A metamodel for modelling and simulating complex processes

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Modelling and Simulation are inexpensive and computationally efficient manners to analyze virtually any system. The technique has attracted the attention of cross-disciplinary practitioners due to easiness when abstracting systems to models and its fast and reliable solution mechanisms for assessing performance. The present work discusses a metamodel for modelling and simulating complex processes, e.g. when intricate relations are present. The objective is to show how to use the metamodel when conducting a broad analysis where several stakeholders must engage to perform better business decisions. We also discuss how to promote early use of modelling and simulation and the main issues arising when evaluating performance in large scale projects. Our aim is to help users and decision makers shorten the analysis phase duration by focusing on key tasks yielding consistent and actionable suggestions for improvements.

Keywords: simulation; modelling; performance evaluation; discrete event simulation

Introduction

Performance difficulties such as poor resource availability, weak responsiveness, presence of bottlenecks, and bad management decisions are commonplace in some industries and enterprises around the globe. In this context, the area of Performance Evaluation is used to inspect systems and to provide numerical means to improve the effectiveness of processes and explore resource allocations that may yield better outcomes. Monitoring, analytical modelling, and simulation are three known approaches to tackle performance.

Due to its high suitability to a plethora of problems, simulations are often used as the most amenable technique to model, map, inspect, and discover bottlenecks within processes or tasks therein. Simulation is well fitted for systems having complex requirements because it allows modelers to learn costly bottlenecks, resource overutilization, and poor task response times due to uncommon behaviors. The technique is considered computationally cheap and helps decision makers to quickly act on problems. The general idea is to represent a system in a model that yields performance indices (e.g., throughput or utilization of the system), inspecting scenarios to help decision makers improve quality requirements.

The present work discusses the advantages of using a metamodel for addressing simulation prospects in early analysis stages where different background stakeholders must reach consensus for taking sets of actions. The choice of this particular approach is due to the possibility of readily inferring performance indices and actionable objectives to achieve better results. Our metamodel is construed as an interesting (and inexpensive) alternative that may influence management decisions and resource contingencies in domains such as manufacturing, healthcare management, electronic component designs, and logistics, to name a few.

Managers must often make the best possible decision with information available at hand. In many times, it causes systems to be deployed with defects or, more seriously, unwillingly exposing customers to unexpected malfunctions. Ideally, one should direct efforts towards the prevention of such problems, trying to anticipate them with procedures that: i) directly affects overall costs; b) reduces wastes and losses; and iii) provides best resource allocations of processes with reasonable quality assurances.

The objective of the present work is two-fold: firstly, we discuss the advantages and limitations of simulations, discussing its phases, mapping procedures, modelling, execution, and reporting. Secondly, it aims to discuss a metamodel suitable for complex processes where modelling and simulation is to be used, showing the most important steps to follow when inspecting performance.

The paper is divided as follows: Section 2 presents common performance evaluation techniques and related works. Section 3 explains our proposed metamodel in detail. Section 4 concludes the paper with final considerations and future works.

2. Performance assessment using modelling and simulation

There is a huge interest to compute and infer performance indices when evaluating systems, processes, algorithms, methods, and resources. Managers, analysts, software developers, decision-making professionals, as well as all personnel involved in process improvements are interested in inspecting systems to enhance business returns or to allocate resources reasonably. It is crucial to identify contingencies in terms of operational settings versus resource allocations in systems to remain competitive in the market. Performance evaluation is a pre-requisite for inspecting system quality, a concern that must be present since early phases, preferably since design. It handles questions concerning bottlenecks, resource distribution and indications as where to direct efforts to improve processes outputs. Influential work on this topic have discussed how to compute performance indices and most important metrics to consider [1][2].

There are three basic ways to evaluate systems: monitoring, analytical modelling, and simulation. Monitoring [2][3] uses specific software to instrument systems and processes by pinpointing critical passage points where crucial data is captured. As a drawback, however, there is a known problem called The *Paradox of Monitoring*, where the excess of monitoring negatively affects performance. Analytical modelling aims at building abstract representations of systems through mathematical formalisms, for example, Markov Chains or Queueing Networks [4], and Petri Nets[5], among others. The idea is to design a scheme consisting of key system characteristics with simple primitives such as states, transitions, and rates and then compute performance indices with linear equations (or other numerical technique). Simulation, on the other hand, presents a compromise between previous approaches offering better trade-offs in terms of easiness to use and system level abstractions. It provides high confidence to users since it closely imitates the reality under study, allowing several executions (e.g. replications) to be made in a timely fashion.

