MULTIPLE CAN-ORDER LEVEL FOR CAN-ORDER POLICY OPTIMIZATION:A CASE STUDY

Budi Santosa and Faldy Maulana Yuantoro
***E-mail*: budi_s@ie.its.ac.id**
Department of Industrial Engineering
Institut Teknologi Sepuluh Nopember
Surabaya, Sukolilo 60111, Indonesia

Abstract

Inventory is the products which are stocked for to fulfill the demand in the future. Here the problem may occurrs if the demand of the item is intermittent, since the inventory policy is difficult to be determined due to the uncertain demand of the item that has high error rate in the prediction. This problem is occurred in the spare part needs of Company X. Therefore, a joint replenishment method, can-order policy that has multiple can-order level (s_i, c_{ij}, S_{ij}), can be implemented to coordinate the order of some different items. A non-linear integer programming model, which can be categorized as NP-hard problem, is used to handle the problem. The contribution of this paper is on the use of the approach on the real case which never done before. A metaheuristic approach, simulated annealing, is applied to find a satisfied solution with a fast computation time. Global criterion method is also used to reach the multi-objective function, which are to minimize total inventory cost and number of carriers shipped by supplier. According to experiment done with 3 suppliers and 157 items, the result obtained is better than the existing condition in Company X with number of carrier reduction of 2.6% and cost saving of 14.43% or equal to $ 81,570.79.

Keywords: can order policy, metaheuristic, multiple can-order level, simulated annealing,
spare part

1. Introduction

An effective inventory control, which includes the activity of deciding what to order, how much to order, and when to order, can give an important role related to the supply chain management of the company. Generally, inventory control is implemented to reduce the cost of investment, such as holding cost, order cost, and purchasing cost, and also to increase the customer service level by avoiding shortage.

The strategy to determine the inventory control policy is based on the demand classification, which can be categorized as smooth, erratic, intermittent, or lumpy [1]. Problem that occurred in item with intermittent demand is the difficulty in determining the right inventory control policy, since it has uncertain demand pattern that is difficult to be predicted.

This problem also arises in the spare part needs of Company X. Company X is known as one of the aluminum smelter company in Indonesia. To maintain the reliability of the production machine, the company needs to implement a maintenance strategy. One of the action done regarding to the maintenance strategy is to do preventive maintenance, which needs spare part as the supporting components of the machines. When the stock of spare part is not available, the maintenance activity cannot be done until there is a sufficient stock of spare part available. This condition can lead to the delay in production process, which can make the customer demand cannot be fulfilled. This indicates the importance of spare part inventory control in Company X, which currently has the responsibility to control 14,000 types of item.

It is found from the fact that 61% of mechanical parts needed in 2018 are classified into intermittent demand, in which the needs are difficult to be forecasted. Moreover, spare part order that is done independently between each item in the current condition of Company X makes the ordering cost becomes high. Even though actually the tender activity in spare part does not give a significant impact, since the item order has to be done in many items and the tender process has to be done based on the conformity of part specification. Therefore, an efficient inventory policy is necessary in order to have minimum inventory cost and number of item stock out.

According to Ghorbel [2], an (s, S) replenishment policy is implemented to overcome the variance occurred in quantity of supply and period of order. In multi-item inventory control, joint replenishment problem (JRP) can be implemented to coordinate the order of some items in the same warehouse [3]. When there are some items ordered to the same supplier, the order cost will be based on number of order frequency and number of items ordered. But, in the existing condition, the quantity of order is set independently between each item eventhough actually it is ordered to the same supplier. Therefore, a can-order policy, which is developed from (s, S) policy, can be implemented to control the order coordination that can accommodate correlated item [4] and has better result compared to uncoordinated policy by resulting 20% of saving [5]. Can-order policy is implemented by setting 3 parameters (s, c, S), which are re-order level (s), can-order level (c), and order-up-to level (S).

In the model proposed by Nagasawa & Irohara [3], the (s, c, S) policy is known to be non-linear integer programming that can be categorized as NP-Hard problem. Solving the problem using exact method needs long computation time due to the high number of spare parts that need to be calculated. Thus, a metaheuristic approach is used in order to get a satisfied solution with shorter computation time. We consider Simulated Annealing to solve the problem since it is not based on population. Therefore we expect that SA will provide good solution in shorter time. The main contribution of this paper is on the use of can order policy to solve real case and solving it using a metaheuristics.

