Stochastic Production Planning for Maximisation of Shareholder Wealth in the MTS Supply Chain Mode

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Abstract: The capacitated lot sizing policy is pivotal to stochastic production planning. This paper attempts to formulate a general lot sizing model for a stochastic MTS (make-to-stock) manufacturing environment under demand uncertainty. To better reflect real-world manufacturing, general distributions are used as a substitute for unrealistic theoretical assumptions on involved random variables. Instead of the traditional optimisation objectives, this research aims at maximisation of the full interest of investors, that is, the shareholder wealth. A quantitative comparison between these optimisation objectives is carried out to offer guidance on the decisions on these performance measures. Numerical experiments validate the significance of the shareholder wealth to production planning. It not only reveals the relevance of the proposed model to production planning, but also highlights the similarities and differences in applications among these commonly used performance metrics.

Key words: Stochastic programming, shareholder wealth, MTS (make-to-stock), lot sizing, CFROI (cash flow return on investment).

1. Introduction

The uncertain lot sizing problem has been a key research focus in SCM (supply chain management) [1-3]. Relatively small lot sizes enhance responsiveness to varying demands, but reduce capacity utilization due to frequent setups. In contrast, larger lot sizes reduce setups but often compel upcoming orders to wait for further processing. Therefore, to search for an optimal lot size is practically beneficial to the entire production planning procedure.

• General uncertainty formulation

Although numerous approaches have been developed to solve this tough issue, most of them are more or less based on unrealistic theoretical assumptions. Typically, the interarrival times are assumed to follow a Poisson process and the processing times to follow a negatively exponential distribution. Some studies even assume that certain stochastic parameters are deterministic. The main aim of these assumptions is to either simplify the model derivation or to achieve a closed-form solution to their target research issues, or even both.

In most cases, however, these assumptions are misleading for a great number of real manufacturing systems [4-6], leading to restrictive or even unreliable optimisation results. For example, some researchers suggest that the theoretical assumptions should be extremely restrictive and unrealistic in practice, even although it had the advantage of improving tractability [7].

Instead, this paper puts weight on a more general production planning environment, where all relevant random variables are treated as generally distributed without any theoretical assumption.

• Manufacturing supply chain mode

Most firms have thus far organized their manufacturing systems as one of the three dominant supply chain modes, that is, MTO (make-to-order), MTS, and mixed MTO/MTS [8-10].
MTO is concerned mainly about efficient execution of orders and timely delivery of finished goods. Its performance metrics are therefore always order oriented, such as lead time, order delay and order acceptance/rejection and so forth. Finished goods produced in the MTO strategy typically tend to be more customer-specific and expensive.

Comparatively, MTS emphasizes how to meet the estimated future demands. It concerns primarily about the inventory planning, the lot sizing policy and the demand estimate. Compared with MTO, MTS caters to a lower variety of bespoke finished products.

In the most recent decade, some firms have adopted the combined MTO/MTS strategy to take full advantage of these two supply chain modes [9-11] in order to produce varieties of products with varying logistical demands and production characteristics for different market segments.

In this paper, we choose to study the MTS manufacturing system since our intended problem is a production circumstance involving a single product. Also, from the perspective of model formulation, it is effortless to convert an MTS model to either an MTO one or a mixed MTO/MTS one. More important, the MTS production planning model can better reflect the practical demand of the manufacturing industry due to its extensive applications in reality.

- Full interests of equity holders

So far, a wide range of optimisation objective functions have been developed so as to better enhance different manufacturing performances, among which are primarily work flow time, cost and profit. However, these objectives can at best be viewed as a certain form of local or short-term optimisations, not necessarily in line with the overall business goal of the shareholder wealth maximization [3, 12].

Despite its conceptual superiority to other performance metrics in terms of investors’ interests, the shareholder wealth has been rarely considered in current research because of its complicated computation and tedious financial adjustment. Although the concept of shareholder wealth has been in existence for a long time and attracted considerable attention, it is still not commonly applied in practice, mainly because practitioners find it difficult to handle and implement.

The current reality is that other performance metrics are frequently selected as objective functions by reason of their simplicity in calculations, but it may not necessarily represent the full interests of equity holders.

In contrast, the shareholder wealth is a complete performance metric to measure the shareholder interest, but it is not widely adopted due mainly to its complexity in applications. Nevertheless, its explanatory and representative power is worthy of its complexity.

