SIMULATION-BASED FRAMEWORK TO COMPUTE POPULATION RISK RELATED TO TRAFFIC ACCIDENTS

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ABSTRACT
A new family of indicators for the assessment of the risk of not being properly attended after a traffic accident has been defined. Its name is Dynamic Population Risk (DPR) and it is based on the dynamic behaviour of the traffic system (weather, congestions, population) and not just on the static location of the ambulances at the hub. Its development has been verified and validated using a simulation-based framework. Possible uses for policy development are mentioned.

1. INTRODUCTION

There is an increasing need in health systems to develop and quantify indicators that may be used for policy development. Indicators of efficiency and efficacy should help in compensating the economic investment and the return via improved public health (Ministerio de Sanidad 2010). In other words, there has to be a balance in the staffing of resources assigned to an activity and the level of service that wants to be achieved.

In this case, the system to be simulated is the assistance of victims of traffic accidents by ambulances or special mobile units where the quickness of the reaction is critical (Sánchez-Mangas et al., 2010), especially in rural areas (Muelleman a Mueller, 1996). The response time should obviously be as short as possible since it is well known that "the quicker the rescue, the higher the possibility of the patient recovering". The Golden Hour principle is widely accepted as a requisite for public health, that is, the probability of recovering greatly decreases if a traffic victim is not properly assisted within one hour.

This system of assisting traffic accidents is known as EMS, Emergency Medical System. The system works as follows. The ambulances are located at the base or hub. If an accident occurs, the ambulance is occupied (not available for another call) during a certain time period which covers the following tasks:

1. Preparation of the assistance: before leaving the base, the staff needs to prepare matters.
2. Travelling to location: the ambulance moves towards the location of the accident
3. At the accident site: the staff actuates to assist and pick the injured up
4. Travelling to hospital: the ambulance moves from the site towards a medical centre.
5. At the hospital: the staff actuates to drop the injured off
6. Travelling back towards the base to report and be ready for a new call.

A complete survey of applications of simulation to EMS was published in 2013 (Aboueljinane et al., 2013). It divides the types of decisions into long-term (potential bases location, dimensioning of resources), mid-term (deployment problem, shift scheduling) and short term (resource dispatching, destination hospital selection, redeployment problems). A simulation optimization framework may become necessary to address the corresponding optimization problem (Zhen et al, 2014) in any of the above situations.

For decision making, two types of indicators have been used in the past to quantify the level of service in EMS deployment. (Aboueljinane et al., 2013): time/distance (average response time, coverage within a standard time T, coverage within a time greater than T, round trip time, service time, vehicle utilization rate, # of calls served per vehicle/base, dispatching time, travel time to scene, waiting time, size of queue, loss ratio, overtime, total mileage) and survival cost (survival rate, cost effectiveness).

The most common one is the response time (for example, Aboueljinane, Sahin, Jemai and Marty, 2014), which is usually calculated as the average time that the resources take to arrive to the scene of the accident. This indicator is related to the proportion of time the response time is within the Recommended Safety Time Threshold (Ramirez-Nafarrete, Baykal, Gel and Fowler 2014). This second indicator sometimes is called "Maximal Expected Coverage", the measure that is complementary to the risk (Gendreau, Laport and Semet, 2006).

In terms of survival, or at least potential survival, we can mention the population risk, which is frequently stated as "the percentage of the population that lives outside a given time threshold from the hub of resources" (Ministerio de Sanidad 2010). It represents the percentage of population covered within the given subjective time threshold.

All the indicators are of course related and based on the response time (and hence the adequacy of using simulation as the modelling tool), but the computation of the response time has to rely on historic data and is dynamic in nature, whereas the quantification of the population at risk is based on static population and location data and the response time is just the subjective threshold.

