# Vaccination Planning in Peru using Constraint Programming

Willy Ugarte[a]
*Universidad Peruana de Ciencias Aplicadas (UPC), Lima, Peru*

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Abstract: Vaccination has been proven to be the most effective method to prevent infectious diseases, specially nowadays with the global pandemic of CoViD19. Millions of people are not immunized yet in various countries because of low vaccine availability resulting from inefficiencies and/or lack of access to the vaccines. We propose a constraint programming model, kwnown as Constraint Satisfaction Problem (CSP) as a distribution model for vaccination to address the unique characteristics and challenges facing vaccine dose assignation. This CSP model capture the uncertainties of demand for vaccinations such as the age range of the vaccination campaign and the location of vaccination centers. The objective is to maximize the percentage of fully immunized people facilitating the access by location and capacity of the vaccination centers while respecting the health ministry dispositions (e.g., age range, number of doses, etc.). Our research examines how these can be optimized with a constraint optimization problem in a single objective function. We tested the model using Peru open data on vaccination planning of their national health ministry. We make many experiments to show the feasibility of our proposal to increase their immunization coverage.

## 1 INTRODUCTION

Due to the fact that a pandemic was generated by the CoViD19, in order to retain its transmission, many countries had to enter a situation of social isolation. This isolation brought with it many problems such as the closure of different public areas and negative effects on the country's economy. At present, after various months, a vaccine was developed that allows us to fight this virus, thus, vaccination centers need to organize themselves to be able to attend to unvaccinated people, therefore, a method is needed that relates these people, distributed in 5 different districts of Lima with the respective vaccination centers. Evenmore, Data about the vaccination process, such as vaccine identification and the number of persons who have been vaccinated, is crucial for vaccine manufacture and distribution in order to reach the target level of immunization in a country (Carniel et al., 2021).

Constraint Programming (CP) is a paradigm that allows solving combinatorial problems based on different techniques and that its success is based on its simple formulation, since it describes the problems in the form of decision variables where values are assigned and restrictions are established to find assignments to the variables with the established rules. For example, the solution of an optimization problem begins with a conversion of said problem to an appropriate CSP, which treats the objective function as one of the constraints, which after that evaluates the value of said function with all feasible solutions, and choose the best solution found.

Apart from this, another of the important characteristics of CP is its expressive modeling power and its great capacity to guarantee the determination of optimal solutions. That is, expressive modeling would help to create compact models that adapt to each different type of problem, while domain reduction through constraint propagation ensures the determining optimal global solutions, without getting caught up in local solutions. Besides, there are already various applications of CP for problems related to the Pandemic (Manlove et al., 2017; Nasrabadi et al., 2020; Ugarte, 2020).

From all that has been said previously, in this work we are going to rescue the main theories in order to create a CSP model in which it will be focused on vaccinations to Peruvian people in various regions. Thus, accelerating the vaccination process of the entire population, considering the distance of the patients to the vaccination centers, the age of the patients and the capacity of patients that a hospital has.

Our contribution are as follows:

[a] https://orcid.org/0000-0002-7510-618X



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- We propose that the challenge of assigning vaccinations to people be formulated as a Constraint Satisfaction Problem (CSP). The CSP model described here is simple to comprehend, and when combined with a CP toolkit[1], it produces an ideal outcome utilizing real data from Peruvian people.
- We illustrate how the CSP model can be used as a foundation for imposing additional restrictions, allowing us to handle versions of the bed assignment problem that may arise naturally in practice but are difficult to solve with existing algorithms.
- We show that CSPs are a simple paradigm that does not need training a model or obtaining any previous data, and that they are an elegant solution to address this type of problem by explaining the results.

This paper is organized as follows. Section 2 discusses related work. Section 3 introduces the relevant concepts and defines the problem formally, then presents our approach and our development. This is evaluated in Section 4 after which we show the results of our experiments, and finally we conclude.

