Spread of COVID-19 in Iran: A Scenario Analysis

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March 14, 2017

Edited by Dan Gordon

Introduction

- A system dynamics model was used to investigate 3 scenarios for the spread of COVID-19 in Iran.
- The model includes major feedback loops that represent the nature of the virus spread and the response of public and government to the spread of COVID-19.
- One feedback loop captures the transmission of the virus from infected to susceptible susceptible people through personal contact.
- A pair of feedback loops capture the effect of the perceived death rate on
    - the public's willingness to observe social distancing and the government strictness in enforcing it.
    - the completeness of personal measures (e.g. wearing masks) to reduce viral transmission during social contacts.

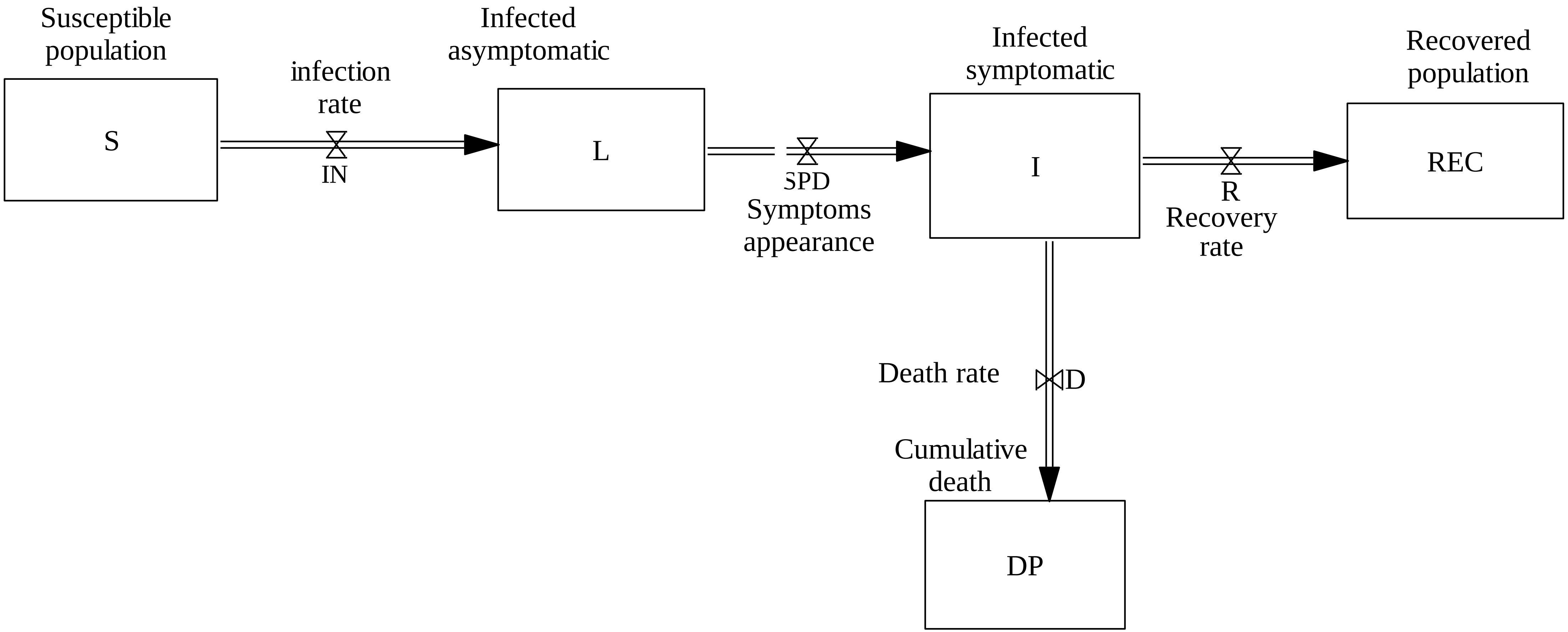
Introduction (2)

- One feedback loop shows that when the number of infected people increases more hospital beds are allocated to care for severely affected cases.
- One feedback loop goes from death rate to increase quarantining of infected persons, by means of personal compliance and government enforcement.

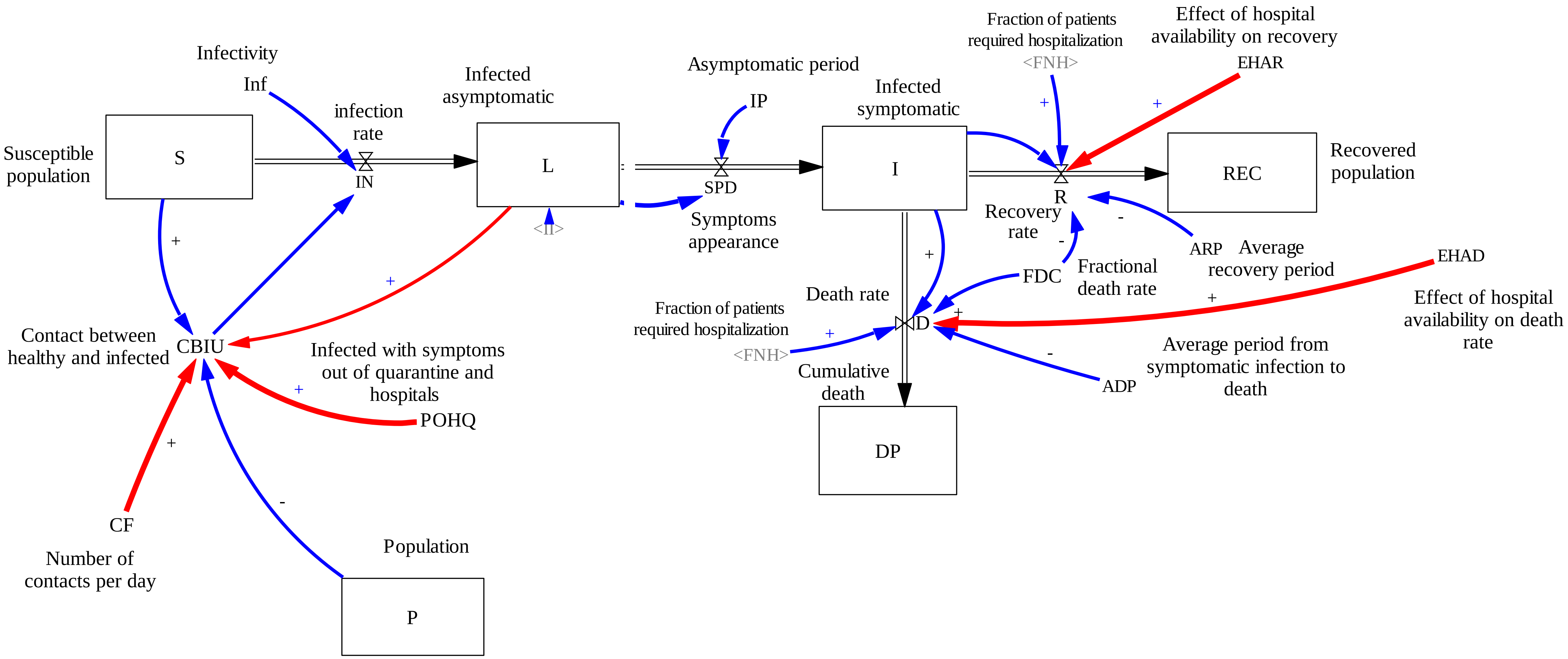
Introduction (3)

- Three scenarios are presented
    - Scenario 1: from the beginning of the epidemic both social distancing (reduced number of contacts per day) and infection protection (masks, hand washing, etc.) are carried out to a high degree.
    - Scenario 2: infection protection is high but social distancing is carried out to a lesser degree.
    - Scenario 3: both social distancing and infection protection are both carried out to a lesser degree.
- It will be shown that the number of infected persons and deaths are drastically different across the scenarios.
- At the end, policy implications of these scenario results are discussed.

Major Stock and Flow Structure



Key flows (rates) and their determinants

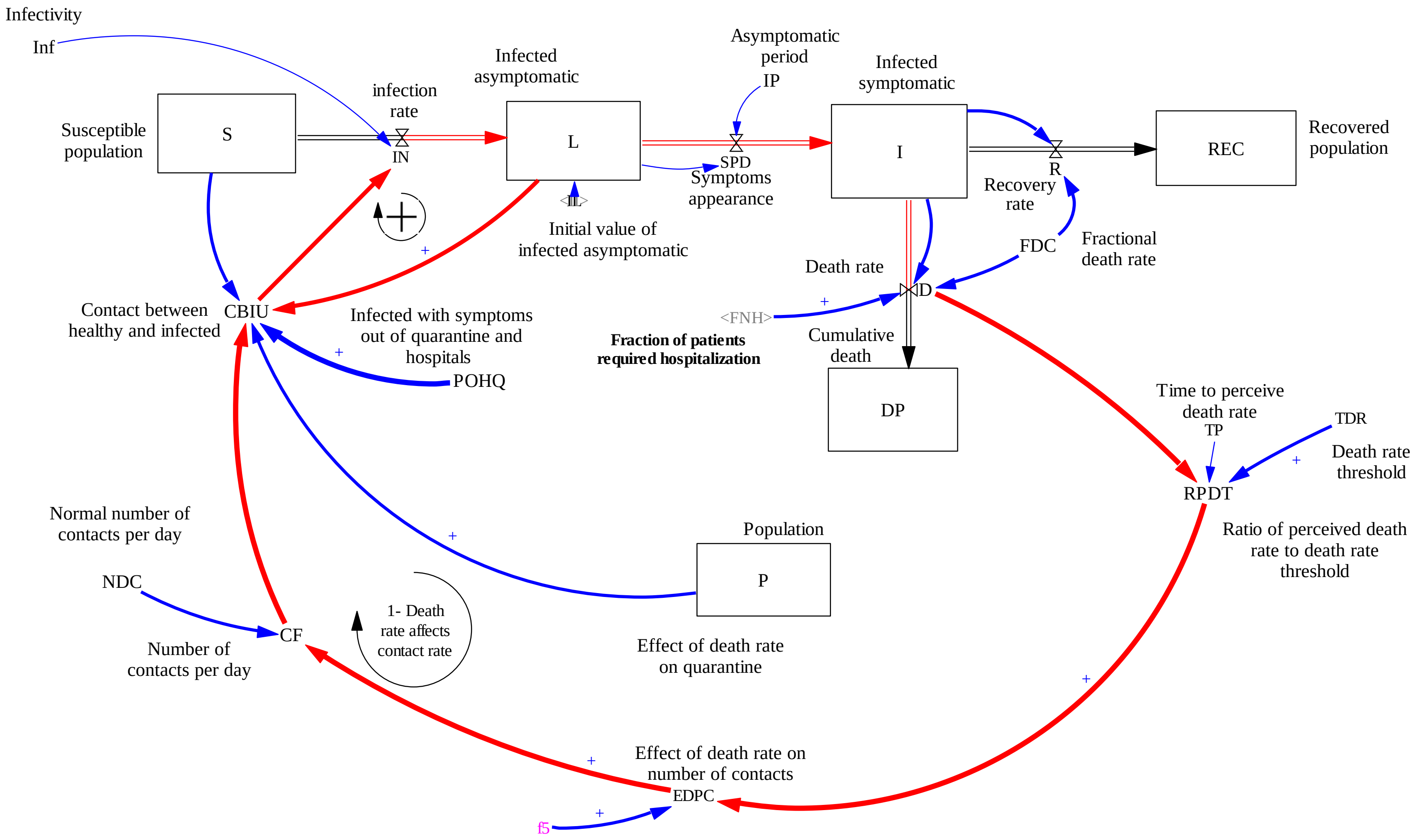


This figure shows the factors that determine the rate variables. Red arrows denote feedback loops that shape the major behavior of the model.

