Writing About Simulation

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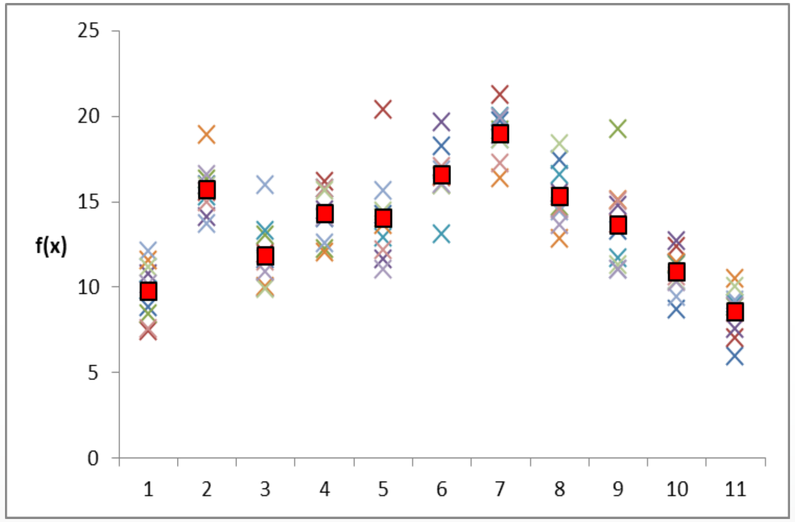
Overview



Accounting for Output Variability

Reporting Simulation Models

Decision-Making via Simulation

Focus: what happens after the model is built

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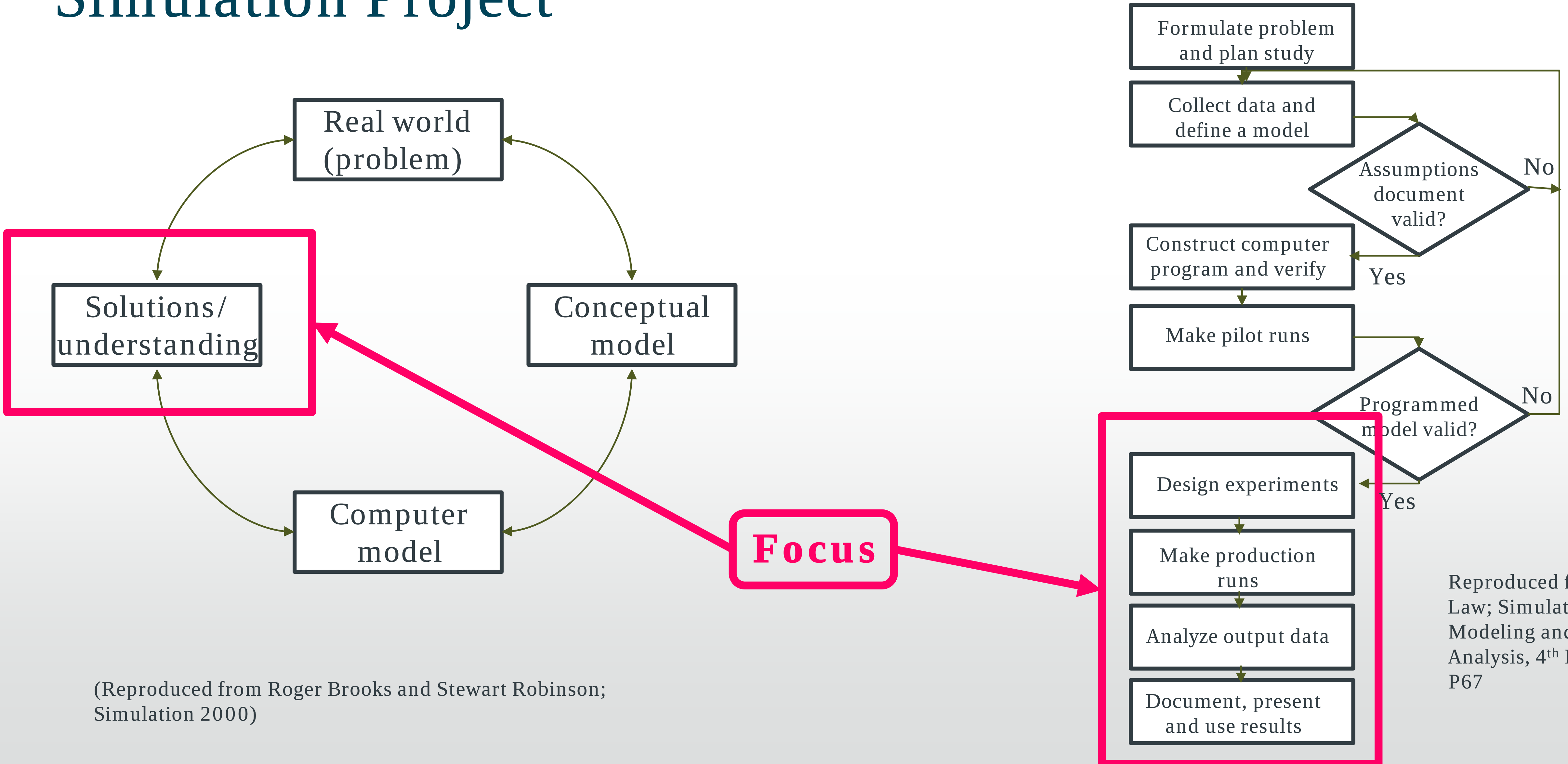
INTRODUCTION

Simulation Project



(Reproduced from Roger Brooks and Stewart Robinson; Simulation 2000)

Reproduced from Law; Simulation Modeling and Analysis, 4th Edition, P67

Good analysis and reporting adds value

- **C**larity aids model reuse and replication
- **H**onesty about the assumptions made develops trust in the model
- **A**ccuracy in the estimates of uncertainty allows a decision-maker to take this into account
- **I**nsights develop from high quality analysis and imaginative descriptions