## 2 RELATED WORKS

As various studies reveal, the majority of efforts on perishable inventory deal with food, particularly fresh produce (Bakker et al., 2012; Goyal and Giri, 2001; Li, 2010; Gregor et al., 2018). Although the study is based on public health, it is comparable to our environment in that it only evaluates one party, not the full supply chain.

In (Duijzer et al., 2018), the authors survey the literature on vaccine supply chains. The majority of these research focus on supply chain issues for one of two types of vaccinations: seasonal vaccines like influenza and non-seasonal vaccines like pediatric immunizations. Only a few studies in the literature present models for designing a cold supply chain network for influenza vaccines (Hovav and Tsadikovich, 2015). Some research look into the supply chain contracting issue with influenza vaccines (Chick et al., 2008; Dai et al., 2012). In contrast, our work does not aim to tackle the supply chain of vaccination, but rather its assignment process for the people.

Other research look at vaccine allocation decisions during pandemics (Westerink-Duijzer et al., 2017; Westerink-Duijzer et al., 2020). The focus of our research is only for CoViD vaccines.

Other methodologies, such as lean, simulation, and Markov decision process (MDP) models, have been employed in recent research on relevant topics in addition to these mathematical modeling approaches. In (Mofrad et al., 2014), the authos recently developed a Markov Decision Process model that calculates the best time to preserve vials based on the current vial inventory, time of day, and remaining clinic days until the next refill. The authors provide a realistic strategy for minimizing open-vial waste while giving sufficient vaccines. Based on this finding, the authors of (Mofrad et al., 2016) compared optimum and heuristic policies in the presence of random vial yield and examined numerous operational techniques to maximize coverage while controlling open vial waste. A simple-to-use decision-making tool was also created and made available online.

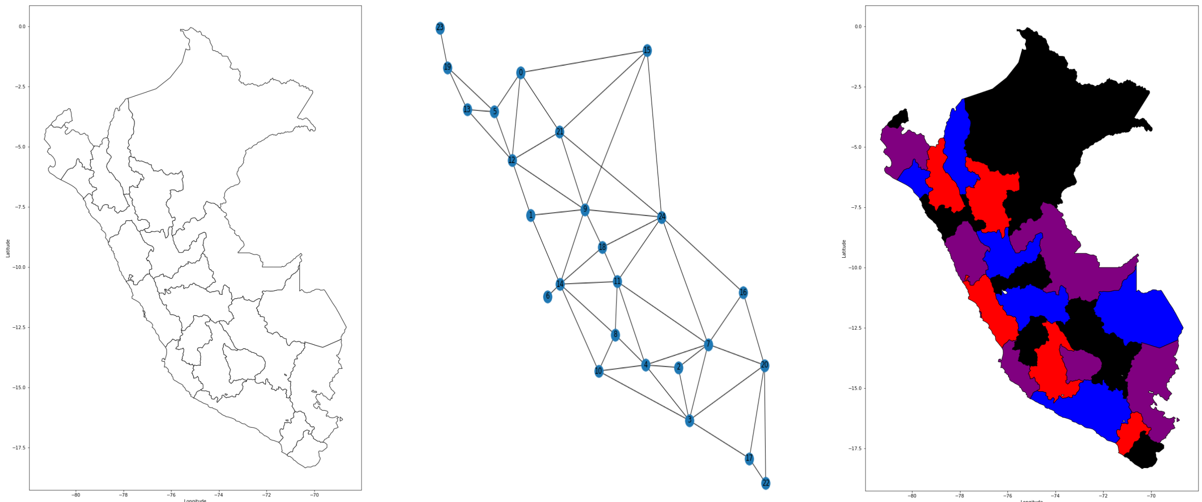
Patient scheduling duties fall into three categories, according to (Cardoen et al., 2010; Marynissen and Demeulemeester, 2019): Dynamic patient scheduling, dispersed patient scheduling, and coordinated patient scheduling. Unlike our strategy, which focuses on vaccination center assignment during a pandemic, all of these focus on enhancing hospital resources to reduce patient waiting times (Vermeulen et al., 2009).