Rate Equations

IN=Inf*CBIU	Infection rate
Inf=0.05	Infectivity
CBIU	Contact between healthy and infectious per day
SPD=L/IP	Symptoms appearance
L	Infected asymptomatic
IP	Asymptomatic period
R=(EHAR*FNH*I*(1-DC)+(1-FNH)*I*(1-DC))/ARP	Recovery rate
EHAR	Effect of hospital availability on recovery
FNH	Fraction of patients requiring hospitalization
FDC	Fractional death rate
I	Infected symptomatic
ARP	Average recovery period
D=(FNH*I*DC*EHAD+(1-FNH)*I*DC)/ADP	Death rate
EHAD	Effect of hospital availability on death rate
ADP	Average period from symptomatic infection to death

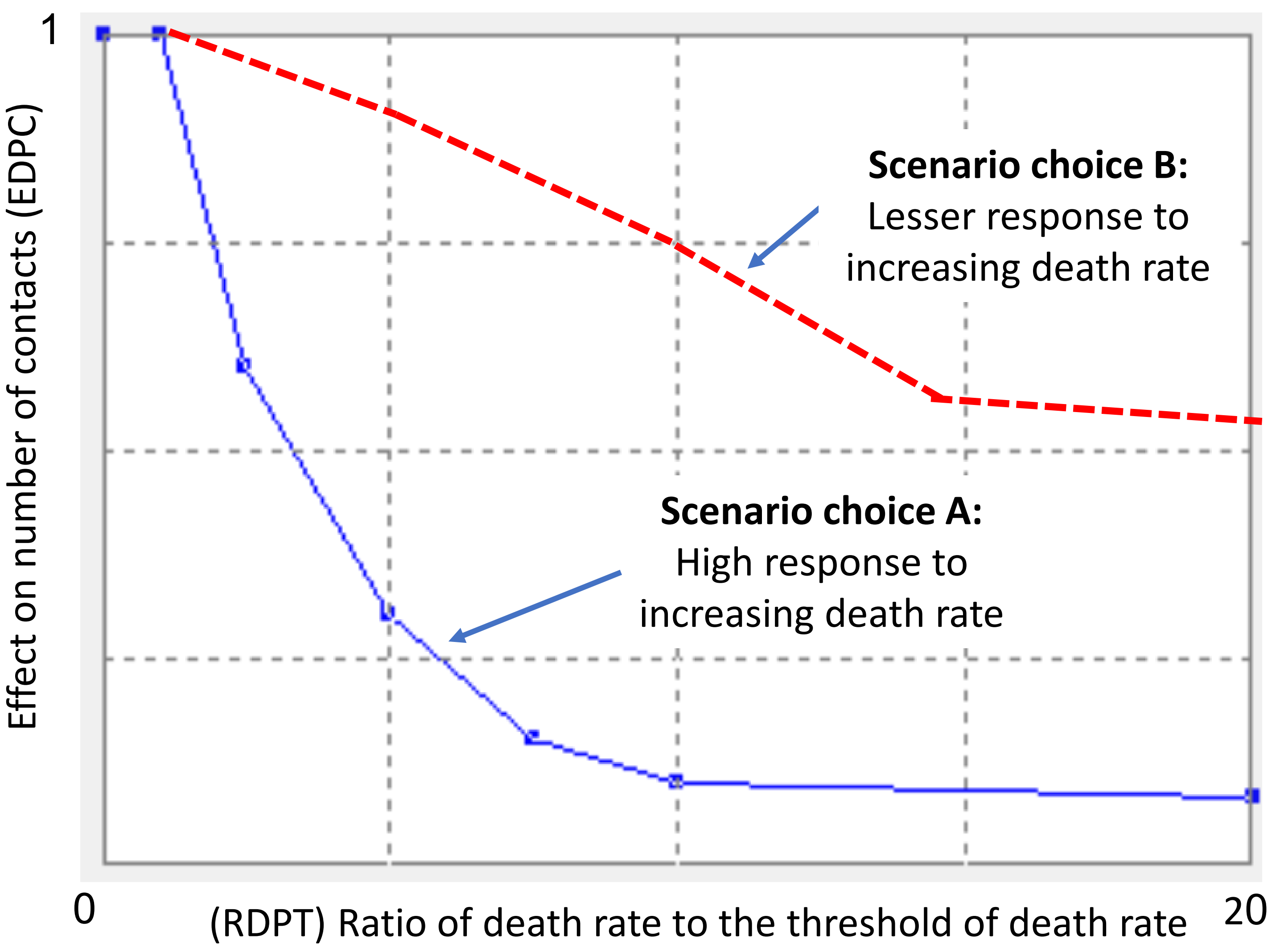
Feedback from death rate on number of contacts per day



As the death rate rises, both public and government become more concerned about COVID-19 and increase social distancing, which lowers the number of contact per day. As the number of contacts decreases so does the infection rate, leading to fewer cases and lower death rate.

The figure also shows a reinforcing loop from number of asymptomatic cases to number of contacts, which leads to more transmissions and a greater number of asymptomatic cases.

Scenario choice: effect of perceived death rate on average number of contacts per day

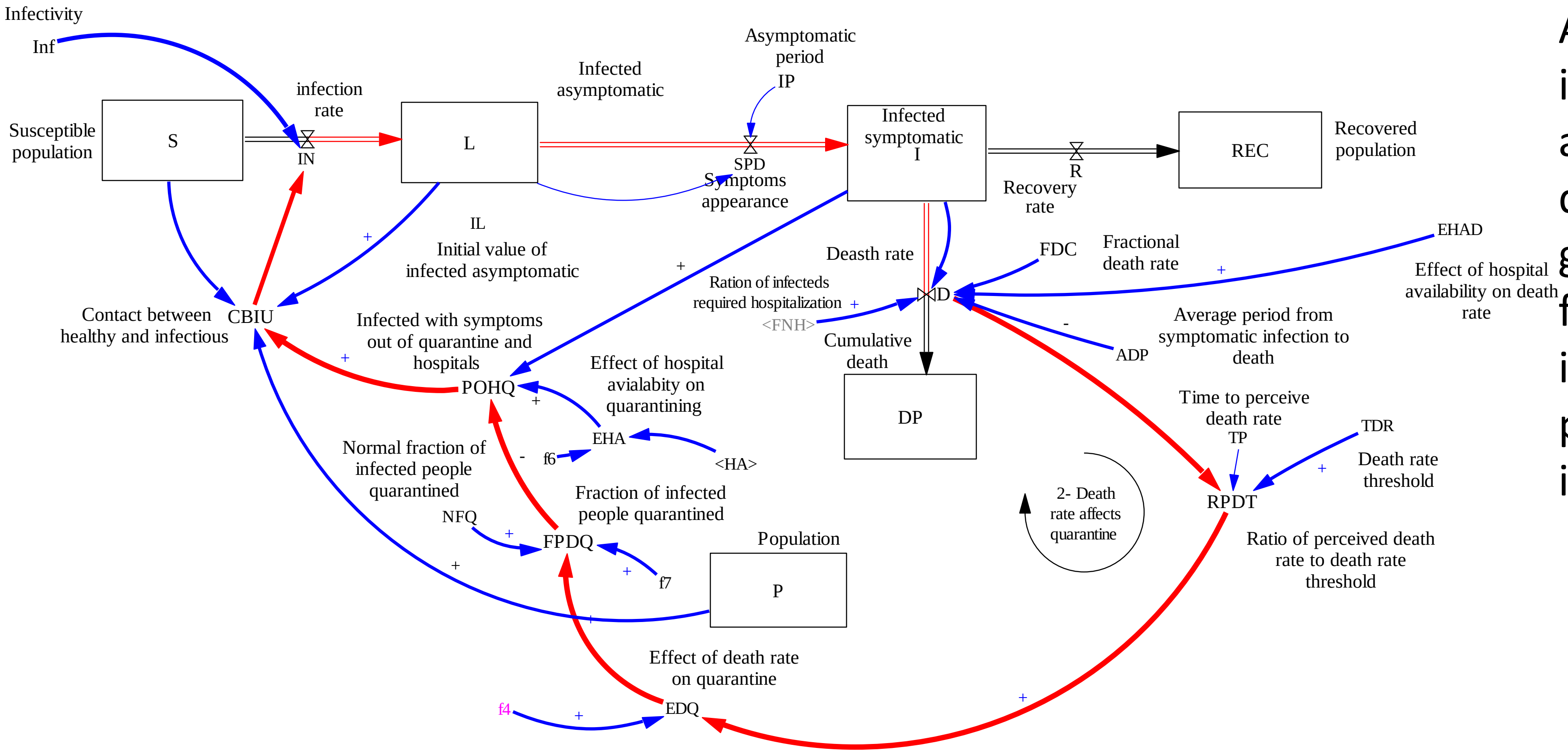


As the death rate increases beyond a certain threshold value, both people and government become concerned about the disease. The government provides guidelines and regulations to decrease contact frequency and people will turn to self-protection and refrain from gathering.

The lower curve represents a society that responds strongly. As the death rate approaches 20 times the threshold value, contact frequency is reduced to 10% of its usual value.

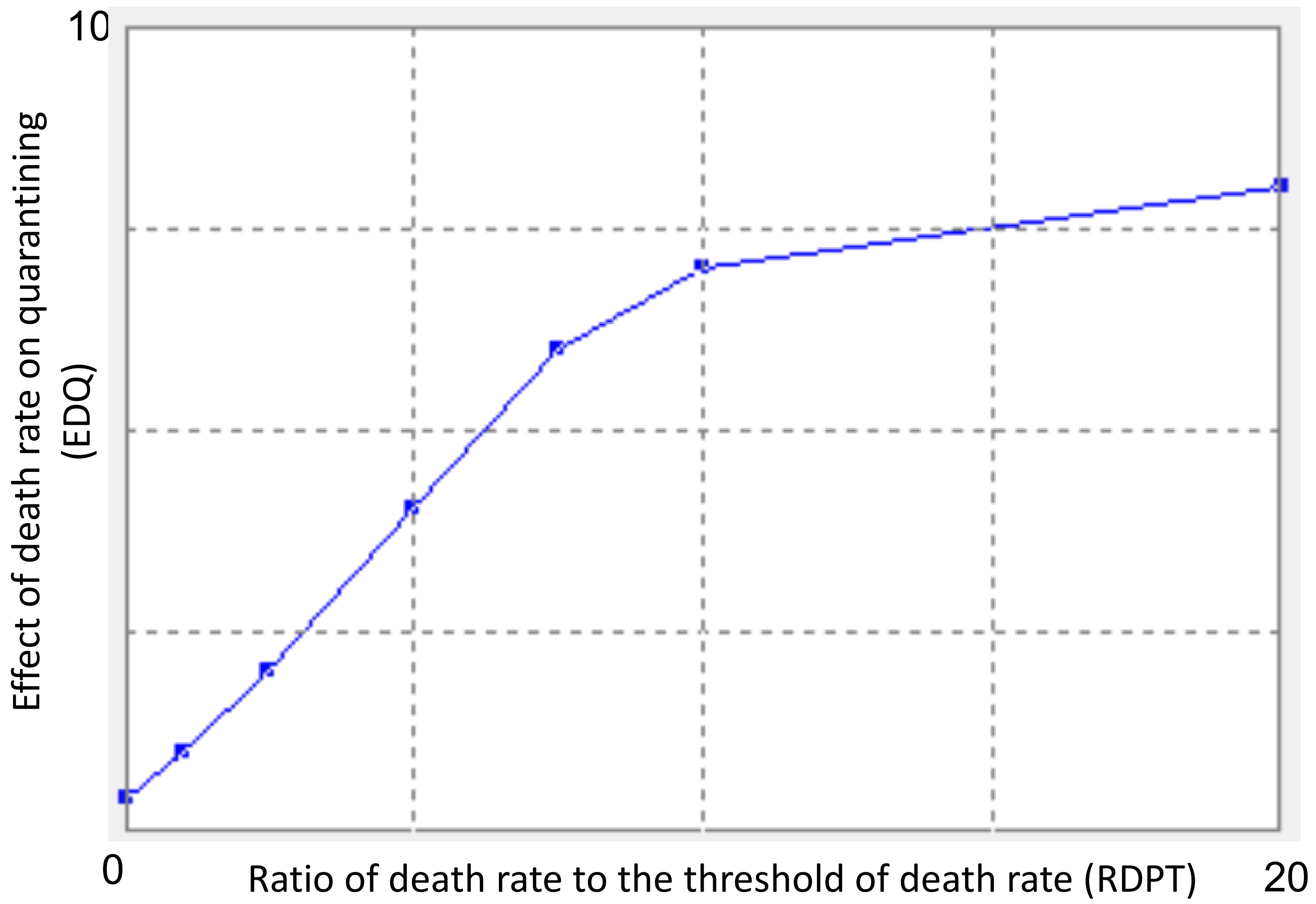
The upper curve represents a society that responds less strongly. As the ratio becomes 20, contact frequency is reduced only to 60% of usual.