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Russell Cheng

ACCOUNTING FOR OUTPUT VARIABILITY

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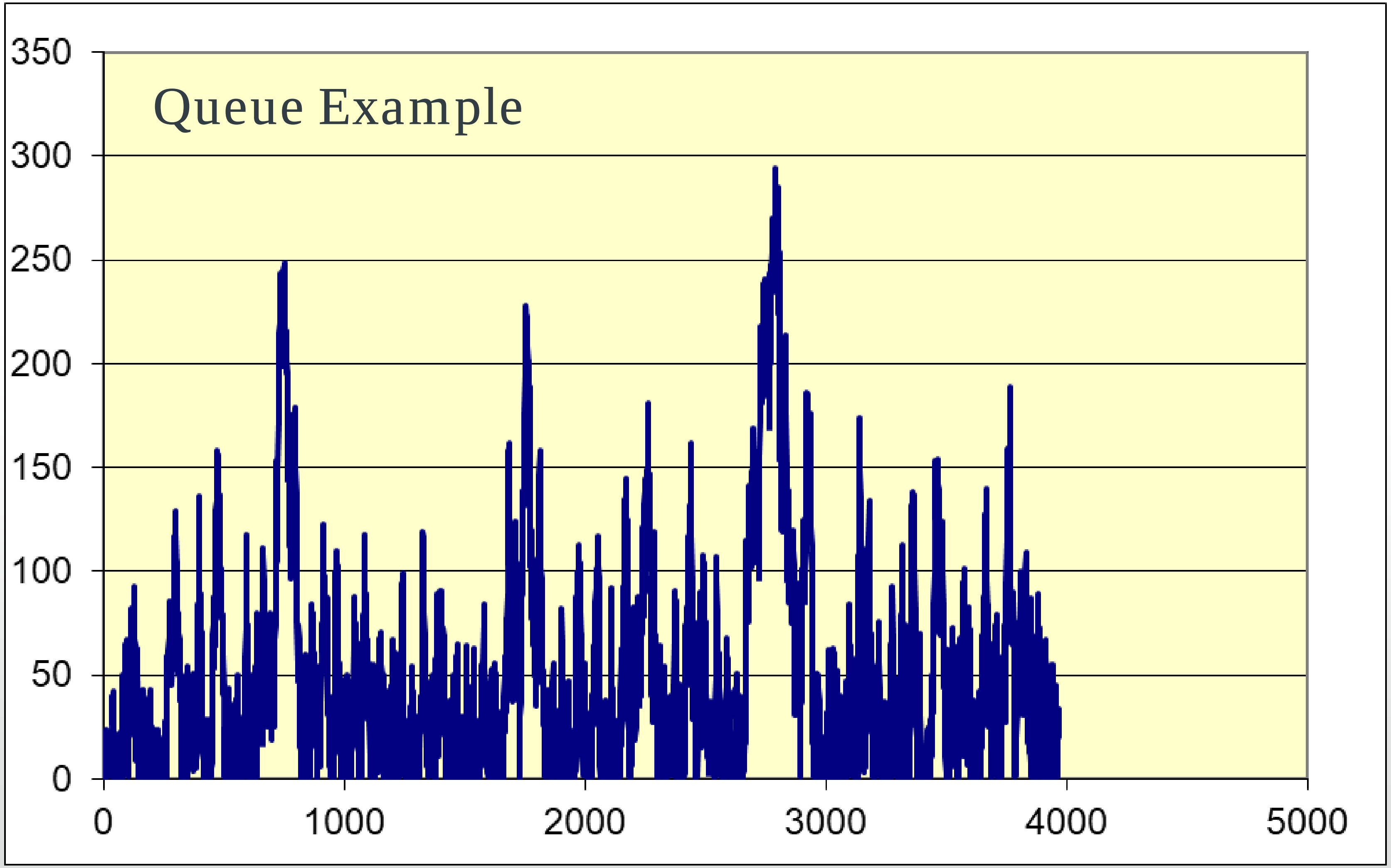
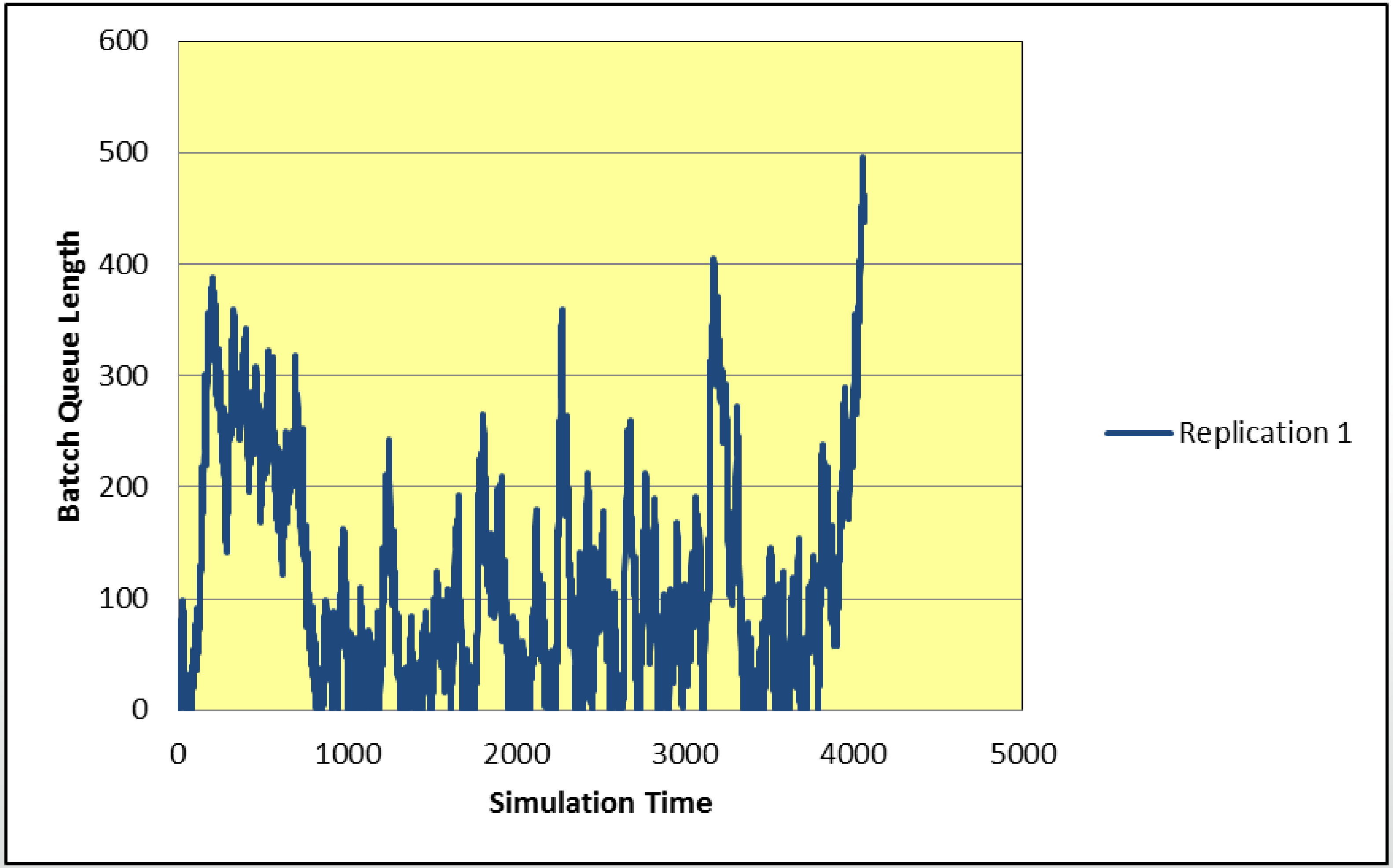
Simulation output is stochastic



