VOL. 6, NO. 4, APRIL 2011 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

OPTIMAL DISPATCHING IN A PERIODICALLY REVIEW IN ON-LINE MANUFACTURING SYSTEM WITH VENDORS EVALUATION

Dipak Ranjan Jana, K. V. Santha Kumari and B. K. Singh
Eritrea Institute of Technology, Mainafhi, Eritrea
E-Mail: drjana_nitjsr@yahoo.co.in

ABSTRACT

This paper, we consider dynamic dispatching control of a fully flexible online manufacturing system. Hence, vendors, who supply the materials, play an important role in this system. So, selection of vendors is much important. In a periodically reviewed, online manufacturing system where materials are dispatched from a central control station to different manufacturing sales. After production process, the parts are routed to inspection and quality control room. Hence optimal dispatching policies are pursued to minimize the in-process inventory carrying / holding cost over finite horizon. A dynamic programming formulation is developed for optimal dispatching which shows that the dynamic recursive functions (i.e. cost - to go - function) are convex and monotonic under the condition of low defects rates and relative low cost material handling. From the derivation we conclude that optimal dispatching sales for a combination of zero inventory and Non- zero inventory policies. Thus, the optimal input control is proved to be in the form of a pulling system.

Keyword: online manufacturing system, material dispatching control, in-process inventory, vendors evaluation, monotonic properties.

1. INTRODUCTION

In lean manufacturing, cellular manufacturing [John J. Liu, 1989] a blend of group technology and flexible manufacturing (FMS) has been gaining popularity in modern industries. An automated flexible manufacturing [George E. Monahan and Timothy L. Smunt-1987] process is asset of computer control work station connected by automated material handling which is used to produce multiple variations of parts at low to medium volume. In a cellular manufacturing, each cell consists of several machining centre and is capable of manufacturing different parts. Based on computer cluster analysis of global manufacturing process information, each particular type of cells is configured to efficiently manufacture a particular family of parts. With the extended machine ability at each cell, major setups and inter cell routing can be eliminated or gradually reduced, while the product mixed can be changed periodically.

In this paper we consider dynamic dispatching control of a fully flexible manufacturing system which is commonly adopted by U.S. FMS venders (Ref. Kearney and Trecker 1983 for sample system). The system has “n” manufacturing cells with limited local buffers and one central control situation with an unlimited central buffer. Each part in the current part population can be manufactured with one cell. After a part is finished at cell “i”, it will be sent to the central buffer where inspection is conducted with a failure rate of “p_i”. In order to keep on time delivery, a defective part must result in a new work order, either for reworking the parts or for initiating a new job order.

All parts are loaded or unloaded in the central buffer. The system is reviewed by a timesharing computer every”t” time interval (e.g. one hour) over a time span of T, which represents a short-term planning horizon. Hence, we allow time breaks due to tea time between review periods and the processing rates at each cell in each review period are independent random variables with general probability distributions. We assume no machine breakdowns within T.

Now we consider the following dispatching problem

i) Input control that is the determination of the number of new parts to enter the system at the beginning of each review period.
ii) Internal dispatching control, that is, the determination of the number of parts in the central buffer to be dispatched to each cell at the beginning of each review period. The objective of the dispatching control is to achieve a desirable level of in-process inventory, which includes the costs associated with parts waiting, machine idling and material handling.

In the research process we will stress mainly on input control and internal dispatching system in flexible manufacturing system with random processing time has focused on the analysis of aggregate steady-state performance (e.g. average system throughput and average time in system) by using queuing network models.