Feedback from death rate on quarantine



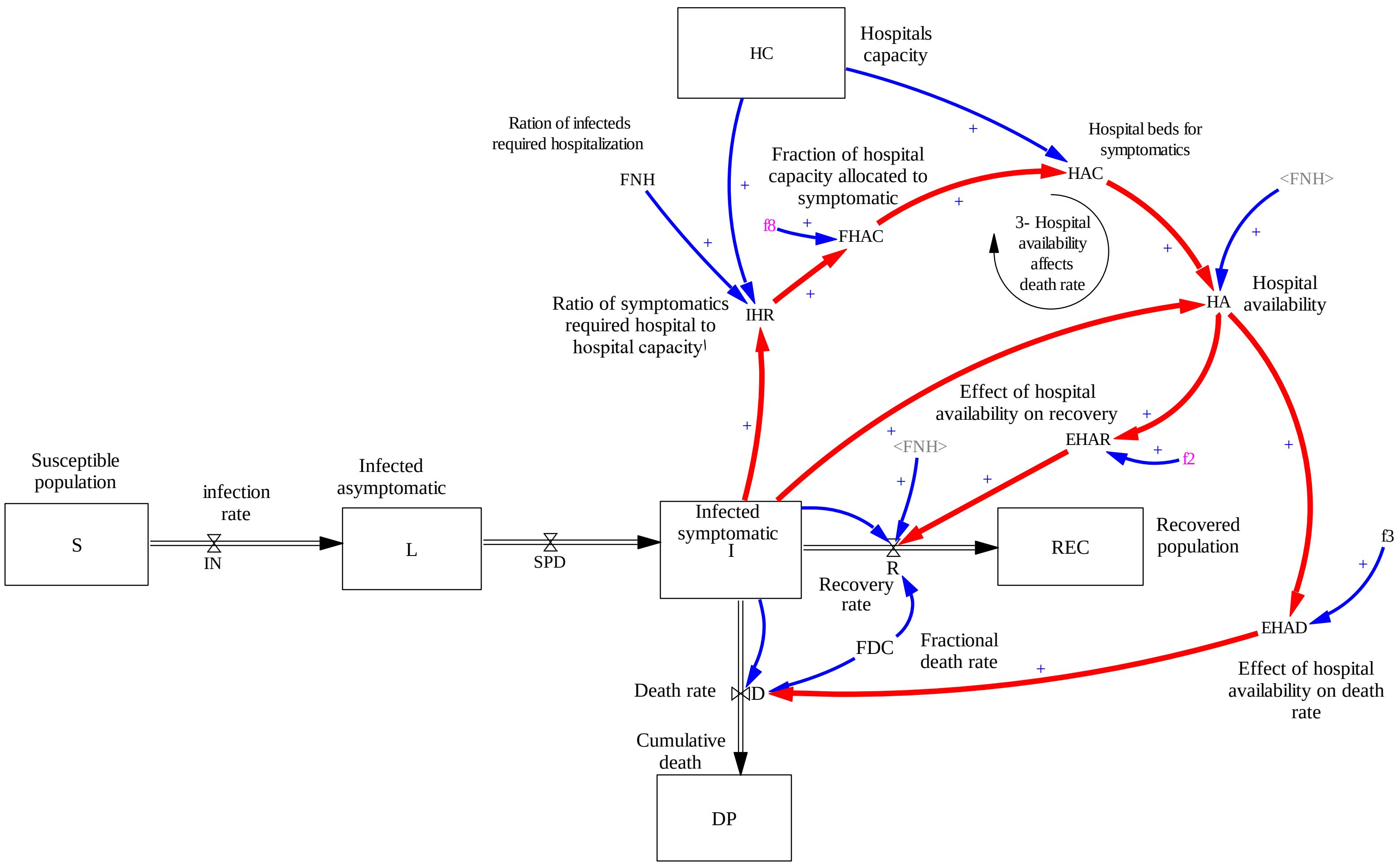
As death rate increases, more infected people who are not already hospitalized go into quarantine. As more people go into quarantine there are fewer contacts between infected and susceptible people, which lowers the infection rate.

Key assumption: effect of perceived death rate on quarantining



As death rate increases more infected people go to quarantine, whether voluntarily or through government policy.

Feedback from availability of hospitals on death rate and recovery rate

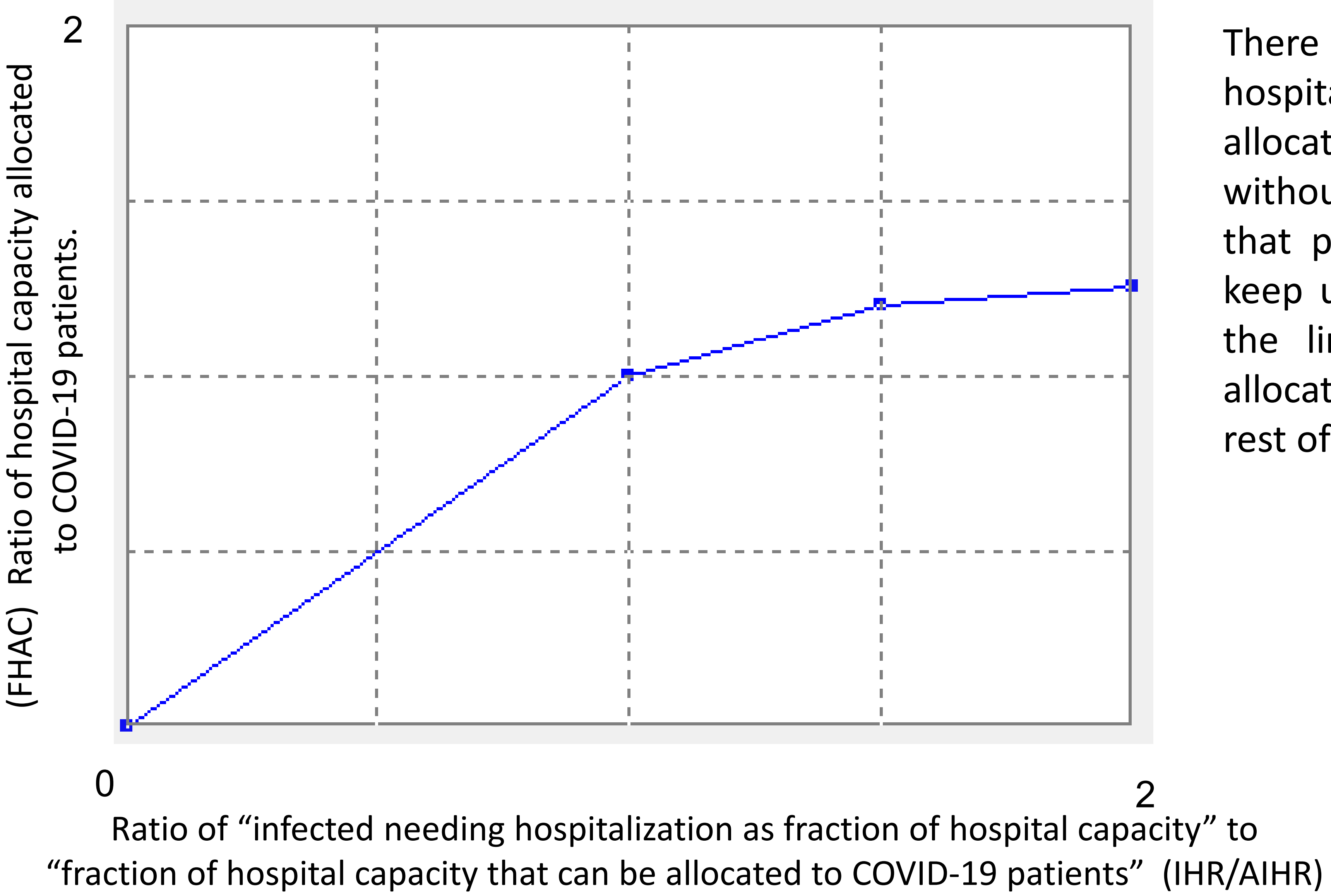


As the number of infected people increases the number of persons who need hospitalization increases.

Hospital capacity is limited, so if the number of infected becomes large, hospital bed availability becomes a problem.

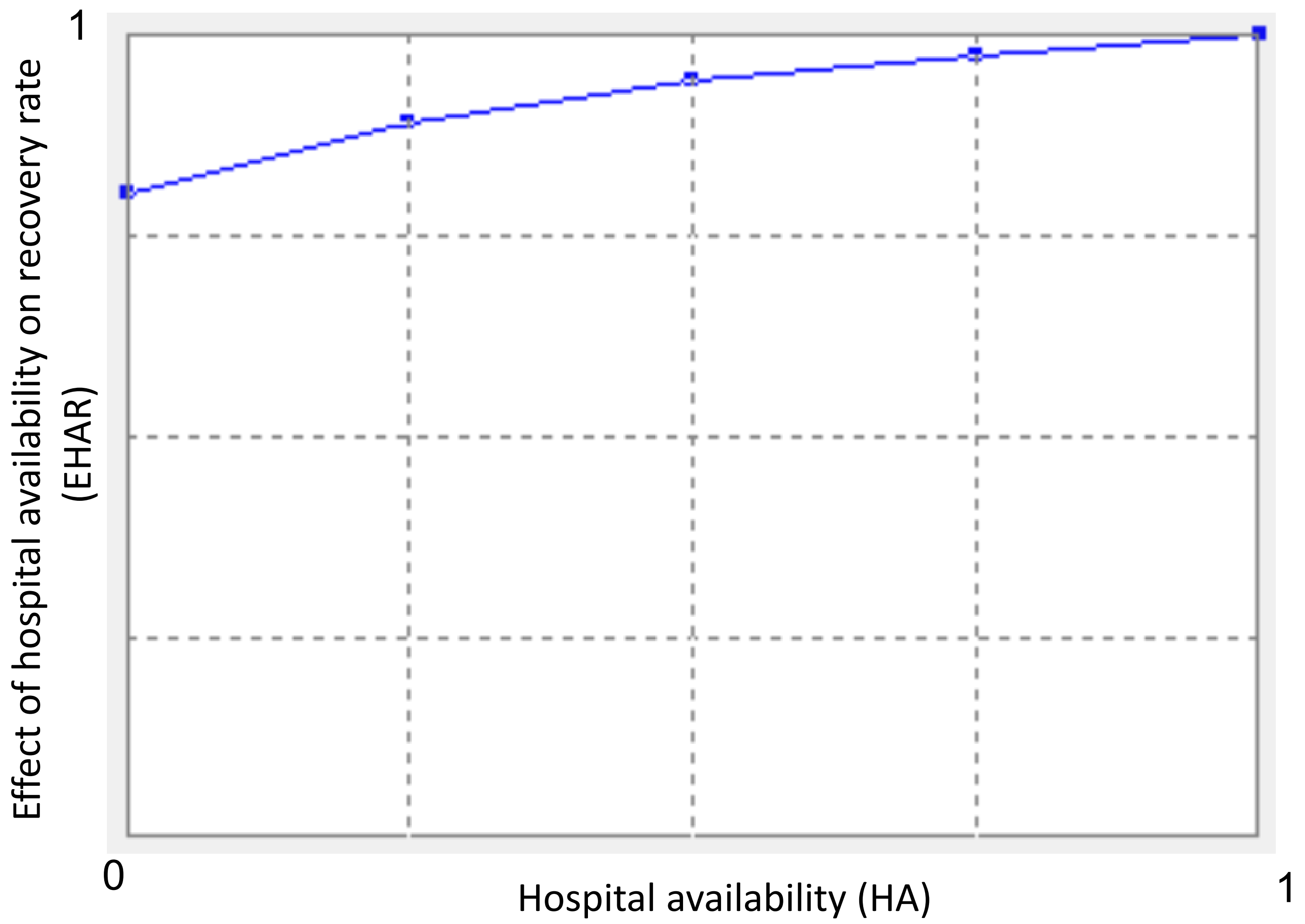
Low hospital availability decreases recovery rate and increases death rate.

Key assumption: limitation on availability of hospital capacity for COVID-19 cases



There is a limit on the fraction of hospital capacity that can be allocated to COVID-19 patients without disruption (AIHR). Beyond that point bed availability does not keep up with need. At most 1.25 of the limit capacity AIHR would be allocated as other patients need the rest of hospital capacity.

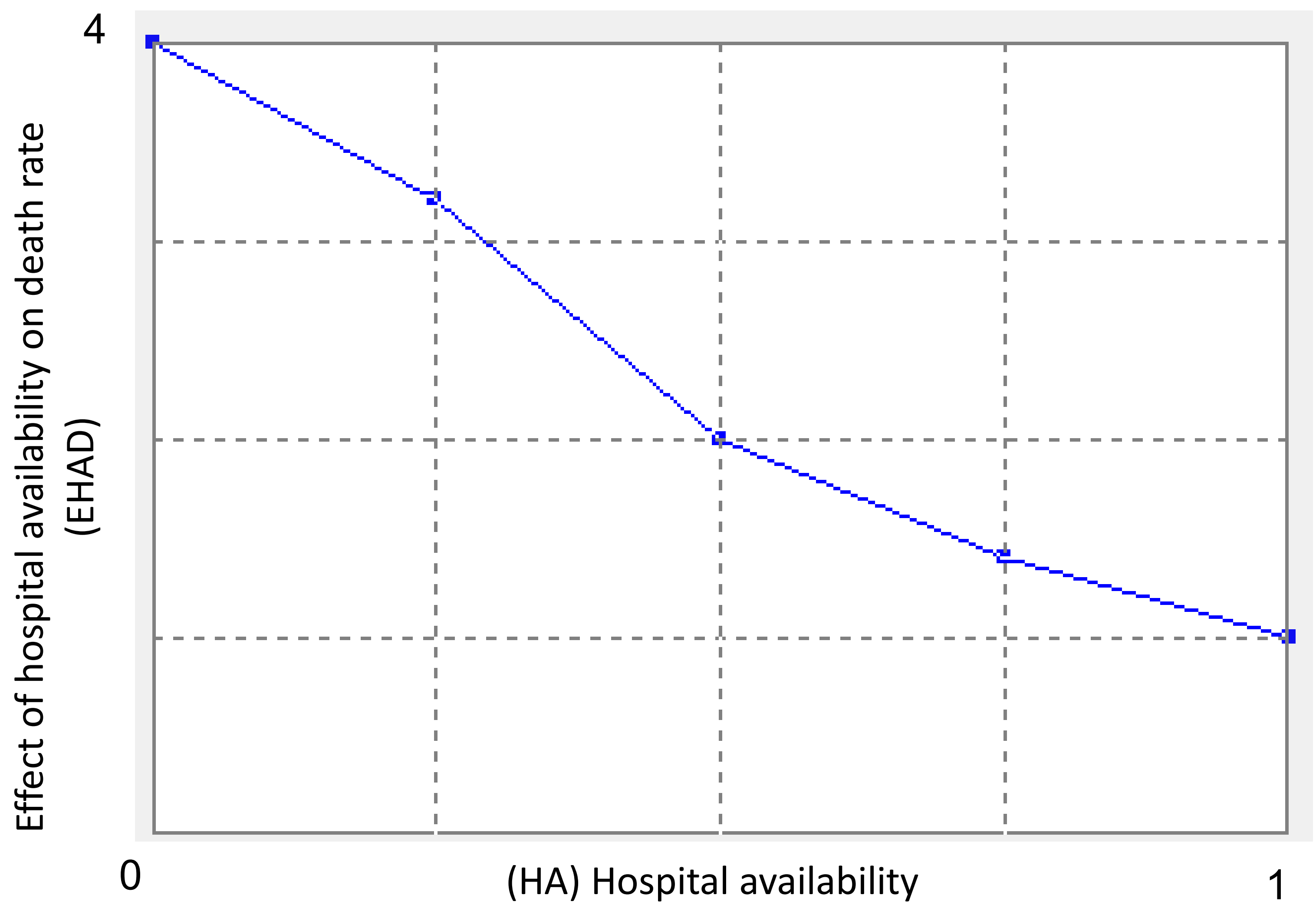
Key assumption: effect of hospital availability on recovery rate



If hospital availability is 1 (i.e., all severe cases can be hospitalized) the effect would be 1 (recovery rate is not decreased).