Therefore, here we built a multi-objective model of can-order policy and solved using Simulated Annealing in order to get good solution and shorter computation time. Global Criterion method is also used to obtain multi-objective function that consider the deviation between objective function and the optimal solution. The objective function is to minimize total inventory cost and carrier number shipped by supplier considering the inventory capacity and multiple can-order level to coordinate the order of some items originated from the same supplier.

2. Literature Review

Syntetos et al. [1] proposes a matrix in which the value of cut-off is determined mathematically by comparison of Mean Squared Error. The matrix is divided into four quadrants as shown in Figure 3, which is determined based on the demand quantity variability obtained from squared covariance (CV^2) and *average demand interval* (ADI). The cut-off value obtained by Syntetos [1] is 0.49 and 1.32. According to those two aspects, demand can be classified into smooth, erratic, lumpy, and intermittent.

As an example, the demand of maintenance material or spare part has intermittent and lumpy demand pattern. Spare part demand can be categorized as intermittent or sporadic if it has long average demand interval depends on the maintenance need (ADI>1.32), and categorized as lumpy if the variability between each demand is high (CV^2>0.49).

Inventory is the products which are stocked for to fulfill the demand or other needs [6]. Customer service is described as the availability of the item to fulfill the customer demand. Inventory is used to maximize customer service level by overcoming the uncertainty of demand. Inventory that is used to overcome fluctuation caused by demand or lead time is called safety stock. One of the company objective in implementing inventory control is to minimize total inventory cost [7]. The cost of inventory can be classified into three components, which are procurement cost, holding cost, and stockout cost [8].

A replenishment policy is implemented to control the inventory of multiple items. According to Ghorbel [2], there are four inventory policies that can be categorized as continuous review system and periodic review system. The examples of replenishment policy mentioned are (s, Q) Policy, (s, S) Policy, (T, S) Policy, and (T, s, S) Policy.

Sipper & Bulfin [9] also classified the inventory policy by considering whether there is an intermittent demand. For continuous time, a continuous review policy is implemented by using EOQ model, (s, Q) policy, base stock, or two bins inventory. If the interval time between each demand is intermittent, then a periodic review policy can be implemented by using EOQ, (s, T) policy, (s, S) policy, or optional replenishment / joint replenishment.

Inventory is not only controlled individually between each item, otherwise the purchasing process can be done simultaneously between some different items. This indicates that inventory control is able to be done for some groups of items that have correlation, such as items that are ordered from the same supplier. This inventory control that coordinate quantity of order of some different items in the same warehouse is called joint replenishment policy (JRP) [3]. Porras & Dekker [10] approached single items for inventory on 20 products using a joint replenishment strategy. The JRP strategy can result in a total cost savings of 13% when compared to the EOQ method. JRP can be done with some policy, like Order Point System, (s, c, S) system, periodic review system, dan Time-Phased Order Point (TPOP) System [6].

Can-order policy or (s,c,S) policy is one of the method of joint replenishment policy. Balintfy [5] concluded that can-order policy is at least better than other coordinated replenishment policy. Can-order policy (s,c,S) is implemented to control coordinated items by using 3 parameters, which are order-up-to level (S), can-order level (c), and must-order level or re-order level (s) [11]. When the inventory level of an item is below the value of s level, the order is made by the company until the amount of item stock reaches the value of S level. For another item that has the amount of item stock below c level, then the order is also made by the company until the amount of that item stock reaches the value of S level. Federgruen, et al. [12] modeled a can-order policy with semi-Markov containing poisson demand and positive lead time. They show that a can-order policy has a better cost-side result of 20% than an uncoordinated policy. The illustration of inventory using can-order policy can be seen in the figure below.

