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# An Incentivized Crowdsourcing Network for Contact Tracing

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***Abstract*—It is a well-known fact that contact tracing is an effective mechanism for identifying and isolating "at risk" individuals from population who came in contact with infected individuals. In this paper, the authors propose a contact tracing mechanism which uses smartphones to automatically establish contact between their owners when they are in close proximity to each other. On the backend of the mechanism, a graph data structure is maintained where the vertices of the graph denote the individuals and the edges denote contact between them. This allows for not only maintaining information about direct contact between individuals but also maintains secondary contact information and helps in clustering. Since the maximum possible engagement is required from users to generate the best results, therefore, an incentive model is also discussed in the paper to provide "rewards" to users depending on their level of engagement.**

***Keywords—contact tracing, mobile network, crowdsourcing, incentive mechanism***

## I. Introduction

Contact tracing process is a traditionally used technique for removing individuals who have come into contact with infected individuals from the general population so that if and when the individuals become infected, they cannot transmit the disease further. Along with this, the other aim of contact tracing is to identify and provide the "at risk" individuals with healthcare services as quickly as possible. Generally, this contact tracing procedure is undertaken by medical staffs and are done manually. Whenever individuals test positive for an infection, they are inquired about the people they have come into contact with. These individuals are then kept under observation or isolation, depending on the nature of the disease.

Contact tracing is considered as an important procedure that can help in controlling the spread of infection during an endemic or pandemic scenario. For example, during the spread of Severe Acute Respiratory Syndrome, contract tracing was deemed successful to a certain extant [1]. Even in the case of COVID-19 pandemic, where there are massive similarities between the virus and SARS [2], contact tracing procedures are being considered effective in controlling the spread, although empirical research needs to be done to confirm this claim.

However, to be effective, contact tracing needs to be done in a rapid pace. The individuals who came into contact with infected personals need to be identified, tracked and isolated as quickly as possible so that they do not have the time to spread the disease further. In the foot and mouth disease epidemic that took place in 2001, contact tracing was considered ineffective because enough number of dangerous contacts were not identified & removed quickly [1] [3].

Manual contact tracing, is generally thought of as time consuming and depends on the information provided by the infected person [4], which may not be reliable all the time.

These issues, combined with the fact that about 3.5 billion people have access to smartphones worldwide [5] motivated us to create a contact tracing algorithmic model that automatically establishes and maintains contact information between individuals. The mechanism only requires Bluetooth facility and basic internet connectivity, both of which are available to a large section of the population. Also, the algorithms in the paper are general in nature and can be tweaked as per the nature of the disease.

## II. Brief Review of Related Works

The interconnectedness of epidemic and contact tracing networks is a well-studied topic with numerous literatures published. In this paper [6], the authors investigated the utility of contact tracing for disease control and found a relationship between the efficiency of contact tracing for eradication of the disease and the reproductive ratio of the disease. The authors concluded that the efficiency was also dependent on the disease along with other constraints.

In this review article [7], the authors analyze and explain the most common types of networks that are implemented in studying the spread of diseases. One of the studied networks is the traditional "Contact Tracing Networks" where the authors remark that although these types of networks can provide good information about past outbreaks but they have very less predictive power because these networks may not take into account some potential important contacts.

From the traditional manual contact tracing method, the paradigm is shifting towards implementing computer techniques for tracking and controlling infected or high-risk population. This is partially due to the fact that computers have become cheaper and more accessible to general population. India's new initiative to track covid-19 patients and suspects came in the form of a mobile application named "Aarogya Setu" which along with tracking also provides other services such as online consultation [8]. The authors of this paper [9], developed an IOT based wearable band for



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detecting and tracking COVID-19 subjects. Another IOT based paper [10] proposes a non-removable IOMT wearable device named “EasyBand” whose objective is to limit the growth of COVID-19 cases when stay-at-home restrictions are lifted.

These emergence of IOT based devices and mobile applications show that contact tracing is shifting from manual to digital.

