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Lead Acid Battery Material Inventory Control with Periodic Review Method

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Abstract. At lead acid battery companies, the main material from lead has a limited shelf life. This study uses a case in the lead acid battery company in Indonesia, artificial neural networks forecasting is used to accommodate erratic demand for XYZ lead acid battery companies. The continuous review model is used to determine the minimum inventory and time between orders. The continuous review model is expected to have less total inventory costs compared to the company policy model. There is a lot of research on inventory control in the supply chain, but almost all research assumes durable products. This study uses an artificial neural network method to minimize demand forecasting errors and then the continuous review approach is used to minimize the total inventory cost by considering material life due to quality considerations.

1. Introduction

Saturated or sluggish national automotive market, have a direct impact on the OEM (Original Equipment Manufacturer) spare parts business segment, Battery Manufacturing is no exception. As one of biggest Battery Seller in Indonesia, PT XYZ will deal with the condition of the automotive industry which is predicted to remain stagnant by further exploring the export of replacement parts market.

Fig. 1. Saturated Indonesia 4 Wheels Sales 2010-2018 (Gaikindo)

PT XYZ expected to be able to do supply chain operational excellence to remain competitive and sustainable in business competition. The condition faced by PT XYZ is an uncertain demand so that it has difficulty in forecasting. PT XYZ focuses on the replacement parts market in accordance with 56% export and 39% domestic market products as shown in Figure 2.

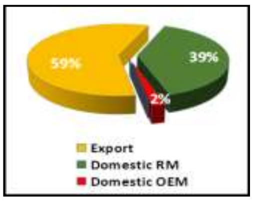

Fig. 2. Product Market PT XYZ

Supply chain performance depends on the accuracy of demand forecasting [7]. Demand and sales forecasting in 6-24 months is crucial for automotive production planning [3].

Order fluctuations can have a biased impact on demand forecasts and cause overstock or shortage due to material planning that misses. And overstock or shortage has the potential to cause: high cost, loss of opportunity (order), production not achieved, or additional costs for material procurement.Another section of your paper

2. Literature Review

2.1. Inventory Control

For many companies, inventory is reflected as an investment, and this investment is often greater than it should be because the company is easier to have just in case inventory (just in case something happens) than just in time inventory (necessary inventory). Companies can reduce costs by reducing the level of inventory in hand, otherwise consumers will feel dissatisfied if a product or an operation stops / runs out.

If the amount of inventory is too large which can result in the emergence of funds embedded in the inventory, increased storage costs and greater risk of damage to goods. However, if there is too little inventory, there is a risk of a shortage (stockout) because often goods cannot be brought in suddenly and as large as needed so as to cause production processes, sales delays, and even loss of customers.

There are 4 types of inventory that companies must maintain to accommodate inventory functions according [8]:

1. Raw material inventory

Materials that are usually purchased, but have not yet entered the manufacturing process and are used to decouple (separate) suppliers from the production process.

2. Inventory of semi-finished goods (WIP inventory)

Components or raw materials that have gone through several changes, but not yet completed. WIP exists because of the time required to complete a product (called cycle time).

3. MRO (Maintenance, Repair, Operating)

Supplies are provided to provide maintenance, repairs, operations, which are needed to keep machines and processes productive.

4. Inventory of finished goods

The finished product is just waiting for delivery but is still an asset in the company's books.

Costs in controlling inventory can be classified as:

1. Ordering Costs

Ordering costs are costs incurred in connection with ordering parts from the time of ordering until the goods arrive. These costs include administrative costs and order placement, supplier selection fees, transportation costs, receipt fees and goods inspection fees for each order made.

2. Holding Costs

These costs are related to material inventory in the company. These costs may include warehouse rental fees, warehouse administration fees, warehouse employee salaries, electricity costs, capital costs embedded in inventory, insurance costs, or damage, loss or depreciation of goods during storage. Capital costs are the largest component of storage costs in the form of interest if capital comes from loans and opportunity costs if the capital is one's own.

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3. Shortage Costs

These costs arise as a result of the unavailability of goods when needed. These costs are in the form of lost opportunity costs arising from the interruption of the production process due to material shortages, additional administrative costs, the cost of delayed receipt of profits, or the severity of the cost of losing customers.

