Integrated Production Planning and Scheduling in Multi-Stage Batch Processing Systems

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***Abstract*—This research addresses the integrated problem of production planning and scheduling in a complex multi-stage, multi-product, multi-machine batch production environment, typical of industries such as chemicals, food, glass, pharmaceuticals and tyres. These industries are increasingly challenged by high product variety, low volumes, variable demand and short planning cycles, often resulting in excess inventory and poor capacity utilisation. The study considers production settings where raw materials, intermediate products, by-products and recycled materials interact across multiple stages, with equipment shared across products. The environment is characterised by perishability of products, high set-up times, transfer lot sizes, and deterministic demand over a finite horizon. The decisions involve determining production quantities, inventory levels, aggregate capacity requirements and detailed schedules at minimum cost.**

A sequence of mathematical models is developed to address these decisions. A mixed-integer programming (MIP) model is proposed for production planning with the objective of minimising inventory, set-up and raw material costs, while determining aggregate capacity needs. A variant model integrates sales and production planning under market constraints. For scheduling, an MIP model is formulated to generate equipment-wise schedules, minimising earliness and tardiness penalties. Heuristics and analytical results are developed for flow shop scheduling problems with common due dates, while intermediate products are scheduled using job shop heuristics with re-entrant flows.

I. INTRODUCTION

In the present industrial scenario, business competition has intensified to a great extent. Manufacturing enterprises are compelled to release the importance of adopting structured manufacturing strategies to remain viable in both domestic and international markets. They are under constant pressure to reduce customer response time, expand product range, and manage fluctuating demand while maintaining competitive prices. In the absence of proper planning, many firms face situations where some products are in critical shortage while others pile up in excess inventory, thereby blocking capital and reducing efficiency. This imbalance not only affects customer satisfaction but also impacts profitability and long-term growth. Thus, the challenge for industry today lies in maintaining a balance between minimizing costs and ensuring responsiveness to customers. Internally, organizations are under further pressure to enhance profitability by increasing manufacturing efficiency, reducing operational expenditure, and utilizing resources optimally. These factors bring the focus on production planning and scheduling, which are vital for ensuring stability and competitiveness in the present environment.

1.1 Production Planning and Scheduling Problem

In this section, the production planning and scheduling problem undertaken in this research is presented in detail. The discussion begins with a description of the production environment, motivated primarily by observations on the operational characteristics of chemical plants. The inherent complexities of this environment are then highlighted, particularly those arising from the nature of multi-stage processing and the interdependence of resources. Finally, attention is directed towards the key decisions to be addressed in the production planning and scheduling problem, which form the central focus of this study.

1.2 Production Environment

The research considers a multi-stage production environment in which both intermediate products and finished goods are produced. Each stage in the production process corresponds either to the manufacture of an intermediate product or to the final production of a finished good. The concept of multi-stage production, as examined in this study, is analogous to a multi-level product structure. For illustration, Figure 1.1 presents a typical product structure where level 0 represents the finished goods (E1, E2, E3), while levels 1 and 2 represent intermediate products (I1, I2, …, I6). The different levels in the diagram correspond to the various stages of the production process. Specifically, the intermediate products at level 2 serve as inputs for the intermediate products at level 1, which in turn act as inputs for the level 0 products. The level 0 products constitute the finished goods, and their production represents the final stage in the multi-stage environment.

