"STRATEGIC MARKETING, PRODUCTION, AND DISTRIBUTION PLANNING OF AN INTEGRATED MANUFACTURING SYSTEM

by

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Printed at INSEAD,
Fontainebleau, France

Strategic Marketing, Production, and Distribution Planning of an Integrated Manufacturing System

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ABSTRACT

This paper extends Pourbabai's (1991) results for generating a strategic marketing and production plan for an Integrated Manufacturing System (IMS) to include distribution decisions. The paper introduces additional distribution decision variables and constraints for both of **loading models** proposed by Pourbabai (1991). The new models optimize the utilization of the processing capabilities of an IMS consisting of a set of heterogeneous workstations. The objective to be maximized includes, the fixed and variable market values of each job, the fixed and variable processing costs of each job, the setup costs, and the fixed and variable distribution costs. Each job requires a single aggregated stage of operation; job splitting is allowed; and the processing priorities of all jobs during the planning time horizon are given. **Setup times collapsing** is also allowed, to shorten the completion times of some jobs. The proposed models are fixed charge problems which can be solved by a mixed integer programming algorithm.

Key Words: Loading Strategy, Aggregate Scheduling, Aggregate Production and Distribution Planning, Decision Support System, Optimization.

1. INTRODUCTION

Computer Integrated Manufacturing (CIM) concepts such as CAD, CAM, Group Technology (GT), etc. are implemented in many manufacturing industries. Many companies have improved the entire supplier/ customer chain by sharing information through better communication systems across the full spectrum of the supply chain and by implementing other CIM concepts. However, the potential benefits of CIM have not yet been fully realized. One of the major requirements for achieving full benefits is a general revision of the techniques of planning and control of production and distribution. A careful planning of production and distribution is vital for an efficient exploitation of production capabilities of Integrated Manufacturing Systems (IMS).

In this paper, quantitative decision making models developed by Pourbabai (1991) are extended in order to include distribution decisions. This is necessary when workstations (production lines) are in different locations, in order for the proposed models to properly tradeoff profit components with various costs involved in production and distribution. Indeed, transportation time introduces another constraint which needs to be considered in order to meet the due dates set. In some cases the transportation time is far longer than the manufacturing throughput time. Examples of this type of environment are car or hifi manufacturers who have several production lines in different countries and produc their goods **Just-In-Time**. In such situations the costs and the role of distribution cannot be neglected.

The new models include :

i) distribution costs such as short term holding costs and transportation costs from workstations to distribution centers and from distribution centers to customers;

ii) additional constraints to explicitly consider the transportation times from workstations to distribution centers and from distribution centers to customers.

The objective to be maximized models the tradeoffs between total sales income, total processing costs, total distribution costs, and total setup costs of the supply chain. The new models can assist operations managers in selecting potential customer orders such that the net operational profit during the planning horizon will be maximized. Based on these models, the profitable orders and the lot-sizes of each component of each job at each workstation (production line) will be identified. Furthermore, based on the solutions of these models, the resulting operational plans can be plotted on Gantt charts for shop floor supervisors.

The models are designed to react under dynamic manufacturing environments where a central information system is available. Similar to Pourbabai (1989-b), we recommend to incorporate either the proposed models or their enhanced tailor made versions in an appropriate Decision Support System (DSS), see Figure 1. Such a computer support system will enable the decision makers to plan and control various activities of a modern CIM system. The advantage of having such a computer support system is that whenever the values of those internal and external parameters which influence the outcomes of the decision making process change, those new inputs can readily be considered, and thus a new realistic and comprehensive operational plan can be generated, even on a short term planning horizon. A more detailed discussion of the components of an appropriate DSS can be found in Pourbabai (1989-b). For a discussion of CIM and flexible manufacturing systems, see Randy (1983) and Hartley (1984).

The organization of this paper is as follows. Section 2 includes the assumptions made, the notation, a short discussion about assigning jobs priorities and the mathematical programming models. In section 3, a solution algorithm is presented. Finally, in section 4, some conclusions are drawn.

