Exploring Cannulation Process in Chemotherapy through a Computer Simulation

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Abstract

The aim of this study is twofold. Firstly, to demonstrate how combining computer simulation, data from multiple data sources, and statistical methods, can extend the understanding of the issues associated with process modelling and analysis in healthcare environment, and therefore contribute to improvements in resource utilisation and safety in hospitals. Secondly, to provide simple re-useable methodology for cross-validation of multiple data-sources such as interviews, hospital IT data management systems and simulation results. The insights from this study are threefold. Firstly, the accuracy of the estimates of duration of cannulation obtained through the interviews with the nurses and the chemotherapy unit manager is very high. Secondly, although the duration estimates were precise, the process descriptions obtained through interviews with nurses were oversimplified or incomplete and therefore did not realistically reflect complexity of a medical process with a significant number of relatively rarely occurring exceptions. Thirdly, by combining multiple data-sources it is possible to reduce costs associated with observation as a most expensive data-capturing approach. A detailed exposure of the methodology including step-by-step description is provided to facilitate conducting similar research in hospitals in the future.

Keywords: **process modelling, simulation methodology, chemotherapy process, cannulation.**

I. INTRODUCTION

Chemotherapy is the use of anti-cancer drugs to destroy cancer cells [1]. In Australia, chemotherapy is usually administered in chemotherapy treatment units (outpatient oncology clinics). In this paper we focus on intravenous (IV) cannulation, referred as cannulation in the rest of the paper, which is an important sub-process that is often a part of chemotherapy process. The cannulation is a technique in which a cannula is placed inside a vein to provide venous access. Venous access allows sampling of blood as well as administration of fluids, medications, parenteral nutrition, chemotherapy, and blood products [2].

Chemotherapy consumes significant resources, therefore an assessment of the utilisation and productivity of such resources is important [3]. Here, we consider utilisation of resources associated with cannulation, because we identified cannulation as the source of significant variation in chemotherapy nursing resource utilisation. This study was undertaken as a part of a larger project that has objective to improve the performance of a chemotherapy treatment unit by increasing the throughput and reducing the average patient's waiting time. Similar work undertaken in Canada and supported by CancerCare Manitoba, with a focus on development of a scheduling template for chemotherapy treatment, was described by Ahmed et al. in [4].

As reported in [3], the Basic Treatment Equivalent (BTE) model was developed in radiotherapy to measure complexity and treatment duration differences between external beam radiotherapy treatments. It was derived from the time measurements of radiation treatment fractions and then developed from mathematical modelling of the data [5]. It was shown to be a more sensitive productivity measure than fields per hour when tested in radiation oncology departments in New South Wales [6] and other locations in Australia and New Zealand [7]. Further enhancements of the model have subsequently occurred [8].

II. METHODOLOGY AND INPUT DATA

The input data used in this study comes from four different sources; interviews with nurses and a chemotherapy treatment units manager, electronic sources such as ARIA [9] (an oncology information system), samples collected by direct observations and the simulation itself. The data is processed in R, open source programming language and software environment for statistical computing [10], using the "data.table" and "ggplot2" libraries [11, 12]. The results are provided in accessible, easy to understand, visual format that allows for interactive exploration, comparison and validation.

The examined data from ARIA contained 19,937 rows, each representing a patient visits, of which 9,210 (46.2%) were rows without cannulation attempt data. We are unable to provide the snapshot of this table due to its size. The descriptive statistics for number of cannulation attempts is provided in Tables I and II, as a function of sex and year in which the cannulation occurred.

TABLE I
DESCRIPTIVE STATISTICS FOR MEAN NUMBER OF CANNULATION ATTEMPTS BY SEX AND YEAR

	Total	2013	2014	Male	Female
N	10,727	5,251	5,476	5,487	5,240
Mean	1.33	3.35	3.31	1.29	1.36
SD	0.72	0.74	0.7	0.68	0.75
Median	1	1	1	1	1
Range	1-5	1-5	1-5	1-5	1-5

Further statistical analysis is provided in Table III and Figure 1 which shows the distribution of the mean number of cannulation attempts, each dot represents a patient. In this figure, the y-axes represents the total number of cannulations for the specific patient and colour denotes the sex of the patient.