Therefore, instead of using the traditional optimisation objectives, this paper aims at maximisation of the full interests of equity holders, that is, the shareholder wealth.

- Metrics to measure the shareholder wealth

In practice, the limitations of current optimisation objectives have caused a research focus shift to the interests of equity holders. A handful of research studies have started to discuss this problem in their production planning optimisations.

For example, a batch storage network model is applied into a production plant with both production and financial constraints considered, with an aim to minimize the opportunity cost of the annualized capital investment and cash/material inventory minus the benefit to shareholders [13]. A holistic model is derived for the short-term SCM with an objective to optimize the change in equity, which can exert straightforward effects on the shareholder wealth [14]. An integrated financial-operational lot sizing queuing model for a single-item, single-server case was established to maximise EVA (economic value added) [15].

To precisely represent the shareholder wealth, it is vital to design an appropriate financial measure. In
practice, some financial performance metrics, such as NPV (net present value), ROI (return on investment), EVA, and CFROI (cash flow return on investment) are available to estimate the shareholder wealth.

NPV is one of the key financial ratios for valuation of the capital budgeting projects. It is widely used to evaluate the priorities of projects across the business world. However, NPV is mostly based on book values, emphasizing more on accounting profits than on cash flows, even by excluding the cost of capital in its discount rate [16]. These shortcomings, to a great extent, limit its use for measuring the shareholder wealth.

ROI was developed by DuPont Power Company in early 1900s to help manage vertically integrated enterprises with the intent to evaluate a firm’s performance by comparing its operating income to its invested capital. However, the primary limitation of ROI is that it can readily bring about the principal-agent problem [17]. In other words, management tends to make decisions based on their own interests instead of on the best interests of investors.

EVA and CFROI examine to what extent the shareholder wealth would change as a result of management decisions made and implemented [18]. EVA takes into account the total cost of capitals, and it is not constrained by GAAP (generally accepted accounting principles) [19]. However, Kramer et al. mentioned four application limitations of EVA, encompassing the size difference, the financial orientation, the short-term orientation, and the result orientation [20]. De Villiers argued that inflation can distort EVA and suggested that EVA is not suitable for evaluating the shareholder wealth without adjustment under inflationary conditions [21]. Some researchers even found little relationship between EVA and the shareholder wealth [20, 22].

In comparison with these financial metrics, CFROI is defined as the sustainable cash flow a firm generates in a given year as a percentage of the outlay invested in its assets [23]. Instead of being a measure of economic profit, CFROI calculates the IRR (internal rate of return), in terms of real purchasing power of capital, to provide a consistent basis for evaluation of a firm’s performance, regardless of its size [24]. As such, CFROI eliminates the adverse distorting impingement of both inflationary and deflationary conditions on a firm’s performance. These superior merits of CFROI to other financial measures persuade us to adopt it as the financial performance metric for the shareholder wealth in our paper.

To summarize, we propose a shareholder wealth maximisation mechanism for the stochastic single-product MTS manufacturing environment, with a primary concern of the sustainable long-term profitability in terms of the real purchasing power, measured by CFROI. The uncertain single-product manufacturing environment is formulated as a stochastic lot sizing queuing network without any impractical distribution assumptions on the random variables.

The balance of the paper is organized as follows: In Section 2, we formulate an economic model of a stochastic lot sizing queuing production system for single-product MTS manufacturing with the intent to maximise the shareholder wealth; Section 3 presents some illustrative numerical experiments to validate efficiency of the proposed model; Section 4 finally concludes the research study.

2. Model Formulation

2.1 Problem Description

Fig. 1 provides a graphical illustration of the stochastic
lot sizing issue under consideration, where one type of product is being processed at a single machine station at a given batch size. The mutually independent items, such as work pieces, individually arrive at the gathering stage, where as soon as $Q$ units are gathered, they are transferred as a batch to the setup stage and the processing stage on a batch-by-batch basis. Both the setup stage and the processing stage only involve batches of items, so they can be combined into a single batch service stage. Finally, once completed, finished goods leave the entire manufacturing procedure and enter a finishing goods warehouse for storage, where the batches are broken down into individual finished products and then delivered to meet the market demand on an individual basis.

The interarrival time, setup time, processing time and market demand are all treated as generally distributed random variables. Moreover, all service stages involved are assumed to be mutually independent. For each stage, items and batches are served in accordance with a FCFS (first-come-first-served) rule once they compete for limited resources.

