ABSTRACT

JAJU, PAVAN JAIKISHAN. Inventory Control of Life-limited products (Under the direction of Dr. Stephen D.Roberts and Dr. Javad H. Taheri)

Inventory control is the one of the important performance goals of any manufacturing or service organization. Models related to inventory control, of products having limited life-time, have been proposed in literature. Most of these models assume cases of instantaneous replenishment. However, in any manufacturing process, positive lead-time is common, and a formal analysis of such cases under realistic conditions is necessary.

In this paper, a scheduling heuristic to address the problem of inventory control of life-limited or perishable products has been proposed. This heuristic has been adapted from the scheduling rules of Process Flow Scheduling literature, and modified, especially, for production scheduling issues in the pharmaceutical industry. Two simulation models, each representing a 'make-to-stock' and 'make-to-order' system for a generic process, have been constructed. Sensitivity analysis study of the proposed method for various factors such as product quality yield, variability in the setup durations, variability in processing duration, etc. is conducted by experimental design. Results of this study will serve as an excellent guideline for industries facing the problem of perishability of raw materials and intermediate products.

Inventory Control of Life-Limited Products

by

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APPROVED BY:

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Co-Chair	Co-Chair

To

Mom and Dad

Biography

Pavan Jaju is a graduate student in the Industrial Engineering Department at North Carolina State University at Raleigh. He received his Bachelors of Engineering (B.E.) from Veermata Jijabai Technological Institute (VJTI) in Mumbai, India. After his undergradute degree, he worked for a year in Whirlpool(India) as Operations Engineer. Pavan joined the Master of Science program at North Carolina State University in August'2001. His research interests lies in the areas of Simulation Modeling and Analysis, Operations Management, Production and Inventory Control and Operations Research.

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I appreciate the support of Sachin, who is currently pursuing Masters Program at Rochester Institute of Technology. Vicky, Sudhir and Ketan have been excellent companions and I thank them for making my stay at North Carolina State University enjoyable. This work is dedicated to my parents for motivating me to come so far and for teaching me to be successful in life.

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Glossary

Entity: Entity is the basic component of Discrete Event Simulation. Entities can represent batches, parts, persons, equipments, etc. Entities possess attributes, are modified and used during the simulation.

Factor: A variable or parameter of interest, whose effect on the system outputs is to be tested.

Process Units: The lowermost component in the hierarchy of Process Flow Scheduling. Process units may represent individual equipments or machines.

Process Cluster: A combination of process units, either in series or in parallel.

Process Stages: A process unit having inventory buffers at the input or the output.

Process Train: A groups of process clusters arranged to produce a family of products.

Replication: A set of experimental runs resulting from combinations of different levels of the factors of experimental design.

System – A process converting inputs into outputs. For example, a small work cell takes raw materials as input and converts them into finished goods using resources such as machines, labor, etc.

Sub model: A hierarchical structure of simulation modeling, consisting of simulation constructs interacting with the main model.

1. INTRODUCTION

Successful inventory control is one of the major goals for any organization in today's extremely competitive market conditions. Every organization expects to maintain sufficient inventory to satisfy demands, and simultaneously optimize cost components such as ordering and production cost, setup cost, carrying cost and shortage cost.

According to Nahmias (2000a), the motive behind holding products in inventory is:

a. To counter the fluctuations in demand, and to serve the customers in such conditions.
b. To optimize the production or ordering and carrying cost.
c. To maintain stock of obsolete items.
d. To obtain quantity discounts and take advantage of economies of scale.

Certainly, maintaining economical quantity of inventory for the above-mentioned reasons is not a simple task. Often, due to the uncertain nature of demand, situations such as excess inventory or shortages occur. Moreover, resources may be scarce and their effective utilization is also an important objective to be pursued. Over the past many decades, researchers have addressed this issue of inventory control and proposed several mathematical models to address this problem. These inventory models adopted different sets of assumptions and aimed at optimizing specific performance measures such as cost, service levels, work in process (WIP), etc. Some of the relevant assumptions adopted in these studies were as follows:

a. *Type of demand pattern*: Deterministic or stationary Stochastic
b. *Replenishment schemes*: Instantaneous or under conditions of fixed or stochastic lead- time.
c. *Type of review policy*: continuous or periodic in time.
d. *Order filling policies*: with "backordering" or with "no backordering"

One of the simplest models is referred to as the "Economic Order Quantity (EOQ)" model, assumes uniform demand rate (λ) and instantaneous replenishment. This model, being the simplest of its class, achieves a balance between the ordering and the carrying cost to decide for the optimal quantity. Nahmias (2000) obtains the expression for optimal quantity (Q) as given in Equation (1).

$$Q = \sqrt{\frac{2k\lambda}{h}} \tag{1}$$

where, k = ordering cost

h = carrying cost per unit

Besides these basic inventory models, operational policies also play an important role in the overall inventory management process. A sizable number of organizations implement either a **Material Requirement Planning** (MRP) strategy or **Just in Time** (JIT) strategy to control inventory. MRP and JIT are philosophically opposite in the way they operate. MRP is targeted to maintain constant throughput, while JIT aims at maintaining constant Work in process (WIP) (Bonvik et al. 1997). With an aim to maintain a constant throughput using MRP, organizations often find that WIP is inflated. In order to maintain a constant WIP, manufacturing organizations are required to have flexible processes, agile workforce, and stable plans (Grosfeld-Nir et al. 2000). However, applications and success of these techniques vastly depends on the type of product under consideration and the manufacturing processes involved.

1.1 Motivation

One of the implicit assumptions made in research related to inventory control and highlighted in case studies pertaining to MRP and JIT are the infinite lifetime of the product under consideration. Thus, it is usually assumed that once the product is in inventory, there will be no loss of value of the product. However, a sizable number of products do not meet these requirements. Often, we encounter products such as fruits, milk, drugs, photographic films, gas, etc., which have a defined period of lifetime. Such products are commonly referred as deteriorating or perishable items. Deterioration as defined by Wee (1993) is decay, damage, spoilage, evaporation,

obsolescence, pilferage, and loss of utility or loss of marginal value of a product over a period of time.

Drugs are the best example of deteriorating products. Raw material and intermediate products used in making drugs expire or perish during the manufacturing process, if they are not consumed before explicitly specified deadlines. Once the drug is manufactured and packed, it is subjected to limited shelf life in the market as well. An immediate objective that comes to mind in such industries is the minimization of manufacturing lead-time, so that the products are available for maximum time in the market. The deadlines imposed on utility of these products are externally controlled mainly by governmental regulations. Very little or almost nothing can be done to modify or change these deadlines. Pharmaceutical manufacturing industries are left with no choice, but to abide by these deadlines and align the manufacturing processes and supply chain to meet them.

Along with the constraint of meeting the manufacturing deadlines, this industry is unique in the manufacturing processes employed. Figure 1 shows the Product-Process matrix proposed by Taylor and Bolander (1994). The product differentiation is shown along the abscissa with product variety increasing from left to right. Corresponding to the type of product, processes are differentiated along the ordinate. Clearly, drug manufacturing is placed almost at the center, suggesting the batch type of process used. A generic model of the pharmaceutical manufacturing process will have a limited number of raw materials to start with and the product structure expands with the material flowing in the upstream processes. It represents a 'V' type product structure as against the commonly observed 'A' type of product structure in many industries for e.g. automobile industry. Process equipments are special purpose and very expensive in these companies. Efficient utilization of resources is an important and formidable goal for the management, as they have to deal with a non-discrete nature of the product. Products are transformed from raw material in form of powders or batches into intermediate products and finally into packaged or assembled discrete units. Taylor and Bolander proposed a body of knowledge mentioned as 'Process Flow Scheduling' (PFS) to manage inventory and schedule the equipment effectively. All the processes are either scheduled by using a process-dominated rule or material-dominated rule.

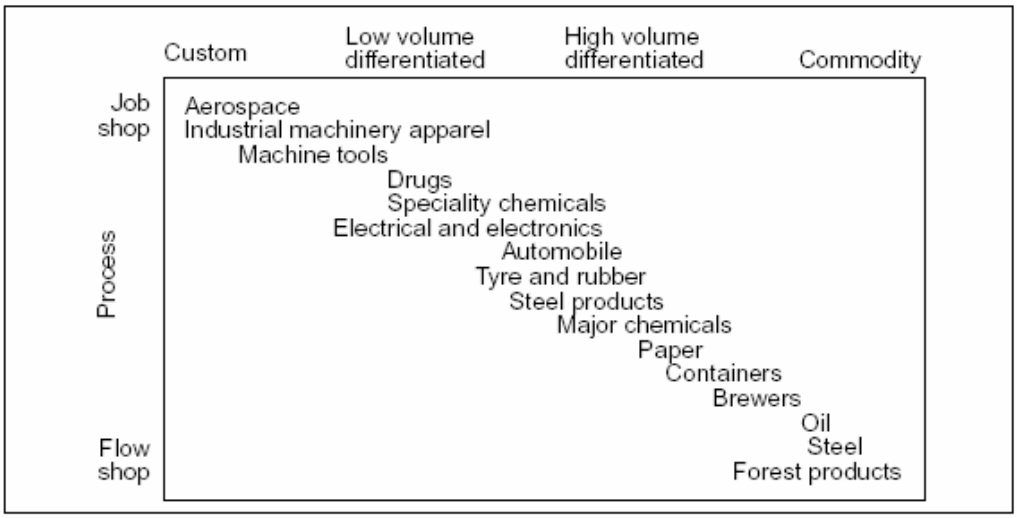

Figure 1: Product –Process Matrix (Taylor and Bolander 1994)

In literature, two distinct types of perishable products have been identified and studied. Products are classified as either having a fixed lifetime for their utility or deteriorating continuously over time. Research related to items deteriorating continuously dominates the literature. It is observed that most of the models proposed in the perishable inventory literature, did not consider the case of positive lead-time for manufacturing or procurement.

According to Schmidt and Nahmias (1985), for cases of positive lead-time, the solution is analytically intractable and no closed form expression exists. Application of the traditional inventory control schemes, and their feasibility under such conditions, remains to be tested. The primary goal of this thesis is to propose and validate appropriate methodology for this class of industry. This method is tested for 'make-to-stock' and 'make-to-order' environments, either of which or a combination of both is typically adopted in industry. Implementation and testing of this method under conditions, which emulate the real life situations, is equally important. Thus, simulation serves as an excellent tool for validating the method proposed and deriving appropriate conclusions from the analysis of results obtained from the model.

1.2 Organization of Thesis

The thesis is organized as follows: Chapter 2 covers a brief review of literature related to the methods for inventory control of perishable products, Material Requirements Planning (MRP), Just in Time (JIT) philosophy and Process Flow Scheduling. In Chapter 3 we propose a production and inventory control methodology that can be implemented in drug manufacturing and other pharmaceutical companies. A generic simulation model of a drug manufacturing process is constructed, assumptions are stated and the results are analyzed for different conditions by using experimental design. In Chapter 4, we present the results of the experimental design; and provide insight in the system under consideration. We conclude in Chapter 5 and provide direction for future research.

2. LITERATURE REVIEW

Production planning and inventory control is a promising field of research pursued over the past several decades. To date, research has primarily led to evolution of two inventory control operational policies: Material Requirement Planning (MRP) and Just in Time (JIT). These techniques are commonly referred to as *"Push"* and *"Pull"* strategies. The terms *Push* and *Pull* differ in the way material and information flow. A conceptual model distinguishing the two strategies is shown in Figure 2.

2.1. Push System (Material Requirements Planning)

Usually, in a push system, a job or work-order is initiated on a starting date that is computed by taking into account the estimated lead-time (Spearman and Zazanis, 1992) of the process. Material Requirements Planning (MRP) is referred as *Push* system, since the material is conceptually believed to be pushed from one station or operation or cell to following ones or in the inventory buffers in the process sequence. By using the Bill of Materials (BOM) as the guiding element, the demand plan for end products is exploded to the lower levels in the product structure. Computer software available in the market perform a good job of automating the process of exploding the forecast to the downstream processes, calculating buffer quantities and projecting inventory levels at various stages. These programs and software products provide excellent accountability, but the inflexibility still lies in the system itself. MRP asks for stable and reliable demand forecasts, but these are rare in practice.

MRP has dominated the production and inventory control strategies in research and practice. In his book, Nahmias (2000) has discussed several types of inventory control mechanisms under two, deterministic and stochastic demand, conditions. In the deterministic case, the Economic Order Quantity is the simplest model that assumes a uniform demand rate and instantaneous replenishment. Stochastic demand formulations are categorized as either continuous in time- or periodic- review. In continuous time review, it is assumed that the inventory level is monitored at all times and an order is placed whenever inventory falls below a fixed calculated number. In periodic review case, the inventory status is monitored only at pre-defined instances

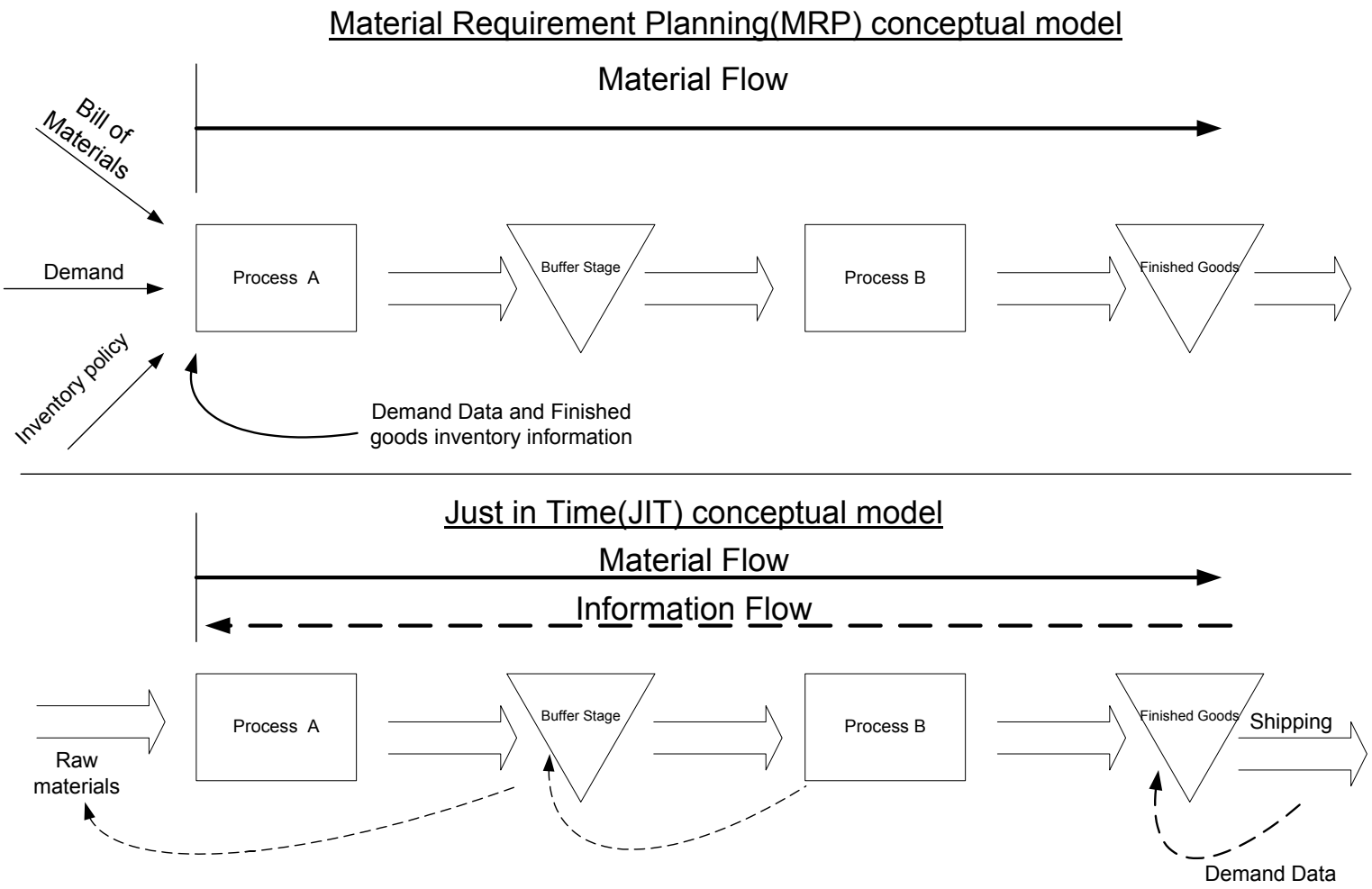

Figure 2: Conceptual Model of MRP and JIT

of time, and based on the inventory level, an order decision is made if the inventory on hand is less than a critical number. Frankly, application of these models depends on the type of product, the infrastructure available and the performance measurement criteria. Some of the important performance measurement criteria's considered in industry are service levels, overall cost, shortage cost, goodwill cost, customer satisfaction, Work in Process (WIP), etc.

Although MRP seems to be a robust methodology, it has several distinct disadvantages. Manufacturing plans in MRP production control environment are highly inflexible and require accurate shop floor information for execution. MRP is driven by forecasts, which inherently have a margin of error. Lack of demand or excess demand seriously affects the performance measures such as WIP, service levels etc. Loss of data integrity and system maintenance is a prime cause for the failure of MRP in many organizations.

2.2 Pull System (Just in Time)

In contrast to the MRP systems the *Pull* systems are driven by the external demands and represent 'make-to-order' systems. The *Pull* system, which is commonly referred as Just in Time (JIT), can be visualized as a relentless never-ending crusade for the total elimination of waste towards a goal of inventory minimization and achieving high service level. JIT adapts itself to the external demand, behaves and adjusts accordingly. The basic premise of JIT system is that what is manufactured is only as much as is consumed by the following processes or customers. This places more stress on the reliability of the equipment and workers, and aim to serve a stable and uniform demand pattern. As described by Ohno (the inventor of JIT system) JIT success mandates low setup times between product changeovers, high quality products and reliable equipment. On the shop floor, JIT is executed by use of cards called as "Kanbans", which regulate the flow of material. The number of Kanbans is usually calculated by using the Equation (2):

$$\text{Number of Kanbans (N)} = \frac{D * L * (1+\alpha)}{k} \tag{2}$$

where, D = Demand rate

L = Lead time for replenishment

α = safety factor

k = number of parts per container.

An immediate observation from the above formula is that in the long run, the JIT system requires a stable demand pattern. Besides, success of JIT in cases of high lead-time processes is doubtful, as reported by Kimura and Terada (1981). In the study conducted, they examined demand amplification for a multi-echelon production system operating as JIT systems. A number of case studies have proved the success of JIT, in both, manufacturing and service organizations (Freeland 1991)

Much of the literature in late 80's and early 90's is devoted to the implementation case studies and issues associated with Kanban calculations. Researchers compared both the policies and even proposed an integrated approach, which is a combination of both. In an integrated approach, manufacturing plans and shop requirements are generated by MRP, while operational details and scheduling is managed by using JIT (Spearman and Zazanis 1992).

2.3 Inventory Control for Life-limited Products

Due to the unconventional problem of deterioration, traditional models formulated in literature do not serve the purpose of operating at the optimal cost for the problem under study. The simplest of all cases for inventory control of perishable products is that of single period, single item model, commonly called as *"Newsboy problem"*. This problem involves defining shortage and deterioration cost, in which, shortage cost is due to loss of customer good will or loss of profit, and deterioration cost is the cost to dispose of the product. The optimal quantity procured or ordered (Q^*) is such that the cumulative probability [$F(Q)$] of satisfying the demand is given by the critical ratio. The critical ratio is formulated as shown in Equation (3).

$$\text{Critical ratio} = \frac{C_u + C_o}{C_o} \tag{3}$$

where,

C_o = overage cost (deteriorating cost)

C_u = underage cost (shortage cost)

(For details, *see* Nahmias 2000)

Raafat (1991) provides an excellent review of the literature for perishable commodities. In his work, the inventory models related to perishable products are categorized as:

- Single and multiple items
- Deterministic demand and Probabilistic demand during the lead time
- Static and varying demand
- Single period and multiple periods
- Purchase and production model
- Quantity discounts
- No shortage and shortage
- Constant and changing deterioration rate

Ghare and Schrader (1963) were the first to address the problem of continuously decaying products. In their discussion, they assumed that the product deteriorates according to exponential deteriorating function and derived the economic order quantity for such items. Misra (1975) embellished this assumption and obtained an economic order quantity formula by considering a constant and variable deterioration rate with no backlogging. Hwang (1981) considered Misra's model and developed an inventory model with Weibull distribution deterioration and LIFO issuing policy. Mak (1982) also examined the problem for similar type of assumptions and obtained approximate expressions for the optimum production lot size, production cycle time and inventory cycle time with no backlogging.

Shah and Jaiswal (1976) developed an order level inventory model by assuming instantaneous delivery and constant rate of deterioration. This model was then extended for stochastic demand rate. Nahmias and Wang (1979) also developed a heuristic lot size reorder point model (Q, r) for exponentially decaying inventories. This model is a continuous review model with random demand and positive lead-time. They developed approximate expressions that gave a worst case error rate of 2.77% under simulated conditions. Early work in this field was also applied to the problem of blood bank inventory management.

Blood banks represent a dynamic environment, where the life of a blood sample is only 21 days. Jennings (1973) studied the problem of blood bank inventory management and proposed methods for their management. He developed a conceptual

model of the system of blood banks, in which, they interact with other blood banks in the same region. In his research, Jennings proposed a model of blood bank inventory management that involved finding the critical number 'S' as on ordering decision variable. A number of conditions were simulated and shortage cost was plotted against outdating cost, with 'S' as a decision variable.

Apart from the study related to products deteriorating continuously over time, a limited amount of research has also been conducted on products having fixed lifetime. A fixed lifetime product has no utility after a pre-specified time period has elapsed. For such products, Nahmias (1982b) provided a detailed review of cases related to multi-product models, multi-echelon models, periodic review models and queuing models with impatient customers. Nahmias clearly stated that the problem of inventory control of perishable items with finite lead-time for replenishment is non-trivial and analytically intractable. Some researchers have developed heuristics under a defined set of conditions and assumptions to address this problem.

Van Zyl (1964) was the first to address the problem of perishable products subjected to fixed lifetime. His model provided a solution method for a product, that expires after two periods. Nahmias and Pierskalla (1973) also based their research on similar kind of problem with **F**irst **I**n **F**irst **O**ut (FIFO) issuing policy for products in inventory. Their model was based on calculation of expected number "outdating" occurring one period in future of the current order quantity (y), which has a lifetime of two periods.

