A Comprehensive Review and Computational Perspective on Simulation in Operations Research and Programming Language C

Abstract:

In this paper, we attempt to draw a conclusion about the topics related to our study, as specifically operations research, simulation, and simulation programming languages. The use of operations research nowadays can be felt in every aspect of life, like network scheduling, traffic, transportation, military operations, and many more areas. Simulation, being one of the techniques to optimize operations research problems and to formulate a system model, becomes an important area of study. A comprehensive literature review was conducted, covering key works in simulation, operations research, and simulation programming languages. Operations Research (OR) development phases were reviewed to understand the procedural basis for simulation modelling. This study adopts an interdisciplinary methodological framework, integrating mathematical operations research, computer science, and simulation theory. Various simulation classifications—deterministic vs. stochastic, continuous vs. discrete, and discrete-event models—were compared to determine appropriate modelling applications. This study demonstrates that simulation, extending beyond mathematics and operations research, is fundamentally interdisciplinary—supporting advancements in physics, economics, management sciences, education, and computing. By examining simulation methods, random-variable generation, and simulation programming languages, the research highlights how computational modeling enhances decision-making, system optimization, and real-world problem solving, offering insights and guidance for future simulation-based research and applications. Various researchers have worked in the field of operations research, simulation, and simulation languages separately or as a combination of the two. But not too much attention has been paid to studying these areas altogether. This study uniquely integrates the mathematical foundations of Operations Research with the evolving landscape of simulation programming languages to present a unified interdisciplinary perspective. By linking classical simulation theory, modern SPLs, and computational modeling approaches, the work highlights conceptual advances, historical evolution, and methodological gaps. It offers a consolidated framework valuable for future researchers developing or applying simulation-based decision-support systems.

Keywords: *Operations Research, Simulation, Computer Simulation Languages, Random Variable, Random Variate, Probability Distribution Function.*

Introduction:

During the research work, we found that simulation is not only a part of operational research in the subject of mathematics but also related to Physics, Economics, Management-Sciences, Education, and with the advent of computer technologies, it is being implemented in the form of many applications using the programming languages known as simulation programming languages (SPLs). Hence, when we found the topic of research to be an interdisciplinary topic, we aimed to have a conclusive study in this field so that we may mark the aspects, projects, and shortcomings of the research done earlier in this field and may come up with some suggestions that will certainly benefit the forthcoming researchers in this field.

We will present in this paper how simulation is being implemented using simulation programming languages by the use of computers to benefit the world and human beings.

Simulation as a part of Operations Research in the subject of Mathematics:

Operations Research has a vast range of computer-oriented applications these days, as the approaches of Operations Research are applicable in business industries as well as the government sector, or both. The areas where operations research applications are useful are – Accounting, Construction, Facilities Planning, Finance, Marketing, Manufacturing, Human Resources, and others. Operations Research, being a part of mathematics, is also implemented in management to make appropriate decisions by optimizing the problem

(Savage, 2003), Simulation is one of the tools and approaches of Operations Research. A number of existing literatures present a wide variety of diagrams and conceptual frameworks describing the essential stages of a simulation study, with each author offering a slightly different perspective. Notable contributions include those by Shannon (1975, 1998), Szymankiewicz et al. (1988), Hoover and Perry (1990), Ulgen (1991), Dietz (1992), Gogg and Mott (1992), Musselman (1992), Nordgren (1995), Law and Kelton (2000), and Banks et al. (2001). Other tools and approaches in the subject of mathematics are linear programming, integer programming, game theory, decision theory, dynamic programming, and others (Shing Chih Tsai, 2022). The mathematical model is required to describe the overall system when any of the above-stated techniques/ methods is used to simulate a problem.

