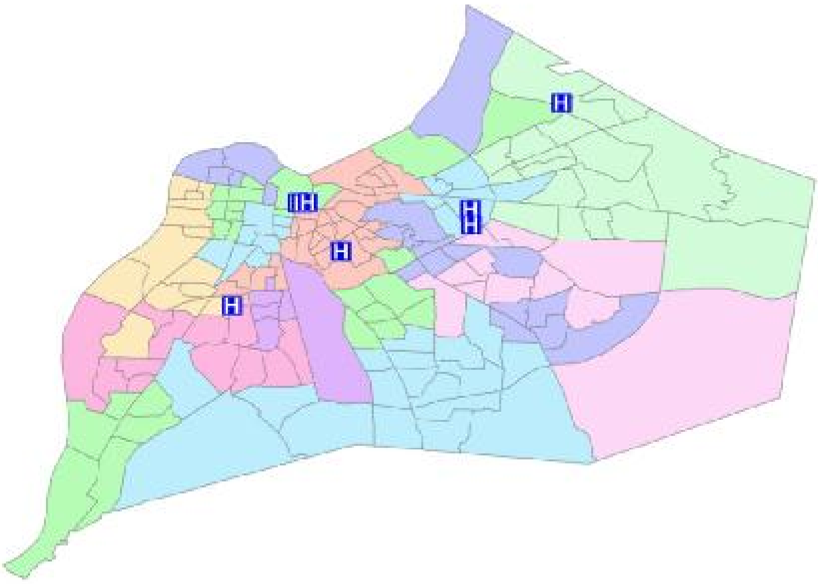
EMS- & Hospital-Cluster determination with Linear Programming



Marcel Ploeg

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Industrial Engineering at the J.B. Speed School of the University of Louisville

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Introduction

One of the problems concerning a medical surge is how to transport the patients, in need for emergency medical aid, to the hospital in an optimal way with the available resources. This problem is tried to be answered in this study with a LP-model.

Problem description

First, a clear description of the area where medical aid is given is needed. In a region (think of a state or county) there are several medical institutes were medical aid is given to patients. In this case, only hospitals will be taken into account. Within the region, there are several hospitals which have their own area to work in. These areas are called clusters. Within the hospital-clusters, there are EMS (Emergency Medical Services)-stations which provide the transport for the patients to the hospital. These EMS-stations also have their own area to work in, called EMS-cluster (See Figure 1).

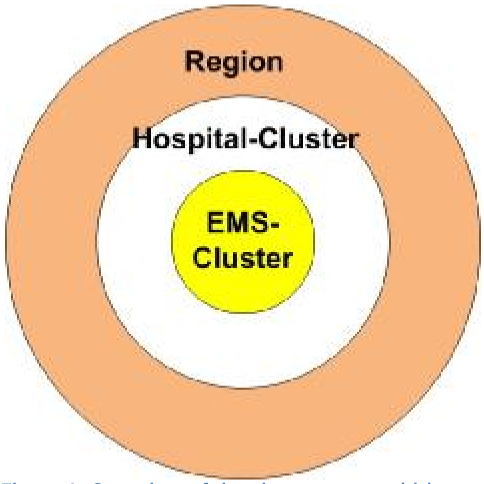

Figure 1: Overview of the cluster-types within a region.

During normal operations, each hospital receives patients at its ER-department at any time. The patients a hospital receives are normally patients from its own cluster. These hospital-clusters are determined to divide the total demand in the region in such a way that patients are served as quick as possible and the demand of each hospital is proportional to its capacity.

Within a hospital-cluster there are EMS-clusters. In each EMS-cluster there is an EMS-station located, which contains EMS-vehicles who transport patients to the hospitals. The size of these clusters and the place of the EMS-stations, are chosen in such a way that EMS-vehicles arrives at the patients within time limits.

The two cluster issues described above are forming the planning problem. This planning problem then consist two problems (see paragraph: Problems).

Although during normal operations, these clusters are supposed to work sufficient, during a medical surge many problems arise. During a medical surge, the demand increases rapidly and the demand might be fluctuating in each hospital-cluster or EMS-cluster. This can result in shortage of EMS-vehicles and hospital capacity in different EMS-clusters or even in different hospital-clusters. Next to capacity problem, there are many different problems which arise during a medical surge (traffic jams, sick personnel, etc.). This problem forms the EMS-allocation problem (see paragraph: Problems).

Another issue to consider is that the clusters used during normal operations, might be re-determined due to the cause of the medical surge. In case of let's say influenza, clusters with a higher percentage of children and elderly, might need higher capacity for a longer period. This problem extends the planning problem into two situations: normal operations and medical surge (see paragraph: Problems).

Problems

The problems recognized in the introduction, are the following:

1. Planning:
    a. Normal operations : *Determine the size en location of*
        i. EMS-clusters
        ii. Hospital-clusters
    b. Medical Surge: *Determine the size en location of*
        i. EMS-clusters
        ii. Hospital-clusters
2. Allocation: Allocating the EMS-vehicles during a medical surge with the given EMS-stations, preferred clusters and hospital capacity.

In this paper only the planning problem will be tried to be solved.