In this paper, we approximately characterize each stochastic event by two statistical parameters, i.e., the expected value and variance, instead of any unreal distribution assumption. The ratio of the variance to the squared expected value of a random variable is defined as its SCV (squared coefficient of variance).

Then we will derive the expected values of WIP (work in process) holding time and inventory time of finished goods so as to determine the fixed lot size that can optimise either operational or economic objectives. Four categories of optimisation objectives, consisting of lead time minimisation, cost minimisation, net income maximisation and the shareholder value maximisation, will be considered for the purpose of comparison. Relevant parameters are defined as follows:

\(X\) The interarrival time of items;
\(X_i\) The interarrival time of the \(i\)th item;
\(E_X\) The mean value of \(X\) and \(X_i\);
\(D_X\) The variance of \(X\) and \(X_i\);
\(Y\) The setup time of batches;
\(Y_i\) The setup time of the \(i\)th batch;
\(E_Y\) The mean value of \(Y\) and \(Y_i\);
\(D_Y\) The variance of \(Y\) and \(Y_i\);
\(Z\) The processing time of batches;
\(Z_i\) The processing time of the \(i\)th batch;
\(E_Z\) The mean value of \(Z\) and \(Z_i\);
\(D_Z\) The variance of \(Z\) and \(Z_i\);
\(F\) The delivery time of finished products;
\(F_i\) The delivery time of the \(i\)th finished product;
\(E_F\) The mean value of \(F\) and \(F_i\);
\(D_F\) The variance of \(F\) and \(F_i\).

### 2.2 Model Derivation

As illustrated in Fig. 1, the work flow involving WIPs can be separated into two stages, the gathering stage and the batch service stage. Thus, the total work flow time involving WIPs is the sum of these two parts, as in

\[
W_{\text{WIP}} = W_c + W_s
\]

that is

\[
E(W_{\text{WIP}}) = E(W_c) + E(W_s)
\]

where

- \(W_{\text{WIP}}\) The work flow time involving WIPs;
- \(W_c\) The gathering time for each item;
- \(W_s\) The batch service time;
- \(E(\cdot)\) The expected value function.

It is obvious that \(W_c\) is completely dependent upon \(X_{i}\). Logically, we can get

\[
W_{ci} = \begin{cases} 0, & \text{if } \lceil i\%Q \rceil = 0 \\ \sum_{n=\lceil i\%Q \rceil+1}^{\lceil i\%Q \rceil+Q-1} X_{i\%Q+n}, & \text{otherwise} \end{cases}
\]

So,

\[
E(W_{ci}) = \begin{cases} 0, & \text{if } \lceil i\%Q \rceil = 0 \\ (Q - \lceil i\%Q \rceil) E_X, & \text{otherwise} \end{cases}
\]

Additionally, we have
\[
W_c = \frac{\sum_{i=1}^{D} W_{Ci}}{D} = \frac{\sum_{j=0}^{\lfloor D/Q \rfloor \cdot Q} \left[ \lfloor i/(j+1) \rfloor \cdot Q \right] W_{Ci} + \sum_{j=0}^{\lfloor D/Q \rfloor \cdot Q + 1} W_{Ci}}{D}
\]  
\[
E(W_c) = \frac{Q}{D} \frac{(Q+1)}{2} E_x + \sum_{j=0}^{\lfloor D/Q \rfloor \cdot Q + 1} E(W_{Cj}) \\
\approx \frac{(Q+1)}{2} E_x
\]

where
- \( W_{Ci} \) is the waiting time for gathering of the \( i \)th item;
- \([i\%Q]\) is the remainder of \( i/Q \), representing the relevant position of the \( i \)th item in a batch;
- \([i/Q]\) is the integral part of \( i/Q \), representing the batch number where the \( i \)th item resides;
- \( D \) is the population size of all items.

The reason for Eq. (6) is that the population size is so much larger than the batch size that the \( Q/D \) is virtually close to zero. Thus, the equation \( [D/Q]Q/D \approx 1 \) approximately equals to one. Meanwhile,

\[
0 < \frac{\sum_{j=0}^{\lfloor D/Q \rfloor \cdot Q + 1} E(W_{Cj})}{D} < \frac{\sum_{j=0}^{\lfloor D/Q \rfloor \cdot Q + 1} (Q-1)E_x}{D} < \frac{Q(Q-1)E_x}{D} \approx 0
\]

and therefore, the mathematical expression

\[
\sum_{j=0}^{\lfloor D/Q \rfloor \cdot Q + 1} E(W_{Cj}) \approx \frac{(Q+1)}{2} E_x
\]

Next, we try to calculate the time consumption during the batch service stage. The upcoming batches are mutually independent and generally distributed because of the independence and generalization of individual. So we can treat the interarrival batches as generally distributed with the expected time \( E_x \), and variance \( D_x \).