Operations Research Development Phases

When we think about the processes or phases required in operations research development, it can be classified into the following six respective steps (Wayne L. Winston, 2004):

1. Take note for formulating the O.R. problem
   Until the observation of the problem environment is not done, as the first step, we can not have proper information about how to formulate the problem. This phase includes the activities, likely conferences, observations, site visits, and research.
2. Scanning and Defining the Concerns of the O.R. Problem
   After observing the problem, the second step that should be taken to formulate OR problem is defining and analyzing. We discover in this step the aims, possible inputs, and constraints that define the problem. Also, this results in the information about the actual requirement for a solution and its nature.
3. Creating a model
   With the help of the mathematical model that must represent either hypothetical or real-world situations, the third step of operations research is met. This mathematical model comprises variable definitions, equations, formulae, and linkages that describe the systems and the processes of the problem being formulated. Once the model is constructed, it is put on trial in the concerned field under various environmental conditions and then fine-tuned to make it work. In this prospect, the requirements of the management should also be considered.
4. Selection of accurate input data
   The main focus of this step is to obtain a stream of data to test and run the mathematical model designed in the previous step. For testing and executing the mathematical model, the selection of accurate input data, a crucial phase of Operations Research Development, becomes compulsory. Some of the tasks related to this phase are External/ Internal data and fact analysis, opinion gathering, and utilization of computer data banks.
5. Furnishing a solution and its testing
   Both the above phases of operations research development, when completed accurately, can lead to the solution to the problem being reached. This solution may not appear as an adaptable solution in some cases when it is tested with the created mathematical model, but it can be used to identify the other constraints affecting the solution of the problem in such cases. So to support current organizational objectives, it becomes necessary to make the adjustments and redesign the mathematical model.
6. Implementation of the obtained formulation of the problem
   If everything happens to be correct and a proper solution has been obtained and tested successfully, then, resolving the issues of implementation authority, which is a behavioural issue to assure a quality of work and get the support of management, the solution is implemented in the concerned hypothetical or real work situation.

Literature Review:

While reviewing the existing literature related to operational research, it is important to understand that the nine taxonomies required for preservation and development of knowledge in related scientific or other such fields are being taken into account. These are tutorial review, scoping review, selective review, theoretical review, algorithmic review, computational review, meta-analysis, qualitative systematic review, and meta review. Between the years 2008-2020, a total of 38 journals and 709 reviews were published in OR and management science journals. After reviewing many of these published papers, we found that the literature reviewed in them is pursuing different goals and provides different natures of contributions. Surprisingly, these reviews provide knowledge of different types of applications of operations research, along with important information about the research gaps, as well as the provision of research agendas. Methodological prospective variance has also been found in the earlier reviews.

We also agree with the fact that reviews of existing literature play a significant role in numerous scientific disciplines and have been extensively acknowledged as a research genre as well as methodology. We are listing here some of the scientific disciplines that have been reviewed earlier, and these reviews are showing different applications to various domains and topics, with diversity in the methodology of reviewing the literature of operations research. Such as particularly in psychology (Baumeister and Leary, 1997; Cooper, 2010; Siddaway et al., 2019), social sciences (Hart, 1998; Petticrew and Roberts, 2006), information system research (Webster and Watson, 2002; Schryen, 2010; Rowe, 2014; Paré et al. 2015; Schryen, 2017; Budgen et al., 2018; Rios et al., 2018), management (Tranfield et al., 2003; Zorn and Campbell, 2006; Alvesson and Sandberg, 2011; Cubric, 2020), organization science (Denyer and Tranfield, 2009; Aguinis et al., 2023), health sciences (Grant and Booth, 2009; Lachkhem et al., 2018; Marsilio and Pisarra, 2021), software engineering (Kitchenham et al., 2010; Cruzes and Dyba, 2011; Garousi and Mäntylä, 2016; Hoda et al., 2017; Oliveira et al., 2018; Barros-Justo et al., 2019; Curcio et al., 2019), supply chain management (Seuring and Gold, 2012; Kache and Seuring, 2014; Hochrein et al., 2015; Durach et al., 2017; Carter and Washispack, 2018; Martins and Pato, 2019; Bai et al., 2021; Barata, 2021; Seuring et al., 2021) and engineering (Diaz et al., 2020; Kim and Kim, 2021; Lassalle, 2021).

As it is well known fact that simulation is a branch of operational research and has implementations in a number of fields related to it like Healthcare, Transportation, Accounting, Construction, Facilities Planning, Finance, Marketing, Manufacturing, Human Resources etc. we agree that to highlight the importance, applicability and implementation of simulation through simulation programming languages using an application it is important to review the earlier work conducted in above mentioned fields.