For the classification of material inventory, based on the ABC inventory control method, the distribution relationship on the material cost structure of a product 80% of the cost is centered on a small portion of individuals at 20% of the total population. This distribution relationship also occurs in inventory. This inventory control method is known as the ABC method. According to the inventory classification, high-value inventories are classified in class A, inventories that are of moderate value are classified in class B and low-value inventories are classified in class C. To minimize costs, class A and B inventory items must be pressed and monitored closely. Whereas class C inventory items can be provided more considering the low cost.

2.2. Artificial Neural Network

Because of its ability to study non-linear functions from samples without requiring any distribution assumptions, Artificial Neural Networks have attracted the attention of many practitioners and researchers in recent years [2]. For example, Carmo and Rodrigues (2004), Gutierrez et al. (2008), Nasiri Pour et al. (2008); Mukhopadhyay et al. (2012), and Kourentzes (2013) have conducted studies using artificial neural networks [2].

Single-hidden layer neural networks show a promising approach [2], with the advantage of being able to generalize non-linear functions so that they are suitable for intermittent demand [5].

a. Preprocessing (data transformation)

Input and target data need to be normalized or called by data scaling (Bahagia, 2006):

$$X' = (0.8\,(x-b))/((a-b)\,) + \,0.1 \qquad (1)$$

Notes :

X'= linear transformation into interval (0.1: 0.9)

x = data that will be forecasted

a = minimum data

b = maximum data

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b. Training BackPropagation ANN

The process of training in neural networks backpropagation replication is a procedure to do learning about recognizable pattern. Neural network model limitation applied is with several layers of hidden layers. Multi layer perceptron is a network that is have many layers.

c. Postprocessing

When in preprocessing use formula to normalizing, then in postprocessing after training data with ANN, use the following formula to denormalization:

$$X = ((x' - 0.1)(b-a))/0.8 + \,a \qquad (2)$$

Notes :

X = denormalized data

x' = normalized data
a = minimum data
b = maximum data

2.3. Periodic Review

Because of its ability to study non-linear functions from Based on the interval at which the request arises, a material can be classified as continuous material or intermittent material. Intermittent material is a material that gets a request with a large enough time interval between requests and compatible using the Periodic Review policy [4].

Periodic Review applies the concept that at every time (R) the level of inventory will be checked. If the inventory position is at or less than the reorder point (s), the order will be placed up to the maximum inventory level. If the inventory position is above (s), then the order will not be made until the next inspection.

3. Methodology

Four factors are used as dependent variables to forecast demand: sales data, price, delivery days and exchange rate. And the collected data is divided into:
1. Data Input Training (2016-2017)
2. Validation Data (2018)
3. Training Data Target (2017-2018)

TABLE 1
INPUT AND TARGET FOR NEURAL NETWORK

Pattern	Input Data	Target
1	Forecast Data for Month 1 to 12	Demand Data Month 13
2	Forecast Data for Month 2 to 13	Demand Data Month 13
3	Forecast Data for Month 3 to 14	Demand Data Month 13
.	.	.
.	.	.
12	Forecast Data for Month 12 to 23	Demand Data Month 13

ANN Forecasting Steps – Metode Backpropagation :
a. Data entered into network input (feedforward)
b. Calculation and back propagation of the error in question
c. Weight adjustment and bias.

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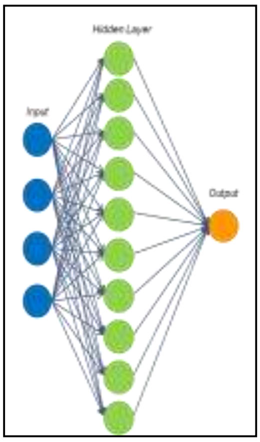

Figure 3. 4 Input and 1 Output Neural Network

Matlab R2016b software is used to create neural networks and perform ANN forecasting in the form of training and validation processes with the backpropagation method.
At the training stage, trials and errors are carried out to get the smallest possible errors. This means that it is expected that training recognize patterns so that the output produced approaches the training target.