Fries' (1975) generalized the 'two' period problem to 'm' periods. In his model, he assumed that demand occurs according to a specified probability density function and the replenishment of new order occurs in zero lead-time. Nahmias (1975c) discussed the same problem independently, however the outdating costs in his research were considered differently. Both Nahmias and Fries categorized the on-hand inventory depending on the age of the products. Thus, the inventory status at any time is expressed as a vector $x = (x_1, x_2, \ldots\ldots x_i)$ where x_i is the inventory of product having exactly *"i"* time periods of life left. They formulated a dynamic programming cost equation for a Markov renewal process of inventory replenishment, with the decision

variable being the quantity ordered in the current period (y). Computation of the dynamic program formulation for a feasible solution is not the easiest of the tasks. A question that comes to mind is whether these policies are applicable to the real world situations. The assumptions made for simplifying the problem suggest the inapplicability of most of the methods. These methods do not consider the non-discrete nature of the product in the present study Thus it is clear from the literature review that very few researchers have attempted to solve the problem of inventory control of life-limited products.

2.4 Process Flow Scheduling

As outlined in Section 2.1 and 2.2, material management is an important process for any industry. MRP and JIT are not particularly applicable to all the industries. A totally different framework, called as Process Flow Scheduling, is proposed in literature to address problems of flow and batch manufacturers. The American Production and Inventory Control Society (APICS) have defined process flow industry as:

A manufacturer, who produces with minimal interruptions in any one production run or between production runs, products, which exhibit process characteristics such as liquids, fibers, powders, gases.

2.4.1 What is Process Flow Scheduling?

Process Flow Scheduling is a framework proposed by Taylor and Bolander (1994) for "Flow Manufacturing" companies. "Flow Manufacturing" can be described as manufacturing processes, in which, the materials and products follow a fixed and common process routing. Product differentiation in such companies is considerably less as compared to job shops, but volumes are higher. High lead-time, specialized equipment, high volumes, uniform WIP, capital-intensive processes and common routings for multiple products typically characterize flow-manufacturing companies. Commonly implemented material management policies such as JIT and MRP are not necessarily feasible in such companies due to the non-discrete nature of raw materials

and intermediate products. At the same time, setup and product changeovers are lengthy due to the nature of the product, and often cleanup operations are required before product changeovers. In order to achieve maximum utilization of the capital-intensive equipment, it is desirable to plan a minimum number of setups necessary to satisfy the demand. It is important to note that the production schedules in flow manufacturing industries is driven more by production plans, short-range demand forecasts and distribution requirements plan than by customer orders.

Process Flow scheduling has been dominant in the process industry and batch manufacturing companies. Pharmaceutical companies are an example of batch manufacturing companies (see Figure 1 to identify the position of pharmaceutical companies). The process flow scheduling literature has a nomenclature and concept that is completely different from the one mentioned in traditional industry. A detailed review of these concepts follows:

Process Units: In the process flow scheduling hierarchy, process units are at the lowermost level. Process Units are the basic elements representing the individual processes. For example, a blending operation, a mixing operation or a drying operation is a process unit. A single process stage consists of one or more process units, decoupled by inventory buffers. Some of the reasons to de-couple process units in different stages are identified as follows:

Utilization: In any flow or batch-manufacturing environment, it is desirable to have a balanced capacity and processing rate for each process unit. However, it is important to guard the plans against the uncertainties in the demands, process operations, etc. Inventory buffers between the adjoining process units serve as cushions to safeguard against unplanned maintenance or breakdowns to maintain uniform and consistent utilization of the equipment.

Planning: In order that the plans for any two adjoining process units are not related, process units must be separated from each other. Inventory at the intermediate location helps to schedule the two process units independently of each other, however, in alignment with the plans and schedules of process train.

Often, situations arise, in which, a single process unit produces several varieties of products in a single period. In these conditions, it becomes imperative to schedule the process unit in the most optimal manner.

Process Clusters: Process Clusters is/are a group of processes coupled together with inventory buffers to represent a process stage. Process clusters are the building blocks of any process train. Process clusters may consist of one or more processing equipments, and the adjoining process clusters are de-coupled by inventory buffers. Usually, two kinds of process clusters have been identified: “tightly coupled” and “loosely coupled”. In a tightly coupled process cluster, two or more process units are sequenced in sequential order with no inventory buffers between them. For example, in a process, where fermentation is done immediately after blending or mixing the chemicals, the two processes are said to be tightly coupled, and have no inventory buffers between them. The schedule for blending is forced on the fermentation process as well, and the Blending process, in this case, is called as the ‘key’ process unit. In a loosely coupled cluster, the equipments or processes are in parallel, and the processes perform similar operations utilizing the same raw material to produce similar end products. For example, in a packing cluster, two or more packing equipments operate in parallel and perform similar operations. The guidelines and targets mainly dominate schedule for equipments in a loosely coupled cluster. Figures 3a and 3b represent loosely coupled and tightly coupled process clusters respectively.

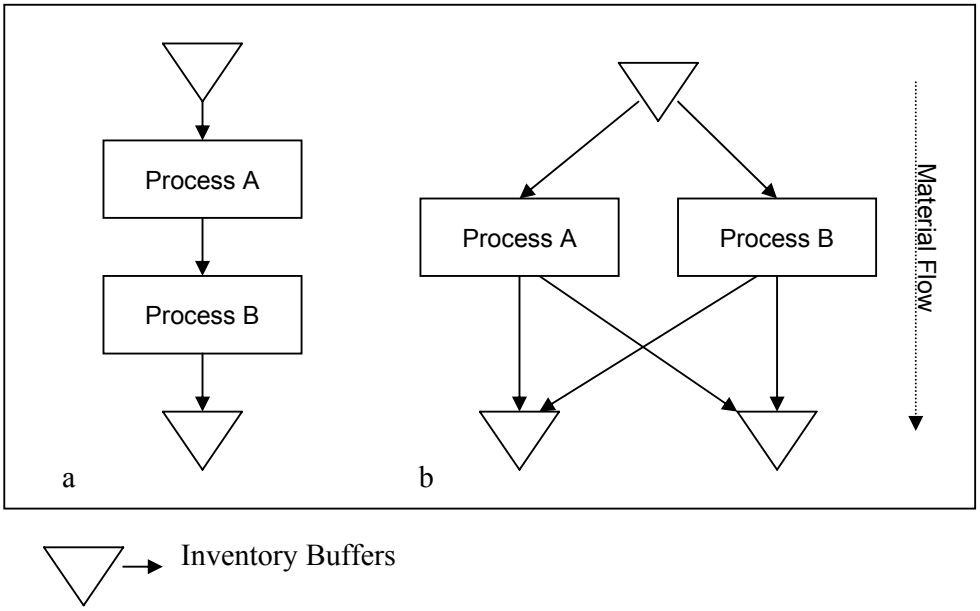

Figure 3: (a) Tightly Coupled Process Cluster (b) Loosely Coupled Process Cluster

Process Trains: At the highest strata of classification for process flow scheduling is the concept of process train. A process train is/are a process/group of processes manufacturing a family of products. By family of products, we mean, products that have more or less same process requirements, and share common raw materials and intermediate products. Non-identical objectives and product families drive schedules for process trains. A single plant may consist of one or more process trains depending on the variety of final products made, and the processes and raw materials involved.

2.4.2 How does Process Flow Scheduling Work?

Process Flow Scheduling is guided by the process structure in developing plans and scheduling individual processes. Based on the forecast for a specific time period, a scheduling scheme, a forward flow, reverse flow or mixed flow, is selected for a process train. Figure 4 shows the hierarchical steps in process flow scheduling.

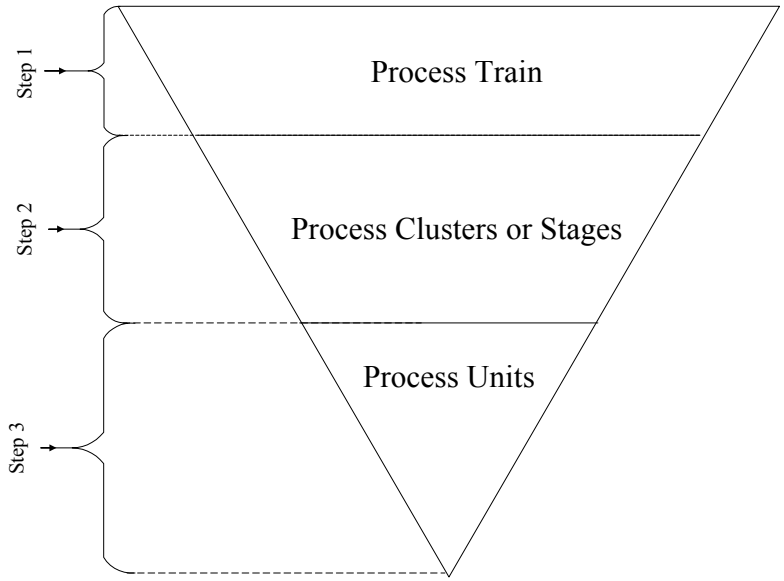

Figure 4: Hierarchical steps in Process Flow Scheduling

According to Taylor and Bolander (1994), process flow scheduling observes the following tenets:

a. Process Flow Scheduling is dominated by the process structure. Process structure is stratified into process trains, process clusters and process units as mentioned in Section 2.4.1. Usually, no material is transferred across process train and products are scheduled on only on a single process train.

b. The second principle is related to the scheduling of process units. Process units are scheduled using either a **P**rocessor **D**ominated **S**cheduling strategy (PDS) or a **M**aterial **D**ominated **S**cheduling (MDS) strategy. In the PDS method, the processes are scheduled with a goal to obtain of optimum utilization of the individual process units. An attempt is made to deliver the finished goods with the least number of setups and other miscellaneous activities related to product changeovers that result in loss of production time. Each process unit is operated for a target cycle length or a campaign cycle length before the product sequence is repeated. A campaign cycle is the minimum time required to cycle through all the processes possible or required on individual process units. It is determined by solving Equation (4):

$$T_c = \frac{T_r}{d} \tag{4}$$

$where, T_c =$ Target Cycle Length

T_r = Time required to produce product having minimum demand

$d =$ proportion of net demand for product under consideration

Thus, lesser the campaign cycle length, will be the WIP required to support the upstream processes. Campaign cycle lengths have also been referred as 'schedule wheels', the idea being that faster the wheel turns, better it is for the organization to maintain low inventory buffers. Once the processes are scheduled for optimum capacity utilization, materials are then checked for the minimum and maximum inventory levels set. The minimum and maximum inventory levels are management-enforced constraints to achieve desired service level. On occasions where the inventory falls below the minimum level, production lots or batches are re-scheduled through the process. Minimum inventory levels are usually determined by conducting statistical analysis of demand during the lead-time period or based on the external constraints, such as minimum batch size, minimum service level. Maximum inventory levels are governed by constraints such as space, shelf life of finished goods, etc. This constraint is relatively difficult to manipulate, and is mostly forced on the organization by storage requirements or by governmental regulations, as in case of pharmaceutical companies. Once the material and capacity requirements are satisfied, the process cluster is supposedly scheduled and other process clusters in the sequence are targeted to generate the feasible schedule for the entire process train. Often, the schedules or forecasts are required to be adjusted, if material requirements at the input or output inventory buffers are not realized.

A MDS method is totally opposite from the PDS approach. In a MDS method, materials have priority while deciding the schedule. Scheduling of materials might be important in cases where the cost of lost demand is extremely high or products have limited life in the inventory buffers. On scheduling the materials, both input and output, feasibility of the schedule is checked against the available capacity. If the capacity constraints are not met, schedules need

to be revised. Thus, PFS is an iterative process, in which, capacities and material requirements are checked at each stage before proceeding to another stage. GANTT Charts are used to reflect the schedules in a graphical format. Projected inventory levels are plotted to determine non-violation of minimum and maximum inventory levels.

Often, management needs to ask following questions to decide for selecting between PDS approach and a MDS approach:

a. Is the capacity relatively expensive?

b. Is the process unit a bottleneck?

c. Are setups long and expensive?

d. Are the materials expensive and difficult to manage?

e. Does the production unit have excess capacity as compared to the demand or production capacities of other process units?

f. Can the setup times be minimized or is the setup cost less?

In deciding for a particular process unit, if the answer to questions a, b and c is affirmative, PDS is advisable for that particular process unit. A MDS approach is recommended if the answer is positive for cases e and f. For example, a simple flow chart shown in Figures 5 and 6 can be used as a guideline for scheduling as per PDS and MDS rule respectively.

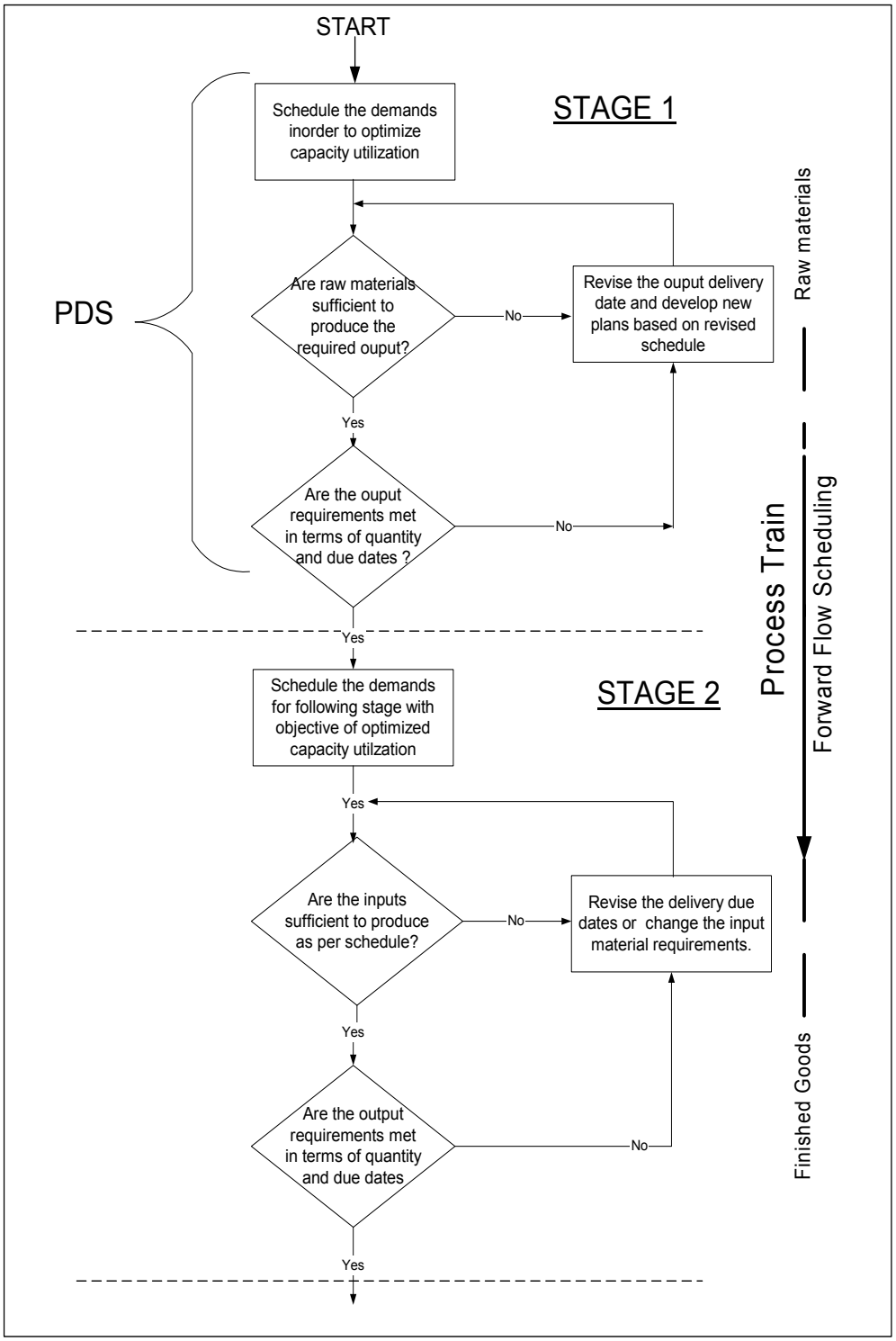

Figure 5: Flow Chart for PDS Rule Implementation.

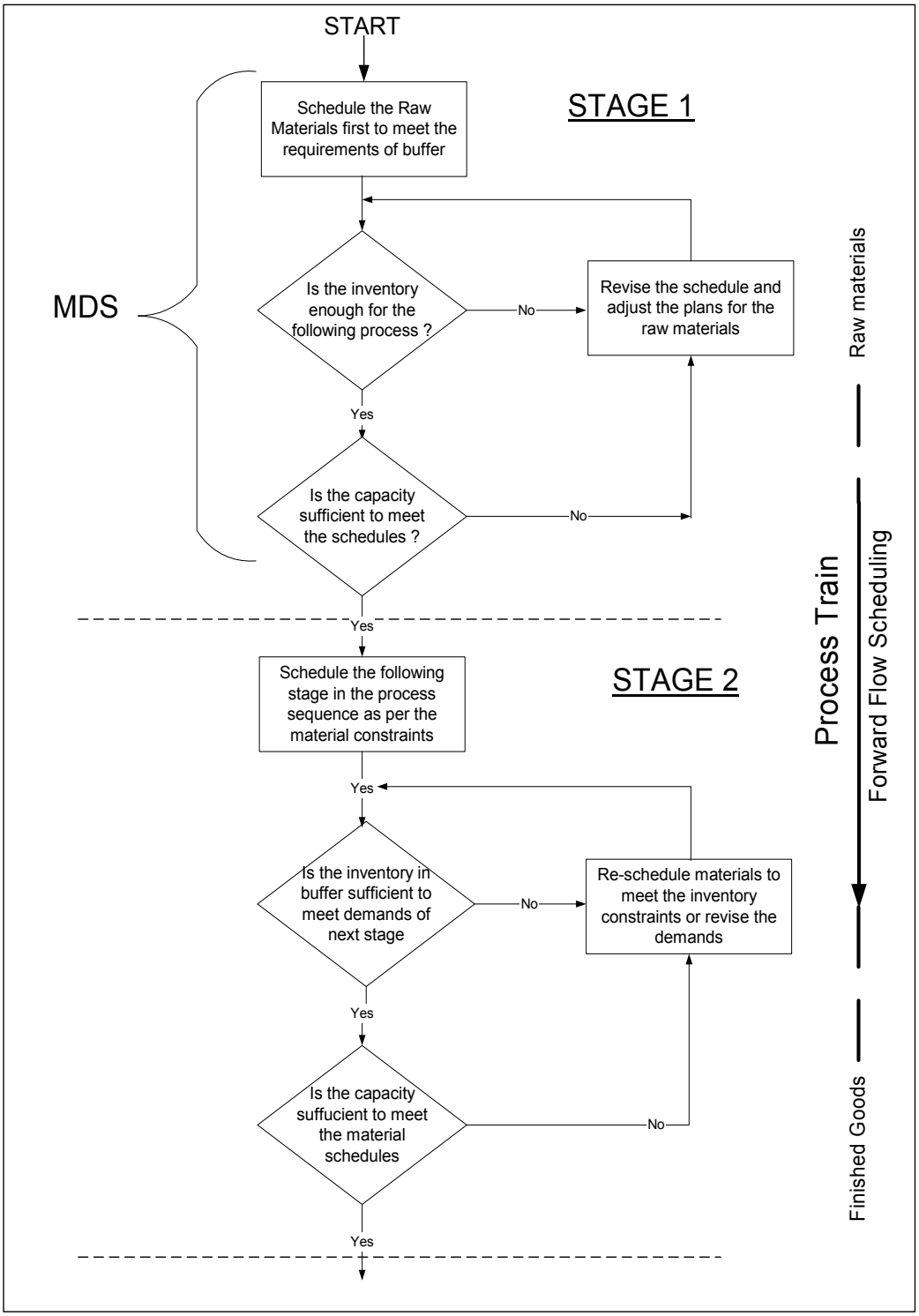

Figure 6: Flow Chart for MDS Rule Implementation.

Taylor and Bolander (1994) provide an excellent overview of the requirements and methods of process cluster scheduling. According to them, cluster-scheduling inputs are of two types: data inputs and scheduling inputs. Data can be further identified as material requirements, inventory status, resource availability, and production activity data. The material requirements for a cluster are the customer requirements or the input requirements of the downstream stage. Cluster scheduling also requires data on inventory status. This data must include on hand balances by stock-keeping unit. Additional stock data may include shelf life, lot-tracking information etc.

Scheduling inputs are in the form of priorities, targets, rules, and procedures. Priorities are the business rules that help in scheduling in conflicting situations. Priorities specify the relative importance of service, cost, inventory and quality objectives. For example, a scheduler may need to decide whether to accept a rush order. However, the scheduler might have dilemma. Producing the rush order might disrupt the least cost optimized production sequence. If the business strategy emphasizes fast delivery, the scheduler should accept the order.

Scheduling rules are the management set guidelines and procedures, which need to be considered while developing schedules. They restrict the capacity availability, material handling or impose constraints. For example, management may decide restricting the overtime to a certain number of hours. Scheduling targets include minimum and maximum inventory, target cycle lengths and production sequences.

The rules mentioned above address the scheduling methods to be followed while scheduling any process unit. It is important to have the overall picture in mind while scheduling individual process units. Process train scheduling strategies define the inventory requirements at the intermediate and final buffers the direction of material and information flow. The following process flow scheduling strategies have been proposed in literature (Taylor and Bolander 1994):

a. <u>Forward flow scheduling</u>: In this strategy, the upstream processes starting with the raw materials are planned and scheduled, before other downstream ones. Either a PDS or MDS approach described in section 2.4.2 is used to

schedule the starting process unit. This is analogous to what is commonly referred as *"Push system"*. Once a feasible schedule meeting the capacity and material requirements has been identified, the technique is re-applied to the downstream processes in the process structure. For example, a simple process train may consist of certain operations such as Blending, Filling, etc. in series. In forward flow scheduling, the Blending process is scheduled first for products as per the forecast. Once the capacity and material requirements are guaranteed, the Filling process is scheduled next. If any of the material or capacity constraints is not met, the forecasts are either revised or demand is backlogged depending on the management policy. Figure 6 is a case of forward flow scheduling.

b. Reverse Flow Scheduling: As the name suggests, Reverse Flow scheduling is opposite to the forward flow scheduling. In reverse flow scheduling strategy, the end final or finishing processes are scheduled first as per the requirements to satisfy the demand. Once the material and capacity requirements are met, the other processes downstream are scheduled. Clearly, one can discern that reverse flow scheduling is more adaptive to the customer demands.

c. Mixed Flow Scheduling: In a mixed flow scheduling approach, an intermediate process is selected for scheduling and it is forward scheduled as described in 'a' by the forecasted requirements. At the same time, the material requirements obtained by forward scheduling the process are compared with the requirements generated by reverse scheduling the upstream process. For the schedules to be feasible, these demands and supply should align completely with each other. Thus, mixed flow scheduling is more complex than forward and reverse flow scheduling methods.

