

Factors Associated with Production Input Difference of a Manufacturing Plant in Sri Lanka: A Case Study

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Abstract

The supply chain is a system of organizations, peoples, activities, information, and resources involved in moving a product or service from supplier to customer. As the whole supply chain is linked together, any inconsistency in one link can badly affect the overall supply chain. Each organization in the supply chain has its own internal individual supply chains. The internal supply chain is mainly based on the production demand and material supply to the production. Any inconsistency between the demand and the supply, directly affects the status of internal supply chain. Only few studies have been done on internal supply demand variance, and this study is one of the few approaches into this area. The main objective of this study is to identify the factors associated with production input difference of a manufacturing plant. This is an explanatory research, which is done using appropriate sampling methods and Vector Auto regressive (VAR) modeling. Eviews (7.0.0.1) version is used to analyze the data. First of all the data has been checked for stationary property and the related lag length has been selected. Then the VAR modeling techniques has been applied and later the diagnostic tests have been performed on the resulted models. In briefing the results, it is stated that style of the product (Style) does not impact the input variance models or downtime models. Considering input variance models, it is found that downtime at lag 1 does not have any impact on the input variance. Furthermore, the previous day input variance has a significant impact to the next day input variance. The style and previous day downtime influence the demand variance only in special cases. As heteroskedasticity is present in some of the models, exponential & power transformations have been done in order to avoid heteroskedasticity. But the results do not dramatically change due to transformations.

Keywords: Factors, Internal Supply Chain, Manufacturing Plant, Vector Auto Regressive

INTRODUCTION

The apparel sector plays a vital role in current Sri Lankan economy, contributing towards nearly 50% of the earnings from exports. Therefore improving the output of the apparel sector is very important in increasing the earnings from exports. The garment factory considered in this study is one of the leading garment manufacturing facilities in Sri Lanka, serving world leading intimate brands. The production of this plant is done based on value stream level. A value stream is a set of sewing lines which is dedicated to a certain customer. The number of lines dedicated for each customer depends on the size of each order placed by the customer. Larger the order more lines will be added to related value stream and smaller the order, the number of lines will be reduced based on the garment delivery and garment quantity.

Individual manufacturing plants have own internal supply chains. As the customer places his orders to the production plant this internal supply chain comes to life. The whole supply chain process can be shown as follows.

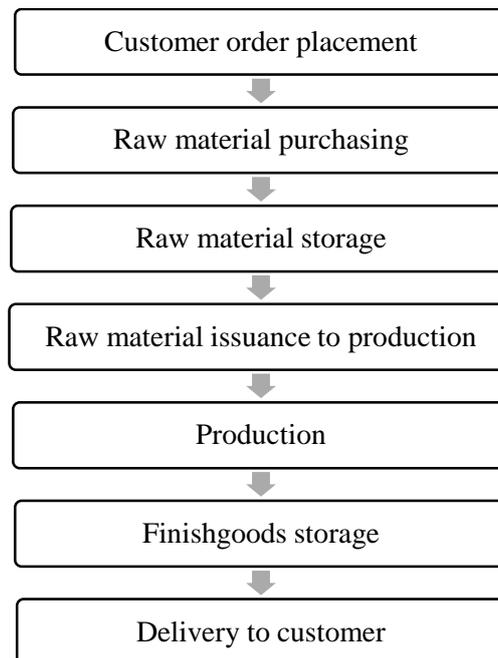


Figure 1.1: Supply Chain Flow

The smooth flow of this internal supply chain is required to meet the customer garment deliveries on time. The unevenness of the internal supply chain can be caused due to various reasons. It is mainly caused due to differences within the supply chain. These differences appear between,

- I. Customer projected order quantities and actual order placement quantities
- II. Order quantities placed with supplier and actual delivered quantities by the supplier
- III. Production planned quantities and actually requested quantities by production
- IV. Planned number of finished goods and actual number of finished goods transferred on time.

