Title: **Determining worker training time for precast component production in construction: Empirical study in Taiwan**

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Abstract

This study is aimed at determining the worker training time and proficiency threshold for each activity in precast component production based on the learning curve theory. Training data for precast component production for the past 5 years were collected in Taiwan, including 317,832 datasets for 14 production activities involving a total of 4,352 worker participations and 492 completion times. A learning curve model for workers to master the manufacture of precast component was developed, yielding the major finding that training time for workers to learn precast component production has a learning curve slope = -0.75. The training time required to reach proficiency varies from 3.87 to 26.15 days for non-complex activities. The findings also show that 4 out of 14 activities can be identified as complex with a learning curve slope of -0.75. Practitioners should mainly focus on worker training for those complex activities as the critical path to improving precast component productivity. The findings also provide thresholds (in days) for all activities which helps to quantify how much time is needed to efficiently train workers for precast component production.

Keywords: learning curve, precast component, training time, productivity, construction management

1. Introduction

In recent years, the construction industry in general had been faced with a shortage of technical manpower, especially a shortage of skilled workers (Construction 2012; Sandelands et al. 2009). The development of new technology-oriented practices may be one direction for improvement, helping to move the construction industry towards industrialization. It is suggested that practitioners could invest in equipment and technology to increase production and improve quality (Warszawski 2003). Studies in 2013 encouraged the development of the precast method as an important part of the industrialization process (Ågren and Wing 2013). This process has matured and been developed in the construction industry, playing an important role in overcoming the shortage of workers, improving productivity in the construction industry, and assuring project quality (Jaillon and Poon 2009; Ko and Wang 2010; Nasirian et al. 2019; Wuni and Shen 2019). Worker costs account for 17-30% of the total construction costs, making it the second most expensive component (Hong et al. 2018). Improving productivity and reducing worker costs are both important in the precast industry. Some studies have also focused on alternatives such as improving the efficiency of human resource allocation (Al-Bazi and Dawood 2010; Arashpour et al. 2018; Nasirian et al. 2019). The literature on the construction of industrial human resource management has also emphasized the importance of developing skilled human resources (Karimi et al. 2018). Such resources are often the key to scheduling and cost control (Nasirian et al. 2019). Project productivity is heavily dependent on skilled workers especially in the construction industry. The training of newly employed workers is critical to increasing productivity and meeting project needs(Goodier 2008; Wang et al. 2018). The two challenges most often encountered in the process of training skilled workers in the precast factory are: (1) the training time for newly employed workers in precast component production remains uncertain or is dependent on empirical access, so the process is highly vulnerable to error making corporate or project management unreliable; (2) the threshold for determining when the newly employed workers have become skilled is not clear.

This study is aimed at determining the worker training time and skill threshold for each activity in the precast component production process based on learning curve theory. Due to the nature of data sampling and collection process over a long period of time, the scope of this study is limited to construction workers with no previous experience in precast component production, disregarding past experience possibly linked to precast component production, and ignoring the effect of interruption to the training process due to the economic situation.

2. Precast production management

The precast method has come to be regarded as a key technology for promoting innovation and improvement to the methods traditionally used in the construction industry, and one of the most effective alternatives to the traditional construction methods (Arashpour et al. 2016; Li et al. 2017; Pan et al. 2012). It has significant potential advantages for solving common problems that have troubled the industry for a long time, such as the lack of technically skilled workers, low productivity, poor engineering quality, waste of resources, and high uncertainty (Chen et al. 2017; Jin et al. 2018; Nasirian et al. 2019). There are many different terms used to describe the components which can be precast during the construction process, referring to the units and components (such as columns, beams, walls, plates, etc.) for various parts of the construction project. The units are first produced in a factory or at the construction site in an industrialized process in normalized, standardized, and modular form, then transported to the site and assembled into a structure. Some define this method as a mixture of construction and manufacturing (Innella et al. 2019; Mao et al. 2015; Wuni and Shen 2019; Yang et al. 2016). The above process can be divided into parts, namely, production planning, component manufacturing, storage and transportation, and so on. The manufacture of precast components has been the most widely studied and discussed topic with the main focus being on the production mode, process reengineering, allocation of resources and manpower, and process arrangement of component production operations (Al-Bazi and Dawood 2010; Chen et al. 2016; Khalili and Chua 2014; Nasirian et al. 2019; Yang et al. 2016). Earlier research studies on precast processes have divided the production of precast components into the following 14 processes: (1) steel mold cleaning (clearing the mold), (2) module assembling, (3) lofting (positioning of iron components), (4) dipping the steel rod cage, (5) laying of embedded parts, (6) checking before concrete pouring, (7) concrete pouring, (8) whitewashing surfaces, (9) concrete curing operation and curing time, (10) mold removal, (11) demolding, (12) component repair, (13) inspection of finished components and (14) warehouse storage (Chen et al. 2020; Chen et al. 2019; Tai 2017). In a