If hospital availability decreases to 0, recovery rate is reduced by 20%.

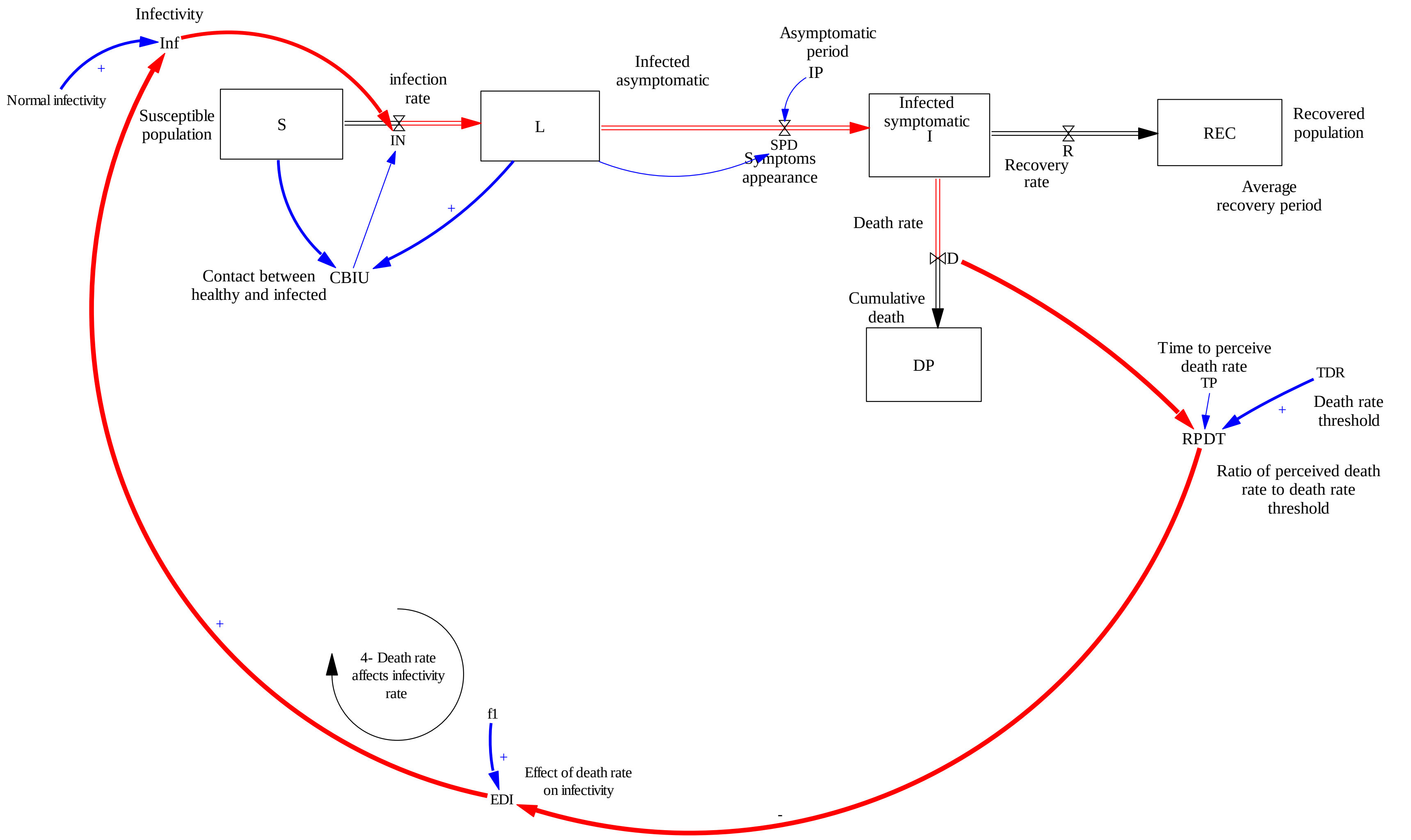
Key assumption: effect of hospital availability on death rate



If hospital availability is 1 (i.e., there is sufficient capacity for all patients who need hospitalization) the effect would be 1 and the death rate is what considered a normal death rate.

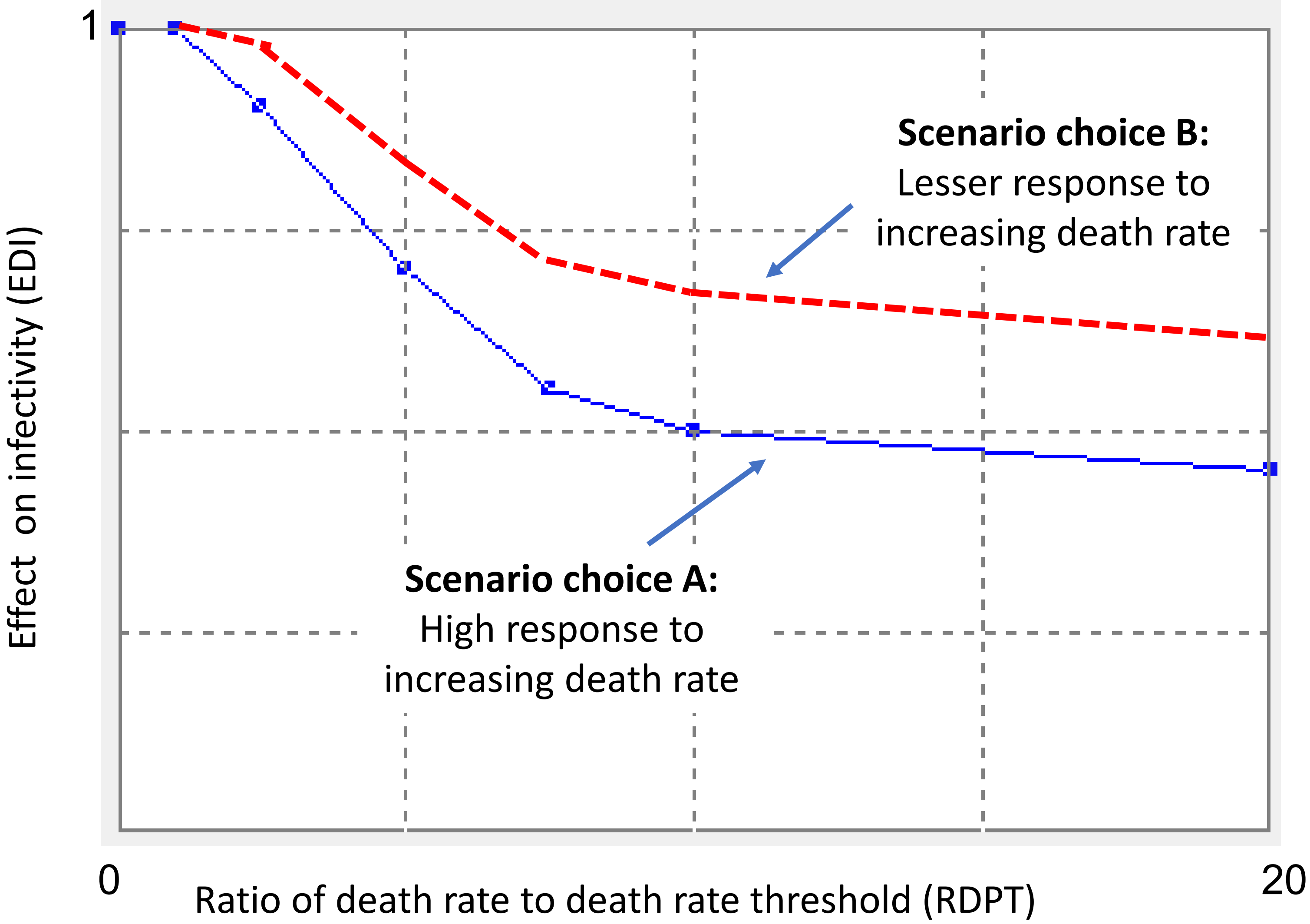
It is assumed that as hospital availability decreases towards 0, death rate rises to be 4 times higher than normal.

Feedback from death rate on infectivity



As death rate increases, people become more careful in their contacts and observe medical advice to protect themselves and decrease infectivity.

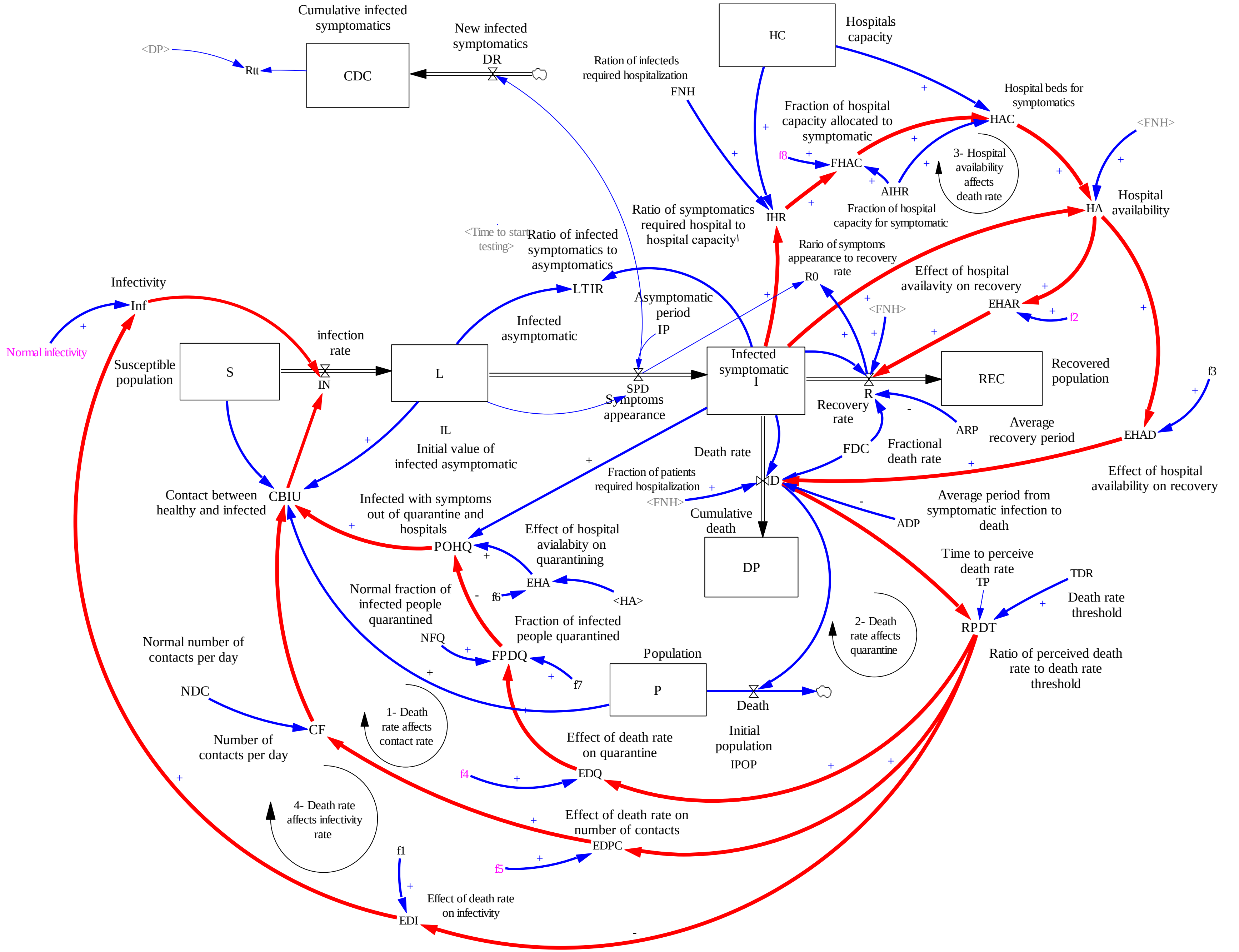
Key assumptions: effect of death rate on infectivity (probability of transmission per contact)



When death rate increases beyond a certain threshold people become more careful in their contacts by using masks, gloves and keeping distance to protect themselves

The lower curve represents the scenario for a society that responds strongly to an increasing death rate.

