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A SYNTHESIZED METHOD FOR CONDUCTING A BUSINESS PROCESS SIMULATION STUDY

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ABSTRACT

When a company wants to use business process simulation to support decision-making, a simulation study needs to be conducted. Using a clear stepwise method can avoid overlooking key activities during the simulation study and improves the study's credibility towards decision-makers or project sponsors. In this tutorial, a method to perform a simulation study is proposed, which consists of nine steps and uses continuous assessment as a central feedback mechanism. It synthesizes existing methods proposed in literature and positions the actual construction of a simulation model in specialized software in a wider perspective. Given the method's high-level nature, its operationalization is illustrated making use of a real-life simulation study at the emergency department of a hospital, showing that the relative weight of different steps in the method depends upon the project's specificities.

1 INTRODUCTION

Business process simulation (BPS) refers to the imitation of business process behavior through the use of a simulation model (Melão and Pidd 2003). By mimicking the real process, BPS can contribute to the analysis and potentially the improvement of business processes (Rozinat et al. 2008). Simulation enables the organization to verify the consequences of proposed process modifications prior to implementation (Melão and Pidd 2003) and, hence, provides support to decision-makers.

In order to use BPS to evaluate policy alternatives, a simulation study needs to be conducted. After investigating the modelling behavior of 20 experts, Ahmed and Robinson (2013) conclude that BPS models are typically not constructed following an explicit or clearly delineated modelling process. Based on a set of key steps, experts tend to have their own habits and their modelling behavior is contingent upon factors such as the objectives and model size (Ahmed and Robinson 2013). This entails the risk of overlooking key activities during the simulation study, especially for less-experienced simulation analysts, which can lead to significant time investments to rectify these errors. It can also raise questions with decision-makers or project sponsors regarding the methodological underpinning of the study and, hence, can reduce the credibility of its results. In this respect, following a clear method outlining the key steps that need to be taken during the entire study can mitigate these risks. Moreover, it provides guidance to non-simulation experts or junior simulation analysts. Using an agreed-upon method does not restrict a modeler's freedom given its high-level nature. Consequently, it does not impede the development of a personal toolbox with preferred techniques. The operationalization of the method will also depend upon project-specific factors such as the available time for the project and access to domain experts and decision makers.

In simulation literature, a multitude of methods describe how a simulation study should be conducted (Altiok and Melamed 2007; Balci 1990; Carson 2005; Chung 2004; Fishman 2001; Kelton et al. 2015; Law

2007; Law 2009; Hlupic and Robinson 1998; Nordgren 1995; Robinson 2004; Rossetti 2010; Shannon 1998; van der Aalst 2015). Even though key components such as data collection are included in most methods, differences can also be observed. An example of such a difference is the actual implementation of process changes: while Rossetti's (2010) model includes this step, other authors disregard it. Despite such differences, existing methods defined in literature tend to be reported in isolation and are not positioned in relation to the work of other others.

This tutorial tackles this lack of integration by proposing a stepwise method to conduct a BPS study, which is based on a critical synthesis of existing methods. By combining their strengths and leveraging their points of improvement, this tutorial presents a comprehensive method for administering a simulation study. Given its firm foundation in literature, it provides a reliable basis to guide simulation projects in practice. Besides avoiding to overlook key activities, the use of the presented method can also be useful to demonstrate to decision-makers that the simulation study follows a clear and established methodology. The latter will support the credibility of the resulting simulation model and the study's results. The proposed method positions the actual construction of a simulation model in specialized software in a broader context. In this way, it is complementary to other tutorials focusing on specific topics related to simulation model development.

The remainder of this tutorial is structured as follows. Section 2 presents the method, where each subsection briefly discusses a particular step. Due to space limitations, a detailed overview of existing methods and their relationship to the developed synthesis method is omitted. However, an overview table summarizing the latter relationship is available upon request. Section 3 outlines the validation of the method by means of expert validation (Section 3.1) and its application to a real-life simulation project at the emergency department of a hospital (Section 3.2). The tutorial ends with a discussion and conclusion in Section 4.

2 SYNTHESIZED METHOD TO CONDUCT A SIMULATION STUDY

This section presents a method for performing a simulation study, which is based on a critical analysis of the following existing methods: Balci (1990), Nordgren (1995), Hlupic and Robinson (1998), Shannon (1998), Fishman (2001), Chung (2004), Robinson (2004), Carson (2005), Altiok and Melamed (2007), Law (2007), Law (2009), Rossetti (2010), Kelton et al. (2015), and van der Aalst (2015). These references originate from both simulation textbooks and scientific articles. Consistent with Schryen (2015) and Webster and Watson (2002), the collection of additional textbooks or articles stopped when the addition of consecutive references adds no new content in terms of fundamental concepts or structures. The method has been validated by presenting it to six simulation experts, three active in academia and three in industry. After agreeing to review the simulation study method, the experts received an outline. Their feedback was gathered by e-mail or through a face-to-face discussion. This evaluation approach corresponds to the notion of expert evaluation in Peffers et al. (2007), i.e., the assessment of an artifact by one or multiple experts.

