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LEAD TIME PREDICTION FOR SHEETER MACHINE PRODUCTION IN A PAPER CONVERSION INDUSTRY

Muhammad Talha Siddique[1], Muhammad Dawood Idrees[1*] Atif Jamil[2], Arsalan Ansari[3], Abdul Sami[3], Muhammad Rauf[3]

[1] Department of Industrial Engineering & Management, Dawood University of Engineering & Technology, Karachi, Pakistan
[2] Department of Computer Systems Engineering, Dawood University of Engineering & Technology, Karachi, Pakistan
[3] Department of Electronics Engineering, Dawood University of Engineering & Technology, Karachi, Pakistan
** muhammad.dawood@duet.edu.pk*

Lead time is a critical performance measure in any manufacturing setting Key Performance Indicator (KPI). The same is true in the paper conversion industry, which has a significant degree of product variability. Due to the great variety of their products, all industries must be able to foresee and plan ahead in order to meet client demand. With contemporary research concentrating on machine learning and simulation techniques, businesses must implement a manufacturing execution system (MES) to track data. However, without such a framework, applying machine learning and simulation approaches becomes difficult. This study introduces a novel method for forecasting lead time (special to sheeter machines used in the paper conversion sector) by combining the time required to process the reel (sheeting time) with the human (setup) elements. The method used to calculate the sheeting time takes product parameters into account, allowing for product-specific lead time forecast. As a result, a very successful 'product-specific' lead time prediction approach for small scale enterprises has been developed that enables production planning without relying on current and data-intensive prediction methods such as machine learning and simulation.

Keywords: lead time prediction, manufacturing execution system, machine learning, paper conversion industry, simulation

1 INTRODUCTION

For any modern manufacturing industry, forecasting and planning are crucial to success. Therefore, knowing how much time a product might take to get through the system is vital and it is often that most KPIs revolve around this piece of information. Also, in order for industries to provide high volume with variety, they have to have high flexibility of processes and resources [1]. This can only come from good planning. For industries with high variability in products that they produce, planning is based on the knowledge of lead times of the product being produced. The degree to which this plan is executed depends largely upon the ability to accurately predict lead time [2, 3]. Therefore, formulating a reliable method to predict lead times in a production environment with high variability is important to meet customer demands on a consistent basis.

Lean manufacturing is a Japanese concept developed by the Toyota production system. It uses various tools to reduce waste and improve productivity in production systems. For lead time calculation and analysis, lean manufacturing uses a tool called value stream mapping (VSM). In some of the recent studies, Gherghea, Bungau [4] employed VSM to present the lead time of the product. While VSM is a great tool for calculation of lead time, it does very little in predicting it since the lead times in VSM are calculated with the help of work in process inventory. Large data needs to be collected if one wants to predict lead times for various products using VSM. This is because VSM only provides a static picture of the system.

To replace this static picture with a dynamic one, discrete-event simulation (hereafter referred to as simulation) approach has also been applied to making decisions in scheduling and control, related to production applications [5-7]. Solomon, Jilcha [8] applied simulation techniques using Arena software and Monte carlo method to predict lead time. In this case, the lead time prediction was based on past operational or assembly orders. Although simulation produces better results than VSM, similar to VSM, it also requires large amount of historic data in order to give fruitful results

VSM & simulation are not the only techniques that can help in lead time prediction. Other new techniques have also been developed. Gyulai, Pfeiffer [2] studied the effectiveness of various analytical and machine learning techniques to predict lead time and concluded that machine learning techniques far outperform analytical techniques, but the effectiveness depends on the process under study. Singh and Soni [9] applied machine learning techniques for predicting lead time in a just in time (JIT) production environment using error measuring methods like mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE) and mean absolute percentage error (MAPE). However, the prerequisite to selecting the lead time prediction method is the availability of properly collected data which is usually available through a proper system like manufacturing execution system (MES).

