Proceedings of the Operational Research Society Simulation Workshop 2021 (SW21)
M. Fakhimi, D. Robertson, and T. Boness, eds.
DOI: https://doi.org/10.36819/SW21.021

DEVELOPING A DISCRETE EVENT SIMULATION MODEL USING QUALITATIVE AND QUANTITATIVE DATA SOURCES

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ABSTRACT

This paper will discuss the development process of discrete event simulation models with regards to using data from multiple sources, that may be gathered both quantitatively and qualitatively, before being incorporated into a single simulation model. The aim of this paper is to more formalise the less discussed qualitative practices in simulation modelling. There will be a brief overview of where this has been touched upon previously in literature, before moving on to the most commonly occurring research methods and types of data gathered; and how these can be incorporated into a model. This paper will go on to consider potential benefits and drawbacks to this approach before presenting an application of how this thinking was applied to a research project.

Keywords: Discrete Event Simulation, Mixed Methods, Police Custody

1 INTRODUCTION

Computer based simulation models are developed using a variety of information from different sources. In many published papers that review the development of an operational research-based simulation model for an application, the quantitative dataset is often the only data source discussed. There is little mention of the other data sources that contribute to the development and testing of discrete event simulation models. However, in order to develop an accurate imitation of a system, the modeller must first have some understanding of this system, such as the inputs, outputs, order of processes, etc. This information cannot usually be gleaned from quantitative data alone, so it stands that the modeller must have learned about the system from an alternate source. This could be from conversations with managers/operators within the system, from spending time observing the system, from previous literature, etc. Experienced simulation modellers often incorporate this information into the simulation modelling process intuitively and with little discussion. Consequently, there is little guidance on how this can be achieved, or how the information can be extracted for novice modellers. This paper will attempt to will describe the data collection needs and to define the process for modellers to follow, so as to further understand how, as modellers, we develop our simulations. This paper will specifically look at discrete event simulation modelling and provide an example of an application of the process.

2 LITERATURE REVIEW

A simulation is a computer-based model that aims to replicate a real-life situation, where the modelled can experiment with different parameters to better understand how the system may behave under different circumstances (Law 2007; Robinson 2004; Pidd 2004). In order to build such a model, the relevant system is broken down into its components; including but not limited to, the service receiver, the resources available within the system and the tasks/stages that make up the system as a whole. There are various simulation modelling approaches including agent-based modelling, continuous modelling, and discrete event simulation. A system dynamics (or continuous modelling) simulation model represents environments through stocks and flows and is applicable to a wide range of situations from engineering to socioeconomics. Agent based modelling works by modelling the 'agents' within a system and their behaviours and interactions and is commonly used in modelling pharmacological systems. Monte Carlo simulation focuses more on the outcomes of scenario and is most often used to model risk. However, this paper is going to focus specifically on discrete event simulation modelling (DES). A DES model 'models the operation of a system as a discrete sequence of events in time' (Sharma, 2015). Once an event or activity ends, the simulation moves onto the next activity, and this repeats until the service receiver has reached the end of the activities relevant to their path and they exit the system. The completion time for each stage is commonly based on statistical distributions, derived from a quantitative dataset, so as to accurately imitate the length of time the service receiver spends in the system.

Pidd (2004) describes the 3 types of data collection for the purpose of modelling – contextual data, model realisation and model validation. Contextual data is information used to understand the system being modelled, model realisation data is required to develop the model and model validation data used to check the model is fit for purpose. Contextual data is primarily what this paper is discussing for the use of qualitative data, however depending on the situation being simulated, this discussion may also apply to the model realisation data and model validation.

Mixed methods research has multiple definitions but for the purpose of this paper will be defined as the type of research in which a researcher, or a team of researchers, integrates qualitative and quantitative approaches within a single study or a set of closely related studies (Creswell and Plano-Clark, 2007; Johnson et al, 2007) Research methods can usually be classified into either quantitative or qualitative quite clearly. Quantitative methods are generally considered to be empirical studies where variables can be reliably measured; whereas qualitative methods are variables that are better described rather than measured (Newman et al., 1998). The difference is that with simulation modelling, whilst usually considered to be quantitative, there are the multiple stages of data collection, as defined above, that contribute to the overall simulation model, and these are not necessarily all quantitative.