As shown in Figure 1, the method consists of nine steps with continuous assessment as a central feedback mechanism. Even though this tutorial focuses on business process simulation, it is likely that the key steps proposed by the method are also applicable for simulation studies outside a business context. Hence, simulation modelers from other areas than business process simulation can also benefit from the insights conveyed in this tutorial. However, the operationalization of these steps might differ. Consider data collection approaches as an example: while data are often collected by observing the real-life process in BPS, it might be impossible to observe the problem context when simulating the impact of a natural disaster in a particular region. The illustrations in the remainder of this tutorial will focus on simulating business processes. The following subsections describe each of the steps and the central feedback mechanism depicted in Figure 1.

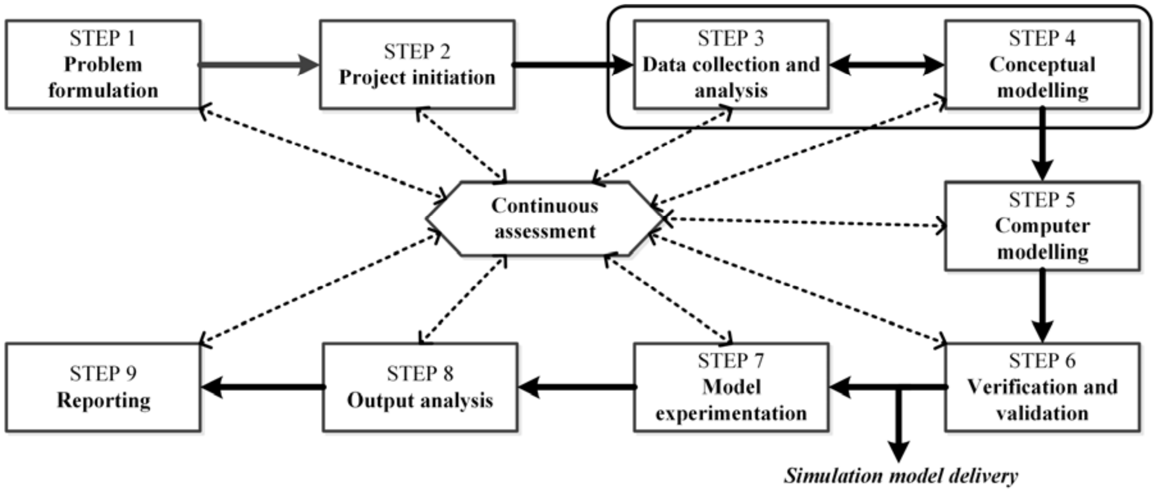

Figure 1: Method to conduct a simulation study.

2.1 Step 1: Problem Formulation

A BPS study is typically instigated by a specific problem that is reported by a decision-maker in a company (Balci 1990; Law 2007; Law 2009; Rossetti 2010). The latter can be called the **communicated problem** (Balci 1990) and might be stated in very general terms or can be expressed in terms of symptoms (Carson 2005). As a consequence, a more detailed specification might be required to obtain a **formulated problem** which can be used to launch a research project (Balci 1990). Such a clarification can be obtained during a preliminary discussion with the decision-maker.

The modeler should **understand the problem and its context** (Robinson 2004) and gain **basic insights in the process** in which the issue is embedded (Chung 2004), i.e., obtain a bird's eye view on the business process. This is required in order to establish, e.g., specific goals and process boundaries in the project initiation step.

If formalization is important for the project under consideration, the problem formulation can be converted to a **written statement** (Chung 2004; Rossetti 2010), outlining the problem under consideration and basic contextual information. The problem formulation can be rather generic in this phase of the study. Consequently, it can be used as a draft document that will be integrated with more detailed project decisions made in the project initiation step.

2.2 Step 2: Project Initiation

The problem formulation step focuses on the specification and clarification of the problem at hand. When proceeding to the project initiation step, the focus shifts to the project, i.e., how the problem should be analyzed to support the decision-maker.

In this step, a distinction can be made between project management and preliminary modelling issues. As the decisions made in this step lay the foundation for the remainder of the project, they should be taken with great care as, e.g., an inaccurate goal specification can result in correctly answering the wrong questions. Even though decisions should be well-advised, they should remain flexible, as will become apparent in Section 2.10.2.

With respect to project management, the rather business-oriented formulated problem from the first step needs to be translated into guiding principles for the project (Altiok and Melamed 2007). The **goal** of the study needs to be specified (Nordgren 1995; Shannon 1998), which can be split into several modelling **objectives** (Carson 2005; Chung 2004; Hlupic and Robinson 1998; Kelton et al. 2015; Robinson 2004) and specific **questions** that should be answered at the end of the BPS study (Carson 2005; Nordgren 1995; Shannon 1998; van der Aalst 2015). When the study's objective is the **delivery of a simulation model** that the company can use autonomously, questions should not be answered at the end of the study, but it should become clear which questions the model should be able to answer.

