How Sensitive are My Conclusions to Model Assumptions: Insights from Health Care Models

Professor Stephen Chick INSEAD Technology and Operations Management Area Fontainebleau, France

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Type of Model

✓ "keeping models simple enhances understandability and theoretical utility but that using models for disease control decisions often requires realism that adds considerable complexity."

- Roy Anderson

Factors for choosing a model

- ▲ Why Patient Level Simulation?
 - ▲ Need patient-level information from model
 - Sufficiently heterogeneous populations (many risk groups, many stages of natural history, geography)
 - Constrained resources (queuing and health outcome)
 - Patient interaction (e.g. infectious disease transmission)
- ▲ Purpose: understand one system (sensitivity) or select best of finite set or optimize
- ▲ Estimand: Mean? Variance? Distribution?

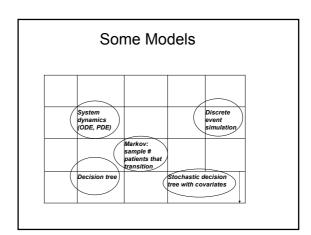
Factors for choosing a model

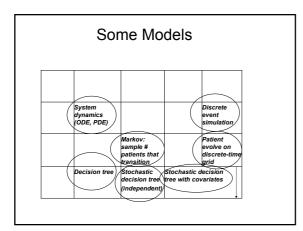
- ▲ Also:
 - ▲ Stationary versus transient
 - ▲ Time invariant versus time varying parameters ▲ Continuous time versus discrete time versus untimed
 - ▲ Deterministic versus stochastic
 - ▲ Large or small population
- ▲ The simplest model to answer a question is preferred (Occam's razor)
- Different model types can give different conclusions
- ▲ Goal: Understand how models relate, and what systematic implications are due to model choice

Roadmap

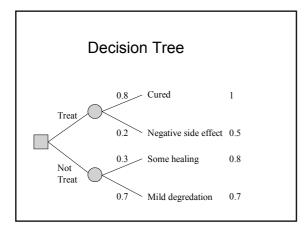
▲ Model Type

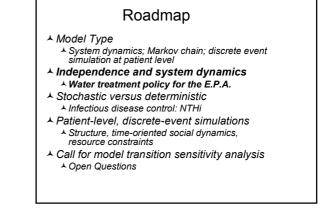
- System dynamics; Markov chain; discrete event simulation at patient level
- ▲ Independence and system dynamics
- Water treatment policy for the E.P.A.
- ▲ Stochastic versus deterministic
- ▲ Infectious disease control: NTHi
- ▲ Patient-level, discrete-event simulations Structure, time-oriented social dynamics, resource constraints
- ▲ Call for model transition sensitivity analysis ▲ Open Questions

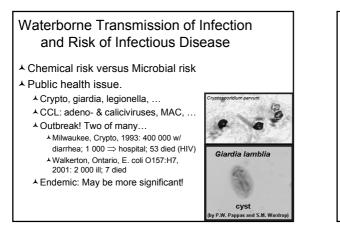


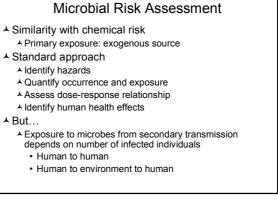


	Aggrega	ata laval	Datio	at laval
	Aggregate level		Patient level	
	Deterministic continuous state	Stochastic discrete counts	Stochastic Markovian individual	Stochastic general distribution individuals
Continuous time	System dynamics (ODE, PDE)	Stochastic Markov model (queue,)	Patient- level simulation (interact)	Discrete event simulation
Discrete time	Finite difference model	Markov: sample # patients that transition		Patient evolve on discrete- time grid
Untimed	Decision tree	Stochastic decision tree	Stochastic decision tree with covariates	



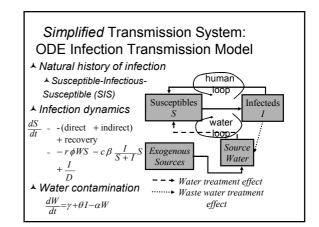


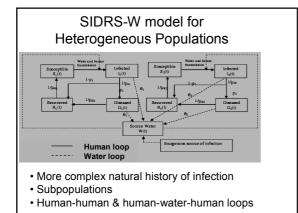


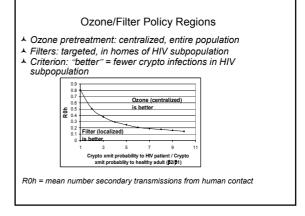


Comparative Analysis: Milwaukee in Retrospect

- HIV community more susceptible? Did suffer more serious outcomes
- Chemical Risk: Filter (local) vs. Ozone (global)
 - ▲ Contaminated water \Rightarrow exposure to HIV community ▲ <u>\$100 Million question</u>
 - Assessment: Filters 10x more effective than ozone
- ▲ Microbes: Secondary transmission
 - ▲ Even with 100% effective filters, human-human
 - transmission might continue infection!
 - Can ozone be more effective than filters?



