Stochastic Lot Sizing for Shareholder Wealth Maximisation under Carbon Footprint Management

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***Abstract*—There is a growing consensus that human beings must cut greenhouse gas emissions to mitigate global warming and the resultant impacts on the environment. However, production optimisation has rarely taken this issue into consideration, often leading to environmentally unsustainable operation decisions. This paper presents a lot sizing batch optimisation model for a stochastic make-to-order production environment under the carbon emission trading mechanism—currently the most effective market-based carbon emission controlling system, with an aim to maximise the long-term sustainable interests of corporate owners, well-known as the shareholder wealth. To more closely reflect the real-world manufacturing environment, the proposed model adopts general distributions, instead of unrealistic theoretical assumptions, for random variables. We apply the model to investigate the impacts of the carbon emission trading mechanism on shareholder wealth, and test its hedging capability against a series of risk factors. The analytical results provide insights into production optimisation with carbon footprint management.**

***Index Terms*—carbon emission, stochastic programming, shareholder wealth, lot sizing, make-to-order**

I. Introduction

In recent decades, environmental protection has aroused much global attention, because of its far-reaching influences on the social and economic developments of the world [1]. The International Panel on Climate Change (IPCC) has reported that global warming due to fossil fuel burning and deforestation poses serious threats to the ecological system [2], [3]. For example, very dry areas (Palmer Drought Severity Index, PDSI <-3.0) in the world have more than doubled since the 1970s, while very wet areas (PDSI >3.0) shrunk by about 5% [4]. In order to mitigate the damages of greenhouse gas (GHG) emission, various countries and regions have enacted laws to curb carbon footprints. For example, China introduced in2006 a mandatory energy efficiency standard for building construction, aimed at reducing energy use by 50% [3].

Despite emission of carbon dioxide (CO_2) is a dominant issue in the real-world manufacturing, study on its close relationship with operation optimisation has rarely been reported in literature, leading to a widening gap between the academic research and the industrial needs.

Therefore, we attempt to explore this relationship by focusing on a single-product, single-period operation planning model for stochastic make-to-order productions, aimed to maximise the shareholder wealth under a carbon emission trading mechanism. Our proposed optimisation approach is characterised in the following three aspects.

A. *Shareholders-oriented Optimisation*

To date, most operation optimisation approaches aim at only short-term or local objectives. Ref. [5], for example, modelled a job shop as a simple queuing system to minimise the involved work flow time. Ref. [6] developed a cost minimisation model with several relevant costs taken into account. Ref. [7] chose to maximise the accounting profit in a multi-product, capacity-constrained lot sizing manufacturing circumstance.

Although these optimisation objectives, either time minimisation or accounting cost minimisation or profit maximisation, may be somewhat helpful to operation optimisation, they may not necessarily align with the long-term full interests of corporate owners, especially in adverse market conditions, such as unexpected inflations and recessions in a business cycle [8], [9]. In some cases, improper selection of objective functions may even lead to undesirable optimisation consequences.

We instead address this problem by focusing on the sustainable full interests of corporate owners, well-known as the shareholder wealth [10]-[12], represented by the financial metric—cash flow return on investment (CFROI), to take advantage of its superior characteristics in comparison with other peer measures, such as net present value (NPV) [13], return on investment (ROI) [14], and economic value added (EVA) [15], [16]. CFROI is estimated based on the real cash flow, rather than the accounting items. Thus, it is widely considered as an ideal metric for the long-term full interests of corporate owners [11], [12], [17], namely the shareholder wealth.

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B. General Queuing Network

We focus on a single-product, make-to-order stochastic batch production environment involving lot sizing decisions, due mainly to its widespread applications in the academia and industry. For instance, Ref. [18] established an M/M/1 queuing model with lot sizing, and validated that the lot sizing policy was a crucial determinant of the queuing delay for closed job shops. Ref. [19] formulated two queuing problems for designs of new systems. Not only was lot sizing incorporated into these two models, but also the capacity issue was examined. Ref. [20] explored a capacitated lot sizing problem with setup time, safety stock and demand shortage, where demand could not be backlogged, but could be totally or partially lost. Another dynamic lot sizing issue, allowing inventories to be replenished jointly with the same quantity whenever a production occurs, can be found in [21].

