



Modelling People's Behaviour using Discrete-Event Simulation: A Review

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Abstract

Purpose

The purpose of this paper is to provide a contribution to the area of behavioural operations management by identifying key challenges in the use of discrete-event simulation (DES) to model people's behaviour in Operations Management (OM).

Design/methodology/approach

A systematic literature review method is undertaken in order to assess the nature and scale of all publications relevant to the topic of modelling people's behaviour with DES in OM within the period 2005 to 2017.

Findings

The publications identified by the literature review reveal key challenges to be addressed when aiming to increase the use of DES to model people's behaviour. The review also finds a variety of strategies in use to model people's behaviour using DES in OM applications.

Research limitations/implications

A systematic literature review method is undertaken in order to include all publications relevant to the topic of modelling people's behaviour with DES in the OM domain but some articles may not have been captured.

Originality/value

The literature review provides a resource in terms of identifying exemplars of the variety of methods used to model people's behaviour using DES in OM. The study indicates key challenges for increasing the use of DES in this area and builds on current DES development methodologies by presenting a methodology for modelling people's behaviour in OM.

Keywords: behavioural operations, discrete-event simulation, human behaviour, simulation methodology, systematic literature review

1. Introduction

Interest in behavioural operations management has a long history with Cummings (1977) stating that both behavioural and system constructs are crucial in studying, designing and evaluating production systems. Bendoly and Schultz (2006) present a special journal issue on the topic of incorporating behavioural theory in Operations Management (OM) empirical models. Within that journal issue an article by Bendoly et al. (2006) provide a review of papers published between 1985 and 2005 on behavioural research in operations management. They state that the success of the implementation of operations management tools and techniques, and the accuracy of its theories, relies heavily on our understanding of human behaviour. A 'follow on' special issue is presented in 2013 (Croson et al., 2013). Here the importance of the identification of individual differences, rather than the average response of people is emphasised. A further overview of behavioural operations management studies is provided in Zhao et al. (2013). Neumann and Dul (2010) report on an increasing interest in human issues in operations management and find through a systematic review of literature that operating system performance co-varies with the effects of human behaviour in 95% of studies that looked at both elements in human factor applications. Operations management areas such as lean management, with its related topics of mass customisation, flexibility and agility stress the very important role of the workforce, seen as a main asset and a source of competitive advantage (Liker and Convis, 2011). The modern workplace is characterised by frequent product and process change in addition to worker turnover and absenteeism. In this environment, workers must adapt to learn new tasks frequently, while at the same time responding to demand in the shortest possible time (Nembhard, 2014). Workers in these systems will have specific skills and a level of flexibility, which are highly individual qualities and the treatment of all employees as identical in terms of their manual skills, ability to learn and ability to cope with difficult situations is a major simplification (Malachowski and Korytkowski, 2016).

One way of studying the effect of human behaviour on operations performance is to use modelling techniques and the representation and prediction of human behaviour is seen by some authors as currently the most significant and unanswered modelling challenge (Taylor et al., 2015). However models have been criticized for their failure to attend to human aspects in the operations management domain. For example while recognising the essential role of simplification in model building, Boudreau et al. (2003) state that OM researchers and managers may not always be aware of the consequences these simplifications can have on decision making. Amongst the common assumptions used to represent people in OM models that can lead to omission of important features of the system are that people are not a major factor (many models look at machines without people, so the human side is omitted entirely), people are deterministic and predictable, people have perfect availability (no breaks, absenteeism, etc.), task times are deterministic, mistakes do not happen, or mistakes occur randomly and workers are identical (work at the same speed, have the same values, and respond to the same incentives) (Boudreau et al., 2003). Dode et al (2016) found that models that do not include human aspects may provide unreliable results in terms of productivity and quality estimates. However it is clear that it is difficult for humans to model themselves for a number of reasons which include the fact that people are complex entities that generate various behaviours that are often context dependent and people acting as modellers often have constrained understanding, knowledge and data about themselves, about the modelling context and about related causal impacts (Ajaefobi et al. 2010).

One technique that has shown the capability to model human behaviour in OM systems is that of Discrete-Event Simulation. One example of this is in Nembhard (2014) who states that simulation is used to study a dynamic workplace due to the extreme complexity of using closed form analytical models. Discrete-Event Simulation (DES) (Pidd, 2006; Robinson, 2014) is widely used in the design of manufacturing (Greasley, 2005) and service operations (Shi et al., 2015). Simulation offers a way to investigate the behaviour of complex systems, and through the building of computer models and what-if experimentation, to explore and better understand the system behaviour (Kelton et al., 2007). There are a number of different approaches to simulation, including System Dynamics (SD) (Sterman, 2000, Morecroft, 2007), Agent Based Modelling (North and Macal, 2007) and Discrete Event Simulation (Kelton et al., 2007). Discrete Event Simulation involves building models of systems that consist of a number of building blocks including processes, entities and resources (Pidd, 2006) and so is particularly suited to the process orientation of OM.

The need for DES studies to include the modelling of human behaviour in OM systems has been recognised for some time with for example Juran and Schruben (2004) reporting the need for DES to incorporate accurate representations of individual worker behaviour in highly technical industries such as semiconductor manufacturing and service industries such as banking. However in 2004 Baines et al. (2004) found that human aspects were rarely included in DES studies and can be seen as the 'missing link' in manufacturing simulation. Hudlicka and Zacharias (2005) found that the standard approach in DES to modelling people is to model *nominal* behaviour, resulting in simulations that can be highly predictable across distinct situations and uniform across individuals. More recently Nembhard (2014) remarks how simulation studies in OM still commonly base their findings on a homogeneous and hypothetical workforce and presents a DES of a heterogeneous population informed by an empirically measured workforce. A systematic literature review of articles that have used DES to model human behaviour in OM since the 'missing link' article of Baines covering the years 2005-2017 is undertaken to assess the nature and scale of articles published in this area and to identify challenges to the wider use of DES to model human behaviour in OM.

