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CLOUD BASED DATA CAPTURE AND REPRESENTATION FOR SIMULATION IN SMALL AND MEDIUM ENTERPRISES

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ABSTRACT

The data collection and representation phase is an important phase within the lifecycle of a DES study. It is recognized that for large companies the data collection and representation phase differs when compared to SMEs. DES is not widely used by small to medium sized enterprises (SMEs) due to complexity and related costs being prohibitively high. DES-related data can be stored in a variety of formats and it is not always evident what data is required (if even available) to support a DES model in relation to specific problem scenarios. Building on previous research output, this paper presents the implementation of a Cloud based SaaS application to process input data from a SME in the medical industry and to output this information to in a usable format towards data-driven automated simulation model building.

1 INTRODUCTION

DES is a powerful problem solving method and decision support tool available to organizations. It allows for experimentation with a simulated system that might not be cost-effective or feasible in reality. While the use of DES is prevalent in large organizations, within small and medium enterprises (SMEs) it is not widely used. In this paper the implementation of a cloud based input data capture and representation application for simulation in SMEs is described. The work presented in this paper builds on work previously presented in the Winter Simulation Conference, namely Byrne et al. (2013) and Byrne et al. (2014) towards a tool to support the *Data Collection and Representation (DC&R)* phase of a discrete-event simulation study.

This paper is structured as follows: Section 2 gives background research relating to the input data capture phase in the context of the simulation lifecycle. Section 3 describes a real world simulation project, the implementation of the DC&R application to support this project and the benefits and shortcomings of using such a tool within this context. Both simulation input data specific to the simulation project and a structured walkthrough using the tool are described in this section. Finally, Section 4 gives conclusions and future work.

2 BACKGROUND

SMEs are most widely seen as companies typically with less than 500 employees in the USA (U.S. Small Business Administration 2014), or in Europe with less than 250 employees and a turnover of less than €50 million or a balance sheet total of less than €43 million (European Commission 2003). In Europe alone, SMEs are seen as principal drivers for economic growth and innovativeness. In a European Union (EU) context alone, there are over 20 million SMEs which account for 99% of businesses thus making SMEs a key driver for economic growth, innovation and employment (European Commission 2014). In 2012, SMEs within the EU accounted for 66.5% of all European jobs. More specifically, over 5.1 million companies operate in the manufacturing and construction sector, of which 99.6% are SMEs. The manufacturing sector was reported to have provided €1.6 trillion of which manufacturing SMEs contributed to 44% (€707 billion) of the sectoral value add (European Commmission 2013).

There are some reported cases where DES has been applied to SMEs (Geraghty and Heavey 1999; Byrne and Heavey 2004; Jain and Leong 2005; Mosca et al. 2005; O'Kane 2003; Swarnkar and Harding 2009; Ahmed and Latif 2010; Mahfouz, Shea, and Arisha 2011; Hvolby, Svensson, and Steger-Jensen 2012; Liotta 2012; Nisula and Pekkola 2012; Jarkko et al. 2013). Studies of SME simulation have been sporadic and mostly explored on a one off, case-by-case basis (Jarkko et al. 2013; Hvolby, Svensson, and Steger-Jensen 2012; Mahfouz, Shea, and Arisha 2011) which is in line with reported expectation, as investigating simulation within the SME context presents a number of additional challenges (O'Kane 2003; Liotta 2012). Examples of such additional challenges relate to the complex process of simulation in comparison to the scale of the organisation, availability and format of data for simulation modelling, time and resources required to execute the model, lack of awareness, cost and experience factors and the under-estimation of the advantages that can be gained through the use of DES tools (Law and Kelton 1991a; O'Kane, Papadoukakis, and Hunter 2007; Liotta 2012). It is within this context that this paper presents the implementation of a cloud based data capture and representation application for simulation in SMEs. It describes the use of the tool by an SME in the medical industry and to output this information in a format that enables automated simulation model building.