The upper curve shows the scenario for a society with a weaker response.



All feedback loops shown together

Assumptions about Values of Key Variables in this Model

- These values may need to change as better information becomes available.
- Total population is 80 million
- 60% of population is susceptible and at-risk.
  - The remaining 40% are not susceptible, because of low age, sparse geographic distribution, and/or strong immune competence (S=0.6*P)
- Probability of transmission is estimated at 5% per contact.(Normal Infectivity=.05)
- Under normal condition, every person comes in contact with 15 persons daily (NDC=15)
- If medical care is available, death rate among infected is 2.4%.
- 20% of infected patients become critically sick and need hospitalization. (TNH=0.2)
  Whether they are hospitalized depends on hospital availability.
- Average duration of illness is 17 days, and the infection can be transmitted to others during the entire period. Newly infected persons are asymptomatic for 7 days, on average, after which they become symptomatic.

Simulation with Different Scenarios

- In the absence of solid empirical data about key variables and relationships, scenarios let us explore the model's overall behavior, and view the possible range of plausible results.
- We use the results of the scenarios to identify and understand the mechanisms, relationships and values that govern the behavior and outcomes of the system.
- Scenario results can serve to guide public policy making.
- We present results of three scenarios:
  - Scenario 1: High degree of both social distancing and infection protection
  - Scenario 2: Low attention to social distancing, high infection protection
  - Scenario 3: Low social distancing and low infection protection

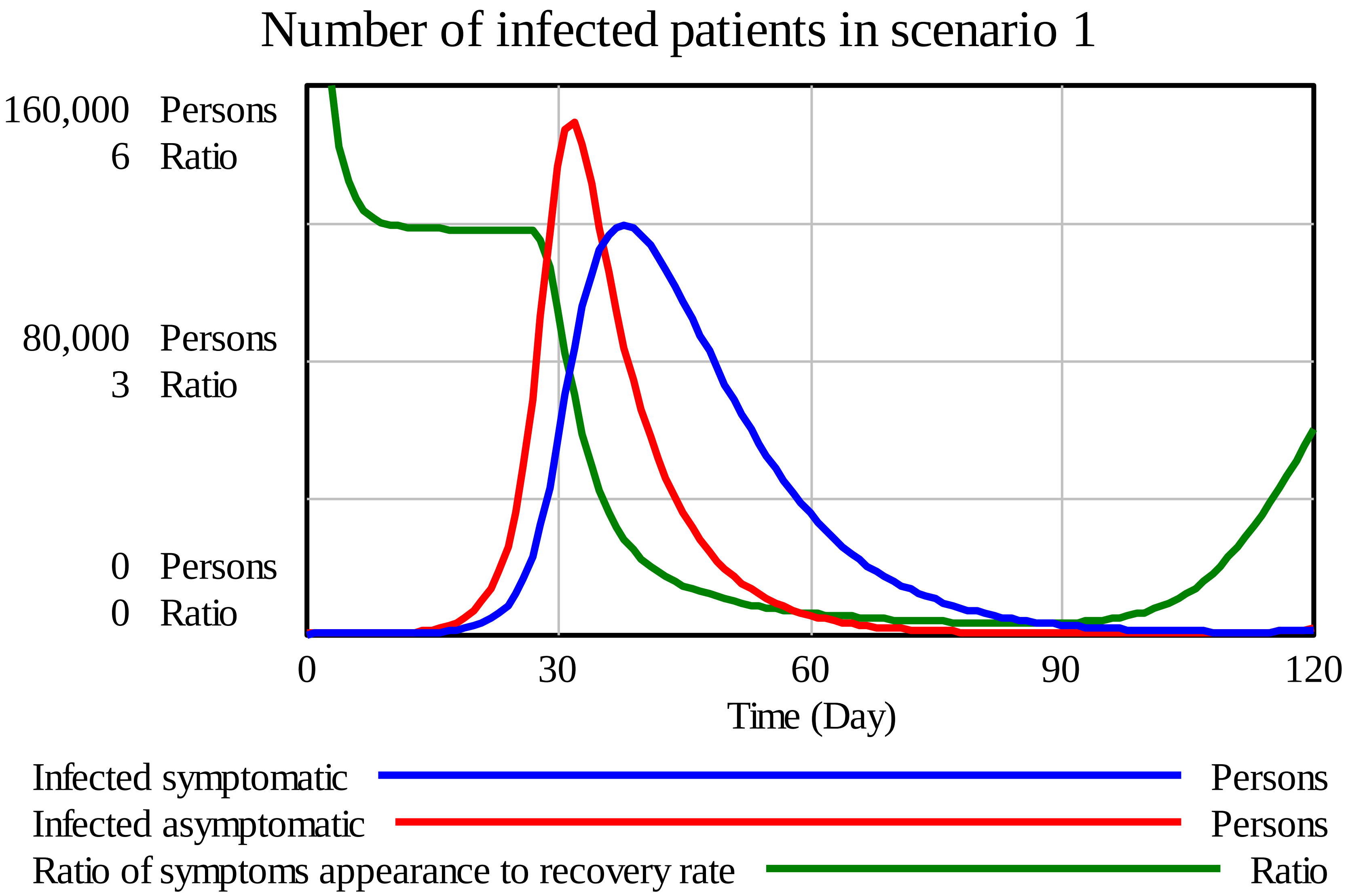
Scenario 1: High degree of both social distancing and infection protection

Scenario details:

- Contact frequency: Scenario choice A (high response)
- As death rate increases to 20 times the threshold death rate, daily contacts decrease down to 8% of normal.
  - EDPC=f5(RPDT)
  - F5=[(0,0)-(20,1)],(0,1),(1,1),(2.5,0.6),(5,0.3),(7.5,0.15),(10,0.1),(20,0.08)

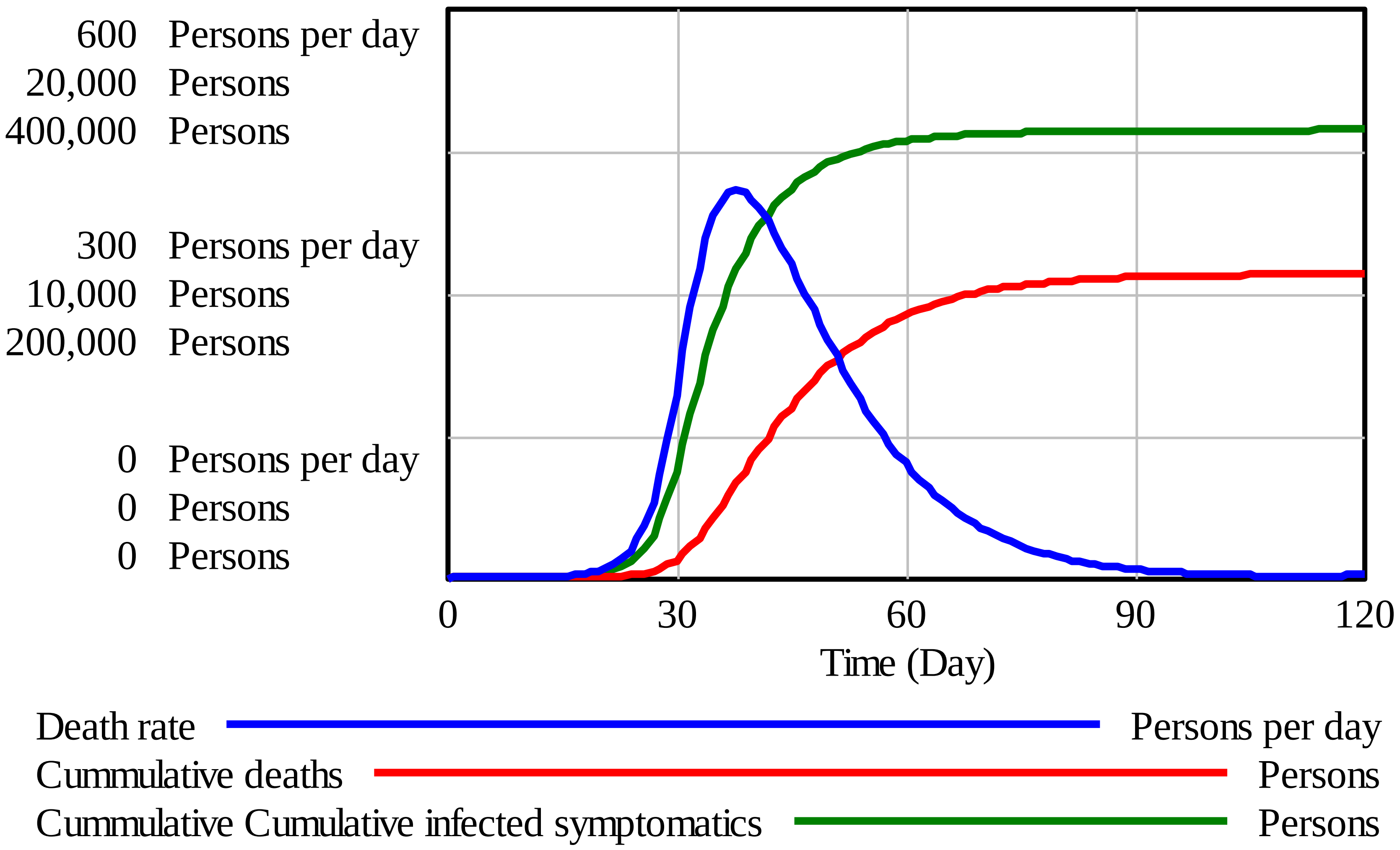
- Infectivity (probability of transmission per contact: Scenario choice A (high response)
- As death rate increases to 20 times the threshold death rate, protection measures become increasingly thorough, reducing the probability of infection to as low as 45% of normal.
  - EDI=f1(RPDT)
  - f1=[(0,0)-(20,1)],(0,1),(1,1),(2.5,0.9),(5,0.7),(7.5,0.55),(10,0.5),(20,0.45)

Number of infected in Scenario 1



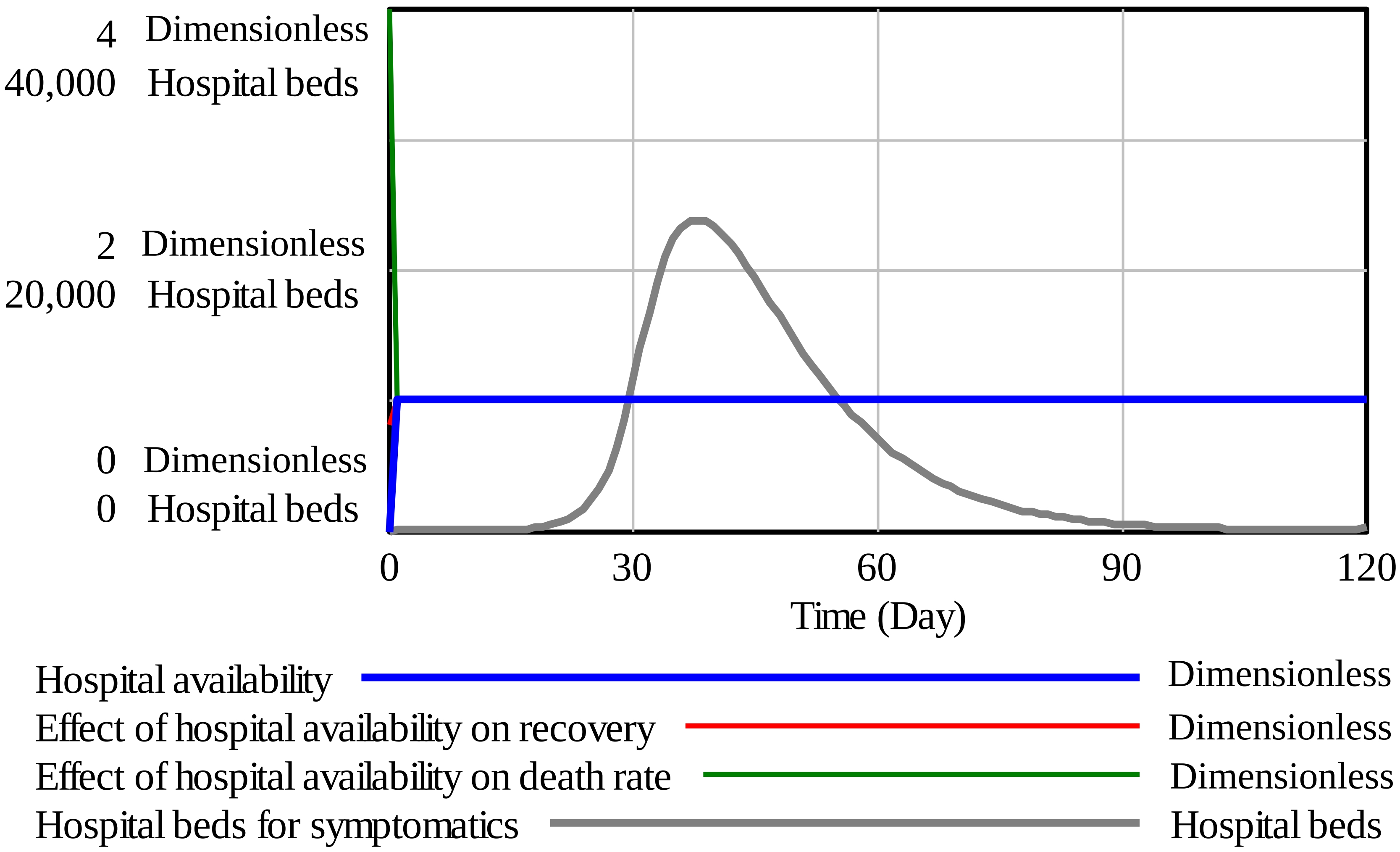
Around day 40 the number of symptomatic patients reaches its maximum of 120,000 person. This first wave of the epidemic subsides in 3-4 months.