The following table is important to understand the applicability of simulation in the field of health care, which presents the data about the focus area and the key themes of the reviews conducted earlier. The data tabulated in Table 1 is enough to conclude that a substantial and increasing size of review literature on simulation across healthcare has been conducted earlier, covering diverse domains (listed in the third column of Table 1) as the review focus area listed in the first column of Table 1. Depending on the requirement and interest, like implementation, technique, setting, or outcome, of the research scholars in this field, there exist rich materials to investigate.

Review Focus Area	**Number of Included Reviews/ Studies**	**Key themes covered**
DES implementation (2010-2022)	616 publications (349 case studies)	Patient flow, resource management, trends

QI + Simulation integration (2015 – 2021)	18 studies	Patient care, education, safety threats, process/ design
Umbrella review of Simulation reviews	37 systematic reviews	Techniques, applications, data sources, software
Simulation as assessment tool	21 studies	Competency evaluation methods, reliability, validity
Human factors via simulation training	72 studies	Team skills, effectiveness, simulation training impact
System Dynamics simulation review	253 papers	Operations, diseases (Communicable & non-communicable), patient flow
Historical simulation research review	250 articles	Broad simulation techniques, implementation, software
Simulation in cancer care	51 papers	Scheduling, resource allocation, patient flow

Table 1

Similarly, we found a number of reviews and research conducted earlier in the field of transportation covering topics like transportation infrastructure Resilience, Deep Reinforcement Learning (DRL) in transportation, Transport–Territory Interaction Models, Continuum Approximation (CA) Models in Logistics, Simulation in Public Transportation, and Maas System Simulation Tools. The focus area elaborated in these reviews in the field of transportation include Resilience & robustness simulations; various methods (Monte Carlo, ABM, etc.), DRL applications across transport domains and discussion on implementation issues, Spatial – temporal scale; interdisciplinarity; model topologies, CA models in facility location; SCM; comparative advances & Gaps, Discrete; agent-based; multilevel; hybrid models; implementation steps; whole-system simulations; tool efficacy; modeling of demographics and mode choice respectively.

As we go to look at the studies and reviews conducted in the field of finance, we found that more than 15000 review papers exist about bibliometric studies in 487 publications deemed high quality for analysis. Out of these studies, 85 papers are related to elaborate Financial Modeling (FM), and 47 papers elaborate Risk Modeling (RM). Studies conducted in the field of finance in the category of Systematic Review of Deep Learning (DL) for Financial Time Series Forecasting (Tsai, S. C. et. al., 2021) during the span of time between 2005 and 2019 focused on areas for forecasting of stock indices, forex markets, commodities, analysis according to DL model choice, etc. On the other hand, studies conducted on a survey on Multilevel Monte Carlo (MLMC) in Finance highlighted the key concept of progress and development of MLMC techniques, their implementation across pricing, risk, and stochastic simulations tasks, as well as challenges and future research suggestions.

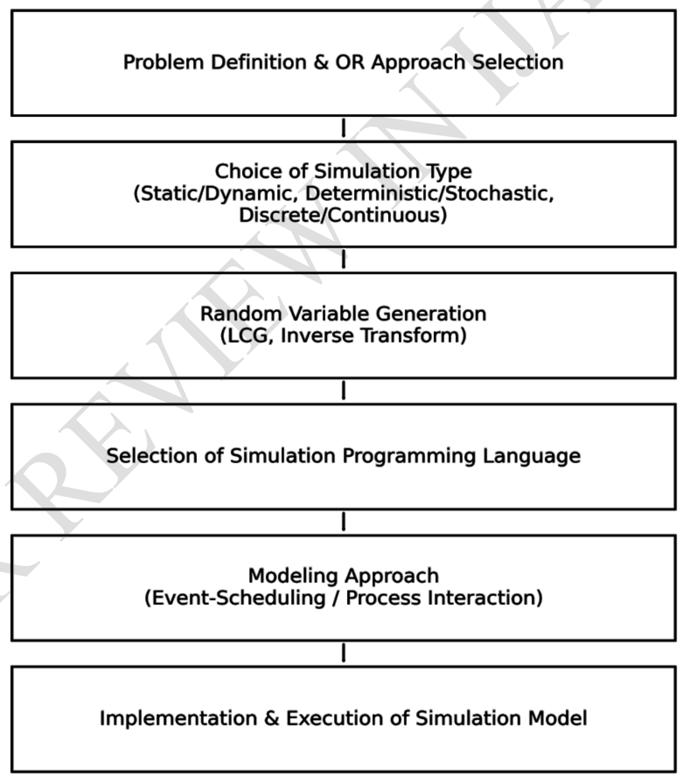
Intending driving and traffic simulators that allow validating and training driving automation from an artificial and algorithmic point of view, many of the simulators oriented towards vehicle automation exist in the literature authored by Michael Aeberhard, 2018, Institute for Transport Studies (ITS), 2016, Dosovitskiy, A., et. al., 2017, Costa, V. et. al, June, 2016, Apollo, 2018, MADRaS, 2018, Taheri, S.M., et. al., 2017, Dubey, O. P., & Pawan, A. (2024)..