As noted earlier, this paper continues the narrative from papers included in the proceedings of two previous Winter Simulation Conferences. In Byrne et al. (2013), the architectural design of a Cloud-based SME data adapter was presented. This data adapter design was influenced from two perspectives. The first was the progress and limitations of reported past work in and around this field of research (Leong, Lee, and Riddick 2006; Huang, Ramamurthy, and McGinnis 2007; Riddick and Lee 2008; Bengtsson et al. 2009; Liston et al. 2010; Bergmann, Stelzer, and Straßburger 2011). This work evaluated the efficacy of using standards, including UML, SysML and CMSD, to represent the data that defined the system of interest and would subsequently be used to populate a simulation model. In each case merit was found in using a standard to organize and represent the data but challenges were uncovered in terms of representing all necessary system descriptors, handling data generation requirements and/or possessing suitable authoring tools that met the needs of potential stakeholders. Furthermore, little of this research addressed the specific needs of the SME market. The second source of influence for the architectural design was from the case study requirements of four SME partners. These four companies varied in scale, business sector (food, medical, healthcare and automotive) and process complexity and each provided input to both functional and non-functional requirements. In response to the identified requirements the architectural design incorporated three deployment approaches (on-premise, on-device, on-demand) to address accessibility, data connectivity considerate of the data systems in situ in the type of companies of interest and template driven knowledge collection that supports an iterative process to replace assumptions with validated information as it becomes available.

Byrne et al. (2014) illustrated how and where the data collection and representation activities fit into the life-cycle of a DES study. The high level steps of a simulation study have been published by many (Nance and Arthur 2006; Banks 1999; Rabe, Spieckermann, and Wenzel 2008; Sargent 2001; Kreutzer 1986; Pidd 1989; Law and Kelton 1991; Balci 1994; Bengtsson et al. 2009) but all follow a similar set of steps with a comparable level of granularity. All certainly include reference to the necessity to collect and manage data but (perhaps surprisingly, given that past studies (Skoogh and Johansson 2007; Trybula 1994) found that the input data phase of a simulation study can take 10-40% of the overall time for a project) not all dedicate a distinct step to this activity with Law and Kelton (1991) for instance defining the second step of the process as "Collect data and define model". To provide deeper analysis of the "collect data" task, the second paper in this series presented a Simulation Data Collection and Representation Sub-Process that was mapped to the Bengtsson et al. (2009) overview framework for a DES project. The complete sub-process is defined in Byrne et al. (2014) together with a graphical representation, but in brief the sub-process is as follows.

The first step in the sub-process is to define the data modelling components. These components are used to build a representation of the data. An example of a data model component from the manufacturing domain would be a *machine*. The modeller goes through a validation step with the modelling components to validate that the correct components are being used to collect the relevant DES data. Next, the structure of the data model is developed using the components defined in the previous process (the modeller can typically carry this out in parallel with the conceptual model development in the main framework phases).

After developing the structure, the next step is to identify both the location of source of the data and to identify what data (content) is to be collected. If the data can be sourced, the data is then collected at source. If the data cannot be sourced, the data will need to be represented in some fashion. There are a number of ways that this *data gap* can be filled through generating representative data. One method is to treat the data as a "black box" and make assumptions about this data, in this case the data is not available but represented in a simpler form. Another way is to estimate this data using the data modeller's experience. A third way is to use a tool to generate this data that is representative of the actual data that could not be collected.

The data analysis step follows both the data collection and representative data generation steps. In this step, the data is analysed in order to understand if the correct data is being collected. Some methods that this can be done are through manually looking at the data on paper, analysing the direct data through a screen on a software tool, or analysing and possibly interacting with a visualisation of the data. Following this, the data goes through a validation step, and if the data is incorrect, there is the option to either reject the data or to filter, modify or clean the data for further analysis. If the data is validated at the analysis step the data model can be updated with the data. At this stage, the option is there to identify more data and/or update the data model components and/or modify the structure of the data model. If no more data is to be identified, the modeller exits the sub-process and moves to the base model development process. The DES data collection and representation sub-process can again be re-entered if the base model is not validated, in which case it starts by redefining the data modelling components.

