Emergency Ambulance Deployment in Val-de-Marne Department
A Simulation-based Iterative Approach

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Abstract: The French Emergency Medical services, known as SAMU, are public safety systems responsible for the coordination of pre-hospital care under emergency conditions throughout a given geographic region. The goal of such systems is to respond timely and adequately to population calls by providing first aid services and transferring patients, when needed, to the appropriate care facility. In this paper, we propose a multi-period version of the Maximum Expected Covering Location Problem applied to the case of the SAMU 94 responsible for the Val-de-Marne department (France). The assumption that the busy fractions are identical for all demand points is relaxed by adopting an iterative method to compute a priori estimates of these parameters in the model using an ARENA discrete-event simulation model of the SAMU 94. The solutions obtained from the mathematical model are then assessed by simulation regarding the time required to respond to an emergency call by getting to the patient location, known as response time, which is a critical aspect for the SAMU providers. Experimental results showed that the proposed method increased average percentage of most serious calls responded to within the target time of 15 minutes up to 15% compared to the current system performance.

1 INTRODUCTION

Pre-hospital care refers to first aid services provided to patients under emergency conditions from incident reporting, i.e. an incoming call via an emergency number, to definitive care, involving facilities, equipment and personnel trained to provide phone support, stabilization of patient's condition and transportation to an appropriate care facility. In France, the emergency medical service (EMS) system responsible for providing such services is known as the SAMU system which stands for the French acronym of "Urgent Medical Aid Service". It was established in 1968 to coordinate the activity of the "Mobile Emergency and Resuscitation Services", named SMUR teams, which are mobile response vehicles staffed with qualified personnel and operated by public hospitals. The SAMU rescue process is organized according to two types of operations: *Central operations*, performed in a reception and regulation (R&R) centre, that aim to provide phone support and to decide the proper response for each call received depending on its degree of urgency, and *External operations* that aim at sending one or several SMUR team(s) to perform pre-hospital care for two types of rescues: primary rescues which are related to major injuries or illnesses that require immediate medical assistance outside of the hospital (e.g., cardiac arrest, trauma, childbirth...) and secondary rescues which correspond to the transport of patients from one hospital to another, in case medical staff assistance is needed during the transfer. Between rescues, SMUR teams are placed in fixed positions, called bases that are currently located in public hospitals. The SAMU system is managed at a department level (i.e. a French administrative division corresponding to a median area of about 6 000 km²) in order to provide a 24-hour service for each department.

One of the critical performance measures for the SAMU providers, particularly in case of life-threatening emergencies, is the response time, defined as the period between the receipt of a call and the first arrival of a SMUR team at the scene of incident. Several authors observed the association between low response time and high survival rate of patients (Cummins, 1989); (Vukmir, 2006); (White et al., 1996). Hence, having a high coverage, i.e.

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percentage of calls responded to within a specific bound, is a commonly expressed objective for the SAMU managers. Another concern of the SAMU system is to reduce the significant expense involved in its management, including capital (acquisition of physical plant, vehicles, equipment, communication etc.) and operating costs (salaries, training, maintenance, etc.).

Both timeliness and economical goals can be achieved through the optimization of several design and operation decisions that are highly interrelated and may be classified according to the following classical operations management hierarchical decision framework:

- Long term decisions such as setting service level objectives, identifying the location and the capacity of the fixed facilities needed to perform central operations as well as a set of potential locations for SMUR teams bases throughout the covered department ;
- Mid-term decisions: such as allocating SMUR teams to bases selected among those specified in the long term level so as to ensure a brief delay in reaching every call location (known as the deployment problem) and scheduling shifts for human resources;
- Short-term decisions: such as determining the rules of assigning one or several available SMUR teams to a call (known as the dispatching problem), allocating SMUR teams to bases in order to improve coverage of future requests under temporal and geographical fluctuations of demand pattern (known as Multi-period redeployment) or depending on the number of SMUR teams available following the allocation or release of a team (known as dynamic redeployment);

In literature, several operations research tools have been used to improve the performance of EMS systems through the optimization of these decisions. The current research addresses the multi-period redeployment problem as an improvement opportunity to develop service coverage performances of the SAMU system in the Val-de-Marne department (south east of the city of Paris), named SAMU-94, under limited number of resources. In this regard, we propose an iterative method that combines the use of a probabilistic mathematical covering model to find the optimal locations of the existing SMUR teams throughout the service area for different periods of time, with the use of a discrete-event simulation model of the system, implemented in ARENA software, in order to evaluate the busy fraction parameter (i.e. the probability for a SMUR team of being unavailable to answer a call) required to solve the analytical model as well as to analyze the performance of the system under the redeployment solutions obtained from this model.

The paper is organized as follows: Section 2 briefly describes the literature review on the use of simulation and mathematical models in EMS management. Section 3 describes the detailed methodology used to build the SAMU-94 simulation model, including the process description, the data collection and the validation of the initial configuration of the model. In Section 4, we present the probabilistic covering model and the iterative approach to estimate the busy fraction parameters. Experimental results are described in Section 5. Finally, Section 6 provides conclusions and presents some directions for future research.