Kimemia and Gershwin (1985) considered part routing control by optimizing the static flow rates of each part to each station where local queues are assumed to be unlimited and the production rates of each part are assumed to be predetermined. Buzacott and Shanthikumar (1985) discussed average time in the system for a job shop where the external arrivals are controlled in a dispatching area. Yao and Buzacott (1986) employed a queueing network model with limited local buffers and reversible routings to evaluate the aggregate system performance of FMSs with the shortest-queue dispatching mechanism. Yao and Shanthikumar (1987) studied the problem of allocating the steady-state input rates among m cells so that the total throughput is maximized. See Yao and Buzacott (1986) for a survey on queueing network applications. In these queueing network models, the

ARPN Journal of Engineering and Applied Sciences

discrete and dynamic nature of manufacturing processes has not been reflected adequately.

Another group of researchers (e.g. Akellla and Kumar, 1986; Sharifnia, 1988; Maimon and Gerrshwin, 1988) have concentrated on dynamic control of the systems with failure-prone machines and defect-free processing. In these models, optimal production rates are dynamically determined to minimize some operational costs subject to random machine breakdowns. Most recently, Bielecki and Kumar (1988) showed that zero-inventory policies are optimal for a single- product failure-prone manufacturing system where the time between machine failures is an exponentially distributed random variable.

Some initial research work on dynamic control of machine-reliable systems with random processing times can be found in Seidmann and Schweitzer (1984), Maimon and choong (1987) and Liu (1989). Seidmann and Schweitzer consider one manufacturing cell that feeds the finished part to one production line. The processing times are assumed to be exponential. The optimal rule for the selection of parts at the cell is determined to minimize the expected shortage cost per unit time. Maimon and Choong use a stochastic optimal control model for the internal routing problem of a two-station FMS. They consider optimal allocation of the parts between two stations to minimize work-in-process (WIP), shortage and transportation cost. Liu discussed the periodic routing in a flexible machining system where flexible machining centers are utilized in parallel, and the processing times at each center are assumed to be stochastically stationary.

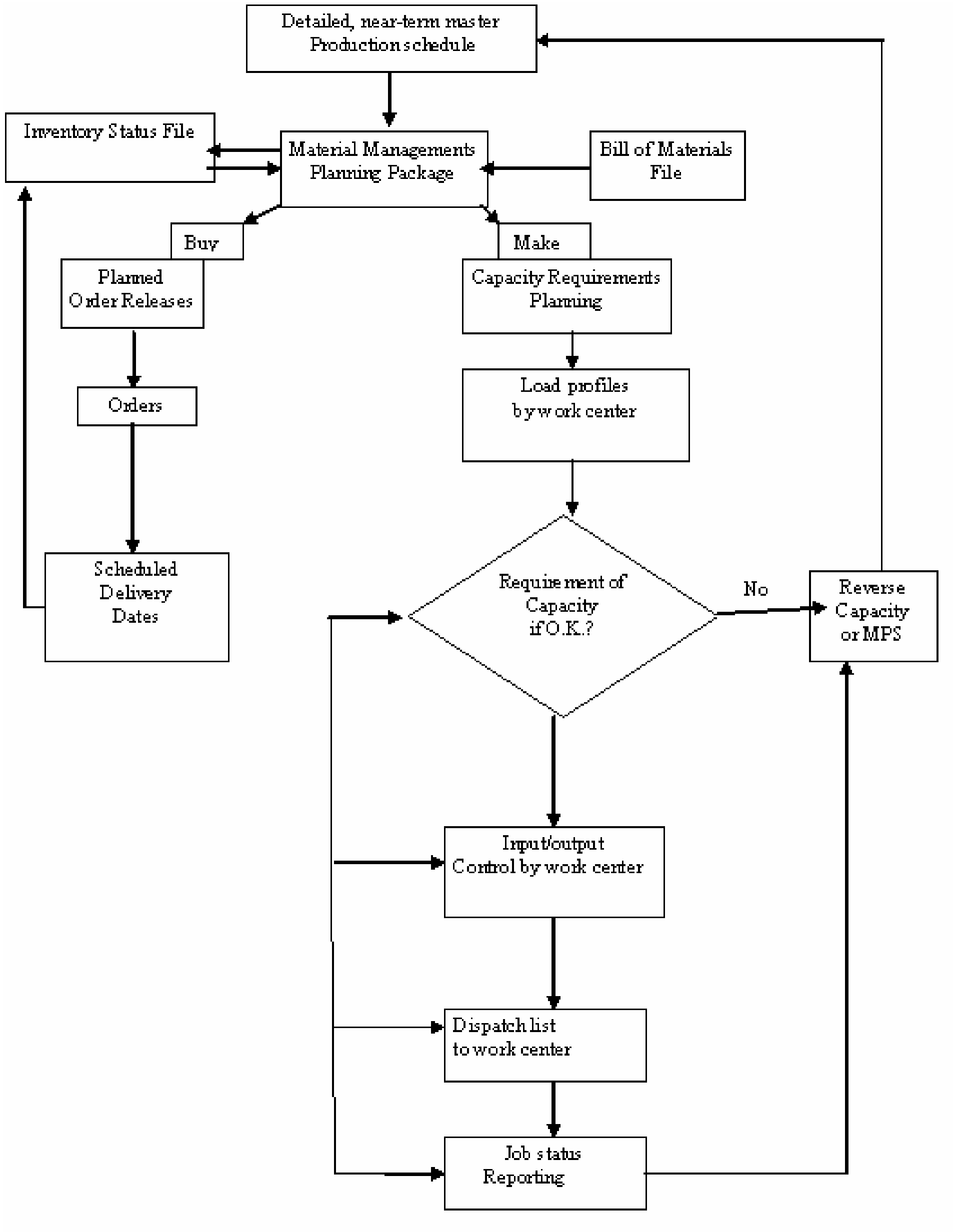
The problem we discuss in this paper concerns four basic elements in cellular manufacturing: dynamic routing, random processing rate, inspection failure and limited local buffer space. The machines are assumed to be reliable. We stress in-process inventory behavior and optimization of dynamic dispatching. First, we establish a set of typical per period costs as the measure of in-process inventories. Then, a dynamic programming formulation is developed for optimal dispatching control. The distributions of the in-process inventory flows are then derived.