2. Method

Current reviews of the use of simulation are usually based within an application domain such as manufacturing (Negahban and Smith, 2014) or focus on a specific application (Gul and Guneri, 2015). In order to provide an overview of the nature and scale of articles presenting the use of DES to model people's behaviour in OM, and due to the lack of any current reviews of this nature, a systematic literature search was performed using the Scopus, ScienceDirect, Google Scholar and Emerald Insight databases. To focus on contemporary implementations of discrete-event simulation it was decided *a priori* that the search would be restricted to studies from 2005 to 2017. The identified keyword terms *simulat** in combination with either *discrete-event* or *discrete event* was searched to identify studies in the domain of discrete-event simulation. These keywords were combined with the keyword terms *human**, *people*, *person*, *individual** to identify discrete-event simulation studies in the domain of modelling people's behaviour. Papers were filtered for relevance to the field of OM and providing simulation model implementation details by title and then at abstract and article level in accordance with inclusion and exclusion criteria (see table 1).

Take in Table 1 Inclusion and exclusion criteria for the studies reviewed

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3 The review of titles, abstracts and articles was undertaken independently by the authors of this
4 article during January and February 2017 and January 2018 to ensure validity. The review follows the
5 Preferred Reporting Items for Systematic reviews and Meta-Analysis (PRISMA) guidelines (Moher et
6 al., 2009) and the procedure is shown in figure 1.
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9 **Take in Figure 1** PRISMA flow diagram illustrating the literature review procedure

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11 The inclusion criteria restrict articles to those that demonstrate the use of DES to model the effect of
12 human behaviour on performance in the area of operations management and provide details of an
13 application of this with reported results. This is to enable an analysis to be made of the actual
14 methods employed to model human behaviour in the context of a DES study which could be placed
15 within an application framework. The exclusion criteria (numbered 1 to 5) are shown in brackets in
16 figure 1 and can be cross-referenced with the criteria numbered in table 1. Exclusion criteria number
17 4 concerns a particular type of article that was excluded on the basis that it modelled outcomes in
18 terms of human performance itself rather than the effect of human behaviour on operations
19 performance. These articles generally use task analysis conducted using the Micro Saint DES which
20 may be embedded in human performance modelling tools such as the Improved Performance
21 Research Integration Tool (IMPRINT), the Man-Machine Integration Design and Analysis System
22 (MIDAS) and the Integrated Performance Modeling Environment (IPME) (Harriott and Adams, 2013).
23 Thus the literature review found 29 articles that met the criteria filtered from an original search
24 count of 4401. These articles are listed in table 2.
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29 **Take in Table 2** Articles reporting on the use of DES to model people's behaviour (2005-2017)

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31 In terms of a statistical analysis of the review results it is apparent that there are relatively few
32 applications of DES that model people's behaviour in the literature. Figure 2 shows the distribution
33 of the articles presented in table 2 over the publication years 2005-2017. Although each year has at
34 least one publication the level of publication output is generally low throughout the publication
35 period covered. One reason for this low level of publication is due to the strict criteria of the
36 literature review of requiring implementation details of the model within the papers selected which
37 is essential in order to conduct a critical assessment of the methods used to model people's
38 behaviour. The lack of detail in documentation of discrete event simulation modelling efforts
39 reported in the literature and its implications for reproducible research is discussed in Uhrmacher et
40 al. (2016).
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44 **Take in Figure 2** Articles of Modelling People's Behaviour using DES by Year

45 46 **3. Findings**

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48 In order to assess how people's behaviour was modelled using DES within the articles identified by
49 the literature review we need to consider the initial phases of the simulation study process. Once
50 the modeller has gained an understanding of the problem situation they will need to determine the
51 simulation study objectives. These objectives then lead to the design of a conceptual model which
52 provides a specification for the data requirements of the different areas of the model such as
53 customer arrivals and process times. In a traditional simulation study methodology these data
54 requirements do not consider the issue of modelling people within the model specifically. Here we
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use these generic definitions of the areas of data requirements and relate them to the areas in which we can model people's behaviour. Thus based on the data requirements of a simulation model defined in Greasley (2004) the aspect of people's behaviour we may wish to model can be classified as following:

- Modelling People's Decisions (Decision Points) : Logic data defining the process flow undertaken by people in the model including decision points. Decision points may be modelled using conditional (if.. then, else) rules or probability distributions.
- Modelling People's Availability (Resource Availability) : This defines the availability of a person over time, such as a work schedule.
- Modelling People's Task Performance (Process Timing) : Process or task durations which define the time taken by a person to undertake a task.
- Modelling People's Arrivals (Demand Pattern) : The arrival rate of people into the simulation, such as customer arrivals.
- Modelling People's Movement (Process Routing) : The movement of people through the process represented in an animated display.

Each article from the literature review is now placed within one or more of the modelling area categories defined above and a critical assessment made of the implementation focusing on the data requirements challenges in these areas.

Modelling People's Decisions

Four articles have been identified that model people's decisions from the literature review. Here no cognitive models are employed so the main issue is the codification of the decision process. This is generally achieved using data gathered from observation and interviewing of the decision makers involved. For example Elliman et al. (2005) codify 'at-will' tasks (tasks for which people can decide themselves on the sequence that they are attempted) by the use of variables that were related to the task itself (for example task deadline) but also to organisational variables such as the importance of the customer of the task. Majid and Herawan (2013) codify the proactive behaviour of staff in a customer processing system. The speeding up of service is triggered by the appearance of long customer queues. Hannah and Neal (2014) treat the decision process as a 2-stage process with tasks selected for execution but then considered for either immediate execution or deferral until a later time depending on variables such as workload and time to deadline. Finally Kokkinou and Cranage (2011) use an online scenario-based survey to identify relevant variables and derive a regression equation for the choice between self-service or manual service in a hotel check-in process. The authors cite the use of an online survey design as a relatively inexpensive and fast way to collect data on customer preferences before implementation of a system.

