

Section 1

The Structure of the Courses, the Delphi Method, the Purpose of MCS and its Background

Lecture 3

The Purpose of Monte Carlo Simulation

Objectives

Having seen a “manual” simulation with the Delphi Method, this lecture will clarify the purpose of simulation

It will also present the 2 main benefits of MCS

- 1) Increasing the confidence in our estimates and
- 2) Getting a better understanding of our real cases

But there will be more benefits

Agenda

- A. The Components of a Formulation or the Model
- B. Where Can Monte Carlo Simulation be Used?
- C. Main Benefit 1:** Resolving the Problem of Estimation
- D. Dynamic Formulation using Simulation
- E. Main Benefit 2:** Matching the Model with Reality
- F. Other Benefits of Monte Carlo Simulation

A.

The Components of A Formulation or Model

"Simulation is the process of designing a **model of a real system** and **conducting experiments** with this model for the purpose

- 1) Either of understanding the behavior of the system or
- 2) For evaluating various strategies (within the **limits** imposed by a criterion or a set of criteria) for the operation of the system." (1975)



Claude Shannon (1916-2001)

One of the main problems in business analytics is that we often have to depend on **fixed** or **static** estimates in our calculations.

Using fixed values for our input variables can only give **1 result** . . .

Shannon's definition recommends a "**dynamic**" experiment

Let us look into "**static**" formulations and then see how "**dynamic**" models of Monte Carlo Simulations will resolve this problem

A Formulation Model has **4 Components**

- 1) Input variables
- 2) Constants
- 3) Computational procedures
- 4) Output variables

A Simple Formulation of a Static Model:

Prepare a Proposal to Supply 500 units to a client

- 1) The **green** cells are our input variables
- 2) The **yellow** cells are the constants
- 3) The **blue** cell shows the expected Net Profit Margin, our output
- 4) Computations are in the cells with formulas shown in the right column