Before validation, the data is denormalized first as equation (2).

$$X = ((x' - 0.1)(b - a))/0.8 + a$$

Error forecasting is calculated using *Mean absolute percentage error* (MAPE). MAPE indicates how much error in predicting compared to the actual value. Here is the MAPE formula :

$$MAPE = \sum(((|Actual - Forecast|/Actual)\ x\ 100\%)/n) \quad (3)$$

The ANN forecasting data is then used as input data for material requirement planning in the following year. The periodic review method is used to make an approach to improving inventory control with a lifetime limit on lead material as the main composition for making lead acid batteries with quality considerations.

The periodic review model used is as follows :

1. First, we have to calculate the ordering cost (A)

A = Monthly FOH * 12 / One Year PO (4)

Notes :
FOH = Factory Overhead
PO = Purchase Order

2. Calculate the holding cost (H)

I = Bank interest * Material prices
B = THP * MP * 12 / One Year Material
H = I + B (5)

Notes :
THP = Take Home Pay
MP = Man Power

3. Calculate the shortage cost (Sc)

Sc = (18% * Material prices) + FOH + Labour Cost (6)

Notes :
FOH and Labour cost in 30 minutes

4. Determine the NG cost of lead material

Because lead material is easily oxidized. And this directly affects the performance and lifetime of the battery. PT XYZ limits the lifetime of the Work In Process (WIP) lead material in the form of lead parts and formed plates for 14 days.

Lead parts and formed plates that exceed 14 days will be recycled back to 3rd parties at a cost of NG cost in the amount of 26% * Material prices.

This means that the lead time for the procurement of raw materials until they become WIP material must not exceed 14 days.

5. Calculate the standard deviation (S)

Standard deviation is used to compare the spread or deviation of data on the number of demand and purchases of material.

$$S = ((X1 - (x)^2 + X2 - (x)^2 + \ldots + Xn - (x)^2) / n - 1))^{1/2} \quad (7)$$

6. Calculate time period between orders (T)

$$T = ((2 * A))/(D * H))^{1/2} \quad (8)$$

7. Calculate α and maksimum level inventory (R)

$$\alpha = (T * H))/(Sc) \quad (9)$$

$R = D(T + L) + Z\alpha \ (T + L)^{1/2}$ (10)

Notes:
$Z\alpha$ from normal dist. table
$(T + L) \leq 13$ days

8. Possibility or prediction of shortage

$N = S\ (T+L)^{1/2}\ (f_{(Z\alpha)\text{-}Z\alpha X\omega z\alpha})$ (11)

Notes:
F (Zα) = NORMDIST (Zα,0,1,0)
ωZα=NORMDIST(Zα,0,1,0)-((Zα(1-NORMDIST(Zα,0,1,1))
$(T + L) \leq 13$ days

9. Optimal total cost of materials

$Ot = Dp + A/T + (R - DL + DT/2)H + (Sc/T + H)\ N$ (12)

Notes:
F (Zα) = NORMDIST (Zα,0,1,0)
ωZα=NORMDIST(Zα,0,1,0)-((Zα(1-NORMDIST(Zα,0,1,1))

To get the optimal cost, after getting the initial total cost value, add the initial T value with 0.005 and return to the calculation α. Iterate and stop if the total cost is equal to or greater than the previous total cost. Remember that (T + L) should not exceed 13 days, Then make a reduction to the T value with 0.005 and return to the calculation α. Iterate and stop if the total cost is equal to or greater than the previous total cost.

4. Result

Before being processed by ANN forecasting, the data is normalized first as equation (1).

$$X' = (0.8\ (x - b))/((a - b)\ ) + \ 0.1$$

The collected data is divided into:

1. Data Input Training (2016-2017)
2. Validation Data (2018)
3. Training Data Target (2017-2018)

Initialization (TanSig Activation Function) :

a. 4 node input layer
b. 10 hidden layer (trial & error)
c. 1 output node

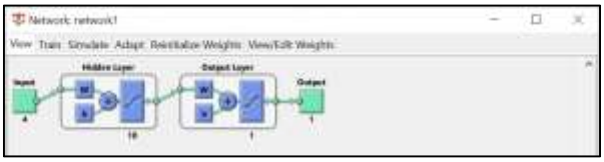

Fig. 4. Matlab Neural Network

As an example, N50 series battery data is used for forecasting with ANN and inventory control using the periodic review method.