Problem definition

How to determine the optimal size and location of the clusters which in the hospital or EMS-station operates?

Although this problem definition sounds clear, several terms has to be defined more detailed.

Area

The area for which the problem is solved, should defined by:

- Geographical location
- Geographical boundaries
- Population
- Accessibility

Seize and location EMS station

The location of an EMS-station should be given by geographical coordinates within the area. The size of the EMS-station should be defined by the number of vehicles and its capacity available at the EMS-station.

Seize and location Hospitals

The location of a hospital should be given by geographical coordinates within the area. The size of the hospital should be defined by the number of patients able to take care of expressed is number of beds.

Objective

The objective, to which the problem should be optimized, can be defined in several ways:

- Minimize the total idle time of the EMS-vehicles
- Maximize the throughput of all the EMS-vehicles (area overall or for each cluster)

- Minimize the driving distance between patients and hospitals

In this case, the last objective will be taken as objective.

Input data

A very import issue is the input data. Not only is the data crucial for the calculation, it also determines the shape of the calculations. Because these problems concerns with geographical data, a huge amount of data coming from the census will be used. The data coming from the census are arranged in so called tract areas. These are geological areas with all its data (size, population, wages, etc.).

Not only will the data of the census will be used, also data from the area in issue will be needed. Think of EMS resources, hospital resources, etc.

Assumptions

A number of assumptions are made, to simplify the model. The following assumptions are made:

- Each EMS-vehicle has equal patient capacity.
- Each EMS-cluster contains one EMS-station.
- Each EMS-station has the same number of EMS-vehicles.
- Each EMS-cluster is located within one hospital cluster.
- A hospital-cluster can contain multiple hospitals.

LP (BIP) formulation

The LP formulation consists of two parts. The first part of the objective (left part) will assign tract-areas to the EMS-stations. The second part of the objective will take care of the hospital-clusters and assigns EMS-stations to hospitals. This second part actually needs information from the EMS-clusters. Before the hospital-clusters can be calculated, the actual amount of population assigned to an EMS-station must be known to check the hospital capacity constraint. Therefore the calculation will be split into two consecutive parts:

- Determining the EMS-clusters
- Determining the hospital-clusters.

Due to the fact that the LP model is a binary integer programming model, the model will be referred as a BIP-model. Below the linear programming formulation is given for both the hospital-cluster problem and the EMS-cluster problem.

Objective: Minimize the total driving distance between EMS-stations and tract-area and the total driving distance between the hospitals and EMS-stations.

Constraint 1: Each EMS-station should serve at least one tract area.

Constraint 2: Each tract-area can only be served by one EMS-station.

Constraint 3: Each hospital should serve at least one EMS-station.

Constraint 4: Each EMS-station can only be served by one hospital.

Constraint 5: The sum of the population of the tract-areas served by an EMS-station, has to be equal or more than the EMS-capacity minus β_{lb} and has to be equal or less than the EMS-capacity plus β_{ub}.

Constraint 6: The sum of the population of the EMS-stations served by a hospital has to be equal or less than the hospital capacity plus α.

$$Min \sum_{t=1}^{R}\sum_{i=1}^{N}\sum_{j=1}^{M} X_{tij}D_{ij} + \sum_{t=1}^{R}\sum_{k=1}^{L}\sum_{i=1}^{N} Y_{tki}G_{ki}$$

1) $\sum_{j=1}^{M} X_{tij} \geq 1 \quad \forall\, i, t$
2) $\sum_{i=1}^{N} X_{tij} = 1 \quad \forall\, j, t$
3) $\sum_{i=1}^{N} Y_{tki} \geq 1 \quad \forall\, k, t$
4) $\sum_{k=1}^{N} Y_{tki} = 1 \quad \forall\, i,\ t$
5) $V_i - \beta_{lb} \leq \sum_{j=1}^{M} X_{tij} * P_j \leq V_i + \beta_{ub} \quad \forall\, i, t$ with $V_i = \frac{TotalPopulation}{NrEMSCStations}$
6) $\sum_{i=1}^{N} Y_{tki} * (\sum_{j=1}^{M} X_{tij} * P_j) \leq C_k \quad \forall\, k, t$ with $C_k = \left(\frac{TotalPopulation}{TotalNrBeds} + \alpha\right) * B_k$

X_{tij} : Is 1 if tract-area j is assigned to EMS-station i for each hospital type t, else 0.

Y_{tki} : Is 1 if hospital k is assigned to EMS-station i for each hospital type t, else 0.

D_{ij} : Is the distance between tract-area j and EMS-station i.

G_{ki} : Is the distance between hospital k and EMS-station i.

P_j : Is the population of tract-area j.

V_i : Is the capacity of EMS-station i.

C_k : Is the capacity of hospital k.

B_k : Is the number of beds of hospital k.

β_{lb} : Is the variable which can regulate how the lower bound of constraint 5 is met.

β_{ub} : Is the variable which can regulate how the upper bound of constraint 5 is met.

α : Is the variable which can regulate how constraint 6 is met.

k : Is the range of the hospitals, k=1..L.

i : Is the range of EMS-stations, i=1...N.

j : Is the range of tract-areas, j=1..M.

t : Is the range of hospital types, t=1..R.

