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Production Decision Support System: Real-life Emulsion Plant Case Study

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As the world becomes increasingly globalised, chemical manufacturers have to make timely decisions and right strategies in order to stay competitive in marketplace. Numerous formal techniques have been suggested for aggregate planning but industry finds these models complicated and lack practicality. The objective of this paper is to develop an industry adoptable Production Decision Support System (PDSS) for multi-product and multi-processor batch industries. The construction of this system is initiated with the development of a general batch production planning framework which will be eventually translated into an algorithm tool. This tool will be able to support the investigation of required sales forecasts against plant capacity by providing a complete overview with different scenarios on multi-product batch processes, thus improving effectiveness and efficiency of operational decision-making, as well as assisting in strategy establishment. The production contributory factors that are being considered for plant capacity include cycle time, batch size, plant availability, number of production lines and product mixes. The practicality and beneficial use of this PDSS system is then demonstrated through a real-life emulsion plant where its production capacity has been successfully stretched giving additional volume which has translated into additional revenue of RM 10 M to the company.

1. Introduction

As the world becomes increasingly globalised, chemical manufacturers have to make timely decisions and right strategies in order to stay competitive in marketplace. All these strategies are heavily tie-down to three main company decisions categories based on time horizon, namely long, medium and short. Strategic planning support the long term, aggregate planning support the medium and operational planning support the short term (Anthony, 1965). Aggregate planning is also called tactical planning and acts as a bridge between strategic and operational planning as well as the blue print for all operational planning activities.

Given the importance of the aggregate planning in the business, numerous formal techniques have been suggested for aggregate planning since the early 1950s, which started Linear Decision Rule (Holt et al., 1955) as well as other kinds of mathematical and heuristics based techniques. These works are summarised in some of the review papers (Martinez-Costa et al., 2014). Although these observations have been complemented by numerous studies, there are sources pointed out that industry often does not adopt these formal aggregate planning models due to practicality and complexity issues (Charabortty et al., 2015).

Process Integration was later further extended in aggregate planning (Tan et al., 2015). This was started with the graphical pinch analysis (Singhvi et al., 2004) and followed by algebraic techniques (Foo et al., 2008). The optimality of this approach is further enhanced through extending automated targeting model into inventory management (Foo, 2016). These methods do not demonstrate how to deal with multiple products with multiple processors in batch industry.

In this work, a Production Decision Support System is (PDSS) developed to help the batch industry performed medium term decision. It will also consider multiple products with multiple processors. The problem statement for this study is “Given a set of production contributory factors such as cycle time, batch size, plant availability,

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and number of line and product mixes, a match between production and sales forecast is desired, using a generic framework and assisted with an algorithm tool that can guide production strategies".

2. Methodology

This section presents an overall framework for batch production capacity planning and supports the establishment of manufacturing strategies. The detailed procedures for designing and developing the Production Decision Support System (PDSS) in this study are outlined in the following flow chart of Figure 1.