Overall, in selecting any the general strategy in such industries, the process trains scheduling scheme is finalized first. The next step concentrates on the process clusters keeping in mind the various scheduling inputs described above. Lastly, the process units are scheduled as per the material or process dominance rule.

2.5 Role of Simulation

Simulation is the process of designing a model of real life systems and conducting experiments with this model for the purpose of understanding the behavior of the system or of evaluating different strategies for the operation of the system (Shannon 1975). Simulation modeling is an experimental technique and applied methodology that seeks (Centeno 1976):

a. To describe the behavior of the system.
b. To construct theories or hypotheses that account for the observed behavior.
c. To use these theories to predict the future behavior or the effect produced by changes in the operational input set.
d. To manipulate the parameters of the system through the model and conduct sensitivity analysis on the outcomes.

Simulation proves a very useful tool in systems and problems that are analytically intractable. One can build the models according to the "as-is" conditions and then play with the parameters to observe the behavior of the system in response to the change made. Simulation serves as a valuable tool in estimating the values of performance measures of interest and comprehending the relationship amongst them. Simulation is an excellent optimization tool to find the best feasible alternatives in a highly complex system, in which, number of entities interact with one another incomprehensibly.

Almost all simulation software packages provide an opportunity to perform tests and run alternative scenario comparisons with optimization capabilities. According to Law et.al. (1994), a simulation modeling and analysis study can be categorized in the following activities:

- Formulating the problem,
- Collecting system information,
- Collecting data,
- Modeling input,

- Developing a valid and credible model,
- Selecting simulation software,
- Designing and analyzing simulation experiments, and
- Management of the simulation project.

In order to obtain valid results from a simulation model, it is important to parameterize the simulation inputs as accurately as possible. Stochastic data and distribution are typically used to drive the simulation models. A wide variety of probabilistic distributions such as the exponential distribution, gamma distribution, beta distribution, etc. can be used to mimic real life occurrences. For example, demand occurrence or arrival of customers at a store is often represented by a discrete time event occurring with exponentially distributed inter-arrival time.

2.5.1 Why Simulation?

Production and inventory control of life-limited products is a non-trivial problem. Nahmias (1982b) has reported that the problem of life-limited products with finite lead-time replenishment process to be analytically intractable. The tenacity of this problem is compounded in situations, where deadlines for use of the intermediate as well as final products exist. The problem is particularly difficult because it calls for solving complex mathematical formulations. For example, Nahmias suggests a dynamic program formulation for these types of products. The goal of this thesis is to analyze the problem of inventory management, and suggest appropriate policy in circumstances of product deterioration after fixed period of time. A representative case of these types of products can be a drug manufacturing process. In a pharmaceutical company, raw materials are mainly available in the form of batches. Once the process for any raw material is initiated, it is usually subjected to usability deadlines. Physical nature of material changes as it progresses through the process sequence. Even the final product has a limited shelf life.

In addition to the inherent problems described above, the application of "*Pull System*" in this class of industry is not completely addressed in literature. By building a faithful and general model of the case under study, it is possible to observe the

behavior of system for different operational policies. The model, once validated, will provide an excellent platform for testing of various alternatives, and for experimentation. In addition, a general policy for this category of industry can be developed, and compared with other conventional ones. A simulation study will help in gaining insight in the system, and provide an easy and convenient method to test various parameters.

3. PROBLEM STATEMENT AND SIMULATION MODEL DEVELOPMENT

In this chapter, the problem under study is clearly stated. Various assumptions related to model development are explicitly mentioned, and overall model structure is explained.

3.1 Problem Statement

Based on the literature reviewed, we can infer that the problem of perishable products with fixed lifetime is complex. Several mathematical models have been proposed and validated to solve the problem. However, most of these models, and solutions obtained therefrom, are inappropriate in realistic situations mainly due to the following observations:

a. Almost all the models developed and the mathematical relationships established in them, assume an instantaneous replenishment, suggesting their primary applicability in a purchasing and ordering environment. In any manufacturing process, a definite lead-time, greater than zero time, undoubtedly exists.
b. A ubiquitous assumption is that the demand rate or demand pattern is constant and predictable. This assumption is questionable in many situations, in which, the demand pattern exhibits a stochastic behavior and distribution statistics such as mean and variance are rarely known.
c. A generic structure can be identified with a drug manufacturing process observed in any pharmaceutical company. In these structures, the raw materials are mainly in form batches, and intermediate and final products have limited lifetime for use. These types of multi-echelon systems having series of deadlines for the intermediate and final products. Such issues have not been discussed in literature. Calculation of the batch sizes or economic production quantities for such systems will require considerable effort from a shop floor engineer or a planner.

d. Drug manufacturing equipments are highly automated and many of them are special purpose machines requiring high capital investment. Thus, capital constraints force the companies to schedule multiple product families on a single machine, unless strictly required by law. Obviously, resource utilization is one of the main objectives in mind while operating these equipments.
e. *Pull System* is a popular material management philosophy and it's feasibility in such environments remains to be verified.

Hence, it becomes necessary to analyze the problem under more realistic conditions. These conditions can be in the form of availability schedules for the resources, or modeling the loss of production time due to equipment failures, or by using random variables to represent the processing times, etc. By including these factors in this study, we will be able gain a thorough understanding of the system, and compare it with similar sort of real life systems. Simulating such systems is the best alternative, because it allows the user to change the parameters on a fly, try different scenarios and develop reasonable conclusions from the output obtained by running the models. It needs to be mentioned that the inputs driving the simulation play a key role in the overall study.

3.2 Proposed Methodology

As indicated in Section 3.1, planning and scheduling in the pharmaceutical companies is a critical activity. Demand management under constraints of life-limited inventory buffers and non-discrete nature of products is challenging. In this section, we describe the scheduling method adapted from the one proposed by Taylor and Bolander (1994) in the Process Flow Scheduling literature.

In Process Flow Scheduling, a family of products is usually produced in a single process train. One or more process clusters are combined together to form a process train. Clusters are formed from process units, which represent the basic elements of any process structure. The process units within these clusters are either scheduled as per material dominance or process dominance rule (*see* Section 2.4.2 for details).

In this research, we realize the importance of failure of batches, and hence, suggest using **M**aterial **D**ominated **S**cheduling (MDS) policy for those process clusters, that use potentially expiring materials as inputs. This policy will guarantee the earliest possible usage of limited shelf-life materials; however, it is important to note that the utilization of equipments will be affected. In a true sense, the MDS rule provides very less flexibility for scheduling, but at the same time, appears intuitive as it focuses on reducing the number of expiring raw materials. For other process clusters in the process train, in which, the products expiry date is relatively longer as compared to the lead-time of the process to that point or the demand rate, we suggest using a **P**rocess **D**ominated **S**cheduling (PDS) rule. Thus the overall scheduling policy can be thought of as a combination of PDS and MDS, depending on the rules identified above for their usage.

It is important to note that in such situations, the process-dominated unit must have adequate raw materials in the buffer to realize high utilization of equipments. At the same time, the output from the material dominated unit, in terms of product type, is not uniform. Thus, in such situations, average inventory maintained in intermediate buffers may be higher than usual. To counter this mismatch in scheduling policies of two adjoining process units, additional inventory is required in the buffers. A step-by-step approach for implementing this method and scheduling in such industries follows:

1. The first step is to choose between a 'Forward flow scheduling' or 'Reverse Flow scheduling' method for a process train. This decision is related to the business objectives and external conditions such as demand patterns, volume variations, customer satisfaction model, etc. In forward flow scheduling method, the first process in the sequence will be scheduled at the beginning and the remaining processes follow this, in sequence. The scheduling of the process units in reverse flow scheduling is in opposite. Scheduling begins with the end processes in this case.
2. Once the process train scheduling method is finalized, the process clusters and process structure are identified. The reader is referred to Section 2.4.1 for detailed description of process clusters and their identification methods. It is important to note that all the process units in a single cluster

are scheduled identically, and thus, selection of process cluster scheduling method is critical. For example, in a process cluster consisting of identical process units operating in parallel, all the process units are scheduled as per the same policy.

3. On identification of the process clusters, the process units are scheduled by either a MDS or PDS rule. An MDS approach is selected for process units using raw materials with limited shelf life. This will aid in realizing early consumption and minimize expiry. On completion of the detailed plan for a process unit, the inventory levels for the current period are checked for non-violation of the 'hard' and 'soft' constraints discussed in Chapter 3. Simultaneously, capacity requirements and availability are confirmed and checked. If the capacity is insufficient, the production schedules are modified strictly adhering to the policy selected. This may result in demand adjustment or change in the production schedule of the adjoining processes.
4. A feasible schedule for the process unit is supposed to meet the capacity constraints, and support upstream processes with adequate raw material. This procedure may involve several iterations using schedule revision and capacity checks to ascertain non-violation of inventory and capacity constraints. Once the schedule for the process unit under consideration is confirmed to be feasible and fixed, other upstream or downstream processes are scheduled, depending on the process train scheduling method chosen in step 1.In scheduling the other process units, we follow steps 2 to 4, until all the process units in a process train have been scheduled. We suggest scheduling of the non-critical processes by the PDS rule to obtain maximum utilization of the capital intensive equipment. A non-critical process unit is identified to have reasonable deadlines for consumption of its raw material before expiry and lower utilization of the equipment (approximately 75-90%). Selection of the MDS rule for a particular process cluster also depends on the number of process units, average waiting time for products in any or all of the process units, etc. Average waiting time in any particular process unit can be determined by simulation, queuing theory or by actual measurement.

3.3 Case Description

As outlined in the previous sections, the goal of this thesis is to suggest and validate policies for inventory control in drug manufacturing and similar companies. As a summary of the literature review and Section 3.1, the following distinguishing characteristics of the pharmaceutical industry are as follows:

1. Pharmaceutical industry represents a batch type of manufacturing process, in which, the raw material is usually in the form of powder or liquids and is converted into discrete units. The yield in such processes is inconsistent, and thus, it becomes imperative to test new scheduling policies by using analytical methods or by simulation.
2. In a manufacturing process as unique as this, the products lose value over their life-time. Governmental regulations strictly enforce the deadlines product use. Products expiring are required to be disposed by law, and thus they cost in terms of lost materials, disposal costs, and lost production.
3. A V-type of product structure is observed in almost all the drug manufacturing processes. In these kinds of processes, several end products are produced from a single type of raw material.

A simulation model representing a simple drug manufacturing process has been developed. The elements of this simulation model are generic, such that, almost all companies have the same or similar structural components in their manufacturing process. This model represents a manufacturing sequence of three suites or departments: Blending, Filling and Packing. In the Blending suite, three varieties of end products are blended or mixed. They are denoted as A, B and C (*see* Figure 7 for the product structure). These end products represent the dosage strength of the drug. Blending suite is a single equipment department. Blending equipment is scheduled for maximum utilization as possible to meet the requirements, since it is a single equipment process. The mean processing time for blending any type of batch is 5 hours with variability aspect described in Section 3.6. Quality check and lot tracking are important aspects of cGMP (commercial **G**ood **M**anufacturing **P**rocesses) in the pharmaceutical industry, and these are enforced after each process. Various chemical and physical properties are confirmed during the testing process, and quality test

success rate is modeled as yield percentage in the simulation. It is worth mentioning that the quality test processes in the entire process sequence are purposefully modeled so that they are not the bottlenecks. However, it is assumed that the Blend Testing laboratory is operational for five days a week and can only accept the Blended batches for testing during a single shift of eight hours per day. This assumption is realistic and is usually observed in most of the companies. On any given day, a maximum of eight batches can be tested in the Blend Testing laboratory. Equipment time consumed for testing a single batch is one day and the batch is "on hold" for approximately another four days.

Post blend testing, batches are stored in buffer. An important constraint of limited life usability is imposed on the blended batches. **Any batch can be used only for a limited period from the day it is blended.** For the present study, this period is assumed to be 14 days. Thus, if the batch is not used for following process within 14 days from the day it was blended, it expires and is not suitable for production. This is the most important constraint for this study, and the central idea of the thesis. Products qualified as usable, are processed in the Filling suite. The Filling suite/Filling process is a multi-equipment process. As per the nomenclature outlined in section 2.4.1, the Filling suite represents a process cluster having common inputs and outputs. The Filling suite consists of three machines, operating in parallel, each capable of "filling" any type of blended batch in form of products rolled on spools. Products are filled in 2 doses: D1 and D2 (*see* Figure 7 for product structure). Approximately, a batch yields 20 spools of dose D1 and 41 spools of dose D2. For simplicity, it is assumed that 1,000 units of end products are rolled on a single spool in the form of filled strip. The mean times for filling spool of dose D1 and D2 are 25 minutes and 50 minutes respectively. A sample of filled spool is then tested for quality in the "Fill Testing" laboratory. This facility adheres to a similar working schedule as the blend-testing laboratory i.e. 5 days a week and 8 hours per day. Spool samples passing the fill test are held for 4 days before the quality results are declared. Spool sample testing process requires one day of equipment time of the laboratory.

As the fill samples are tested, the rolled products in spools form are stored in the inventory buffer. They are consumed by the demand from "Packaging" department /suite. Packing is a simple operation, in which, the rolled products of each dose type

are packed in plastic containers or bottles. The packaging suite is a three-machine department. The equipments in the packaging department are functionally identical and each machine is capable of packing products of any spool type, blend type and dose. Nine different varieties of final products are packed from the six varieties of filled spools. It is to be noted that for synchronous operations of all the three departments, their throughput should be nearly the same.

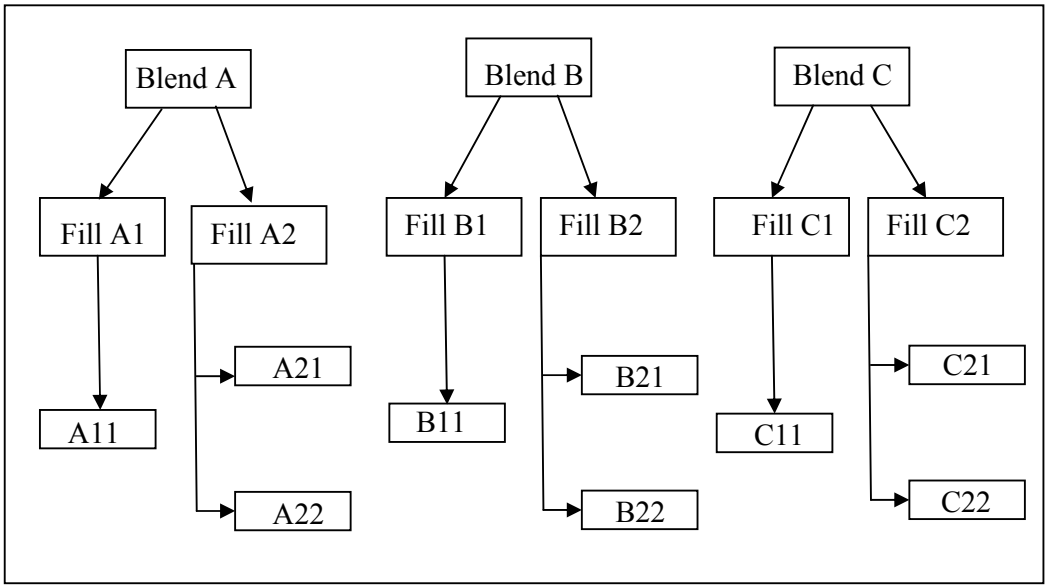

Figure 7: Product Structure

The packed products are tested in the final packed products testing laboratory. This testing facility is scheduled to operate 5 days a week and 8 hours per day. Some packed products are lost or damaged during the initial setup operation or poor quality raw materials, and are rejected in the final quality test. Packed products await the results of fill sample testing before they are classified as finished goods inventory and deemed fit for sale to the end customer. A conceptual model of the entire process is shown in Figure 8.

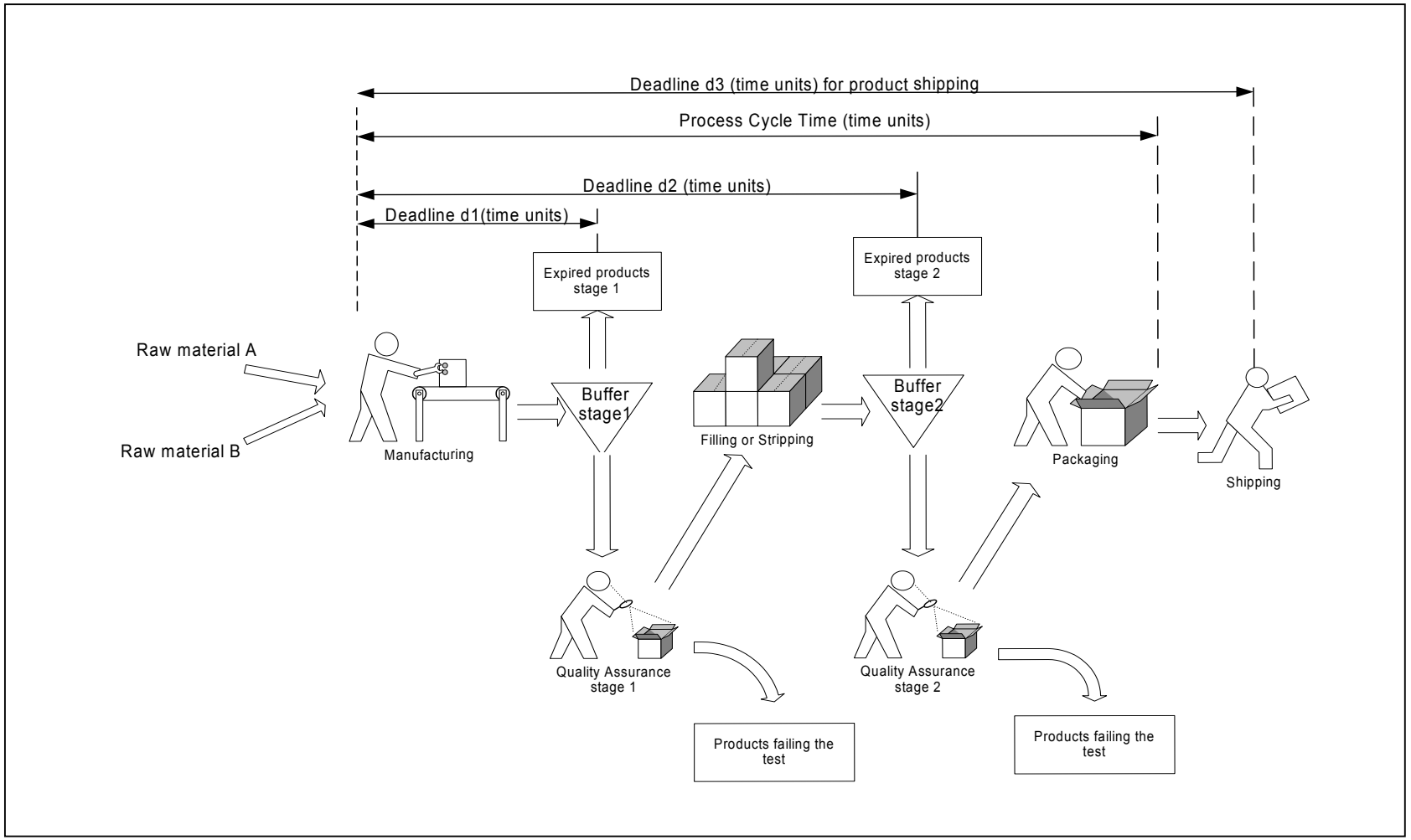

Figure 8: Process Flow Diagram for the Case Study

3.3.1 Model Components

A simulation model of the aforementioned case has been constructed in *Arena 5.0* (www.rockwellsoftware.com). Software selection was based on the availability in the university and proficiency of author. The model represents a complex network of several modules, in which the entities representing the system components flow. The main model consists of three separate sub-models, each representing the individual suites/departments as discussed this section. Global variables are used to keep track of products in inventory of each type, work schedules for the Blending Laboratory, Filling laboratory, Final Testing Laboratory, etc. These variables are also used to regulate setups and suite cleaning, whenever product changeover is required. Various equipments such as Blending machine, Filling machine and final Packing machine are represented as resource elements, which obey strict availability schedules. Inventory buffers are modeled as queue elements in the simulation. Demands for the end products are on a daily basis, and are generated by using the expressions specified in "Advanced Process Panel" of *Arena*. The production plans for each department are modeled explicitly and schedules are tracked with respect to these production plans.

Simulation "Entities" flowing through the model represent the "batches" of the production process. Entities modify the variables; update the counters and expressions, as they are passed from one module to another. Routing decisions for the entities are made by using decision modules, and are based on the values of different variables and conditions, on the scheduling policy implemented and other decision criteria. Various important statistics are obtained at the end of the simulation run using the "Statistics" module in *Arena*. The important statistics of interest are average service levels for individual products and for the process train in general, average inventory of batches, spools and finished goods, number of products expiring per month, number of setups per month in the Filling suite, etc.

