Learning curve for precast component production in construction

Abstract

The study objective is to establish the learning curve model for precast component productivity in construction, verified using cross-validation empirical data for over 90% of these facilities' precast component production activities over the past five years, with a total of 373,077 datasets across 14 production activities, sorted among a total of 4,352 workers. By applying the learning curve theory to the analysis, the results show that relative to the straight-line model, the learning curve was established using exponential models. The exponential model can effectively mitigate the unreasonable fluctuations present in the cubic model's representations of learning curves during initial training periods. This study therefore suggests the adoption of the Exponential model to model the learning curves for production workers learning to make precast components. The model has a satisfactory degree of fit ($R^2 > 0.88$), and the post-cross-validation results also show that the model has a highly accurate prediction capability (MAPE value < 10%). The finding can serve as an important reference for the creation of production personnel allocation plans, personnel reserve plans, and training plans at precast factories in the construction industry.

***Keywords**: learning curve, exponential model, precast components production, construction industry*

Introduction

The global precast construction system has developed rapidly in recent years, with an annual rate of about 5% [1], and the market size of the precast industry reached nearly USD 200 billion in 2017 [2]. In China, over 600 precast factories have been established the past three years, and over 1,000 precast factories cover more than 30,000 m^3 [3]. Facing the rapid growth of market, urgent issue of the shortage of skilled labor in precast industry has been discussed frequently. Production methods and manufacturing processes used for precast components are different from traditional ones and demands workers greater both knowledge and technical precision [4].

Skilled workers are undoubtedly important because they could provide high and stable productivity. However, on the other side, the productivity of unskilled workers seems often being ignored. As the saying goes, "Rome wasn't built in one day," newly employed workers wouldn’t become a skilled one of a sudden. They have to go through a learning process to be skillful, and researchers have studied on that and developed the learning theory, which has been applied to many different industries, including construction industry [5-11]. During the learning process, the productivity of unskilled workers will increase over time and gradually become stable. If the manager regards unskilled workers’ productivity as a constant, their productivity may not be fully utilized. Therefore, a precise model to describe the changes of the productivity of unskilled worker is critical. However, literature shows that only simple models such as the straight-line model or cubic model been applied in the construction or precast industry[10,9,12,13,11,14]. Considering the complexity of precast industry, whether these simple models could precisely describe the learning status is doubtful.

Therefore, the purpose of this study is as follows: (1) to develop different learning curve models for trainees during their initial learning of each precast component production process; (2) to evaluate different learning curve models and find out the best one. Since measuring productivity difference for individual due to workers' ages is complicated, we have assumed that workers whose ages are in the range of 15-65 have the same productivity.

Precast production management and process

Precast method has been considered to be effective production methods to control cost, improve productivity, and ensure quality within construction industry, while maintaining fast and automatic production processes [15]. It is regarded as one of the most common and advanced industrialization methods in the construction industry, with the utilization of the methods of normalization, standardization, and modularization. The building is divided into many elements or components, such as columns, walls, beams, plates, and so on. After being produced in a factory via industrial processes, these elements or components are transported to the construction site to be assembled into a building structure [16].

Studies have been conducted to improve the productivity of precast factories through various methods, such as management practices, process reengineering, and simulation [17,16,18-20].

Li et al. organized the literature in the Management of Prefabricated Construction (MPC) research field between 2000 and 2013. These studies are categorized into five major themes within, including the "Future Development of the Industry", "Technology Development and Application", "Performance Evaluation", "Technology Application Environment" and "Design, Production, Transportation and Assembly Strategies".[19].

The production process of the precast industry have also been reviewed. By reviewing studies based on production process models of precast factories, the manufacturing processes for precast components can be understood [21]. Based on previous research, we regard the production processes of precast components as the following 14 basic activities (photos of some construction activities are shown in Figure 1), including: (1) Steel mold cleaning (clearing molds); (2) Module assembly; (3) Lofting (positioning for iron components); (4) Dipping of steel rod cages; (5) Laying of embedded parts; (6) Checking before pouring concrete; (7) Pouring concrete; (8) Surface whitewashing; (9) Concrete curing; (10) Mold removing; (11) Demolding; (12) Component repair; (13) Inspection of finished components and (14) Warehouse storage, [22-24]. Further work including data collection, analysis and discussion will base on 14 activities in this study.

Learning curve theory and its application

In 1936, Wright found that when yield is doubled in aircraft component production lines, the required work time can be reduced by 20%. He then proposed a straight-line model that speculates a constant rate of learning or improvement, by which the work time of a given production cycle can be reduced by a constant percentage each time a new cycle is added [25,9,5]. After Wright proposed the straight-line learning curve model, many other learning curve models that are different from this model were proposed. Since Wright's discovery of the learning effect on repetitive activities in aircraft component production lines in 1936 [5], the question of how to use the learning curve effect to improve the productivity of repetitive production activities has been a subject of concern to many scholars and applied to many industries. Many studies have published papers on whether this theory can improve productivity, predict output value, assess project progress, and improve cost-effectiveness [26-28,7,29]. In addition, construction industry related researches have applied the learning curve theory to improve industry productivity [25,11].

Jordan Srour et al. divided the various learning curve models proposed by scholars based on Wright's straight-line model into five categories: (1) the Wright model and its variations; (2) Polynomial models; (3) Exponential models; (4) Hyperbolic models; (5) The recursive model proposed by Srour himself [11] . Among these models, 7 learning curve models are well-known and frequently used, and include the following:

1. Straight-line Model:

   This model assumed that the degree of improvement of work time is a result of learning at a fixed logarithmic ratio, resulting in a straight line forming in double logarithmic coordinates (Equation 1) [30,5,31,10].

   $$\mathrm{Y} = \mathrm{a}X^{-n};\ \ \mathrm{L} = 2^{-n} \tag{1}$$

   Where,

   Y： Time required to produce unit X (cost or man-hours)

   X： Quantity of units reproduced

   a： Time required to produce unit 1 (in cost or man-hours)

   n： Slope of learning curve in double logarithmic coordinates

   L： Learning rate

2. Stanford B Model:

   With concern that the straight-line model was not fully applicable to certain data from the WWII era, Stanford Research Institute of the United States Department of Defense took into account the existing experience of the workers that the straight-line model did not include. An improved model named the Stanford B model was proposed based on straight-line model theory in 1949 (Equation 2) [32,11].

   $$\mathrm{Y} = \mathrm{a}(X + b)^{-n};\ \ \mathrm{L} = 2^{-n} \tag{2}$$

Where b is the degree of experience that already exists $(1 \leq \mathrm{b} \leq 10)$, and the rest of the parameters are set the same as those set by the straight-line model.

Parameter b in this model is generally preset to 4. When b = 0, it represents the complete absence of existing experience on the part of the operator, under these conditions the Stanford B model is identical to the straight-line model [33].

3. DeJong Model:

J.R. DeJong developed the DeJong model in 1957, considering whether mechanized operations would affect the learning curve. He argued that if operations were primarily controlled by machinery, the potential compression of production time proportional to the increase in the number of operations could be damped, and added an 'incompressibility factor' to the learning curve model to define the degree to which the production time could be compressible(Equation 3) [6,34].

$$\mathrm{Y} = \mathrm{a}[\mathrm{m} + (1 - \mathrm{m}) \times X^{-n}]; \ \ \mathrm{L} = 2^{-n} \qquad (3)$$

Where,

m: Incompressibility factor $(0 \leq \mathrm{m} \leq 1)$.

In general, if the operation is performed manually, m = 0.25; if m = 0, it means that the operation is under complete manual control, in which case the DeJong model is identical to the Straight-line model. Meanwhile, if m=1, the operation is fully automated, and as such undergoes no learning effect [31].

4. S-Curve Model

The S-Curve Model was developed by G.W. Carr in 1946. Since subsequent studies found that the Stanford B model was more suitable for the first half of the curve and the DeJong model was more suitable for the second half of the curve, Carr combined these two learning curves into the S-Curve model(Equation 4), where the parameter settings are the same as those of the above model [35,32,26].

$$Y = a[m + (1 - m)(X + b)^{-n}]; \quad L = 2^{-n} \qquad (4)$$

5. Cubic Model:

The cubic model included the effects of existing experience and the cessation of productivity improvement after operational proficiency had been achieved and assumed that the learning rate would not be constant(Equation 5) [36,10].

$$\log Y = \log a - n(\log X) + c(\log X)^2 + d(\log X)^3; \quad L = 2^{-n} \quad (5)$$

6. Exponential Model:

The concept of the exponential learning curve was first developed by Thurstone in 1919 and was refined by Kientzle, Kientzle, Towill, et al. [37-40,8,41], The mathematical formula of the constant time model developed by Towill is shown in Equation 6.

$$Y = A + B * (1 - e^{c(x-1)}); \quad L = 2^{-n} \qquad (6)$$

Where,

A: Initial performance, the time it takes to produce the first unit (synonymous with the above variable a).