Since both setup times and processing times are generally distributed and mutually independent, the batch service time can also be viewed as a random variable following a general distribution with the expected time \( E_s \) and variance \( D_s \). Thus, the batch service stage can be treated as a simple GI/G/1 queuing system and we can use the standard queuing result from pioneering researchers.

The batch service time can be computed as follows:

\[
W_s = W_{s0} + W_{s1}
\]

So,

\[
E(W_s) = E(W_{s0}) + E_s = E_x \rho \left( \frac{c_a^2 + c_s^2}{2} \right) \frac{g}{2(1-\rho)}
\]

where

- \( W_{s0} \) is the waiting time for the batch service;
- \( W_{s1} \) is the batch service time.

From a pioneering conclusion on the standard GI/G/1 queuing model [25], it follows that

\[
E(W_{s0}) = E_x \rho \left( \frac{c_a^2 + c_s^2}{2} \right) \frac{g}{2(1-\rho)}
\]

where

- \( c_a^2 \) is the SCV of the batch interarrival time,
- \( c_s^2 \) is the SCV of the batch service time,
- \( \rho \) is the traffic intensity.

Furthermore, \( g \) is defined as follows:

\[
g = \begin{cases} 
\exp \left[ -\frac{(1-\rho)(1-c_s^2)}{3\rho} \right], & c_s^2 < 1 \\
1, & \text{otherwise}
\end{cases}
\]

It is clear that

\[
X_{ai} = \sum_{m=1}^{Q} X_{Q+i+m}
\]

Due to the independence of incoming batches,

\[
E_{X_s} = E(X_{s0}) = E \left( \sum_{m=1}^{Q} X_{Q+i+m} \right) = \sum_{m=1}^{Q} E(X_{Q+i+m}) = QE_x
\]
\[ D_{X_i} = D(X_m) = D \left( \sum_{m=1}^{Q} X_{Q_{i,m}} \right) \]  
\[ = \sum_{m=1}^{Q} D(X_{Q_{i,m}}) = QD_X \]  

Similarly,
\[ S_i = Y_i + Z_i \]  
\[ E_s = E(S_i) = E(Y_i) + E(Z_i) = E_y + E_z \]  
\[ D_s = D(S_i) = D(Y_i) + D(Z_i) = D_y + D_z \]

where
\[ X_m \] The interarrival time of the \( m \)th batch;
\[ E_X \] The mean time of the batch interarrival;
\[ D_X \] The variance of the batch interarrival;
\[ S_i \] The batch service time for the \( i \)th batch.

Finally, we can get
\[ \rho = \frac{E_y + E_z}{QE_X} \]
\[ \sigma_a^2 = \frac{D_{X_i}}{E_{X_i}^2} = \frac{D_X}{QE_X^2} \]
\[ \sigma_s^2 = \frac{D_s}{E_s^2} = \frac{D_y + D_z}{(E_y + E_z)^2} \]  

By substituting the corresponding items in Eq. (19) into Eq. (11),
\[ E(W_i) = \frac{D_X (E_y + E_z)^2 + (D_y + D_z)QE_X^2}{2QE_X^2 (QE_X - (E_y + E_z))} \cdot g \]  

where \( g \) is rewritten like this:
\[ g = \begin{cases} \exp \left\{ \frac{2(QE_X - (E_y + E_z))}{3(E_y + E_z)} \right\} \cdot \sigma_a^2, & \sigma_a^2 < 1 \\ \left[ \frac{D_X (E_y + E_z)}{2QE_X^2 (QE_X - (E_y + E_z))} + \frac{D_y + D_z}{QE_X^2 (D_y + D_z)} \right] \cdot \sigma_s^2, & \text{otherwise} \end{cases} \]

So finally, we can get the expected time for holding WIPs, as in
\[ E(W_{WIP}) = \frac{(Q+1)E_x}{2} + \frac{D_X (E_y + E_z)^2 + (D_y + D_z)QE_X^2}{2QE_X^2 (QE_X - (E_y + E_z))} \cdot g \]

