Stochastic models for SARS-CoV-2 epidemics

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Compartmental epidemiological models

- models for spread of the epidemics in population divided into several disjoint compartments or classes (e.g. susceptible S, exposed E, infected I and recovered R individuals)
- population is of either constant size N or it could vary with time $(N_t,\,t\geq 0)$
- deterministic case e.g. systems of difference equations; systems of ODEs
- stochastic case e.g. multidimensional Markov chains in discrete or continuous time; systems of SDEs governed by Brownian motion or some other type of process
- models depend of several parameters the most important is the per-capita transmission rate $\beta > 0$ which governs the dynamics of transition from class S to class E



Introduction

SEIR model



• system of ODEs

$$dS(t) = \left(\Lambda - \left(\frac{\beta}{N(t)}I(t) + \mu\right)S(t)\right)dt$$

$$dE(t) = \left(\frac{\beta}{N(t)}I(t)S(t) - (\kappa + \mu)E(t)\right)dt$$

$$dI(t) = (\kappa E(t) - (\gamma + \delta)I(t))dt$$

$$dR(t) = (\gamma I(t) - \mu R(t))dt$$

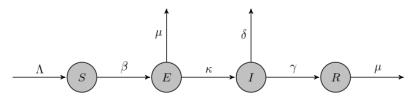


Figure 1: SEIR model scheme

• is it sensible to identify more compartments within the population?

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SEIPHAR model - compartments



the human population is divided into seven mutually exclusive compartments:

- S susceptible individuals
- E individuals exposed to the virus SARS-CoV-2, but not yet infectious to others
- *I* symptomatic infectious individuals
- P infectuous superspreaders
- A asymptomatic infectious individuals
- *H* hospitalized infected individuals
- R recovered individuals
- the total population size at time t is given by

 $N(t) = S(t) + E(t) + I(t) + P(t) + A(t) + H(t) + R(t), \quad t \ge 0$

SEIPHAR model - parameters



Parameter	Description	Units
Λ	Estimated daily number of newborns in Wuhan in 2019	per day
β	Transmission coefficient due to infected individuals	per day
l	Relative transmissibility from hospitalized individuals	—
β'	Transmission coefficient due to superspreaders	per day
κ	Rate at which exposed individuals become infectious	per day
$ ho_1$	Proportion of transitions from exposed do infected class	—
$ ho_2$	Proportion of transitions from exposed to superspreaders	—
γ_a	Hospitalization rate	per day
γ_r	Recovery rate for hospitalized patients	per day
γ_i	Recovery rate for non-hospitalized patients	per day
k_1	Weight for recovery rate due to infected class	—
k_2	Weight for recovery rate due to superspreaders	—
δ_i	Disease induced death rate for infected class	per day
δ_p	Disease induced death rate for superspreaders	per day
δ_h	Disease induced death rate for hospitalized class	per day
μ	Natural death rate	per day

SEIPHAR model - scheme



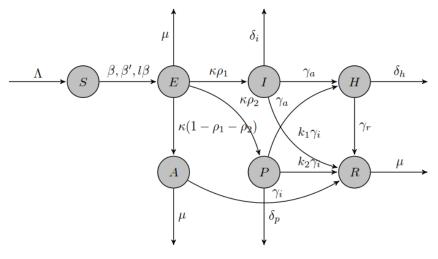


Figure 2: SEIPHAR model scheme

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SEIPHAR model - ODEs dynamics



$$dS(t) = \left(\Lambda - \left(\frac{\beta}{N(t)}\left(I(t) + lH(t)\right) + \frac{\beta'}{N(t)}P(t) + \mu\right)S(t)\right)dt$$

$$dE(t) = \left(\frac{\beta}{N(t)}\left(I(t) + lH(t)\right)S(t) + \frac{\beta'}{N(t)}P(t)S(t) - (\kappa + \mu)E(t)\right)dt$$

$$dI(t) = (\kappa\rho_1 E(t) - (\gamma_a + k_1\gamma_i + \delta_i)I(t))dt$$

$$dP(t) = (\kappa \rho_2 E(t) - (\gamma_a + k_2 \gamma_i + \delta_p) P(t)) dt$$

$$dH(t) = (\gamma_a(I(t) + P(t)) - (\gamma_r + \delta_h)H(t)) dt$$

$$dA(t) = (\kappa (1 - \rho_1 - \rho_2) E(t) - (\gamma_i + \mu) A(t)) dt$$

$$dR(t) = (\gamma_i(A(t) + k_1 I(t) + k_2 P(t)) + \gamma_r H(t) - \mu R(t)) dt$$

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Stochastic models for SARS-CoV-2 epidemics

