CS711A : Game Theory and Mechanism Design
Isolation versus Mobility Dilemma : Comparative study of models with Non-Cooperative Strategies

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Abstract

In this work, we establish the dilemma of a working individual during a pandemic, the predicament of choosing between commuting to work or staying back and work from home. We propose a mixed strategy profile for a *two-player non-cooperative game* between an individual and the Government. We find the **best strategy** probability values for both players such that they don't benefit on unilaterally deviating from that distribution. Our experiments are based on two economy-based pandemic models, SEIR-SH and Normalized.

1 Introduction

The ongoing worldwide pandemic of COVID-19 raises pertinent questions on new norms of social behaviour that needs to be established with respect to health and economic issues. We propose a game-theoretic model to address a recurring conundrum for two entities - a working individual and the government. Governments have implemented policies like quarantining the population, mobility restrictions and enforce social distancing regulations at public places. With an increasing barge of cases, India enforced the largest lockdown in the world. As the working population went out of daily work, the economy dived into a structural recession, reflected in huge drop of economic indicators like GDP, stock markets, increasing unemployment and inflation rates. As the lockdown was lifted in a staggered manner, economy took a reverse turn, albeit very slowly as much economic activity had halted by then.

Simultaneously, social distancing and self isolation became the norm with increase in usage of masks, sanitizers and PPE kits(conclusion). Self isolation establish negligible physical proximity between people and help arrest spread. But it exerts an economic cost on the individual. When the economy opened slowly, people commuted for work and other essential reasons maintaining social distancing. This strengthened economic activities by modelling behaviour realistically. With time herd immunity establishes its importance. When the population and recovered patients become immune to infection, temporarily or otherwise or as vaccine becomes available, government relaxes its policies on strict social measures.

1.1 Literature Review

In [**1**], an analytical model has been designed as an N player game. Model utility is derived summing two terms namely *Social distancing* and *Isolation*. A non cooperative game hits when government puts weights on the above two terms. Their results report that incentives provided by the government increases up to 85% when the percentage of home isolation is increased from 25% to 100%. In [**4**], consequences of COVID-19 on daily life has been explored from three aspects; Healthcare, Economic and Social.

Further, we discuss some literature built on epidemiological models. In [**2**], authors have modelled behavioral dynamics considering compliance and non-compliance of individuals with strict lockdown. Compliance with strict lockdown is associated with an economic cost while non-compliance adds infection cost to the overall utility. Simulations are conducted on compartmental epidemiological models (an extension of SIER compartmental model of epidemic [**10**]). Their results conclude that compliance with lockdown relaxes over time when cost of staying at home is high. In [**6**], controlled-SIR model evaluates effectiveness of actions (social distancing, lockdown, etc.) taken at the outbreak of pandemic. Containment Efficiency Index (CEI) is calculated for countries which measure the efficiency of containment policies. They also analysed total medical and socio-economic cost associated with containment policies. Interestingly their results report how containment policies, implemented over short period of time, yield higher cost than when implemented over longer duration.

Joel Hellewell et al.[**3**] developed a stochastic transmission model to measure the potential effectiveness of isolation and contact tracing with respect to spread of COVID-19. Model parameters include basic reproduction number R_0 (also modelled in [**5**]), initial number of infected cases, delay between symptom onset and isolation of individuals, probability "p" with which contacts were traced, proportion of individuals infected by an infected individual before symptoms were spotted. They assume asymptomatic transmission is the only way for the virus to spread and patients with symptoms are isolated. Their major findings built a relation between R_0 and proportion of individuals to be contact traced to control the outbreak.

1.2 Motivation

As we go through the literature, we find that most analytical studies related to pandemics are broadly classified into works on behavioural dynamics [**2**], vaccinating strategies [**12**], machine learning approaches of controlling spread [**9**] and epidemiological and clinical characteristics of the virus. In this project, we have focused on the health and economic costs to the pandemic simultaneously. We propose to find a best strategy probability distribution in the game for a month (it can be temporally scaled and decisions taken accordingly at a much quicker even at micro level). This can further be stretched where given an area and some user-fed parameters into the system, users get the probability of going out. We subsequently aim to stabilize economic and clinical payoff of an area and population while minimizing risks.