However, most of these research studies made some theoretical assumptions on relevant random variables, such as the Poisson process for the interarrival times of customer orders and the negatively-exponentially distribution of the processing time. These theoretical assumptions, to a significant extent, are not true and sometimes even misleading for a great number of real manufacturing systems. Ref. [22] argued that these factitious assumptions were extremely restrictive and unrealistic. More specifically, Ref. [23] suggested using an Erlang process, instead of the Poisson process, in the event of a small number of independent demand sources.

In order to tackle this problem, we formulate the proposed lot sizing batch production environment as a stochastic lot sizing queuing network without any theoretical assumptions on distributions of involved random variables. Instead, we characterize all these random variables by their own statistical merits, so as to improve the generality, as well as the exactness of the proposed approach.

C. Carbon Footprint Management

There seems a universal consensus on the need to reduce emission of GHGs, especially CO_2, in order to mitigate their environmental impingements. To this end, a growing variety of regulating measures have evolved.

Among these carbon emission reducing mechanisms, one common approach is to constrain firms to emit GHGs less than a specified volume. Ref. [20] referred to four possible carbon emission constraints, including the periodic carbon emission constraint, the cumulative carbon emission constraint, the global carbon emission constraint, and the rolling carbon emission constraint.

Typically, optimisations involving these constraints seek to search for the optimal solutions under the absolute carbon emission constraint, that is, carbon emission exceeding a specified limit is not allowed.

As an alternative, the carbon emission trading mechanism allows firms to freely trade their carbon credit, which is defined as one ton of carbon dioxide equivalent. In this trading system, the carbon emission of a firm is capped. If the firm emits more GHGs than the specified cap, it has to purchase the right for the excessive carbon emission from the carbon emission trading market. Conversely, the firm can sell its surplus carbon credit in the same market for profits.

The carbon emission trading mechanism is practically the most effective market-based mechanism, which has been broadly adopted by UN, EU, and other governments [24]. Thus, we incorporate carbon footprint management into manufacturing in the form of carbon emission trading to examine its impact on operation optimisation and environmental protection.

To summarize, we propose a shareholder wealth maximisation model for stochastic single-product make-to-order batch production under carbon footprint management, with an aim to maximise sustainable long-term profitability measured in terms of CFROI. The uncertain manufacturing circumstance is formulated as a stochastic lot sizing queuing network without any impractical distribution assumptions on random variables. In addition, the carbon emission trading system is incorporated into the proposed lot sizing model to explore its implications on the shareholder wealth and the environmental responsibility of a firm.

II. Production Formulation

A. Stochastic Production Formulation

Fig. 1 illustrates the workflow of a stochastic lot sizing make-to-order production circumstance which processes one type of product at a time.

Individual orders arrive randomly. When these orders accumulate to a batch of size Q, they are gathered and transferred to be setup on a batch-by-batch basis, and then to the processing stage to be processed one by one. Each of the completed orders is delivered immediately to customers without having to wait until the whole batch is finished.

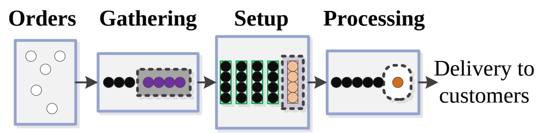

Figure 1. Stochastic lot sizing production

All the stages of the workflow are assumed to be mutually independent. In the case of competition for capacitated resources, all orders would be serviced in accordance with the first-come-first-served principle. Without loss of generality, we further suppose that each customer order encompasses only one product. In addition, the manufacturer is a price taker in either the perfect or the monopolistic competition environment, that is, product prices are exogenous.

