A Methodology of Discrete-Event Simulation of Manufacturing Systems: An Overview

Peter P. Groumpos*, **Yuri Merkuryev****

* Laboratory for Automation & Robotics

University of Patras, GR-265 00 Rion, Greece

groumpos@ee.upatras.gr

** Department of Modelling and Simulation

Riga Technical University, LV-1658 Riga, Latvia

merkur@itl.rtu.lv

Abstract: The paper considers a general structure of discrete-event simulation of manufacturing systems. It starts by specifying the approach of discrete-event, computer-based simulation, and then proceeds to discuss a structure and main steps of a simulation study, with a more detailed discussion of simulation-based optimisation of manufacturing systems. Finally, examples of successfully conducted simulation studies are given.

Keywords: Simulation methodology, discrete-event simulation, simulation-based optimisation, manufacturing systems

1. Introduction

Modern manufacturing systems are complicated, highly automated, computer controlled integrated systems. They ask for essential investments at all stages of their life-cycle, from designing through operation to re-engineering and modernisation (Groumpos and Krauth, 1997). This combination of complexity and necessity for large investments cause existence of such potential decisions that could essentially increase efficiency of manufacturing systems. Traditionally, these decision are defined with extended use of discrete-event simulation. Generally speaking, manufacturing systems are considered to present one of the areas where discrete-event simulation is the most widely used (Pierreval and Caux, 1996). For instance, one could specify the following application areas of simulation in manufacturing:

- as a design and analysis aid for factory layouts, equipment decisions, operating policies;
- as a scheduling tool for production processes;
- as a part of a real-time, on-line control system (e.g., generating a new schedule when a piece of equipment has broken down).

On the other hand, success of a simulation study is highly dependent on correct use of a corresponding methodology. For instance, following are some potential reasons for getting unsatisfactory results from a simulation study (Gogg and Mott, 1992):

- insufficient training of simulation team members;
- simulation objectives are not clearly defined;
- trying to build too much details into a model;
- making conclusions from a single simulation run rather than from multiple runs;
- making conclusions from animation rather than from statistical reports;
- lack of interaction between model builder, management and operational personnel.

The present paper discusses a general structure of a discrete-event simulation study of manufacturing systems. After a brief description of main steps of a simulation study, it considers in more details a situation when simulation is aimed to optimise performance of a simulated system.

2. Simulation approach

Prior to speaking about a simulation study, let us define the simulation itself. As for many concepts of a general nature, there are different definitions of simulation. We shall refer to (Pegden et.al., 1995) that defines it "as the process of designing a model of a real system and conducting experiments with this model for the purpose of understanding the behaviour of the system and/or evaluating various strategies for the operation of the system." For the aims of this paper we shall narrow this general definition by making the following remarks:

- simulated system (i.e., the original one) could be either a real or not (yet) existing system. The latter is valid, for instance, when simulating a designed system, aiming to find the best design that will be later implemented in reality;

- simulation usually takes into account random factors that influence operation of the original system (one exception from this rule is valid when a sequence of deterministic simulation models is developed for the aims of industrial training (Villegas, 1996));
- simulation is usually computer-based, e.g., is performed using a computer;
- simulation considers the simulated system in dynamics, taking into account its evolution through time (in contrast to Monte Carlo, or static, simulation, where time is not considered (Banks et.al., 2001));
- aim of a simulation study is, generally speaking, to improve operation of the system under consideration;
- we are considering one specific kind of simulation, namely, discrete-event simulation, that deals with discrete-event systems which change their state instantaneously, at discrete time moments (e.g., queuing systems). Thus, under term "simulation" we shall actually mean "discrete-event simulation".

An idea of the simulation approach may be generally defined in the following way:

- describe how the modelled system operates, i.e., specify its operation algorithm;
- develop a computer programme that realises this algorithm, i.e., develop a simulation model;
- experiment with the developed computer programme, as you would like to experiment with a real system (if it would be possible), i.e., simulate;
- analyse and interpret results of simulation experiments, make related decisions and implement them.

3. Structure of a simulation study

Traditionally, it is considered that a simulation study incorporates the following main steps (Banks et.al., 2001):

- problem formulation,
- setting the objectives and overall project plan,
- model conceptualisation,
- data collection,
- model translation,
- verification, validation,
- experimental design,
- production runs and analysis,
- documentation and reporting,
- implementation.