Out of these variations in the internal supply chain, the third variation can be considered as the hardest to control and generally the most costly. The fourth and fifth blocks of the Figure 1 are the points where this difference occurs. When the production planned quantities are less than actually requested quantities by production, it can cause the garment being finished in advance (increase finished goods stock holding days). On the other hand, if production planned quantities are larger than actually requested quantities by production it can cause garment delivery delays and increasing raw material stock holding days. In both ways, this has a considerable impact to the production plant.

This study has been done taking the difference between planned line demand and actual line input, along with other measurable factors which are assumed to affect the line demand.

Objective

The objective of this study is, to identify the factors associated with production input difference of a manufacturing plant at the value stream level.

LITERATURE REVIEW

Supply chain is a phenomenon flourished in early 1990' or late 80's. Cavinato (1992) stated that, the development of the idea of the supply chain owes much to the emergence from 1950s of systems theory, and the associated notion of holism. Beamon (1998) defines supply chain as an integrated process wherein the suppliers, manufacturers, distributors, and retailers work together in an effort to: (1) acquire raw materials for production, (2) convert these raw materials into specified final products, and (3) deliver these final products to retailers.

Within the supply chain, every member is either a supplier or a customer of the next member. This concept of customers being suppliers is recognized as 'customer-supplier duality.' a company's supply chain, either internal or external, is a resource to be exploited for better market position and enhanced competitive advantage. (Monczka and Morgan, 1997) here

Monczka and Morgan discussed about an internal supply chain. Here each single entity in the supply chain has an own internal supply chain.

The demand inconsistency in a supply chain can be caused externally as well as internally. Baganha and Cohen (1998), Kahn (1987), Lee, Padmanabhan and Whang (1997) describes increment in demand variability as one moves up a supply chain.

The causes for demand variance vary within the supply chain and Lee. *et al.* (1997), has identified five main causes for this effect. They are given as demand signal processing, the rationing game and order batching and price variations. Demand signal processing refers to the situation where demand is non stationary and one uses past demand information to update forecasts. The rationing game refers to the strategic ordering behavior of buyers when supply shortage is anticipated. When the fixed order cost is non zero, ordering in every period would be uneconomical, and batching of orders would occur. Finally, price variations refer to non-constant purchase prices of the product. (Lee, *et al.*, 1997). In order to minimize the demand variance, there have been experimental studies done. Eppen and Schrage (1981) have done a study at the intermediate supplier, where the supplier receives his inventory at fixed intervals. Then as soon as the supplier receives the inventory, it was shipped out to the retailers. By this method, the supplier carries no stock. Therefore there is a minimum chance to have a massive variance in the demand and the supply. In 1999, a paper presented by Cachon suggests a method to minimize the demand variance between one supplier and n retailers. It shows that the supplier demand variance declines as the retailer' order interval is long or the batch size (order quantity per order) is increased. Kahn (1987) was the first to model the demand variance by AR (1) process. He also observed that the variability in demand has double effect. First is that, as the raw material stock replenish in the production line, the variability is reproduced. The second is that as the inventory level are being adjusted in order to represent the changes in the forecasts, the variability is amplified. Cachon *et al.* (2007) observed that manufacturers with highly seasonal demand, is most likely to smooth the demand variability amplification.

Based on the experiences of production teams, it was noted that machine downtime has an impact to the sewing line input variance. Therefore, the variable, machine downtime also been considered in the study. Downtime due to machine breakdowns increases the cost of ownership and can reduce the lifetime of the asset. Also it causes purchasing costs for the

