# Demand estimation and logistics optimization of oxygen supply amid COVID-19 pandemic

By: Arnab Paul Choudhury
Varun Pandey

# 1 Problem statement

Let’s start with the problem at hand

## Some figures

# 7,127 MT*

Daily oxygen production capacity

# 8,500 MT*

Liquid oxygen produced

# 4,880 MT*

Demand for oxygen in 12 high-risk states

(*Figures as of 20 April)

## Major challenges

- Un-optimized demand-supply gap.
- Improper demand estimation.
- Turnaround time for pick-up and delivery over 1 week.
- Oxygen rich states concentrated in the eastern and southern regions of India.

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# Solution

Our methodology for solving the problem

# Characteristics of our Solution

Our solution to the problem statement is divided into two parts:

- Demand estimation using mathematical modeling.
- Optimizing allocation for given constraints.

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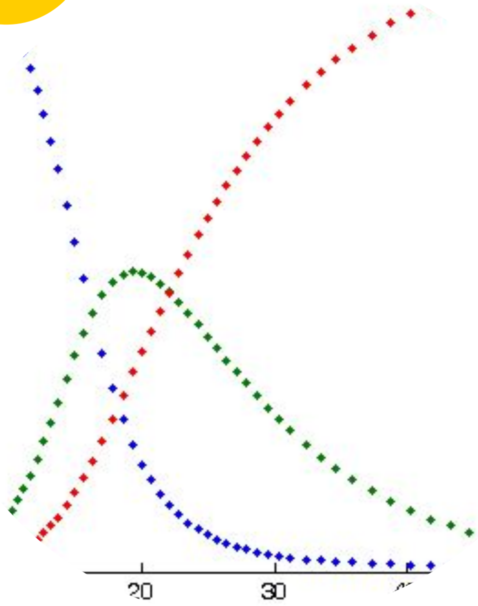
# Estimation of demand

Our approach for estimating demand of oxygen

## Characteristics

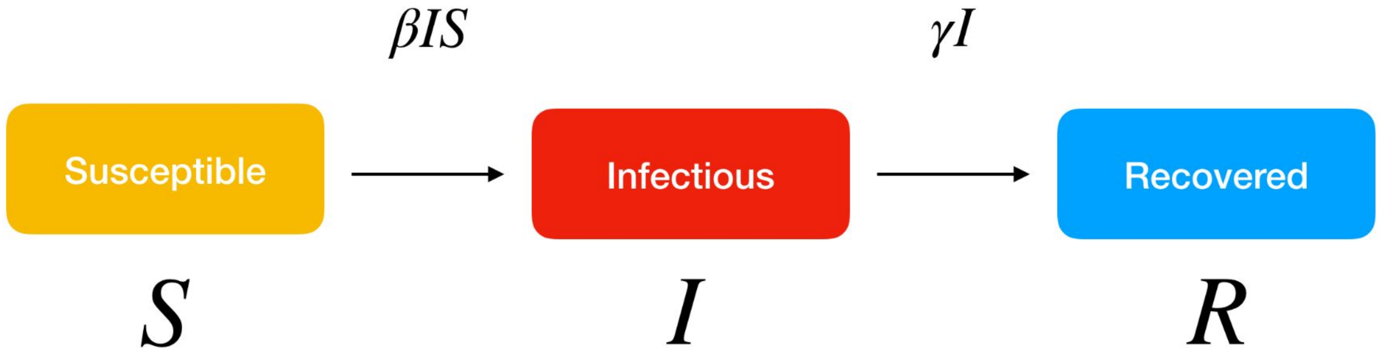
We have used two mathematical models to estimate demand for a particular state using previous data:

- SIR Model
- SUTRA Model




# SIR Model

## Flowchart of the model



## Important parameters

There are two key parameters used in the model:

- $\beta$ : Effective contact rate of the disease. A infected person comes into contact with $\beta N$ individuals per unit time, out of which the susceptible fraction is $S/N$.
- $\gamma$ : The mean recovery rate. The mean time taken for an infected individual to pass the infection is $1/\gamma$.

## Variables used in the model

***S(t)***

Population susceptible to the disease.