2014 summary of the literature from 2000 to June 2013 pertaining to the afore-mentioned management methods and technologies related to the precast industry Li et al. concluded that research in the field of prefabrication and construction management (management of prefabricated construction, MPC) can be divided into the following major themes: "the future development of the industry", "development and application of technology", "performance evaluation", "technical application environment" and "design, production, transportation and assembly strategy" (Li et al. 2014).

Human resource related study is an extremely important part of management research in the precast industry. The main reasons being that: (1) worker cost expenditure accounts for a very high proportion of the total cost (17- 30%) (Hong et al. 2018); (2) the lack of skilled human resources often hinders development (Hu et al. 2019; Mao et al. 2015); (3) the improper allocation of human resources often results in project delays and increases costs (Nasirian et al. 2019; Nasirian et al. 2019; Wang et al. 2018).

3. Worker training in construction

In the labor-intensive construction industry, worker costs account for 30-50% of the total project cost, of which skilled human resources play an extremely important role. Traditionally, these skilled technical resources are trained and nurtured through different channels before becoming stable, reliable and productive. The main training channels include: training provided by the company, nurturing through apprenticeships, engineering-related training, and training in the technical systems (Karimi et al. 2018; Wang et al. 2008). In recent years, the shortage of skilled technical human resources in the construction industry has become increasingly serious, resulting in rising wages for skilled workers, which in turn has created tremendous pressure and lead to increasing costs of construction. The training of skilled workers in traditionally both time-consuming and costly. For example, the US Department of Worker's apprenticeship program includes 44 hours of on-site guidance and at least 3 years or 6,000 hours of on-the-job training (Li et al. 2015). Therefore, in both real-world practices and research, in addition to the development of new technologies such as precast methods that can reduce the dependence on skilled manpower, studies have begun to explore how to reduce the threshold for master of the technology and provide more effective training. For example, Wu et al. applied innovative technologies such as VR and MR for training in the engineering fields, aimed at reduce technical barriers for novice students with no work experience as well as technical experts with skilled work experience (Wu et al. 2019). Li et al. used real-time positioning and data visualization techniques to assist in the training of precast workers, aiming to improve the safety and effectiveness of the training (Li et al. 2015).

In the precast industry, cross-training is often used to nurture multi-skilled workers that are already familiar with multiple engineering skills, thereby increasing the flexibility of human resource scheduling for the production of precast components, mitigating the uneven distribution of human resource and enhancing productivity (Arashpour et al. 2015). The time spent in training plays a vital role in production management (An and Subramanian 2011; Arashpour et al. 2018). All training methods analyze the number of training days for precast component production activities from which they determine whether the newly employed workers have completed the training for different activities, sometimes by setting a fixed value or only based on an empirical value. However, this evaluation method is prone to error resulting in the waste of resources and time, sometimes providing workers who are not sufficiently productive becausee they might not have completed the training. Therefore, this study adopts the learning curve model developed in a previous study to understand the changes in the productivity of newly employed workers during the training process, and analyze the number of training days required for each activity for the production of precast component.

