Methods of Modelling People using Discrete-event Simulation

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Abstract: Discrete-event simulation (DES) is a developed technology used to model manufacturing and service systems. However, although the importance of modelling people in a DES has been recognised, there is little guidance on how this can be achieved in practice. The results from a literature review were used in order to identify examples of the use of DES to model people. Each article was examined in order to determine the method used to model people within the simulation study. It was found that there are no common methods but a diverse range of approaches used to model human behaviour in DES. This paper provides an outline of the approaches used to model people in terms of their decision making, availability for work, task performance and arrival rate. The outcome brings together the current knowledge in this area and will be of interest to researchers considering developing a methodology for modelling people in DES and to practitioners engaged with a simulation project involving the modelling of people's behaviour.

1 INTRODUCTION

The need to incorporate people, when modelling systems, is demonstrated by Baines et al. (2004), who found that the results from a simulation study, when incorporating human factors, could vary by 35% compared to a traditional study, when no human factors were considered. Juran and Schruben (2004) found that individual difference variables explain as much as 80% of the variability in the productivity of serial work-sharing teams. These differences can either be across individuals or be changes in the performance of a person over time. An example of the latter is a change in performance of an individual in response to direct changes such as training or environmental changes such as working conditions. The ability to model people provides the ability to avoid abstracting away individual differences and thus achieve a more accurate model for prediction.

The article encompasses the application of simulation to modelling people using the widely used techniques of discrete-event simulation (DES). Although other simulation methods such as Agent based simulation (ABS) are used to model human behavior, and indeed are considered by some authors as more suited to this task (Elkosantini, 2015; Siebers et al., 2010), the scope of this study is restricted to DES.

Papers taken from a structured literature review which reports on academic publications regarding discrete-event simulation applications that model people over the 10 years from 2005 to 2014 forms the basis of this review. The review followed the steps of a search of the Scopus citation database and filtering of papers for relevancy using the CiteSpace visualisation tool, abstract reviewing and full-text reviewing. The final sample was supplemented by reference chasing to identify additional papers of relevance, some of which fall outside of the original search period of 2005 to 2014.

The data requirements for modelling people in DES are now defined and used to categorise the methods employed to model people in the papers identified in the literature review. The methods are then assessed in terms of the approaches of human performance modelling and human behaviour modelling.

2 METHODS OF MODELLING PEOPLE IN DES

In order to consider the different aspects of people's behaviour we wish to model we define the data requirements to model a person in a DES model. These can be categorised as for the data requirements

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for any DES model as outlined in Greasley (2004). Data requirements can be classified as:

- 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 defining the probability of following alternative process flow routes.
- Process or task durations which define the time taken by a person to undertake a task.
- Resource Availability – this defines the availability of a person over time, such as a work schedule.
- Demand Pattern – the arrival of people into the simulation, such as customer arrivals.
- Process Layout – a diagram/schematic of the process which can be used to develop the simulation animation display.

The methods of modelling people will be categorised under these data requirements and considered under four main headings of 'Modelling People's Decisions' which relates to the logic data that controls the flow of people through the model, 'Modelling People's Availability' which relates to resource availability, in this case people's availability to do work, 'Modelling People's Task Performance' which relates to the process/task durations which are defined in the model and 'Modelling People's Arrivals' which relates to the demand pattern of people entering the simulation model. The final category of process layout relates to the requirements of the simulation animation facilities to display people which is not considered here.

2.1 Modelling People's Decisions

The traditional method of modelling people's decisions in a DES model is to either implement a conditional if..then..else rule or to assign a probability to the decision outcomes. Both of these methods are normally implemented as generalised to an average person and do not take into account changes in behaviour over time. The following articles provide examples of methods that attempt to model how people make decisions.

