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Published in:
International Manufacturing Conference (IMC33)

Document Version:
Peer reviewed version

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IDENTIFYING THE IMPACT OF INCOMPLETE DATASETS ON PROCESS CYCLE TIME PREDICTION IN AN AEROSPACE ASSEMBLY LINE

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ABSTRACT

Supply Chain Simulation (SCS) is applied to acquire information to support outsourcing decisions but obtaining enough detail in key parameters can often be a barrier to making well informed decisions.

One aspect of SCS that has been relatively unexplored is the impact of inaccurate data around delays within the SC. The impact of the magnitude and variability of process cycle time on typical performance indicators in a SC context is studied.

System cycle time, WIP levels and throughput are more sensitive to the magnitude of deterministic deviations in process cycle time than variable deviations. Manufacturing costs are not very sensitive to these deviations.

Future opportunities include investigating the impact of process failure or product defects, including logistics and transportation between SC members and using alternative costing methodologies.

KEYWORDS: Supply Chain Simulation, Incomplete Datasets, Variable Cycle Times

1.0 INTRODUCTION

Supply Chain Simulation is applied to inform outsourcing decisions but the data requirements and modelling approaches can be a significant challenge given the diverse range of factors which can influence any decision and how these can vary over time.

Despite being a significant obstacle in simulation, there is no formal procedure in the event required data being unavailable [1]. It should be kept in mind the right model is one that accurately mirrors the real or proposed system in all ways important to the user and does so as simply as possible [2]. Simulation models should only be used and developed until the decision maker has been informed to a level where they know what decision to make [3].

A variety of modelling methods to gain information regarding the behaviour of SCs have been explored; it was found the level of fidelity used in models had a significant influence on the results [4], the use of approximations had a greater impact on SC analysis than customer demand [5] while simplifying demand distributions tended to lead to underestimation of SC performance than
would normally be expected and the effect of demand distributions is statistically significant [6].

One avenue that is relatively unexplored in SCS is the impact of inaccurate data around delays. To investigate the impact of data accuracy, the magnitude and variability of process cycle times is studied. QUEST Discrete Event Simulation (DES) software package was used to simulate likely production scenarios of an aerospace assembly line.

2.0 CASE STUDY

One aspect that has been relatively unexplored is the impact of inaccurate data around delays in SCS. To investigate the impact of data accuracy, the magnitude and variability of process cycle times is studied. An aerospace assembly line is used as an exemplar and the QUEST Discrete Event Simulation (DES) software package is used to simulate likely production scenarios.

The assembly line consisted of two main subassemblies made alongside each other in parallel workstations created from a series of “kits” introduced throughout the line before they were brought together for the final assembly.

Constant and random process cycle time deviations from the industrial standard are investigated to reflect circumstantial changes in production conditions. Key Performance Measures (KPI) used in the study reflect those commonly measured in a SC context, namely manufacturing costs, cycle time, throughput and Work In Progress (WIP) [1] [7] [8].

The model was validated using a rate tool model to calculate the arrival times for parts entering the assembly line and by comparing the theoretical assembly cycle time to the simulated result (table 1).

<table>
<thead>
<tr>
<th>Theoretical Assembly Line Cycle Time</th>
<th>Simulation Assembly Line Cycle Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.5</td>
<td>5.5</td>
</tr>
</tbody>
</table>

2.1 Modelling Assumptions

- Since the case study is an internal assembly line, transportation and logistics costs were neglected
- Factors related to quality such as rework and process failures were beyond the scope of this study and are an opportunity for further study
- All parts entered the system at regular intervals regardless of the current state of the system
- All costs associated with the individual processes and their overheads were included in an hourly rate for each process, known as the “wrap rate”. The values presented have been normalised from the actual costs due to their sensitive nature.
- All the parts on the assembly line were considered WIP, even while waiting to undergo a process - nothing goes into storage
- The equation used to calculate the cost of an output part upon completion of a process is:

$$ Part\ Cost = \sum Input\ Part\ Cost + (\text{time\ to\ complete\ process}) \times (\text{process\ wrap\ rate}) $$
3.0 Constant, Factored Cycle Times

Constant deviations in process cycle time were investigated first, representing the possibility of over- or underestimating the process cycle time. The cycle time deviation was modelled by factoring the cycle time by a predefined coefficient. As the deviation in cycle time is constant, any variation in cycle time or WIP would be due to the dynamic nature of the simulation (bottlenecks form, leading to increasing cycle times etc.) and so the variance in the KPI’s were measured.