Once the aforementioned decisions are made, preliminary modelling decisions are required. A choice that is crucial, but often overlooked in existing methods, is the **selection of the most appropriate analysis technique** to deal with the problem (Balci 1990; Kelton et al. 2015). Balci (1990) states that all plausible techniques should be listed, which can be seen as a rather extreme view on this issue. However, the analyst should be aware that, compared to simulation, techniques might exist that generate equivalent results quicker. Kelton et al. (2015) recognize that technique selection is not straightforward. A basic cost-benefit analysis can be used to determine which technique is the most appropriate given the problem under consideration and the project context (Balci 1990; Kelton et al. 2015). Even though this is not recognized by Balci (1990) and Kelton et al. (2015), the intrinsic potential of a BPS model once it is developed should be taken into account. It can typically be used to answer a wide range of follow-up questions and can easily be adjusted to new situations. In the remainder of this tutorial, it is assumed that simulation will be used to tackle the problem.

Based on the established objectives and project questions, the **boundaries of the modelled process** are determined (Carson 2005; Chung 2004; Hlupic and Robinson 1998; Kelton et al 2015; Nordgren 1995; van der Aalst 2015). Kelton et al. (2015) state that model boundaries should not be rigid, which is consistent with the aforementioned call for flexibility regarding project initiation choices.

During the problem formulation step, preliminary insights are gained in the process under study. This knowledge, combined with the specified model boundaries, should make it possible to develop a **preliminary input parameter list** (Altiok and Melamed 2007; Balci 1990; Chung 2004; Fishman 2001; Kelton et al. 2015; Shannon 1998), including, e.g., the entity arrival rate and relevant **output measures**, i.e., metrics quantifying process performance (Altiok and Melamed 2007; Carson 2005; Chung 2004; Fishman 2001; Hlupic and Robinson 1998; Kelton et al. 2015; Nordgren 1995; Shannon 1998). Output measures are chosen in accordance with the study's objectives and research questions, e.g., the average waiting time (Kelton et al 2015). Besides model performance metrics, performance indicators for the simulation study itself can also be specified such as the extent to which the pre-specified timing is respected (Kelton et al 2015).

Based on the study's objectives and preliminary list of output measures (Law 2007; Law 2009), the **level of model detail** can be deduced (Carson 2005; Kelton et al. 2015; Law 2007; Law 2009). The selected model granularity should make it possible to retrieve the selected performance metrics in order to answer the questions at hand. As a BPS model is by definition a simplification of reality (Altiok and Melamed 2007; van der Aalst 2015), the analyst should not aim for the most detailed representation of the process. The higher the model's granularity, the more extensive the data collection and modelling efforts will be, which might lead to violations of, e.g., time or budget constraints.

Another point of attention is the **tool** that will be used to implement the BPS model (Chung 2004; Law 2007). This can, for instance, be a programming language or dedicated software (Law 2007). Law (2007) positions this decision within the first step of his method, whereas Chung (2004) postpones this choice to the fifth phase of the simulation study, i.e., right before computer modelling. As the selected tool determines the available representational and modeling functionalities, it is recommended to consider this issue in an early phase. Moreover, terminology might differ across languages and platforms. Using the tool's vocabulary in preparatory documents can help to avoid confusion in later phases of the project.

When the aforementioned preliminary modelling choices are made, project management decisions related to **project planning** are made. This involves estimating the required time and costs to perform the study. This estimation might force the decision-maker to alter the project's scope or, in case disproportional efforts are required, to discontinue the study (Carson 2005). If the decision is made to proceed with the project, potentially with an adapted scope, the analyst must ensure that, e.g., all required staff is available (Shannon 1998). Tools such as a Gantt chart can be used to support project planning (Chung 2004).

From a practical point of view, the above activities can be executed during one or multiple **kick-off meetings**. Besides the simulation analyst, decision-makers and staff members that will be part of the project team should be present (Carson 2005; Law 2007; Law 2009). The results of these meetings can be formalized in a **project protocol** containing the study's objectives, the required inputs and delivered outputs, the model's scope, etc. (Kelton et al. 2015). Note that, until now, no detailed process information is collected or modelling efforts have been performed. Starting these activities might require **formal approvals** such as drafting and signing non-disclosure agreements or receiving the consent of an ethical committee. For this purpose, the project protocol can be used. The necessity to receive formal approvals is not included in existing methods, even though it is highly relevant in, e.g., a hospital context.

2.3 Step 3: Data Collection and Analysis

After project initiation, data need to be gathered and analyzed. Because the conceptual model and the computer model will be heavily influenced by the inputs gathered in this step, errors or inaccuracies can be detrimental for the model's quality (Altiok and Melamed 2007; Robinson 2004) as the well-known mantra 'garbage in, garbage out' holds (Shannon 1998; Chung 2004). Within the data collection and analysis step, **three substeps** can be distinguished: data collection, data preparation, and data analysis. The alternating relationship with the conceptual modelling step will be discussed in the following subsection.

Data collection, an activity that can require a significant amount of time (Shannon 1998), involves gathering both structural data and data to model input parameters. According to Robinson (2004), three types of data are required: preliminary, model specification, and validation data. Preliminary data are necessary to grasp the process basics such as its main activities (Kelton et al. 2015; Law 2007; Law 2009; Nordgren 1995; Robinson 2004) and resources (Nordgren 1995). This can be done by gathering, e.g., flowcharts or physical layout schemes. Structural information is not sufficient to construct a BPS model. Data to model input parameters such as the entity arrival rate, activity durations and resource availability are also required (Altiok and Melamed 2007; Carson 2005; Chung 2004; Law 2007; Law 2009; Nordgren 1995; Shannon 1998). This is referred to as model specification data. Besides preliminary and model specification data, the analyst should also check whether validation data is present or can be collected for model validation in step 6 of the study.

