International Journal of Engineering Research and Development
e- ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 22, Issue 2 (February 2026), PP 56-61

9-1-1 Emergency Response System Probabilistic Demand Characterization by Day of the Week and by Time of the Day of a Police Precinct in New York City, U.S.A.

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ABSTRACT *Emergency Response Systems (ERS), represented by the emergency service provided by phone numbers including 911 in the United States of America, Canada, and Mexico, 112 in the European Union and India, 110, 120 and 119 in China, 110, 119 and 118 in Japan, 190, 192 and 193 in Brazil, and 999 in Russia, provide emergency support to events including public security, medical, and fire. ERS are fundamentally necessary to assist society in its public safety, medical, fire, among others, to respond to urgent events. The main performance parameter of ERS is response time, which is measured from the time the phone is answered, or starts ringing, to the time the assisting unit arrives to the location of the event. The response time regulation depends on the particular system and government regulations. As an example, in the United States of America, the National Advisory Commission on Criminal Justice Standards and Goals, identified the ideal maximum response time of three minutes for law enforcement urgent events. To achieve this performance goal, adequate allocation of resources is required. Likewise, the characterization of the demand for ERS services is as well required to determine an ideal allocation of resources that is capable of complying with the ideal response time. In this research, we identified one police precinct in the New York City ERS, to characterize its demand for service as an input to a simulation model in the future to evaluate potential improvements in the adequate or ideal allocation of resources.*

KEY WORDS *Emergency Response System, Response Time, Spatial Temporal Demand Probabilistic Characterization, Public Safety, Resource Allocation, New York, Central Park*

Date of Submission: 24-01-2026 Date of acceptance: 06-02-2026

I. INTRODUCTION

According to the European Emergency Number Association EENA (Venhuizen, 2025), the global demand for emergency services continues to increase reporting a 6 % increment in 2024 in Europe and a 4% increment in the United States of America in 2021 as reported by the National Emergency Number Association (NENA). This trend, as it is understood simply by the gradual population increases and technology availability, imposes an incremental amount of resources on the Emergency Response Systems. However, Venhuizen (2025) also states that not only the volume of calls to the ERS is increasing, but also the public´s expectations of the emergency services are as well increasing. Venhuizen (2025) establishes also, that multiple strategies are being considered including technology, staff support, and policy changes to manage the growing demand and improve outcomes.

Our research selected the city of New York, U.S.A., to evaluate the service demand of a police precinct of the 9-1-1 Emergency Response System, and to generate its spatial and temporal probabilistic characterization as an input to a discrete stochastic simulation model to evaluate present and proposed operating strategies to optimize response time by identifying ideal configuration of resources. The New York City 9-1-1 Emergency Response System is composed of five police boroughs or sectors identified as Bronx, Brooklyn, Manhattan, Queens and Staten Island, and seventy-eight police precincts presented in Figure 1 (www.nyc.gov, 2025). This source stablishes that the distribution of police precincts by borough is as follows: Bronx 12 (15.4 %), Brooklyn 23 (29.5 %), Manhattan 22 (28.2 %), Queens 17 (21.8 %), and Staten Island 4 (5.1 %). Similarly, according to the New York City Government, its 9-1-1 Emergency Response System is the nation´s largest emergency communications system, which receives around nine million calls each year.

According to the U.S. Census Bureau (www.census.gov, 2025), the total population of New York City in 2020, was 8,804,190 inhabitants. With this statistic New York City was the largest city in the United States of America by population. The population density by borough in New York City is described as follows as per the

U.S Census Bureau in the year 2020: Bronx (1,472,654; 16.7%), Brooklyn (2,736,074; 31.1%), Manhattan (1,694,251; 19.2%), Queens (2,405,464; 27.3%), and Staten Island (495,747; 5.6%). In terms of population