Case description

For this case the Jefferson County in Kentucky will be taken as a region. The data concerning demographics of the Jefferson County is gathered from Census 2000 (see reference 2). The Jefferson County is the county of the Louisville metropolitan area, which inhabits almost 700.000 inhabitants. In Table 2 a short overview of the county is given (for EMS info, see reference 1). In Table 1 a short overview of the hospitals is given, used in the cluster calculations (for origin data, see references 3-7). Although there are 2 types of hospitals in these data, all hospitals will be assumed to be of the same type to simplify the calculations. *All data in both tables are approximations.*

Hospital	Total Bed Capacity	Hospital Type
Jewish Saints Mary and Elizabeth Hospital	331	Adult
Jewish Hospital	517	Adult
Norton Hospital	719	Adult
Norton Kosair Children's Hospital	263	Children
University of Louisville Hospital	404	Adult
Norton Audubone Hospital	480	Adult
Baptist Hospital East	519	Adult
Norton Brownsboro Hospital	127	Adult
Norton Suburban Hospital	380	Adult

Table 1: Overview hospitals Jefferson County with ER.

Jefferson County, KY	Data
Total population	693604
Total Area	385 (mi$^{2)}$
Density	1801.6 (pers./ mi^2)
Number of Tract Areas	170
Number of EMS-stations	26

Table 2: Summary Jefferson County, KY.

Simulated Annealing

The linear model given before will be solved with use of program Lingo©. Due to the fact that this problem contains binary integers, Lingo© will try to solve this minimization problem with a branch-and-bound method. As can be seen in the case description, the problem contains 170 tracts areas and 26 EMS-stations which results in more than 4000 binary variables. Due to this large amount of integer variables, the runtime of the problem will be long. Also take in mind that this is a relative small problem, so with an even larger amount of input data (larger region) the runtime will be even longer. In the case of a medical surge, new up-to-date information will be used and the results are needed as soon as possible. Therefore relative long runtimes are not acceptable.

To reduce the runtime to solve this problem, a search method will be used. In this case simulated annealing (S.A.) will be used to reduce the runtime. S.A. starts as a global search method and will finish in a local search method. The solution which S.A. will produce is not an optimal solution but an approximation of the optimal solution. How good this approximation is, will depend on the cooling scheme and several parameters.

The basic idea of S.A. is that it will use an initial solution and will randomly change (swapping) this solution until the temperature (*c*) is below a limit (c_{stop}) in order to find a better objective. The temperature will decrease during each loop of the algorithm with a decrease-factor ε, giving the so called cooling schedule. During each loop, the S.A. algorithm will perform a number of swaps equal to *k* (Markov Chain length).

As an example of the randomly change of the solution, think in this case of swapping the assignment of a tract-area from EMS-station A to B. If the swap results in an equal or better objective, the swap will be saved. If it results in a worse objective, it will be saved with a chance P or the swap will be undone. The chance P will be large in the beginning, making many swaps possible, and goes to zero as the temperature drops during the runtime making only swaps possible which will give a better objective. The swaps can only be performed in the so called 'neighborhood' of a current variable. This neighborhood must be chosen carefully to obtain the best results.

The chance P is defined as follows:

$$P_{AB}(c) = \begin{cases} 1 \ \ if \ B \leq A \\ e^{\frac{A-B}{c}} \ \ else \end{cases}$$

The temperature is defined as follows:

$$c_t = c_{t-1} * \varepsilon$$

The other parameters are:

c : The temperature

c_0 : Start temperature

c_{stop} : The final temperature, if the temperature drops below this limit the algorithm will stop.

ε : The decrease factor with which the temperature will drop each loop.

k : The number of proposed swap each loop.

The values of the parameters will be given in the result section.

Sensitivity Analysis

To see what the impact is of the parameter values on the objective value, first a sensitivity analysis will be performed, as well for the BIP-model as well for the S.A.-algorithm. Although these two different analyses cannot be compared exactly, due to the fact that the S.A.-algorithm is bases on random solution, it will give insight in what parameter values are preferred.

BIP-model

For the BIP-model, first an analysis is performed for the EMS-cluster part. The results are shown in Table 3. The table shows the values for the upper- and lower-bound capacity constraint for the EMS-clusters. The results show that if the value for the upper-bound becomes larger, the objective becomes smaller. The same conclusion can be made for the values of the lower-bound; if the values become larger, the objective becomes smaller. This is as expected, due to the fact that the constraint is more relaxed. The table also shows a column named 'Larg. Diff. Pop.'. This column shows the largest difference between the populations served by the EMS-stations. On this way the boundaries can be checked.

BIP - Solution	β -UB	β - LB	Larg. Diff. Pop.	Obj.	Runtime (hh:mm:ss)
EMS-Clusters					
1	3,000	3,000	5,913	4.642000	01:00:00+
2		4,000	6,653	4.605108	00:02:00*
3		5,000	7,933	4.559911	00:02:00*
4	4,000	3,000	6,835	4.600843	00:02:00*
5		4,000	7,410	4.529710	08:34:00+
6		5,000	8,788	4.469245	00:02:00*
7	5,000	3,000	7,720	4.535960	16:28:00+
8		4,000	8,450	4.506123	00:02:00*
9		5,000	9,639	4.433107	00:02:00*

Table 3: Optimal results for EMS-clusters from branch-and-bound.