2 LITERATURE REVIEW

In literature, mathematical programming is one of the most studied analytical tools used to improve the performance of EMS systems. Mathematical models have been focused mainly on the decision of assigning rescue teams to bases, in both mid-term (deployment problem) and short term (dynamic and multi-period redeployment) settings. Research on this area has been largely derived from two early deterministic models: The Location Set Covering Problem (LSCP), developed by (Toregas et al., 1971), which aims to minimize the number of rescue teams needed to cover all demand points within a target distance (time), and the Maximal Covering Location Problem (MCLP), proposed by (Church and ReVelle, 1974), which maximizes the population coverage within a target distance (time) using a limited number of available rescue teams. These two basic models overestimate coverage since they ignore some stochastic aspects such as the fact that dispatched rescue teams become unavailable to answer incoming calls. Two extensions have therefore been proposed to provide more robust location solutions. One extension is to consider the deterministic covering problem with an extra coverage, i.e. to maximize the demand covered by more than one rescue team to serve simultaneous or close calls (Daskin and Stern, 1981); (Eaton et al., 1986); (Gendreau et al., 1997); (Hogan and ReVelle, 1986). The other extension consists of probabilistic models that explicitly consider rescue teams' potential unavailability through the use of the busy fraction parameter. These models include the expected covering location models that aim to maximize the expected demand covered, expressed as a function of the busy fraction, such as the MEXCLP (Maximum Expected Covering Location Problem) of (Daskin, 1983) and its applications and extensions (Bianchi and Church, 1988); (Fujiwara et al., 1987); (Goldberg et al., 1990b); (Repede and Bernardo, 1994). Another probabilistic approach consists of the formulation of the deployment problem as a chance constrained stochastic program that incorporates the unavailability aspect as a linear constraint. This constraint uses the busy fraction to compute a lower bound of rescue teams required to achieve a given reliability level α in serving each demand point (ReVelle and Hogan, 1989); (ReVelle and Marianov, 1991). These models typically assumed that all rescue teams operate independently and have the same busy fraction q, estimated by dividing their total workload by their total operating time, regardless of their location and the overall number of teams servicing each demand point. These assumptions are obviously not valid since the team's location affect the travel time to the call location and therefore the total workload. Moreover, the larger is the fleet size covering an area, the lower is the probability of a team to be busy. The difficulty of estimating the busy fraction parameters which are related to the location of teams is that this location is precisely the solution obtained from the optimization model, while the latter requires these parameters to be known *a priori* in order to provide a solution. Yet, for a specific deployment plan, several authors used descriptive tools such as hypercube queuing models (Batta et al., 1989); (Larson, 1974); (Marianov and Revelle, 1994) and computer simulation (Ingolfsson et al., 2003); (Su and Shih, 2003) to pre-compute more accurate estimations of these parameters.

Apart from the mathematical programming approach mentioned above, computer simulation has been one of the most widely used technique to identify potential areas of improvement in EMS systems without considering simplifying assumptions needed to solve analytical models. Indeed, the main advantage of simulation in dealing with such problems is its ability to describe the system in a high degree of detail, to estimate several performance measure predictions and to handle several sources of uncertainty such as time-dependent arrival rate and location of calls, available capacity and location of rescue teams, duration of service time depending upon the medical needs of patient and bed availability of definitive care facilities. Research that is available in this area may be classified into two groups:

- Simulation models used to estimate the impact of several scenarios (i.e. changes applied to simulation model assumptions, algorithms and/or data) on some selected performance outputs.
- Simulation models primarily developed to assess the performance of solutions that are obtained from analytical models in a more realistic framework

The scenarios considered in the first group are typically related to the design and operation decisions described in Section 1. The most explored long term decisions related scenarios consist of adding more rescue teams or new potential bases. These two scenarios are usually explored concurrently to be compared in terms of cost and quality performance (Gunes and Szechtman, 2005); (Inakawa et al., 2010); (Ingolfsson et al., 2003); (Savas, 1969). Another scenario tested consists of assessing the effect of an increase in demand following for instance the growth of population or the enlargement of the scope of EMS system (Lubicz and Mielczarek, 1987); (Silva and Pinto, 2010). As for the mid-term decisions related scenarios considered in EMS literature, they mainly focused on the deployment problem which is usually evaluated jointly with the long term scenario of considering new potential bases in order to assess the relocation of rescue teams close to high demand areas (Fitzsimmons, 1971); (Goldberg et al., 1990a); (Henderson and Mason, 2005). Finally, the available literature in the area of short term decisions related scenarios addresses changes either in dispatching rules (Koch and Weigl, 2003); (Su and Shih, 2003), destination hospital assignment policies (Wang et al., 2012); (Wears and Winton, 1993), multi-period redeployment strategy (Peleg and Pliskin, 2004), dynamic redeployment strategy (Ingolfsson et al., 200)3; (van Buuren et al., 2012) and travel speeds of emergency vehicles (Aringhieri et al., 2007); (Liu and Lee, 1988).