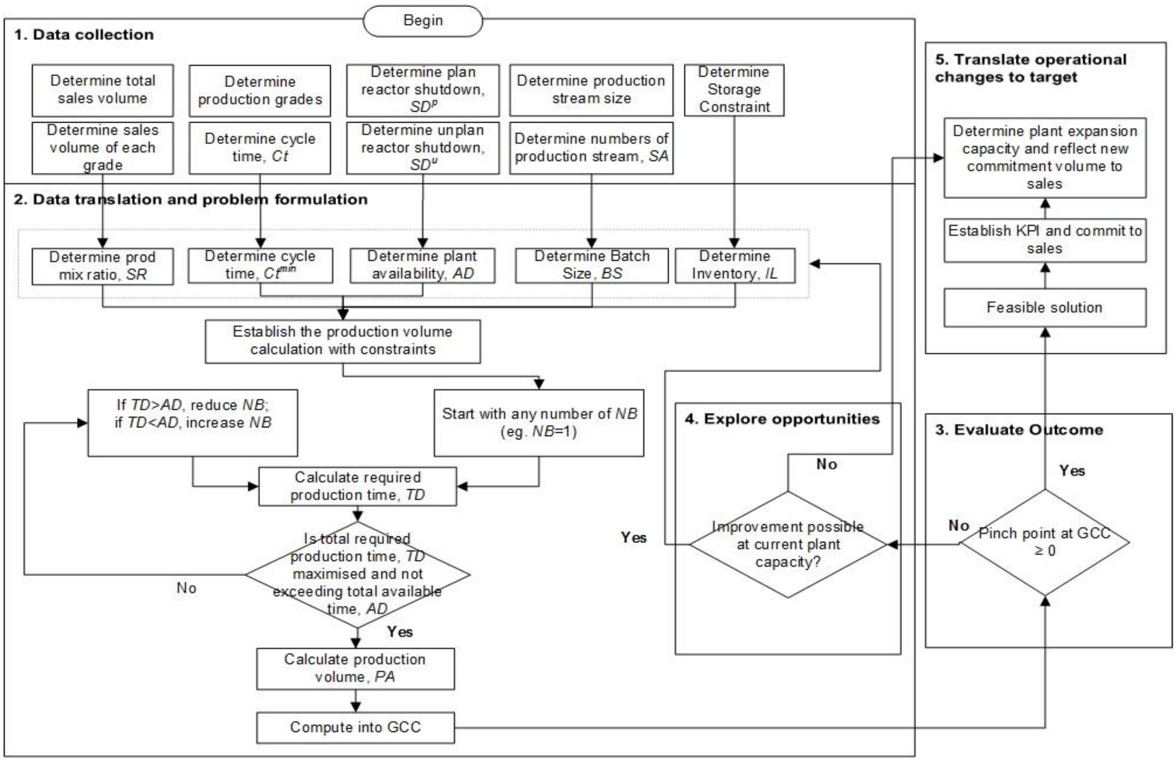

Figure 1: Production Decision Support System (PDSS) flow chart

Data collection is to be gathered. This includes the annual sales forecast to be tabulated according to respective grades, plant performance i.e. cycle time of each grades, plant reliability (historical unplanned shut down), shut down requirement of the year (planned maintenance), plant set up i.e. line size and storage constraint. These available data will be translated to formulate a relationship between the parameters and constraints using a spread sheet.

This is to be followed by trial and error approach where the number of batches (*NB*) is manipulated until all constraints have been satisfied. The outcome will be then evaluated and when the ultimate simulated production volume is found to be less than the sales forecast, further improvement opportunities will be explored. These opportunities will serve as the operation target for the following year. A real-life example, which consists of multiple product types and product grades with multiple reactors, has been used to demonstrate the practicality of the proposed methodology.

3. Results and Discussion

Due to the sensitivity nature of the business, the real-life example has been identified as Plant A. In this case, the Plant A that adopts batch processing and operates 24 h for 7 d a week is used. Given the annual sales forecast, the first task is to evaluate whether or not the plant capacity would be able to cope with the sales forecast, as shown in Table 1. If the plant capacity is able to cope, no issues should arise. If the opposite transpires, then the type of measures that must be put in place to achieve the budget and when to implement them should be discussed beforehand.

Table 1: Annual sales forecast on Product Type I and Product Type II for Plant A

Grade,*j*,(t)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
P1	1,704	1,546	1,238	1,399	1,476	1,458	1,422	1,494	1,474	1,265	1,029	1,036
P2	602	585	452	549	579	572	579	608	600	515	419	422
P3	358	348	269	326	344	340	344	361	356	306	249	251
P4	1,252	1,216	940	1,141	1,203	1,188	1,203	1,264	1,247	1,070	871	877
P5	30	50	55	68	45	56	67	73	78	76	76	356
P6	298	290	224	272	287	283	318	334	330	283	230	232
P7	25	47	100	150	185	205	259	308	300	280	150	124
P8	4,605	3,898	2,810	2,950	3,116	3,083	3,166	3,326	3,280	2,815	2,291	2,307
P9	3,681	4,118	3,696	3,818	3,866	3,979	4,029	4,234	4,175	3,611	2,930	2,920
P10	-	-	371	2,044	2,630	2,598	2,739	2,878	2,838	2,435	1,982	1,956
P11	299	322	360	360	290	275	-	-	-	-	-	-
P12	234	341	235	254	323	210	-	-	-	-	-	-
Total	13,088	12,760	10,750	13,332	14,343	14,246	14,126	14,881	14,678	12,656	10,226	10,480

3.1 Step 1 - Data Collection

Plant A has five identical production lines. In total, there are two product types and one product grades that are produced in the plant. Based on the sales forecast given in Table 1, Product Type I accounts for the most production while Type II only has a 2.3 % share of the total sales forecast volume. Each of the product grades has its own reactor conditioning time, processing time, and batch size, as indicated in Table 2, whilst each product type has a changeover time effect. Due to product compatibility issue, about 4 d of special procedure is required when the production switches from Product Type II to Product Type I and 0.5 d of special procedure is required when the production is switched from Product Type I to Product Type II. By considering the time lost effect due to switching as well as the small volume of Product Type II, it is suggested that Product Type II is to be produced in a special campaign and the allocated storage tanks be filled up to maximum for each campaign. In this scenario, two campaigns are allocated for Product Type II.

