Investigation about Inventory Management Model for Raw Materials in Steel Industry

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Abstract. With the continuous development of the economy, the steel industry, as one of the important components of the national economy faces lots of challenges. Effective inventory management for firms can not only achieve the optimal state of inventory cost benefit but also improve the efficiency of capital use, which can also improve the efficiency of the firm's operational management. It is of great significance to enhance the market competitiveness of enterprises. This article examines raw material inventory management in steel companies. As the world's second-largest steel producer, Japan's high dependence on imported raw materials makes it a typical example of how Japanese steel companies manage their inventory levels. This paper focuses on Kosuke Kawakami's model of a non-flush gamma process for Nippon Steel Corporation, which has been effective in reducing inventory levels in practice. The paper then suggests ways of optimizing the model in light of new research in inventory management in recent years.

Keywords: Safety stock management; Two-stage model.

1. Introduction

Japan is a major producer and exporter of steel. Since the 1970s, it has maintained its crude steel production at around 100 million tonnes, ranking second in the world. Its steel technology is a world leading. Japan holds the world's largest number of patents for the production of high-grade steel. At the same time, Japan's resources are scarce and it relies on overseas imports for raw materials such as iron ore, coal, and oil to produce steel. Raw material inventory management has become a key research priority for the Japanese steel industry due to its sheer size and total dependence on imported raw materials.

There has been some previous research on inventory management of bulk materials such as iron ore and coal. Nechval [1] investigates the effect of estimated risk on the simplest inventory problem. Matheus and Gelders [2] consider an inventory problem subject to a probabilistic non-unit size demand pattern and propose an exact and approximate method for calculating reorder points for (R, Q) inventory policy. Relph and Barrar [3] argue that excess is important because there is evidence that a significant proportion of inventory is excess at any given time, even in well-managed firms. Silver and Zufferey [4] use a descent-based and taboo search algorithm to deal with the seasonal storage time of raw materials under constant and fixed demand. Kim et al. [5] optimize the placement of raw materials in the yard, taking into account the yard capacity, depending on how the raw material piles are stacked.

Although a variety of inventory models have been proposed in previous studies, the application of any of these models to real situations will be very difficult. Because the specific mill to which a ship arrives involves human intervention, we cannot model the probability of the frequency of delivery of raw materials to each steel mill, and the accuracy of the model would be greatly reduced.

In response to the problem of steel inventory management in Japan, Kosuke Kawakami [6] proposes a model for calculating raw material inventories under conditions of multiple suppliers, multiple plants, and supply disruptions. The model can be adapted to changes in inventory groups, making it well-suited to practical applications. The seasonal inventory management model has been adopted by Nippon Steel Corporation and, in practical application, has reduced Nippon Steel's total inventory by 11% without any serious inventory shortage events.

Therefore, the second section of the paper will be an analysis of how Kosuke Kawakami's model solves Nippon Steel's inventory management problem and the results of its practical application. The third section will propose appropriate improvements to address some of the shortcomings of the model. The fourth section concludes the whole paper.

2. Analysis

2.1 Problem Analysis

At present, the following problems are faced by Japanese steel producers.

2.1.1 Limited yard capacity

Limited yard capacity for stacked raw materials. When inventory levels are too high, ships loaded with raw materials arrive at the plant unable to unload and incur high demurrage charges if they remain in port.

2.1.2 High idle costs

The cost of maintaining a steel company's production facilities is extremely high, and restarting the facilities (turning on the furnaces) requires a lot of electricity. Therefore, when stocks are depleted and the supply of raw materials is interrupted, companies incur high idle costs.

2.1.3 Seasonal Disasters

The main suppliers of steel raw materials to Japan, Brazil, and Australia, are subject to seasonal disasters. Brazil is prone to flooding during the rainy season and Australia to cyclones. Steel companies, therefore, need to build up safety stocks to avoid supply disruptions due to seasonal disasters.