1.3 Problem Statement

Find the best strategy profile (probability distribution) for a two player (individual and government) non-cooperative game with complementary strategies. Here, one player's (government's) utility from one strategy depends on another player's (individual's) salary utility. We want to establish a mixed equilibrium between the strategies of the players where no unilateral deviation gives an overall better payoff. Thus in turn we achieve maximum overall utility in an area (minimizing pandemic spread and maximizing economic payoffs).

2 Analytical Model and Best Strategy Equilibrium

2.1 Strategies and Definitions

Each individual P has two strategies, either go **Out** or stay **In** home. Government G also has two strategies, it can either emphasize on **Economy** or focus on **Health**. We have designed this to be complementary strategies because government with limited resources can either push its resources (finances) to boost economy or improve health infrastructure and services. An interesting observation is the relationship between players in this game - an individual and government. Government's payoff from *Economy* and *Health* depend on the strategies every individual follows. Proximity is breached for 2 individuals P_1, P_2, when their distance $|P_1^x - P_2^x| + |P_1^y - P_2^y| \leq p$. (P_1^x, P_1^y) and (P_2^x, P_2^y) are (x, y) co-ordinates of P_1 and P_2 respectively. Two scenarios of before and after a move by nature (pandemic) can be represented by either a strict lockdown and one where the whole population (working and continuously moving) commute to their jobs.

2.2 SEIR-SH Model and Assumptions

We propose a pandemic model called SEIR-SH model. This is an agent-based model with deterministic strategy to simulate an SEIRS epidemic, although the meaning of each category differs from the SEIRS pandemic model. The SEIR-SH model **Figure 1** below shows how individuals move through each category in the model.

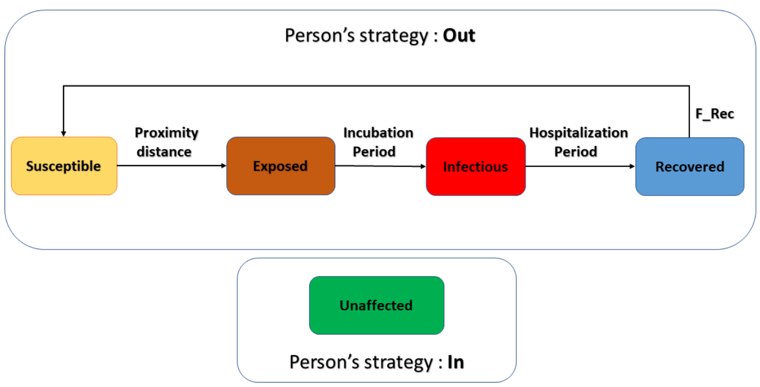

Figure 1: SEIR-SH Model

People choosing *Out* (categorized into *Susceptible(S)*, *Exposed(E)*, *Infectious(I)* and *Recovered(R)*) are prone to risk of contracting virus and individuals at home are categorized as *Unaffected*. Population Universe $U = \{S \cup E \cup I \cup R \cup H, |S| + |E| + |I| + |R| + |H| = N\}$. Susceptible individuals (people choosing **Out** to get more salary) may get *Exposed* by coming in contact with other *Exposed* people. They buy masks and protective equipment to protect oneself outside and lose a constant health utility. The government runs risk of losing a huge utility as sum of negative health utilities $\forall P \in S$. *Exposed* people continue receiving same salary but don't lose any health utility (as they cannot be at any more risk). They remain outside for the incubation period before symptoms are visible and they are hospitalized (shifting them to *Infectious* category). *Infectious* population don't work and don't get a salary. But they have to pay for medical bills, ventilators and specialized medical care losing health related utility. Government needs to maintain such medical infrastructure as hospital and medical staffs, so it gets negative utility too. **Infectious** people remain infectious for a mandatory hospitalization period before being discharged and becoming **Recovered**. They start receiving their salary again but don't bear any extra negative health utility. With some probability, **Recovered** people become **Susceptible** again (recovery doesn't guarantee immunity lifelong). The rest gain **herd immunity**.