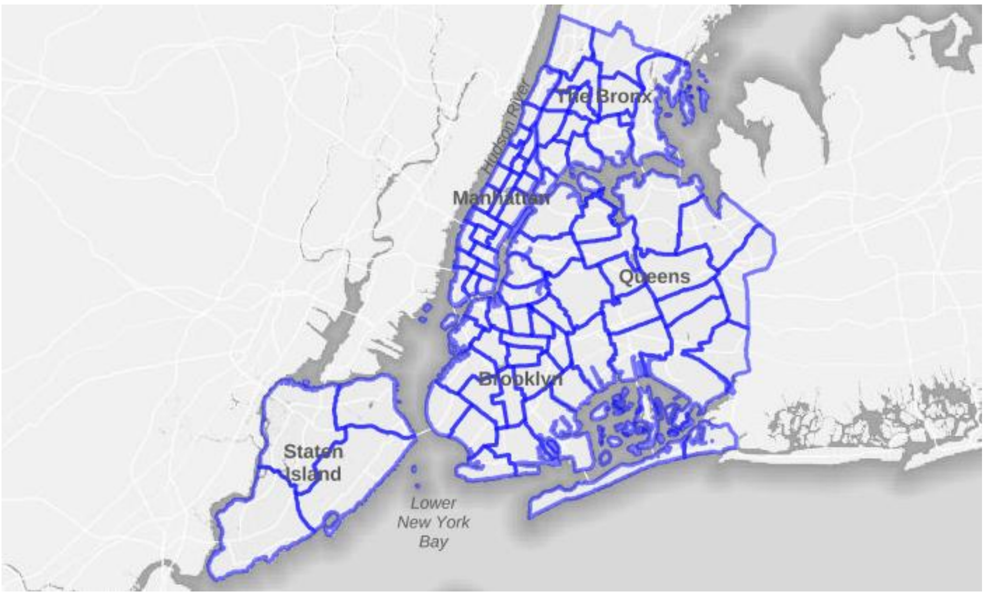

Figure 1: New York City Police Boroughs / Sectors and Precincts (www.nyc.gov, 2025)

density in people/square mile, the U.S. Census for the year 2020 states the following statistics for the five boroughs: Bronx 35,790; Brooklyn 38,640; Manhattan 74,240; Queens 22,179; and Staten Island 8,480. Moreover, the Combined Statistical Area that includes surrounding urbanized areas in New York, New Jersey, Connecticut, and Pennsylvania reached approximately 23.5 to 23.6 million people, according to the 2020 U.S. Census.

Based on the high population density of the Manhattan borough, we evaluated the 9-1-1 Emergency Response System service demand of all precincts in Manhattan, and selected precinct No. 22, which corresponds and it is exclusive for a public park known as Central Park. In Figure 2 a section of the Manhattan borough is presented where Central Park is identified.

Figure 2: Central Section of Manhattan Borough Indicating Precinct 22 Central Park, New York City, NY (www.nyc.gov, 2025)

Central Park is a public park with 843 acres (341.15 hectares) which receives over 42 million visitors annually, generates more than $1 billion in annual economic activity and 5,000 local jobs (www.centralparknyc.org, 2025). According to the New York City government (www.nyc.gov), Central Park is home of seven naturalistic water bodies, fifty eight miles of pedestrian paths , six miles of roads, almost five miles of bridge paths, approximately twenty thousand trees, thirty tennis courts, twenty six ball fields, twenty one playgrounds, two ice skating rings, one zoo, and one swimming pool.

About the perception of public safety of New York City, The Asian American Foundation conducted a safety study in 2023 (TAAF, 2023) interviewing one thousand New York City inhabitants with Asian origin, where it was found that 50% experienced hate because of race, 75% reported fear of being targeted, and more than 70% felt unsafe in different public settings. Similarly, The Siena Research Institute at Siena University, conducted a research study in 2023, finding that: 61% of New Yorkers are either very (21%) or somewhat (40%) concerned that they might be a victim of a crime; 50% worry about their safety in public places; and that New York City residents are more likely to see crime as a serious problem in their community and as a treat to them personally.

The demand characterization of the 9-1-1 Emergency Response Systems in any community, is fundamentally necessary to conduct a resource allocation strategy that could meet an ideal goal of performance parameters such as response time (Martin et al., 2021). The demand characterization is also required as a basic input to mathematical, simulation and optimization models with the objective of identifying improved strategies in the allocation of resources such as personnel conducting patrolling or processing calls for service Brooks et al. (2011).

II. LITERATURE REVIEW

For Emergency Response Systems (ERS), safety, medical, fire or other type, providing the required level of service at the proper time and at the proper place, is the primary goal to fulfill their mission (Zhang and Brown, 2013; Devia and Weber, 2013). Similarly, Leigh et al. (2017), establish that the capacity of deterring crime in areas of high criminal incidence could be achieved by police patrolling. Additionally, deterring and preventing crimes are necessary roles conducted by police patrols to conserve public safety as stated by Zhang and Brown (2012). Moreover, Guo et al. (2010), believe that deployment of police patrols not only collaborates in deterring criminals and reducing crime, but also improves people´s sense of security.

