PRODUCTION PLANNING USING HYBRID OPTIMIZATION–SIMULATION BASED APPROACH

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SUMMARY

In this research, hybrid optimization–simulation framework has been implemented and tested for deterministic as well as stochastic flowshops. A capacity adjustment scheme has been proposed based on the bottleneck machines completion time. Under stochastic shop-floor settings, the effects of the completion time estimation (viz., using the mean completion time, and using the prediction interval) have been analyzed. It has been found that capacity adjustments using the prediction interval of the completion time gives improved results. Also, in general, the optimum-cum-realizable plan converged to the local optima, since sequence constraints are not captured within the optimization model. The effects of product sequencing/dispatch on system performance have been analyzed and results discussed.

INTRODUCTION

Production planning is fundamental to the effective operation of a manufacturing system. Traditionally linear programming (LP) based models are used for production planning. But these models often lack realism. Simulation models allow any amount of realism, but are descriptive models. Combination of both these types of models can be exploited to achieve an optimum cum realizable plan.

LP formulation for multi-period multi-product production planning

Demand: d_{it}
Costs: c_{it}, h_{it}, π_{it}
Process times: a_{ik}
Capacity: MC_{kt}

$$\min \sum_t \sum_i \left(c_{it} x_{it} + h_{it} I^+_{it} + \pi_{it} I^-_{it} \right)$$

$$\text{s.t.} \sum_i a_{ik} x_{it} \le MC_{kt} \quad \forall\, k,t$$

$$x_{it} + I^-_{it} - I^+_{it} = d_{it} - I^+_{it-1} + I^-_{it-1} \quad \forall\, i,t$$

x_{it} : Quantity of product i to be produced in period t

Plan from above LP may not be realizable in the actual shopfloor, since process time variations, machine breakdown, set-up changes, operational sequences, etc not modeled.

Hybrid approaches for multi-period multi-product production planning

Figure 1 illustrates a general hybrid framework that employs optimization and simulation models iteratively to converge to a optimum-cum realizable plan. Achieving 'best' plan depends on how the capacity and/or other parameters are adjusted based on simulation output.

- ➢ Bryne and Bakir (1999) adjusted resource capacity based on the ratio of gross capacity to the consumed simulation time.
- ➢ Kim and Kim (2001) extended this model by capturing an effective loading ratio in the capacity constraints that depends on effective machine workload.
- ➢ Lee and Kim (2002) used hybrid framework to provide realistically optimal operation time required for production-distribution plans of supply chain, in stochastic scenario.
- ➢ Feldman and Shtub (2006) decreased the machine capacity, thus the production, until a realizable plan was found.
- ➢ Elkin *et al*. (2009) adjusted the machine idle time and product waiting time based on simulation output.

Limitations in literature

- Mainly considered deterministic cases. Impact of stochasticity not explicit.
- Demands are assumed to know with certainty at the start of planning horizon
- Resulting optimum-cum-releasable plan may not be global optimum.