That is the reason why in many places, Spain in particular, mid-term and long-term planning of resources is based on static population risk. There is no need to have real data other than population to establish the number of resources that should be installed at each response hub. For example, in Spain (Ministerio de Sanidad 2010), following international principles, there is a rule-of-thumb that determines that there should be an emergency unit per 50000 habitants.

The objective of this article is to keep on defining new indicators that could be used for policy development in EMS systems. This article proposes a set of survival indicators that combine the individual indicators that have already been mentioned. These new indicators will be classified as dynamic population risk indicators, in the sense that the value of the risk (or coverage) will not be constant over time to overcome the problems of the static risk indicator but it will still be based on the correct quantification of the response time.

Using as the initial measure the static population risk, the new idea is to incorporate dynamic conditions to its calculation. The proposed indicator accounts for unexpected conditions that might increase the response time: weather and traffic conditions or road maintenance. It also takes into account the variation in population and the related accident rate, for example during the weekends or holiday periods. As a result of the time penalties associated to these sources of variation, the availability of resources changes and the potential survival rate may decrease significantly over certain periods of time.

The proposed dynamic population risk indicator (DPR) will be then calculated as the time-weighted average of the static population risk (SPR). As long as there are units outside the hub, the DPR will be different to the SPR: if the units are available, they may be spread out in such a way that DPR is momentarily smaller than the SPR; if they are not available at all, the SPR will be lower than the DPR.

Both the DPR and SPR will depend on the time threshold that wants to be subjectively set. For that reason, there is a value of the indicator for each threshold K. The specific indicators therefore should be referred as DPR (K) and SPR (K), leaving DPR and SPR for the specification of the set or family of indicators.

The development of this new family of indicators, DPR and SPR, is the core of this article. We build a simulation model to verify its robustness and validate its use in a real problem. We first embed their calculation in a MsExcel framework, and finally we show their application in a traditional EMS setting in which the optimum number of ambulances is determined after taking into account dynamic conditions..

2. THE EMS SIMULATION MODEL

The aim is therefore to derive and quantify robust indicators, using a simulation model that can represent the system under study. A researcher must then choose a tool that conveniently fulfils this objective.

In this case, the model is going to be set in MsExcel because it is a perfect tool to implement easy routines that help define, verify and validate any decision making framework with the required level of detail. Then, if the model wants to be implemented for ad-hoc utilization, the model may be updated accordingly with the necessary complexity.

The abstraction process of the EMS starts with the definition of the **map** that represents the region that is going to be analysed with its roads. The map is easily represented with a grid composed of cells (i,j) that cover the whole region. One of those cells holds the base.

The **population** at each cell (i,j) is f_{ij} (absolute frequency), with the relative percentage of the population being defined as:

$$\Psi_{ij} = \frac{f_{ij}}{\sum_i \sum_j f_{ij}}$$

The roads are represented as **travel times** d_{ij}^t, which are the travel times from the current position at the current time from where the ambulance is to the cell (i,j) in the spreadsheet grid. It is calculated by adding time jumps to adjacent cells with the jump being defined as a random variable, ξ. Perfect or static conditions are set when there are no congestions at any road and the weather does not affect the driving behaviours.

This variable is adjusted with a factor δ that accounts for the **time penalties** that may be incurred due to imperfect traffic conditions. δ is a non-negative value that adds to the static times under perfect conditions. It is worth mentioning that the way this matrix of time distances is defined and modelled is based on the underlying assumption that the resources are intelligent and always select the shortest route in terms of the response time.

The **movement** of the ambulances are the key of the model. The base receives a call and then a free ambulance drives towards the location of the accident, assists the injured people, moves then to the hospital and back to the base. It is very important to note that the ambulance that leaves the base is not available to give service to any other accident until reaching the base again. In other words, any ambulance is unavailable during a period of time. In the case of a given region staffed with just one ambulance, the whole population is at risk whenever that lonely ambulance is not at the base. Moreover, only ambulances at the base count since those are the only ones that can immediately react to incoming calls. This reasoning is critical for understanding the system and for the development of the model and calculation of the indicator.

