ON TIME DELIVERIES IN APPAREL MANUFACTURING

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Summary: This research provides insights into root causes that are leading to missed on-time deliveries in apparel manufacturing industries. On time delivery is a critical parameter to measure Make to Order firm's supply chain performance. From procurement of raw materials to planning of production systems, all interlinked processes play a crucial role in meeting promised delivery dates. Through extensive literature review and industry visits pertaining to make to order apparel manufacturing systems, reasons for production delays are identified. Simulation studies to study the impact of the identified root causes on final on-time delivery performance are performed and the results are analyzed to make the recommendations.

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1. Background

MAP Apparel is one of the leading garment producers in the world offering manufacturing and logistics services across stages of apparel supply chain. Currently, MAP is facing a few additional delays in their production systems and seeks to understand the key reasons for the missed on-time deliveries observed in one of their garment manufacturing locations.

2. Apparel Manufacturing

Apparel manufacturing starts with preparation of paper pattern and computer markers. Garments are cut according to the planned cut dates and the cut garments are released into the pre-defined sewing lines based on the line availability. The sewn garments are then passed to wet processing or end packing depending on the type of the order. Operational due dates for each order are defined in the Master Production Scheduling (MPS) and meeting these milestones are essential to avoid the penalties of missed on-time deliveries.

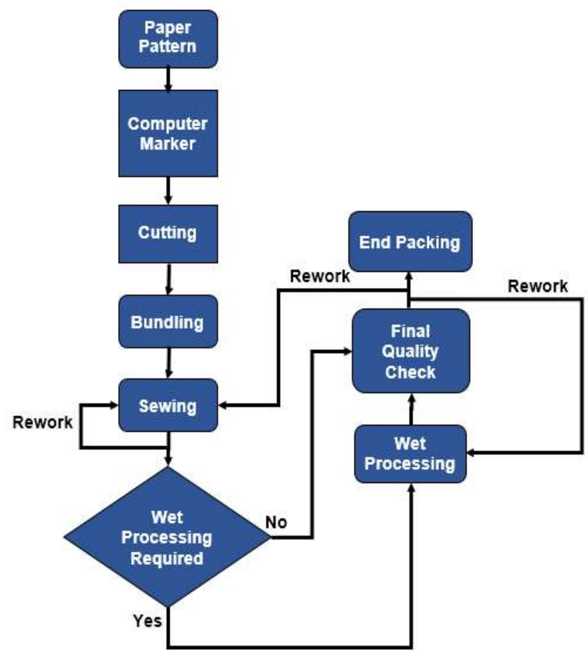

Figure 1 Apparel Manufacturing Process

KEY INSIGHTS

1. Delays at beginning and end for various processes are analyzed and found that the majority of the delays are contributed by the downstream processes (wet processing and end packing).
2. Unused or non-value added empty days in between the current processes are quantified and their impact on overall delays are analyzed.
3. The Production environment is simulated to study the impact of reducing identified delays on the final on-time delivery performance. These analyses confirm that more significant delays are caused by wet processing and end packing compared to sewing.

3. Literature Review

MPS has been suggested as the key criterion for improving most of the production measures. Baker (1974) defined production scheduling as "the allocation of resources over time to perform a collection of tasks".

Setting and evaluating performance measures regularly is also considered one of the crucial factors in meeting the on-time deliveries. One way to recognise the priority of operations is to utilise operation milestones. Milestones are essentially set in place to show when each operation should complete if the job is to progress smoothly towards on-time completion. These milestones are known as operation due dates, and they break job flow allowance into as many pieces as number of operations in the job.

Sawik (2003) proposed and analyzed integer programming approach to production scheduling in Make to Order environment with various due date related performance measures. To achieve the desired results, following four performance measures were considered and analyzed:

- Number of tardy orders
- Total tardiness
- Maximum tardiness
- Tardy work ratio

Variability in a manufacturing setting arises from unreliable equipment, unpredictable yields, glitches in human performance, fluctuations in order rates and sizes, and numerous other sources.