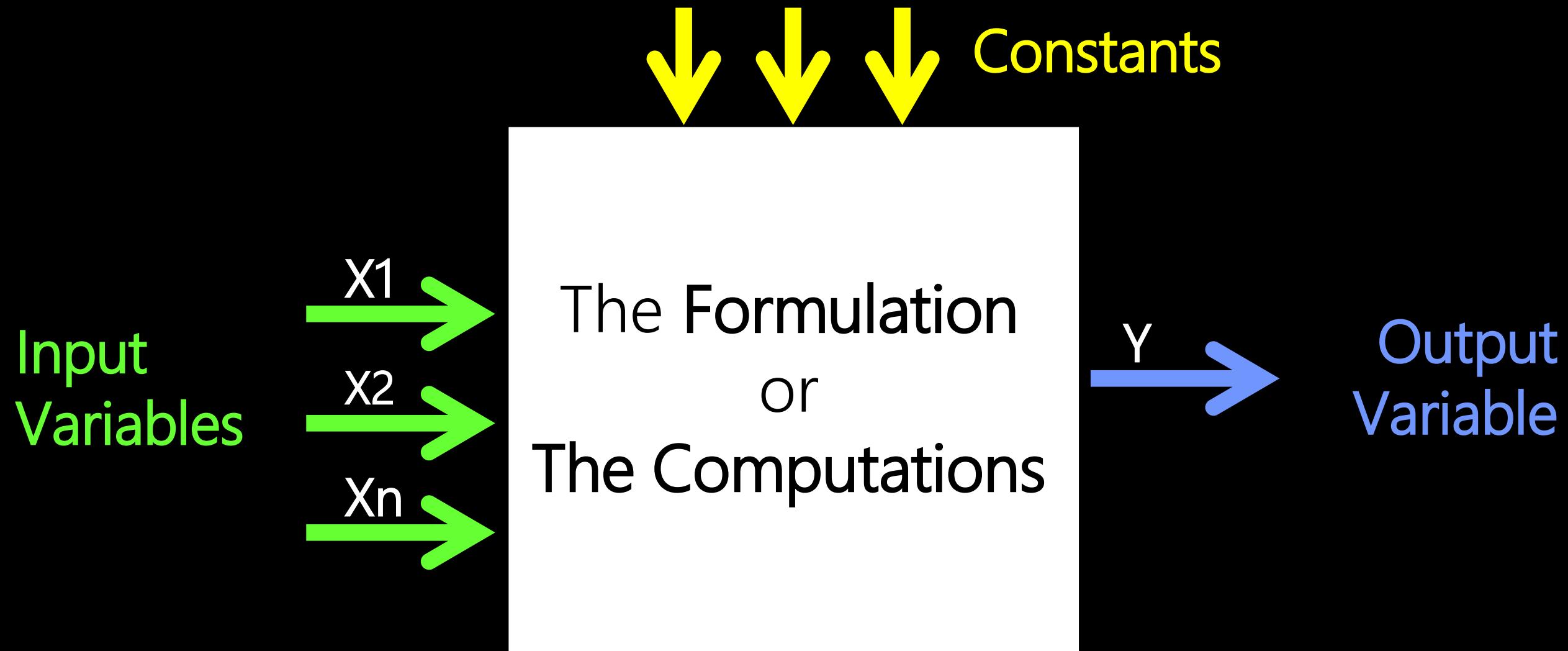
Costing Elements

Materials	40	=SUM(B2:B4)
Equipment Rental	50	
Labor	60	
Subtotal Variable Costs	150	
Units to Build	500	=B7*B5
Total Variable Cost	75,000	
Unit Sales Price	200	
Total Revenue	100,000	=B9*B7
Profit Margin	25,000	=B10-B8
Net Profit Margin	25.00%	=B11/B10

Other Examples of Formulations or Models

- 1) Calculating the **Net Present Value** of a 5-year project
- 2) Calculating the **Utilization Rate** of a production line
- 3) Calculating the **Reliability** of a multi-component system
- 4) Projecting the **Consumption of Material** in a warehouse using demand patterns and orders in the pipeline
- 5) Conducting an acceptance sampling process by calculating the **Operational Characteristics** or OC Curve
- 6) Calculating the **Total Duration** of a 50 Task project (most of which are conducted in parallel)

A Static Model or Formulation



Component 1: the Input Variables

These are the **drivers** of the formulation or the model

These are what we need to estimate to get our output values

- 1) They are often called the **Change Variables** because we are interested in how their changes affect our results
- 2) Some call them the **Independent Variables** because the way they vary is beyond our control (and because our end-result depends on them)

Component 1: the Input Variables (Cont.)

Here are some **Examples**:

Equipment costs

Number of arrivals per hour

Sales demand

Financial returns of a stock

Number of credit cards lost

Number of room bookings

Cancellations of bookings

Value of discounts

Current interest rates

Total ATM withdrawals

If we knew the Input Variables precisely,
we **would not need** to simulate



Component 2: the Output Variables

These are the results of our computation

These are often called **Dependent Variables** as they depend on the Input Variables

A model may have several output variables

Examples:

Net Profit Margin

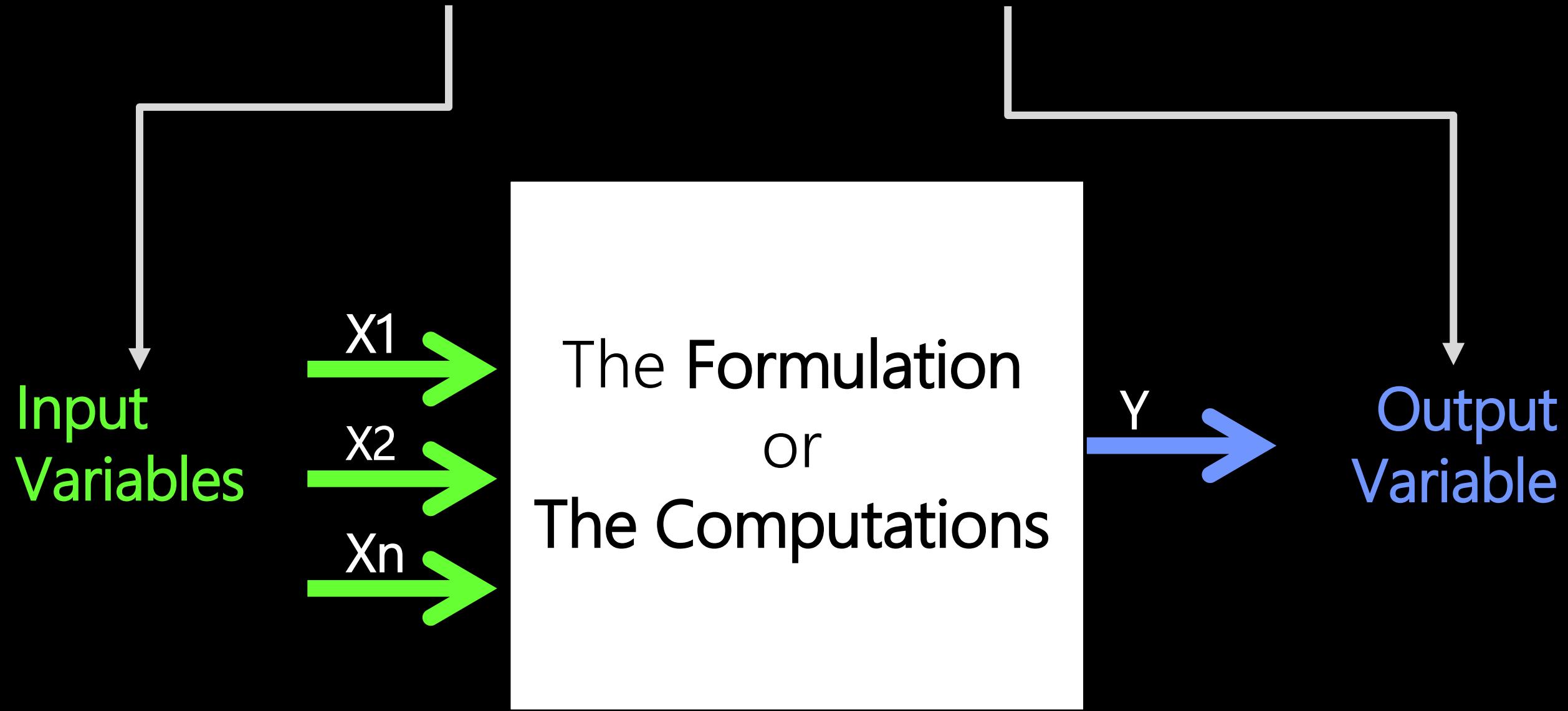
Total Cost of Equipment

Utilization Rate of a Truck

Total Project Duration

Estimated cost of missed sales due to shortage in stock

Independent and Dependent Variables



Component 3: the Constants

These values that do not change throughout the formulation

If your constants might change . . .

You need to consider them as **input variables**

Examples:

Maintenance rate

Number of years

Exchange rates

Growth rate of expenses

Number of working hours / day

Maximum salary

Capacity of a pallet in KG's

Cost of airline ticket

Think of the equations we had in high school algebra :

$$Y = 5 X^2 + 3 X + 1$$

The **X**'s are our **input** (or independent or change) variables

The coefficients **5, 3** and **1** are the **constants**

The **Y** is our **output** (or dependent) variable

The right side of the equation is our formulation

Y depends on the values the independent **X**'s take . . .

As we mentioned before,
if we had such a clearly defined equation,
we **would not need** to develop a
simulation model



B.

Where Can Monte Carlo
Simulation be Used?

In its earliest applications

MCS was used in strictly mathematical scientific areas

For example, complex Integrals or differential equations could be solved using MCS

Typical Objectives of Monte Carlo Simulation

- 1) To arrive at estimates with a reliable confidence
- 2) To calculate specific values using elaborate formulations
- 3) To analyze existing processes: utilization, bottlenecks, KPI's, etc.
- 4) To model and analyze the design of new processes
- 5) To assess the risks of choosing wrong estimates
- 6) To assess the sensitivity of output results based on variations in the input variables

Typical Sectors and Lines of Business where Monte Carlo Simulation can be applied:

Sales and Marketing

Queuing Systems

Project Management

Acceptance Sampling

Material Management

Bookings and Reservation

Human Resources

Financial Analysis

Risk Management

Reliability Engineering

Production Management

Workflow Analysis

And more . . .

C.

Main Benefit 1: Resolving the
Problem of Estimation

The validity of the resulting **output variable(s)** is totally dependent on the **confidence** we have in our estimates of the **input variables**

Traditional Static
Estimation is the **Poison**
of Data Analysis, Data
Science, Machine
Learning, etc.



We are often under Pressure to Estimate . . .

- 1) Costs
- 2) Timings / Durations
- 3) Counts (failures, arrivals, applicants, inventory levels)
- 4) Rates (escalation, interest, inflation, charges)
- 5) Financial Values (risks, exchange, ratios, balances)
- 6) KPI's of all Sorts

The list is endless

If we do not resolve the estimation problem,
we will get the following bad results . . .

Errors in individual variables will **compound** which will result in
larger global errors

Analysts will use **guesses** based on their experience
But is their experience valid or applicable?

Analysts will **copy** other estimates or formulations . . .
But are copies valid or applicable or even correct?

Analysts will implement **a single scenario** out of others
But this will avoid considering different effects