4. Learning curve theory

The learning curve can also be called an experience curve. As mentioned earlier, this concept was first proposed by Wright in 1936. Wright found that a doubling of the production line for the fabrication of aircraft components, required a 20% working time reduction. Hence, he proposed a straight-line model that suggests a constant rate of learning or improvement, wherein the operation time of the cycle can be reduced by a constant percentage every time the length of the cycle is increased (Everett and Farghal 1994; Jarkas 2010; Wright 1936). Since Wright first proposed the straight-line learning curve model, other different learning curve models have been proposed. Jordan Srour et al. proposed a learning curve model based on an iterative mode operation in their 2015 study. They also divided the various learning curve models based on the straight-line model into five categories: (1) Wright Model and Variations; (2) Polynomial Models; (3) Exponential Models; (4) Hyperbolic Models; (5) Recursive Models (Jordan Srour et al. 2015).

Learning curve theory has been applied by many to improve productivity in the construction industry. However, there has been little practical documentation combining the emerging precast industry and learning curve theory in the construction field. In 1986, Thomas et al. collected data related to 65 sets of precast components used at a construction site, which they fitted using five learning curve models including the straight-line, Stanford B, cubic, piecewise and exponential models to produce the R2 values. The results show the cubic model to have the best fit to historical data and also be best suited to predict the production time of independent sample data in the same phase (Thomas et al. 1986). Everett and Farghal studied the suitability of 12 learning curves for predicting future performance from historical data based on 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 the other models but performs the worst for predicting future production data; the straight-line model performs the worst in terms of fitting existing historical data but the best for predicting future production data (Everett and Farghal 1994).

Here, we analyze the learning curve for each precast activity, to be used as a pilot study. We visited a building precast factory in Taiwan to obtain production data for newly employed workers during their initial training to carry out precast activities for the past five years. We collected 317,832 data points for 14 production activities involving 492 personnel. The final analysis was based on the production training data for the newly employed workers collected by the team, and the precast production training activities. The results are presented in the form of the learning curves for the cubic model (Table 1). The verified results indicate that the learning curve model proposed in this study demonstrates a very good fit to the historical data (R^2 values are above 0.9), as well as excellent predictive ability for the production data of newly employed workers in the initial learning curve (with the exception of a learning curve model with a mean absolute percentage error (MAPE) of 10.97%, the remaining models have a MAPE value of less than 10%) (Chen et al. 2019).

5. Research propositions and methods

Using the concept of the learning curve and the deviation level to measure training time for each activity of the precast component, we arrive at the following two propositions:

Proposition 1

The MAE can be used to measure the convergence level for the learning curve based on Equation (1):

$$\text{MAE} = \frac{\sum_{i=1}^{n} |a_i - f_i|}{n}, \quad (1)$$

where a_i is the actual production time of the testing group on the i^{th} day, f_i is the model forecasting production time on the i^{th} day. Notice that the mean absolute error (MAE) itself defined in Equation (1) is a measure of the distance between the testing and actual results. The less deviation there is between the testing and the actual results, the smaller the MAE value yielded. In other words, the given activity is less complex.

Proposition 2

According to Proposition 1, it is considered that convergence is reached when 90% or more of the results fit the learning curve. A fit of 90% or more in a certain space or function is usually sufficient to explain the majority of the statistical meaning; therefore, this is the proposed threshold to for convergence of the learning curve within 1.2 standard deviations (MAE-1.2σ). The corresponding slope of the learning curve at MAE-1.2σ is the learning rate for each precast component activity.

6. Data collection and analysis

The proposed work and previous studies are parts of a larger research projects funded by the Ministry of Science and Technology (MOST) in Taiwan (MOST-108-2221-E-008 -002 -MY3, MOST-106-2221-E-008-020-MY2, and MOST-105-2221-E-008 -113) requiring data sampling and collection associated related to precast component production over the last 10 years (2008-2019). The collected databank can be divided into 3 parts, namely, production time by well-trained workers, production time by workers undergoing training, and detailed production costs. Up to now, 5 papers related to these projects have appeared: 1. Process reengineering for building precast production (Chen et al. 2016); 2. Association rules for precast component activities (Chen et al. 2020); 3. Complexity of precast component production (Tai 2017); 4. Learning curve for precast component production (Tai et al. 2019); and 5. the current work. We participated in the data collection process, which was carried out in order to understand and explore the realities of the current situation of production management in Taiwan's precast industry. At the same time, this study verifies the situation in precast factories through observation and measurement. The relevant basic data and production time for component production are analyzed. Therefore, the data collected regarding the workers' experience is limited to the following range: (1) all workers have experience in construction but are new to precast component production; (2) inspections show that all workers work under healthy working conditions; (3) all workers are within the age range of 20-65 years old; (4) no worker has experience greater than 6 years in the construction industry. These limitations ensure the reduction of noise in the data sample that could affect the research propositions, observations, and even the results. The data sampling of the production time of workers undergoing training continued for 5 years (2015-2019). Field visits to building precast factories in Taiwan were conducted. The data sampling was carried out in 2 steps: scheduled observations at jobsites and the recording and measuring of working details through CCTV video recording. Each CCTV video observation measured in minutes contains at most 6 datasets of completed activities for precast component production, from the first day, until the workers' performance stabilized. From the records and according to the observation process, on average, the time it took for the workers performance to stabilize ranged from 10 to 100 days, as can be seen in Table 2.