An important criterion for the success of any simulation study is the input that is used to run the models. In the present case, data availability was scarce, thus, following assumptions are made with the belief that they adequately represent situations in a generic process.

a. "Throughput" of all the processes is almost same. Throughput is the number of products produced per time unit and is required to maintain balanced flow of products through the entire process. If a bottleneck exists, true effect of any scheduling policy or rule will not be reflected and alternative philosophies such as Theory of Constraints (TOC) will be appropriate to address the bottleneck issues first (Goldratt 1990). Obviously, among the three processes, one will be the slowest, but even with this slowest process, final demands are met. In our case, the system is assumed to produce approximately 23 batches per week.
b. Demand quantities are not backlogged in any period. For example, if the final packing cannot provide sufficient products to meet the demand, excess demand will be lost and this will be appropriately represented in the service level measures.
c. For the method proposed in Section 3.2, a periodic review policy is implemented. Inventory status of each intermediate buffer and finished goods buffer is reviewed on a weekly basis to define production quantities and schedules. In using a MDS rule for any intermediate process, the product requirements are "netted" with the forecast errors from the previous period and accordingly the demands are adjusted. For example, due to the forecast errors, any extra batches produced by Blending suite are adjusted in the demand requirements of the current period.
d. Since the physical and chemical nature of the products changes as they pass from one process to another in the process sequence, it is valid to assume that quality test yields are applicable to products of those units only. To elaborate more, a Blend suite produces a 'batch' of a particular type as the end product. These 'batches' are tested, and a failed batch is completely scrapped. However, when a spool produced from a particular batch, fails in the Fill testing laboratory, the disposal of the products is in the form of spools, and not in batches. A single batch produces approximately 20 spools of Fill Type 1 and 41 batches of Fill Type 2. Each spool consists of 1000 rolled products. It is important to make this clarification because a batch failing in Blend testing is less desirable as compared to the products failing in Fill Testing, if demands are to be met.

3.3.2 Model Types

Predominantly, in the production and inventory control management body of knowledge, two main types of material flow policies are observed. They are referred as 'make-to-order' and 'make-to-stock'. One of the goals of this study is to identify the feasibility of proposed methodology in both environments and identify opportunities for performance improvement. For this purpose, two separate models have been developed. These models are discussed in detail in the following sections.

- Make-to-order model

In a make-to-order environment, the material flow is driven by external demands. Available products in finished goods buffer fulfill external demands occurring on a daily basis. Demands are accumulated over a 7-day planning horizon. Packed units produced in the packaging suite replenish the finished goods buffer. The packaging suite consumes the spools to produce the packed products. The number of spools released to the packing department is recorded, and derived requirements for batches are placed at the blending suite. In this system, one can visualize demand propagating from final packaging stage to the blend raw material stage in a coherent manner. This system is totally governed by the demands, and the goal of each process/department is to maintain uniform buffer quantities. A base case has been constructed to determine the buffer quantities such that a minimum service level is obtained.

Various decision variables such as spool release quantity, batch production numbers, final demand accumulation, etc. are calculated by programs written in Visual Basic for Application (VBA), which is a programming interface with *Arena*. Special care and attention is given to convert the product consumption at each stage to appropriate units, while calculating demands for the upstream processes. For example, a consumption of 10,000 finished goods of any type is equivalent to 10 filled spools.

3.3.2.1 Implementation of PFS in Make-to-Order Environment

Demand is the key control element in these environments. If the demand is low, products stall in inventory. This inventory is undesirable for the present problem, because the products will expire as they are held in inventory waiting to be consumed. In certain cases, product expiry might lead to lost demand at the final stage. In our case, a single batch yields approximately 41,000 products of dose 2 and 20,000 of dose 1. Thus, any batch that gets expired, might easily lead to lost demand. Moreover, a pull type of strategy is rarely tested and implemented in a 'batch-flow' kind of environment. A point of interest is to test the application of PFS principles to these situations. We suggest implementing a similar method proposed in Section 3.2 i.e. a combination of PDS and MDS for individual process clusters, depending on the resource capacity constraints and urgency of product use.

For the present case, demands for a 7-day period are accumulated and passed to upstream processes. The filling and blending process units are combined to represent a single process cluster. The idea still remains the same. We want to implement PDS for the Blend process cluster, followed by MDS for the Fill process cluster and PDS again for the packing process. Ideally, all the process clusters should be scheduled similarly, but the deadline for use of the blended batch suggests use of a MDS strategy for the filling process units. It is to be noted that the utilization of the equipments might be affected due to this policy

One can relate this system to 'Kanban' production systems practiced in discrete unit manufacturing industries. An important point to be reiterated is that the products unavailable in the inventory are not backlogged, as stated in the assumptions. Products expiring in inventory buffers as per the specified guidelines are disposed. This expiration of products is the one of the most important performance measure for this study, the goal being, to reduce the number of expired products, and at the same time to achieve maximum service level. On certain occasions the 'hard' and 'soft' constraints come into picture. These are in the form of capacity, space or product sequence constraints. In cases, where the capacity of a process cluster is lesser than the requirements, the capacity is divided proportionately among the various demands for that period. These constraints have been appropriately modeled in the simulation.

- Make-to-stock model

Driven by the forecasts, these production planning and control philosophies target constant throughput. Forecasts are periodically updated to align with the demands. Revising of forecasts often leads to excess inventory or production shortfall. It is important to consider this practice of forecast revision in the simulation model development, as we expect that this would have a tremendous impact on the number of products expiring and overall demand fulfillment measures.

The implementation of the PFS concept for this case is similar to the make-to-order, except the difference lies in information flow. In our model, forecasts of demand for the Blending suite are made. Blending suite produces according to these forecasts; however, this forecast is revised in the following week. The idea behind this is that as the delivery date gets closer, the demand prediction becomes more accurate. By the time that the forecasts are revised, most of the blended batches have passed the quality testing phase and are ready to be filled. Thus, the revised forecasts are now the demands for the Filling suite. Since we suggest implementing a MDS strategy for the Filling process cluster, all blended batches are filled in the earliest expiry due date order, in spite forecast revisions; however, extra batches filled or deficit of blend batches is recorded and adjusted in the demand calculation of batches for Blending suite. It is to be observed that the output of the Filling process cluster is not guaranteed to be uniform. By this we mean that the output of Filling cluster at any given time will not necessarily be of the same blend or fill type, because of the stochastic nature of the processing time, setup, etc.

In order to schedule the packing stage according to PDS guidelines, all the raw material for the demand should be available. Scheduling of Filling cluster by MDS forces to introduce a buffer period of a one planning cycle (7 days for the present problem) before these filled spools can be passed to final packing stage, which is scheduled as PDS. Filled spools are maintained in inventory for additional period before being released to the packing stage. A tradeoff between the reduction of expired products and excess inventory has to be made at this point. We choose to reduce the number of expired products by holding additional inventory after filling.

For all the cases, it is assumed that the system is capable of delivering approximately 23 batches per week. The schedules for each department, test processing times and various delays used in the model are shown in Table 1 and Table 2. The equations for forecast generation used in the model are given in Table 3. In Table 3, the 'norm' variable represents a standard normal variable. The demand random variable for any product is normally distributed with standard deviation of approximately 10% of the mean.

Table 1: Schedules for Various Departments

Department Name	**Schedule**
Blending Department	24 hours a day , 6 days per week
Blend Testing Lab.	8 hours a day , 5 days per week
Filling Department	24 hours a day, 6 days per week and 8 hours on 7th day
Fill Testing Lab.	8 hours a day ,5 days per week
Packing Department	21 hours a day,6 days per week; 3 hours for breaks
Packed Products testing	8 hours a day, 5 days per week

Table 2: Testing Durations in each Department

Testing Stage	**Duration**
Blend Testing	8 hours of equipment time
Fill Testing	8 hours of equipment time
Pack Testing	8 hours of equipment time
Blend batches hold	5 days
Filled products hold	4 days
Packed products hold	4 days

Table 3: Forecast Generation Equations
for Blending Department

Product	Demand per day in Integers
A11	13200+1300*norm(0,1)
A21	2460+200*norm(0,1)
A22	18450+1800*norm(0,1)
B11	7800+780*norm(0,1)
B21	11070+1100*norm(0,1)
B22	11070+1100*norm(0,1)
C11	9000+900*norm(0,1)
C21	2460+200*norm(0,1)
C22	2460+200*norm(0,1)

3.4 Verification and Validation

The credibility of output of any simulation run largely depends on the model's ability to mimic reality. A simulation model should be free of any programming bugs (Verification) and should also reflect the "as-is" situation or perform in the way it is expected (Validation). One should be able to draw valid and acceptable conclusions from results by running the simulation models. The first step, in any kind of simulation study, is to develop a "conceptual" model of the system. Once the conceptual model has been programmed in a simulation language, it is the job of the analyst to verify that the code is error-free and does not have any syntactical errors. Though verification is a time consuming process, the simulation programming languages available in market simplify this process. Many of the concepts recommended in this part of the methodology are taken from Law and Kelton (1991).

To verify the model, the analyst can question himself as follows:

a. Is the flow of entities through the system as expected?

b. Is any resource or process continuously idle?
c. Is any particular queue continuously growing (Unless it is an exponentially growing system)?

A convenient method to verify the model is to animate various system components such as resources, queues, variables and counters. A step-by-step verification by tracking the flow of entities for some initial simulation run time can also be performed. A verified model can then be tested for different scenarios, once it is validated.

The next step after verification, before any detailed study of the system can begin, is validation. Validation is an important step for the analyst and other users of the simulation output to gain faith in the simulation study. Validation confirms that the model represents the "as-is" system. Several approaches listed below can be adopted to validate the model:

a. The output obtained from the simulation model is compared to that obtained from any existing analytical model of the system. Although, exact comparison is very rare; reasonable approximations should be pretty close to the analytical values.
b. The model is subjected to extreme conditions such as high delays or processing time, stalling the flow of entities or extreme routing decisions, and the performance of the system under such conditions is observed.
c. The results obtained from the simulation runs are compared to the real life observations and performance measures. Also, this is an excellent way to validate the assumptions made for purpose of building the models.
d. Usually, performance measures such as utilization, queue lengths, and counter variables are plotted against time to detect any abrupt behavior of the system.

For the present case, the model is verified by using standard functions of *Arena.* Validation is mainly done by subjecting the system to extreme cases such as increasing the processing time of the Filling suite, decreasing the quality yields drastically, etc. If the model is accurate representation of the system, then the results for the extreme cases will be reflected in the form of unacceptable outputs in the simulation reports. Besides, we observe the transient behavior of the system as well; plot the finished goods and intermediate buffer quantities to detect any sudden surges

or drops. A graph can be created showing the comparison of the actual data versus the simulation data. Observation of plots is not sufficient to validate the simulation model. Some statistical measures should be conducted on the data sets. The difference in the cumulative distribution of the actual data and the simulation data can serve as a goodness-of-fit test to compare the model results to actual conditions. Sometimes, a compromise has to be made while attempting to obtain precise estimates from the simulation runs. Often, differences between two systems are sufficient to serve the purpose of simulation study.

3.5 Warm –up and Run Length

To start with, simulation models are often begun empty and idle. By this we mean, there are no entities in any queue, no resource is busy, etc. The system in such cases typically undergoes a transient behavior at the beginning of the run. In certain studies, this is acceptable. For instance, in a simulation study for resource utilization in a store that has fixed operating schedules and opening and closing hours, we are primarily interested in daily performance measures. However, in many situations, a long run average value of the performance measure is required rather than one with a short period. Such simulations are referred as "steady-state simulations". In a steady state simulation, an attempt is made to remove or minimize the effect of initial bias on the values of the performance measures reported at the end of simulation run. Several methods have been implemented to obtain observations that are independent and uncorrelated. Some of the methods to remove the initial bias in the steady state simulation are as follows:

a. By loading the system with entities to mimic the real life situations instead of starting it empty and idle.
b. By extending the simulation run until the effect of initial bias is negated
c. By deleting the statistics being collected to a certain point in time that the analyst believes the system has reached steady state then. This deletion is usually done by plotting the various performance measures of interest against time, and identifying the time value at which, the system is observed to be in steady-state.

We have adopted method 'c' to study the system in steady state for the present case. The main performance measures of interest are service level, WIP etc. Figure 9 shows the plot of average inventory in the system (WIP) against time for the 'make-to-stock' environment. The plot is similar for make-to-order system. Several replications have been plotted to determine the appropriate warm-up period for deletion of statistics. Clearly, the system appears to have reached steady state in approximately 50 days for both systems. From a simulation run length of one year, it is possible to obtain reasonable estimates of the performance measures of interest.

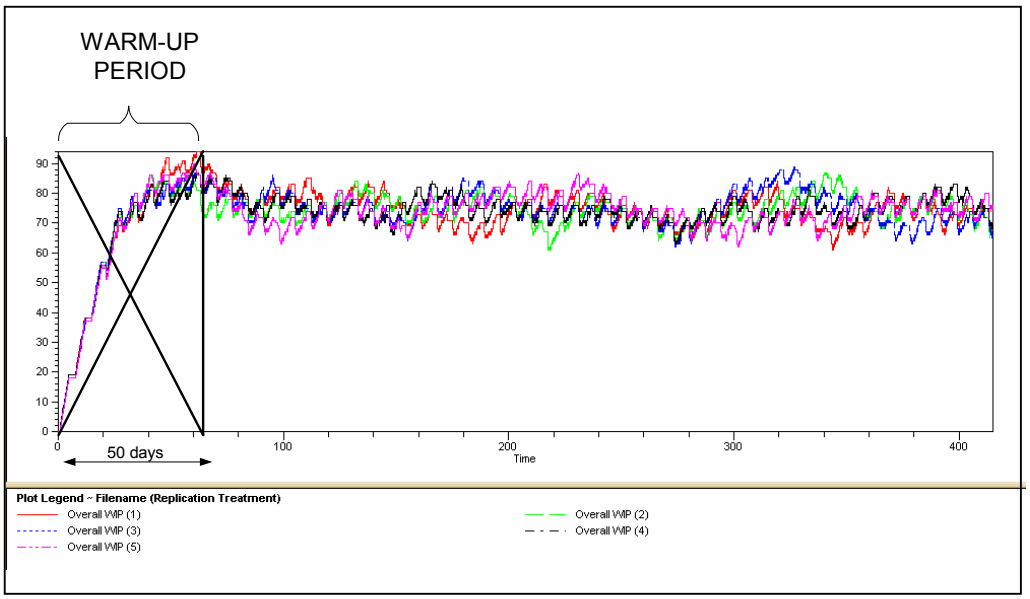

Figure 9: Plot for Warm-up Period Determination

3.6 Design of Experiments

The goal for any organization is to operate the manufacturing processes to obtain optimum performance. The primary performance measures are service levels (quantitative measure for demand fulfillment), inventory turnovers, average inventory levels, customer satisfaction, etc. Some of the performance measures are tangible and quantitative, while others are subjective. Quantifying the subjective performance measures, optimizing the processes performance for these measures is best done by using formal group process for collective decision-making. However, in case of

quantitative factors, one needs to consider various factors affecting the process output and possible interactions amongst them.

Design of Experiments (DOE) is one of the best techniques to address the problem of the relationship among factors. In a DOE study, responses are stated, and variables affecting the responses are controlled to observe their significance on the output. These variables are commonly mentioned as factors. In the present study, it is important to identify the key variables or parameters that might have an effect on the various performance measures while implementing the proposed methodology. The main performance measure of interest is the customer satisfaction, which is measured in terms of the service level. Service level for this study is the number of requests filled in from the finished goods buffer. Another important performance measure is the number of expired products (in batches or spools) per month. Minimizing the number of expired products is a major motivation of this research. We also consider the average Work in Process (WIP) over the long run in comparing the two systems: make-to-stock and make-to-order. Since the models for two systems: make-to-stock and make-to-order are not same functionally, we choose to conduct the analysis for them separately.

In a make-to-order environment, we select four factors for analysis. Although, other factors can also be cited along with the ones selected, we choose the following because of their suggested importance in literature. Various experiments with different levels and combinations of the factors are executed and analyzed for optimum performance. We choose the method of Common Random Numbers (CRN) for variance reduction within the simulation results. Every source of stochastic input is seeded with different random number streams, but for model runs of various levels of a single factor, the random number streams are same. This design will also serve as an excellent opportunity for performing sensitivity analysis study of the system. Some of the important factors of interest are as follows:

a. **Processing Time:** Usually, experts in the industry or shop floor personnel use commonly observed values of processing time for planning purposes. Mostly, the mean (μ) is not known and only subjective values of the maximum or minimum processing time are speculated. The **variability in the processing**

time is rarely characterized in research or practice. By making this as an experimental factor, the proposed method will be tested for conditions of high and low variability in processing time with the same mean. For our experiments we use a *Beta* distribution to characterize the processing time for Blending process, Filling process and Packing process. We use higher values of the parameters α_1 and α_2 of *Beta* distribution to characterize low variability and lower values to characterize higher variability respectively. Apart from the two parameters mentioned above for the *Beta* distribution, two additional parameters, namely, *a* and *b* for the lower and upper limit are also required. Figure 10 shows the Beta distribution with same mean for different values of the parameters α_1 and α_2. Table 4 outlines the various processing times and their levels used for this factor. The equations for use in simulation model were obtained by using *Arena Input analyzer.*

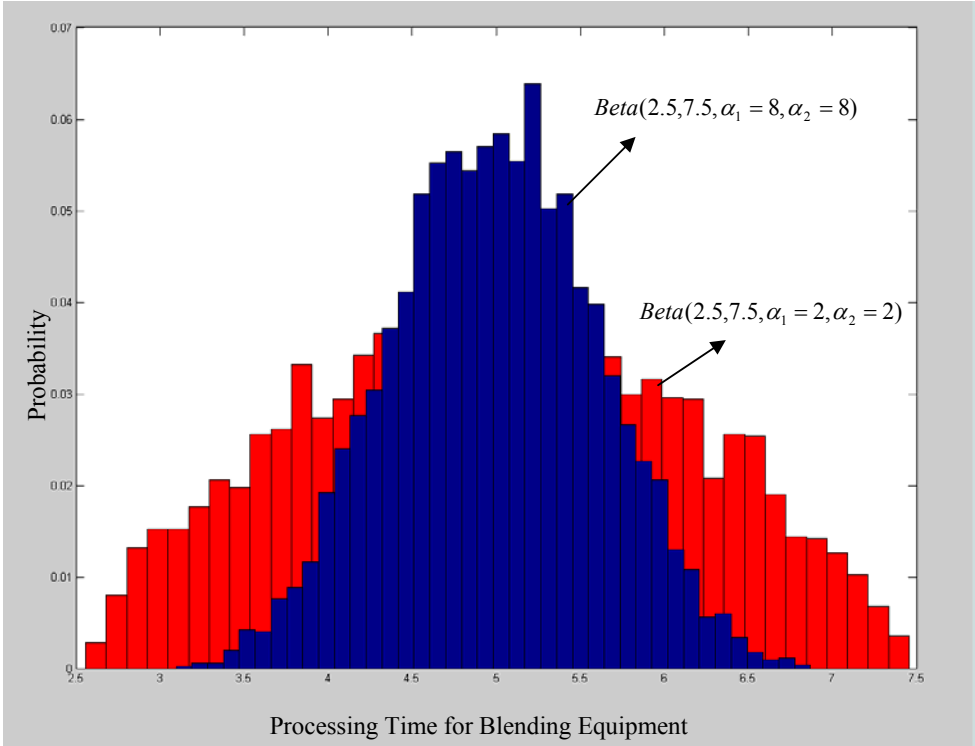

Figure 10: Processing Time Variability

Table 4: Levels for Processing Time

Factor	High	Low
Blend Processing Time	2.05 + 5.93 * BETA(2.96, 3.02)	2.57+4.43*BETA(6.53,5.43)
Fill Processing Time	15 + 3 * BETA(2.3, 2.24)	15.1+2.72*BETA(6.51,6.45)
Pack Processing time (Fill 1)	40 + 20 * BETA(2.28, 2.21)	41+17*BETA(7.68,6.7)
Pack Processing time (Fill 2)	20 + 10 * BETA(2.21, 2.28)	21+8*BETA(4.9,4.92)

b. **Product Yield:** Batch manufacturing is often troubled with inconsistent product yields (see Fransoo and Rutten 1994). The nature of the products in powder or liquid form in process industries makes this a very important factor. Inconsistencies in the raw material quality, operation of the process equipment and stringent quality requirements, especially in the pharmaceutical companies, call for observing the effect on production system with these parameters in mind. In the present analysis, we study the system for product yield of 90% and 80% as high and low levels respectively. Note that when the quality success rate is high, it is 90% at all the testing phases i.e. Blending, Filling and Packing.

c. **Demand Patterns:** External demand holds the key to the effectiveness of any production policy. The ultimate goal of any organization is to achieve high service levels with minimum inventory possible. Often, demand is an external variable, which can be rarely controlled, but analysis for some general demand patterns will definitely throw some light on the effectiveness of suggested methodology. We consider two types of demand patterns:

    1. **Stable:** This pattern exhibits a relatively constant demand per period. However, a normally distributed random variable is added to the constant to model stochastic behavior. The constant component is set such that the effective utilization of the Filling resource is in the 90-100% range.
    2. **Seasonal:** Analysis of the model under such demand patterns is necessary as they are commonly experienced in industry. A rational seasonal pattern exhibits peak demand during the beginning and end of the end year with a less than average demand during the mid-year period. In addition to this, seasonality of demand in each quarter is also embedded in the overall pattern. Stochastic behavior is modeled in similar manner to that of stable demand pattern. Figure 11 shows seasonal demand pattern used in the design of experiments analysis.

