Simulation

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Course overview

Welcome to this graduate course on **Discrete-Event Simulation**, a hybrid discipline that combines knowledge and techniques from Operations Research (OR) and Computer Science (CS) (Figure 1). Due to the fast and continuous improvements in computer hardware and software, Simulation has become an emergent research area with practical industrial and services applications. Today, most real-world systems are too complex to be modeled and studied by using analytical methods. Instead, numerical methods such as simulation must be employed in order to study the performance of those systems, to gain insight into their internal behavior and to consider alternative ("what-if") scenarios. Applications of Simulations are widely spread among different knowledge areas, including the performance analysis of computer and telecommunication systems or the optimization of manufacturing and logistics processes. This course introduces concepts and methods for designing, performing and analyzing experiments conducted using a Simulation approach. Among other concepts, this course discusses the proper collection and modeling of input data and system randomness, the generation of random variables to emulate the behavior of the real system, the verification and validation of models, and the analysis of the experimental outputs.

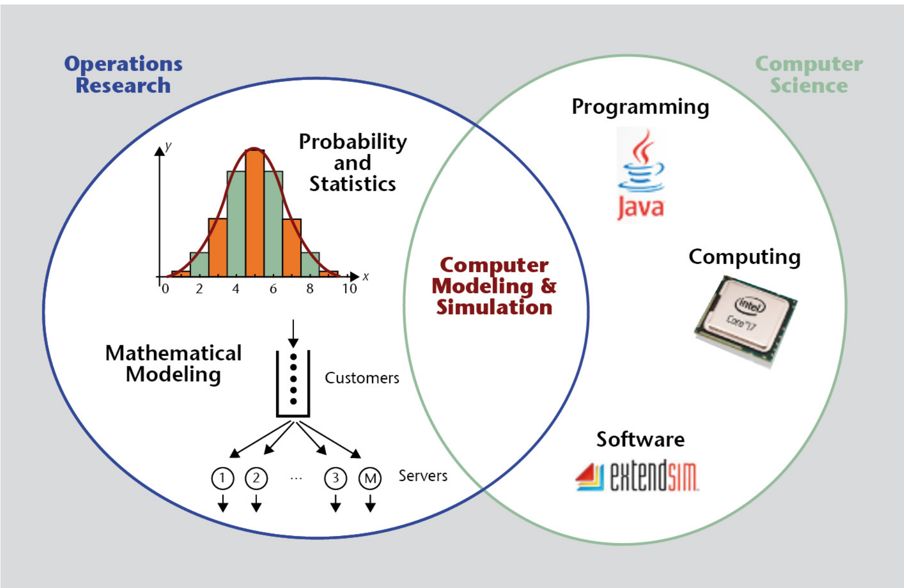

Figure 1. Simulation combines Operations Research and Computer Science

Audience and prerequisites

This course is designed for graduate students in any of the following degrees: Computer Science, Telecommunication Engineering, Business Management, Industrial Engineering, Economics, Mathematics or Physics. Some **mathematical background** is required –it is assumed that the student has successfully completed at least three undergraduate courses on mathematics, one of them in probability and statistics. Also, some **programming skills** are desirable although not necessary. Finally, the student must be able to read technical documentation written in **English**.

Goals and objectives

The main **goals** of this course are:

- To introduce students in the prolific research field of **discrete-event simulation**. In particular, this course offers a set of powerful system modeling and analysis tools (concepts, techniques and skills) that students can use both in their research and professional careers.

- To develop students' **modeling**, **analytical-thinking and synthesis skills**. In particular, throughout the course students will have to: model systems or processes in order to analyze them, read scientific papers, and develop their own simulation skills.

Course **objectives** are derived from the course goals and designed to be assessable. By the end of this course, students should be able to:

- Apply scientific thinking to the analysis of complex systems and processes.

- Comprehend important concepts in computer modeling and simulation.

- Model uncertainty and randomness by means of statistical distributions.

- Form a hypothesis and design a computer experiment to test it.

- Collect and model data, estimate errors in the results and analyze simulation outputs.

- Understand how computers generate (pseudo-)random numbers and variables.

- Realize the application scope and limitations of computer simulation techniques.

- Employ statistical techniques to construct scientific statements and conclusions.

- Construct, verify and validate system and processes models.

- Understand the main ideas described in scientific papers on simulation.

Learning resources

This course is based on the book ***Simulation: The Practice of Model Development and Use***, authored by Stewart Robinson (Figure 2). This is an introductory text to most Simulation concepts and techniques, and it provides an excellent overview of the subject without requiring too much statistical or mathematical background. The book also emphasizes how simulation can be applied to a huge variety of fields, including: computer and telecommunication networks, manufacturing and logistics processes, and system reliability and availability issues. Of course, there exist other excellent books on the subject. Although some of them might require certain mathematical or statistical background, we encourage advanced or curious students to take a look at them. Among others, we could highlight the following ones: *Simulation Modeling and Analysis* (Law 2006), *Discrete-Event System Simulation* (Banks et al. 2009), *Simulation with Arena* (Kelton et al. 2009), *Simulation* (Ross, 2006), *Simulation Modeling and Analysis with ARENA* (Melamed 2007), *Simulation Modeling and Arena* (2007), etc.

Figure 2. Basic learning resources for the course

Another fundamental source of Simulation learning resources is the **Winter Simulation Conference** or WSC (www.wintersim.org). Every year, this international event is the central meeting point for hundreds of Simulation scientists, engineers and users who share their knowledge and research results. Papers published in the WSC proceedings are not only available from the most prestigious databases (ACM Digital Library or IEEE Digital Library) but they can also be freely downloaded from the **INFORMS Simulation Society** website (http://informs-sim.org). The WSC proceedings contain top-quality research papers covering almost any imaginable Simulation topic –from introduction tutorials to advanced applications– and, therefore, they will constitute an invaluable learning resource for both the beginner and the advanced researcher or practitioner. Moreover, several international journals have Simulation as their main topic, among others: *Simulation, Journal of Simulation*, or *Simulation Modelling Practice and Theory*.

Finally, it is worthy to remember that Internet is today a great source of learning materials for almost every knowledge area. In particular, there are thousands of resources on issues related to system modeling and analysis, probability and statistics, programming languages and simulation software, etc., that can be useful for students registered in this course. Two websites that usually offer interesting contents are **Wikipedia** and **MathWorld** (http://mathworld.wolfram.com).

Methodology

Instructors will provide guidance and support to students through the **UOC Virtual Campus** by posting notes on the virtual-class forums, answering students' doubts, submitting recommendations, providing personalized feedback whenever possible and proposing specific lectures, debates and assessment activities as scheduled in the course syllabus.

It is expected that students maintain an **open**, **constant** and **creative attitude** throughout the course, showing real interest in learning new –and sometimes challenging– concepts, and working hard on their learning process according to instructors' recommendations.

When performing mathematical and/or statistical operations –which are frequently necessary to solve certain problems and exercises–, use of **mathematical** and/or **statistical software** is not only allowed but strongly recommended. Simulation students, researchers and practitioners should be familiarized with at least one mathematical software (e.g.: Wiris, Maple, Mathcad, Mathematica, Matlab, GNU Octave, etc.) and one statistical software (e.g.: Minitab, R, Excel, SPSS, S-Plus, etc.).

Evaluation system

This is an online graduate course with a demanding educational program based on quantitative contents. Therefore, in order to achieve the proposed academic goals and objectives, students must actively participate in the online forums and complete the different activities that constitute the **continuous evaluation process**. This continuous evaluation process will consist of a set of deliverables (typically three or four) that must be submitted to the instructor on or before their associated deadlines. The deliverables might include theoretical concepts as well as practical model developments and analysis. Also, there will be a **final proctored test** which will contribute to validate the authorship of the aforementioned deliverables as well as to determine the final score. More details about this evaluation process will be provided in the course syllabus at the beginning of the academic semester.

Chapters

1. Simulation: What, Why and When?

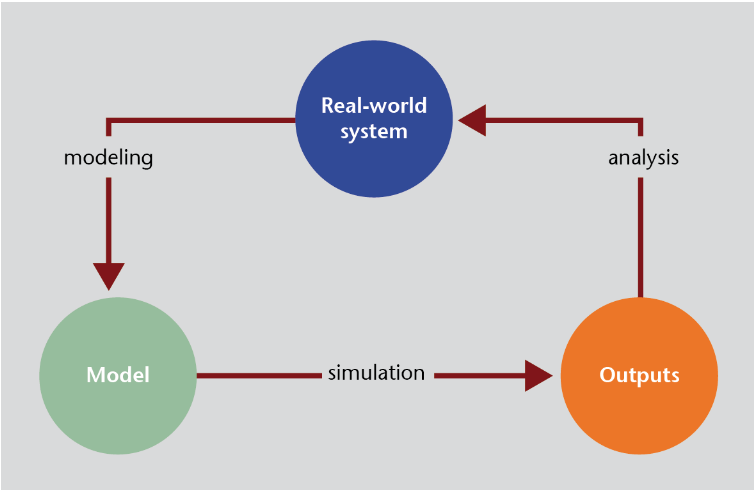

Figure 3. Modeling, Simulation, and Analysis

Main study material

Read carefully Chapter 1, **"Simulation: What, Why and When?"**, from the Robinson's book. This chapter describes the basic concepts and ideas associated with computer modeling and simulation. The chapter includes some definitions and a discussion on the advantages and limitations of simulation-based techniques.

Summary of basic concepts

- An **operations system** is defined as a group of objects that are joined together in some regular interaction or interdependence toward the accomplishment of some purpose.
- The **state** of a system is defined to be a collection of variables necessary to describe the system at any time.
- An **event** is defined as an instantaneous occurrence that might change the state of the system.
- A **discrete system** is one in which the state variables change only at a discrete set of points in time.
- The behavior of a real-world system as it evolves over time can usually be studied by developing a computer simulation **model**. This model usually takes the form of a set of mathematical or logical assumptions concerning the operation of the real system.

- **Simulation** involves the generation of an artificial history of the model representing the system and the observation of that artificial history to draw inferences concerning the operating characteristics of the real system.

- **Discrete-event simulation (DES)** refers to the simulation of systems in which the state variable changes only at a discrete set of points in time.

- Once developed and validated, a model can be used to investigate a wide variety of **"what-if" questions** about the real system: potential changes to the system can first be simulated, in order to predict their impact on system performance.

- The availability of special-purpose simulation languages and software and of massive computing capabilities have made simulation one of the most **widely used** and accepted tools in operations research and systems engineering.

- Simulation takes **data** on the real system. If no data is available, simulation might not be advised.

- Some **modeling approaches** attempt to provide optimum answers (e.g. linear programming) or near optimum answers (e.g. heuristics and meta-heuristics). A simulation simply predicts the performance of an operations system under a specific set of inputs or scenario ("what-if" analysis).