The industry in which this study was conducted had little historic data in place. The available data was in the form of traditional documentation rather than in a proper MES. Therefore, the problem this study tends to solve is to devise a reliable method for predicting lead time in a paper conversion industry, where there is no MES in place. Having said that, it is also worth noting that doing a traditional time study is not a feasible solution since the product variability is too high and it would simply take too long to cover every single product. Like any other manufacturing environment, the lead time for each product is closely linked with the machine and some of its parameters. Since these parameters have a direct bearing on the lead time itself, these parameters need to be studied along with the effect they have on the lead time of the product, before formulating an actual method of calculation.

2 METHODOLOGY

Due to the lack of data available at the industry where this project was executed, a rather novel approach had to be adopted to solve the problem using available resources. First step is to collect data which encompasses important data features that are to be studied. After statistical analysis, machine parameters that affect the lead time come under the scrutiny and a thus a better understanding of the situation can be gained.

After having performed the statistical analysis, next stage is to develop a method for calculation of lead time. In this study, as shown in figure 1, a “sheeting + time study approach” is used to achieve this task. Formula part of the calculation will provide the ‘unwinding and sheeting’ time of the reel being sheeted. This formula has to be able to encapsulate the product features and machine parameters at the same time in order to give a reasonable answer. This is where the statistical analysis done at the second stage comes into play and helps in using the right formula.

On the other hand, the second element of the calculation is time study. Time study part of the calculation is done to cover the human elements of the process. The main human elements include reel setup, size and angle checking, sorting (separating damaged sheets from good ones) and pallet changeover. The nature of these activities remains the same regardless of the product being produced. Thus, it made sense to use the time study tool to calculate the human element of the process. The number of observations to be taken for this purpose are determined using a statistical method.

Lastly, the results form formula and time study are combined to formulate the final answer. The final result is then verified with real data collected on production floor.

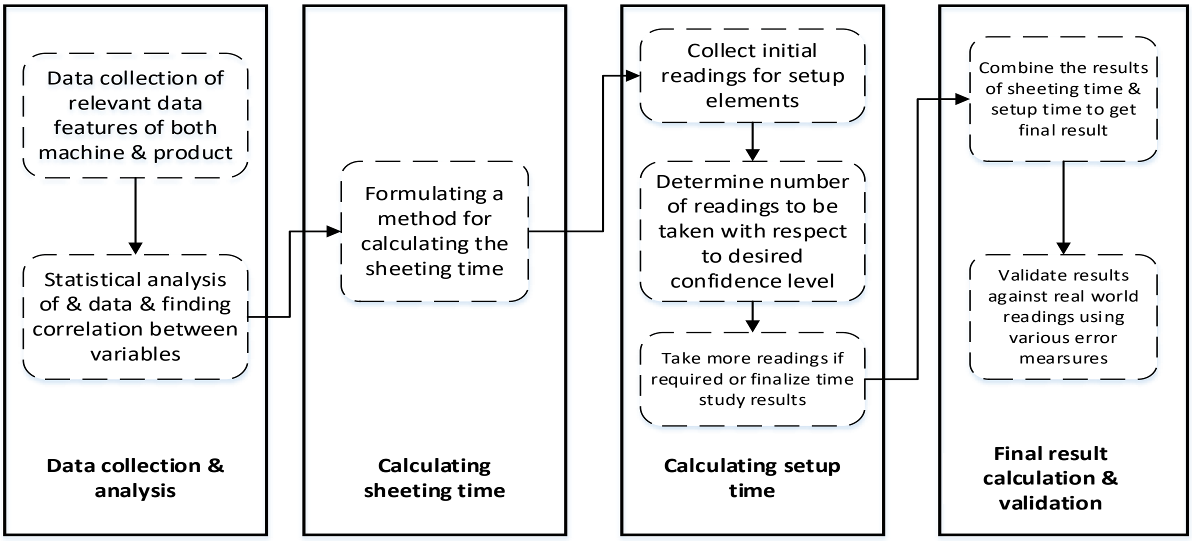

Fig. 1. Flow diagram of research approach.

2.1 Statistical analysis of product features and machine parameters

2.1.1 Data Collection

For data to be meaningful, it has to include all important data features of both product and machine. This would allow for a fruitful statistical analysis to take place between the data of machine and product. Important data features of product and machine are shown in table 1. The conveyer speed refers to the speed of conveyer which carries the sheets to the pile unit.