The second use of simulation with analytical models has also largely been adopted in EMS literature. Typically, this combined approach involves using a location or a relocation mathematical programming model first, in order to determine sets of optimal locations, given the set of feasible locations, and then using simulation to estimate system performance under the resulting deployment/redeployment plan. In the literature, the mathematical programming models proposed in such approach include deterministic models with simple coverage (Berlin and Liebman, 1974); (Uyeno and Seeberg, 1984), deterministic models with multiple coverage (Aringhieri et al., 2007) and probabilistic models (Fujiwara et al., 1987); (Harewood, 2002); (Repede and Bernardo, 1994).

In this paper, we propose to apply this combined approach to the EMS of Val-de-Marne department (SAMU-94) in order to improve the response time performance of the system. For this purpose, we proposed a multi-period extension of the MEXCLP (Daskin, 1983) that integrates some specificities related to call priorities as well as site-specific busy fraction parameters depending on the number of rescue teams serving each site and the time period. Busy fraction parameters are estimated using an iterative method, derived from (Lee et al., 2012), that uses a discrete event simulation model of the system in each step to update the busy fraction estimates based on the location solution obtained from the optimization model in the previous step. The updated estimates are subsequently used in the optimization model to provide updated location solution. This iterative process continues until the location solution converges.

3 SIMULATION MODEL

3.1 Problem Description

This simulation study used the discrete event simulation software ARENA (Rockwell Automation, Milwaukee, Wisconsin) to build a model that takes the SAMU 94 system as its subject and seeks to compute credible estimates of busy fraction and response time performance measures. A first step in the methodology of performing the study consists of conducting meetings and interviews with the SAMU-94 experts in order to clarify the input parameters and the detailed process associated with the system which involves various types of human and material resources which are:

- Operators: Located in the R&R centre, they are responsible for answering calls, identifying inappropriate calls, creating a medical file and recording the basic information relative to the nature of the request;
- Regulators: Located in the R&R centre, they are responsible for performing medical evaluation of calls and deciding on the best solution for the patient. There are two types of regulators: emergency physicians, named “SAMU regulators”, responsible for high priority calls, and general practitioners, named “PDS regulators”, responsible for remaining calls;
- SMUR teams: consisting of a vehicle staffed by one physician, one driver, one nurse and/or one emergency medical technician. There are two types of vehicles: well-equipped ambulances, called Mobile Intensive Care Units (MICU), and medical vehicles (MV) which are usually dispatched for the most serious calls because they are faster than MICU but do not allow for the transport of the patient. The SMUR teams are currently located in two bases: one central base located at Henri-Mondor Hospital (HM) and one auxiliary base located in Villeneuve-Saint-Georges Hospital (VSG);
- Rescue physician: an emergency physician who can either operate as a SAMU regulator or as a physician in a SMUR team.

The SAMU-94 central operations are triggered when a call is first received by an operator in the R&R centre which is located in the central base HM. Depending on the potential severity of the call, the operator chooses to redirect the call to a SAMU or a PDS regulator. The regulator performs a medical evaluation which can lead to several possible decisions: In the case of primary rescues, if the call is not urgent, a simple advice is given to the patient or a private ambulance is dispatched. If the request is a relative emergency, the call is transferred to a basic life support or BLS system such as fire-fighters or red-cross. However, if the incident turns out to be more urgent than the first evaluation, the BLS calls back an operator to ask for the dispatch of a SMUR team. These calls are referred to as primary rescues with sending BLS as first effector. Otherwise, if the request is an absolute emergency, a SMUR team is immediately dispatched to the call location, which is known as primary rescues with sending SMUR team as first effector.

In the case of a secondary call, an appointment is taken with the origin hospital in order to send a SMUR team when more than one team is available in the central station.

Once the regulator decides to send a SMUR team, he evaluates the availability and the geographical location of the fleet and notifies the closest available unit. This is the beginning of external operations. The interval between the arrival of the call until a SMUR team is notified is referred to as the *dispatching time*. The selected rescue team prepares the rescue by gathering any necessary equipment that may not be available on the vehicle, inquiring information concerning the incident and rushing to the vehicle. The interval between the time the SMUR team receives the notification to the time it leaves for rescue is called *preparation time*. Note that this step is only performed if the SMUR team is located at a base when notified of a call. The SMUR team then leaves for rescue. The *travel time* is the time elapsed from the initial movement of the vehicle until the arrival at the scene.

The SMUR team spends some time to stabilize the patient. If more advanced care is deemed necessary, the SAMU regulator determines the appropriate destination hospital and communicates this decision to the SMUR team. The choice of a primary rescue' destination hospital may depend on several factors such as the proximity of hospital, its available capacity and appropriate facilities for the patient (specialists, particular equipment...) or patient choice. The SMUR team therefore prepares the patient for transportation and leaves the scene. The interval between the time the rescue team arrives at the scene and the time it leaves is usually called *on-site time*. Before the transport to the destination hospital, the patient may need a diagnostic or therapeutic radiography (DTR) such as MRI, X-ray (if the destination hospital does not have the appropriate equipment or have long waiting times). In this case, the SMUR team takes the patient to the medical service where the DTR is performed. The time interval between the SMUR team arrives at the DTR medical service and the time it leaves is called *diagnostic or therapeutic radiography time*. After arriving at the destination hospital, the rescue team transfers the patient to the hospital staff and spends some time completing paperwork. The time needed to perform these tasks is called *drop-off time*. Finally, the SMUR team becomes available and can travel for another rescue or return to the base to which it is assigned to wait for the next mission.