- the basic reproduction number R₀ the expected number of secondary cases generated by one infected individual during its
 - lifespan as infectious in a fully susceptible population
- deterministic SEIPHAR model R₀:

$$R_0^D = \frac{\kappa}{\kappa + \mu} \frac{\omega_h(\beta \rho_1 \omega_p + \beta' \rho_2 \omega_i) + l\beta \gamma_a(\rho_1 \omega_p + \rho_2 \omega_i)}{\omega_h \omega_i \omega_p},$$

 $\omega_i = \gamma_a + k_1 \gamma_i + \delta_i, \quad \omega_p = \gamma_a + k_2 \gamma_i + \delta_p, \quad \omega_h = \gamma_r + \delta_h$

• R₀ - a threshold value that is epidemiologically significant and determines the potential of an infectious disease to spread in a population

SEIPHAR model (ODEs) - R_0



SEIPHAR model - **SDEs dynamics**



• stochastic SEIPHAR model - constructed as system of SDEs by introducing the perturbation in the form of the environmental white noise in transmission coefficients β and β'

$$\beta dt \rightarrow \beta dt + \sigma_1 dB_1(t), \quad \sigma_1 > 0$$

$$\beta' dt \to \beta' dt + \sigma_2 dB_2(t), \quad \sigma_2 > 0$$

where $B_1 = \{B_1(t), t \ge 0\}$ and $B_2 = \{B_2(t), t \ge 0\}$ are independent standard Brownian motions with intensities $\sigma_1 > 0$ and $\sigma_2 > 0$

SEIPHAR model - SDEs dynamics



$$dS(t) = \left(\Lambda - \left(\frac{\beta}{N(t)} \left(I(t) + lH(t)\right) + \frac{\beta'}{N(t)} P(t) + \mu\right) S(t)\right) dt \\ - \frac{\sigma_1}{N(t)} \left(I(t) + lH(t)\right) S(t) dB_1(t) - \frac{\sigma_2}{N(t)} P(t) S(t) dB_2(t)$$

$$dE(t) = \left(\frac{\beta}{N(t)} \left(I(t) + lH(t)\right) S(t) + \frac{\beta'}{N(t)} P(t)S(t) - (\kappa + \mu)E(t)\right) dt \\ + \frac{\sigma_1}{N(t)} \left(I(t) + lH(t)\right) S(t) dB_1(t) + \frac{\sigma_2}{N(t)} P(t)S(t) dB_2(t)$$

$$dI(t) = (\kappa \rho_1 E(t) - (\gamma_a + k_1 \gamma_i + \delta_i)I(t)) dt$$

$$dP(t) = (\kappa \rho_2 E(t) - (\gamma_a + k_2 \gamma_i + \delta_p)P(t)) dt$$

$$dH(t) = (\gamma_a (I(t) + P(t)) - (\gamma_r + \delta_h)H(t)) dt$$

$$dA(t) = (\kappa (1 - \rho_1 - \rho_2)E(t) - (\gamma_i + \mu)A(t)) dt$$

$$dR(t) = (\gamma_i (A(t) + k_1I(t) + k_2P(t)) + \gamma_r H(t) - \mu R(t)) dt$$

(1)

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SEIPHAR model - probability space and space of values

- complete filtered probability space $(\Omega, \mathcal{F}, \mathbb{F}, \mathbb{P})$
- filtration $\mathbb{F} = \{\mathcal{F}_t, t \ge 0\}$ is generated by natural filtrations of Brownian motions B_1 and B_2
- space of values of the process $\{(S(t), E(t), I(t), P(t), H(t), A(t), R(t)), t \ge 0\}$:

$$\mathbb{R}^{7}_{+} = \{ (x_1, x_2, x_3, x_4, x_5, x_6, x_7) : x_i > 0, \, \forall i = 1, \dots, 7 \}$$