## III. NEED FOR INCENTIVE

The effectiveness of the contact tracing procedure is highly dependent on the amount of user engagement. The maximum possible number of users need to contribute in the system to make it efficient. Hence, the proposed method relies on a typical crowdsourcing mechanism. More specifically, it can be considered as an opportunistic crowdsourcing mechanism, where the input information is generated by the crowds’ devices automatically [11]. For this, the application needs to be running in the background which adds to the cost of the user. Along with the cost, there is also a risk exposure of user privacy being compromised. These factors generally limit the amount of user engagement required for optimum results. We argue that to compensate the users for their contribution and to encourage higher level of engagement, the digital contact tracing mechanisms require a carefully designed reward component in which the users are rewarded based on their contribution. This reward can be monetary or otherwise, but nevertheless it will ideally generate more engagement compared to a purely voluntary mechanism.

## IV. PROPOSED MECHANISM

The mechanism is further categorized into 3 separate sections. In the first section, we tackle the technological aspect of the mechanism, in the second section we propose the procedure of creating and maintaining the graphical network in the background and in the third section we address the incentive model to reward users based on their contribution.

### *A. Technological Model*

Contact tracing in the case of STIs/STDs is simple in the sense that we have a clear definition of a dangerous contact. However, in the case of other diseases such as SARS or COVID-19, the definition of a dangerous contact becomes ambiguous. Therefore, it is safe to assume that individuals who have come into close geographical proximity of infected individuals are at risk of being infected and act as carriers for the pathogen.

Hence, for designing a smartphone-based contact tracing mechanism for such diseases, the most logical solution seems to be the usage of Bluetooth technology. Bluetooth allows us to transfer data packets between different smartphones by creating a common network channel called piconet. This piconet can be extended into a larger network called scatternet [12]. We use this property of Bluetooth to exchange packets of data between two individuals when they come into the range of each other (figure1). The components which make up the data packet is depicted in figure2. The information gained from the packet transfer is used to construct the graphical network which runs in the background of the mechanism.

In the above figure, we can see that participant1 and 4 are in the range of participant2. Due to this, a piconet is formed and

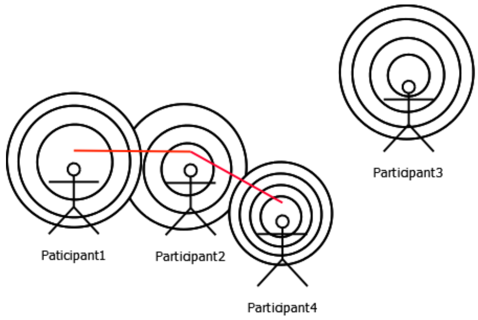


**Figure 1**

packets are transferred between them. Participant3 is out of the range of the piconet and hence no packet transfer between participant3 and others take place.

| ID | DATE : TIME | Geo Location | Status |
|---|---|---|---|

**Figure 2**

Figure2 is the visual representation of the packets that are exchanged between two participants in the network. The components of the packet are, the ID of the sending device, the date and time of the packet sent, a coarse geolocation where the transaction took place and the status of the sender. The ‘status’ component is explained in the ‘graphical network’ subsection. Whenever an exchange of packets takes place between 2 participants for the first time, an edge is created between the two vertices representing the participants in the graphical network.

The following algorithm depicts the instruction for sending and receiving packets from the network.

<u>ALGORITHM1</u>

```
Search for Devices
        IF FOUND:
            Establish Connection
            Check Status of paired Device
            IF RED:
                Alert USER
                Update SELF Status
                REPEAT
            ELSE:
                SEND Packet
                RECEIVE Packet
                REPEAT
        REPEAT
```

In algorithm1, the application actively searches for other devices. If another device is found, a connection is established. At first, the status of the other participant is



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checked. If it is RED, which denotes infected, then the user is alerted. Else, exchange of packets between the paired devices takes place via Bluetooth. This exchange is performed after a regular time interval say 1-2mins.

*B. Graphical Network*

The information about the contacts is maintained in the backend as a graphical network. By backend, we mean that this information is abstracted from the end users and can be maintained from a remote centralized server.

The graph G is represented as $G = (V, E)$, where $V$ denotes the set of vertices and $E$ denotes the set of edges which connect the vertices. In the proposed mechanism, the vertices denote the registered users which we will denote as $\mathcal{P}$ and the edges denote contact between users which we will denote as $\mathcal{E}$.