TABLE II
DESCRIPTIVE STATISTICS FOR MEAN NUMBER OF CANNULATION ATTEMPTS BY SEX FOR EACH YEAR (EXPERIMENT B)

	Male 2013	Female 2013	Male 2014	Female 2014
N	2,772	2,479	2,715	2,761
Mean	1.32	1.38	1.26	1.35
SD	0.72	0.76	0.95	0.74
Median	1	1	1	1
Range	1-5	1-5	1-5	1-5

TABLE III
NUMBER OF CANNULATION ATTEMPT FREQUENCY FOR ALL VISITS THAT INVOLVED CANNULATION

Number of cannulations	1	2	3	4	5
Frequency	7,822	1,442	524	154	85
Percentage	78.01	14.38	5.23	1.54	0.85

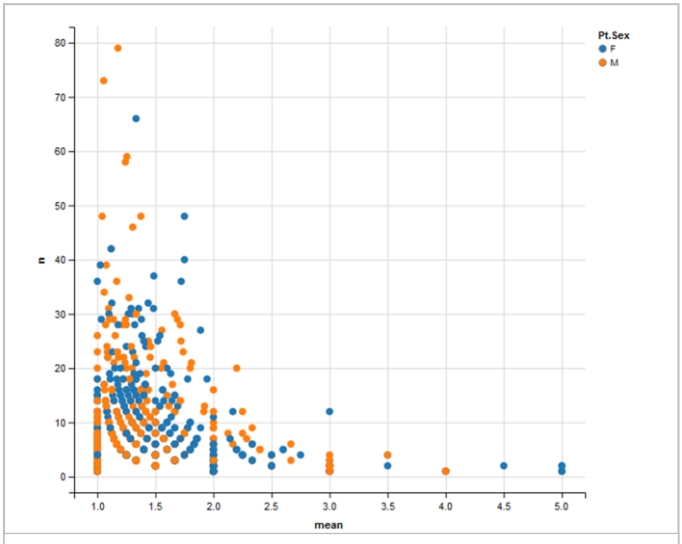

FIG. 1 Distribution of the mean number of cannulation attempts (x-axes) for all patients (each dot represents a patient) as a function of the total number of cannulations for the specific patient (y-axes), colour denotes the sex of the patient.

Through the interviews with nurses and the unit manager we obtained process descriptions and parameters for the duration of the cannulation in chemotherapy (triangular distribution, min=5, max=20 and mod=10).

Further data is collected through independent observation conducted at a chemotherapy treatment unit in Newcastle, NSW, Australia during the period September-December 2015. In total, we collected 107 samples of the duration of cannulation attendance that in addition to already described data on number of attempts also included the number of cannulation re-tries by multiple nurses. The descriptive statistics for this data is provided in Table IV.

In the continuation of the paper we study the difference between simulation outcomes when cannulation duration and process description data was provided by nurses (**Experiment A**) as an estimate based on their experience, and when the same data is captured as samples through observations (**Experiment B**).

TABLE IV
DESCRIPTIVE STATISTICS FOR CANNULATION PROCEDURE DURATION FOR ALL OBSERVATIONS (EXPERIMENT B)

Mean cannulation time	Median	Standard deviation	Standard error	Range
10.35	7.67	7.73	0.75	2-50

As the final stage in the modelling process, we created a discrete event driven computer simulation in AnyLogic®, a multimethod simulation modelling tool [13], using the

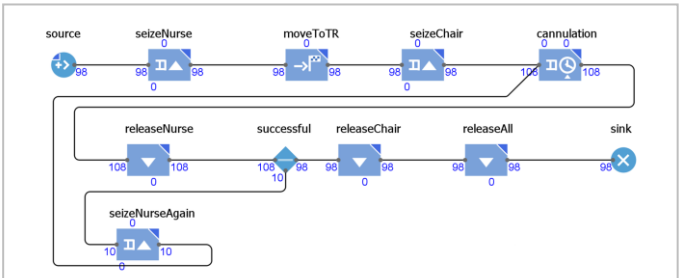

FIG. 2 The visual process definition as depicted in AnyLogic® simulation software

data obtain through the two previously described steps. The process descriptions are validated by exposing the animation and stepwise process descriptions to nurses and the unit manager.