In addition to holding WIPs, inventory of finished goods is another key determinant to the overall flow time. We have mentioned previously that inter-delivery time is also generally distributed with an expected time \( E_r \) and variance \( D_r \). In the similar way that we solve \( E(W_{C}) \), we can readily conclude that
\[ E(W_p) \approx \frac{(Q-1)E_r}{2} \]  

2.3 Optimisation Objective Formulation

- Overall lead time
  Apparently, the overall lead time is the summation of \( W_{WIP} \) and \( W_F \), so we can easily achieve the expected overall lead time by adding these two parts, as in
\[ E(W) = E(W_{WIP}) + E(W_F) \]

where \( W \) stands for the overall lead time.

- Total cost
  In addition to the operational consideration, another typical concern is the relevant economic or financial factors, such as a variety of costs incurred.

  In the first place, order cost and raw material cost are incurred before work pieces arrive at a manufacturer. The order cost is fixed and independent on the lot size. The raw material cost involves all of the fees which are expended to prepare the raw material for subsequent treatments and thus are variable.

  During the gathering stage and the batch service stage, WIP holding cost will be incurred when items wait in a queue. Meanwhile, setup cost is incurred before batches are transferred to the processing stage, where it incurs processing cost. Once batches are finally processed, they will leave the processing stage and enter the warehouse as finished goods, where the holding costs of finished goods is incurred. Moreover, other implicit expenses, such as lease payment cost, administration cost, labour cost and so forth, should be considered to improve the exactness of the proposed model.

  All of such costs can be separated into two categories: the fixed costs and variable costs. The fixed costs consist of the order cost, lease payment, administration cost, sale cost, depreciation cost and
labour cost, while the variable costs are mainly composed of the raw material cost, WIP holding cost, setup cost, processing cost and inventory cost of finished goods. The total cost is the summation of all the fixed costs and variable costs:

\[ C = C_v + C_f = r \frac{E_x}{E_x Q} + s \frac{E_x Q}{E_x} + d \frac{E_x Q}{E_x} + h_{WIP} E(W_{WIP}) + h_{F} E(W_{F}) + C_f \]  

(24)

where

- \( C \) Total cost;
- \( C_v \) Total variable cost;
- \( C_f \) Total fixed cost;
- \( r \) Unit raw material cost;
- \( s \) Setup cost per batch;
- \( d \) Processing cost per batch;
- \( h_{WIP} \) Unit cost of WIPs per unit time;
- \( h_{F} \) Unit cost of finished goods per unit time;

- Profit maximisation

As one competitive advantage, lead time can exert straight effects on selling prices. Customers are willing to pay more for relatively shorter lead times; conversely, they incline to pay less for products with longer lead times, or simply go for substitutes. For simplicity, we assume an inverse linear relationship between these two parameters:

\[ p = -\kappa (E(W) - E(W)_{AVG}) + p_{AVG} \]  

(25)

where

- \( p \) Unit sales price;
- \( \kappa \) Customer sensitivity to product delivery;
- \( p_{AVG} \) Industrial average selling price;
- \( E(W)_{AVG} \) Industrial average lead time.

Then we can estimate the operational profit by subtracting the total cost from the revenue:

\[ OP = \frac{-\kappa (E(W) - E(W)_{AVG}) + p_{AVG}}{E_x} - C \]  

(26)

where \( OP \) represents the operational profit. Further, based on the operational profit, the net income is

\[ NI = \frac{p}{E_x} - r \frac{E_x}{E_x Q} - s \frac{E_x Q}{E_x} - h_{WIP} E(W_{WIP}) - h_{F} E(W_{F}) - OP \times (1 - r) - C_f \]  

(27)

where \( NI \) stands for net income and \( r \) for tax rate.

- Shareholder wealth maximisation

In order to formulate the shareholder wealth, we firstly have to estimate the periodic cash flows adjusted for inflation during the useful life of total assets [26]. The nominal cash flows for each period can be calculated by adding the periodic net income and corresponding noncash expenses [27]. Then, these nominal cash flows must be adjusted for the inflation to get the real amounts.