There is some literature regarding how qualitative data can be included in a discrete event simulation model. One example of this is Partisim (Kotiadis and Tako, 2015), a framework for conducting facilitated workshops with the various stakeholders within a system and how the information gleaned from these sessions can be incorporated into a simulation model. On the subject of problem definition, the first stage of developing a simulation model, Kotiadis (2007) discussed how Soft Systems Methodology can be used to define study objectives. The ideas in these papers are quite specific, whereas this paper aims to give a more general approach to qualitative and quantitative data in a simulation model.

There are seven generally accepted stages of discrete event simulation modelling – problem definition, conceptual modelling, data collection and analysis, model development, validation and verification, experimentation, and implementation (Tako, 2011). Each one of these stages requires data to progress and move on to the consequent stage of the process. In the next sections, these stages will be broken down as to the type of data that is required and the possible sources to obtain that data from.

3 DATA SOURCES

Incorporating the qualitative research into a simulation framework is something that has been touched upon in literature and specific frameworks developed (Partisim, etc.) but there is minimal general guidance on how to blend qualitative research with a quantitative simulation approach for a novice modeller. With the data collected through the various methods as outlined above, the findings can be applied at the different stages of modelling, to fill in or expand on the knowledge required for a more accurate simulation model. It is worth noting that due to the iterative nature of simulation modelling, data collection may take place at any point in time during the model development process, even this data could be used in the initial modelling stages such as problem definition.

The most commonly discussed data used to develop a simulation model is the quantitative type of data often used for the model realisation and model validation. For a discrete event simulation model, this can be a series of times activities take place, a timetable/count of available resources, etc. However, contextual data required for understanding the situation and for developing a simulation model, normally part of the earlier modelling stages, may come from alternative sources as it is difficult to gain a sufficient understanding of the system solely by viewing the quantitative dataset. For this at least one further source of data is required.

Data sources can be either qualitative or quantitative or both and can be collected formally, by following the traditional data collection techniques, e.g., ethnographic observations, structured/semi-structured interviews, scientific experiments, questionnaires, etc., or informally, for example through general meetings, conversations, etc. Examples of data sources for simulation could be a meeting with a stakeholder/manager where the system and the aims for the simulation model are discussed, ethnographic observations conducted by the researcher, discussions with various staff within the system, etc. While the data the researcher takes away from these actions may not be as obviously impactful as a large dataset, it can still provide context, and result in amendments made to the model throughout the process, thus contributing to the simulation process.

4 MODELLING STAGES

As discussed in the previous sections, the modelling process can be broken down into seven stages and the possible incorporation of data at each stage will be discussed below, but it should be noted that this list is not exclusive. Depending on the system being modelled and the aims of the research, there may be further possibilities to incorporate data from alternate sources.

Problem definition is the first stage in developing a simulation model, where the aims of the project and the system being modelled are defined. In order to narrow down the problem, the modeller must acquire some relevant knowledge of the system being modelled and the situation within the system that requires attention. This can come often from a stakeholder as an issue that they are having in the form of a conversation – whether by email, in person, etc. In this manner a modeller is receiving data relevant to their model that will assist them in eventually developing their simulation. This data can often initially be considered qualitative – close to the form of an informal interview or survey. A modeller then may perform some simple analysis to identify themes within the responses and further define the problem and narrow down their focus and aims for the model.

Conceptual modelling can be defined as ‘a non-software specific description of the computer simulation model (that will be, is or has been developed), describing the objectives, inputs, outputs, content, assumptions and simplifications of the model’ (Robinson, 2008). The data to develop a conceptual model can be gathered from a multitude of sources, for example, through observations. The quantitative dataset can be used to deduce the stages of a system and its inputs and outputs, but qualitative data may give the modeller a better overview of the different stages of a system and an idea of what data is recorded throughout the process and how the entities flow through the process and the different paths they may take.