spares and if they need to be transported from far areas, the freight costs also get included (Dunks, 1998). Considering lost production costs due to downtime, there are three common costs identified. Cost of lost opportunity (Crumrine and Post, 2006; Dunks, 1998), bottleneck costs (Crumrine and Post, 2006), Work In Progress (WIP) costs (Dunks, 1998). Here the lost production cost can be defined as the cost incurred due to incapability of producing the goods. The cumulative work in progress (WIP), held up in the sewing lines due to downtime, causes this cost. Due to WIP being held in the line, daily actual input quantity varies from the plan. Due to production being held up, other supporting teams also get affected down the line. Most of the studies on supply chain demand variance, have assumed that the demand process is a non-seasonal and stationary process and have modelled it as an Auto-Regressive Moving Average (ARMA) process type of order one. Some studies has studied the demand variance under a base-stock policy applying the mean squared error optimal forecasting method to an Auto-Regression (AR (1)) and investigated further the stochastic nature of the ordering process for an incoming ARMA (1,1) using the same inventory policy and forecasting technique. Due to this subject being new, the number of studies done on supply chain demand variance is few and there was not any significant study done on internal supply chain demand variance.

Based on studied literature, in most of the instances demand variance has been assumed as non-seasonal and stationary series and has been analyzed using univariate models. Univariate modeling will facilitate to model one variable with the impact of other variables on it. It is not allowed to model several variables together. Most of the researchers might have followed univariate modeling due to data limitations, such as lack of recorded data, lack of qualitative data measuring methods (ex: methods to measure operator skill without bias), lack of methods to relate qualitative data into the model and etc. Mainly, there have not been many researches done on internal supply chain demand variance of a manufacturing facility. Therefore these and other limitations have not been discussed in detail. This study has extended the univariate demand variance studies into multivariate demand variance studies, using VAR modeling. So, the currently using univariate model in demand variance has been improved into multivariate modeling.

METHODOLOGY

This is an explanatory research done, in order to identify the factors associated with the internal supply chain demand inconsistency in a manufacturing plant. Here the considered

variance of the internal supply chain is the difference between planned line input and actual line input. The data has been collected for 6 months from 1st May 2014 to 31st Oct 2014. The total 45 sewing lines in the factory were considered as the study population. Out of the total 45 sewing lines, it was decided to select a sample of size 14 (one third) of the study population. The sewing lines for trivial customers were excluded from the study.

Sample selection

Due to production separation based on customer groups, stratified random sampling was selected as the desired sampling method.

Stratified random sampling: The major requirement of this sampling method is the homogeneity within the sub groups in the population. There are several methods to determine the sample size of the subgroups. Optimal allocation, Neyman allocation and proportional allocation are three main allocation methods. Optimal allocation is used when the precision need to be maximized while the cost is fixed within the strata and Neyman allocation is used when the precision need to be maximized while the sample size of the strata is fixed. Here proportional allocation is considered as the cost per stratum is unknown. With proportional allocation, the sample size is proportional to the size of the strata. The sample size calculation formula is as below,

$$n_h = \left(\frac{N_h}{N} \right) * n \quad (1)$$

Where,

n_h = sample size for stratum h

N_h = size of the stratum h

N = size of the population

n = total sample size

After the sample size selection by above method, simple random samples of the determined sizes were selected from each strata.

Data collection

From each of the selected samples, below data was collected from each line.

- Related line number/customer
- Daily sewn garment style
- Daily planned input quantity

- Daily requested input quantity
- Daily downtime minutes

The data has been collected from work study department, cutting department, planning department and other supporting teams.

Description of variables

Below variables were created based on above data set.

- Diff – the difference between planned line input and actual line requested quantity this has been calculated from the planned input values from production planning documents and the actual line requested quantity is taken from raw material issuance documents which are recorded manually. Both of these data is recorded daily and the difference is calculated.
- DT- down time caused on each line each considered day. This is collected from work study department's daily records.
- Style- the style continued in each value stream in the considered time period. This has been extracted from planning department's production planning documents. As the Styles continue in production, one after another (i.e. for a particular customer value stream, the styles continue one after another. For example, for customer VS, Style1 & 2 will not be sewn in the same value stream at the same time.) they have been considered separately as dummy variables.

Data analysis

Data processing and analysis were done using Eviews enterprise edition 7.0.0.1 version. As the data is time based, a time series method was decided to use as the method of analysis.