The solution of the problem results in a series of nonlinear integer optimization problems. We prove that the necessary and sufficient condition for the convexity of the expected one-period cost is a low inspection failure rate and a relatively low part handling cost in comparison to machine-idling and holding costs. We show that the condition of low defect rate and low cost material handling is also sufficient for the dynamic recursive functions (i.e., cost-to-go functions) to be convex and monotonic. These convex and monotonic properties reveal that a combination of zero-inventory and nonzero-inventory policies may be necessary to achieve optimal dispatching. Finally, we propose two solution procedures, one by decomposition and the other by duplication that can reduce the complexity of computation and implementation.

In the next section, we develop the dynamic optimal dispatching (DOD) model and derive probability distributions for in-process inventory flows. In section 2, we discuss the convexity and monotonic of dynamic recursive functions. In the last section, we present applications of the convex and monotonic properties. The structure of the solution procedures is also discussed.

VOL. 6, NO. 4, APRIL 2011 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com



Flow chart for Material Requirements and Resource Planning

2. MODEL FOR VENDOR SELECTION

2.1 Vendor selection criteria

Under the following condition, vendor selection for L_1 (lowest) bidder following criteria should be strictly followed.

1. Quality of the products in terms of

(i) Fitness for the purpose at reasonable cost or moderate cost.
(ii) Conforming to the specifications and freedom from all defects.
(iii) Degree to which an inherent characteristics fulfill its requirements.
(iv) Customer satisfaction.

2. Cost of the product in terms of

(i) High quality at low cost.
(ii) High quality at moderate or suitable cost.

3. After sales and service

It means that after reporting fail or breakdown how much time it takes to repair it.

4. Giving prompt action and correct information.
5. Exhibit desire for business.
6. Technical Competence.
7. Source (Particular organization) used before.
8. Payment terms.
   It means paying installment basis with discount etc.