Modelling People's Availability

Two articles were identified as modelling people's availability in the literature review. A relatively straightforward approach was taken by Lassila et al. (2005) who used a theoretical distribution to represent the unavailability of workers due to off-station work tasks or not work related activities. Neumann and Medbo (2009) (earlier version in Neumann et al., 2006) consider operators work autonomy and operators work capacity (ability to work at a standard pace). Autonomy is postulated as the ability to take breaks (which occur randomly) with low autonomy equal to 20% of rest breaks taken when desired and high autonomy equal to 100% of rest breaks taken when desired. The authors note that validating this relationship requires a field experiment that remains for future research.

Modelling People's Task Performance

The area of task performance dominates the articles found by the literature review with 19 from 29 articles in this category.

A number of articles presented implementations that gather data on operator performance in order to provide sample data for a task time theoretical distribution. For example Mason et al. (2005) collect empirical data on operator performance using an automated measurement system within a factory and then use curve fitting software to fit a distribution to the activity data. Kozine (2007) (previously in Kozine, 2006) investigates the probability of task (action) failure at a Nuclear power plant. The data collection method is not defined but the task duration is modelling using an exponential distribution and the successful completion of a task within a set time is viewed as a consequence of the ability of the person and the demands of the task. Silva et al. (2014) models the variation in performance of assembly line operators which uses empirical data regarding each operator's performance. Whilst the majority of studies required the instigation of data collection activities for the model this investigation was enabled by the use of current data held by the company on a database. Perez et al. (2015) and Neumann and Medbo (2017) both model variation in cycle times of factory operations using a gamma distribution as suggested by Law and Kelton (1991) as being appropriate for modelling manual work. Shewchuk et al. (2017) collect data using observation and video recording for use in distributions to represent activity times in a multi-worker construction process. McHaney (2008) provides a method of modelling personas which are fictionalised descriptions of people using archetypes of people's behaviour. The collection of data through observation at the archetype level of abstraction provides a way of improving model accuracy without the need to collect data at the individual level.

Rather than using a theoretical distribution to represent task times a number of articles presented implementations that collected data on a range of variables that were used within a mathematical equation to represent worker tasks time. For example Nehme et al. (2008) simulated differences in operator performance using a parabolic function that relates operator utilisation to performance. Khalil and Weston (2009) model worker performance as the multiplication of worker accuracy (percentage of successfully completed jobs) and worker speed (rate of jobs completed). Nembhard (2014) models cross-training policies using empirical data collected by observation that is used to parameterise an equation of individual worker learning and forgetting. It was found that a number of articles make use of learning curve equations but again approaches differ in terms of the parameters of the equations and the context in which they are used. These include Ilar (2008) who studies the impact of worker competence on productivity in a highly automated press line. Neumann

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3 and Medbo (2017) assess the effect of 3 levels of learning rate on operator performance. All
4 operators are assumed to have the same learning rate and the authors note that there is little data
5 available on inter-individual learning rate variability in assembly work. Wang et al. (2013) collect
6 empirical data related to variables such as experience, age and dexterity which are used as
7 parameters for a worker's performance. Dode et al. (2016) model the learning effect at a
8 workstation level rather than at the individual worker level. Malachowski and Korytkowski (2016)
9 model multiple skilled operators on a production line by the use of a set of competences required at
10 each workstation to each of which is assigned a different learning curve. The article shows how
11 work experience on one working post translates into performance on other posts, thus enabling
12 better workforce scheduling.
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15 The next approach is to use empirical data applied to models of human behaviour. For
16 example Plott (2006) uses empirical data from human factors and material handling literature so
17 that the impact of excessive work stress on decreasing productivity (i.e. task time) could be
18 modelled. Kazmierczak et al. (2007) use a variety of data collection methods including the use of
19 video recording of operator actions. As with Plott (2006) the main focus of the article is regarding
20 physical aspects of performance but again behavioural factors were incorporated into the analysis
21 including level of operator experience, operator cycle time at work stations and cycle time variation
22 at work stations. Colombi and Ward (2010) use Human Computer Interaction (HCI) models to assess
23 the surveillance time for people when controlling unmanned aircraft from a computer terminal.
24 Ajaefobi et al (2010) model the effect of the competence of operators in a manufacturing plant. A
25 standard mix of basic, practitioner and expert operators are compared to a system with expert
26 operators only.
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29 Finally one example is presented of the use of a cognitive model of human behaviour. Riedel
30 et al. (2009) model human competence based on the PSI theory (Detje and Kuenzel, 2003). Task
31 performance is modelled over time showing how competence oscillates dependent on experienced
32 success and failure at a new task. This approach provides an alternative to the traditional learning
33 curve effect which implies a continuous improvement over time without any setbacks in
34 performance due to failures.
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39 *Modelling People's Arrivals*

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41 Two articles were identified as modelling people's arrivals in the literature review. Knight et al.
42 (2012) attempt to codify the decision of individual patients when choosing a hospital unit to attend
43 and deciding whether to actually attend that hospital. The decision is codified using hospital
44 reputation, waiting list at the hospital, travel distance to that particular hospital from a demand
45 node and level of irrational attraction or repulsion of a patient for a particular hospital unit.
46 Brailsford et al. (2012) (previous version is in Brailsford et al., 2006) however employs a cognitive
47 modelling approach in the form of the Theory of Planned Behaviour (TPB) cognitive model (Ajzen,
48 1991) to predict attendance for breast cancer screening sessions. The TPB takes empirical data on
49 demographic variables and personality traits and transforms these to attitudes towards behaviour,
50 subject norms and perceived behavioural control.
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54 *Modelling People's Movement*

Two articles were identified as modelling people's movement in the literature review. Dubiel and Tsimhoni (2005) present a DES model in Automod which provides an animation of a theme-park where people interact with objects and other people in their environment to get directions and then walk or take a tram to their final destination. Robinson (2015) presents a DES model on the platform of the Excel spreadsheet with the simulation coded in the embedded Visual Basic for Applications (VBA) programming software. Customers move across a grid using a shortest path rule (expressed as an equation). The article states that the approach used is arguably a mixed DES/ABS model and Dubiel and Tsimhoni (2005) also describe their implementation as an hybrid approach in which an agent-based module within the discrete-event simulation environment is used to model the movement of people.

