CHAPTER 5

IMPROVING ON TIME, IN FULL DELIVERY

5.1 INTRODUCTION

The orders which are not yet shipped or invoiced to customer are called backlog orders. The various reasons for accumulation of stock, i.e. causes for slow moving inventory have been identified in the previous chapter. This chapter focuses on finding ways to reduce the backlog orders and/or the slow moving inventory. The inventory meant here is the Board of various sizes for different customers. The industry procures material as per the customer sales order projection. Due to various reasons, the industry can’t achieve more than 95% On Time In Full (OTIF) and hence the customer’s production gets disturbed a lot. Hence, this chapter focuses on different ways by which the OTIF can be improved in the printing and packaging industry by means of various tools and methods like traceability, data warehouse, ANN and Runge-Kutta method.

5.2 TRACKING AND IMPROVING THE ORDER FULFILMENT PROCESS

5.2.1 Study of the Present System in the Industry

The entire supply chain management of the company has been analyzed and found some constraints where some actions can be done to improve the OTIF. In the existing system in industry in processing sale order, customer sends the purchase order through mail, courier and fax to the marketing department. The marketing department raises the sale order and gives the customer requirement to every department and Product Introduction
Process (PIP) Generates the Bill of Material (BOM) and as per that order the materials department procures the material from the supplier and sends it to company manufacturing division to manufacture as per the customer specification. After the confirmation from the Customer, production department checks for the print plan in the available Board and completes its production and sends the material for dispatch. This is illustrated in Figure 5.1.

![Order fulfillment processing flow chart](image-url)

**Figure 5.1 Order fulfillment processing flow chart**
In this process, it is observed that there is a long time gap between purchase order (PO) date and sale order (SO) date which leads to increase in lead time. Ten orders has been taken to calculate its average time gap between SO date and PO date. An average of five days is the time gap as shown in Table 5.1, which is very high; so it is suggested to the company to reduce the time gap between PO date and SO date.

### 5.2.2 Recommendation for improving order processing

It is recommended that sale order should be raised within 24 hrs of receipt of purchase order. This can be done by the marketing team. The marketing team should have regular contact with the customer so that they can get the purchase order and raise the sale order immediately.

#### Table 5.1 Time gap between PO and SO

<table>
<thead>
<tr>
<th>Sl.No.</th>
<th>Purchase order date</th>
<th>Sale order date</th>
<th>Difference (PO-SO) days</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>5-Jan-09</td>
<td>12-Jan-09</td>
<td>7</td>
</tr>
<tr>
<td>2.</td>
<td>2-Jan-09</td>
<td>8-Jan-09</td>
<td>6</td>
</tr>
<tr>
<td>3.</td>
<td>27-Jan-09</td>
<td>30-Jan-09</td>
<td>3</td>
</tr>
<tr>
<td>4.</td>
<td>2-Feb-09</td>
<td>6-Feb-09</td>
<td>4</td>
</tr>
<tr>
<td>5.</td>
<td>4-Feb-09</td>
<td>9-Feb-09</td>
<td>5</td>
</tr>
<tr>
<td>6.</td>
<td>10-Feb-09</td>
<td>15-Feb-09</td>
<td>5</td>
</tr>
<tr>
<td>7.</td>
<td>3-Dec-08</td>
<td>8-Dec-08</td>
<td>5</td>
</tr>
<tr>
<td>8.</td>
<td>12-Dec-08</td>
<td>16-Dec-08</td>
<td>4</td>
</tr>
<tr>
<td>9.</td>
<td>26-Dec-08</td>
<td>31-Dec-08</td>
<td>5</td>
</tr>
<tr>
<td>10.</td>
<td>31-Dec-08</td>
<td>6-Jan-09</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td></td>
<td>5 days</td>
</tr>
</tbody>
</table>
After implementing the above suggestion, the lead time was reduced from 20 days to 16 days causing gradual increase in OTIF delivery.