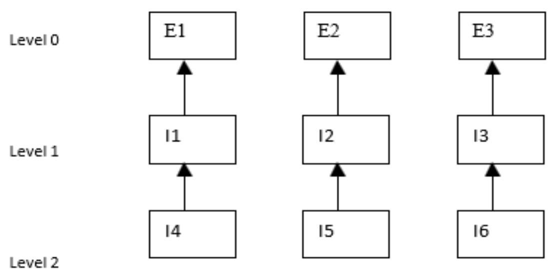

Fig: 1.1 Multi-level Product Structure and Concept of Stage

The production environment under consideration consists of multiple plants engaged in the manufacture of both intermediate products and finished goods. Each production plant comprises a set of equipment, referred to as ‘machines’, on which the processing activities are carried out. Products, whether intermediate or finished, undergo processing on these machines in a specified sequence. The processing of a product on an individual machine is termed an ‘operation’. A sequence of such operations required for producing a product defines its ‘route’. To illustrate these concepts, Figure 1.2 presents an example of a product ‘P’, which requires four operations in a production plant comprising five machines (M1, M2, …, M5). As shown in the figure, there exists a choice of machines for the third operation, which may be carried out either on machine M3 or on machine M4. Accordingly, two alternate routes are available for manufacturing product P. Route 1 consists of the sequence M1–M2–M3–M5, whereas Route 2 consists of the sequence M1–M2–M4–M5. This illustration highlights the flexibility and complexity inherent in determining routes in a multi-machine production environment.

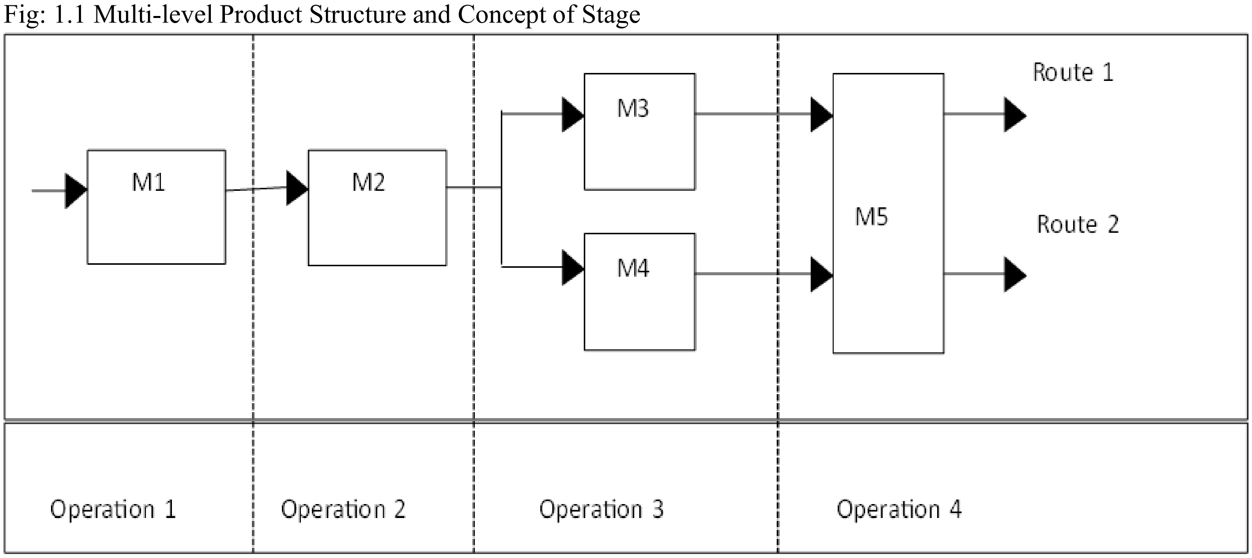

Fig 1.2 Machines, Operations and Routes of a Product

1.2.1 Complexities in the Production Environment

In this sub-section, the major complexities associated with the production environment are described. These complexities, along with the features of the production environment discussed earlier, form the foundation for the production planning and scheduling decisions considered in this research. As shown in Figure 1.3, raw materials are recovered from by-products through a recycling process and reused in the production plants. Since raw materials account for a significant proportion of production costs, maximum recovery of reusable materials is essential to minimize the consumption of fresh raw materials. This introduces the need for close coordination between production and recycling plants. Recycling is most effective when undertaken simultaneously with production, as the storage capacities of by-products and reusable raw materials are limited. By synchronizing these processes, the requirement for fresh raw materials is reduced, resulting in overall cost savings.