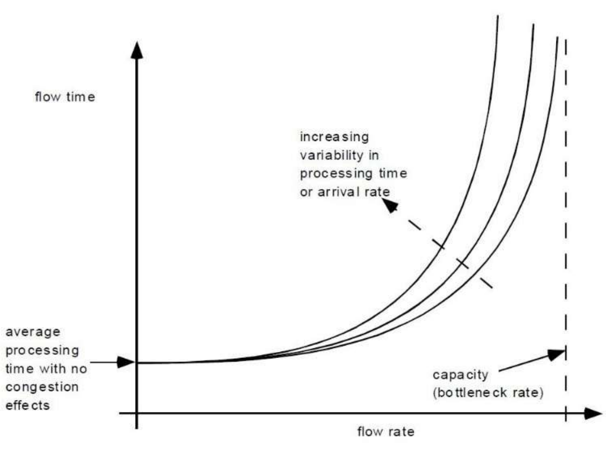

Figure 2 Impact of variability on Flow rate vs Flow time Hopp(2000)

When a production system whose components are working at close to full capacity is subjected to the stress of high variability, resulting waiting times can become very long compared with actual processing times. This is predicted by a scientific principle known as queuing theory.

John Mapes (2000) studied process variability and its effect on the industry performance. Few key results underlying variability as a key factor have been observed through a survey of plants facing process variability in their manufacturing and the impact of variability has been discussed.

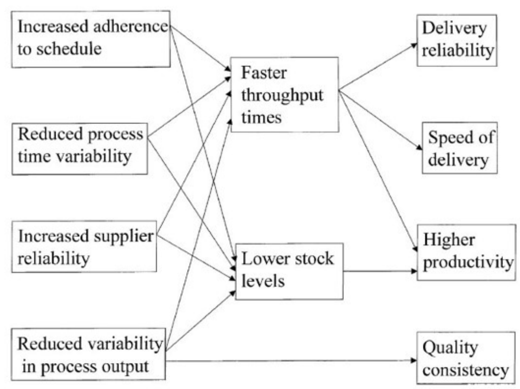

Figure 3 Key Drivers of Plant performance Mapes(2000)

4. Methodology

The approach followed in this research consists of five sequential steps. First, a hypothesis is defined followed by a review of historical data to filter data for further analyses. Then, statistical analysis is performed on the filtered data to identify the key reasons behind missed on time deliveries. Finally, a simulation model is developed to study the impact of identified reasons on missed deliveries and sensitivity analysis is performed to provide potential on-time performance metrics when the identified reasons are controlled.

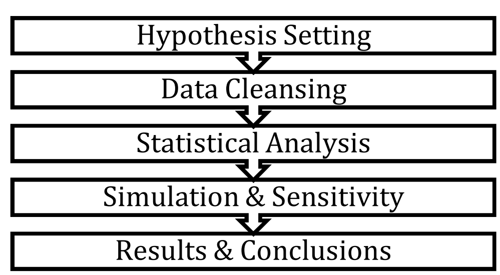

Figure 4 Methodology

As sewing is the most capacity constrained and labor intensive process in apparel manufacturing and all other processes are assumed to have infinite capacity, most of the missed on-time deliveries are considered to be contributed by sewing process. Hence, the following hypotheses are established and examined by performing several analyses in this research:

Null Hypothesis (H0): On-time performance will be significantly improved by controlling delays at sewing process.

Alternate Hypothesis (H1): On-time performance will not be significantly improved by controlling delays at sewing process.

5. Data Analysis

Interviews with process owners and site visits are conducted to map the production process and to gather the historical data. Various planning and production reports for two consecutive months are gathered. Orders with missing data are eliminated for data analysis. 591 orders remained after data cleansing and this data is used for further analyses.

The approach used for data analysis is to analyze the discrepancies between the planned dates and the actual production dates. An ideal system will adhere to the planned dates and hence faces no delays in meeting the deadlines. The delays obtained from the planning versus actual production reports are used to pinpoint the reasons that are leading to the missed on-time deliveries. If the total delays are higher than the planned buffer days, order will be finished late and hence would miss the on-time delivery.

From the planning and production data, the process times for orders are calculated. The results tabulated below suggest that on an aggregate level, sewing takes 30% more process time than planned time whereas end sew to end pack takes about 110% more process time than planned time.

Process	Total Number of process days
Planned Sew	1157
Actual Sew	1619
Planned End Sew to End Pack	2911
Actual End Sew to End Pack	6011

Table 1 Planned vs Actual process days

Also, planned versus actual process start and end dates are compared at the operational milestones. The number of orders delayed or started early at cutting, sewing and end packing processes are plotted.