Every individual $P \in (S \cup E \cup R)$ are assumed to get same salary S_S, while every $P \in H$ get salary S_H ($S_H < S_S$). Salary of *Infectious* person is 0. S, E, I, R and H are mutually exclusive and independent sets. The health cost for category S is $-H_S$. Similarly for infectious category I, health cost is $-H_I$. For category E and R, the health costs are 0. We make a standard assumption that each player chooses their non-cooperative strategies independent of other individuals [**8**] (don't imitate other players either). We assume all *Susceptible* person wear a mask while outside. We also assume everyone works for a fixed number of hours per day and a fixed number of days per week (that is the only time they move in the day).

		Government	
Strategies		**Economy** (α)	**Health** $(1-\alpha)$
Out (β)	**Susceptible(S)**	$S_S, \sum_{\forall p \in S} S_S$	$H_S, \sum_{\forall p \in S} H_S$
	Exposed (E)	$S_S, \sum_{\forall p \in E} S_S$	0,0
	Infectious (I)	0,0	$H_I, \sum_{\forall p \in I} H_I$
	Recovered (R)	$S_S, \sum_{\forall p \in R} S_S$	0,0
In $(1-\beta)$	**Unaffected (H)**	$S_H, \sum_{\forall p \in U} S_H$	0,0

Table 1: Utility Matrix in **SEIR-SH model** (Person Vs Government)

In Table 1, $S_S = Constant$, $S_H = \frac{1}{f_{sal}} \cdot S_S$, $H_S = R \cdot N_E$, $H_I = Constant$ and R can be calculated using equation 1

$$R = \begin{cases} \frac{N_E - {N_E}^{previous}}{{N_E}^{previous}}, & \text{if} {N_E}^{previous} \neq 0 \\ 1, & \text{otherwise} \end{cases} \tag{1}$$

2.3 Objective Function

Average utility from salary and health for a player P, when P chooses strategy **Out** is calculated by for *Susceptible(N_S)*, *Exposed(N_E)*, *Infectious(N_I)* and *Recovered(N_R)* players.

Utility of a player P choosing *Out* from *Economy* and *Health* is :

$$U_P^{Out} = \alpha \cdot \left[\frac{S_S \cdot (N_S + N_E + N_R)}{(N_S + N_E + N_I + N_R)} \right] + (1-\alpha) \cdot \left[\frac{N_S H_S + N_I H_I}{N_S + N_E + N_I + N_R} \right] \tag{2}$$

Utility of a player P, choosing *In*, from *Economy* and *Health* is :

$$U_P^{In} = \alpha \cdot S_H \tag{3}$$

Utility of a player P from *Economy* and *Health* given best strategy profile (α, β) per day is :

$$U_P(\alpha, \beta) = \alpha\beta \cdot \left[\frac{S_S \cdot (N_S + N_E + N_R)}{(N_S + N_E + N_I + N_R)} \right] + (1-\alpha)\beta \cdot \left[\frac{N_S H_S + N_I H_I}{(N_S + N_E + N_I + N_R)} \right] + \alpha(1-\beta) \cdot S_H \tag{4}$$

By equating Eq 2 and 3, we can find α each day. With this probability, government can prioritise between its strategies daily. The β we obtain by maximizing Eq 4 in that month (over a plot) is the best strategy for P, from which it should not deviate for the following month.