We assume a stable macroeconomic environment, where there is almost a uniform inflation rate each year. Under this assumption, the real cash flows for the \( j \)th period is computed as follows:

\[ CF_j = \frac{NI_j + NE_j}{(1+t)^j} \]  

(28)

where

- \( CF_j \) Real cash flow in the \( j \)th period;
- \( NI_j \) Net income in the \( j \)th period;
- \( NE_j \) Noncash expense in the \( j \)th period;
- \( t \) The inflation rate;

Finally, based on the periodic real cash flow, we can figure out the CFROI performance metric like [28]:

\[ TA = \sum_{i=1}^{H} \left( \frac{CF_i}{(1+CFROI)^i} \right) + \frac{NA}{(1+CFROI)^H} \]  

(29)

where \( TA \) is the initial total asset investment and \( NA \) the non-depreciating assets, released at the end of the useful asset life; \( H \) represents the useful life of total assets.

3. Numerical Examples

Four numerical experiments are conducted to test the efficiency of the proposed stochastic model.

The first experiment examines a traditional operational optimisation, i.e., to minimize the overall lead time.

The second one concerns mainly about the minimisation of the total cost incurred during the manufacturing procedure, while the profit maximization is researched in more depth in the third experiment.
In the final experiment, we focus on the overall business goal—the shareholder maximisation, and then compare the optimisation result with those from the preceding three optimisations to gain a full understanding of their differences than and similarities to the overall business goal optimisation.

Furthermore, we use sensitivity analysis to examine the impacts of various risks inherently involved in the lot sizing manufacturing on the shareholder wealth. The results provide a clear picture of the susceptibility of the shareholder wealth to various financial and operational risks, as well as insights into how possible and at what level these risks can affect the interests of investors.

3.1 Lead Time Minimisation

Before conducting numerical experiments, we need to assign appropriate values to the relevant parameters. We adopt relevant operational data, as listed in Table 1, from a pioneering research [29], which were collected from a real work shop floor without any distribution assumption. These empirical data help improve the generality of the proposed model.

By substituting these empirical data into Eq. (23), we obtain

$$E(W) \approx \frac{10.0625Q + 55.125}{2Q^2 - 21Q} - g + 1.125Q + 10.375$$ (30)

From $c_o = \frac{D_i}{QE_x} = \frac{1}{2Q} < 1$, it follows $g$ can be computed using Eq. (12), as in

$$g = \exp \left[-\frac{21(Q-10.5)(Q-0.5)^2}{3Q(10.0625Q + 55.125)}\right]$$ (31)

The optimal lot size for minimizing the lead time is figured out using numerical methods. By solving Eq. (30), the optimal lot size is 13 with a minimum lead time of 25.9229 and a traffic intensity of 80.77%. Fig. 2 illustrates the changing trend of the expected lead time in relation to the lot size.

3.2 Cost Minimisation

Next, we consider how to effectively reduce the total cost. The unit raw material cost $r$ is assumed to be $2 per unit, while the setup cost $s$ and the processing cost $d$ are $150 per batch and $100 per batch respectively. Additionally, we also assume that $h_{WIP} = h_F = 1$, $C_F = 10$.

Eq. (24) is optimised with the above values. Fig. 3 shows the relation between the lot size and the total cost. The minimum total cost of 56.0846 corresponds to the lot size of 16 with a traffic intensity of 65.63%.

Under the cost minimisation case, the optimal lot size of 16 leads to a lead time of 28.4596, up from the minimum lead time of 24.9299 under the lead time optimisation case. It can be seen that the lead time optimisation is not in line with the cost optimisation when relevant costs are considered.

This great distinction highlights the importance of choosing an appropriate optimisation objective for stochastic lot sizing in MTO manufacturing.

Moreover, we take a closer look at how sensitive the total cost is to certain key parameters. Table 2 lists the effects of the unit setup cost, $s$, the unit cost of holding WIPs, $h_{WIP}$, and the unit cost of holding finished products, $h_F$, on the optimal lot size under the cost minimisation scenario.

Obviously, the lower the unit setup cost, $s$, the closer the optimisation result under the cost minimisation case is to the result under lead time minimisation case.
As $s$ gradually increases, the resulting difference between both cases becomes more substantial.

Besides, when either the cost of holding WIPs or finished products is small enough, there is a large difference in the optimising results between the lead time minimisation case and the cost minimisation case. Once either increases to a certain degree, the cost optimisation would lead to a similar result to the one under the lead time minimisation case. Table 2 also shows that the optimisation results are mostly susceptible to $h_F$ and then to $h_{WIP}$, finally followed by $s$.