Two extra notes have to be made. First, the value range of the upper- and lower-bound is chosen to be 3,000 and higher. Two reasons are responsible for this. The first reason is that the values cannot be lower than two thousand, because in that case the solution is infeasible. The second reason is that this range forms the smallest values used by the S.A.-algorithm, to get acceptable results. This becomes more clearly in the sensitivity analysis of the S.A.-algorithm.

The second note to be made is about the runtime of the solutions. Three runtimes are marked with a plus, meaning that the calculation has been stopped at the given runtime. This means that the runtime could be much larger. The highest runtime is that of solution 7, meaning that solutions before number seven, also should have taken at least the same runtime due to the tighter constraints. Furthermore, it was noticed that the objectives in these three cases almost were reached after a short runtime. That is the reason that the other runtimes (marked with an asterisk) are terminated after two minutes. On this way, calculation time was saved but still a good approximation of the optimal solution was found.

An analysis also has been performed for the hospital-clusters. However, changing the values of α within reasonable ranges did not have any effect on the objective. Therefore the values of α has been fixed. The values for the hospital-cluster solution can be found in Table 17 in Appendix III. Also the combined result of the EMS- and hospital-cluster solutions can be found in Table 18 in Appendix III as well.

Simulated Annealing algorithm

For the S.A.-algorithm a sensitivity analysis has been performed also. Again, first the analysis has been performed for the EMS-clusters. The results are shown in Table 12 in Appendix I. The same effect of changing the upper- and lower-bound values can be found here. When the values become larger, the constraint becomes more relaxed and the objective becomes smaller. However, the effect the in this case is larger. When the values for the upper- and lower-bound are set to 4,000, the objective becomes very large compared to the objective values found in the sensitivity analysis for the BIP-model. Therefore the lowest value is set to 4,000 to make sure the objective doesn't become too large. This is also the reason why the upper- and lower-bound values for the BIP-model are chosen in this range and not much lower. On that way, a benchmark can be set later from the BIP-model, which lies within the range of the S.A.-algorithm.

For the hospital-clusters, the same conclusion can be made as at the BIP-model. Changing the value of α within reasonable range doesn't influence the objective. Therefore the value of α has been fixed. The values for the hospital-clusters can be found in Table 13 in Appendix I. Also the combined values for the EMS-clusters and the hospital-clusters can be found in Appendix I in Table 14.

Results

In this section the results will be given of the calculations to determine the clusters. First the results will be given of the optimal solution of the BIP-model, determined with a branch-and-bound method to set a benchmark. Second the results will be given of the S.A. calculations.

As explained before, the calculation consists of two parts; the EMS-cluster part and the hospital-cluster part. The results will be discussed in the same order. As last a check will be made to see if the S.A.-algorithm works properly.

BIP Solution

For the results, the same solutions will be used as for the sensitivity analysis. For the EMS-clusters, the results are shown in Table 3. For the hospital-clusters the results are shown in Table 17 in Appendix III and the combined results can be found in Table 18 in Appendix III. Considering the range of the constraints used for the S.A.-algorithm, solution number 5 is taken as the final solution and will be used as a benchmark (see Table 4).

BIP-solution	α	β -UB	β - LB	EMS Obj.	Hospital Obj.	Total Obj.	Runtime (hh:mm:ss)
5	10	4,000	4,000	4.529710	2.097550	6.627260	08:35:16+

Table 4: The final solution of the BIP-model calculated with Lingo© which will be used as a benchmark.

Another comment has to be made about the runtimes of the solution. As said before at the sensitivity analysis, the runtimes are expected to be larger than sixteen hours which is not acceptable. This confirms the reason to use S.A. to reduce the runtime to a more acceptable value.

Simulated Annealing Solution

For the S.A. algorithm the parameters values are given in Table 5.

Parameter	Value
c_0	1
c_{stop}	0.001
ε	0.995 / 0.998
k	25

Table 5: Parameters used for S.A.

The S.A. algorithm tries to swap values in the matrices X_{tij} and Y_{tki} . The algorithm uses a random number to select a column and then swaps values within the column. During each loop, the algorithm swaps values within one column. The number of swaps is in this case equal to k, representing the number of possibilities (the number of EMS-stations minus one). This means for X_{tij} that the algorithm tries to assign a different EMS-station for a tract-area.

Again, the results of the sensitivity analysis will be used for the results. The results for the EMS- and hospital-clusters are shown in Table 14 in Appendix I. The solutions are calculated with ε=0.995. With this lower value for ε, the runtime is lower and calculation-time is saved. On this way a larger range of solutions is generated with limited runtime. The solutions which are within 35% from the benchmark, have been recalculated but with ε=0.998 to improve the objectives.