The literature on simulation is extensive as well as examples, successful use cases, and applications in several domains [6][7][8][4][9][10]. Several works present methodologies to address complex systems dynamics and evolution. Examples are, for instance, *System Dynamics and Dynamic Systems* [11], *Agent Based Simulation* (ABS) [12][13] and the focus of the current work, *Discrete Event Simulation* (DES) [7][9],[10]. In DES, the system is represented by states where the changes occur in precise time steps, i.e., according to discrete events, causing the time to advance whenever an event has occurred. Examples where such behaviors occur are, for instance, the arrival and departure of customers in a bank queue, the manufacture of items in industries and many others.

Simulation allows the development of personalized solutions [14] written in robust programming languages (usually C/C++), proprietary or open source tools such as Arena™ software[15],[16], SIMUL8 [17], OMNeT++ [18], adevs [14], Java Modeling Tools (JMT) [19], or SimPy [20]. For a broader discussion, refer to [21], where a thorough explanation of discrete event simulation software is shown. Despite licensing costs for some tools, simulation is viewed as an inexpensive approach with substantial market acceptance and academic respect. The massive amount of input data passes through rigorous statistic treatment that exposes incoherencies and measurement problems due to improper equipment calibrations or other factors.

Besides the properties for each entity in the simulation, as results, one computes performance indices such as throughput, average resource utilization, average population (for entities present in the model) traversing the system, and average response time, to name a few. Other indices could be computed as well, such as attributes or variables that are stamped within entities, saving data for posterior analysis.

Figure 1 lists the main simulation phases for a wide-ranging study. From a clear objective, the analyst work initially on a draft of the system (usually very raw, or a sketch) to indicate the main system operation – this could be revised later – and then use previously measured input data to parameterize the model, creating some simulation *scenarios*. The next phase concerns the experimentation of previously defined scenarios where the model is executed several times, ending with the analysis phase, where the analysts inspects results to determine whether the model reflects the reality and how changing parameters affects the performance indices. Finally, results are compiled in a report for advanced analysis and what-if discussions.

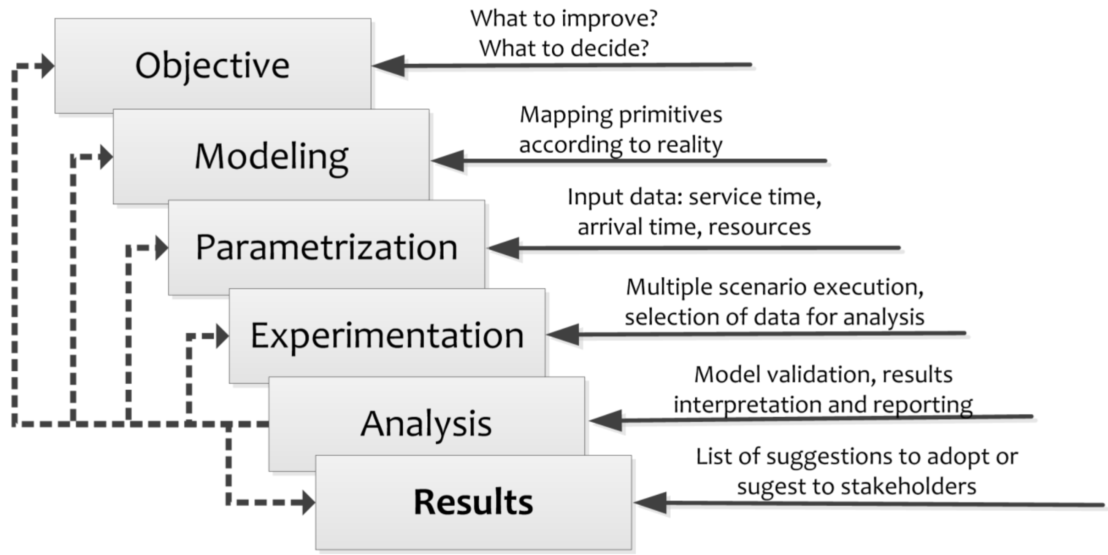

Figure 1. Common phases for modelling and simulation.

The analysis phase is the most important one because stakeholders are advised on how to redistribute workload, assign new resources, reallocate teams to different locations, consider other processes or reduce the existing ones, among many other decisions that could be considered. It is worth explaining that this model is *cyclic*, i.e., it is repeated throughout the course of an analysis. After this step, if parameters are deemed impossible to conform to its physical counterparts, the model should be reviewed and another round of experimentation and analysis must be performed.