B: Difference between the asymptotic and initial performance.

A+B: Asymptotic or final performance, the production time that tends to stabilize after the learning process has been completed.

c: Learning constant.

7. Piecewise Model:

The Piecewise Model is a linearized approximation of the Cubic Model, and can be divided into three distinct phases, namely operation learning phase, routine acquiring phase and standard production phase(Equation 7). In the literature, it was found that the Piecewise Model is more difficult to use than other models.[10].

$$\log Y = \log A - n_1 \log X - n_2 J_1 (\log X - \log x_{p1}) - n_3 J_2 (\log X - \log x_{p2}) \quad (7)$$

Where,

n_1 : slope of the first segment;

J_1 = 1 when $X > x_{p1}$, 0 otherwise;

n_2 = additional slope of the second segment, total slope = $n_1 + n_2$;

J_2 = 1 when $X > x_{p2}$, 0 otherwise;

n_3 = additional slope of the third segment, total slope = $n_1 + n_2 + n_3$;

x_{p1} = first point where the slope changes, usually in the operation learning phase; and x_{p2} = second point where the slope changes, the end of the routine-acquiring phase. This is called the standard production point.

The comparison among these 7 methods is listed in Table 1. In addition, the time used in this formula is slightly different from that used in the several aforementioned formulas, the aforementioned time x is defined as the production efficiency on the x-th day, and here the time is defined as the production efficiency after x days of study, so x-1 is taken as the parameter for the equation.[11,26].

Since the learning curve theory came into being, many scholars have also applied it toward the cause of improving the productivity of the construction industry. As far as the learning process is concerned, it can be divided into the initial operation learning phase and the later routine procedure phase [42,43]. In 1986, Thomas et al. collected data from 65 of precast component utilization procedures at construction sites, conducted fitting to five learning curve models including the straight-line, Stanford B, cubic, piecewise, and exponential models in order to examine their R^2 value. The results show that the cubic model has the best fit to historical data and is also best suited to predict the production time for independent sampling data at the same phase [10]. Everett and

Farghal studied the fit of 12 learning curves to historical data and ability to predict future performance against 60 sets of construction data covering the on-site assembly process of precast components. The results show that the cubic model is more suitable for fitting existing historical data compared to other models. However, the cubic model performs the worst at predicting future production data; the straight-line model performs the worst in fitting existing historical data but the best at predicting future production data [9].

Learning curve theory was also applied to different construction projects in other studies. Lee et al. studied cases of high-rise buildings in Korea and developed a set of learning curves which considered several factors that could affect the learning curve in the construction of high-rise building projects and were then converted into another set of suggested learning curves to improve labor productivity [14]. Based on the data of 15-storey concrete buildings in Italy, Pellegrino et al. conducted a fitting using a straight-line model and discussed the influence of interrupting construction projects on the learning curve [13]. Many scholars also have applied the learning curve theory to formwork engineering, reinforcement fixing operations, roof insulation engineering, and other projects[44,45,25]. Based on the above literature, it is found that the learning curve models most commonly used in the construction industry are the straight-line model and cubic model. Researches attempt to apply learning curve theory to increase the productivity of construction industry have a very long history with many research results having been achieved in this field [11,10]. However, the application of learning curves in precast industry has only involved a few analysis on the assembly operation of precast components at construction sites [9,10], and there has been little research on the production processes of precast components. Furthermore, regarding the complexity of construction industry, both the straight-line model and the cubic model could be questioned as too simple. Therefore, this study will analyze the training data of precast workers in learning the production process of precast components and validate the fit and predictive accuracy by using straight-line, cubic, and exponential models, allowing the results of the analysis to help the precast industry improve its productivity.

Data collection and basic analysis

This study gathered and analyzed the precast structural component data from more than 90% of new precast construction projects in Taiwan among five years (2015-2019). To participate, understand and investigate the production system of precast plants through thorough field study, we observed, measured, collected and verified the characteristics and the duration of each manufacturing activities in the field. Data collected mainly targeted on the main production time of three types of structural components, namely the main beam, minor beam and column. Our team measured every trainee's daily production time based on 14 basic activities mentioned above, and the production data was collected from the first day they learned to work on those activities until their performance becomes steady. There are 4352 workers involved in the data collection project where 354,240 data points are recorded from the field and none of them has been used or published in any other work. The research contents of 14 activities in precast factories conducted by the research team are described as follows:

1. Type of Projects for Data Collection

   There are 7 project types for the collected data, including collective housing, schools, office buildings, large shopping malls, technology plants, biotech factories, and composite shopping malls, as shown in Figure 2. The data collected include production times for basic activities in the primary construction of precast building structures, and the recorded production times are calculated in minutes.

2. Objects for Data Collection

(1) Newly employed workers: The manager of the precast factory will allocate training activities as need, and each newly employed worker is considered able to formally conduct production activities after completing one of the 14 training activities.

(2) In-service workers: The training of other activities is carried out to increase worker's skill levels according to human resource planning and assignment of the precast factory, as well as personal preference on the part of the workers themselves.

(3) The trainees include both domestic workers and foreign workers.

3. Object Background Information for Data Collection

(1) The trainees used for data collection in this study are all actively employed workers at a precast factory.

(2) Each trainee has undergone a physical examination and was in good health before becoming an active employee.

(3) The experience of the trainees, whether related to the precast industry or not, is irrelevant to the training activities.

4. Data Collection Methods

(1) In the first year, our team observed the training status of workers within the precast factory, and during each training session at the precast factory, the team mainly performed measurement and video recording from 8:00 AM to 5:00 PM that day. However, some activities (such as lofting, laying of embedded parts, surface whitewashing, and component repair) were trained on a non-periodic basis, and the team also made appropriate cooperative efforts. The next four years, with the consent of the precast factory, data collection was mainly performed via CCTV video recording, and videos were regularly exported for data analysis.

(2) In this study, data were collected for each individual's training sessions across all 14 activities, via random sampling mode. If the person exited the training period

prematurely, that data was excluded.

(3) The collected data correspond to the training modules produced on that day, with a maximum of 6 sets and a minimum of 3 sets, and the work time of various production processes have been recorded for each of the 14 activities.

(4) The training of some activities is sometimes conducted privately by the workers themselves, mainly for activities such as lofting, the laying of embedded parts, surface whitewashing, and component repair (evidence states that employee pay is increased after they have completed training for the above four activities), so training time does not necessarily occur during working hours.

5. Analysis of Production Trainee Numbers

The analysis of the number of production trainees in this study is shown in Table 2, and the total number of trainees for whom data has been collected is 4,352. There are 3,432 domestic (78.9%) and 920 foreign (21.1%) workers participated during training. In terms of age distribution, the highest proportion for domestic workers in Taiwan is at age of 30-39 (1,605 persons, 46.8%), while the largest proportion for foreign workers is at age of 20-39 (396 persons, 43.0%). The total average time of employment of those involved in precast projects was 1.61 years, and the overall time employed of those involved was not high. The total average time employed of domestic workers was 1.68 years, while that of foreigners was 1.53 years.

This study distinguishes 14 activities into 3 modules according to the categories used by Chen et al.: the molding module, the filling module, and the repair and storage module (Chen et al. 2016). The data analyses of component production trainees are described separately below:

(1) Molding module

The analysis of data from the molding module is shown in Table 3 and consists of five activities: steel mold cleaning (mold clearing), module assembly, lofting, dipping of steel rod cages, and laying of embedded parts. Within the research database of this module, domestic workers accounts for over 70% in most training activities, except in the laying for embedded parts, where it was 59.6% (293 persons). Most of the trainees aged 20-39 (over 70% in every activity of this module), and more than one-third of them aged 30-39. In terms of the average time employed for participants in precast projects, the average time employed of personnel in lofting and laying of embedded parts is significantly higher than that of other activities in this module.

(2) Filling module

The analysis of the data for the filling module is shown in Table 3 and consists of four activities: checking before pouring concrete, pouring concrete, surface whitewashing, concrete curing. Within the research database of this module, domestic workers accounts for over 50% in every training activity, with the highest ratio being in concrete pouring at 86.2% (424 persons). Over 70% workers aged 20-39 for all four activities. In terms of the average time employed of participants in precast projects, the average time employed of employees engaged in surface whitewashing is significantly higher than that of other activities in this module.