In this paper, the use of the prototype DES data support tool, as introduced in Byrne et al. (2014), is presented in the context of a modelling project with one of the case study companies from Byrne et al. (2013). To provide greatest value to the modelling community, it is important that this tool not only caters for the activities outlined in the Simulation Data Collection and Representation Sub-Process but also considers the transfer of this data to the next model building phase of the DES life-cycle. To this end, the functionality to export the data in the Simulation Interoperability Standards Organization (SISO) Core Manufacturing Simulation Data (CMSD) standard has been incorporated into the prototype. For more details and information on the current development status of CMSD, the interested reader is referred to (Simulation Interoperability Standards Organization (SISO) 2015). CMSD provides neutral structures for the exchange of manufacturing data in a simulation environment. As such, it offers a common interface to any simulation engine with an appropriate adapter. The standard is beginning to gain wider use and examples of implementation in the automotive (Johansson et al. 2007; Kibira and Leong 2010) and aerospace (Lu et al. 2008) industries have been published. In terms of the simulation software that has been proven to work with the standard (with the aid of translators in most cases) there is a growing list that includes Enterprise Dynamics (Johansson et al. 2007), Arena (Boulonne et al. 2010), Quest (Kibira and Leong 2010), ProModel, FlexSim (Fournier 2011) and ExtendSim (Hossain et al. 2012). It should be noted however that CMSD is still an emerging standard and has not yet been proven to work in all cases. More work is also required by the simulation community to further develop appropriate adapters to simulation engines for more robust use. In this paper, the open source simulation engine SimPy (SimPy 2015) has been used to initially test and validate the data to simulation model transfer via CMSD.

The prototype that is presented is a cloud based application, a design decision taken primarily in response to the user requirements elicited in Byrne et al. (2013) but one that also complements a recent move in the simulation modelling software world towards cloud-based solutions. Examples of this trend can be seen in SIMUL8 (2015) and in CLOUDES (2015). Such a move towards the utilization of cloud for deployment of an SaaS application supporting the DC&R phase provides a number of benefits. These include increased accessibility, increased collaboration support both between SMEs and between the vendor and SME, potential to develop interoperability with existing cloud based simulation applications, and reduced vendor technology infrastructure spend, savings which can be passed onto the SME in the form of on-demand pricing model options.

3 STRUCTURED SIMULATION SCENARIO WALKTHROUGH SUPPORTED BY CLOUD BASED DC&R TOOL

This section describes a real world simulation project, the implementation of the DC&R application to support this project and the benefits and shortcomings of using such a tool. Referring to Byrne et al. (2013), the DC&R tool has been designed with three deployment approaches for use by SMEs, namely on-premise, on-device and on-demand, as follows:

- *On-Premise:* On-premise covers anything that exists within the walls of the SME, whether this is internally on private Cloud, on local servers with client access, on client, or (in the case of data) in hard-copy format or knowledge not formally recorded (in people).
- *On-Device:* On-device covers any mobile device used internally or externally to the SME capable of connecting to a network and with an operating system supporting Web browsers or Web-capable applications.
- *On-Demand:* On-demand includes any part of the SME data adapter that is deployed (in this case) in the Cloud and can be accessed through a software-as-a-service (SaaS) deployment model.