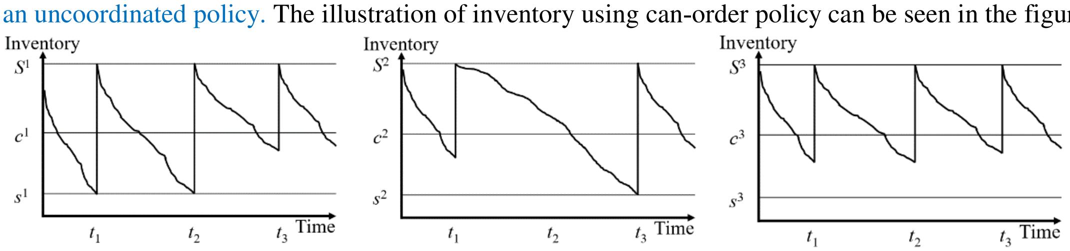

Figure 1. Can-Order Policy System for 3 items

Nagasawa [3] adopted the model in ordering policy that considers correlation between items. Correlated demand is the impact of demand from two or more types of item in one order with high probability. From the can-order policy model, changes are made in can-order level and order-up-to level depend on the ordering trigger item.

In the model developed by Nagasawa [3], for each item i, the ordering policy is done by using (s_i, c_{ij}, S_{ij}) parameters. When the inventory level of item i lies below re-order level s_i, it will trigger the replenishment order to increase the inventory level of item i to reach order-up-to level (S_{ii}) of that item. The illustration of can-order policy of multiple can-order level can be seen in the figure below.

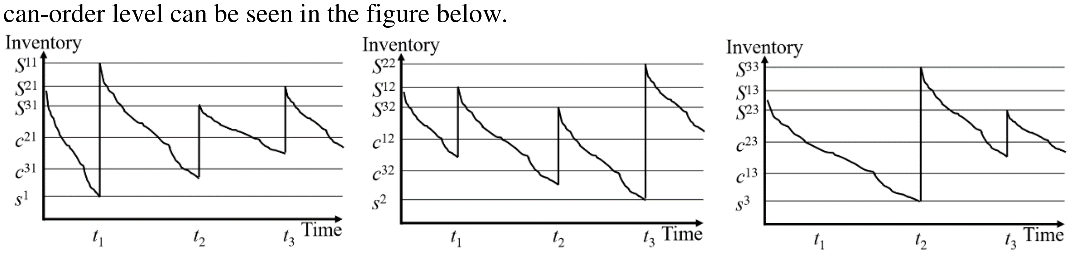

Figure 2. Multiple Can-Order Level for 3 Correlated Items

Multi-objective optimization is an optimization problem that has more than one objective functions, which possibly makes conflict arises between each objective function [13]. The common engineering classification which focuses on solving some of the objective function problems is classed into 3, such as A Priori, A Posteriori, and Progressive Preference [14]. Global criteria is one of the a priori approach that explains the method to solve objective function problem by turning it as a single function. The purpose is to measure how close the decision maker can decide the optimum solution. Multi-objective function that is used in the global criteria is shown below [15].

$$Min \qquad F = \sum_{l=1}^{K} \left[\frac{f_l(x^*) - f_l(x)}{f_l(x^*)} \right]^p \tag{1}$$

where, $f_l(x)$ = objective function l, $f_l(x^*)$= optimum value of objective function l (solution of ideal function), p = weight of deviation value

3. Problem Identification

PT. X is known as one of the biggest aluminium smelter company in Southeast Asia. To do the production process from raw material to become a finished product, the company needs the production machine to have a good performance. Therefore, the reliability of the machine and supply tools in production process are some of the important factors that can contribute to the ability of the company to fulfill the demand.

When the spare part is not available, the maintenance process, which is actually supposed to be done, becomes postponed until the spare part needed to do the maintenance is available. This can lead to delay in the production process, which can make the demand cannot be fulfilled. This problem indicates the importance of inventory control in spare part. The item is also classified based on the criticality level. Majority of spare part demand in PT X is intermittent.Since most of the spare part demand are categorized as intermittent, lumpy, or erratic, it makes the inventory control cannot be done by using EOQ and the regular safety stock formula, which needs the distribution rate to follow normal distribution. If that policy is implemented, the inventory cost that includes safety stock cost will increase due to high variability caused by zero demand in some periods.

Spare part order that is done independently between each item in PT. X can lead to high ordering cost. Although, actually the tender activity in spare part does not give a significant impact, since the item order has to be done in many items and the tender process has to be done based on the conformity of part specification. So, when there are some items needed originated from the same supplier that are needed in different period, these item will still be ordered independently in the period when the item is needed. The data below is the example of data that will be used to solve with the model.