Cumulative number of deaths and infected in Scenario 1



In scenario 1 daily death rate reaches around 400 persons per day. During the first 120 days total deaths reach 11,000 and total number of infected people (cases) is around 320,000 persons.

Effect of hospital availability on recovery and death rate in Scenario 1



In scenario 1, the need for hospital beds never exceeds the supply, and hospital availability remains 1 through out the simulation.

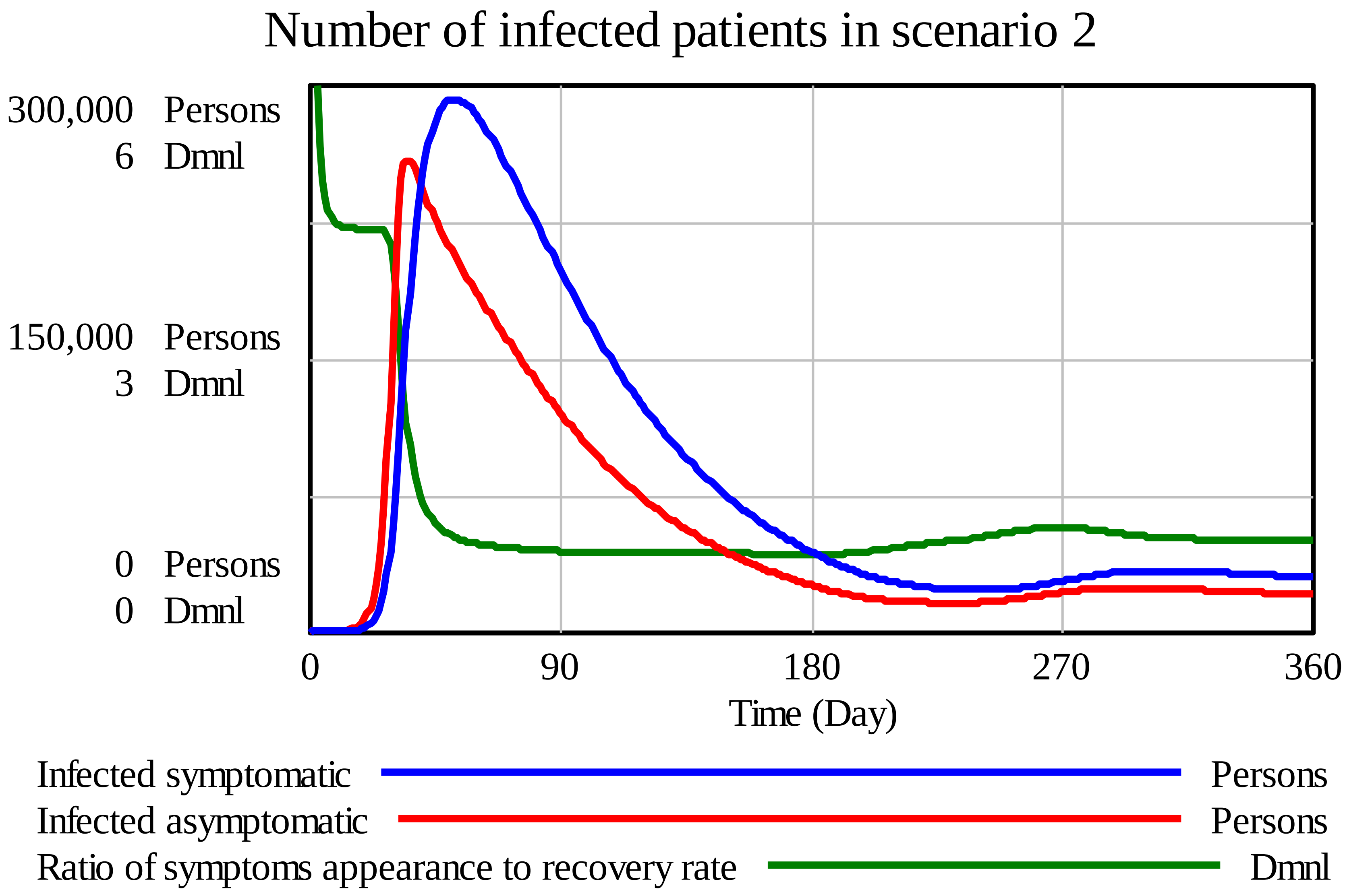
Scenario 2: Low attention to social distancing

Scenario 2 details:

- Contact frequency: Scenario choice B (low response)
- As death rate increases to 20 times the threshold death rate, daily contacts decrease to 60% of normal.
  - EDQ=f4(RPDT)
  - f5=[(0,0.4)-(20,1)],(0,1),(1,1),(2.5,0.9),(5,0.75),(7.5,0.65),(10,0.62),(20,0.6)

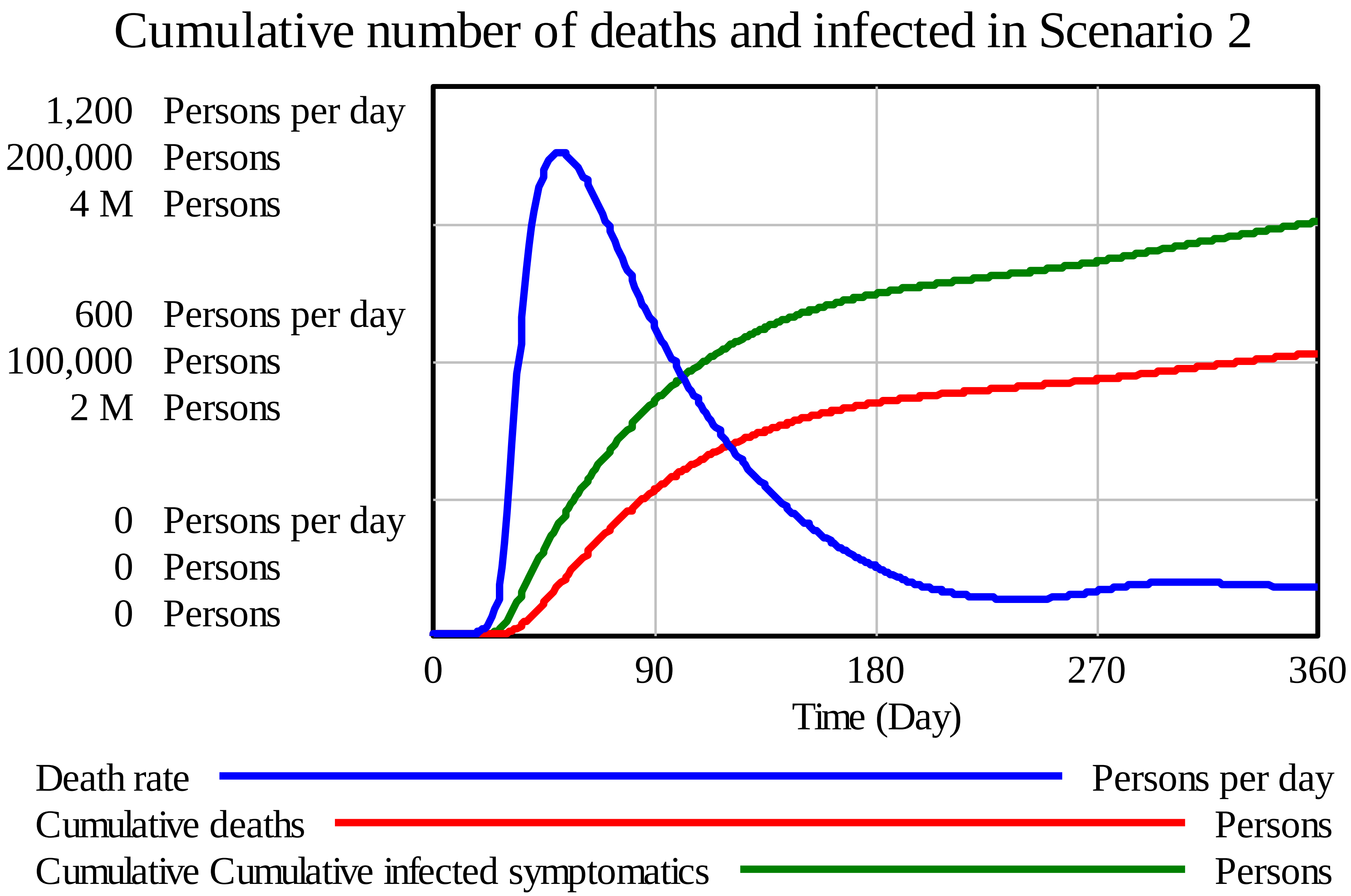
- Infectivity (probability of transmission per contact): Scenario choice A (high response)

- In scenario 2 one of the negative feedback loops that control the growth of infection - feedback 1 in slide 8 - is weakened.



In scenario 2, around day 50 the symptomatic patients reaches its maximum at 300,000 patients, compared with 120,000 in Scenario 1. It also takes longer than scenario 1 for the number patients to a minimum around day 210.

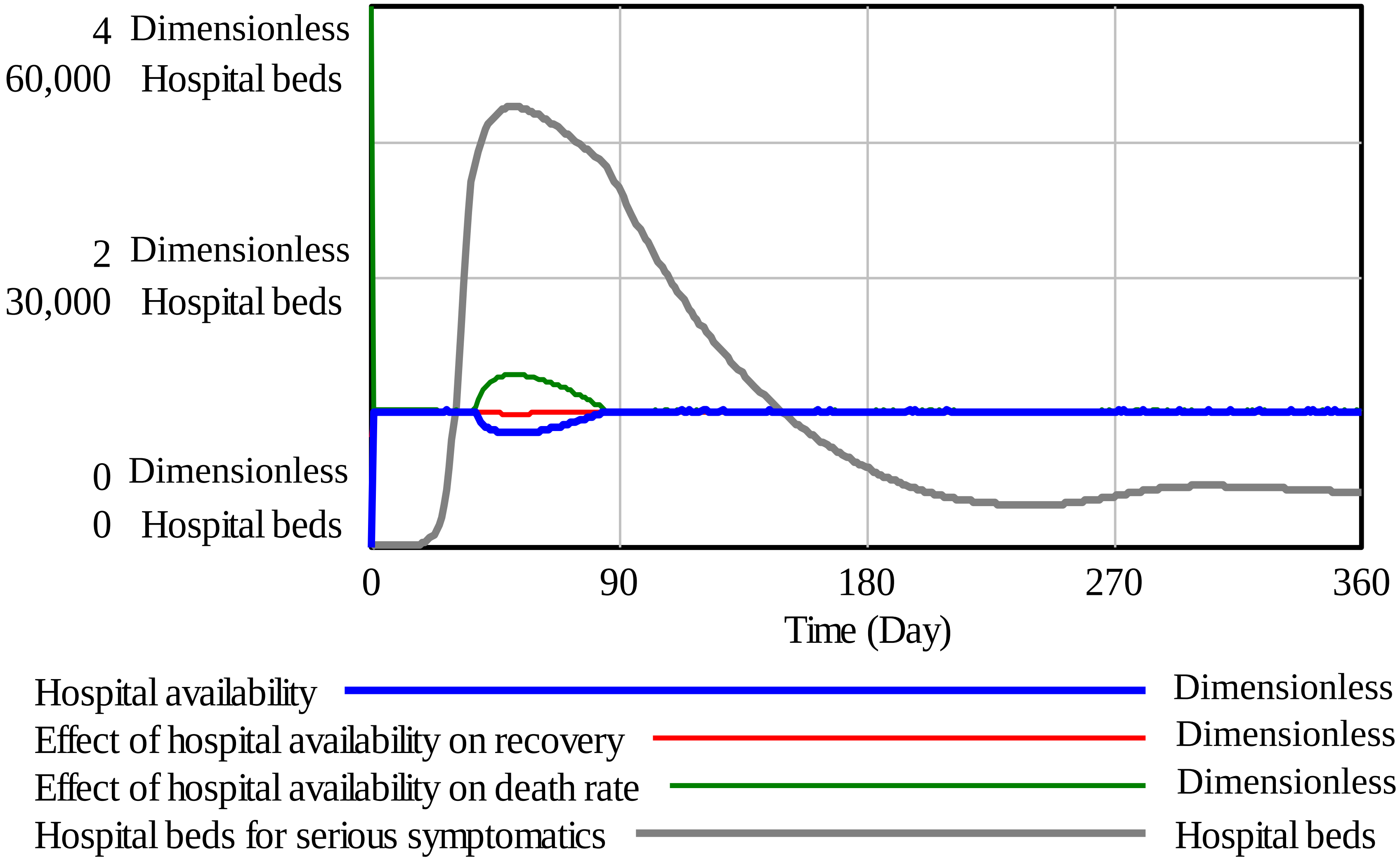
The ratio of symptoms appearance to recovery that drops below 1 around day 50 rises again slightly above 1 on day 210 which may indicate the start of a new wave of the disease.



