1. Effect of Vaccines (GOOD) :

- Most of research have pointed out: due to the introduction of vaccination programs, the morbidity and mortality associated with the infectious diseases decreased substantially such as whooping cough[?], measles (the incidence of measles decreased by over 98% and the 2–3-year epidemic cycles no longer occurred) [?], influenza [?].
- Measles was eliminated from U.S. since 2002. In other countries, especially in developing countries, measles vaccination has not extensively popularized. Consequently, it is still very important to model the transmission dynamics of measles and investigate the effect of vaccination on the spread of measles [?].
- Vaccination, is one of the most effective strategies in preventing morbidity and mortality associated with various infectious diseases, has also been included in modeling.
  - The impacts of vaccination policy on the level of vaccination coverage and found that voluntary vaccination was unlikely to reach the group-optimal level.
  - Complex dynamics such as oscillations and chaos in measles epidemic models and the persistence of disease ars affected by : the population size of the community, the spatial structure and connectedness of the regional population, and the seasonal forcing.

2. Effect of Vaccines (BAD) :

Bad effects:

- Hospital admissions and fatalities related infectious diseases are still evident for all people (children/adolescents/adults) [?, ?, ?], but particularly in young infants.
- There is a dramatic increase in cases occurred [?].
- The yearly U.S. mass influenza vaccination campaign has been ineffective in preventing influenza in vaccine recipients. That points out a potential for an influenza pandemic in the future [?].

Reasons: (the possible causes for the disease outbreaks and resurgence are still under debate).

- unvaccinated or incompletely vaccinated infants who are younger than 12 months [?].
- A decrease in vaccine effectiveness over time (warning immunity) and pathogen adaptation (Mooi, 2010; Klein et al., 2012; Misegades et al., 2012; Sheridan et al., 2012).
- The recent epidemiological features could be the consequence of failures in current vaccine effectiveness.
- Low vaccination coverage [?]. In general, vaccination protects not only those who are vaccinated but also their neighbors. As a result, many others in the community can also be benefited. However, whether or not to vaccinate largely depends on the perceived risk of infection and the vaccination behavior of neighboring individuals

3. Method of vaccination (vaccination policies)

3.1. **Khai thac cac THAM SO :.**

- Pang2015 [?] gave two critical threshold values, μ_{c1} and μ_{c2}, of the vaccine coverage ratio. Measles will be extinct when the vaccination ratio $\mu > \mu_{c1}$, endemic when $\mu_{c2} < \mu < \mu_{c2}$, and outbreak periodically when $\mu < \mu_{c2}$. In addition, the authors applied the optimal control theory to obtain an optimal vaccination strategy $\mu * (t)$ and gave some numerical simulations for those theoretical findings. Finally, they used the model SEIR to simulate the data of measles cases in the U.S. from 1951 to 1962 and design a control strategy.
  - Valuable information on how to more effectively prevent the outbreaks of measles and accordingly adopt appropriate vaccination policies are very important. They study the effect of vaccination by mathematical modeling and analysis and determine the level of vaccination coverage that can the most effectively prevent the spread of measles.
  - We will study the nonlinear dynamics of the SEIR measles epidemic model (1.1) and investigate the effect of vaccination in controlling the spread of measles.
  - Two goals: (1) To make the number of infectious individuals z(t) as small as possible during a certain vaccination period. (2) To keep the vaccination ratio of measles as low as possible during a certain vaccination period.
  - Focusing on exploiting the Basic reproduction number R_0 following μ ($\mu < r$) the effective vaccination coverage ratio of the susceptible.
  - Results :
    - Results are right for a single population in the deterministic model.
    - We need to verify a signle population or multipopulation in the stochastic model.

* I don't understant the vaccination policy here, they made the vaccination one time or many times with the μ. It is different from our vaccinationpolicy (pulsation policies).

Optimal control theory has been used to explore optimal control strategies for various infectious diseases, see, for example, Kirschner et al. [25], Culshaw et al. [13], Karrakchou et al. [22], Kar and Batabyal [21], Lenhart and Workman [26], and the references cited therein.

3.2. **Khai thac cac Mo Hinh (build models as transportation network models therein we have vaccine allocations, frameworks for determining optimal vaccine allocation).**

- Louis Boguchwal [?] provided a novel framework that models infectious disease propagation throught a population, and determines socially optimal vaccine allocation with a stock of vaccines fixed. They proved that both the network attributes and the demographic characteristics are critical in determining whether one region is more important than another in term of vaccination.

  Transportation network models.
  - Model based on the air transportation network [?, ?]: Shaw et. al. (2010) [?] modeled influenza spread using a rudimentary **air transportation network** in the United States (NODES by airport). (1) the speed of disease propagation is quicker in small cities than in big cities. Disease is easier to engulf a small city in comparison to a big city. The likelihood of an infected individual comming out of a small city is greater than that of a large city.
  - Wu et. al. (2007) [?] partitioned the network into ten nodes by regions (following the documents about the United States Office).
  - We consider gravity transportation theoretic models. Balcana et. al. [?]used global commuting patterns as well as global air traffic flows to model short and long distance travels. They pointed out that the most important network when considering infectious disease propagation is the long distance air transportation network.

  Vaccine allocations about the georaphic:
  - In order to enact socially optimal vaccination policies, policy-makers not only need to be well-informed with regard to infectious disease dynamics, but also with regard to vaccination policy analysis.
  - The network structure (The allocation of populations, vaccines) plays an important role for the effectiveness of a vaccination policy.
  - Wu et. al. [?] viewed vaccine allocation as a nonlinear optimization problem in which the objective was to minimize the total number of infections across a population. The authors proposed two vaccination policies : a portion of the total vaccine supply was designated to be distributed pro-rata, which is equitable distribution by population, and the other portion of the vaccine supply was to be discretionarily distributed. The result : the purely equitable distribution was the least efficient allocation in terms of minimizing the total number of infections in the population. The purely discretionary policy is efficient, but highly inequitable.