Table 1. Data of Demand, Volume, and Initial Inventory (Testing Data 1)

Material Number	Vendor	Initial Inventory	Volume (cm^3)	Demand t1	t2	t3
A822	AD2	0	443.7	0	1	0
A823	AD2	1	1841.508	1	0	3
A075	AD2	6	116.28	8	4	4

Table 2. Data of Inventory Cost (Testing Data 1)

Material Number	Price	Holding Cost	Ordering Cost	Backordering Cost
A822	$ 323.42	$ 33.96	$ 25.70	$ 371.93
A823	$ 272.13	$ 28.57	$ 24.67	$ 312.95
A075	$ 516.24	$ 54.21	$ 29.56	$ 774.36

4. Model and Algorithm Development

The mathematical model developed based on the model built by Nagasawa [3] on multiple can-order level problem: Here we only show the objective functions

Minimize Total Carrier +Total Purchasing Cost + Total Holding Cost + Total Ordering Cost
+ Total Backorderring Cost

The development of the algorithm is based on the model that has been made. The following is an explanation of the steps contained in the SA algorithm used :

Step 1: Initialize

The SA algorithm parameters used to complete this case study are the temperature reducing factor (*cr*) and the number of cycles (*n*). The initial temperature parameter is determined by taking the average value of the objective function value of the random value of the generated solution.

Step 2: Solution Generation

In the simulated annealing algorithm, solutions are generated randomly. The initial solution used consists of several variables such as, re-order level (s_i), can-order level (c_{ij}), order-up-to level (S_{ij}), and the number of shortage items (o_{it}).

Step 3: Objective Functions Calculation

In the solution of multi purpose problems, the model will solve both problem objective function 1 and objective function 2 first. Then, the model is performed running again with a multi purpose function using the global criteria method as in Equation (1). In this paper stopping criteria used is temperature value near 0.

To validate the algorithm we compare with LINGO software. From the results of the multi objective model calculation, the result is the same as the exact calculation. However, to achieve the same result it requires a large amount of replications. Here is a recapitulation of verification and validation results using 3 item and 3 period data.

Table 3.Comparison of SA Verification Results with Exact Calculation on Test Data 1

Objective Function		Solution Result			Computation Time (sec)		
		Exact	SA	Gap%	Exact	SA	Gap%
Single Objective	Z1	1	1	0.0%	3	19.8	560.00%
	Z2	6441.25	6441.25	0.0%	18	23.6	31.11%
Multi Objective	Z1	1	1	0.0%	870	40.8	-95.31%
	Z2	7187.63	7187.63	0.0%	870	40.8	-95.31%

We see that the SA calculation does not have a significant difference in the exact calculation. Differences occur when a multi-purpose running model is implemented. This occurs because the SA generated random numbers which will then be corrected by searching for a decision variable based on Neighborhood Search. Whereas, when viewed at computational time, the SA algorithm on an objective single model has a longer time than the exact calculation. However, when compared with the multi objective model, the SA algorithm is faster than the exact calculation. This is because there are non-linear functions in the multi objective function.

Once the model with 1 supplier with 3 items and 3 periods is valid, the model will be tried running again using multi supplier problem with 2 supplier size with 3 items from supplier 1 and 2 item from supplier 2 with 3 period. Here is a recap of the results on the second issue.

Table 4. Comparison of SA Verification Results with Exact Calculation on Test Data 2

Objective Function		Solution Result			Computation Time (sec)		
		Exact	SA	GAP%	Exact	SA	GAP%
Single Objective	Z1	1	1	0.00%	4	36.14	803.5%
	Z2	8788.61	8788.61	0.00%	49	38.15	-22.1%
Multi Objective	Z1	1	1	0.00%	445	273	-38.7%
	Z2	9644.32	10371	7.53%	445	273	-38.7%

In multi supplier problem, the result of solution with the biggest difference in the multi objective model of cost destination function is 7.53%. From these results, the Simulated Annealing can be said to have been valid. Thus, the built model can be continued for problems with larger size or on the real problems.