The next stage is data collection and analysis. This is required so as the conceptual model can be actualised into the computer model. Clearly the quantitative dataset is key at this stage and will principally be featured in the analysis. However, the qualitative, background data can be used to decide what quantitative data is available or useful.

Developing the computer simulation model is a combination of the conceptual modelling stage and the quantitative data analysis, so the data that was used in these stages is indirectly used and combined for this stage.

Validation and verification are necessary to ensure the model is fit for purpose. There are various ways to validate and verify a simulation model, as documented in literature. Verification in this paper will be defined as “ensuring that the computer program of the computerized model and its implementation are correct” (Sargent, 2013) and can be assessed through comparison with analytic results, input-output combinations, etc. Qualitative approaches to validating the computer model is correct can include having it checked by shareholders through focus groups, interviews and other research methods featuring interactions between modellers and participants and can be defined as "the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model" (Thacker et al., 2004).

Experimentation is the testing of various scenarios using the simulation model to achieve the objectives defined for the study. Deciding the appropriate scenarios to test is one of the key challenges for a modeller, as the results from these experiments determine the outcomes and conclusions drawn that inform the stakeholders. The scenario testing needs to be robust enough for the modeller to have confidence in their results, but specific enough that they are still of use to the shareholder. Determining these scenarios can be deduced from a quantitative dataset, however in order to do this the modeller would need to have a clear understanding of the system, which comes from the contextual data. Observations of the system can give the modeller an idea of what scenarios may need to be tested, and discussions with people within the system (through interviews, meetings, focus groups, etc.) can provide the modeller with direction and/or confirmation of which scenarios to test and on what scale.

While implementation of the results ordinarily falls to the stakeholders of the project, the modeller has responsibility for the recommendations provided based on their simulation model. Having a good understanding of the system and its limitations, through contextual data, can aid the modeller in providing more realistic recommendations to managers, etc. of the system. This ultimately makes the model more useful and valuable to stakeholders.

5 BENEFITS AND DRAWBACKS OF USING QUALITATIVE DATA

The benefits to using a mixed method approach to research has been widely discussed (Amalki, 2016; Mayoh and Onwuegbuzie, 2013, etc.), so this paper will discuss the benefits of incorporating qualitative data into the simulation modelling process, as discussed above. One of the clear advantages is that the modeller would have more detailed knowledge of the system being modelled and a better understanding of the problem being explored. This can allow the modeller to determine what is more useful for the problem being modelled and exclude aspects deemed irrelevant leading to a, potentially, more relevant simulation. However, the possible danger in doing this, is that if irrelevant information is not removed, the simulation model may become overcomplicated with too much detail making the results harder to analyse for purpose and the model slower to run on the computer (Robinson, 2004).

Another benefit to this approach is that using multiple types of data/data sources can offset the weaknesses of a single source or data type. Quantitative data sets alone may not give a modeller the full picture, and qualitative data can be used to fill in the gaps. Multiple data sources may also aid to limit the bias in the data and any bias from the researcher. The obvious drawback to collecting data from multiple sources, is that it can be time consuming. There may also be data gathered that is a repeat of previous data, so the modeller may be duplicating work. Alternately data from two sources may produce conflicting data, in which case the modeller must decide how to mediate this.

One of the difficulties in this method of working is that it may be difficult for the modeller to gain access to certain data, or it may take more resources to gather. This may be particularly true for qualitative data when using a method such as interviews or focus groups, which can be hard to arrange or incentivize. However, it does offer the opportunity to include the stakeholders and people who work within the system to have more involvement in the modelling process. This can help stakeholders to remain interested in the research, and to be more motivated to implement results.