TABLE 2
NORMALIZED DATA

Data Train	Jan-16	Feb-16	Mar-16	Apr-16	May-16	Jun-16
N50	0.62387	0.48028	0.55807	0.10000	0.60014	0.41240
Harga	0.10000	0.21397	0.25012	0.18162	0.16343	0.16704
Hari Kerja	0.60000	0.60000	0.70000	0.70000	0.70000	0.80000
IDR to S	0.90000	0.45653	0.33329	0.25076	0.77345	0.28102

Target_Train	Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17
N50	0.41481	0.59236	0.45052	0.28130	0.34856	0.25882

Validasi	Jan-18	Feb-18	Mar-18	Apr-18	May-18	Jun-18
N50	0.27232	0.36290	0.45057	0.26733	0.19266	0.19692
Harga	0.90000	0.88563	0.65586	0.60639	0.62424	0.72636
Hari Kerja	0.81111	0.54444	0.72222	0.72222	0.81111	0.10000
IDR to S	0.12809	0.27979	0.28830	0.35106	0.34362	0.52872

Then the normalized data used as input, target and validation variable of ANN forecasting process. The training parameters set obtained are as follows :

1. Learning rate (α) = 0.3
2. Maximum error = 0.001
3. Maximum epoch = 200
4. Trainlm training function

From the ANN forecasting process using matlab R2016b with NN tools, the output demand forecast is obtained as follows

Fig. 5. Output Network

Before validation, the data is denormalized first as equation (2).

$$X = ((x' - 0.1)(b - a))/0.8 + a$$

And error forecasting is calculated using *Mean absolute percentage error* (MAPE).

TABLE 3
N50 MAPE

Demand N50	ANN Forecasting	APE
8,882	8,589	3.41%
10,840	10,382	4.41%
12,735	12,745	0.08%
8,774	8,294	5.79%
7,160	7,422	3.53%
7,252	7,599	4.57%
5,157	5,160	**0.06%**
18,041	20,510	**12.04%**
22,450	19,784	**13.48%**
16,546	15,880	**4.20%**
13,572	14,835	8.51%
9,943	10,705	7.12%
MAPE		5.60%

In the same way, we obtain demand forecasting for the 6 variants of the N50 series batteries as follows.

