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#### Abstract

Most planning models treat lead time as a constant independent of workload, but the resulting order rate implies capacity utilization which in its turn affects the lead time. An important factor that determines production order rate is the batch size, one expects therefore a relationship between batch-sizing and lead time. This dependency is examined for different operational conditions using system dynamics simulation of a manufacturing model comprising a quality control unit which is also the bottleneck of the system. It is shown that there is an optimal batch size that results in a minimum lead time and that inventory level at optimum matches desired inventory. Below optimal batch, lead time increases sharply due to congestion at the bottleneck. The reported results have implications for production planning and implementation of process improvement.


Keywords: lead time, optimal batch size, system dynamics, simulation, production policies, capacity utilization

[^1]
## 1. Introduction

Lead time ${ }^{1}$ is a key performance indicator which besides being a crucial measure of service levels is the only parameter in the objectives scheme described by Hopp and Spearman (2000, P. 196) that supports both lower manufacturing costs and high sales. Hence insight on how lead times might vary with factors such as arrival rate, variability and batch size is essential for effective planning and scheduling. The dependency on batch size is especially important given that in many optimising models for example the Economical Order Quantity, Penido 2007, or using Material Requirement Planning (MRP) procedures, lead times are treated as a constant independent of planning policy.

In this work system dynamics (SD) simulation is used to investigate lead times in a manufacturing environment where one of the processing units is a bottleneck. Similar workflows are found in the pharmaceutical and chemical industries where semi-finished products have to undergo thorough testing before being packaged and released to the market. It is often the case, especially in pharmaceutical manufacturing, that quality testing is time consuming, labour intensive and administered by a unit independent from production although from the perspective of supply chain it is an integral part of the workflow. When demand increases planers feel the pressure to send more orders into production thereby risking congestion at the bottleneck and ending up in long queues and delays.

### 1.1 Related work

Karmarker 1987, 1993 examined the relationship between lot-sizing and lead times from the perspective of queue theory. He showed that as batch sizes are reduced, utilization i.e. the ratio between arrival rate and throughput approaches unity, the average time an item spends in the system increases very rapidly. At the other end of the scale as batch size increases, waiting times dominate the process and the average lead time starts to increase. In between there is a minimum lead time. Hopp and Spearman (2000, P. 305) computed optimal batch sizes for different batching processes. Their results are similar to those of Karmarker cited above. Gung 1999 considered the effect of set up time and batch size reduction on lead times. The author describes a workload balancing model and suggests a minimum set up time reduction ratio. Chandra and Gupta 1997 studied lead time reduction in a semiconductor facility where batch processing is a part of the manufacturing line. They outline a procedure whereby the bottleneck station pulls its requirements from the assembly section. Lee and Chung 1998 investigated batching decisions in a multi product environment. They used a non linear mixed integer program to minimize the flow in a closed job shop. Enns 2001 analysed the relation between planned lead times and batch size in the context of MRP logic. Olinder and Olhager 1998 studied the effect of different lot sizing models controlled by MRP logic on lead times. Ocrun et al. 2006 compared a number of capacity models using system dynamics simulations. The authors conclude that at high utilization many models used in production planning and system dynamics fail to capture the non-linear behaviour involved, while a saturated concave clearing function ${ }^{2}$ does. Recently Pahl et al. 2007 reviewed different models of load dependent lead times in

[^2]the context of production planning.

### 1.2 System Dynamics

System Dynamics is a method for analysing policies and solving complex problems by using computer simulation models. The models capture the causal interlinks within the system and project them as a structure of feedback loops. The use of SD in Supply Chain Management is dated back to the seminal work of Forrester 1958, 1961 and it has been applied to a wide range of problems related to manufacturing and supply chain management Sterman 2000, Angerhofer and Angelides 2000, Akkermans and Dellaert 2005, Min Huang et al. 2007. SD takes an aggregate view on policies, the level of aggregation and the boundary of the model should reflect the time scale for the dynamics of interest and the problem studied.

## 2. Production Model

An overview of the manufacturing model is shown in Figure 1, some links are omitted in order to simplify the sketch. The model is adapted from the generic structure by (Sterman 2000 chap. 18), neglecting those elements of the supply chain that deals with procurement or administrative delays since the concern of the study is the effects of batch-sizing on lead time. The simulation experiments were performed using VENSIM software. Further details regarding the underlying equations are given in the appendix.