We have opted not to model the movement of the ambulance but instead calculate the availability of the ambulances at regular intervals of time. Indeed, for any instance, we determine if there is at least one ambulance at the base. At each instance that we simulate, we use a binomial distribution ρ to represent the **availability** of the ambulances. If the count of ambulances in the system is c, then ρ = B(c, p), where p is the probability of each ambulance being available, and therefore, the availability of at least one ambulance is:

Availability $\alpha = 1 - P(\rho = 0)$.

The **location** at any instance of the ambulance is modelled with a bi-dimensional random variable (βx, βy).

The execution of the model is performed as follows:

1. Definition of the maps
    a. Population
    b. Time distances
    c. Hub location
2. At each instance:
    a. Location of ambulance within the map
    b. Availability (or not) of ambulance
    c. Recalculation of time distances
    d. Calculation of instantaneous population risk
3. At the end of the simulation
    a. Calculation of SPR and DPR
    b. Drawing of functions

The model is run to cover a total number of instances T (t=0, 1, … ,T).

3. POPULATION RISK INDICATORS

The calculation of the indicators and the drawing of their corresponding functions is therefore the key of article.

Population risk is defined as the percentage of the population that lies outside a given subjective time threshold. We can differentiate between static or perfect conditions with full availability of ambulances and no time penalties, and dynamic conditions. In the first case, the SPR, static population risk indicator, is defined and, in the second case, the DPR, dynamic population risk indicator, is defined.

The population risk depends on the time threshold that is subjectively and a priori established. For generality, we define K thresholds and calculate the population risk, each with a different value k. Therefore, we define two families of indicators, SPR (K) and DPR (K).

Both families are based on the following definition of the coverage of population based on the k^{th} threshold at time t, Π_k^t:

$$\Pi_k^t = \frac{\sum_i \sum_j \phi_{ijk}^t \Psi_{ij}}{ij}$$

where

$$\phi_{ijk}^t = \alpha * \begin{cases} 1, if\ d_{ij}^t \le \Omega_k, \\ 0, if\ d_{ij}^t > \Omega_k \end{cases}$$

is the indicator of coverage of cell (i,j) at time t. If the travel time from the current position at the current time d_{ij}^t is less than the threshold time Ω_k that corresponds to the k^{th} threshold, the instantaneous coverage is calculated to 1, and 0 otherwise. The coverage is further multiplied by the availability of the set of ambulances for the final calculation of the indicator at time t corresponding to the k^{th} threshold.

The static indicator of population risk is then:

$$SPR(k)=1-\Pi^0_k$$

and it is just the sum of population outside the threshold, since $\alpha=1$.

The dynamic population is therefore the average over the total number of samples obtained at regular intervals of time:

$$DPR(k)=1-\Pi_k = \frac{\sum_k \Pi_k^t}{T}$$

4. THE SOFTWARE

In this section, the adequacy of the MsExcel software that has been developed is shown with a simple example. As input, the software asks for several data. Figure 1 shows the population percentage at each of the cells (i,j) of the map which in this case is a matrix of 10x10.

0.5%	1.1%	1.0%	1.7%	1.6%	1.4%	1.6%	2.0%	0.7%	0.5%
0.1%	0.4%	0.7%	0.8%	1.2%	0.9%	1.7%	1.9%	0.4%	0.1%
1.1%	1.3%	0.3%	1.9%	2.1%	0.1%	0.1%	2.0%	0.4%	0.9%
0.3%	0.4%	1.3%	0.9%	1.7%	0.2%	0.0%	0.6%	0.0%	0.1%
0.2%	1.7%	0.2%	1.9%	2.0%	0.8%	0.6%	0.4%	0.8%	1.9%
2.1%	0.3%	0.8%	1.0%	1.4%	1.6%	0.6%	1.5%	1.8%	1.3%
1.9%	1.0%	0.8%	1.6%	0.6%	1.4%	0.8%	1.1%	0.1%	0.3%
2.1%	0.3%	1.0%	0.3%	0.4%	1.6%	2.0%	1.5%	1.1%	1.3%
0.8%	1.0%	1.0%	1.3%	1.3%	1.2%	1.4%	1.4%	0.8%	1.2%
0.5%	0.8%	1.3%	1.3%	1.5%	1.2%	0.5%	0.6%	0.3%	0.4%