Figure 1 shows the average cycle time when each process was factored by the coefficient. It’s interesting to note the assembly line cycle time was more sensitive to increases in process cycle time compared to decreases of the same magnitude for some processes. One explanation for this would be the need to the capacity of the assembly line is limited to that of the critical process; decreasing the cycle time for a single process may not be sufficient to achieve this unless it is a critical process. In contrast, an increase in process cycle time may cause a bottleneck, causing parts to queue and making the assembly line unstable.

Knowing the impact on the average cycle time is not sufficient however as the dynamic nature of the assembly line is not captured. Variance was used to identify sensitive processes; each process identified was found either in the critical process path or at the shared workstation; any delays caused at these workstations would have caused bottlenecks to form while delays elsewhere were absorbed by the time the parts would normally be waiting for other processes or resulted in an change.

![Figure 1: Average Cycle Time and Variance due to Deterministic Deviation](image-url)
in cycle time proportional to the deviation. When the WIP variance was plotted against the cycle time variance a strong linear correlation was found (figure 2). Processes which are sensitive to constant deviations in cycle times are likely to cause significant variance in WIP and assembly line cycle times. Accurate data regarding these processes would therefore be needed to avoid increasing in WIP and cycle times.

\[
R^2 = 0.9743
\]

\[
R^2 = 0.9986
\]

The impact of constant deviations in cycle time depended on the process in question, although when the coefficient was less than 1 for any process it had no effect on the throughput. In addition, the sensitivity of the throughput was dependent on the process as well as the coefficient. In this case the processes where there was a decrease in the throughput were those identified by their impact on the assembly line cycle time variance.

4.0 Variable Cycle Time

To obtain an understanding of the level of data accuracy required for a model, random deviations in cycle time were modelled with triangular distributions as the industrial data was limited to constant process cycle times. The coefficient was used to establish the maximum and minimum cycle times possible in each scenario by adding and subtracting the mode time.

\[
\text{Min Time} = \text{Mode Time} - (\text{Mode Time} \times \text{Coefficient})
\]

\[
\text{Max Time} = \text{Mode Time} + (\text{Mode Time} \times \text{Coefficient})
\]

The impact of constant deviations in cycle time depended on the process in question, although when the coefficient was less than 1 for any process it had no effect on the throughput. In addition, the sensitivity of the throughput was dependent on the process as well as the coefficient. In this case the processes where there was a decrease in the throughput were those identified by their impact on the assembly line cycle time variance.

![Figure 2: WIP Variance against Cycle Time Variance](image)

![Figure 3: Illustration of the triangular distribution used for process cycle times](image)
factored by the coefficient (figure 3).

The process named in each scenario had its coefficient changed to 0.2 while the rest remained at 0.1. 20 simulation runs were performed for each scenario; providing between 2000~2100 data points for each KPI per scenario.

A baseline simulation using a coefficient of 0.1 was used for all of the processes to understand the nature of the output. In some cases the distributions for particular KPI were skewed by extreme values which rarely occurred. Therefore the mean average, maximum, minimum, standard deviation, variance and skewness of the KPI distributions were measured.