(3) Repair and storage module

The analysis of the data for the repair and storage module is shown in Table 3, and this consists of five activities: mold removing, demolding, component repair, inspection of finished components, and warehouse storage. Within the research database, domestic workers accounts for over 60% in every training activity, with the ratios of component repair and inspection for finished components being as much as 74.6% (367 persons) and 73.6% (362 persons) respectively. Over 70% workers aged 20-39 for all four activities. In terms of average time employed for participants in the precast projects, time employed for those trained in mold removal and component repair was significantly higher than those of other activities in this module.

Due to the different degree of difficulty for each activity, the number of days required to perform data collection also varied. For some activities, the work time of workers tended to stabilize within ten days, but other activities required more than a hundred days to stabilize. The number of observations, observation days, and data points collected for each activity are shown in Table 4 Each worker produced 3-6 sets of modules per day, and the work time was recorded according to the 14 prescribed activities. Within the production data of 14 activities, work time on the final measurement day can be reduced by 32-87% compared with that of the first day, as shown in Table 5. I It follows that the learning effect clearly increases productivity in trainees. However, if human resources are to be deployed to take advantage of this effect, it is important to know how the trainees' work time changes before they enter a stable phase under the learning effect. Therefore, in the next section, various models of learning curve theories will be applied to identify the most suitable model to describe the changes in production data for trainees during the initial learning phase, which can serve as an important foundation for subsequent research or practical applications in improving the productivity of precast factories.

Learning curve model and validation for precast component production

To acquire the learning curve for each activity, we analyzes the obtained data through 10-fold cross-validation and makes ten analyses by dividing the 354,240 datasets for all 14 activities in the building precast structure into ten equal parts. In each analysis, 90% of the data are used as training data to perform regression analysis of the straight-line, cubic, and exponential learning curve models, and the R^2 value is used to check the degree of fit. The other 10% of the data are then used as testing data to perform validation, and the MAPE value is then calculated to judge the prediction accuracy of the model. The results of the analysis are shown in Table 6, for each activity, there is a range of R^2 values and MAPE values due to a total of 10 times of cross-validation. For each activity, both the R^2 and the MAPE value of the cubic and exponential learning curve models perform better than those of the straight-line learning curve model. It is thus known that, for the precast component production data at the initial production phase, the cubic and exponential models can more accurately fit the historical data than the straight-line model, and also are more suitable for predicting the production data of trainees. Therefore, this study will continue the subsequent analysis based on the cubic and exponential models and generate learning curves for each activity.

In the above-mentioned cross-validation, the data have undergone ten cross-validation analyses, so ten sets of learning curves are generated for each activity. In the analysis results of the cubic and exponential models, the difference between the maximum and minimum values of R^2 is within 0.008, and the difference between the maximum and minimum values of MAPE is within 10%, so the ten sets of learning curves for each activity can be regarded as being very similar curves. In order to generate a learning curve representing each activity, the study has selected the minimum MAPE value among the ten sets of learning curves of each activity as the learning curve *LCbest* represented the activity.

After comparing the *LCbest* curves of the cubic and exponential models, it is found that the differences in MAPE values for the two models are within 5%, indicating that the two models have similar performance. Among these differences, the biggest comes from the activity of lofting, in which the MAPE value of the exponential model exceeds that of the cubic model by 4.07%. In addition, if the learn curve is actually drawn, it can be found that many activities are affect by the cubic model's characteristics of inflection points and more inconsistent fluctuations in the initial phase, while the exponential model can mitigate this problem (as shown in Figure 3). Therefore, we suggest that the learning curve of each activity in the precast factory should adopt the exponential model.

The exponential model learning curve, initial learning rate, R^2 value, and MAPE value for each activity are shown as Table 7. The R^2 values for all the activities are above 0.88, indicating that the degree of fit is extremely high and the MAPE values are all less than 10%, in line with the high-accuracy prediction defined by Lewis in 1982 [46]. Therefore, the learning curve model of 14 basic activities developed in this study can fit the data collected by this study and can also accurately predict the production data of newly employed workers having undergone initial training.

Based on the above research results, learning rate can be seen to not be a fixed value in learning processes in which trainees have learned how to conduct precast component production activities, so the finding of this study is in line with that of Thomas et al. in 1986 [10]. Moreover, we know that the cubic learning curve model proposed by Thomas et al. in 1986 has both good fit and predictability. However, the performance of the cubic model in the initial learning of some activities undergoes major fluctuations, so we propose that the exponential model performs as a more appropriate model to represent the learning curve of precast component production activities.

Results and discussion

According to the above research results, we further divide the learning curves of all activities into two groups (as shown in Figure 4) by using the K-means algorithm and the learning curve formula from Table 9. The result of this grouping can be seen from Table 8, and there are 10 activities in the first group while 4 activities in the second. The initial performance (A) and the asymptotic performance of the second group are both high, and the absolute value of the learning constant is lower. As a result, the complex activities can be defined including: lofting, laying of embedded parts, surface whitewashing, and component repairs. This helps managers to understand training difficulty for each activity and take advantage of it to ensure sufficient professional human resources for each activity. Figure 5 shows the exponential learning curves for all activities where Figures 6 to 8 illustrate closer looks at the learning curves for each modules. As observed, it takes a long time for the complex activities to stabilize. When further analyzing the asymptotic performance ($A + B$) for each activity (as shown in Table 9), it is found that those complex activities indicate at negative extremes for lofting and surface whitewashing. These two activities difficultly achieve convergence because their learning constants are particularly small (< 0.01). The other two complex activities achieve high asymptotic performance, as observed, due to their learning constants rational for convergence. This specifies that it still takes longer to complete these two activities than that of the others even if workers are skilled.

To sum up, the exponential model provides the value of asymptotic performance serving as the production time that workers may achieve under maximum proficiency. This study therefore suggests the adoption of the exponential model to model the learning curves for production workers learning to make precast components. The model has a satisfactory degree of fit ($R^2 > 0.88$), and the post-cross-validation results also show that the model has a highly accurate prediction capability (MAPE value < 10%). The other findings show that 4 difficult activities have been identified as lofting, laying of embedded parts, surface whitewashing, and component repairs. No matter how well trained workers carry out these four activities, their performance does not show much learning effect by the reason of various circumstances on-site, customized orders, and high-quality demands.

Conclusion

Based on literature and field visits, and the production data of 14 basic precast activities obtained from precast factories in Taiwan are studied and analyzed using the learning curve theory. Using a total of 373,077 datasets regarding 14 production activities sorted among a total of 4,352 workers, the findings show that exponential model is more suitable than the straight-line model for fitting historical data and predicting the production data of trainees during their initial training. This also indicates that that the learning rate is not a fixed value during the learning process as previously considered in the construction industry. The second finding expresses that the learning curve model proposed in the study has a good fit to the historical data (R^2 values all > 0.88), and the model is highly accurate in predicting the production data of trainees through their initial learning curves (MAPE values < 10%). The third finding reveals that, through using the K-means method, the 14 basic activities are divided into two groups due to the convergence of their learning curves respectively. As a result, the complex activities can be defined including: lofting, laying of embedded parts, surface whitewashing, and component repairs. This helps managers to understand training difficulty for each activity and take advantage of it to ensure sufficient professional human resources for each activity. It is an important reference for the production planning and personnel training planning of precast factories to improve the productivity of the precast industry. The contributions by the study are substantial especially for practitioners.

The results of this study can serve as a well-developed and accurate foundation, and it is suggested that future studies make efforts in this direction. Follow-up studies focus on the threshold value for worker proficiency standards that is another important step for managerial practice. To achieve it, since asymptotic performance for those difficult activities ($1\text{-}e^{c(x\text{-}1)}$) in the model is as close as 1, it implies that the workers' training never goes effective. Therefore, it is suggested that future research can seek a threshold as standard proficiency for workers based on the level of difficulty or complexity toward each activity. Studies dealing with formulas grouped to a couple of general formulas for all activities are also recommended to possibly simplify and to increase practicability for the findings. Additionally, since productivity difference for individual based on workers' ages and nationality is possible, future work regarding productivity difference among workers' ages and nationality is practicable to enhance the current work.

Acknowledgement

This research is partly supported by the Ministry of Science and Technology (MOST), Taiwan, for promoting academic excellent of universities under grant numbers of MOST 109-2622-E-008-018-CC2 and MOST 108-2221-E-008-002-MY3.