9. Research and development facility.
10. Favorable reputation of the organization.
11. Faull clause under this a supplier can be black listed for three years. Hence Faull clauses means after short supplying, not supplying at all.
12. Used before it means that the particular product has been used for its serviceability with respect to quality.

3. MATHEMATICAL FORMULATION OF VENDOR SELECTION PROBLEM (VSP)

(Multi-vendors Multi-customers Multi-items Situation)

3.1 Assumptions and notations

1) Only one item can be purchased from different vendor.
2) Quantity discounts are not taken into consideration.
3) Lead time and demand of the item are constant and known with certainty.
4) No shortage of the item is allowed for any of the vendor.
5) All the vendors can have the same number of items.

3.2 Index set

i = index for customer, for all i = 1, 2, ------, m
j = index for vendor, for all j = 1, 2, ----------, n
k = index for item, for all k = 1, 2, -------------, l

3.3 Decision variable

x_{ijk} = quantity of item k purchased by the i^{th} customer from vendor j

3.4 Parameters list

p_{ijk} = price of per unit item k of the ordered quantity by the i^{th} customer from vendor j
D_{ik} = aggregate demand of item k by the customer i
U_{ijk} = upper bound (limit) of the quantity of item k available from vendor j by the i^{th} customer
B_{jk} = budget allocated to item k for vendor j
W_{jk} = upper bound (limit) of supply quantity of item k by the j^{th} vendor
y_{ijk} = supply for item k from vendor j to the i^{th} customer

3.5 Model formulation

The objective function for the vendor selection problem is as follows:

$$\min z = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l} p_{ijk}x_{ijk} \quad \text{(Cost function)}$$

Subject to the constraints:

$$\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ijk} \geq D_{ik}, k = 1,2,......,l$$

(Demand constraint of each item)

$$\sum_{i=1}^{m}\sum_{j=1}^{n} p_{ijk}x_{ijk} \leq B_{jk}, k = 1,2,......,l$$

(Budget allocation constraint for each item)

$x_{ijk} \leq U_{ijk}$, i=1,2,…,m; j=1,2,…,n; k=1,2,….,l (Capacity constraint of the vendors)

$$\sum_{i=1}^{m}\sum_{j=1}^{n} y_{ijk}xi_{jk} \leq W_{jk}, k = 1,2,......l$$

(Vendors quota allocation constraint)

$x_{ijk} \geq 0$ (Non-negativity restriction)

4. THE MODEL FOR OPTIMAL DISPATCHING

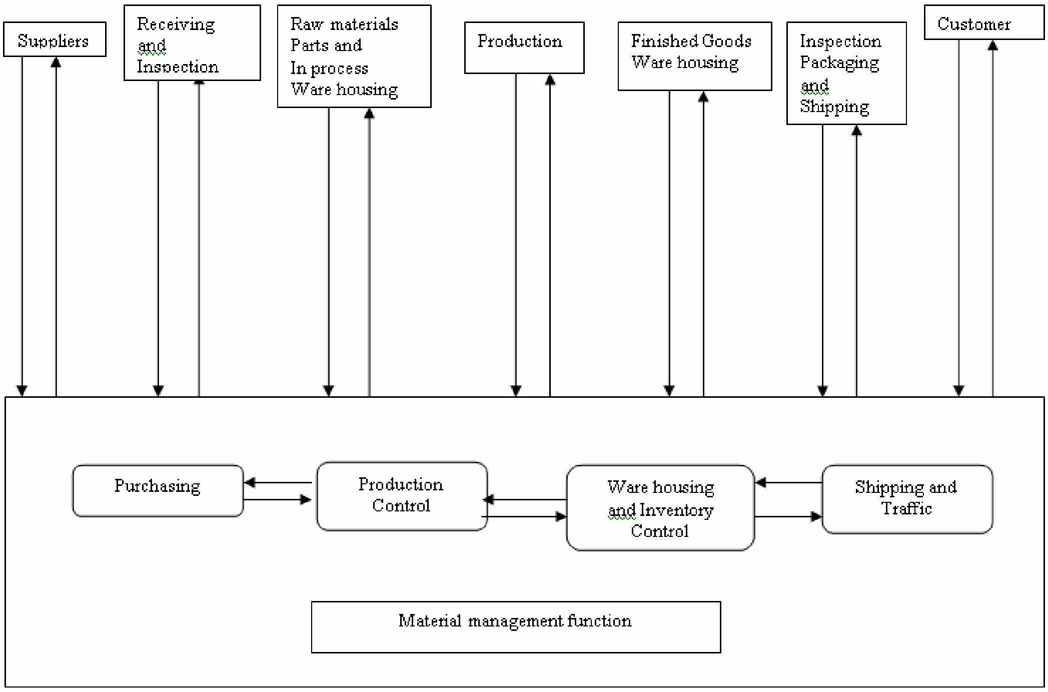
For the sake of presentation, we summarize the basic assumptions:

- n manufacturing cells, each with independent processing rates in each period;
- no intercellular routings;
- inspections are the Bernoulli type;
- each inspection failure results in a new work order;
- the finite planning horizon over which no machine breakdowns will occur;
- the travel time between cells is negligible; and
- the processing rate of a rework part follows the same probability distribution as that of a new part.

4.1 A dynamic programming formulation

The following notations will be used.

x_{ij} the number of parts in cell I before dispatching in period j;
q_{ij} the number of parts dispatched to cell I at the beginning of period j;
d_{ij} the potential processing rate at cell i in period j;
σ_{ij} the actual number of the parts produced at cell i in period j;
θ_{ij} the number of defective parts produced at cell i in period j;
Y_j the number of parts in the central buffer at the beginning of period j;
Z_j the number of new parts launched into the central buffer in period j;
R_i the buffer capacity of cell i;
P_i inspection failure rate for the parts completed at cell i;
T, the total number of review periods.



4.2 Implementation and computation of optimal dispatching

In this section, we discuss the effects of convexity and monotonic on optimal dispatching. As we can see, the convexity and monotonic properties result in simplifying both the implementation and computation of optimal dispatching policies.

Since Φ_j and B_j are shown to be non-decreasing in Y_j for all j, zero-inventory policy should be applied to the control of the central station. However, Y_j is not definitely controllable due to random feedback flows. Realistically, only initial recovery (x_1, Y_1) may be subject to control. Note that the minimum total expected cost under optimal dispatching is implied by $\Phi_1(x_1, Y_1)$. By the monotonic of Φ_j, the total expected cost attains its minimum only if $Y_1 = 0$, and therefore, zero initial inventories should be established at the central station. For local control, zero-inventory policy may not be optimal because the one-period cost B_j is not necessarily no decreasing in x_j. The following lemma presents another important result derived from the convex and monotonic properties.

4.3 Lemma 4

Given each state (x_j, Y_j) for any optimal policy (u_j^*, W_j^*)

$$W_j^* = \max\left\{\sum_{i=1}^{n}(u_{ij}^* - x_{ij}), Y_j\right\}$$

4.4 Proof

The result follows from V_j that is no decreasing in W_j. Using Theorem 2, the non-decreasing ness of V_j in W_j can be verified from (1), (2) and (6) by induction in index j. Then optimal input policy for period j is $Z_j^* = W_j^* - Y_j$, which is given by

$$Z_j^* = \begin{cases} \sum_{i=1}^{n}(u_{ij}^* - x_{ij}) - Y_j & \text{if } Y_j \langle \sum_{i=1}^{n}(u_{ij}^* - x_{ij}) \\ 0 & \text{if } Y_j \geq \sum_{i=1}^{n}(u_{ij}^* - x_{ij}) \end{cases}$$

Lemma 4 suggests a pulling control policy for the optimal input control. The term $\sum_{i=1}^{n}(u_{ij}^* - x_{ij})$ represents the number of parts pulled by local optimal control. Thus, the optimal input policy reads as follows: no new parts are launched to the system if there are enough parts at the central station to be pulled by the local cells; otherwise, new parts are launched so that the total number of parts available at the central station equals the number of parts required for the local cells.