### 4.1 Impact of Variability on Assembly Line Cycle Time

Table 2: Cycle Time and Throughput Impact due to Variable Cycle Time Deviations

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Mean</th>
<th>Max</th>
<th>Min</th>
<th>S. Dev</th>
<th>Var</th>
<th>Skew</th>
<th>Throughput</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline - constant</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Baseline - variable</td>
<td>1.01</td>
<td>1.07</td>
<td>0.96</td>
<td>0.58</td>
<td>0.33</td>
<td>0.62</td>
<td>1.00</td>
</tr>
<tr>
<td>Process 3</td>
<td>1.02</td>
<td>1.11</td>
<td>0.95</td>
<td>0.75</td>
<td>0.56</td>
<td>0.19</td>
<td>0.99</td>
</tr>
<tr>
<td>Process 4</td>
<td>1.04</td>
<td>1.17</td>
<td>0.96</td>
<td>1.09</td>
<td>1.19</td>
<td>0.75</td>
<td>0.99</td>
</tr>
<tr>
<td>Process 5</td>
<td>1.04</td>
<td>1.41</td>
<td>0.95</td>
<td>1.62</td>
<td>2.62</td>
<td>3.32</td>
<td>0.99</td>
</tr>
<tr>
<td>Process 6</td>
<td>1.05</td>
<td>1.38</td>
<td>0.95</td>
<td>1.40</td>
<td>1.95</td>
<td>1.37</td>
<td>0.99</td>
</tr>
<tr>
<td>Process 7</td>
<td>1.04</td>
<td>1.19</td>
<td>0.94</td>
<td>1.16</td>
<td>1.33</td>
<td>0.46</td>
<td>0.99</td>
</tr>
<tr>
<td>Process 12</td>
<td>1.01</td>
<td>1.09</td>
<td>0.95</td>
<td>0.62</td>
<td>0.38</td>
<td>0.15</td>
<td>1.00</td>
</tr>
<tr>
<td>Process 14</td>
<td>1.05</td>
<td>1.39</td>
<td>0.95</td>
<td>1.89</td>
<td>3.56</td>
<td>2.62</td>
<td>0.99</td>
</tr>
</tbody>
</table>

From comparing the cycle time of each scenario to the baselines in table 2 it can be seen that introducing variability into the system increases the range of possible cycle times and average cycle time. The impact on throughput is limited in comparison to the loss when constant deviations were considered. The maximum cycle time in each scenario was more sensitive to variability compared to the mean average or minimum cycle time. In addition, the assembly line cycle time was not as sensitive to variable process cycle times compared to the constant deviations; while there was variation in all cases, this would have in part been due to variability in other processes.

Table 3 shows the influence of variability to the final cost of the assembly. The final cost was not very sensitive to variability as the largest deviation was a small percentage compared to the baseline; the higher variance is mainly due to the high values involved in measuring the final cost.
4.2 Impact of Variability on Final Manufacturing Cost

Table 3: Final Cost Impact due to Variable Cycle Time Deviations

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Mean</th>
<th>Max</th>
<th>Min</th>
<th>S. Dev</th>
<th>Var</th>
<th>Skew</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline - constant</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Baseline - variable</td>
<td>1.00</td>
<td>1.01</td>
<td>0.99</td>
<td>28.78</td>
<td>828.53</td>
<td>0.12</td>
</tr>
<tr>
<td>Process 3</td>
<td>1.00</td>
<td>1.01</td>
<td>0.99</td>
<td>33.16</td>
<td>1099.86</td>
<td>-0.08</td>
</tr>
<tr>
<td>Process 4</td>
<td>1.00</td>
<td>1.01</td>
<td>0.99</td>
<td>33.23</td>
<td>1110.67</td>
<td>-0.04</td>
</tr>
<tr>
<td>Process 5</td>
<td>1.00</td>
<td>1.01</td>
<td>0.99</td>
<td>31.70</td>
<td>1004.98</td>
<td>-0.05</td>
</tr>
<tr>
<td>Process 6</td>
<td>1.00</td>
<td>1.01</td>
<td>0.99</td>
<td>29.31</td>
<td>858.90</td>
<td>-0.11</td>
</tr>
<tr>
<td>Process 7</td>
<td>1.00</td>
<td>1.01</td>
<td>0.99</td>
<td>30.57</td>
<td>934.28</td>
<td>0.00</td>
</tr>
<tr>
<td>Process 12</td>
<td>1.00</td>
<td>1.01</td>
<td>0.99</td>
<td>32.23</td>
<td>1103.87</td>
<td>-0.07</td>
</tr>
<tr>
<td>Process 14</td>
<td>1.00</td>
<td>1.01</td>
<td>0.99</td>
<td>30.39</td>
<td>923.75</td>
<td>-0.15</td>
</tr>
</tbody>
</table>