4. Discussion

An important outcome of the review is the identification of a number of articles published presenting implementations of the modelling of people's behaviour. These articles cover modelling using DES in all the main areas of a model requiring data collection. The papers also cover many aspects of people's behaviour in operations including the modelling of stress, physical tiredness, competence, attendance, skill levels, capability and flexibility. In order to facilitate the incorporation of people's behaviour in OM models there now follows a discussion regarding the nature of the cost and workload required when modelling human behaviour. Key challenges will then be discussed in the areas of data collection needs and validation requirements for a DES when modelling human behaviour. There then follows a categorisation of the articles found and a methodology is presented to guide the use of DES to model people's behaviour in OM.

As stated in the introduction the ability to model people's behaviour provides an ability to avoid abstracting away people's differences and thus provide a more accurate model for prediction. The abstraction level or level of detail in the model should be based on the study objectives. This can be considered in terms of does the human behaviour affect the goals (output variables) to a sufficient degree that they require consideration in the model? In fact Mason et al. (2005) found that when dealing with larger models with complex system dynamics it is difficult to predict whether the inclusion of people's behaviour will have a significant effect on overall performance or not. However as well as the study objectives there is also a need to consider the effort required to incorporate the modelling of people in the DES in relation to the gains obtained from doing so. In terms of this Bruzzone et al. (2007) discuss the need when contemplating modelling human behaviour to evaluate the modelling impact in terms of cost and workload to introduce these aspects. Within the literature review Ilar (2008) judges an approach suggested (but not implemented) by Baines and Benedettini (2007) might be too complex to be industrially applicable and puts forward a more straightforward method which in their view offers most of the advantages with much less effort. Hannah and Neal (2014) provide a highly simplified representation of the tasks undertaken by people but determine that the level of abstraction is appropriate for the aims of the study. This trade-off between meeting simulation study objectives against the cost and effort of doing may be resolved by adjusting the conceptual model specification in an iterative process until a feasible solution is found (Robinson, 2014). This process is likely to be particularly important in DES studies that incorporate human behaviour because of challenges in two areas.

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3 The first challenge apparent from the literature review is the extensive data collection
4 requirements that are often required when modelling human behaviour. A detailed outline of the
5 enhanced data requirements necessary for modelling people's behaviour is provided by Kazmierczak
6 et al (2007) who used a combination of data collection methods including document analysis, semi-
7 structured group interviews, observation and activity analysis of video recordings. Elliman et al
8 (2005) found that decision-making by knowledge workers (who had discretion over the timing and
9 duration spent on tasks) was complex and based on many factors such as other work commitments
10 implying extensive data collection needs. Some authors presented approaches to limit data
11 collection requirements. For example Neumann and Medbo (2009) operationalised the autonomy of
12 individuals as their ability to take breaks at will from their duties. Two scenarios of high and low
13 autonomy were modelled. This approach limits the need for data collection by using task and
14 environmental variables, rather than individual characteristics to model individual behaviour.
15 McHaney (2008) suggests the use of archetypes to model groups of people who display similar
16 behaviour and so avoid collection of data on behaviour at an individual level. When making
17 customer decisions in service systems Kokkinou and Cranage (2011) make use of an on-line survey to
18 quickly collect data on customer preferences. Finally in most cases simulation practitioners will need
19 to initiate data collection activities but Silva et al. (2014) were able to use current data of people's
20 performance held in a company database.

21
22 The second challenge when modelling people's behaviour, apparent from the literature
23 review, is the difficulty of ensuring model validation. Model validation relates to the idea that the
24 model is wholly adequate and appropriate for the task for which it is intended. Simple though this
25 notion of validation may sound, in practice it can be very difficult to validate a simulation model
26 properly (Pidd, 2006). In terms of validating models that incorporated the behaviour of people a
27 number of authors recognized the difficulty of this process. For example Neumann and Medbo
28 (2009) found difficulty in obtaining empirical evidence to validate the operationalization of human
29 behaviour in their model and suggest the need for field research to provide this validation. They did
30 however find they could study the interaction effect between multiple human factors by using a
31 factorial approach to the simulation experimental design. Colombi and Ward (2010) suggested that
32 the effectiveness of their model could have been improved with additional validation to the real
33 system. Hannah and Neal (2014) used data collected from the behaviour of just two people for their
34 model and recognized the challenge of generalizing the model across different people and different
35 work environments. There are particular challenges when using and validating a DES that uses a
36 cognitive model as in Brailsford et al. (2012) who was able to undertake a validation exercise by
37 comparing simulation results to historical data. The TPB model used in Brailsford et al. (2012) has
38 been widely applied but the challenge in the use of cognitive models is that they are often not
39 validated for a particular implementation context such as an OM system (Silverman et al., 2003).

40
41 Notwithstanding the above challenges the articles presented show that modelling human
42 behaviour using DES in OM is feasible and can lead to more accurate model results. However it is
43 apparent from the literature that there are a number of modelling strategies for achieving this. We
44 will now define these strategies by introducing the categories of modelling approach and modelling
45 method.

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47 Figure 3 outlines the modelling approaches of 'scenario', 'impact' and 'individual'. Each approach is
48 related to a level of abstraction and data requirements when modelling people's behaviour.