Replication 1



Average number in queue = 22.1

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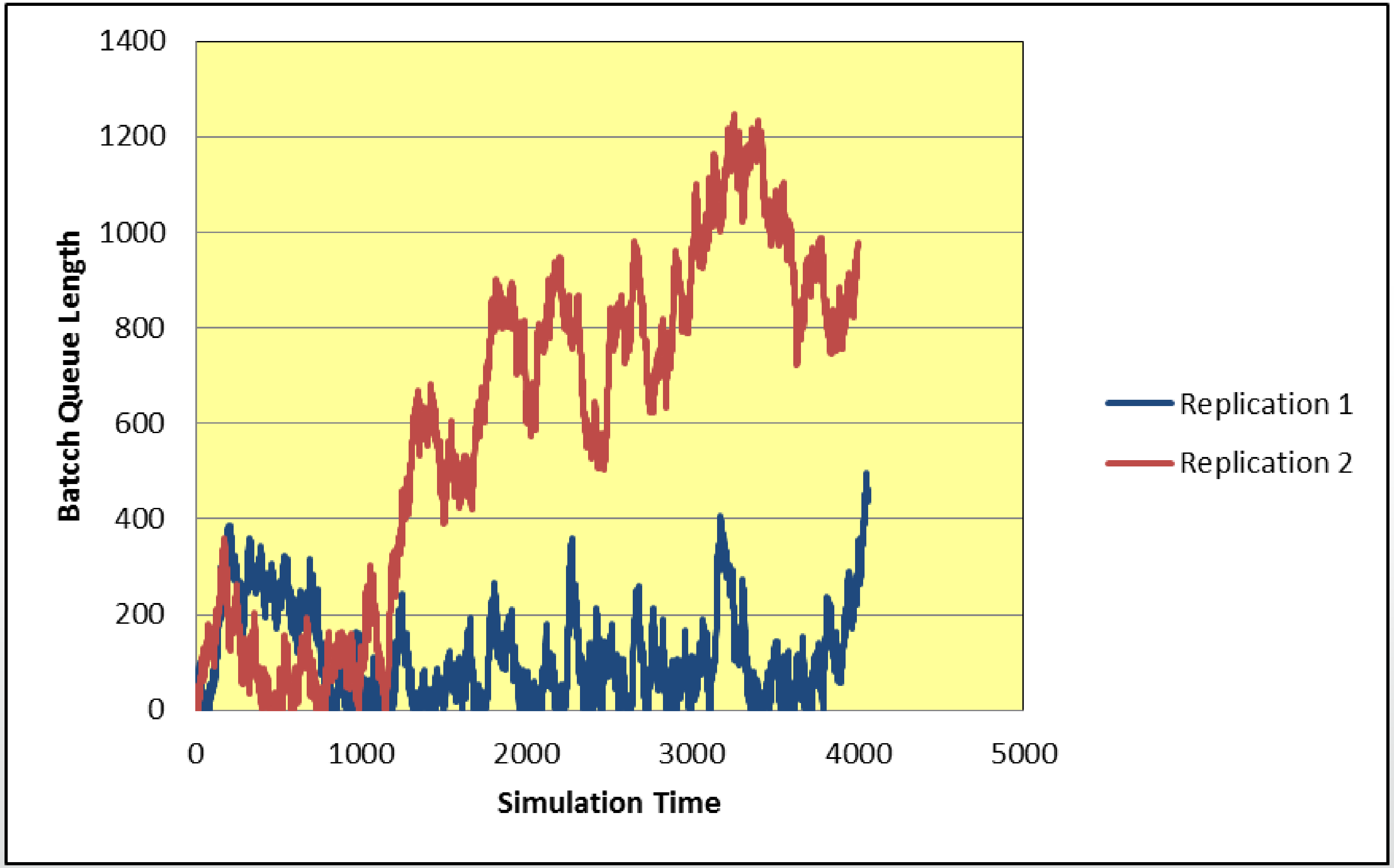
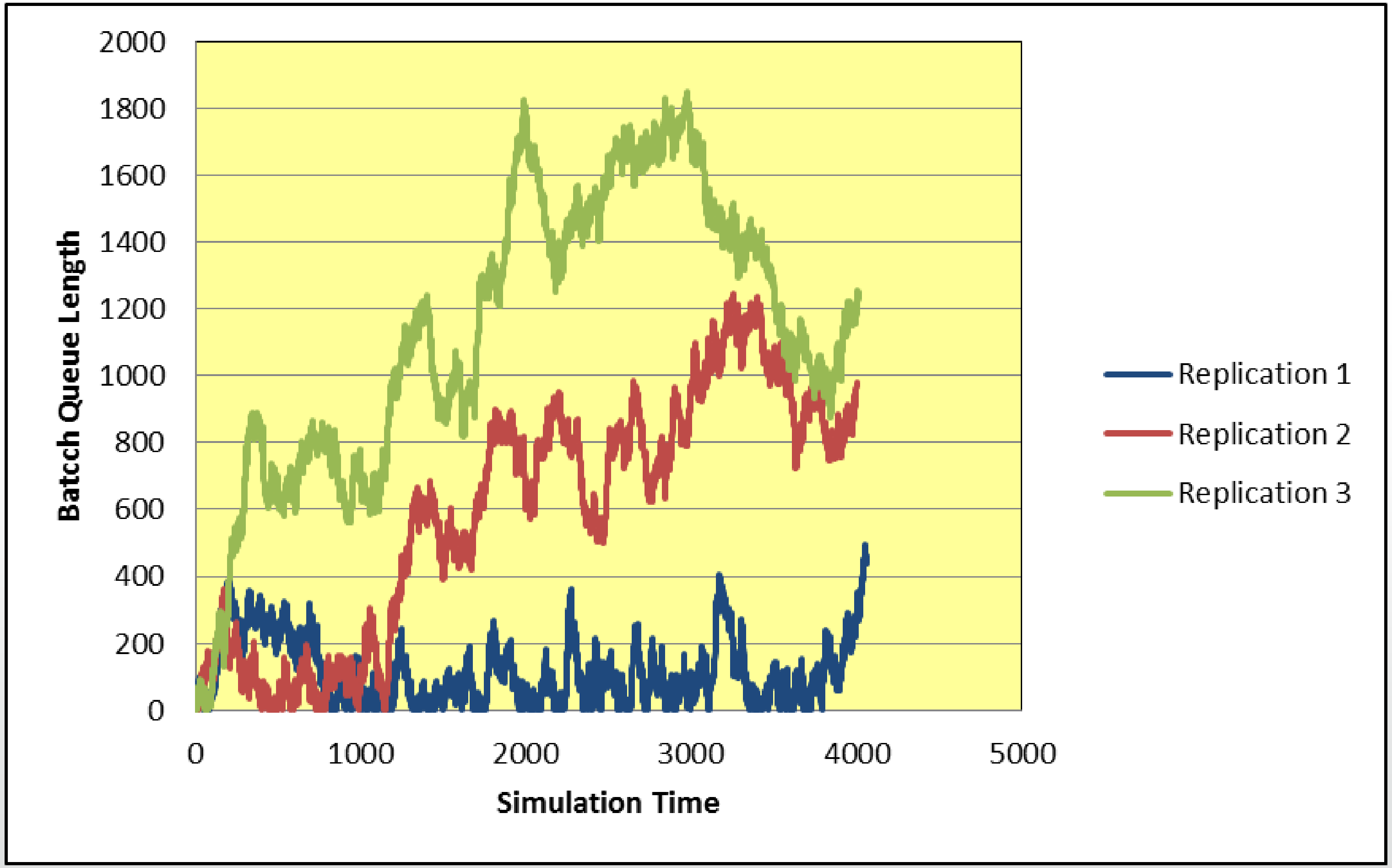
Replication 2