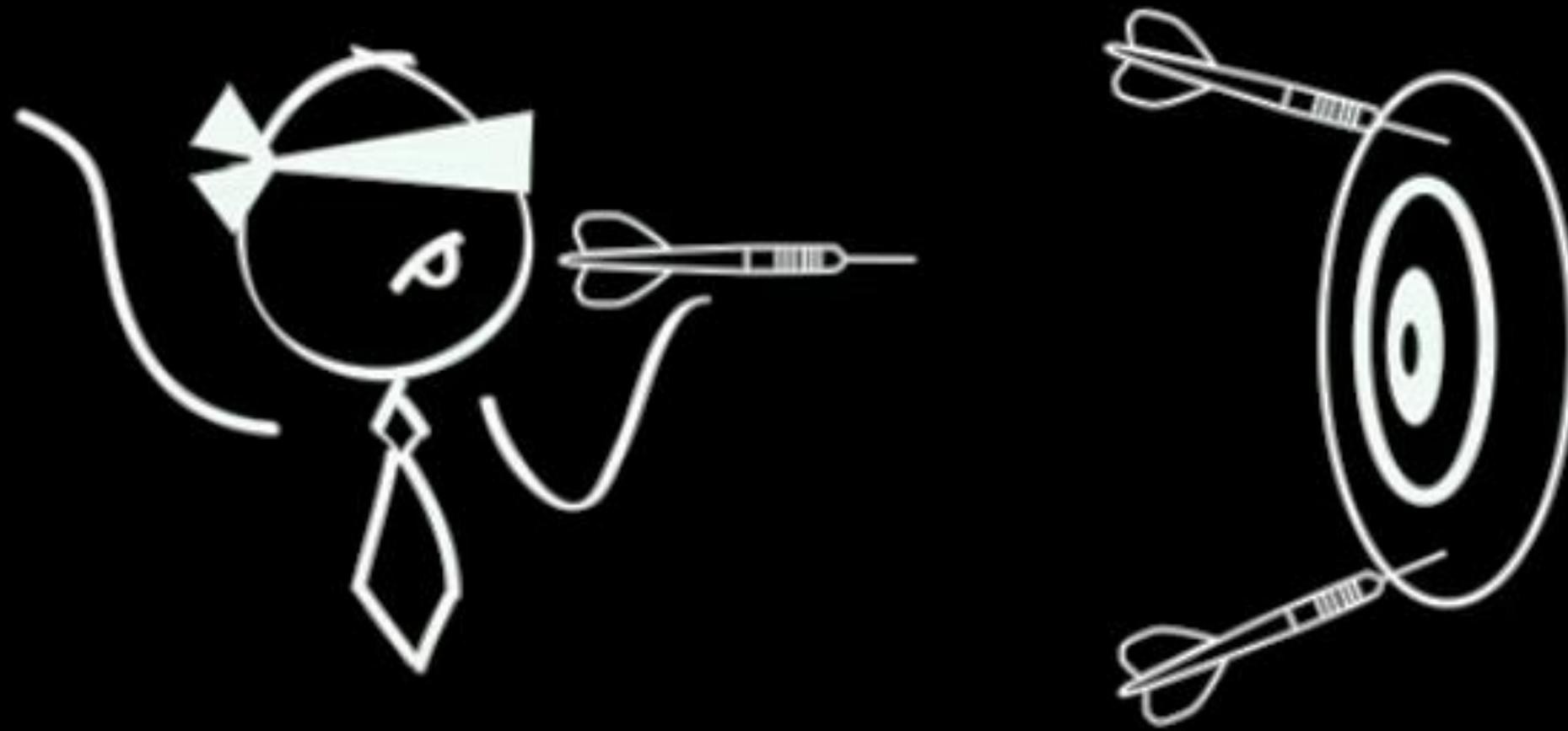


Image Courtesy: Jonathan Rasmusson (agilenutshell.com)

We need a **robust method** that generates a variety of feasible values that can give us a **measured confidence** in our estimates

The method should also give us an insight into the **margin of error** in our estimates or the **risk** of making errors in our estimates

D.

Dynamic Formulation using Simulation

Just a Reminder:

Our Static Model



Workout 1: Assume we ask N experts
to estimate each of the 3 input variables:

Materials, Labor and Equipment

Let use the input variables values as the average of the 5 respondents

Materials = 42 (not 40)
Equipment = 48 (not 50)
Labor = 56 (not 60)

Costing Elements	
Materials (Average)	42
Equipment (Average)	48
Labor (Average)	56
Subtotal Variable Costs	146

=SUM(B2:B4)

The Net Profit Margin is now
27% and not 25%

Units to Build	500
Total Variable Cost	73,000
Unit Sales Price	200
Total Revenue	100,000
Profit Margin	27,000
Net Profit Margin	27.00%

=B7*B5

=B9*B7

=B10-B8

=B11/B10

Output?

Don't you feel more **confident** in the new **values** of the model?