References

1. prefabAUS (2014) prefabAUS 2014 Inaugural Conference. https://www.prefabaus.org.au/prefabaus-conference-2014. Accessed 3, June 2020

2. Luo Y (2018) The development of prefabricated building industry. China Science and Technology Journal 9:72-77

3. International Building Industrialization of Construction Exhibition Asia B (2020) China has been the most compact market for precast concrete parts and concrete goods in APAC area. International Building Industrialization of Construction Exhibition Asia(BIC). https://www.bicchina.com.cn/en/PressReleases/233454. Accessed 3, June 2020

4. Alviano P (2015) Job Skills in Prefabricated Construction. International Specialised Skills Institute, Melbourne

5. Wright TP (1936) Factors Affecting the Cost of Airplanes. Journal of the Aeronautical Sciences 3 (4):122-128. doi:10.2514/8.155

6. DeJong JR (1957) The Effects Of Increasing Skill On Cycle Time And Its Consequences For Time Standards. Ergonomics 1 (1):51-60. doi:10.1080/00140135708964571

7. Yelle LE (1979) THE LEARNING CURVE: HISTORICAL REVIEW AND COMPREHENSIVE SURVEY. Decision Sciences 10 (2):302-328. doi:10.1111/j.1540-5915.1979.tb00026.x

8. Towill DR (1990) Forecasting learning curves. International Journal of Forecasting 6 (1):25-38

9. Everett JG, Farghal S (1994) Learning curve predictors for construction field operations. Journal of construction engineering and management 120 (3):603-616

10. Thomas HR, Mathews CT, Ward JG (1986) Learning Curve Models of Construction Productivity. Journal of Construction Engineering and Management 112 (2):245-258. doi:doi:10.1061/(ASCE)0733-9364(1986)112:2(245)

11. Jordan Srour F, Kiomjian D, Srour IM (2015) Learning curves in construction: A critical review and new model. Journal of Construction Engineering and Management 142 (4):06015004

12. Thomas HR (2009) Construction learning curves. Practice Periodical on Structural Design and Construction 14 (1):14-20. doi:10.1061/(ASCE)1084-0680(2009)14:1(14)

13. Pellegrino R, Costantino N, Pietroforte R, Sancilio S (2012) Construction of multi-storey concrete structures in Italy: Patterns of productivity and learning curves. Construction Management and Economics 30 (2):103-115. doi:10.1080/01446193.2012.660776

14. Lee B, Lee HS, Park M, Kim H (2015) Influence Factors of Learning-Curve Effect in High-Rise Building Constructions. Journal of Construction Engineering and

Management 141 (8). doi:10.1061/(ASCE)CO.1943-7862.0000997
15. Wakisaka T, Furuya N, Inoue Y, Shiokawa T (2000) Automated construction system for high-rise reinforced concrete buildings. Automation in Construction 9 (3):229-250. doi:https://doi.org/10.1016/S0926-5805(99)00039-4
16. Chen JH, Yan S, Tai HW, Chang CY (2017) Optimizing profit and logistics for precast concrete production. Canadian Journal of Civil Engineering 44 (6):393-406. doi:10.1139/cjce-2016-0401
17. Yu H, Al-Hussein M, Al-Jibouri S, Telyas A (2013) Lean transformation in a modular building company: A case for implementation. Journal of Management in Engineering 29 (1):103-111. doi:10.1061/(ASCE)ME.1943-5479.0000115
18. Chen J-H, Yang L-R, Tai H-W (2016) Process reengineering and improvement for building precast production. Automation in Construction 68:249-258
19. Li Z, Shen GQ, Xue X (2014) Critical review of the research on the management of prefabricated construction. Habitat International 43:240-249. doi:10.1016/j.habitatint.2014.04.001
20. Mostafa S, Chileshe N, Abdelhamid T (2016) Lean and agile integration within offsite construction using discrete event simulation: A systematic literature review. Construction Innovation 16 (4):483-525
21. Leu S-S, Hwang S-T (2001) A GA-based model for maximizing precast plant production under resource constraints. Engineering Optimization 33 (5):619-642
22. Chen J-H, Hsu S-C, Cheng J-Y (2019) Integrating Precast Big Data and System Simulation to Improve Manpower Allocation for Construction Precast Production. Paper presented at the International Conference on Innovation and Management (IAM2019 Summer), Hiroshima, Japan,
23. Tai H-W (2017) Integrating precast big data and computational intelligence to classify the levels of construction difficulty. National Central University (NCU), Taoyaun, Taiwan
24. Chen J-H, Hsu S-C, Chen C-L, Tai H-W, Wu T-H (2020) Exploring the association rules of work activities for producing precast components. Automation in Construction 111:103059. doi:https://doi.org/10.1016/j.autcon.2019.103059
25. Jarkas AM (2010) Critical investigation into the applicability of the learning curve theory to rebar fixing labor productivity. Journal of Construction Engineering and Management 136 (12):1279-1288
26. Anzanello M, Fogliatto F (2011) Learning curve models and applications: literature review and research directions. International Journal of Industrial Ergonomics, 41, 573-583. International Journal of Industrial Ergonomics - INT J IND ERGONOMIC 41:573-583. doi:10.1016/j.ergon.2011.05.001

27. Rubin ES, Azevedo IML, Jaramillo P, Yeh S (2015) A review of learning rates for electricity supply technologies. Energy Policy 86:198-218. doi:10.1016/j.enpol.2015.06.011
28. Ball WT, Sharieff W, Jolly SS, Hong T, Kutryk MJB, Graham JJ, Fam NP, Chisholm RJ, Cheema AN (2011) Characterization of operator learning curve for transradial coronary interventions. Circulation: Cardiovascular Interventions 4 (4):336-341. doi:10.1161/CIRCINTERVENTIONS.110.960864
29. Cunningham JA (1980) Management: Using the learning curve as a management tool: The learning curve can help in preparing cost reduction programs, pricing forecasts, and product development goals. IEEE Spectrum 17 (6):45-48. doi:10.1109/MSPEC.1980.6330359
30. Jaber MY (2016) Learning curves: Theory, models, and applications. CRC Press,
31. Jaber M (2006) Learning and Forgetting Models and Their Applications. Handbook of Industrial and Systems Engineering:30-31. doi:10.1201/9781420038347.ch30
32. Badiru AB (1992) Computational Survey of Univariate and Multivariate Learning Curve Models. IEEE Transactions on Engineering Management 39 (2):176-188. doi:10.1109/17.141275
33. Asher H (1956) Cost-quantity relationships in the airframe industry. The Ohio State University,
34. Glock CH, Grosse EH, Jaber MY, Smunt TL (2019) Applications of learning curves in production and operations management: A systematic literature review. Computers and Industrial Engineering 131:422-441. doi:10.1016/j.cie.2018.10.030
35. Carr GW (1946) Peacetime cost estimating requires new learning curves. Aviation 45 (4):220-228
36. Carlson JG (1973) Cubic learning curves-precision tool for labor estimating. Manufacturing Engineering & Management 71 (5):22-25
37. Knecht G (1974) Costing, technological growth and generalized learning curves. Journal of the Operational Research Society 25 (3):487-491
38. Thurstone LL (1930) The learning function. Journal of General Psychology 3:469-493. doi:10.1080/00221309.1930.9918225
39. Anzanello MJ, Fogliatto FS (2007) Learning curve modelling of work assignment in mass customized assembly lines. International Journal of Production Research 45 (13):2919-2938. doi:10.1080/00207540600725010
40. Kientzle MJ (1946) Properties of learning curves under varied distributions of practice. Journal of Experimental Psychology 36 (3):187
41. Leibowitz N, Baum B, Enden G, Karniel A (2010) The exponential learning

equation as a function of successful trials results in sigmoid performance. Journal of Mathematical Psychology 54 (3):338-340. doi:https://doi.org/10.1016/j.jmp.2010.01.006
42. Gottlieb SC, Haugbølle K (2010) The repetition effect in building and construction works: A Literature Review. Danish Building Research Institute, Hørsholm
43. Nations U (1965) Effect of Repetition on Building Operations and Processes on Site: Report of an Enquiry. UN,
44. Mályusz L, Pém A (2013) Prediction of the learning curve in roof insulation. Automation in Construction 36:191-195. doi:10.1016/j.autcon.2013.04.004
45. Jarkas A, Horner M (2011) Revisiting the applicability of learning curve theory to formwork labour productivity. Construction Management and Economics 29 (5):483-493. doi:10.1080/01446193.2011.562911
46. Lewis CD (1982) Industrial and business forecasting methods : a practical guide to exponential smoothing and curve fitting. Butterworth Scientific, London ;