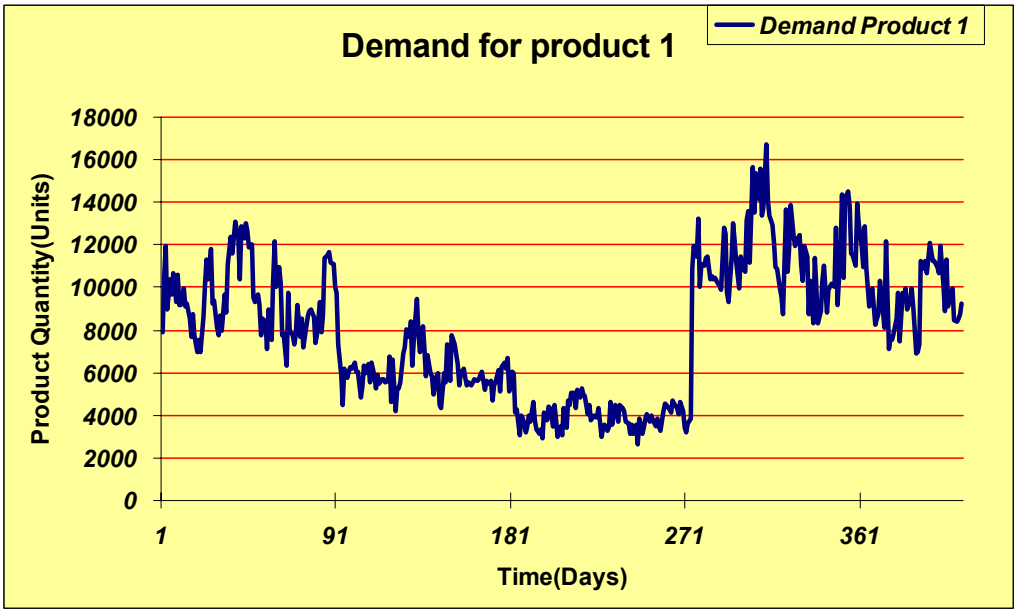

Figure 11: Seasonal Demand Pattern

d. **Setup time:** Setup time is an important factor, which affects the lot sizing and scheduling decisions, especially, while scheduling a single machine for multiple products. In addition, we are implementing Material Dominated Scheduling (MDS) in the intermediate process (Filling process), and expect many setups due to frequent product changeovers. Blends of different strengths are filled in various doses at the filling process cluster. At this stage, two types of setups are associated: setup related to dose change and setup related to strength change. The more the number of setups there are, the less will be the throughput, but the number of expired batches will be less as well. Clearly, the proposed method has a tradeoff associated between multiple setups and expired batches. However, in certain cases, the setups are inevitable. In such cases, the response and behavior of the system to the variability in the setup operation durations becomes significant. A considerable amount of potential benefit of the proposed method rests on the setup operations. Due to the strict regulations and standard procedures to be followed during product changeovers, minimizing setup time is difficult. But, the variability in the setup time also plays a major role in such cases. Thus, we have included this as a categorical variable in the study with two levels: High and Low variability. The setup durations for these two levels are shown in Table 5.

Table 5: Levels for Setup Time Variability (hours)

	Dose change	**Strength change**
High	UNIF(2,6)	UNIF(2,6)
Low	UNIF(3,5)	UNIF(3,5)

e. **Forecast Error:** Apart from the above factors, an additional factor that is of interest in make-to-stock environment is the forecast error. Although, it is very difficult to predict the forecast errors accurately, an effort has been made to include this factor for sensitivity analysis by enumerating it as a categorical variable with two levels: High and Low. Table 6 shows Mean absolute percentage error (MAPE) selected for these two levels of the forecast error. MAPE is calculated as shown in equation (5).

$$\text{MAPE} = \left| \frac{(D_t - F_t)}{F_t} \right| \times 100 \tag{5}$$

where, F_t = Forecast for period 't'

D_t = Demand for period 't'

Table 6: Levels for Forecast Error

	MAPE
High	15%
Low	5%

In case of make-to-order model, a 2^{4-1} fractional factorial experiment is designed. Two replicates of the all the treatments (combination of factor levels) are done to get an estimate of the pure error (ε). A DOE study with simulation models does not necessarily require the run order to be randomized, because each run is made with a

separate random number sub-stream in *Arena*. Table 7 shows the experimental plan for the make-to-order system.

Table 7: 2^{4-1} Experimental Plan for Make-to-Order System

Run Order	Processing time	Setup	Demand	Quality Yields	Service Level (%)
1	High	High	Stable	Low	71.52
2	High	High	Stable	Low	70.19
3	High	High	Seasonal	High	78.29
4	High	High	Seasonal	High	75.05
5	High	Low	Stable	High	82.64
6	High	Low	Stable	High	83.42
7	High	Low	Seasonal	Low	70.4
8	High	Low	Seasonal	Low	68.82
9	Low	High	Stable	High	82.91
10	Low	High	Stable	High	81.06
11	Low	High	Seasonal	Low	72.16
12	Low	High	Seasonal	Low	69.55
13	Low	Low	Stable	Low	66.88
14	Low	Low	Stable	Low	70.86
15	Low	Low	Seasonal	High	72.19
16	Low	Low	Seasonal	High	78.45

Similarly, an experimental plan for the make-to-stock system is devised and is shown in Table 8. It is a half fraction factorial experiment with two replicates. An additional factor considered in this experiment is the forecast error.

Table 8: 2^{5-1} Experimental Plan for Make-to-Stock System

Run No.	Processing Time	Setup time	Demand Pattern	Quality Yield (%)	Forecast Error (%)	Service Level (%)
1	High	High	Seasonal	High	Low	72.59
2	High	High	Seasonal	High	Low	72.24
3	High	High	Seasonal	Low	High	57.86
4	High	High	Seasonal	Low	High	58.89
5	High	High	Stable	High	High	92.88
6	High	High	Stable	High	High	94.25
7	High	High	Stable	Low	Low	86.73
8	High	High	Stable	Low	Low	83.87
9	High	Low	Seasonal	High	High	72.71
10	High	Low	Seasonal	High	High	73.1
11	High	Low	Seasonal	Low	Low	58.2
12	High	Low	Seasonal	Low	Low	60.09
13	High	Low	Stable	High	Low	93.02
14	High	Low	Stable	High	Low	93.81
15	High	Low	Stable	Low	High	87.98
16	High	Low	Stable	Low	High	85.76
17	Low	High	Seasonal	High	High	74.32
18	Low	High	Seasonal	High	High	72.54
19	Low	High	Seasonal	Low	Low	61.95
20	Low	High	Seasonal	Low	Low	60.29
21	Low	High	Stable	High	Low	94.12
22	Low	High	Stable	High	Low	93.91
23	Low	High	Stable	Low	High	86.3
24	Low	High	Stable	Low	High	84.85
25	Low	Low	Seasonal	High	Low	70.98
26	Low	Low	Seasonal	High	Low	72.5
27	Low	Low	Seasonal	Low	High	61.14
28	Low	Low	Seasonal	Low	High	59.63
29	Low	Low	Stable	High	High	94.12
30	Low	Low	Stable	High	High	93.46
31	Low	Low	Stable	Low	Low	85.97
32	Low	Low	Stable	Low	Low	84.37

4. RESULTS AND DISCUSSION

As discussed in the previous section, we conducted an experimental design study on the two material flow systems commonly observed in industry: 'make-to-stock' and 'make-to-order'. The factors chosen and the experimental plan have been discussed in Section 3.6

4.1 Regression Analysis

Based on the responses obtained from the simulation model, we attempt to fit a regression model to characterize the response with respect to the parameter values of interest. We use the statistical software JMP by SAS, Inc for extensive analysis. A 2^{5-1} fractional factorial design of resolution V is selected for the 'make-to-stock' system. With this design plan, it is possible to estimate all the main effects and two factor interaction effects only. Basic assumptions in selecting this design are that all the three and above factor interactions are negligible, and thus can be excluded from the mathematical model. An initial fit of the model including all the main effects and two-factor interaction effects reveals the insignificance of certain factor levels and their combinations. The insignificance is judged by comparing the ratio of mean squares of the treatments and the mean square of pure error to an F-statistic. Certain factor combinations and levels that have F-ratio less than 2 are excluded from further analysis. After eliminating all the insignificant factors, a revised model is fitted to the data with reduced number of parameters. Table 9 shows the goodness of fit of the proposed model to the data.

Table 9: Summary of Fit of Proposed Model for Make-to Stock System

Parameter	Value
R-Square	0.994317
R-Square Adjusted	0.993224
Root Mean Square Error	1.08412
Mean of Response	77.95094
Observations (or Sum Wgts.)	32

The goodness of fit table shows R-square value of 0.99, indicating an excellent fit of the model proposed to the data values obtained from the simulation. Also, the R-square Adjusted value is close to 1.0. The model proposed based on the inferences from the goodness of fit table given by equation (4) is:

$$Y = \beta_0 + (\beta_1 \times [\text{Demand Pattern}]) + (\beta_2 \times [\text{Quality Yield}]) + (\beta_3 \times [\text{Demand Pattern}] \times [\text{Quality Yield}]) \quad (4)$$

where,

Y = response variable i.e. service level, β_0 = intercept (mean service level)

β_1 , β_2 , β_3 = regression coefficients for the independent variables.

Results of the Analysis of Variance Test (ANOVA) conducted on the fitted model are shown in Table 10. The F-Ratio shows that the model is an excellent fit to the data, indicating that the model can easily predict the variability associated with the response measure. The F-ratio is much greater than 2.0, which is the standard value used to characterize the significance of the fitted model. The significant effects of the model are clearly identified from the parameter estimates table shown in Table 11.

Table 10: Analysis of Variance for Make-to-Stock System

Source	DF*	Sum of Squares	Mean Square	F Ratio
Model	5	5346.5519	1069.31	909.8070
Error	26	30.5582	1.18	Prob > F
C. Total	31	5377.1101		<.0001

*DF-degrees of freedom

Table 11: Parameter Estimates Table for Make-to-Stock System

Term	Estimate	Std Error*	t Ratio	Prob>|t|
Intercept	77.950937	0.191647	406.74	<.0001
Proc Time[High]	-0.202187	0.191647	-1.05	0.3011
Demand Pattern[Seasonal]	-11.76156	0.191647	-61.37	<.0001
Quality Yield[High]	5.2084375	0.191647	27.18	<.0001
Proc Time[High]*Demand Pattern[Seasonal]	-0.277188	0.191647	-1.45	0.1600
Demand Pattern[Seasonal]*Quality Yield[High]	1.2246875	0.191647	6.39	<.0001

*Std. Error – standard error

The effects that have higher values of the F-ratio are highly significant. The parameter estimates table shows the reduced model, after excluding the non-significant effects from the model. A short discussion about the inferences drawn from the parameter estimates table follows:

a. As seen in the parameter estimates table, demand pattern is a significant factor that affects the service level. A negative estimate for the seasonal demand pattern indicates that this factor is associated with lower values of service level. Thus, for any organization that identifies itself with process and flow manufacturing, a seasonal demand pattern drastically affects the customer satisfaction. The results obtained also support our intuition, since capacity is highly inflexible in such manufacturing organizations.
b. Apart from the demand pattern, quality yield is another significant factor as inferred from its F-ratio of 27.18 from the parameter estimates table. It is always desirable to obtain high quality yields from the processes and raw materials in the process and batch industries. This result is primarily attributable to the non-discrete nature of the product. For example, in the case discussed in Chapter 3, a batch failing in the Blend testing laboratory is more detrimental to the service level than the failure of a spool after Fill testing. A failed batch results in a loss of 41,000 products of type 21 and type 22(see Figure 7 for product structure), or 20,000 products of type 11 against a failed spools resulting in a loss of only 1,000 products.
c. Other factors such as 'variability in the processing time' along with its interaction effect with 'demand pattern' are also observed to be marginally significant. Processing time variability can be presumed as a micro-level variable as compared to the actual processing time, to have an effect on the service level.
d. An interaction effect of Demand pattern and Quality yield is also fairly significant as shown by the t-ratio value of 6.39>>2.0. This is mainly due to both main factors involved in the interaction terms being significant.

Table 12: Effect Tests for Factors of Make-to-Stock System

Source of Variation	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Proc Time	1	1	1.3082	1.1130	0.3011
Demand Pattern	1	1	4426.6993	3766.392	<.0001
Quality Yield	1	1	868.0903	738.6018	<.0001
Proc Time*Demand Pattern	1	1	2.4587	2.0919	0.1600
Demand Pattern*Quality Yield	1	1	47.9955	40.8363	<.0001

*Nparm – Number of parameters, DF-degrees of freedom.

Figure 12 shows the Normal Quantile plot for the effect estimates. The significant effects are clearly plotted away from the red line that indicates the root mean squared error from the residuals. The farther the point lies from the red line, the higher is its significance on the model. Figure 13 shows a Pareto plot of significant effects. Clearly, demand pattern, quality yield, and interaction effect of demand pattern and quality yield are seen to be the significant factors for the system under consideration.

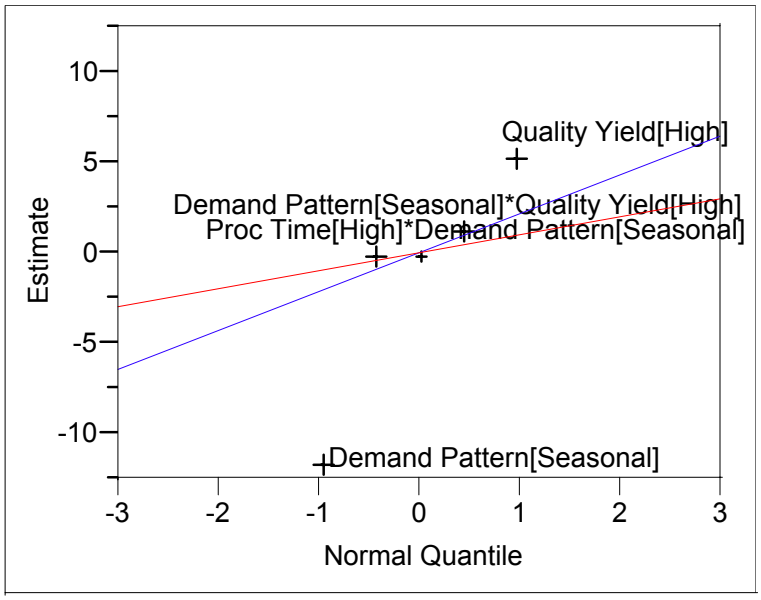

Figure 12: Normal Quantile Plot of Estimates

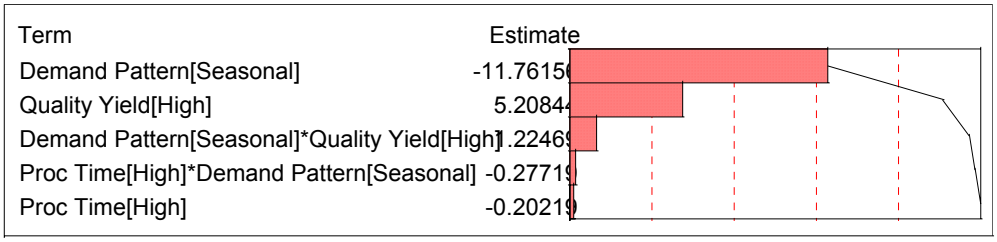

Figure 13: Pareto Plot of Estimates

As a result of reduced number of runs in a fractional factorial design, some factor interactions are confounded with other main effects or interactions. It is difficult to estimate the true effect of any single factor in a set of confounded factor combinations. In these situations, an interaction plot as shown in Figure 14 aids in identifying any significant interactions between the factors. A significant interaction is obvious when the two lines indicating the factor levels cross each other. The interaction plot shown below shows a marginal interaction between demand pattern and quality yield on the performance measure, with higher values obtained at stable demand patterns and high quality yields in the process. No interaction is observed between the demand pattern and processing time variability.

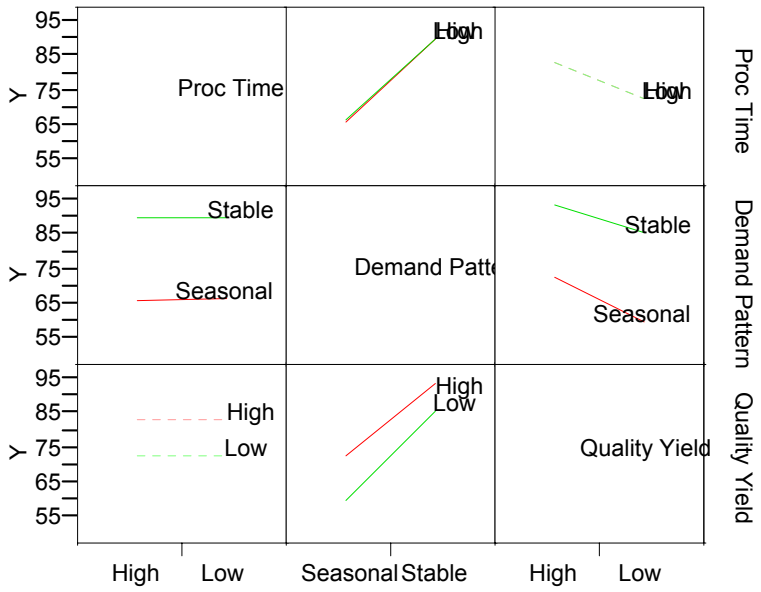

Figure 14: Interaction Plots of Factors

Figure 15 shows the maximum number of batches expiring during the simulation run length in a make-to-stock model. As seen the in figure, it is noticeable that the number of batches expiring is less under the effect of proposed method. Table 13 outlines the important statistics obtained from the model for the factors of interest. The average number of batches of any type failing per week is very low.

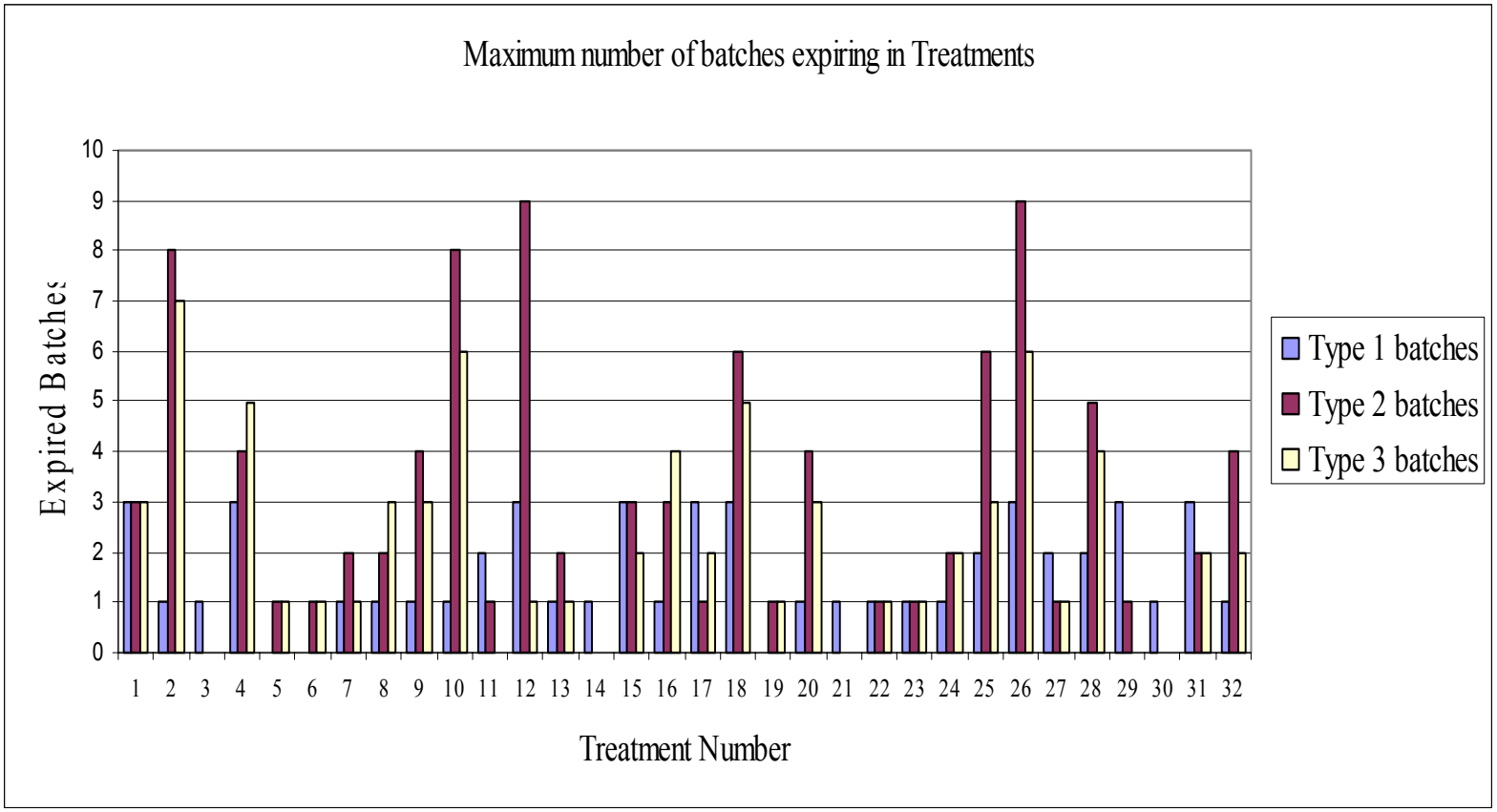

Figure 15: Plot of Maximum Number of Batches Expired Per Month

Table 13: Vital Statistics from Experimental Runs of Make-to-Stock System

Parameter	Value
Percent Expiry in Blend	1.8-2.0%
Average Inventory (WIP)	65-75 batches
No of spools expiring	0
Average number of batches failing per week (Type 1)	0.166~1 batch
Average number of batches failing per week (Type 2)	0.166~1 batch
Average number of batches failing per week (Type 3)	0.30~1 batch

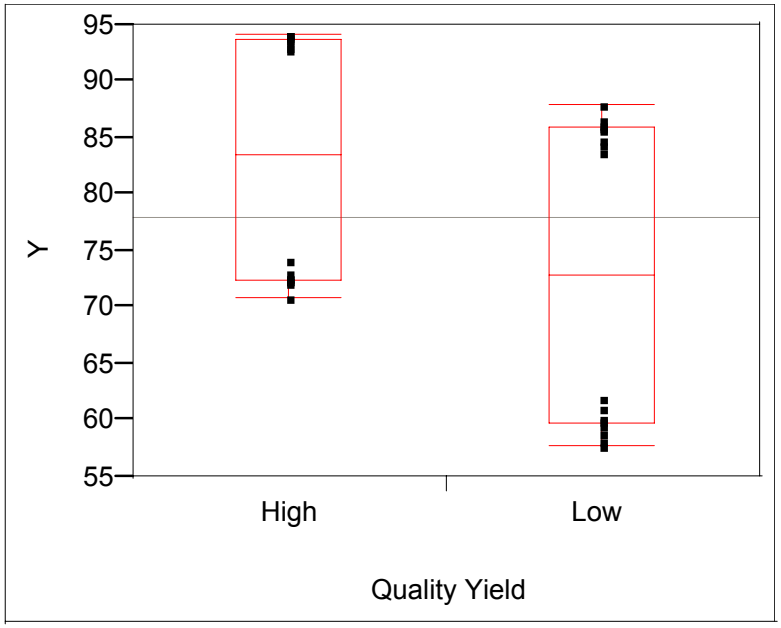

Figure 16: One Way Analysis of Variance for Quality Yield

Table 14: Means Comparison (alpha = 0.05) for Quality Yield

Dif=Mean[i]-Mean[j]	High	Low
High	0.000	10.417
Low	-10.417	0.000

A similar analysis is performed for the experimental runs of the **'Make-to-Order'** (MTO) model. The response values are shown in Table 7. Based on the responses obtained, we formulate a regression model with the factors as independent variables. An initial fit to the data by using the method of least squares helps to identify the non-significant factors. The resultant summary of fit table after excluding the non-significant factors is shown in Table 15.