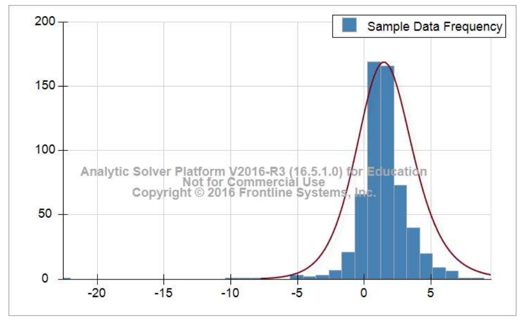

Figure 5 Cut Start Delays

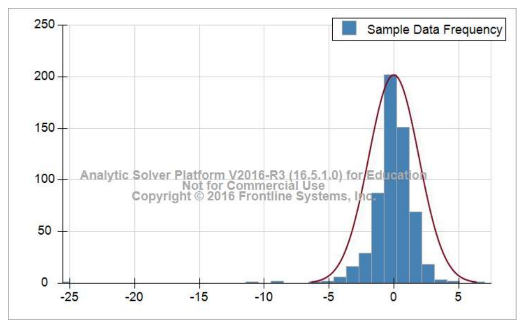

Figure 6 Sew Start Delays

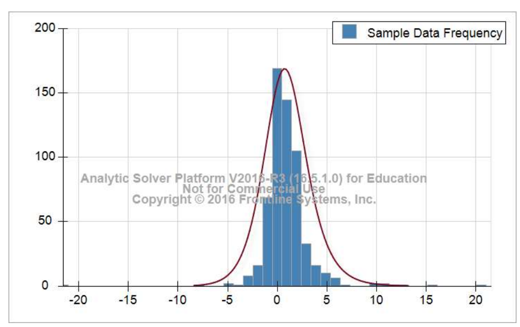

Figure 7 Sew End Delays

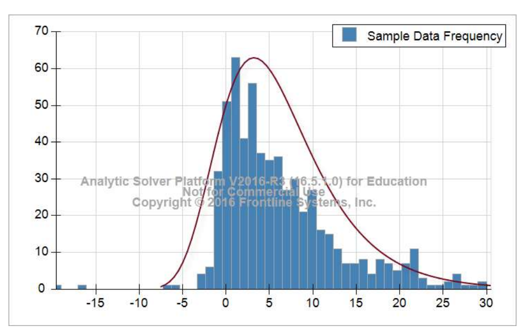

Figure 8 End Pack Delays

The delay parameters calculated from the above analysis is tabulated below:

	Mean	Standard Deviation
Cut Start	1.7	2.2
Sew Start	0.1	1.9
Sew End	0.9	2.4
End Pack	6.2	6.8

Table 2 Delay Parameters

These preliminary analyses suggest that most of the delays are contributed by processes after end sewing. Hence, additional analyses are performed to identify the reasons behind the delays occurring in the downstream processes.

To visualize the process flow of garments, production data is arranged chronologically based on processed order quantity and conditional formatting is applied to observe the number of garments produced per day. Based on the tabulated data, number of intermediate days (between process start and end date) in which no output quantity is produced are calculated.

Order ID	1/9/2016	2/9/2016	3/9/2016	5/9/2016	6/9/2016	7/9/2016
25477	0	0	0	0	0	1228
25479	204	1006	0	380	1128	1215
25481	1547	1727	540	0	0	1582

Table 3 Sample Process outputs for empty days calculation

As observed from above sample order data, order 25479 has an empty (no output) day on 3/9/2016 and order 25481 has two empty days on 3/9/2016 and 4/9/2016. To identify the impact of empty days on final order delays, the empty days for the orders across all the processes are calculated and tabulated below:

Process	Number of empty days	Number of orders with empty days
Cutting	78	34
Sewing	168	58
Pressing	167	86
Softening	610	172
End Packing	1229	275

Table 4 Empty Days in Processes

The above analysis clearly demonstrates that currently, after an order is started, it is often not processed continuously till the complete order quantity is finished. It also demonstrates that the number of instances of empty days increased in the downstream processes (pressing, and softening are sub-processes of wet processing).