The stochasticity in our proposed production model refers to the interarrival times of customer orders, the setup times, and the processing times are all unpredictable with certainty. As stated previously, in order to improve the generality and exactness of the proposed model, we characterize each involved random variable by its two statistic merits—its first and second central moments, respectively, rather than by making any relatively unrealistic assumption on its theoretical distribution. In probability theory and statistics, the central moment is a moment of a probability distribution of a random variable about the random variable's mean, that is, the expected value of a specified integer power of the deviation of the random variable from this mean. For example, for a random variable U, its n^{th} central moment is defined as

$$\mu_n^U = E\left[\left(U - E(U)\right)^n\right]. \tag{1}$$

B. Lead Time Derivation

The lead time is defined as the time spent between when a customer order is received and when the product is delivered to the customer, that is,

$$\begin{aligned} E(W) &= E(W_{qc}) + E(W_c) + E(W_{qs}) \\ &\quad + E(W_s) + E(W_{qp}) + E(W_p), \end{aligned} \tag{2}$$

where $E(g)$ represents the expected value function, and

- W = Lead time;
- W_{qc} = Queuing time for the gathering service;
- W_c = Stochastic gathering time;
- W_{qs} = Queuing time for the setup service;
- W_s = Stochastic setup time;
- W_{qp} = Queuing time for the processing service;
- W_p = Stochastic processing time.

Once placed, a customer order enters the gathering stage immediately without queuing, leading to

$$E(W_{qc}) = 0. \tag{3}$$

Given that i $(1 \le i \le Q)$ represents the relative position of an order in a given batch, the expected time spent in the gathering stage can be estimated as

$$E(W_c \mid i) = E\left(\sum\nolimits_{j=i+1}^{Q} X_j \mid i\right) = (Q-i)E(X), \tag{4}$$

which may be perceived as a discrete random variable with the following distribution law

$$p_i = P\left(E(W_c \mid i) = i\right) = 1/Q,\ i \in [1, Q]. \tag{5}$$

Thus,

$$E(W_c) = \sum_{i=1}^{Q} p_i E(W_c \mid i) = \frac{Q-1}{2} E(X), \tag{6}$$

where the symbol $P(g)$ denotes the probability function; X_j represents the interarrival time of the j^{th} order. All $X_j, j \in [1, Q]$ are independent and identically distributed with the identical distribution, denoted by X.

To solve for $E(W_{qs})$, we suppose that a completed order would not leave the processing stage immediately. Instead it would wait until all the orders in its batch are completed, as illustrated in Fig. 2.

By way of supposition treatment, the setup and processing stages can be transformed to a standard GI/G/1 queuing model, which is identical to the original production environment, except for overestimations on processing times for orders, but without any impingement on W_{qs}.

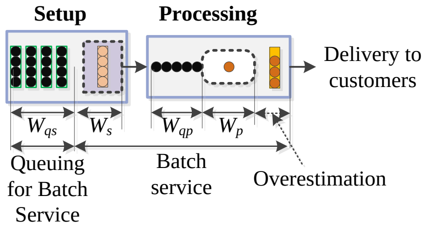

Figure 2. Assumed batch production environment

Using the standard equation for the GI/G/1 queuing model suggested in [25], we have

$$E(W_{qs}) = \frac{V(X^b) + V(T^b)}{2[E(X^b) - E(T^b)]}, \tag{7}$$

where X^b represents the interarrival times of batches of customer orders, and T^b denotes the batch service time under the assumed GI/G/1queuing model; $V(g)$ represents the variance of the random variable specified in the bracket.

Based on the production procedure illustrated in Fig. 1, we can readily figure out

$$\begin{cases} E(X^b) = QE(X) \\ V(X^b) = QV(X) \\ E(T^b) = E(Y) + QE(Z) \\ V(T^b) = V(Y) + QV(Z) \end{cases} \tag{8}$$

with the utilization rate $\rho = E(T^b)/E(X^b)$, which is also called the traffic intensity in some cases.

Here we use Z_j to represent the processing time of the j^{th} customer order. All $Z_j, j \in [1, Q]$ are independent and identically distributed with the identical distribution, denoted by Z. Similarly, Y_j is used to denote the setup time that the j^{th} batch of customer orders takes for the setup service. They are all independent and identically distributed random variables, and thus we may use Y to delineate their identical distribution.