Lofting

Laying of embedded parts

Concrete surface whitewashing

External-wall reserved reinforcement

Removal of all related molds

Figure 1 Related production activities of precast structure

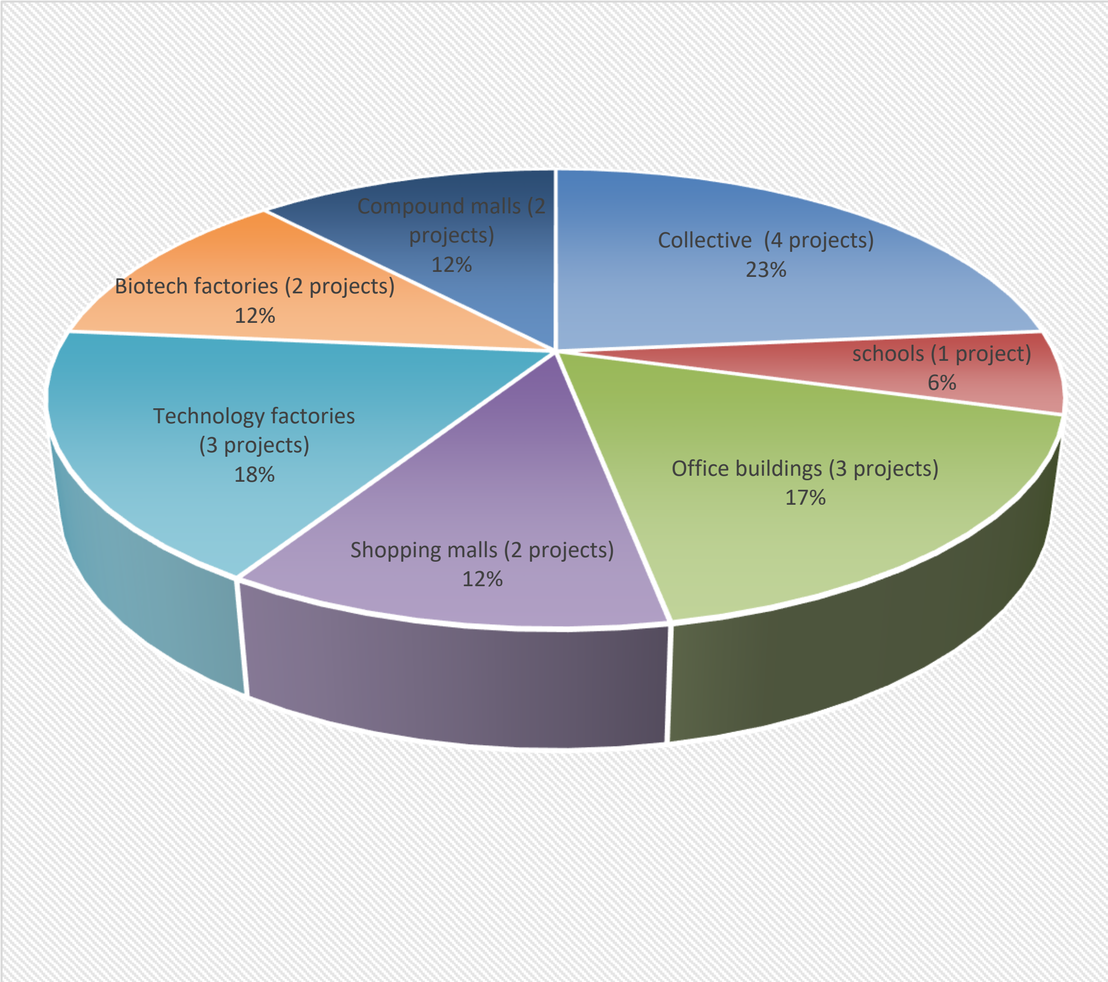

Figure 2 Scope analysis of precast projects

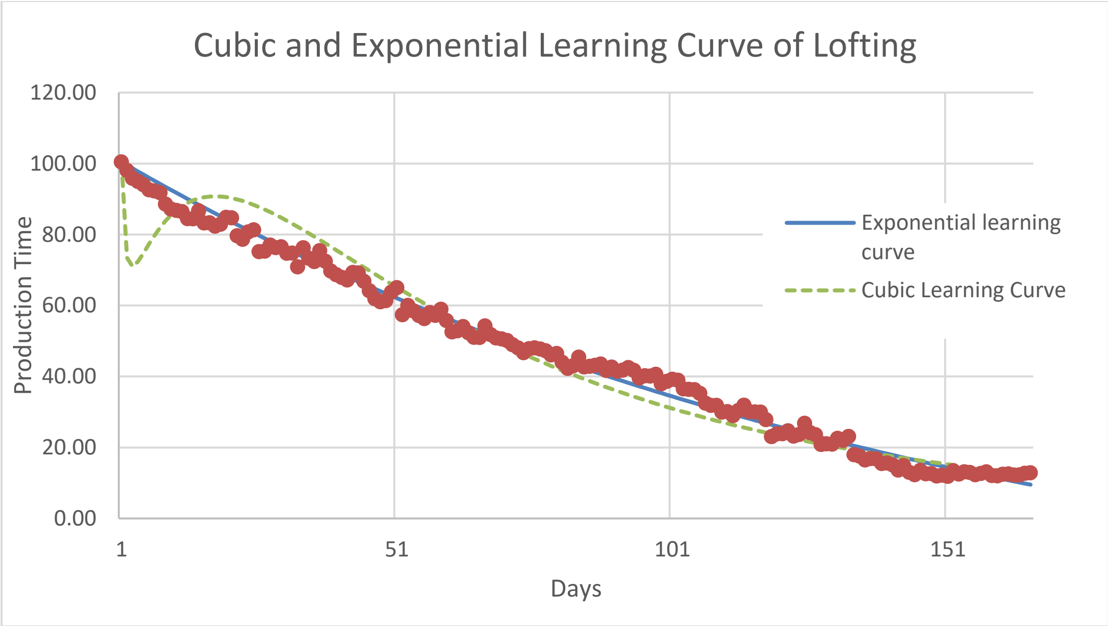

Figure 3 Cubic and Exponential Learning Curve of Lofting

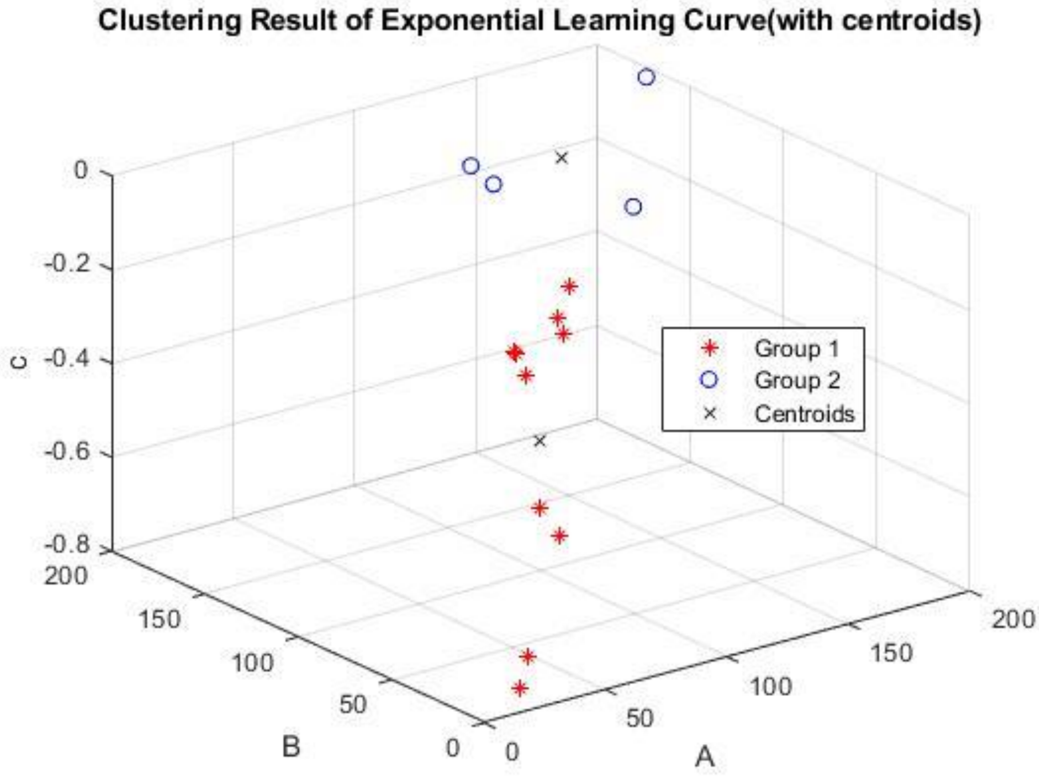

Figure 4 Clustering Result of Exponential Learning Curve(with centroids)