Utility of government G from players choosing strategies either *In* or *Out* given best strategy profile (α, β) per day is :

$$U_G(\alpha, \beta) = [\beta\alpha \cdot (S_S \cdot (N_S + N_E + N_R))] + [(1-\beta)\alpha \cdot (S_H N_H)] + [\beta(1-\alpha) \cdot (H_S N_S + H_I N_I)] \quad (5)$$

2.4 Simulation Setup and Experiments

Our simulation runs on a square grid denoting a region with N people randomly distributed at the beginning of the experiment. Initially **N = {1000,2000}** people are given tags. Tag H doesn't change throughout one experiment. Given tags S, E, I or R, they change amongst themselves deterministically throughout the experiment but don't affect H at all through one experiment. All tags are set before a simulation starts. We fix α, β at the start of the simulation (remains constant during one experiment) and calculate utility of P, U_P everyday. In our simulation we don't allow P to vary β. We sum U_P of each day over **Duration: {60,90}** days of a simulation and find average utility per day for P. So we fix α and varying β between {0,1} of interval size 0.1, we maximize Eq 4 over the duration of simulation (plot in graphs).

Parameters : At the start of experiment, N is divided into three categories. $p\%$ (assumed to be the previous best strategy probability) of people are initially moved randomly (individuals don't follow a fixed path) in a grid of size **GS = {(500,500), (1000x1000), (1500x1500)}** (to model those who chose **Out** and assumed to get salary S_S **= 360** and considered to get minimum wage working 8 hours per day). $(100 - p)\%$ gets a **fraction** $f_{sal} = \frac{1}{10}$ **of** S_S, working from home. The value of H_I, which is the hospital cost per day, has been taken to be 500 in our simulation. Amongst people outside, fraction $f_{EBeg} = \frac{1}{100}$ are presumed **Exposed** (set at the beginning to model previous exposed population). This fraction just determines the exposed population in the experiment only once.

In simulation, *Susceptible* people move randomly and may come in proximity **(ProxDist= 5 units)** of **Exposed** people, getting themselves exposed and losing some health utility H_S. **Exposed** people receive salary but don't lose any health utility. After **Incubation period = 5 days**, **Exposed** people are hospitalized and moved to *Infectious* category. *Infectious* people remain **hospitalised for 15 days**, discharged to a **Recovered** tag. Now they again receive their salary but don't bear negative health utility anymore. A **fraction** $f_{Rec} = \left[\frac{1}{10}, \frac{6}{10}\right]$**th** of **Recovered** people become **Susceptible** again and others develop **herd immunity**.

α is calculated everyday of the duration by equating Eq 2 and 3 with updated values after each day, given β is fixed for a simulation. Once we fix α for a day, for $\beta = \{0, 0.1, 0.2, ..., 0.9, 1.0\}$, maximize U_P to get best strategy values for corresponding α.

Code Repository : https://github.com/9paramraol/CS711_2020

2.5 Results

1. Our model has varying population in SEIR-SH categories as shown in figure 2 (it has 2 peaks, one around day 35 and other around day 78, corresponding to I). After sometime, the number of *Susceptible* people becomes almost constant and we get higher first peak and a lower second peak.
2. With reference to Figures 3, 4 and 5, government give more importance to *Health* by undertaking relevant policies like lockdown. But later it starts giving more importance to *Economy* and we predict that government will focus on *Health* again in future. This graph denotes daily variations of α to get best U_G on that day.

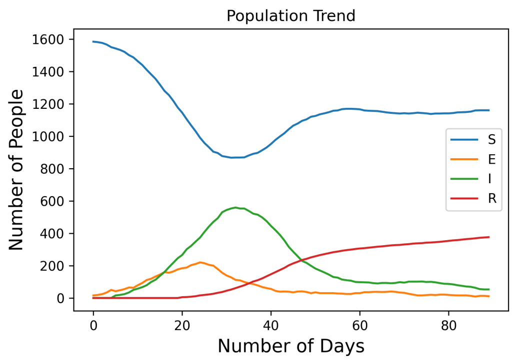

Figure 2: $(a) duration = 90, N = 2000, f_{EBeg} = 0.01, GS = 1500, ProxDist = 5, Beta = 0.8, f_{Rec} = 0.7$