5.3 TRACEABILITY FOR WAREHOUSE INVENTORY

Traceability is the ability to follow or study out in detail a step-by-step history of certain activity or a process. The change in global economy has significantly redefined the way enterprises are operated. In warehouse, accurate monitoring and measurement of resources can be derived only from timely and quality information, which many lack currently.

Hence, in this research an RFID based warehouse management system is designed and proposed for the printing and packaging industry. Planning and control of warehouse facilities system is more complex. RFID resource management makes it easy to detect the material in the warehouse and timely delivery to the production area by using real time data of RFID tags to solve the picking up of correct material and information and location of the material.

5.3.1 Current Status of the warehouse

Normally in present situation, it is increasingly difficult in locating the material, even though they have an entry and a record. The data of material and the amount that has been lost, for an industry of considerable reputation in Chennai, due to inadequate traceability, during the past six months (Sep 2007 to period ending Feb 2008) is shown in Table 5.2 and also in bar chart Figure 5.2.
### Table 5.2 The Data for non-traceable items in Warehouse

<table>
<thead>
<tr>
<th>S.No</th>
<th>Not traceable Items</th>
<th>Material quantity (Tons)</th>
<th>Material cost (Rs)</th>
<th>Warehouse cost (Rs)</th>
<th>Total cost (Rs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Film</td>
<td>47</td>
<td>705,000</td>
<td>16,309</td>
<td>721,309</td>
</tr>
<tr>
<td>2</td>
<td>Board</td>
<td>43</td>
<td>806,500</td>
<td>18,309</td>
<td>824,809</td>
</tr>
<tr>
<td>3</td>
<td>Inks</td>
<td>0.5</td>
<td>200,000</td>
<td>6,600</td>
<td>206,600</td>
</tr>
<tr>
<td>4</td>
<td>Glues</td>
<td>0.8</td>
<td>60,000</td>
<td>3,000</td>
<td>63,000</td>
</tr>
<tr>
<td></td>
<td><strong>Total</strong></td>
<td></td>
<td><strong>1,771,500</strong></td>
<td><strong>44,218</strong></td>
<td><strong>1,815,718</strong></td>
</tr>
</tbody>
</table>

**Figure 5.2 Material cost for non-traceable items**

The present status of materials arranged in racks and warehouse floor are indicated in Figures 5.3 and 5.4 respectively. Figure 5.5, shows a forklift, a material handling equipment used to move material from warehouse to production area.
Figure 5.3 Storage Racks in the warehouse

Figure 5.4 Stacking of materials in warehouse floor
5.3.2 Layout re-design with RFID

The layout plan of warehouse floor is indicated in Figure 5.6, the total area being 1783.73 sqm of which rack occupies 445.93 sqm and the rest being the floor space. Film, glue, inks are stored in racks and the boards are stored on the floor space.
Radio frequency identification (RFID) technology has been widely used in many areas of supply chain such as manufacturing, distribution of physical goods, inventory management etc. Although RFID is primarily an automatic identification and data collection technique, it has made a significant contribution to resource management in warehouse. The RFID architecture shown in Figure 5.7 depicts the warehouse design for RFID technology.
Figure 5.7 System architecture of RFID
The front end of RFID architecture contains two types of data collection modules, namely, fixed and variable logistics data modules, which provide functional applications on radio frequency signal transferring, data filtering and processing. In the front end the tag is read using reader and then the information passed to hub.

The back end of RFID consists of a resource tracking module and a resource management engine. The former manipulates all real time based active tag data that represent resource identity and status within the warehouse while the latter adopts a CBR engine and performs the function of resource matching and performance measurement. In this module, the database that supports the above-mentioned resource management process is present and runs the business application of the RFID-RMS (Resource management system), the warehouse management system and other related logistic services.

The resource-tracking module is a server that stores all passive tags data and provides an executive environment for the data manipulation software to manage, filter and transmit all useful data to the resource management engine, so as to formulate business logic and make decisions. Figure 5.8 gives the operating mechanism of designed RFID technology.
Figure 5.8 Operating mechanism of RFID
Case browsing process issues a list of order sequence and pick planning chart is first created from the warehouse management system and transmitted to the resource management engine.