Choudhury and Urena (2020), present the context of overcrowded emergency departments as a global concern. They addressed the nature of stochastic arrival of patients, or demand of service, as the main factor, which is complex to manage. The authors also explain that more than 50% of hospital´s emergency departments have a tendency to operate beyond its normal capacity, and eventually they fail to deliver the expected high quality medical service, causing delays and medical errors during the process of treatment. The authors applied and compared several demand forecasting methods including auto-regressive integrated moving average (ARIMA), Holt-Winters, TBATS, and neural networks to hourly patient arrivals or demand, where the ARIMA method provided the best fit model. The authors concluded that hourly forecasts can be applied to emergency department arrivals as a decision making tool for scheduling and adjusting emergency department arrivals. The concept of scheduling and adjusting is not completely understood for an institutional service unless third party contractors could assist in serving part of the demand with bureaucratic procedures that could be a delay of service and risk because of the delay.

Shahidian et al. (2025), used machine learning techniques to forecast short-term demand in Emergency Medical Services (EMS) and stated that forecast is necessary or fundamental for improving resource allocation, optimizing response times, and enhancing overall system efficiency. The authors also established that immediate allocation of personnel and vehicles is the key to ensure ideal response times and optimizing survival rates. The research utilized nine machine learning algorithms including Gaussian Mixture Models, Naive Bayes, KNearest-Neighbors, Support Vector Machine, Random Forest, Extremely Randomized Trees, Gradient Boosting, Adaptive Boosting, and Bagging for accuracy purposes. According to the authors the study demonstrated that the combination of different methods influences both performance and computational complexity. The models were useful to optimize personnel scheduling, location and relocation of emergency vehicles and as a result improving efficiency and performance of the system.

According to Martin et al. (2021), ambulance demand in an Emergency Medical Service, is known to vary spatially and temporally based on the time of the day and day of the week. As a result, authors established that staffing and redeployment planning require call volume forecasts. The authors utilized a multi-layer perceptron (MLP) artificial neural network model to create predictions of series of daily, hourly, and spatially distributed hourly call volume. Results showed that the MLP models generated better results compared to benchmarked models. Other demand furcating approaches including time of day, day of week and location of Emergency Medical Services are referred by Sariyer et al. (2017), Steins et al. (2019), and Cantwell et al. (2015).

Brooks et al. (2011) characterized demand for service of a safety Emergency Response System based on probability characterizations of incoming calls for service and service rates as inputs to stochastic simulation models to evaluate resource allocation such as the number of police patrols or the number of call answering agents. Other examples of similar approaches to characterize demand for service of Emergency Response Systems are presented by van Buuren et al. (2015), Conley and Grabau (2013), Ibrahim et al. (2012), L'Ecuyer and Olson (2018), Li et al. (2019), Seada and Eltawil (2015), and Steinmann and de Freitas Filho (2013).

Cramer et al. (2011) developed a two-step modeling approach, where first hot spots or areas with high demand for service are identified spatially where main contributor factors or causes are determined, and subsequently they are applied to prediction or forecasting models. The authors established that these evaluations allow policy makers distribute resources fairly and also can assist in developing prevention strategies.

Alternatively, Sariyer et al. (2017) acknowledge the dependency of response time of Emergency Medical Services on effective planning based on historic data behavior. They analyzed demand of these services as a function of time and location trends, and it was descriptively evaluated as a heat-map.

III. METHODOLOGY

Our research methodology was based on a spatial and temporal demand probabilistic characterization. Data analyzed integrated all continuous calls for service registered in the 9-1-1 Emergency Response System from January 1st to February 26th of 2025 including all different call categories and priorities made available by the New York City Police Department. From the five New York City boroughs we selected the Manhattan borough, which is the most populated. However, from the twenty-two precincts integrated in Manhattan, we selected the precinct with the smallest number of calls for service as our first effort evaluating this ERS, which corresponded to precinct number twenty-two dedicated exclusively to the public park named Central Park.