2.1 Related works

Simulation is an established technique for performance evaluation, so it is only natural that several books exist to describe applications, modelling and assessment [15][14][8][9][10]. An interesting analysis is discussed in [1], a seminal work showing product form solutions for queueing networks. Some authors focus on methodologies for industrial processes, where [24] gives the closest work about the approach presented here with a proposition for simulating processes using VBA (*Visual Basic for Applications*) programming language [24]. Besides, [25] describes the use of simulation to model and study complex behaviors present in different realities. The approach considered by [26] consists of providing a modelling framework that encompasses System Dynamics, Agent Based Simulation, or DES very broadly, calling it AnyLogic. These ideas have a strong relation with our present proposition since we advocate the importance of the model itself while building a valid representation of a complex system. Some explanations concerning System Dynamics and its relation to DES can be found in [27], whereas [28] proposes a framework to aid managers and stakeholders to model and define business processes with the utilization of a metamodel to ease and drive the specification. Other works are directed towards *Business Process Management* (BPM) concepts and the integration with simulation [1][29][30][23][22].

Some researchers have considered the creation of a new area called *Business Process Simulation* (BPS), where [31] proposes a general framework to help the simulation of business processes. Following these approaches [32][33] discusses BPS relating several simulation tools and analysis techniques for application in different contexts, showing the growing interest of the community to devise and assess process simulation. Regarding tools, it is mandatory to cite the Bizagi suite [34], a modelling and simulation environment where users are provided with natural mechanism to develop business models, assign resources, and assess performance.

Defining and working with simulation and modelling methodologies depends on the subject of interest. The work present in [35] has defined a framework to work with low and high level designs to help domain experts define and work with DEVS (*Discrete Event System Specification*), i.e., a modular and hierarchical formalism to work with discrete events. In Systems of Systems research, [36] offers a broad discussion on such models, explaining methods and related considerations.

We observe that few approaches are interested in defining metamodels that could be broadly used before embarking in a complex simulation investigation. We advocate the use of a metamodel that focuses on addressing key system behaviors. Next, we describe our proposition and show how stakeholders could inspect and assess performance of complex processes.

3. A metamodel for simulation

When modelling, one must invariably work with processes, tasks, times (or rates), and resources. A process, depending on the abstraction used, has usually a broad scope and encompasses the set of procedures, activities (also called actions, or tasks) that are followed to produce items, treat patients, process clients, for example. A large process could be simplified to contain simpler processes (called sub-processes). The model complexity is driven by the modeler, and the grain is set according to the problem under consideration.

The objective of this section is to present our metamodel applied to complex processes. A methodology called DEGREE (*Define-Establish-Generate-Rank-Evaluate-*

Execute) [34] can be used if the modeler is using the Arena™ software suite. We have chosen to combine ideas from different methodologies and merge them into one single metamodel that optimistically will add value to a performance assessment analysis. When modelling systems, resources may have important characteristics that affects the outcomes of the model, i.e., could be more or less skilled personnel, machinery (e.g., cheap or expensive, fixed or mobile), conveyor belts (with different velocities and attributes), or produced items (e.g., items that must be ready before the execution of other processes). Other characteristics are associated with different resources such as failures, maintenance, acquisition of hiring/firing expenses, and other variations that eventually cause production costs to elevate or even start to cause financial losses.

So, before any serious performance consideration, it is important that stakeholders understand the operation in its entirety, first identifying the most critical list of processes at hand, and then considering the necessary steps to improve them in a systematic fashion. It is useful to keep in mind that managers often need to maximize profits while reducing waste, helping sustainability concerns and focusing improvement efforts only on the main processes. The proposed metamodel aids to achieve these goals as it encompasses several phases, described in Table 1.

Table 1: Metamodel phases describing necessary phases for a broad system analysis.

	#	***Phase***	***Description***
DEFINITION / PROJECT	**1**	*Problem definition and list of critical processes (stakeholder brainstorming)*	The problem must be clearly defined for all stakeholders. Devise a *List of Critical Processes*, e.g., the processes that potentially yield the best/worst gains for the study.
	2	*Set objectives according to the problem definition*	Precisely define the objective of the study.
	3	*Definition of the base model*	Create a base model, where results are a close match to current operation in terms of performance metrics.
	4	*Design of scenarios for analysis*	Create some simulation scenarios based on objective. Choose most important parameters (and variations).

EXECUTION AND EVALUATION	**5**	*Data assessment and treatment*	Proceed to data capture and treatment. Outlier removal and statistics; Instrument selected tasks and processes; Process data to improve analysis (sampling, etc.).
	6	*Execution and parametrization of simulation from designed scenarios*	Define simulation parameters (replications, time, etc.) Execute simulation scenarios and save reports.
	7	*Model refinements and optimizations (if possible)*	Refine models and re-execute some selected scenarios. Study opportunities for better modelling.
	8	*Evaluation of results, analysis and reporting*	Review and interpret results. Generate reports with charts and suggestions for stakeholders.