Table 1. Important data features

Product	Machine
Cut size	Conveyer speed (m/min)
	Blade speed (RPM)

Data of four different sheeter machines was taken, however only one machine’s data is presented in this paper (Annexure a).

2.1.2 Data Analysis

Coefficient of correlation is used as an analysis tool to find the strength of relationship between product and machine parameters. The negative and positive correlations shown in the scatter plots in figure 2 describe the two different relationships of cut sizes with blade and conveyer speed respectively.

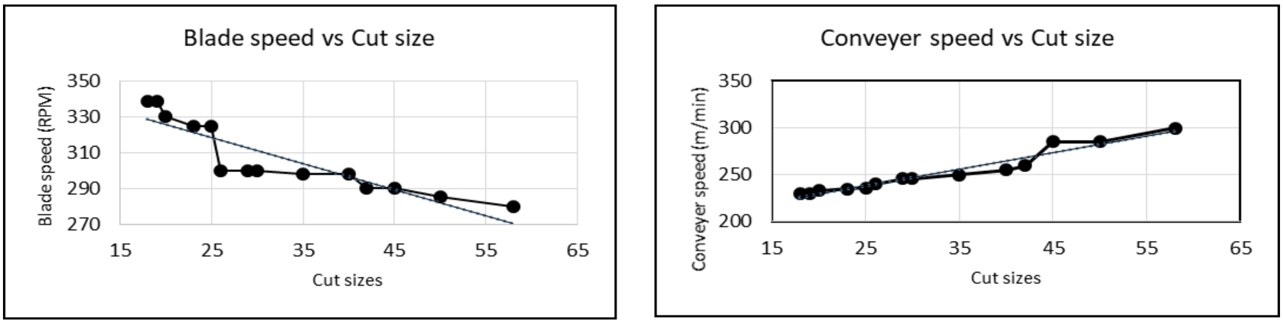

Fig. 2. Scatter plot of cut sizes with blade and conveyer speed respectively

2.1.3 Results and statistical analysis

After computing the coefficient of correlation, it is observed that the blade speed decreases as the cut sizes increase. Vice versa, the conveyer speed increases as the cut size increases. All the values lie in the 0.8 to 1 range, it is quite evident from above analysis that there is quite a strong relationship between product feature and machine parameters.

2.2 Method for calculation

2.2.1 Sheeting time calculation

Out of the two elements necessary for calculation, sheeting time and time study, the sheeting part of the formula part of the calculation is presented first, followed by the time study part of the calculation. As established in the previous section, the relationship between cut size (product feature) & conveyer speed (m/min), blade speed (rpm) is strong. Therefore, keeping in view this fact, the formula used for providing an average time is shown in equation 1.

$$Time = \frac{L_L}{S_{avg}} \tag{1}$$

Here;

L_L = Linear length of the reel

S_{avg} = Average speed of the machine (conveyer speed)

This formula takes its inspiration from the average speed formula. The time obtained from this formula will be relatively accurate. The reason for this is because a sheeter machine never operates at a full speed, all the time. Thus, average values need to be considered.

Furthermore, above formula perfectly encapsulates both the product and machine features. The nominator represents the product specifications that have a bearing on the lead time of a product and the denominator represents the machine parameters which are also determined by a product feature (cut size).

While the data for machine speed has already been collected, the information for 'linear length of the reel' is determined based on product specifications. Major reason for using this method is because it allows us take into account the product specifications, thus giving us the ability to calculate time as per the specifications of the product. The formula is as follows:

$$Linear\ length\ of\ the\ product = \frac{W_t\ x\ 1000}{GSM\ x\ R_s} \tag{2}$$

Here;

W_t = *Reel weight*

GSM = *Grammage per square metre of the reel*

R_s = *Reel size*

2.2.2 Time study calculation

Before defining the elements to be studied, a clear method for the time study and determination of time needs to establish first. Following is the methodology used:

1. Collect first data sample
2. Discard any out of range data (data not with in two standard deviations of the mean)
3. Based upon the resulting sample size, determine the achievable confidence level and degree of precision

4. Decide whether a larger data sample is needed to achieve desired confidence level and degree of precision
5. If a larger data sample is needed, collect additional data (step 1) and repeat entire process

Human elements of the process, that are the same for any given product, are considered under the term 'setup time'. Setup time constitutes of the following elements:

1. *Reel setup time:* This is the time taken to uncover the reel, place it between the hydraulic arms, lift it up, and pass the sheet between the rollers.
2. *Sorting time:* This is the time taken by the operator and assistant operator to ensure the size and angle of the sheets is correct and sort the damaged sheets. During this time period, the machine runs at a slower speed. Size of the sheet refers to its conformance with the length and width of the sheet as required by the customer. The angle of the sheet refers to the perpendicularity of the sheet.
3. *Pallet changeover time:* This is the time taken to remove and replace the pallet once required number of packets (it refers to 100 sheets) have been attained.

After having determined the elements that need to be studied, two things need to be decided i.e. number of appropriate readings to be taken and the required confidence level. Since the sample time is the foundation of calculating the final answer, accuracy of the former affects the latter. Usually in production work, the accepted confidence level is 95% and the precision error is 5%. 95% means that the sample represents just 95% of the population and the 5% is not represented.

Data collected (table 2) showed that these elements are normally distributed (table 3). This means that most of the values are concentrated around the mean of the data and some of the outliers are at the extreme ends. The difference between the value of a given member of a population and the mean value of the overall population is typically expressed as 'standard deviation' [10]. Formula for standard deviation is given in equation 3.

$$S_x = \sqrt{\frac{\sum(t_i - t)^2}{n}} \quad (3)$$

t_i = value of an individual data point

n = number of data points in the sample

For any given value expressed in the form of standard deviations from the mean value (z), normal distribution table is used to calculate the proportion of values Q(z) in the overall population that lie between the value in question and the mean value

The Q(z) associated with a given confidence level is calculated using equation 4.

$$Q(z) = \frac{1 + confidence\ level}{2} \quad (4)$$

The selected confidence level is 95%, therefore;

$$Q(z) = \left(\frac{1+0.95}{2}\right) = 0.975$$

Since the normal distribution table only provides distributions to one side of the mean, reduce the above figure by 0.5. By finding the resulting value (0.475) [11], following value of z is obtained:

$$z = 1.96$$

The above value will be used in calculating the size of the data sample which supports the desired confidence level. Equation 5 shows the formula for determining the right sample size:

$$n = \left[\frac{(k\ x\ S_x)}{(r\ x\ t)}\right]^2 \quad (5)$$

Here;

t = average time for performing the element (sec)

S_x = sample variance for the element

n = number of data points in the data sample

k = number of standard deviations (designated as "z" in the normal distribution table) at the confidence level

r = measure of error precision

While S"x" reflects the inherent variation of the element being measured, the variable 'r' represents the variation in the precision with which the value is measured. This value compensates for human errors that can be made while performing time study. The measure of error precision 'r' indicates the overall tolerance for measurement error that can be accepted. A typical 'r' value used in time studies is 5% (0.05). Although, the elements studied here do not have a short cycle time, therefore the error precision used is 0.03% (0.003).

Table 2. Time study data set

S. No.	Reel setup (sec)	Sorting time (sec)	Pallet changeover (sec)
1	181.9	299.9	121.8
2	180.2	299.6	118.9
3	178.8	299.1	119.7
4	180.5	299.0	118.9
5	180.9	300.2	120.0
6	179.7	299.4	119.3
7	180.7	299.3	121.6
8	178.3	300.7	120.5
9	180.2	297.9	122.3
10	180.9	298.7	120.1
11	178.3	298.6	119.3
12	178.7	299.1	119.7
13	179.4	300.5	120.4
14	179.4	299.5	121.1
15	180.9	300.0	120.2
16	180.5	299.4	120.5
17	179.4	300.3	120.2
18	179.8	298.7	119.2
19	179.3	299.4	120.5
20	180.7	301.3	120.8