Case retrieving process, retrieves a list of potential past cases after matching with the specification of order attributes.

Case ranking is a list of ranked cases according to similarity, generates and sends for further processing.

Data warehouse is a large database that stores all data from external sources. The internal data source contains operational data, resource identity, specification, and utilization rate as well as performance measurement data that come from the resource management engine and the resource tracking engine. In contrast, example of external data is suppliers and clients.

5.3.3 Operating Procedure of Warehouse Management System

The flow chart of operating procedure of warehouse management system (WMS) created is given in Figure 5.9, which follows the algorithm given as a series of steps (1-8) below.
Figure 5.9 Operating procedures of WMS
Step 1: Retrieve and store all relevant logistics service specifications and warehouse operating parameters in the data warehouse in a relational table format. They are then transferred to the engine for performing the resource matching and planning functions with the relevant order attributes.

Step 2: Retrieve similar cases using the case retrieval process utilizing an inductive indexing approach and the nearest neighbor algorithm. In the beginning of the case retrieval cycle, potential cases are retrieved by the inductive indexing approach. Types of specifications are first matched to identify a searching path, following the tree structure where cases containing a set of indexed attributes are stored.

Step 3: Rank similar cases

In this case, five retrieved potential cases containing different similarity levels are retrieved as shown in Figure 5.7. The similarity value of the retrieved cases is calculated by the nearest neighbor algorithm to rank cases in a descending order for selection purpose.

Step 4: Accept the ‘retrieved case’

This step decides whether a resource usage package should be chosen. Based on the result of step 3, the warehouse manager can either choose the case of the highest similarity value in step 6 to select available resources to perform the order, or modify the retrieved case of resource usage package in step 5. The checklist of the resource usage package for the selected case is either accepted / modified.
Step 6: Select available equipment to perform the order according to the result of selecting checklist of resource usage package in Step 4, with the two types of preferable material handling equipment: electrically powered pallet truck and forklift with slip sheet.

Step 7: Pick order at storage zone. Once the driver reaches the right picking location and picks up the pallet needed for the production, the RFID tag reader on the forklift will automatically read the RFID tag on the pallet when the pallet comes within the reading range of the RFID reader. The tag data is transmitted to the forklift’s computer to verify the identity and quantity of the picked item. If the ordered pallet contains the right product in the right quantity, the computer of the forklift will transmit the order information to the warehouse management system so that the inventory and storage zone status will automatically be updated.

Step 8: When the shipped order passes the loading bay, the reader on the forklift will automatically read the RFID tag located at the side of the dock door. In doing so, the real time order status will be updated and recorded in the warehouse management system.

5.3.4 Results of Layout Redesign to Incorporate RFID in Warehouse Management

The layout has been modified to incorporate RFID in the Warehouse management system. An intelligent system incorporating CBR technique with automatic data identification has been proposed. The architecture of the RFID and the operating procedure of warehouse management system has been designed and developed.
5.4 ARTIFICIAL NEURAL NETWORKS

A neural network is a software (or hardware) simulation of a biological brain (sometimes called Artificial Neural Network or “ANN”). The purpose of a neural network is to learn to recognize patterns in the data. Once the neural network has been trained on samples of the data, it can make predictions by detecting similar patterns in future data. Software that learns is truly “Artificial Intelligence”). An inventory item having a slower rate of consumption than the average consumption in the inventory is called slow moving inventory item. It reduces the profit because capital is locked in the inventory. The traditional forecasting approach in the study of inventory systems is to give more importance to items whose demands are either large or very difficult to forecast. Since less importance is given to inventory items with small demand the study and analysis of slow moving inventory items gains significance.