Therefore, an appropriate inventory management model for Japanese steel producers should ensure safety stocks and seasonal factors while keeping inventory levels as low as possible.

2.2 Model Analysis

Ships are transported from where the raw materials are mined to the factories in Japan in two stages: first, arrive in Japan from the local area; second, travel to the factories that require the raw materials.

2.2.1 First Stage

Although the exact time a ship arrives in Japan is subject to factors such as unexpected weather, it is still possible to model the ship based on its planned arrival time. The time it takes for a ship to arrive in Japan with a full cargo of raw materials at a given time is found to follow an exponential distribution (Figure 1).

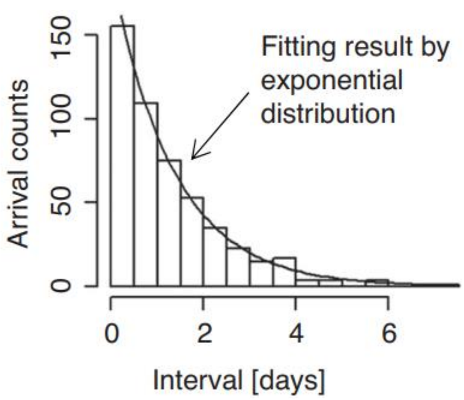

Figure 1. Actual Arrival at All Mills for an Iron Lump Ore

An exponential distribution is a probability distribution of events that occur continuously and independently at a constant average rate, with a probability density function of

$$f(x) = \lambda \exp(-\lambda x), x \geq 0, \lambda > 0 \tag{1}$$

Given the scheduled arrival time of each vessel, the average arrival interval λ of the vessels over a period can be calculated. It is well known that an arrival process where the arrival interval follows an exponential distribution is called a Poisson process.

2.2.2 Second Stage

There is randomness in the dispatch of a ship to a factory after its arrival in Japan. We can count a total of Q ships arriving in Japan in a given time period T, of which qi ships go to Mill i. Thus, for every Ni (Ni =Q/qi) ship arriving in Japan, one will go to Mill i. Since the intervals between ships arriving in Japan follow the Poisson process, the intervals between arrivals at steel mills follow the gamma distribution.

$$\gamma\left(\lambda, \frac{Q}{qi}\right) = \gamma(\lambda, Ni) = \frac{\lambda^{Ni} x^{Ni-1}}{\gamma(Ni)} e^{\lambda x} \tag{2}$$

2.2.3 Seasonal Effect

The possibility of seasonal disasters affecting the supply of raw materials must also be taken into account in the inventory model. According to the survey, heavy rains and hurricanes are mainly seasonal hazards. During periods of high disaster, it is difficult for ships to reach Japan, which means that the average arrival interval λ for ships will increase.

There are several ways to model seasonal variations, such as Holts-Winters (Winters [7], Holt [8]) and autoregressive integrated moving averages (Box et al. [9]). However, the advantage of the Poisson process is that the interval between events is not constant but random. To model seasonal variation, it is therefore more appropriate to use the non-homogeneous Poisson process. It is assumed that the trend of seasonal influences never changes, but that the average arrival rate varies over time. Define the past intensity function as $\lambda^{past}(t)$ and the current average intensity over the analysis period is λ^{now}. The seasonal intensity function $\lambda^{now}(t)$ is defined as

$$(t) = \frac{\lambda^{now}}{\int_0^P \lambda^{past}(t)/Pdt} \lambda^{past}(t) \tag{3}$$

2.3 Model Verification

Both the Kolmogorov-Smirnov test (K-S test) and the Inventory simulation are used to validate the feasibility of the model. The results of the K-S test showed the p-value was well above the 5% significance level under the null hypothesis that the distributions of these two datasets were identical. Therefore, we cannot reject the null hypothesis and there is no significant difference between the arrival time distribution obtained from the simulation using the non-homogeneous Poisson process and the actual distribution. Inventory simulation uses the initial stock levels calculated by the model to simulate the stock shortage rate over a period of time in a realistic production situation and shows that the stock shortages occurring at the stock levels provided by the model are within an acceptable range.