### 3.3 Profit Maximisation

Minimising costs do not necessarily constitutes the profit increase, since the expense spent in minimising costs may offset the benefit brought by the cost decrease. Indeed, it is practically necessary to directly optimise a certain type of profit of interest, as presented by Eq. (27), to better represent a firm’s performance. To illustrate the behaviour of profit maximisation, we consider a manufacturing scenario with the following data: $k = 0.1$, $p_{AVG} = 100$, $E(W)_{AVG} = 25$, and $r = 10\%$.

When the lot size equals 15, we can get the maximum net income of 39,2952 with a traffic intensity of 70.00%. Although the optimal lot size of 15 is far from that of the lead time minimisation case, it is very closer to that of the cost minimisation case. Fig. 4 illustrates the changing trend of the total net income against the lot size.

Then, we will conduct the sensitivity test of the net income to certain key parameters to better improve a firm’s profit by hedging against some financial or operational risks.

Effects of $k$, $E(W)_{AVG}$ and $p_{AVG}$ on the net income are presented in Table 3. It can be seen that a relatively smaller value of $\kappa$ results in a much larger optimal lot size than both the lead time and cost optimisation cases. As $\kappa$ gradually increases, the optimal lot size becomes firstly closer to the optimisation results of the cost optimisation case, and then to the optimisation results of the lead time minimisation case.

In addition, it can be noticed that changes of $E(W)_{AVG}$ and $p_{AVG}$ impose no effects on the optimal lot size. The optimal lot size of 15 remains unchanged as either $E(W)_{AVG}$ or $p_{AVG}$ changes.

Table 4 shows the impacts of the setup cost, the WIP holding cost and the finished goods holding cost on the maximisation of profit.
Table 3  Effects of $k$, $E(W)_{AVG}$ and $p_{AVG}$ on profit.

<table>
<thead>
<tr>
<th>$k$</th>
<th>$Q$</th>
<th>$E(W)_{AVG}$</th>
<th>$Q$</th>
<th>$p_{AVG}$</th>
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<td>100</td>
<td>15</td>
<td>400</td>
<td>15</td>
</tr>
<tr>
<td>5</td>
<td>13</td>
<td>1,000</td>
<td>15</td>
<td>500</td>
<td>15</td>
</tr>
</tbody>
</table>

Table 4  Effects of $s$, $h_{WIP}$ and $h_{F}$ on profit.

<table>
<thead>
<tr>
<th>$s$</th>
<th>$Q$</th>
<th>$h_{WIP}$</th>
<th>$Q$</th>
<th>$h_{F}$</th>
<th>$Q$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>13</td>
<td>0</td>
<td>18</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>50</td>
<td>14</td>
<td>0.1</td>
<td>18</td>
<td>0.1</td>
<td>19</td>
</tr>
<tr>
<td>100</td>
<td>14</td>
<td>1</td>
<td>15</td>
<td>0.5</td>
<td>17</td>
</tr>
<tr>
<td>150</td>
<td>15</td>
<td>10</td>
<td>*</td>
<td>1</td>
<td>15</td>
</tr>
<tr>
<td>200</td>
<td>16</td>
<td>100</td>
<td>*</td>
<td>5</td>
<td>13</td>
</tr>
</tbody>
</table>

on the net income. It can be seen that the impacts are similar to those on the total cost.

However, the difference in optimisation result becomes more substantial as the setup cost increases from 0 to 200. Furthermore, when either the WIP holding cost or the finished product holding cost is small enough, there is a large difference in the optimisation results between the lead time minimisation case and the profit maximisation case. The optimisation results will become gradually closer to the cost minimisation and then to the lead time minimisation as either of the WIP holding cost or the finished goods holding cost increases. The asterisk means the optimisation results has become ineffective because the utilization rate of machines is larger than 100%.

3.4 Shareholder Wealth Maximisation

The profits are based on accounting profit. Furthermore, it does not take into account of the distorting effects of the inflation and deflation, debt structure, and firm size on production planning. These limitations drive us to select a more ideal economic metric to better reflect the interests of equity holders, that is, the shareholder wealth.

First, we assume $TA = $100, $NA = $2, $NE_j = $5, $H = $3 and $t = 2\%$. Fig. 5 illustrates the changing trend of the shareholder value as the lot size increases. The maximum shareholder value of 14.18% corresponds to the optimal lot size of 15 with a traffic intensity of 70.00%. This optimisation result is the same as the profit maximisation while it is distinguishable from both the lead time and cost minimisation cases.