The peak death rate of over 1,000 persons per day is more than in scenario 1 (400/day). During the first year, total deaths exceed 100,000 and cumulative symptomatic infections reach 4 million, far higher than in scenario 1.

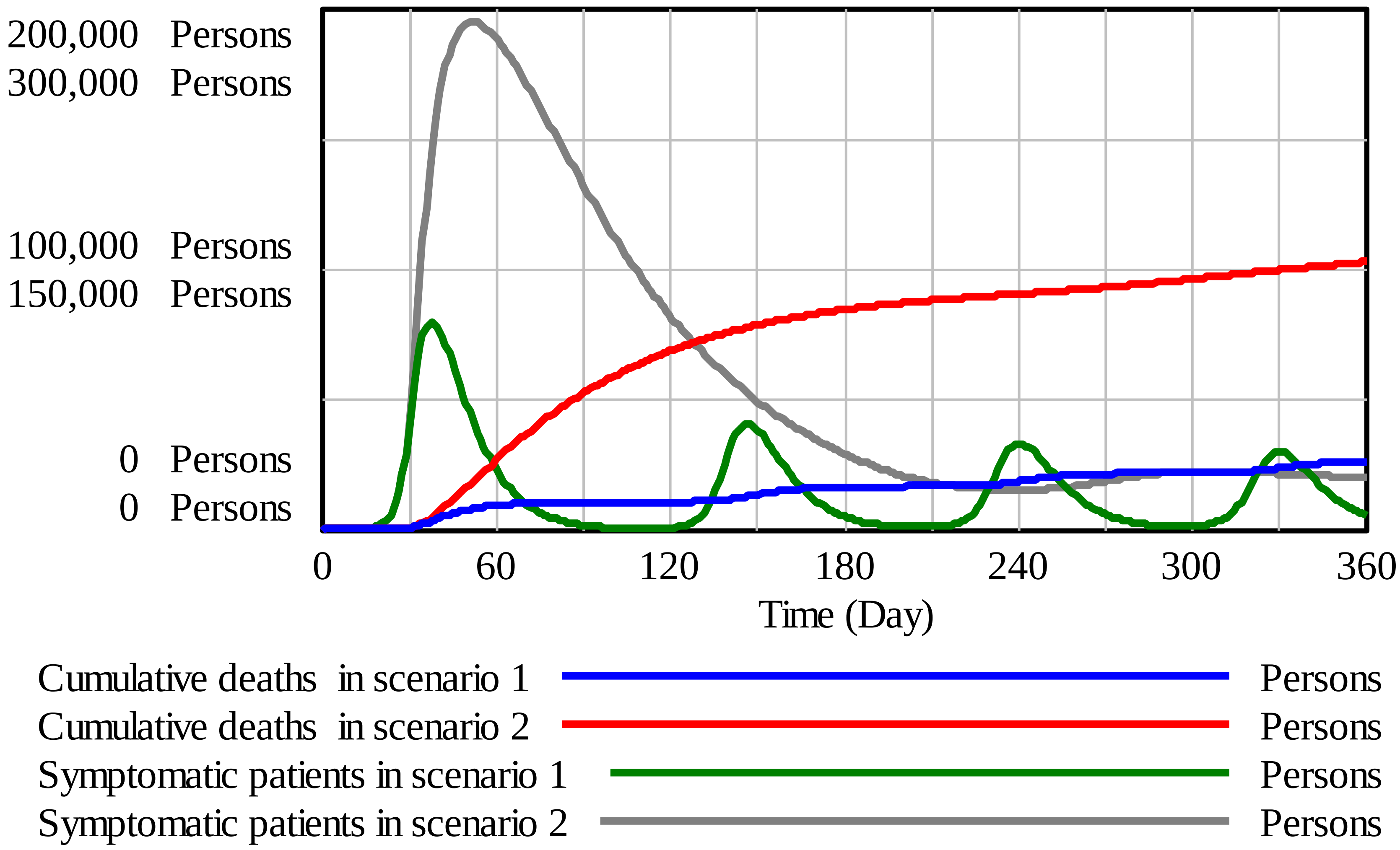
This scenario shows the large effect of social distancing, practiced from beginning of the epidemic, in reducing infections and fatalities.

Effect of hospital availability on recovery and death rate in scenario 2



Between day 40 and day 80, the number of patients needing hospitalization exceeds the system's capacity, leading to increased death rate during that period.

Comparing symptomatic and cumulative deaths in scenario 1 and 2



Cases and deaths are far lower in Scenario 1.

The first "wave" in Scenario 1 is much shorter but note the appearance of successive small waves afterward.

Scenario 3: Low Social Distancing and Low Infection Protection

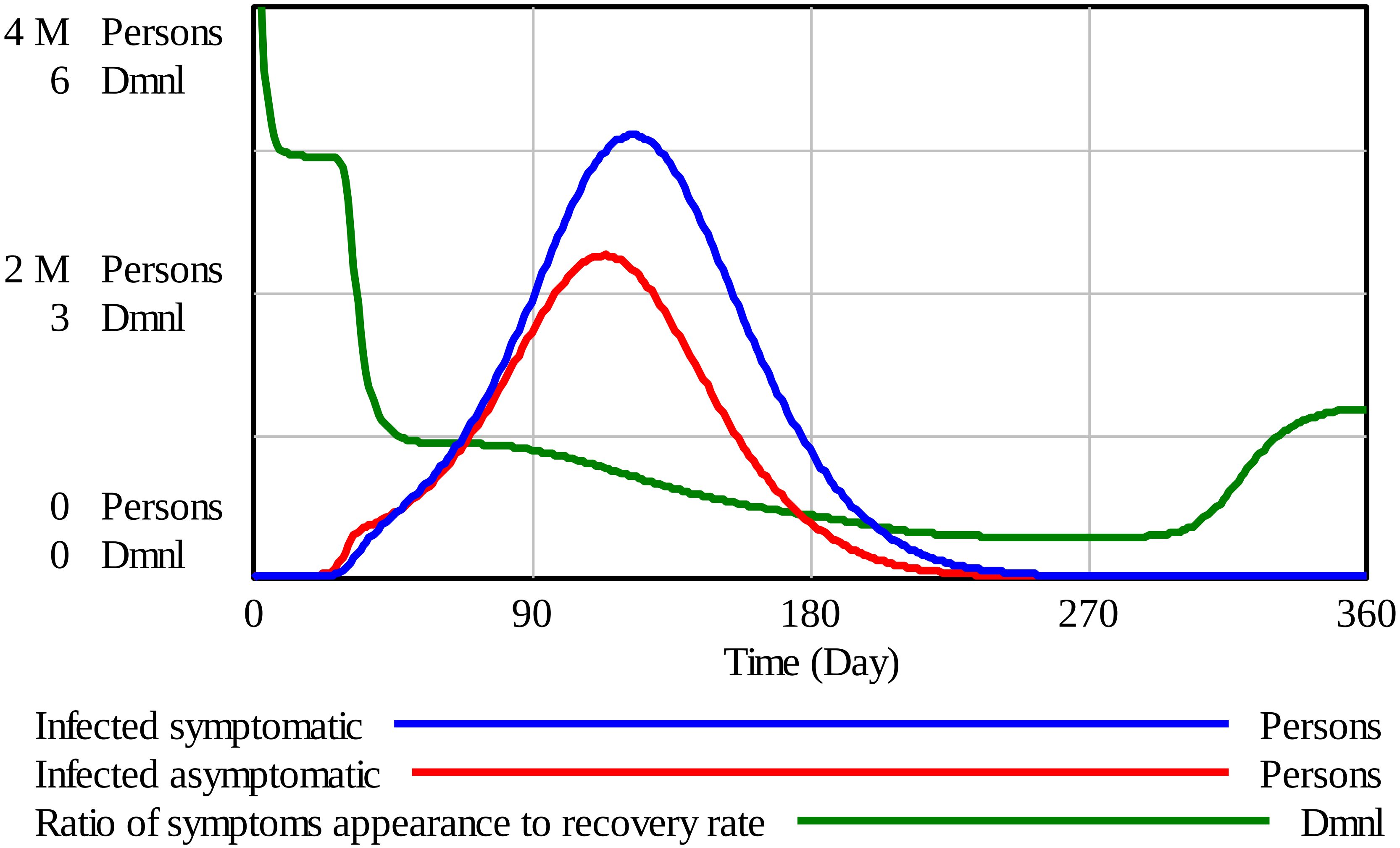
Scenario 3 details

- Contact frequency: Scenario choice B (low response)

- Infectivity (probability of transmission per contact): Scenario choice B (low response)
- As death rate increases increases to 20 times the threshold death rate, infectivity decreases down to 60% of normal
  - EDI= f1(RPDT)
  - f1= [(0,0)-(20,1)],(0,1),(1,1),(2.5,0.98),(5,0.85),(7.5,0.7),(10,0.65),(20,0.6)

- In scenario 3 another negative feedback loops that weakens the growth of the disease, feedback 4 in slide 16, is weakened. As a result the disease with two weakened feedback that should control its growth, would be expected to grow more rapidly and produce a higher number of cases.

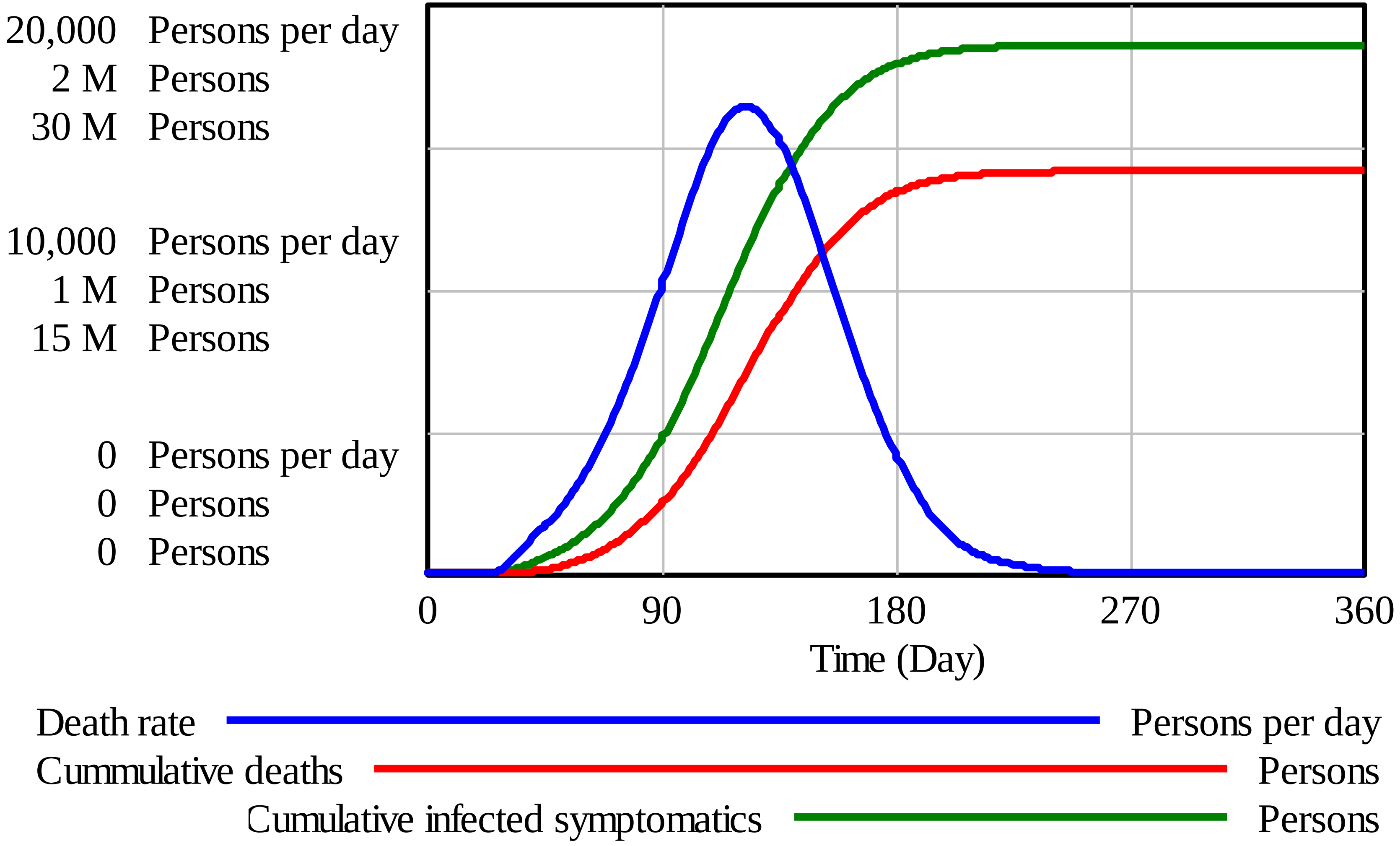
Number of infected patients in scenario 3



Symptomatic cases reach a maximum of 3,086,000 persons on day 121. The ratio of symptoms appearance to recovery rate drops below 1 on day 121. It takes about 9 months for the epidemic to subside.