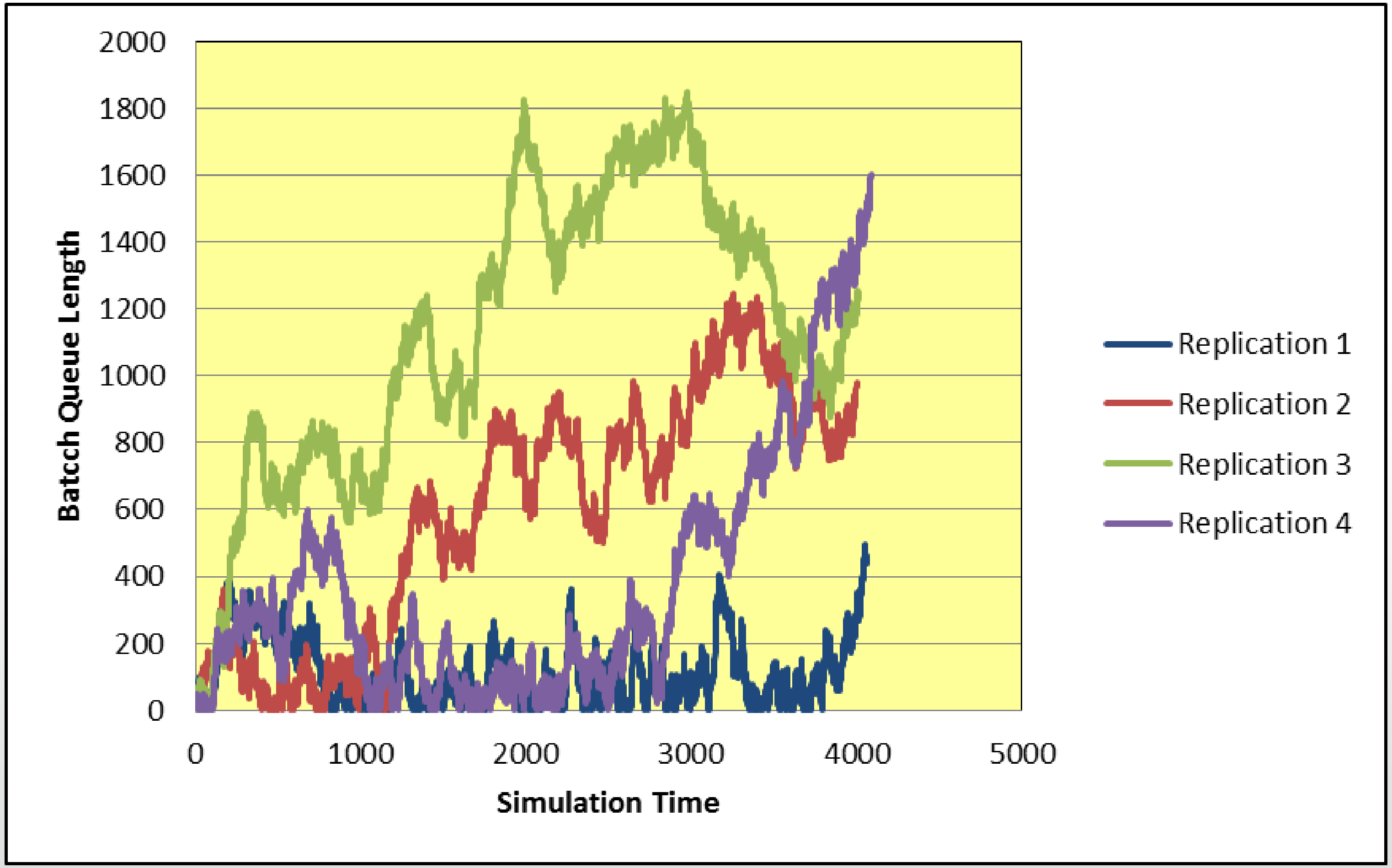
Average number in queue = 70.45

Replication 3



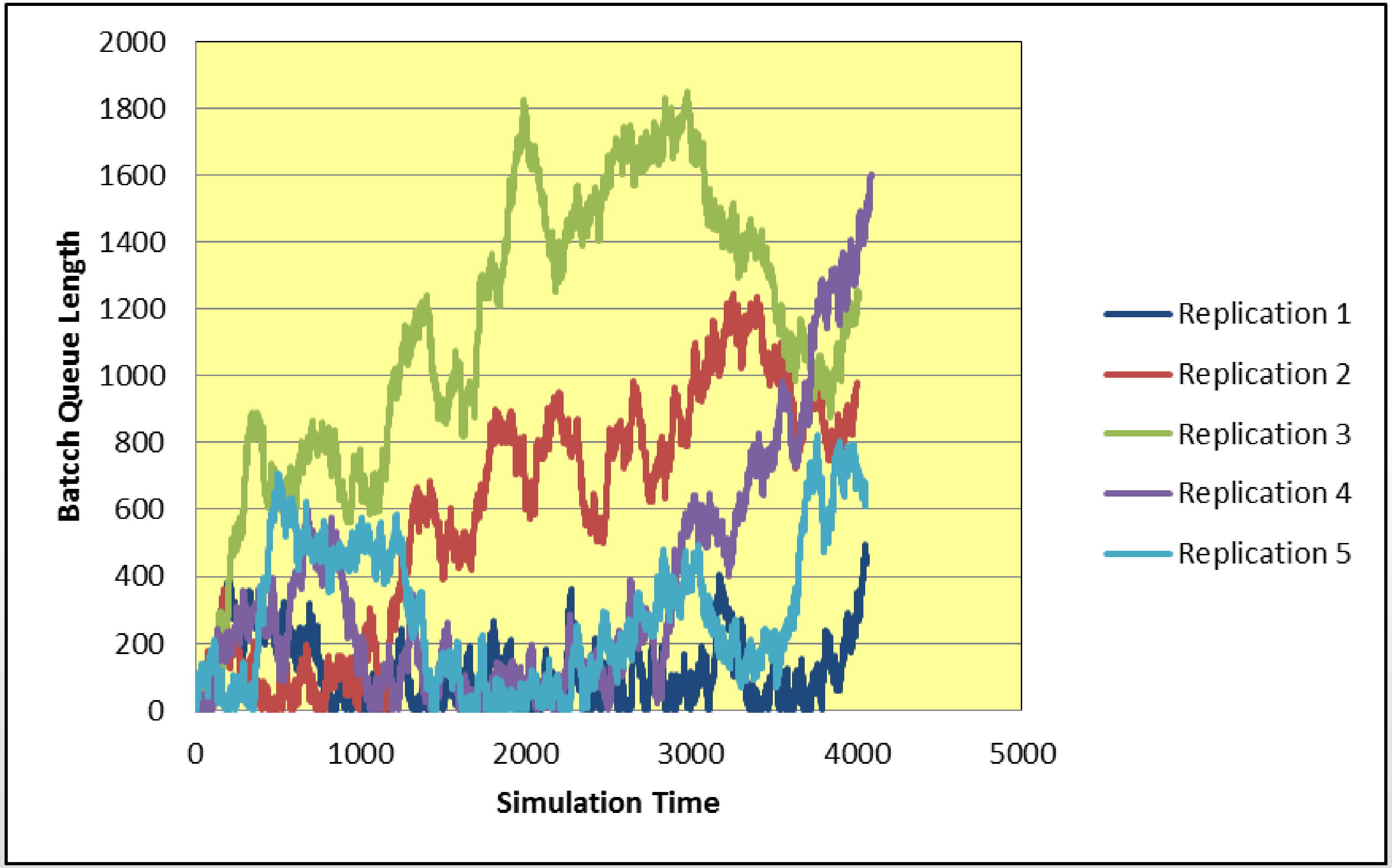
Average number in queue = 122.2

Replication 4



Average number in queue = 110.2

Replication 5

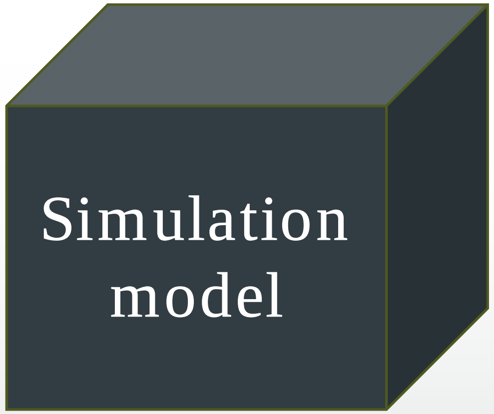


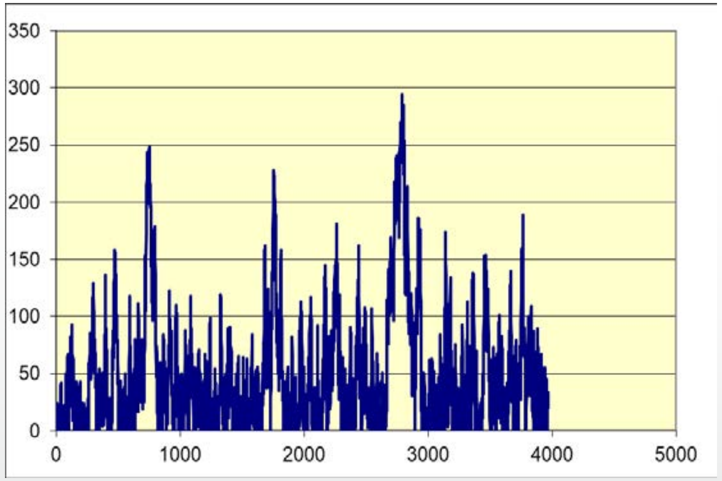
Average number in queue = 99.4

But that isn't all that's random: input uncertainty

x1	x2	x3	X4
1.34	[illegible]	[illegible]	5.30
3.25	[illegible]	[illegible]	0.04
…	…	…	…

EDF Input





α, β, γ

Fitted parameters

Uncertain output
- Input uncertainty
- Natural variability

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Quick Assessment of Input Uncertainty