II. PRODUCTION PLANNING MODEL

The production-planning model is formulated to address medium-range time horizon decisions in the production environment. The primary objective of this model is to minimise overall production costs. These costs comprise inventory costs of finished goods, intermediate products, by-products, and recovered raw materials, as well as setup costs incurred for end products and intermediate products. Additionally, the cost of procuring fresh raw materials is included in the objective function. The production-planning model thus integrates all these cost components to provide an optimal plan that balances production quantities, inventory levels, and resource utilisation. The detailed mathematical formulation of the production-planning model is presented in the following section.

$$\min z \square\square\square hi.Iit \square\square\square Sij.Oijt \square\square\square hs.ISst \square\square\square hm.IMmt \square\square\square fs.Fst$$

The production-planning model is subject to a set of constraints that ensure feasibility and practical applicability in the production environment. Constraint 1 ensures that the demand for each end product is satisfied in every time period. Constraint 2 relates to the derived demand of intermediate products, indicating that their demand in each period depends on the production of intermediate and end products in which they serve as inputs. Constraint 3 specifies the capacity constraint of dedicated production plants by limiting the production of intermediate and end products based on plant capacity in each time period.

2.1 Production Scheduling Model:

In this section, we present the formulations of the scheduling models used to derive detailed scheduling decisions for the production planning and scheduling problem. The scheduling decisions specify, for each job and each machine, the start time and the completion time. The aggregate production plan generated by the production-planning model serves as input to the scheduling models and imposes feasibility constraints on them. The overall scheduling task is divided into two parts: finished goods scheduling and intermediate products scheduling. These are treated separately because the production environments differ for finished goods and for intermediate products. As discussed in Chapter 1, finished goods follow a flowshop pattern in which every product undergoes the same sequence of operations. When all machines process jobs in an identical sequence, the environment is termed a permutation flowshop. Determining an optimal schedule for a general flowshop, where job sequences may differ across machines, is significantly harder than for a permutation flowshop (Baker, 1974; Pinedo, 1998); therefore, we adopt the permutation flowshop setting for finished goods.

$$\min z \square\square Ei \square Ti \square\square Cie^{Li} \square d$$

2.1.1 Solution Procedure for Production Planning Problem:

The production-planning model is solved using the branch and bound algorithm. The demand for finished goods in each period of the planning horizon serves as a key input to the model. Aggregate capacity is incorporated in the planning stage, with different considerations for dedicated and flexible plants. For dedicated plants, the capacity of the bottleneck machine is taken as the overall plant capacity, while for flexible plants, the capacity of each machine that processes multiple products is considered individually.

To implement and solve the mathematical model, we employ the General Algebraic Modelling System (GAMS), version 19.8, along with the solvers integrated in the compiler. Specifically, the branch and bound algorithm available in the CPLEX solver is utilized for obtaining optimal solutions to the production-planning problem