For data collection purposes, several information sources can be used. Typical information sources include business documents, interviews with business experts, and observations of the process. Despite the valuable insights that can stem from these information sources and their common use, their limitations should also be recognized. Process documentation can deviate from real-life process behavior (Măruşter and van Beest 2009), interviews can result in contradictory and biased information (Vincent 1998), and observational data can suffer from the Hawthorne effect, which refers to the performance increase of staff members due to the mere fact that their actions are observed (Robinson 2004). Data from information systems is less influenced by human perception. For instance, systems such as Enterprise Resource Planning systems record process execution information in files called event logs (van der Aalst 2011). However, data availability and data quality issues need to be taken into account. Consequently, information sources should be combined in an intelligent way taking into account the fact that each information source has limitations.

Once data on a particular topic are collected, the **data should be prepared** for analysis purposes. This can involve changing their level of aggregation or removing outliers or straightforward errors to improve their accuracy (Robinson 2004). With Shannon (1998) and Carson (2005) as notable exceptions, limited reference is made to data preparation in existing methods.

Data analysis refers to a wide range of techniques which are used to convert the collected and prepared data into relevant knowledge for the construction of the simulation model. The applied techniques will depend upon the type of data and the task at hand. Even though the focus in literature is on the parameter data analysis, it is important to note that structural data also need to be analyzed. Consider, e.g., the analysis of a series of flowcharts drawn by process experts or the retrieval of a process model from an event log using process mining techniques (Martin et al. 2016a; van der Aalst 2011). Regarding the analysis of parameter data, Altiok and Melamed (2007) suggest to generate descriptive statistics and draw histograms to gain basic insight in the data at hand. Afterwards, the choice is often made to fit a theoretical probability distribution to the observed data (Law 2007). To fit a theoretical distribution, the analyst should ensure that a representative set of observations is collected (Chung 2004). In this respect, Chung (2004) states that at least 25 to 30 observations are required to perform statistical tests to verify the correctness of the fitted distribution. Research has also been performed on the use of process mining to support the specification of input parameters such as a probability distribution for the interarrival times (Martin et al. 2015; Martin et al. 2016b) and the phenomenon of batch processing (Martin et al. 2017). A recent overview of research efforts is presented in Depaire and Martin (2018).

2.4 Step 4: Conceptual Modelling

After basic data collection and analysis, **conceptual modelling** can start. In contrast to the other steps of the method, the third and fourth step are connected using a two-headed arrow and combined using a box with rounded angles in Figure 1. This is due to the strong interaction between these phases. On the one hand, the development of the conceptual model is initiated and proceeds through data collection and analysis. On the other hand, the construction of the conceptual model will highlight knowledge hiatuses indicating that new data need to be gathered. Steps 3 and 4 should be closely linked to avoid that the conceptual model becomes so complex that insufficient data are available to support it (Onggo and Hill 2014). Both steps could have also been placed in parallel to stress the alternating relationship between the data collection, data analysis, and conceptual modelling. However, the analyst needs to gather some process insights before being able to start with preliminary conceptual modelling. As a consequence, both steps are put in a sequential relationship, but the importance of their interaction is stressed using the visual aids outlined above.

Despite its critical importance within a simulation study (Chwif et al. 2013; Wang and Brooks 2007), an agreed-upon **definition** of conceptual modelling is absent (Onggo 2009; Robinson 2008a). Definitions in existing methods range from a set of assumptions and data (Carson 2005) to a preliminary graphical or pseudo-code model (Shannon 1998). However, in any case, the conceptual model is an abstract process description, defined independently of the chosen tool. In the proposed method, a conceptual model is an abstract and preferably visual representation of the real-life process containing sufficient details to enable the development of a computer simulation model. This description is largely consistent with the perspectives of Shannon (1998) and Rossetti (2010). Note that, even though the conceptual model should be independent from the used tool, terminology of the tooling can be used. This will ease the conversion of the conceptual model to a computer model, as was already highlighted in Section 2.2.

The development of a conceptual model can start with the development of a **basic process flowchart**, which is a high-level representation of the activities in the process and their relationships. Even though it conveys important basic process information, Chung (2004) states that it is often overlooked by practitioners. The flowchart can be helpful to guide data collection (Nordgren 1995; Robinson 2004): it can, e.g., help to draw up a detailed list of input parameters, specifying which data need to be collected or which questions should be addressed. This illustrates the close relationship between the third and fourth step in the method.

At this point, the conceptual model consists of activities and relationships between activities (Shannon 1998). However, **other model components** also need to be included, such as the definition of entities that will flow through the model (Nordgren 1995; Shannon 1998) and the resources associated to activities.

The conceptual model is also complemented with **input parameters**. This includes both activity parameters, e.g., activity duration, and parameters of the other model components such as resource availability. Including input parameters finalizes the conceptual model that includes all information required to build the computer model.