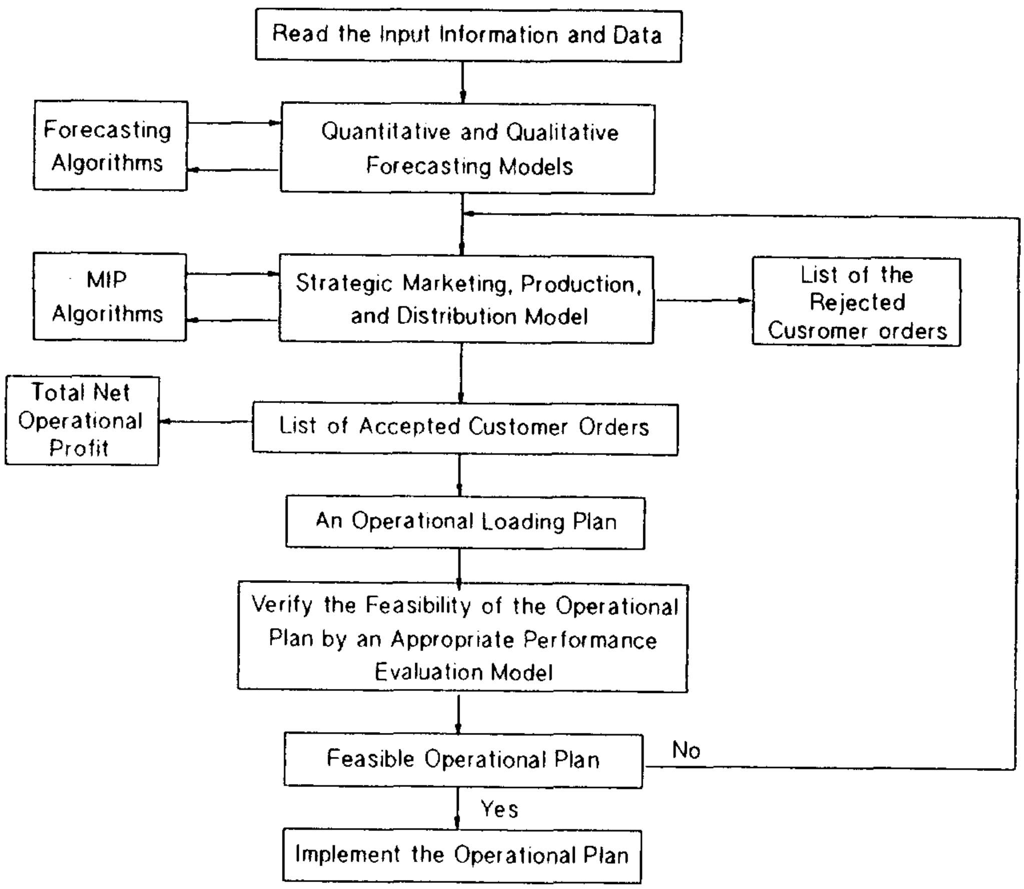

Figure 1. Flowchart of the proposed Model, Pourbabai (1989-c)

2. MODEL COMPONENTS

2.a. Limitations and Capabilities

1. The planning horizon needs to be sufficiently short to enable decision makers to explicitly or implicitly consider all changes due to the internal and external information at the beginning of each planning horizon. Hence, new operational plans can be generated as frequently as needed.

2. Workstations (production lines) are situated in different locations.

3. Based on the bill of materials, the following parameters should be identified;

   i) the number of units of each component of each product. Note that a component may be used in different products. In this paper, the term "job" refers to a batch of identical parts;

   ii) the due date of each job; and

   iii) the release date of each job; i.e. the earliest time that a job can start.

4. Each workstation (production line) is designed based on the GT concept (see Waghodekar and Sahu (1983) and Ham et al. (1985)). Furthermore, all operations on a job are assumed to be executable on at least one of the workstations. Hence, we only require an estimate of the total required processing time for each job at each compatible workstation.

5. The required aggregated processing time at each workstation is a random variable and could consist of the following corresponding time components (random variables):

   i) summation of the processing times of all operations of each generic workpiece belonging to the family of parts at the corresponding workstation;

   ii) the routing delay time;

   iii) the operator delay time;

   iv) the machine loading delay time;

   v) the machine unloading delay time;

vi) the breakdown times and the corresponding repair times;

vii) the material handling delay time.