## Figure 1

Orders arrive continuously and batching is accomplished using DELAY BATCH function which takes a continuous input stream and returns it as pulses when the amount accumulated is equal to the specified batch size. Following the first manufacturing stage (production) a given number of samples are sent for quality testing. Meanwhile semi-finished products are kept in quarantine pending release. When quality control is completed, finishing (packaging, labelling etc.) is carried out and products are sent to finished goods inventory for delivery. Unfilled orders are backlogged and lead time is calculated from

$$
\begin{equation*}
\text { lead time }=\text { backlog/ order fulfilment rate } \tag{1}
\end{equation*}
$$

For an order rate D and batch size Q , the waiting time to reach Q is $\mathrm{Q} / \mathrm{D}$, also the frequency of sample arrivals to quality control is $\mathrm{ND} / \mathrm{Q}$, where N is the number of samples sent to quality control for every batch produced. Hence decreasing batch size shortens the waiting time but increases the load on the bottleneck causing congestion and delays. Increasing Q will have the opposite effect. An intermediate batch size results in a minimum lead time.

### 2.1 Delays at the Work Centres

The outflow from stocks is described by first order material delay (Sterman 2000 p. 415)
Outflow = WIP/delay time

The delay time at Production and Finishing is set to 0.5 weeks irrespective of batch size. In the range of batch sizes considered this a reasonable assumption since many facilities may have additional capacity. More importantly, making the delays at these work centres time dependent will have little effect on the main results as long as these delays are kept shorter than the delay at the bottleneck. The output rate at the bottle neck is taken to be labour constrained which is a common situation in control laboratories. Maximum throughput becomes

$$
\begin{equation*}
T H_{\max }=\frac{p w}{T_{0}}=\frac{W_{0}}{T_{0}} \tag{3}
\end{equation*}
$$

$p$ is the productivity (samples cleared by unit labour), $w$ the workforce and $T_{0}$ is the raw process time, i.e. the time it takes to perform quality control when there is ample capacity and no congestion and $W_{0}=p w$ is the critical WIP level.
The delay time at quality control is modelled using the concepts of best-case performance and practical worst-case performance (PWC), two special cases described by Hopp and Spearman 2000 for a balanced line consisting of a number of single machines. Best case performance is the scenario where there is no process variation. The delay time is constant up to a point where load is equal $\mathrm{W}_{0}$. Beyond that point delay time increases proportionally with the load. It should be noted that the absence of variability referred to does not imply a FIFO discipline in the present study since a first order material delay assumes mixing of the units in the stock; it is rather referring to the regularity of processing times of the samples. The equations for the outflow rate and delay time for best-case performance are

$$
\begin{align*}
& T H_{\text {best }}= \begin{cases}\frac{\text { WIP }}{T_{0}} & \text { if WIP } \leq W_{0} \\
T H_{\max } & \text { otherwise }\end{cases}  \tag{4}\\
& \text { Delay time }= \begin{cases}T_{0} & \text { if WIP } \leq W_{0} \\
\frac{W I P}{T H_{\max }} & \text { otherwise }\end{cases} \tag{5}
\end{align*}
$$

Practical worst-case performance describes the situation where there is a maximum randomness in the system and every possible state has the same probability, for example presence or absence of labour occurs with the same frequency.

The outflow rate and delay time are

$$
\begin{equation*}
T H_{P_{W c}}=\frac{W I P}{W_{0}-1+W I P} T H_{\max } \tag{6}
\end{equation*}
$$

$$
\text { Delay time }=T_{0}+\frac{W I P-1}{T H_{\max }}
$$

The delay time in this case reduces to its minimum $\mathrm{T}_{0}$ when there is only one sample in transient. Equations (4) and (6) are examples of the clearing functions mentioned earlier used to model capacity versus work load. In the terminology of Orcun et al. 2006 these equations correspond to capacitated constant proportion and concave saturating clearing functions. Karmarker 1993, used an empirical parameter k in Eq. (6) instead for $\mathrm{W}_{0}-1$ to determine the output rate.

## 3. Simulation and Results

The aim of the simulation experiments is to investigate the variation of lead time with batch size under different operational conditions. The design of the simulation runs is given in Table 1.

## Table 1

In these runs the productivity is held constant equal to one, but since $\mathrm{W}_{0}$ the critical WIP is calculated from the product of labour with productivity the results can equally well be interpreted as if workforce is constant and productivity is changing. The demand rate is assigned a value of 5 pallets/week. Random demand is generated from random numbers in the range 3 to 7 resulting in a series that has an average value of 5.1 and standard deviation 1.5 pallets/week. The same sequence of numbers is used for all random demand runs. The purpose of the run with $\mathrm{T}_{0}=0.5$ and $\mathrm{w}=5$ is to investigate the systems performance when work force and raw process time are reduced simultaneously keeping the bottleneck rate constant at 10 pallets/week.
For a given batch size the simulation covers a period of 60 weeks, lead time is taken as the average of the last 40 weeks where transient effects have faded out. For small and large batches, lead times increase systematically with time resulting in average values that depend on the averaging period. However for batch sizes just smaller than optimal and up to roughly 20 pallets, lead times are either constant (constant demand) or vary randomly (random demand). The results of the simulations are summarized in Tables 2a and 2b, typical plots of lead time against batch size are shown in Figure 2.