Note that further data collection and analysis might show that a further **refinement or extension** of the conceptual model is required to adequately capture the real-life process. The developed model should also be consistent with the level of detail, as determined during project initiation.

Based on the prior discussion, one might state that **data analysis** should be included in step 4. However, data analysis is included as the input for conceptual modelling in the proposed method as it focuses on a single data element, such as one particular parameter, while conceptual modelling involves the combination of various data elements in one integrated model.

Certain concepts in existing methods are comparable to the definition of a conceptual model in the proposed method. Several authors mention the creation of an **assumptions document** (Carson 2005; Law 2007; Law 2009; Nordgren 1995). Even though no consensus exists on its specific content, the assumptions document should describe the structure of the process, specify its resources, contain information on model parameters, and outline assumptions (Nordgren 1995; Law 2007; Law 2009). In this way, it is presented as the blueprint of the final simulation model (Nordgren 1995). Consequently, the content of the assumptions document is consistent with the perspective on conceptual modelling presented in this work. The same holds, e.g., for Fishman (2001), where the development of a formal abstraction that includes the logical and mathematical relationships is advocated. In literature, some methods for conceptual model development have been proposed. Consider, for instance, Robinson (2008b) and the related method by Chwif et al. (2013).

2.5 Step 5: Computer Modelling

Computer modelling involves converting the conceptual model in an executable model (Robinson 2004; van der Aalst 2015). To this end, the tool selected during project initiation is used. Consequently, computer modelling can involve either creating statements in a programming language (Fishman 2001; Law 2007; Rossetti 2010; Shannon 1998) or using the interface of a software package to create a simulation model (Hlupic and Robinson 1998; Kelton et al. 2015; Law 2007; Law 2009). Computer model development is an iterative process in which a relatively simple process is extended, verified and refined in a stepwise way (Hlupic and Robinson 1998; Nordgren 1995).

2.6 Step 6: Verification and Validation

The computer model is subject to verification and validation activities. Verification involves checking if the model does not contain errors, while validation encompasses determining the correspondence between the model and reality (Chung 2004; Shannon 1998). This subsection focuses on the position of verification and validation in the method and providing some key ideas regarding the activities that need to be performed.

2.6.1 Positioning within the Method

Even though all analyzed methods mention verification and validation, the way it is inserted tends to differ. Most existing methods position verification and validation **after the development of a computer model** (Altiok and Melamed 2007; Chung 2004; Hlupic and Robinson 1998; Kelton et al. 2015; Nordgren 1995; Shannon 1998; van der Aalst 2015). Robinson (2004) states that inserting these activities at a specific point in the model is deceitful, but deals with this issue by excluding it from the visualization of the method, which does not recognize its key importance. In the same line of thoughts, Rabe et al. (2008) state that verification and validation is required during each stage of a simulation study. Other methods add verification and validation activities **at multiple positions**: Law (2007; 2009) states that both the validity of the assumptions document should be checked and that the programmed model should be verified and validated, while Carson (2005) explicitly mentions data validation besides verification and validation of the programmed model. Balci (1990) takes it a step further and adds a multitude of verification and validation types to the model's visualization, making it rather complex.

Discussions with simulation experts to validate the proposed method showed that the position of verification and validation after computer modelling is the most suitable, which is consistent with the majority of existing methods. This is due to the fact that verification and validation are established concepts within both simulation research and practice. To avoid introducing a state of conceptual confusion, also for practitioners, the proposed method inserts verification and validation after computer modelling. However, the observation that evaluative actions are also required at other points in the process is accounted for by including continuous assessment as a central feedback mechanism, as will be discussed in Section 2.10. The latter anticipates upon the aforementioned critique of Robinson (2004) and Rabe et al. (2008) without introducing ambiguity regarding the established definitions of verification and validation.

2.6.2 Verification and Validation Activities

This paragraph will highlight some key activities in this step of the project. For a detailed discussion on this topic, the reader is referred to, e.g., Sargent (2013).

Verification of the computer model involves debugging the model (Law 2007; Law 2009; Rossetti 2010) to ensure that it operates as intended. As indicated during the discussion of the computer modelling step, a stepwise approach is recommendable in which a model is partly developed and immediately checked for errors (Chung 2004). Erroneous model behavior can be detected by simulating some entities step by step (Chung 2004; van der Aalst 2015), potentially using animation (Carson 2005; Chung 2004). A stress test can also be performed, in which the simulation model is tested under extreme, but realistic, circumstances (Carson 2005; van der Aalst 2015). Several types of errors can occur including the incorrect flow of entities and the assignment of wrong attribute values. Besides verification by the analyst himself, potentially supported by dedicated tools in simulation software, verification can also be performed by revision by a senior simulation analyst (Carson 2005).