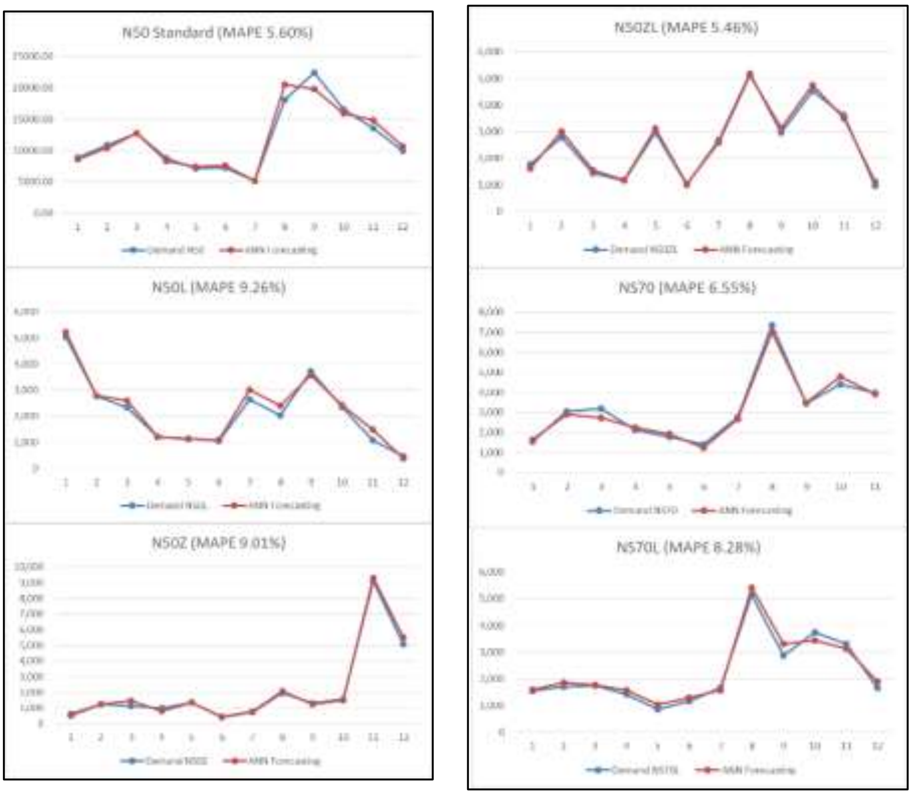

Figure 6. Actual Demand And ANN Forecasting

MAPE for N50 Series from 6 variant as shown as figure 7 is 7,36%. The ANN forecasting data is then used as input data for inventory control calculation. First, we should classified the material. We will use the periodic review model for inventory class A and B.

ABC Classification, Vilfredo Pareto Principle (80 : 20) [1]:

TABLE 4
ABC CLASSIFICATION

Part Number+C7C78:G101	% Usage	Class	% Price	Price (IDR)
PW-UNPL-CG80/79CPOS-L65-K	26.09%	Class A	76.15%	227,110
PW-UNPL-CG85CNEG-V3A-K				
PK-CONN-C5DR				
PK-CONN-C5DL				
PK-POLE-P7T				
PW-LEST-BATANG				
PK-SPAC-RC04-BLA	17.39%	Class B	20.00%	59,664
PK-SEPA-PE10R4				
PK-COPR-N50LC375BLA				
PK-COVB-N50ORAVP-BLU-TYP				
PP-KABO-N50-ASA-MEN	57.69%	Class C	3.85%	11,485
PP-STYR-N50-HAN				
PA-ACCE-TERMCAP-019-RED				
PA-ACCE-WARRANTYCARD				
PA-ACCE-LABELAWEE-03				
PC-ASSU-1800				
PK-SPAC-RC04-BLA				
PA-STIC-N50ASA-T01-V01				
PA-STIC-BRANDASAHPE-JIS				
PA-STIC-BRAND-INC				
PA-STIC-MII-M01				
PA-STIC-SEQUENCENUMBER				
PA-STIC-MFN50-T02-V05				

Then calculate the aggregation and standard deviation calculations are as follows as in the methodology.

1. First, we have to calculate the ordering cost (A)
   A = 825,184 * 12 / 1290
   A = 7676.13
2. Holding cost (H)
   H = 6%*1698 + (8,300,000 * 26 * 12 / 402,157)

H = 6541,16

TABLE 6
HOLDING COST

Holding Cost	Price (IDR/ unit	Holding Cost/ unit/year
PK-POLE-P7T	1698	6541.16
PK-CONN-C5CR	1541	6531.74
PK-CONN-C5CL	1541	6531.74
PW-FOPL-CG80POS-L87	116059	13402.82
PW-FOPL-CG87NEG-V3A	106490	12828.68
PW-LEST-BATANG	1323	6518.66
PK-COVB-N50ORAVP-BLU-TY	15854	7390.52
PK-COVB-N50WHIVP-BLA-NEI	15854	7390.52
PK-COVB-NS70LORAVP-BLU-	15854	7390.52
PK-COPR-N50LC375BLA	18804	7567.52
PK-SEPA-PE10R4	25006	7939.64
PW-FOPL-CG82POS-L87	121964	13757.14

3. Shortage cost (Sc) and NG Cost (On)

TABLE 7
SHORTAGE COST

Shortage Cost	Price (IDR/ unit)	Loss Opportunity/ unit	NG Cost	Shortage Cost/ unit
PK-POLE-P7T	1,698	7,582	441	8,023
PK-CONN-C5CR	1,541	7,582	401	7,983
PK-CONN-C5CL	1,541	7,582	401	7,983
PW-FOPL-CG80POS-L87	116,059	7,582	30,175	37,757
PW-FOPL-CG87NEG-V3A	106,490	7,582	27,687	35,269
PW-LEST-BATANG	1,323	7,582	344	7,926
PK-COVB-N50ORAVP-BLU-TY	15,854	7,582	15,854	23,436
PK-COVB-N50WHIVP-BLA-NEI	15,854	7,582	15,854	23,436
PK-COVB-NS70LORAVP-BLU-	15,854	7,582	15,854	23,436
PK-COPR-N50LC375BLA	18,804	7,582	18,804	26,386
PK-SEPA-PE10R4	25,006	7,582	25,006	32,588
PW-FOPL-CG82POS-L87	121,964	7,582	31,711	39,293