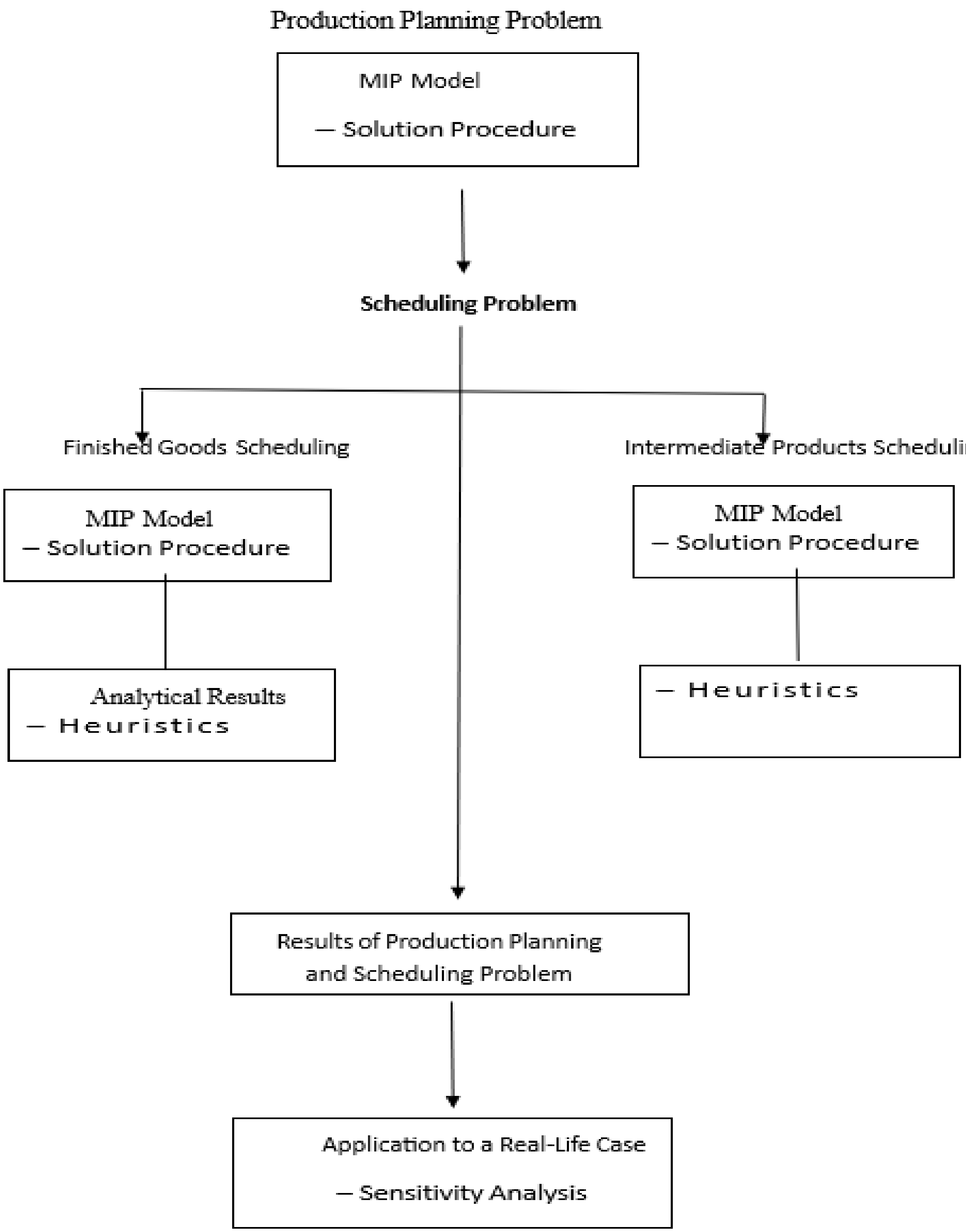

Fig 1.3 Schematic of Solution Procedure for Production Planning and Scheduling Problem

2.1.2 Solution Procedure for Finished Goods Scheduling Problem

The finished goods scheduling problem is modelled as a permutation flow shop with a common due date. The primary objective of this scheduling model is to minimize earliness and tardiness (E/T) penalties. In Chapter 2, we reviewed existing results on E/T scheduling, noting that most of the literature has focused on single-machine scheduling problems. Specifically, Baker and Scudder (1990) examined the case of unrestricted due dates in single-machine scheduling. Let us denote the unrestricted due date for a single-machine problem as d0d_0, and let dd represent the common due date for all jobs in our problem.

2.1.3 Procedure for Generating Alternate Optimal Sequences at d=d0d = d_0d=d0 (GAOS):

Step 1: Initialize j=1j = 1j=1.

Step 2: Set x=j+1x = j + 1x=j+1.

Step 3.1: Is $p_{xm} = p_{jm}$

Yes Create new sequence by interchanging j and x

$x = x + 1$

is $x = n + 1$

yes $j = j + 1$ and go to step 3.2 no

repeat step 3.1

No $x = x + 1$ and repeat step 3.1

Step 3.2 if $j = n$

STOP else got step 2

2.1.4 Procedure for Removing Idle Time at Last Machine (RIT)

Let the sequence s be 1, 2…. n

.