Thus, the aggregated processing time is in effect the resulting convolution of a finite number of random variables (e.g., routing delay time, loading delay time, etc.). In our models, only the expected value of the aggregated processing time at each workstation is used.

6. If there are jobs that can be processed at compatible workstations, job splitting is allowed for each job. That is, each batch of identical parts can be split among all the compatible workstations which are individually capable of processing all operations. The primary effect of job splitting is to reduce the completion time of each job;

7. The processing order of the jobs is prespecified according to a desirable dispatching rule during the short term planning horizon (see section 2.c).

8. Setup times can sometimes be saved by combining batches of the same job types but with different due dates.

2.b. Notations

Indices:

i : the job type index;
$(i=1,\ldots,N)$

j : the workstation (production line) index;
$(j=1,\ldots,M)$

k : the due date index (i.e. k=1 is the first order to be delivered, k=2 the second order to be delivered and so on.);
$(k=1,\ldots,K)$

l : the distribution center index;
$(l=1,\ldots,L)$

Parameters:

$J_{i,j,k}$:= the job with job type index i of the customer with the due date index k which has to be produced at workstation j;

$d_{i,k}$:= the number of units of the job type index i of the customer with the due date index k (demand quantity);

$t_{i,j}$:= the time required to process the job type index i at workstation j;

$D_{i,k}$:= the due date of the job i of the customer with the due date index k;

$s_{i,j}$:= the setup time required for job i for processing at workstation j;

P_i := the variable market value of each unit of the job with type index i;

P^*_i := the fixed market value of each unit of the job with type index i;

$C^*_{i,j,k}$:= the fixed cost for processing job $J_{i,j,k}$;

$C'_{i,j,k}$:= the variable cost for processing job $J_{i,j,k}$;

$C_{i,j,k}$:= the fixed setup cost for job $J_{i,j,k}$;

$\alpha_{i,j,k,l}$:= a sufficiently large constant (e.g. $\alpha_{i,j,k,l} \geq d_{i,k}$);

$a_{i,j,l}$:= the variable transportation cost for handling one unit of job i from workstation j to distribution center l;

$b_{i,k,l}$:= the variable transportation cost for handling one unit of job i from distribution center l to customer with due date index k;

$tw_{j,l}$:= traveling time between workstation j and distribution center l;

$tc_{k,l}$:= traveling time between distribution center l and customer with due date index k;

$r_{i,l}$:= holding cost per unit of time for job i at distribution center l;

B := $\max_{i,k} \{D_{i,k}\}$

$EC_{i,k}$:= earliness cost for one unit of the job with type index i and due date index k. This cost is the average holding cost per unit $(1/L^*\Sigma_l\ r_{il})$.

Decision Variables:

$Q_{i,k}$:= 1 , if the job with type index i and due date index k is going to be manufactured;
0 , otherwise;

$X_{i,j,k,l}$:= the number of units of the job with type index i of customer with due date index k to be produced at workstation j and delivered via distribution center l;

$Y_{i,j,k,l}$:= 1 , if $X_{i,j,k,l} > 0$
0 , if $X_{i,j,k,l} = 0$.

$Z_{i,j,k,l}$:= the completion time of the job with type index i of the customer with due date index k to be produced at workstation j and delivered via distribution l;

$R_{i,k}$:= $\max_{j,l} \{Z_{i,j,k,l} + tw_{j,l}\, Y_{i,j,k,l} + tc_{k,l}\, Y_{i,j,k,l}\}$ = delivery time of the job with type index i to the customer with due date index k.

$A_{i,j,k,l}$:= $Z_{i,j,k,l} * Q_{i,k}$

$E_{i,k}$:= earliness time of the job with type index i and due date index k.

2.c Assigning Priorities

The reason for specifying the processing order of jobs is that, because of the dynamic nature of the manufacturing process, the plan recommended by the operations managers may not be implementable by the shop floor supervisors. Commonly, by the time the plan to be implemented, the parameters used for generating it may have changed. For this reason, we assume that during the short term planning horizon, the processing order of the jobs is specified based on a dispatching rule which is mutually acceptable by operations managers and shop floor supervisors.