Figure 1: Software input: population

The colour coding is such that the darkness increases with the population. Cell (5,5) is where the base is located, cell that is indicated by a dark border.

Figure 2 includes the time distances from the base in static conditions.

9.7	8.2	6.3	4.5	4.5	4.9	6.5	8.2	8.6	9.0
6.1	4.4	3.5	3.4	3.4	5.3	6.0	7.6	8.5	9.3
8.4	6.8	4.9	3.4	2.2	3.1	3.6	5.1	6.2	6.4
5.1	3.9	3.3	2.9	1.1	1.5	3.5	5.3	5.7	7.6
5.7	4.5	2.5	1.2	0.0	2.0	2.9	3.1	4.0	5.0
6.0	5.4	4.0	3.0	1.2	2.4	2.6	4.2	4.8	6.5
7.8	7.0	5.0	3.2	1.9	2.1	2.8	4.0	4.2	4.2
8.3	6.8	5.5	3.8	2.8	4.3	4.9	6.4	7.9	8.2
8.4	6.9	6.9	5.0	3.4	3.8	5.0	5.8	7.6	8.5
9.1	7.3	7.3	6.6	5.0	7.0	9.0	10.2	10.7	12.4

Figure 2: Software input: time distances

The rest of the necessary input values are:

- The number of ambulances, c=1
- Availability of each ambulance, p=0.9
- Time penalty = 2

As output, the software shows a calculation of both the SPR(K) and the DPR(K) for easy comparison. Graphically, the calculations are shown as a function of different time thresholds K, which could be also specified a priori. In this case, K = 0, 2, 4, …, 18, 20.

Figure 3 shows that the static risk is 0, SPR(12) = 0, if the time threshold is 12 minutes or more. In other words, all the population is within 12 minutes of the hub. However, 4% is at risk if the threshold is set to 10 minutes, SPR(10) = 4%.

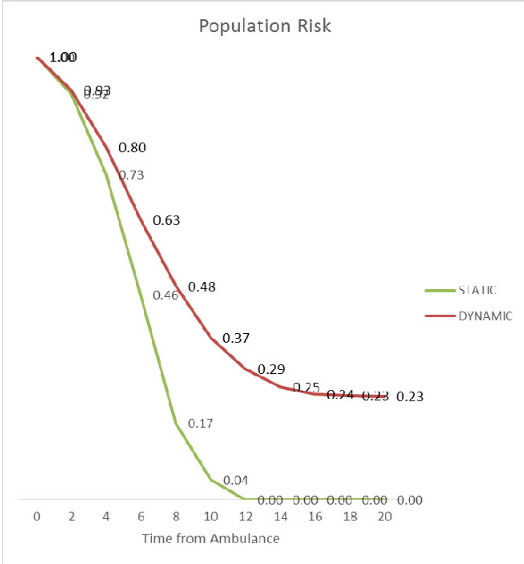

Figure 3: Software output: Static vs Dynamic Population Risk

If penalties are included in the calculation of the new dynamic indicator, then 23% of the population is on average outside the 20 minute mark and 29% outside 12 minutes, DPR (20)=23% and DPR (12) = 29%.

The time distances from the dynamic location of the units are also shown over the region that is being analysed using a heat map. Figure 4 depicts the situation under static conditions, or time distances from the hub. The map is arranged in cell format for easiness of representation. Almost all of the population is within 10 minutes, expect for 4 cells at the right corners.

