Implementation of Lean Manufacturing Through Learning Curve Modelling for Labour Forecast

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Abstract

In this paper, an implementation of lean manufacturing through learning curve modelling for labour forecast is discussed. First, various learning curve models are presented. Then the models are analyzed in terms of their advantages and limitations. As a case study, the learning curve modelling is presented with the data derived from a production company. With the application of the learning curve, labour need can be more accurately predicted and scheduled on time.

Keywords: Forecast, Labour, Lean Manufacturing, and Learning Curve.

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1. Introduction

The term learning curve describes the relationship between the amount of learning and the time taken to do so [2, 3, 5-7]. In this paper, learning curves are used to forecast labour-hours for the purpose of planning to meet future demands.

There are many different models for learning curves. Each will focus on a different aspect or may be for a different application. Each company or industry will have its own unique learning curve. Learning curves are based on data collected from preliminary units so this data must be accurate.

There are several factors that may influence the learning curve. Changes in staff, design or procedure will alter the learning curve. Learning curve for workers, indirect labour and material are different from each other. Culture of workplace or resource availability may change curve (i.e. at the end of tasks operators lose interest). When working on multiple projects workers forget and reduce learning curves.

In order to maintain learning curves and study it, the management's ability to plan, implement and control activities of the organisation have to be of an acceptable standard.

In the next sections, nomenclature and various types of learning curve models are discussed. A case study in a production company is presented to show the learning curve modelling for labour forecast. Finally, a list of learning curve models in terms of advantages and limitations are summarized.

2. Nomenclature

The following parameters are used in learning curve modelling:

t_n = Performance time to complete n^{th} cycle (seconds)

t_1 = Performance time to complete 1st cycle (seconds)
Φ = Rate of learning (%)
b = Learning curve constant
n = Cycle number
$\hat{t}_n$ = Cumulative average of the time to complete the nth cycle (seconds)
B = Experience factor
M = Incompressibility factor
R_t = Production rate at t
R_c = Starting production rate
R_f = Steady state production rate
τ = Time constant
d = Number of times production has doubled.
t = Repetition number
MAD = Mean Absolute Deviation
MSD = Mean Squared Deviation
A(t) = Actual data for t
f(t) = Predicted values for t

3. Learning Curve Models

Various types of learning curve models are discussed below.

3.1 Power Model

This basic model was first described in 1936 by Theodore Paul Wright in the aircraft industry as the first mathematical model for learning [8]:

$$t_n = t_1 \cdot n^{-b} \tag{1}$$

Where $\phi = 100 \cdot (2)^{-b}$

This is a basic approximation of the learning phenomenon. It does not account for the smoothing of the curve, i.e. learning does not go on forever. Each time production is double the performance time is reduced by fraction *b* [1].

3.2 Arithmetic Model

This is the simplest method of modeling learning curves:

$$t_n = t_1 \cdot \phi^d \tag{2}$$

This model lacks flexibility as production times can only be determined for quantities doubled, i.e. 2, 4, and 8 [4]. Note the change of nomenclature in the equation for arithmetic approach. This was to avoid confusion of parameters amongst different models.

3.3 Cumulative Average Power Model

This model is based on the relationship between direct labour man-hours to the cumulative number of units produced:

$$\hat{t}_n = t_1 \cdot n^{-b} \tag{3}$$

This model was developed by researchers when the regression value with the power model was unacceptably low. This model dampens out the 'wild' data points because it is a continually averaging process [1]. It has higher R^2 values compared to the power model.

3.4 Stanford B Model

This is another modification of the Power model:

$$T_n = t_1 \cdot (n + B)^{-b} \tag{4}$$

B is the experience factor of the operator (between 1 and 10) and a typical value of 4 is usually used. For small values of B this model asymptotes fairly rapidly to the regular power model. Clearly this model was indented for use on learning curves of large products like aircrafts [1].

3.5 DeJong's Learning Model

This model takes into account the manual and machine processing times. It includes an incompressibility factor (M) for tasks that have machine components. It is based on the fact that machine times do not increase and remain constant regardless of experience [1].

$$t_n = t_1 \left\{ M + (1 - M) \cdot n^{-b} \right\} \quad (5)$$

Where M is the ratio of performance time after infinite cycles over performance time after 1st cycle ($0 \le M \le 1$). When there is no machine content M = 0.1 cycles are required to reach the limiting value. There has been no field data to support this model.