Table 2: Example of min cycle time for respective product grade in Plant A on January

Product Type, *k*						I					II	
Grade, *j*	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
Batch Size, *BS* (t)	85.0	85.8	82.1	83.6	83.6	83.6	81.9	83.1	83.1	75.7	87.6	89.0
Ct^{min}, (h)	19.5	16.5	19	23.5	24	23.5	40	23.5	24	18.8	15	17

Note: The cycle time of P2, P3, P4, P5 and P6 are expected to be improved by an hour and they will be shorter by an hour starting from April onwards.

3.2 Step 2 - Data Translation and Problem Formulation

Further processing of raw data is required to determine the cycle time of the limiting step, reactor available day, number of production line, product mix and calculate the production volume.

3.2.1 Determine the Minimum Cycle Time, Ct^{min}

By assuming a batch process with *n* steps with each step being executed in a different piece of equipment, the minimum cycle time of the overall process is equal to the maximum duration over all steps, t_i, as per Eq(1).

$$Ct^{min} = \max_{i=1\ldots n} t_i \tag{1}$$

3.2.2 Determine the Reactor Available Days, AD_t

Total shut down days, SD_t, consists the average total numbers of planned SD^p and unplanned shut down days SD^u of all those identical reactors, m at the same period of t. Reactor available day, AD_t is calculated as total number of calendar day in the month t, FD_t minus the total shut down days, SD_t. Detail calculation is presented as Eq(2) and Eq(3).

$$SD_t = \frac{\sum_m (SD^p{}_{t,m} + SD^u{}_{t,m})}{\sum m}, \forall t \tag{2}$$

$$AD_t = FD_t - SD_t, \forall t \tag{3}$$

Since the plant A has just undergone inspection in June, the next inspection would be sometime in September the following year. Based on previous year's record, about 1.8 d was the average monthly unscheduled delays/shut downs whilst 13.2 d for planned shutdown. Total available days, AD_t, are tabulated in Table 3.

3.2.3 Determine the number of Reactor Line, *SA*

The production of Product Type II was consolidated into two campaigns after considering the Product Type II storage limitation at 2,000 t i.e. 1,791 t and 1,712 t each. Based on Eq(4), the required production day, TD_t will be 13.45 d and 12.87 d for each campaign, on top of a 4.5 d changeover period. Therefore, a total of 17.95 d and 17.37 d are required to run the Type II product campaign in Jan and April. This would also mean product Type II will occupy 0.58 line of production each time, as per Eq(5), $SQ_{t,k}$ and resulted the available production lines for Product Type I, $SA_{t,k'}$ in January and April will be 4.42 and 4.3 whilst the remaining time will have 5 full lines, as per Eq(6).

$$TD_t = \sum_j \frac{PA_{j,t} \times Ct_{j,t}^{min}}{BS_{j,t}}, \forall t \quad (4)$$

$$SQ_{t,k} = \frac{TD_{t,k}}{FD_t}, \forall t \quad (5)$$

$$SQ_{t,k'} = S_t - SQ_{t,k}, \forall t \quad (6)$$

where $Ct_{j,t}^{min}$ is the minimum cycle time for product j for month t, $PA_{j,t}$ is the production volume of product j for the month t, $BS_{j,t}$ is the batch size of product j for the month t, S_t is the total number of production lines, $TD_{t,k}$ is the total required production days of other product type k for the month t.

3.2.4 Determine the Product Mix, PR_j

In this stage, the production product mix ratio of the respective grade, $PR_{j,t}$ is assumed the same as the given sales forecast product mix ratio, $SR_{j,t}$. Each product in the respective month is calculated based on a fraction of the total sales in that particular month. Eq(7) is used as the basis of the result that is tabulated in Table 3.

$$PR_{j,t} = SR_{j,t} = \frac{S_{j,t}}{SF_t}, \forall j, \forall t \quad (7)$$

where $S_{j,t}$ is total sales of the product j for the month t, SF_t is total sales forecast for the month t.