The validation of the computer model should ensure the correspondence between the model's behavior and output on the one hand and reality on the other hand (Shannon 1998; Rossetti 2010; van der Aalst 2015). Several types of validity can be distinguished such as face validity and statistical validity (Chung 2004; Rossetti 2010). To establish face validity, the analyst must ensure that the model mimics reality at first sight by, e.g., having thorough discussions with process experts (Chung 2004; Law 2007; Law 2009; Rossetti 2010; Shannon 1998). Statistical validity involves the comparison of output measures of the simulation model and the real-life system. If no significant differences are shown, the model is considered valid (Carson 2005; Chung 2004; Kelton et al 2015; Law 2007; Law 2009; Rossetti 2010).

2.7 Step 7: Model Experimentation

The output of the previous step is an executable and valid BPS model. When the study's objective is the delivery of a simulation model, the method ends after step 6, as visualized by the escape arrow. However, when the simulation study is conducted to answer particular questions, the main focus of this work, the analyst can proceed to experimentation, i.e., specifying scenarios and running them.

Scenario specification requires the definition of a base scenario that serves as a benchmark for the other scenarios. The alternative scenarios are specified by considering adjustments to the process and, hence, reflect potential future situations which should be consistent with the study's questions (Nordgren 1995). As these scenarios might be described in rather generic terms, they need to be converted into a set of specific input parameters (Carson 2005; Shannon 1998) or structural process changes, making them directly implementable in the BPS model. When the number of parameters that need to be investigated becomes large, a formal technique such as a factorial design can be applied for scenario definition purposes (Balci 1990).

Besides scenario definition, **run parameters** also need to be specified for the experiments. These parameters are not related to the simulation model as such, but determine the technical execution of the model. It involves the specification of parameters such as the length of each run (Carson 2005; Law 2007; Law 2009; Shannon 1998; van der Aalst 2015), the length of the warm-up period for each run (Carson 2005; Law 2007; Law 2009) and the number of replications (Altiok and Melamed 2007; Carson 2005).

Based on the specified scenarios, model experimentation involves **running the simulation model** for each scenario according to the specified run parameters (Altiok and Melamed 2007; Law 2007; Nordgren 1995; Shannon 1998). This will generate model outputs, which form the basis for the output analysis.

2.8 Step 8: Output Analysis

When the experiments are executed and the output is generated, the latter needs to be **analyzed** (Kelton et al. 2015; Law 2007; Law 2009). Output analysis can study each scenario in both an absolute and relative sense (Law 2007) and mainly focuses on the output measures agreed upon during project initiation (Carson 2005; Nordgren 1995).

Literature focuses on the **statistical output analysis**, referring to the application of standard statistical techniques such as the creation of confidence intervals to analyze performance metrics over different runs of a single scenario or among several scenarios (Altiok and Melamed 2007; Chung 2004; Hlupic and Robinson 1998; Nordgren 1995; Shannon 1998; van der Aalst 2015). However, it is also important to perform a **business analysis** of these statistical results, implying that the statistical results need to be attributed business meaning. Despite its critical importance, this type of analysis is only occasionally mentioned in literature, e.g., by Altiok and Melamed (2007) and Chung (2004).

After thoroughly analyzing the generated output, the analyst should explicitly formulate **an answer to the simulation study questions**. These are mainly based on the results of model experimentation, but can also contain insights gathered during the simulation model construction process.

2.9 Step 9: Reporting

In the final step of the proposed method, the results of the simulation study need to be disseminated. The simulation model and its results will typically be documented in a **written report** (Carson 2005; Chung 2004, Balci 1990; Law 2007; Rossetti 2010; Shannon 1998; van der Aalst 2015), including an answer to the questions that instigated the simulation study. The report's further content and required degree of formality highly depend on the specificities of the simulation project. Involved staff members might require a very detailed report in which the entire simulation model is outlined in great detail. In that case, it is recommendable to add an executive summary for decision-makers indicating the key results.

Besides a written document, further reporting might be required in the form of a **presentation** (Balci 1990; Carson 2005; Chung 2004; Law 2007; Law 2009). During this presentation, both the model construction process and the obtained results can be discussed (Law 2007). The method presented in this work can help to structure the presentation and enhance its credibility. Even though giving a presentation is only mentioned explicitly here, intermediate formal or informal presentations might be useful to, e.g., involve decision-makers or get feedback from process experts. This underlines the importance of communication with stakeholders (Onggo 2009).

Both the written report and the presentation should contain **recommendations for the decision-makers**. Based on both the insights gathered during model construction and the results of the simulation study, the analyst should be able to formulate suggestions for process improvement (Altiok and Melamed 2007; Hlupic and Robinson 1998). Based on these propositions, decision-makers can decide whether or not process changes are implemented. Consequently, the actual implementation of process changes is outside the scope of the simulation study.

2.10 Continuous Assessment

As indicated in Section 2.6, continuous assessment is included as a central feedback mechanism in the method. It includes all evaluative actions that can cause the simulation project to return to a prior step or redo work in the current step.

2.10.1 Evaluative Actions

The verification and validation step is widely recognized as a moment at which the simulation model is assessed, potentially leading to adjustments of the computer model. However, evaluative actions are required during each step of the simulation study, not only after computer modelling. Even though these activities might have a less formal character, the analyst should be aware of their importance. Consider, e.g., the kick-off meeting during **project initiation**. This meeting can already be a platform to check the accuracy of the formulated problem as process experts are typically present. If the problem statement does not comply with the actual issues that the organization is confronted with, the problem needs to be respecified, necessitating a return to the first step of the method. Moreover, Section 2.2 already indicated that project planning efforts can cause a reduction in the project's scope, causing rework in step 2.