Next, we turn to the other workflow times involved. The i^{th} order, where i denotes its relative position in a given batch, has to wait before undergoing the processing service

$$E(W_{qp} \mid i) = E\left(\sum\nolimits_{j=1}^{i-1} Z_j \mid i\right) = (i-1)E(Z). \tag{9}$$

So,

$$\begin{aligned} E(W_{qp}) &= E(E(W_{qp|i})) \\ &= E(Z) \sum_{i=1}^{Q} \frac{i-1}{Q} = \frac{Q-1}{2} E(Z). \end{aligned} \tag{10}$$

Moreover, it is easy to get

$$\begin{cases} E(W_s) = E(Y) \\ E(W_p) = E(Z) \end{cases}. \tag{11}$$

Substituting (3), (6), (7), (10), and (11) into(2), we can estimate the expected lead time as follows:

$$E(W)=\frac{Q-1}{2}E(X)+\frac{V(X^b)+V(T^b)}{2[E(X^b)-E(T^b)]} +E(Y)+\frac{Q+1}{2}E(Z) \tag{12}$$

C. Carbon Emission Trading

A crucial consideration in our research is how to manage carbon footprint effectively for maximisation of shareholder wealth under the carbon emission trading mechanism. Our proposed lot sizing batch production circumstance involves two carbon emission sources, i.e., all the production procedure stages and the work-in-process (WIP) holding inventory.

Carbon emission involved in each production stage results mainly from the manufacturing procedures, such as consumptions of fossil fuel and power. The volume of carbon emission for production can thus be formulated as

$$e_m=\kappa_0+\kappa_1\frac{1}{E(X)} \tag{13}$$

where e_m represents the volume of carbon emission from production. κ_0 and κ_1 are respectively the fixed and variable carbon emission factors, pertinent to production.

In a similar fashion, carbon emission quantity from holding WIPs can be expressed as

$$e_{WIP}=g_0+g_1\frac{1}{E(X)}E(W) \tag{14}$$

where e_{WIP} denotes the carbon emission arising from holding WIPs, and g_0 and g_1 are respectively the fixed and variable carbon emission factors, pertinent to the WIP inventory.

It is worth noting that, with the WIP carbon emission, the variable carbon emission factor does not only relate to the market demand volume $\frac{1}{E(X)}$, but also to the expected lead time $E(W)$.

Hence, given the carbon emission quota K commonly imposed by the environmental regulator, the tradable carbon credit ξ can be formulated as

$$\xi=K-(e_m+e_{WIP}) \tag{15}$$

where ξ can be either positive or negative.

A negative ξ means the manufacturer emits more GHGs than imposed, and it needs to purchase sufficient carbon credit from the carbon emission trading market. In contrast, when ξ is positive, the firm emits less GHGs than the cap K, enabling it to sell its surplus carbon credit to make profit.

D. Shareholder Wealth Optimisation

We have previously stated that CFROI is a practicable financial metric to measure the long-term full interests of equity holders. Indeed, CFROI is a real, cross-sectional internal rate of return (IRR) estimated at a time point from a firm's aggregate business data. The basic valuation of CFROI is basically rooted in the discounted cash flow (DCF) [12]. Thus, the conceptions of IRR and DCF can be adopted to estimate the shareholder wealth in terms of CFROI, as in

$$TA=\sum_{j=1}^{T}\frac{CF_j}{(1+CFROI)^j}+\frac{NA}{(1+CFROI)^T} \tag{16}$$

where TA and NA respectively represent the total asset investment and the non-depreciating asset investment, and T denotes the length of planning time horizon.

As we focus on the single-period optimisation, then $T=1$, leading to

$$CFROI=\frac{CF+NA}{TA}-1 \tag{17}$$

In (17), CF can be computed by subtracting the variable cost C_V and the fixed cost C_F from the revenue, and adding the non-cash expense NC [26], giving

$$CF=\left(\frac{1}{E(X)}\gamma-C_F-C_V\right)(1-r)+NC \tag{18}$$

with

$$C_V=\left(s\frac{1}{Q}+E(W)h+\omega\right)\frac{1}{E(X)} \tag{19}$$

where γ is the unit sales price and r is the tax rate. In (19), s is the unit setup cost; h represents the unit WIP holding cost. ω is used to denote the sum of other unit variable costs, such as the purchasing cost, sales cost, and so forth. Since all of these variable costs are unrelated to lot sizes, we add them together and denote the sum by ω.