5. Experiment And Analysis

In the SA algorithm there are several parameters used to generate solutions such as cr (temperature reducing factor) and n (number of cycles). The value of these parameters will affect the quality and speed in generating the solutions so it is necessary to test the parameters to determine the exact parameter value to get the best solution. The values of cr tested were 0.9 and 0.6. While the maximum iteration value for each tested cycle is 100 and 1000.

To test the parameters of the simulated annealing algorithm, the data used in each test data sets was used with different number of items, periods and suppliers. The following is the data size used in the parameter test experiment.

Table 5. Test Data Size

Data	Products	Periods	Suppliers	Variables	Constraints
Test Data 1	3	3	1	163	304
Test Data 2	5	3	2	363	452
Test Data 3	10	12	3	3482	4046
Case Study Data	157	12	3	49.455++	57.000++

These data sets are taken from the case study of PT X spare part inventory by sampling by taking into account the items and suppliers that most contribute or have the highest value of the entire inventory control process. The following is the exact result of the test data 1, 2, and 3.

Table 6. Result of Exact Calculation of each Test Data

Result	Test Data 1	Test Data 2	Test Data 3*
Carrier Number (unit)	1	2	37
Total Cost ($)	7187.63	9644.32	276464.2
Multi objective value	0.013	0.009	-
Computation Time (sec)	870	445	68965
Iterations Number	3578609	978242	15100856

*Local Optimum Result

Based on the parameter test with the test data 1,2, and 3, obtained the optimum parameter input with the temperature reducer value of 0.6 and the number of iterations per cycle of 1000 iterations. After obtaining the parameters that get the best solution, each test data will be re-experimented by looking at the difference of solution that occurs when compared to the optimal solution of 10 replication. Here's the average gap or difference in results against the exact calculation of each test data.

Table 8. Average Differences of SA Algorithm Results with Exact Calculations

Data	Average Gap %		
	Carrier	Cost	Time
Test Data 1	0.00%	2.04%	-95.30%
Test Data 2	15.00%	-1.59%	-90.81%
Test Data 3	-14.60%	-61.20%	-93.70%

PT X is currently applying the inventory policy (*s, T*) with s is a re-order level and *T* is a replenishment period. When inventory touches or below the re-order level, set by the company for safety stock, the company will place order items as much as demand for the next 3 months from the period in which the inventory level is below the re-order level. Of the 157 items supplied by 3 suppliers, the following is the calculation of inventory cost and total carrier suppliers in the existing condition.

Table 9. Result of Inventory Cost Calculation on Existing Condition

Cost Component	Value
Orderring Cost	$ 20,756.84
Purchasing Cost	$ 406,771.11
Holding Cost	$ 158,657.64
Total Cost	**$ 586,185.59**

Table 10. Result of Carrier Number Calculation on Existing Condition

Supplier	Carrier Number (unit)
CI10	13
AD2	41
GE16	22
Total	**76**

After obtaining the parameters that resulted in the best or faster convergent solution, the SA algorithm was attempted to solve real problems in the case study of PT X spare part inventory. Here is the result obtained from SA algorithm with temperature reducing parameters of 0.6 and maximum 1000 cycle iterations.

Table 11. Results of SA Algorithm Running of Case Study Data

10 Replications	***Carrier Number (unit)***	**Total Cost ($)**	**Computation Time (sec)**
Average	**75.5**	**595,019**	**31,127.3**

From these results can be known from 74 carriers, 44 of those are carriers of supplier CI10, and the lowest cost lies in the cost of ordering. While at backorder cost value of $ 0, because there is no shortage. These results will then be compared with the existing conditions applied by the company.

6. Result and Analysis

In the existing condition, the company implements policy that sets the re-order level to be equal to safety stock, with order quantity equal to cumulative demand of the next 3 months. The existing spare part order, which is done independently between each item, results in high ordering cost. This makes the number of carriers shipped by the supplier becomes high, due to the high number of order made by the company. According to the calculation, total cost spent by the company in the existing condition is $586,185.59 with number of carriers shipped by supplier equal to 76 units.