Of course, these steps are not isolated from each other, but are connected in a consistent way, reflecting logic of a simulation project. Moreover, this general set of steps could be further developed by including additional ones and inter-connections, thus reflecting experiences of particular authors in performing simulation research.

Based on our experiences in performing simulation studies, we developed our vision of a typical simulation study, that is presented in Figure 1 in the form of a flow chart. This general structure is realised in each particular study in a specific way, depending on simulation aims, available resources and nature of a simulated system. For instance, when simulating manufacturing systems in a design mode, general simulation goals (e.g., such as better understanding of behaviour of the simulated system, analysis of its operation in different situations (so-called "what-if analysis"), analysis and removal of bottlenecks, parameter optimisation, comparing alternative decisions, evaluating different control algorithms, personal training) are typically realised in the form of following questions:

- What will be the throughput of a particular design ?
- Where are the bottlenecks ? How can we remove them ?
- How does the system performance change in a function of number and type of machines, number of workers, in-process storage and transportation, etc. ?
- How will breakdowns affect the throughput ?

Another example of customising the general simulation scheme comes to consideration when simulation is aimed to optimise parameters of the simulated system, aiming to improve value of the chosen performance function (i.e., the optimisation criterion). In that case, steps 15 – 17 could be interpreted in the following way:

- Continue optimisation with another criterion ?
- Specifying optimisation criterion.
- Correct optimisation algorithm ?

4. Main steps of a simulation study

Following is a brief description of the main steps of a simulation study, presented in Figure 1.

1. *Problem formulation.* A problem to be solved should be identified.
2. *Training project participants.* All persons, involved into performing the project, might be aware of the used methodology and steps to implement it. Project participants without preliminary knowledge about simulation studies (e.g., those from the customer's side) should be informed about the main aspects of performing the study. Everybody should understand his role in the whole team-work, and realise what other people are doing as well.
3. *Setting objectives and overall project plan.* Objectives of the study should be specified at this stage, with the aim to solve the above-formulated problem. The overall plan for reaching these objectives includes identifying involved people (including those from the customer's side), resources available, used methodology, parameters to be varied and alternatives to be tested, calendar planning, etc.
4. *Model conceptualisation* means specifying operation algorithm of the simulated system: abstraction of its essential features (referring to a Pareto law, stating that each system has an essential minority, that mainly determines its behaviour, and a trivial majority; exactly that essential minority should be identified and included into the model) and development of its conceptual model (distinguishing the simulated system from its environment, deciding about the level of details, identifying main elements and relations, specifying parameters and variables).
5. *Data preparing* should be organised very carefully. A well known simulation principle is "Garbage In – Garbage Out", that means that even a well developed model could not produce close-to-reality results, if its input data differ from what is present in reality. Statistical considerations should be taken into account, when describing random factors, e.g., random variables.
6. *Checking model concepts and macro data.* Here the simulation team comes together in order to discuss decisions made about the conceptual model and descriptions of input data. For instance, types of probability distributions, used to describe random input variables, have to be discussed.
7. *Model translation* means implementing the conceptual model in the form of a corresponding software programme. The resulted programme is actually what is called "a simulation model". A choice between using general software tools and special simulation tools (e.g., simulation languages (like GPSS/H (Schriber, 1991)) or systems (like Arena (Kelton et.al., 2002))) should be made at this stage.
8. *Verification* means checking if the developed programme indeed realises the operational algorithm of the simulated system. At this stage the model developing team actually asks itself: "Does the developed model operate as we think the original system does ?"
9. *Testing model with macro data.* Here sensitivity of simulation results is checked towards changes of parameters of probability distributions of model random input variables. If some of the parameters seem to be critical from that point of view, it should be checked if there values were evaluated enough precisely. Otherwise, additional efforts should be spent for specifying values of these parameters with a higher confidence.
10. *Validation* is the second stage (after verification) where the developed model is checked for adequate presenting of the modelled system. In this case operation of the model is compared with that of the modelled system. A question that should be answered at this stage actually is: "Does the developed model operate as the original system does ?" A positive answer to that question would mean that simulation results indeed reflect operation of the modelled system in a corresponding situation.
11. *Strategic planning of simulation experiments* means planning experiments with the simulation model: choosing values of model parameters to be investigated or tuned, deciding about alternatives to be compared by simulation, etc. It is performed in the same way, as it would be done, planning experiments with a real system (e.g., using a full factorial design or fractional factorial design).

