

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/322205736>

General Simulation Techniques for Decision-Making in Real Situation, A proficiency of STEM Research

Conference Paper · August 2015

CITATIONS

0

READS

5,663

1 author:



[Alexander Okhuese Victor](#)

Pan African University, Institute of Basic Science, Technology and Innovation

55 PUBLICATIONS 146 CITATIONS

[SEE PROFILE](#)

Some of the authors of this publication are also working on these related projects:



Economic Competitiveness [View project](#)



Sustainable Business Models for Delivering Digital Financial Services to Lower Income Unbanked Citizens of Nigeria [View project](#)

General Simulation Techniques for Decision-Making in Real Situation, A proficiency of STEM Research

Victor, Alexander O.

Department of Mathematics, University of Abuja, Nigeria

Abstract

This paper describes a multi-dimensional approach to the classification of the research literature on simulation and modelling. The aim of the study was to analyse the relative frequency of use of a range of operational research modelling approaches in management decision-making, along with the specific domains of application and the level of implementation. The results provide new insights into the level of activity across many areas of application, highlighting important relationships and pointing to key areas of omission and neglect in the literature. In addition, the approach presented in this article provides a systematic and generic methodology that can be extended to other application domains as well as other types of information source in management decision-making simulation process.

Introduction:

The technique of modelling and simulation has long been used by the designers and analysts in physical science and it promises to become an important tool for tackling the complicated problems of managerial decision-making. Scale models of machines have been used to simulate the plant layouts and models of aircrafts have been tested in wind tunnels to determine their aerodynamic characteristics. Modelling and Simulation, which can appropriately be called management laboratory, determines the effect of a number of alternate policies without disturbing the real system. It helps in selecting the best policy with the prior assurance that its implementation will be beneficial.

Probably the first important application of simulation was made by John Von Neumann and Stanislaw Ulam (1940) for studying the tedious behaviour of neutrons in a nuclear shielding problem which was too complex for mathematical analysis. With the remarkable success of the technique on neutron problem, it became popular and found many applications in business and industry. Development of digital computers in early 1950s is further responsible for the rapid progress made by the simulation techniques. The range of simulation application varies from simple queuing models to models of large integrate systems of production.

When to use simulation?

There are several techniques for solving various types of managerial decision-making problems. Techniques like linear programming, dynamic programming, queuing theory, network models, etc., are not sufficient to tackle all the important managerial problems requiring data analysis. Each technique has its own limitations.

Linear programming models assume that the data do not alter over the planning horizon. It is one time decision process and assumes average values for the decision variables. If the planning horizon is long, say 10 years, the multiperiod linear programming model may deal with the yearly average data, but will not take into account the variations over the months and weeks with the result that month to month and week to week operations are left implicit (Chen, 2006). Other important limitation of linear programming is that it assumes the data to be known with certainty. In many real situations the uncertainties about the data are such that they cannot be ignored. In case the uncertainty relates to only

few variables, the sensitivity analysis can be applied to determine its effect on the decision. But, in situations, where uncertainty pervades the entire model, the sensitivity analysis may become too cumbersome and computationally difficult to determine the impact of uncertainty on the recommended plan.

Dynamic programming models, however, can be used to determine optimal strategies, by taking into account the uncertainties and can analyse multiperiod planning problems. In other words, this technique is free from the two main limitations of linear programming. But it has its own shortcomings (Chen, 2006). Dynamic programming models can be used to tackle very simple situations involving only few variables. If the number of state variables is a bit larger, the computation task becomes quite complex and involved.

Similar limitations hold good for other mathematical techniques like dynamic stochastic models such as inventory and waiting line situations. Only small scale systems are amenable to these models; moreover, by making a number of assumptions the systems are simplified to such an extent that in many cases the results obtained are only rough approximations.

From the above discussion, it is good to conclude that when the characteristics such as uncertainty, complexity, dynamic interaction between the decision and subsequent event, and the need to develop detailed procedure and finely divided time intervals combine together in one situation, it becomes too complex to be solved by any of the techniques of mathematical programming and probabilistic models. It must be analysed by some other kind of quantitative technique which may give quite accurate and reliable results. Many new techniques are coming up, but, so far, the best available is simulation.