4.3 Impact of Variability on Assembly Line WIP

Table 4: WIP Impact due to Variable Cycle Time Deviations

The top value is quantity, the bottom value is WIP value

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Mean</th>
<th>Max</th>
<th>Min</th>
<th>S. Dev</th>
<th>Var</th>
<th>Skew</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline - constant</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Baseline - variable</td>
<td>1.00</td>
<td>2.13</td>
<td>1.00</td>
<td>0.88</td>
<td>0.77</td>
<td>0.52</td>
</tr>
<tr>
<td>Process 3</td>
<td>1.00</td>
<td>1.01</td>
<td>0.63</td>
<td>2.28</td>
<td>5.21</td>
<td>0.36</td>
</tr>
<tr>
<td>Process 4</td>
<td>1.25</td>
<td>1.06</td>
<td>1.00</td>
<td>3.31</td>
<td>14.57</td>
<td>0.07</td>
</tr>
<tr>
<td>Process 5</td>
<td>1.13</td>
<td>1.00</td>
<td>0.63</td>
<td>4.15</td>
<td>14380867.74</td>
<td>0.10</td>
</tr>
<tr>
<td>Process 6</td>
<td>1.25</td>
<td>1.06</td>
<td>1.00</td>
<td>4.12</td>
<td>17257939.82</td>
<td>0.05</td>
</tr>
<tr>
<td>Process 7</td>
<td>1.25</td>
<td>1.05</td>
<td>1.00</td>
<td>4511.29</td>
<td>20351700.92</td>
<td>0.07</td>
</tr>
<tr>
<td>Process 12</td>
<td>1.00</td>
<td>1.00</td>
<td>0.63</td>
<td>4.15</td>
<td>17.26</td>
<td>0.11</td>
</tr>
<tr>
<td>Process 14</td>
<td>1.25</td>
<td>1.06</td>
<td>1.00</td>
<td>4629.53</td>
<td>21432506.23</td>
<td>0.05</td>
</tr>
</tbody>
</table>

In table 4 it can be seen the amount of WIP in the system is sensitive to variability when it is uncontrolled (i.e. action was not taken in response to the WIP level in the system).
The skewness in the cost and quantity of WIP were relatively consistent with differences being due to each part having a different cost associated with it rather than the exact same value. Most scenarios had extreme levels of WIP although the skewness were different; build up in the system that was released in between cycles, causing oscillation between the extremes to occur without the line to becoming unstable.

5.0 CONCLUSION

Processes which cause significant variance in system cycle time and WIP are likely to cause the system to become unstable. Accurate data for these processes is therefore of greater importance than those that cause little or no variance in assembly line cycle time.

The throughput and cycle times were more sensitive to the deterministic deviations than variable deviations. In addition, they were more sensitive to deviations which caused an increase in process cycle time compared to decreases of the same magnitude. When looking from a SC perspective, these points are of importance when scheduling deliveries and determining supplier capacity.

The manufacturing cost was not very sensitive to deterministic or variable deviations in process cycle time (the maximum deviation being a few percent of the baseline). In this study, process cycle time variability was of little importance in this study for estimating the manufacturing cost for a supplier / bid for work.

The amount and value of WIP was very sensitive to variability in the system. Skewness was a useful metric in determining the distribution of the WIP to identify how often extreme levels of WIP occurred. WIP control policies in this context were not modelled although in a SC context, maintaining greater control over these processes may be recommended to avoid requiring additional storage to accommodate WIP build up.

Future opportunities include investigating the impact of process failure or product defects, considering logistics and transportation between SC member, modelling WIP control policies, using alternative costing methodologies and investigating deviations in parts delivery.

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