Altogether, 4,352 workers participated in the data sampling, completing each activity 492 times. A total of 317,832 production data points was collected. These covered 90% of all precast projects in Taiwan over the past five years, including the construction of collective housing, schools, office buildings, large shopping malls, technology plants, biotech factories and composite shopping malls, as shown in Figure 1. The production data for 14 activities showed a 32-87% reduction in work times on the final measurement day compared to the first day, as shown in Table 3, meaning a cumulative reduction of production time of up to 557.7 minutes. Work time for each activity varied, ranging from a few days to several weeks. These results show that training does have a significant effect on the process of precast component production.

Learning curves corresponding to each activity are drawn. It can be seen from the diagrams that the changes in production time tend to be stable. Figure 2, for example, graphically illustrates the tendency for productivity. The MAE values for 14 activities are shown in Table 4. According to the propositions, the less the deviation between the testing and actual results, the smaller the MAE value yielded. In other words, the given activity is not complex. The average MAE = 1.71. Comparison shows that 4 out of a total of 14 activities are relatively complex, with corresponding MAE values >1.71 including lofting, laying of embedded parts, surface whitewashing, and component repair. The other 10 activities are relatively less complex, or non-complex activities. Table 5 presents the information for those 10 having an average MAE of 0.84, standard deviation of 0.08, and threshold (MAE-1.2σ) of 0.75. As a result, the corresponding slope of -0.75 for the learning curve at MAE-1.2σ indicate the learning rate where convergence occurs for those 10 non-complex activities. As can be seen in Table 6 workers need to take 3.87 to 26.15 training days to achieve proficiency when the slope = -0.75. The convergence time varies dramatically for the 4 complex activities and sometimes cannot be obtained. The average MAE is 3.87, as shown in Table 5. This indicates that the training program may need to be re-reviewed.

7. Evaluation and discussion

Data related to the production time by well-trained workers is collected as supported by the MOST projects for evaluation in the proposed work. The database regarding production time by well-trained workers covers a wider range, with 772,212 datasets containing information for over 90% of all precast components produced for construction over the past 10 years (2008-2017) (Chen et al. 2019; Chen et al. 2020). The data used for the evaluation are for well-trained workers contributing to the production of construction precast components over the past 10 years in Taiwan. Thus, it is totally different from the data used in our current work. The difference between the two databases can be seen in 5 aspects: observed subjects, observation duration, project quantity, number of data points, and participating workers, as shown in Table 7. These data represent almost the entire sample in the investigated region. Directly plugging the data into the proposed work is straightforward and can help us to evaluate the effectiveness of the research propositions. It is not necessary to run 5-fold (80-20) or even 10-fold (90-10) cross-evaluation methods since the evaluation is based on almost the entire sample. Table 8 summarizes the evaluation data characteristics in minutes. An examination of Table 9 shows that the results verify the research propositions. Warehouse storage is the only one non-complex activity that does not show good convergence with an average deviation of 11.43 minutes, relatively larger than the others. Examining its MAE compared with the overall average MAE in Table 4, we can find that this activity is close to the level for a complex activity but slightly lower than the average, although it is categorized as a non-complex activity. In practice, it is very likely that warehouse storage processes vary due to the practices of different factories even though the storage steps themselves are similar and simple. Even given the variation in warehouse storage, propositions 1 and 2 still stand.