Unit root test

In order to apply the VAR modeling, the data sets need to be stationary. A stationary series is a data series where its parameters such as mean and variance do not change over time. To check the stationary status of the data, unit root test is used here. As the sample size is large and the time series model can be complicated, ADF is selected out of all the unit root test options.

If the series is proven stationary from above test, then the analysis can be continued. Else, the series need to be differenced until it becomes stationary.

Lag length selection

After checking for stationary status of the data set, the lag length need to be selected for each model which will be fitted. First fit VAR (p) models with orders $p = 0, \dots, p_{\max}$ and choose the value of p which minimizes some model selection criteria.

VAR model

VAR model extends the AR model to multiple equations. VAR model estimates multiple endogenous variables in one regression, with some exogenous variables incorporated in the model. These endogenous variables are organized together to forecast using an autoregressive method, with multiple dependent variables. VAR model describes the development of a set of endogenous variables over the same period as a linear function of only their past values. This is mostly used for forecasting systems with interrelated time series.

VAR model can be given as,

$$Y_t = \alpha_1 y_{t-1} + \dots + \alpha_p y_{t-p} + \beta x_t + \varepsilon_t \quad (2)$$

$Y_t = k$ vector of endogenous variables

$X_t = d$ vector of exogenous variables

$\alpha_i = i^{\text{th}}$ coefficient

$\varepsilon_t =$ error term

VAR model can be applied to set of different variables as below.

$$Y_t = \alpha_1 y_{t-1} + \alpha_2 x_{t-1} + \beta_1 y_{t-2} + \dots + c_1 + \varepsilon_{1t} \quad (3)$$

$$X_t = \alpha_3 y_{t-1} + \alpha_4 x_{t-1} + \beta_3 y_{t-2} + \dots + c_2 + \varepsilon_{2t} \quad (4)$$

Then using the selected lag length, apply the VAR model to the data set as given above. The output gives the model fitting. After the model fitting, the adequacy of the model is then tested by diagnostics tests as described below.

Diagnostic tests

Residual serial correlation LM tests: out of several serial correlation tests, Lagrange multiplier (LM) test is used here. The basic idea is to regress the residuals from the ordinary least square regression on all of the independent variables and on the lagged values of the residuals.

The test statistic is,

$$LM = (n-1) R^2 \quad (5)$$

$(n-1)$ = the number of observations in the regression

R^2 = coefficient of determination

Under the null hypothesis of no serial correlation of any order up to p , we reject H_0 if $LM > c$ and if we want a test with a 5% significance level, we find the critical value c from,

$$\text{pr}(LM > c) = .05 \quad (6)$$

VAR residual normality tests: Jarque-Bera residual normality test is used here. This compares, third and fourth moments of the residuals to those from the normal distribution and can be used for large samples. This test is a goodness of fit test, testing whether the residuals have skewness and kurtosis, matching a normal distribution.

The test statistic is,

$$JB = \frac{n}{6} \left(S^2 + \frac{1}{4}(K - 3)^2 \right) \quad (7)$$

S = sample skewness

K = sample kurtosis

n = number of equations

This test tests normality against a null hypothesis of each variable is having a normal distribution. If the data belongs to a normal distribution, JB test statistic follows chi squared distribution with two degrees of freedom.

Heteroskedasticity test: white (with cross terms) – this test, tests whether the residual variance of a variable in a regression model is constant: that is for homoscedasticity. Also its an estimator for heteroscedasticity-consistent standard errors.

The test statistic is,

$$Lm = n * r^2 \quad (8)$$

n = sample size (or the number of observations)

r^2 = coefficient of determination

The test statistic is asymptotically distributed as a chi squared distribution, with degrees of freedom equal to the number of slope coefficients (excluding the constant) in the test regression. The null hypothesis of, no heteroskedasticity is tested against the alternative hypothesis of heteroskedasticity of some unknown general form. The null hypothesis assumes that the errors are both homoskedastic and independent of the regressors, and that the linear specification of the model is correct. Failure of any one of these conditions could lead to a

significant test statistic. Conversely, a non-significant test statistic implies that none of the three conditions is violated. With cross terms version of the white heteroskedasticity test is the original version of white's test that includes all of the cross product terms.