4. Calculate time period between orders (T for P7T)

$T = ((2 * 7676.13))/(5843.9 * 6541.2\ ))^{1/2}$

$T = 0.0200404\ years$ = 7.3 days

5. Calculate α and maksimum level inventory (R)

$\alpha = (0.0200404 * 6541.2))/(7582)$

$\alpha = 0.0173$

$Z\alpha = 0.293$

$R = 5843.9\ (0.02004 + 0.011) +\ 0.293\ \ (0.02004 + 0.011)^{1/2}$ $\qquad R = 181.2$

Notes :

Zα from normal dist. table

(T + L) ≤ 13 days

6. Possibility or prediction of shortage

N = 111832.7 $(0.02004 + 0.011)^{1/2}$ $(f_{(Z\alpha)\text{-}Z\alpha X\omega z\alpha})$

N = 75.66

Notes :

F (Zα) = NORMDIST (0.293,0,1,0)

ωZα=NORMDIST(0.293,0,1,0)-((0.293(1-NORMDIST(0.293,0,1,1))

(T + L) ≤ 13 days

7. Total cost of materials

$$Ot = 5843.9 * 1698 + 7676.13/0.02004 + (181.2 - 6404.3 + 11711.5/2) + (7582/0.02004 + 6541.2)75.66$$

$$Ot = 39{,}425{,}978$$

8. Optimal cost of material

Recalculate step 4 until 7 with add the initial T value with 0.005. (T + L) should not exceed 13 days. Iterate and stop if the total cost is equal to or greater than the previous total cost. Then make a reduction to the T value with 0.005 and return to the calculation α. Iterate and stop if the total cost is equal to or greater than the previous total cost.

TABLE 8
OPTIMAL TOTAL COST

No	Part Number Material	T (Years)	R (Lot)	Total Cost (IDR)
1	PK-POLE-P7T	0.0085	77	34,260,681.26
2	PK-CONN-C5CR	0.0085	66	57,361,799.40
3	PK-CONN-C5CL	0.0085	66	57,361,799.40
4	PW-FOPL-CG80POS-L87	0.0069	6	489,133,504.74
5	PW-FOPL-CG87NEG-V3A	0.0069	7	453,055,128.87
6	PW-LEST-BATANG	0.0085	68	56,539,865.46
7	PK-COVB-N50ORAVP-BLU-TYP	0.0557	19	167,318,397.09
8	PK-COVB-N50WHIVP-BLA-NEM	0.0559	19	167,318,397.09
9	PK-COVB-NS70LORAVP-BLU-TYP	0.0559	19	167,318,397.09
10	PK-COPR-N50LC375BLA	0.0530	16	188,859,442.68
11	PK-SEPA-PE10R4	0.0202	13	234,146,752.75
12	PW-FOPL-CG82POS-L87	0.0069	6	511,398,631.29
	Total Cost Material N50 (*Continous Review*)			2,584,072,797.14

5. Conclusion and Future Research

This research has been performed for to propose inventory control methods for lead acid battery companies with push systems, which have material planning needs in one year, and have uncertain demands.

ANN Forecasting with backpropagation method has the advantage of being able to recognize fluctuating demand patterns well. In the example of the total N50 series, it was found that MAPE was 7.36%. It's already better than the result of forecasting with company policy. And after the results of the N50 demand forecasting series are processed using the periodic review approach, although the time between orders is getting shorter or more often due to the constraint of material life, it is found that the total inventory cost at one year can be reduced by 17.01% from IDR 3,131,637,822 (Company Data) to IDR 2,599,072,797 (Periodic Review).

As for further research it might be possible to add factors that influence demand for forecasting in order to be able to minimize errors. Inventory control can also be developed further with consideration of the production process or other types of companies with material age restrictions.

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