SEIPHAR model - SDEs solution



Theorem

For any initial value $(S(0),E(0),I(0),P(0),H(0),A(0),R(0))\in\mathbb{R}^7_+$ there exists a unique solution

 $\{(S(t), E(t), I(t), P(t), H(t), A(t), R(t)) \, , \, t \geq 0\}$

of the SDE system (1) for every t > 0, which almost surely remains positive for all t > 0. Moreover, since N(t) = S(t) + E(t) + I(t) + P(t) + A(t) + H(t) + R(t) we have that

$$\frac{\Lambda}{\delta} = \liminf_{t \to \infty} N(t) \le \limsup_{t \to \infty} N(t) = \frac{\Lambda}{\mu}$$

where $\delta = \max{\{\delta_i, \delta_p, \delta_h\}}.$

SEIPHAR model - space of values



• positively invariant set of the system (1):

 $\Gamma^{\star} = \{ (S(t), E(t), I(t), P(t), H(t), A(t), R(t)) : S(t) > 0, E(t) > 0,$

 $I(t)>0, P(t)>0, H(t)>0, A(t)>0, R(t)>0, N(t)\leq N\}$

if the system starts from Γ^{\star} , it never leaves Γ^{\star}

Stochastic SEIPHAR model

SEIPHAR model - persistence in mean



- the virus remains persistent in population if there is at least one symptomatic infectious, asymptomatic infectious, hospitalized individual or super-spreader
- persistence in mean we say that the system (1) is persistent in mean if

$$[I(s) + P(s) + A(s) + H(s)] > 0 \qquad \mathbb{P} - \text{a.s.},$$
(2)

where

$$[I(s) + P(s) + A(s) + H(s)] =$$

= $\lim_{t \to \infty} \frac{1}{t} \int_{0}^{t} (I(s) + P(s) + A(s) + H(s)) ds$

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SEIPHAR model - persistence in mean



Theorem

Let initial value $(S(0), E(0), I(0), P(0), A(0), H(0), R(0)) \in \mathbb{R}^7_+$, such that the solution of the system (1) is in Γ^* , where μ, β, β' and l satisfy the relation

$$\Lambda > \left(\frac{\beta}{N(t)}\left(I(t) + lH(t)\right) + \frac{\beta'}{N(t)}P(t) + \mu\right)S(t), \quad \forall t \ge 0$$

and where c is a small fixed constant such that $\inf_{t\geq 0} E(t)/N(t) \geq c$. If we assume that noises satisfy the condition

$$\sigma_1^2 + \sigma_2^2 < c\kappa \left(\rho_1 \frac{\gamma_r + \gamma_a + \delta_p}{(\gamma_a + k_1 \gamma_i + \delta_i)(\gamma_r + \delta_p)} + \frac{\gamma_r + \gamma_a + \delta_p}{(\gamma_a + k_2 \gamma_i + \delta_p)(\gamma_r + \delta_p)} + \frac{1 - \rho_1 - \rho_2}{\gamma_i + \mu} \right),$$

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SEIPHAR model - persistence in mean



Theorem

c

then the solution $\{(S(t),E(t),I(t),P(t),A(t),H(t),R(t))\,,\,t\geq 0\}$ has the property

$$\lim_{t \to \infty} \inf [I(t) + P(t) + H(t) + A(t)] \ge$$

$$\left(\kappa \rho_1 \frac{\gamma_r + \gamma_a + \delta_p}{(\gamma_a + k_1 \gamma_i + \delta_i)(\gamma_r + \delta_p)} + \kappa \rho_2 \frac{\gamma_r + \gamma_a + \delta_p}{(\gamma_a + k_2 \gamma_i + \delta_p)(\gamma_r + \delta_p)} + \frac{\kappa (1 - \rho_1 - \rho_2)}{\gamma_i + \mu} - \frac{(\sigma_1^2 + \sigma_2^2)}{c} \right) > 0.$$

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SEIPHAR model - persistence in mean



• alternative condition for persistence in mean is based on the so-called stochastic R_0 :

$$R_0^S = \frac{(\beta + \beta')\frac{\Lambda}{\mu}}{\kappa + \mu + \frac{1}{2}(\sigma_1^2 + \sigma_2^2)\frac{\Lambda^2}{\mu^2}}$$
(3)