ANALYSIS

Internal supply chain demand inconsistency is so far has not been a major area of study in the subject of supply chain management in Sri Lanka. Therefore, this study will be one of the handful of studies in that subject matter.

In practical world, there can be many factors affecting production input difference. Production idling, line efficiency, over time work, garment delivery date, company holidays, order quantity and absenteeism are few factors to name. Since in calculating the planned line input quantity, almost all of these factors are being considered, they have not been taken separately into the study.

Selection of data

Out of above given factors affecting the internal supply chain demand inconsistency, the major factors outlined below have been incorporated into this study.

- I. The target daily input quantity for each line - this is a value calculated by production planning team for each line, based on the line efficiency, SMV, customer order quantity and garment delivery for each style.
- II. Actual input quantity by each line - this is the actual quantity requested by each line for each day production
- III. Downtime caused by each line - this is the daily production idling time for each line.
- IV. Garment style – this is an exogenous variable, where it differs per line and per time period.

As the SMV value for each style, line efficiency, garment delivery and customer order quantity is already being incorporated into the target daily input value, these figures have not been considered separately in the analysis.

Company holidays and overtime work has not been done throughout the time period of consideration. There are no considerable fluctuations in the absenteeism Figures, therefore its

being considered a constant. After identifying the possible factors affecting the internal supply chain demand inconsistency, the factors will be modeled using a time series model in order to quantify the relationship.

Sample selection

As the data is originally being separated into value stream level strata's, any other basic method of sample selection will result in a bias sample for the analysis. To avoid such error, the stratified random sampling is being used. The samples from each selected strata, have been selected by simple random sampling and the samples size determination is done by proportional allocation. Proportional allocation is chosen over optimal allocation or Neyman allocation, as the sampling cost is considered to be constant and the variability within a strata is very small and equal.

Value stream level results for modeling of each data sets are being discussed below.

Triumph value stream

Triumph value stream has 4 styles running in the particular period. The unit root test results the two data sets (diff-input variance data, DT- downtime data) are stationary. The selected level of significance is 5%.

Table 1: Summery data for above Triumph value stream

Value stream	Style number	VAR model		R ²	Auto correlation	Normality of the residuals	Heteroskedasticity
Triumph	1	Input variance	$\text{Diff} = 0.46 * \text{Diff}(-1) - 0.005 * \text{DT}(-1) + 43.24\text{Style1} + 50.35$	21	×	√	√
		Downtime	$\text{DT} = 0.62 * \text{Diff}(-1) + 0.38 * \text{DT}(-1) + 113.29\text{Style1} + 366.79$	16	×	×	√
	2	Input variance	$\text{Diff} = 0.46 * \text{Diff}(-1) - 0.004 * \text{DT}(-1) + 5.09\text{Style2} + 54.27$	21	×	√	√
		Downtime	$\text{DT} = 0.63 * \text{Diff}(-1) + 0.37 * \text{DT}(-1) - 131.94\text{Style2} + 413.04$	16	×	×	√
	3	Input variance	$\text{Diff} = 0.31 * \text{Diff}(-1) - 0.005 * \text{DT}(-1) - 179.07\text{Style3} + 106.61$	33	×	√	×
		Downtime	$\text{DT} = 0.93 * \text{Diff}(-1) + 0.36 * \text{DT}(-1) + 341.99\text{Style3} + 282.80$	17.5	×	×	√