In general, the simulation technique is a dependable tool in situations where mathematical analysis is either too complex or too costly.

What is simulation?

Simulation is an imitation of reality. A children cycling park, with various crossings and signals, is a simulated model of the city traffic system. In the laboratories a number of experiments are performed on simulated models to determine the behaviour of the real system in true environment (Taylor SJE *et al*, 2009).. A simple illustration is the actual aircraft model in a wind tunnel from which we determine the performance of the actual aircraft under real operating conditions. Planetarium shows represent a beautiful simulation of the planet system. Environments in a geological garden and in a museum of natural history are other examples of simulation.

In all these situations, it has been tried to imitate the reality to see what might happen under real operating conditions. These imitations of reality which may be in the physical form or in the form of mathematical equations may be called *simulation*.

The simple instances cited above are of simulating the reality in physical form, and are referred to as (*environmental*) *analogue simulation*. For the complex and intricate problems of managerial decision-making, the analogue simulation may not be practicable, and actual experimentation with the system may be uneconomical. Under such circumstances, the complex system is formulated into mathematical model for which a computer programme is developed, and the problem is solved by using high speed electronic computer, and hence it is named as *computer simulation* or *system simulation*.

With this background it will be in order to define simulation. According to one definition '*simulation is a representation of reality through the use of a model or other device which will react in the same*

manner as reality under given set of conditions. Simulation has also been defined as *'the use of a system model that has the designed characteristics of reality in order to produce the essence of actual operation.'* According to Donald G Malcolm (2007), *a simulated model may be defined as one which depicts the working of a large scale system of men, machines, materials and information operating over a period of time in a simulated environment of the actual real world conditions.* According to Shannon (2004) *simulation is the process of designing a model of the real system by conducting experiments with this model for the purpose of understanding the behaviour of the operation of the system.*

Advantages of the Simulation Technique

The simulation technique, when compared with the mathematical programming and standard probability analysis, offers a number of advantages over these techniques; a few important among them can be summarized as follows:

1. Many important managerial decision problems are too intricate to be solved by mathematical programming and experimentation with the actual system, even if possible, is too costly and risky. Simulation offers the solution by allowing experimentation with model of the system without interfering with the real system. Simulation is thus, often a bypass for complex mathematical analysis.
2. Through simulation, management can foresee the difficulties and bottlenecks which may come up due to the introduction of new machines, equipment or process. It, thus, eliminates the need of costly trial and error methods of trying out the new concept on real methods and equipment.
3. Simulation has the advantage of being relatively free from mathematics and, thus, can be easily understood by the operating personnel and non-technical managers. This helps in getting the proposed plans accepted and implemented.
4. Simulation models are comparatively flexible and can be modified to accommodate the changing environments of the real situation.
5. Computer simulation can compress the performance of a system over several years and involving large calculations into a few minutes of computer running time.
6. The simulation technique is easier to use than mathematical models and is considered quite superior to the mathematical analysis
7. Simulation has advantageously been used for training the operating and managerial staff in the operation of complex plans. It is always advantageous to train people on simulation models before putting into their hands real system. Simulated exercises have been developed to impart the trainee sufficient exercise and experience. A simulated exercise familiarizes the trainee with data required and helps in judging what information is really important. Due to his personal involvement into the exercise, the trainee gains sufficient confidence, and moreover becomes familiar with data processing on electronic computer (Padilla, Jose, Diallo & Tolk, 2011)..

Limitations of the Simulation Technique

In spite of all the advantages claimed by the simulation technique, many operations research analysts consider it a method of last resort and use it only when all other techniques fail. If a particular type of problem can be well represented by mathematical model, the analytical approach is considered to be more economical, accurate and reliable (Collins, Shefrey, Sokolowski, Turnitsa & Weisel, 2011). On the other hand, in very large and complex problems simulation may suffer from the same deficiencies as other mathematical models. In brief, the simulation techniques suffer from the following limitations:

1. Simulation does not produce optimum results. When the model deals with uncertainties, the results of simulation are only reliable approximations subject to statistical errors.
2. Qualification of the variables is another difficulty. In a number of situations it is not possible to qualify all the variables that affect the behaviour of the system.
3. In the very large and complex problems, the large number of variables and the inter-relationships between them make the problem very unwieldy and hard to program. The number of variables may be too large and may exceed the capacity of the available computer.
4. Simulation is, by no means, a cheap method of analysis. In a number of situations, such as corporate planning, simulation is comparatively costlier and time consuming.
5. Other important limitations stem from too much tendency to rely on the simulation models. This results in application of the technique to some simple problems which can more appropriately be handled by other techniques of mathematical programming.

