**Introduction to Simulation Modelling**

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**Learning objectives:**

1. Describe Discrete Event Simulation with an example
2. State when simulation might be more appropriate than other Lean improvement tools

Simulation modelling is the application of computation models built to replicate real life phenomena and/or processes in order to make inferences of interest. It falls within the field of Operations Research and has been applied to complex problems in healthcare since the 1960s [1]. Based on implementation strategy, simulations may be categorized as Continuous, Monte Carlo, Discrete-Event, Agent-Based or Hybrid simulations [2]. The most frequently applied in Healthcare Operations is Discrete Event Simulation (DES), which allows us to emulate real-life processes in a software environment, experiment, and assess the impact of changing the variables of a system on the outcomes of interest. For instance, let's say we wanted to optimize the number of check-out counters open in Hannaford in the last hour of the day to ensure the store is ready for close at the earliest. We could try small tests of change (reduce/hire) until we find the right mix, but quite often, that approach can be too slow or too expensive. Simulation can help. Start by obtaining the number of check-outs from your sales database in the last hour by day of week, then use the trusty clipboard to understand the distribution of check-out time (e.g. 20% took about 2 minutes, 40% took about 5 minutes, and 20% took longer). From these two data points, a simulation model can be used to create several scenarios – such as opening 2, 4, 6 or more stations, redeploying an Associate to assist with packing up groceries instead of running another check-out, etc., and assessing the impact of those choices on both the time taken to clear the queue as well as the utilization of the assigned resources – without actually doing anything!

DES couples the principles of probability models and queuing theory with large scale random sampling. While most of it is done in specialized software, small scale simulation can be done in Excel as well. For instance, going back to the Hannaford example – if we assume that between 50 and 60 people show up to check-out between 8pm and 9pm on a weekday, and it takes approximately four minutes to check-out each person on average – we can build a simple model in excel to get started:

| #Customers | Avg Check Out Time per Customer | #Stations Open (assumed) | Time taken to clear queue |
|---|---|---|---|
| 60 | 3.5 | 2 | 105.0 |
| 60 | 3.5 | 2 | 105.0 |
| 54 | 3.5 | 2 | 94.5 |
| 56 | 3.5 | 2 | 98.0 |
| 52 | 3.5 | 2 | 91.0 |
| 55 | 3.5 | 2 | 96.3 |
| 55 | 3.5 | 2 | 96.3 |
| 58 | 3.5 | 2 | 101.5 |
| 59 | 3.5 | 2 | 103.3 |

=RANDBETWEEN(50,60)

Measured average time per customer

Number you want to test, e.g. 2, 4 etc.

= (B2*D2)/C2

Average of this column is the time taken to clear the queue!

By changing the values in columns B, C and D, you can compare what happens with 2-4-6-more check-out staff. The key, as always with statistical inferences, is to have enough values. That is, the more values we have in column B, the closer the data gets to being normally distributed and the more robust is our estimate of the central tendency. For fun, start with a 1000+ values!

DES has found several areas of application in healthcare at Maine Medical Center - for instance, in streamlining workflows at the Covid Clinics, estimating the impact of the surgical schedule on Intermediate Care (IMC) bed needs, forecasting number of emergency department beds needed over the next 5, 10 and 15 years, and many others.