Lackner (1964) was among the first to advocate for applying systems theory as the foundation for simulation modeling. Building on this idea, Zeigler later advanced a formal theoretical framework for simulation—initially through a 1972 journal article and subsequently in his 1976 monograph. His work, grounded in systems-theoretic principles, significantly influenced efforts to distinguish the conceptual representation of simulation from its implementation in simulation programming languages. Moreover, the unified theoretical structure Zeigler proposed for discrete-event, continuous, and hybrid models established conceptual connections that previously had been difficult for many researchers to articulate.

The study done in this paper is related to Operations Research, Simulation, and Simulation Languages. Many books, journals, and website pages have been studied, and the content of the paper has been prepared, leaving the statements or earlier research. The gist of all the above topics has been presented in this paper contributing to the earlier research by describing the C++ implementation for generating random numbers.

Methodology

The study adopts an interdisciplinary research approach to examine simulation as a mathematical, computational, and applied science tool. A comprehensive literature review was conducted, covering key works in simulation, operations research, and simulation programming languages. Foundational frameworks proposed by Shannon, Hoover and Perry, Law and Kelton, Banks et al., and others were systematically analyzed to map stages of simulation studies. The research synthesizes contributions from mathematics, management sciences, economics, physics, and computer science to contextualize simulation's cross-domain relevance. Operations Research (OR) development phases were reviewed to understand the procedural basis for simulation modelling. Each OR phase—problem formulation, problem definition, model construction, data selection, solution testing, and implementation—was critically examined. Conceptual models from prior studies were compared to identify recurring structures and differences in simulation practices. Emphasis was placed on understanding how mathematical modelling supports simulation within real-world decision-making contexts. Insights derived from this analysis were used to propose recommendations aimed at guiding future interdisciplinary simulation research. This study adopts an interdisciplinary methodological framework, integrating mathematical operations research, computer science, and simulation theory. Both analytical and logical approaches were examined to determine their suitability for simulation-based problem-solving in dynamic and static systems. Mathematical model construction procedures were analysed, including variable specification, equation formation, and system linkage design. Random variable generation techniques, such as linear congruential generators and inverse transform sampling, were evaluated for their role in stochastic simulation. Various simulation classifications—deterministic vs. stochastic, continuous vs. discrete, and discrete-event models—were compared to determine appropriate modelling applications. The study critically assessed simulation programming languages (SPLs), including FORTRAN, GPSS, SIMULA, SLAM, and modern languages like C++, Java, and Python. Core modelling paradigms—process-interaction, event-scheduling, and



entity/attribute/set frameworks—were analysed for their structural and computational advantages. The historical evolution and influence of object-oriented principles originating from SIMULA were examined to understand their role in contemporary simulation modelling. Based on the above analyses, the methodology identifies strengths, limitations, and practical considerations for selecting simulation approaches and tools for future research. The methodology of our study can be depicted in the diagram.

Findings

The study done in this paper has been able to illustrate the processes or phases required in Operations Research Development. For this, we have presented a relation to generate random numbers. Its algorithm and the CPP program have also been presented in this paper. In the CPP program, we have taken care of all the steps of Operations Research Development and tested the program with different accurate data inputs. This CPP program is ready to be implemented either in hypothetical areas or in real-world systems. Thus, we have also tried to summarize one technique related to simulation in the branch of Operations Research of the subject Mathematics, and its implementation using the general-purpose simulation programming language.