In this scenario the society is heavily engaged with the epidemic for a long time.

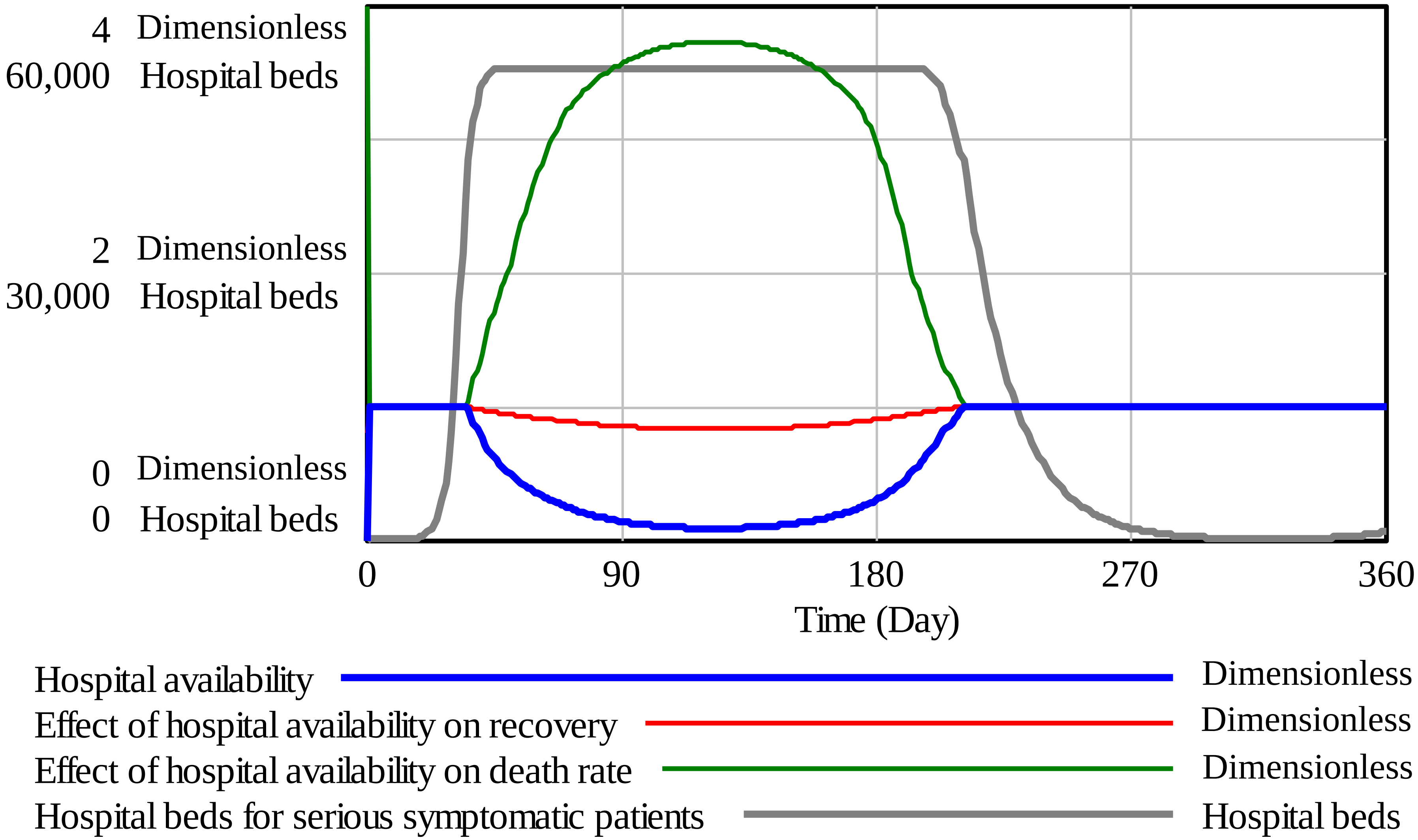
Cumulative number of deaths and infected in Scenario 3



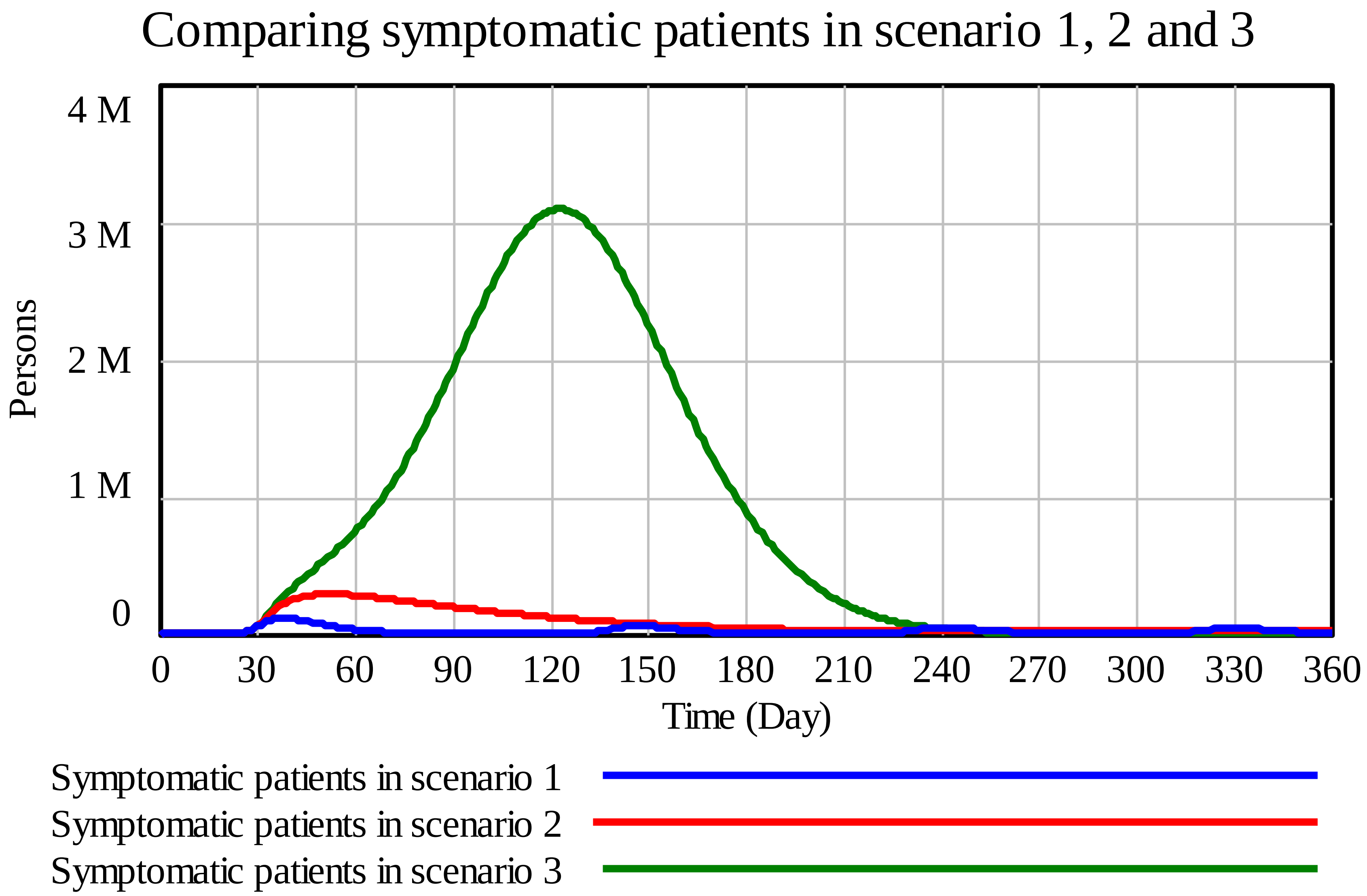
The cumulative number of symptomatic infected patients reaches 27,800,000 persons. Cumulative deaths reach to 1,400,000. Maximum death rate is about 17,000/day.

All these figures are large and show a human catastrophe for the society, with huge economic and social implications.

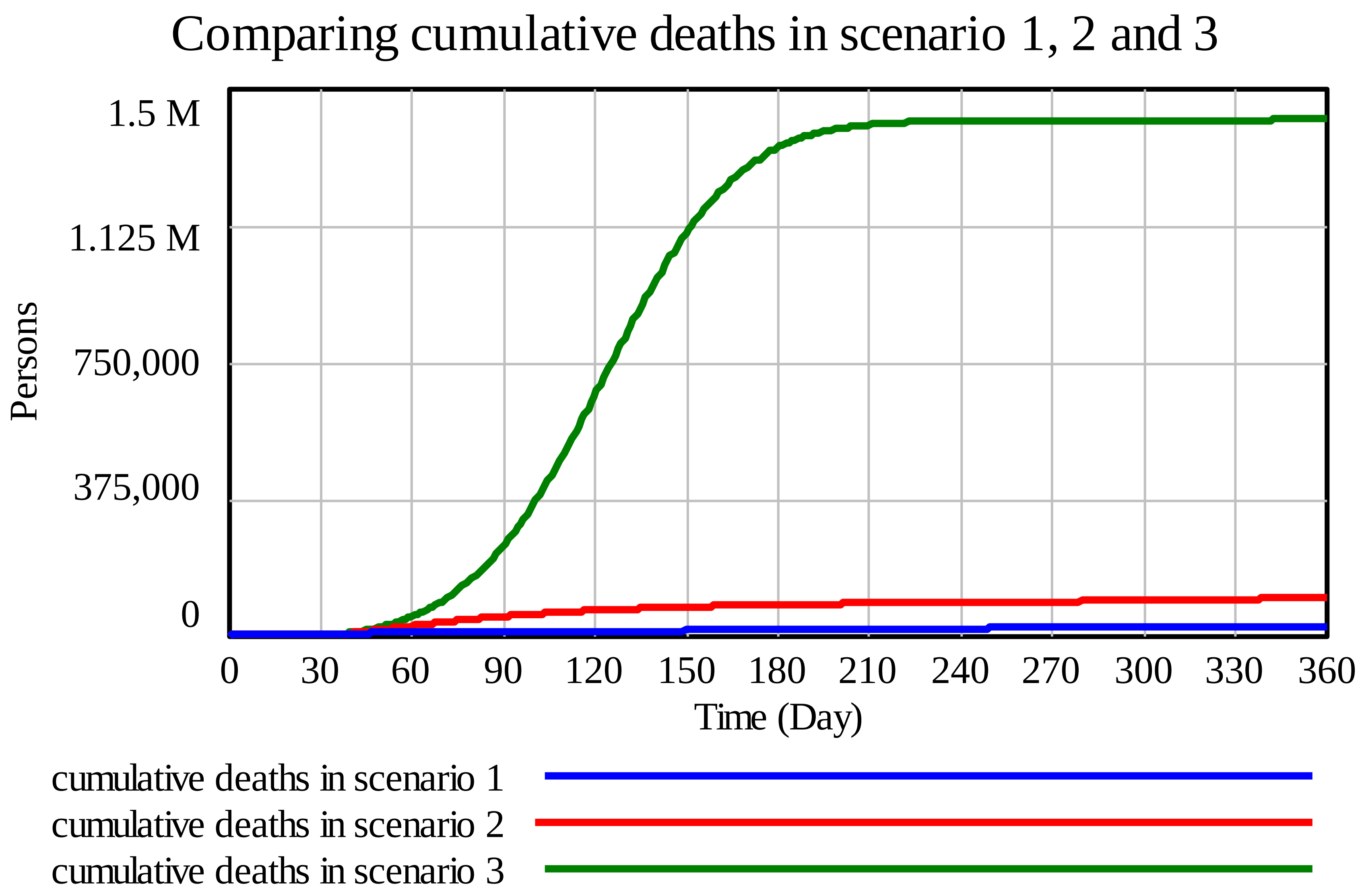
Effect of hospital availability on recovery and death rate in Scenario 3



Between day 40 and day 210 there is a shortfall of hospital beds, which reduces the recovery rate and significantly increases the death rate



Reducing both social distancing and personal infection control dramatically increases the number of cases and the duration of the epidemic



Reducing both social distancing and personal infection control dramatically increases the number of deaths.

Discussion

- Our society faces a great challenge to manage the COVID-19 epidemic.
- Without implementation of social distancing (minimizing contacts), self protection practice and quarantine (isolating the infected), society will face a catastrophe in the numbers of cases and deaths and the length of time that the epidemic persists.
- Society should immediately impose restrictions on social contacts and facilitate work at home for as many people as possible.
- In manufacturing and service organizations where people must be physically present, organizations should carefully implement procedures to minimize close contacts between employees and provide self-protection equipment and clothing.
- Creating this strong societal response requires strong and effective leadership with practical and enforceable plans.

Thank you for your attention

Take care and stay safe