Table 5 illustrates how the non-depreciating asset and the inflation rate affect the shareholder wealth. When the percentage of the non-depreciating assets in the total assets increases from 0 to 50%, the optimal lot size remains constant. However, the resulting shareholder wealth increases from 14.74% to 42.43%. This result suggests that we should increase the relative percentage of the non-depreciating assets in the total assets.

Also, the inflation rate imposes no effects on the optimal lot size. However, the shareholder wealth is gradually undermined with the increase of the inflation rates.

Table 6 shows how the shareholder wealth corresponds to $k$, $E(W)_{AVG}$ and $p_{AVG}$ while the effects Fig. 5  The optimisation result for the shareholder wealth maximization.

Table 5  Effects of $NA$ and $t$ on the shareholder value.

<table>
<thead>
<tr>
<th>$NA$</th>
<th>$Q$</th>
<th>$t$ (%)</th>
<th>$Q$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>15</td>
<td>0</td>
<td>15</td>
</tr>
<tr>
<td>1</td>
<td>15</td>
<td>0.10</td>
<td>15</td>
</tr>
<tr>
<td>5</td>
<td>15</td>
<td>1</td>
<td>15</td>
</tr>
<tr>
<td>10</td>
<td>15</td>
<td>2</td>
<td>15</td>
</tr>
<tr>
<td>50</td>
<td>15</td>
<td>5</td>
<td>15</td>
</tr>
</tbody>
</table>
of $s$, $h_{WIP}$ and $h_F$ are illustrated in Table 7.

$k$, $h_{WIP}$ and $h_F$ impose almost parallel impacts on the shareholder wealth. As each of them increases, the resulting optimal lot size gradually decreases and becomes closer to the result of the lead time minimisation. The increase in each of them may lead to the decrease of shareholder wealth.

Comparatively, the setup cost has an opposite impact on the shareholder wealth. An increase in the setup cost increases the optimal lot size from 13 to 16, and reduces the shareholder wealth from 27.82% to 7.92%. Like their effects on the profit, $E(W)_{AVG}$ and $p_{AVG}$ have no effects on the optimal lot size under the shareholder wealth maximisation case. However, their changes can affect the optimal shareholder wealth.

In Table 7, the asterisks indicate that the current optimisation is impracticable. A single asterisk means the optimisation results are ineffective because the manufacturing capacity has gone beyond 100% while the double asterisks illustrate no proper CFROI value exists for the current optimisation.

### 4. Conclusions

This research attempts to address the infeasibility issue of traditional manufacturing optimisations, and to illustrate to what degree these manufacturing optimisations align with the overall business goal of maximising the shareholder wealth. The proposed model focuses on uncertain lot sizing MTS manufacturing. It not only considers relevant financial and economic parameters, but also adopts the general distributions of random variables, enhancing its generality and extendibility.

Numerical experiments reveal the apparent difference in optimisation results between the traditional operations optimisation and the shareholder wealth maximisation.

More specifically, a dramatic optimisation spread exists between the lead time optimisation and the cost, profit or shareholder value optimisations.

In comparison, the cost optimisation leads to a slightly closer optimisation result to the profit or shareholder value maximisation than the lead time optimisation. However, there still exists a minor optimisation spread among them since the cost optimisation omits the profit- or shareholder value-related key factors, such as the selling price and inflation rate.

In addition, the profit maximisation can bring about the optimisation results nearly in line with the shareholder wealth maximisation in spite of their little optimisation difference. Yet, the profit cannot reflect the effects of a firm’s capital structure, such as the percentage of non-depreciating assets in total assets, on the equity holders. Also, the distorting impacts of inflation or deflation are not eliminated in the profit optimisation. Therefore, the shareholder wealth is really the best metric to reflect the full interests of equity holders.

These optimisation results validate that the traditional optimisation functions are not necessarily in line with the overall business goal of maximising the shareholder wealth, and thus highlight the importance of not only considering financial and economic parameters but also incorporating the shareholder wealth into production planning.
A limitation of the proposed model is that it considers only a single-item, single-machine stochastic lot sizing scenario. It would therefore be worthwhile to extend it for dealing with relatively more complicated manufacturing environments. Moreover, further research work would be needed to investigate into the specific linkage between the lead time and the selling prices.

References