- In contrast to optimization models, simulation models are numerically **"run"** rather than analytically solved.

- A **simulation** can be defined as experimentation with a simplified imitation (on a computer) of an operations system as it progress through time, for the purpose of better understanding and/or improving the system.

- Many operations systems are subject to **variability**. This might be predictable variations (controlled by the system manager) or unpredictable ones (random events which generate uncertainty conditions).

- Most modern systems and processes are so **complex** that their internal behavior can be treated only through simulation.

- **Combinatorial complexity** is related to the number of components in a system or the number of combinations of system components that are possible. **Dynamic complexity** arises from the interaction of components in a system over time.

- **Simulation models** are able to represent the variability, interconnectedness and complexity of a system. As a result, it is possible with a simulation to predict system performance, to compare alternative system designs and to determine the effect of alternative policies on system performance.

- Simulation is used to modeling **queuing systems**, i.e. systems of entities being processed through a series of stages, with queues forming between each stage if there is insufficient processing capacity.

- **Simulation models** are used by many organizations (e.g. manufacturing companies, financial services organizations, transport companies, etc.) to plan future facilities and to improve current ones.

- **Advantages** of simulation: (i) experimenting with the real system is likely to be more costly and time consuming than simulating the system; (ii) while experimenting with the real system, it can be difficult to control (modify) the experimental conditions; (iii) the real system might not even exist; (iv) simulations are able to model variability and its effects in a natural way; (v) simulation requires few, if any, assumptions; (vi) simulation is more transparent ("white-box" approach) for the manager than pure mathematical approaches.

- **Disadvantages** of simulation: (i) simulation software might be expensive; (ii) simulation is still a time consuming approach; (iii) most simulation models require a significant amount of data; (iv) simulation requires expertise; (v) because of the animated displays offered by current software, there is a danger that simulation results receive credit without a proper validation process.

- The **applications** of simulation are vast, including fields such as Manufacturing, Computer and Telecommunication Networks, Health Care, Logistics and Transportation, Construction Engineering, Risk Analysis or Business Process. The Winter Simulation Conference (www.wintersim.org) is an excellent way to learn more about the latest in simulation applications and theory. WSC programs with full papers are available from http://www.informs-sim.org/.

Articles to read

Banks, J. (1999). "Introduction to Simulation". In: *Proceedings of the Winter Simulation Conference*, pp. 7-13.

Banks, J. (2001). "The Future of Simulation". In: *Proceedings of the Winter Simulation Conference*.

Goldsman, D. (2007). "Introduction to Simulation". In: *Proceedings of the Winter Simulation Conference*, pp. 26-37.

Ingalls, R. (2002). "Introduction to Simulation". In: *Proceedings of the Winter Simulation Conference*, pp. 7-16.

Raychaudhuri, S. (2008). "Introduction to Monte Carlo Simulation". In: *Proceedings of the Winter Simulation Conference*, pp. 91-100.

Sanchez, P (2006). "As simple as possible, but no simpler: a gentle introduction to simulation modeling". In: *Proceedings of the Winter Simulation Conference*, pp. 2-10.

Saraph, P. (2004). "Future of Simulation in Biotechnology Industry". In: *Proceedings of the Winter Simulation Conference*, pp. 2052-2054.

Shannon, R. (1998). "Introduction to the Art and Science of Simulation". In: *Proceedings of the Winter Simulation Conference*, pp. 7-14.

Activities to learn more

1) Get a copy of a recent WSC Proceedings and report on the different applications discussed in an area of interest to you.

2) Using your favorite search engine, search the web for the following terms: "discrete event simulation", "web based simulation", "supply chain simulation" and "parallel simulation". Prepare a brief report explaining each of these terms.

3) Search for other international conferences focused on computer modeling and simulation and prepare a brief report with basic information on them.

4) Try to complete exercises E1.1, E1.2, and E1.3 from the Robinson's book.

Complementary lectures

Specific examples of use of some simulation programming languages and environments can be found at the WSC proceedings.

2. Inside Simulation Software

$$X_{i+1} = (aX_i + c) \bmod m \qquad i = 0, 1, 2, \ldots$$

$$R_i = \frac{X_i}{m} \qquad i = 1, 2, \ldots$$

Uniform(0,1)	Binomial(10,0.5)	Normal(10,2)	Weibull(2,1)	Geometric(0.20)
0.729854	5	9.8903	0.39443	2
0.942597	6	8.8125	0.56438	8
0.935772	5	11.2554	1.25931	1

Figure 4. Modeling variability through random numbers

Main study material

Read carefully Chapter 2, "**Inside Simulation Software**", from the Robinson's book. This chapter describes the principles of the simulation techniques. The chapter provides an overview of how simulation works, including the modeling of time progression as well as the modeling of variability. Three approaches are presented to modeling time progression: time-slicing, discrete-event, and continuous simulation. Discrete-event simulation constitutes the main approach in this course and it is explained in detail. The chapter also includes a discussion on random numbers generation.

Summary of basic concepts

- Uncertainty (variation) in real-world systems is usually modeled by means of **random variables**. Each of these random variables follows a statistical distribution.

- For each random variable in the model, data from the real system must be collected and analyzed. Ideally, this data should be fitted by a theoretical **statistical distribution**. If no theoretical distribution can be chosen to adequately represent the input data, then an empirical distribution should be used instead.

- Fitted statistical distributions or probabilistic models of input data are then used in **generating random events** in a simulation experiment.

- One simple method for modeling the progress of time in a simulation is the **time-slicing** approach. In this approach, a constant time-step is used, i.e. the **simulation clock** advances at regular time intervals. However, this approach is computationally inefficient since during most of the time-steps there is no change in the system state.

- A more efficient method for modeling the progress of time is the **discrete-event** approach. Here, only the points in time at which the state of the system changes are considered, i.e. the system is modeled as a series of random events in time which might change the system state.

- In a discrete-event simulation, events are randomly generated using the appropriate probability distributions. A **list of scheduled events** is maintained and updated, and the simulation clock is advanced to the next event in the list. Each time an event occurs, the variables related to the system status are updated, and reactive actions to the event are taken, including the scheduling of new randomly generated events.

- Some systems or processes are not subject to discrete changes in state, but the state of the system/process changes continuously through time. **Continuous simulation** is widely used in engineering, economics and biology.

- **Random numbers** are a fundamental ingredient in any discrete-event simulation. Most computer and simulation languages generate random numbers that are used to generate event times and other random variables.

- A sequence of random numbers must have two important statistical properties: **uniformity** –i.e., they follow a continuous uniform distribution in the (0,1) interval– and **independence** –i.e., each new number is independent of its predecessors.

- Since they use deterministic algorithms, computers do not generate real random numbers. Computers generate **pseudo-random numbers**, which imitate the ideal properties of uniform distribution and independence as closely as possible.

- The **cycle length** or period of a random number generator (RNG) represents the length of the random number sequence before previous numbers begin to repeat themselves in an earlier order. The generator algorithm should have a sufficiently long cycle.

- The **linear congruential method** produces a sequence of integers, X_1, X_2, … between 0 and m – 1 by following a recursive relationship $X_{i+1} = (aX_i + c) \bmod m$ (i = 0, 1, 2, …). Then, random numbers between 0 and 1 can be generated by considering $R_i = X_i/m$ (i = 1, 2, …). The initial value X_0 is called the **seed**. If $c \neq 0$, the form is called the **mixed** congruential method; otherwise it is known as the **multiplicative** congruential method. The selection of the values a, c, m, and X_0 drastically affects the statistical properties and the cycle length. Some of these generators can reach periods close to $2*10^9$.

- **Combined linear congruential generators** mix two or more multiplicative congruential generators to increase the cycle length while maintaining good statistical properties. Some of these generators can reach periods close to $3*10^{57}$.

- A long-period RNG can be divided into a set of disjoint sequences or **streams**. That way, a single random-number generator with k streams can act like k distinct virtual random-number generators. This can be useful, for example, when comparing two or more alternative systems via simulation, since it allows assigning specific streams to generate the same random behavior in each of the simulated systems –e.g. in a queuing system, one stream could be assigned to generate interarrival times, another stream could be assigned to generate service times, etc.

- **Frequency tests** are used to check for uniformity of random numbers. In particular, the Kolmogorov-Smirnov (for both large and small samples) or the chi-square test (only for large samples) can be employed to compare the distribution of the set of numbers generated to a uniform distribution. Also, **autocorrelation tests** can be used to check for independence of random numbers.

- Well-known procedures exist for obtaining **random variates** from a variety of widely-used continuous and discrete distributions. Most of these procedures assume that a source of uniform (0, 1) random numbers is readily available.

- The **inverse-transform technique** is a general methodology that can be used to sample from the exponential, the uniform, the Weibull, the triangular distributions, empirical distributions and discrete distributions.

- The **acceptance-rejection technique** is a general methodology that can be used to sample from the uniform, Poisson and gamma distributions among others.

- Some probability distributions –e.g. the Normal, the Lognormal or the Erlang– have special properties that allow for specific-purpose variate-generation techniques.

Articles to read

Kelton, D. (2007). “Representing and generating uncertainty effectively”. In: *Proceedings of the Winter Simulation Conference*, pp. 38-42.

Law, A. (2003). “How to conduct a successful simulation study”. In: *Proceedings of the Winter Simulation Conference*, pp. 66-70.

Law, A.; McComas, M. (2001). "How the ExpertFit distribution-fitting software can make your simulation models more valid". In: *Proceedings of the Winter Simulation Conference*, pp. 256-261.

L'Ecuyer, P. (1997). "Uniform random number generators: a review". In: *Proceedings of the Winter Simulation Conference*, pp. 127-134.

L'Ecuyer, P. (2001). "Software for uniform random number generation: distinguishing the good and the bad". In: *Proceedings of the Winter Simulation Conference*, pp. 95-105.

Medeiros, D.; Swenson, E.; DeFlitch, C. (2008). "Improving patient flow in a hospital emergency department". In: *Proceedings of the Winter Simulation Conference*, pp. 1526-1531.

Mehrotra, V.; Fama, J. (2003). "Call center simulation modeling: methods, challenges, and opportunities". In: *Proceedings of the Winter Simulation Conference*, pp. 135-143.

Activities to learn more

Exercises E2.1, E2.2, and E2.3 from the Robinson's book.