- Identifies the largest contributors to input uncertainty
  - Provides evidence of where more input data might be needed
  - Helps to give an honest view of the model results
- Assume we have limited real-world data $\{X_1, X_2, \ldots, X_m\}$

For i = 1 to b
    Generate a bootstrap sample of the real-world data $\{X_{i1}^*, X_{i2}^*, \ldots, X_{im}^*\}$
    Fit an input distribution $\hat{F}_i^*$ to $\{X_{i1}^*, X_{i2}^*, \ldots, X_{im}^*\}$
    Simulate r replications of the simulation model using $\hat{F}_i^*$
    Record outputs Y_j $(j=1, \ldots, r)$
    Calculate μ_i = mean of the Y_j
Next b
Calculate σ_I = standard deviation of the means μ_i, $i = 1, \ldots, b$
Report $\gamma = \frac{\sigma_I \sqrt{n}}{\sigma}$

Ankenmann and Nelson (2012): WSC

Bootstrapping

- Used to estimate the distribution of statistics calculated from data
- Works by resampling from the data many times and recalculating the statistic

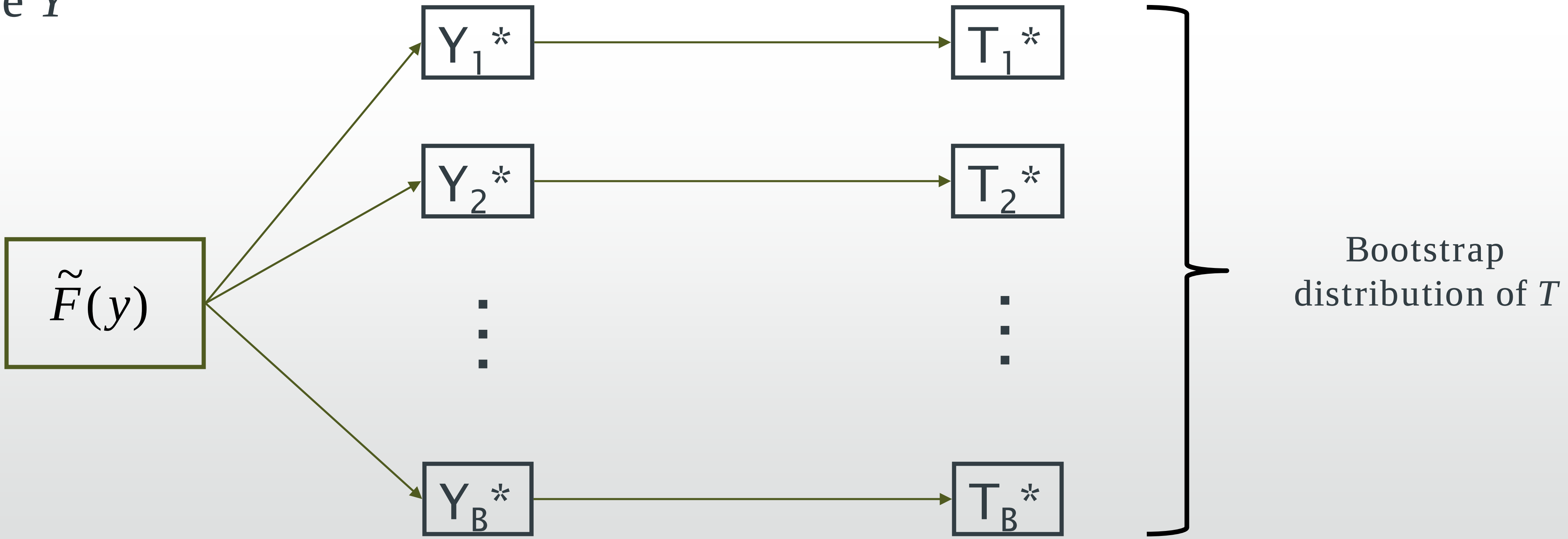
$$F_0(y) \rightarrow Y \rightarrow T(y)$$

Null distribution | Sample | Test statistic

Ideally repeat basic process B times: $\{T_1, T_2, \ldots, T_B\}$

Bootstrapping

- Repeating the original process may not be possible/desirable
  - Instead: the best estimate of the original distribution is the EDF of the sample Y



More details: Cheng and Currie (2009)

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Ankenmann and Nelson (2012): WSC

Reporting input uncertainty

- High γ implies input uncertainty could be a problem
  - Report these parameters as requiring more input data
  - Highlight this as an additional level of uncertainty
- Low γ (< 1) implies simulation variability accounts for more of the uncertainty
- One approach is to increase the input data until input uncertainty is negligible
- Probabilistic sensitivity analysis as used by health economists
- More work needed determining how to report input uncertainty

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Tom Monks, Martin Kunc, Stephan Onggo, Stewart Robinson, Simon Taylor

REPORTING SIMULATION MODELS

What is the purpose of reporting?

- Understand what has been done
  - Appreciation of the approximations
  - Develop trust in the results
- **Reuse and reproducibility**
  - Applied research that cannot be reproduced is not useful
  - Commercial models that cannot be reused or learned from waste resources
- Knowledge management
  - Maintaining knowledge and understanding within the organisation

What has gone wrong?

- Academic simulation papers rarely contain enough detail to enable reproducibility
- Rahmandad and Sterman (2012) reviewed all papers in System Dynamics Review 2010-2011
  - 27 papers reported an SD model
  - 16 papers (59%) included no equations at all
  - 2 papers (7%) reported 'some' equations
- Why?
  - Models are complex: lengthy model descriptions can be dull
  - The "code" may not be sufficient: proprietary software; poor explanations
  - Data are commercially sensitive: see previous question!

Can reporting guidelines help?

STRENGTHENING
THE
REPORTING OF
EMPIRICAL
SIMULATION
STUDIES

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ORIGINAL ARTICLE

OPEN ACCESS Check for updates

Strengthening the reporting of empirical simulation studies: Introducing the STRESS guidelines

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ABSTRACT

This study develops a standardised checklist approach to improve the reporting of discrete-event simulation, system dynamics and agent-based simulation models within the field of Operational Research and Management Science. Incomplete or ambiguous reporting means that many simulation studies are not reproducible, leaving other modellers with an incomplete picture of what has been done and unable to judge the reliability of the results. Crucially, unclear reporting makes it difficult to reproduce or reuse findings. In this paper, we review the evidence on the quality of model reporting and consolidate previous work. We derive general good practice principles and three 20-item checklists aimed at Strengthening The Reporting of Empirical Simulation Studies (STRESS): STRESS-DES, STRESS-ABS and STRESS-SD for discrete-event simulation, agent-based simulation and system dynamics, respectively. Given the variety of simulation projects, we provide usage and troubleshooting advice to cover a wide range of situations.