The basic idea of allocating indices of parameters and decision variables of the proposed models according to a prespecified dispatching rule is now described. In general, a job cannot be processed at any workstation, delete its corresponding parameters and decision variables from the model. Note that the proposed models are developed based on the following specific sequence for all jobs to be processed at workstation j;

$\{[J_{1,j,1},J_{2,j,1},\ldots,J_{N,j,1}];[J_{1,j,2},J_{2,j,2},\ldots,J_{N,j,2}];\ldots;[J_{1,j,K},J_{2,j,K},\ldots,J_{N,j,K}]\}$ for $j=1$ to M.

Now, **depending on a desirable dispatching rule,** the above indices should be accordingly assigned to various jobs. The following dispatching rule is proposed to demonstrate how this can be implemented at workstation j;

i) among all the K available due dates, accordingly assign due date index $k=1,2,\ldots,K$ to the jobs with the earliest due date, next earliest due date,..., and the latest due date, respectively;

ii) among all the N available jobs types with a common due date index, arbitrarily assign the job type index $i=1, 2, \ldots,$ and N, to those jobs.

Note that for example, a job with the highest job type index (e.g., $i=1$) indicates a particular part type which is different than another part type with the lowest job type index (e.g., $i=N$). It is also noted that for setup times collapsing, all jobs with an identical job type index and different due date indices can be processed together.

The above dispatching rules can be simply restated to accommodate a new discipline by accordingly reassigning the corresponding indices if one desires to use any other dispatching rule.

2.c. **First Model**

In this model, an operational plan is obtained by finding the optimal lot-sizes such that the total net operational profit is maximized, while setup times collapsing is allowed. The model is as follows.

$$\max.\ \Omega = \{ \sum_{i=1} \sum_{k=1} P_i^* \cdot Q_{i,k} + \sum_{i=1} \sum_{j=1} \sum_{k=1} \sum_{l=1} P_i \cdot X_{i,j,k,l}$$

$$- \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{K} \sum_{l=1}^{L} (C_{i,j,k} + C^*_{i,j,k}) \cdot Y_{i,j,k,l} - \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{K} \sum_{l=1}^{L} C'_{i,j,k} \cdot X_{i,j,k,l}$$

$$- \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{K} \sum_{l=1}^{L} (a_{i,j,l} + b_{i,k,l}) \cdot X_{i,j,k,l}$$

$$- \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{K} \sum_{l=1}^{L} r_{i,l} \cdot (D_{i,k} - tw_{j,l} - tc_{k,l} - Z_{i,j,k,l}) \cdot X_{i,j,k,l} \} \qquad (1)$$

Subject to:

$$\sum_{j=1}^{M} \sum_{k'=1}^{k} \sum_{l=1}^{L} X_{i,j,k',l} \geq \sum_{k'=1}^{k} Q_{i,k'} \cdot d_{i,k'} \qquad (2)$$

$(i=1,\ldots,N\ ;\ k=1,\ldots,K)$

$$\sum_{j=1}^{M} \sum_{k=1}^{K} \sum_{l=1}^{L} X_{i,j,k,l} = \sum_{k=1}^{K} Q_{i,k} \cdot d_{i,k}$$

$(i=1,\ldots,N)$ (3)

$$Z_{i,j,k,l} \geq Z_{i-1,j,k,l} + t_{i,j} \cdot X_{i,j,k,l} + s_{i,j} \cdot Y_{i,j,k,l}$$

$(i=2,\ldots,N\ ;\ j=1,\ldots,M\ ;\ k=1,\ldots,K\ ;\ l=1,\ldots,L)$

(4)

$$Z_{1,j,k,l} \geq Z_{N,j,k-1,l} + t_{1,j} \cdot X_{1,j,k,l} + s_{1,j} \cdot Y_{1,j,k,l}$$