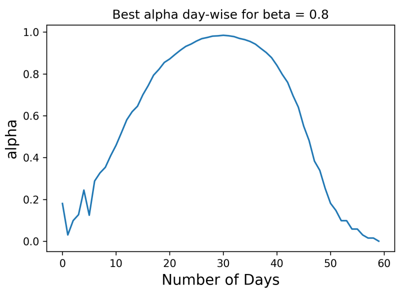

Figure 3: Beta = 0.8

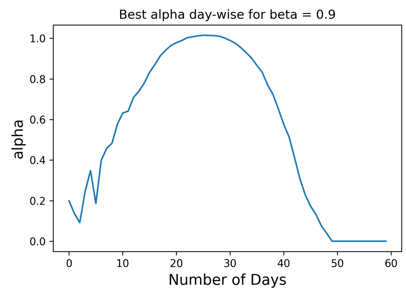

Figure 4: Beta = 0.9

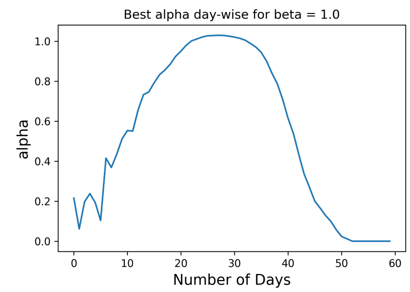

Figure 5: Beta = 1.0

3. With reference to Figures 6, 7 and 8, β denotes the fraction of population who select strategy *Out* so that they get maximum total utility. As we observe the plot, when government favors *Health*, it's suggested that around 60% population should work. As government shifts probability towards *Economy*, the best β slowly shifts toward 100%.

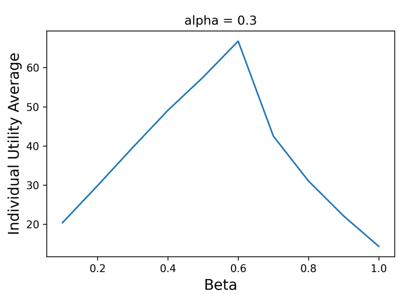

Figure 6: Beta = 0.3

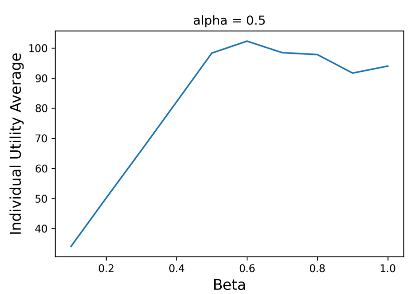

Figure 7: Beta = 0.5

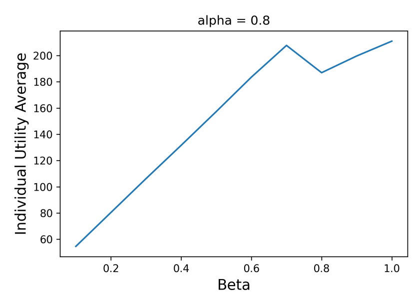

Figure 8: Beta = 0.8

3 Conclusion

A pertinent question is why would a certain percentage of population remain at home and sacrifice salary instead of going to work. Due to fear of getting exposed, avoiding hospital visit if they become infectious, option of work from home albeit lower salary and to refrain infecting family members, individuals may prefer to go outside only during emergencies and for essential needs. Modelling this as a static yet continuous game help us understand social learning dynamics and analyze its effect on the population's psyche. It also gives us insight into the government's perspective, as an enforcer of policies, to achieve social equilibrium and increase individual onus on taking responsibility for their choices. The socio-economic costs of such policies eventually determined their effectiveness.

Government, on average, favors both *Health* and *Economy* as strategies interchangeably. The best strategy profile that we find from the simulation is $\alpha = 0.5$ and $\beta = 0.6$. This signifies that even though government changes α daily, over time its probability is normalized to 0.5 (i.e it supports both of its strategies equally). An individual should choose strategy *Out* for going to work with probability 0.6. This maximizes his utility over duration of the pandemic.

4 Future Work

This project can be extended to helps us analyze whether presented with the probability of going out or putting muscle into economy, what an individual and government prioritizes respectively. Also these can be modelled over time and make predictions on movement of individual and economic benefits. A parallel **Vaccinated** category can be drawn from the whole population who chooses *Out* and receive economic payoff when vaccine is available. This population won't receive any negative health utility from being outside. Individuals with profession related to health like doctors, nurses, COVID warriors by donating plasma can be modelled to get both salary and increase government's health utility. They can be put into **Vaccinated** category.