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3 **Take in Figure 3** Approaches to modelling people's behaviour
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5 The scenario approach considers the effect of people 'outside' of the model by observing model
6 results under a range of scenarios. Using this approach people's behaviour is codified into a model
7 input variable. For example worker capacity is set to 'normal' or 'low' in Neumann and Medbo
8 (2009) and a scenario run for each value of the variable. The approach is related to DES studies when
9 data is not available for collection and is treated as an experimental factor rather than a fixed
10 parameter. As Robinson (2014) states this approach can only be applied when there is some control
11 over the data in question. The remaining approaches to modelling people in a DES are termed
12 impact and individual (figure 4) and are implemented 'inside' the model.
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16 **Take in Figure 4** Modelling People's behaviour 'inside' the model by impact and individual
17 approaches
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19 The effect of people's behaviour on system performance can be modelled with the use of impact
20 variables that relate to the task that the person is undertaking or to organizational variables that
21 impinge on a person's performance. An example would be to use the impact variable of 'task
22 deadline' to prioritise tasks for processing by a worker in an office as in Elliman et al (2005). In this
23 example data collection is required in terms of the impact variable but it is not necessary to collect
24 data on individual behaviour regarding the decision of task priority. This approach can reflect
25 organizational policies but if individuals have discretion in their work practices their individual
26 preferences are not reflected using this method. If we do wish to assess the effect of individual
27 characteristics on performance then we will need to model these individual differences within the
28 model itself. Using the 'individual' approach the characteristics of people are used to distinguish the
29 differences in behaviour between different people (termed 'across' differences) or differences in
30 behaviour of an individual over time (termed 'within' differences). An example of an across
31 difference is competence level at an operation which will differ across people (for example
32 Malachowski and Korytkowski (2016)). A within difference would be an increase in operating
33 performance of an individual over time such as due to learning effects (for example Nembhard
34 (2014)).
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39 Modelling method strategies can either be data driven to predict human behaviour or cognitive
40 architectures to simulate human mental processes (Campbell and Cannon-Bowers, 2000). Data
41 driven methods comprise deriving a theoretical distribution which is similar to standard practice in a
42 simulation study but using data based on human behaviour (for example Mason (2005) and Lassila et
43 al. (2005)), constructing a mathematical equation such as a learning curve equation (for example
44 Nembhard (2014), Dode et al. (2016) and Malachowski and Korytkowski (2016)) or the direct use of
45 empirical data (for example Ajaefobi et al. (2010), Wang et al. (2013)). Cognitive architectures used
46 to represent the cognitive process include the Physical, Emotional, Cognitive and Social architecture
47 (PECS) (Schmidt, 2000) and Theory of Planned Behaviour (TPB) (Ajzen, 1991) (for example Riedel et
48 al. (2009), Brailsford et al. (2012)).
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51 Table 3 summarises the literature review findings and classifies the papers by modelling
52 method used within each modelling area and modelling approach. These studies should be
53 considered as exemplars rather than prescriptions on the best method to use for a particular
54 modelling area and modelling approach. Indeed in some areas there are exemplars offering a choice
55 of different methods and in some areas no examples have been found from the literature at present.
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3 However an area which shows no current examples does not imply that they could not be
4 appropriate options for a study.
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6 **Take in Table 3** Methods of Modelling People's behaviour categorised by Modelling Area and
7 Modelling Approach
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10 In order to guide the user when modelling people's behaviour figure 5 presents a methodology for
11 modelling people's behaviour based on a development of current DES methodologies presented in
12 Law (2014) and Banks et al. (2014).
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15 **Take in Figure 5** A Methodology for Modelling People's Behaviour in DES
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17 Here simulation objectives are identified which lead to a conceptual model containing a detailed
18 specification of the model requirements. At this stage the user is guided to make choices for
19 modelling people's behaviour in terms of modelling area, then choice of modelling approach and
20 finally choice of modelling method. The current exemplars can be considered from table 3 which
21 may provide useful guidance in these choices.
22

23 At this point we need to assess the feasibility in terms of effort and cost of data collection
24 requirements for the particular modelling aspect chosen. As identified by the literature review this is
25 a key challenge in the model development process and may require that the conceptual model
26 specification be adjusted and a reassessment of the modelling area, approach and method used for
27 modelling people's behaviour. This could mean implementing model simplification strategies
28 (Robinson, 2014) to reduce the scope and level of detail required in the model. This could then
29 remove the need to model some aspects of human behaviour or to replace for example an
30 'individual' modelling approach by a 'scenario' or 'impact' approach which require less demanding
31 data collection needs. The next stage of a traditional simulation methodology is to build the
32 simulation model and to check for coding errors termed verification.
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35 Once verified the validation stage is to ensure that the model represents the real system
36 adequately in terms of meeting the simulation study objectives. This represents the second
37 challenge for representing people's behaviour and if validation cannot be ensured could again
38 involve the redefinition of the conceptual model and a reassessment of the modelling area,
39 approach and method used for modelling people's behaviour. Once validated the DES model can
40 then be used for experimentation and presentation of results.
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45 **5. Conclusions**

46 Bendoly and Prietula (2008) discuss how modelling the behavioural dynamics observable among real
47 humans in various tasks emblematic of OM practice can help refine, occasionally support and, often
48 refute past modelling assumptions and hence present essential contributions that truly can help
49 close gaps between operations research and effective management practice. This article aims to
50 advance the incorporation of behavioural responses in OM models by providing the following
51 contributions. It brings together a record of the publications that demonstrate the use of DES to
52 model people's behaviour in the OM domain. These publications show the relative scarcity of
53 research in this area. This can be seen as due to the lack of model implementation detail provided in
54 the literature and to the major challenges faced when modelling people's behaviour in the areas of
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3 data collection and model validation. The review also found a number of different strategies
4 employed when modelling people's behaviour using simulation and the article presents a new
5 perspective in terms of a methodological approach to making a choice between these strategies in
6 the context of the cost and effort required to implement them.
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8
9 In terms of further work it is apparent that additional publications are needed of modelling
10 people's behaviour using DES which provide sufficient implementation detail to act as exemplars for
11 future efforts in this area. Further work is also needed to provide an assessment of the modelling
12 strategies identified in the literature review. For example a comparison could be made between the
13 use of learning curve equations and cognitive models to represent people's learning behaviours in a
14 particular modelling area at a certain level of required detail. This would require case studies making
15 a critical comparative assessment of these methods in areas such as the effort required in data
16 collection and the improvement in model accuracy. Finally there is an extended literature on
17 cognitive models of human behaviour in areas such as organisational behaviour, defence and health
18 systems and work is needed to apply and test these models for use in an OM context.
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22 In terms of limitations this article is based on a systematic literature review method that
23 although made every effort to include all publications relevant to the topic of modelling people's
24 behaviour with DES in OM, some articles may not have been captured. Furthermore, the process of
25 evaluation and interpretation of the articles is reliant on the academic judgement of the author
26 team.
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TABLES

