# Centralising maternity care access in England to achieve $24 / 7$ consultant presence 

Emma Villeneuve, Michael Allen<br>NIHR CLAHRC South West Peninsula, University of Exeter, United Kingdom<br>\{e.villeneuve, m.allen\}@exeter.ac.uk

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## 1 Introduction

The maternity network of England consists of 177 obstetric units. The Royal College of Obstetricians and Gynaecologists (RCOG) recommends a $24 / 7$ presence of senior obstetric staff in order to provide immediate medical care when necessary. In theory, such level of presence is possible in units with more than 6000 births per year. Our objective is to evaluate the necessary changes in number and location of maternity units in order to achieve 6000 births per year in all units.

## 2 Problem statement

Let's consider the space of possible locations given by the existing $H=177$ obstetric units of England. Combinations are described by vectors $\boldsymbol{u}=\left\{u_{1}, u_{2}, \ldots, u_{h}\right\}$, where $\forall i \in \llbracket 1 ; h \rrbracket u_{i} \in \llbracket 1 ; H \rrbracket$ without repetition. Given a number of $h \in \llbracket 1 ; H \rrbracket$ available units, we want to find the optimal combination of unit locations to optimize the following objectives:

1. Minimise the average distance from mother to available unit.
2. Minimise the maximum distance from any mother to available unit.
3. Maximise the proportion of births occurring in units with more than 6000 births per year.
4. Minimise the maximum number of admissions for any unit over 6000 births per year.

The first two coverage objectives aim at aligning facility locations with the population distribution. Based on admission numbers, the objectives 2 and 3 are specific to this study and can conflict in areas with sparse population. The objective 3 favours the creation of big units following RCOG recommendation. Facilities have unlimited capacity, but the number of admissions is limited through the objective 4.

With 4 objectives, comparing several solutions requires to refer to the notion of dominance: a vector $a$ of the objective space dominates another vector $b$ if all objectives of $a$ are better or equal to objectives of $b$ and $a \neq b$. Then, there is no best solution but a set of non-dominated solutions called the Pareto Front.

## 3 Method

Our study tackles a combinatorial optimization problem with four objective functions. The problem is to find the non-dominated combination of $h$ units in a list of $H=177$ possible locations. The maximum number of combinations is $1.1410^{52}$, reached with half locations available. Therefore, the brute force method cannot be used and the optimization problem must be solved by heuristic methods.

With such coverage problem, genetic algorithms were shown to produce the best results but are more computationally expensive [1]. Genetic algorithms manage a population of individuals encoded as vectors through a given number of generations. At each generation, 'good' parents are selected from the population, then combined using a cross-over operator, to create children which are finally mutated.

The NSGA-II [2] was chosen for this study after a comparison with SPEA2, MOEAD, and HypE which showed that it provided similar objective performances with a more diverse population. In this method, the tournament selection draws random pairs of individuals and keeps the fittest with a given probability [2]. The new population and the archive are merged and all individuals are ranked according to two steps. First, the merged population is split into layers of non-dominated fronts. Then, the spread of the population is measured by the crowding distance which gives the distance from an individual to its nearest neighbour. Finally, a given number of individuals is selected from the upper layers, preferably with the largest crowding distance.

## 4 Computation

Straight line distances were computed using a Geographic Information System software, between the 6832 Middle Super Output Areas (MSOAs) of England (country divisions with similar population size as defined in 2011) and the 177 existing maternity units. The numbers of births from 2012 to 2014 in existing maternity units were provided by the Hospital Episode Statistics database from NHS England.

The NSGA-II method [2] and the objective functions previously described were implemented using MATLAB software. Objective functions were normalised between 0 and 1 using extreme values. Fitness was computed as the average of normalised objective values. The MOO process was run independently for all $h \in \llbracket 1 ; H \rrbracket$, during 200 generations of 500 individuals. The outputs of the optimisation process are the final Pareto Front layers up to $P$ individuals and their corresponding objective values.


Figure 1: Proportion of births in units with more than 6000 births per year, as a function of the number of units. Optimal number of units to achieve a given proportion.

## 5 Discussion

According to the Figure 1, the current proportion 'over-6000' births, computed using data from 2012 to 2014 and 177 care units, is about $10 \%$.

There is an obvious strong correlation between the number of units and their size, and therefore the proportion of 'over-6000' births. Increasing this proportion implies to reduce dramatically the number of available units. To reach proportions of $100 \%, 95 \%, 90 \%$ and $80 \%$, we estimated that the maximal number of units should be $70,90,100$ and 115 .

In order to achieve $80 \%$ of births with $24 / 7$ consultant presence, the number of maternity care units should be drastically reduced from 177 to 115 . The effect of such centralisation may not be noticeable in main cities but it would be dramatic in term of distance in low-density areas.

## 6 References

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