• if $R_0^S > 1$, the solution

 $\{(S(t), E(t), I(t), P(t), A(t), H(t), R(t))\,,\, t\geq 0\}$

of system (1) is persistent in mean

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Stochastic SEIPHAR model

SEIPHAR model - extinction



Theorem

If noises satisfy that

$$\frac{1}{2\left(\kappa+\mu\right)}\left(\frac{\beta^2}{\sigma_1^2} + \frac{(\beta')^2}{\sigma_2^2}\right) < 1,$$

than for any initial value $(S(0), E(0), I(0), P(0), A(0), H(0), R(0)) \in \mathbb{R}^7_+$, such that the solution of the system (1) is in Γ^* , it follows that

$$E(t) + I(t) + P(t) + H(t) + A(t) \to 0 \quad \mathbb{P}-a.s. \ as \ t \to \infty,$$

while

$$\limsup_{t \to \infty} S(t) = \frac{\Lambda}{\mu} \quad \mathbb{P}-a.s.$$

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SEIPHAR model - extinction



- alternative conditions for extinction in mean are also based on $R_0^{\cal S}$ given by (3)
- if $\sigma_1^2 \leq \beta \frac{4\mu}{\Lambda} \max\{1,l\}$, $\sigma_2^2 \leq \beta' \frac{4\mu}{\Lambda}$ and $R_0^S < 1$, than the disease P-a.s. goes to extinction

Sensitivity analysis and simulations

SEIPHAR model - parameter values



Symbol	Description	Value
Λ	Estimated daily number of newborns in Wuhan in 2019	310 7
β	Transmission coefficient due to infected individuals	2.55 5
l	Relative transmissibility from hospitalized individuals	1.56 5
β'	Transmission coefficient due to superspreaders	7.65 5
κ	Rate at which exposed individuals become infectious	0.25 5
ρ_1	Proportion of transitions from exposed do symptomatic infected class	0.58 5
ρ_2	Proportion of transitions from exposed to superspreaders	0.001 5
γ_a	Hospitalization rate	0.94 5
γ_r	Recovery rate for hospitalized patients	0.5 5
γ_i	Recovery rate for non-hospitalized patients	0.27 5
k_1	Weight for recovery rate due to infected class	0.85 [a
k_2	Weight for recovery rate due to superspreaders	0.95 [a
δ_i	Disease induced death rate for infected class	1/23 [5
δ_p	Disease induced death rate for superspreaders	1/23 5
δ_h	Disease induced death rate for hospitalized class	1/23 [5]
μ	Natural death rate	0.00714 [6
σ_1	Intensity of Brownian motion B_1 due to infected class	0.0005 [a
σ_2	Intensity of Brownian motion B_2 due to superspreaders	0.001 a

Table 1: Parameters values, either based on the epidemics in Wuhan in the period January 4 - March 9, 2020, or rationally assumed $(k_1, k_2, \sigma_1, \sigma_2)$

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SEIPHAR model - sensitivity analysis



- R_0^D and the stochastic model related threshold R_0^S are compared regarding the values of the normalized forward sensitivity indices (NFSI)
- NFSI is the ratio of the relative change in the basic reproduction number R_0^i as a function of the parameter θ to the relative change in the parameter θ , assuming that R_0^i is differentiable with respect to parameter:

$$\Upsilon^{R^i_0}_{\theta} = \frac{dR^i_0}{d\theta} \frac{\theta}{R^i_0}, \quad i \in \{D,S\}$$

• BFSI is used to discover parameters that have a high impact on R_0^i and that should be targeted by specific epidemiological intervention strategies

Sensitivity analysis and simulations

SEIPHAR model - R_0^D sensitivity analysis



- R_0^D is the most sensitive to change in values of parameters $\beta,~\rho_1,~l,~\gamma_i$ and γ_r
- change of $R_0^D = 4.5206$ under the 10% increase in value of parameters β , ρ_1 , l, γ_i and γ_r is given in the following table:

Parameter	Value of R_0^D	Relative change in R_0^D (%)
β	4.9720	+9.98
$ ho_1$	4.9715	+9.97
l	4.8501	+7.29
γ_i	4.4366	-1.86
γ_r	4.2429	-6.14