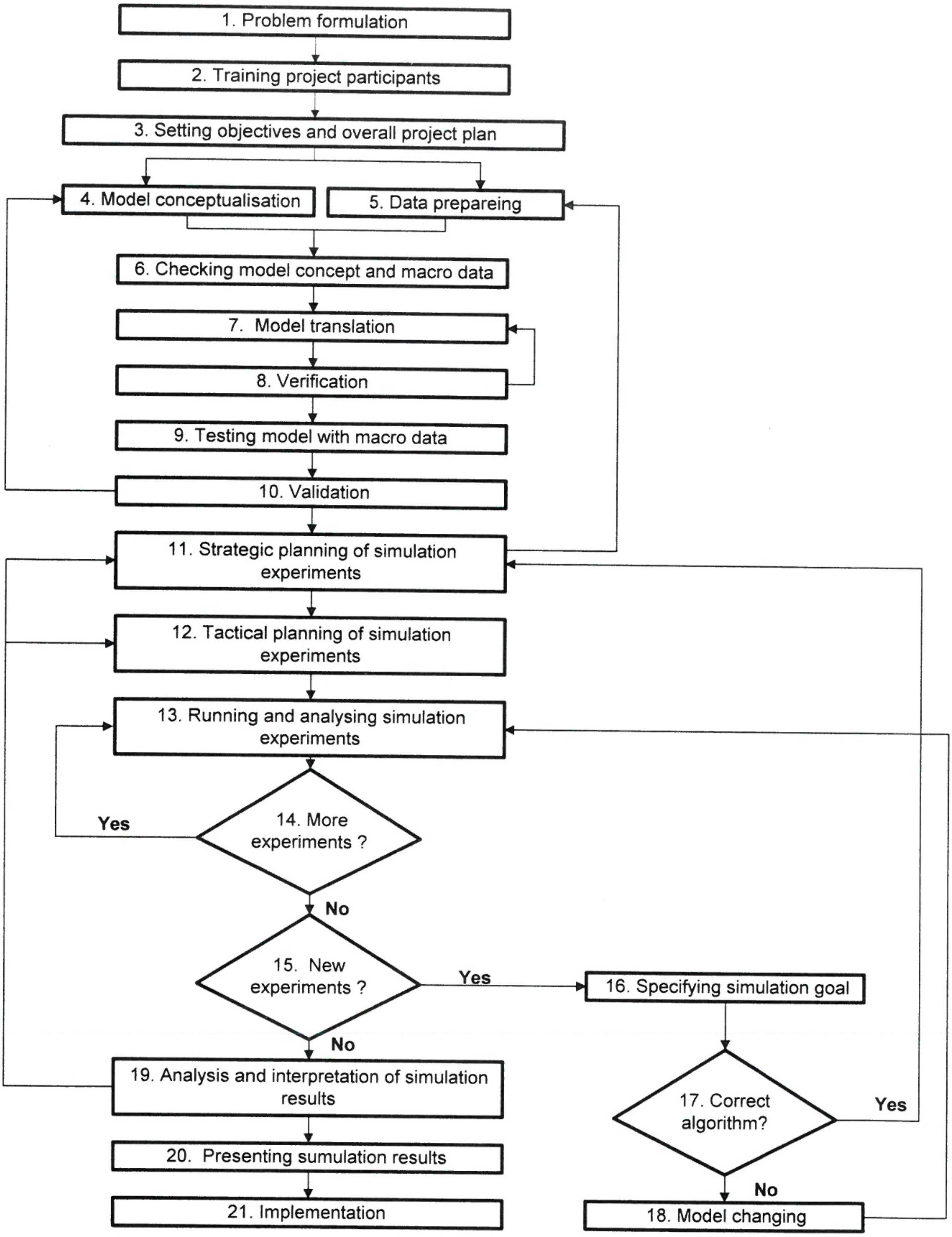

Figure 1: Flow chart of a simulation study

13. *Tactical planning of simulation experiments* reflects specifics of simulation studies. Here realisation of each experiment, designed at the previous stage, is planned. Typical questions to be answered at this stage are the following: How many simulation runs should be performed for each experiment ? Which kind of model behaviour should be evaluated: transient or steady-state ? In the last case, how shall we deal with the warm-up period ? Do we need to take into account correlation in simulation results ?