3.6 Dar-El's Modification of De Jong's Model

The incompressibility factor is redefined as applying to all task elements. By raising the original power curve by A, a new learning curve line is created.

$$t_n = \hat{t}_n + A \quad (6)$$

This model eliminates the drawback of the power model in that it does not tend zero after an infinite number of repetitions.

3.7 Dar-El/Ayas/Gilad Dual Phase Model

This was generated when research data was poorly matched to all known models. Prediction based on early data tends to underestimate and predictions based on later data tend to overestimate. This poor fit occurred due to two separate types of learning occurring simultaneously, cognitive and motor learning.

Cognitive learning includes decision making, following instructions, learning complex sequences, interpreting measurements, etc. This type of learning is much faster.

Motor learning is a lot slower. It consists of the physical movement required in order to complete a task (i.e. lower b value than cognitive).

Cognitive learning dominates initially, after which motor learning dominates as the number of repetitions gets larger.

3.8 Bevis Towill Learning Model

This model uses an exponential law to show the output as a function of time. It has a maximum level which is more realistic than the power model [1].

$$R_t = R_c + R_f \left[1 - e^{-\frac{t}{\tau}} \right] \quad (7)$$

Where τ = the time constant

This model is not practical to apply as the variables on which the model is based are hard to collect. For this reason there are no applications of using this model.

4. Case Study – Production Company

Lean manufacturing is a technique that is commonly implemented by production and project managers to improve productivity and reduce wastage. Metal Skills Ltd is one of New Zealand's largest manufacturers of sheet metal products. Their customers include US, Australian and Domestics manufacturers. The objective of this study was to ultimately improve the company's ability to meet deadlines. This was to be done through the learning curve modelling for labour forecast.

In order to find specific models that can be applied to this company, data was required to be collected. The procedure followed was to get permission from the managing directors to observe the workers after it was cleared by the shop floor manager. Once this was done health and safety regulations needed to be explained and abided by. Finally permission was gained from the worker being observed so that they would not feel singled out.

In order to be able to predict job times it is essential that the current learning rate be evaluated. In order to do this, data was collected from the shop floor and compared to the models for learning previously measured. Then the model and learning rate that is most applicable to the company are derived.

Learning rates will vary between employees, departments and each individual job. There will be a lot of work and data analysis required if there was to be a different model set up for every different variable. Therefore for the scope of this project a general learning curve rate needs to be found as a suitable model chosen.

The required data was collected from the folding department as shown in Figure 1. This department was selected for some of the following reasons: 1) This is one of the bottlenecks in the factory. The other bottleneck was the welding bay, but due to health and safety standards required, data collection would have been difficult, 2) It has more manual components than any other departments, except welding, 3) It is the most utilised department in the factory, 4) Requires careful scheduling as it has the largest number of workers than any other departments.

When collecting data it was important that the first cycle time recorded was taken for the first cycle of that batch so that the n value was valid. Many sets of data were collected but three main batches were used for analysis.

Figure 1. A Press Brake Machine

Using statistical analysis the accuracy of each model to each set of data was calculated, where:

$$MAD = \frac{\sum_{i=1}^{n} \left| f(t) - A(t) \right|}{n} \quad (8)$$

$$MSD = \frac{\sum_{i=1}^{n} \left(f(t) - A(t) \right)^2}{n} \quad (9)$$

$$BIAS = \frac{\sum_{i=1}^{n} f(t) + A(t)}{n} \quad (10)$$

Three sets of data are collected and the highlighted values as the most accurate data for that statistical measure are shown in Table 1.

Table 1. Summary of Learning Curve Models

DATA 1

	Power Model		Cumulative Average Model		Stanford B Model		De Jong's Learning Model		Arithmetic Approach		Dual Phase Model	
	96%	95%	97%	96%	96%	97%	84%	82%	99%	98%	89%	88%
MAD	1.50	1.59	1.54	1.88	1.64	1.89	1.78	1.62	1.60	1.66	2.04	1.95
MSD	3.61	4.41	4.00	6.05	4.65	5.33	4.84	4.28	4.39	6.10	6.77	7.77
BIAS	0.05	-1.02	-0.09	-1.55	-0.51	0.72	0.79	0.44	0.12	-1.66	0.51	-0.63

DATA 2

	Power Model		Cumulative Average Model		Stanford B Model		De Jong's Learning Model		Arithmetic Approach		Dual Phase Model	
	97%	98%	98%	97%	98%	97%	90%	85%	100%	99%	89%	88%
MAD	1.30	1.26	1.27	1.33	1.24	1.28	1.26	1.30	1.40	1.49	1.56	1.60
MSD	2.41	2.32	2.33	2.58	2.26	2.36	2.31	2.40	3.00	3.52	3.77	3.81
BIAS	-0.16	0.09	-0.09	-0.42	0.03	-0.25	0.04	-0.19	0.20	-0.45	0.32	0.04