Complementary lectures

SSJ for simulation in Java:
http://www.iro.umontreal.ca/~simardr/ssj/indexe.html

From Wikipedia:

- Random numbers:
  http://en.wikipedia.org/wiki/Random_number_generation
- Random variates:
  http://en.wikipedia.org/wiki/Random_variate

3. Software for Simulation

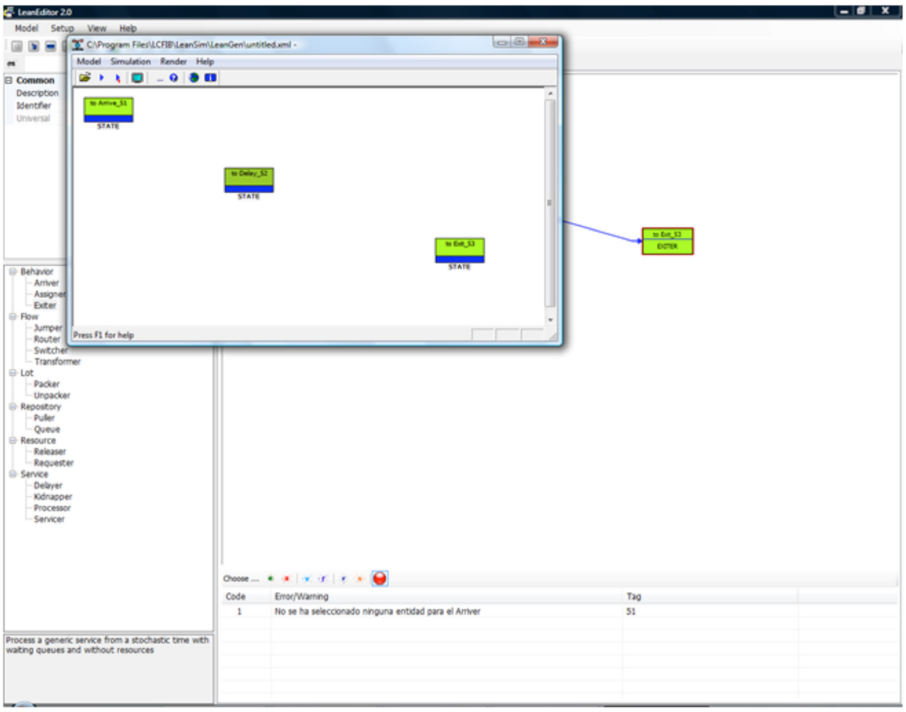

Figure 5. VIMS framework representing a simple model.

Main study material

Read carefully Chapter 3 **"Software for simulation"** from the Robinson's book. This chapter describes some of the main characteristics of the simulation software you can use to implement a model. The selection of specific simulation software in front of others depends on the objectives of the study. It is mandatory to justify this selection.

Summary of basic concepts

- The increase of the number and the quality of simulation software has been closely allied to the **development of computing**.

- From the 1950s until now a wide range of software is available for developing simulation models. Modelers need to **be aware of software possibilities** in order to select the appropriate tool for model development.

- **Visual Interactive Simulation** (VIS) was introduced by Hurrion on 1976. The idea is that a model provides a visual display showing an animation of the model execution. Now the display can range from a simple schematic representation of the model to a truly immersive virtual world. The user often can interact with the model in real-time.

- Simulation modelers **must select** between spreadsheets, programming languages or specialist software.

- Specialist software can be described as **Visual Interactive Modelling Systems** (VIMS). While VIMS referrers to how the model is developed, while VIM refers to the nature of the model.VIS model does not necessarily must be developed using a VIMS, while a model build using VIMS is not necessarily a VIS.

- Depending on the scope of the system we want to model, the **software selection** becomes a key aspect. Although the domains of application of the more powerful simulation systems have been increased, there are few occasions where the software simply cannot model some systems.

- The software selection process has the next five steeps: (i) establish the **modeling requirements**, (ii) survey and **shortlist the software**, (iii) establish **evaluation criteria**, (iv) **evaluate the software** in relation to the criteria, (v) **software selection**.

Articles to read

Hurrion, R.D. (1976). *The design, use and required facilities of an interactive visual computer simulation language to explore production planning problems*. PhD Thesis, University of London.

Hlupic, V., Irani, Z. and Paul, R.J. (1999). ''Evaluation framework for simulation software''. In: *The International Journal of Advanced Manufacturing Technology*, 15(5), pp. 366-382.

Rincon, G., Alvarez, M., Perez, M. & Hernandez, S. (2005). "A discrete-event simulation and continuous software evaluation on a systemic quality model: An oil industry case". In: *Information & Management*, 42, pp. 1051-66.

Seila, A.F. (2002). ''Spreadsheet simulation''. In: *Proceedings of the 2002 Winter Simulation Conference* (Yucesan, E., Chen, C.-H., Snowden, S.L., Charnes, J.M., eds). IEEE, Piscataway, NJ, pp. 17-22.

Pam Laney Markt and Michael H. Mayer (1997). "WITNESS simulation software: a flexible suite of simulation tools". In: *Proceedings of the 29th conference on Winter simulation* (WSC '97), Sigrén Andradóttir, Kevin J. Healy, David H. Withers, and Barry L. Nelson (Eds.). IEEE Computer Society, Washington, DC, USA, pp. 711-717. DOI=10.1145/268437.268613
http://dx.doi.org/10.1145/268437.268613

Jerry Banks (1997). “The future of simulation software: a panel discussion”. In: *Proceedings of the 29th conference on Winter simulation* (WSC ‘97), Sigrén Andradóttir, Kevin J. Healy, David H. Withers, and Barry L. Nelson (Eds.). IEEE Computer Society, Washington, DC, USA, pp. 166-173. DOI=10.1145/268437.268470 http://dx.doi.org/10.1145/268437.268470

David A. Takus and David M. Profozich (1997). “Arena software tutorial”. In: *Proceedings of the 29th conference on Winter simulation* (WSC ‘97), Sigrén Andradóttir, Kevin J. Healy, David H. Withers, and Barry L. Nelson (Eds.). IEEE Computer Society, Washington, DC, USA, pp. 541-544. DOI=10.1145/268437.268564 http://dx.doi.org/10.1145/268437.268564

Thomas J. Schriber and Daniel T. Brunner (2004). “Inside discrete-event simulation software: how it works and why it matters”. In: *Proceedings of the 36th conference on Winter simulation* (WSC ‘04). Winter Simulation Conference, pp. 142-152.

Tamrat W. Tewoldeberhan, Alexander Verbraeck, Edwin Valentin, and Gilles Bardonnet (2002). “Software evaluation and selection: an evaluation and selection methodology for discrete-event simulation software”. In: *Proceedings of the 34th conference on Winter simulation: exploring new frontiers* (WSC ‘02). Winter Simulation Conference, pp. 67-75.

C. Dennis Pegden (2007). “SIMIO: a new simulation system based on intelligent objects”. In: *Proceedings of the 39th conference on Winter simulation: 40 years! The best is yet to come* (WSC ‘07). IEEE Press, Piscataway, NJ, USA, pp. 2293-2300.

Activities to learn more

Following the directions of the book, try to define long list that represents all the simulation software that exist now. Don’t try to be exhaustive, focus in a specific field (for example the automotive sector) and find simulation software that allows simulating this kind of systems.

Compare the evaluation criteria presented in Robinson’s books with the one presented on Rincon et. Alt. (2005). Define a template to evaluate several software alternatives for a specific scope and objective.

Complementary lectures

From Web:

Discret-event Simulation Software Decision Support Venezuelan Oil Industry:
http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.108.3186&rep=rep1&type=pdf

4. Simulation Studies

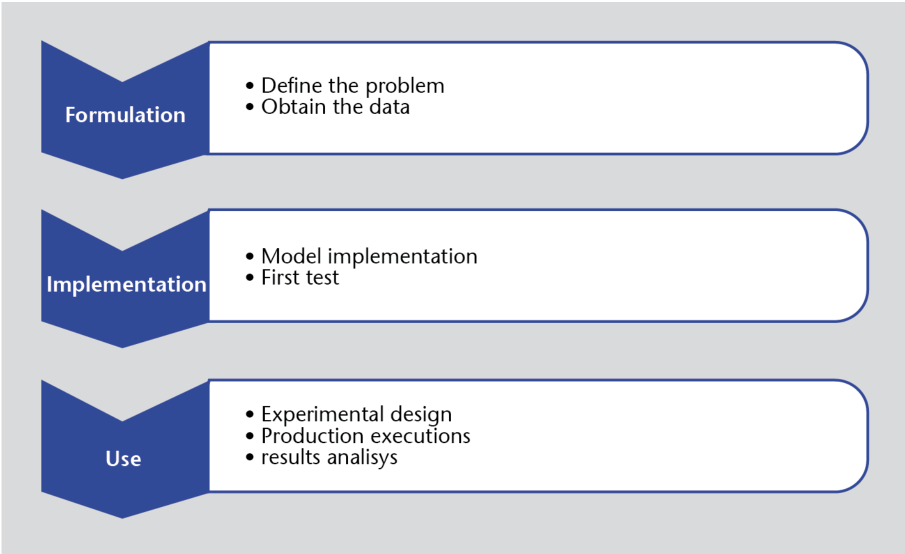

Figure 6. Phases on a simulation study.

Main study material

Read carefully Chapter 4 **"Simulation Studies"** from the Robinson's book. This chapter describes the main concepts that must be taken in consideration when a simulation study must be done. The aim of this chapter is to provide a perspective, an overview of the several main aspects of a simulation study.

Summary of basic concepts

- They are several key stages in a study, like the **conceptual model**, the **computer model**, the **solutions understanding** and the **improvement in the real world**.

- The conceptual modeling consists on (i) develop an **understanding of the problem** situation, (ii) determine the modeling **objectives**, (iii) design the **conceptual model**: inputs, outputs and model content and (iv) collect and analyze the **data** required to develop the model.

- In **model coding**, the conceptual model is converted into a computer model, allowing the **experimentation** that enables the "what-if" analysis.

- The outcome of the **experimentation process** is described as **solutions and/or understanding**. This is because simulation models are not always developed with the aim of obtaining **concrete solutions**. They can also be used to help develop a **better understanding** of the real world.

- Implementation can be thought of in three ways, (i) **implementing the findings** from a simulation study in the real world, (ii) **implementing the model** rather than the findings, the model in this case is developed to help plan weekly production schedules as an example, and (iii) **implementation as learning**, the study has led to an improved understanding of the system.

- A simulation study involves both **repetition and iteration**.

- Validation and verification is **not a single process** but a **continuous one** that is performed throughout model development and use.

- A common **error** in estimating the **duration of a simulation study** is to concentrate solely on the model **coding phase**. As a result, **not enough time** is devoted **to planning** the model and **obtaining and analyzing the data**.

- The typical roles in a simulation project are the **interveners**, the **clients**, the project **team members**, those **interviewed**, and **members of the organization** and society not involved in the project but affected by it.