Whenever a packet is exchanged between two users $\mathcal{P}_i$ and $\mathcal{P}_j$. An edge is created between them. This edge between the two users is represented as $\mathcal{E}(\mathcal{P}_i, \mathcal{P}_j, T_{c(\mathcal{P}_i\mathcal{P}_j)})$. The parameters are the two users and $T_{c(\mathcal{P}_i\mathcal{P}_j)}$ which represents the transfer time of the last packet exchanged between them. This edge is maintained in the graphical network for a time period of $\Delta T_o$ after the last transfer of packet has taken place. The value of $\Delta T_o$ is the sum of the incubation time $\Delta T_{inc}$ and an additional buffer time $\Delta T_{buf}$.

This procedure of removing the edges after a certain time period is done to eliminate the chances of false dangerous contact. Let $T_{Pj}$ denote the time when user $\mathcal{P}_j$ declares that he is infected, then for classifying user $\mathcal{P}_i$ as a dangerous contact, the following condition must hold true.

$$T_{Pj} - T_{c(\mathcal{P}_i\mathcal{P}_j)} < \Delta T_o \qquad (1)$$

If the above condition does not hold then that means although there was a contact between the users $i$ and $j$, but given the incubation period of the pathogen, the user j was not carrying the pathogen during the contact and must have picked up the pathogen at a time after their final packet exchange. Hence, user $i$ is not considered as a dangerous contact.

In the mechanism, we are considering 4 levels of color coding for the participants, each of which denotes the following.

*Red*: *Denotes Infected participant*
*Orange*: *Participant who came in direct contact with Red*
*Blue*: *Participant who came in contact with Orange*
*Green*: *participant who came in contact with Blue or none*

The above color codes are in the decreasing order of the dangerous contact levels. If a participant has come into contact with 2 or more distinct color-coded levels, then the color code of the participant must be updated such that it shows the maximum possible level of dangerous contact.

Another factor that needs to be taken into account while updating the color codes of secondary dangerous contacts, i.e. the color code Blue, the following condition needs to be checked.

$$T_{c(\mathcal{P}_i\mathcal{P}_j)} < T_{c(\mathcal{P}_i\mathcal{P}_k)} \qquad (2)$$

The above condition basically states that if participant $\mathcal{P}_i$ becomes color coded Orange because of participant $\mathcal{P}_j$ becoming infected (Red), then for $\mathcal{P}_k$, who has come into contact with $\mathcal{P}_i$, to be color coded Blue, the time of contact between $\mathcal{P}_i$ and $\mathcal{P}_k$ has to be after the time of contact between $\mathcal{P}_i$ and $\mathcal{P}_j$. Otherwise, the color code of $\mathcal{P}_k$ is not updated because of the new infection ($\mathcal{P}_j$) in the network.

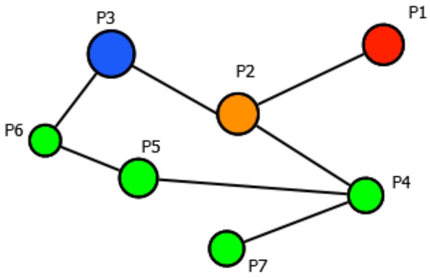


**Figure 3**

In the above example figure3, let us consider the following situation:
$T_{c(\mathcal{P}_2,\mathcal{P}_1)} < T_{c(\mathcal{P}_2,\mathcal{P}_3)}$ and $T_{c(\mathcal{P}_2,\mathcal{P}_1)} > T_{c(\mathcal{P}_2,\mathcal{P}_4)}$
This implies that the contact between $\mathcal{P}_1$ and $\mathcal{P}_2$ has taken place before the contact of $\mathcal{P}_2$ and $\mathcal{P}_3$ while the contact of $\mathcal{P}_1$ and $\mathcal{P}_2$ has taken place after the contact of $\mathcal{P}_2$ and $\mathcal{P}_4$. Hence, when $\mathcal{P}_1$ declares infected, because of $\mathcal{P}_2$, the participant $\mathcal{P}_3$ becomes color coded Blue but it has no effect on participant $\mathcal{P}_4$, even though $\mathcal{P}_2$ and $\mathcal{P}_4$ were in contact.

This color codes are the status of the participants. Due to the high level of abstraction in the mechanism, and for privacy reasons, the participants can only access their self-status and only receives an automated alarm when their device establishes a connection with an infected participant's device.