Table 15: Summary of Fit of Model for Make-to-Order System

Parameter	**Value**
R-Square	0.914701
R-Square Adjusted	0.840065
Root Mean Square Error	2.24491
Mean of Response	74.64937
Observations (or Sum Wgts)	16

The summary of fit table indicates a good fit of the data to the regression model proposed since the R-Square and R-Square adjusted values are high. Table 16 shows the Analysis of Variance (ANOVA) test for the data. Significance of the ANOVA test indicates that model explains the variability in the data. Table 17 shows the results of the effects test. The F-ratio in column 5 of Table 16 is much greater than 2, and hence we conclude that the proposed model is a good fit for the data.

Table 16: Analysis of Variance Test for Make-to-Order System

Source	**DF***	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	7	432.33994	61.7628	12.2555
Error	8	40.31695	5.0396	Prob > F
C. Total	15	472.65689		0.0010

*DF- Degrees of freedom

In order to estimate the significance of an individual factor on the response measured, an effect test is conducted. Clearly, 'demand pattern' and 'quality yield' are the most significant factors affecting the response variable (since the F-ratio>> 2) as in the case of 'make-to-stock' model. A reduced number of runs using a fractional factorial design results in two-factor interactions being confounded. The interaction of 'variability in processing time' and 'variability of setup time' is confounded with that of 'demand pattern' and 'quality yield' as shown in Table 17. However, the main effects, 'demand pattern' and 'quality yield', are highly significant, and thus, it is true to infer that the interaction effect is mainly due to the interaction due to 'demand pattern' and 'quality yield'.

Table 17: Effect Tests for the Factors in Make-to-Order System

Source	Nparm*	DF*	SS*	F Ratio	Prob > F
Processing Time	1	1	2.45706	0.4875	0.5048
Setup	1	1	3.12406	0.6199	0.4538
Demand	1	1	37.73031	7.4867	0.0256
Quality	1	1	338.83606	67.2345	<.0001
Processing Time*Setup = Demand*Quality	1	1	47.36881	9.3993	0.0154
Processing Time*Demand = Setup*Quality	1	1	2.13891	0.4244	0.5330
Processing Time*Quality = Setup*Demand	1	1	0.68476	0.1359	0.7220

*Nparm- Number of Parameters, DF-Degrees of Freedom, SS-Sum of Squares

Table 18 outlines the parameter estimates obtained with a standard least squares fit to the response values. Based on the parameter estimates, the regression model is proposed in equation (5)

$$\begin{aligned} Y = \beta_0 &+ (\beta_1 \times [\text{Demand Pattern}]) + (\beta_2 \times [\text{Quality Yield}]) \\ &+ (\beta_3 \times [\text{Demand Pattern}] \times [\text{Quality Yield}]) \end{aligned} \tag{5}$$

Where, Y = Service Level, β_0 = intercept (mean value)

β_2, β_3 = regression coefficients of the factors

Table 18: Parameter Estimates for Make-to-Order System

Term	Estimate	Std Error*	t Ratio	Prob>|t|
Intercept	74.649375	0.561227	133.01	<.0001
Processing Time[High]	0.391875	0.561227	0.70	0.5048
Setup[High]	0.441875	0.561227	0.79	0.4538
Demand[Seasonal]	-1.535625	0.561227	-2.74	0.0256
Quality[High]	4.601875	0.561227	8.20	<.0001
Processing Time[High]*Setup[High]	-1.720625	0.561227	-3.07	0.0154
Processing Time[High]*Demand[Seasonal]	-0.365625	0.561227	-0.65	0.5330
Processing Time[High]*Quality[High]	0.206875	0.561227	0.37	0.7220

*Std. Error- standard error

In addition, the significance of the effects can also be verified with a Pareto plot of the factor effects as shown in Figure 17. As seen in the plot, Quality is the most significant effect. It is important to note that interaction effect of 'variability in processing time' and 'variability in setup time' are confounded with interaction effect of 'demand pattern' and 'quality yield'.

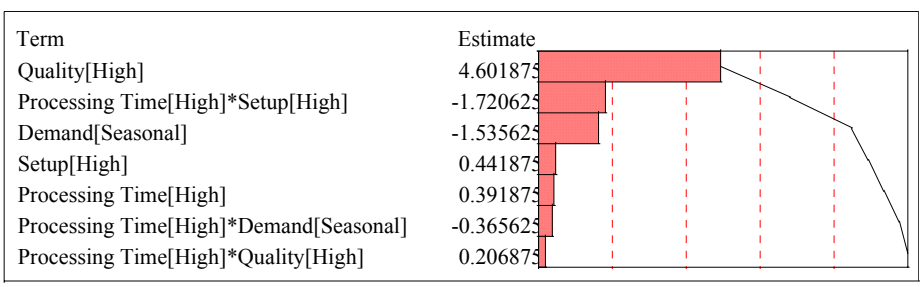

Figure 17: Pareto Plot of Factor Effects for Make-to-Order System

4.2 Discussion of Results

a. Based on the parameter effects test (*see* Table 18) and Pareto plot of effects (*see* Figure 17), we conclude that 'quality yield' and 'demand pattern' are the most important factors in Flow- and Batch- manufacturing type companies. Since the products are in non-discrete form, quality is of paramount

importance. In addition, a ‘make-to-order’ environment is more sensitive to the demand pattern than a ‘make-to-stock’ environment.

b. Seasonal demand patterns cause inconsistencies in the production schedules. Particularly, with the kind of industry being considered, inconsistent demand result in product losses due to expiration. These expirations also impact lost capacity, which is extremely inflexible in batch manufacturing companies. Figure 18 and Figure 19 show the number of spools expiring per month and maximum number of batches expiring per month respectively. Clearly, in case of seasonal demand pattern and low Quality yields, the situation is worst.

c. It is reasonable to conclude that with the method proposed in Section 3.2 for the problem under study, performs well in reducing the number of expired products. Best results for such systems are obtained in a ‘make-to-stock’ environment with low product expirations and higher service levels. However, a higher amount inventory is required to be held in a Push System as compared to the Pull System. Figure 18 and 19 show the maximum number of failed spools and number of spools failing per month respectively. Higher numbers of spools expire in the ‘make-to-order’ model than the ‘make-to-stock’ model. This difference is due to less demand in the case of seasonal demand patterns. Low demand than the usual leads to higher number of expired spools as they wait in the buffer to be pulled from the following process.

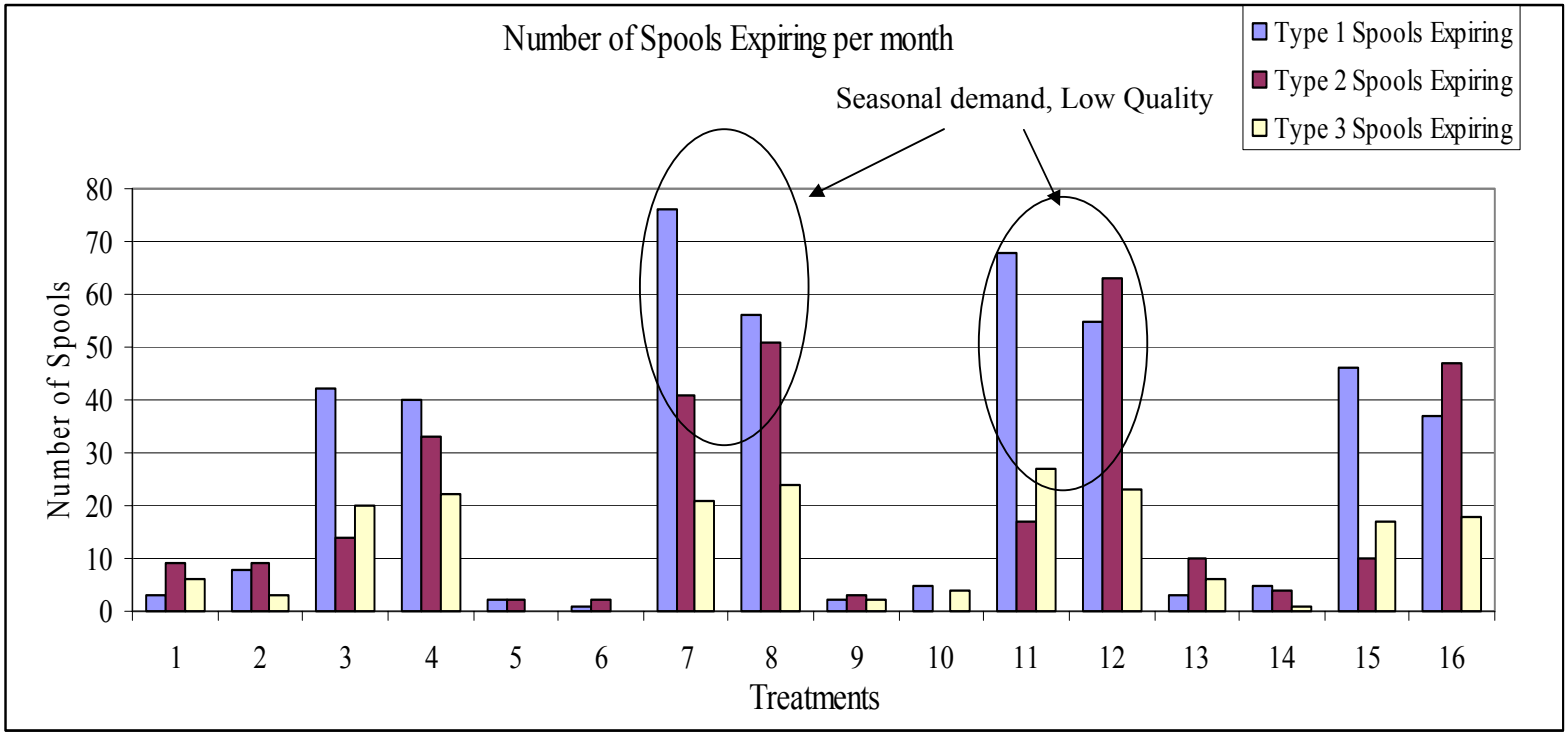

Figure 18: Number of Spools Expiring Per Month

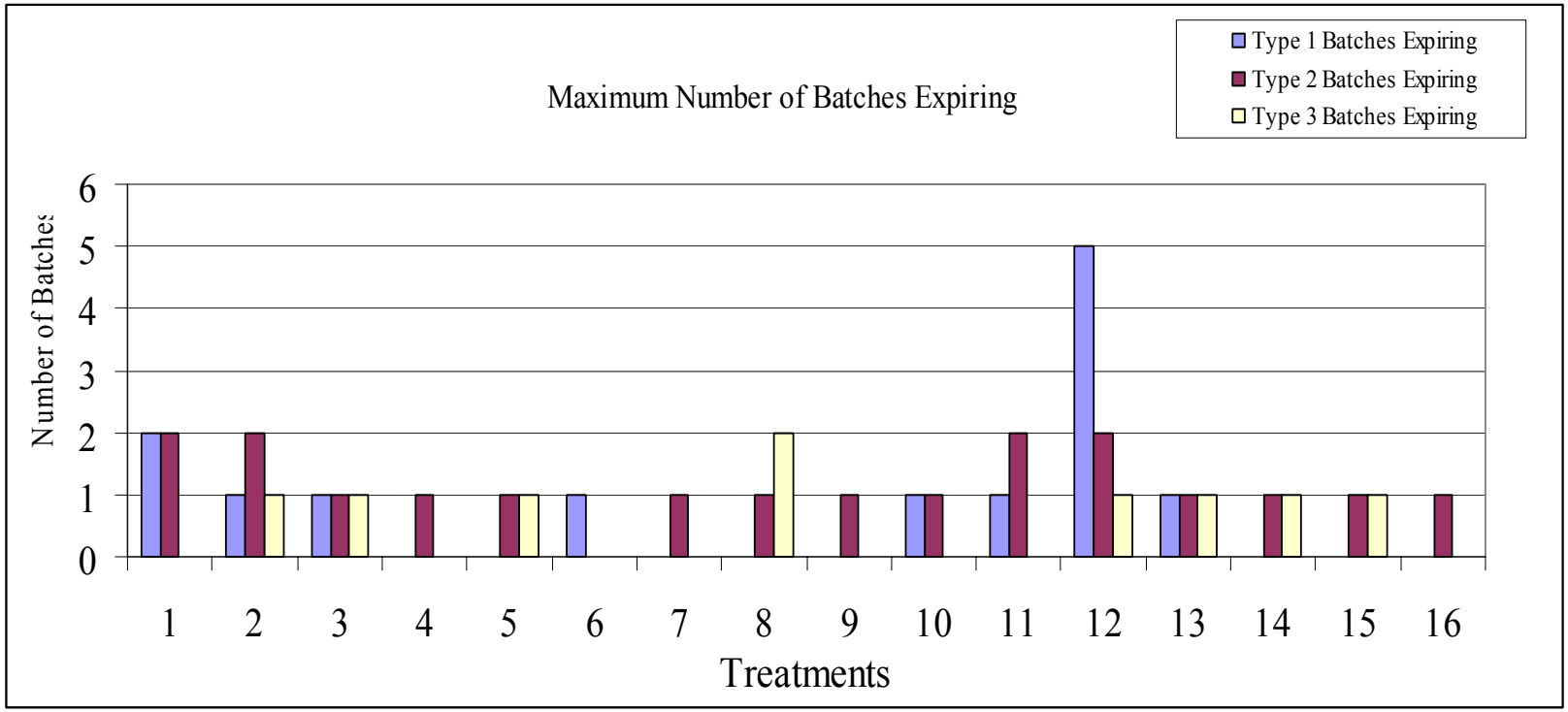

Figure 19: Maximum Number of Batches Expiring Per Month in the Blend Buffer

Figure 20 shows the cube plots that can be used in selecting the best factor combinations to operate the system. As seen in the figure, maximum service level for this method is obtained with a stable Demand Pattern, High Quality Yield and low setup time variability.

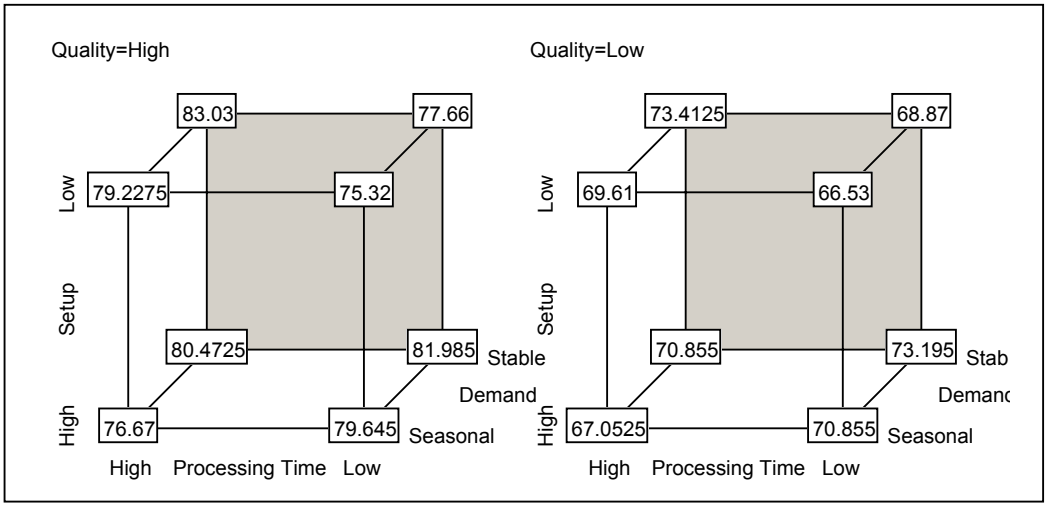

Figure 20: Cube Plot of Factors and Associated Service Levels

5. CONCLUSIONS AND FUTURE RESEARCH

5.1 Conclusions

In this thesis, the critical problem of inventory control of life-limited products in a manufacturing process is addressed. The literature review revealed that inventory control of these products is extremely difficult, and no analytical closed form expression for this problem exists. Simulation serves as an excellent tool in these situations, as it allows modeling stochastic behavior of the system, and deriving reasonable conclusions about the performance measures of interest. We proposed a heuristic approach to address the current problem of interest based on the philosophy of Process Flow Scheduling. The proposed method is tested for various conditions, namely, demand pattern, processing time variability, process yields, setup time variability and forecast error in a make-to-stock and make-to-order environment. A design of experiments approach has revealed the viability of this method and helped in identifying the key factors for its success. Based on the analysis conducted, the following conclusions are made:

a. Process industry (for definition, *see* Chapter 1) is unique due to the nature of the product involved. Constraints such as limited shelf life, inflexible equipments are rarely observed in the discrete unit industries. A process flow scheduling methodology, which is a combination of material dominated schedule and process dominated schedule in a single process train, is proposed.
b. A make-to-stock (MTS) environment is better suited to such kind of industries as compared to the make-to-order (MTO). This result is mainly because products expire as they are held in inventory buffers in MTO systems. Experimental design identified Quality Yield and Demand pattern as the key factors determining the success of any system operating under proposed method. As seen in Figure 19 and Figure 20, the number of batches and spools (product forms) expired are quite less.

5.2 Future Research

Research is a process of evolution and there is always ample scope to build upon the existing work. Some suggestions for future work are presented below:

a. In our analysis, the single equipment process unit was not scheduled in an optimal manner, as it was not directly related to the goals of the thesis. Perhaps, the benefit of the proposed method may enhance on the implementation of algorithms related to optimal single machine utilization.
b. The case considered a representative sample of processes structures occurring in industry. Other process structures producing expanded product variety can be tested in future research studies.
c. Practical implementation case study of the proposed method would be an added reference from the implementation standpoint for industry. Such experience will also provide a selection of models spanning various demand patterns, and operations of this method in a JIT and lean environment.
d. In the experimental design analysis performed, we qualified the experiment variables as categorical with High and Low levels. It is important to note that the results obtained are particularly applicable within the range of the variable values selected. The experimental analysis can also be conducted by setting most of the factors of interest as continuous variables with values obtained from industry.

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APPENDIX A

The construction of the models is explained in the following sections. Specific details of each section have been mentioned and parameters outlined. The main model comprises of mainly three sub-models. They are as shown in the following figure.

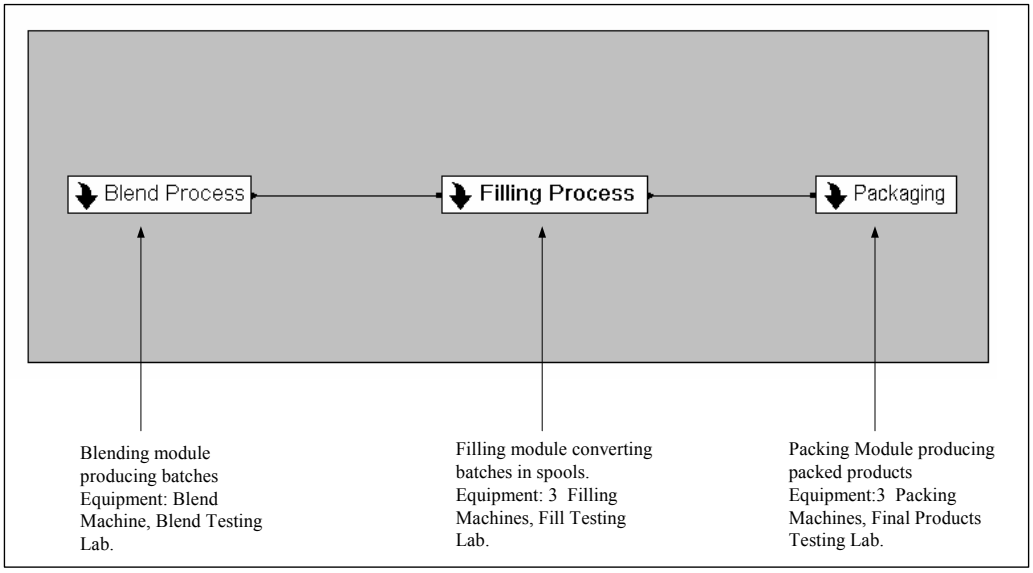

Figure 21: Snapshot of Sub-Models of Make-to-Stock Model

Forecast generation section:

In this sub-module, we generate the forecast for the Blending suite as per the equations given in Table 3. The forecasts are generated for the following seven days (week).

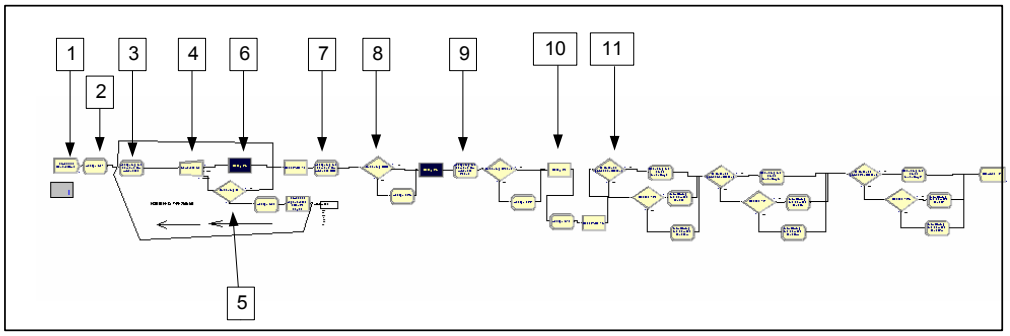

Figure 22: Forecast Generation Section of Make-to-Stock Model

1. CREATE *Forecast Generation*

Task: Creates an entity to generate forecast. Only one entity is created and it is circulated after every 7 days
First Creation: 0.0; Max. Arrivals: 1

2. ASSIGN *fr(1) = 0*
This variable is assigned a value of 0 only at the start. Its value is incremented by 1 in the following modules. fr(1) variable is to record the current day in the simulation run.