2.4 Result

The model has been well received by Nippon Steel, and within a year of implementation, has reduced stock levels by 14% in the summer and 6% in the winter for the Nippon Steel Group's steel plants, giving an average stock reduction of 11%. Nippon Steel confirms that this has resulted in a reduction in ship demurrage costs for the company of US$4.5 million per year and no significant out-of-stock events. The model's reliable, the real-world application makes it an important tool for Nippon Steel in determining the company's raw material inventory levels.

3. Discussion

3.1 Drawbacks

Despite the effectiveness of the model, there are still a number of factors affecting stock levels that are not quantified in the model. a. The model takes the frequency of ship arrivals as a parameter, but in reality, the lot size varies greatly from ship to ship. This parameter does not accurately reflect the exact amount of supply during that time period. b. The model focuses on the level of supply on the raw material supply side and does not take into account changes in the level of demand for raw materials from steel mills. 5 blast furnaces are shut down in Japan in 2020 and pig iron production falls by 19.8%. Demand can vary significantly due to economic fluctuations and other factors. c. The costing in the model only takes into account the demurrage costs of ships when stocks are built up and ignores the costs incurred when blast furnaces are idled in the absence of stocks. In practice, lower inventory levels will result in a more likely depletion of safety stocks and should be weighed against the cost of ship demurrage and the cost of understocking. The next part discusses factors not considered in this inventory management model, which have been the subject of much research in recent years.

3.2 Understocking Cost

In a study on the costs of supply chain disruptions, Schmitt et al. [10] highlight that the risk of supply chain disruptions is often underestimated. In this paper, he presents a calculation of backorder costs: a steel mill waiting for a ship to deliver raw materials faces two possible outcomes: either it receives the delivery (which would bring the mill's inventory level to y) or it receives nothing (in a disrupted period), which would incur costs. Assume that the demand for raw materials is deterministic (d per period) and that unmet demand is backordered. π_i is used to denote the steady-state probability that the system has been disrupted fori consecutive periods. C_u is the backorder cost per unit per period.

$$(s) = \sum_{i=1}^{\infty}[\pi_{i-1} C_u \int_{-\infty}^{id}(id - y) f_y(y) dy], \tag{4}$$

3.3 Demand Change

Pervin et al. [11] quantify the change on the demand side. As the research area of the article is SIM cards, there is a three-stage fulfilment model of supplier->retailer->customer. In addition, the article focuses on goods that are defective, so the reference of the article is mainly in its assumptions on demand variation. Pervin et al. [11] argue that buyer demand is a quadratic function of time when there is no shortage and constant when there is a shortage (see figure 2).

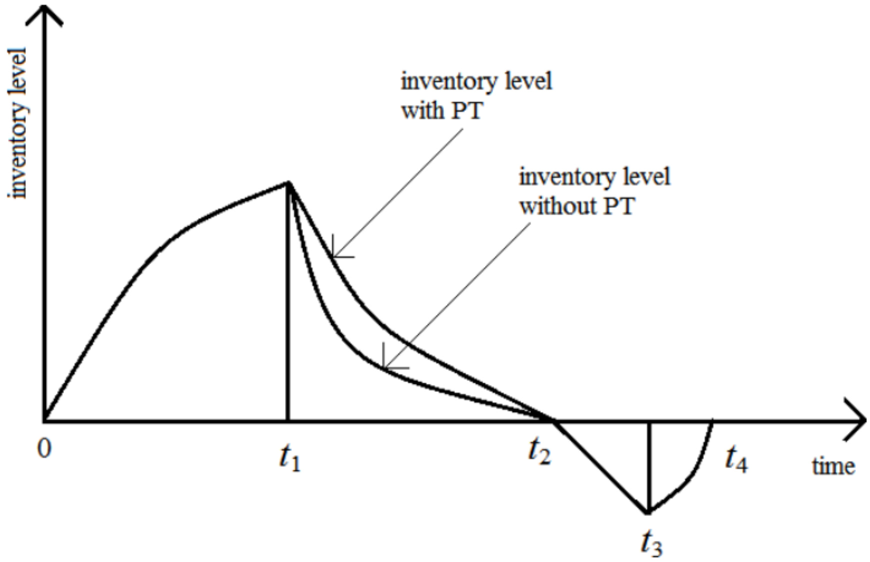

Figure 2. Vendor's inventory model.