3.2 Data Collection and Analysis

The rescue records of the SAMU 94 were collected for a period of 15 months of operations. This database, hereafter referred to as "regulation database", included for each call the following data: (1) The time and date of each call; (2) The origin of the call; (3) The type of call (primary/secondary); (4) The first effector if primary call (SMUR team or BLS); (5) The priorities assigned to the call, by the regulator and by the SMUR team once at call location. Priority 1 is assigned to life-threatening emergencies (e.g. cardiac arrests, serious trauma, etc.) and priority 2 is assigned otherwise; (6) The response team that performs the rescue; (7) The destination hospital; (8) The timing of the different steps in the rescue process: SMUR team notified, SMUR team leaves for the rescue, SMUR team arrives at the scene, SMUR team leaves the scene, SMUR team arrives at the diagnostic or therapeutic radiography service, SMUR team leaves the diagnostic or therapeutic radiography service, SMUR team arrives at the hospital, SMUR team finishes the rescue.

This database was first analysed to exclude any record (call) containing missing data or errors in measures. Only 2.1% of the logged calls were therefore removed, resulting in a database of 9836 calls.

From the verified records, we extracted the empirical distributions of the following:

- The arrival rate of calls per hour of the day, day of the week and type of call (primary/secondary);
- The priority of each type of call: These priorities are used in the developed simulation model to establish a hierarchy in responding to simultaneous calls or calls waiting for the dispatch of a SMUR team;
- The first effector (SMUR team or BLS) for primary calls;
- The location of calls and hospitals: In order to accurately model this geographical distribution, we aggregated the network road nodes based on their proximity in a zone structure corresponding to basic units of approximately 2000 residents, developed by the French National Institute for Statistics and Economic Studies (INSEE) and known as "IRIS" for the French acronym of "aggregated units for statistical information". The Val-de Marne department is composed of 527 IRIS. This division is a reasonable computational trade-off that aggregate the large amount of calls into small areas without having a significant travel time within a given area;
- The processing times per type and priority of calls: These times include the dispatching time, the preparation time, the on-site time, the diagnostic or therapeutic radiography time and the drop-off time for primary rescues. As for secondary rescues, they are considered as low priority calls which aim to provide transport of patient when possible without timeliness constraints. Therefore they were implemented in the model as an aggregated service time so as to properly size the utilization rate of resources ;

The historical data were first fitted to theoretical distributions, using Kolmogorov-Smirnov and Chi-Square goodness-of-fit tests, which provided low p-values (less than 0.05). Therefore, we chose to use the empirical distributions that allow to better capture the characteristics of the data (Kelton et al., 2008).

Unlike processing times, there are no empirical travel times' data available for currently unexplored road networks due to different deployment strategies. Hence, in cooperation with the National Geographic Institute (IGN), we used a shortest path algorithm to pre-compute travel times for every possible origin, destination, time period and priority of call. The origins and destinations correspond to the 527 IRIS of the service area that include all demand points, bases and hospitals. The time periods represent the degree of traffic load at various times of the day according to six shifts that distinguish between weekdays (6:00-10:00, 10:00-15:00, 15:00-21:00 and 21:00-6:00) and weekends (12:00-21:00 and 21:00-12:00). Based on the GPS traces database of the SAMU-94 vehicles, an average travel time per time period was assigned to each section of the road network of the Val-de-Marne department according to its typology (motorway, main road, minor road, local street). For any given combination of origin IRIS, destination IRIS and time period, a sample of 10 pairs of exact addresses were randomly chosen within the two IRIS. For each pair, travel time was computed by summing up the average travel times associated with the sections that form the shortest path between the two addresses. The average of the 10 pairs' travel times provided a good approximation of the combination travel time compared to the common assumption of computing travel times between the centres of the zones. Finally, as SMUR teams are allowed to travel at all possible speed when responding to primary calls of priority 1, related travel times were weighted by a multiplicative factor estimated at 0.937 to decrease them compared to standard travel times.

3.3 Simulation Model Implementation and Validation

The previously described SAMU-94 rescue process and data were summarized in a computerized model implemented using ARENA. The outcome variables of the model included the response time of each priority/effector of primary calls and the utilization rates of each SMUR team for each time period/priority. Different random number seeds were used to replicate the model 20 times. Each replication length corresponds to 15 months of operations and 1 day as a warm up period.

We performed a historical data validation by comparing the system's empirical data to the corresponding simulation-derived distribution. An example of response time measure validation for primary rescues, shown in Figure 1, indicates that model's outputs are quite close to the observed distributions as the differences do not exceed 5.7%.