For the temporal demand segmentation, we evaluated day-of-the-week and four time segments of the day equally divided into the segments of 00:00 hrs. to 06:00 hrs., 06:00 hrs. to 12:00 hrs., 12:00 hrs. to 18:00 hrs. and 18:00 hrs. to 24:00 hrs. Subsequently, the probabilistic characterizations were conducted.

IV. RESULTS

The spatial and temporal demand probabilistic characterization corresponding to the Day-of-the-Week category is presented in Table 1. In this table we included the probability distributions that described the data with a 95% Confidence Interval and they were ranked based on best goodness of fit for every day of the week. It is also observed that for four days the best goodness of fit was Johnson Transformation and for two days it was the second best fit. Likewise, the best fit for one day and the second best fit for four days was obtained by the Box-Cox Transformation. A similar analysis by row or by day, allows us to identify that for Sunday the 3rd best fit was given by the 3-Parameter Weibull probability distribution. For Monday, the third best fit was the 2-Parameter Exponential Distribution. In the case of Tuesday, the best fit was the Exponential Distribution. The third best fit for Wednesday was the 3-Parameter Weibull. The Weibull probability distribution was the third best fit for Thursday. Equally, for Friday and Saturday the third best fit was the 3-Parameter Distribution. We believe it was extraordinarily useful that multiple probability distributions fits were obtained for all week days in case they were needed.

Table 1: Demand Probabilistic Characterization by Day-of-the-Week: Ranking

Parameter	Day of the Week	Probability Distributions (95% C.I.)							Demand %
		Box-Cox Transformation	Exponential	2-Parameter Exponential	Gamma	Johnson Transformation	3-Parameter Weibull	Weibull	
Interarrival Time	Sunday	2nd	4th			1st	3rd		14.83
	Monday	2nd	4th	3rd	6th	1st	5th	7th	13.17
	Tuesday	3rd	1st	2nd	5th		4th	6th	14.24
	Wednesday	1st			5th	2nd	3rd	4th	14.07
	Thursday	2nd				1st		3rd	14.19
	Friday	2nd	5th	4th		1st	3rd		15.64
	Saturday	1st				2nd	3rd	4th	13.85
Average		1.85714	3.50000	3.00000	5.66667	1.33333	3.50000	4.80000	
Frequency		7/7	4/7	3/7	3/7	6/7	6/7	5/7	

In this table we can also observe that the percentage service demand distribution was identified to be fairly even along the seven week days. However, Friday has the highest service demand percentage with a 15.64 %, and the second highest was Sunday with 14.83%. Similarly, Monday presented the lowest service demand percentage with 13.17% and the second lowest percent value was 13.85% for Saturday. Even though there is not a substantial service demand percentage difference between the highest value of 15.64% and the lowest value of 13.17%, giving a value of 2.46%, it is a valuable statistic reference to conduct a more accurate resource planning to be more efficient in the service and cost performances.

In the Average row of this table we can observe a probability distribution ranking based on the overall best fits observed in the seven week days, where the lowest value represents a larger likelihood this probability distribution could represent the characterized probability distribution of the data with a greater *p-value*. Similarly, but in a simpler format, the Frequency row in this table represents how many times the particular distribution was statistically useful to describe the behavior of the data divided by the number of days of the week.

In Table 2 the spatial and temporal demand probabilistic characterization corresponding to the Time-of-the-Day category is presented. This table also presents the probability distributions that are able to represent the data behavior with a 95% confidence interval, and they were as well ranked based on best fit for every time segment of the day selected. In contrast with the prior analysis of Day-of-the-Week demand characterization, this time the Johnson and Box-Cox Transformations probability distributions did not present the highest ranks describing the service demands by Time of the Day only for the case of the Time of the Day of 12 hrs. to 18 hrs. where the Box-Cox Transformation had the highest rank. This time, the Exponential probability distribution was ranked first for the Time of the Day segment of 6 hrs. to 12 hrs. and for the Time of the Day segment of 18 hrs. to 24 hrs. The Time of the Day segment of 0 hrs. to 6 hrs. was best probabilistically characterized by the 2-Parameter Exponential distribution, and for the Time of the Day segment of 12 hrs. to 18 hrs. we observed equal *p-values* for the second best goodness of fit between the 2-Parameter Exponential and the Gamma probability distributions.