Articles to read

Musselman, K.J. (1992). ''Conducting a successful simulation project''. In: *Proceedings of the 1992 Winter Simulation Conference* (Swain, J.J., Goldsman, D., Crain, R.C. and Wilson, J.R., eds), Piscataway, NJ: IEEE, pp. 115-121.

Robert G. Sargent, Richard E. Nance, C. Michael Overstreet, Stewart Robinson, and Jayne Talbot (2006). "The simulation project life-cycle: models and realities". In: *Proceedings of the 38th conference on Winter simulation* (WSC '06), L. Felipe Perrone, Barry G. Lawson, Jason Liu, and Frederick P. Wieland (Eds.). Winter Simulation Conference, pp. 863-871.
http://informs-sim.org/wsc06papers/108.pdf

Daniel J. Muller (1996). "Simulation: "What to do with the model afterward"". In: *Proceedings of the 28th conference on Winter simulation* (WSC '96), John M. Charnes, Douglas J. Morrice, Daniel T. Brunner, and James J. Swain (Eds.). IEEE Computer Society, Washington, DC, USA, pp. 729-733. DOI=10.1145/256562.256796 http://dx.doi.org/10.1145/256562.256796

Law, A.M. and McComas, M.G. (2001). ''How to build valid and credible simulation models''. In: *Proceedings of the 2001 Winter Simulation Conference* (Peters, B.A., Smith, J.S., Medeiros, D.J. and Rohrer, M.W., eds). Piscataway, NJ: IEEE., pp. 22-29.

Law, A. (2003). "How to conduct a successful simulation study". In: *Proceedings of the Winter Simulation Conference*, pp. 66-70. http://informs-sim.org/wsc03papers/009.pdf

Activities to learn more

Review Sargent et. Alt (2006) and Musselman (1992), and detect the improvements in the live cycle of a simulation study.

Complementary lectures

From Web:

Averill M. Law & associates: http://www.averill-law.com/

5. Conceptual Modeling

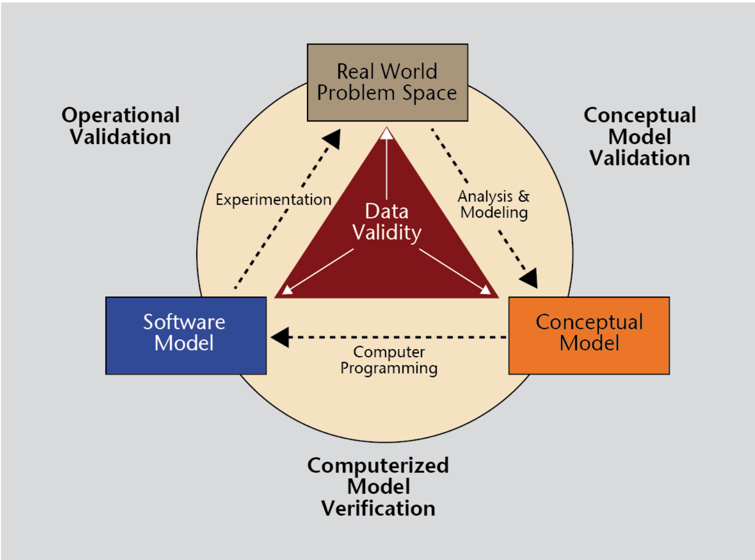

Figure 7. Conceptual model on the definition of a simulation model process

Main study material

Read carefully Chapter 5, **"Conceptual modelling"** from the Robinson's book. Chapter 5 describes the importance of develop a conceptual model while Chapter 6 describes the question of how to design a conceptual model.

Summary of basic concepts

- **The real System** is concerned with the different key elements to be studied. It is the object of the simulation study. It must be defined taking in consideration the objective of the study and the constrains of the project.

- **The experimental frame** represents the limited circumstances under witch the real system has been observed. We cannot obtain a **complete understanding** of the real system.

- **Conceptual Model** is concerned with the representation of the system that is the object of our study. This representation will be as unambiguous as possible in order to simplify the implementation process and the communication between all the actors involved on the project. Is software independent and describes objectives, inputs, outputs, content, assumptions and simplifications of the model.

- The **base model** is capable of accounting for the complete behavior of the real system. This is a very complex model and cannot be fully know, while the **lumped model** is fully know by the modeler.

- The **goals** of the construction of a conceptual model are the simplification of the implementation process and help and improve the communication between the actors involved in the project. This helps in the Validation and Verification process and simplifies the Accreditation.

- The key components of the conceptual model are (i) **objectives**, (ii) **inputs**, (iii) **outputs**, (iv) **content**, (v) **assumptions** and (vi) **simplifications**.

- Assumptions and simplifications are identified as separate facets. **Assumptions** are ways of **incorporating uncertainties** and beliefs about the real world into the model. **Simplifications** are ways of **reducing the complexity** of the model.

- The content of the model is described in terms of two dimensions, (i) the **scope** of the model and (ii) the **level of detail**.

- Conceptual models are becoming more important due to **increasing complexity** of the models and the need of **allow interaction and reuse** of several models and sub models. This allows co-simulation environments, representing in a single simulation environment several simulation models that work together with a common objective.

- Since the modeler still has to make decisions about the content and the **assumptions** of the model, conceptual modeling is a key element, although exists simulation **software that apparently reduced** the needed of a conceptual modeling.

- It is important to **keep the model as simple as possible** to meet the objectives of the simulation study.

Articles to read

Zeigler, B.P. (1976). *Theory of Modelling and Simulation*. Chichester, UK: Wiley.

Robinson, S. (1994). "Simulation projects: building the right conceptual model". In: *Industrial Engineering*, 26(9), pp. 34-36.

Law, A.M. and McComas, M.G. (2001). "How to build valid and credible simulation models". In: *Proceedings of the 2001 Winter Simulation Conference* (Peters, B.A., Smith, J.S., Medeiros, D.J. and Rohrer, M.W., eds). Piscataway, NJ: IEEE, pp. 22-29.

Fonseca, P. (2011). "Simulation hypotheses." In: *International Conference on Advances in System Simulation. Third International Conference on Advances in System Simulation*. Barcelona: 2011, pp. 1-6.
http://upcommons.upc.edu/e-prints/handle/2117/13818

Activities to learn more

From the Robinsons book, try to complete E5.1.

Complementary lectures

From Wikipedia:

Conceptual model: http://en.wikipedia.org/wiki/Conceptual_model

6. Developing the Conceptual Model

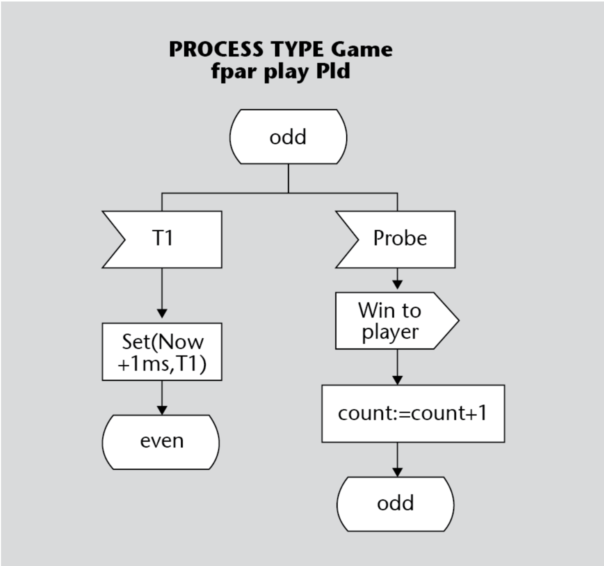

Figure 8. Specification and Description Language process detailing a simulation model behavior

Main study material

Read carefully Chapter 6, **"Developing the Conceptual Model"**, from the Robinson's book. This chapter is related with previous chapter that describes the importance of develop a conceptual model while here is described the question of how to design a conceptual model.

Summary of basic concepts

- To provide the modeler with the understanding of how to develop a conceptual model it is needed to develop a framework. This framework consists in four elements (i) understand the **problem** situation, (ii) determine the modeling **objectives**, (iii) design the **inputs and outputs** and (iv) define the **model content**.

- The **problem** can be **described** sometimes by the **clients**; however the accuracy of this description **may be dubious**. The clients maybe do not have a good understanding of the cause and effect relationship within the problem situation. This problem situation, and its understanding, should not be seen as static.

- In forming the modeling objectives is needed to know (i) what is that the **clients wish to achieve**, (ii) what level of **performance** is required and (iii) what **constraints** must the clients (or modeler) work within? The problem objectives, like the problem are not static. General project objectives, like the time scale of the project must also be carefully taken in consideration.

- **Not** all the **needed data are available** for the simulation model, this makes that some proposed conceptual **models** are **not viable**. It is needed to detect this problem at the beginning of the definition process.

- Throughout the design process the modeler must be cognizant of the four requirements of a conceptual model: **validity**, **credibility**, **utility** and **feasibility**. The aim should also be to develop a model that is **as simple as possible** for the purpose at hand.

- To simplify a model you can (i) **remove components** and interconnections that have little effect on model accuracy or (ii) **represent more simply components** and interconnections while maintain a satisfactory level of model accuracy.

- **Aggregation** of model component reduces the level of detail. Two specific approaches are (i) **black-box modeling** and (ii) **grouping entities**.

- **Excluding components** and details can be used to simplify if the omission of these component in the simulation model have **little or no effect on the accuracy** of the model. Also some components can be replaced with **random variables**.

- **Split a model** can lead to a simplification since the new models are small.

- A simplification is good if (i) have a **small effect** on the model **accuracy**, (ii) do **not compromise** the **credibility** of the model.

Articles to read

Barton, R.; Cheng, R.; Chick, S.; Henderson, S.; Law, A.; Leemis, L.; Schemeiser, B.; Schruben, L. (2002). "Panel on current issues in simulation input modeling". In: *Proceedings of the Winter Simulation Conference*, pp. 353-369.

Biller, B.; Nelson, B. (2002). "Answers to the top ten input modeling questions". In: *Proceedings of the Winter Simulation Conference*, pp. 35-40.

Cowdale (2006). "Lessons identified from data collection for model validation". In: *Proceedings of the Winter Simulation Conference*, pp. 1280-1285.

Law, A.; McComas, M. (1997). "ExpertFit: total support for simulation input modeling". In: *Proceedings of the Winter Simulation Conference*, pp. 668-673.

Leemis (2000). “Input modeling”. In: *Proceedings of the Winter Simulation Conference*, pp. 17-25.

Leemis (2004). “Building credible input models”. In: *Proceedings of the Winter Simulation Conference*, pp. 29-40.

Schmeiser (1999). “Advanced input modeling for simulation experimentation”. In: *Proceedings of the Winter Simulation Conference*, pp. 110-115.

Activities to learn more

From the Robinsons book, try to complete the following exercises related to chapter: E6.1, E6.2, E6.4 and E6.5 or E6.6.