The simulated scenario is the following. A patient enters the waiting room – the inter-arrival time for patients is defined as exponentially distributed with $\lambda = 0.25$. The number of patient per arrival is generated by discrete uniform distribution from the range (0 - 2).

Once the patient is in the waiting room a nurse is notified, if a nurse is available she/he collects the patients from the waiting room, takes the patient to the chemotherapy chair and attempts the cannulation, otherwise the patient waits in FIFO queue until a nurse is available. To create custom (empirical) continuous distribution in AnyLogic® we supplied a list of all observed samples, the descriptive statistics for this data

set is provided in Table IV. Furthermore, based on data obtained through observation (Experiment B) we incorporated 5% chance of a nurse not being able to successfully cannulate a patient after 4 attempts, in which case another nurse will attempt cannulation this time with a rate of success of 33%. This process of dealing with difficult cannulation continues until successful or time limit of 90 minutes has been reached and at which stage the cannulation process is declared unsuccessful and stopped. The number of nurses in the nursing resource pool is 8 and the number of chemotherapy chairs is 12. The AnyLogic® based visual process definition is provided in Figure 2. The simulation time is expressed in minutes and the duration of simulation for this model is limited to one working day (480 minutes).

In contrast to the difference between parameters associated with the experiments A and B, we selected the identical values for all other simulation parameters. In addition to the previously specified inter-arrival time and the number of patients per arrival, the other parameters such as movement speed of the nurses and availability of chemotherapy chairs are purposefully selected to eliminate their influence on the duration of the cannulation process (depicted as step 5 in Figure 2). This was done to decouple the cannulation process from other superfluous steps and by doing so fulfil our goal to analyse only the difference caused by the application of different distributions and process descriptions as conveyed in the previously defined data associated with Experiments A and B.

Independently produced random number generator seeds are used for all distributions in this simulation. When a simulation is repeated, to obtain results depicted in Figures 2 and 3, each day is simulated independently by the Monet-Carlo Method.

III. RESULTS

The simulation provides these outputs: a count of cannulations simulated, a mean and a standard deviation for duration of cannulation, a 2D histogram (displays a collection of two-dimensional histograms) of cannulation time for all processed patients, number of patients as well as current utilisation for resources (nurses and chairs). 2D histograms provided in Figures 2 and 3 are particularly useful for analysing a number of stochastic data sets, e.g. a number of realizations of a stochastic process in time obtained in different simulation runs [13]. Furthermore, each simulation provided an output file in csv format with a dataset containing all cannulation durations. This file is processed in R to obtain the results provided in Table V.

The 2D histograms in Figures 2 and 3 show the results of a Monte-Carlo simulation that is repeated 100 times (100 days), the deeper shade denotes higher frequency of occurrence, y axes the simulated time in the working day and y axes denotes time in minutes. In Figure 2 we show results of simulation when the triangular distribution using estimates provided by nurses is used (Experiment A) and in Figure 3 we show the same simulation when the customised distribution based on observed sample is used (Experiment B).

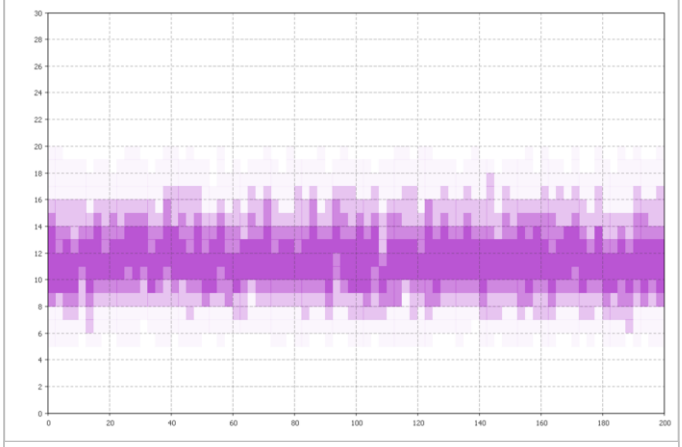

FIG. 2 RESULT A - 2D histogram for distribution of cannulation time when triangular distribution based in estimates provided by nurses is used. Axis- x – simulation time, axis y – duration time

We applied Welch Two Sample t-test to validate hypothesis that the mean duration times for Experiment A and Experiment B are not equal, t = -18.7, df = 19601, p-value < 2.2e-16 and we obtained 95% confidence interval for the difference between means of (-1.48, -1.20). We include this result in the last row of Table V.