Figure 2 shows how to understand the overall process, e.g., using a cyclical approach when working with simulation. This is reviewed at each iteration of a comprehensive study, always considering the original objective in perspective.

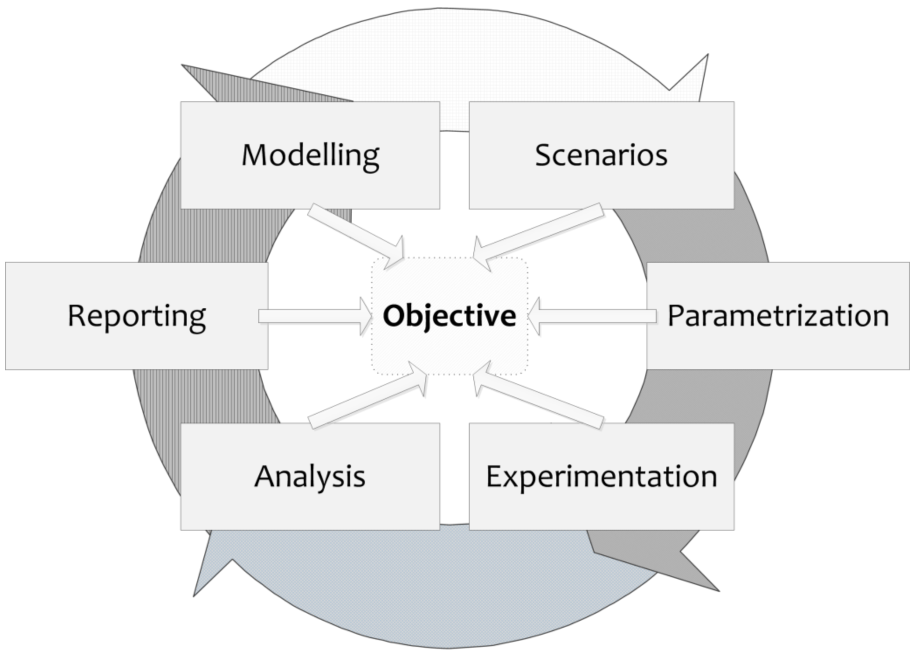

Figure 2: A *cyclic* simulation analysis in conformance to objectives.

The idea of considering a complex analysis as cyclical is crucial when analyzing complex situations where multiple relations exist among entities present in models. This key concept allows the formulation of our metamodel, in Figure 3, listing the most significant aspects to consider when modelling and simulating complex processes.