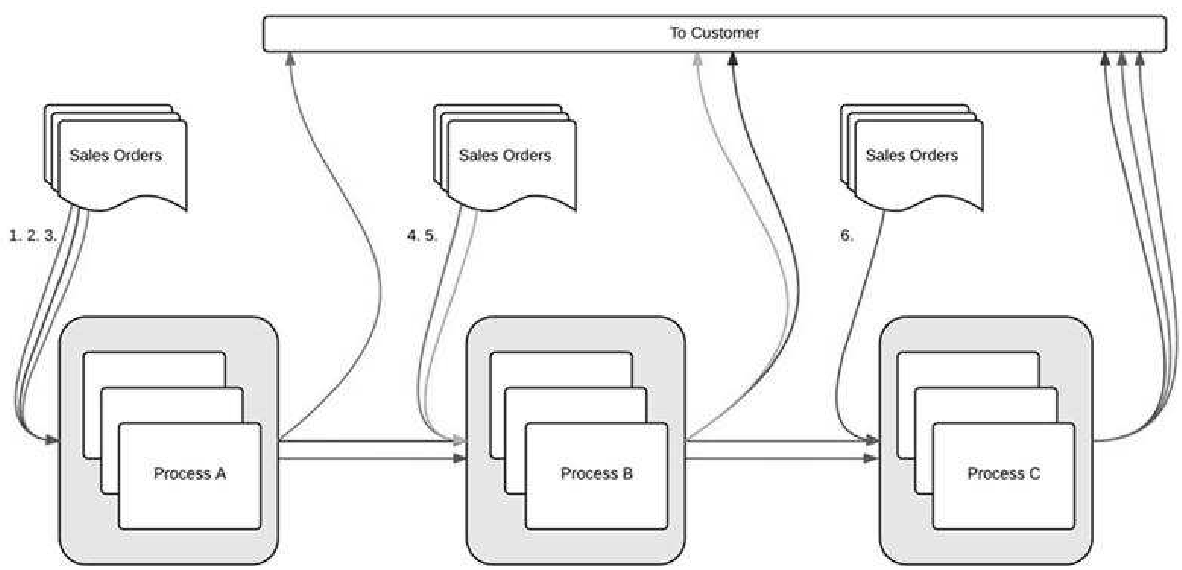

Figure 1: Schematic of the product flows in Company 2.

The application can be deployed inside the "four walls" of the SME where the SME has its own private cloud infrastructure, or can be deployed on the public cloud external to the SME. The simulation project described here was undertaken with Company No. 2 from Byrne et al. (2013), with which the DC&R tool was deployed to the cloud and used during the DC&R phase of the project, both on-device and on-demand. This company operates in the medical sector, has 201-300 employees and stores manufacturing data electronically. Although involving medical grade products and complex equipment, the manufacturing process at Company 2 is relatively straightforward. In fact, the process flow consists of just three different processing steps. The sequence in which parts flow through these steps is also uncomplicated (i.e. Process A before Process B and Process B before Process C). Not all production orders require all three steps but this still only results in six high level routing options as shown in Figure 1. The routing options are complicated however by the fact that there are multiple pieces of equipment available for each process step and not all of these have the same capabilities. Subsequently, specific products have machine specific routings.

Company 2 is experiencing significant challenges with their existing scheduling process for the following reasons:

- Company 2 produces over 4500 distinct items (both high and low volume production orders with a high mix thereof).
- The schedule planned at one process step has significant capacity implications for the other process steps.
- Existing planning process schedules Process C manually in Excel spreadsheet. 'Dependent' and 'Independent' demand for Process A and Process B is scheduled around this.
- Previously Company 2 had enough spare capacity to cope but 'independent' demand has increased and it is now becoming capacity constrained.

Effectively from a simulation based analysis perspective, Company 2 required a model of their manual scheduling process rather than the manufacturing process itself. Although demand is growing steadily, the company believes that they have sufficient capacity to meet demand for some time if they better manage their scheduling process. This will allow them to postpone capital investment until demand reaches a point that necessitates additional equipment therefore providing financial benefits to the company. For the simulation based experimentation Company 2 chose to compare different scheduling rules including: EDD (Earliest Due Date); FIFO (First in First Out); SPT (Shortest Processing Time); and LST (Least Slack Time). The objective was to determine whether or not including such logic into the Excel-based scheduling system would provide significant benefit.

3.1 The Simulation Input Data

Company 2 uses the Overall Equipment Effectiveness (OEE) metric to monitor performance and as such data collection has mostly been focused on providing input to the generation of this metric. This provided a good basis for simulation model input collection as the 'availability' aspect of OEE meant that historical production, changeover and down times were available. Similarly, the 'performance' and 'quality' metric elements meant that process information was available for output losses. Table 1 lists these data categories along with additional data that was available from sales order records. In terms of data gaps (Table 2), there was a shortage of information on the products with which the changeover times were associated in the data records and no matrix existed for expected changeover times.

On exploring this further, it was found that there were multiple product attributes (including length, width and various design features) that could influence machine setup and therefore changeover time but the many possible permutations of these features made it difficult to categorize products by expected changeover time.

Table 1: Available data with description and data source format.

Data	Description	Data source format
Total time	Planned production time	OEE Report - MS Excel spreadsheet
Run times	Production time per work order	OEE Report - MS Excel spreadsheet
Changeover times	Setup time between work orders	OEE Report - MS Excel spreadsheet
Downtimes	Unplanned machine down times	OEE Report - MS Excel spreadsheet
Target outputs	Expected units to be produced in allotted time	OEE Report - MS Excel spreadsheet
Actual outputs	Actual number of units produced	OEE Report - MS Excel spreadsheet
Finished quantities	Number of good units produced	OEE Report - MS Excel spreadsheet
Order quantities	Customer sales order quantities	Sales record - MS Excel spreadsheet
Delivery lead times	Notice (days) to desired delivery date	Calculated from timestamps in sales record - MS Excel spreadsheet

Table 2: Main identified data gaps.