5.4.1 ANN model development

The brain is a collection of about 10 billion interconnected neurons. Each neuron is a cell that uses biochemical reactions to receive process and transmit information. A neurons dendrite tree is connected to a thousand neighbouring neurons. When any one of the neurons is fired, a positive or negative charge is received by one of the dendrites. The aggregate input is then passed on to the soma (cell body). If the aggregate input is greater than the axon hillocks threshold value, then the neuron fires, and the output signal is transmitted down the axon. Neural networks were first introduced by McCulloch and Pitts (1943). Neural networks are non linear mapping systems that consist of simple processors, which are called neurons, linked by weighted connections (Robert Schalkoff 2000).

It is vital to adopt a systematic approach in the development of ANN models, taking into account factors such as data pre-processing, the
determination of adequate model inputs and a suitable network architecture, parameter estimation (optimisation) and model validation (Maier and Dandy 1998). In addition, careful selection of a number of internal model parameters is required. The following steps describe the methodology in developing the artificial neural networks (ANN) model in Matlab software using “NNet toolbox”.

The following steps describe the methodology in developing the ANN model.

Step 1: Create network and input values of hidden neurons and desired output
Step 2: Initialize the weights and the bias term
Step 3: Simulating the Network
Step 4: Training the Network
Step 5: Simulate using MATLAB
Step 6: Model Validation

5.4.2 ANN parameters

The simulation parameters are described below; two input nodes indicate board sizes and seasonal months. Output node is weight of slow moving boards and three numbers of hidden layers has used with Levenberg-Marquardt back propagation algorithm. Twenty learning patterns are used for training and predicting the ten patterns.

5.4.2.1 Back propagation

The term back propagation is used to imply a backward pass of error to each internal node within the network. A back propagation consists of at least three layers of units namely input layer and one intermediate hidden layer and an output layer. Inputs are applied at the input layer as \( p_i \) and
outputs are obtained at the last layer. A multilayer perception trained with back propagation algorithm may be viewed as a practical way of performing a non linear input-output of a general structure.

5.4.2.2 Training the network

Creating the network is the first step in the development of the ANN. The function ‘newff’ creates a feed forward network. The training function used was ‘trainlm’ given in Equation (5.1)

\[
\text{net} = \text{newff} (p,t,3,{},'trainlm');
\] (5.1)

This command creates the network object and initializes the weights and biases of the network; therefore network is ready for training. The number of input parameter in the work was two, namely size of the board and month. Hence they were the first input nodes and the number of output nodes is one, namely, quantity of slow moving materials in tones. The number of hidden nodes depends on the accuracy of the model. Here one hidden layer is used with three neurons. The network is trained with twenty data. Training is the learning process by which input and output data are repeatedly presented to the network. This process is used to determine the best set of weights for the network, which allows the ANN to classify the input vectors with a satisfactory level of accuracy.

5.4.2.3 Simulating the network

The function ‘sim’ simulates the network. ‘sim’ takes the network input ‘p’ and the network objects ‘net’ and returns the network output ‘a’ as given in Equation (5.2)

\[
a = \text{sim} (\text{net}, p)
\] (5.2)
5.4.2.4 Validating the model

After the network was trained, the holdout data (consisting of 10 data) were entered into the system, and trained ANN was used to test the selection accuracy of the network for 10 data. This is where the predictive accuracy of the machine learning techniques is measured. The validation of ANN model was done by testing the prediction accuracy of the model with the actual values that were not used to train the model.

5.4.2.5 Evaluating the performance index

In order to compare the performance of each of the forecasting methods various measures of accuracy are utilised. One measure commonly used in inventory control is the mean absolute deviation (MAD) and mean average percentage error (MAPE). A desirable feature of MAD and MAPE is that it is less affected by outliers than other measures, which Wright et al (1986) noted as being of particular importance in practical forecasting situations where outliers are a frequent occurrence.