Examples of evaluative activities can also be found in **data collection and analysis**. If the analyst wants to fit a theoretical distribution to the input parameter observations, measures are required to verify how a particular distribution fits the data. Such goodness-of-fit tests include a graphical method (Chung 2004; Robinson 2004), chi-square test (Chung 2004; Robinson 2004), Kolmogorov-Smirnov test (Chung 2004; Robinson 2004), Anderson-Darling test (Law 2007) and square error test (Chung 2004).

Evaluation is also required in the **conceptual modelling** step. The correctness of this model can be inspected by organizing a structured walk-through with process experts (Law 2007; Law 2009). This might provide the analyst with valuable insights that can be used to, e.g., update the conceptual model (Law 2009).

A final illustration focuses on the **model experimentation** step. Scenario specification requires, for example, the specification of parameter values for each of the scenarios (Carson 2005; Shannon 1998). It should be evaluated whether these values make sense in a real-life setting. Moreover, the robustness of the final solution for deviations in parameter values can be checked in a sensitivity analysis (Robinson 2004; Shannon 1998). This can show which parameters have a large impact on the output values and, hence, should be carefully specified (Law 2007; Law 2009).

In summary, evaluative actions tend to be solely included in the verification and validation step after computer modelling. This is probably the moment in the study at which the activities have the most explicit character. However, the previous discussion has shown that evaluative actions are crucial during the entire BPS study. In other phases, it refers more to a critical check of the deliverables of a particular step in the method and might have a less formal character.

2.10.2 Feedback Mechanism

Evaluative actions might require the analyst to (i) return to a previous step in the method to improve its deliverables or (ii) redo work in the current step. This is depicted in the method by including feedback loops. This is consistent with simulation practice as simulation experts indicate that repeating steps and moving back and forward between steps occurs in real-life projects (Ahmed and Robinson 2013).

Several methods in literature include **feedback loops** (Balci 1990; Law 2007; Law 2009; Rossetti 2010; van der Aalst 2015). Consider, e.g., van der Aalst (2015), where each phase is linked to its predecessor. However, it might be required that the study returns multiple steps at once, e.g., when the decision is made to adjust the problem formulation during conceptual model development. When following the method of van der Aalst (2015), the modeler should work backwards instead of returning to the first phase of the method and work forward again. This is not satisfactory and is unlikely to occur in practice. A similar remark holds for Robinson (2004), where a cyclical model with double arrows between the phases is proposed.

In contrast to the existing literature, **continuous assessment** is the central feedback mechanism in the proposed method as it is connected to all the other steps in the method using double-edged arrows. This allows both a return to prior steps and to the current step, depending on the result of the evaluative action. This is consistent with the intuition that a modeler will only return to a prior step or redo work in the current step when there is a discrepancy between the aspired result and the actual result. Consequently, continuous assessment is an antecedent for returning to a prior step or redo work in the current step and, hence, functions as the central feedback mechanism.

3 METHOD VALIDATION

The validity of the proposed method is supported because it is firmly anchored within existing literature. Nevertheless, additional validation efforts are conducted. On the one hand, the method has been presented to simulation experts, as will be briefly discussed in Section 3.1. On the other hand, the model was applied to a simulation project at the emergency department of a hospital. This application is outlined in Section 3.2.

3.1 Expert Evaluation

As indicated at the beginning of Section 2, the proposed method has been validated by presenting it to six simulation experts, three active in academia and three in industry. Even though all experts agreed with the key structure of the method and the content of the different steps, some remarks are formulated. These are evaluated and valuable comments are integrated in the outline of the method in Section 2. The majority of the remarks related to the position of verification and validation, as was already discussed in Section 2.6.1. Moreover, the difficulty to obtain validation data in practice is highlighted by several experts. Another change to the original method is the inclusion of the escape arrow after step 6. The latter is added as several experts indicated that the delivery of a simulation model or even building blocks helping the client to construct their own simulation model can also be a goal of a simulation study.

3.2 Application of the Method to a Real-life Simulation Study

For illustrative purposes, the method presented in Section 2 was applied to a simulation study at the emergency department (ED) of a hospital. Even though a full outline of the project is beyond the scope of this work, Table 1 illustrates how the steps of the method can be operationalized.

From Table 1, it follows that the specificities of the project at hand will influence the relative weight of each of the steps outlined in Section 2. For instance: obtaining formal approval of the ethical committee required several weeks in the ED project, while gaining the required approvals might be an informal act in a business context. Consequently, the method provides sufficient direction to its user, but is flexible enough to be applicable to a wide range of simulation projects. Depending on the characteristics of the project or factors such as the available time, particular steps might have a lower relative weight or be treated in a more informal way.

Table 1: Application of the method to an emergency department simulation study.