Complementary lectures

From Wikipedia:

- DEVS: http://en.wikipedia.org/wiki/DEVS
- SDL: http://en.wikipedia.org/wiki/Specification_and_Description_Language
- Petri Nets: http://en.wikipedia.org/wiki/Petri_Nets
- SysML: http://en.wikipedia.org/wiki/Sysml

From Internet:

- Petri Nets Worl: http://www.informatik.uni-hamburg.de/TGI/PetriNets/
- SDL tutorial: http://www.sdl-forum.org/SDL/index.htm

7. Data Collection and Analysis

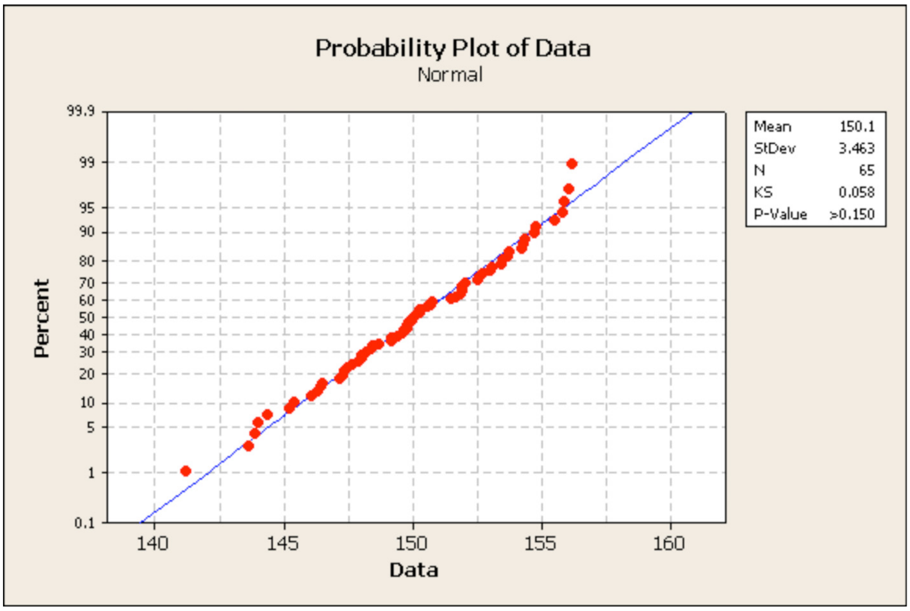

Figure 9. A Q-Q plot for testing normality of data

Main study material

Read carefully Chapter 7, **"Data Collection and Analysis"**, from the Robinson's book. This chapter discusses various issues related to the collection and use of data in simulation studies. It presents four different methods for modeling uncertainty: traces, empirical distributions, statistical distributions, and bootstrapping. The chapter also describes methods for selecting appropriate statistical distributions (input modeling).

Summary of basic concepts

- In real-world simulation applications, coming up with appropriate **distributions** for input data is a major task. Faulty models of the inputs will lead to outputs whose interpretation could give rise to misleading recommendations ("garbage-in-garbage-out").

- There are **four steps** in the development of a useful model of input data: (a) collect data from the real system of interest, (b) identify a probability distribution to represent the input process, (c) choose parameters that determine a specific instance of the distribution family, and (d) evaluate the chosen distribution and the associated parameters for goodness of fit.

- A **trace** is a stream of data that describes a sequence of events. The trace is read by the simulation as it runs and the events are recreated in the model as described by the trace. Traces are normally obtained by collecting data from the real system.

- Uncertainty (variation) in real-world systems is usually modeled by means of **random variables**. Each of these random variables follows a statistical distribution.

- For each random variable in the model, data from the real system must be collected and analyzed. Ideally, this data should be fitted by a theoretical **statistical distribution**. If no theoretical distribution can be chosen to adequately represent the input data, then an empirical distribution should be used instead.

- An **empirical distribution** shows the frequency with which data values, or ranges of data values, occur and are represented by histogram or frequency charts. Empirical distributions can be formed by summarizing the data in a trace. As the simulation runs, values are sampled from empirical distributions by using random numbers.

- **Statistical distributions** are defined by some mathematical function or probability density function. Fitted statistical distributions or probabilistic models of input data are then used in **generating random events** in a simulation experiment.

- Rather than fit a distribution to the data or summarize the data in an empirical distribution, in **bootstrapping** data are simply re-sampled at random with replacement from the original trace. This technique allows extending small-size traces. However, it also has the limitation that data outside the range found in the trace cannot be sampled.

- A random variable X is **discrete** if the number of possible values of X is finite or countably infinite. A **continuous** random variable is one with an uncountably infinite number of possible values.

- A statistical distribution is univocally characterized by its **cumulative distribution function** (CDF), which usually includes a set of **parameters**. Some frequent parameters of statistical distributions are the mean or expected value, the variance and the mode.

- The parameters in an empirical distribution are the observed values in a sample data. An empirical distribution may be used when it is impossible to fit a random variable by some particular parametric distribution.

- Some relevant **discrete distributions** are: the Bernoulli distribution, the binomial distribution, the geometric distribution, the negative binomial distribution and the Poisson distribution.

- Some relevant **continuous distributions** are: the uniform distribution, the exponential distribution, the gamma distribution, the Erlang distribution, the normal distribution, the Weibull distribution, the triangular distribution, the lognormal distribution and the beta distribution.

- Consider a queuing system where arrivals are random and independent events that occur one at a time. For a given time $t \geq 0$, $N(t)$ denotes the number of arrivals by time t. Then, the counting process, $\{N(t), t \geq 0\}$, is said to be a **Poisson process** with mean rate λ.

- The random variable $X = N(t)$ follows a **Poisson distribution** with parameter $\alpha = \lambda t$. Also, the random variable Y = "system inter-arrival times" follows an **exponential distribution** with mean $1/\lambda$.

- The exponential distribution is **memoryless**, meaning that the probability of a future arrival in a time of length s is independent of the time of the last arrival (the probability of the arrival depends only on the length of the time interval, s).

- A frequency distribution or **histogram** is useful in identifying the shape of a distribution. However, a histogram is not as useful as a **Q-Q plot** –which measures the difference between the empirical CDF and the fitted CDF– for evaluating the **fit** of the chosen distribution.

- After a family of distributions has been selected, the next step is to **estimate the parameters** of the distribution. Basically, these estimators are the maximum-likelihood estimators based on the raw data.

- **Goodness-of-fit tests** (e.g.: chi-square, Kolmogorov-Smirnov or Anderson-Darling) provide helpful guidance for evaluating the suitability of a potential input model. Careful must be taken when performing one of these tests: if very little data are available, then a goodness-of-fit test is unlikely to reject any candidate distribution; but if a lot of data are available, then a goodness-of-fit test will likely reject all candidate distributions.

- The **chi-square** goodness-of-fit test formalizes the intuitive idea of comparing the histogram of the data to the shape of the candidate density function. The test is valid for large sample sizes and for both discrete and continuous distributional assumptions when parameters are estimated by maximum likelihood.

- The **Kolmogorov-Smirnov** (KS) test formalizes the idea behind examining a Q-Q plot. It allows testing any continuous distributional assumption for goodness of fit. The KS test is particularly useful when sample sizes are small.

- A test that is similar to the KS is the **Anderson-Darling** (AD) test, which is also based on the difference between the empirical CDF and the fitted CDF.

- Most modern statistical packages implement several goodness-of-fit tests. Usually, these packages provide a **p-value** for the test statistic. This p-value is the significance level at which one would just reject the null hypothesis that the fit is correct.

- Unfortunately, in some situations, a simulation study must be undertaken when there is not possible to obtain data from the system. When this happens, it is particularly important to examine the **sensitivity** of the results to the specific models chosen.

Articles to read

Barton, R.; Cheng, R.; Chick, S.; Henderson, S.; Law, A.; Leemis, L.; Schemeiser, B.; Schruben, L. (2002). "Panel on current issues in simulation input modeling". In: *Proceedings of the Winter Simulation Conference*, pp. 353-369.

Barton, R.; Schruben, L. (2001). "Resampling methods for input modeling". In: *Proceedings of the Winter Simulation Conference*, pp. 372-378.

Biller, B.; Nelson, B. (2002). "Answers to the top ten input modeling questions". In: *Proceedings of the Winter Simulation Conference*, pp. 35-40.

Cowdale (2006). "Lessons identified from data collection for model validation". In: *Proceedings of the Winter Simulation Conference*, pp. 1280-1285.

Kelton, D. (2007). "Representing and generating uncertainty effectively". In: *Proceedings of the Winter Simulation Conference*, pp. 38-42.

Law, A. (1997). "ExpertFit: Total support for simulation input modeling". In: *Proceedings of the Winter Simulation Conference*, pp. 668-673.

Law, A.; McComas, M. (2001). "How the ExpertFit distribution-fitting software can make your simulation models more valid". In: *Proceedings of the Winter Simulation Conference*, pp. 256-261.

Leemis (2000). "Input modeling". In: *Proceedings of the Winter Simulation Conference*, pp. 17-25.

Leemis (2004). "Building credible input models". In: *Proceedings of the Winter Simulation Conference*, pp. 29-40.

Schmeiser (1999). "Advanced input modeling for simulation experimentation". In: *Proceedings of the Winter Simulation Conference*, pp. 110-115.

Tenorio, M.; Nassar, S.; Freitas, P.; Magno, C. (2005). "Recognition of continuous probability models". In: *Proceedings of the Winter Simulation Conference*, pp. 2524-2531.

Vaughan, T. (2008). "In search of the memoryless property". In: *Proceedings of the Winter Simulation Conference*, pp. 2572-2576.

Activities to learn more

Exercises E7.2, E7.3, and E7.4 from the Robinson's book.