4 OPTIMISATION MODEL

In order to optimally locate SMUR teams close to primary demand so as to improve the corresponding response time performance, we propose the use of a probabilistic multi-period model that seeks to maximize the expected primary demand covered using a limited number of SMUR teams. The model, which is derived from the Maximum Expected Covering Location Problem (MEXCLP) of (Daskin, 1983), is as follows:

$$Max \sum_{i\in V}\sum_{p\in P}\sum_{t\in T}\sum_{k=1}^{N_t} \alpha_p d_{itp}(1-q_{ikpt})q_{ikpt}{}^{k-1}y_{ikpt} \qquad (1)$$

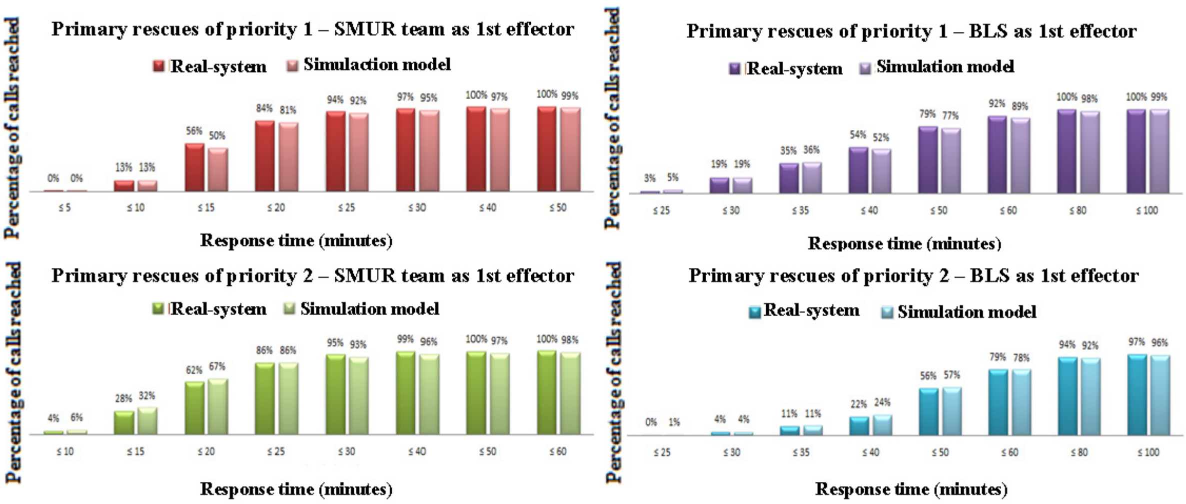

Figure 1: The cumulative distributions of real and simulated response time for primary rescues.

Subject to

$$\sum_{k=1}^{N_t} y_{ikpt} \leq \sum_{j \in W_{it}^p} x_{jt} \ (i \in V)\ (t \in T)\ (p \in P) \quad (2)$$

$$\sum_{j \in W} x_{jt} \leq N_t \quad (t \in T) \quad (3)$$

$$x_{jt} \in IN \quad (j \in W)\ (t \in T) \quad (4)$$

$$y_{ikpt} \in \{0,1\} \quad (i \in V, k = 1, \dots\dots\dots.., N_t, t \in T, p \in P) \quad (5)$$

Set of Index

V is the set of all demand nodes.
W is the set of all potential bases.
T is the set of all periods of time.
P is the set of primary calls' priorities.

Parameters

r_{ijt} is the travel time from the base j to the demand point i during the period t.

$W_{pit} = \{j \in W : r_{ijt} \leq S_p\}$ is the set of all potential bases eligible to serve calls of priority p located in the demand node i within a target travel time S_p.

d_{itp} is the total number of calls of priority p received in the period t associated with the demand node i.

N_t is the number of SMUR teams scheduled in the time period t.

α_p is the weight associated with the priority p demand coverage.

q_{ikpt} is the average busy fraction of k SMUR teams eligible to serve demand of priority p located at node i during the time period t.

Decision variables

x_{jt} is an integer variable that corresponds to the number of SMUR teams assigned to the base j during the time period t.

y_{ikpt} is a binary variable equal to 1 if demand of priority p located in demand node i is covered by at least k SMUR teams during time period t.

The objective function (1) aims to maximize the total expected demand covered over all nodes and all time periods. The weight α_p assigned to priority p demand allows emphasizing the importance of high-priority demand coverage and balancing the effect of a more restrictive target travel time for high priority calls. Constraint (2) ensures that for each time period, a demand of priority p located in node i is assigned to base j only if a team is located at j. Constraint (3) restricts the number of SMUR teams to be located to their scheduled capacity per time period.

For the application of the model, 47 locations corresponding to the centre of the 47 districts of the Val-de-Marne department were selected as potential bases. The 527 IRIS of the department were considered as demand nodes. There are between 3 and 5 available SMUR teams during weekdays and 3 SMUR teams during weekends. Ten periods of time were chosen corresponding to the six travel time periods described in section 3.2 which are subdivided whenever a change in the scheduled number of SMUR teams occurs within a given travel time period. The model was solved using different weights $(\alpha_1,\alpha_2)=\{(1,0);\ (0.75,0.25);\ (0.5,0.5)\}$ and different target travel times in minutes $(S_1,S_2)=\{(5,10);\ (10,10);\ (10,15)\}$. For each target travel time, the vector of nodes that can cover each demand of a given priority at a time period W_{pit} was computed.