	4	Input variance	$\text{Diff} = 0.39 * \text{Diff}(-1) - 0.0002 * \text{DT}(-1) + 98.56 * \text{Style4} + 21.30$	26	×	√	×
		Downtime	$\text{DT} = 0.78 * \text{Diff}(-1) + 0.37 * \text{DT}(-1) - 199.63 * \text{Style4} + 449.68$	16.9	×	×	√

× = no √ = yes

Input variance models: The input variance models for Triumph value stream have the input variance at lag 1 significant, indicating that the data is related to previous day data. Except for style 4, all styles are insignificant in modeling input variance, indicating that style do not play a major role in input variance model for triumph value stream. Also, the downtime variable is insignificant at all triumph input variance models, indicating that the downtime does not have any impact on input variance model. All models explain around 20% of the variables, individually. There is no auto correlation and the residuals of all models are distributed normally. For style 3 and 4, there is no heteroskedasticity involved.

Downtime models: The downtime models for Triumph value stream have the downtime at lag 1 significant, indicating that the data depends on previous day downtime. The input variance at lag 1 is significant only in style 3 and other styles are insignificant for downtime data. This implies that style do not play a major role in downtime model for triumph value stream. In the downtime models for each four styles, around 16-17% of the variables are explained by each model. Also there is no autocorrelation and the residuals for each style are not distributed normally.

VS value stream

VS value stream has 4 styles. For VS value stream, the unit root tests for both input variance and downtime data implies that the data sets are stationary. The selected level of significance is 5%.

Table 2: Summery data for VS value stream

Value stream	Style number	VAR model	R sq	Auto correlation	Normality of the residuals	Heteroskedasticity	
VS	1	Input variance	Diff = 0.16*Diff (-1) + 0.04* DT (-1) + 124.91*Style1 + 16.82	11.8	×	×	×
		Downtime	DT = 0.35*Diff(-1) + 0.305*DT (-1) + 426.79*Style1 + 406.78	15	×	×	√
	2	Input variance	Diff = 0.17*Diff (-1) + 0.05* DT (-1) - 86.88*Style2 + 80.14	11.8	×	×	×
		Downtime	DT = 0.47*Diff (-1) + 0.33*DT (-1) - 25.31*Style2 + 488.52	13	×	×	×
	3	Input variance	Diff = 0.19*Diff (-1) + 0.05* DT (-1) - 0.57*Style3 + 37.17	9	×	×	×
		Downtime	DT = 0.49*Diff (-1) + 0.32*DT (-1) - 254.96*Style3 + 522.74	13.9	×	×	×
	4	Input variance	Diff = 0.19*Diff (-1) + 0.05* DT (-1) + 5.54*Style4 + 36.19	9	×	×	×
		Downtime	DT = 0.42*Diff (-1) + 0.32*DT (-1) - 304.82*Style4 + 524.35	14	×	×	×

× = no √ = yes

Input variance models: The input variance models for VS value stream have the input variance at lag 1 and downtime at lag 1 being significant. This indicates that both previous day input variance as well as previous day downtime impacts the VS input variance model. Except for style 1, all styles are insignificant in modeling input variance, indicating that style do not play a major role in downtime model for VS value stream. Also more than 9-12% of the variables are explained by individual models. There is no auto correlation and the residuals of all models are not distributed normally. Also there is no heteroskedasticity involved in all four models.

Downtime models: The downtime models for VS value stream have the downtime at lag 1 significant, indicating that previous day downtime impacts the downtime models for VS value stream. The input variance at lag 1 is insignificant for all styles. So, it cannot be stated that input variance have any impact on the downtime model for VS value stream. Also the style data do not have any impact on the downtime models except for style 1. Around 13-

15% of the variables are explained by the model. Also there is no autocorrelation and the residuals for each style are not distributed normally. There is no heteroskedasticity involved in for style 2,3 and 4.

VSX value stream

For VSX value stream, they have 6 styles & the unit root tests for both input variance and downtime data implies that the data sets are stationary. The selected level of significance is 5%.

