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EVALUATING COMPLEXITY OF CONSTRUCTION PRECAST COMPONENT: EMPIRICAL STUDY IN TAIWAN

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Abstract. Companies in the construction precast industry usually face lack of skilled manpower, overtime working, and complexity of manpower allocation. The objective of this research is to identify the complexity of precast components using Swarm-Inspired Projection (SIP) algorithm. After conducting a comprehensive literature review regarding precast production, clustering, classification, cost management, manpower allocation, and optimization, expertise from field/head-quarter supervision leads the way to SIP algorithm that drives collected data converted to certain clusters. Data collection was carried out to gather over 90% precast construction data in Taiwan for the recent decade. A total of 1,015,840 datasets were collected and then 772,212 datasets were taken into computation SIP algorithm after data filtering. Evaluation and comparison of models reveal SIP's remarkable efficiency, halving processing time while delivering superior results. The study identifies four complexity tiers linked to the manufacturing of building precast elements. Significant variations exist among these tiers, with workload increments of 18.22%, 11.71%, and 30.08% between Level 1 and 2, Level 2 and 3, and Level 3 and 4, respectively.

Keywords: construction precast, clustering, complexity level, Swarm-Inspired Projection, manpower allocation, component production.

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1. Introduction

The management team at the precast concrete plant in Taiwan typically develops initial working plans based on the design specifications of each project. These plans involve compiling and consolidating information such as the quantity and dimensions of precast structure modules, types and quantities of embedded parts, as well as the allocation of manpower and resources along the production line. The complexity of precast component production plays a crucial role in determining the production duration, often referring to how efficiently a precast component can be completed, such as production time. Various alternative solutions utilizing optimization for precast construction have been under discussion for years. These include approaches such as multi-objective manufacturing, transportation, and assembly (Anvari et al., 2016; Yuan et al., 2018), optimized flow-shop scheduling (Yang et al., 2016; Ma et al., 2018a), optimal single-machine batch scheduling (Kong et al., 2017), as well as decision-making strategies (Arashpour et al., 2017; Wang et al., 2018). Decision makers at the precast concrete plant often rely on subjective judgments to determine the required production duration for each project based on their experience. However, this approach only offers an approximation of the production duration, resulting in disparities between the actual completion date of precast modules in each project and the constantly amended production schedule. This inconsist-

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ency leads to conflicts and wastage of various resources, including manpower, production machinery, raw materials, production areas, and steel molds, among others. Uneven resource allocation further disrupts the normal operation of the precast plant, especially when orders from multiple projects coincide, and shortages of skilled labor occur. Manufacturers may struggle to optimize their resource allocation due to a lack of information regarding the complexity of precast components. Therefore, to achieve precise estimations for precast production duration, it is essential to determine the complexity of precast component production. Providing complexity levels for precast components offers a solution to optimize precast manufacturers' resource allocation and increase profits.

In view of the reasons above, the objective of this research is to identify the complexity level of precast components using Swarm-Inspired Projection (SIP) algorithm, and, thus, requires majority data of the precast components from precast concrete plants in Taiwan over the last decade. The component production complexity for precast components here is the complexity level of precast components measured by workhours. The longer time a precast component is required for manufacture, the more complexity (or the higher complexity level) the component is. We anticipate that the total production time required for all precast components in the project can therefore be estimated and the task attributes of the production procedures of every component can be identified for better planning.

2. Precast engineering and component production

The precast construction method involves carefully planning and designing the decomposition of a building's main structural body into standardized component units, such as beams, columns, and wall panels. Once these precast components are completed in manufacturing plants, they are transported to the construction site for on-site hoisting and assembly. This method is a well-established construction approach (Kieran & Timberlake, 2004). Scholars have classified precast concrete plants into two main types: long-line production for standardized components and short-line production for customized components tailored to specific project specifications (Han et al., 2016). These production methods are further categorized into comprehensive production, where the production location is fixed, and specialized production, which involves a mobile production line in a flow shop mode. Most precast concrete plants currently follow the comprehensive production method, while the specialized method represents an industrialized production line system.

The two production approaches differ significantly due to variations in spatial resources, workforce allocation, and construction sequencing, which affect manpower and resource distribution on-site. Based on the concept of automated production techniques, some studies have proposed models built on the standardized flow shop approach of precast concrete plants (Chan & Hu, 2001, 2002) to study the entire production system (Leu & Hwang, 2002; Ko & Wang, 2010; de Albuquerque et al., 2012). Research on supply chain management in precast construction projects reveals that over 95% of project managers believe more than 20% of project delays are caused by supply issues related to precast components. Additionally, studies have shown that project progress is impacted by factors such as low production quality, component damage, incorrect quantities of supplied components, and production delays (Low & Choong, 2001).

The primary operations in precast concrete plants typically involve production planning, precast component manufacturing, storage and transportation, as well as sales activities. The production of precast components can take anywhere from several weeks to multiple months, depending on the scale and complexity of the project. To ensure efficient scheduling, workforce distribution, and manufacturing site allocation, classifying the complexity of component production is crucial.