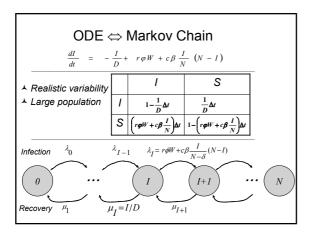


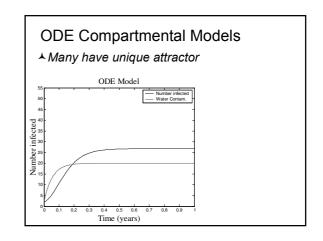


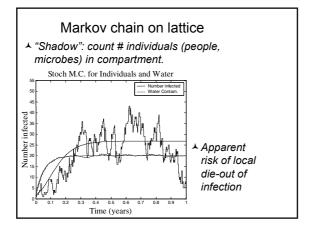
Summary: Independence and System Dynamics

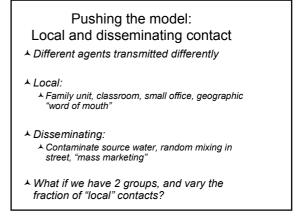
- ▲ Current U.S. water treatment policy for microbes based on invalid risk assessment
- \star Lives of many and hundreds of millions of £¥\$€
- ▲ Dynamics of risk account for dependent outcomes
- ▲ One issue: Unknown transmission parameters
- System dynamics (aka ODE or PDE or compartmental models) embody risk dynamics
- Question: Are conclusions sensitive to the type of model (ODE versus stochastic dynamics)?

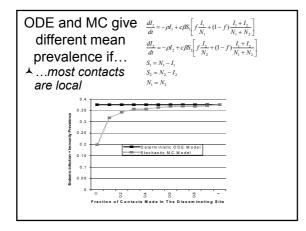
Roadmap A Model Type System dynamics; Markov chain; discrete event simulation at patient level Independence and system dynamics Water treatment policy for the E.P.A. Stochastic versus deterministic A Infectious disease control: NTHi Patient-level, discrete-event simulations Structure, time-oriented social dynamics, resource constraints Call for model transition sensitivity analysis A Open Questions

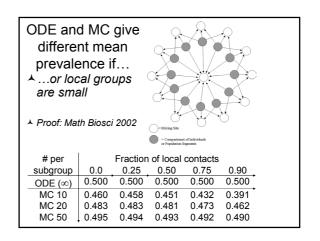












Summary: Stochastic versus deterministic model types

- ▲ ODE: large population limit of MC for some models ▲ (Ethier and Kurtz. Whitt. ...)
- MC behavior differs on two levels ▲ Random outcomes
 - ▲ Long-run averages may differ! (Local die-out of infection).
- ▲ Prevention:
 - Disseminating: municipal water treatment, SARS masks
 Local: hygiene in families,behavioral

 - 10% decrease in disseminating transmission reduces prevalence more than at 10% decrease in local
 Vaccination: target to individuals ⇒ hits both local & global

Roadmap

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How Sensitive are the Conclusions to the Assumptions?

- A Partnership Concurrency and STDs

 - ODE models typically assume one long-term partner, several independent point contacts (e.g. Dietz, ...)
 Prevalence depends strongly upon potential of multiple longer-term partners (Adams Chick Koopman, Math Biosci 2000)
- Smallpox preparedness

 - ODE says mass vaccination more effective than contact tracing, model with service capacity constraint (Kaplan, et al. PNAS 2002). Patient-level simulation with social structures (family, neighborhood), richer natural history of infection implies surveillance, tracing about as effective (Longini et al. 2002, capacity, vaccine sequelae)

Local versus disseminating

Critical fraction of 'random contacts' leads to infection outcomes that are more similar to random mixing versus (Soorapanth, Chick Koopman 2001; social networks)

Service constraints and delays

Breast cancer screening not as sensitive to delays in a stochastic system as to other effects of service delivery program (outreach; frequency of screens; quality/volume, Gunes et al. HCMS 2004) – an ODE is sufficient

Summary: Patient-level models

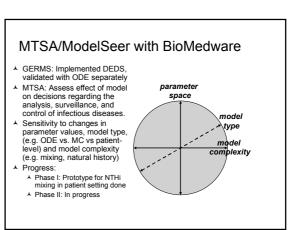
- Outcomes and <u>conclusions</u> may depend upon the type of model, not just to input parameters
- Many patient-level models are 'black boxes', little information given for verification
- ▲ No names given/no blame/ too many 'special cases
 - ▲ Reasonable values if assumptions simplified?