***I(t)***

People who have been infected with the disease

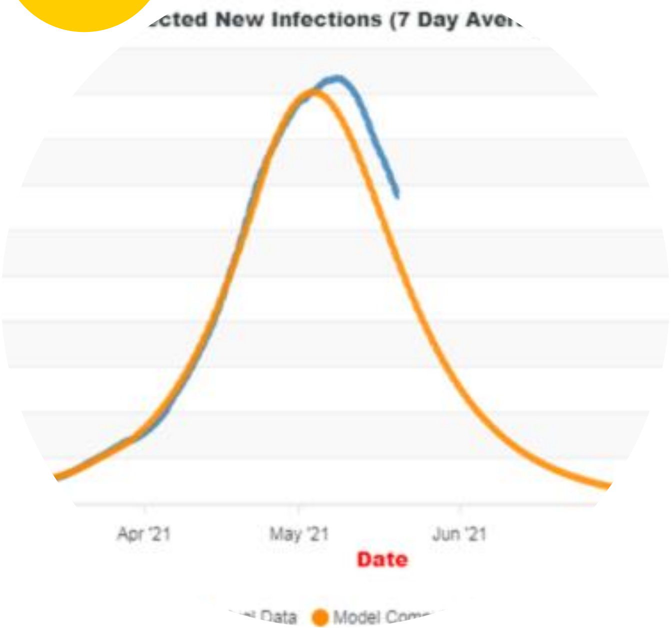
***R(t)***

People who have either recovered or died due to the disease,

## Equations used

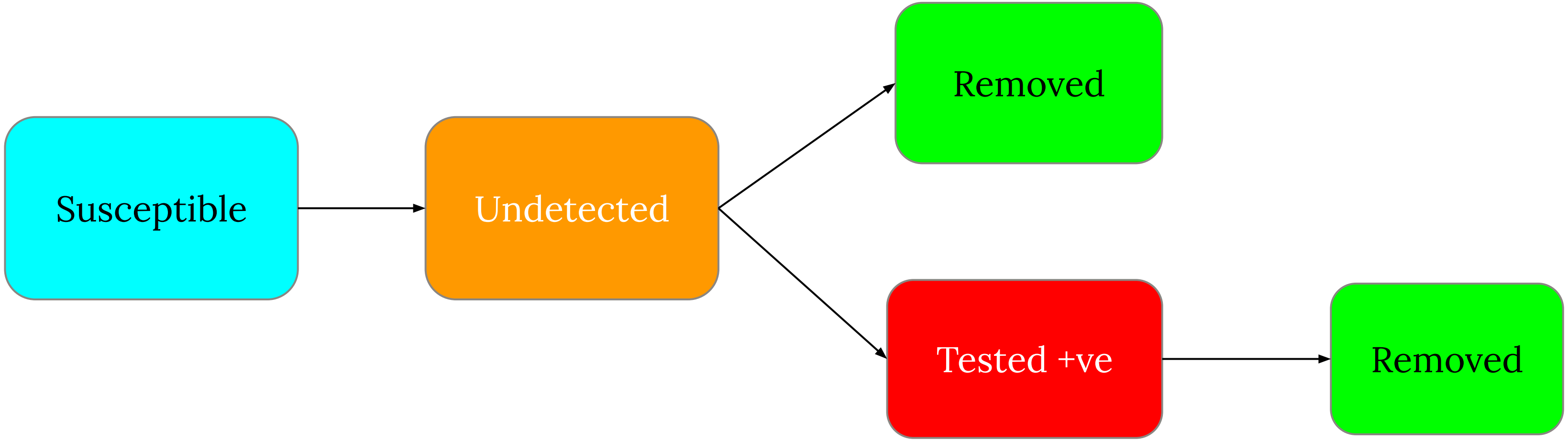
The set of equations used is as follows:

$$\begin{cases} \frac{dS}{dt} & = & -\beta SI \\ \frac{dI}{dt} & = & \beta SI - \gamma I \\ \frac{dR}{dt} & = & \gamma I \end{cases}$$




# SUTRA Model

# Flowchart for the model



## Important parameters

$\beta$

Effective contact rate of the disease. (Similar to SIR model)

$\gamma$

The mean recovery rate. (Similar to SIR model)

$\epsilon$

Ratio of detected infections to total infections.

## Variables used in the model

The model makes use of five variables:

- $S(t)$ : Number of people susceptible to infection.
- $U(t)$: Number of people who are undetected, but infected.
- $T(t)$: Number of people who have tested positive.
- $R_T(t)$: Number of recovered people who were tested positive.
- $R_U(t)$: Number of recovered people who were undetected.

## Equations used

The set of equations used is as follows:

$$\frac{\mathrm{d}S}{\mathrm{d}t} = \beta SU$$

$$\frac{\mathrm{d}T}{\mathrm{d}t} = \beta SU - \gamma T$$

$$\frac{\mathrm{d}U}{\mathrm{d}t} = \beta SU - \epsilon\beta SU - \gamma U$$

$$\frac{\mathrm{d}R_T}{\mathrm{d}t} = \gamma T$$

$$\frac{\mathrm{d}R_U}{\mathrm{d}t} = \gamma U$$

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# Optimising allocation of oxygen

Our approach for allocation of supplies

## Processing the data

- After running the models on our data, we obtained the estimated no. of cases in a particular state in one day for a timestep of 10 days.
- In order to get the estimated demand of oxygen in the state, we applied a conversion factor of 0.01, where:

No.of patients requiring oxygen on a given day (in MT) = 0.01 * Estimated no. of cases in the state on that day

# Methodology and constraints

- We have used least cost methodology to optimize the allocations with some constraints.
- Firstly, each person requiring oxygen will have an estimated demand of 3 MT per day.
- Secondly, the most preferred route will have a distance of less than 200 km, with second preference given to routes from 200 to 400 km, and least preference to longer routes.

## Methodology and constraints

- In order to calculate distance, we have assumed the states as to be points with latitudes and longitudes. The distance for a route from, say, supplier A to the state 1 would thus be the distance between their latitudes and longitudes.
- The suppliers have been assumed to be states as well.

# Dataframe for least cost matrix

| State/UT | 1 | 2 | 3 | …. | 36 | Supply capacity | supplied |
|---|---|---|---|---|---|---|---|
| Supplier | [a,b] | [a,b] | [a,b] | …. | [a,b] | r | s |
| 1 | [a,b] | [a,b] | [a,b] | …. | [a,b] | r | s |
| 2 | [a,b] | [a,b] | [a,b] | …. | [a,b] | r | s |
| … | …. | …. | …. | …. | …. | …. | …. |
| 17 | [a,b] | [a,b] | [a,b] | …. | [a,b] | r | s |
| demand | p | p | p | ….. | p | | |
| Demand fulfilled | q | q | q | ….. | q | | |

## Dataframe for least cost matrix

Where for each iteration:

- a is the distance between the supplier and state.
- b is the amount allocated to this state from the supplier.
- p is the estimated demand in the state.
- q is the demand fulfilled.
- r is the supply capacity of the supplier.
- s is the amount supplied by the supplier.

# Notes

## Possible improvements

- While we have used least cost method, we are also looking at other optimization methods which can be used for the dataset.
- The solution can be improved by considering other factors, such as unavailability of tankers, though this will affect the complexity as more variables will be needed to be introduced.

# Thank you