Table 3: Summery data for VSX value stream

Value stream	Style number	VAR model		R sq	Auto correlation	Normality of the residuals	Heteroskedasticity
VSX	1	Input variance	$\text{Diff} = 0.23 * \text{Diff}(-1) - 0.007 * \text{DT}(-1) - 38.35 * \text{Style1} + 194.36$	5	×	×	√
		Downtime	$\text{DT} = 0.68 * \text{Diff}(-1) + 0.26 * \text{DT}(-1) + 62.94 * \text{Style1} + 525.79$	8.9	×	×	√
	2	Input variance	$\text{Diff} = 0.24 * \text{Diff}(-1) - 0.007 * \text{DT}(-1) + 37.73 * \text{Style2} + 186.74$	5.7	×	×	√
		Downtime	$\text{DT} = 0.67 * \text{Diff}(-1) + 0.26 * \text{DT}(-1) - 22.35 * \text{Style2} + 533.25$	8.9	×	×	×
	3	Input variance	$\text{Diff} = 0.24 * \text{Diff}(-1) - 0.006 * \text{DT}(-1) - 12.08 * \text{Style3} + 195.96$	5.4	×	×	√
		Downtime	$\text{DT} = 0.67 * \text{Diff}(-1) + 0.22 * \text{DT}(-1) + 479.69 * \text{style3} + 355.62$	11.5	×	×	×
	4	Input variance	$\text{Diff} = 0.24 * \text{Diff}(-1) - 0.007 * \text{DT}(-1) + 41.17 * \text{Style4} + 188.04$	5.6	×	×	√
		Downtime	$\text{DT} = 0.69 * \text{Diff}(-1) + 0.25 * \text{DT}(-1) - 442.03 * \text{Style4} + 568.19$	9.6	×	×	×
	5	Input variance	$\text{Diff} = 0.24 * \text{Diff}(-1) - 0.008 * \text{DT}(-1) - 36.41 * \text{Style5} + 198.15$	5.7	×	×	√
		Downtime	$\text{DT} = 0.65 * \text{Diff}(-1) + 0.26 * \text{DT}(-1) - 255.53 * \text{Style5} + 576.65$	9.3	×	×	×
	6	Input variance	$\text{Diff} = 0.24 * \text{Diff}(-1) - 0.007 * \text{DT}(-1) + 21.19 * \text{Styel6} + 187.99$	5.5	×	×	√
		Downtime	$\text{DT} = 0.71 * \text{Diff}(-1) + 0.25 * \text{DT}(-1) - 363.95 * \text{Style6} + 591.68$	9.8	×	×	×

× = no √ = yes

Input variance models: The input variance models for VSX value stream have the input variance at lag 1 being significant, indicating that previous day data impacts the input variance model for VSX value stream. The downtime data is insignificant for input variance model for VSX value stream. All style variables are insignificant in modeling input variance, implying that the input variance model for VSX value stream do not depend on style data. Also around 5% of the variables are explained by each model. There is no auto correlation and the residuals of all models are not distributed normally. Also there is heteroskedasticity involved in all four models.

Downtime models: The downtime models for VSX value stream have the downtime at lag 1 significant, indicating that previous day downtime impacts the downtime model for VSX. The input variance at lag 1 is insignificant for all styles, where the input variance does not have any impact on the downtime model. Only style 3 is significant out of exogenous variables. Indicating that style data do not have any major impact in downtime models. In the downtime models for each four styles, around 8-11% of the variables are explained by the model. Also there is no autocorrelation and the residuals for each style are not distributed normally. There is no heteroskedasticity involved in.

Counter measures for residual diagnostics

As per the analysis above, majority of the VAR models do not pass the residual diagnostic tests successfully. Therefore in order to acquire a better model, below different approaches were taken.

In order to avoid heteroskedasticity, nonlinear transformation of exponential model was considered for two randomly selected models.