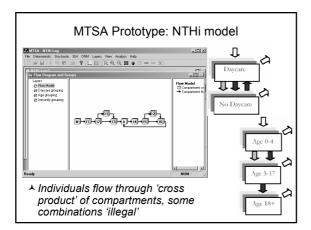
▲ Question:

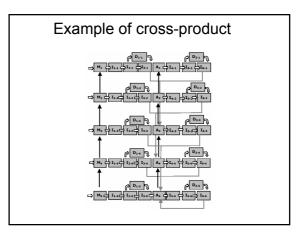
- ▲ How to calibrate conclusions from one model relative to conclusions of another, if both model types can be used?
- + How to dissect the effect of various modeling assumptions at each level, in order to account for the side-effects of modeling in our conclusions?

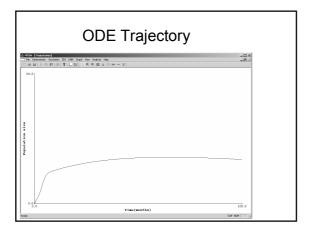


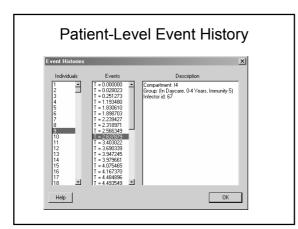
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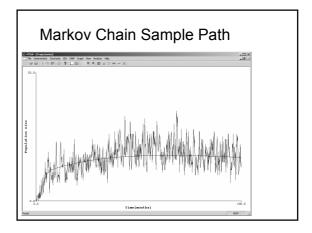


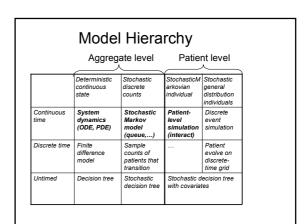












Summary: Model Type Sensitivity

- ▲ Models that can be handed to different simulation engines may / may not give similar results (output or decision), but some differences are predictable
 - ▲ Large numbers
 ▲ Discrete or continuous time
- ▲ Multiple types of models: useful for 'debugging'
- ▲ Some models might only be handed to one type of simulation engine
- People trained to model in system dynamics may approach problems differently than those trained in discrete-event simulation versus decision diagrams
 - Modeling is part of the understanding
 Viva la difference!

Conclusions

- No models are right, some models are useful
- All model types make assumptions: Awareness
- Implied conclusions may depend upon model type A Which model type to choose?
 - A Basic question needs to trace individuals data ⇒ patient level (clinical trial, contact tracing, ...)
 A Interactions (infection, constrained resources) ⇒ don't use 'untimed' model (e.g. decision tree)....
 * "Curse of dimensionality": Much patient/natural history heterogeneity ⇒ patient level simulation

 - A Tightly constrained resources + waits affect health outcomes ⇒ patient level simulation

 - "Law of small numbers": Interactions + small numbers per compartment ⇒ stochastic models
 - A Need to explore variability ⇒ stochastic model
- ▲ Simulation for visualization and communication
- Simulation runtimes and uncertainty analysis

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Professional Resources

▲ Institute for Operations Research and Management Science (INFORMS)

- ▲ Health Applications
- ▲ Simulation (<u>www.informs-cs.org</u>)
- ▲ "The Science of Better" <u>www.informs.org</u>
- ▲ Winter Simulation Conference
- ★www.wintersim.org

Related Works

- Chick SE, Soorapanth S, Koopman JS, 2004, Microbial Risk Assessment for Drinking Water, In Operations Research and Health Care: Handbook of Methods and Applications, Brandeau, ML., Sainfort, F., and W.P. Pierskalla, Eds., p. 467-494, Soorapanth S, 2003, Inferring Infection Transmission Parameters That Influence Water Treatment Decisions, Management Science, 49(7): 920-935. Güneş, E.D., Chick, S.E., Akşin, O.Z., 2004, Breast Cancer Screening: Trade-offs in Planning and Service Provision, Health Care Management Science, 7(4): in press Koopman JS, Chick SE, Riolo CP, Simon CP, Jacquez G, 2002, Stochastic effects on endemic infection levels of disseminating versus local contacts, Mathematical Biosciences, 180: 49-71. Koopman, JS., Jacquez G, Chick, S.E., 2001, New Data and Tools for

- Mathematical Biosciences, 180: 49-71. Koopman, J.S., Jacquez, G., Chick, S.E., 2001, New Data and Tools for Integrating Discrete and Continuous Population Modeling Strategies, In Population Health and Aging: Strengthening the Dialog between Epidemiology and Demography. M. Weinstein, A. Hermalin, M.A. Stoto Eds. Annals of the New York Academy of Sciences, 954: 286-294.
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- Koopman, J.S., Chick, S.E., Riolo, C.S., Adams, A.L., Wilson, M.L., Becker, M.P., 2000, Modeling Contact Networks and Infection Transmission in Geographic and Social Space Using GERMS, Sexually Transmitted Diseases, 27(10): 617-62.