$(j=1,\ldots,M\ ;\ k=2,\ldots,K\ ;\ l=1,\ldots,L)$ (5)

$$R_{i,k} \geq Z_{i,j,k,l} + tw_{j,l} \cdot Y_{i,j,k,l} + tc_{k,l} \cdot Y_{i,j,k,l} \tag{6}$$
$$(i=1,\ldots,N \ ; \ j=1,\ldots,M \ ; \ k=1,\ldots,K \ ; \ l=1,\ldots,L)$$

$$R_{i,k} \leq D_{i,k}$$
$$(i=1,\ldots,N \ ; \ k=1,\ldots,K) \tag{7}$$

$$X_{i,j,k,l} \leq \alpha_{i,j,k,l} \cdot Y_{i,j,k,l}$$
$$(i=1,\ldots,N \ ; \ j=1,\ldots,M \ ; \ k=1,\ldots,K \ ; \ l=1,\ldots,L) \tag{8}$$

$$X_{i,j,k,l} \ , \ Z_{i,j,k,l} \ , \ R_{i,k} \geq 0 \ ;$$
$$Q_{i,k} \ , \ Y_{i,j,k,l} \in \{0,1\} \tag{9}$$
$$(i=1,\ldots,N \ ; \ j=1,\ldots,M \ ; \ k=1,\ldots,K \ ; \ l=1,\ldots,L)$$

Constraints Description:

In constraints (2) and (3) binary variable $Q_{i,k}$ selects which jobs will be manufactured and which jobs will be rejected. Constraint sets (4) and (5) identify the completion time of each job according to the dispatching rule. That is, the completion time of each job must be greater than or equal to the summation of the completion time of its preceding job, its total required processing time, and its required setup time. Constraint sets (6) and (7) are provided to respect the due date given the completion time and transportation times. Constraint set (8) is given to serve three functions;

i) to appropriately account for the setup times of selected jobs;

ii) to identify the workstations to be used for processing each job;

iii) thirdly, to specify the inventory capacity of each workstation by appropriately selecting $\alpha_{i,j,k,l}$; and to prevent allocation of excessive units to the transporter station corresponding to the workstation j.

Objective Function Description:

The first term of the objective function indicates the total fixed selling revenue, the second represents the total variable selling revenue, the third takes care of total fixed and variable processing costs, the forth indicates the setup cost, the fifth represents the total transportation cost while the last term indicates the holding costs.

It is obvious that the last term of the objective function is not linear due to multiplication of $Z_{i,j,k,l}$ and $X_{i,j,k,l}$. However, this term can be linearized by the following assumption. We assume that the production of a job for a given customer is first sent to the distribution center(s) and upon the completion of the whole job, the products are transported from the distribution center (s) to the customer. This assumption which is a good approximation allows us to implement the EOQ concept and replace $\Sigma_j \Sigma_l X_{i,j,k,l}$ by the average inventory size in all distribution centers, $d_{i,k}/2$. Because a job with priority index i for a given customer with due date index k may not be produced at all, we multiply $d_{i,k}/2$ by $Q_{i,k}$. Thus we get $Z_{i,j,k,l} * d_{i,k}/2 * Q_{i,k}$ which is still not linear but can be easily linearized as the term is composed of a continuous and a 0-1 variable. For this purpose we introduce the continuous variable $A_{i,j,k,l}$ as defined in the list of variables. For the linearization we need also to add the following constraints:

$$A_{i,j,k,l} \leq B \cdot Q_{i,k}$$

$$(i=1,\ldots,N \; ; \; j=1,\ldots,M \; ; \; k=1,\ldots,K \; ; \; l=1,\ldots,L) \qquad (10)$$

$$A_{i,j,k,l} \leq Z_{i,j,k,l}$$

$$(i=1,\ldots,N \; ; \; j=1,\ldots,M \; ; \; k=1,\ldots,K \; ; \; l=1,\ldots,L) \qquad (11)$$

$$A_{i,j,k,l} \geq Z_{i,j,k,l} - B \cdot (1 - Q_{i,k})$$

$$(i=1,\ldots,N \; ; \; j=1,\ldots,M \; ; \; k=1,\ldots,K \; ; \; l=1,\ldots,L)$$

(12)

The last term in the objective function, the inventory holding cost, will then change from:

$$\sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{K}\sum_{l=1}^{L} r_{i,l} \cdot (D_{i,k} - tw_{j,l} - tc_{k,l} - Z_{i,j,k,l}) \cdot X_{i,j,k,l} \qquad (13)$$

to:

$$\sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{K}\sum_{l=1}^{L} r_{i,l} \cdot (D_{i,k} - tw_{j,l} - tc_{k,l}) \cdot X_{i,j,k,l} - \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{K}\sum_{l=1}^{L} \frac{r_{i,l}}{L} \cdot \frac{d_{i,k}}{2} \cdot A_{i,j,k,l} \qquad (14)$$