Eq. (18) has yet to consider the impact of carbon footprint management on cash flows. Under the carbon emission trading mechanism, in addition to the cash flows from daily operations, the manufacturer needs to take account of another cash flow source arising from the effective carbon emission management. Our proposed production optimisation model incorporated this in the form of either earnings ($\xi>0$) or costs ($\xi<0$). Eq. (18) can now be transformed as

$$CF=\left(\frac{1}{E(X)}\gamma-C_F-C_V\right)(1-r)+NC+c\xi \tag{20}$$

To consider the impacts of carbon emission on cash flows, where c denotes the unit price of carbon credit.

In addition, in our proposed stochastic production circumstance, the only one non-cash expense is the depreciation of the long-term assets. By the straight-line depreciating approach, non-cash expense can be estimated as

$$NC=(TA-NA)/L \tag{21}$$

where L represents the average estimated life of all the long-term assets invested.

E. Constraint Conditions

The relevant constraint conditions involve the lot size and the utilization rate. Under no circumstance does the lot size Q may be less than one, while the utilization rate has to be less than 100% for a realistic queuing model. Consequently, the constraint conditions can be summarized as follows:

$$\begin{cases} \rho < 100\% \\ Q \geq 1 \end{cases} \tag{22}$$

III. Numerical Experiments

Three numerical experiments are conducted to validate the proposed production optimisation model for maximisation of shareholder wealth under the carbon footprint management.

TABLE I. OPERATIONAL PARAMETERS (IN MINUTES)

Moments	Interarrival time	Setup time	Processing time
First	1.0000	10.0000	0.5000
Second	0.5000	10.0000	0.0625

TABLE II. CARBON EMISSION TRADING PARAMETERS

Parameters	K	c	κ_0	κ_1	g_0	g_1
Values	1000	900	2	0.1	1	0.2
Units	tons	\$/ton	kg	kg/unit	kg	kg/unit/time

TABLE III. ECONOMIC PARAMETERS

Parameters	Values	Units	Parameters	Values	Units
TA	40	\$ million	ω	5	\$
NA	30	\$ million	C_F	2	\$ million
γ	230	\$	r	30%	Nil.
s	1000	\$	L	5	year
h	1	\$	T	1	year

The first experiment compares the proposed model with that without consideration of carbon footprint management, to highlight the important significance of carbon footprint management to both economic interests of equity holders and environmental responsibility of a firm.

The second experiment examines the impact of different carbon emission trading strategies on the shareholder wealth improvement and carbon emission volume.

In the third experiment, we test the hedging capability of our proposed production model against a series of risk factors.

In these three experiments, we choose all relevant operational data, as presented in Table I, from a real production environment without any specific assumptions on distributions of the random variables involved [27]. This purpose is to prove its persuasion power and practicability.

The values of the parameters related to the carbon emission trading mechanism are specified in Table II, which can be obtained from the carbon emission trading market.

The remaining economic parameters can be collected from the manufacturer's managerial accounting systems [28], as illustrated in Table III.

A. Optimimisation Comparison

Irrespective of whether or not carbon footprint management is considered in optimisation, we would need to solve for the optimal lot sizes that can maximise the shareholder wealth, in terms of CFROI.

TABLE IV. OPTIMISATION RESULTS WITH AND WITHOUT CARBON FOOTPRINT MANAGEMENT

Optimisation	Shareholder wealth	Optimal lot size	Carbon credit (tons)	Carbon emissions (tons)
Without carbon footprint management	11.15%	38	-27.8788	1027.8788
With carbon footprint management	11.20%	35	39.5570	960.4430

The resultant optimisation results are listed in Table IV, where the positive value of carbon credit implies the surplus carbon credit that the manufacturer can sell, while the negative value means the excessive carbon emissions over the cap that the manufacturer needs to buy from the market.