There are numerous options for resolving the assignment dilemma. As an example, treating this problem with mixed integer-programming (Ben Bachouch et al., 2012; Turhan and Bilgen, 2017). In real-world scenarios, though, it's occasionally permissible to ignore some restrictions in order to cover others that are more important to their model. Hence the importance of soft constraints.

Contrarily, a few publications have attempted to solve this problem using different types of optimization techniques (e.g., genetic algorithms, local search, ...). In (Demeester et al., 2010), for example, the authors suggest a hybrid tabu search method that assigns patients to hospital beds automatically. Another example of a two-level metaheuristic to handle the operating room scheduling and assignment problem is described in (Aringhieri et al., 2015). They, on the other hand, interpret all patient requests as hard limits, whereas our approach incorporates preferences into the objective function.

To the best of our knowledge, none of these systems deal with simultaneous geolocation for multiple vaccination centers; rather, they employed it to locate people within a single health center or medical facility in order to optimize resources and reduce waiting times.

[1]OR-tools - https://developers.google.com/optimization



(a) Map of regions of Peru (b) Corresponding graph (c) Colored map of regions of Peru

Figure 1: Map of regions of Peru.

# 3 CP FOR VACCINATION PLANNING

Now, we introduce the main notions for defining the problem formally, for the sake of presenting our modeling in CP and its development.

## 3.1 Preliminary Concepts

Many countries' health systems are currently failing, particularly their capacities, due to a lack of cooperation and other issues. This problem is exacerbated for third-world countries, such as Peru, because their health systems were under-prepared and underfunded prior to the pandemic.

### 3.1.1 Problem Statement

Given the current scenario, it is critical to prepare a vaccination campaign with the goal of vaccinating the majority of the population in the event of a COVID-19 pandemic. Assigning people to vaccination centers is a difficult task that necessitates meeting a number of criteria. Like the number of dosages available at each site, the age of the individual, the location of the people, and the location of the centers are all factors to consider. With the aforementioned criteria, it is required that as many people as possible be assigned to vaccination centers as soon as possible. This problem can be simplified to two principles:

1. People should be assigned to the nearest center.
2. Older people should be assigned earlier than the rest.

### 3.1.2 Constraint Programming

**Definition 1** (Constraint Satisfaction Problem (CSP) (Rossi et al., 2006))**.** *A Constraint Satisfaction Problem (CSP) $P = (\mathcal{X}, \mathcal{D}, \mathcal{C})$ is defined as:*

- *a finite set of variables $\mathcal{X} = \{x_1, x_2, \ldots, x_k\}$,*
- *a set of domains $\mathcal{D}$, mapping every variable $x_i \in \mathcal{X}$ to a set of values $D(x_i)$,*
- *a finite set of constraints $\mathcal{C}$.*

The goal is to find a variable-to-value mapping that maps each variable $x_i$ to a value in its domain $D(x_i)$ while meeting all of the $C$ constraints. A solution to the CSP is the name given to this mapping.

**Example 1** (Graph Coloring)**.** *Graph Coloring is the process of coloring the vertices ($v_i$) of a graph $G = (V, E)$ so that no two neighboring vertices are the same color. The following CSP (see Definition 1) can be used to model this problem:*

- *$\mathcal{X} = \{c_1, c_2, \ldots, c_k\}$, where $c_i$ is the color variable for each node $v_i$ in $G$.*
- *$\mathcal{D} = \{1, 2, \ldots, m\}$, where each number represents a label for a color (e.g., 1 is blue, 2 is red, ...).*
- *$\mathcal{C} = \{c_i \neq c_j, \forall (i, j) \in E\}$, where each inequality ensures having no two adjacent vertices are of the same color.*

Fig. 1a depicts a map of Peru divided into regions. This map can be represented by a graph, as shown in Fig. 1b. The colored map matching to the Graph Coloring of 25 locations is shown in Fig. 1c.