ARTICLE HISTORY

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KEYWORDS

Simulation; reporting; reproducibility; discrete-event simulation; agent-based simulation; system dynamics

How to use STRESS

- STRESS comes in three flavours:
  - STRESS-DES
  - STRESS-ABS
  - STRESS-SD
- They are guidelines, not rules
- You can still be creative in how you describe your model and structure your article but STRESS provides a checklist to ensure all necessary details is there
- Use appendices and supplementary information where necessary

Why use guidelines?

There is no silver bullet to ensure reproducibility, but we need to do more than we are.

During the development of STRESS we were asked:

- ‘What motivation do *academic* authors have to follow the guidelines?’
- ‘Why would an author want to do more work?’

Our response:

1. Write and submit better quality papers in the first instance (less rework)
2. Increase the chance of more structured feedback
3. Get their contributions reused (and maybe even cited ☺).

Tom Monks, Marion Penn

DECISION-MAKING VIA SIMULATION

Decision makers are people …

- Emotion can play an important part (Bechara and Damasio, 2005)
- There's rarely just one objective
  - Simulation models allow decision makers to account for multiple criteria intuitively (Belton and Stewart, 2002)
- And we haven't mentioned politics!

… but algorithms can help

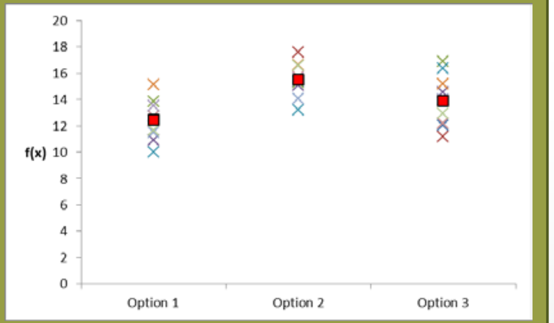
Optimisation via simulation

OvS algorithms:

- Make the simulation tests more efficient
- Provide a measure of the confidence that can be placed in the results
- Work well with automated systems
- Account for uncertainties and allow for complex detail

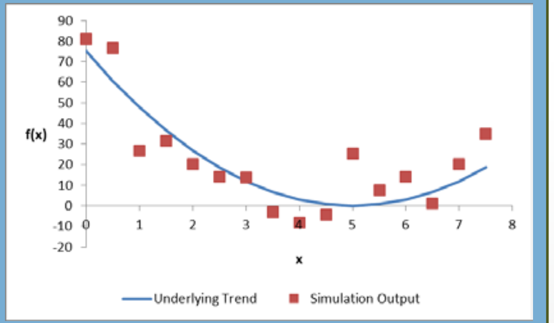
Classification of Problems

1.Small number of solutions



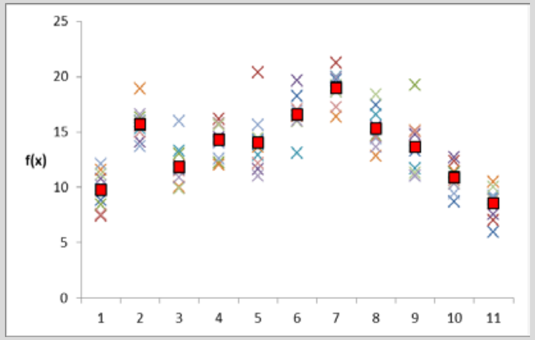
e.g. set-up for a factory/hospital

2.Decision variables are continuous



e.g. stochastic root-finding

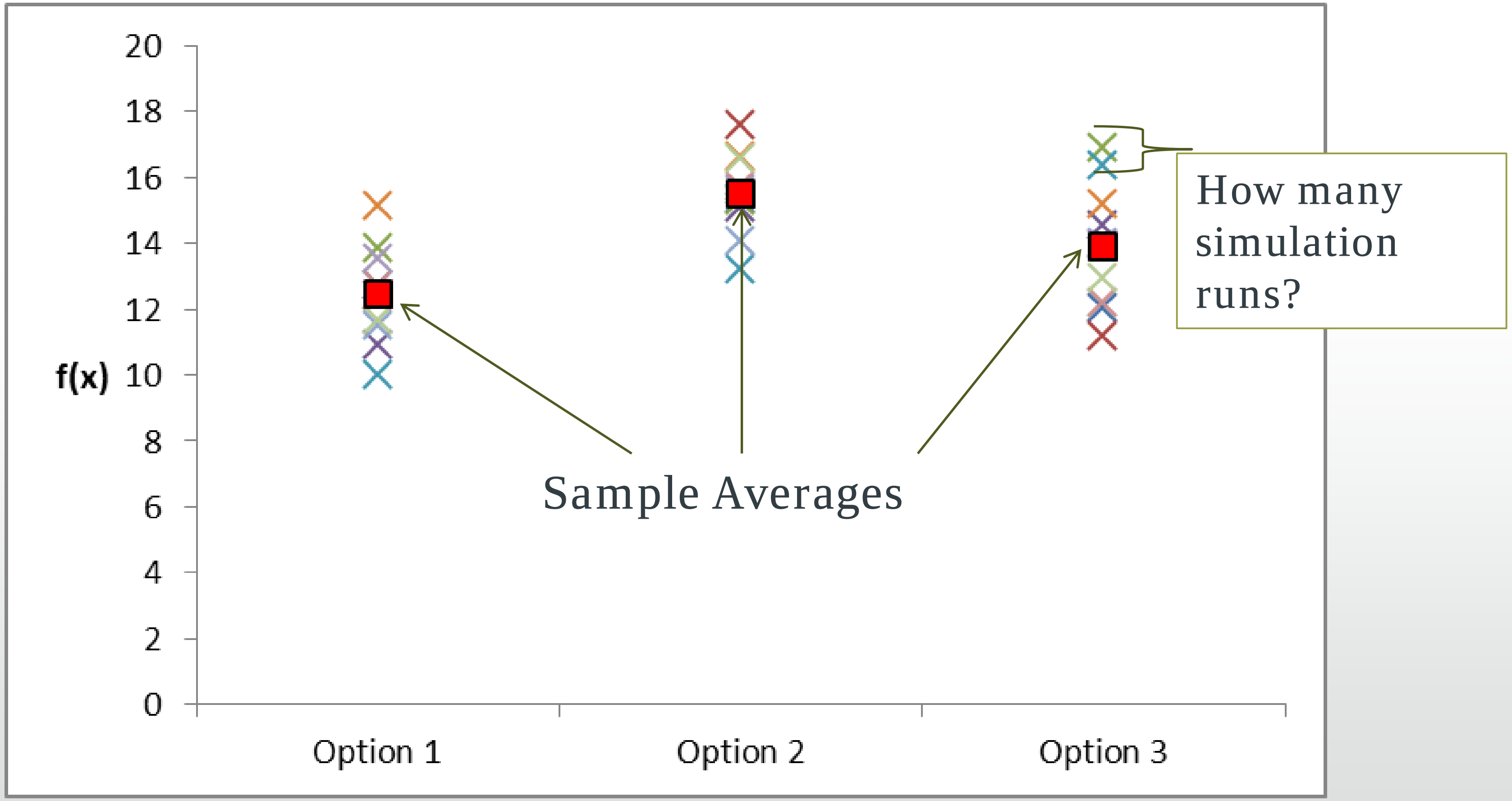
3. Decision variables discrete and integer-ordered