3.2.5 Calculate the Production Volume (PA)

The Production Volume, PA_t, can be estimated by entering the 'number of batches, $NBj_{,t}$ as per Eq(8) and using the same $NB_{j,t}$. the required production days, TD_t can be calculated using Eq(9).

$$PA_t = \sum_j NB_{j,t} \text{ x } BS_{j,t}, \forall t \quad (8)$$

$$TD_t = \sum_j NB_{j,t} \times Ct_{j,t}^{min} \quad (9)$$

In any cases, the required production days, TD_t shall not exceed the reactor available day, AD_t. The $NB_{j,t}$ will have to be altered to a higher or lower value based on the TD_t obtained. The 'Solver' function in Microsoft Excel can be applied to aid in finding the correct $NB_{j,t}$. Refer Table 3.

3.3 Step 3 – Evaluate the Outcome

The information from Table 3 is further assessed using Composite Curves (CC) (Singhvi and Shenoy, 2002) and Grand Composite Curves (GCC) (Foo et al., 2008). Based on the Composite Curves (CC), it can be observed that the plant will experience a severe stock-out scenario from August to December such that the plant may not be able to cope and deliver the required sales volume for the rest of the month. This can be concluded from the supply and demand curves, which are very close to each other.

With backing from the Grand Composite Curve (GCC) in Figure 2, an inventory quantitative insight can be extracted by observing the gap between supply and demand. This shall enable determination of the required action to be incorporated as part of the company objective. These graphical presentations demonstrate that the plant can only match the sales forecast volume in March and not for any other months.

Table 3: Estimated Effective Plant Capacity based on product mix and number of streams available

Month, t	Total days in the month, FD_t (d)	Shut Down Days, SD_t (d)	Avail-able Day, AD_t (d)	Sales Forecast, SF_t (t)	Number of line available for Type I, SA	Number of Batches, $NB_{j,t}$	Product-ion volume, $PA_{j,t}$ (t)	Time required, $TD_{t,m}$ (d)	Accumulated Inventory of the month, I (t)
Jan	31.0	1.8	29.2	12,555	4.4	136.5	11,400.8	29.2	-1,154.0
Feb	28.0	1.8	26.2	12,097	5.0	138.0	11,524.7	26.2	-1,726.5
Mar	31.0	1.8	29.2	10,155	5.0	154.7	12,865.0	29.2	983.5
Apr	30.0	1.8	28.2	12,718	4.3	135.7	11,092.6	28.2	-641.9
May	31.0	1.8	29.2	13,730	5.0	164.3	13,453.0	29.2	-918.9
Jun	30.0	1.8	28.2	13,761	5.0	158.2	12,956.5	28.2	-1,723.4
Jul	31.0	1.8	29.2	14,126	5.0	163.5	13,382.1	29.2	-2,467.4
Aug	31.0	1.8	29.2	14,881	5.0	163.9	13,354.1	29.2	-3,994.3
Sept	30.0	15.0	15.0	14,678	5.0	83.8	6,861.4	15.0	-11,810.9
Oct	31.0	1.8	29.2	12,656	5.0	162.9	13,332.9	29.2	-11,134.0
Nov	30.0	1.8	28.2	10,226	5.0	158.4	12,961.1	28.2	-8,398.9
Dec	31.0	1.8	29.2	10,480	5.0	163.9	13,426.3	29.2	-5,452.6

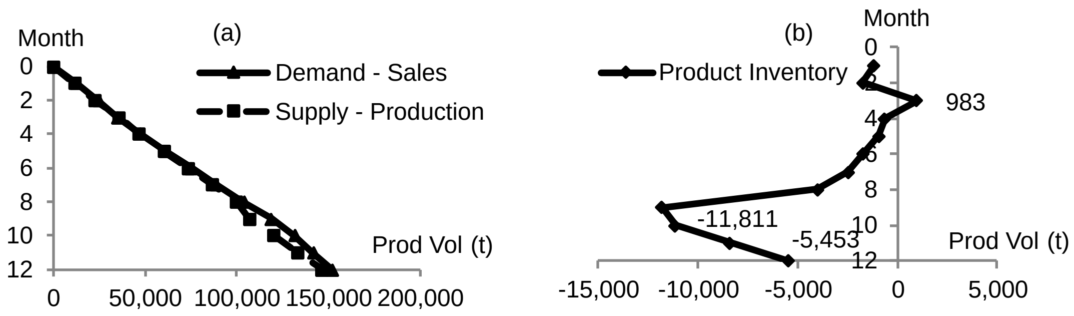

Figure 2: (a) Composite Curve (CC) and (b) Grand Composite Curve (GCC) for original scenario