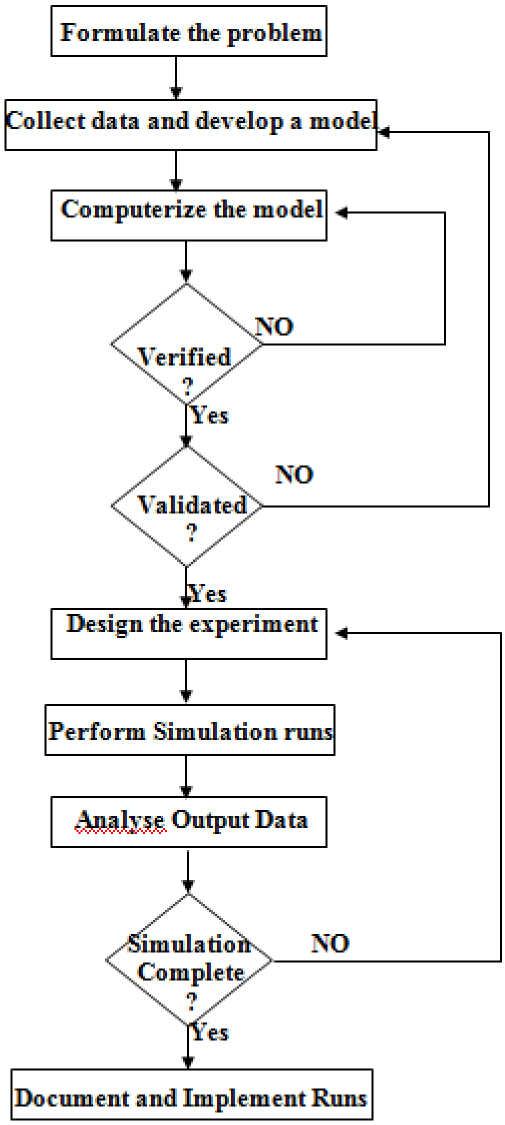
The findings of this study demonstrate that simulation occupies a central and multidisciplinary role extending far beyond its traditional placement within Operations Research and mathematical problem-solving. Its conceptual foundations and methodological practices connect directly with diverse fields such as physics, economics, management sciences, engineering, and education, and its practical relevance has expanded significantly with advances in computer technology and the development of simulation programming languages (SPLs). By examining the theoretical bases, computational techniques, and programming paradigms that underpin simulation modelling, this research provides an integrative perspective that highlights how simulation supports decision-making, optimizes system performance, and models complex, dynamic environments.

The application of this study lies in its capacity to guide future researchers and practitioners toward selecting, designing, and implementing simulation models that align with the structural characteristics of real-world systems. The discussion of Operations Research development phases clarifies how simulation supports problem formulation, model construction, data selection, solution testing, and implementation across a wide variety of industries and organizational contexts. Likewise, the classification of simulation types—static, dynamic, deterministic, stochastic, discrete, continuous, and discrete-event—enables researchers to adopt the most suitable modelling approach for the nature of the system under investigation. Moreover, the detailed examination of random-variable generation methods, including the linear congruential generator and inverse transform technique, equips users with foundational tools for incorporating probabilistic behavior into simulation models. The review of general-purpose and special-purpose simulation languages offers practical guidance for selecting programming environments that support complex modelling tasks. In addition, the analysis of key computational concepts—such as process interaction, entity–attribute–set structures, and object-oriented programming—illustrates how modern simulation environments benefit from computational paradigms originally developed within computer science.

Overall, the study serves as a comprehensive reference for applying simulation to interdisciplinary research problems. It helps researchers identify methodological gaps, understand earlier contributions, and recognize opportunities for advancement. By consolidating theoretical frameworks, modelling techniques, and computational tools, this research ultimately supports the development of more accurate, efficient, and scalable simulation models that can contribute meaningfully to academic inquiry, professional practice, and real-world decision-making. The aim of the study has been achieved.