Table I. Inclusion and exclusion criteria for the studies reviewed

	Inclusion Criteria	Exclusion Criteria
Population	Discrete-Event Simulation Hybrid models of discrete-event simulation and other methods where the DES element incorporates human behaviour Specific modelling of human behaviour in OM	<ol style="list-style-type: none"> 1. <i>Irrelevance of content</i> <ul style="list-style-type: none"> • Other simulation methods such as agent-based simulation and system dynamics • Human's treated as a process element • Other aspects of people such as disease transmission, physical aspects. 2. <i>Duplication of content</i> <ul style="list-style-type: none"> • Duplication across search databases • Duplication in later publication
Outcomes	Evidence of simulation model build and results Effect of study outcomes on system performance	<ol style="list-style-type: none"> 3. <i>Discussion of modelling human behaviour but with no simulation application</i> 4. <i>Effect of study outcomes on operator performance</i>
Study Design	Papers must be in English and accessible	<ol style="list-style-type: none"> 5. <i>Papers not in English and inaccessible</i>

Table II. Articles reporting on the use of discrete-event simulation to model people's behaviour
[2005-2017]

Ajaefobi, J., Weston, R., Wahid, B., Rahimifard, A. (2010)
Brailsford, S.C., Harper, P.R., Sykes, J. (2012)
Colombi, J.M., Ward, J.R. (2010)
Dode, P., Greig, M., Zolfaghari, S., Neumann, W.P. (2016)
Dubiel and Tsimhoni (2005)
Elliman, T., Eatock, J. and Spencer, N. (2005)
Hannah, S.D. and Neal, A. (2014)
Ilar, T.B.E. (2008)
Kazmierczak, K., Neumann, W.P. and Winkel, J. (2007)
Khalil, S.N., Weston, R.H., Ajaefobi, J.O. (2009)
Knight, V.A., Williams, J.E. and Reynolds, I. (2012)
Kokkinou, A. and Cranage, D.A. (2011)
Kozine, I. (2007)
Lassila, A.M., Saad, S.M., Perera, T., Koch, T., Chrobot, J. (2005)
Majid, M.A. and Herawan, T. (2013)
Malachowski, B. and Korytkowski, P. (2016)
Mason, S., Baines, T., Kay, J.M., Ladbrook, J. (2005)
McHaney, R.W. (2008)
Nehme, C.; Crandall, J.W.; Cummings, M.L. (2008)
Nembhard, D.A. (2014)
Neumann, W.P. and Medbo, P. (2009)
Neumann, W.P. and Medbo, P. (2017)
Perez, J., de Looze, M.P., Bosch, T., Neumann, W.P. (2014)
Plott, B. (2006)
Riedel, R., Mueller, E., von der Weth, R., Pflugradt, N. (2009)
Robinson (2015)
Shewchuk, J.P., Nussbaum, M.A., Kim, S., Sarkar, S. (2017)
Silva, E., Donauer, M., Azevedo, A., Pecas, P., Henriques, E. (2014)
Wang Q., Sowden M., Mileham A.R. (2013)

Table III. Methods of modelling people's behaviour by modelling area and modelling approach

		MODELLING APPROACH	
MODELLING AREA	Scenario	Impact	Individual
Decision	Equation (<i>Hannah, 2014</i>)	Equation (<i>Kokkinou, 2011; Hannah, 2014</i>)	
	Empirical (<i>Majid, 2013</i>)	Empirical (<i>Majid, 2013; Elliman, 2005</i>)	
Availability	Empirical (<i>Neumann, 2009</i>)	Distribution (<i>Lassila, 2005</i>)	Empirical (<i>Neumann, 2009</i>)
Task	Empirical (<i>Kazmierczak, 2007; Ilar, 2008; Ajaefobi, 2010; Malachowski, 2016</i>)	Distribution (<i>Mason, 2005; Kozine, 2007; Perez, 2014; Shewchuk, 2017; Neumann, 2017</i>)	Empirical (<i>Kazmierczak, 2007; Ilar, 2008; Wang, 2013; Ajaefobi, 2010; Malachowski, 2016</i>)
	Distribution (<i>Kozine, 2007; Silva, 2014; McHaney, 2008</i>)	Equation (<i>Colombi, 2010; Nehme, 2008; Dode, 2016</i>)	Distribution (<i>Silva, 2014; McHaney, 2008</i>)
	Equation (<i>Colombi, 2010; Nehme, 2008; Ilar, 2008; Khalil, 2009; Malachowski, 2016, Neumann, 2017</i>)	Empirical (<i>Plott, 2006</i>)	Equation (<i>Ilar, 2008; Wang, 2013; Malachowski, 2016; Nembhard, 2014</i>)
Arrivals		Equation (<i>Knight, 2012</i>)	Cognitive (<i>Brailsford, 2012</i>)
Movement		Empirical (<i>Dubiel, 2005</i>)	
		Equation (<i>Robinson, 2015</i>)	