The overall delays in the system are broken down into three types and are used further to analyze the performance of the production system. The three delays identified are:

1. Sew Start Delay (SSD)
2. Sew Process Delay (SSD)
3. End Sew to End Plan Process Delay (ESEPPD)

Following equation is used to calculate the actual buffer days from the delays.

$$\text{Actual Buffer Days} = \text{Planned Buffer days} - \text{SSD} - \text{SPD} - \text{ESEPPD}$$

6. Simulation Studies

As historical data is the best representation of future state of the processes, the three type of delay distributions and the planned buffer days distribution obtained are fit to the closest distribution that best represents the sample data set. These distributions are used to simulate the future state due date performance of the firm.

To understand the interaction between the delays, correlation and statistical significance is checked. It is found that SSD and SPD are closely correlated, but ESEPPD delays are independent from the SSD and SPD delays. Monte Carlo simulation technique is used to generate random delays from the distribution plots and to simulate the On-Time Delivery (OTD) for 10000 trials. OTD performance is defined as percentage of orders finished on or before the due date.

Four scenarios are defined to simulate the production environment under different set of conditions and the generated output probability distribution plots are used as a predictor of the firm's due date performance.

1. The current operations: This scenario will simulate the parameters derived from the base line operations of the firm. This is the "as is" or baseline situation and will be compared against the current operations to verify the reliability of the simulation model.
2. No process variability in sewing: This scenario will simulate the production environment by completely eliminating the sewing process variability.
3. No process variability in wet process to end pack: This scenario will simulate the production environment by completely

eliminating the wet process to end pack process variability.

4. Planned buffer time control: This scenario will simulate the production environment by setting the planned buffer time to be higher than five days and ten days.

The simulated output results are discussed below:

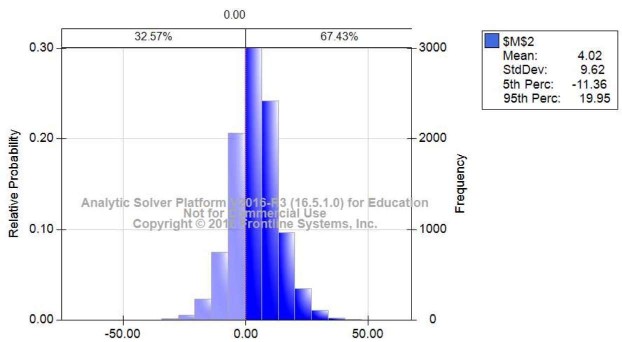

Figure 9 Baseline Scenario Simulation Output

Figure 9 shows the simulated output results of the baseline scenario. As 67.43% of the total simulations resulted in positive buffer days, the OTD performance of baseline scenario is considered 67.43%. Sensitivity analysis is also performed on the simulated outputs by individually varying planned buffer days and end sew to end pack delays to make the final recommendations

7. Conclusions and future scope

Simulation outputs for the defined scenarios are tabulated below:

Scenario	Description	OTD Performance (in %)
1	Baseline	67.43
2	Eliminating Sew Process delays	71.42
3	Eliminating End Sew to End Pack Process Delays	94.37
4 (a)	Planned buffer days to be higher than 5 days	76.56
4 (b)	Planned buffer days to be higher than 10 days	87.95

Table 5 Scenarios OTD Performance

The improvement in OTD performance even after completely eliminating delays at sewing process (scenario 2) is less than 4%. Hence, the initial hypothesis (H0) that sewing process delays significantly affects OTD performance is rejected.

Based on the analysis of the historical data, it is evident that although sewing is a perceived bottleneck, the processes between end sew to end pack contribute majority of the delays leading to the missed on-time deliveries. The simulation studies conducted also affirms the fact that reducing variability in wet processing and end packing is the best way to improve the on-time delivery performance as compared to improving sewing process delays.

Further analysis on end sew to end pack delays revealed that empty days observed in the wet processing and end packing contribute a significant amount of delays observed in the system. Discussions with MAP apparel planners and process owners revealed that reworks at wet processing might contribute to the observed empty days. Hence, the following suggestions are made to further identify the reasons behind empty days:

1. Impose strict controls and gather relevant data on processing of reworks.
2. Setting up additional operational due dates for wet processing and end packing to study the adherence of planned dates.

Future studies to simulate the production systems by varying the correlated SSD and SPD delays can be made and analyzed. Finding the optimum planned buffer days with available delay distributions can help the researcher to devise a new production scheduling heuristic which will result in improved due date performance.

8. References

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