Simulation refers to imitating the operations and processes of a system in the real world; while modelling is the process of understanding and describing the behaviour of a system. The main purpose of applying simulation and modelling (SM) technology is to analyse and evaluate a wide variety of “what-if” questions about a real-world system to predict its performance and outcomes after potential changes to the system. Thus, SM can serve as an analysis tool for predicting the effects of changes to existing systems or as a design tool to predict the performance of new systems under varying sets of input parameters or conditions. Accordingly, SM helps in reducing the cost, risks, and unnecessary human efforts if such experiments are experienced in reality. Moreover, participation in SM development allows concerned decision makers to develop deeper understanding of the problems they tackle and new perspectives about the relationship between the system’s elements of interest and the measures of its performance.

Simulation Tools to Support Decisions Making in Supply Chain Management

Much research have been undertaken to develop SM tools to support decisions making in supply chain management (SCM). Here I briefly mention some examples of this work. Biswas and Narahari (2001) developed “DESSCOM”: a decision support for supply chains through object modelling, which enables strategic, tactical, and operational decision making in SCs. Ding et al. introduced a simulation and optimization tool “One” to support decision during assessment, design, and development of supply chain networks. Blackhurst et al. (1999) developed a decision support system, “PCDM,” for different decisions within the supply chain networks Wartha et al. (2002) developed a specialized and domain oriented decision support tool “DST-SC” that is easy to be used by nonexperts in simulation. DST-SC is also featured by its high degree of flexibility in modelling SC functions and its ability to handle large complex problems.

General Application of simulation)

Simulation is quite versatile and commonly applied technique for solving decision problems. It has been applied successfully to a wide range of problems of science and technology as given below:

1. In the field of basic sciences, it has been used to evaluate the area under a curve, to estimate the value of π , in matrix inversion and study of particle diffusion.
2. In industrial problems including the shop floor management, design of computer systems, design of queuing systems, inventory control, communication networks, chemical processes, nuclear reactors and scheduling of production processes.

3. In business and economic problems, including customer behaviour, price determination, economic forecasting, portfolio selection and capital budgeting.
4. In social problems, including population growth, effect of environment on health and group behaviour.
5. In biomedical systems, including fluid balance, distribution of electrolyte in human body and brain activities.
6. In the design of weapon systems, war strategies and tactics
7. In the study of projects involving risky investments.

Monte Carlo Simulation

The Monte Carlo method of simulation was developed by the two mathematicians John Von Neumann and Stanislaw Ulam (1940), during World War II to study how far neutrons would travel through different materials. The technique provided an approximate but quite workable solution to the problem. With the remarkable success of this technique on neutron problem, it soon became popular and found many applications in business and industry and at present forms a very important tool of operation researcher's tool kit.

The technique employs random numbers and is used to solve problems that involve probability and wherein physical experimentation is impracticable and formulation of mathematical model is impossible. It is a method of simulation by sampling technique. The steps involved in carrying out Monte Carlo simulation are:

1. Select the measure of effectiveness (objective function) of the problem. It is either to be maximized or minimized. For instance, it may be idle time of service facility in a queuing problem or number of shortages or the total inventory cost in an inventory control problem.
2. Identify the variables that affect the measure of effectiveness significantly. For instance, number of service facilities in a queuing problem or demand, lead time and safety stock in inventory control problem.
3. Determine the cumulative probability distribution of each variable selected in step 2. Plot these distributions with values of the variable along x-axis and cumulative probability values along the y-axis.
4. Get a set of random numbers
5. Consider each random number as a decimal value of the cumulative probability distribution. Enter the cumulative distribution plot along the y-axis. Project this point horizontally till it meets the distribution curve. Then project the point of intersection down on the x-axis.
6. Record the value (or values if several variables are being simulated) generated in step 5. Substitute in the formula chosen for measure of effectiveness and find its simulated value.
7. Repeat step 5 and 6 until sample is large enough to the satisfaction of the decision maker.