S.A.-Solution	Diff. Bench.	Total Obj.	Total Runtime (hh:mm:ss)
Hospital- + EMS-clusters ε = 0.998			
4	23%	8.129883	00:20:13
5	24%	8.196534	00:19:26
8	20%	7.966414	00:19:16
9	24%	8.189697	00:19:20
10	27%	8.414579	00:17:21
12	32%	8.716837	00:18:39
13	15%	7.618753	00:20:53
14	16%	7.665917	00:17:52
15	18%	7.793043	00:17:03

Table 6: Total result for hospital- and EMS-clusters from simulated annealing with **ε**=0.998

The combined results are shown in Table 6.
The results for the EMS-clusters and the hospital-clusters are shown in Table 15 and Table 16 in Appendix II. The results in Table 6 show better objectives compared to the objective when using ε=0.995. The best objective (solution number 13) is 15% from the benchmark, which is acceptable. Looking at the runtime, the real benefit of the S.A.-algorithm becomes visible. All runtimes are around the twenty minutes, which is a large improvement compared to the minimum of sixteen hours needed for the BIP-model. This confirms again the use of simulated annealing. The best solution found with S.A. is given in Table 7 with all its parameters.

S.A.-solution	ε	α	β -UB	β - LB	EMS Obj.	Hospital Obj.	Total Obj.	Runtime (hh:mm:ss)
13	0.998	10	6,000	6,000	4.894616	2.724137	7.618753	00:20:53

Table 7: The best solution found with the S.A.-algorithm.

Simulated Annealing Check

To make sure that the S.A. algorithm works properly, the moving average of chance P (or probability) is shown in Figure 2. The chance P decreases gradually from one to zero during the calculations, which indicates that algorithm works good. On this way the algorithm can make changes which give worse objective in the beginning, to get out of local optimums. Later on, chance P decreases making only changes possible which give better objectives. This makes it possible to search globally in the beginning and search locally in the end.

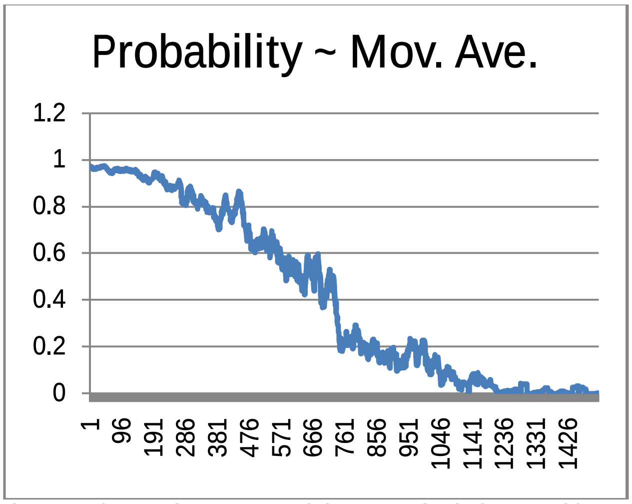

Figure 2: The moving average of chance P of solution 13 with ε=0.998.

Another issue to check is the cooling schedule of the algorithm, which is shown in Figure 3. The cooling schedule shows a high temperature in the beginning and then drops during the runtime of the algorithm. This also makes it possible that the chance P is large in the beginning and small in the end. Furthermore this cooling schedule gives good results in objective and runtime making it an efficient cooling schedule.

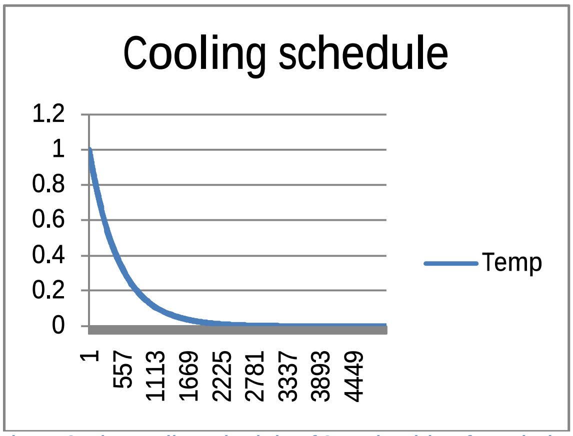

Figure 3: The cooling schedule of S.A. algorithm for solution 13 with ε=0.998.

Improvements

In this section two improvements are suggested; reducing the neighborhood and merging hospitals.

Smaller Neighborhood

The neighborhood used in the calculations in the previous paragraph, is defined as all possible EMS-stations to which a tract-areas can be assigned to. In the situation used in the calculations above, this means that for a tract-area all possible assignments to an EMS-station are tried. This can be improved by reducing the neighborhood by making only the swaps possible which have a distance (between the concerning tract-area and the proposed EMS-station) equal or below σ. On this way the neighborhood is smaller, making the Markov Chain Length smaller and results in a lower runtime. However, the value of σ has to be chosen in such a way that the objective of the solution will not get worse.

For the two best solutions so far, a number of calculations have been performed. The results are shown in Table 8. The results show that reducing neighborhood improves the runtime. Only in one case the objective is worse, resulting in an objective which is 2% larger compared to the same solution with a large neighborhood. The best solution shows a 27% smaller runtime compared to the original runtime of this solution and even has a better objective. This shows the positive impact of reducing the neighborhood on the objective as well the runtime.