3.4 Step 4 - Explore Opportunities for Operational Changes

An assessment is required to overcome the issue with regards to supply and demand. Plant managers can now use this PDSS system to simulate real-time scenarios besides gaining full understanding of the potential impacts of their decision-making and thus set proactive actions for the team. Several options were simulated i.e. provision of year-end stock, rescheduling of shutdowns, creation of more reactor availability days, and reduction of batch cycle time. Each of these options and its impacts were evaluated as per summarised in the Table 4.

Table 4: Summary of the simulated scenarios, which will help establish next year's target, enabling the plant to achieve its sales forecast.

Scenario	Original	1	2	3	4	5	6	7
Shutdown month	Sept	Sept	Dec	Dec	Dec	Dec	Dec	Nov & Dec
Plant availability, %	90.50 %	90.50 %	90.50 %	91.40 %	91.40 %	91.40 %	91.40 %	91.40 %
Cycle time	existing	existing	existing	existing	existing	1 h shorter start from Jul	1 h shorter start from Jun	1.2 h shorter start from Jun
Start inventory, t	0	11,811	0	0	2,500	2,500	2,500	2,500
Number of months stock out	11	0	11	11	4	1	0	0
Lowest inventory, t	-11,811	0	-5,773	-4,586	-2,086	-128	514	1,065
Maximum inventory, t	983	12,794	983	1,365	3,865	4,859	5,501	3,643

3.5 Step 5 - Translate Operation Changes to Target

From the result, the plant manager can now devise a series of plans and actions, which will help the team to constructively achieve their target (See Figure 3). Performance Indicators (KPIs) for the year are listed below.

- Achieve year-end inventory of 2,500 t
- Improve reactor availability by 9.5 % (reduce monthly shutdown/delays from 1.8 d to 1.5 d starting from January to regain a total of 3.3 d/y).
- Reschedule next year's annual shut down from September, to both the November and December.
- Improve respective batch cycle time by 1.2 h from June next year

The plant manager may also revisit the overall situation more frequently from looking at the monthly rolling forecast together with the action progress status. This would help to grasp the situation quickly and stay in control of the business game plan. Through this approach, the plant has successfully increased additional production in year 2015 and has yield additional revenue of RM 10 M to the business.

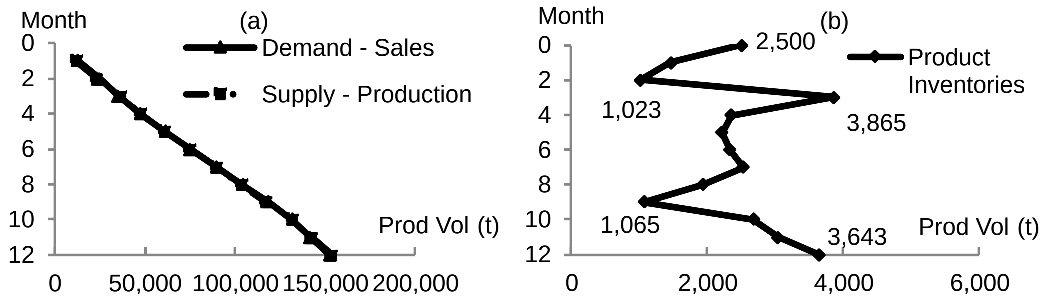

Figure 3: (a) Composite Curve (CC) and (b) Grand Composite Curve (GCC) for ultimate target (Scenario 7)

4. Conclusion

This paper has successfully produced a general framework for batch production planning. The findings have successfully contributed towards the establishment of an algorithm tool to match production capacity against sales forecast by formulating possible batch manufacturing strategies via an aggregate planning methodology using this novel graphical Pinch representation and simulation approach. This study has also demonstrated the possibility of bridging the gap between the academic and industrial world when it comes to aggregate planning. The findings of this study have resulted in the development of a PDSS System that integrates batch processes and tactical planning in a much simpler way. This system provides a fast and true holistic overview of plant capability, and thus helps plant managers to arrive at an effective decision in a timely manner.

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