Method step	Illustration of method operationalization
Step 1: Problem formulation	• Formulated problem: Conduct an exploratory study to find bottlenecks in the process and evaluate the influence of policy measures with the aim to reduce patient flow time, while maintaining high care standards. • The formulated problem is established during meeting with ED management. • The formulated problem is formalized in a project protocol.
Step 2: Project initiation	• Goal of the project is to build a model that allows the ED for gaining insight in the bottlenecks of the process and evaluate policy measures. • Given the wish to evaluate policy measures and the complexity of the ED's operations, simulation is selected as analysis technique. • The scope of the modelled process is limited to the ED's operations and the mobile emergency unit. • Key input parameters include the patient arrival rate, activity durations, and the resources involved. • Key output measure is the patient flow time.

	• To reduce the required level of detail, e.g., no distinction will be made between different medical specialties involved in the ED's operations. • The simulation model will be constructed using dedicated software. • No strict time limitations are put on the project as no financial resources are involved on the part of the hospital. • Project initiation decisions are established during meetings with ED management and staff involved in the project. • Project initiation decisions are formalized in a project protocol. • Formal approval is requested to the ethical committee, using the project protocol.
Step 3: Data collection and analysis	Data collection: • Preliminary data are gathered by means of a site visit and flowchart collection. • Model specification data are gathered by means of process documentation, questionnaires, observations, and a dataset containing process execution information. • Validation data are made available under the form of a dataset containing process execution information. Using this dataset, flow times can be calculated. Data preparation: • In questionnaires, staff members are asked to provide estimates for the minimum, most likely, and maximum duration of an activity. When a staff member states that the most likely duration exceeds the maximum duration, the provided estimates are removed. • In questionnaires, the staff members should indicate the confidence they have in the answer for each question. The reported confidence is taken into account when determining which estimates to include in the analysis. Data analysis: • The synthesis of the collected flowcharts in an aggregated flowchart forms the basis for the questionnaire. • To determine appropriate values for input parameters, the insights from staff estimates, observations and, when available, insights from dataset are combined.
Step 4: Conceptual modelling	• Insights from data analysis are integrated in a single conceptual model. • A document is created, containing all key information required to build the computer model.
Step 5: Computer modelling	The conceptual model is transferred into a computer model using dedicated software.
Step 6: Verification and validation	Verification: • Identified implementation errors are solved. • Step-by-step simulation of some patients is conducted to discover behavioral anomalies. Validation: • Structured walkthrough of the model with staff members is performed. • Model output is compared to flow times retrieved from data.
Step 7: Model experimentation	• Define a base scenario, i.e., the current situation at the ED. • Define alternative scenarios reflecting the policy measures under consideration. • Determine a warm-up period to integrate the fact that the ED does not start from an empty state.

	• Run parameters are specified to proceed to model running.
Step 8: Output analysis	• Compare results of alternative scenarios to the results of base scenario. • Interpret these results in the context of the ED's operations.
Step 9: Reporting	• Report for ED management, including the applied simulation study methodology. • Present the analysis results to ED management.
Continuous assessment	• Discuss draft research protocol with a staff member. • Check the quality of the synthesis flowchart by requesting feedback in questionnaires. • Evaluate the conceptual model with a staff member.

4 DISCUSSION AND CONCLUSION

This tutorial presented a **method for conducting a simulation study**, comprised of nine steps with continuous assessment as a central feedback mechanism. In literature, a multitude of methods prescribe how to conduct a simulation study. However, they tend to be defined in isolation and are not positioned in relation to other methods. The presented method deals with this lack of integration and combines the strengths of several models in literature and leverages their points of improvement. Its comprehensive nature will avoid that key activities are overlooked and, hence, will provide valuable support to its users. Moreover, the method can be used as a methodological underpinning for the study, e.g., when reporting towards managers or project sponsors. The proposed steps are validated by presenting it to six simulation experts in business and academia. Moreover, for illustrative purposes, the method was applied to a real-life simulation project. This shows that the relative weight of the steps in the method depends upon the specificities of the project, demonstrating the flexibility of the proposed method.

The presented method purposefully has a **high-level character** as it aims to highlight key steps and decisions that are required when conducting a simulation study. Even though this approach leaves more freedom to operationalize the method taking into account the modeler's preferences and the project's specificities, future research efforts can convert the method to the **operational level**. More specifically, analyzing an extensive set of real-life simulation studies can allow for identifying best practices regarding the operationalization of the proposed method. However, one should recognize that providing detailed guidelines is far from trivial, given the wide variety of simulation projects.

A final remark relates to the concepts of **verification and validation**. Even though the proposed method includes these activities after computer modelling, an invitation to reconsider the currently established notions of verification and validation is warranted. Despite pleas by several authors in literature, e.g., Robinson (2004), and Rabe et al. (2008), the current perspective on verification and validation is too limited as it typically focuses solely on the computer model. However, evaluative actions are required during each step of the simulation study, which is not recognized in most existing methods. The presented method captures the latter under the term continuous assessment, but it is closely related to the notions of verification and validation. Consequently, it seems sensible to broaden these latter concepts to encompass all evaluative activities that aim to ensure that an artifact, e.g., the conceptual model, the computer model or the experimental setup, is free from errors and in accordance with business reality. In this case, verification and validation could replace continuous assessment as the central feedback mechanism in the method.

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