Notice that the inventory cost is divided by L to get the average holding cost. Another way of linearizing the last term is to replace (13) by:

$$\sum_{i=1}^{N}\sum_{k=1}^{K} EC_{i,k} \cdot E_{i,k} \qquad (15)$$

or the total earliness cost, and change constraint set (7) by:

$$R_{i,k} + E_{i,k} = D_{i,k} \cdot Q_{i,k}$$

$$(i=1,\ldots,N \; ; \; k=1,\ldots,K)$$

(16)

The second approach aggregates more the inventory holding costs and reduces the complexity of the model.

2.d. **Second Model**

In this model, an operational plan is obtained by finding the optimal lot-sizes such that the total net operational profit is maximized, while setup times collapsing is not allowed. The only difference between the second model and the first model is as follows; constraints (2) and (3) in the first model are replaced by the following constraint (17). Thus, the production quantity of each job type must equal its demand quantity.

$$\sum_{j=1}^{M}\sum_{l=1}^{L} X_{i,j,k,l} = Q_{i,k} \cdot d_{i,k} \qquad (17)$$

$$(i=1,\ldots,N \; ; \; k=1,\ldots,K)$$

Note that the above model does have an application in a **just-in-time** manufacturing environment. To provide additional information, figure 2 is given. There, assuming that $X_{i,j,k,l} > 0$, for i=1 to N, j=1 to M, k=1 to K, and l=1 to L, a typical solution is plotted on the corresponding Gantt chart to provide more insights.

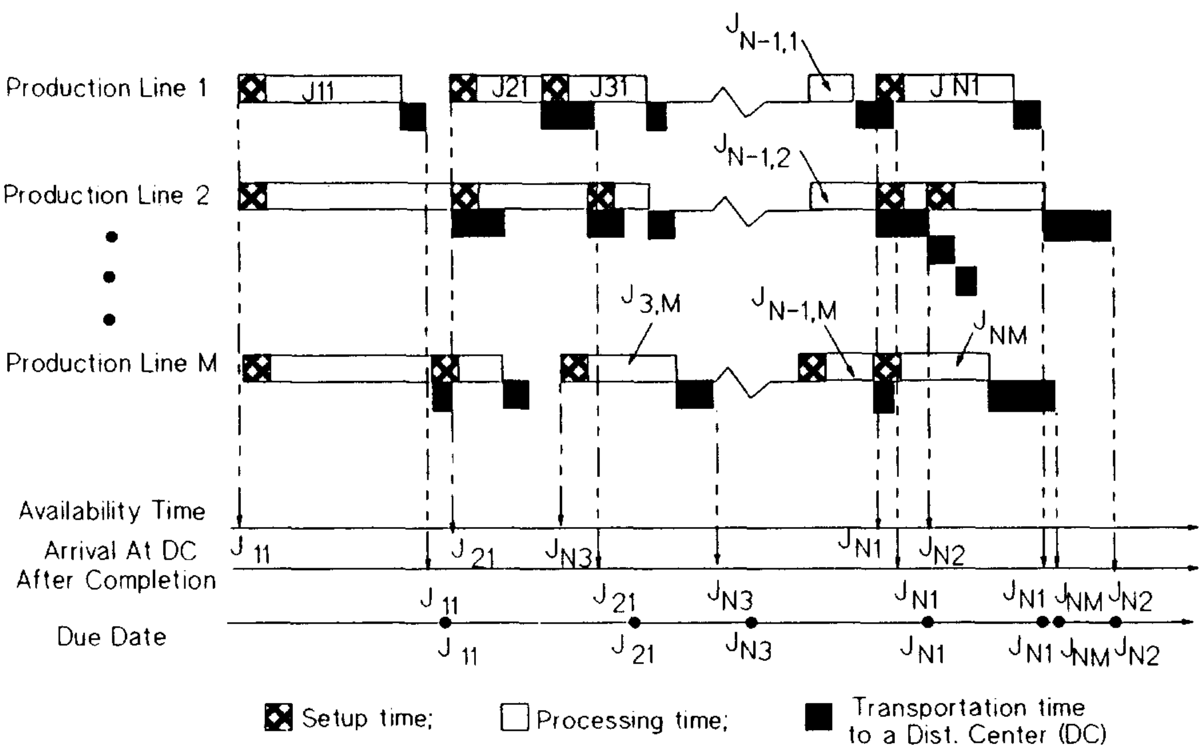

Figure 2. Gantt Chart of an Operational Plan.