6 APPLICATION EXAMPLE

We will now present a case study of how this thinking was applied in practice to develop a police custody simulation model. With budget cuts and resource reduction in UK police forces, it is necessary for the forces to manage their resources effectively, so as to meet demand. Police custody is just one of the aspects of policing that has faced shortages due to the budget cuts. A discrete event simulation model of a police custody suite was developed following the approach discussed previously for the purpose of resource optimization. Previous discrete event simulation models were developed of police custody (Greasley, 1998, 2000 and 2001), one of which addressed resource allocation. However, these were before the current issues, and the system of police custody has faced multiple changes since these models were developed. This research was conducted to update and provide a deeper understanding of this system. The system was broken down into the service receiver (detainees), resources (cells and staff) and the tasks that occur (e.g., booking-in, interviewing etc,). The primary objectives were to model the system and its resources to see if there were any bottlenecks, and if the resources could be more effectively used to meet demand.

6.1 Data Sources

Due to the limited literature available regarding the stages and resources in police custody, combined with the modellers lack of knowledge in this area, it was clear that substantial contextual data was required. Having viewed the quantitative data that was available for the research, it was considered sufficient for model realization data, but it did not provide enough context, so alternative data sources were sought, and quantitative research conducted. The stages of simulation followed are outlined in Figure 1 below, along with the data sources used.

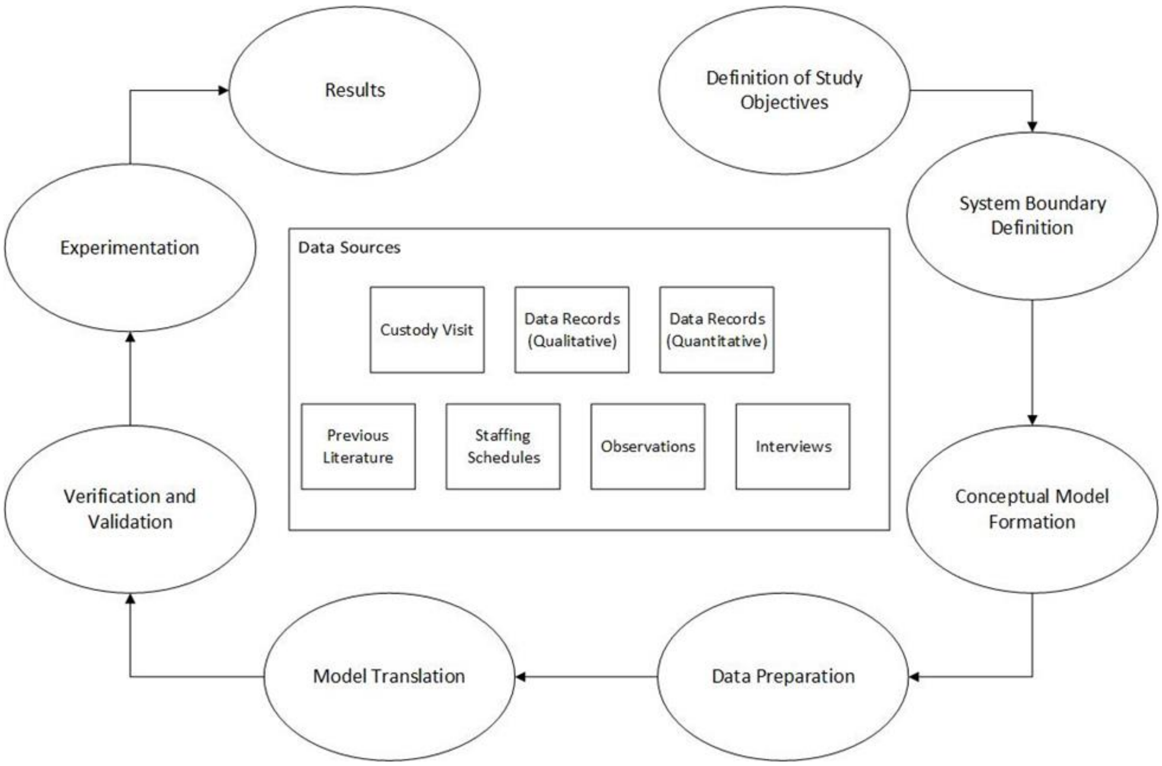

Figure 1. Data Sources and Simulation Process.