Dependent variable (Diff) = log (Diff)

Ex: $LN_DIFF = C(1)*LN_DIFF(-1) + C(2)*DT(-1) + C(3) + C(4)*STYLE1$

The results avoid heteroskedasticity in input difference variable only. Also it causes correlation in input difference variable data.

As the exponential model removes the heteroskedasticity only in the input difference variable, the power model was considered to avoid heteroskedasticity in both the variables,

Dependent variable (Diff) = log (Diff)

Independent variable (DT) = log (DT)

The model ends up in having heteroskedasticity in both models.

As both transformation methods do not meet up to the expectations, there is room for further analysis in this regard.

Summery

In an overall comparison, it is significant that the style data does not impact the input variance models or downtime models in general. I.e. The input variance or the downtime do not depend on the style that continues on the line. This may be due to, style data being included in overall planning procedure i.e. The target daily input quantity for each line as standard minute value (SMV). I.e. For all calculations related to input planning the style data is included as SMV (the standard time taken to complete a garment of each style). Also, except for VS value stream input variance models, each input variance models have only input variance at lag 1 being significant, indicating that downtime at lag 1 does not have any impact on the input variance data. For all downtime models, only downtime at lag 1 is significant except in two cases. This indicates that either the input variance or the style data do not impact the downtime.

Considering all the models regardless of its value stream, only triumph styles 3 and 4 satisfy all the residual analysis tests based on the initial assumptions. Having a set of stationary data, the input variance models at lag 1 have insignificant autocorrelation, normally distributed residuals and no heteroskedasticity being involved in the model. Although other models deviate from some of the residual tests, the final outcome of these models are also the same. Therefore, while all value stream data are stationary, all value stream data can be modeled interpretably and the results are similar.

CONCLUSION

Empirical findings

As per the analysis done on collected data, the empirical findings can be divided into sections based on customer value streams, as the behavior of these value streams differ in terms of ordering and delivery pattern/SMV/style details etc. At 5% level of significance with lag value 1 while all the data being stationary, the identified factors which affect the internal

supply chain demand variance are downtime and the garment style which is being sewn in each line. Based on the above two factors, the output of each value stream differ as below.

Triumph value stream: The input variance of Triumph value stream depends on previous day input difference only. The style/downtime are not significant in the study.

VS value stream: The input variance of VS value stream depends on both previous day input difference and previous day downtime. The style is not significant in the study.

VSX value stream: The input variance of VSX value stream depends on previous day input difference only. The style and downtime are not significant in the study.

Considering the factors which affecting or causing downtime, Except for Triumph style 3, the downtime depends only on the previous day downtime. In triumph style 3, both previous day input difference and previous day downtime are significant. It's the same outcome for VSX value stream that, only 3rd style has an impact on the downtime and other styles has only previous day downtime impacting the current day downtime.

For VS value stream, only for VS style 1 is significant other than previous day downtime. Regardless of the value streams, only Triumph style 3and4 satisfy all the residual requirements. But even though other models deviate from the residual requirements, the same outcome has been seen throughout. . Therefore, while all value stream data are stationary, all value stream data can be modeled interpretably and the results are similar.

In order to avoid heteroskedasticity, exponential transformation & power transformation was used for randomly selected styles. But they do not output a fair result.

Limitations of the study

As the study is done in a reputed manufacturing plant which manufacture garments for global brands, the study encountered a number of limitations which need to be considered.

- The usage of sensitive data, where it can impact the brand protection policies and company policies

- Absenteeism, operator skill etc, were not directly included in the data as for their different measuring mechanisms.
- Availability of heteroskedasticity in the data, where it can be extended to ARCH/GARCH modeling in future research
- Applying individual downtime reasons into the model other than incorporating the total daily downtime into the study.

Recommendations for future research

The limitations given in the limitations chapter can be extended into future research, studying availability of heteroskedasticity in certain value stream data by using ARCH/GARCH (EX: MGARCH) models and liner transformations other than exponential and power transformations. Also, the study can be expanded into detailed downtime reason analysis using any other relevant modeling.

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