.7 seconds to 73.8 seconds. However, the scenario with 2 answering agents produces *ringdown times* with values from 4.33 seconds to 4.95 seconds. In this case, the 10 seconds reference standard from the U.S.A Department of Justice, Bureau of Justice Statistics is met.

Given the stochastic nature of calls demand for service, steady state is not a constant condition within a time period. L'Ecuyer and Olssen (2018), establish that in an ERS, many incoming calls (burst) in a short period of time, can be triggered by single events. The authors propose a methodology on how to simulate the burst process. This is an example of another disturbing factor that can produce situations where demand exceeds operating capacity. Considering both scenarios without and with warm up period (WU), we observe that possibly the ideal number of answering agents could vary from 2 to 9 answering agents, and gradual adjustments could take place according to variations in time of calls demand.

In Figure 3, we present a similar characterization chart where maximum number of calls in the calls receiving locations are evaluated to indentify the number of incoming calls in the patrolling zones queues waiting to be answered. We have as well simulation scenarios without (black bars) and with (white bars) warm up (WU) period. For scenarios without warm up period, we observe that the maximum content of calls waiting to be answered gradually decreases as the number of answering agents is increased and varies from 12.9 to 10 calls. This parameter is an observed maximum value and not an average value. However, the ERS has to be aware of these possible parameter values to monitor its behavior and plan accordingly. Scenarios with warm up (WU) period present maximum content of calls waiting to be answered significantly smaller compared to scenarios without warm up period. These values vary from 2.5 to 3 calls for one answering agent, 1.7 to 1.9 calls for 2 agents, 1.1 to 1.2 for 3 agents, 1 to 1.1 calls for 4 agents, constant values of one for 5, 6, 7, and 8 agents. Based on this criteria the ideal number of answering agents would be at least 5 agents to prevent calls from getting accumulated in incoming locations queues and be prepared with additional agents in the case of increases in the demand for service with larger amounts of incoming calls.

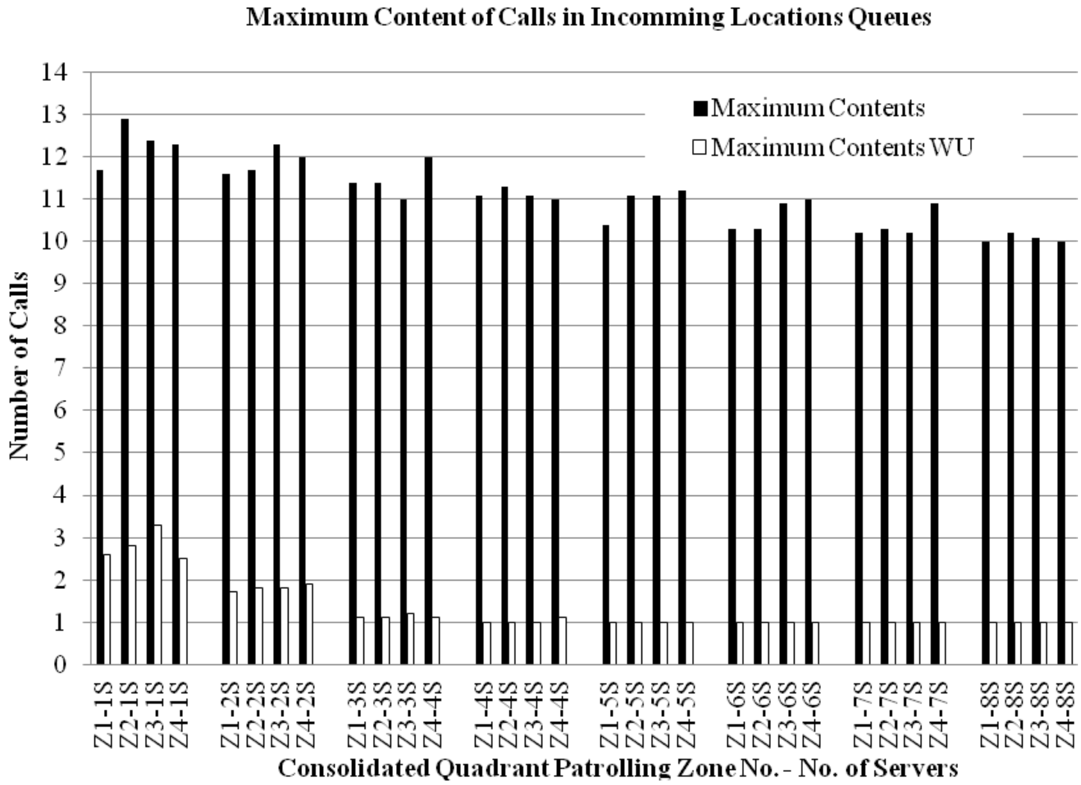

Figure 3: Police district quadrant averages of ten replicates: Maximum content of calls in the calls receiving locations by patrolling zone and by number of servers

It is important to observe that based on these results the minimum staffing levels only for this police district for the call answering and dispatch processes are being identified as levels that need to be maintained at all times and that other staffing factors need to be considered including fatigue, demand fluctuations given time and day of the week, absenteeism, punctuality, breaks, and shifts. Given the two major scenarios of not using or using warm up (WU) time, a start up reference point for ERS staffing in the call answering and dispatching processes would be of nine minimum answering agent at all times with the possibility of decreasing the number of call answering agents to the level that allows to meet the desired performance standard in every hour, day, week, and month of the year. It is also important to consider that, in our research, only security related calls for service to the ERS were included, and that all other calls, that are also served by the ERS need to be added to the call center staffing problem since they represent a significant work load proportion.

V. CONCLUSIONS

We confirm the usefulness of the evaluation tool of stochastic discrete event simulation to characterize, evaluate or design resource allocation strategies to ERS in order to meet and improve performance parameters including total *response time* of the ERS, and *ringdown time* for the ERS´s call center. We believe that these type of life saving services offered by all ERS, could be subject to always provide and comply with the service and minimum performance parameters. This would imply that adequate budgets must be allocated and operations continually supervised and monitored to warrantee the quality of the service provided.

We also observe the need to establish emergency standards for *ringdown times* and total *response times* to be observed at an international level by all safety ERS, and in support with several medical public, institutional, and private organizations, with legal repercussions when this service and service level are not met.

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