Table 2: Demand Probabilistic Characterization by Time-of-the-Day: Ranking

Parameter	Time of the Day	Probability Distributions (95% C.I.)							Demand %
		Box-Cox Transformation	Exponential	2-Parameter Exponential	Gamma	Johnson Transformation	3-Parameter Weibull	Weibull	
Interarrival Time	0 Hrs. to 6 Hrs.	2nd		1st		3rd			35.74
	6 Hrs. to 12 Hrs.	4th	1st	3rd	3rd		2nd	3rd	18.63
	12 Hrs. to 18 Hrs.	1st	3rd	2nd	2nd	6th	4th	5th	29.11
	18 Hrs. to 24 Hrs.	3rd	1st	5th	5th	2nd	4th	5th	16.52
Average		2.50000	1.66667	2.75000	3.33333	3.66667	3.33333	4.33333	
Frequency		4/4	3/4	4/4	3/4	3/4	3/4	3/4	

An evaluation of how the service demand is distributed among the four Time of the Day segments, the Time of the Day segment of 0 hrs. to 6 hrs. presents the highest percentage with a value of 35.74% and the Time of the Day segment of 18 hrs. to 24 hrs. has the lowest percentage of demand for service with a value of 16.52%. Intermediate values of service demand percentage, but very close to both percentage extremes are 29.11% and 18.63% for Time of the Day segments 12 hrs. to 18 hrs. and 6 hrs. to 12 hrs. respectively.

The highest average ranks for the demand probabilistic characterization by Time of the Day Ranking, except for the Box-Cox Transformation, were the Exponential and the 2-Parameter Exponential probability distributions with values of 1.66667 and 2.75 respectively. In relationship of the frequency that these probability distributions were statistically useful to characterize the Time of the Day segments data we observe equal values with 4/4 for the Box-Cox Transformation and for the 2-Parameter Exponential probability distributions. It is also observed in this table that there were Frequency equal values of 3/4 with the remaining five probability distributions.

V. CONCLUSIONS

Public safety has been, is, and will be a part of the social environment that requires permanent monitoring, control, and improvement for the benefit of society having a friendly, peaceful and respectful atmosphere where freedom and recognition of others converge in harmony. In order to reach this goal, performance and efficiency of Emergency Response Systems including the 9-1-1 and similar Emergency Response Systems, require to understand the communities´ safety needs in terms of the nature of the demand for service, and every time in a more precise format, to determine and ideally allocate the proper level of resources to satisfy those needs and expectations. We observed in our research that there are multiple methods to predict and model service demand to evaluate present and hypothetical scenarios. In our research, we were able to probabilistically characterize the demand for service data following a spatial and temporal approach based on the literature recommendations and nature of the variability of the 9-1-1 ERS demand for service. We observed that both, the spatial and temporal characterizations of the demand for service data, are necessary to better understand in more detail the variation dynamics of our variable. Furthermore, we estimate that our Time of the Day segment needs to be evaluated by the hour to increase precision, and consequently adjust the decision making process to timely react to the need. It is known that probabilistic characterizations allow other analytical methods including stochastic discrete simulation to further evaluate complex dynamics of individual or integrated processes in a 9-1-1 Emergency Response System as a permanent improvement effort.

