

Exploring and optimising infectious disease policies with a stylised agent-based model

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Complexity of multi-objective decision making for epidemics and pandemics in a globalised world [Saker et al., 2004] [Bickley et al., 2021]

→ current models for decision-making range from mathematical models [Brauer, 2008] to data-driven simulation models [Buczak et al., 2012]

→ agent-based modelling as a flexible and generic modelling tool particularly suited for decision-making [Miksch et al., 2019] [Minoza et al., 2021]

→ validation, exploration and sensitivity analysis of ABMs and other approaches not frequent in the literature

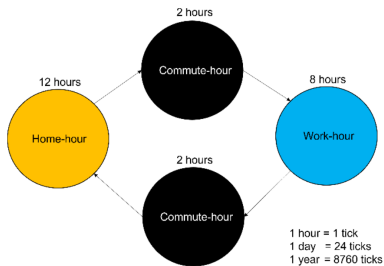
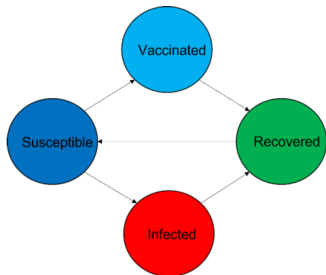
[Baquela and Olivera, 2022][Wu et al., 2013]

→ how can extensive model validation techniques be used for stylised models?

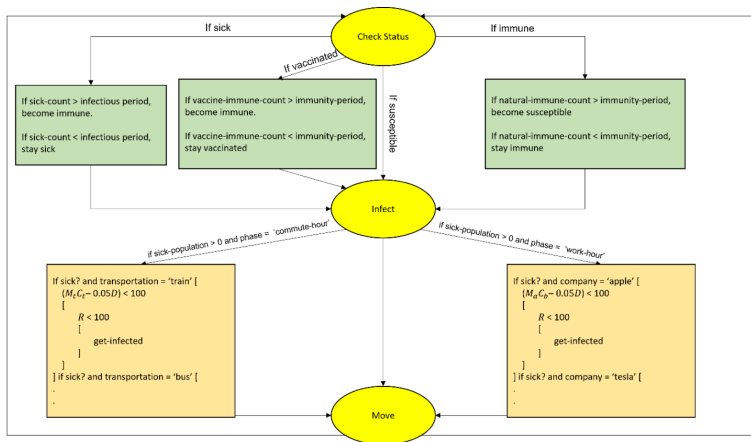
Research question

We build a stylised ABM for the spread of infectious disease which focuses on masking and vaccination and apply model validation methods, to investigate if lack of data and uncertainty can be compensated for through model validation.

- Realistic geographical context, with commuting of workers simulated through the day (1h tick) for 365 days
- Simple SIRV agent dynamics within places (public transport and workplace)
- 4 transportation modes and a stylised setup for company sizes
- $N = 1500$ agents randomly assigned, with less than 1% daily renewed (open world)



(Left) agent states; (Right) daily cycle.



Global variables: stylised contact rates for transport $c_{bus} = 40\%$, $c_{metro} = 35\%$, $c_{train} = 30\%$, $c_{walk} = 10\%$, $c_{car} = 10\%$ and companies $c_{Big} = 40\%$, $c_{Medium} = 35\%$, $c_{Small} = 30\%$

Agent variables: higher infection rate for cardio-vascular sick individuals [Ielapi et al., 2020]
→ predefined infection risk rates depending on agent characteristics: No mask & Cardio = 50% risk rate; Mask & Cardio = 45%; No mask & Cardio = 15%; Mask & No Cardio = 10%

Model parameters explored:

- Infectious period (2-4 weeks)
- Immunity period (9-11 months)
- Vaccination rate
- Social distancing level (3 levels, each reducing contact rate by 5%)

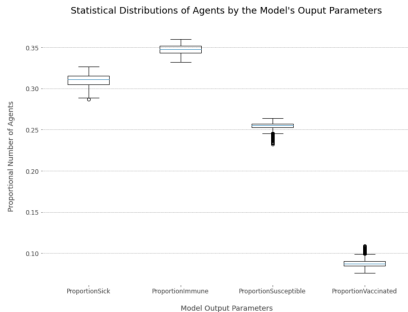
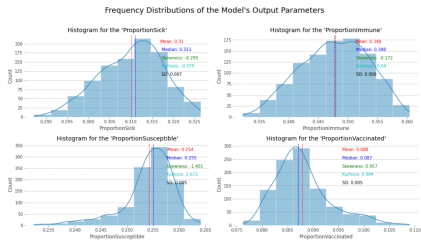
Model indicators: agents in each state, cumulated infections and vaccinations.