Different age groups can be modelled in the population and selective age group wise best strategy policies can be implemented by the government. We did not account for people who lost their lives in pandemic (this may be modelled as *Infectious* people dying with a negligible probability, but costing a huge negative utility for the government. The non-working population may also be modelled in future, simply giving a negative health payoff to the government if they are allowed to move outside.

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Appendix : Normalized Model

Out of N individuals, we assume a factor β of the total population choose strategy **Out**, i.e they commute to work daily by moving in the grid and earning a salary. Individuals belonging to $(1-\beta)$ choose strategy **In**. Both these groups receive salaries proportional to the number of hours they work.

Analytical Model and Assumptions

Every individual is classified as *Affected(A)* (if he commutes to work everyday) or *Unaffected(C)* (if he stays at home). Total population $|A|+|C| = N$, A and C are mutually exclusive. $P \in A$ and $P \in C$ receive salaries $S_A = \log(Sh)$ and $S_C = \log(sh)$ respectively ($S > s$ and h is the number of hours they work). Player $P \in A$ receives payoff $U_P^A = (\log(Sh) - R \cdot [\log(d_i)])$. Player $P \in C$ receives payoff $U_p^C = \left[\log(sh) - \frac{1}{f}\left(\frac{R}{|A|}\sum_{\forall p \in A}\log(d_i)\right)\right]$. R is the reproduction rate of the virus [**11**]. f is a small fraction of the average negative health of $P \in C$, modelled as self-isolation utility.

Similarly, government's economic and health payoff is sum of every individual's salary and health utilities in respective categories. Government chooses between its strategies of either putting priority on economy (by increasing α) or on health of its citizens (by decreasing α). Government's payoff from the *Economy* and *Health* can be denoted by Eq 8 and 9 respectively. Individual and government's payoff are shown in Table 2 below :

		Government	
Strategies		**Economy** (α)	**Health** $(1-\alpha)$
Out (β)	**Affected(A)**	S_A, $\sum_{\forall p \in A} S_A$	-SocDis, $\sum_{\forall P \in A}$ -SocDis
In $(1-\beta)$	**Unaffected(C)**	S_C, $\sum_{\forall p \in C} S_C$	-(SocDis/f), $\sum_{\forall P \in C}$ -(SocDis/f)

Table 2: Utility Matrix in **Normalized model** (Person Vs Government)

Objective Function

Utility of an individual P from Economy and Health with strategy Out is :

$$U_P^{Out} = log(Sh) - R\left(\sum_{\forall t} log(d_i)\right) \tag{6}$$

Utility of an individual P from Economy and Health with strategy In is :

$$U_G^{In} = log(sh) - \frac{R}{f}\left(\frac{1}{|A|}\cdot\sum_{\forall t}\sum_{\forall p\in A}\log(d_i)\right) \tag{7}$$

Total utility from *Economy* and *Health* received by the government from its whole population, denoted with $U_G^{Economy}$ and U_G^{Health} respectively are given by Eq 8 and 9.

$$U_G^{Economy} = \left[\sum_{\forall p\in A} log(Sh) + \sum_{\forall p\in C} log(sh)\right] \tag{8}$$

$$U_G^{Health} = -R\sum_{\forall t}\left[\cdot\sum_{\forall p\in A} log(d_i) + \frac{1}{f}\left(\frac{1}{|A|}\cdot\sum_{\forall p\in C}\sum_{\forall p\in A} R\cdot\log(d_i)\right)\right] \tag{9}$$

Total utility for the Government is denoted by $U_G = U_G^{Economy} + U_G^{Health}$.

Experimental Setup

We run our simulation on a square grid denoting a certain region with a certain population where players are randomly distributed at the beginning of the experiment. Tags A or C are assigned to an individual before the simulation starts and it doesn't change throughout the experiment.