Data gap	Description
Changeover time drivers	Changeover times recorded for production orders but difficulty in determining drivers behind longer/shorter times
Product categories	Effective product categories to aggregate SKUs for model assumptions and simplifications
Documentation of the scheduling process	The existing scheduling process had not been formally documented with many steps relying on the tacit knowledge of the planner

3.2 DC&R Tool Walkthrough as Used to Support Company 2 Simulation Scenario

The DC&R tool is launched through a web browser by typing the relevant URL. The simulation model developer is then presented with a user authentication screen where they input their username and password to access their Cloud-based account for the application. The user then has the option to open an existing simulation data model or start a new simulation data model in the application to describe their system.

Referring to Figure 2, upon opening a data model a canvas is presented to the user onto which defined data modeling components can be "dragged and dropped" with representative lines describing the relationships between them. In the case of Company 2 machine objects were added to the model through this mechanism. By starting with the canvas, the user is driven towards a mindset of visually describing their process. This graphical representation forms the central point of the data model from which quantitative data capturing is later guided. In the case of Company 2, the starting point was to engage with the client through a Microsoft Visio style layout diagram of the factory floor, and to then conceptually model the processes relevant to the problem using the drag and drop canvas feature of the D&CR tool.

Tabs are specifically tailored to each of the modelling component types in the canvas (with each distinct model component having its own tab in which parameter information can be added, files can be attached and data can be manipulated and analyzed). In addition, a general "model" tab is provided, in which data can be manipulated relevant to data stored for the overall model. The next step in the data capture process for Company 2 was to identify sources for data relating to demand, process times, changeover times, downtimes, target outputs, actual outputs and finished quantities. For each of these, the data was available in Microsoft Excel format in a report for OEE calculation or a sales record file. The

Cloud based DC&R tool includes support to display and edit Microsoft Excel sheets through a browser interface. Therefore the data from these Microsoft Excel files were seamlessly integrated into the tool, for further filtering, cleaning and manipulation. Referring to Figure 3, the tool also includes automated visualization of data from the cloud based spreadsheet component in the form of charts, allowing for easy visual analysis of data. In this way, potential gaps in data required by a simulation model could be easily identified and action taken to respond to these data gaps.