Discussion

There are two different approaches to performing all the above-mentioned phases of Operations Research Development, one is analytical and the other is logical (D. S. Hira, P. K. Gupta, 2014). The benefit of a logical approach is that we can come up with a solution for the real-world system as it changes over time. Here, we will find simulation as the best operations research technique for such problems. *Static* and *Dynamic* simulation models are the two types of simulation. The problems of a system at a particular point in time can be formulated using a *static simulation model*, whereas on the other hand, the problems of a system that changes over time can be formulated using a *dynamic simulation model*. (Kao, 1996) The problems with no random variable can be formulated using *deterministic simulation*, and those that have one or more random variables can be formulated using *stochastic simulation*. Based on the model constructed to formulate a problem, the simulation can be classified into two categories: *discrete* and *continuous* models. When the decision variables vary only at discrete points of time, *discrete simulation* is applicable, and when the decision variable changes randomly over time, *continuous simulation* is applicable. Using a simulation model to formulate problems in which the decision variable changes in discrete time intervals is known as a *discrete-event simulation* model. The steps in a simulation study can be represented by using the figure presented below.



Simulation Programming Languages:

Computer programming languages are important tools running on computers as application software to develop other required programs or software, including operating systems, utilities, and other required application software. Writing the code to develop any program or software requires proper knowledge about the problem and/ or perspective for which the computer-oriented solution is going to be implemented. Writing the code for a complex simulation model is also a tedious and challenging task. (Fourer, Gay & Kernighan, 2003) For this very reason and to simplify the programming for simulation models, special computer-oriented languages known as computer simulation languages have been developed (Mobin Ahmad, 2017). ForTran, Basic, GPSS, GASP IV, and SLAM, as well as several others, are best-known simulation programming languages. In modern days, programming languages that are part of academic education in several universities at the graduate and post-graduate levels, like C, C++, Java, Python, and several others that suit the management authority, are also being used to program simulation models.

The process concept, the entity/ attribute/ set concept, and the object-oriented programming concept have had the most important control in the advancement of computing technology and in the areas of computer science.

The Process Concept. Initially implemented in a limited form within the GPSS transaction framework and later articulated more comprehensively through the process-interaction perspective of SIMULA, the process concept represents a foundational contribution to both simulation and operating systems. In simulation, it enabled the explicit modeling of an entity whose evolving behavior the model sought to emulate. Within operating systems, the process served as a quasi-autonomous executing program segment and became central to the development of computational models. SIMULA's co-routine–based execution environment further strengthened this concept, offering a highly effective mechanism for describing and managing complex system behaviors.

The Entity/Attribute/Set Concept. Kiviat et. al. (1968) introduced this conceptual framework in SIMSCRIPT II, offering a systematic method for representing static relationships among objects. Under this paradigm, entities could simultaneously belong to sets and own them, while also maintaining distinct attributes that defined their individual characteristics. When combined with Mealy's (1967) formal treatment of relationships among entities, this approach foreshadowed the core principles of the entity–relationship model later formalized in the database field—nearly a decade after these ideas had already appeared in simulation modeling.

Object-Oriented Programming. The development of SIMULA 67, an extension of the earlier SIMULA I, marked the introduction of object-oriented programming (OOP) through mechanisms such as abstract data types, encapsulation, inheritance, and message passing. Building upon the earlier co-routine structure, these OOP features enabled an exceptionally expressive and robust approach to simulation programming. Over the following two decades, OOP evolved into the dominant paradigm in software development more broadly. Its influence is evidenced by the fact that four of the eight languages recognized as historically significant at the 1993 History of Programming Languages II Conference—Ada, C++, CLU, and Smalltalk—trace substantial aspects of their design to SIMULA (Bergin & Gibson, 1996). Despite its broad impact, Nygaard (1978), one of SIMULA's creators, noted that the full extent of its power could only be appreciated by those who had used the language specifically for simulation.

Two different modeling approaches can be used according to the selection of computer simulation languages to program a simulation model (Seila, Ceric & Tadikamalla, 2003). One such approach is the event-scheduling approach, in which we have to identify the characteristic events to model the system and then write the required modules to describe the state changes occurring at the time of each event. Another approach is the process interaction approach, in which we depend on the entity (or a customer) that necessarily goes through the system to create the model of the system. ForTran, Basic, C, C++, and Java, like general-purpose languages, use an event-scheduling approach, and on the other hand, the process-interaction approach is used in GPSS. The system modeler, while using SLAM, can use either of the two approaches or even a mixture of the two that suits the model being analysed.