Though in any real problem to be solved by simulation, the variables in the problem are probabilistic in nature, we first consider below a problem where they are fixed and constant and see how simulation technique which involves repetitive experimentation can be used to analyse such a problem. The remaining problems involve variables that are probabilistic in nature.

Event-type and Queuing Simulation Problems

Customers at a Service Facility

A common instance is when customers arrive at a service facility to get the required service. Assuming the interarrival and service times are known and constant and are 1.8 minutes and 4 minutes respectively. Simulating the system for 14 minutes will help determine the average waiting time of a customer and idle time of the service facility.

The arrival times of customers within 14 minutes period will be:

Customer	:	1	2	3	4	5	6	7	8
Arrival time	:	0	1.8	3.6	5.4	7.2	9.0	10.8	12.6

(Minutes)

Data source: First Bank Plc, Gwagwalada Branch

The time at which the service begins and ends within time period of 14 minutes is shown below:

Waiting time of customers and idle time of service facility are also calculated.

Customer	Service		Waiting time of customer	Idle time of service facility
	Begins	Ends		
1	0	4	0	0
2	4	8	4-1.8=2.2	0
3	8	12	8-3.6=4.4	0
4	12	16	12-5.4=6.6	0

Data source: First Bank Plc, Gwagwalada Branch

The waiting time of the first four customers is calculated above. For the remaining, it is calculated below:

Customer	:	4	6	7	8
Waiting time:		14-7.2=6.8	5.0	3.2	1.4

$$\begin{aligned} \therefore \text{Average waiting time of a customer} &= \frac{0 + 2.2 + 4.4 + 6.6 + 6.8 + 5 + 3.2 + 1.4}{8} \\ &= \frac{29.6}{8} = 3.7 \text{ minutes} \end{aligned}$$

Since the service time is 4 minutes and the average waiting time of a customer is 3.7 minutes then the average time the facility is idle will be:

$$= \text{Service time} - \text{average waiting time}$$

$$= 4 \text{ minutes} - 3.7 \text{ minutes} = 0.3 \text{ minute and by approximation its zero minute, hence}$$

$$\text{idle time of facility} = \text{nil}$$

Distribution at a Station Assembly Line

Two persons A and B work on a two-station assembly line. The distributions of activity times at their stations are:

Time in seconds	Time frequency for A	Time frequency for B
10	4	2
20	7	3
30	10	6
40	15	8
50	35	12
60	18	9
70	8	7
80	3	3

Data Source: Coca-Cola Bottling Company, Kano Production Unit.

Using simulation techniques

- Simulate operation of the line for eight items
- Assuming B must wait until A completes the first item before starting work, will he have to wait to process any of the other seven items? What is the average waiting time of items for B.
Using the following random numbers:
For A : 83, 70, 06, 12, 59, 46, 54 and 04.
For B : 51, 99, 84, 81, 15, 36, 12 and 54.
- Determine the inventory of items between the two stations
- What is the average production rate?

Therefore,

- Table below shows the cumulative frequency distribution for A. Eight random numbers given for person A are also fitted. The serial numbers of random numbers are shown in the parenthesis.

Time in seconds	Time frequency for A	Cumulative frequency	Range	Random numbers fitted
10	4	4	00 – 03	06(3), 04(8)
20	7	11	04 – 10	
30	10	21	11 – 20	12(4)
40	15	36	21 – 35	
50	35	71	36 – 70	70(2), 59(5), 46(6),
60	18	89	71 – 88	54(7)
70	8	97	89 – 96	83(1)
80	3	100	97 – 99	

Data Source: Coca-Cola Bottling Company, Kano Production Unit.

Thus the eight times for A are 60, 50, 10, 30, 50, 50 and 10 seconds respectively.

Likewise, the eight times for B are derived from his cumulative distribution below.

Time in seconds	Time frequency for B	Cumulative frequency		Range	Random numbers fitted
		(i)	(ii) = 2 × (i)		
10	2	2	4	00 – 03	
20	3	5	10	04 – 09	
30	6	11	22	10 – 21	15(5), 12(7)
40	8	19	38	22 – 37	36(6)
50	12	31	62	38 – 61	51(1), 54(8)
60	9	40	80	62 – 79	
70	7	47	94	80 – 93	84(3), 81(4)
80	3	50	100	94 – 99	99(2)

Data Source: Coca-Cola Bottling Company, Kano Production Unit.