  Vaccine allocations about the time side:
  - Matrajt2010[?]
    * they used a mathematical model to find the optimal vaccine allocation at different time points of an epidemic. For both developed and less developed countries, when faced with low supplies of vaccines, it is always optimal to concentrate vaccine in high-risk children to provide them with direct protection, as they are part of the high-transmission chain and they are among the most vulnerable.
    * pointed out that : Choosing the optimal strategy before or early in the epidemic makes an important difference in minimizing the number of influenza infections, and consequently the number of influenza deaths or hospitalizations, but the optimal strategy makes little difference after the peak. When averting deaths, it is better to allocate vaccine in the high-risk groups first and then cover high- transmission groups. Once vaccine supplies reach a certain coverage level, then it becomes important to vaccinate the high- transmission groups in the earlier stages of the epidemic, but this policy becomes suboptimal once the peak of the epidemic has passed. This is because by allocating this much vaccine in children earlier on in the epidemic, we would be able to block transmission and mitigate the disease, but if vaccination took place later on in the epidemic, there are too many people already infected and this strategy is no longer optimal

Limitation :

- A limitation of the network models presented above is that they are all specific to disease propagation. However, network models applied to more general contexts also provide insight into the vaccine allocation problem.
- The limitation of these framework is that many attributes described in the research depend upon a well-defined notion of community structure. However, it is exceedingly difficult to detect and distinguish communities within a larger network.
- In fact, the big differences between perceived risk of infectious disease and actual risk of infectious disease. Therefore, individuals likely make great errors when making their choices for vaccination. Thus, these errors must be taken into account when considering policy actions to be taken to move toward a socially optimal allocation [**?**].
- The triple of network structure, disease propagation, and vaccination policy are three very important factors to build the network attributes. The degree centrality, closeness centrality, betweenness centrality, and node significance are important network attributes to consider in context of disease spread.

3.3. **Using the optimal algorithms.**

3.3.1. *Evolutionary Algorithms (EA) policies.*

- Shaw2010 [**?**] extended the model to include a supply of vaccine, which is to be distributed in an optimal fashion. By mathematical analysis of this model, they determined the feasibility of a vaccination policy by using the Evolutionary Algorithms (EA), they searched for vaccination policies that minimize the number of infected people. They compared these policies to plausible benchmark policies to verify that the EA policies are more effective.
  - Analysis of the EA policies indicates that the vaccine is generally distributed to (1) the city of origin for the virus, (2) cities that are traveled to most often, and (3) smaller cities.

3.3.2. *Convergence in Evolutionary Programs with Self-Adaptation [Greenwood 2001]- proposed by YANN.*

- Reason:
  - Evolutionary programs are capable of finding good solutions to difficult optimization problems.
  - Previous analysis of their convergence properties has normally assumed the strategy parameters are kept constant, although in practice these parameters are dynamically altered. - In this paper, we propose a modified version of the 1/5-success rule for self-adaptation in evolution strategies (ES). Evolutionary programs are probabilistic algorithms that use the principles of population genetics to search for problem solutions. They are capable of finding good solutions to a wide variety of optimization problems, including NP-hard combinatorial optimization problems (Back, 1996).
  - Problem $(\mu + \lambda) - ES$: These μ parents (candidate solutions) produce λ offspring (new solutions) by mutating one or more problem parameters. Parents and offspring compete equally for survival; only the μ best (i.e., those with the highest fitness) will survive to reproduce in the next generation. Done properly, the population will evolve towards increasingly better regions of the search space by means of reproduction and survival of the ttest.
  - Problem $(\mu, \lambda) - ES$ μ parents produce λ offspring, but only the best μ offspring survive. Thus individuals live for only a single generation regardless of their tness level. This approach may result in short periods of recession, but it does avoid long periods of stagnation. [Back 1996]

3.3.3. *Reinforcement learning in vacination policies - proposed by JEAN Daniel Zucker (very complex).* Reinforcement learning, a subfield of artificial intelligence, is the study of algorithms that learn how to choose the best actions depending on the situation. In a reinforcement learning problem the algorithm is not told which actions give the best results, but instead it has to interact with the environment to learn when and where to take a certain action. When the agent has learned about each situation or state of the environment, it will arrive at an optimal sequence of actions (Barto and Sutton 1998). Instead of finding the best results, we find an optimal result for the state of the evironnement at time t.

- The optimization of vaccination policies by using the reinforcemnt learning: for a given population structure, where and when to vaccinate to minimize the number of infected or maximize the probability of global eradication.
- SARSA : State-Action-Reward-State-Action

- One state at time t : ($\in N^4$)

$$S = ((s_1, e_1, i_1, r_1), (s_2, e_2, i_2, r_2), ..., (s_n, e_n, i_n, r_n)$$

- Set of states : $N^{4*nbCities}$
- Action at time t, vaccinated or not vaccinated.
- Sum of rewards of a policy:

$$\sum_{t=0}^{\infty} \gamma^t r_t = r_0 + \gamma r_1 + \gamma^2 r_2 + \gamma^3 r_3 + ...$$

This problem is a Markov Decision Process. However, the number of states at time t is very big. It is the reason for that it is an expensive simulator. In this case, we desire an MDP planning algorithm that minimizes the number of calls to the simulator, runs in time polynomial in the relevant problem parameters, and outputs a policy that is approximately optimal with high probability [**?**].