Parameters of simulations : We consider the following factors and their corresponding values in our simulation :

- Grid Size (GS): 250x250, 500x500, 1000x1000.
- Number of people in U (N) : 500, 1000, 1500, 2000.
- Salary per $p \in A$ per hour (S) : 360.
- Salary per $p \in C$ per hour (s) : 0, 36, 18
- Fraction of average utility lost in self-isolation ($\frac{1}{f}$) : $\frac{1}{5}$, $\frac{1}{10}$, $\frac{1}{20}$.
- R-factor (R) : 1.5, 1.7, 2

In order to optimize government's overall utility, we analyze the graph obtained for a given α to β for various percentage of people outside. We created the simulation in Python. Initially, we take N people in a grid of size GS and randomly place all the people in it. We tag β factor of the population with A and the rest with C. All individuals work for 8 hours a day and 6 days a week. A population moves continuously. We vary β from $\{0, 1\}$ as follows : $\{0, 0.05, 0.1, ..., 0.95, 1.0\}$ and utilities calculated for different values of N, GS and α are observed.

Results

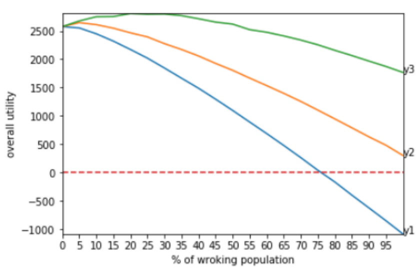

Figure 9: Effect of density

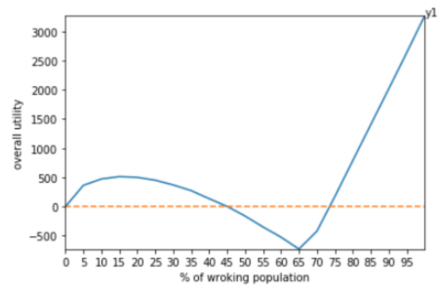

Figure 10: Too high density

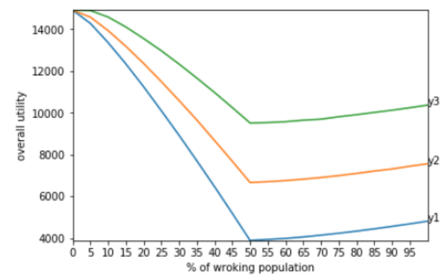

Figure 11: $\alpha = 0.7$, $\beta = 0.3$

Impact of Population Density : Fixing values $N = 500$, $S = 360$, $s = 0$, $\frac{1}{f} = \frac{1}{100}$ and $R = 2$, we varied the grid size GS ={250x250, 500x500, 1000x1000}, The first graph shows that as density is reduced, optimal percentage of people allowed to get out to get maximum utility for government increases.

Too high population density: Fixing values $N = 1500$, $S = 360$, $s = 0$, $\frac{1}{f} = \frac{1}{100}$ and $R = 2$, we varied the grid size GS ={500x500}. The second graph shows that the global maxima occurs when all the people choose **Out**. The reason is explained in Conclusions below).

Impact of Population Density : Fixing values $N = 500$, $S = 360$, $s = 36$, $\frac{1}{f} = \frac{1}{100}$ and $R = 2$, we varied the grid size GS ={250x250, 500x500, 1000x1000}, The third graph was obtained, so maxima occurs when 100% people work from home even if they receive one-tenth of the salary that people outside get.

Conclusions and Future Work

- From the first graph the conclusion is that the government can allow more people to get outside if the density of the place is less although to get the optimal percentage of people to get out and work will depend on the maxi ma.
- From the second graph the conclusion is that there is not point in allowing 70% of people to get out as compared to 100% of people cetris-paribus. as the negative payoff received after 60% saturates because it is not possible to maintain it after 60% of people get out.
- Even if as small as 10% of wage is given to the people who work from home it is beneficial for the government to not allow any person to get out.

Government can introduce other strategies such as environment and individuals can consider mental health as decreasing health utility while staying at home [**7**]. This would make the model more realistic and exhaustive.