Table 3. Time study initial results

Element	t (sec)	S_x
Reel setup time	180	0.953
Sorting time	300	1.181
Pallet changeover time	120	1.064

After obtaining the results shown in table 3, upper and lower limits are calculated using equations 6 & 7 (table 4) to discard any data that is out of range.

$$Lower\ limit = t - 2Sx \tag{6}$$

$$Upper\ limit = t + 2Sx \tag{7}$$

Table 4. Upper & lower limits

Element	Lower limit	Upper limit
Reel setup time	177.9	181.9
Sorting time	297.9	301.1
Pallet changeover time	118.4	122.1

Upon discarding all the out of range of values, new sample size data is calculated and shown in table 5.

Table 5. Sample size data

Element	Sample sizes
Reel setup time	18
Sorting time	17
Pallet changeover time	17

Last step is to determine the sample size which satisfies the 95% confidence level. For this, equation 5 is used and the results are presented in table 6.

Table 6. Sample sizes that satisfy 95% confidence level

Element	Sample sizes
Reel setup time	10
Sorting time	2
Pallet changeover time	13

Since the available sample size is greater than the sample sizes that satisfy the selected confidence level, there is no need to collect more readings. Final results of time study are shown in table 7.

Table 7. Final time study results

Element	t (sec)	S_x
Reel setup time	179.7	0.88
Sorting time	299.6	0.59
Pallet changeover time	120.01	0.66

2.2.3 Adding sheeting and time study calculations

Finally, the results obtained from sheeting time and time study are to be added to produce the lead time of any given reel (product)

Lead time = sheeting calculations + time study calculations

3 RESULTS

The method presented in this study for predicting lead time is specific for the paper conversion industry that uses modern sheeter machines. For validation of results obtained from this method, information from production floor was collected and compared with the results of the presented method. Actual & predicted lead times are presented in the table 8. After analyzing the differences between predicted & actual values and making floor observations, it became clear that the size of order (order weight) has some bearing on the time differences between predicted & actual values. Since larger orders require more setups, worker fatigue becomes one reason for larger differences between actual and predicted time. These can be resolved by simplifying setups to reduce discrepancies between values.

Table 8. Result comparison for machine

order weight (kg)	reel size	cut size	gsm	predicted lead time (min)	actual lead time (min)	difference
2210	31	43	300	49	57	8
5061	36	26	290	123	130	7
873	21	30	210	52	60	8
1212	34	26	300	33	35	2
2284	38	27	340	48	54	6

Upon comparing the results with the results of machine learning & simulation techniques in reviewed literature, the accuracy is better than most machine learning algorithms. However, some gaps are worth mentioning. Since the method is dependent on formula, the information put in the formula needs to accurate as well. Usually in paper products, properties like GSM can never be constant throughout the entire reel and therefore the weight varies. It is very difficult to incorporate this difference into the formula calculations. Thus, little difference in actual and predicted lead time is observed in the above-mentioned result.

For future research, a software can possibly be made using the methodology presented in this paper. Such a software can then be used for production planning purposes. The accuracy of the software results can also be compared with results of machine learning and simulation-based techniques. Another possible direction can be to introduce a factor which compensates for the variation in results caused by the variation in product properties.

4 CONCLUSION

High product variability often tends to make supply chain planning complicated. Lead times are essential for scheduling, production planning and controlling. Latest studies have used techniques that take advantage of big data and produce fruitful results for production planning and operations management. This study took a simple yet effective approach for paper conversion industry with regards to predicting lead times in the absence of extensive data logging. While the importance of big data analytics has already been proven in the light of latest research, this paper has given a practical solution to a problem widely present in small scale industries that do not log data in an organized manner and therefore, are unable to perform big data analytics.

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6 APPENDIX A

Data obtained from Machine		
Cut size	Blade Speed (RPM)	Conveyer speed(m/min)
18	339	230
19	339	230
20	330	233
23	325	235
25	325	236
26	300	240
29	300	246
30	300	246
35	298	250
40	298	255
42	290	260
45	290	285
50	285	285
58	280	300

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