Sensitivity analysis and simulations

SEIPHAR model - R_0^S sensitivity analysis



- R_0^S is the most sensitive to change in values of parameters $\beta,\,\beta',\,\sigma_1$ and σ_2
- change of $R_0^S = 1.0298$ under the 10% increase in value of parameters β' , β , σ_1 and σ_2 is given in the following table:

Parameter	Value of R_0^S	Relative change in R_0^S (%)
β'	1.1071	+7.51
eta	1.0556	+2.51
σ_1	0.9883	-4.03
σ_2	0.8817	-14.38

SEIPHAR model - simulation parameters



- theoretical results (persistence, extinction) are, for reasonable set of values of model parameters for which the global positive solution of system (1) exists, verified within the simulation study
- simulation parameters adjusted values from Table 1 in order to satisfy the theoretical assumptions of persistence and extinction theorems
- simulations confirm that the trajectories of the stochastic model either oscillate around (on the short time-scale) or are close to (on the long time-scale) the trajectories of the deterministic model, showing the robustness of such stochastic model to the Brownian noise

Persistence in mean



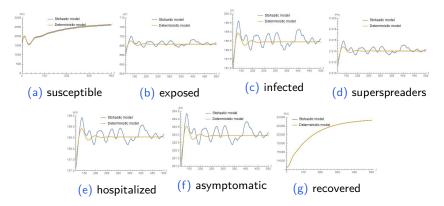


Figure 3: Persistence - stochastic (blue) and deterministic (orange) model

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Sensitivity analysis and simulations

Extinction



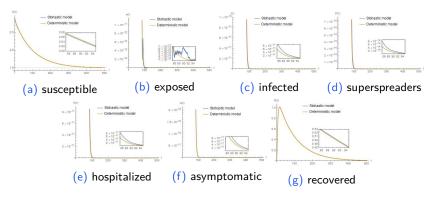


Figure 4: Extinction - stochastic (blue) and deterministic (orange) model

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Delayed SVEIR model - main characteristics



- V vaccinated individuals (new compartment)
- cumulative number of exposed individuals by time t > 0 (A_* is a unit-rate Poisson process):

$$A_E^n(t) = A_*\left(n\int_0^t \beta(t)S^n(s)I^n(s)\,ds\right)$$

• cumulative number of vaccinated individuals by time t > 0, independent of $(A_E^n(t), t \ge 0)$:

$$A_V^n(t) = A_* \left(n \int_0^t \alpha(t) S^n(s) \, ds \right)$$

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Future work Delayed SVEIR model - scheme



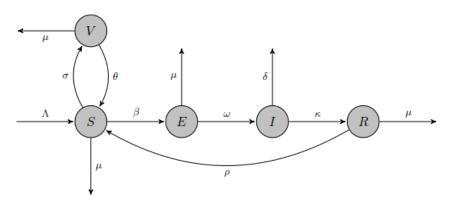


Figure 5: SVEIR model scheme

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Delayed SVEIR model - delays



- the individual *i* going through the S E I R path has the following time epochs: τ_i , $\tau_i + \mathcal{E}_i$, $\tau_i + \mathcal{E}_i + \mathcal{I}_i$, $\tau_i + \mathcal{E}_i + \mathcal{I}_i$, representing the times of becoming exposed, infected, immune and then again susceptible
- \mathcal{E}_i is the exposure period, \mathcal{I}_i is the infectious period and \mathcal{W}_i is the natural immunity period
- an individual can initially be exposed ($\mathcal{E}^0_i)$, infected ($\mathcal{I}^0_i)$ or recovered ($W^0_i)$

Future work

Delayed SVEIR model - distributions of delays



$$\begin{aligned} G^{c}(t) &= P(t < \mathcal{E}_{i}) \\ \Psi(t) &= P(\mathcal{E}_{i} \leq t < \mathcal{E}_{i} + \mathcal{I}_{i}), \\ \Phi(t) &= P(\mathcal{E}_{i} + \mathcal{I}_{i} \leq t < \mathcal{E}_{i} + \mathcal{I}_{i} + \mathcal{W}_{i}), \\ \Xi(t) &= P(\mathcal{E}_{i} + \mathcal{I}_{i} + \mathcal{W}_{i} \leq t) \end{aligned}$$