**Definition 2** (Constraint Optimization Problem (COP) (Chen et al., 2020; Rossi et al., 2006))**.** *A constraint optimization problem (COP) is defined as $P' = P \cup \{f\}$, where P is a constraint solving problem (CSP) (see Definition 1) and f is the objective function to be optimized (either maximized or minimized).*

Apart from identifying mappings from variables to values, the task is to optimize (either maximize or minimize) these mappings in order to discover the best mapping based on an objective function $f$.

**Example 2.** *Example 1 is being continued. Consider the graph $G = (V,E)$ and the COP (see Definition 2) for Graph Coloring. $P = (\mathcal{X} = \{c_1, c_2, \ldots, c_k\}, \mathcal{D} = \{1,2,\ldots,m\}, \mathcal{C} = \{c_i \neq c_j, \forall(i,j) \in E\})$ and $f = \#of\,colors$ are defined as $P' = P \cup \{f\}$.*

Figure 1c shows the Graph Coloring of 25 regions with only 4 colors. This result is optimal since, it cannot be done with fewer colors.

## 3.2 CP Model

To model our problem as a CSP, we must first define a triplet $(\mathcal{X}, \mathcal{D}, \mathcal{C})$ that a solver will process and solve.

### 3.2.1 Variables

Let $C$ a set of vaccination centers, $V_i$ the set of available vaccine doses in center $i$ and $P$ be the set of people. The set of variables is defined as:

$$x_{ijk} \in \{0,1\} \quad \text{where} \quad (i,j,k) \in C \times V_i \times P \quad (1)$$

$$nd_k \in \{0,1,2\} \quad \text{where} \quad k \in P \quad (2)$$

$$age_k \in [0..100] \quad \text{where} \quad k \in P \quad (3)$$

If at the center $i$, the vaccination dose $j$ is taken by the person $k$, then $x_{ijk} = 1$. $nd_k$ is the number of doses received by the person $k$. $age_k$ is the age of the person $k$. The goal is to develop a set of variables that satisfy all of our requirements in order to correlate each vaccine dose of a center with a matching person.

### 3.2.2 Constraints

Constraints are crucial in a CSP model because they determine whether or not a variable assignment is possible and whether or not the problem can be addressed.

The following are the essential principles (i.e., hard limitations) that vaccination centers must follow in order to solve this problem:

- **There Must Be at Most a Single Person Assigned to Each Vaccine Dose**. This can be modeled as:

$$\forall i \in C, \forall j \in V_i, \sum_{k \in P} x_{ijk} \leq 1 \quad (4)$$

- **There Must Be at Most a Single Vaccine Dose Assigned to Every Person.** This can be modeled as:

$$\forall k \in P, \sum_{i \in C} \sum_{j \in V_j} x_{ijk} \leq 1 \quad (5)$$

- **If the Person is Already Vaccinated, He/She Must not Be Assigned to Any Center.** This can be modeled as:

$$\forall i \in C, \forall j \in V_i, \forall k \in P, x_{ijk} \Longleftrightarrow (nd_k < 2) \quad (6)$$

- **If the Person Is Not in the Age Range for Vaccination, He/She Must not Be Assigned to Any Center**. This can be modeled as:

$$\forall i \in C, \forall j \in V_i, \forall k \in P, x_{ijk} \Longleftrightarrow (age_k >= min_{age}) \quad (7)$$

Therefore, the CSP $P_{vacc} = (\mathcal{X}, \mathcal{D}, \mathcal{C})$ for this problem is defined as:

- $$\mathcal{X} = \left\{ \begin{array}{c} \{x_{ijk} \mid \forall(i,j,k) \in C \times V_i \times P\} \\ \bigcup \\ \{nd_k \mid \forall k \in P\} \\ \bigcup \\ \{age_k \mid \forall k \in P\} \end{array} \right\}$$
- $$\mathcal{D} = \left\{ \begin{array}{rl} x_{ijk} \in \{0,1\} & \forall(i,j,k) \in C \times V_i \times P \\ nd_k \in \{0,1,2\} & \forall k \in P \\ age_k \in \{0,..,100\} & \forall k \in P \end{array} \right\}$$
- $$\mathcal{C} = \left\{ \begin{array}{c} \{\sum_{k \in P} x_{ijk} \leq 1 \mid \forall(i,j) \in C \times V_i\} \\ \bigcup \\ \{\sum_{i \in C} \sum_{j \in V_j} x_{ijk} \leq 1 \mid \forall k \in P\} \\ \bigcup \\ \{x_{ijk} \Longleftrightarrow (nd_k < 2) \mid \forall(i,j,k) \in C \times V_i \times P\} \\ \bigcup \\ \{x_{ijk} \Longleftrightarrow (age_k >= min_{age}) \mid \forall(i,j,k) \in C \times V_i \times P\} \end{array} \right\}$$

### 3.2.3 Preferences

Preferences, also known as *soft constraints* (Bistarelli et al., 1995; Cooper et al., 2010), are highly desired; in other words, a solution to this problem should aim to fulfill them as much as feasible, but they are not required to find a solution. These are some of the rules:

- Ideally, every person should have access to a vaccination center if necessary. This can be modeled as:

$$\max_{sol} \sum_{i \in C} \sum_{j \in V_i} \sum_{k \in P} x_{ijk} \quad (8)$$

- If possible, everyone should be vaccinated at the closest vaccination center. This can be modeled as:

$$\min_{sol} \sum_{i \in C} \sum_{j \in V_i} \sum_{k \in P} \left( x_{ijk} \times distance(i,k) \right) \quad (9)$$

where $distance(i,j)$ is the distance from center $i$ from patient $k$.

- Mostly, elder people should be prioritized when there are not enough vaccines. This can be modeled as:

$$\max_{sol} \sum_{i \in C} \sum_{j \in V_i} \sum_{k \in P} (x_{ijk} \times age_k) \tag{10}$$

Preferences are not treated as a (in)equality, but as a maximization (resp. a minimization), because we prefer to satisfy them as much (resp. as least) as possible. These three preferences can be combined into a single goal function that can be optimized as follows:

$$f = \sum_{i \in C} \sum_{j \in V_i} \sum_{k \in P} \left( x_{ijk} \left( 1 - \frac{distance(i,k)}{\max_{dist}} + \frac{age_k}{\max_{age}} \right) \right) \tag{11}$$

The objective function (11) requests that the overall patient attention be maximized. It's worth noting that if $x_{ijk} = 0$, the person isn't counted in the total. The distance $distance(i,k)$ (resp. the age $age_k$) must be normalized by dividing it by the maximum value $max_{dist}$ (resp. $max_{age}$), yielding $\frac{distance(i,k)}{\max_{dist}}$ (resp. $\frac{age_k}{\max_{age}}$). Nonetheless, because the distance should be minimized and $f$ is maximized, the distance is negative. Therefore, the COP is defined as: $P'_{vacc} = \{P_{vacc} \cup \max(f)\}$.

# 4 EXPERIMENTS

In this section, experiments will be carried out to show the feasibility of our approach, starting from the experimental protocol and the results, as well as its discussion.

## 4.1 Experimental Protocol

All of the tests were carried out on a personal computer with a Linux operating system, an i5-8600 CPU core processor running at 3.10 GHz, and 16GB of RAM. The implementation was carried out in OR-tools[1]. All source codes and data sets are publicly available at https://colab.research.google.com/drive/13ndIi8BsgoY9gQrwpq_YcO_s-uTTwvVh?usp=sharing.

**Data.** In this case, two main sources of information were needed:

- **Vaccination Centers:** The information on vaccination centers in Peru, and their geographical location were found at https://www.datosabiertos.gob.pe/dataset/centros-de-vacunacion then exactly plotted with geojson with the Polygonal District Map of Peru at https://github.com/juaneladio/peru-geojson/blob/master/peru_distrital_simple.geojson.