Complementary lectures

From Wikipedia:

- Probability distribution: http://en.wikipedia.org/wiki/Probability_distribution
- List of probability distributions: http://en.wikipedia.org/wiki/List_of_probability_distributions
- Goodness-of-fit: http://en.wikipedia.org/wiki/Goodness_of_fit
- Chi-square test: http://en.wikipedia.org/wiki/Pearson's_chi-square_test
- Kolmogorov-Smirnov: http://en.wikipedia.org/wiki/Kolmogorov-Smirnov

From MathWorld:

- Statistical distribution: http://mathworld.wolfram.com/StatisticalDistribution.html
- Chi-square test: http://mathworld.wolfram.com/Chi-SquaredTest.html
- Kolmogorov-Smirnov: http://mathworld.wolfram.com/Kolmogorov-SmirnovTest.html

8. Model Coding

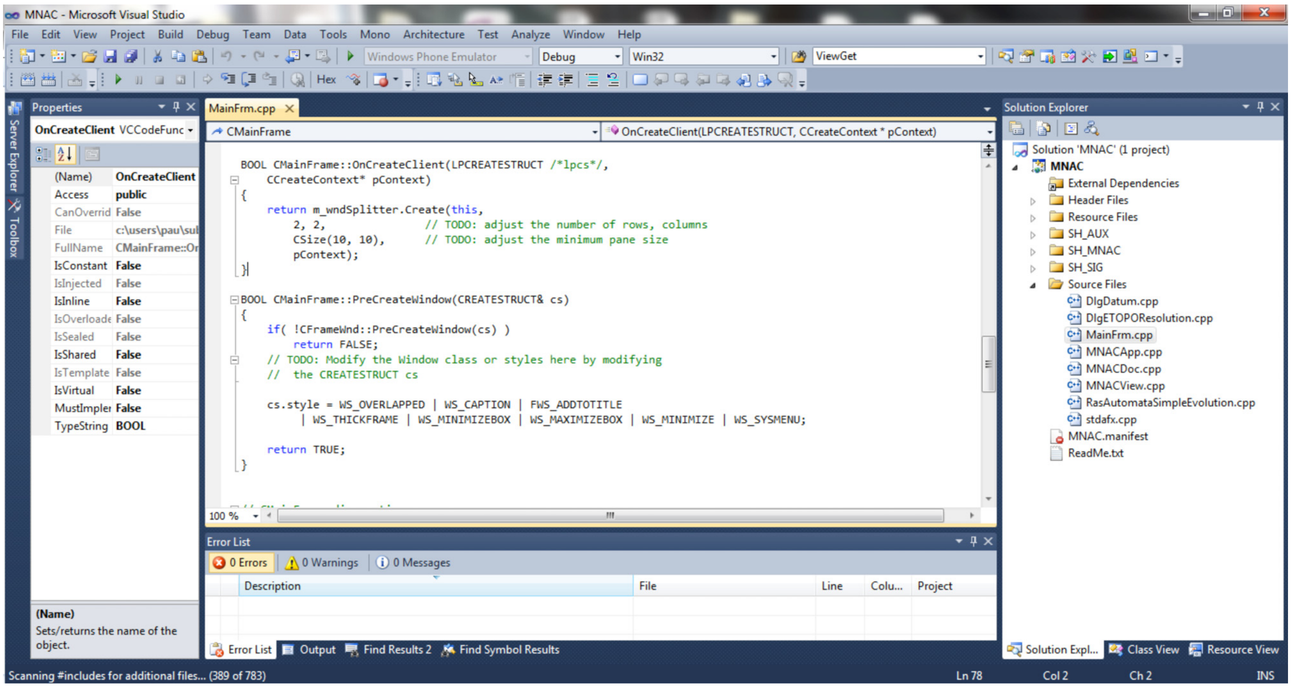

Figure 10. Microsoft Visual Studio® IDE.

Main study material

Read carefully Chapter 8, **"Model Coding"** from the Robinson's book. This chapter describes the process of convert a conceptual model into a computer model. The specific development of the model can be done using several tools, like spreadsheets or common programming languages like C++. This process involves the development of the model structures and the technical documentation.

Summary of basic concepts

- Remember that it is needed to spend some time determining the **structure of the code** in the chosen software. As a conceptual model is a non-software specific description of the simulation model, so the model structure is a software specific description of the model.

- In designing the model structure the modeler must consider (i) **Speed of coding** (the speed with which the code can be written), (ii) **transparency** (the ease with which the code can be understood), (iii) the **flexibility** (the ease with which the code can be changed) and (iv) **run-speed** (the speed with which the code will execute).

- Coding has three main activities (i) **coding**, (ii) **testing** and (iii) **documenting**. Remember to separate the data from the results.

- Documentation must be complete and must be composed by the **conceptual model**, the **models assumptions**, the **model structure**, the **input** and the **experimental framework and factors**, the **results** format, a **glossary** defining meaningful names for components, variables and attributes.

- Remember to **comment** the code, and also note that a **visual display** of the model is always useful.

- The project documentation must include (i) the project **specification**, (ii) the **minutes** of the meetings, (iii) the **validation and the verification** performed, (iv) the **experimental** scenarios run, (v) the **results** of the experiments, (vi) the **final report** and (vii) a **project review**.

- Remember that a good practice is to allow **different levels of documentation** for different audiences.

Articles to read

Oscarsson, J. and UrendaMoris, M. (2002). ''Documentation of discrete event simulation models for manufacturing system life cycle simulation''. In: *Proceedings of the 2002 Winter Simulation Conference* (Yucesan, E., Chen, C.-H., Snowden, S.L., Charnes, J.M., eds). Piscataway, NJ: IEEE, pp.1073-1078.

Richter, H. and März, L. (2000). ''Toward a standard process: the use of UML for designing simulation models''. In: *Proceedings of the 2000 Winter Simulation Conference* (Joines, J.A, Barton, R.R., Kang, K. and Fishwick, P.A., eds). Piscataway, NJ: IEEE, pp. 394-398.

Articles to read

From the Robinson's book, try to complete the following exercises related to chapter 8: E12.1, E8.2 or E8.3.

Complementary lectures

From Wikipedia:

Software engineering: http://en.wikipedia.org/wiki/Software_engineering

9. Obtaining Accurate Results

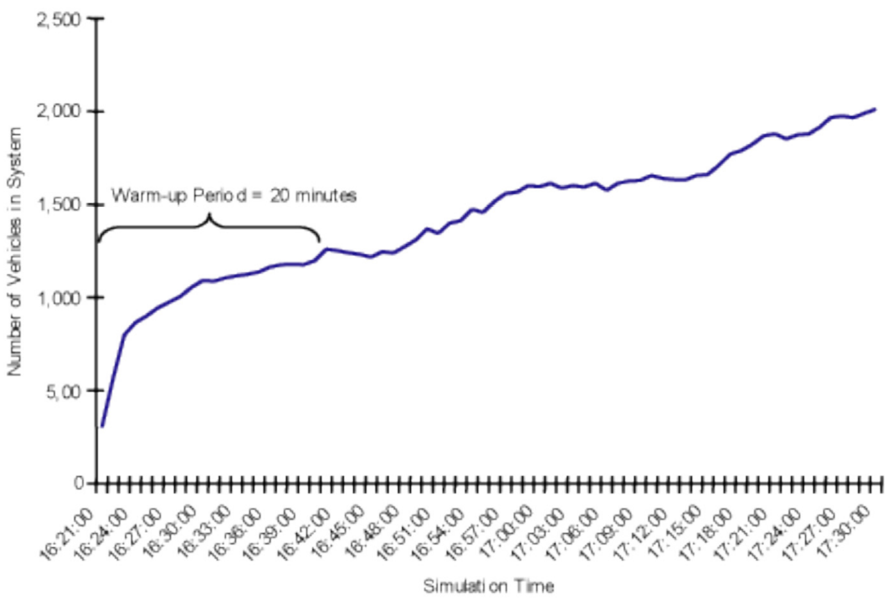

Figure 11. Determining the warm-up period through a time series

Main study material

Read carefully Chapter 9, **"Experimentation: Obtaining Accurate Results"**, from the Robinson's book. This chapter discusses the nature of simulation models and simulation output. The chapter also introduces some methods for obtaining accurate results on model performance. These methods aim at dealing with issues such as initialization bias (i.e. warm-up periods and setting of initial conditions) and obtaining sufficient output data through multiple replications or long runs.

Summary of basic concepts

- **Output analysis** is the examination of data generated by a simulation. Its purpose is either to predict the performance of a system or to compare the performance of two or more alternative system designs.

- A simulation model can be classified as one of two types: terminating and non-terminating. For a **terminating simulation** there is a natural end point that determines the length of a run, e.g. a special system condition, a system lifecycle, or a the completion of a trace of input data. Meanwhile, a non-terminating simulation does not have a natural end point, e.g. a model of a non-stop production facility.

- For non-terminating simulations, the output often reaches a **steady state**, i.e. a state in which the output is varying according to some fixed distribution.

- The period at the start of a simulation run in which the model is not in a steady-state level is known as the initial transient or **warm-up period**. The output data obtained during the initial transient are unrealistic. The inclusion of such data would bias the results obtained from the simulation (initialization bias).

- Usually, the analyst wants to study **steady-state**, or long-run, properties of the system –that is, properties that are not influenced by the initial conditions of the model at time 0. In those situations, **"warm-up" periods** –initial periods in which the system has not reach its steady state already– should be identified and removed from the analysis.

- The main aim of **simulation output analysis** is to obtain an accurate estimate of average performance, although measures of variability are also important. There are two key issues in assuring the accuracy of the estimates obtained from a simulation model: (a) removal of any initialization bias; and (b) ensuring that enough output data have been obtained from the simulation to obtain an accurate estimate of performance.

- There are two ways of handling initialization bias: (a) to run the model for a warm-up period; and (b) to set initial conditions in the model, i.e. to place the model in a realistic condition at the start of the run (e.g. by placing work-in-progress into the model at the run start).

- There are also two ways of ensuring that enough output data have been obtained from the simulation: (a) to perform a single long run with the model; (b) to perform multiple replications (a replication is a run of a simulation model that uses specified streams of random numbers). By performing multiple replications and taking the mean of the results, a better estimate of model performance is gained.

- In order to identify initialization bias and to determine the warm-up period, several methods can be employed, among others: (a) performing a time-series of the simulation output; and (b) the **Welch's method**, also based on time-series (in particular, in the concept of plotting moving averages to smooth out the noise in the time-series data).

- The need of **statistical output analysis** is based on the observation that the output data from a simulation exhibits random variability when random number generators are used to produce the values of the input variables. Therefore, if the performance of the system is measured by a

parameter θ, the result of a set of simulation replications will be an estimator $\hat{\theta}$ of θ. The precision of the estimator can be measured by its standard error or by a confidence interval for the parameter.

- For each parameter of interest, an unbiased **point estimator** should be provided together with its corresponding standard error or, alternatively, by a **confidence interval** for the parameter based on the point estimator.

- **Confidence intervals** provide an efficient way of determining the accuracy of the estimate obtained for the model average performance. When applying confidence intervals to simulation output, more replications (samples) are performed until the interval becomes sufficiently narrow to satisfy the model user.

- It is always possible to reduce the **width of a confidence interval** by increasing the sample size, i.e., the number of replications in the simulation experiment. However, in order to divide by 2 the width of a confidence interval, it is necessary to multiply by 4 the current number of replications.

- Several **variance-reduction techniques** can be employed to reduce the number of replications that are necessary to reach a certain value for the estimation accuracy.

- One of the aims of **variance reduction techniques** is to obtain an accurate estimate of model performance while reducing the number of replications required. The two most popular variation reduction techniques are common random numbers and antithetic variates.