e.g. optimizing the number of call-centre staff

Nelson and Hong, 2009

Ranking and selection: problem description



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Ranking and Selection: Assumptions

- We have a set of m design points $\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_m$
- Each design point has an underlying true mean associated with it $\mu_1, \mu_2, \ldots, \mu_m$
- We run the simulation n_i times at each of the design points $\boldsymbol{x}_i$, $i=1, \ldots, m$ and find the sample averages of the output

Design Point	Number of Runs	Simulation Output	Sample Average
$\boldsymbol{x}_1$	n_1	$y_1(\boldsymbol{x}_1), y_2(\boldsymbol{x}_1), \ldots, y_{n_1}(\boldsymbol{x}_1)$	$E[Y(\boldsymbol{x}_1)]$
$\boldsymbol{x}_2$	n_2	$y_1(\boldsymbol{x}_2), y_2(\boldsymbol{x}_2), \ldots, y_{n_2}(\boldsymbol{x}_2)$	$E[Y(\boldsymbol{x}_2)]$
…	…	…	…
$\boldsymbol{x}_m$	n_m	$y_1(\boldsymbol{x}_m), y_2(\boldsymbol{x}_m), \ldots, y_{n_m}(\boldsymbol{x}_m)$	$E[Y(\boldsymbol{x}_m)]$

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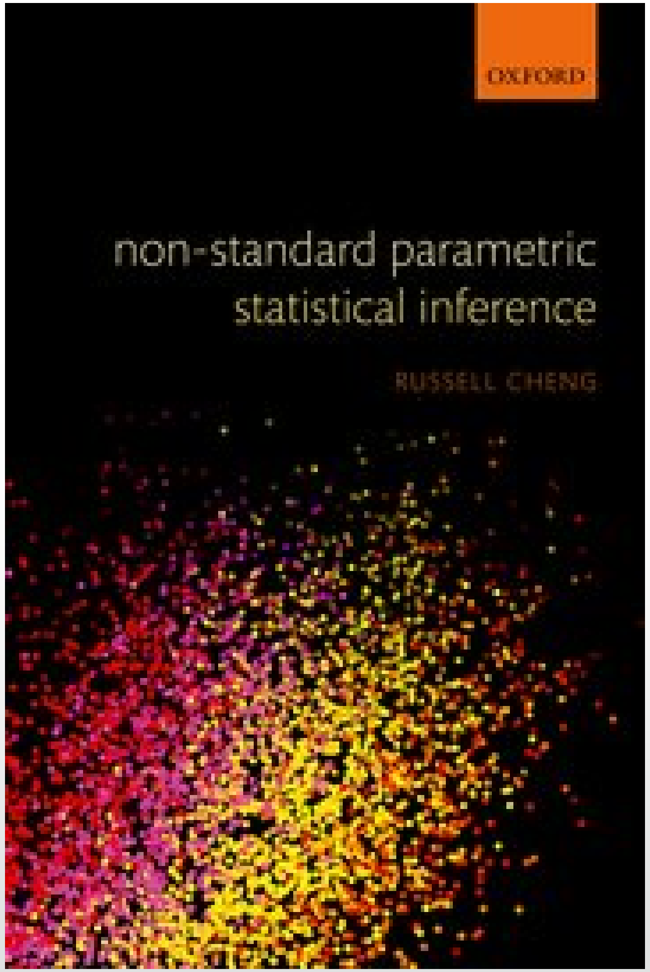
Example: R&S for decision making

- Produce a shortlist of solutions
- Allow for multiple objectives by imposing chance constraints
- Develop a method that works for general output
  - No normality assumptions!
- And that allows for common random numbers (CRN)
  - Exploits the variance reduction of CRN
- Easy-to-use, downloadable, minimal software engineering!

https://github.com/CLAHRCWessex/BootComp

Two-stage procedure

- Two stages to reduce interactions with the simulation software
- Depends heavily on bootstrapping
  - Excellent introduction in Cheng (2018)



Stage 1:
Run n_1 replications of the simulation model for ALL systems using CRN if available

Primary outputs X_{ij}
Secondary outputs Y_{ijl}

Stage 2:
Run n_2 replications of the simulation model for systems likely to satisfy chance constraints and of a high quality using CRN if available

Shortlist of feasible, high-quality solutions

Monks and Currie, WSC (2018)

CONCLUSION

Conclusion

- Simulation has always worked well to involve decision-makers in the process
  - Incorporating new ideas about the impact of emotions on decision-making could improve this further
  - Elegant solutions to optimisation via simulation problems are valuable
- Better reporting of simulation studies will give them more value
  - Reuse and reproduce
- Being honest about all of the variability will engender more trust
  - More work is needed on practical reporting of input uncertainty

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The Acronym …

- **C**lear
- **H**onest
- **A**ccurate
- **I**nsightful

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