14. *Running and analysing simulation experiments.* Simulation experiments are performed at this stage in accordance with the above-developed (at stages 11 and 12) plans, and there results are accordingly processed.

15. *More experiments ?* If necessary, additional experiments are performed (e.g., if it is necessary to achieve a higher preciseness of simulation results: to get narrower confidence intervals for evaluated values, etc.)

16. *New experiments ?* This stage, together with stages 16 (*Specifying simulation goal*), 17 (*Correct algorithm ?*) and 18 (*Model changing*) allow turning, if necessary, to another simulation goal. Such necessity could appear if during the simulation study some new aspects come to consideration, that ask for analysing another aspects of modelled system behaviour. In such situation a new strategic plan of simulation experiments could be developed, if necessary; otherwise, the simulation model will be changed (at stage 18) in accordance with the previously developed strategic plan.

19. *Analysis and interpretation of simulation results.* Simulation results are analysed and interpreted at this stage, that is a basis for making corresponding decisions (e.g., deciding about the best values of parameters of the modelled system, or choosing the best control algorithm).

20. *Presenting simulation results* to a customer of the simulation study.

21. *Implementation* of results of the simulation study.

5. Simulation-based optimisation

Let us discuss in more details a strategic planning of simulation experiments in a situation, when simulation is used for optimisation of a considered system. In this case simulation is aimed to optimise certain parameters of a simulated system, in order to improve a value of the chosen performance function (i.e., the optimisation criterion). Such situations are often met at a design stage of manufacturing systems. For instance, the following examples could be mentioned:

- designing a material handling system, consisting of a large automated storage and retrieval device, automated guided vehicles (AGVs), AGV stations, lifters and conveyors (Banks et.al., 2001). Here the optimisation parameters (to be tuned) are the number of AGVs and the load per AGV, but overall investment and operation costs could be considered as a performance function;
- solving a buffer allocation problem, when optimisation is aimed to find the best sizes of buffers between workstations (e.g., designing an assembly line for automobile engines (Banks et.al., 2001)). Buffers are aimed to smooth fluctuations in operation of consecutive workstations (providing a room were parts could wait while a current workstation is busy, without blocking operation of the previous one), thus increasing the system throughput. On the other hand, increasing of sizes of buffers results in a corresponding increasing of a work-in-process inventory (WIP) that decreases the overall manufacturing efficiency. In this case optimisation is aimed to find such sizes of buffers, when the maximum throughput is achieved, while keeping WIP at an acceptable low level (Papadopoulos et.al., 1993).

In simulation-based optimisation, a performance function is estimated by means of simulation: after the current values of tuned parameters were defined, simulation is performed, and its results are used for evaluation of a corresponding value of a performance function.

It should be noted that in this case a goal function of the optimisation process (that should be optimised: minimised or maximised) does not coincide with the above mentioned performance function. It is caused by a random nature of a simulation model that reflects randomness in operation of a modelled system. As a result, here the performance function is a random variable. Each simulation experiment gives several realisations of the performance function that are used for estimating its mathematical expectation.

A traditional approach to formulating a goal function in simulation-based optimisation is to use a mathematical expectation $E(Y)$ of the performance function Y (Banks et.al., 2001). In this case, the optimisation problem could be formulated in the following way:

$$E(Y(x_1, x_2, ..., x_n) \rightarrow \min_{X \in R}(\max),$$

where $X = [x_1, x_2, ..., x_n]$ is a vector of tuned parameters, and R is an area of its allowed variations. This specific feature of simulation-based optimisation causes its additional (comparing with a traditional optimisation) difficulties. Indeed, here the optimisation procedure asks for much more calculation efforts, as far as several realisations of the performance function should be received (for instance, by performing multiple simulation runs) for each set of values of tuned parameters. Therefore, many of traditional methods of mathematical optimisation (that guarantee asymptotic convergence of an optimisation process, but could ask for an unrealistic high amount of calculations) could be hardly used in this situation.