Step 1: $i = n$

Step 2: $t = S_{im}$-C_{i-1m}

Step 3: If $t > 0$

Yes for $x = 1$ to $i-1$

$S_{xm} = S_{xm} + t$ $C_{xm} = S_{xm} + p_{xm}$

If $i = 1$, STOP else

$i = i - 1$ and go to Step 2

No If $i = 1$, STOP else

$i = i - 1$ and go to Step 2

2.2 Heuristic Algorithm

The proposed heuristic for solving sub-problem 2 is based on constructing a permutation sequence of jobs at the bottleneck machine. The bottleneck machine is identified as the machine with the maximum total processing time across all jobs among all machines.

In solving multi-machine scheduling problems, it is often effective to decompose the problem into an equivalent single-machine problem. Accordingly, we reformulate the flow shop E/T problem into a single-machine E/T problem at the bottleneck machine

Thus, the problem reduces to a single-machine E/T problem with release dates and distinct due dates, denoted as:

n/1/ri/∑(Ei+Ti). n/1/r_i / \sum (E_i + T_i). n/1/ri/∑(Ei +Ti)

To solve this problem, we draw upon the results of Chu (1992) and Chu and Portmann (1992), who proposed sequencing rules for the n/1/ri/∑(Ei+Ti) n/1/r_i / \sum (E_i + T_i) n/1/ri/∑(Ei+Ti) problem. In our heuristic, a priority function (defined in the subsequent steps) is used to iteratively select a job, which is then appended to a partial sequence

2.2.1 Dedicated Plant Scheduling Heuristic:

Dedicated production plants are facilities that produce only one type of product, which simplifies the production environment compared to multiproduct or flexible plants. Since the plant is restricted to a single product, sequencing across different product types is not required. However, scheduling remains important to align production runs with customer orders and available inventory. The main challenge lies in deciding the number and timing of batches to ensure demand is satisfied without creating unnecessary earliness, tardiness, or excessive inventory holding costs.

III. RESULTS OF PRODUCTION PLANNING AND SCHEDULING PROBLEM

we present the results obtained from the solution procedures developed for addressing the production planning and scheduling problem, along with a sensitivity analysis of these results. The data for this study has been sourced from a pharmaceutical company in India. The solution methods applied were introduced in Chapter 4, where the production-planning problem is solved using the branch-and-bound algorithm of a commercial solver, while analytical results are derived for sub-problem 1 of finished goods scheduling. Prior to applying these methods to the complete production planning and scheduling framework, we evaluate the performance of the heuristic algorithms for sub-problems 2 and 3 using benchmark instances from the flow shop scheduling literature.

LBCi is considered a weak lower bound (Kim, 1995). As discussed earlier, estimating a reliable lower bound on earliness is challenging, which makes LBETi a very weak measure of earliness and tardiness. This weakness is evident from the results on small problem instances (n = 5, 10; m = 5), where the average percentage deviation of the optimal solution from the lower bound is extremely high. Specifically, for n = 5, m = 5 with 50 instances, the deviation is 326 percent, while for n = 10, m = 5, it is 284 percent. Figures 5.1 and 5.2 illustrate the average percentage deviation of heuristic solutions from the lower bound for 5-machine and 10-machine problems, respectively. Although the deviations remain high, this is expected since the lower bound itself deviates significantly from the optimal solution. Importantly, for smaller problems, both the heuristic and optimal solutions show nearly the same deviation from the lower bound, indicating that the heuristic solutions are close to the optimal ones.