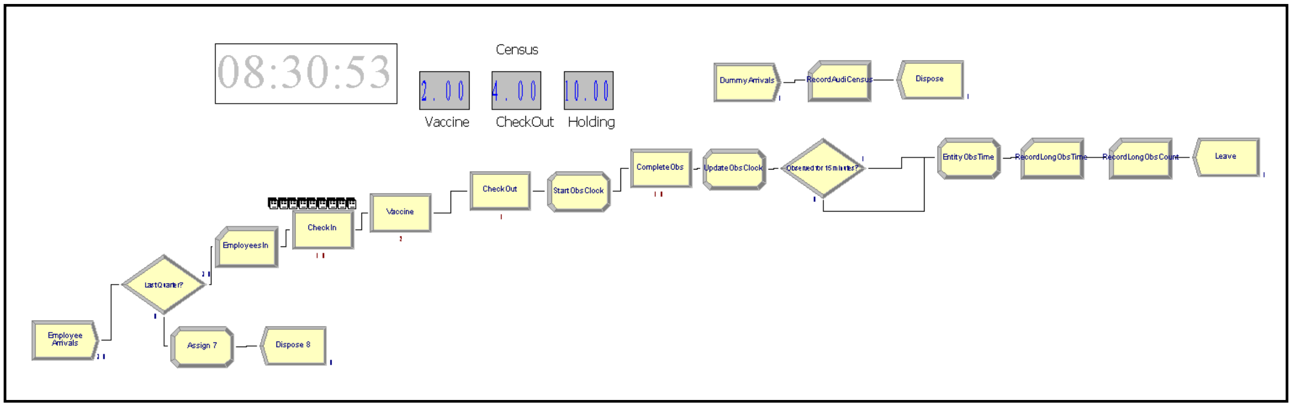


*Figure 1 A simulation model to assess workflows at one of the Covid Vaccine Clinics*

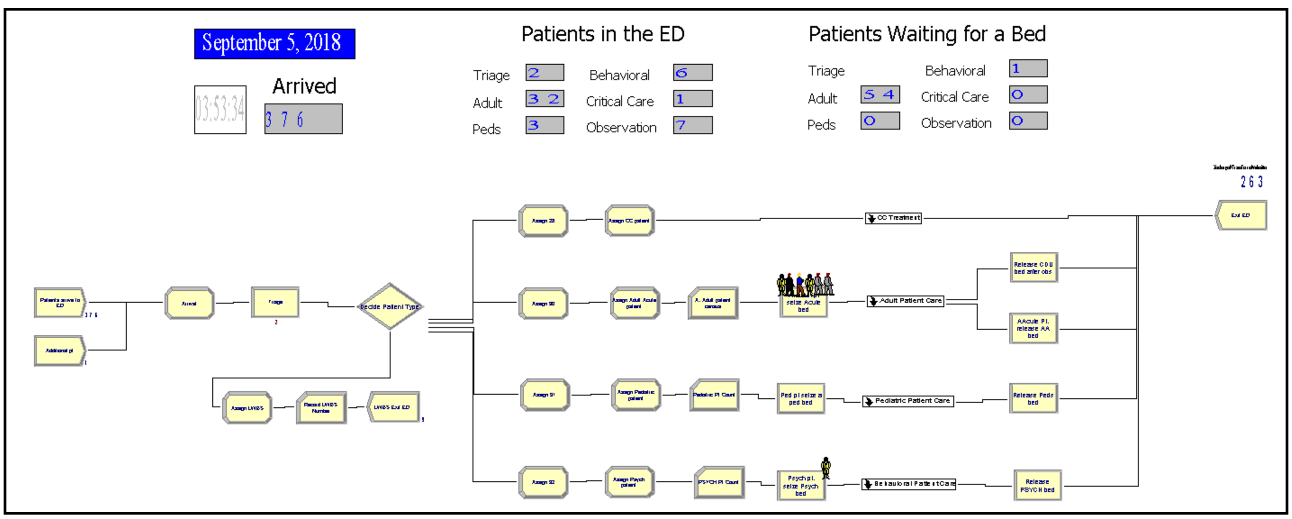


*Figure 2 A model to simulate ED capacity and project needs for the next decade*

Given the effort involved in building a good simulation, it is always best to first ask “what are you trying to achieve?” In Process Improvement, it never hurts to start with understanding the process (preferably with the right control charts!) by conducting a root-cause analysis and trying out a few PDCA (Plan-Do-Check-Act) cycles. If, however, we find ourselves dealing with a complex system comprised of many interacting factors and expensive tests-of-change, simulation can help build and test different solutions or alternatives to recommend the best place to start.

**References:**

[1] Henderson, S.G., Biller, B., Hsieh, M.H., Shortle, J., Tew, J.D., Barton, R.R., Brailsford, S.; Tutorial: Advances and challenges in healthcare simulation modeling. In Proceedings of the 2007 Winter Simulation Conference.
[2] Preston White Jr., K; Ingalls, R.G.; The Basics of Simulation. In Proceedings of the 2020 Winter Simulation Conference.