- The **common random numbers** (CRN) technique applies when comparing two or more alternative configurations of a system. CRN requires synchronization of the random number streams, which ensures that in addition to using the same random numbers to simulate all configurations, a specific random number used for a specific purpose in one configuration is used for exactly the same purpose in all other configurations.

- **Antithetic variates** are the inverse of the random numbers normally generated by a pseudo random number stream. A pseudo-random number stream {u1, u2, ...} is inverted to become the stream {1-u1, 1-u2, ...}. The idea is that the mean result from the two replications (original and antithetic) gives a better estimate of model performance than from two completely independent replications. This is specially the case when the sampling distribution is symmetrical.

- The advantage of performing multiple replications is that confidence intervals can easily be calculated, and they are an important measure of accuracy for simulation results. The disadvantage is that if there is a warm-up period, it needs to be run for every replication that is performed.

Articles to read

Alexopoulos, C. (2006). "A comprehensive review of methods for simulation output analysis". In: *Proceedings of the Winter Simulation Conference*, pp. 168-178.

Centeno, M.; Reyes, M. (1998). "So you have your model: what to do next". In: *Proceedings of the Winter Simulation Conference*, pp. 23-29.

Kelton, D. (1997). "Statistical analysis of simulation output". In: *Proceedings of the Winter Simulation Conference*, pp. 23-30.

Kelton, D. (2000). "Experimental design for simulation". In: *Proceedings of the Winter Simulation Conference*, pp. 32-38.

Law, A. (2007). "Statistical analysis of simulation output data: the practical state of the art". In: *Proceedings of the Winter Simulation Conference*, pp. 77-83.

Lecuyer, P. (2006). "Variance reduction in the simulation of call centers". In: *Proceedings of the Winter Simulation Conference*, pp. 604-613.

Nakayama, M. (2006). "Output analysis for simulation". In: *Proceedings of the Winter Simulation Conference*, pp. 36-46.

Activities to learn more

Exercises E9.1, E9.2, E9.4, E9.5 and E7.12 from the Robinson's book.

Complementary lectures

From Wikipedia:

- Standard error: http://en.wikipedia.org/wiki/Standard_error_(statistics)
- Confidence interval: http://en.wikipedia.org/wiki/Confidence_interval
- Variance reduction: http://en.wikipedia.org/wiki/Variance_reduction

From MathWorld:

Confidence interval: http://mathworld.wolfram.com/ConfidenceInterval.html

10. Searching the Solution Space

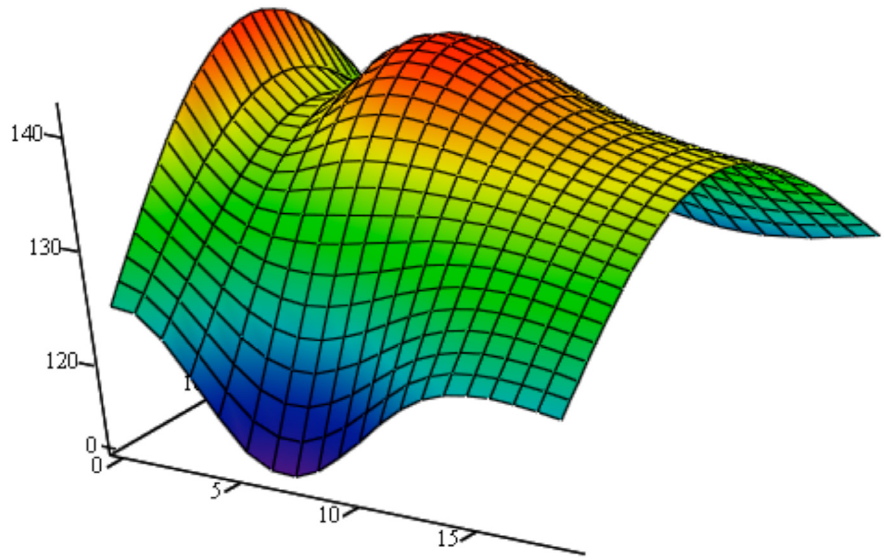

Figure 12. A response surface for optimal design

Main study material

Read carefully Chapter 10, **"Experimentation: Searching the Solution Space"**, from the Robinson's book. This chapter introduces the comparative evaluation of alternative system designs or scenarios based on data collected from simulation runs.

Summary of basic concepts

- One of the most important uses of simulation is the **comparison of alternative system designs**. Because the observations of the response variables contain random variation, statistical analysis is needed to discover whether any observed differences are due to differences design or merely to the random fluctuation inherent in the models.

- A practical strategy to compare two system designs is to compute point and **interval estimates** of the difference in mean performance of a specific system parameter. **Significant differences** between both designs will exist whenever the resulting confidence interval will not contain the zero value.

- It can be sometimes desirable to **reduce the variance** of the estimated difference of the performance measures and thus provide, for a given sample size, more precise estimates of the mean difference that the ones obtained through independent sampling. This variance reduction can be attained by using the **common random numbers** (CRN) technique.

- The basic idea behind the CRN technique is to **assign the same source of randomness** to each random variable in both systems. Each random number used in one model for some purpose should be used for the same purpose in the second model –e.g. by dedicating one random-number stream to a specific purpose. Notice that this implies the necessity of synchronizing the use of random numbers throughout the simulation experiment, which is not a trivial task.

- Comparison of several system designs is also possible by using the Bonferroni approach, **Analysis of Variance** (ANOVA) techniques or even regression analysis.

- In the so called **"optimization through simulation"**, the goal is to optimize (minimize or maximize) some measures of system performance when system performance is evaluated by running a computer simulation. When the inputs that define the behavior of a system or process are not deterministic but stochastic (i.e. they are random variables), the output value representing the system performance, Y, will depend upon the specific values of the inputs and, therefore, it cannot be optimized. In those cases, however, the goal will be to optimize the **expected value**, $E[Y]$, or long-run average of that performance parameter.

- Many **heuristics** and **random-search algorithms** have been developed for deterministic optimization problems. Most of these heuristics use randomness as part of their strategy, e.g.: genetic algorithms (GA), tabu search (TS), simulated annealing (SA), GRASP, ant colony optimization (ACO), etc. These algorithms do not guarantee finding the optimal solution, but they have shown to be very effective on difficult, practical problems, e.g.: vehicle routing problems, scheduling problems, etc.

- There are many additional topics of potential interest in the realm of statistical analysis techniques relevant to simulation. **Experimental design models** –whose purpose is to discover which factors have a significant impact on the performance of system alternatives–, or **variance reduction techniques** –which are methods to improve the statistical efficiency of simulation experiments– are just two of these topics.

Articles to read

Baesler, F.; Araya, E.; Ramis, F.; Sepulveda, J. (2004). "The use of simulation and design of experiments for productivity improvement in the Sawmill industry". In: *Proceedings of the Winter Simulation Conference*, pp. 1218-1221.

Barra, J.; Ferreira, A.; Leal, F.; Silva, F. (2007). “Application of design of experiments on the simulation of a process in an automotive industry”. In: *Proceedings of the Winter Simulation Conference*, pp. 1601-1609.

Carson, Y.; Maria, A. (1997). “Simulation optimization: methods and applications”. In: *Proceedings of the Winter Simulation Conference*, pp. 118-126.

Faulin, J.; Gilibert, M.; Juan, A.; Ruiz, R.; Vilajosana, X. (2008). “SR-1: A simulation-based algorithm for the capacitated vehicle routing problem”. In: *Proceedings of the Winter Simulation Conference*, pp. 2708-2716.

Juan, A.; Faulin, J.; Marques, J.; Sorroche, M. (2007). “J-SAEDES: A java-based simulation software to improve reliability and availability of computer systems and networks”. In: *Proceedings of the Winter Simulation Conference*, pp. 2285-2292.

Kleijnen, J. (2008). “Design of experiments: overview”. In: *Proceedings of the Winter Simulation Conference*, pp. 479-488.

Moore, L.; Ray, B. (1999). “Statistical methods for sensitivity and performance analysis in computer experiments”. In: *Proceedings of the Winter Simulation Conference*, pp. 486-491.

Olafsson, S.; Kim, J. (2002). “Simulation optimization”. In: *Proceedings of the Winter Simulation Conference*, pp. 79-84.

Activities to learn more

Exercises E10.3 and E10.10 from the Robinson’s book.

Complementary lectures

From Wikipedia:

- Design of experiments: http://en.wikipedia.org/wiki/Design_of_experiments
- Search algorithm: http://en.wikipedia.org/wiki/Search_algorithm

From MathWorld:

ANOVA: http://mathworld.wolfram.com/ANOVA.html

11. Implementation

Figure 13. Implementing the solutions in the industry. Source Wikipedia.

Main study material

Read carefully Chapter 11, **"Implementation"** from the Robinson's book. This chapter describes the process of implement, implementing the findings from the simulation study, implementing the model or the implementation as a learning process. As we can understand in this book, this is an iterative process, and the tree meanings of "implementation" in the simulation world can be done in a single simulation project.

Summary of basic concepts

- **Implementation** is concerned with putting something into effect. Basically it represents the modification of the organization according to the findings of the simulation model.
- Implementation can be **implementing the findings** from the simulation study, **implementing the model** in a computer using a programming

language or a specific simulation tool. This representation is unambiguous and represents, as closer as possible, the conceptual model. It is a part of the iterative process of build a simulation model. Also implementation can be performed **to learn**.

- The **final report** should describe the problem situation and more important, the objectives of the project (remember that a model can be valid for one purpose and invalid for other). It should provide a summary of the model, describe the experiments performed, outline the key results, list the conclusions and recommendations and make suggestions for further simulation work if it is required.

- If the clients wants to perform their **own experiments** with the model or they want to share the experimentation with the modeler, or if the simulation model is used recurring to make decisions we are talking about **implementing the model**. The model might be handed over to the clients for their own use, in which case the clients become the modeler users.

- Model implementation requires adequate **user documentation** and **training**.

- The whole process of developing and using the simulation model increases the user and clients understanding of the system, not just from the results of the simulation experiments, but from its implementation. This learning is often much wider than the direct focus of the simulation study. It is for this reason that the outcome of a simulation study is described not just as solutions to the problem being tackled, but alsoas an improved understanding.

Articles to read

Banks, J. Chwif, L (2010). "Estimating the implementation time for Discrete-Event Simulation model building". In: *Proceedings of the Winter Simulation Conference*, pp. 1774-1785. http://informs-sim.org/wsc10papers/165.pdf

Ozturk, O (2003). "Conceptualization, Design and implementation of a static capacity model". In: *Proceedings of the Winter Simulation Conference*, pp. 1774-1785. http://informs-sim.org/wsc03papers/172.pdf

Sargent, R. (2007). "Verification and validation of simulation models". In: *Proceedings of the Winter Simulation Conference*, pp. 124-137.