Thus the eight times for B are 50, 80, 70, 70, 30, 40, 30 and 50 seconds respectively. Note that the cumulative frequency has been multiplied by 2 to make it 100.

- b) The above times for persons A and B are used to calculate the waiting time, if any.

Item no.	Person A		Person B		Waiting time on the part of B	Waiting time on the part of item
	Time in	Time out	Time in	Time out		
1	0	60	60	110	60	-
2	60	110	110	190	-	-
3	110	120	190	260	-	70
4	120	150	260	330	-	110
5	150	200	330	360	-	130
6	200	250	360	400	-	110
7	250	300	400	430	-	100
8	300	310	430	480	-	120

Data Source: Coca-Cola Bottling Company, Kano Production Unit.

Thus person A will not have to wait for the remaining seven times.

$$\text{Average waiting time of items} = \frac{0 + 0 + 70 + 110 + 130 + 110 + 100 + 120}{8}$$

$$= \frac{640}{8} = 80 \text{ seconds}$$

- c) In all there are 6 items waiting between the two stations.
 d) Total time taken to process 8 times = 480 seconds = 8 minutes

$$\therefore \text{Average production rate} = \frac{8}{8} = \frac{1 \text{ item}}{\text{minute}}$$

Investment and Budgeting Simulation Problem

Investment Corporation's Investment Projects

An investment corporation want to study the investment projects based on three factors:

- i) Market demand in units
- ii) Price per unit minus cost per unit
- iii) The investment required

These factors are felt to be independent of each other. In analysing a new consumer product, the corporation estimates the following probability distributions:

Annual demand	Probability	(Price – Cost) per unit (\$)	Probability	Investment (\$)	Required probability
25,000	0.05	3.00	0.10	27,50,000	0.25
30,000	0.10	5.00	0.20	30,00,000	0.50
35,000	0.20	7.00	0.40	35,00,000	0.25
40,000	0.30	9.00	0.20		
45,000	0.20	10.00	0.10		
50,000	0.10				
55,000	0.05				

Data Source: Schemas Group of Companies, Abuja HQ

Using simulation process, repeat the trial 10 times. Compute the return on investment for each trial, taking these factors into account. Approximately, what is the most likely return? Use the following random numbers for annual demand, (price – cost) and the investment required:

28, 57, 60, 17, 64, 20, 27, 58, 61, 30, 19, 07, 90, 02, 57

28, 29, 83, 58, 41, 18, 67, 16, 71, 43, 68, 47, 24, 19, 97

Therefore, the yearly return can be determined by the formula:

$$\text{Return (R)} = \frac{(\text{Price} - \text{Cost}) \times \text{Number of units demanded}}{\text{Investment}} \times 100$$

The results of the simulation are shown in the table given below:

<i>Trials</i>	<i>Random number for demand</i>	<i>Simulated demand (000's)</i>	<i>Random number for profit (Price – Cost) per unit</i>	<i>Simulated profit (\$)</i>	<i>Simulated number for investment</i>	<i>Simulated investment (000's) (\$)</i>	<i>Simulated Return (%) Demand × Profit per investment</i>
1	28	35	19	5.00	18	2,750	6.36
2	57	40	07	3.00	67	3,000	4.00
3	60	40	90	10.00	16	2,750	14.55
4	17	35	02	3.00	71	3,000	3.50
5	64	40	57	7.00	43	3,000	9.33
6	20	35	28	5.00	68	3,000	5.83
7	27	35	29	5.00	47	3,000	5.83
8	58	40	83	9.00	24	2,750	13.10
9	61	40	58	7.00	19	2,750	10.18
10	30	35	41	7.00	97	3,500	7.00

Data Source: Schemas Group of Companies, Abuja HQ

Above table shows that the highest likely return is 14.55% which is corresponding to the annual demand of 40,000 units resulting a profit of \$10 per unit and the required investment will be \$2,750,000.