DATA 3

	Power Model		Cumulative Average Model		Stanford B Model		De Jong's Learning Model		Arithmetic Approach		Dual Phase Model	
	94%	93%	95%	96%	94%	93%	60%	55%	96%	97%	87%	88%
MAD	1.84	1.98	2.11	2.18	2.23	2.56	2.40	2.46	3.11	2.14	1.82	1.70
MSD	4.70	5.87	6.72	6.15	7.56	10.80	7.57	8.28	16.58	6.64	4.78	4.98
BIAS	-0.28	-1.31	-1.17	0.25	-1.05	-2.18	-0.36	-0.70	-3.11	-1.63	-0.26	0.85

5. Limitations and Summary of Learning Curves

There are some limitations of using learning curves that a company need to be made aware of in order to make proper use of learning curves [4]:

- Learning curves vary from one industry to another and also between companies in the same industry. So it is important that a company's own learning curve is developed rather than just applying someone else's.
- Learning curves are based on the data collected for times observed. So it is important that this data is consistent and as accurate as possible. To maintain accuracy re-evaluation is necessary as times progress.
- The learning curves developed for a company are unique to that company and the personnel employed at the time of the data collection. As staff changes so will the learning curve.
- Learning curves are only applicable to direct labour and not for indirect labour and materials.
- Learning curves are also affected by resource availability and changes in the process as well as cultural changes.

Learning curve models are summarized below in Table 2 according to their advantages and limitations:

Table 2. Comparison of Learning Curve Models

Model	Advantages	Limitations
Power Model	**•Simple and easy to use**	**•Performance time approaches zero as number of repetitions becomes large**
Cumulative Average Model	**•Dampens out 'wild' data points**	**•Smoothing masks important changes**
Stanford B Model	**•Includes an experience factor**	**•Intended for use in industries with large products like aeroplanes •With small B values it is almost identical to power model**
DeJong's Learning Model	**•Takes into account that machining time is not compressible with respect to experience**	**•No field data to support this model**
Dar-El's Modification to DeJong's Model	**•Incompressibility factor redefined to apply to all tasks •Eliminates the drawbacks of power model**	**•When the number of repetitions is less than 150 the incompressibility has no effect**
Dual Phase Model	**•Account for separate cognitive learning and motor learning rates**	**•Complex to apply •Requires electronic spreadsheet to find parameters**
Bevis/Towill Learning Model	**•Has a maximum learning rate**	**•Great difficulty in finding the parameters to apply this model**
Arithmetic Approach	**•Simplest method**	**•Lacks Flexibility •Only finds times for doubled units.**

From the eight models investigated only six were actually compared against data collected at the company. The Bevis/Towill model was excluded as the parameters are difficult to obtain from field data and there are no known examples of this being used. Dar El’s modification to De Jong’s model was also excluded as the time in motion tables appropriate for this company were not made available.

Data set 1 and 3 demonstrated the expected trend. The trend of data collected in sample 2 was unexpected. A reason for the fluctuating times was that the actual cycle time was so small that the human error greatly affects the data. The other two samples had cycle times that were much longer so the human error made up a smaller component of the time.

In order to get as accurate as possible times to normal production rates it was important that the workers were comfortable being timed and that they were made aware of the reasons for the observations. Workers were timed for the end of a batch and then the data recorded was from the start of the next batch. This was done so that workers would be accustomed to the data collector before the essential data was taken, thus reducing some of the error.

Using each model a prediction was made using several different learning rates. Each of these was statistically compared to the actual data collected. Each set of data had different models that were most accurate, but on the whole the power model was consistently one of the most accurate. Minimization of the MSD, MAD and BIAS were done using solver to find the optimum learning rate for each model. The most suitable learning curve rate was 96%.

6. Conclusion

A variety of learning curve models were considered and analysed. A learning curve has been identified to suit the company's production. This is the Power Model with a learning rate of 96%. This was selected as it is applicable to a wide range of production processes throughout the factory. The other models were rejected after analysis as they were found to be insufficient to the needs of the company. The selected model was then validated against data collected in the factory and thus its application was justified. Application of this learning curve will better equip the company to manage job times and therefore be able to schedule more accurately and quoted due dates achieved with higher success rate.

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