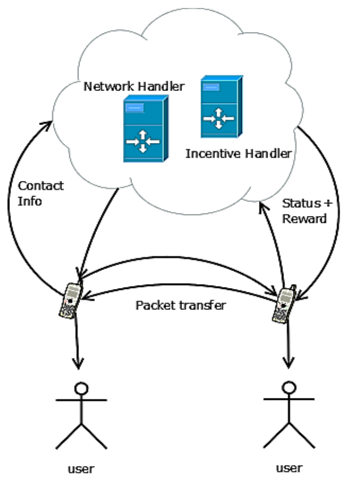


**Figure 4**

Figure4 represents the network architecture and shows the high level of abstraction present in the mechanism. The smartphones automatically pair and exchanges packets between them. This info is sent to the centralized cloud where two servers are present. One server maintains the graphical



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network while the other one handles the reward mechanism. From the cloud, only the self-status and reward is sent back to the devices which is accessible to the participants.

Whenever a participant in the network declares itself as infected, the following algorithm is triggered to update the status of all the connected participants.

ALGORITHM2

Make SELF: RED
∀ adjacent NODES to SELF:
    Update ORANGE
    ∀ adjacent NODES to ORANGE:
        Check condition $T_{c(\mathcal{P}_i,\mathcal{P}_j)} < T_{c(\mathcal{P}_i,\mathcal{P}_k)}$
        Update BLUE
    END
END

In the above algorithm, ∀ denotes For All.

Whenever in a region of the graphical network, the ratio of the sum of Red and Orange status participants to the total number of registered participants exceeds the value of 0.6, the region is clustered and is classified as a potential "hot zone".

Whenever any other participant $P_o$ who was not part of the cluster makes a contact with a participant who is part of the cluster, $P_o$ receives an Alert on its device.

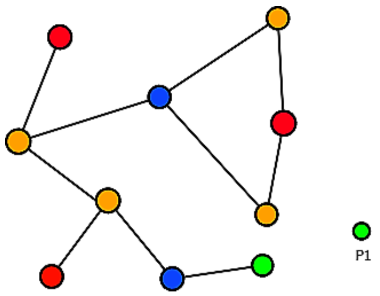


**Figure 5**

In figure5, the network represents a hot zone and if P1 comes near any one of the participants in the network, it will receive a warning.

*C. Incentive Model*

The reward distribution to the participants is handled by the Incentive Handler Server (IHS) which is part of the centralized cloud (figure4).

The incentive model proposed for the mechanism is utilitarian in nature. This paper [13] puts forward a utility function of Mobile Users for crowdsourcing. In the paper, the utility of the $i^{th}$Mobile User is given as

$$u_i = f_i(x_i) + \phi(x_i, X_{-i}) + r(x_i) - c(x_i) \qquad (3)$$

In the above equation, $f_i(x_i)$ is the internal utility of the mobile user, $\phi(x_i, X_{-i})$ is the utility gained by the $i^{th}$Mobile User due to the engagement of other users in the mechanism, $r(x_i)$ is the reward that is paid to the Mobile user for his engagement and $c(x_i)$ is the cost that is endured by the User for his participation. The authors formulated the internal utility as $f_i(x_i) = ax_i - bx_i^2$ where $a, b > 0$ . In our incentive model, we are using the same equation for the internal utility $f_i(x_i)$ but are changing the formulation of $\phi(x_i, X_{-i})$ to capture the essence of contact tracing mechanism. $\phi(x_i, X_{-i})$ is being formulated as

$$\phi(x_i, X_{-i}) = h_i\left(\frac{k}{G_{Rm}}\right) + e_i(\rho^2) \qquad (4)$$

In equation4, $h_i$ and $e_i$ are variable which capture the intrinsic property of the $i^{th}$Mobile User and are greater than 0. $k$ is the number of users who are actively participating in the crowdsourcing network, $G_{Rm}$ is the total population in region Rm and $\rho$ denotes the number of infected people participating actively in the network. Hence, the utility gained by Mobile User $i$ is dependent on the ratio of active users to the total population and is proportional to the square of the number of infected people actively participating. Therefore, as more and more individuals participate in the mechanism, the utility gained by the individual participant due to others increases.