3. SOLUTION ALGORITHMS

The models introduced in the previous section are fixed charge problems which are represented by compatible mixed binary linear programming models and can be solved by one of the standard algorithms which have been developed for solving such problems. For a review of some of those algorithms see Shapiro (1979). In this paper, in order to improve the computational performance of the model, it is assumed that each integral $X_{i,j,k,l}$ variable can be treated as a continuous variable. Note that this latter assumption is justified given that the production quantities at each workstation are sufficiently large.

There already exist computationally effective commercial softwares for solving our models. For example, see IBM Mixed Integer Programming/370 Program Reference (1975) and IBM Mathematical Programming system Extended/370 Program Reference Manual (1979), or IBM Optimization Subroutine Library (OSL) (1990). These later softwares have extensively been applied in Crowder, Johnson, and Padberg's (1983) study of large scale binary linear programming problems. MPSARX developed by Van Roy and Wolsey (1987) is a state-of-the-art Mathematical Programming system (MPS) that can be implemented for solving our models. MPSARX consists of two modules, an MPS system including all standard features and techniques for solving linear programming and mixed integer programming and an Automatic Reformulaion Executor (ARX) whose goal it is to speed up the solution of MIP problem, by producing an improved formulation based on pre- and post-processing of the problem and dynamic cut generation procedures. For additional references, see also Van Roy (1983), Van Roy and Wolsey (1983), Van Roy (1989), Mikhalevich (1983), Jackson and O'Neil (1983), Cote and Laughton (1984), Glover (1984), and Jeroslow (1984-a and b). Finally, for a review of the performance evaluation literature of mixed binary programming algorithms, see von Randow (1985, pp. 198 and 199).

Obvisouly for large problem the models may be hard to solve to optimality with current computer hard and software. In such cases one may therefore be forced to stop the procedure early or to develop an appropriate heuristic. Solution techniques such as Simulated Annealing or Tabu search have the potentials to be implemented for large scale problems. Computational work is the subject of our current research to be reported in a follow-up paper. We are confident that in the near future, more cpowerful computer hardware will become available in an affordable price range. This will make our models more accessible and applicable.

4. CONCLUDING REMARKS

Increasing implementation of Computer Integrated Manufacturing concepts raises issues in planning of production and distribution of an IMS. The issues relate to interaction and impacts of different production and distribution decisions on company profit. In order to tackle these issues we extended the models developed by Pourbabai (1991). The extended models have considered the integrated tradeoffs among several marketing, manufacturing, and distribution factors on the net operational profit during the short term planning horizon. The models can be distinguished from many other available models because of the fact that they always result in an optimal feasible solution. The following propositions indicate this fact.

Proposition 1:

The proposed models result in optimal feasible solutions.

Proof

Because of the term $Q_{i,k}$, for $i = 1$ to N and $k = 1$ to K, the proposed models are guaranteed to have feasible solutions (e.g., all orders may be rejected). Then, from standard arguments for mixed integer programming algorithms, the optimality can be guaranteed.

The following proposition indicates that setup times collapsing could increase the net operational profit during the planning horizon.

Proposition 2:

$$\Omega \geq \Omega^*$$

Proof:

Setup times collapsing may shorten the completion times of some jobs. Thus, the maximum of the net operational profit accordingly increase, which results in $\Omega \geq \Omega^*$.

In summary, the models provide insights for the decision makers. Depending on the capabilities required for a specific application, an operations manager should select the required features of the models before using them. The extension shows that the models can be improved further if necessary by considering additional technological and operational limitations and capabilities.