  For instance, for districts of Cieneguilla, Ate, Chaclacayo, Lurigancho and La Molina, the 8 principal health centers are listed in Table 1.

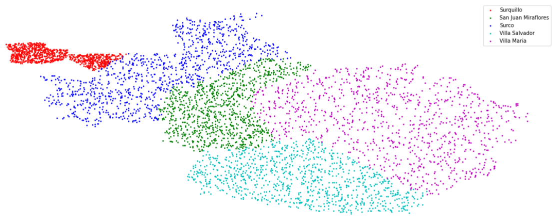


Figure 2: Example of people Distribution.

- **People:** For defining the quantity of people per district, information was used from the 2017 census of National Institute of Statistics and Information (INEI) at https://www.inei.gob.pe/estadisticas/indice-tematico/poblacion-y-vivienda/. Finally, for the vaccination capacity at the district level, we used statistics from the National Ministry of Health at https://www.minsa.gob.pe/reunis/data/vacunas-covid19.asp.

  The National Authority of Personal Data Protection protects people's geolocation data under Peru's National Law on Personal and Health Data (see http://bvs.minsa.gob.pe/local/MINSA/5118.pdf).

  Lacking real information about the location of infected people, it was required to generate locations following their pupulation distribution (see Fig. 2).

## 4.2 Results

Now, we report and discuss the numerical results on synthetic problems when comparing vaccination assignments of various combinations of districts.

Figures 3a and 3b show the location of vaccination centers for some districts in Lima, Peru, the location of people as colored points (red points are assigned according to their distance to the vaccination center and the age range allowed by the ministry, green points are people already vaccinated and blue points are people that are infected, and thus must wait in quarantine before vaccination).

Now, two test scenarios will be described. For the first one, only the districts of Cieneguilla, Ate, Chaclacayo, Lurigancho and La Molina will be considered, while in the second one, only the districts of Surco, San Isidro, San Borja, Surquillo y Miraflores will be considered.

Table 1: Lisf of 8 health centers.

| Id | District | Name | Latitude | Longitude |
|---|---|---|---|---|
| $C_1$ | La Molina | La Molina Center | -12.090 | - 77.017 |
| $C_2$ | Cieneguilla | Loza Deportiva Municipal | -12.092 | - 77.070 |
| $C_3$ | Cieneguilla | Tambo Viejo | -12.106 | - 77.046 |
| $C_4$ | Lurigancho | Mall Santa Anita | -12.101 | - 77.035 |
| $C_5$ | Chaclacayo | Pachacutec Stadium | -12.106 | - 77.055 |
| $C_6$ | Ate | Wholesale Market | -12.128 | - 77.017 |
| $C_7$ | Ate | Elitte | -12.103 | - 77.029 |
| $C_8$ | Ate | District Health Center | -12.115 | - 77.033 |

**Scenario 1 (See Figure 3a):**

For this case, only the districts of Cieneguilla, Ate, Chaclacayo, Lurigancho and La Molina will be considered. Ten execution tests were performed. An average execution time of 12.2 seconds was achieved, managing to assign 1,500 people.

**Scenario 2 (See Figure 3b):**

For this case, only the districts of Surco, San Isidro, San Borja, Surquillo y Miraflores will be considered. Ten execution tests were performed.

An average execution time of 36.1 seconds was achieved, managing to take 10,000 people. Also in Figure 3b, we can see that most of the centers have assignments from people nearby. Contrarily, some centers take assignments further, even if this might seem counter-intuitive, it may indicate that any of those center has a limited capacity. This happens because the objective function (see Equation (11)) tries to minimize distance and simultaneously maximize the attention.

**Time Analysis**

The typical execution times for allocating vaccination locations for a certain number of centers at a specific percentage of capacity with an age range are shown in Table 2.