3. ASSIGN *i = i+1; fr(1)= fr(1)+1;Blend demand 1(1)= Demand Type 1(1); Blend demand 1(2)= Demand Type 1(3); Blend demand 1(1)= Demand Type 1(3);bd1(1)= Blend demand 1(1); bd1(2)= Blend demand 1(2); bd1(3)= Blend demand 1(3).*

The forecasted demands are updated in the "Blend demand 1" variable using the values of fr(1) variable in the "Demand Type 1" expression. Demand Type 1, Demand Type 2 and Demand Type 3 are expressions comprising of the demand generation equations. The attributes bd1(1) is an array of size 3 used to record the demand with the corresponding entity for the three Blend Types.

4. DUPLICATE *the entity. Original entity is routed to the module 6 explained in the following section. Duplicate is used to generate the forecast after another 7 days of simulation time.*

5. IF i < 7 THEN
Pass this entity to module 3 above.
ELSE
Delay the entity for 7 days of simulation time and then pass it to module 3 above after setting the value of variable i to 0.
END IF

6. DELAY
Delay the entity from module 4 for 7 days.

7 ASSIGN *ifill = ifill+1; Fill demand 1(1) = AINT(bd1(1)+ bd1(1)*UNIF(u1(1),u1(2)));*
*Fill demand 1(2) = AINT(bd1(2)+ bd1(2)*UNIF(u1(1),u1(2)));*
*Fill demand 1(3) = AINT(bd1(2)+ bd1(3)*UNIF(u1(1),u1(2)));*
fd1(1) = Fill demand 1(1); fd1(2) = Fill demand 1(2); fd1(3) = Fill demand 1 (3)
ifill is the control variable maintaining the current day ; Fill demand 1 is the variable recording the forecast for Filling Department. Note that the forecast is different from the Blend Forecast and is adjusted by using the "u1" variable of forecast error. The variable values are assigned to the entity attributes fd1 which is an array of size 3 for a single Blend type. This attribute is used to adjust the forecast for the Packing department to be described later.

8 IF *ifill < 7* THEN
delay the entity by 14 days
ELSE
Reset the value of ifill to 0 and delay it for 14 days before passing to the following module. This is necessary since the "Fill demand 1" variable is an array of size 7 only.
END IF

9 ASSIGN *ipack = ipack+1; del(1) = del(1) +1*
*Pack demand 1(1) = AINT(fd1(1)+ fd1(1)*UNIF(u1(1),u1(2)));*
*Pack demand 1(2) = AINT(fd1(2)+ fd1(2)*UNIF(u1(1),u1(2)));*

*Pack demand 1(3) = AINT(bd1(2)+ bd1(3)*UNIF(u1(1),u1(2)));*
Pd(1) = Fill demand 1(1); pd(2) = Fill demand 1(2); pd(3) = Fill demand 1 (3)
de = del(1)
ipack is the control variable maintaining the current day while generating the 7 day forecast; Pack demand 1 is the variable recording the forecast. This variable is an array of size 7. The forecast values are assigned to the entity attribute pd(1), which is an array of size 9. This attribute becomes the demand later on. "del (1)" is the variable to regulate the flow of entities during demand realization. We want the demand to occur on a daily basis. If we don't use this variable, the demand for all 7 days will occur on a single day. "de" is an attribute used for delaying the entity appropriately.

10 DELAY: *The entity is delayed by duration = (6+ de). On passing this delay module, the demand is realized by using the value of attribute pd(1).*

11 IF *pd(1) < FG(1)* THEN
FG(1) = FG(1)-pd(1)
ELSE IF *pd(1) –FG(1) > on hand(1)* THEN
On hand(1) = 0; pd1 = 0
ELSE
On hand(1) = on hand(1)- (pd(1)-FG(1)); FG(1) = 0;
service level(1) = service level(1)+ 1
END IF
END IF
Service level is a variable of array size 9 to record the customer demand satisfaction. The variable's value is used to calculate the "service level" performance measure.

Similar routing logic as in case 11 is implemented for product type A21 and product type A21. The entity is finally disposed. A similar logic is implemented for Blend Type 2 products (i.e. product type B11, B21 and B22) and Blend Type 3 products (i.e. C11, C21 and C22).

Table 19: Attributes used in Make-to-Stock Model.

Number	Attribute Name	Value	Description
1	Blend Type	1-3	used to assign the blend types to the entities
2	Fill Type	1,2	used to assign the Fill type to the entities
3	Product Type	1-9	used to assign the 9 different product types of the case
4	blendstart	real	used to assign the birth-time to the batch in Blending department
5	bd1(1-3)	real	used to record the forecasted demand in Blending Department
6	fd1	real	used to record the forecasted demand in Filling Department
7	pd(1-9)	1-9	used to record the forecasted demand in Packing Department. This is also the final demand quantity
8	filltestin	real	used to record the entry time of the spool sample in the Fill testing Laboratory
9	de	1-7	used to delay the 'forecast' entity during demand realization
10	prod id	real	a batch(entity) identity attribute used to remove the expired batches from the blend batch buffer.
11	Fill enter	real	used to record the time any batch(entity) enters the buffer
12	SC(1-2)	20,41	used to assign the number of spools produced from a batch depending on the Fill type
13	rem	1-6	used to assign the spool type identity after the batch(entity) is filled
14	R	real	used to delay module to hold the entity for additional period after it has passed the Filling department
15	Product Yield	real	used to assign the yield for each spool after it is packed. Particularly, this yield is obtained from a single spool. The value of this attribute is changed, when the products fail in final pack testing.

Blending Suite sub-model:

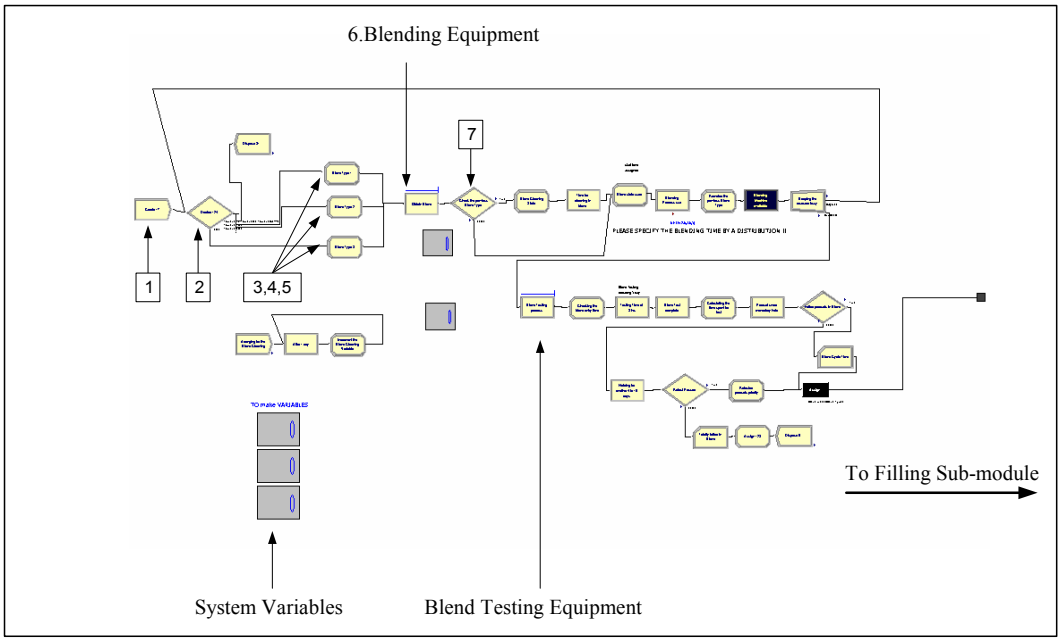

Figure 23: Blending Suite Sub-Model

1. CREATE Blend Batches

Task: Creates an entity to initiate Blend production in each period. Inter-arrival time for creation of entities is 7 days.
First creation: 0.5 days; Max. Arrivals: Infinite

2. IF *Tomake(1) +Tomake(2)+Tomake(3) = O* THEN
    Dispose the entity.
  ELSEIF *Tomake(1) > 0* THEN
    Pass this entity to the module described in 3.
    ELSEIF *Tomake(2) > 0* THEN
      Pass this entity to the module described in 4.
    ELSE
    Pass this entity to the module described in 5.
    END IF
  END IF
END IF

In the module described above, the entity is routed as per the number of batches remaining to be produced in the current period. Tomake(1), Tomake(2), Tomake(3) are the variables that are updated with the demand quantities by VBA block. If demand for all the 3 types of batches is completed, the entity is disposed off or else, the demands are produced one by one.

3. ASSIGN *Blend Type = 1;Tomake(1) = Tomake(1)-1;*
  Binventory(1) = Binventory(1)+1;

The blend type is set to value 1. Tomake(1) variable is updated and batch inventory is incremented

4. ASSIGN *Blend Type = 2;Tomake(2) = Tomake(2)-1;*
   Binventory(2) = Binventory(2)+1;
   The blend type is set to value 2. Tomake(2) variable is updated and batch inventory is Incremented.

5. ASSIGN *Blend Type = 3;Tomake(3) = Tomake(3)-1;*
   Binventory(3) = Binventory(3)+1;
   The blend type is set to value 3. Tomake(3) variable is updated and batch inventory is Incremented.

6. SEIZE *Blending Equipment is obtained and blending process is completed.*

7. IF *(Previous Blend <> Blend Type) or (BClean >14)* THEN
   delay the entity by the cleaning operation duration
   ELSE
   The entity is passed to the following module.
   END IF

In this module, we check if the blend is not cleaned since last 14 days or if the new batch to be processed is of different dose than the previous one processed. If the condition is true the blending equipment is cleaned.
The entity is delayed by the appropriate Blend processing time obtained by evaluating an expression from "Advanced Process Panel". The expression is "Blend Proc. Time". The blending equipment is then made available to the other batches waiting to be blended. This entity follows to enter the Blend testing Laboratory and consumes one day of Blend testing equipment time. It is "on hold" for another 3 days to check other quality properties. Once testing is completed, the entity is passed to the Filling sub-model. Note that we have not modeled any transfer time for the batches.

Filling Suite sub-model:

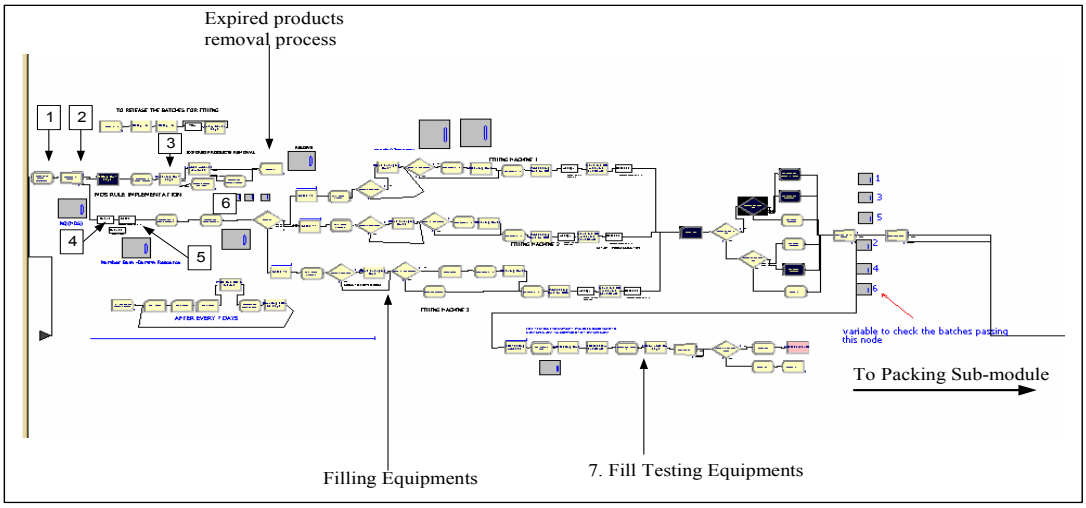

Figure 24: Filling Suite Sub-Model

1. ASSIGN *Torelease(Blend Type) = Torelease(Blend Type)-1*
The "Torelease" variable is decremented by 1, whenever a batch passes in the Filling suite.

2. DUPLICATE *The entity is duplicated and the duplicate entity is passed to module 3 that is described below. The original entity is passed to the module 4.*

3. DELAY *The duplicate entity from module 2 is delayed till 14 days have elapsed from the day it was made in the Blending department. This is logic is implemented to remove the expired batches from the Fill buffer. The expired batches are removed from the queue of batches waiting to be filled by using a* SEARCH *and* REMOVE *module. The blend inventory variable, "Binventory" and "batchinv" are appropriately decremented if an expired batch is encountered. The duplicate entity is finally disposed.*

4. MDS QUEUE The *original entity from module 2 described above joins the MDS queue. The entities are ranked as per the descending order of "blendstart" attribute. "blendstart" is the birth time of the entity(batch) in the Blending department. Thus, we are implementing MDS by this method.*

5. SEIZE *The entities wait in the MDS queue till they obtain one of the Filling resources. A resource named "dummy resource in fill" is also seized at the same time. This resource is used to restrict the flow of entities to the Filling machines directly.*

6. ASSIGN *Fill type = DISC (BFcomb(Blend Type),1,1.0,2)*
The entity (batch) is assigned a fill type based on a discrete distribution. "BFcomb" variable has been updated in VBA block 1. This variable has the proportion of Fill type(1-2) for each Blend Type(1-3).

Once the Filling resource is available, the entity is delayed by appropriate filling time for the batch. The entity (batch) is then duplicated into the appropriate number of spools depending on its fill type (either 20 or 41). On filling of a batch, the Filling resource is made available to the other batches waiting in MDS queue. The Filling resource follows a schedule given in Table 1 in Chapter 3.

An entity is duplicated after filling and the duplicate entity is passed to the Fill testing Laboratory section. The original entity is passed to the Final Packing sub-model.

7. SEIZE *Fill Testing Resource.*
The Fill testing resource is available only 5 days a week and 8 hours per day. It is a multi-capacity resource having a capacity of 8. Spool samples for a single batch wait in for the availability of Fill testing resource. The entities are delayed appropriately to model the fill testing time. The spool sample yield is modeled with an expression named "Quality Yield". Spool samples failing the test are recorded and the entities representing the spools are appropriately disposed in the Final packing department.

Final Packing sub-model:

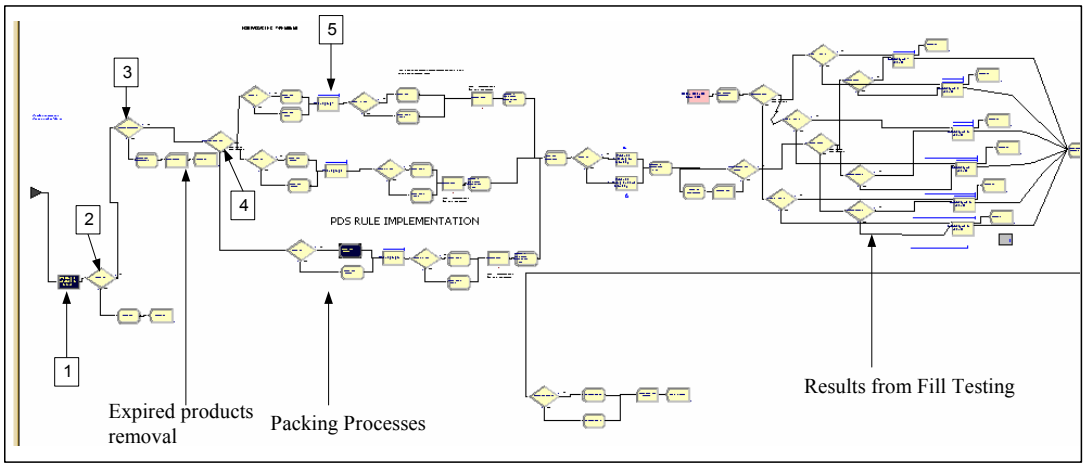

Figure 25: Final Packing Sub-Model.

1. DELAY The *entities from Filling sub-model are delayed for time: (R-tnow) +0.2. "R" is an attribute, allowing to hold the entity (spool) for additional period to guarantee use of Process Dominated Scheduling in Packing Department. "tnow" is the current simulation time. The time unit for this "DELAY" is days.*

2. IF *disp(rem) = 0* THEN
   pass the entity to module 3
   ELSE
   Dispose the entity and record the number of failed spools.
   END IF

"disp" is a variable (of array size 6) used to record the number of spool samples failing the quality test. This variable is incremented in the Fill testing section described above. "rem" is the product attribute for each spool type. It has a value ranging from 1-6 depending on the spool type. This module is used to eliminate the spools that have failed in the Fill testing process and preventing them from passing to the final packing department.

3. IF *(tnow –blendstart) <= 35* THEN
   pass the entity to module 4
   ELSE
   Dispose the entity and record the number of expired spools.
   END IF

In this module, we check the expiry date condition for the spools passed to Final packing department. The expired spools are removed and recorded.

4. IF *Blend Type = 1* THEN
    pass the entity to packing machine 1 queue
    ELSEIF *Blend Type = 2* THEN
        Pass the entity to the packing machine 2 queue
    ELSE
        Pass the entity (spool) to the packing machine 3 queue
    END IF
  END IF

In this module, the spools are routed to the appropriate pre-specified packing machines. Packing machine 1 is used to manufacture product type 1, 2 and 3. Packing machine 2 is used to manufacture product type 4, 5, and 6. Packing machine 3 is used to manufacture product type 7, 8, and 9. This is precisely done to implement PDS rule in the Packing area.

5. *The spools wait in a queue for the availability of the respective packing machines. Packing machines availability follows a schedule described in main document.*

6. *Packed products wait for another 4-6 days in Pack Testing Lab. The spool product yield is adjusted after final pack testing. The yield is 800-1000 products per spool. The entities representing the spools are finally disposed.*

Description of VBA Block 1:

In this VBA module, the forecasted fill demands are accumulated and appropriate number of batches demanded by filling department is calculated. This demand is "netted" as described in the main document of the thesis. Depending on the number of expected setups, the capacity required is calculated. In addition, the "BFcomb" variable is updated depending on the demand proportions of each Fill type of each Blend Type. Any demand that is not satisfied from the Final packing department is also considered by the "Final make" variable in Fill demand calculations. Number of each fill and blend type required are assigned to the "BFcomb" variable.

Description of VBA Block 2:

In this VBA module, the blend forecasted demanded are accumulated over a period of 7 days. Based on the demand, the number of batches of each type is derived. This requirement is checked against the capacity of Blending department. If the demand is more than the capacity, the demands are distributed proportionately. The demands are then updated in the "Tomake" variable.

Description of VBA Block 3:

All the final demands from variable "Pack demand" are summed up for the 7 days planning horizon period. Safety stocks and products in finished goods are also considered

and the final packing demand quantities are re-evaluated. These demand quantities are then entered in the "final make" variable. Note that the demand quantities are in spools. Besides, the proportion of products of Product A21 and A22 from Spool type 2 are calculated and updated in the "dist" variable. This variable is an array of size 3 for each Blend Type product. This concept will be clearer if the reader refers to the product structure in Figure 3.3.

It is important to mention the order in which these VBA blocks are fired. VBA Block 3 is fired first, followed by VBA block 2 and then VBA block 1.

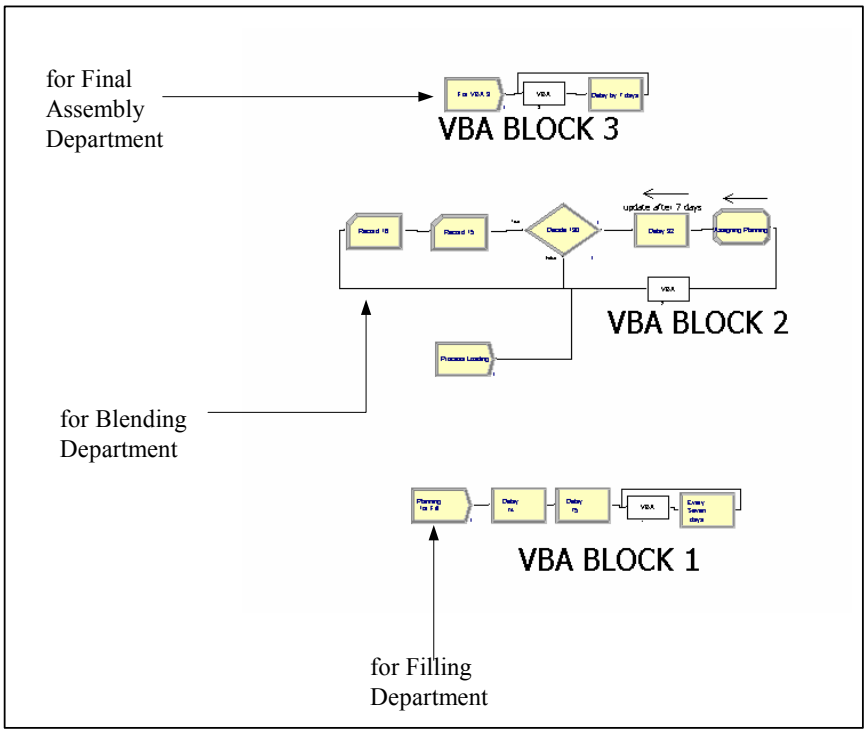

Figure 26: VBA Blocks of Make-to-Stock Model

Table 20: List of Variables in Make-to-Stock Model

Variable Name	Rows	Col.	Description
Bcleaning			for maintaining the days from last cleaning
Previous Blend			for maintaining the previous blend type in setup calculation
Binventory	3		for maintaining the blend inventory
Previous Fill	3		for maintaining the previous fill type in setup calculations in Filling suite
BClean			counting the number of days since last cleaning of Blend equipment
bfailures			Quality Yield variable in Blend
Previous Fill A	3		Fill variable to regulate setups
batches	3		for regulating maximum number of batches of same type in Blending suite
BatchNumber			product identification number assigned in Blending Department
Blend Setup	3		Setup time for Blend Change
Blend Demand 1	7	3	Forecasted demand for Blend Type 1 in Blending Department
i			counter variable used in generating forecast of Blend Type 1
i2			counter variable used in generating forecast of Blend Type 2
i3			counter variable used in generating forecast of Blend Type 3
BProc Time			Blend Processing Time
Blend Demand 2	7	3	Forecasted demand for Blend Type 2 in Blending Department
Blend Demand 3	7	3	Forecasted demand for Blend Type 3 in Blending Department
Tomake	3		Variable used for netting purposes between demands of Fill and production in Blend
planning			for maintaining the current period in forecast calculations
Fill Demand 1	7	3	Demand for Blend Type 1 in Filling Department
Fill Demand 2	7	3	Demand for Blend Type 2 in Filling Department
Fill Demand 3	7	3	Demand for Blend Type 3 in Filling Department
mean fill time			mean filling time for a batch
Torelease	3		Variable used to maintain the products coming in the Filling department
Screate	2		variable array of size 2 to maintain number of spools created for each Fill Type
BFcomb	3		variable array of size 3 to maintain the proportion of Fill Types for batches in Filling Department
Pack Demand 1	7	3	Demand for Blend Type 1 in Packing Department
Pack Demand 2	7	3	Demand for Blend Type 2 in Packing Department
Pack Demand 3	7	3	Demand for Blend Type 3 in Packing Department