If we compare the utility gain and the cost of participation without any kind of reward, we get

$$f_i(x_i) + \phi(x_i, X_{-i}) < c(x_i) \qquad (5)$$

The above equation shows the condition of no participation. This is because the utility gained by the user is less than the cost that needs to be endured. This difference needs to be filled by providing a reward $r(x_i)$ to the users for participation.

$$f_i(x_i) + \phi(x_i, X_{-i}) + r(x_i) > c(x_i) \qquad (6)$$

We are proposing an incrementing method for computing the reward to be paid by the IHS to the participating users.

Let the total reward that will be given to the active participants be $r_t$ and the minimum percentage of active user engagement required for contact tracing to be effective be $\mathbb{Z}$% then we increase the reward according to the following formula until we get the required engagement amount.

$$r_{t+1} = r_t + h_{av}(G_{Rm} - k) \qquad (7)$$

In the above equation, $h_{av}$ is the estimated coefficient of utility that takes into account the utility gained by a user in the population due to the participation of other users. The initial value of $r_t$ is put as $r_t = h_{av}(G_{Rm})$.

The following algorithm shows the steps of determining the reward value to be paid by the IHS to the active participants.



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ALGORITHM3

START:
  Observe level of engagement ← A%
  Required level of engagement ← Z%
  If A≥Z:
    Pay Reward $\frac{r_t}{k}$ to $MU$
    STOP
  Else:
    $k \leftarrow no.of\ current\ Users$
    $G_{Rm} \leftarrow Total\ Population$
    $r_{t+1} = r_t + h_{av}(G_{Rm} - k)$
    $r_t = r_{t+1}$
    Declare incentive
    GOTO: START
END

The level of engagement is observed, if it is greater than or equal to the required level then the computed reward is paid to the mobile users (MUs). If it is below the required level, we raise the reward using equation7 and declare the new value. This is repeated until we receive the required level of engagement from the population.

## V. DISCUSSION

Let the level of engagement be denoted as percentage value, hence, it can be between 0 and 100. The following plot (figure6) shows the internal utility curve $f_i(x_i)$ for a participant whose $a, b > 0$.

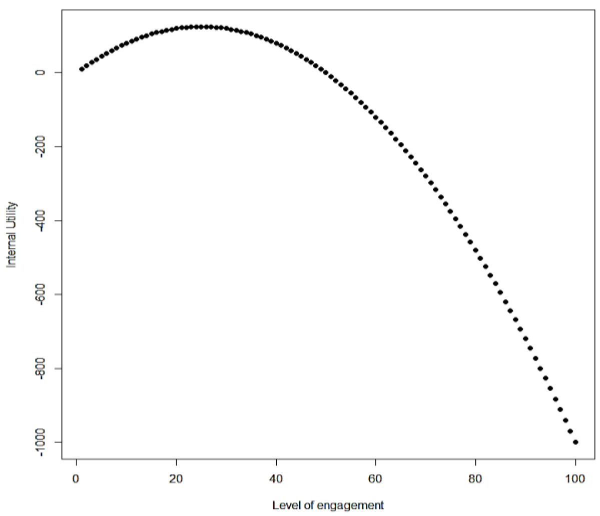
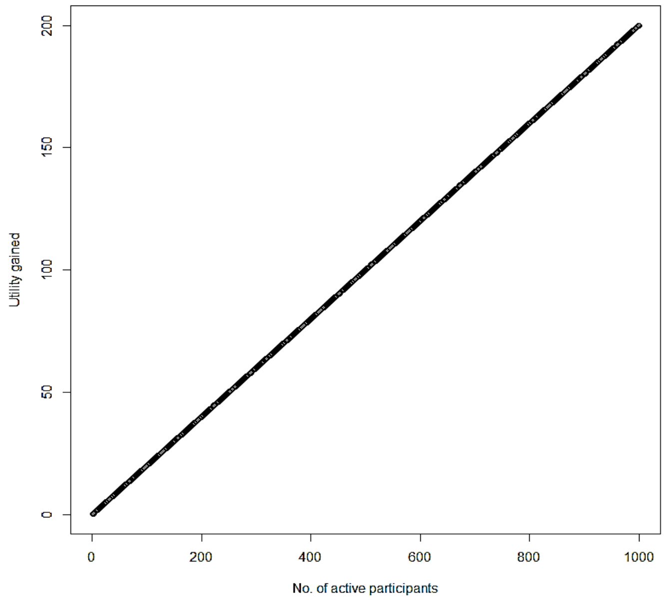