S.A. Solution	σ	EMS Obj.	Hospital Obj.	Total Obj.	Obj. Diff.	Runtime (hh:mm:ss)	Time reduction (%)
ε=0.998							
13	0.2	4.928332	2.882937	7.811269	+2%	00:17:46	-15%
13	0.3	4.894616	2.724137	7.618753	0%	00:15:41	-25%
14	0.2	5.072387	2.416836	7.489223	-3%	00:13:06	-27%
14	0.3	4.982508	2.683409	7.665917	0%	00:16:17	-10%

Table 8: Result for EMS-clusters from simulated annealing with a different sigma, reducing the size of the neighborhood.

The new best S.A.-solution is given in Table 9. The new objective is 13% larger from the benchmark, an improvement of 2% compared to the former best solution of the S.A.-algorithm.

S.A.-solution	ε	σ	α	β -UB	β - LB	EMS Obj.	Hospital Obj.	Total Obj.	Runtime (hh:mm:ss)
14	0.998	0.2	10	6,000	7,000	5.072387	2.416836	7.489223	00:13:06

Table 9: The new best solution found with the S.A.-algorithm and with a reduced neighborhood.

Hospital Merging

Another way to reduce runtime and improve the results is by merging hospitals which are located close together. On this way the number of hospitals decreases making the size of the problem smaller. This results in a lower runtime, but also makes the hospital-clusters more logical. In the case that hospitals are located close together, strange cluster shapes may occur (see Figure 4). By merging the hospitals into one fictional hospital, one large hospital-cluster will be formed with a less strange shape.

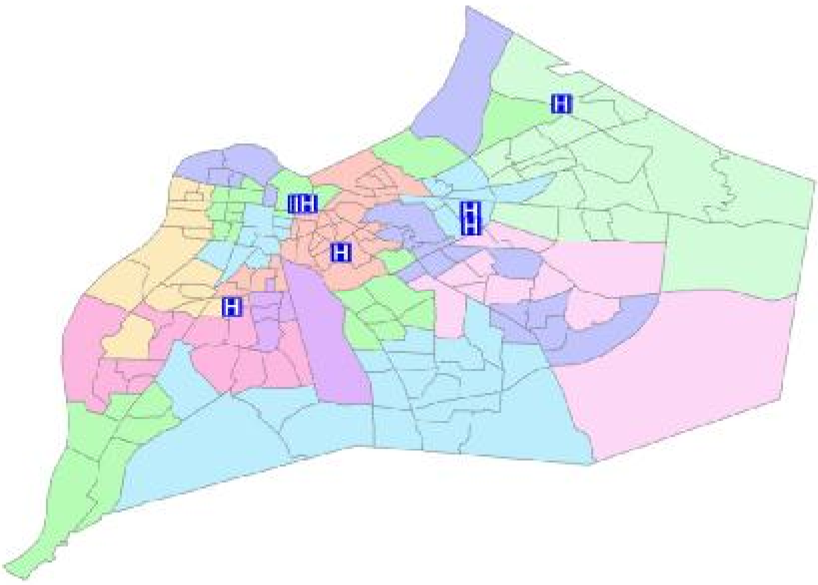

Figure 4: GIS map of the Hospital-clusters of the BIP-model. Each color represents a different hospital cluster.

Two calculations have been made with merged hospitals. When the distance between hospitals is equal or lower than ρ, then the hospitals are merged together. With ρ=0.011, a number of hospitals merged together resulting in 5 hospitals in total instead of the original 9 hospitals. First a calculation has been made for the BIP-solution to see the impact on the hospital-cluster. The results are shown in Table 10. The objective is slightly better, due to the fact that the distances between the merged hospitals are smaller than the original hospitals. The runtime has been reduced to one second, which is a good improvement. Also the shape of the clusters have become more logical (see Figure 5), which are therefore better in operations itself.

Opt. Solution	ρ	α	Diff. Pop.	Obj.	Runtime (hh:mm:ss)	Time reduction (hh:mm:ss)
5	0.011	10	1.07% - 7,422	2.033716	00:00:01	00:01:15

Table 10: Optimal solution for the hospital-clusters with merged hospitals.

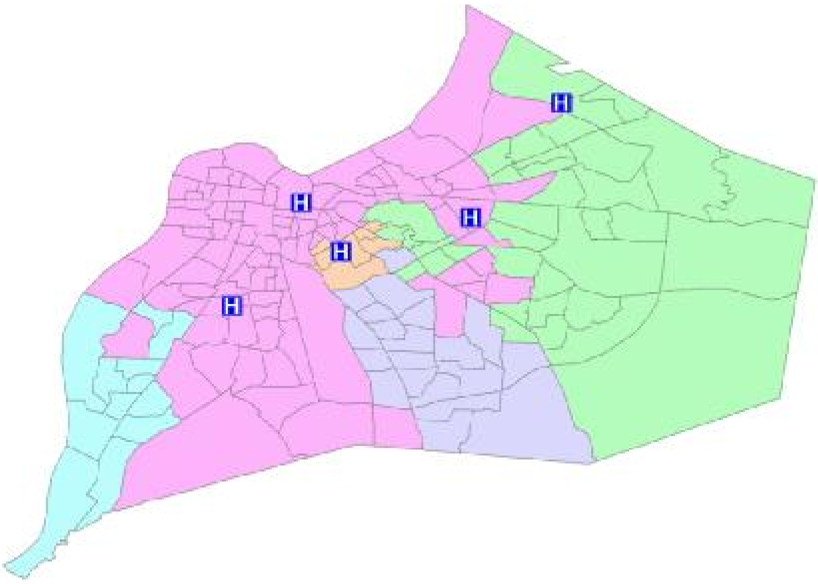

Figure 5: GIS map of the hospital-clusters of the BIP-model with hospital merging, resulting in smaller number of clusters.