8	8	8	8	6	8	10	12	12	12
8	6	6	4	4	6	8	8	10	10
8	8	6	4	4	4	6	6	8	8
8	6	6	4	2	4	4	4	6	6
4	2	2	2	2	2	4	6	6	8
6	4	4	2	2	4	6	6	8	10
8	6	6	4	4	4	4	6	6	8
10	8	8	6	6	6	6	8	8	10
10	8	8	6	6	6	6	8	10	10
10	10	8	8	8	8	8	10	10	12

Figure 4: Software output: Time distances from hub under static conditions

Figure 5 shows dynamic conditions, indicating the average time distance from the location of the closest unit. In the average dynamic map, there is only one cell in the grid which is covered on average within 6 minutes. The corners are on average at a distance of 14 minutes.

14	12	12	10	10	10	12	12	12	14
12	12	10	10	10	10	10	12	12	14
12	10	8	8	8	10	10	10	12	14
10	10	8	8	6	8	10	10	10	12
10	10	8	8	8	8	10	10	10	10
10	10	8	8	8	8	8	8	10	10
10	10	8	8	8	10	8	10	10	12
12	10	10	10	10	10	10	10	12	14
12	12	10	10	10	10	10	12	12	12
14	12	12	10	10	12	12	12	12	14

Figure 5: Software output: Time distances from random location of ambulances

5. EMS SIMULATION OPTIMIZATION FRAMEWORK

If using this software for a real application in which decisions might be taken by varying the values of the input parameters, a simulation optimization framework may become necessary to address the corresponding optimization problem (Zhen et al, 2014). Therefore, an additional output of our work is a simulation-optimization framework to test the new family of indicators within real applications.

5.1. Definition

The decision problems faced in industry, commerce, public administration, and the society in general keep growing in size and complexity. For the study of these decision problems, it is necessary to develop efficient methodologies and tools, so it is possible to try and evaluate many different alternatives and to take the correct decision in a reasonable amount of time. One of the main example problems of this complex type that a manager faces is that of deployment of the EMS (the real system in our case, Fig. 6).

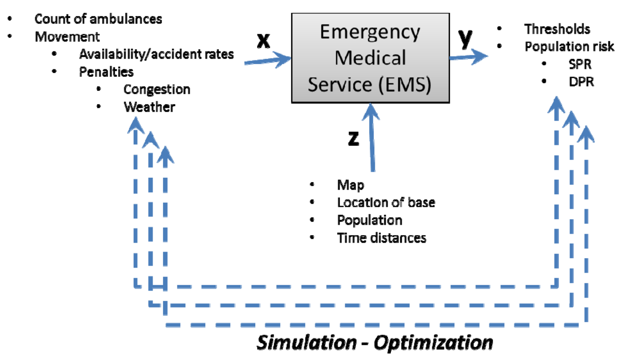

Fig. 6. Description of the EMS optimization framework.

The first source of complexity is the number of decision variables (or control parameters or input variables, x), or to be more precise, the number of different alternatives that a manager faces in the process. The total number (n) is the multiplication of the feasible values for each of the variables ($n_c * n_a * n_p$):

- Count of ambulances (c): from a minimum to a maximum value for a total of n_c.
- Accident rate (a): at least, base and peak for a total of n_a.
- Penalties (p): at least with no penalties and with a penalty, for a total of n_p.

The number of different criteria (or output variables or objectives, y) also adds to the complexity of the analysis, mainly because usually they independently work in opposite directions. At least a measure of cost and another of level of service are usually included in any study. Then, if the level of resources is increased to improve the level of service, the cost criterion will pay the price, and vice versa. In this case we will concentrate just of the new family of survival indicators, SPR(K) and DPR(K).

The third source of increased complexity is the volume of available data (z). Not only that, the data is available at a much quicker pace that the manager can handle. The improvement in online information systems has called for shorter decision making periods.