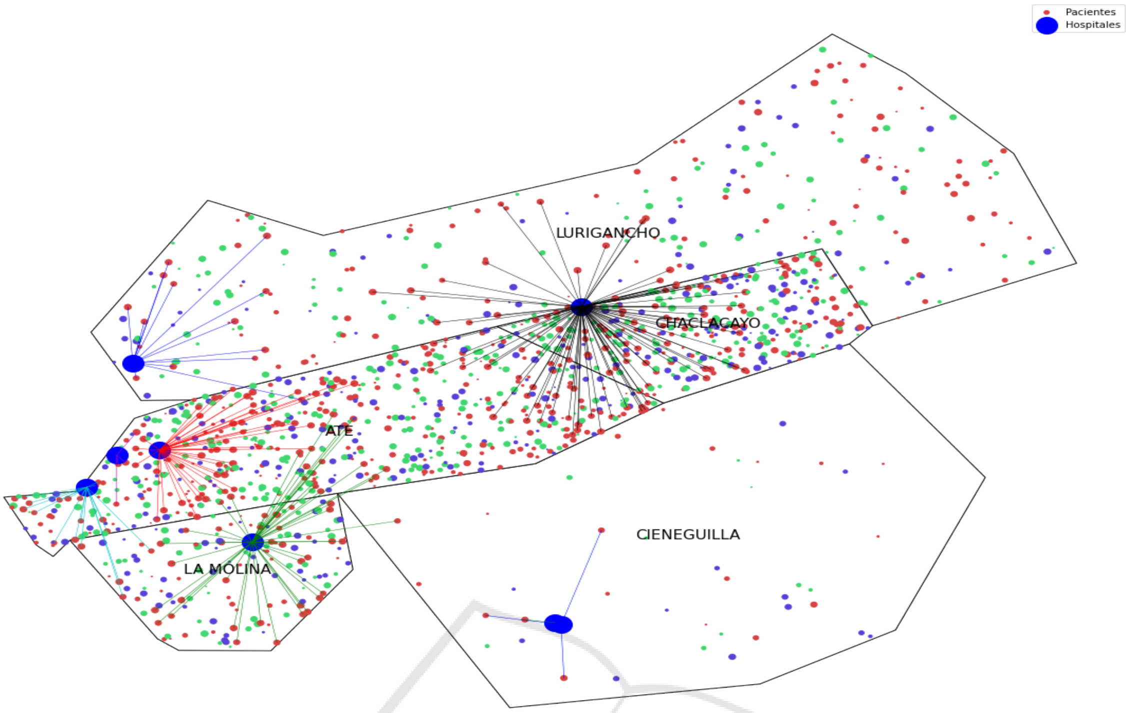
For instance, in Scenario 1, it takes 0.79 (resp. 1.71) seconds for 20% (resp. 100%) of centers to assign the people older than 60 years. For instance, in Scenario 2, it takes 2.41 (resp. 4.32) seconds for 20% (resp. 100%) of centers to assign the people older than 40 years.

Table 2: Times for assignments (in seconds).

| | % of Centers | | | | |
|---|---|---|---|---|---|
| | 20% | 40% | 60% | 80% | 100% |
| Scenario 1 | | | | | |
| $min_{age} = 60$ | 0.79 | 0.99 | 1.29 | 1.36 | 1.71 |
| $min_{age} = 50$ | 1.17 | 1.29 | 1.49 | 2.16 | 2.83 |
| $min_{age} = 40$ | 1.45 | 1.49 | 1.69 | 2.34 | 3.11 |
| $min_{age} = 30$ | 1.57 | 1.67 | 1.90 | 2.67 | 3.33 |
| $min_{age} = 18$ | 1.78 | 1.90 | 2.14 | 2.76 | 3.78 |
| Scenario 2 | | | | | |
| $min_{age} = 60$ | 1.67 | 1.93 | 2.33 | 2.46 | 2.81 |
| $min_{age} = 50$ | 2.25 | 2.36 | 2.47 | 3.26 | 3.93 |
| $min_{age} = 40$ | 2.41 | 2.45 | 2.65 | 3.43 | 4.32 |
| $min_{age} = 30$ | 2.48 | 2.64 | 2.99 | 3.72 | 4.45 |
| $min_{age} = 18$ | 2.67 | 3.88 | 3.21 | 3.86 | 4.87 |