Another calculation has been with made with merged hospitals, now in the case of S.A. The results are shown in Table 11. The objective is slightly higher than without merging the hospitals. The runtime has been reduced to one second..

S.A. Solution	ρ	α	σ	Diff. Opt.	Diff. Pop.	Obj.	Runtime (hh:mm:ss)	Time reduction (hh:mm:ss)
Hospital-Clusters ε=0.998								
15	0.011	10	0.3	31%	1.41% - 5,063	2.746009	00:00:01	00:00:04

Table 11: S.A. solution for hospital-clusters with merged hospitals and limited neighborhood.

In this case the improvements may not look significant, but when dealing with a larger problem the improvement will be more significant. Not only the runtime will be improved, but also the shape of the clusters will be more logical.

Conclusion

This BIP model gives a way to calculate the optimal hospital- and EMS-clusters. In the case of the hospital-clusters, the model gives a global optimum in a very short and acceptable time. However, the calculation for the EMS-cluster takes a very long time which is not acceptable due to high need of the information. The branch-and-bound method used by Lingo© is therefore not an efficient method.

The simulated annealing method is therefore a good way to improve the runtime dramatically. The S.A.-algorithm used brings the runtime from over 16 hours back to 20 minutes. The objective of the S.A.-solution is 15% larger compared to the benchmark of the BIP-model, which is acceptable.

The runtime and the objective is even further reduced when reducing the neighborhood and merging hospitals. The runtime of the best S.A.-solution is reduced to even 13 minutes and the objective is also reduced to become 13% larger compared to the benchmark of the BIP-model. Therefore the S.A.-algorithm with a reduced neighborhood and merged hospitals is a good method to determine the EMS- and hospital-clusters instead of the BIP-model. The next step to be taken in this process is to make a dynamical model which allocates and re-allocates the actual ambulances using the generated EMS- and hospital-clusters.

Appendix I

In this appendix three tables are given with the results of the S.A.-solution for the EMS- and hospital-clusters and the combined results with ε=0.995. Below some of the names of the columns will be explained.

β –UB : This beta-upper-bound for constraint number 5.

β – LB : This beta-lower-bound for constraint number 5.

Diff. Bench. : This is the difference in percentage from the benchmark of the BIP-model.

Larg. Diff. Pop : This is the largest difference between populations served by the EMS-clusters.

Obj. : Objective of the solution.

α : This alpha, the upper-bound for constraint 6.

Diff. Pop. : This is the largest difference between the actual population served by a hospital and the theoretical population determined by the hospital capacity. The difference is expressed in percentage as well as in population.

Total Obj. : Sum of the EMS-cluster objective and the hospital-cluster objective.

S.A. Solution	β -UB	β - LB	Diff. Bench.	Larg. Diff. Pop.	Obj.	Runtime (hh:mm:ss)
EMS-Clusters ε = 0.995						
1	4,000	4,000	69%	7,532	7.657279	00:07:24
2		5,000	48%	8,242	6.693308	00:07:25
3		6,000	39%	9,884	6.308974	00:07:27
4		7,000	27%	10,428	5.766947	00:07:24
5		8,000	32%	11,067	5.982725	00:07:43
6	5,000	4,000	70%	8,863	7.692892	00:06:58
7		5,000	34%	10,574	6.064022	00:08:58
8		6,000	25%	10,441	5.666163	00:07:44
9		7,000	24%	11,841	5.615465	00:06:30
10		8,000	20%	12,847	5.414707	00:07:28
11	6,000	4,000	54%	9,150	6.979614	00:07:51
12		5,000	29%	10,877	5.841300	00:06:30
13		6,000	33%	11,466	6.032145	00:07:40
14		7,000	30%	12,634	5.891077	00:06:47
15		8,000	26%	13,803	5.698162	00:09:41

Table 12: Results for EMS-clusters from simulated annealing calculations with ε=0.995.

S.A. Solution	α	Diff. Bench.	Diff. Pop.	Obj.	Runtime (hh:mm:ss)
Hospital – Clusters ε=0.995					
1	10	61%	1.53% - 10,612	3.375168	00:00:06
2	10	34%	1.16% - 8,045	2.816306	00:00:05
3	10	31%	1.71% - 11,860	2.756468	00:00:06
4	10	26%	1.37% - 9,502	2.648397	00:00:06
5	10	15%	0.93% - 6,450	2.420910	00:00:06
6	10	39%	1.64% - 11,375	2.913949	00:00:06
7	10	51%	0.55% - 3,814	3.159491	00:00:06
8	10	25%	1.22% - 8,461	2.617133	00:00:05
9	10	60%	1.92% - 13,317	3.358910	00:00:05
10	10	14%	1.32% - 9,155	2.390627	00:00:06
11	10	39%	2.55% - 17,687	2.909813	00:00:06
12	10	21%	0.94% - 6520	2.543864	00:00:05
13	10	40%	2.61% - 18,103	2.937376	00:00:05
14	10	15%	1.77% - 12,276	2.414526	00:00:06
15	10	48%	1.62% - 11,236	3.101697	00:00:06

Table 13: Results for hospitals-clusters from simulated annealing calculations with ε=0.995.