Figure 8

From the curve, we can see that the internal utility for 80% level of engagement is $-480$. This value is without taking into account the cost component. For simplicity, let the cost coefficient $c$ be 1, then the total negative utility for the participant becomes $-480 + (-80) = -560$. To ensure desired level of participation, the utility gained by the participant must be greater than zero. According to equation3, it becomes $\phi(x_i, X_{-i}) + r(x_i) + f_i(x_i) - c(x_i) > 0$.

If the $e_i(\rho^2)$ component of equation4 is ignored, then we get a linear dependency of utility gain from other users' engagement.

Figure 6




Therefore, it can be seen that the utility of the participant is not only dependent upon his internal utility but also on how

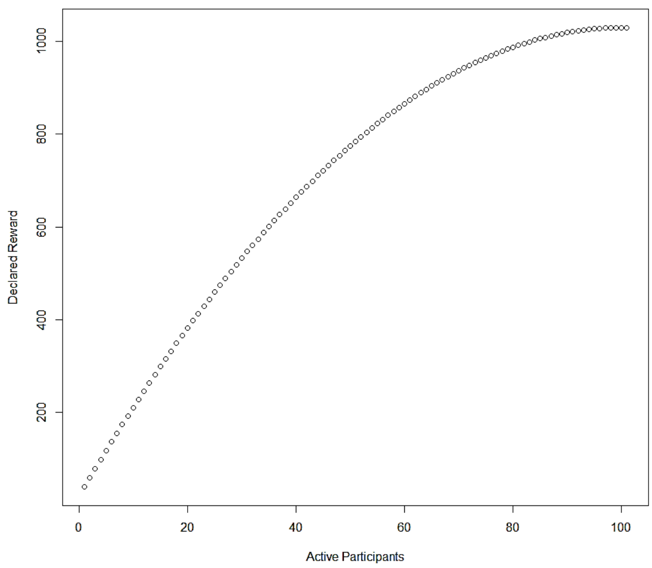



Figure 7

much it values the participation of other users. Since it is not possible to estimate the utility of every member of the population simultaneously therefore, we simply estimate $h_{av}$ and raise the reward amount depending on the number of active participants gained. The plot below shows the declared reward curve versus the active participants.



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The above curve is under the condition that there is a unit increment of active participants which makes up the x-axis and with respect to that the declared reward is updated. This may differ in real scenario but it shows that as we reach 100% level of active participation, the increment of the reward becomes 0.

The technological model discussed in the paper is designed such that it can be implemented in any epidemic situation. Nevertheless, one flaw that arises due to the usage of Bluetooth is that we cannot control the range of Bluetooth using programing techniques as the range is dependent on the hardware of the device. This limitation causes us to use the device's Bluetooth range as the contact range. If we had control over this contact range, then the mechanism could be made more sophisticated as different pathogens have different ranges up to which they can spread.

One of the ways this range can be controlled is by using "acoustic waves" instead of radio waves (Bluetooth). This paper [14], discusses the use of acoustic waves to control the connectable distance between smartphones. The ability to manipulate the contact range would greatly benefit the mechanism because then we can set the range beforehand depending on the pathogen's nature thus making the mechanism more effective.

## VI. CONCLUSION

In this paper we presented a contact tracing mechanism that uses the Bluetooth feature present in smartphones to establish contact between their owners via packet sharing. Based on the contact information, a graphical network is maintained on a centralized server where the vertices represent the users and edges between them denote contact history between the users. The status of a person is color-coded as either Red, orange, blue or green and the user receives only his or her individual status from the network handler server. Whenever a participant becomes infected (red), the status of all the connected participants in the region is updated depending on the time and degree of contact.

To encourage higher level of participation from the population, we also proposed an incentive model where the participants are rewarded based on their level of participation. The incentive model is utility based, where we incrementally increase the reward value until the required level of engagement for effective result is received from the population.

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