A comparison of the results obtained in this work with a previous work (Chen et al. 2019) show them to be mostly consistent in terms of the level of activity complexity. Further discussion and comparison to previous studies brings us to the following considerations. The outcomes for the four activities of lofting, laying embedded parts, surface whitewashing, and component repair match the outcomes from the previous study (Chen et al. 2019). Only the training time for the laying embedded parts activity converges, but there is still a significant gap, greater than 30 minutes, from the average value for technical proficiency. As in the previous work by Chen et al. (2019), these four activities remain categorized as complex, requiring professional technical skills to complete in practice, and the fluctuation in production time for the acquisition of these professional technical skills is large. The production time for these four activities by professional technical workers also varies greatly, depending upon product complexity. The results show that training times for these four activities are long, so there are fewer human resources available to work on them. Therefore, it is necessary to pay more attention to these activites as comprising critical paths for improvement. The worktime, training time, and average daily reduction time for the non-complex activities, with the exception of warehouse storage activities, are detailed in Table 10. The average daily reduction time results show the greatest amount of time saved by training is for concrete curing, reaching 9.79% daily, an almost 10% gain in efficiency. On the other hand, there is a reduction of only 2.57% of the time saved for steel mold cleaning. The major economic consequences derived from this study lie in the following. In developed regions, there is usually a shortage of skilled labor or cost escalation for the workforce. In Taiwan, the cost of labor usually makes up from 30% to 60% of the total cost for the construction project, depending on the project type. A saving of 10% of the worktime for conducting the concrete curing activity, for example, results in significant cost savings or an increase in the profit margin of 10% for the manpower allocation contractors. In other words, savings of as little as 2.57% to nearly 10% of training time can still be valuable in terms of either increasing corporate profits or reducing manpower requirements. Detailing such savings is the practical contribution of this study.

8. Conclusion

Training workers is important for project management and for the efficient manufacture of precast components. This study focuses on determining worker training times and the threshold for proficiency for each activity in the precast component production process based on learning curve theory. With the use of large quantities of on-site survey data and the suggested propositions, the major contribution lies in finding the training threshold for the learning curve slope which is = -0.75. The corresponding training times for non-complex activities are determined as follows: 25.67 days for steel mold cleaning, 7.03 days for module assembling, 12.54 days for dipping steel rod cagess, 14.51 days for checking before concrete pouring, 6.05 days for concrete pouring for, 3.87 days for concrete curing, 4.21 days for mold removing, 13.95 days for stripping, and 8.95 days for the inspection of finished components. The findings also show that the four complex activities exactly match those found in the previous studies and fit the empirical outcomes identified including lofting, laying of embedded parts, whitewashing surfaces, and component repair. In addition, we quantify the average daily reduction time for non-complex activities in the range from 9.79% to 2.57%. These contributions can substantially improve the training programs for precast component production.

The research is limited in scope to construction workers who have had no previous experience in precast component production, ignoring past experience that may be linked to precast component production. It is feasible that rule association among features of past experience and background (e.g. age, education, and economic status) could reveal more clues about precast component production. In addition, the data sampling ignores the effects of interruptions to the training process. It is possible that workers could be a bit out of practice if frequent interruptions occur or they last too long. The effects may be incremental is measurement continues over a long period of time. Follow-up studies are encouraged to analyze complex activities using different approaches, and to comprehensively explore and quantify the factors that improve productivity for precast component production based on the findings in this work.

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Data Availability Statement

All data, models, and code generated or used during the study appear in the submitted article.

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Table 1 Data for cubic model of each activity