S.A. Solution	Diff. Bench.	Total Obj.	Total Runtime (hh:mm:ss)
Hospital- + EMS-clusters ε = 0.995			
1	66%	11.032447	00:07:30
2	43%	9.509614	00:07:30
3	37%	9.065442	00:07:33
4	27%	8.415344	00:07:30
5	27%	8.403635	00:07:49
6	60%	10.606841	00:07:04
7	39%	9.223513	00:09:04
8	25%	8.283296	00:06:39
9	35%	8.974375	00:06:35
10	18%	7.805334	00:07:34
11	42%	9.432875	00:07:57
12	27%	8.385164	00:06:35
13	35%	8.969521	00:07:45
14	25%	8.305603	00:06:53
15	33%	8.799859	00:09:47

Table 14: Total results for hospital- and EMS-clusters from simulated annealing with ε=0.995.

Appendix II

In this appendix two tables are given with the results of the S.A.-solution for the EMS- and hospital-clusters with ε=0.998. The combined results are shown in Table 6 in the results paragraph. For explanation of the column names, see Appendix I.

S.A. Solution	β -UB	β - LB	Diff. Bench.	Larg. Diff. Pop.	Obj.	Runtime (hh:mm:ss)
EMS-Clusters ε = 0.998						
4	4,000	7,000	18%	10,715	5.323466	00:18:37
5	4,000	8,000	22%	11,347	5.521821	00:19:20
8	5,000	6,000	18%	10,353	5.341427	00:19:10
9	5,000	7,000	17%	11,703	5.314526	00:19:14
10	5,000	8,000	14%	12,754	5.146138	00:17:16
12	6,000	5,000	22%	10,859	5.510132	00:18:33
13	6,000	6,000	8%	11,807	4.894616	00:20:48
14	6,000	7,000	10%	12,757	4.982508	00:17:47
15	6,000	8,000	8%	13,745	4.897195	00:16:58

Table 15: Result for EMS-clusters from simulated annealing calculations with ε=0.998.

S.A. Solution	α	Diff. Bench.	Diff. Pop.	Obj.	Runtime (hh:mm:ss)
Hospital-Clusters ε = 0.998					
4	10	34%	1.39% - 9,641	2.806417	00:00:05
5	10	28%	1.48% - 10,265	2.674713	00:00:06
8	10	25%	1.23% - 8,531	2.624987	00:00:06
9	10	37%	1.03% - 7,144	2.875171	00:00:06
10	10	56%	1.59% - 11,028	3.268441	00:00:05
12	10	53%	2.41% - 16,716	3.206705	00:00:06
13	10	30%	0.84% - 5,826	2.724137	00:00:05
14	10	28%	0.93% - 6,450	2.683409	00:00:05
15	10	38%	2.79% - 19,352	2.895848	00:00:05

Table 16: Results for hospital-clusters from simulated annealing calculations with ε=0.998.

Appendix III

In this Appendix two tables are given with results of the BIP-model for the hospital-clusters and results for EMS- and hospitals-clusters combined. The EMS-cluster results can be found in Table 3 in the sensitivity analysis paragraph. For explanation of the column names, see Appendix I.

BIP Solution	α	Diff. Pop.	Obj.	Runtime (hh:mm:ss)
Hospital-Clusters				
1	10	1.64% - 11,375	2.451652	00:01:13
2	10	1.37% - 9,502	2.292421	00:00:16
3	10	1.57% - 10,889	2.175382	00:03:10
4	10	1.30% - 9,016	2.363737	00:00:41
5	10	1.73% - 12,000	2.097550	00:01:16
6	10	1.73% - 12,000	2.032737	00:00:26
7	10	1.73% - 12,000	2.163120	00:00:48
8	10	1.73% - 12,000	2.071460	00:00:07
9	10	1.73% - 12,000	1.983343	00:00:09

Table 17: Optimal results for hospital-clusters from branch-and-bound.

BIP Solution	Total Objective	Total Runtime (hh:mm:ss)
EMS- + Hospital-Clusters		
1	7.093652	01:01:13+
2	6.897529	00:02:16*
3	6.735293	00:05:10*
4	6.964580	00:02:41*
5	6.627260	08:35:16+
6	6.501982	00:02:26*
7	6.699080	16:29:00+
8	6.577583	00:02:07*
9	6.416450	00:02:09*

Table 18: Total optima results for hospital- and EMS-clusters from branch-and-bound.

References

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4. Information about Norton Hospitals Louisville, www.nortonhealthcare.org .
5. Information about UofL Hospital Louisville, www.UofLhealthcare.org .
6. Information about Baptist Hospitals Louisville, www.baptisteast.com .
7. General information about healthcare US, www.newchoicehealth.com .