- 1) The Unit Cost
- 2) The Profit Margin
- 3) The Net Profit Margin

They are now based on N estimates rather than 1 as in the static model

Costing Elements

Materials (Average)	42
Equipment (Average)	48
Labor (Average)	56
Subtotal Variable Costs	146

=SUM(B2:B4)

Units to Build	500
Total Variable Cost	73,000
Unit Sales Price	200
Total Revenue	100,000
Profit Margin	27,000
Net Profit Margin	27.00%

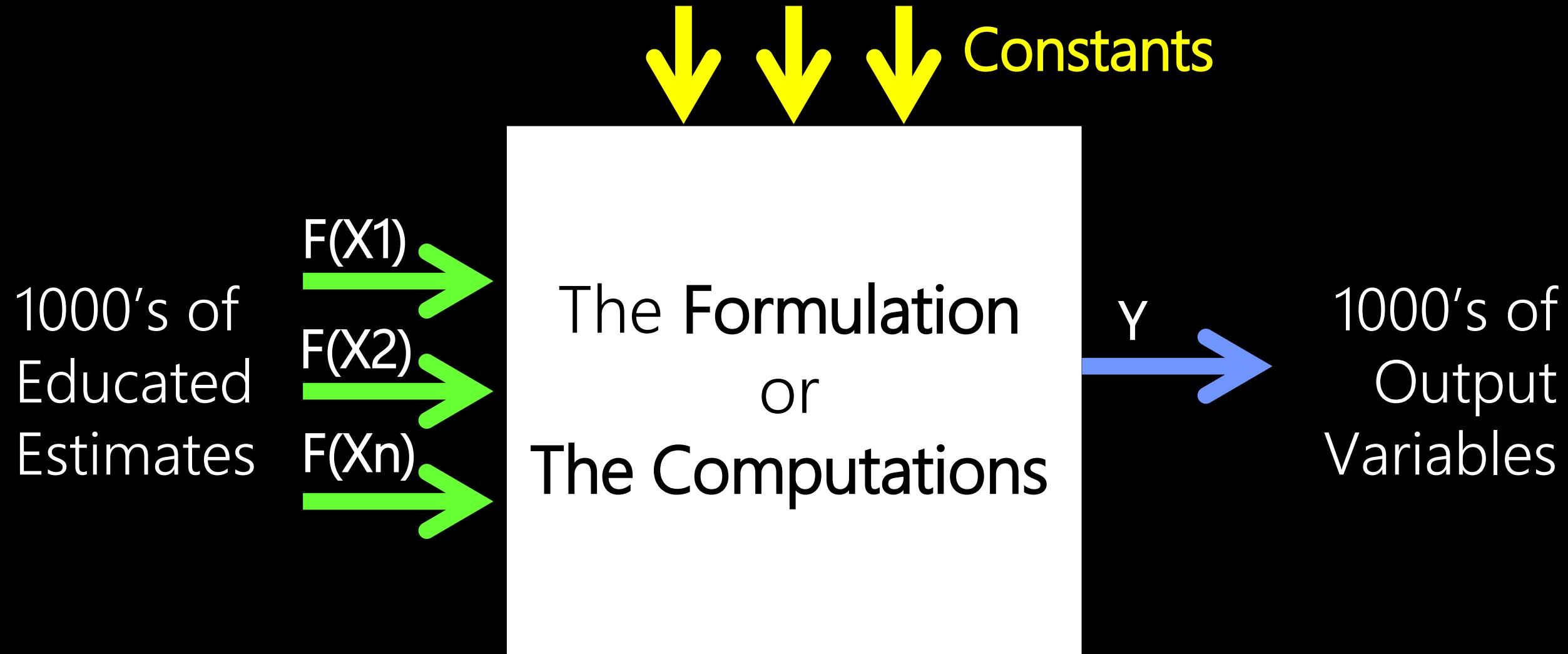
=B7*B5

=B9*B7

=B10-B8

=B11/B10

A Dynamic Model or Formulation



The Heart of the Dynamic Model

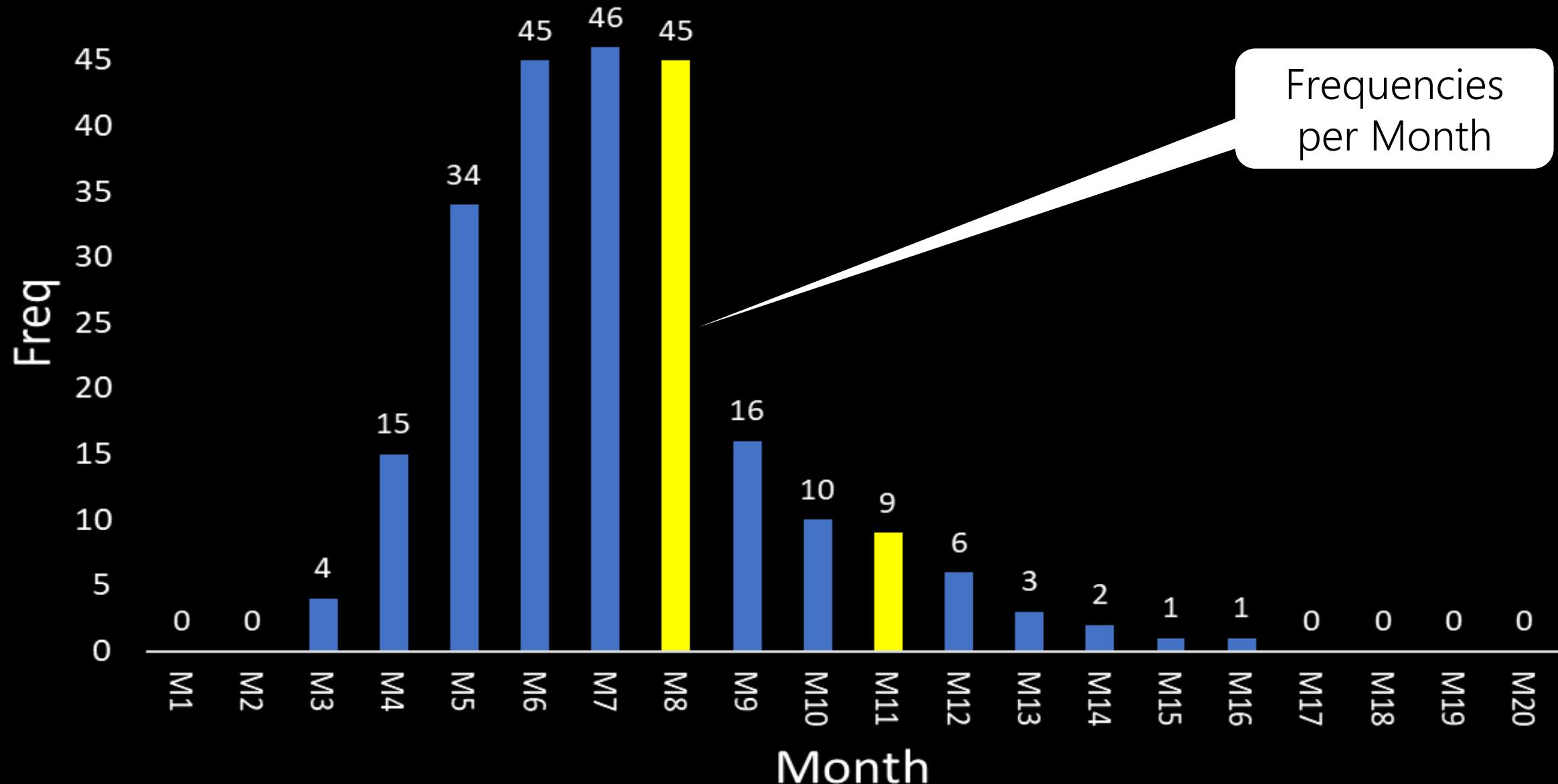
For **each input variable** . . .

- 1) We identify a pattern of data from which to extract random samples (this is our Frequency or Probability Distribution)
- 2) Such distributions always have “parameters”: averages, standard deviations, rates, etc.,
- 3) We need to determine such parameters for each of our input variable distributions
- 4) We generate **N Random Values** based on these distributions instead of getting expert estimates

Convert these Steps into a **Generic Broad** Monte Carlo Simulation Process

- 1) Develop a **static formulation** and identify its input and output variables and constants
- 2) Identify a **distribution** and its **parameter** that best represents the behavior of each input variable
- 3) Generate **1000s of formulations (scenarios)** where each will have a randomly generated value from the distributions
- 4) Analyze the **1000s of output values** statistically

But what is a Data Distribution?



In Section 4 of this course, we will be presenting a more detailed **8-Step Process** for Monte Carlo Simulation based on these generic steps