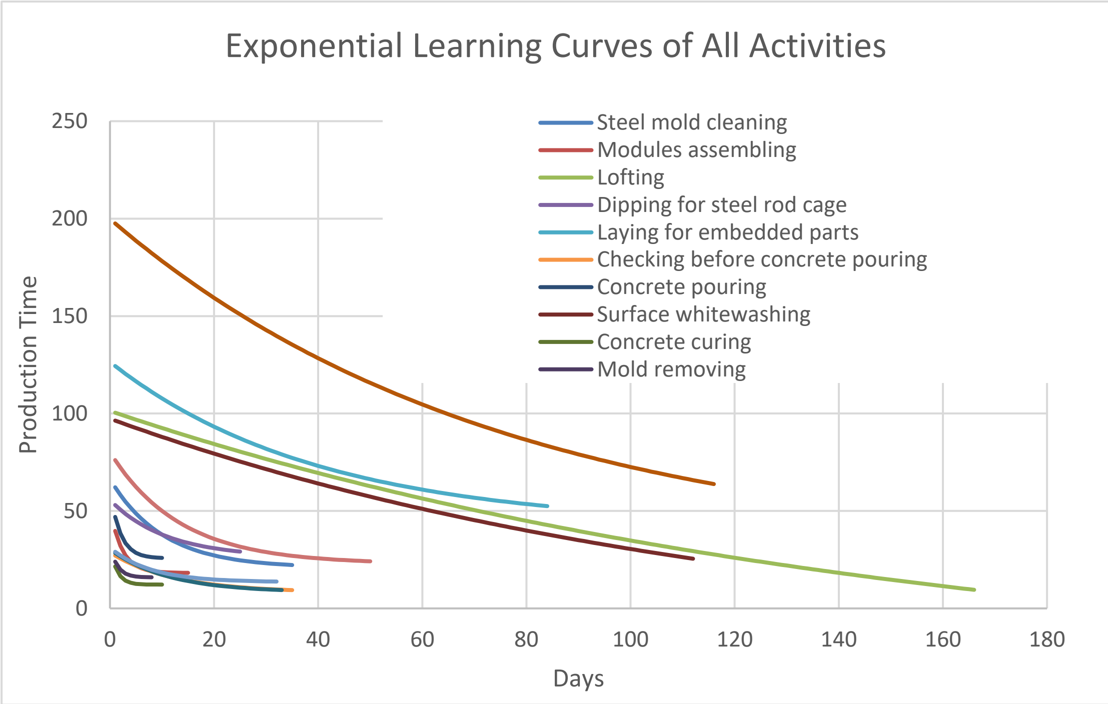

Figure 5 Exponential Learning Curves of All Activities

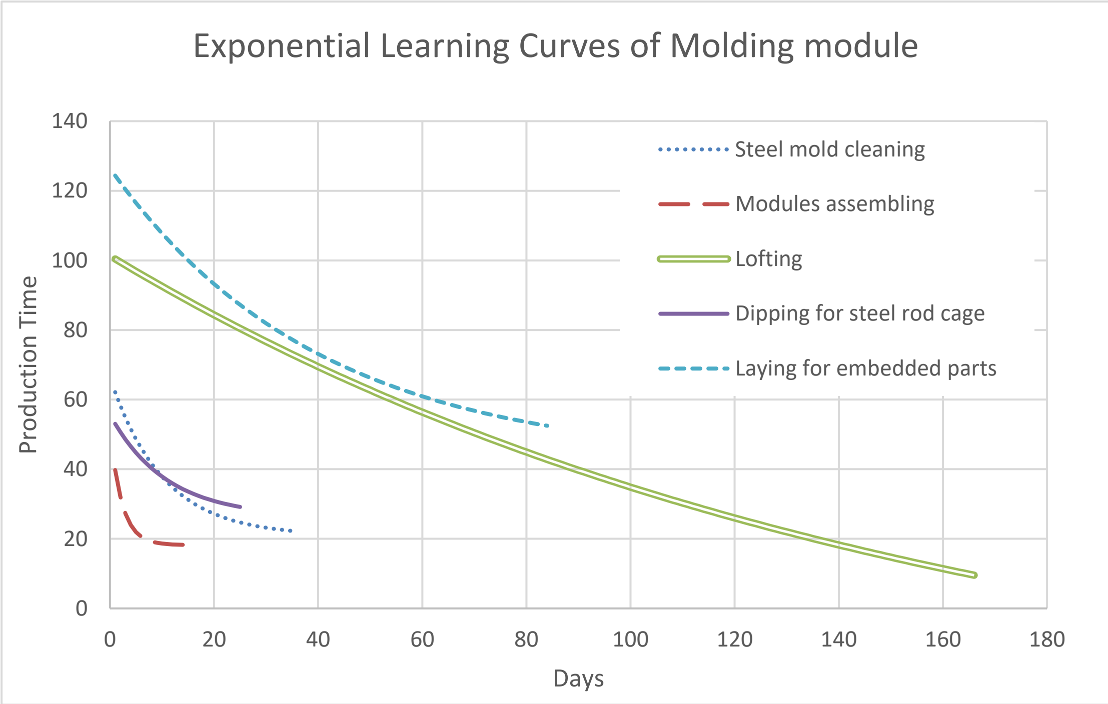

Figure 6 Exponential Learning Curves of Molding module

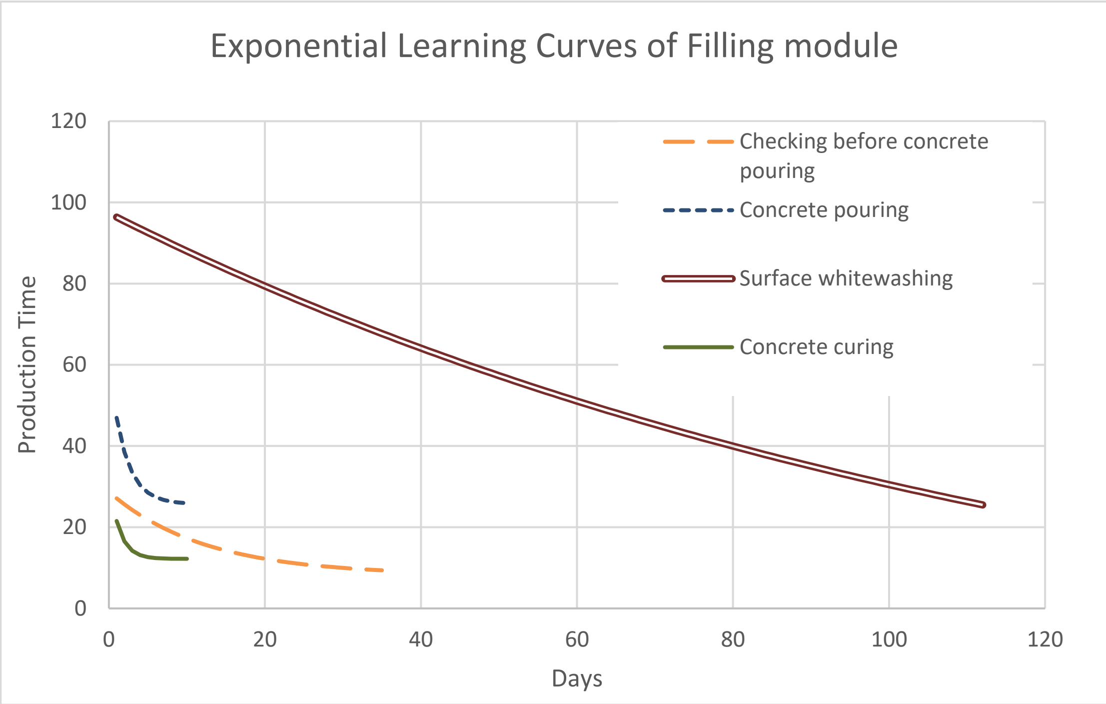

Figure 7 Exponential Learning Curves of Filling module

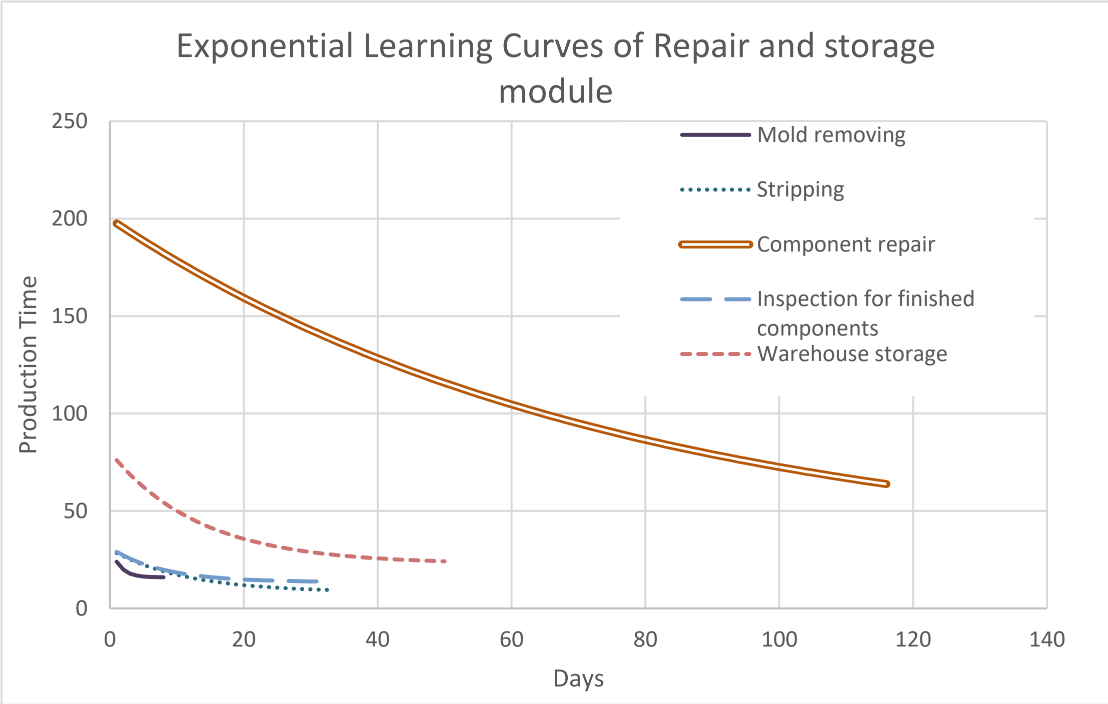

Figure 8 Exponential Learning Curves of Repair and storage module

Table 1 Comparison between common used learning curve models

Model	Formula	Comparison
Straight-line	$Y = aX^{-n}$	The original model proposed by Wright in 1936[5]. It assumed that the learning rate is a fixed value.
Stanford B	$Y = a(X + b)^{-n}$	Improved model considering the existing experience of the workers that the straight-line model did not include.
DeJong	$Y = a[m + (1 - m) \times X^{-n}]$	Improved model considering whether mechanized operations would affect the learning curve[6].
S-curve	$Y = a[m + (1 - m)(X + b)^{-n}]$	Improved model combined the concept and assumption of the Stanford B and DeJong Model[33].
Cubic	$\log Y = \log a - n(\log X) + c(\log X)^2 + d(\log X)^3$	The cubic model included the effects of existing experience and the cessation of productivity improvement after operational proficiency had been achieved and assumed that the learning rate would not be constant[37].
Exponential	$Y = A + B * (1 - X^{c(x-1)})$	The model is based on the concept that subject to improvement will be reduced after a constant number of cycles, and the time will gradually approach an ultimate or lowest value[9].
Piecewise	$\log Y = \log A - n_1 \log X - n_2 J_1(\log X - \log x_{p1}) - n_3 J_2(\log X - \log x_{p2})$	A linearized approximation of the Cubic Model, it is found that this model is more difficult to use than the others[10].

Table 2 The analysis of the number of production trainees

Item	Age	number of trainee	percentage	precast experience(year)
Domestic workers	20-29	1011	29.5%	1.1
	30-39	1605	46.8%	1.6
	40-49	618	18.0%	1.8
	Above 50	198	5.8%	2.2
	Sum	3432	78.9%	1.68
Foreign workers	20-29	396	43.0%	0.8
	30-39	322	35.0%	1.7
	40-49	202	22.0%	2.1
	Above 50	0	0.0%	0
	Sum	920	21.1%	1.53
Total		4352	Total average	1.61

Table 3 Analysis of trainee data

Item			Domestic workers								Foreign workers					
molding module	Steel mold cleaning (mold clearing)	Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	
		Count	95	19.3%	182	37.0%	75	15.2%	10	2.0%	31	6.3%	58	11.8%	41	8.3%
		precast experience(year)	0.3		0.6		1.3		1.4		0.3		1.6		2.2	
		Total	362				73.6%				130				26.4%	
	Module assembly	Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	
		Count	161	32.7%	151	30.7%	91	18.5%	28	5.7%	22	4.5%	29	5.9%	10	2.0%
		precast experience(year)	0.4		0.6		0.9		1.3		0.6		0.8		1.8	
		Total	431				87.6%				61				12.4%	