In comparison, the optimisation result with carbon footprint management has an optimal lot size of 35, shifted slightly down from 38 of the optimisation result without it. This leads to a marginal increase in the shareholder wealth from 11.15% to 11.20%, but a dramatic decrease in the carbon emission volume from 1027.8788 to 960.4430 tons.

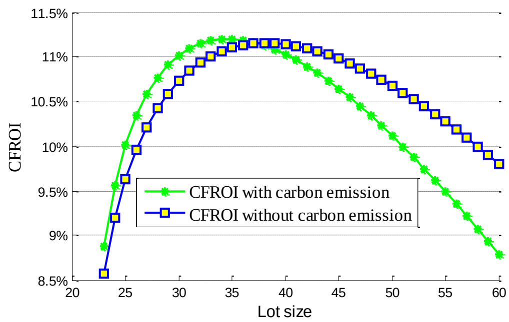

Figure 3. Comparison of optimisation results

The managerial logic behind these changes is twofold. First, the manufacturer seeks to make use of the carbon emission trading mechanism to build up its shareholder wealth by trimming down its carbon emission from 1027.8788 to 960.4430 tons. As a result, its carbon credit increases from -27.8788 to surplus 39.5570 tons, which can be offered for sale in market. Second, the dramatic reduction of carbon emission greatly enhances the image of the firm as being environmentally responsible, which is in line with the goal of GHG regulating agencies. It can be seen that incorporation of the carbon emission trading mechanism in operation optimisation can not only advance a firm's shareholder wealth, but also enhance the firm's contribution to environmental protection.

B. *Implications of Carbon EmissionTrading*

In the first experiment, we have illustrated the benefits of carbon emission management to both economic interests of shareholders and environmental protection. Nevertheless, its managerial effectiveness relies much on the carbon emission trading market environment.

Thus, we conduct the second experiment to examine the possible impacts of different carbon emission trading environments, such as distinct trading prices and carbon emission caps, on shareholder wealth improvement and carbon emission alleviation, with an aim to search for an optimal point, where both the firm's economic interests and environmental responsibility can be maximized at the same time.

Table V lists the different optimisation results when the carbon credit price increases from US$0 to US$2000 per ton. It can be seen that changes in carbon credit price impact apparently on the shareholder wealth and the carbon credit of a firm, as illustrated in Fig. 4 and Fig. 5.

TABLE V. IMPACTS OF CARBON CREDIT PRICES ON OPTIMISATION

Carbon CreditPrice (US$ per ton)	CFROI	Optimal lot size	Carbon credit (tons)	Carbon emission (tons)
0	11.15%	38	-27.8788	10107.0967
500	11.16%	36	6.2770	976.9530
1000	11.20%	35	39.5570	960.4430
1500	11.28%	33	55.7513	928.4430
2000	11.37%	32	71.5570	913.1230
10000000	48.70%	26	154.9970	845.0050

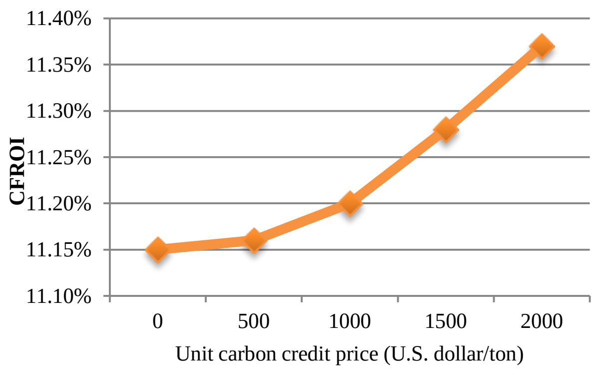

Figure 4. Effects of carbon credit price on CFROI

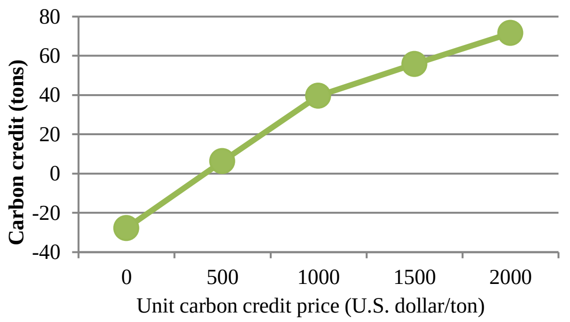

Figure 5. Effects of carbon credit price on carbon credit

With the increase of the carbon credit price, the firm adjusts its operational strategies by gradually trimming down the optimal lot sizes, in order to maximise its shareholder wealth and at the same time reduce its carbon emission. The higher the carbon credit price, the better the optimisation results with higher shareholder wealth and less carbon emission.