REFERENCES

[1]. Brooks, J.P., Edwards, D.J., Sorrel, T.P., Srinivasan, S. and Diehl, R.L. 2011. Simulating Calls for Service for an Urban Police Department. Proceedings of the 2011 Winter Simulation Conference, Phoenix, AZ, USA, December 11, 2011.
[2]. Cantwell, K.,Morgans, A., Smith, K., Livingston, M., Spelman, T., and Dietze, P. 2015. Time of Day and Day of Week Trends in EMS Demand. Prehospital Emergency Care, January-March, 1-7.
[3]. Central Park, New York City 2025. www.centralparknyc.org
[4]. Choudhury, A. and Urena, E. 2020. Addressing Overcrowding and Emergency Department Management: A Time Series Analysis. British Journal of Healthcare Management, 26(1),34–43. https://doi. org/10.12968/bjhc.2019.0067
[5]. Conley, Q. and Grabau, M. 2013. Simulating Modified Hybrid Approach to Resource Assignment in a Shared Billing and Claims Call Center. Proceedings of the 2013 Winter Simulation Conference, Washington, D.C., USA, December 8, 2013.
[6]. Cramer, D., Brown, A.A., and Hu, G. 2011. Predicting 911 Calls Using Spatial Analysis. Conference on Software Engineering Research, Management and Applications, SERA 2011, Baltimore, MD, USA, August 10-12, 15-26.
[7]. Devia, N. and R. Weber, R. 2013. Generating Crime Data Using Agent-Based Simulation. Computers, Environment and Urban Systems, 42, 26-41.
[8]. Guo, S., Fang, X., Tong, H., Rui, L. 2010. Police Cars Deployment and Patrol Models. 2010 International Conference on Computational Intelligence and Software Engineering, Wuhan, China.
[9]. Ibrahim, R., L'Ecuyer, P., Regnard, N. and Shen, H. 2012. On the Modeling and Forecasting of Call Center Arrivals. Proceedings of the 2012. Winter Simulation Conference, Berlin, Germany, December 9, 2012.
[10]. L'Ecuyer, P., Gustavsson, K., and Olsson, L. 2018. Modeling Bursts in the Arrival Process to an Emergency Call Center. Proceedings of the 2018 Winter Simulation Conference. Gothenburg, Sweden, December 2018.
[11]. Leigh, J., Dunnett, S. and Jackson, L. 2017. Predictive Police Patrolling to Target Hotspots and Cover Response Demand. Ann Oper Res, DOI 10.1007/s10479-017-2528-x
[12]. Levy, D. 2023. Crime and Safety in New York Survey. Siena Research Institute at Siena University. Loudonville, NY
[13]. Li, S., Koole, G. and Jouini, O. 2019. A Simple Solution for Optimizing Weekly Agent Scheduling in a Multi-Skill Multi-Channel Contact Center. Proceedings of the 2019 Winter Simulation Conference, National Harbor, MD, U.S.A., December 8, 2019.
[14]. Martin R.J., Mousavi R., and Saydam, C. 2021. Predicting Emergency Medical Service Call Demand: A Modern Spatiotemporal Machine Learning Approach. Operations Research for Health Care, 28, 1-12.
[15]. New York City Government 2025. www.nyc.gov
[16]. Sariyer, G., Ataman, M.G., Akay, S., Sofuoglu, T. and Sofuoglu, Z. 2017. An analysis of Emergency Medical Services Demand: Time of Day, Day of the Week, and Location in the City. Turkish Journal of Emergency Medicine, 17, 42-47.
[17]. Seada, A.A. and Eltawil, A.B. 2015. Modeling and Analysis of Workforce Management Decisions in Modern Call Centers. Proceedings of the 2015 International Conference on Industrial Engineering and operations Management, Dubai, United Arab Emirates (UAE), March 3, 2015.
[18]. Shahidian, N, Abreu, P., Santos, D., and Barbosa-Povoa, A. 2025. Short-term Forecasting of Emergency Medical Services Demand Exploring Machine Learning. Computers & Industrial Engineering, 200, 1-15.
[19]. Steinmann, G. and de Freitas Filho, P.J. 2013. Using Simulation to Evaluate Call Forecasting Algorithms for Inbound Call Center. Proceedings of the 2013 Winter Simulation Conference, Washington, D.C., USA, December 8, 2013.
[20]. Steins, K., Matinrad, N. and Granberg, T.A. 2019. Forecasting the Demand for Emergency Medical Services. Proceedings of the 52nd Hawaii International Conference on System Sciences. January 8-11, 2019.
[21]. The Asian American Foundation 2024. New York City Safety Study: A Report Examining the Safety of Asian Americans in New York City. TAAF
[22]. United States Census Bureau 2020. www.census.gov
[23]. van Buuren, M., Kommer, G.J., van der Mei, R. and Bhulai, S. 2015. A Simulation Model for Emergency Medical Services Call Centers. Proceedings of the 2015 Winter Simulation Conference, Huntington Beach, CA, U.S.A.
[24]. Venhuizen, R. 2025. The Rising Demand for Emergency Services and How Call Centres are Looking to Technology to Help. European Emergency Number Association EENA 112. Brussels, Belgium.
[25]. Zhang, Y. and Brown, D.E. 2012. Police Patrol District Design Using Agent-Based Simulation and GIS. ISI 2012: 2012 IEEE International Conference on Intelligence and Security Informatics: Cyberspace, Border, and Immigration Securities, Washington D.C., U.S.A.
[26]. Zhang, Y. and Brown, D.E. 2013. Police Patrol Districting Method and Simulation Evaluation Using Agent-Based Model & GIS," Security Informatics, 2, 1-13.