REFERENCES

1. Cote, G. and M.A. Laughton, (1984), Large Scale Mixed Integer Programming: Bender-type Heuristics, E.J. of Operational Research, 16, 327-333.

2. Crowder H., E. L. Johnson, and M. Padberg (1983), Solving Large-Scale Zero-One Linear Programming Problems, Operations Research, 31, 5, 803-834.

3. Glover, F., (1984), An Improved MIP Formulation for Products of Discrete and Continuous Variables, J. of Information & Optimization Science, (Dehli), 3, 196-208.

4. Ham, I., Hitomi, K., and Yoshida, T., 1985. Group Technology: Applications to Production Management, International Series in Management Science/Operations Research, Kluwer-Nijhoff Publishing.

5. Hartley, J., 1984, FMS at Work, IFS (publications) Ltd., UK and North-Holland Publishing Co.

6. IBM Mixed Integer Programming/370 (MIP/370) Program Reference Manual, (1975), Form number SH19-1099, IBM Corporation.

7. IBM Mathematical Programming System Extended/370 (MPSX/370) Program Reference Manual, (1979), form number SH19-1095, IBM Corporation.

8. IBM's OSL Reference Manual, (1990), IBM Corporation, NY, USA.

9. Jackson, R.H.F. and R.P. O'Neil, (1983), Mixed Integer Programming Systems, A Joint Publication of the Computer Programming Society, Washington, D.C., USA, ca, 100 p.

10. Jeroslow, R.G., (1984), Representability in Mixed Integer Programming, l: Characterization Results, Working Paper, Atlanta: Georgia Institute of Technology, School of Industrial and Systems Engineering, 59 p.

11. Jeroslow, r.G., (1984), Representability in Mixed Integer Programming, l: A Lattice of Relaxations, Working Paper, Atlanta: Georgia Institute of Technology, School of Industrial and Systems Engineering, 79 p.

12. Mikhalevich, V.S., L.V. Volkovich, A.F., Voloshin, and S.O., Maschenko, (1983), A Successive Approach to Solution of Mixed Problems of Linear Programming, (Russian), Kibernetika (Kiev), 1, 34-39.

13. Pourbabai, B., (1989-a), A Strategic Integrated Marketing and Production Planning Model, Int. J. of Integrated Manufacturing Systems, 2, 6, 339-345.

14. Pourbabai, B., (1989-b), Components of a Decision Support System for Computer Integrated Manufacturing, in Int. J. of Integrated Manufacturing, 1,4, 253-261.

15. Pourbabai, B., (1989-b), A Short Term Production Planning and Scheduling Model, to appear in Int. J. of Engineering Costs and Production Economics.

16. Pourbabai, B., (1991), Developing A Startegic Marketing and Production Plan for An Integrated Manufacturing System: With Setup Time Collasping, Working Paper, Dept. of Mechanical Engineering, The University of Maryland, U.S.A.

17. Randy, P.G., (1983), The Design and Operation of FMS, Flexible Manufacturing Systems, IFS (publications) Ltd., UK North-Holland Publishing Col.

18. Shapiro, J., (1979), Mathematical Programming: Structures and Algorithms, New York, Wiley.

19. Van Roy, T.J., (1983), Cross Decomposition for Mixed Integer Programming, Mathematical Programming, 25, 46-63.

20. Van Roy, T.J., and L.A. Wolsey, (1983), Valid Inequalities for Mixed 0-1 Programs, CORE Discussion Paper 8316, Louvain-la-Neuve: Center for Operations Research and Economics, 19 p.

21. Van Roy, T.J., and L.A. Wolsey, (1987), Solving Mixed 0-1 Integer Programming by Automatic Reformulatio, Operations Research, 35, 45-57.

22. Van Roy, T.J. (1989), A Profit-maximizing Plant-loading Model with Demand Fill-rate Constraints, Journal of Operational Research Society, 40, 1019-1027.

23. Von Randow, R. (1985), Integer Programming and Related Areas, Classified Bibliography, 1981-1984, Lecture Notes in Economics and Mathematical Systems, (ed. R. von Randow), Springer-Verlag.

24. Waghodekar, P.K. and Sahu, S., (1983), Group Technology: A Research Bibliography, Research, 20, 4, 225-249.