$$\begin{aligned} G_0^c(t) &= P(t < \mathcal{E}_i^0) \\ \Psi_0(t) &= P(\mathcal{E}_i^0 \le t < \mathcal{E}_i^0 + \mathcal{I}_i) \\ \Phi_0(t) &= P(\mathcal{E}_i^0 + \mathcal{I}_i \le t < \mathcal{E}_i^0 + \mathcal{I}_i + \mathcal{W}_i) \\ \Xi_0(t) &= P(\mathcal{E}_i^0 + \mathcal{I}_i + \mathcal{W}_i \le t) \end{aligned}$$

$$\begin{aligned} G_1^c(t) &= P(t < \mathcal{I}_i^0), \\ \Phi_1(t) &= P(\mathcal{I}_i^0 \le t < \mathcal{I}_i^0 + \mathcal{W}_i) \\ \Xi_1(t) &= P(\mathcal{I}_i^0 + \mathcal{W}_i \le t) \end{aligned}$$

$$G_2^c(t) = P(t < \mathcal{W}_i^0)$$

$$G_2(t) = P(\mathcal{W}_i^0 \le t).$$

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Delayed SVEIR model - counting process



- denote the proportion of individuals at time t in compartment X by $X^{n}(t)$
- the counting process

$$(S^{n}(t), V^{n}(t), E^{n}(t), I^{n}(t), R^{n}(t), t \ge 0)$$

is given as follows:

$$S^{n}(t) = S^{n}(0) + \sum_{i=1}^{V^{n}(0)} I_{\{\mathcal{Y}_{i}^{0} \leq t\}} + \sum_{i=1}^{E^{n}(0)} I_{\{\mathcal{E}_{i}^{0} + \mathcal{I}_{i} + \mathcal{W}_{i} \leq t\}} + \sum_{i=1}^{I^{n}(0)} I_{\{\mathcal{I}_{i}^{0} + \mathcal{W}_{i} \leq t\}} + \sum_{i=1}^{A^{n}_{V}(t)} I_{\{\mathcal{I}_{i}^{0} + \mathcal{Y}_{i} \leq t\}} + \sum_{i=1}^{A^{n}_{E}(t)} I_{\{\tau_{i} + \mathcal{E}_{i} + \mathcal{I}_{i} + \mathcal{W}_{i} \leq t\}} - A^{n}_{E}(t) - A^{n}_{V}(t)$$

$$V^{n}(t) = \sum_{i=1}^{V^{n}(0)} I_{\{\mathcal{Y}_{i}^{0} > t\}} + \sum_{i=1}^{A_{V}^{n}(t)} I_{\{T_{i} + \mathcal{Y}_{i} > t\}}$$

$$E^{n}(t) = \sum_{i=1}^{E^{n}(0)} I_{\{\mathcal{E}^{0}_{i} > t\}} + \sum_{i=1}^{A^{n}_{E}(t)} I_{\{\tau_{i} + \mathcal{E}_{i} > t\}}$$

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Delayed SVEIR model - counting process



$$\begin{split} I^{n}(t) &= \sum_{\substack{i=1\\R^{n}(0)}}^{I^{n}(0)} \mathrm{I}_{\left\{\mathcal{I}_{i}^{0} > t\right\}} + \sum_{\substack{i=1\\I^{n}(0)}}^{E^{n}(0)} \mathrm{I}_{\left\{\mathcal{E}_{i}^{0} \le t < \mathcal{E}_{i}^{0} + \mathcal{I}_{i}\right\}} + \sum_{\substack{i=1\\E^{n}(0)}}^{A^{n}_{E}(t)} \mathrm{I}_{\left\{\tau_{i} + \mathcal{E}_{i} \le t < \tau_{i} + \mathcal{E}_{i}\right\}} + \sum_{\substack{i=1\\E^{n}(0)}}^{A^{n}_{E}(t)} \mathrm{I}_{\left\{\mathcal{E}_{i}^{0} + \mathcal{I}_{i} \le t < \mathcal{E}_{i}^{0} + \mathcal{I}_{i} + \mathcal{W}_{i}\right\}} + \\ &+ \sum_{i=1}^{A^{n}_{E}(t)} \mathrm{I}_{\left\{\tau_{i} + \mathcal{E}_{i} + \mathcal{I}_{i} \le t < \tau_{i} + \mathcal{E}_{i} + \mathcal{I}_{i} + \mathcal{W}_{i}\right\}} \end{split}$$