	Lofting	Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	
		Count	164	33.3%	218	44.3%	78	15.9%	3	0.6%	10	2.0%	17	3.5%	2	0.4%
		precast experience(year)	4.5		5.1		5.9		5.3		3.7		3.9		4.2	
		Total	463				94.1%				29				5.9%	
		Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	

Item			Domestic workers								Foreign workers					
	Dipping of steel rod cages	Count	86	17.5%	201	40.9%	77	15.7%	16	3.3%	77	15.7%	25	5.1%	10	2%
		precast experience(year)	0.2		1.0		0.9		1.3		0.2		1.0		2.2	
		Total	380				77.2%				112				22.8%	
	Laying of embedded parts	Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	
		Count	97	19.7%	143	29.1%	42	8.5%	11	2.2%	91	18.5%	85	17.3%	23	4.7%
		precast experience(year)	1.9		2.3		2.8		3.5		1.6		3.4		3.6	
		Total	293				59.6%				199				40.4%	
Filling module	Checking before pouring concrete	Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	
		Count	122	24.8%	89	18.1%	81	16.5%	31	6.3%	65	13.2%	71	14.4%	33	6.7%
		precast experience(year)	2.3		2.8		3.4		5.1		1.8		1.9		2.8	
		Total	323				65.7%				169				34.3%	
		Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	

Item		Domestic workers								Foreign workers					
Pouring concrete	Count	79	16.1%	118	24.0%	93	18.9%	19	3.9%	101	20.5%	72	14.6%	10	2.0%
	precast experience(year)	0.6		0.8		1.1		2.3		0.3		0.6		0.8	
	Total	309				62.8%				183			37.2%		
Surface whitewashing	Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	
	Count	41	8.3%	239	48.6%	87	17.7%	0	0.0%	28	5.7%	91	18.5%	6	1.2%
	precast experience(year)	1.9		2.8		3.3		0.0		2.4		4.3		4.9	
	Total	367				74.6%				125			25.4%		
Concrete curing	Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	
	Count	102	20.7%	79	16.1%	49	10.0%	38	7.7%	111	22.6%	85	17.3%	28	5.7%
	precast experience(year)	0.1		0.7		0.9		1.2		0.5		0.5		0.8	
	Total	268				54.5%				224			45.5%		
	Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	

Item			Domestic workers								Foreign workers					
Repair and storage module	Mold removing	Count	122	24.8%	89	18.1%	81	16.5%	31	6.3%	65	13.2%	71	14.4%	33	6.7%
		precast experience(year)	2.3		2.8		3.4		5.1		1.8		1.9		2.8	
		Total	323				65.7%				169				34.3%	
	Demolding	Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	
		Count	79	16.1%	118	24.0%	93	18.9%	19	3.9%	101	20.5%	72	14.6%	10	2.0%
		precast experience(year)	0.6		0.8		1.1		2.3		0.3		0.6		0.8	
		Total	309				62.8%				183				37.2%	
	Component repair	Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	
		Count	41	8.3%	239	48.6%	87	17.7%	0	0.0%	28	5.7%	91	18.5%	6	1.2%
		precast experience(year)	1.9		2.8		3.3		0.0		2.4		4.3		4.9	
		Total	367				74.6%				125				25.4%	
		Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	
		Count	118	24.0%	116	23.6%	93	18.9%	35	7.1%	53	10.8%	59	12.0%	18	3.7%