Fortunately, some of the complexity of these studies has been diminished by the improvement not only of the solution techniques but also of the information technology. These improvements call these days for the experimentation with models instead of with the real system, models which are embedded in the information systems of the company. Among these models, simulation has grown as one of the most reliable abstraction tools due to its very good compromise between the level of detail in the representation of the real system and the execution time of the model, which calls for an appropriate experimentation and decision making.

On that regard, computer simulation has received a lot of attention in the last decades to model complex systems under uncertainty, in many areas but specifically in traffic (Ingolfsson et al., 2003). Its success does not rely mainly upon improvements in theoretical aspects but in hardware and software, especially in terms of efficiency, allowing for the study of even more complex, uncertain systems within the allotted analysis time. The use of simulation opens the possibilities of further research into decision processes which are specific to this tool.

To study a given system via simulation, the first step is to formulate the problem and to develop the model that represents the system. The model will simultaneously include the mathematical and logical relations between the elements of the system as well as random variables for the necessary data (for example, travel times or location of bases). The data must be easily read into the model. The next step is to build credibility. The model is executed repetitively to confirm that it has sound foundations. For each run, a different set of values is taken from each random variable to verify that the model works correctly. At the same time, a different combination of values for the decision variables is used so that the objectives are not only calculated but compared numerically.

Different alternatives are tried, the objectives quantified and the best alternative is chosen for implementation. This step is usually carried out using a user-friendly interface that automatically tries many different alternatives, performing also the comparison and the selection step for the manager. During implementation, this interface is also used to see the results for the selected alternative.

Therefore, in this final step of the analysis process, the desire is to obtain information about the values of the input or decision variables that improve the values obtained for the objective function. In the EMS example, the objective may be to calculate the optimum number of EMS units according to reasonable values of the new family of indicators.

5.2. Experimenter

The developed software also includes an experimenter that will help with the trial of different possibilities automatically (by pressing the button "EXECUTE") (Figure 7) by trying each and every combination of feasible values for the different variables. We run a test case with the following settings:

- Count of ambulances, c={1,2,3,4,5}
- Availability, α={0, 0.1, 0.2, …, 0.9, 1}
- Time penalty, δ ={0, 0.5, 1, …, 3.5, 4}

The total count of scenarios is calculated as the product of the feasible levels (Fig. 4: 5*11*9=495 scenarios). 100 runs are executed of each scenario, for a total of 49500 runs.

A pivot table as well as a pivot figure summarize the result for both SPR(10), SPR(20), DPR(10) and DPR(20) for each variable independently.

6. AN APPLICATION: THE PROBLEM OF DEPLOYMENT

The problem addressed in this article as a test-bench is that of deployment, or to correctly staff the EMS with ambulances or emergency units. More specifically, the number of ambulances has to be enough to guarantee that those involved in an accident receive attention quickly, but not so many so as to incur in excessive costs.

Deployment has been addressed in the literature in recent years due to the importance of designing correctly the rescue service and of staffing properly the resources. For example, a simulation tool is used to measure the "time to rescue" in the Val-de-Marne department in France (Aboueljinane et. al, 2014). The time is translated into coverage, defined as the percentage of calls that are attended within a 20 minutes threshold. This service indicator in decision making is then used to propose the level of resources as well as the location of the base.