Experiments conducted using SA algorithm to get best parameters of 1000 maximum cycles and 0.6 temperature reducer. When viewed in the results of each parameter, the longer the computation time or the greater the number of iterations, the solution obtained can be much more optimal. In the test data 1 and 2, the resulting solution is easier to achieve the optimal value because of the small data size. But when tested with larger data sizes on test data 3, the results of each replication can be much different. In fact, when an experiment is done using the exact method, the result cannot achieve its optimal value due to memory and time constraints. If number of iterations can be increased more, the built model can get the best solution.

The table below shows the result of calculation of both existing condition and optimization model. It can be seen that there is an improvement in the optimization result, shown by the amount of saving between those two different conditions.

Table 12. Comparison of Result of Existing Condition and Optimization Result

Objective Function	Existing Condition	SA Result	*Saving %*
Total Cost	$ 586,185.59	$ 501,610.00	**14.43%**
Total Carriers	76	74	**2.63%**

Table below shows the detail explanation of improvement in number of carriers shipped by supplier and the cost.

Table 13. Comparison of Carrier Number of Existing Condition and Optimization Result

Supplier	Carrier Number (unit)		*Saving %*
	Existing Condition	SA Result	
AD2	13	14	-0.08%
CI10	41	44	-0.07%
GE16	22	16	27.27%
Total	**76**	**74**	**2.63%**

A change in the result between existing condition and optimization model result arises due to the different policy in setting the re-order level and quantity order or order-up-to level. In the existing condition, there are some items that have bigger re-order level compared to the optimization model

Table 14. Cost Comparison of Existing Conditions and Results of Optimization

Cost Components	Cost Value ($)		*Saving %*
	Existing Condition	SA Result	
Orderring Cost	$ 20,756.84	$ 4,994.80	75.94%
Purchasing Cost	$ 406,771.11	$ 358,750.00	11.81%
Holding Cost	$ 158,657.64	$ 140,870.00	11.21%
Total Cost	**$ 586,185.59**	**$ 504,614.80**	**14.43%**

In the cost aspect, it shows that significant change arises in ordering cost that becomes 75.94% lower. The ordering cost in optimization model becomes lower, since the multiple can-order level in improvement optimization model makes it possible for coordinating the order of some grouped items that have the same supplier.

While for total unit and holding costs become 11.81% and 11.21% lower than the existing. Purchasing cost becomes lower, since there is a difference in order quantity between the existing condition and optimization model result. Change in policy of re-order level and order quantity also change the number of items ordered. This change can lead to reduction in holding cost. For backorder cost, both existing condition and optimization model have the result of $0.

7. Conslusions

Based on the experiments, it can be seen that SA algorithm can find the solution which is close to optimum. But, it is still hard to reach the global optimum result if the model running is done with large amount of data. Based on the result of experiment that had been done, the gap arises between the result of SA algorithm and exact method calculation is large. This happened because when data size becomes bigger, the generated variable value is also increased exponentially. Therefore, the computational time needed is also increased.

According to the experiment with 3 suppliers and 157 items using multiple can-order level with can-order policy resulted from Simulated Annealing algorithm, it obtained a better result compared to the existing condition in PT. X with inventory cost of $501,610.00 and number of carriers equal to 74 units. This result shows that there is a saving of 2 units of carrier, and also cost saving equal to 14.43% or $81,570.79 (Rp 1,060,420,270).

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Biography

Budi Santosa is a professor and Head of Department at Industrial Engineering Department, Institut Teknologi Sepuluh Nopember (ITS), Surabaya Indonesia. He earned B.S. in Industrial Engineering from Institut Teknologi Bandung (ITB), Indonesia, Masters and PhD in Industrial Engineering from University of Oklahoma, USA. He has published journal and conference papers. Dr Budi Santosa has done research projects in application of methaeuristics techniques in logistics, transportation and scheduling. His research interests include optimization, metaheuristics, scheduling and data mining.

Faldy Maulana Yuantoro is Bachelor of Industrial Engineering, Institut Teknologi Sepuluh Nopember (ITS) Surabaya. His study is majoring in computation and optimization. He is also laboratory assistant and lecturers' assistant for several disciplines, such as operation research, engineering optimization, simulation, and statistic. Becoming a laboratory assistant, he got many experiences and knowledge, especially in industrial and computation discipline. As a student, he is also active in academic and non academic field so that he got many experiences coordinating some events held in ITS Surabaya.