Activity	Cubic model						
	Initial learning rate	R^2	MAE	LC_{best} coefficient			
				n	c	d	a
Steel mold cleaning	86.59%	0.9730	4.32%	0.2077	0.2331	-0.2286	62.20
Module assembling	82.32%	0.9853	2.50%	0.2806	-0.2693	0.2208	39.76
Lofting	62.98%	0.9521	10.97%	0.6671	1.0507	-0.4139	93.76
Dipping the steel rod cage	124.14%	0.9438	3.66%	-0.3120	-0.7944	0.3200	53.21
Laying embedded parts	108.39%	0.9696	3.90%	-0.1162	-0.1669	0.0008	124.82
Checking before concrete pouring	96.25%	0.9743	4.22%	0.0551	0.1267	-0.2519	26.98
Concrete pouring	97.07%	0.9926	2.20%	0.0429	-0.8810	0.6822	47.09
Whitewashing surfaces	83.25%	0.9793	0.51%	0.2644	0.4699	-0.2299	94.04
Concrete curing	73.05%	0.9941	1.38%	0.4531	0.1592	0.0484	21.38
Mold removing	101.56%	0.9095	4.00%	-0.0223	-1.0740	0.9599	23.87
Stripping	92.10%	0.9702	4.31%	0.1187	0.1643	-0.2496	28.48
Component repair	84.55%	0.9708	4.57%	0.2421	0.3735	-0.1828	197.11
Inspection of finished components	92.33%	0.9724	3.36%	0.1151	0.0115	-0.0947	29.08
Warehouse storage	90.40%	0.9764	4.33%	0.1456	0.0678	-0.1114	7.62

Table 2 Data features

Activity	Completion Times	Collecting days	Number of data points
Steel mold cleaning	492	25	12,300
Module assembling		15	7,380
Lofting		161	79,212
Dipping the steel rod cage		25	12,300
Laying embedded parts		76	37,392
Checking before concrete pouring		22	10,824
Concrete pouring		10	4,920
Whitewashing surfaces		106	52,152
Concrete curing		10	4,920
Mold removing		8	3,936
Stripping		22	10,824
Component repair		106	52,152
Inspection of finished components		20	9,840
Warehouse storage		40	19,680
Total		646	317,832

Table 3 Production time comparison between the first and final measurement for each activity

Activity	T_1	T_2	$T_1 - T_2$	$\frac{T_1 - T_2}{T_1} \times 100\%$
Steel mold cleaning	62.1	24.4	37.6	61%
Module assemblage	39.8	19.2	20.6	52%
Lofting	93.7	12.3	81.4	87%
Dipping the steel rod cage	53.1	31.0	22.1	42%
Laying embedded parts	124.4	55.4	69.0	55%
Checking before pouring concrete	27.0	10.3	16.8	62%
Concrete pouring	47.1	27.2	19.8	42%
Whitewashing surfaces	94.1	31.7	62.4	66%
Concrete curing	21.3	12.2	9.1	43%
Mold removal	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 of finished components	29.1	13.9	15.1	52%
Warehouse storage	76.1	25.6	50.5	66%

T_1: Average working time on the first day
T_2: Average working time on the final measurement day

Table 4 MAE values for 14 activities

Activity	MAE
Steel mold cleaning	1.49
Module assembling	0.52
Lofting	*4.74*
Dipping the steel rod cage	1.40
Laying of embedded parts	*3.14*
Checking before concrete pouring	0.65
Concrete pouring	0.66
Whitewashing surfaces	*2.54*
Concrete curing	0.19
Mold removing	0.70
Stripping	0.63
Component repair	*5.04*
Inspection of finished components	0.60
Warehouse storage	1.61
Average	1.71

Table 5 Average MAE and thresholds

	Average MAE	Standard deviation (σ)	MAE-1.2σ
Non-complex activities (10)	0.84	0.08	0.75
Complex activities (4)	3.87	-	-

Table 6 Production time for non-complex activities at learning rate = 0.75

Activity	Learning curve slope (learning rate)	Production time (minutes)	Training time (days)
Steel mold cleaning	-0.75	21.09	25.67
Module assembling	-0.75	20.08	7.03
Dipping the steel rod cage	-0.75	34.22	12.54
Checking before concrete pouring	-0.75	13.91	14.51
Concrete pouring	-0.75	26.72	6.05
Concrete curing	-0.75	13.23	3.87
Mold removing	-0.75	16.10	4.21
Stripping	-0.75	14.44	13.95
Inspection of finished components	-0.75	19.16	8.95
Warehouse storage	-0.75	31.40	26.15
Average	-	21.04	12.29
Maximum	-	34.22	26.15
Minimum	-	13.23	3.87
Standard Deviation	-	7.44	8.12