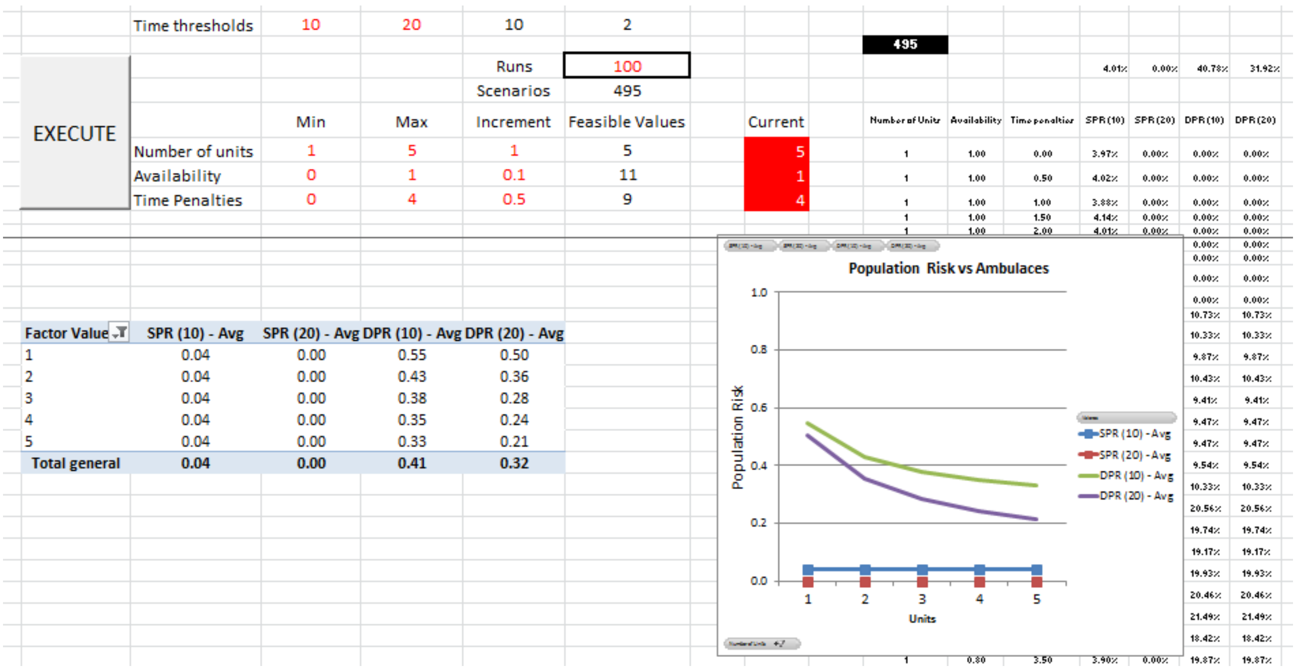

Figure 7: Experimenter screen

The experimenter is run using the setting included in section 5.2., varying the number of ambulances between 1 and 5. Figure 8 depicts the results as a function of the number of ambulances. The x-axis represents the ambulances and the y-axis the risk. The whole population is within 20 minutes (SPR (20)=0) and 96% within 10 minutes (SPR (10)=0.04).

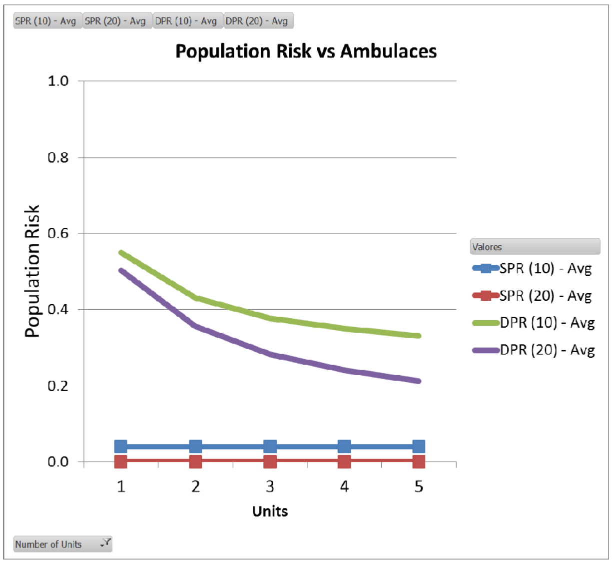

Figure 8: Experimenter output for the count of ambulances

The dynamic values are obviously much worse, with population risk as high as 20% even with 5 ambulances and a 20-minute threshold. With only 1 ambulance, the risk is above 50%.