→ model implemented in NetLogo (role of visualisation and interactivity in the model construction process)

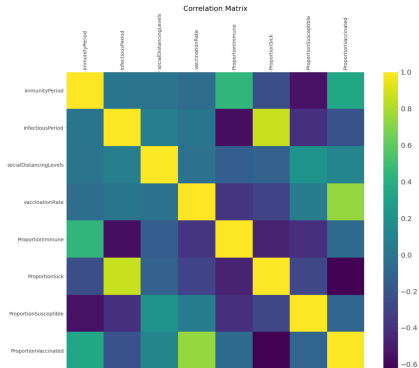
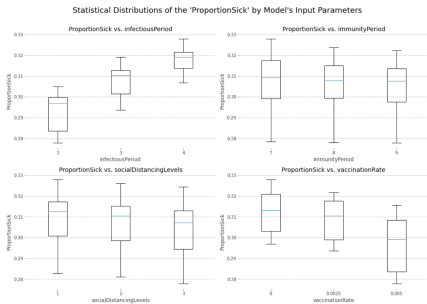
→ embedded into the OpenMOLE platform for model exploration and validation [Reuillon et al., 2013]



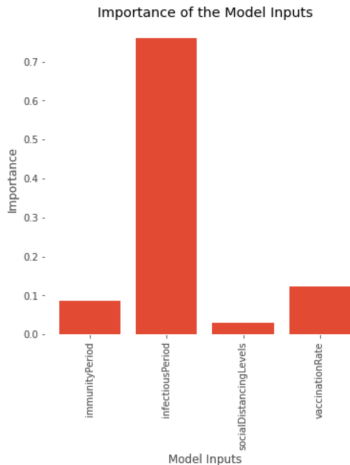
→ 4 dimensions parameter space explored through numerical experiments



LHS sampling (10,000 points) to study statistical properties of model indicators: skewed distributions (Left), distributions of the proportion of agents in each state (Right)



Grid exploration of 81 parameter points (125 stochastic repetitions for each): various amplitude of parameter influence (Left), confirmed with an OLS regression, and correlation matrix of model inputs and outputs (Right)

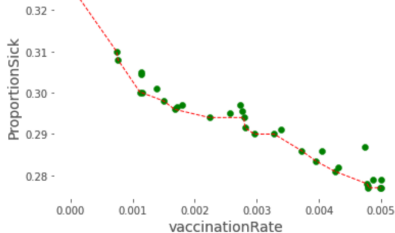


Random forest model surrogate trained on LHS simulation data (performance: MAE=0.001): feature importance of input parameters.

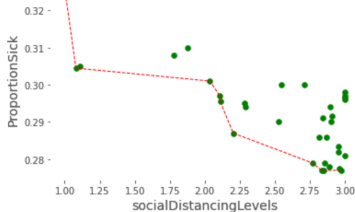
Outputs	infectiousPeriod	immunityPeriod	vaccinationRate	socialDistancingLevels
ProportionImmune	0.72	0.333	0.665	0.7
ProportionSick	0.692	0.09	0.365	0.143
ProportionVaccinated	0.516	0.319	0.587	0.337
ProportionSusceptible	0.341	0.066	0.92	0.277

Saltelli total order indices [Saltelli et al., 2008] to quantify parameters' influence on model indicators.

ProportionSick vs. vaccinationRate (Pareto Front)



ProportionSick vs. socialDistancingLevels (Pareto Front)



NSGA2 bi-objective optimisation to find compromise points between disease burden and vaccination (cost): Pareto front of proportion of sick vs. social distancing levels (Left), and corresponding points on other objectives (Right).




- proof-of-concept of how model exploration and validation can compensate for parameter uncertainty and the lack of data
- open question: transfer to policy scenarios, which practical validated insights from such hybrid approaches
- model can be refined in several ways (e.g. agent states, more characteristics)
- sensitivity to geography and to the company setup [Raimbault et al., 2019] to be explored




→ a simple and stylised ABM based on SIRV accounting for geography and commuting




→ systematic exploration and sensitivity analysis: prospects on how to design and optimise health policies in cases where data or modelling resources are lacking




Open repository

<https://github.com/henry-kang-7/CASA0004>

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