The probability that a randomly selected SMUR team is busy is estimated using the following equation:

$$q_{ikpt} = \frac{\sum_{j \in W_{it}^p} T_{tpj}^{worked}}{T_t^{total} \times k} \ (i \in V, k = 1, \dots, N_t, t \in T, p \in P, Card(W_{pit}) = k) \quad (6)$$

where T_{tpj}^{worked} is the average amount of time worked to serve demand of priority p in time period t by all SMUR teams located at base $j \in W_{it}^p$, T_t^{total} corresponds to the total work time available at period t for each SMUR team and k is the total number of SMUR teams located at bases in W_{pit}. In case the number of SMUR teams located within S_p is different from k, we used the mean of the existing estimates over the set of demand nodes to approximate the busy fraction parameter, i.e. (6) is replaced by:

$$q_{ikpt} = \frac{\sum_{l \in V_{pit}} q_{lkpt}}{Card(V_{pit})} \ \left(i \in V, k = 1, \dots, N_t, t \in T, p \in P,\ Vpit = \{i \in V: Card(W_{pit}) = k\}\right) \quad (7)$$

We intuitively believe that this assumption will provide good estimates for q_{ikpt} that will avoid any excessive underestimation or overestimation of the ability of the system to cover a demand node under a given number of vehicles, which will lead to fast convergence of the iterative method.

We then apply the iterative method described in (Lee et al., 2012) that consists of using the integer program to obtain optimal location solution for a given estimation of q_{ikpt} and then running the simulation model with the obtained location solution to tune the estimates of q_{ikpt} using (6) and (7). The initial values of $q_{ikpt}^{(0)}$ were computed based on the "initial scenario" model that represents the current SAMU-94 system. Using this initial estimation, the integer program is solved to provide the optimal location solution $(y_{ikpt}^{(1)}, x_{jt}^{(1)})$, which is in turn used as an input in the simulation model. The resulting simulated service time worked allows updating the estimates of $q_{ikpt}^{(1)}$for the next iteration. This process is repeated until the location solution converges, i.e. remains the same for two successive rounds of iterations, i.e. $(y_{ikpt}^{*}, x_{jt}^{*}) = \left(y_{ikpt}^{(n)}, x_{jt}^{(n)}\right) = (y_{ikpt}^{(n-1)}, x_{jt}^{(n-1)})$.

For each value of weight/target travel time parameters, the model has been solved at each iteration using CPLEX 12.5 on an Intel Core i3, at 2,30 GHz, with 4Go of RAM memory. Solution times ranged from 3.2 to 9.7 minutes. The obtained redeployment solution was then fed in the simulation model and run for twenty 15 months-replications in order to re-compute the corresponding busy fractions per time period and priority of calls.

5 EXPERIMENTAL RESULTS

As the purpose of this study is to achieve a substantial improvement in response time performance for primary rescues with SMUR team as first effector, the percentage of calls responded to within target times of 15 minutes and 20 minutes were set as the main performance measures used to compare simulation results for priority 1 and 2 respectively. The optimal redeployment policies resulting from the alternatives of weight/target travel time combination, described in Table 1, were analysed in sequence.

We were first interested in analysing how the system performances behave through the steps of the iterative method. In all eight tested alternatives, the method converged within few iterations ranged from 4 to 7. Examples of the expected coverage performances obtained from the optimization model and the response time performances obtained from the simulation model for each iteration step of alternatives 1 to 3 are shown in Figure 2. The green boxes show the 95% confidence interval for the percentage of calls responded to within the target response time metric, and the whiskers show the best and worst cases of the 20 independent runs of each alternative. As illustrated in the figure, the larger marginal differences in performances are achieved between the initial scenario (iteration 0) and iteration 1 solution, achieving an absolute difference of 14,8% ± 0,3% and 9,3% ± 0,2% in the simulated percentage of calls responded to within the target response time for priority 1 and 2 respectively. The results obtained from the subsequent iterations showed no significant marginal differences that do not exceed 0,9% ± 0,3% in the percentage of calls reached within the target response time for both priorities.

Table 1: Description of the alternatives.