In order to evaluate the accuracy and performance of the network, this work adapts Mean Absolute Percentage Error (MAPE) to evaluate the performance in each model and is given in Equation (5.3).

\[
MAPE=\frac{1}{a} \sum_{i=1}^{n} \left( \frac{F_i - A_i}{A_i} \right) \tag{5.3}
\]

where ‘\(F_i\)’ is the expected value for the period ‘i’, ‘\(A_i\)’ is the actual value for the period ‘i’ and ‘a’ is the number of periods. The smaller the values of MAPE, the better the forecasting models. Having smaller values means that the calculating results are closer to the historic data generation of slow moving items. ANN prediction results are discussed in details in chapter 7.
5.5 RUNGE-KUTTA METHOD

Existing mathematical models fit well for slow moving items on yearly basis only (James and Krupp 1977, Richard and Richard 1992). For weekly and monthly bases a new model based on modified Runge-Kutta method is proposed for identifying the slow moving items on weekly and monthly bases in addition to yearly basis. The conventional Runge-Kutta method is tedious and time consuming and hence a modification is imposed and used for identifying the slow moving items in stock (Richard and Richard 1984).

5.5.1 Illustration of Runge-Kutta Method

The following inputs are needed for the Runge-Kutta method.

(i) Board size
(ii) Period (month of survey)
(iii) Actual board weight in Tons (stored in the variable ‘\( x \)’)
(iv) Predicted board weight in Tons (stored in the variable ‘\( y \)’)

The predicted data are compared with the actual data. The error, generally the difference between the estimated value and the true of desired value (Gupta and Kapoor 2000), is calculated and tabulated by using the following formulae and method given in Equations (5.4) to (5.10).

\[
 f_0(x,y) = \frac{dy}{dx} = \left[ \frac{(y_i - x_i)}{x_i} \right] 
\]

\[ x_i = x_i \times c_i \text{ for } i = 0,1,2,3, \ldots \] (5.5)

\[ y_i = y_i \times c_i \text{ for } i = 0,1,2,3, \ldots \] (5.6)
where

\[ k = hf(x_i, y_i) \text{ for } i = 0,1,2,\ldots \tag{5.7} \]

\[ 1 = hf(x_i + h, y_i + k) \tag{5.8} \]

hence

\[ y_{i+1} = y_i + \frac{1}{2}(k+1) \tag{5.9} \]

where

\[ x \rightarrow \text{actual slow moving board weight in tones} \]
\[ y \rightarrow \text{predicted slow moving board weight in tones} \]
\[ c \rightarrow \text{cost per board} \]
\[ x_i \rightarrow \text{actual total cost (} x \times c) \]
\[ y_i \rightarrow \text{predicted total cost (} y \times c) \]
\[ y = c_i - c + (c \times n \times h) \tag{5.10} \]

where

\[ n \rightarrow \text{required month} \]
\[ h \rightarrow \text{fraction of the selected month} \]

When the above equation is used in the existing Runge-Kutta method, the error in comparison between predicted slow moving board and actual slow moving board gives negative value. This shows that the inventory is liquidated, and the performance is not satisfactory.
The following are the limitations of the model:

- If the actual slow moving board weight in tones is less than or equal to predicted slow moving board weight in tones, and the actual slow moving board weight in tones per cost is less than predicted slow moving board weight in tones per cost ($c_1$), the value of equation becomes positive which means good performance.

- If the actual slow moving board weight in tones is greater than the predicted slow moving board weight in tones and the actual slow moving board weight in tones per cost is less than the predicted slow moving board weight in tones per cost ($c_1$), the value of the equation becomes negative which means low performance.

- If the actual slow moving board weight in tones is less than predicted slow moving board weight in tones and the actual slow moving board weight in tones per cost is greater than the predicted slow moving board weight in tones per cost ($c_1$), the equation becomes negative which means low performance.