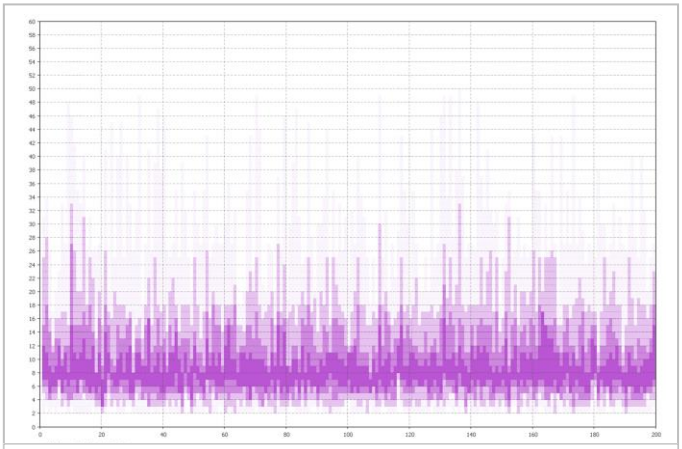

FIG. 3 RESULT B - 2D histogram for distribution of cannulation time when sample from observations is used to construct a custom distribution of cannulation duration.

The simulation results for duration of the cannulation process for the Experiment B indicate significantly higher variation than in the previously developed model simulated in the Experiment A. The practical implication of this finding is that due to high variability in the duration of cannulation more nursing resources and better informed scheduling practices are required than initially estimated (Experiment A) although the mean cannulation time may be lower. Further investigation of the process has revealed that main difference stems from the case when

cannulation was attempted by the second or even third nurse because multiple initial attempts were not successful. When we include this into our analysis and consider such an event as a unique cannulation attempt we obtain the mean cannulation time of 11.56, the SD of 11.93 and the 95% confidence interval for the mean of 0.23. This mean represents just 0.43% increase when compared to the mean cannulation time in the Experiment A. However, it is important to note that for this case the SD is 3.06 times larger than what was obtained in the Experiment A and therefore emphasises requirement for more nursing resources than what was indicated by the initial model.

TABLE V
DIFFERENCE BETWEEN MEANS FOR CANNULATION PROCEDURE DURATION BETWEEN EXPERIMENTS A AND B

n	Mean cannulation time	SD	Median	Standard error
Experiment A				
12,514	11.51	3.91	11.15	0.03
Experiment B				
12,514	10.17	7.01	7.65	0.06
Difference (as % of results for A), instead of Standard error we provide margin of error for the difference between means*				
0 (0%)	-1.34 (11.64%)	3.1 (79.28%)	3.5 (31.39%)	0.14 (10.45%)*

IV. CONLUSION

In this study we used four diverse sources of data to inform, calibrate and validate a simulation and analysis of a medical process. The main findings are the following. Firstly, the accuracy of the estimates of duration of cannulation obtained through the interviews with the nurses and the chemotherapy unit manager is very high. The difference when cannulation attempts by multiple nurses for a single patent are considered is only 0.43% (Table 2 and 4) which highlights that the interviewed nurses were able to estimate the duration of cannulation very accurately. However, as evident from the difference in the mean cannulation time provided in the Table 5, the triangular distribution, that is often assumed when simulating such a process, does not adequately capture variation in the duration of the cannulation time so an important component that effects the resource utilisation is lost. Therefore, we can conclude that it is important to sample, examine and, when necessary, include in a simulation model relatively infrequent events and/or outliers such as previously discuss cannulation attempts done by multiple nurses on a single patient.

Secondly, although the duration estimates were precise, the process descriptions obtained through interviews with nurses were oversimplified or incomplete and therefore did not realistically reflect complexity of a medical process with a significant number of relatively rarely occurring exceptions. Consequently, we can conclude that the observations often may represent a data source important for the overall accuracy.

Thirdly, by combining multiple data-sources it is possible to reduce costs associated with observation as a most expensive data-capturing approach. This can be achieved by resorting to observations for specific sub-processes with higher complexity (e.g. large number of exceptions or steps) or processes that involve infrequent but resource intense steps while using estimates for other simpler processes.

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