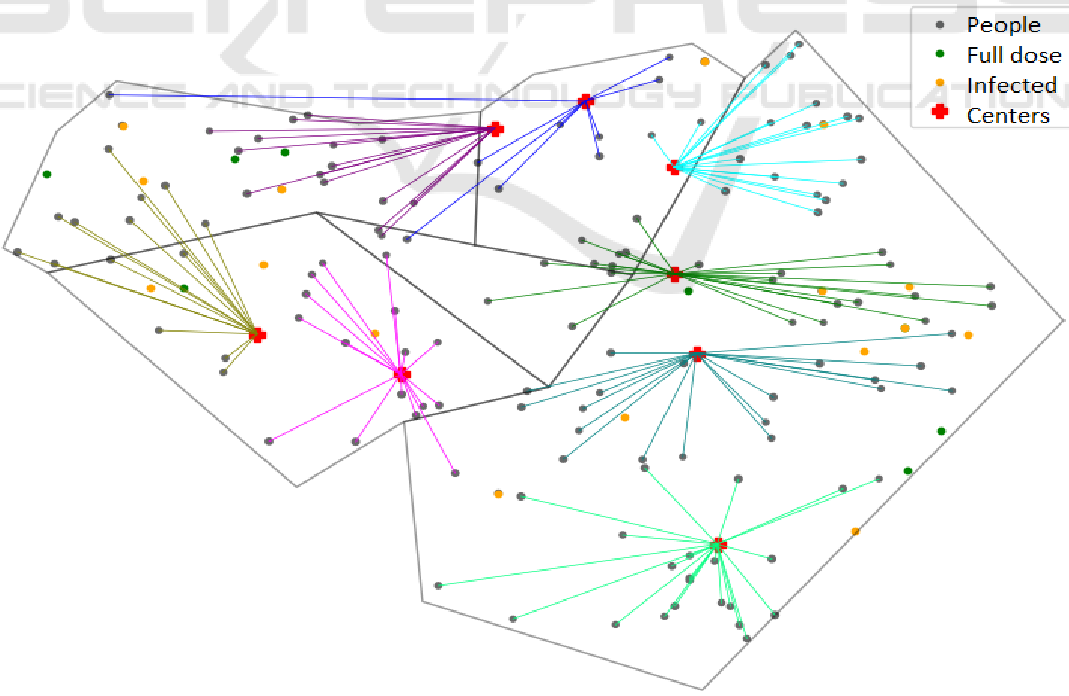
## 5 CONCLUSIONS

Throughout the development of this work, we have realized that it is possible to solve current problems using the CP paradigm, with useful information in Peru, that is easy to access. In addition, on the subject of heuristics, we have been able to observe that, through a good modeling of our exercise, it can be simplified to a few steps, which gives us to understand the importance of using Constraint Programming, which allows us to, both in the execution time and in the coding part, it provides us with great ease. This includes the use of objective functions, as we have seen in the part of restrictions, which we have been able to use as minimum objectives.




(a) Scenario 1






(b) Scenario 2

Figure 3: Comparison of vaccination assignments for Scenario 1 (a) and Scenario 2 (b).

On downfall, if this kind of problem is tackled with machine learning, is that it needs a lot of data to train, in Peru and in general, many times there is not enough (available) data. In contrast, CP works to find solutions from the data set that must respect given restrictions, optimizing an objective function with simple heuristics, without training or a lot of data.

As a future work, we would like to scale our approach, with more instances, or evenmore with new constraints that appear on the fly, for instance now some countries have a booster shots policies, that require to rethink some of the constraints, such as Dynamic CSPs (Verfaillie and Schiex, 1994)

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