## Figure 2

As batch size approahes $\mathrm{ND} / \mathrm{TH}_{\max }$, that is U comes close to 1 there is a sharp increase in lead time while to the right of the minimum there is a slow and initially almost linear increase. Comparing constant and random demand, the minimum occurs practically at the same batch size but the lead time is longer in the later case. Shortest lead times are obtained when utilization is aproximaely 0.85 or 0.5 depending on whether it is best case or practical worst case. $\mathrm{T}_{\text {cal }}$ is the waiting time to reach a given batch size plus the shortest delays at the work centers. The values obtained agree with lead times for constant demand. Table 2 lists also the inventoy levels at steady state. These levels are qual to, or for the case of random demand some what above, desired inventory specified by the model. Lower than optimum batch sizes results in lesser inventory but deliveries will not be able to cope with demand causing a steady increase in backlog. Increasing the batch size results in periodic oscillations and raises inventory level. In this sence short lead times are consistent with optimal inventory management.

Table 2a
Table 2b

### 3.1 Relation to Queue theory

Treating quality control as an M/M/1 queuing system (Hopp and Spearman 2000, p. 269) the average lead time can be written as

$$
\begin{equation*}
T(Q)=\frac{Q}{D}+\frac{T_{0}}{1-\frac{N D}{Q T A_{\max }}}+T_{p r}+T_{f i n} \tag{8}
\end{equation*}
$$

the last two terms are due to production and finishing. Equation (8) is graphed in Figure 3, the curve is similar to those obtained by SD simulation but is less flat.

## Figure 3

An expression for the batch size that minimizes $\mathrm{T}(\mathrm{Q})$ can be found by taking the derivative and setting it to zero giving

$$
\begin{equation*}
Q^{e}=D T_{0}\left(\frac{N}{W_{0}}+\sqrt{N / W_{0}}\right) \tag{9}
\end{equation*}
$$

The second term is due to randomness because $Q^{*}=\mathrm{DT}_{0} \mathrm{~N} / \mathrm{W}_{0}$ is equivalent to $100 \%$ capacity utilization. Eq.(9) gives results that agree well with practical worst-case scenario, for example substituting the data used to plot Figure 3, Eq. (9) gives 12 pallets as in Table 2.

### 3.2. Many Product System

So far the analysis has been limited to a one product system and samples having identical raw process time. To model the general case where process times at the testing unit are different (this may be the case even for a homogenous batch) requires indexing the individual batches as well as the samples, a procedure that considerably complicates the simulation. Moreover identifying the individual items raises issues such as scheduling and prioritisation which are beyond the scope of this work. Nevertheless by expressing the workload in time units it is possible to estimate the degree of capacity utilization and total batch size resulting in smallest average lead time.
Let $D_{\text {tot }}=\Sigma_{i}^{m} D_{i}$ be the total demand and $Q_{\text {tot }}=\Sigma_{i}^{m} Q_{i}$ the total number of batches. The proportion of the in individual batches in the production mix should reflect demand i.e. $Q_{i} / Q_{\text {tot }}=$ $D_{i} / D_{\text {tot }}$ otherwise there will be an access inventory of one product and shortage of another. This production mix generates $N_{\text {tot }}=\Sigma_{j}^{n} N_{j}$ samples each having a raw process time $T_{j}$. In time units the workload generated is $\Sigma_{j}^{n} N_{j} T_{j}$ and maximum throughput for sample type j becomes $\left(T H_{\max }\right)_{j}=p_{j} w_{j} T_{j} / T_{j}=p_{j} w_{j}$ where p and w are productivity and work force as in Eq.(3). Since the output is considered to be constrained only by labour sample analysis is carried out in parallel, hence the maximum total throughput is $T H_{\max }=\Sigma_{j}^{n} p_{j} w_{j}$. If the number of samples exceeds available workforce than some of the $w_{j}$ in the summation will be zero. This is equivalent to assigning some analysts more than one sample and considering these as a single unit of work with a process time equal to the sum of the individual process times. The summation is then taken over the number of analysts available. With these definitions Eq.(7) and Eq.(8) can be rewritten as

$$
\begin{align*}
& \text { Delay time }=\left\langle T_{0}\right\rangle+\frac{W L-1}{\sum p_{j} w_{j}}  \tag{10}\\
& T\left(Q_{\text {tot }}\right)=\frac{Q_{t o t}}{D_{t o t}}+\frac{\varepsilon_{0} T_{0}}{1-\frac{K_{t 0 t} U_{\text {wt }}}{Q_{t o t} T H_{\operatorname{mas}}}}+T_{p r}+T_{f i n} \tag{11}
\end{align*}
$$