Item		Domestic workers								Foreign workers					
Inspection of finished components	precast experience(year)	0.9		0.8		1.0		1.8		1.2		1.4		1.8	
	Total	362				73.6%				130				26.4%	
Warehouse storage	Age	20-29		30-39		40-49		Above 50		20-29		30-39		40-49	
	Count	136	27.6%	98	19.9%	46	9.3%	18	3.7%	101	20.5%	76	15.4%	17	8.8%
	precast experience(year)	0.9		1.5		1.8		1.9		0.9		1.8		2.9	
	Total	298				60.6%				194				39.4%	

Table 4 Collected data

Activity	Observations	Observation days	Data points
Steel mold cleaning		35	17,220
Modules assembling		15	7,380
Lofting		166	81,672
Dipping for steel rod cage		25	12,300
Laying for embedded parts		84	41,328
Checking before concrete pouring		35	17,220
Concrete pouring		10	4,920
Surface whitewashing	492	112	55,104
Concrete curing		10	4,920
Mold removing		8	3,936
Stripping		22	10,824
Component repair		116	57,072
Inspection for finished components		32	15,744
Warehouse storage		50	24,600
Total		720	354,240

Table 5 Production time comparison between the first and final measurement for each activity

Activity	T_1	T_2	$T_1 - T_2$	$\frac{T_1 - T_2}{T_2} \times 100\%$
Steel mold cleaning	62.1	24.4	37.6	61%
Modules assembling	39.8	19.2	20.6	52%
Lofting	93.7	12.3	81.4	87%
Dipping for steel rod cage	53.1	31.0	22.1	42%
Laying for embedded parts	124.4	55.4	69.0	55%
Checking before concrete pouring	27.0	10.3	16.8	62%
Concrete pouring	47.1	27.2	19.8	42%
Surface whitewashing	94.1	31.7	62.4	66%
Concrete curing	21.3	12.2	9.1	43%
Mold removing	23.8	16.3	7.5	32%
Stripping	28.5	10.9	17.6	62%
Component repair	197.3	69.0	128.2	65%
Inspection for finished components	29.1	13.9	15.1	52%
Warehouse storage	76.1	25.6	50.5	66%

T_1: Average work time of the first day

T_2: Average work time of the final measurement day

Table 6 Learning Curve Model comparative analysis for each activity

Activity	Straight-line model		Cubic model		Exponential model	
	R^2	MAPE(%)	R^2	MAPE(%)	R^2	MAPE(%)
Steel mold cleaning	0.8581~0.8554	9.15%~13.23%	0.9422~0.9447	6.67%~11.02%	0.9637~0.9662	5.76%~10.62%
Modules assembling	0.9420~0.9453	4.85%~10.93%	0.9826~0.9853	3.36%~10.20%	0.9817~0.9844	3.82%~10.26%
Lofting	0.4426~0.4455	46.71%~47.47%	0.9605~0.9607	10.90%~13.22%	0.9905~0.9913	6.83%~10.77%
Dipping for steel rod cage	0.7919~0.7973	7.83%~10.21%	0.9394~0.9426	4.92%~8.30%	0.9156~0.9191	6.04%~8.68%
Laying for embedded parts	0.7006~0.7030	11.83%~13.65%	0.9737~0.9740	4.63%~8.52%	0.9680~0.9701	4.71%~8.51%
Checking before concrete pouring	0.7913~0.7944	13.26%~14.79%	0.9378~0.9390	7.99%~10.45%	0.9512~0.9564	8.50%~10.99%
Concrete pouring	0.9190~0.9321	6.19%~13.49%	0.9889~0.9928	4.27%~13.49%	0.9835~0.9862	4.76%~13.42%
Surface whitewashing	0.5380~0.5478	22.71%~23.67%	0.9807~0.9837	4.84%~8.41%	0.9800~0.9809	5.45%~8.88%
Concrete curing	0.8662~0.8820	6.00%~8.66%	0.9928~0.9944	3.44%~6.86%	0.9895~0.9903	3.82%~7.09%
Mold removing	0.7400~0.7609	7.07%~10.75%	0.9058~0.9099	5.39%~8.77%	0.8840~0.8912	5.43%~9.43%
Stripping	0.8168~0.8180	12.28%~14.18%	0.9412~0.9431	7.22%~10.53%	0.9679~0.9689	7.06%~10.39%
Component repair	0.6085~0.6098	18.99%~20.09%	0.9716~0.9729	5.41%~7.90%	0.9817~0.9824	5.43%~7.92%
Inspection for finished components	0.9330~0.9367	7.43%~9.13%	0.9777~0.9796	6.56%~8.15%	0.9850~0.9861	6.43%~7.97%
Warehouse storage	0.8519~0.8540	11.90%~12.36%	0.9640~0.9646	8.44%~8.82%	0.9734~0.9749	7.85%~8.21%

Table 7 Exponential model data for each activity

Activity	Exponential Model		
	R^2	MAPE	LC_{best} formula
Steel mold cleaning	0.9658	5.76%	y =62.2-41.38(1-*exp(-0.09877*(x-1))) =20.82+41.38*exp(-0.09877*(x-1))
Modules assembling	0.9840	3.82%	y =39.76-21.55(1-*exp(-0.4388*(x-1))) =18.21+21.55*exp(-0.4388*(x-1))
Lofting	0.9907	6.83%	y =100.41-138(1-*exp(-0.006511*(x-1))) =-37.59+138*exp(-0.006511*(x-1))
Dipping for steel rod cage	0.9177	6.04%	y =53.04-26.77(1-*exp(-0.09279*(x-1))) =26.27+26.77*exp(-0.09279*(x-1))
Laying for embedded parts	0.9683	4.71%	y =124.37-82.13(1-*exp(-0.02508*(x-1))) =42.24+82.13*exp(-0.02508*(x-1))
Checking before concrete pouring	0.9520	8.50%	y =27.11-18.9(1-*exp(-0.08162*(x-1))) =8.21+18.9*exp(-0.08162*(x-1))
Concrete pouring	0.9857	4.76%	y =46.94-21.25(1-*exp(-0.5042*(x-1))) =25.69+21.25*exp(-0.5042*(x-1))
Surface whitewashing	0.9809	5.45%	y =96.36-120.6(1-*exp(-0.007981*(x-1))) =-24.24+120.6*exp(-0.007981*(x-1))
Concrete curing	0.9903	3.82%	y =21.53-9.321(1-*exp(-0.7737*(x-1))) =12.21+9.321*exp(-0.7737*(x-1))
Mold removing	0.8886	5.43%	y =23.98-8.064(1-*exp(-0.708*(x-1))) =15.92+8.064*exp(-0.708*(x-1))
Stripping	0.9686	7.06%	y =28.44-20.18(1-*exp(-0.08944*(x-1))) =8.26+20.18*exp(-0.08944*(x-1))
Component repair	0.9823	5.43%	y =197.54-170.5(1-*exp(-0.01334*(x-1))) =27.04+170.5*exp(-0.01334*(x-1))
Inspection for finished components	0.9855	6.43%	y =29.05-15.57(1-*exp(-0.1282*(x-1))) =13.48+15.57*exp(-0.1282*(x-1))
Warehouse storage	0.9736	7.85%	y =76.1-53.31(1-*exp(-0.07469*(x-1))) =22.79+53.31*exp(-0.07469*(x-1))

Table 8 K-means grouping results

group	A		B		C		Activity numbers
	mean	Standard Deviation	mean	Standard Deviation	mean	Standard Deviation	
1	40.815	18.334	-23.63	13.994	-0.299	0.28	10
2	123.967	46.905	-127.808	36.81	-0.013	0.008	4

A：Initial Performance: Time required for produce the first unit

B：Asymptotic Performance and Initial Performance deviation

C：Learning constant

Table 9 Asymptotic Performance of All Activities

Activity	Asymptotic Performance	Complex Activity
Lofting	-37.59	Yes
Surface whitewashing	-24.24	Yes
Checking before concrete pouring	8.21	No
Stripping	8.26	No
Concrete curing	12.21	No
Inspection for finished components	13.48	No
Mold removing	15.92	No
Modules assembling	18.21	No
Steel mold cleaning	20.81	No
Warehouse storage	22.79	No
Concrete pouring	25.69	No
Dipping for steel rod cage	26.27	No
Component repair	27.04	Yes
Laying for embedded parts	42.24	Yes