In the chart above, t_1 to t_2 represents normal availability and t_2 to t_3 represents demand in the event of a supply disruption. It is the inventory level for a vendor at time t during the production period, it varies from t_1 to t_3.

The study by Pervin et al. [11] focuses on deteriorated goods, so the following assumptions exist in this equation: a. shortages are allowed to occur, b. a fraction β_1 of goods are returned and the rest are lost normally, c. $\lambda(a)$ is the rate of deterioration per unit time unit when the preservation technology is applied.

$$I_2(t) = \frac{k}{\lambda(a)}\left(e^{\lambda(a)(t_2-t)} - 1\right)(t \in [t_1, t_2]) \tag{5}$$

$$(t) = \beta_1[a_0(t_2 - t) + \frac{b_0}{2}(t_2^2 - t^2) + \frac{c_0}{3}(t^3 - t_2^3)] \ (t \in [t_1, t_2]) \tag{6}$$

3.4 Tradeoff

Tang et al. [12] in their study of the raw material inventory management problem of Baosteel Group using lot size and supply interval as decision variables, innovation was to use an optimization approach to the cost of ship demurrage and the cost of understocking for the trade-off.

Each time material is ordered, a fixed cost of K_i will be incurred and m_i represents the quantity of raw material ordered. An inventory holding cost of h_i will be incurred per unit of raw material, and the maximum inventory quantity is Q_i.

$$C_{LR} = \sum_{i \in N} K_i m_i + \sum_{i \in N} \frac{1}{2} h_i (Q_i + s_{0i}) + \sum_{k=1}^{n} u_k (\sum_{i \in l_k} Q_i - V_k) \tag{7}$$

Based on the constraints, a Lagrangian relaxation algorithm is used for this equation to de-minimize the total cost.

3.5 Summarise

Although the methods proposed by these scholars are not necessarily applicable to Nippon Steel's inventory management problem, their ideas are still very informative; Pervin et al. [11] and Schmitt et al. [10] quantify demand and out-of-stock costs, while Tang et al. [12] provide a method for finding cost-optimal solutions.

4. Conclusion

The issue of steel inventory management in Japan is a major focus of research within the industry, and effective measures to address this issue can generate savings of tens of millions of dollars per year for the company. Kosuke Kawakami, in Seasonal Inventory Management Model for Raw Materials in Steel Industry, proposed an innovative inventory management model for Nippon Steel's steel inventory, which has been proven to work in practice. This paper summarises the model and discusses its shortcomings.

Kosuke Kawakami's non-simultaneous gamma model requires only two parameters to determine the optimum inventory level: the frequency of ship arrivals and the ratio of goods to be delivered to each plant. The method is simple and can be recalculated in response to changes in raw material or ship distribution schedules. However, the model does not take into account the costs of supply chain disruptions and changes in demand, so in practice, safety stocks are often too low. In response to these shortcomings, models from related fields have been used to complement the optimization discussion.

Many issues remain to be investigated in the future. The method used in this paper to test the validity of the model is the Kolmogorov-Smirnov test, which has low validity for distributions where the parameters are estimated from the data, and both λ and n in the gamma distribution in this paper are approximate estimates. Therefore, the model needs to be further validated using a more appropriate test, such as the Anderson-Darling test or the Shapiro-Wilk test. On the other hand, this method has only been validated for Nippon Steel, and validation for other steel companies will be the focus of future research.

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