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Stochastic models for SARS-CoV-2 epidemics

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Delayed SVEIR model - system of Volterra integral equations

• according to [6], we want to prove that the law of large number limit of the above described counting system is the unique solution of the following system of deterministic Volterra integral equations:

$$\begin{split} S(t) &= S(0) + V(0)\Upsilon_0(t) + E(0)\Xi_0(t) + I(0)\Xi_1(t) + R(0)G_2(t) - \\ &- \int_0^t (\beta(s)S(s)I(s)(1 - \Xi(t - s)) + \alpha(s)S(s)\Upsilon(t - s) - \\ &- V(s)\Upsilon(t - s) - R(s)\Xi^c(t - s)) \, ds \end{split}$$

$$V(t) &= V(0)\Upsilon_0^c(t) + \int_0^t (\alpha(s)S(s)\Upsilon^c(t - s) - V(s)\Upsilon(t - s)) \, ds$$

$$E(t) &= E(0)G_0^c(t) + \int_0^t \beta(s)S(s)I(s)G^c(t - s) \, ds$$

$$I(t) &= I(0)G_1^c(t) + E(0)\Psi_0(t) + \int_0^t \beta(s)S(s)I(s)\Psi(t - s) \, ds$$

$$R(t) &= R(0)G_2^c(t) + I(0)\Phi_1(t) + E(0)\Phi_0(t) + \\ &+ \int_0^t (\beta(s)S(s)I(s)\Phi(t - s) - R(s)\Xi(t - s)) \, ds \end{split}$$

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Stochastic models for SARS-CoV-2 epidemics

(4)



Delayed SVEIR model - stochastic perturbation



• transmission coefficient $\beta(t)$ - Ornstein-Uhlenbeck process $\beta = (\beta(t), t \ge 0)$ given by the stochastic differential equation (SDE)

$$d\beta(t) = \theta \left(\beta_e - \beta(t)\right) dt + \sigma dB(t), \quad t \ge 0,$$

where β_e is the mean of the stationary Gaussian distribution with variance $\sigma/\sqrt{2\theta}, \ \theta>0$ determines the speed of the mean reversion, σ is the intensity of volatility and Brownian motion $B=(B(t), \ t\geq 0)$ is the driving process

• explicit solution:

$$\beta(t) = \beta_e + (\beta(0) - \beta_e) e^{-\theta t} + \sigma \int_0^t e^{-\theta(t-s)} dB(s),$$
$$\sigma \int_0^t e^{-\theta(t-s)} dB(s) \sim \mathcal{N}\left(0, \frac{\sigma^2}{2\theta}(1 - e^{-2\theta t})\right)$$

• existence of unique positive solution, analysis of persistence and extinction of the disease

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Bibliography

Bibliography



- Y. Cai, J. Jiao, Z. Gui, Y. Liu, W. Wang (2018) Environmental variability in a stochastic epidemic model, Applied Mathematics and Computation, 329, 210–226
- 2 J. Đorđević, I. Papić, N. Šuvak (2021) A two diffusions stochastic model for the spread of the new corona virus SARS-CoV-2, Chaos, Solitons and Fractals, 148: 110991,
- **3** J. Đorđević, B. Jovanović, J. Manojlović, N. Šuvak (2022) Analysis of stability and sensitivity of deterministic and stochastic models for the spread of the new corona virus SARS-CoV-2, Filomat (to appear)
- A. Idris, Modu G.U. et al. (2021) A mathematical model of coronavirus disease (COVID-19) containing asymptomatic and symptomatic classes, Results in Physics 21: 103776
- 5 F. Ndaïrou, I. Area, J.J. Nieto, D.F.M. Torres (2020) Mathematical modeling of COVID-19 transmission dynamics with a case study of Wuhan, Chaos, Solitons and Fractals 135: 109846
- 6 Pang G., Pardoux E. (2022) Functional Limit Theorems for Non-Markovian Epidemic Models, arXiv:2003.03249v3
- 7 Statista

https://www.statista.com/statistics/250650/number-of-births-in-china

StatSem MathOs, 3.2.2022