This result seems to suggest that the governmental or regional carbon emission regulators should set the carbon credit price as high as practicable. The higher the unit carbon credit price, the more weight of the carbon emission management would be on enhancement of the shareholder wealth. Indeed, firms would be forced to concern more about carbon footprint management, rather than to focus exclusively on operation optimisation without due regard of its environmental impacts. The last row in Table V further illustrates this key point by assuming a dramatically high carbon credit price, although it is virtually impracticable in real market trading.

Next, we turn to the effect of carbon emission cap on optimisation. Table VI shows that changes in carbon emission cap have no impact on the manufacturer's optimal operation strategy. The optimal lot size stays constant at 35 when the carbon emission cap increases from 0 to 2000 tons of GHGs. The constant optimal operation strategy implies that the carbon emission volume of a firm is also independent of its emission upper constraints. In other words, the carbon emission level remains constant at 960.4430 tons, regardless of any changes in carbon emission cap.

TABLE VI. IMPACTS OF CARBON EMISSION CAPS ON OPTIMISATION

Carbon emission cap (tons)	CFROI	Optimal lot size	Carbon credit (tons)	Carbon emission (tons)
0	8.7%	35	-960.4430	960.4430
500	9.95%	35	-460.4430	960.4430
1000	11.20%	35	39.5570	960.4430
1500	12.45%	35	539.5570	960.4430
2000	13.70%	35	1039.5570	960.4430

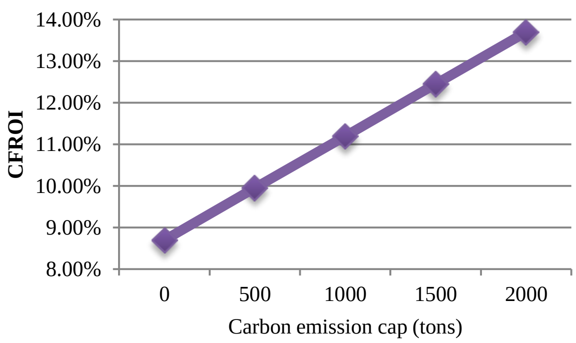

Figure 6. Effect of carbon emission cap on CFROI

However, raising the carbon emission cap leads to enhancement in the shareholder wealth and increases in carbon credit, as represented in Fig. 6 and Fig. 7. But the absolute carbon emission level remains unchanged at

960.4430 tons with the increase of the emission cap. Thus, it is obvious that changes in carbon emission cap exercise powerful influences on the economic interests of equity holders, but no effect on the carbon emission mitigation.

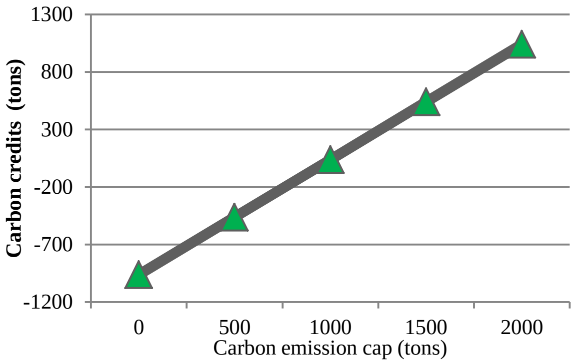

Figure 7. Effects of carbon emission cap on carbon credits

C. Hedging Capability Testing

While in pursuit of shareholder wealth, a firm should at the same time manage its various risk factors, especially in unstable operation circumstances and market fluctuations. From the perspective of shareholders, risks refer to such factors that would impact on long-term sustainable economic interests. The more dramatic impact, the riskier a factor becomes. Obviously, the management should focus mainly on the riskiest factors, rather than on a myriad of relatively trivial ones.