Alternatives	S_1	S_2	α_1	α_2
Alt. 1	5	10	0.5	0.5
Alt. 2	5	10	0.75	0.25
Alt. 3	5	10	1	0
Alt. 4	10	10	0.5	0.5
Alt. 5	10	10	0.75	0.25
Alt. 6	10	15	0.5	0.5
Alt. 7	10	15	0.75	0.25
Alt. 8	10	15	1	0

Now we examine the iterative method solution quality by comparing the converging points' performances of all the eight alternatives with each other and with the initial scenario model (See Table 2). The converging redeployment solution performances obtained from the optimization model indicated that the expected coverage of priority 1 rescues could be improved by increasing the value of the weight α_1. This improvement is more significant for low values of target times and achieved up to 13%, while the corresponding priority 2 expected coverage showed either a slight or no decrease. This was however not supported by the simulation framework. Indeed, simulation results showed that fair coverage weights for both priority 1 and 2 rescues, associated with small target times seem to significantly positively impact the response time performance. Thus, implementing the redeployment policy resulting from alternative 1 improved the percentage of calls responded to within 15 and 20 minutes by 15,0% ± 0,3% and 9,1% ± 0,1% for priority 1 and 2 respectively when compared to the current SAMU-94 performances, which represents an average relative improvement of 29,7% and 13,7%.

Differences between the simulation performances and the optimization model coverage seem to derive from the fact that the latter ignores several aspects. First, a part of primary demand may be served by the rescue physician who is necessarily located in HM base since he also operates as a SAMU regulator in the R&R centre. Thus, the location of this resource cannot be considered as a decision variable in the linear program, but yet affects the response time performance in the simulation model. Second, unlike the simulation model, the temporal dimension of the arrival rate as well as the service time distribution are ignored in

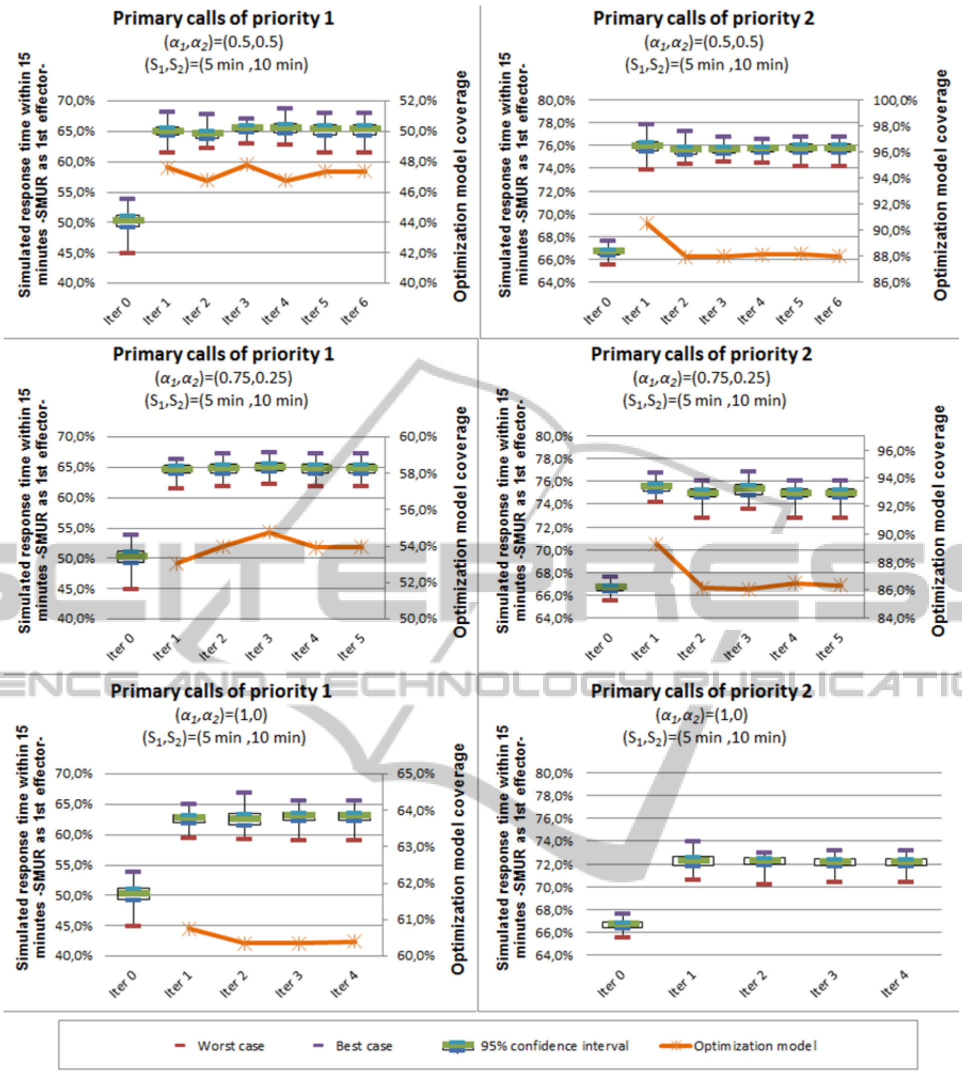

Figure 2: Iterative method performance measures for the (S1,S2)=(5min,10min) alternatives.

model, the temporal dimension of the arrival rate as well as the service time distribution are ignored in the optimization model as it uses the total number of calls received in each time period and an estimation of the average busy fractions. At this point, the performances obtained from the simulation model can be said to be more relevant and reliable.