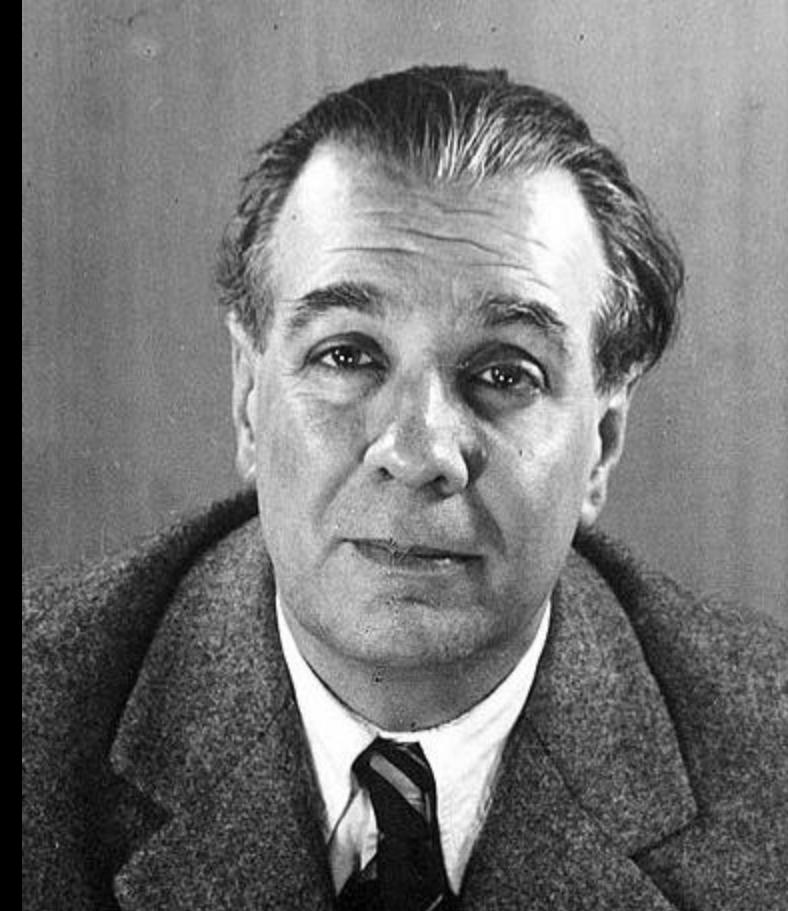
E.

Main Benefit 2: Matching
the Model with Reality

In Jorge Luis Borges's "Collected Fictions",
there is a brilliant short story called "**On
Exactitude in Science**".

Borges tells the story of a cartographer
who was not satisfied with the accuracy of
traditional maps.

He kept on increasing the scale of the map
until it had the same size as the empire,
matching the map with real locations, point
by point.



Simulation is like Cartography

Your model is a **pseudo-realistic map** of your real business process

The more realistic the model, the nearer to the truth

But, the more realistic the model, the more complex and costly it will be to produce

(and harder to fold).



The City of Monte Carlo

Why are we looking at this story?

Because it shows the reason for preparing models

We prepare them so we can test our **understanding of reality**

Setting up our Monte Carlo Simulation model and analyzing its results also allows us to verify **how far** we are from reality

A Real Case

Managing the Trolleys in Airline Catering



An **Airline Catering Company** had this Issue

- 1) It was operating in an airport that was handling 70 incoming and 70 outgoing flights a day
- 2) Incoming food trolleys on incoming flights had to be removed and sent to the kitchen to be cleaned
- 3) Outgoing food trolleys on all flights had to be prepared in the kitchen then transported all the way to an airplane where they can replace incoming trolleys

The company's operations unit was complaining that with the expansion of the operations of the airport, **they would need to recruit more staff . . .**

The Concerns of the Manager

The Manager was certain that the **current head count** was already inflated, hence can be used for any increase in the number of flights

But the Manager had no way of **proving** this . . .
Nor did the Operations Unit

Until he learnt about simulation . . .

What Results was the Manager Looking for?

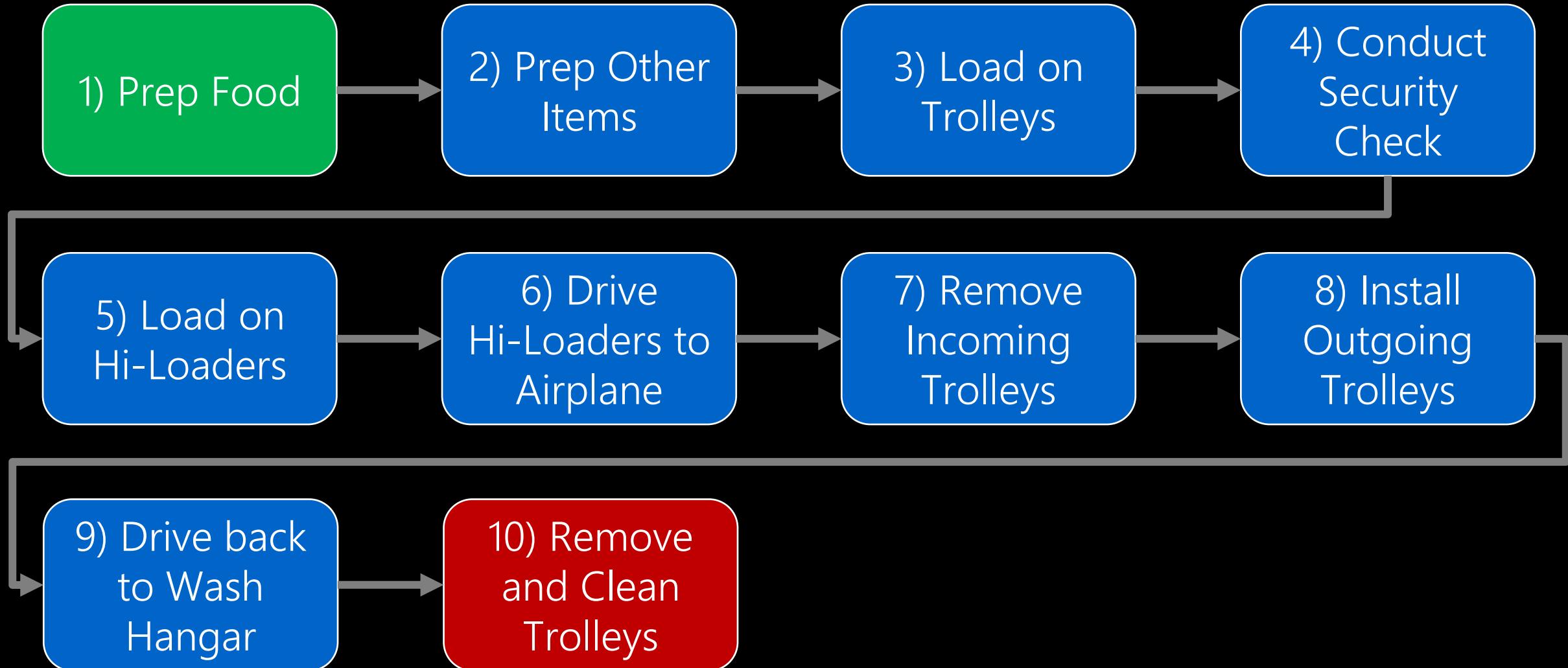
Utilization rates: kitchen throughput, loading efforts, transport . . .