Therefore, we conduct risk analysis in the third experiment to distinguish key risk factors from those insignificant ones.

We are more concerned about $V(Y)$, $V(Z)$, γ, ω, and c on account of their mutability and large influences on optimisation results. $V(Y)$ and $V(Z)$ can be used to measure the operational stability in production; γ and ω are mainly used to estimate the impingement from susceptible market swings; and c is used to test the proposed model's sensitivity to changes in the carbon emission trading mechanism.

The base values for these risk factors are listed in Table VII, where we simulate their changes by moving these base values up and down, respectively, by 10%. The corresponding optimisation results are represented in Table VIII and Table IX.

It can be observed that CFROI is most susceptible to the sales price, followed by other aggregate variable costs ω, such as purchasing cost, while the impacts of other risk factors seem negligible.

TABLE VII. SWINGS OF KEY RISK FACTORS

Risk factors	Base value	High value	Low value
$V(Y)$	10	11	9
$V(Z)$	0.0625	0.0688	0.0563
γ	230	253	207
ω	5	5.5	4.5
c	1000	1100	900

TABLE VIII. SUSCEPTIBILITY OF CFROI TO RISK FACTORS

Risk factors	Base value	High value	Low value	Changing
$V(Y)$	11.20%	11.19%	11.22%	-0.27%
$V(Z)$	11.20%	11.20%	11.21%	-0.09%
γ	11.20%	16.22%	6.18%	89.64%
ω	11.20%	11.10%	11.31%	-1.88%
c	11.20%	11.22%	11.19%	0.27%

TABLE IX. SUSCEPTIBILITY OF CARBON EMISSION TO RISK FACTORS

Risk factors	Base value	High value	Low value	Changing
$V(Y)$	39.5570	37.8930	41.2210	8.41%
$V(Z)$	39.5570	39.1901	39.9181	1.84%
γ	39.5570	39.5570	39.5570	0%
ω	39.5570	39.5570	39.5570	0%
c	39.5570	39.5570	39.5570	0%

In addition, instabilities in manufacturing influence most on the carbon emission. In contrast, the sales prices and variable costs have no effect on carbon emission.

The impact of carbon emission cap on carbon emission volumes is worth noting. Table IX shows the cap has no impact on carbon emission volumes.

On the contrary, this impact in the second experiment is very clear. Such conflicting result arises from the fact that the carbon emission volume is largely insensitive to changes in the emission cap. The impact on carbon emission of the 10% change in c in the third experiment is too little to be reflected in the numerical results. However, when changes in carbon emission cap is sufficiently large, its effects on carbon emission can be easily observed, just as shown in the second experiment.

IV. CONCLUSIONS

We have presented in this paper a lot sizing batch optimisation model for a stochastic make-to-order production environment under carbon footprint management, with an aim to maximise the shareholder wealth and to enhance the environmental responsibility. The proposed model adopts random variables by their statistic merits, instead of by making relatively unrealistic assumptions on their distributions. This approach improves the generality and extensibility of the model.

Numerical experiments have demonstrated the benefits of incorporating the carbon emission trading mechanism in operation optimisation for advancement of shareholder wealth and environmental protection by cutting down emission of GHGs.

Moreover, the results show that the management should keep more tabs on the exogenous sales price and the variable costs, due to their significant influences on the shareholder wealth. On the other hand, the regulatory agencies may focus more on the improvement and innovation of manufacturing technologies, for manufacturing stability impacts hugely on carbon emission volume.

Some potential extensions to the proposed optimisation model are being considered for future work. For example, the stochastic lot sizing batch manufacturing model may be extended to cope with multi-product stochastic manufacturing environments. A multi-stage stochastic programming may be adopted as a more practical tool in line with periodic accounting purposes. Furthermore, it may be worthwhile to explore the possibility of incorporating other carbon emission control mechanisms in the model for more effective advancement of shareholder wealth and environmental protection.

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