The analysis shows that most probably the appropriate number of rescue units should be 3. The risk functions start to flatten down at 25%.

We have also performed a sensitivity analysis on each factor. The availability of at least one ambulance greatly influences the risk (Figure 9). The EMS requires that the accident rate is such that the availability is at least 0.6 so that the risk is controlled below 20%.

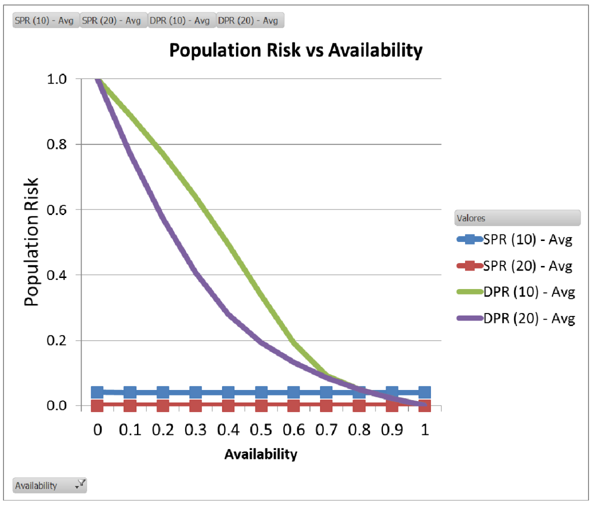

Figure 9: Experimenter output for the Availability of ambulances

Finally, it looks like size of the time penalty does not have an effect on the risk (Figure 10). The graphs are flat throughout the whole range of penalty values.

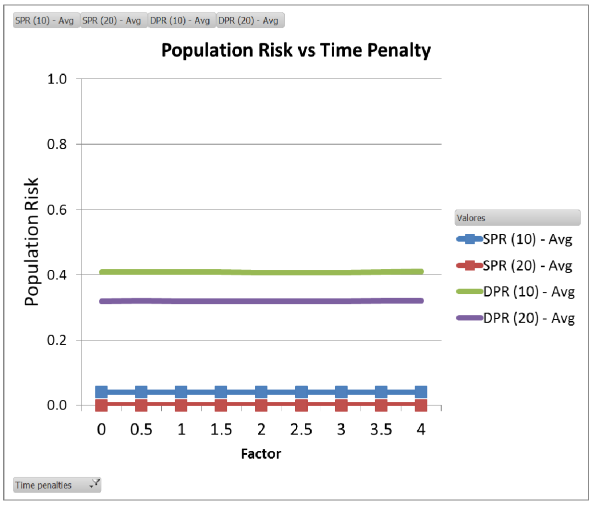

Figure 10: Experimenter output for time penalties

7. DISCUSSION

We have designed a simulation-optimization framework to represent the EMS and validate our proposal of a new family of indicator to measure the potential risk of the population.

A simplistic model in MsExcel has allowed for the proper definition and testing of the indicators. Most of time, the model should be a means to an end, so the level of detail is critical while developing a credible, reliable and usable tool for decision making. In this setting, it was not necessary to model the movement of the ambulances in detail in order to develop robust indicators of survival in dynamic traffic conditions.

It is our aim to further develop and apply the framework to real situations. On that regard, we are developing a model in C++ to fully represent the movement of the ambulances so the analysis of real EMSs over a given region can be carried out. It will include travelling times both under normal conditions or under changing weather (fog (Mueller and Trick, 2012) or snow (Kunkel and McLay, 2013)) and traffic conditions.

Then, the framework could have more uses within decision simulation support systems (DSSS) related toemergency situations.

Online dynamic assignment of ambulances to accidents and the redeployment of ambulances (Maleki and Majlesinasab, 2014) or the analysis of the so-called diversion problem (allocation of ambulances to hospitals) (Lin et al., 2015) are types of situations that could be addresses via modifications of the current framework.

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