Robinson, S. (1998). ''Measuring service quality in the process of delivering a simulation study: the customer's perspective''. In: *International Transactions in Operational Research*, 5(5), 357-374.

Law, A.M. (2009). ''How to build valid and credible simulation models''. In: *Proceedings of the Winter Simulation Conference*.
http://informs-sim.org/wsc09papers/003.pdf

Articles to read

Review carefully Law 2009 and Sargent 2007. Try to outline the more important messages related to the good practices in order to achieve a successfully result in a simulation study.

Activities to learn more

From MSCO:

- Main page: http://www.msco.mil/
- How to provide transparency: http://www.msco.mil/surfboard.html

12. Verification & Validation

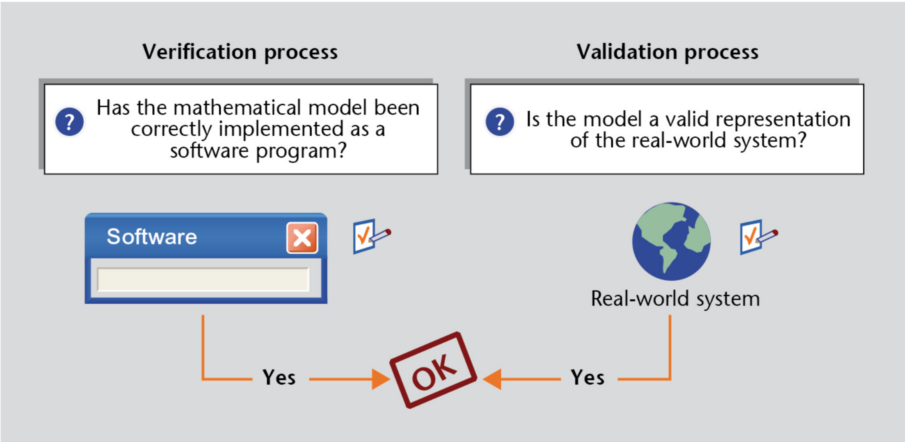

Figure 14. Key questions of the verification and validation processes

Main study material

Read carefully Chapter 12, **"Verification, Validation and Confidence"**, from Robinson's book. This chapter describes methods that have been recommended and used in the verification and validation processes, which constitute two fundamental elements to keep always present in any simulation project.

Summary of basic concepts

- **Verification** is concerned with building the model correctly. It proceeds by comparison of the conceptual or mathematical model to the computer representation that implements that conception. It asks the questions: Is the mathematical model implemented correctly in the simulation software? Are the input parameters and logical structure of the model represented correctly?

- **Validation** is concerned with building the correct model. It attempts to confirm that a model is an accurate representation of the real system. Validation is usually achieved through the calibration of the model, an iterative process of comparing the model to actual system behavior and using the discrepancies between the two, and the insights gained, to improve the model.

- The goal of the validation process is to increase, to an acceptable level, the **credibility** of the model. The credibility of the model is related to the model purpose. A model can be valid for a specific purpose and invalid for another. Increase the credibility on the model by the managers and other decision maker is crucial, since the model must be used to take decisions.

- Verification and validation of simulation models are of great importance. Decisions are made on the basis of simulation results; thus, the **accuracy** of these results should be subject to question and investigation.

Articles to read

Balci, O. (1997). “Verification, validation and accreditation of simulation models”. In: *Proceedings of the Winter Simulation Conference*, pp. 135-141.

Carson, J. (2002). “Model verification and validation”. In: *Proceedings of the Winter Simulation Conference*, pp. 52-58.

Caughlin, S. (2000). “An integrated approach to verification, validation, and accreditation of models and simulations”. In: *Proceedings of the Winter Simulation Conference*, pp. 872-881.

Metz, M.; Jordan, J. (2001). “Verification of object-oriented simulation designs”. In: *Proceedings of the Winter Simulation Conference*, pp. 600-603.

Rabe, M.; Spieckermann, S.; Wenzel, S. (2008). “A new procedure model for verification and validation in production and logistics simulation”. In: *Proceedings of the Winter Simulation Conference*, pp. 1717-1726.

Robinson, S. (1997). “Simulation model verification and validation: increasing the users’ confidence”. In: *Proceedings of the Winter Simulation Conference*, pp. 53-59.

Sargent, R. (2007). “Verification and validation of simulation models”. In: *Proceedings of the Winter Simulation Conference*, pp. 124-137.

Activities to learn more

From the Robinson’s book, try to complete the following exercises related to chapter 12: E12.1, E12.2, E12.5 and E12.6.

Complementary lectures

From the web:

http://www.defence.gov.au/capability/adso/docs/pt_8-vvag_v1-0.pdf

From Wikipedia:

Verification and validation:
http://en.wikipedia.org/wiki/Verification_and_Validation_(software)

13. The practice of simulation

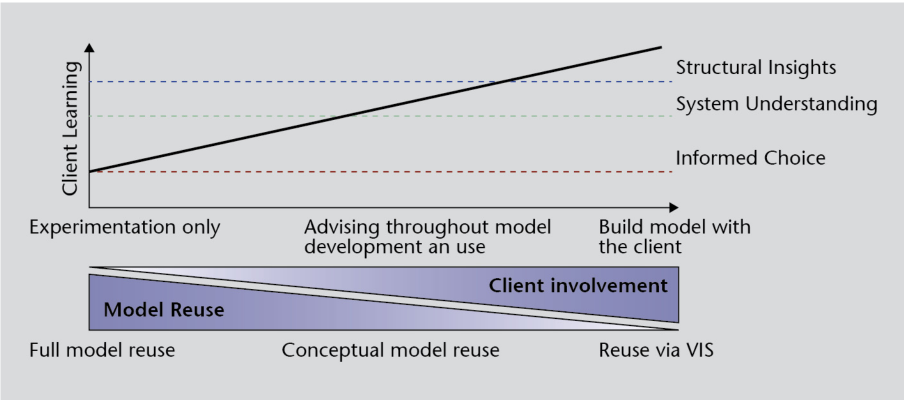

Figure 15. Learning outcomes linked to a spectrum of reuse and involvement (Monks, T. et alt 2009) .

Main study material

Read carefully Chapter 13, **"The practice of simulation"**, from Robinson's book. This chapter describes different types of simulation practices. This is useful for giving a modeler some guidelines for adopting the appropriate simulation practice on a real project.

Summary of basic concepts

- Five types of simulation model are identified here: (i) **throwaway**, (ii) **ongoing use**, (iii) **regular use**, (iv) **generic**, and (v) **reusable**.

- A **throwaway model** is used for the duration of a simulation study and then **never used again**. Such models are developed to investigate one or more issues of concern to the clients.

- An **ongoing use model** is defined when the wider project within which the model is being used requires continued use of the model to **answer a variety of questions** and to determine the effect of changes to the real system. The **model evolves** as time progresses.

- A **regular use model** is developed for **operational use**, which is, aiding decision-making on a regular basis (e.g. scheduling decisions).

- A **reusable model** implies that it could be used in another context and/or for another purpose to that for which it was originally intended.

- A **generic model** is a simulation of a particular context that **can be used across a number of organizations**. For instance, a generic model could be developed to represent a conveyor area at an airport. Generic models are a special case of reusable models/components.

Articles to read

Taylor, S.J.E. and Paul, R.J. (2002). ''What use is model reuse: is there a crook at the end of the rainbow?''. In: *Proceedings of the 2002 Winter Simulation Conference* (Yucesan, E., Chen, C.-H., Snowden, S.L. and Charnes, J.M., eds). Piscataway, NJ: IEEE, pp. 648-652.

Drake, G.R. and Smith, J.S. (1996). ''Simulation system for real-time planning, scheduling, and control''. In: *Proceedings of the 1996 Winter Simulation Conference* (Charnes, J.M., Morrice, D.J., Brunner, D.T. and Swain, J.J., eds). Piscataway, NJ: IEEE, pp. 1083-1090.

Pidd, M. (2002). ''Simulation software and model reuse: a polemic''. In: *Proceedings of the 2002 Winter Simulation Conference* (Yucesan, E., Chen, C.-H., Snowden, S.L. and Charnes, J.M., eds). Piscataway, NJ: IEEE, pp. 772-775.

Osman Balci, James D. Arthur, and Richard E. Nance (2008). "Accomplishing reuse with a simulation conceptual model". In: *Proceedings of the 40th Conference on Winter Simulation* (WSC '08), Scott Mason, Ray Hill, Lars Mönch, and Oliver Rose (Eds.). Winter Simulation Conference, pp. 959-965.
http://informs-sim.org/wsc08papers/115.pdf

Thomas Monks, Stewart Robinson, and Kathy Kotiadis (2009). "Model reuse versus model development: effects on credibility and learning". In: *Winter Simulation Conference* (WSC '09). Winter Simulation Conference, pp. 767-778.
http://informs-sim.org/wsc09papers/074.pdf

Activities to learn more

Read the complementary lecture provided and review the software engineering practices applied on the MSCO that try to assure a good result in a simulation project.

Complementary lectures

From MSCO:

Best practices: http://goo.gl/bKEf7

Appendix: Books and Links

14. Books

Banks, J.; Carson, J.; Nelson, B.; Nicol, D. (2009). *Discrete-Event System Simulation Prentice Hall*. ISBN: 0136062121. (This course is based on this book and it constitute an excellent reference for all students and simulation practitioners.)

Faulin, J.; Juan, A.; Martorell, S.; Ramirez-Marquez, E. (eds.) (2010). *Simulation Methods for Reliability and Availability of Complex Systems* (Springer Series in Reliability Engineering). ISBN: 978-1-84882-212-2. (This book has been co-edited by one of the course's instructors and it shows state-of-the-art applications of simulation techniques to reliability and availability issues.)

Law, A. (2006). *Simulation Modeling and Analysis*. McGraw-Hill Publishing Co. ISBN: 0071255192. (An outstanding reference for simulation students and researchers.)

McHaney, R. (2009). *Understanding Computer Simulation*. Ventus Publishing ApS. ISBN: 978-87-7681-505-9. (Free book available at www.bookboon.com.)

15. Links

- http://dpcs.uoc.edu
  Website of the DPCS research group (the Academics section contains examples of our CMS-related research lines).

- http://www.wintersim.org/
  Website of the Winter Simulation Conference (WSC).

- http://informs-sim.org/
  Website of the Informs Simulation Society (contains papers published at the WSC).

- http://mathworld.wolfram.com/
  Website containing mathematical resources.

- http://cv.uoc.edu/webapps/calculadora/es/index.html
  Wiris mathematical software at the UOC Virtual Campus

- http://www.itl.nist.gov/div898/handbook/index.htm
  Online handbook of Engineering Statistics