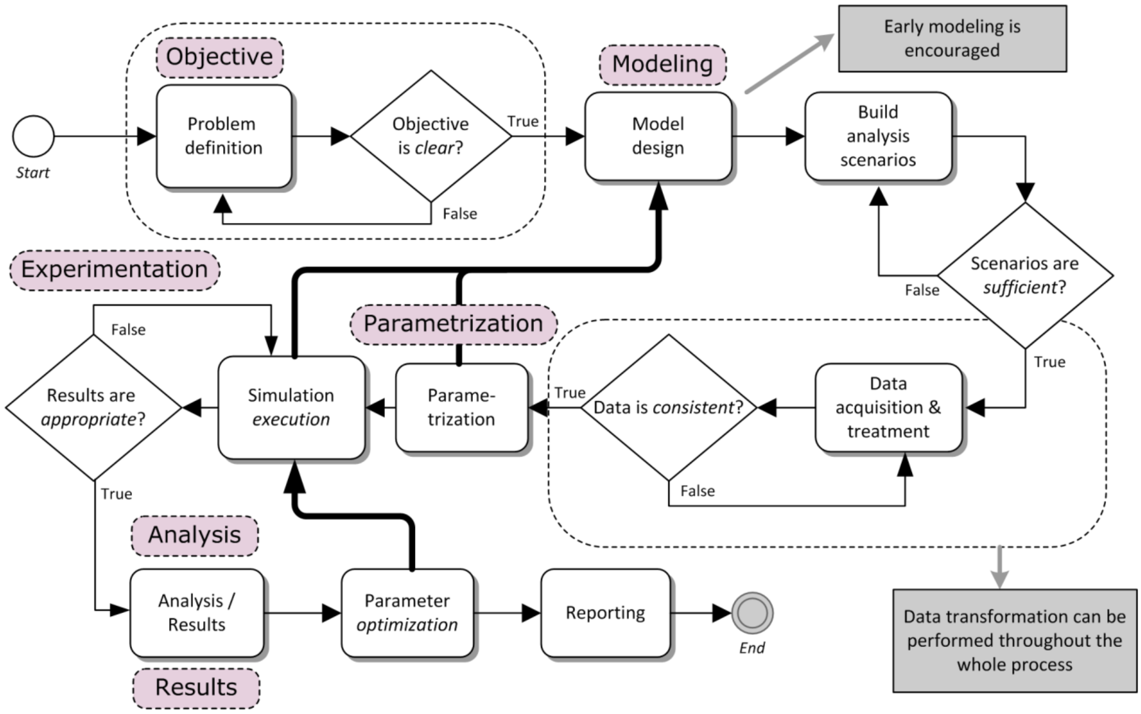

Figure 3: Metamodel for evaluating performance of complex processes.

The idea of using our metamodel stems from the fact that broad analysis should be carried out with caution. Applying the metamodel has the advantage of knowing precisely where other stakeholders are working on, indicating how to better cope with associated risks inherent to such complex endeavors. External and uncontrollable issues are commonly present such as the use of validated data (e.g., by domain experts, for instance) or observe times and durations that effectively represents actual values (the best practice in such cases orient us to validate and treat the data to discover problems, as mentioned earlier).

One should also be aware that some managers (perhaps unwillingly, in good faith) could be working with wrong input data, or even using incorrect measurements, causing invalid conjectures from results. Table 2 shows the key risks and opportunities while dealing with such contexts. The idea is to understand the key issues arising when working with modelling and simulation and some comments on to readily act to avoid losses, resource misuse, or general waste, considerations that impact business finances.

Table 2: Risks and opportunities while modelling and simulating processes.

Risk/Opportunity	***Comments***
Processes as black boxes	Hard to instrument tasks within processes. Wrong measurements or validations.
Invalid input data	Poor data validation. Statistics are calculated without validations. Wrong interpretations for durations or assigned resources to tasks.
Choosing processes for improvements	Process chosen is not amenable for improvements. Stakeholders do not meet consensus on target process for study. Process is not well understood by stakeholders.
Modelling & Simulation	Stakeholders do not employ modelling and simulation for analysis. View that simulation is not reliable or fit for analysis. Simulation does not represent the operation, yielding invalid results. Suggestions for improvements are very hard to attain.

The financial reality of many enterprises and industries ensures the appropriate use of resources, avoiding surpluses, wastes, or reworking. A large set of processes, however, present a bottleneck (or more) or maybe other performance problems at some level. The obvious approach, undertaken by many uninformed business analysts, is to keep appending (through hiring, or acquisition) new resources to problematic processes. Managers under strict budget know that the associated costs are too high so other less costly approaches must be taken in consideration. Business managers need to deal with many operational details, observing real improvements without financially impairing the business with unnecessary hiring or unjustified equipment acquisitions that may or may translate to added value to the company. Our metamodel is an alternative for analysts since it provides a conceptual framework that not only explains the overall technique for stakeholders but, at the same time, provides system performance awareness and foments early inspection to avoid waste or poorly resource allocations.

4. Final considerations

The present work aimed to formulate a metamodel for performance evaluation suitable for modelling and simulation of complex processes. The 'complex' definition here is broad, i.e., for our case we are taking into consideration systems with intricate or difficult to understand relations. Our metamodel is presented here in detail, showing its scope and how to enable comprehensive decision making for stakeholders when working with process improvement. We discussed some aspects to consider when assessing performance of processes through a set of performance metrics such as throughput, utilization, response time, and queue population (e.g. number in queue waiting for service).

Despite the fact that simulation is used in many contexts, it should be viewed as another tool to inspect and evaluate systems. We stress the fact that it should be used in conjunction with other techniques since the major concerns are directed towards bottleneck identification and steps to take to prevent bad operations, improving processes both consistently and efficiently. For instance, stakeholders could use other *Operational Research* mechanisms such as Linear Programming, Metaheuristics, Markovian Processes (analytical modelling), as well as Stochastic Programming techniques, to cite a few [37] to improve operations.

The discussions presented here show some indications for future works. For instance, we are interested in applying our metamodel in a large scale project, showing to stakeholders and domain experts how to better cope with problems at each analysis phase, something that is very hard to handle if no analysis framework is used at all. Our idea is to use our metamodel to improve processes and pointing out early defects and problems in large scale projects. Another by-product of our approach is allowing managers to discover susceptible processes (or tasks) for enhancements, something that is viewed by many researchers as an open problem in business process modelling.

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