FIGURES

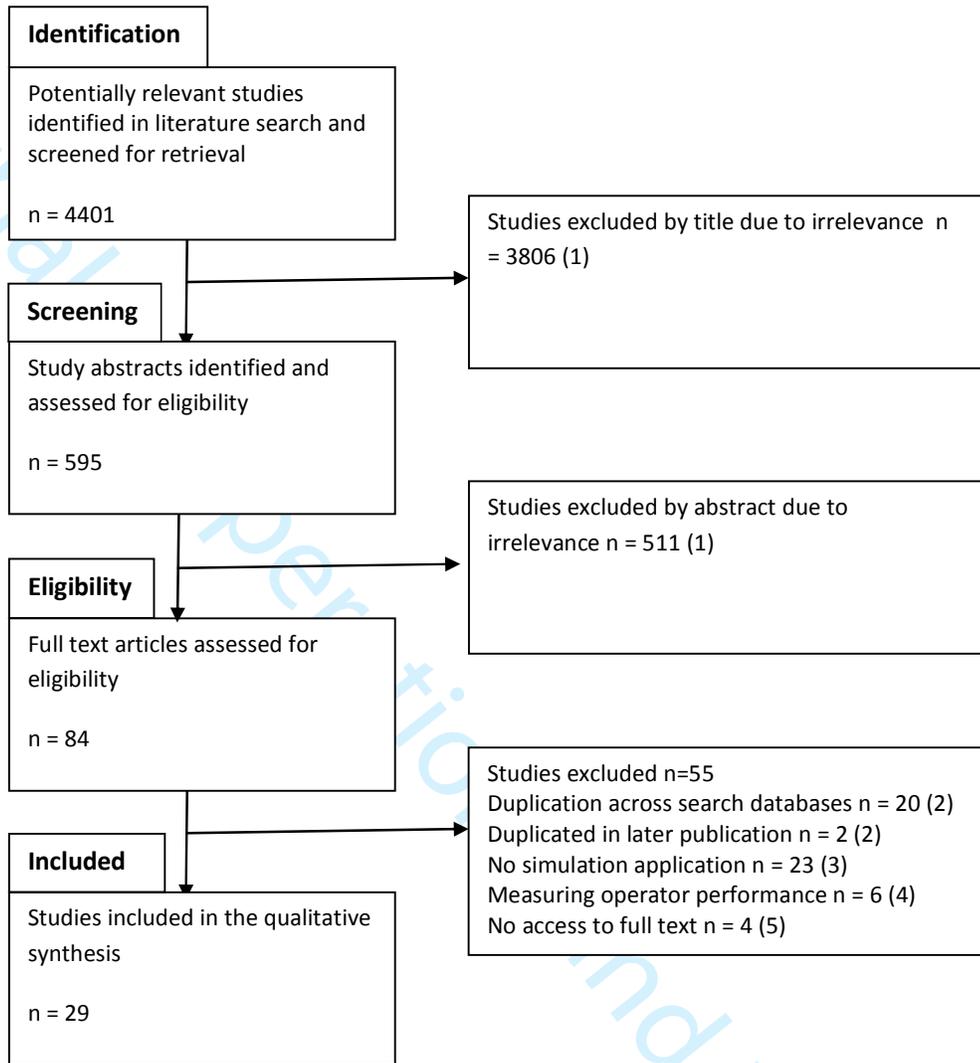


Figure 1.

PRISMA flow diagram illustrating the literature review process

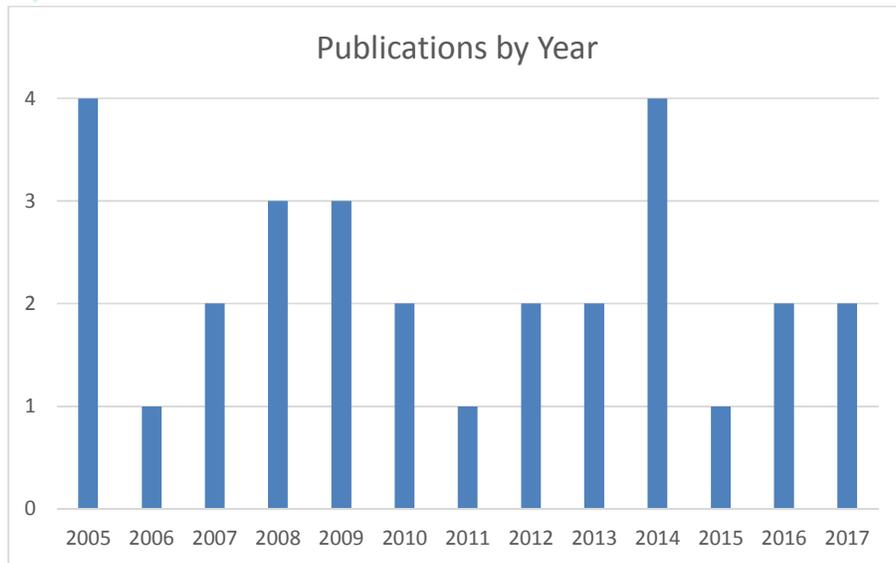


Figure 2.

Modelling people's behaviour using discrete-event simulation by year

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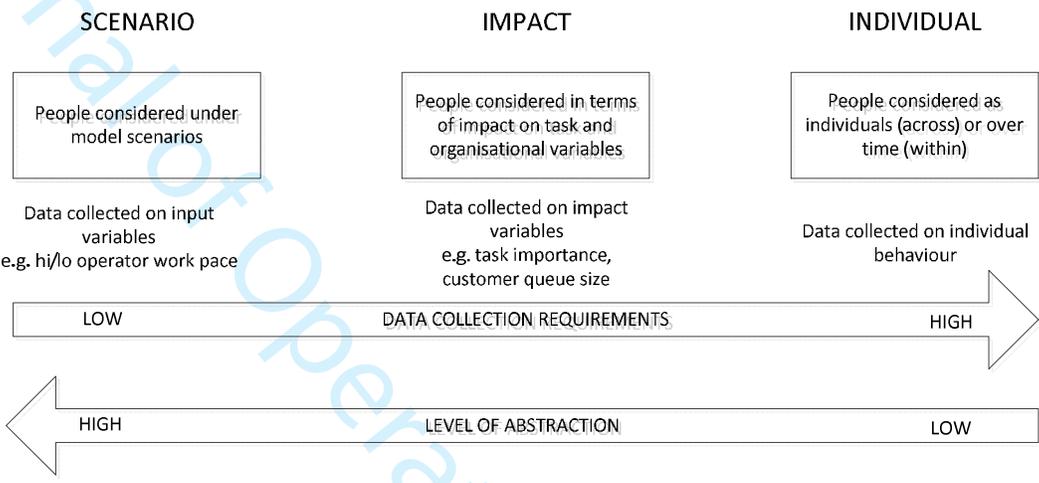