Further comparisons between the best solution (alternative 1) and the initial scenario were made by using the distribution of response time in order to test the robustness of the redeployment solution by insuring that the responses that occur within larger target times' performances are not decreased compared to the actual performances. The results depicted in Figure 3 show that up to a target time of 50 minutes, the redeployment plan based on the alternative 1 solution always provided better response time performances than those obtained from the initial model for both priorities 1 and 2.
The larger differences are obtained for a target time of 15 minutes (15% ± 0,3% for priority 1 and 13,9% ± 0,1% for priority 2).

6 CONCLUSIONS

This research used a multi-period probabilistic mathematical model for the location of rescue teams and a discrete event simulation model embed in an iterative method to help the SAMU-94 managers in improving the system response time performances. The optimization model aims to maximize the demand covered within a target time under limited resources, while the simulation model is used both to

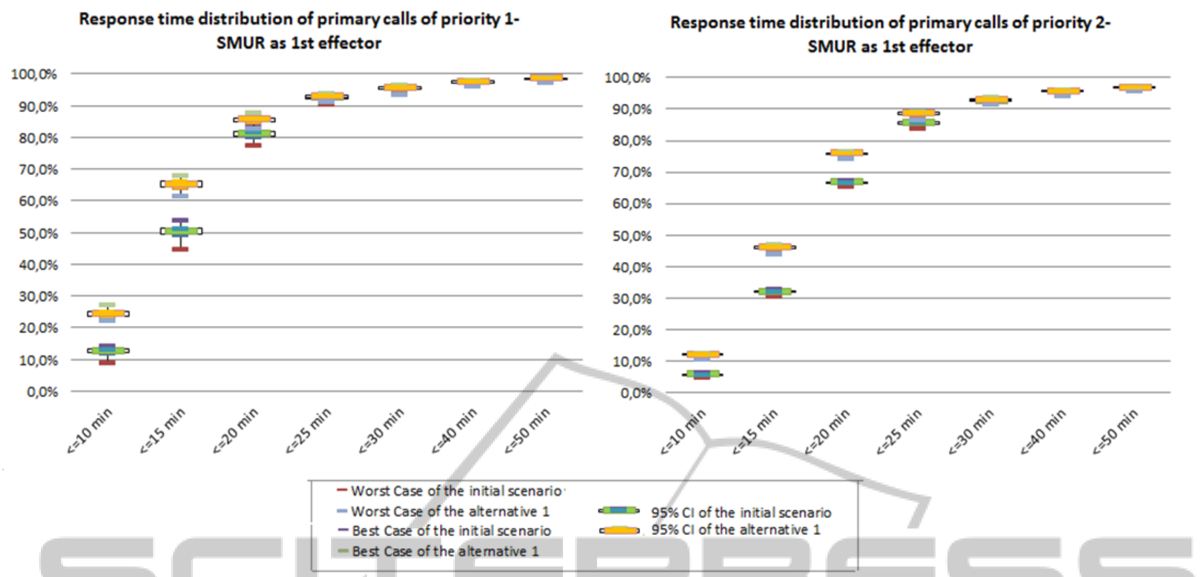

Figure 3: Comparison between the initial scenario and the alternative 1 response time distribution.

Table 2: Comparison of performance measures between the initial scenario and the converging points for the different alternatives.

Alternative	Number of iterations to convergence	Priority 1		Priority 2	
		Optimal expected coverage within S_1	Simulated response time within 15 min	Optimal expected coverage within S_2	Simulated response time within 20 min
Alt. 1	7	47,4%	65,3% ± 0,9%	88,0%	75,8% ± 0,3%
Alt. 2	6	54,0%	64,7% ± 0,7%	86,3%	75,0% ± 0,3%
Alt. 3	5	60,4%	63,1% ± 0,7%	-	72,2% ± 0,3%
Alt. 4	6	96,7%	63,4% ± 0,8%	89,0%	75,7%± 0,3%
Alt. 5	6	97,6%	63,7%± 0,6%	89,1%	75,8%± 0,4%
Alt. 6	4	98,2%	63,5% ± 0,8%	98,3%	74,8% ± 0,3%
Alt. 7	7	98,5%	62,3% ± 0,9%	98,5%	74,7% ± 0,4%
Alt. 8	4	99,0%	63,2% ± 0,8%	-	73,8% ± 0,3%
Initial scenario	-	-	50,3% ± 0,9%	-	66,6% ± 0,3%

estimate the busy fractions needed as input data in the analytical model and to obtain reliable estimates of the system performances given the location solutions obtained from the optimization model. The experimental results suggested that the iterative method could increase the percentage of the demand covered within 15 minutes up to 29,7% and 43,3% compared to the current SAMU-94 system for priority 1 and 2 respectively.

One shortcoming of the proposed redeployment solution is that it is obtained from the historical demand data of the SAMU-94. One possible extension of this work can therefore be based on forecasting the number of expected emergency calls so as to derive sufficiently robust relocation strategy of SMUR teams that covers future demand at the desired service level. Another area of improvement for this study is to combine the iterative method solutions with other scenarios such as increasing the number of the SAMU-94 resources or implementing efficient dispatching policies so as to achieve more considerable improvements in response time performances.

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