Variable Name	Rows	Col.	Description
dist	3		variable array of size 3 to maintain the proportion of product types 2 and 3, 5 and 6, 8 and 9 respectively
FG	9		variable to maintain finished goods inventory
P Blend	3		variable of array size 3 to maintain the setup due to strength change in Filling Department
PSetup	3		variable of array size 3 to maintain the setup due to dose change in Filling Department
SpoolInv	6		variable to maintain spool inventory (6 types of spools)
spool	6		Variable to maintain spool inventory
Finalmake	6		Variable used for netting purposes between demands of packing and production in Filling
InvSpool	2		Variable used to maintain inventory as per Fill Type 1 and Fill Type 2
OH	6		Variable to maintain on hand inventory of spools in Packing Department
Relieve			Variable used to time the release of spools in Packing Department
checker			Variable used for actual demand occurrence. Array size 9 for each product type
dt			maintaining the current day for the demand variable
SS	9		amount of Safety Stock to be maintained
on hand	9		on hand quantity of finished goods when they are below SS
service level	9		Variable to record the fulfillment of service for each product type (9)
Blend made	3		Variable to track number of batches made in Blending department in a 7 day period
cats			Variable used at run begin to assign the "on hand" variable equal to "SS"
total service	9		counting the number of demand occurrences. Used to calculate the service level statistic
prod id var			used to assign product identity in Packing Department
temp count	6		used as a control variable in Packing sub-module
ifill			control variable used in generating forecast of Blend Type 1 for Filling Department
ifill3			control variable used in generating forecast of Blend Type 2 for Filling Department
ifill2			control variable used in generating forecast of Blend Type 3 for Filling Department
iPack			control variable used in generating forecast of Blend Type 1 for Packing Department
iPack2			control variable used in generating forecast of Blend Type 2 for Packing Department
iPack3			control variable used in generating forecast of Blend Type 3 for Packing Department
expiry	3		counter variable to record the number of batches expiring per month
del	3		counter variable used to time the demand occurrence in Forceast sub-module
batchinv			counting the number of batches in WIP

Variable Name	Rows	Col.	Description
u1	2		Variable to adjust the forecast error(0.1=10% error)
bcount			
seasonal index	91		Variable of array size 91 used to get the seasonality within a quarter
Fr	3		Variable of array size 3 to be used in Seasonal Demand Equation for 3 Blend Types
lost demand	9		demand lost in Final Packing Department
days			
qtr	4		Variable of array size 4 used to get seasonality within quarters
season			Variable having the current value of seasonality of a quarter
coun			
disp	6		Variable of array size 6 to guarantee removal of expired spools in Final Assembly
SS1	9		additional variable to change the safety stock during sensitivity analysis
Ser			variable used to re-set the service level and total service level variable after the warm-up period
input	3		Variable to record the number of batches made in entire simulation
output	3		Variable to record the number of batches expired in entire simulation

APPENDIX B

Description of the Make-to-Order model

This model has a similar structure to that of Make-to-Stock model, but the difference lies in the logic. The conceptual model has been described in main thesis document under the "Make-to-Order" model section. This model is comprised of three sub-models. The three sub-models represent the Blending, Filling and Packing Department respectively. Demand generation is a key process in Pull model and it is explained in the following section:

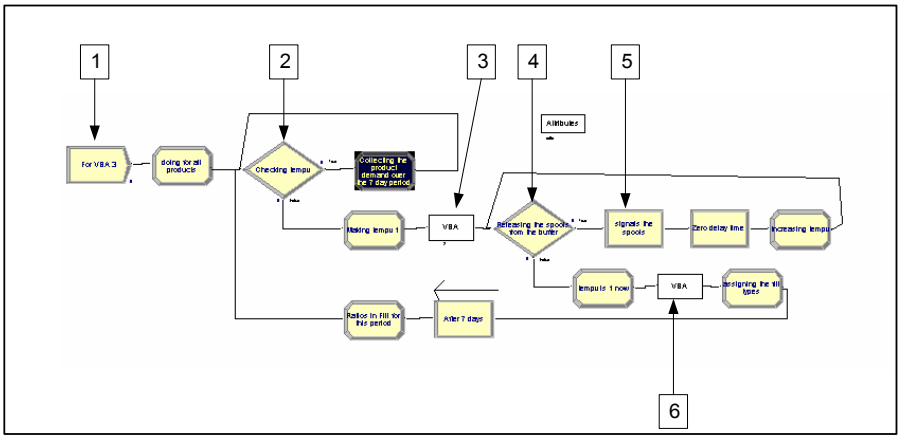

Figure 27: 7-Day Demand Accumulation

1. CREATE *for VBA3*
Task: Creates entities to the record the 7 day demand for each product type
Max. Arrivals: 1; First creation = 17.1 days;
We allow the system to be filled with some batches, spools and finished goods at the start, and hence, the first creation time for an entity in this module is 17.1 days. Only one entity is created and it will be circulated within the different modules explained in the following module descriptions. The variable "tempv" is set to 1 immediately after this.

2. IF *tempv <=9* THEN
    Pack Demand = Demand(tempv); Demand(tempv) = 0; tempv =tempv+1.
  ELSE
    Assign tempv to 1 and send to module 3.
  END IF
In this module, we assign the cumulative demand over the planning horizon to the Pack Demand variable for all the 9 products. Note that "Demand" and "Pack Demand" are arrays of size 9. Each row is for a product type.

3. FIRE VBA2
The entity fires the VBA code. Explanation of VBA code is provided later.

4. IF *tempv <=6* THEN
send the entity to module 5
ELSE
send the entity to module 6
END IF

The request for spools required by Packing department is calculated in the VBA2 block. In this module, we check if spools for all the product types are released from the Spool buffer. If the spools requests for all products are completed, the entity is passed to module 6.

5. SIGNAL *the spools and increment the "tempv" variable by 1*
In this module, we signal the release of spools from the HOLD block according to the product type. The number of spools to be released is stored in the variable "Srelease". This variable is an array of size 6.

6. "*tempv" is re-assigned the value 1 and the entity fires the VBA block 1. Depending on the number of spools released from the Spool buffer and its current inventory, the number of batches to be ordered to Blending Department is calculated in this block. The "tempv" variable is re-assigned the value 1 and the entity is delayed for 7 days of simulation time.*

Daily Demand Generation Modules:

These modules generate the demand quantities for the final packing on a daily basis. The demands are checked against availability of products in finished goods and service levels are monitored.

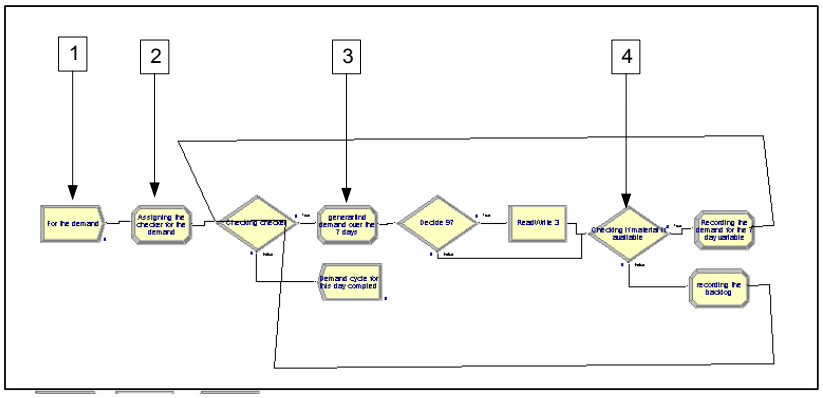

Figure 28: Daily Demand Module

1.CREATE *for daily demand*
Task: Creates an entity representing the daily demand for all the 9 product types.
Max. Arrivals= 1; First Creation: 11.0 days.

2. ASSIGN *checker = 1; dt = dt +1;*
In this module, the checker variable is initialized to 1. "checker" is a control variable used to generate demands for all the 9 product types. "dt" variable is used to monitor the current day.

3. ASSIGN *tempDemand = Final Demand(checker)*
"tempDemand" records the demand for a product type on a day. "Final Demand" is an expression in the Advanced Process Panel that generates the demand quantities as per the formulae shown in Table……

4. IF *FG(checker) > tempDemand* THEN
FG(checker) = FG(checker)-tempDemand;
Demand(checker) = Demand(checker) + tempDemand;
tempDemand = 0; service level(checker) = service level(checker)+1;
total service(checker) = total service(checker)+1;checker = checker+1
ELSE
Demand(checker) = Demand(checker) +tempDemand;
FG(checker) = 0; total service(checker) = total service(checker) +1;
Checker = checker +1;
END IF

In this module, we check if the demand quantity is greater than the available finished goods. If the finished goods are sufficient, the demand is fulfilled and "service level" variable is incremented by 1 along with the "total service level" variable. If the demand is greater than the finished goods inventory, we record the lost demand and only the "total service level" variable is incremented in this case.

The main sub-models i.e. the Blending sub-model; Filling sub-model and Packing sub-model in this case are very similar to that of the Make-to-Stock models discussed in Appendix A. Some subtle differences that exist are explained in the following sections.

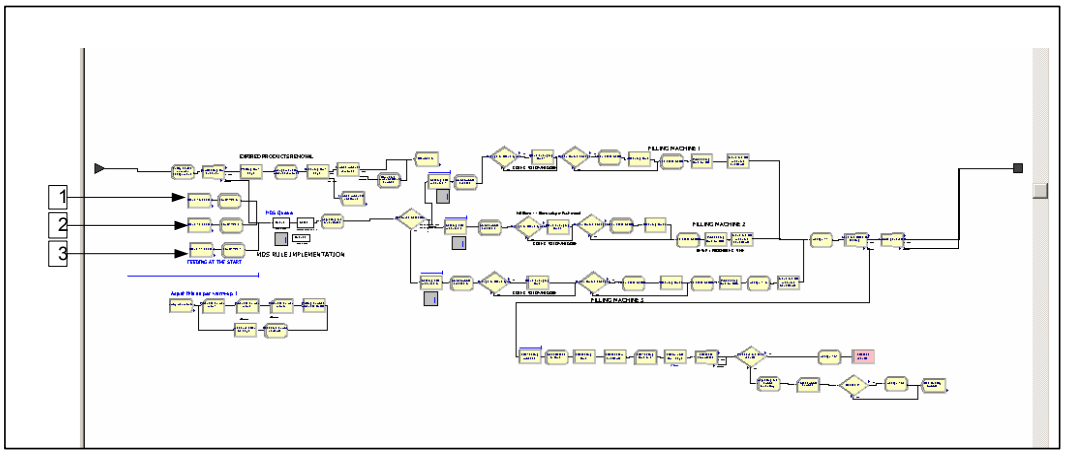

Figure 29: Filling Sub-Model of Make-to-Order Model.

1. CREATE *Blend T3 start*
Max. Arrivals = 1; Entities per arrival = 6; First creation = 0.0
Task: This module creates entities (batches of Blend Type C) for the Filling Department at the start of simulation. The number of entities created is dependent on estimated weekly demand of batches by Filling Department for batches of Type 3. As soon as the entities are created, they are assigned the attribute values such as Blend Type and Fill type and the system variables "Binventory" and "blendinv" are updated. "Binventory" variable records the WIP of batches of a particular Blend Type and "blendinv" records the total WIP of batches in the system.

2. CREATE *Blend T2 start*
Max. Arrivals = 1; Entities per arrival = 10; First creation = 0.0
Task: This module creates entities (batches of Blend Type B) for the Filling Department at the start of simulation. The number of entities created is dependent on estimated weekly demand of batches by Filling Department for batches of Type 2. As soon as the entities are created, they are assigned the attribute values such as Blend Type and Fill type and the system variables "Binventory" and "blendinv" are updated. "Binventory" variable records the WIP of batches of a particular Blend Type and "blendinv" records the total WIP of batches in the system.

3. CREATE *Blend T1 start*
Max. Arrivals = 1; Entities per arrival = 12; First creation = 0.0
Task: This module creates entities (batches of Blend Type A) for the Filling Department at the start of simulation. The number of entities created is dependent on estimated weekly demand of batches by Filling Department for batches of Type 1. As soon as the entities are created, they are assigned the attribute values such as Blend Type and Fill type and the system variables "Binventory" and "blendinv" are updated. "Binventory" variable records the WIP of batches of a particular Blend Type and "blendinv" records the total WIP of batches in the system.

Expired Products monitoring section:

In this modeling logic, we record the number of expired products per month. After recording the number of expired products in any given month, the variables are reset to zero. This process is repeated every 30 days of simulation time. At the end of simulation run, observational statistics related to number of expired batches for each Blend Type are obtained from the 'Statistics' module. A short description of labeled items from figure follows:

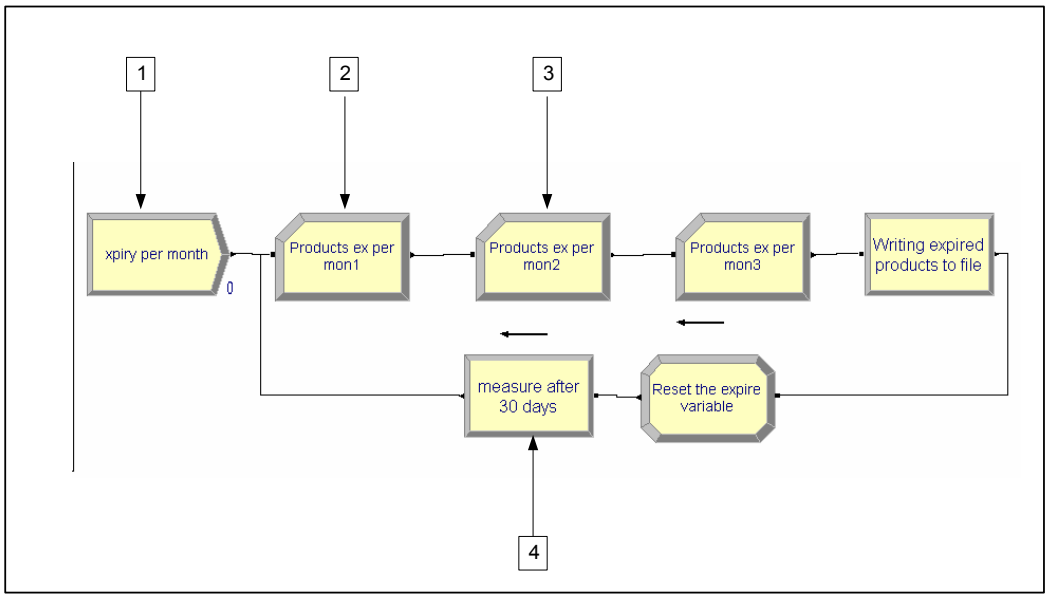

Figure 30: Expired Products Counting in Make-to-Order Model

1. CREATE *xpiry per month*
Max. Arrivals: 1; First Creation: 30 days
Task: An entity is created in this module to perform the function of recording number of batches of each product type expiring per month. The first entity is created on 30th day and this entity is circulated within the following modules every 30 days.

2. RECORD *products ex per mon1*
In this module, we record the number of batches of Blend Type A expiring in a month.

3. RECORD *products ex per mon2*
In this module, we record the number of batches of Blend Type b expiring in a month. Similarly, we record the number of batches of Blend Type C expiring in "products ex per mon3" module.

4. DELAY *measure after 30 days.*
The entity is delayed for duration of 30 days of simulation time. After 30 days the steps 1 to 3 are repeated.

The following figure shows the "Packing sub-module". As seen in the figure, this sub-module consists of three sections: expired products removal, Spool processing/packing and Fill results checking. The functionality of all these modules is almost similar to those explained for Make-to-Stock model in Appendix A.

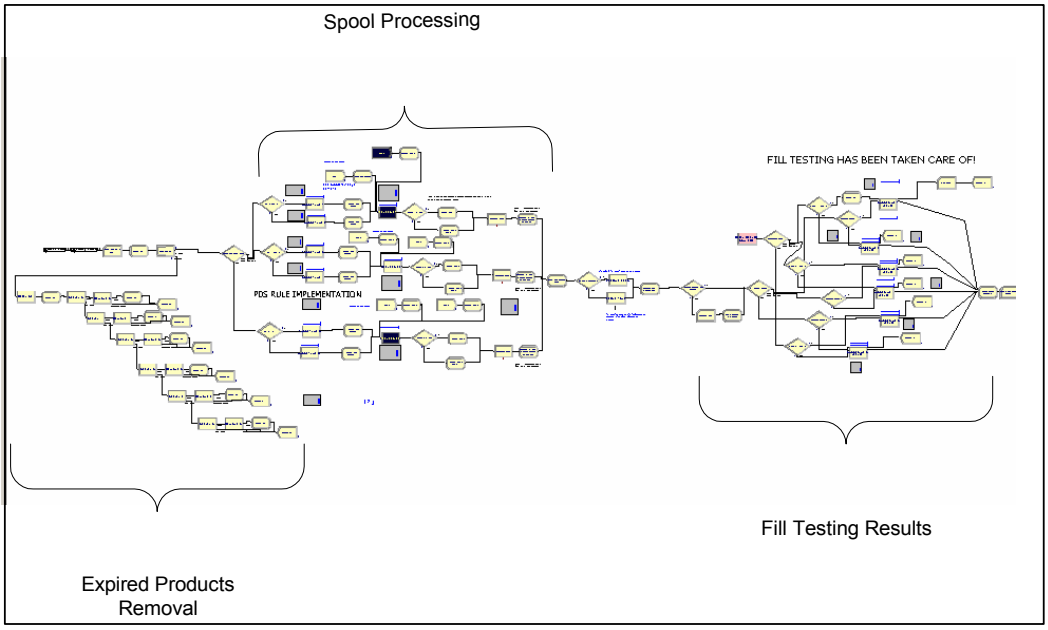

Figure 31: Packing Sub-Module of Make-to-Order Model

Explanation of the VBA block code:

This model consists of two VBA blocks that are fired by entities in the simulation. The reader is referred to Figure … for the procedural logic of these modules.

VBA block 2: This module consists of code that performs the following tasks:

a. The demand over the past 7 days is accumulated and converted appropriately in the number of spools required. The "Srelease" variable is updated accordingly. "Srelease" is the variable used to release the required number of spools from the spool buffer to the Final packing area. The "Srelease" variable is equivalent to "Kanbans" in a Pull System.
b. In addition, the proportion of product types A21 and A22, B21 and B22, C21 and C22 are updated in the "dist" variable as per the demands occurring for these product types(see Figure 3.3 for product structure)

VBA Block 1: This module consists of code that performs the following tasks:

a. The number of spools released from the fill buffer and unsatisfied demand for spools is recorded. These demands are then converted to the number of batches

required to replenish the fill buffer. If the demands are high, they are proportionately divided according to the available capacity.

b. Other variables related to the required batches of a particular fill type are also updated. We assign the Fill types in the Blend sub-model itself in this model.

The variables used in the Make-to-Order model are listed in the following table.

Table 21: List of Variables for Make-to-Order Model

Name of the Variable	Rows	Col.	Description
Bcleaning			for maintaining the days from last cleaning
Previous Blend			for maintaining the previous blend type in setup calculation
Binventory	3		for maintaining the blend inventory
Previous Fill	3		for maintaining the previous fill type in setup calculations in Filling suite
BClean			counting the number of days since last cleaning of Blend equipment
bfailures			Quality Yield variable in Blend
batches	3		for regulating maximum number of batches of same type in Blending suite
BatchNumber			product identification number assigned in Blending Department
Blend Setup	3		Setup time for Blend Change
BProc Time			Blend Processing Time
Tomake	3		Variable used for netting purposes between demands of Fill and production in Blend
planning			for maintaining the current period in forecast calculations
mean fill time	2		mean filling time for a batch
Torelease	3		Variable used to maintain the products coming in the Filling department
Screate	2		variable array of size 2 to maintain number of spools created for each Fill Type
BFcomb	2	3	variable used to maintain the number of batches for a particular combination of Blend Type and Fill Type
Pack Demand	9		Variable to record the demand for all the 9 product types over a 7 day planning horizon
dist	3		variable array of size 3 to maintain the proportion of product types 2 and 3, 5 and 6, 8 and 9 respectively
FG	9		Variable to maintain finished goods inventory
P Blend	3		variable of array size 3 to maintain the setup due to strength change in Filling Department
PSetup	3		variable of array size 3 to maintain the setup due to dose change in Filling Department
Spool Inv	2		variable to maintain the spool inventory according to Fill Type
spool	6		variable to maintain spool inventory (6 types of spools)
tempv			control variable used in accumulating the demand over a planning horizon
spool backlog	6		variable to record the unsatisfied request of spools in a planning period
Srelease	6		variable to release the spools from the filing buffer to Packing department
Blend Back	3		variable to record the number of batch requests unfulfilled.
Demand	9		variable to accumulate the daily demand

Name of the Variable	Rows	Col.	Description
checker			control variable used in daily demand generation
tempDemand			variable to record the current day's demand
dt			variable to record the current day's demand
prod id var			used to assign product identity in Packing Department
service level	9		variable to record the service level
total service	9		variable to record the instances of demand for a particular product type
day			variable to regulate schedule of Testing Lab.
mean blend time			mean blend processing time
expiry	3		variable to record the number of batches expired in a month
Previous Fill A	3		Fill variable to regulate setups
blendinv			variable to monitor the current inventory(WIP) of batches
seasonal index	91		quarterly seasonal index factor
factor			used to adjust the demand magnitude
New batch Blend	2	3	used to order a new batch on failure of spools in Fill testing Lab
Limit	2		control variable used with New Batch Blend
qtr	4		variable for quarter season index
season			season variable for current period
coun			control variable used for assigning seasonality
ser			variable used to re-set the service level after warm-up period
spool id			variable used to spool identification attribute to remove expired spools from the buffer
sid			spool identification number
Sxpired	6		number of spools expired per period
input	3		total number of batches produced
output	3		total number of batches expired