Table 7 Comparison between the training and evaluation dataset

Features	Training dataset	Evaluation dataset
Observed subject	Under trained workers	Well-trained workers
Observation duration	5 years (2015-2019)	10 years (2008-2017)
Project quantity	17	100
Data points	317,832	772,212
Participating workers	4,352	102,222

Table 8 Details for evaluation data (Unit: minutes)

Activity	Average	Standard deviation	Maximum	Minimum
Steel mold cleaning	23.46	2.47	31.90	17.76
Module assembling	18.73	3.27	27.87	12.91
Lofting	*8.58*	*4.58*	*19.32*	*2.01*
Dipping the steel rod cage	26.03	6.51	44.95	14.82
Laying of embedded parts	*35.16*	*19.60*	*105.91*	*17.05*
Checking before concrete pouring	13.79	3.28	22.94	8.06
Concrete pouring	19.78	6.19	35.97	12.06
Whitewashing surfaces	*41.63*	*9.65*	*67.95*	*25.13*
Concrete curing	11.75	1.75	16.95	8.04
Mold removing	13.28	6.01	29.76	3.02
Stripping	14.55	2.71	21.99	8.71
Component repair	*50.35*	*18.79*	*91.87*	*20.12*
Inspection of finished components	14.11	2.95	24.18	8.04
Warehouse storage	19.97	1.68	24.98	14.71

Table 9 Evaluation results (in minutes)

Activity	Average	V_1	V_2	Deviation of averages	Proposition stands or not
Steel mold cleaning	21.09	31.90	17.76	2.37	Yes
Module assembling	20.08	27.87	12.91	1.35	Yes
Dipping of steel rod cage	34.22	44.95	14.82	8.19	Yes
Checking before concrete pouring	13.91	22.94	8.06	0.12	Yes
Concrete pouring	26.72	35.97	12.06	6.95	Yes
Concrete curing	13.23	16.95	8.04	1.47	Yes
Mold removing	16.10	29.76	3.02	2.82	Yes
Stripping	14.44	21.99	8.71	0.11	Yes
Inspection of finished components	19.16	24.18	8.04	5.05	Yes
Warehouse storage	*31.40*	*24.98*	*14.71*	*11.43*	*No*

V_1: The upper limit of the verification interval
V_2: The lower limit of the verification interval

Table 10 Daily reduction time by training

Activity	T_1	T_s	T_1-T_s	Training days	$\frac{T1 - Ts}{T_1} \times 100\%$	S
Steel mold cleaning	62.1	21.09	41.01	25.67	66%	2.57%
Module assembling	39.8	20.08	19.72	7.03	50%	7.05%
Dipping the steel rod cage	53.1	34.22	18.88	12.54	36%	2.83%
Checking before concrete pouring	27	13.91	13.09	14.51	48%	3.34%
Concrete pouring	47.1	26.72	20.38	6.05	43%	7.15%
Concrete curing	21.3	13.23	8.07	3.87	38%	9.79%
Mold removing	23.8	16.10	7.70	4.21	32%	7.68%
Stripping	28.5	14.44	14.06	13.95	49%	3.54%
Inspection of finished components	29.1	19.16	9.94	8.95	34%	3.82%

T_1: Working time on the first day
T_s: Working time needed to reach proficiency
S: Average daily reduction time as a percentage