Kokkinou and Cranage (2011) use an online scenario-based survey to identify relevant variables in the decision of customers when choosing between self-service and manual facilities in a hotel check-in process. A regression equation is derived that describes an individual's decision to select self-service or manual service. Hannah and Neal (2014) investigate the decision making process for air traffic controllers faced with multiple tasks referred to as "on-the-fly" scheduling. The decision process is treated as a 2-stage process. Tasks are selected for execution but then considered for either immediate execution or deferral until a later time. The initial selection rule used was "first come-first served" but the model uses an equation incorporating variables for airspace complexity, conflict duration, workload and time to deadline for the deferral decision. In Brailsford at al. (2006) the Theory of Planned Behaviour (TPB) cognitive model (Ajzen, 1991) was used for breast cancer screening policies. The TPB takes empirical data on demographic variables and personality traits and transforms these to attitudes, subject norms and perceived behavioural control. These 3 aspects then lead to behaviour. Majid and Herawan (2013) investigate the behaviour of staff and customers in a customer processing system. Proactive behaviour in response to a busy operation is considered in terms of staff refusing customer entry, staff speeding up service and customers skipping the queue. Elliman et al (2005) looks at the nature of how people schedule their tasks. In particular people often have "at-will" tasks which they can decide themselves when to execute. In this study 4 factors of task deadline, length of task, customer importance of task and importance to the business of the task are identified in the task scheduling process. In summary the methods identified are as follows:

- Fit empirical data to a probability distribution as in Majid and Herawan (2013).
- Use empirical survey data to undertake a regression analysis to form an equation which can be used to formulate the decision point (Kokkinou and Cranage, 2011)
- Develop an equation from theory and test by comparing with real system data (Hannah and Neal, 2014)
- Use cognitive models and other data to derive a decision probability distribution (Brailsford et al., 2006)
- Use empirical data gathered on task and organisational factors to derive a work schedule (Elliman et al, 2005)

2.2 Modelling People's Availability

The traditional method of modelling people's availability in a DES model is to treat them as a resource and assign them as available or unavailable for time periods during the simulation run. The following articles provide examples of methods that attempt to model the factors that affect worker availability.

Lassila et al (2005) investigate the operation of assembly lines in an automotive plant. Operators were modelled using a triangular distribution to represent task durations and a further random distribution was used to represent the unavailability of workers due to off-station work tasks or not work related activities. Neumann and Medbo (2009) investigate human factors (HF) also called ergonomics using DES. 2 kinds of HF are considered; operators work autonomy and operators work capacity (ability to work at a standard pace). Autonomy is modelled as the ability to take breaks (which occur randomly) and operator capacity is modelled at 50% pace to represent a new employee, an older employee or an employee returning to work from injury. Silva et al (2014) models a mixed automatic/manual assembly line. The variation in performance of assembly line operators uses empirical data regarding each operator. Each operator's task mean and standard deviation are used as parameters in a log-normal distribution. Operator non-availability for shifts plans and lunch breaks are also modelled. Freudenberg and Herper (1998) use a central worker disposition mechanism to assign workers to a task dependent on their availability and qualification for the task. Freudenberg and Herper (1998) states one of the main elements of modelling human behaviour is to explicitly model machine availability and worker availability separately. Resources such as equipment and machinery is normally available permanently (assuming maintenance and breakdowns are not being modelled), but a distinction is to model worker unavailability due to factors such as other tasks or lunch breaks is incorporated into the model. In summary the methods identified are as follows:

- Worker availability is modelled as a schedule and workers are allocated work when available (Freudenberg and Herper, 1998).
- Workers unavailability due to shift plans and lunch breaks are modelled as a schedule of availability within the model (Silva et al, 2014).
- Model worker unavailability by the use of a probability distribution derived from data on worker behaviour when undertaking tasks not related to the scope of the model (Lassila et al., 2005).
- Factors such as worker autonomy can be operationalised as having control over the timing of rest breaks. These breaks are then modelled as worker unavailability (Neumann and Medbo, 2009).