WL is the work load in time units and $\left\langle T_{0}\right\rangle=\Sigma_{j}^{n} N_{j} T_{j} / N_{\text {tot }}$ is the average raw process time. From Eq.(11) one gets

$$
\begin{equation*}
Q_{t o t}^{*}=D_{t e t}<T_{0}>\left(\frac{N_{\text {tot }}}{\sum_{j j} w_{j}}+\sqrt{N_{t e t} / \sum p_{j} w_{j}}\right) \tag{12}
\end{equation*}
$$

Which reduces to Eq.(9) when one item with constant raw process time is considered. Simulation runs after adapting the model to the definitions above and expressing the delay time by Eq.(10) generates curves as in Figure 2. Numerical results are reported in Table 3.

## Table 3

## 4. Summery

System dynamics is a useful tool for studying the effectiveness of different policies. The model presented above reproduces a simple manufacturing system where product must be tested before being released. The quality control is assumed to be the bottleneck section of the workflow. The maximum output rate at the testing station is constrained by labour, productivity and raw process time. In both cases it is shown that as capacity is heavily exploited WIP levels and lead times increase indefinitely due to congestion at the bottleneck. Also there is an optimum batch size which results in minimum lead times. These insights are important in two ways. Firstly, constantly pushing production rate beyond a certain point results in a viscous circle of missed due dates, increased workload and longer queues. Preliminary Eq.(9), or a utilization level in the range 0.5 to 0.8 can be used to estimate a passable work load. Secondly, one should take a systemic approach to process improvement. Streamlining and enhancing the workflow in one sector may turn out to be counter productive unless measures are also taken to manage the side effects generated at the bottleneck.

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## Appendix

Further details regarding the model
shipment rate $=\operatorname{MIN}($ desired shipment rate, finished goods inventory/minimum delay time), that is the firm ships either what it wants or what it is able to.
finished goods inventory (initial value)= customer order rate * minimum delivery delay
order fulfilment rate $=$ shipment rate; formulated as MIN(back log/time step, shipment rate) in order to prevent the backlog becoming negative
backlog(initial value) $=$ customer order rate $*$ minimum delivery delay
desired shipment rate $=$ customer order rate
minimum delivery delay $=$ delay time production $+\mathrm{T}_{0}+$ delay time finishing delay time production $=$ delay time finishing $=0.5$ weeks
adjustment for inventory $=($ desired inventory - finished goods inventory)/inventory adjustment time inventory adjustment time $=4$ weeks
expected order rate $=\mathrm{SMOOTH}$ (order rate, averaging time), this term calculates a time average
based on an exponential smoothing of the input
averaging time $=4$ weeks
desired inventory $=$ expected order rate $*$ minimum delivery delay + safety stock
safety stock $=2.5$ pallets
number of samples $=10$ samples
Runge-Kutta integration method was used, time step 0.016 week


Figure 1. Stocks and flow structure of the manufacturing model studied


Figure 2. Lead time vs. batch size, (a) best-case, (b) practical worst case. For both runs w $=8, P=1, \mathrm{~T}_{0}=1$


Figure 3. Plot of Eq.(8) for $\mathrm{N}=10, \mathrm{D}=5, \mathrm{TH}_{\max }=8, \mathrm{~T}_{0}=1$

| Table 1. Design variables and their attributes |  |  |  |  |  |
| :---: | :---: | :---: | :--- | :---: | :---: |
| Work force | Delay time | Demand | $\mathrm{T}_{0}$ |  |  |
| 10 | Equations (5) and (7) | Constant and random | 1 |  |  |
| 8 | Equations (5) and (7) | Constant and random | 1 |  |  |
| 6 | Equations (5) and (7) | Constant and random | 1 |  |  |
| 5 | Equations (5) and (7) | Constant and random | 0.5 |  |  |