General-purpose programming languages provide greater flexibility and are widely used and available. On the other hand, computer simulation and special-purpose languages offer a number of advantages. Most of the features required to program a simulation model and a natural framework are provided by the latter. For example, SLAM – special-purpose simulation language- provides us with the features to program simulation models as discrete event models, continuous models, network models, or any combination of these.

Random Variable Generation

(Minh, 2001; Anthony Hayter, 2012) The Probability distribution helps represent Random Variables. The method of generating random variables from a set of given probability generation is known as *Monte Carlo Sampling* or *random variate generation*. The theory of such sampling is rooted in the interpretation of probability frequency and is entailed by a stable stream of random numbers.

Definition: A congruential method known as the linear congruential method, with the following relation, is used to generate random numbers:

$$x_{i+1} = (ax_i + c)\ modulo\ m \qquad (i = 0,1,2, \ldots.)$$

Proof: The above-represented linear congruential generator gives the remainder after performing the division of $(ax_i + c)$ by m, and random numbers are thus generated by the relation

$$R_i = \frac{x_i}{m} \qquad (i = 0,1,2, \ldots..) \qquad (1)$$

The inverse transformation method, requiring a cumulative frequency distribution in closed form, can be used, and the *algorithm* can be represented as:

Step 1: $f(x)$ is a given probability density function, and for this, the cumulative distribution function is to be derived by using the relation

$$F(x) = \int_{-\infty}^{x} f(t)dt$$

Step 2: Random number r is now generated.

Step 3: Setting $F(x) = r$, a solution is obtained for x. Hence, the obtained variable x is a random variate for a probability distribution function (pdf) given by $f(x)$.

CPP Program to Generate Random Numbers:

We now develop a CPP program to generate random numbers using the relation (1) presented earlier.

Suppose x in the relation is represented in the CPP language as an array of integers and is written as:

```
int  x[] = {10, 20, 30, 40, 50, 60, 70, 80, 90, 100};
```

and m is 100.

i is the location or index of the element in x, starting with 0 and ranging up to 9 (i=0,1,2,3,4,5,6,7,8,9)

The set of random numbers R_i, also represented as an array in the CPP language as:

```
int  R[10];
```

is calculated by using the following CPP program:

```
#include<iostream.h>
#include<stdlib.h>
#include<time.h>
#include<conio.h>
void main() {
int x[]={10,20,30,40,50,60,70,80,90,100}, m=100, R[10], i;
clrscr();
for(i=0;i<10;i++) {
R[i]=random(x[i]%m);
cout<<R[i]<<"\t";
}
}
```

When the program is tested, the following output of the above program is 10 random computer-generated numbers after execution, as follows:

0 0 10 1 17 13 37 15 63 0

Also, if the content of the array x[] and the value of m are changed, the random numbers during each time of the program execution get changed.

Conclusion:

Operations Research, being a part of mathematics, is also implemented in management to make appropriate decisions by optimizing the problem. Simulation is one of the techniques for optimizing the problem and creating models for the system that suit management authorities. Other techniques for Operations Research are analytical or more theoretical, whereas simulation appears to be logical. Hence, the implementation of a simulation model by using a computer becomes an easy task. For this special purpose, simulation programming languages as well as general-purpose programming languages can be used.

Limitations

This study is primarily conceptual and relies heavily on secondary literature, which may limit the depth of empirical validation. The interdisciplinary scope of simulation—spanning mathematics, operations research, computer science, healthcare, transportation, and finance—makes it challenging to capture every methodological nuance within a single review. Many referenced studies differ in purpose, taxonomy, and methodological rigor, which may introduce inconsistency in comparative interpretation. The implementation component focuses only on a basic C++ illustration of random number generation, which does not represent the full complexity of modern simulation practice. Additionally, the study does not include experimental results or real-world case applications.

Authors' Contribution

The authors collectively conceived and structured the study, recognizing simulation as an interdisciplinary domain that bridges mathematics, operations research, computer science, and applied fields such as healthcare, transportation, and finance. They conducted an extensive and integrative review of literature spanning simulation theory, modeling approaches, and simulation programming languages. The authors analyzed foundational concepts, identified methodological advancements, and highlighted gaps in existing research. They further contributed original implementation insight by demonstrating the generation of random numbers through C++-based Monte Carlo methods. Together, these efforts provide a consolidated understanding of simulation's evolution, applications, and computational realization for future researchers.

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