Queue lengths and averages: at each step in the process

Overall time in system: the time it needs to prepare a trolley until it is installed in an airplane

And many other measurements . . .

The Trolley Preparation Process



Stage 1 of the Simulation Project

To verify that the model represents the reality of operations

Stage 1: Verification Tasks

- 1) The timing of all activities were measured
- 2) For each activity, we identified the data distribution that best described it (Normal, Uniform, Binomial)
- 3) A suitable random number generator generated random variables for each input variable from their identified distributions
- 4) The formulation was run 1000 times resulting in 1000s of output values

First Result . . .

The model was compliant with the **reality** of work

- 1) They got the right **throughput** figures
- 2) And the right **utilization** rates
- 3) And the right **duration** (whole process + single steps)

The model could now be used to predict future situations

Stage 2: Extending the Model

Now that the model **represented reality** well, the Manager could start **extending** it . . .

- 1) Provide different parameters for the Input Variables to check if the **same staff can handle a larger number** of flights
- 2) Provide different parameters for the Input Variables to check if the same staff can handle **a larger number of trolleys** (due to larger airplanes or larger bookings per flight)

Other Extensions

- 3) Classify flights by source in order to evaluate passenger loading
- 4) Classify flights by flight number to apply parameters for input variables based on equipment (airplanes)
- 5) Simulate periods in a year with different flight volumes
- 6) Simulate periods during the day with different flight volumes

Result

The Manager could prove that for the short to medium term increases in the number of flights, the current staff count would be sufficient

All this was achieved by simulating the operations

Another Real Case

Estimating the
Cost (hence
pricing) in a Hotel



Objective:

To Estimate the Right Price per Room

The Hotel had 2 types of Rooms: **regular** and **suites**

- 1) The number of bookings when a room was available
- 2) The number of regular room bookings when a room was not available, and the client was upgraded to a suite (if available)
- 3) The number of suite bookings when a suite was available and when it was not available
- 4) The duration of the stay in regular rooms or in suites
- 5) The costs: per room type per day, free upgrades, etc.

We can easily see that a feasible **Room Rate** would be impossible to estimate through manual calculations

The reason?

Too many input variables with built in estimation errors to be used in a complicated formulation

F.

Other Benefits of Monte Carlo Simulation

So far, we have presented 2 main benefits:

- 1) Getting estimates with a measured confidence
- 2) Representing the reality of our business processes so we can manipulate them, plan them or reengineer them

Anymore? A lot more . . .

Here are some more benefits of MCS

- 1) **Applicability**: models (such as queuing, utilization, reservations, event flow) can be used in different business domains
- 2) **Flexibility**: MCS modeling allows analysts to extend models to analyze new operations or solutions
- 3) **Risk Assessment**: analyze risk impacts, identification of worst-case scenarios, evaluation of potential risks and budgeting costs when responding to risks.

And more . . .

- 4) **Cost-effectiveness**: since MCS is based on computer modeling, it is a lot cheaper than investigating actual implementations
- 5) **Sensitivity and Influence Analysis**: spreadsheet modeling is well suited to identify and rank the input variable with the highest influence on the output variable.

Thank you for
viewing this
lecture.