| Table 2a. Results summery, constant demand |  |  |  |  |  |  |  |  | $\mathrm{Q}^{\mathrm{a}}$ | $\mathrm{T}_{\text {min }}$ | $\mathrm{FGI}^{\mathrm{b}}$ | $\mathrm{Std}^{\mathrm{c}}$ | $\mathrm{U}^{\mathrm{d}}$ | $\mathrm{T}_{\text {cal }}^{\mathrm{e}}$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{T}_{0}=1$ | Work force | $\mathrm{Q}^{\mathrm{a}}$ | 6 | 3.6 | 12.5 | 0.0 | 0.83 |  |  |  |  |  |  |  |
| Best case | 10 | 6 | 3.2 |  |  |  |  |  |  |  |  |  |  |  |
| Best case | 8 | 8 | 3.7 | 12.5 | 0.1 | 0.78 | 3.6 |  |  |  |  |  |  |  |
| Best case | 6 | 10 | 3.9 | 12.5 | 0.2 | 0.83 | 4.0 |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| PWC | 10 | 11 | 4.4 | 12.5 | 0.2 | 0.45 | 4.2 |  |  |  |  |  |  |  |
| PWC | 8 | 12 | 4.5 | 12.5 | 0.3 | 0.52 | 4.4 |  |  |  |  |  |  |  |
| PWC | 6 | 15 | 4.8 | 12.5 | 0.4 | 0.56 | 5.0 |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| $\mathrm{~T}_{0}=0.5$ |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Best case | 5 | 6 | 2.9 | 10 | 0.1 | 0.83 | 2.7 |  |  |  |  |  |  |  |
| PWC | 5 | 9 | 3.4 | 10 | 0.1 | 0.56 | 3.3 |  |  |  |  |  |  |  |

${ }^{\text {a }}$ batch size corresponding to shortest lead time $\mathrm{T}_{\text {min }}$
${ }^{\mathrm{b}}$ average finished goods inventory at $\mathrm{Q}^{*}$
${ }^{\mathrm{c}}$ standard deviation finished goods inventory
${ }^{\mathrm{d}}$ utilization $\mathbf{U}=\frac{\mathrm{ND}_{\mathrm{Q}}}{\mathrm{TH}_{\text {max }}}$
${ }^{e}$ theoretical lead time calculated by $\mathrm{T}_{\text {cal }}=\mathrm{Q}^{*} / \mathrm{D}+\mathrm{T}_{0}+1$

| Table 2b. Results summery, random demand |  |  |  |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{T}_{0}=1$ | Work force | $\mathrm{Q}^{* \mathrm{a}}$ | $\mathrm{T}_{\text {min }}$ | $\mathrm{FGI}^{\mathrm{b}}$ | $\mathrm{Std}^{\mathrm{c}}$ | $\mathrm{U}^{\mathrm{d}}$ |  |
| Best case | 10 | 6 | 5.2 | 13.5 | 2.2 | 0.83 |  |
| Best case | 8 | 7 | 5.2 | 13.5 | 2.3 | 0.89 |  |
| Best case | 6 | 9 | 5.4 | 13.5 | 2.2 | 0.93 |  |
|  |  |  |  |  |  |  |  |
| PWC | 10 | 10 | 5.9 | 13.5 | 2.3 | 0.5 |  |
| PWC | 8 | 12 | 6.0 | 13.6 | 2.3 | 0.52 |  |
| PWC | 6 | 14 | 6.3 | 13.5 | 2.1 | 0.64 |  |
|  |  |  |  |  |  |  |  |
| $\mathrm{~T}_{0}=0.5$ |  |  |  |  |  |  |  |
| Best case | 5 | 6 | 4.4 | 10.8 | 2.1 | 0.83 |  |
| PWC | 5 | 7 | 4.9 | 10.8 | 2.2 | 0.71 |  |


| Table 3 . Results for many product system |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\left\langle\mathrm{T}_{0}\right\rangle$ | Work force | $\mathrm{N}_{\text {tot }}$ | $\mathrm{Q}^{*}{ }^{\mathrm{a}}$ | $\mathrm{Q}^{*}{ }^{\text {b }}$ | $\mathrm{T}_{\min }$ | U |  |
| 1 | 8 | 10 | 12 | 12 | 4.5 | 0.53 |  |
| 1.5 | 8 | 10 | 17 | 18 | 5.5 | 0.53 |  |

$D_{\text {tot }}=5$ pallets/week
Productivity $\mathrm{p}=1$ for all samples.
${ }^{\text {a }} Q_{\text {tot }}$ corresponding to shortest lead time $\mathrm{T}_{\text {min }}$ obtained form model simulation
${ }^{\mathrm{b}}$ Optimal $Q_{\text {tot }}$ obtained from Eq.(12)


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[^1]:    *Email: nabil@xInt-performance.com

[^2]:    ${ }^{1}$ In this work lead time is taken to be the average time from order arrival to shipping
    ${ }^{2}$ More on clearing functions in section 2.1, for details see Pahl et al. 2007