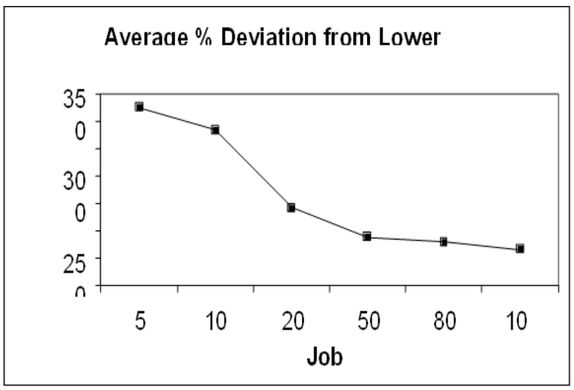

Fig 1.4 Average % Deviation of Heuristic Solution from Lower Bound: 5 Machines

The heuristic's performance for smaller problems is further evaluated by comparing it with the optimal solution using a random common due date selected between d1d_1 and d2d_2. This approach helps in assessing the quality of the heuristic across the full range of intermediate due dates. For n=5,m=5n = 5, m = 5 with 50 instances, the heuristic solution shows an average deviation of 0.846 percent from the optimal solution. Similarly, for n=10,m=5n = 10, m = 5 with 50 instances, the average deviation is 1.247 percent, confirming that the heuristic remains consistently close to the optimal solution across varying due dates.

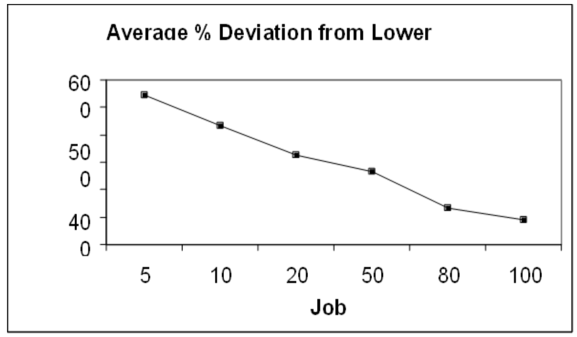

Fig 1.5 Average of Deviation of Heuristic Solution from Lower Bound: 10 Machines

As noted earlier, the lower bound of sub-problem 2 is quite weak; therefore, the performance of the heuristic for larger problems is evaluated using the common due date value d1d_1 (derived in sub-problem 1). This approach is chosen because the optimal solution of the flow shop E/T problem with common due date d1d_1 can be obtained in polynomial time. Table 5.2 presents the results of this comparison, showing the average percentage deviation of the heuristic solution from the optimal solution at d=d1d = d_1 for each job–machine combination considered in the experiment design.

	Machines			
Jobs	5	10	15	20
5	0.000	0.000	0.235	0.000
10	0.084	0.081	0.099	0.276
20	0.074	0.020	0.012	0.023
50	0.323	0.153	0.152	0.146
80	0.865	0.642	0.617	0.644
100	1.744	1.168	1.175	1.129

Fig1.6. Average Percentage of Deviation of Optimal Solution from Heuristic Solution

Finally, we presented results for the production planning and scheduling problem using real-world data from a pharmaceutical company in India. We analysed the production plan generated by the planning model and examined machine-wise schedules produced by the scheduling model. These results provided insights into production quantities, setups, inventory levels, and overall scheduling outcomes. In the next chapter, we extend this analysis through a case study application in the pharmaceutical company, where we apply the proposed models, report solution results, and conduct sensitivity analysis to evaluate their practical effectiveness.

3.1 Application of Production Planning and Scheduling Models

we apply the production planning and scheduling models developed in Chapter 3 to a real-life case study. The application is carried out in a pharmaceutical company in India that was experiencing operational challenges such as excess inventories, frequent stockouts, and low-capacity utilization while attempting to meet fluctuating demand forecasts. The frequent demand variations led to constant revisions in production plans and shop floor schedules, making the process of adjusting schedules to meet changing market requirements both time-consuming and complex. To address these issues, we develop a decision support system aimed at effectively solving the company's production planning and scheduling problem.

3.1.1 Application of Production Planning Model

The production environment described in Section 6.1 is modelled in two steps. In the first step, a mixed-integer linear programming (MILP) model is developed for production planning, where demand is forecast over the planning horizon and plant capacities are incorporated. For dedicated plants, the model considers the monthly available capacity of the entire plant, while for flexible plants with shared machines, machine-wise monthly available capacities are taken into account. The key decisions of the model include determining production quantities of finished and intermediate products, the number of setups required, and the inventory levels of finished and intermediate products across the planning horizon, with the objective of generating a cost-effective and feasible production plan.