The data sources, as specified above, were a custody visit, the data records – both qualitative and quantitative information, previous literature, staffing schedules, observations, and interviews. When the project was first initiated, a visit and tour of a custody suite was organized first. During this, officers explained the processes and stages of police custody and answered any questions about the system. The data records provided by the involved police forces contained quantitative timings for each of the stages being modelled, as well as some qualitative data in the form of written comments attached to the relevant stage. This dataset did not provide data on the types of resources available in the system, or which resources were required at each stage of the process. Staffing schedules were also provided. The previous literature (Greasley, 1998, 2000 and 2001), provided some contextual data of the system but due to time of publishing of these papers, this data was considered informative but outdated. Observations conducted in police custody took place in multiple suites, over a period of months on varying days and times. This was to ensure the modellers view of the system was not biased by a particular suite or time of day, so the modelling was more robust. Interviews took place with staff members in every role within a custody suite, in different custody suites, again to reduce bias.

6.2 Modelling Process

There were a few aspects to the problem definition stage of modelling – defining the system to be modelled, the issue to be explored and the objectives of the study. In this study the data sources used to define these were the custody visit, the observations, the interviews, and the previous literature. The previous literature (including the custody inspection reports) were used to give a general view of the situation within custody and how issues had been tackled previously. The custody visits and observations allowed for the system to be viewed and observed to help define the system from the researchers' point of view, whereas the interviews took into account the problems as considered by the experts. This stage of the modelling process was conducted entirely through qualitative data; it would have been very difficult to complete it without this.

The next stage was the conceptual modelling stage. The data sources used for the conceptual model of police custody were previous literature, custody visit, the qualitative aspect of the data records and the observations. The previous literature gave a base model to build on with further data gleaned about the system from the additional data sources. The qualitative data gleaned for the data set and the custody visit helped to update this initial model. During the observations attention was paid to the paths detainees took through the system and the resources that were involved at each stage, which aided in fleshing out the conceptual model. This stage, again, was completed almost entirely from qualitative data.

Data collection and analysis were conducted next. The quantitative data records are clearly an integral part of this stage; however, the previous literature and custody visit were used to help define what data specifically needed to be collected. Based on the previous literature, particularly Greasley (1998) where resource allocation was discussed, a general idea could be gathered of the stages of custody, as they had used data to model these stages. The custody visit gave a tour of custody and the shareholders explained what data was collected at each stage, making it easier to choose what was relevant and available.

Developing the computer simulation model was a combination of the conceptual modelling stage and the quantitative data analysis, so the data that was used at this stage is indirectly used for this one too. The staffing schedules were also incorporated into the model when considering resource levels and availability.

Validation and verification are necessary to ensure the model is fit for purpose. In this instance, a second smaller quantitative dataset was analysed and measured against the simulation model for validation. Through observations, the modeller was able to verify the model and in interviews, the model was presented to the staff in the various roles within custody, for them to verify as well. The quantitative aspect to this stage made the verification stage more robust, in that it was verified by multiple people within depth knowledge of the system being modelled.

The experiments, the testing of various scenarios using the simulation model, were run with the model developed in the previous stages. The scenarios that were tested were deduced using data obtained through interviews and observations. The input of people working within this system was invaluable at this stage, as it provided guidance and much more insight the modeller could have gained alone.

This research is still ongoing, but in the final stage of implementation, it is believed that the contextual data gathered from the custody visit, observations, and interviews, will give the modeller a better sense of judgement as to what recommendations were realistic, and more likely to be implemented in practice.

7 CONCLUSION

In conclusion, discrete event simulation modelling is generally considered to be a quantitative research method, but this paper has discussed how the data used in developing a simulation model for an application usually comes from multiple sources, particularly the contextual data, and tried to further the discussion in how this can more formalized. These data sources could be either quantitative or qualitative and may contribute to the simulation model at different stages. Whilst there are both advantages and disadvantages to using multiple data sources or research methods, there are situations where it can be of benefit, such as the example explained, where there was a lack of contextual data available. The next stage in this research would be to develop a framework on how quantitative and qualitative data can be clearly incorporated into a single process, to develop a simulation model.

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