ABC Company's Profit Optimization Project

The management of ABC Company is considering the question of marketing a new product. The fixed cost required in the project is \$4,000. Three factors are uncertain and they are:

- i) The selling price
- ii) Variable cost
- iii) The annual sales volume

The product has a life of only one year. The management has the data on these three factors as under:

<i>Selling price (\$)</i>	<i>Probability</i>	<i>Variable cost (\$)</i>	<i>Probability</i>	<i>Sales volume (units)</i>	<i>Probability</i>
3	0.2	1	0.3	2,000	0.3
4	0.5	2	0.6	3,000	0.3
5	0.3	3	0.1	5,000	0.4

Data Source: ABC Company

Consider the following sequence of thirty random numbers:

81 32 60: 04 46 31: 67 25 24: 10 40 02: 39 68
 08: 59 66 90: 12 64 79: 31 86 68: 11 98 16

Using the sequence (First 3 random numbers for the first trial, etc.) simulate the average profit for the above project on the basis of 10 trials.

First of all, random numbers 00 – 99 are allocated in proportion to the probabilities associated with each of the three variables as given under:

<i>Selling price (\$)</i>	<i>Probabilities</i>	<i>Cumulative probabilities</i>	<i>Random numbers assigned</i>
3	0.2	0.2	00 – 19
4	0.5	0.7	20 – 69
5	0.3	1.0	70 – 99
<i>Variable Cost (\$)</i>			
1	0.3	0.3	00 – 29
2	0.6	0.9	30 – 89
3	0.1	1.0	90 – 99
<i>Sales volume (Units)</i>			
2,000	0.3	0.3	00 – 29
3,000	0.3	0.6	30 – 59
5,000	0.4	1.0	60 – 99

Data Source: ABC Company

Let now simulate the output of ten trials using the given random numbers in order to find the average profit for the project:

<i>S.No.</i>	<i>Random No.</i>	<i>Selling price (\$)</i>	<i>Random No.</i>	<i>Variable cost (\$)</i>	<i>Random No.</i>	<i>Sales volume ('000 units')</i>
1	81	5	32	2	60	5
2	04	3	46	2	31	3
3	67	4	25	1	24	2
4	10	3	40	2	02	2
5	39	4	68	2	08	2
6	59	4	66	2	90	5
7	12	3	64	2	79	5
8	31	4	86	2	68	5
9	82	5	89	2	25	2
10	11	3	98	3	16	2

Data Source: ABC Company

$$\text{Profit} = (\text{Selling price} - \text{Variable cost}) \times \text{Sales volume} - \text{Fixed cost}$$

Simulated profit in ten trials would be as follows:

<i>S.No.</i>	<i>Profit</i>
--------------	---------------

1	$(\$5 - \$2) \times 5,000 \text{ units} - \$4,000 = \$11,000$
2	$(\$3 - \$2) \times 3,000 \text{ units} - \$4,000 = -\$1,000$
3	$(\$4 - \$1) \times 2,000 \text{ units} - \$4,000 = \$2,000$
4	$(\$3 - \$2) \times 2,000 \text{ units} - \$4,000 = -\$2,000$
5	$(\$4 - \$2) \times 2,000 \text{ units} - \$4,000 = 0$
6	$(\$4 - \$2) \times 5,000 \text{ units} - \$4,000 = \$6,000$
7	$(\$3 - \$2) \times 5,000 \text{ units} - \$4,000 = \$1,000$
8	$(\$4 - \$2) \times 5,000 \text{ units} - \$4,000 = \$6,000$
9	$(\$5 - \$2) \times 2,000 \text{ units} - \$4,000 = \$2,000$
10	$(\$3 - \$3) \times 2,000 \text{ units} - \$4,000 = -\$4,000$
Total= \$21,000	

Data Source: ABC Company

$$\text{Therefore, average profit per trial} = \frac{\$21,000}{10} = \$2,100$$

Quality control simulation problem

Inspecting the output of a production line

The output of a production line is checked by an inspector for one or more of three different types of defects, called defects A, B and C. If defect A occurs, the item is scrapped. If defect B or C occurs, the item must be reworked. The time required to rework a B defect is 15 minutes and the time required to rework a C defect is 30 minutes. The probabilities of an A, B and C defects are 0.15, 0.20 and 0.10 respectively. For ten items coming off the assembly line, determine the number of items without any defects, the number scrapped and the total minutes of rework time.