2.3 Modelling People's Task Performance

The traditional method of modelling people's task performance in a DES model is to model task duration as a probability distribution derived from a sample of process times. The following articles provide examples of methods that attempt to model the factors that affect people's task performance and thus the task duration.

Mason et al (2005) investigates the operation of assembly lines in a factory. Empirical data was collected on operator performance on 10 operations within the factory. Curve fitting software was used to fit a distribution to the activity data and the curve that gave the most reliable fit was the Pearson Type IV. Baines et al. (2004) investigates the effect of age and circadian rhythm on worker performance in a production system. Equations are used to quantify the decrease in performance due to age and work time in terms of task durations. The impact on throughput performance is measured. Colombi and Ward (2010) assess the task load on people when controlling unmanned aircraft from a computer terminal. Operator tasks are decomposed into a series of mouse and keyboard inputs. The task time for these keystroke-level inputs are estimated using the Keystroke-level model (Card et al. 1983). For the timing of transition movements between tasks around the computer screen Fitt's Law was employed (Keele, 1986). For the time taken to choose options on the computer screen the Hick-Hyman Law (Wickens and Hollands, 2000) is employed which takes into the consideration the number of options (pages, menus, links) available on the screen at any one time. Ilar (2008) studies the impact of worker competence on productivity in a highly automated press line. The model covers both the main processes but also support processes such as tool preparation, setup and maintenance processes. Each operator has an assigned competence level at a particular task based on empirical data such as interviews with personnel. Each competence level is adjusted when the operator performs the task using a learning curve equation. Wang et al (2013) investigates the potential loss of output due to training when attempting to increase the flexibility of workers. The output of workers during training has been modelled using a learning curve equation. The performance of a worker is initially set to a value measuring assembly time per unit. This value falls, as a task is repeated, until a steady-state working speed is reached. Empirical data related to variables such as experience, age and dexterity are used as parameters for a worker's learning curve.

Wang et al (2007) models the variation of performance due to fatigue and skill level of assembly line operators. A normal distribution is used to model worker assembly times. The time to walk between assembly areas is also modelled. Juran and Schruben (2004) model individual differences by assigning a probability distribution to the parameters of the probability distribution for the task. This can be done indirectly from a sample of workers or directly from empirical data on factors such as personality and age for an individual. In summary the methods identified are as follows:

- Fit human task performance to a generalised distribution, in this case Pearson Type IV (Mason et al., 2005).
- Factor in a decrease in performance using an equation expressing age and circadian rhythm parameters (Baines et al, 2004).
- Decompose tasks and estimate task time using a theoretical model (Colombi and Ward, 2010)
- Use empirical data to assign work competence level to a task (Ilar, 2008)
- Use a learning curve equation to adjust task performance over time (Ilar, 2008; Wang et al., 2013).
- Model variation of individual differences as a probability distribution of the parameter of the task duration probability distribution (Juran and Schruben, 2004).

2.4 Modelling People's Arrivals

The traditional method of modelling people's arrivals is as a probability distribution derived from a sample of interarrival times. The following articles provide example of methods that attempt to model the factors that affect people's arrival behaviour. Brailsford and Schmidt (2003) investigate the probability of attendance at a clinic for diabetes from individual factors such as stage of process, anxiety, knowledge of disease and educational level. These where classified into the components of the PECS cognitive model (Schmidt, 2000) and given a score. A compliance factor for attendance was then calculated from the PECS score in combination with the number of previous visits and a motivation score. Knight et al (2012) covers the decision making of individual patients when choosing a hospital to attend and deciding whether to actually attend that hospital. A cost function is assigned to each facility-patient pair dependent on the hospital reputation, waiting list at the hospital and travel distance to that particular hospital from a demand node. The human behaviour element of the model is the assignment of a level of irrational attraction or repulsion of a patient for a particular unit. This is derived from a normal distribution. In summary the methods identified are as follows:

- Use cognitive models and other data to derive a probability of arrival (Brailsford and Schmidt, 2003)
- Use a normal distribution to model the attraction/repulsion to a hospital unit and thus probability of arrival (Knight et al., 2012)

3 DISCUSSION

As can be seen a variety of methods have been utilised to model people using DES with no one method being favoured. The methods have been implemented in a range of manufacturing and service applications and attempt to model differences across individuals and differences in behaviour within an individual over time. A variety of individual, task and organisational variables are used to model people's behaviour. The methods identified cover the use of empirical data, mathematical equations, theoretical distributions and cognitive models. In order to assess the challenge of implementing these methods their implementation is considered within two modelling approaches.

The first approach involves modelling the action of humans in response to a pre-defined sequence of tasks and is often associated with the term *human performance modelling*. Human performance modelling relates to the simulation of purposeful actions of a human as generated by well-understood psychological phenomenon, rather than modelling in detail all aspects of human behaviour not driven by purpose (Shaw and Prichett, 2005). In order to undertake this we will need to identify either the characteristics of individuals that are affecting the performance of the organization (e.g. age) or those characteristics of the task such as workload or those characteristics of the organisation or environment such as ambient temperature. A combination of individual, task and organizational characteristics may be incorporated in the model. The key challenge of the human performance modelling method is the collection of the empirical data required to model the actions of humans. The difficulty in practice of collecting this data is reported in Benedettini et al. (2006). Another issue is model validation, with Neumann and Medbo (2009) finding difficulty in obtaining empirical evidence to validate the operationalization of human performance in their model. This approach covers the use of the methods of empirical data, mathematical equations and theoretical distributions.

The second approach to modelling people makes use of cognitive architectures to represent the cognitive process of human beings. This involves modelling how humans actually behave based on their individual attributes such as perception and attention and attempts to model the internal cognitive processes that lead to human behavior. This approach can be termed *human behavior modelling*. A number of architectures that model human cognition, such as PECS (Schmidt, 2000) and TPB (Ajzen, 1991) have been developed. The challenge of modelling people's human behavior by modelling their internal cognitive processes is even greater than that of modelling human performance. Silverman (2004) states 'there are well over one million pages of peer-reviewed, published studies on human behavior and performance as a function of demographics, personality differences, cognitive style, situational and emotive variables, task elements, group and organizational dynamics and culture' but goes on to state 'unfortunately, almost none of the existing literature addresses how to interpret and translate reported findings as principles and methods suitable for implementation or synthetic agent development'. Another barrier is the issue of the context of the behavior represented in the simulation. Silverman (1991) states 'many first principle models from the behavioral science literature have been derived within a particular setting, whereas simulation developers may wish to deploy these models in different contexts'. Further issues are the difficulty of use of these architectures (Pew, 2008) and the difficulty of validation of multiple factors of human behavior when the research literature is largely limited to the study of the independent rather than the interactive effects of these factors.

It is clear that modelling people using either approach presents challenges in terms of gathering the empirical data necessary in order to drive and validate these models. Furthermore the need to be aware of what human performance and human behavior methods are appropriate and to understand how they can be deployed for a particular simulation application adds another skill to the already wide skillset of the simulation practitioner. These challenges may imply a team approach to simulation development when modelling people. In respect to the challenge of modelling human behavior, Bruzzone et al. (2007) discuss the need to evaluate the modelling impact in terms of the cost and workload required to introduce these aspects.

4 CONCLUSION

This article presents a summary of published work in the area of modelling people in a DES, categorised into the main data requirements for this task. The methods employed are then discussed in terms of the approaches of human performance modelling and human behaviour modelling. Methods identified that implement a human performance modelling approach include the use of empirical data directly, derived mathematical equations and derived theoretical distributions. A method identified that implements a human behaviour modelling approach is the use of a cognitive model.

Further work is needed to provide a critical assessment of the appropriateness and validity of these methods and to derive a methodology for their use in a DES study.

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