Surveys of optimisation methods, suitable for simulation-based optimisation, could be found in (Visipkov et.al., 1994; Andradottir, 1998; Swisher, 2000). They discuss various approaches that are aimed to increase efficiency of simulation-based optimisation, providing a so-called "sub-optimal" solution (when an essential improvement of the goal function asks for an acceptable amount of efforts). Let us mention 2 examples of such approaches:

- organising optimisation in two steps:
    - firstly, using a relatively simple and fast optimisation method for approximating a target solution. Resulted values of tuned model parameters serve as an initial point for continuing optimisation at the second step. As the optimisation problem at this stage is solved roughly, it is not necessary to spend a lot of efforts for estimating the performance function. For instance, (Merkuryev and Visipkov, 1992) suggest to use here a deterministic analogue of the simulation model, substituting its random variables with their mathematical expectations; a theoretical consideration of this technique could be found in (Merkuryev et.al., 1995). Methods of global optimisation should be used at this step, e.g., random search or genetic algorithms;
    - secondly, improving the previous solution by means of a local optimisation method (e.g., Hook-Jeeves or steepest descent)
- using heuristic algorithms, that are based on real-life improvement processes, e.g. genetic algorithms, tabu search, simulated annealing, neural networks (Banks et.al., 2001; Visipkov, 1999).

Heuristic algorithms are widely used in software tools of simulation-based optimisation. For instance, the package OptQuest, designed for the simulation system Arena, explores tabu search and scatter search (Kelton et.al., 2002). Another example of a software tool, designed for simulation-based optimisation, is ISSOP ("Intelligent System for Simulation and Optimization") from the DUALIS GmbH (Krug, 1997; Krug et.al., 2001). It supports a genetic algorithm and evolution strategy, as far as a quasi-gradient method, component-wise enumeration, Monte-Carlo method, threshold accepting and cuboid strategy.

6. Sample simulation studies

An example of a simulation study, had been performed in accordance with the above-mentioned methodology, is presented in (Lopatenok and Merkuryev, 2000). In that case the simulation research was aimed to balance a throughput and work-in-process of a designed production line at a factory of a major telecommunication company. The main objective was to optimise buffer capacities between workstations in accordance with the following criterion: buffers capacities should be sufficient enough to smooth fluctuations of processing times, set up times, handling times and transportation times of workstations in the production line, providing maximum of a daily throughput, while the work-in-process volume is as minimal as possible.

To simplify the optimisation problem, it was assumed that all buffers have the same capacity. It was found (by simulation) that increasing the buffers capacity from 0 to 5 increased the throughput from 77% to 99%; further enlargement of buffers practically did not change the throughput, but caused a linear increasing of WIP. Therefore it was decided to set the capacity of buffers equal to 5, thus providing increasing of the throughput by 22%, with an acceptable level of work-in-process inventory.

Another example of simulation-based optimisation is presented in (Law and McComas, 2000). In that study a manufacturing system with 4 workstations and 3 buffers was simulated, with the aim to find such numbers of workstations of each type and buffer capacities that maximises a mathematical expectation of manufacturing efficiency. The total number of possible combinations of different values of tuned parameters (i.e., configurations of the considered manufacturing system) was equal to 81,000.

The manufacturing efficiency was calculated as a difference between sales of parts, produced in a 30-day period of time, and installations expenses for workstations and buffers. Optimisation was performed using two software tools: the OptQuest and WITNESS Optimizer. The last one supports optimisation of models, developed with the WITNESS simulation system. Both packages demonstrated there efficiency: sub-optimal solutions (that could be expected to be located close to the "exact" solution) were found, asking for a reasonable number of evaluated configurations (100 for OptQuest and 500 for WITNESS Optimizer). Authors of this study underlines importance of a successful choice of parameters of used optimisation algorithms, as far as the choice of parameter settings can have a big impact on the quality of the solution obtained.

Conclusions

Simulation study of manufacturing systems is a complex process, incorporating various steps, related to analysing a simulated system, building an adequate simulation model, experimenting with it, and analysing and interpreting simulation results.

The methodology of discrete-event simulation was discussed, including describing an overall structure of the simulation study and specifying its separate stages. Special attention was paid to simulation-based optimisation, when simulation is aimed to optimise performance of a considered system.

Finally, two examples of simulation-based optimisation of manufacturing systems were referenced. An importance of a successful choice of parameter settings of used optimisation algorithms was underlined.

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