Use the following random numbers:

RN for defect A: 48 55 91 40 93 01 83 63 47 52

RN for defect B: 47 36 57 04 79 55 10 13 57 09

RN for defect C: 82 95 18 96 20 84 56 11 52 03

Data Source: DANSA Foods, Lagos.

The probabilities of occurrence of A, B and C defects are 0.15, 0.20 and 0.10 respectively. So, the numbers 00 – 99 are allocated in proportion to the probabilities associated with each of the three defects.

Defect A		Defect B		Defect C	
Exists?	Random numbers assigned	Exists?	Random numbers assigned	Exists?	Random numbers assigned
Yes	00 – 14	Yes	00 – 19	Yes	00 – 09
No	15 – 99	No	20 – 99	No	10 – 99

Data Source: DANSA Foods, Lagos.

Simulating the output of the assembly line for 10 items using the given random numbers in order to determine the number of items without any defect, the number of items scrapped and total minutes of rework time required.

Item No.	RN for defect A	RN for defect B	RN for defect C	Whether any defect exists	Rework time in minutes	Remarks
1	48	47	82	None	-	-
2	55	36	95	None	-	-
3	91	57	18	None	-	-
4	40	04	96	B	15	-
5	93	79	20	None	-	-
6	01	55	84	A	-	Scrap
7	83	10	56	B	15	-
8	63	13	11	B	15	-
9	47	57	52	None	-	-
10	52	09	03	B,C	15+30=45	-

Data Source: DANSA Foods, Lagos.

During the simulated period, 5 out of the ten items had no defects, one item was scrapped and 90 minutes of total reword time was required by 4 items.

Summary and Conclusion

Simulation as seen in chapter 3 helps for forecasting and informed managerial or business decision making. This seminar paper canvases around general business models, simulating various events for optimal decision-making.

The advantages of simulation cannot be overemphasised ranging from simplifying a complex mathematical models to applying them to real life situations and reducing risk effects.

Despite the various limitations, simulation in this research has been unveiled as a ready tool to solving complex problems and aiding decision-making in business.

The Monte Carlo simulation procedure also makes it quite obvious that if the various algorithm required for a complete simulation process is well followed, it should yield an optimal solution to any problem under consideration.

However, as logically envisaging as the Monte Carlo algorithm is, chapter three gives an almost practical application of simulation ranging from event management of customers service at a public facility through distribution assembly lines to quality control simulation of inspecting output of a production line. Simulations has a wide range of application from generic to logical which in this study aims at enhancing managerial decision-making ability for customer satisfaction and profit optimization.

Further research can be initiated based change in situations surrounding real life effects.

Reference

Chen C (2004). Searching for intellectual turning points: Progressive knowledge domain visualization. Proceedings of the National Academy of Sciences 101(1): pp 5303–5310.

Chen C (2006). CiteSpace II: Detecting and visualizing emerging trends and transient patterns in scientific literature. J Am Soc Inf Sci Tec 57(3): 359–377.

Taylor SJE *et al* (2009). Simulation modelling is 50! Do we need a reality check? J Opl Res Soc 60(S1): S69–S82.

Lin, K., Travlos, D. V., Wadelin, J. W., & Vlasses, P. H. (2011). Simulation and Introductory Pharmacy Practice Experiences. *American Journal of Pharmaceutical Education*, 75(10), 209. doi: 10.5688/ajpe7510209

Padilla, Jose; S.Y. Diallo, A. Tolk (October 2011). ["Do We Need M&S Science?"](#) *SCS M&S Magazine* (4): 161–166.

Vyas, D., Wombwell, E., Russell, E., & Caligiuri, F. (2010). High-fidelity patient simulation series to supplement introductory pharmacy practice experiences. *Am J Pharm Educ*, 74(9), 169.

Collins, A.J.; S.R. Shefrey, J. Sokolowski, C.D. Turnitsa, E. Weisel (January 2011). "Modeling and Simulation Standards Study: Healthcare Workshop report". *VMASC Report, Suffolk VA*.

National Science Foundation (NSF) Blue Ribbon Panel (2007). Report on Simulation-Based Engineering Science: Revolutionizing Engineering Science through Simulation. NSF Press, May