1. Quantity of each product to be produced on each plant in each time period of the planning horizon
2. Inventory levels of end products, intermediate products, solvents and by-products in each time period of the planning horizon
3. Quantity of fresh raw material consumed in each time period of the planning horizon.

3.1.2 Results of Production Planning Model

We compare the actual production plan developed by the company with the production plan proposed by the cost minimization model (production-planning model) over a given period. The problem instance in this application consists of 10 finished goods, 30 intermediate products, 50 by-products, and 40 reusable raw materials, processed across 15 production plants—8 dedicated and 7 flexible. The planning model formulated for this instance includes 576 discrete variables, 5974 continuous variables, and 3016 constraints. To evaluate the model, five months of data from January 2002 to May 2002 were considered, with each month treated as one time period.

	Cost Difference (%) (Actual Production Plan – Production Plan Proposed by the Model)	
Cost	Scenario 1	Scenario 2
Inventory Carrying Cost of Intermediates and End Products.	61.20	60.90
Setup Cost of Intermediates and End Products.	38.46	24.79
Fresh Raw Materials Cost	20.50	6.38
Inventory Carrying Cost of By-Products and Reusable Raw Materials	8.58	6.69
Total Cost	33.87	24.65

Fig 1.7 Comparison of Model Results with Actual Production Plan Costs

3.2 Application of Scheduling Model

the scheduling problem using the solution procedures developed in chapter 4. The production-planning model serves as the input to the detailed scheduling model. As illustrated in the product structure diagram, products at level 0 represent finished goods. These finished goods are scheduled using the flow shop E/T (Earliness/Tardiness) procedures outlined earlier.

Their due dates are determined based on customer orders and demand forecasts. Since finished goods are shipped multiple times within a month in response to customer requirements, the flow shop E/T scheduling problem is applied weekly. The common due date for finished goods is set at the end of each week, and the objective of their scheduling is to minimize penalties associated with earliness and tardiness.

3.2.1 Sensitivity Analysis on Production Planning and Scheduling Results

we conduct sensitivity analysis on the production planning and scheduling results discussed earlier. The analysis focuses on four key factors: demand of finished goods, initial inventory of finished goods and intermediates, capacity of dedicated and flexible plants, and the ratio of setup cost to inventory cost for intermediate products and finished goods. Demand is chosen due to inherent variability in the environment, making its sensitivity critical for aligning marketing and production decisions. Initial inventory is analysed to assess the trade-off between purchasing intermediates externally versus in-house production. The solved instance from the previous section serves as the base case. Since scheduling costs are relatively small compared to production costs, they are excluded from the analysis.

3.2.2 Implementation Issues

The benefits of the production planning model were demonstrated to the company using five months of operational data. These results encouraged management to consider wider implementation of the models, though the long-term savings remain difficult to estimate. Currently, the company is in the process of applying both production planning and scheduling models across its full operations, with the scheduling model still not completely functional. To support adoption, on-site training was provided for personnel engaged in planning and shop floor scheduling. In addition, a Decision Support System (DSS) was developed and documented, covering problem definition, key decisions, model structure, interpretation of results, and sensitivity analysis. The planning model built in GAMS was also integrated with Microsoft Excel to simplify parameter input and adjustments.

During implementation, one major observation was that managers did not easily internalize the benefits of optimization tools. In particular, many plant managers were initially resistant to the idea that maximizing capacity utilization could lead to significantly higher operational costs. However, the results of the models provided concrete evidence, helping managers recognize the importance of demand-driven planning rather than relying solely on capacity-based production decisions. This shift in perspective was crucial in highlighting how structured production planning can lead to cost savings and efficiency improvements.