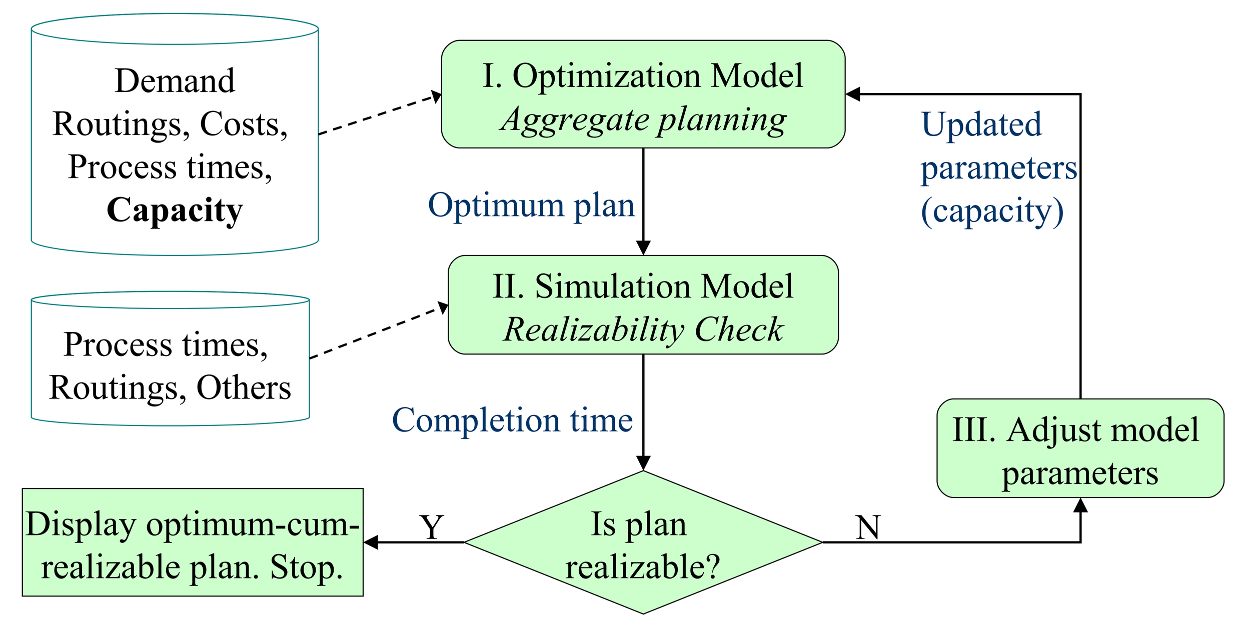


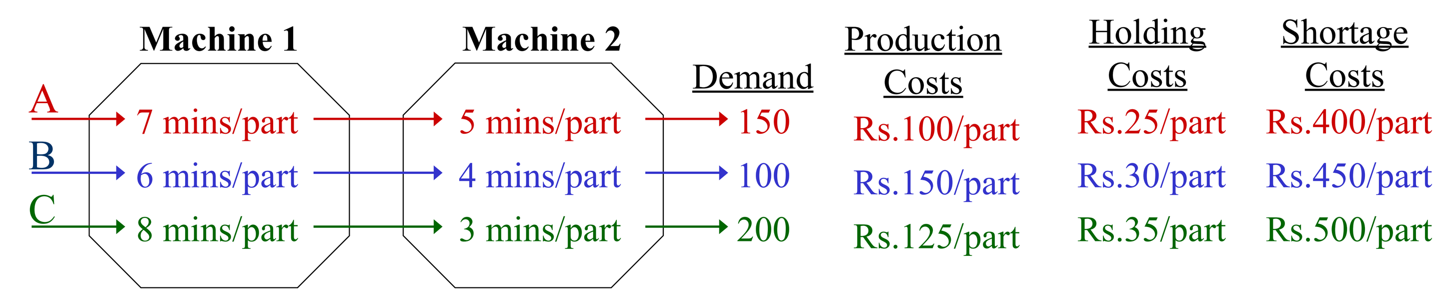
Figure 1: Hybrid Optimization – Simulation Architecture

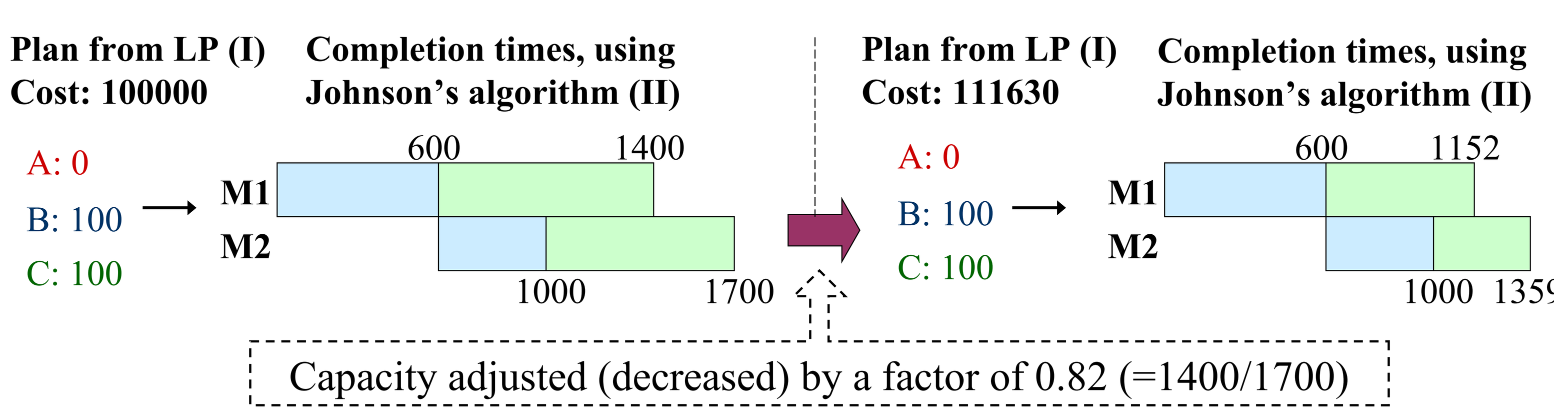
PROBLEM STATEMENT

- ➢ Identify gap between global optimum and optimum-cum-realizable plan.
- ➢ Propose and test hybrid scheme to handle stochasticity in system.