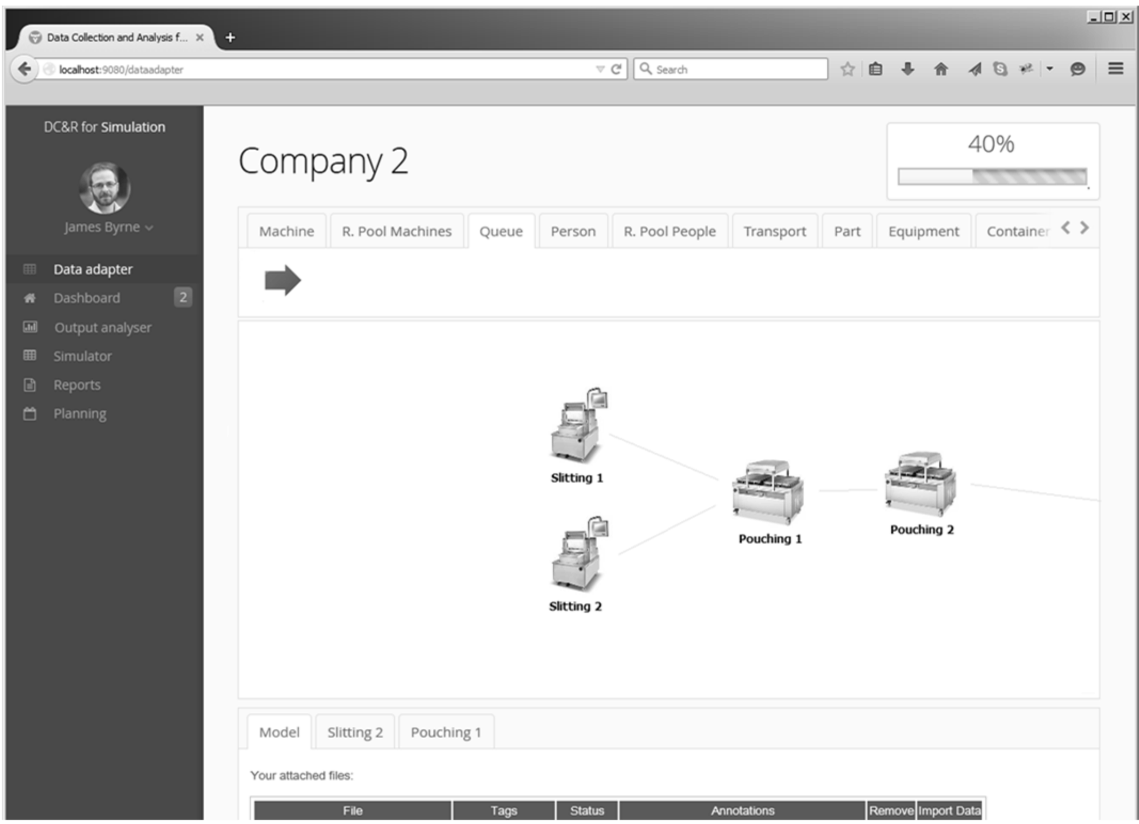

Figure 2: Modelling canvas and associated tabs for cloud DC&R prototype.

Collaboration throughout the process was accomplished through providing user accounts to the client in Company 2, with access limited to the specific simulation project being undertaken. This allowed for remote collaboration with the client, saving both time and cost, an important feature for the SME. In addition, verification and validation was carried out through the use of these collaborative features provided by the application. The input data required was verified to be correct by collaboration between the SME human decision maker and (in this case) the application developer for the problem under consideration. Validation of the input data was supported by visual aids through the same collaborative process, for example Figure 3 displays the changeover times in minutes against the frequency of these times occurring. Validation is supported through the use of automated chart generation with relevant data being displayed. Any errors in the data can be visually detected and modified by the user as appropriate.

As data is captured for the simulation model, progress is tracked through the use of a user-defined weighted "traffic light" system with a percentage display bar at the top of the screen (see Figure 2). The user can apply a weighting to the importance of the data to be captured, and track the capturing of the data as "green", "orange" or "red". Green represents a scenario where all data is fully captured with respect to the specific data, orange represents a situation where data capture is in progress, and red represents data yet to be captured. The weighting indicates the importance of the data, and an algorithm evaluates this across the whole data model, enabling the display of an overall percentage. In addition, data components can be flagged where there are gaps in the data which cannot be sourced. A summary report of flags and progression is available to users and supports the collaborative development of the data model.