Figure 3.
Approaches to modelling people’s behaviour using discrete-event simulation

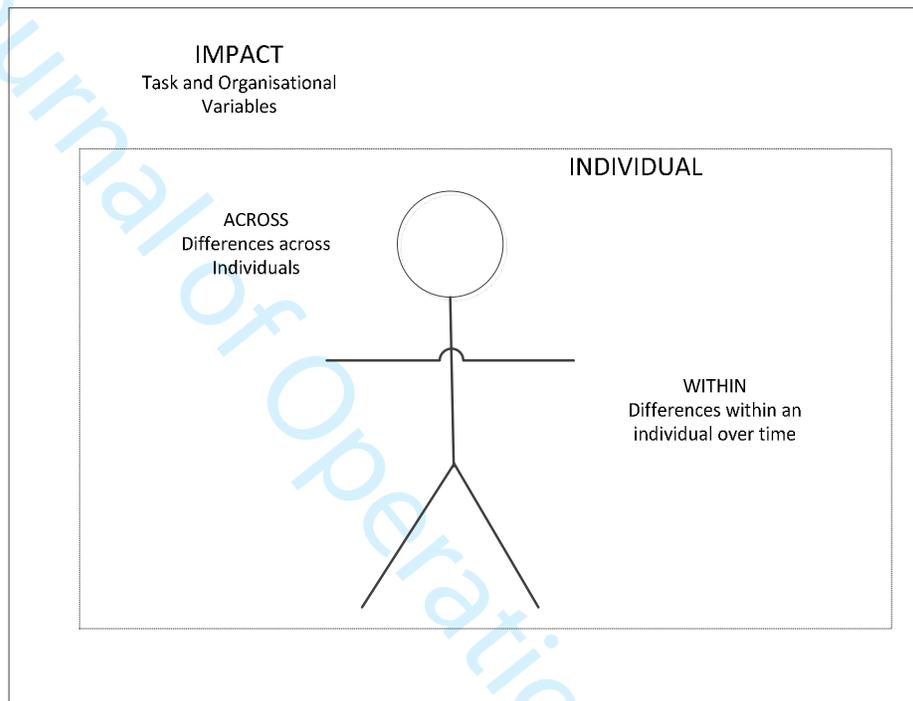


Figure 4.

Modelling people's behaviour 'inside' the model by impact and individual approaches

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MODELLING PEOPLE'S BEHAVIOUR

SIMULATION STUDY METHODOLOGY

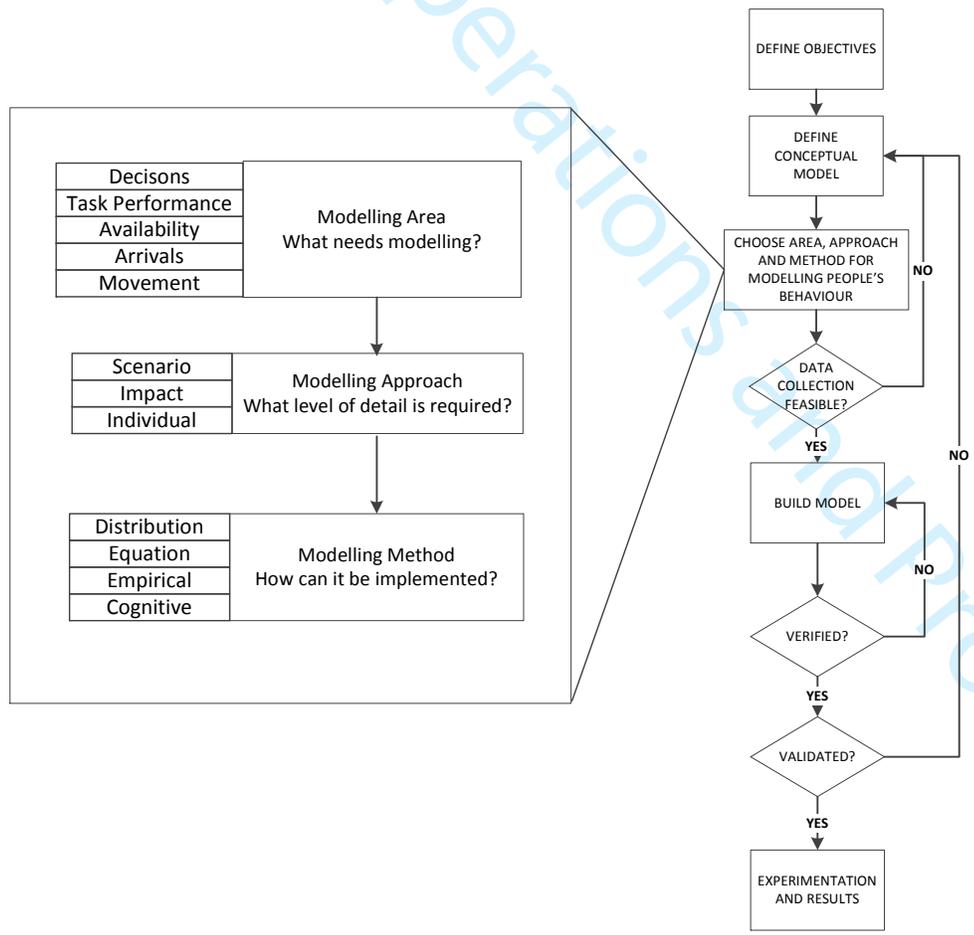


Figure 5.

A methodology for modelling people's behaviour in discrete-event simulation