The key is then to determine the local optimal control u_j^*. However, the local optimal control u_j^* is intricately related to (x_j, Y_j) because of the cross-cell constraints and random feedback flows. Determination of

u_j^* remain a difficult task. In what follows, we discuss two solution procedures that can reduce the burden in computing u_j^*.

The determination of optimal dispatching requires iterations in Φ_j for each (x_j, Y_j), where Φ_j, as given in (8), actually represents an $(n+1)$-dimensional non-linear integer programming problem. The first procedure, called Procedure 1, is a direct result of Lemma 4. By Lemma 4, for each (x_j, Y_j), the $(n+1)$-dimensional programming Φ_j can be decomposed into two n-dimensional minimization problems

$$\Phi_j = \min \{\Phi_j^1, \Phi_j^2\}$$

Where

$$\Phi_j^1 = \min\{V_j(.):$$
$$W_j = \sum_{i=1}^{n}(u_{ij} - x_{ij}) \geq Y_j,\ x_j \leq u_j \leq R\}$$
$$\Phi_j^2 = \min\{V_j(.):$$
$$W_j = Y_j \geq \sum_{i=1}^{n}(u_{ij} - x_{ij}),\ x_j \leq u_j \leq R\}$$

Let u_j^1 and u_j^2 be optimal solutions to Φ_j^1 and Φ_j^2, respectively. If $\Phi_j^1 \leq \Phi_j^2$, then $u_j^* = u_j^1$ and $W_j^* = \sum_{i=1}^{n}(u_{ij}^* - x_{ij})$. Otherwise, $u_j^* = u_j^2$ and $W_j^* = Y_j$.

The second solution procedure, called Procedure 2, uses Lagrangian multipliers. By duality theory, there is no duality gap for problem (8) since V_j and $M(.)$ are convex, and $H(.)$ is concave (see Chapter 6, Bazaraa and Shetty). Therefore, Φ_j can be evaluated by solving the associated Lagrangian dual problem

$$\xi_j^* = \max\{\psi_j, (\nu \mid x_j, Y_j) : \nu \geq 0\}$$

Where

$$\psi_j(\nu \mid x_j, Y_j) =$$
$$\inf\left\{V_j(.) + \nu\left(\sum_{n=1}^{n}(u_{ij} - x_{ij}) - W_j\right) : (u_j, W_j) \in U_{(u_j, Y_j)}\right\}$$
$$U_{(x_j, Y_j)} = \{(u_j, W_j) : x_i \leq u_i \leq R, W_j \geq Y_j\}$$

Further, ψ_j is concave (also see, Chapter 6, Bazaraa and Shetty) which means that a local optimal of ψ_j is also a global optimal. Note that for the DOD model, the Lagrangian multiplier ν is a scalar. The dual problem is then concerned with the maximization of ψ_j over the one-dimensional region $\{\nu : \nu \geq o\}$ where an ascent direction is also the steepest ascent direction. For the one-dimensional concave dual problem, an efficient Ascent Algorithm can be constructed (see pp. 194-201, Bazaraa and Shetty for more about ascent methods in the Lagrangian Dual Problem). With-in each iterations of the Ascent Algorithm, a search point ν_λ is first determined, and then $\psi_j(\nu_j \mid x_j, Y_j)$ is solved where the objective function for each given ν_λ isconvex and the constraint region $U_{(x_j, Y_j)}$ r is rectanglu. For each (x_j, Y_j), the Ascent Algorithm is carried out to find an optimal dispatching (u_j^*, W_j^*). It should be noted that ψ_j represents an $(n+1)$-dimensional nonlinear programming problem.