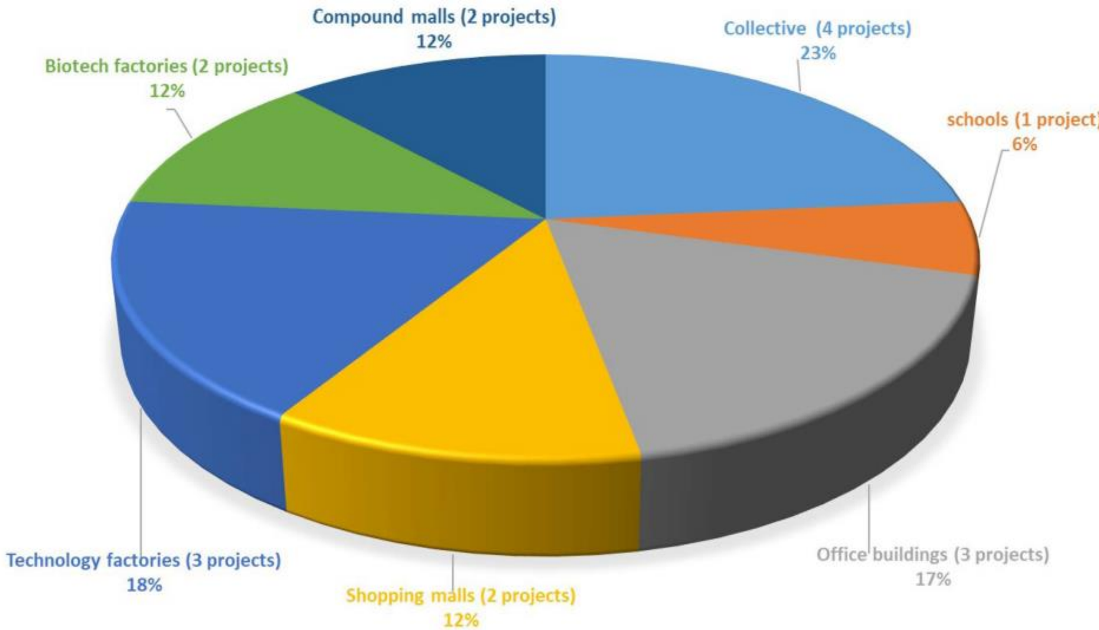

Fig. 1. Project types for precast component production.

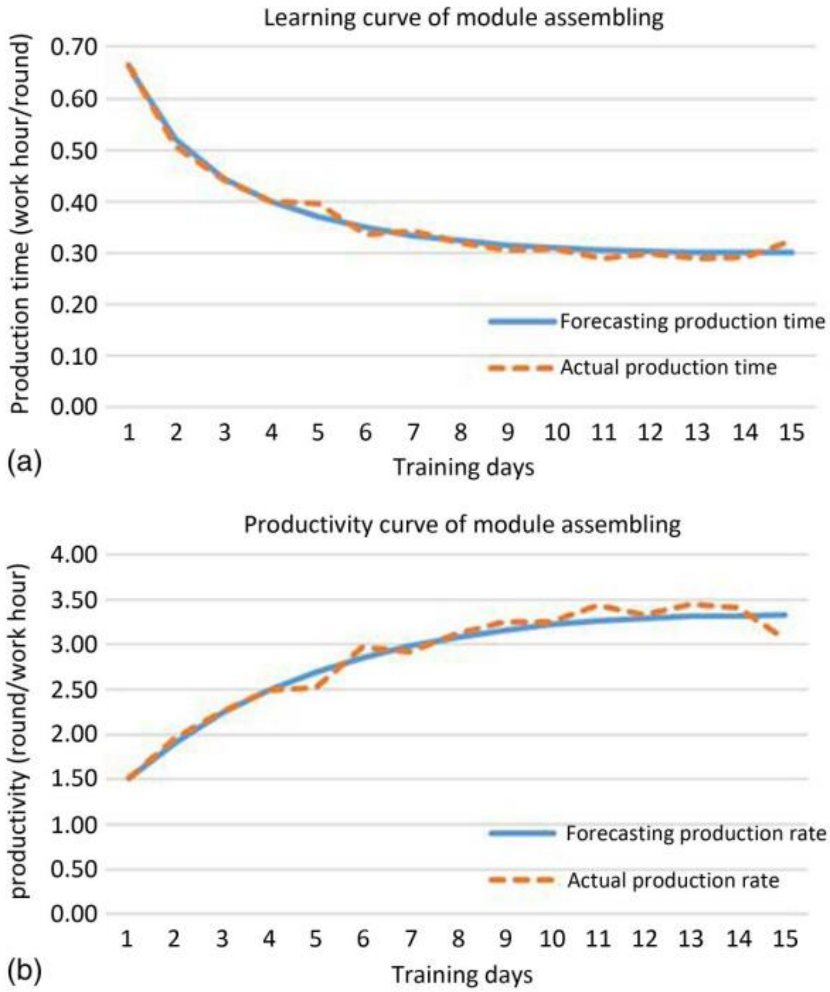

Fig. 2. Cubic learning curve for module assembling activity.