IV. SUMMARY, CONTRIBUTION AND FUTURE RESEARCH

In this research, we investigate the potential of production planning and scheduling in reducing operational costs for manufacturing firms operating in complex production environments. Manufacturing industries today face increasing challenges such as greater product variety, declining product volumes, fluctuating demand, and shorter customer response times. As a result, operating costs have become a critical concern for firms. In this context, we argue that effective production planning and scheduling can play a significant role in minimizing costs and improving efficiency. Motivated by the complexities of chemical plants, we focus on production planning and scheduling problems in both process industries and discrete parts manufacturing, considering multi-stage, multi-product, multi-machine, and batch-processing settings. Our approach models decision-making in two stages: first, a mixed integer linear programming (MIP) model for production planning, and second, MIP-based

scheduling models for finished and intermediate goods. The production-planning model determines product quantities, inventory levels, and aggregate resource capacities, with the objective of minimizing production costs. The scheduling models determine the start and completion times of products on machines, with the objective of minimizing earliness and tardiness penalties, while ensuring consistency with the production plan.

4.1.1 Contribution

In this research, we address complex production planning and scheduling problems arising in discrete parts manufacturing and process industries. The study considers a multi-stage, multi-product, multi-machine, batch-processing environment, reflecting the complexities typically found in real-world manufacturing systems. Unlike traditional studies, our work incorporates additional challenges in the production environment. Specifically, we model the production of both finished goods and intermediate products, along with by-products that are recycled to recover reusable raw materials. This recycling process introduces a unique level of complexity not generally addressed in the literature. Further, the production system operates with flexible machines that are used to process both finished and intermediate products, significantly complicating scheduling decisions. Demand forecasts are considered over a finite planning horizon, with finished goods following a flow shop production process and intermediate products following a general job shop process with re-entrant flows.

To tackle these challenges, we model production planning and scheduling decisions through a hierarchical sequence of mixed integer programming (MIP) models. The first model addresses production planning decisions with the objective of minimizing costs associated with inventories, setups, by-products, reusable raw materials, and fresh raw materials. The second and third models address scheduling decisions for finished goods and intermediate products, respectively. In particular, the objective of the scheduling models is to minimize the absolute deviation of job completion times from a common due date. The production-planning problem is solved using the branch-and-bound algorithm. For scheduling, we report several new results. The finished goods scheduling problem, modelled as a flow shop problem of minimizing the deviation of job completion times from a common due date, has not been studied previously in the literature. We derive analytical solutions for specific ranges of due dates and propose heuristic algorithms for cases where analytical solutions are intractable. For special structures in flow shop scheduling, including problems of minimizing tardiness, flow time, and completion time, we develop new heuristics that show superior computational performance compared to existing methods. Similarly, we design heuristic algorithms for solving intermediate products scheduling problems in job shop environments.

4.1.2 Future Research

In this research, we decomposed the overall production planning and scheduling problem and developed sequential models to address the associated decision-making processes. A natural extension of this work would be to further explore the benefits of hierarchical production planning. In particular, we did not consider product aggregation, as discussed in Bitran and Tirupati (1993). Products can be aggregated into families and families into types, where a *type* is a collection of products with similar demand patterns and production rates, and a *family* is a subset of products within a type that share a common setup. The aggregation of products offers significant advantages, including reduced dimensionality of mathematical programs and reduced dependence on detailed demand forecasts (since only type-level forecasts would be required). Subsequent stages would then involve disaggregation models to derive production plans for product families, followed by further disaggregation to determine the exact production quantities for individual products.

Another promising extension of this research would be to incorporate uncertainties that are common in real-world production environments. Practical situations often involve stochastic factors such as machine breakdowns, demand forecast errors, variability in job processing times, and fluctuations in process yields, particularly in process industries. Our research has focused primarily on deterministic scheduling, where problem parameters are assumed to be known with certainty. Extending the models to incorporate stochastic parameters would allow a more realistic representation of production environments, thereby improving the robustness of scheduling decisions. In addition, while this work has examined finished goods scheduling under a permutation flow shop setting with common due dates, extending the analysis to general flow shop configurations with distinct due dates would be another valuable contribution.

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