We tested the algorithms, coded in PASCAL by the author, for two cases (i.e., $n = 3$ and $n = 6$) on a mainframe computer (a Unisys 7000/40), using different system data sets (e.g., buffer capacity varies from 1 to 9 lots, the length of review period ranges from 60 to 240 minutes, and the number of review periods ranges from 4 to 12). For $n = 3$, the required CPU time ranges from 0.5 to 4 minutes, and the CPU time for the $n = 6$ case is within a range of 1.5 to 14 minutes. According to our experiments, there seems to be no significant difference in computational performance between the two solution procedures. Further algorithm refinement and a detailed report on computational experience can be obtained from the author.

5. SUMMARY AND DISCUSSIONS

A dynamic optimal dispatching (DOD) model is developed for minimizing in-process inventory costs in on-line manufacturing network system with general independent processing rates. The cost-to-go function is shown to be convex provided that a low processing defect rate and low cost material handling can be attained. With the convexity and monotonic, efficient solution procedures can be constructed that simplify the computation and implementation. This result identifies two important factors in improving productivity of flexible manufacturing systems and indicates the importance of work-in-process and quality control in manufacturing processes. Our analysis also shows that zero-inventory policy is not always applicable, and an optimal policy can well be a combination of zero-inventory and nonzero-inventory strategies.

Note that the solution of the problem is still complex. Future research on this topic includes the study of the general form of optimal dispatching policies and development of efficient heuristic algorithms. It is also of theoretical and practical interest to examine the case of the heterogeneous part population and infinite planning horizon.

REFERENCES

Akella R. and P.R. Kumar. 1986. Optimal Control of Production Rate in a Failure Prone Manufacturing Systems. IEEE Trans Auto. Control. 31: 116-126.

Bazaraa M.S. and C.M. Shetty. 1979. Nonlinear Programming: Theory and Algorithms. John Wiley, New York.

Bielecki T. and P.R. Kumar. 1988. Optimality of Zero-Inventory Policies for Unreliable Manufacturing Systems. Opns. Res. 36: 532-541.

Buzacott J.A. and J.G. Shanthilkumar. 1985. On Approximate Queuing Models of Dynamic Job Shops. Mgmt. Sci. 31: 870-887.

Denardo E.V. 1978. Dynamic Programming: Models and Applications. Prentice-Hall, Englewood Cliffs, N. J.

Kearney and Trecker Co. 1983. KT's World of advanced Manufacturing Technologies. Kearney and Treeker Co., Milwaukee, Wise.

Kimemia J.G. and S.B. Bershwin. 1985. Flow Optimization in Flexible Manufacturing Systems. Int. J. Prod. Res. 23: 81-96.

LIU J.J. 1989. The Periodic Routing of a Flexible Manufacturing System With Centralized In-Process Inventory Flows. Int. J. Prod. Res. (27).

Maimon O.Z. and Y.F. Choong. 1987. Dynamic Routing in Reentrant Flexible Manufacturing System. Robot, Comput. Aided Manufact. 3: 295-300.

Maimon O.Z. and S.B. Gershwin. 1988. Dynamic Scheduling and Routing for Flexible Manufacturing Systems That Have Unreliable Machines. Opns. Res. 36: 279-292.

Seidmann A. and P.J. Schwehzer. 1984. Part Selection Policy for a Flexible Manufacturing Cell Feeding Several Production Lines. IIE Trans. 16: 355-362.

Sharifnia A. 1988. Optimal Production Control of a Manufacturing System with Multiple Machine States. IEEE Trans. Auto. Control. 33: 620-625.

Yao D.D. and J.A. Buzacott. 1986. Models of Flexible Manufacturing Systems with Limited Local Buffers. Inst. J. Prod. Res. 24: 107-118.

Yao D.D. and J.G. Shanthikumar. 1987. The Optimal Input Rates to a System of Manufacturing Cells. INFOR. 25: 57-65.