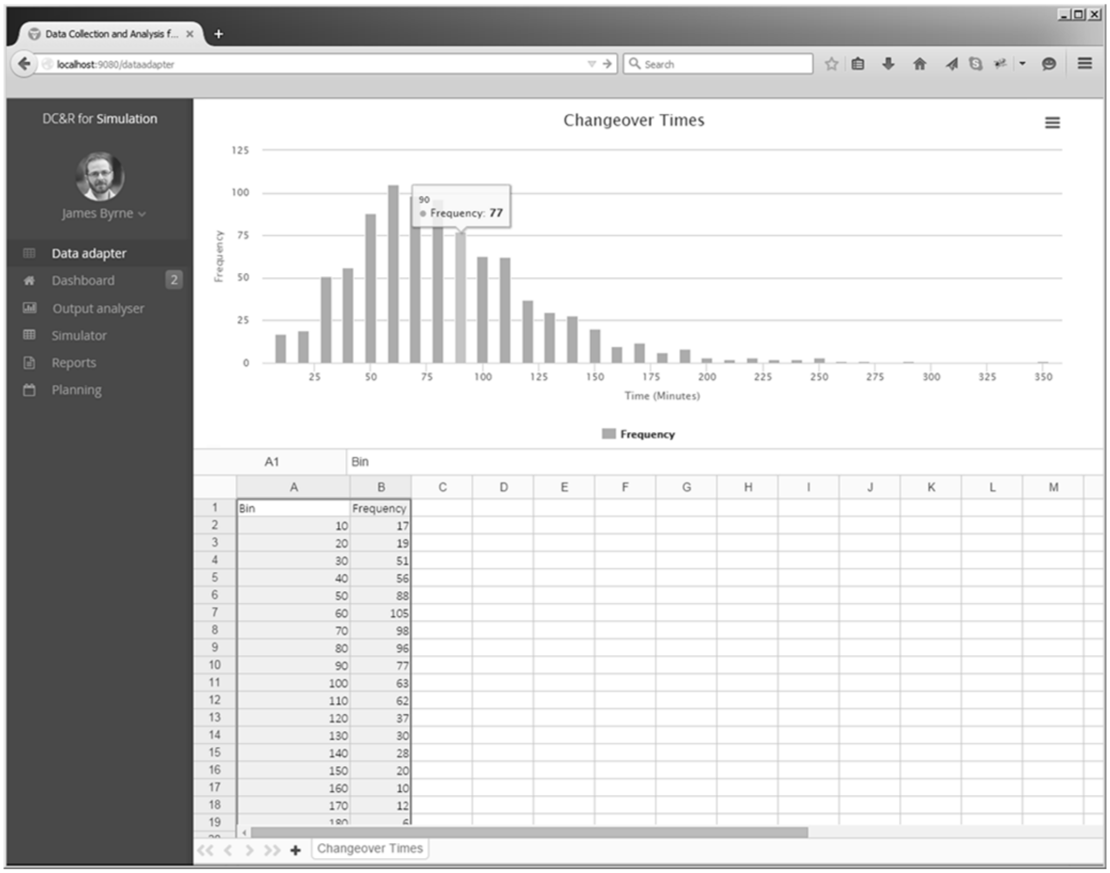

Figure 3: Cloud DC&R prototype spreadsheet component and associated visualization supporting data analysis of changeover times for Company 2.

The data model can be exported in CMSD format for automated population of data into a simulation tool. Data components and associated parameters are translated to the XML representation of CMSD as outlined by the Simulation Interoperability Standards Organization (SISO) (2012). This allows for the data to be automatically populated into a simulation tool, both cloud based and desktop based. In the Company 2 case, it was found that the basic manufacturing process structure (machines and routing) and associated parameters (times and yields) were successfully communicated via CMSD and generated in the simulation model but manual intervention was required to incorporate the more complicated logic. The DC&R tool however did provide a validated reference for this logic which in itself was found to be advantageous.

While development of the application is ongoing, testing has been carried out on the tool in the form of initial unit testing, performance testing in terms of response time and resource utilization, and usability testing internally with end users. In terms of unit tests, construction errors have been caught and fixed, and the application is currently in a stable state. The application has been deployed to a production cloud environment with response times for all requests currently averaging between 2-3 seconds, availability at

100% and low resource utilization on one virtual machine. However in terms of performance, it has yet to be tested at scale. Initial usability testing has been successful which focused on the ability of each user to input all input data required from the Company 2 case, perform analysis of this data and to successfully generate CMSD from the inputted data. Future work includes further user acceptance testing with the decision maker in Company 2, as well as carrying out more formal tests at scale for performance and load testing , functional and non-functional testing and user acceptance testing.

4 CONCLUSIONS AND FUTURE WORK

The use of DES in the SME sector has been limited as barriers that prove challenging for larger organizations (e.g. cost, time, expertise) are often insurmountable for these less resourced companies. The Data Collection and Representation application presented here offers some help in addressing this problem by simplifying the introduction to DES and proving that the SME market can be provided with an accessible tool to centralize their data and format it in preparation for use in a simulation model. The application provides a platform to change the manner in which simulation modelers interact with clients whereby an initial system description can be outlined by the modeler during early engagement and then access granted to the client to allow them to populate the model as they source the necessary data. By supporting data requests, delivery and validation in this remote fashion the necessity for onsite engagement (and associated cost) is reduced. Additionally, the clients participate more actively in the project and therefore ownership of, and subsequent confidence in, the model is promoted.

Future work includes developing the expert system and template features from the original architectural design. These features would significantly enhance the data capture process by guiding the users (both modelers and stakeholders) to ask and answer pertinent questions about the system of interest based on both the initially stated objectives of the simulation study and the information already captured in the tool. In this manner, the input requirements would evolve over the data capture process and the application would prompt users about what additional data would be appropriate given the current system description (e.g. if the model is found to contain parallel process steps then the application would request data on the routing logic). Furthermore, as the application builds up a history of input data modelling it could suggest potential sources of requested data. Future work also includes further investigation of the use of CMSD towards automated simulation model data population for different cases, and simulation model experimentation with the outputted data from the DC&R application.

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