DETERMINISTIC (TRIVIAL) EXAMPLE

Consider a single period planning for a two machine flowshop with three products. Available machine capacity 1400 mins, each.





The plan obtained above is optimum and realizable but is not global optimum. By including precedence constraints in the LP we can obtain an *global* optimum plan of (A, B, C) = (57, 99, 37) at a cost of Rs.106830 which is also realizable (max completion time = 1400.

'Simple' capacity adjustment scheme will never achieve the global optimum plan. However, including precedence constraints in the LP makes it combinatorial complex.

CAPACITY ADJUSTMENT FOR STOCHASTIC SYSTEMS

Stochasticities considered are variable processing times and random machine breakdowns. In this case, it is proposed that prediction interval estimates of the simulation completion times be used for adjusting (step III) the machine capacity parameter in optimization:

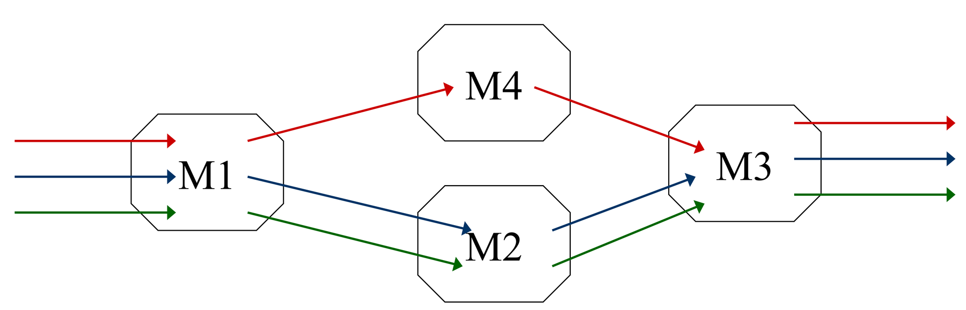
$$MC_{r+1,k,t} = MC_{r,k,t} AF_{r,t}$$

$$AF_{rt} = MC_{Kt} \Big/ \left(\overline{MC}_{Kt} + t_{\frac{\alpha}{2},n-1} s \sqrt{1 + \frac{1}{n}} \right)$$

$MC_{r,k,t}$ is capacity of machine k in period t in iteration r in LP model.

$AF_{r,t}$ is capacity adjustment factor

Manufacturing Scenario



Planning for 3 period horizon
Known deterministic demand
Stochastic process times
Machine breakdowns
Machine capacity: 2400 min
No backlogs allowed

Deterministic vs. Stochastic scenarios

Table 1: Results with deterministic process time

Iteration 1			Iteration 5		
I. LP Obj	II. Simulation time (in each period)	III. AF (for each period)	I. LP Obj	II. Simulation time (in each period)	III. AF (for each period)
1888140	(2773, 2834, 2761)	(.87, .85, .87)	233700	(2399, 2400, 2395)	(1, 1, 1)

Table 2: Results with stochastic process time & machine breakdowns

Iteration 1			Iteration 3		
I. LP Obj	II. Simulation time (Avg per period)	III. AF (for each period)	I. LP Obj	II. Simulation time (Avg per period)	III. AF (for each period)
1888140	(2809, 2889, 2801)	(.85, .82, .86)	241775	(2356, 2379, 2336)	(1, 1, 1)

Under stochastic process times, the upper bound of 95% prediction interval obtained based on 5 simulation runs are used to compute the adjustment factor for machine capacity. This causes a larger decrease in the capacity, leading to faster convergence to a realizable solution. Also, the use of prediction interval gives better solutions than the simplistic use of means.

Effect of dispatching rules

Results obtained in Table 1 are with the dispatching rule that all of product A are processed first, then B and then C. For comparison, another dispatching rule is used: one product of each type are queued in batches. This resulted in the hybrid framework to converge after 7 iterations but with a lesser cost of 221125. This is because of higher utilization of machines that was achieved.

CONCLUSIONS

The hybrid optimization-simulation environment provides a viable method to obtain a realizable production quickly. Further investigation are on for the convergence of the solution to a globally optimum and realizable plan; and 'adjustment schemes' that explicitly account for stochastic simulation outputs. Also, the effectiveness of the hybrid framework for more complex and realistc scenarios are to be analyzed.

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