Illustration

The illustration uses the Equations (5.11) through (5.18)

**Board Size - 200 gsm**

**Period of study - 7th month**

To find ‘h’

Total period = 12 months / year
One month = 1h = 1/12 of a year

h = 1/12

h = 0.083

For 7th month = 7h = 7 x 0.083 = 0.581

In the existing Pareto Analysis the slope of the equation is given by the function $f(x,y)$

$$f(x,y) = \frac{dy}{dx} = \frac{(y-x)}{x} \quad (5.11)$$

Where $y =$ Predicted slow moving board weight in tones
and $x =$ Actual slow moving board weight in tones

$$y(x_o) = y_o \quad (5.12)$$

$$x_o = 0.58, \quad y_o = 0.018,$$

Also $y_1 = y_o + 1/2 (k+l) \quad (5.13)$

Where $k = h f(x_o, y_o) = h \left[ \frac{(y_o - x_o)}{x_o} \right] \quad (5.14)$

$$k = 0.083 \left[ \frac{(0.018 - 0.58)}{0.58} \right]$$

$$k = -0.080$$

Also $l = h f(x_o +h y_o +k) \quad (5.15)$

$$l = 0.083 \left[ \frac{(0.58 + 0.083 + 0.018 + (-0.080))}{0.663} \right]$$

$$l = 0.083 \left[ \frac{y_o - x_o}{x_o} \right]$$

$$l = 0.083 \left[ \frac{(-0.062 -0.663)}{0.663} \right]$$

$$l = -0.090$$
Substituting in (5.13)

\[ y_1 = y_o + \frac{1}{2} (k+1) \]

\[ = 0.018 + \frac{1}{2} (-0.080-0.90) \]

\[ y_1 = -0.067 \]

\[ y(x_o) = y_o \]

\[ y(0.663) = -0.067 \]

(y_1 for 7th month becomes the value of y_o for the 8th month)

**Board size = 200gsm**

**Period of study = 8th month**

\[ y(x_o+h) = y_o \quad (5.16) \]

\[ y(0.58+0.083) = -0.067 \]

\[ y (0.663) = -0.067 \]

now \( x_o = 0.663 \) and \( y_o = -0.067 \)

and \( k = 0.083 f(0.663, -0.067) \)

\[ k = 0.083 \left[ \frac{-0.730}{0.663} \right] \]

\[ k = -0.091 \]

also \( l = 0.083 f(0.743, -0.0158) \)

\[ l = 0.083 \left[ \frac{-0.0158 - 0.743}{0.743} \right] = -0.1006 \]
Substituting in (5.16)

\[ y_1 = -0.1628 \]

i.e \( y(x_0) = y_0 \)

\[ y(0.743) = -0.1628 \]

(y_1 for the 8th month becomes the value of \( y_0 \) for the 9th month)

Now

\[ y(0.663) = -0.067 \]

\[ y(0.743) = -0.1628 \]

Hence it is proved that in the conventional Runge-Kutta method, for board size of 200 gsm, the slow moving inventory items yield negative equations, in all those months which is considered as low performance level.

Now it is possible to generalize the Runge-Kutta method using the following formulae given in Equations (5.17) through (5.20), which can be used for finding the slow moving inventory behaviour of other board sizes of 215 gsm, 240 gsm, 300 gsm, and 400 gsm.

\[ y_i = \left[ \frac{y_{i} - x_i}{x_i} \right] \text{ for all } i = 0,1,2,3,\ldots \] \hspace{1cm} (5.17)

where \( k = h f (x_i, y_i) \) for all \( i = 0,1,2,3,\ldots \) \hspace{1cm} (5.18)

\[ l = h f (x_i + h, y_i + k) \text{ for all } i = 0,1,2,3,\ldots \] \hspace{1cm} (5.19)

and

\[ y_{i+1} = y_i + 1/2 (k+l) \text{ for all } i = 0,1,2,3,\ldots \] \hspace{1cm} (5.20)
5.6 SUMMARY

The existing models are very less efficient while dealing with real life industrial data sets, whereas this proposed model is tested and proved efficient with real life industrial data sets. It requires only the functional values at some selected points on the sub intervals which are a major advantage of this model. Further this model is flexible and capable to analyze large number of items. It employs the simple screening rule to identify the slow moving inventory items. The analysis of this system is simple and more realistic. Since this system is associated with cost parameter, keeping of inventory item for long period may not be treated as having the effect of slow moving item. In this model ordering policy and distribution are associated with cost and hence less frequency of ordering period of item may not be considered as slow moving item. The main limitation of this model is its dependence on historical data.