To develop the study framework, interviews were conducted with experts who were conveniently sampled and have over 10 years of experience in precast manufacturing. Scholars recommend that an optimal Delphi panel size for construction management studies ranges from 8 to 20 participants (Hallowell & Gambatese, 2010; Ameyaw et al., 2016). Table 1 outlines the background of the 14 interviewees, who are experts in precast research, design, production, and engineering. Their expertise in the production process is depicted in Figure 1 (Chen et al., 2016b), and the data collection is categorized into three main components: beam, minor beam, and column. Figure 1 also illustrates the overall production process, while the sequence and detailed descriptions of the component production are provided as follows:

1. Cleaning the steel mold: Remove the residual contaminations and hardened blocks of concrete on the steel mold.
2. Assembling modules: The base mold, side mold and steel bar positioning are assembled for each precast component type.
3. Lofting (positioning of iron components): Installation datum lines of the embedded parts are measured and marked on steel mold with level and perpendicular lines.
4. Dipping the steel rod cage: Steel cage is hoisted into steel mold, where the length and position of dowel bars are adjusted.
5. Laying of embedded parts: Rubber sealing gasket, upper and lower wood spacer panels are first installed, interfacial steel components are next installed.
6. Checking before pouring and concrete pouring: Steel reinforcement bars, steel wire mesh and other embedded parts are checked and verified if they are placed correctly and their dimensions are installed as designated.

7. Concrete placement.
8. Concrete surface whitewashing.
9. Concrete curing works and curing time: Upper part of the steel mold is covered with canvas cloth for hot steam curing and to ensure even heating of the concrete.
10. Removal of all related molds: Related molds are dismantled.
11. Mold removal: The completed precast component is removed from the steel mold.
12. Component repair: If relatively large air voids or significant damage is formed on the casted component, cement-sand grout is used to patch up the visible damages.
13. Inspection of finished components: The final product of the precast concrete component is inspected for its marking, labelling and dimension accuracy.
14. Warehouse storage: The completed components are transported to the storage warehouse for aggregated storage.

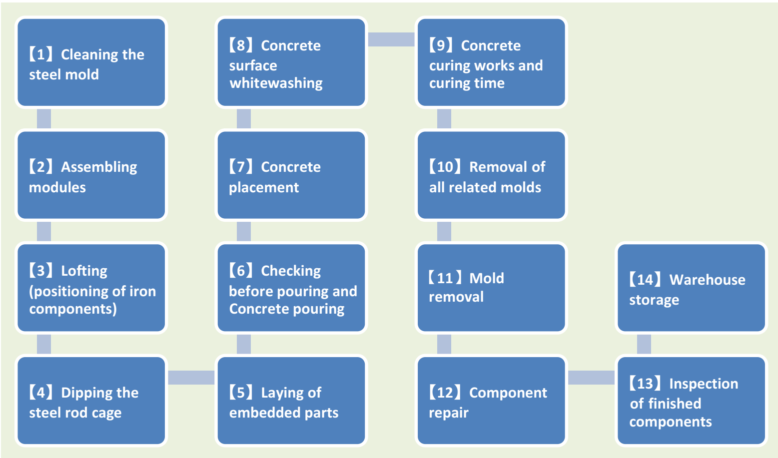

Figure 1. Steps for production of precast components

Table 1. Experts' information

Order	Department	Position	Specialization	Years of precast experience
1	President's Office	Senior President	Management of planning, manufacturing and construction of precast	33
2	Precast Production Department	Senior Vice President	Management planning and manufacturing of precast	30
3	Precast Production Department	Senior Project Manager	Planning and manufacturing management of precast	29
4	Precast Production Department	Senior Associate	Planning, manufacturing and management of precast production	28
5	Precast Production Department	Senior Associate	Planning and manufacturing management of precast	24
6	Precast Research Department	Vice President	Design and planning, technical innovation, research and improvement of precast system	20
7	Precast Research Department	Associate	Technical innovation, research and improvement of precast system	14
8	Precast Engineering Department	Senior Vice President	Management of planning, manufacturing and construction of precast	31
9	Precast Design Department	Senior Associate	Precast design and planning	30
10	Precast Design Department	Senior Associate	Precast design and planning	24
11	Precast Design Department	Senior Manager	Precast design and planning	27
12	Precast Design Department	Vice President	Management of design and planning, manufacturing and construction of precast	21
13	Precast Design Department	Vice President	Management of design and planning and manufacturing for precast	20
14	Precast Design Department	Manager	Precast design and planning	19

3. Related work to clustering analysis

The theory and methodology of computational intelligence have reached a mature stage and are widely applied across various fields, including shift rotation and personnel allocation in aviation companies (Chou & Ngoc-Tri, 2018; Yeung et al., 2016, 2018; Arabameri et al., 2017), supply and dispatch issues in ready-mix concrete (Holimchayachotikul & Leksakul, 2017; Cao et al., 2015), workforce scheduling for emergency road repairs (Liu et al., 2022; Zhang & Atkins, 2015; Fasanghari et al., 2015; Chou & Anh-Duc, 2014), and decision support systems (Davi et al., 2014; Salama & El-Gohary, 2013). In terms of clustering techniques, data classification is primarily based on the characteristics or degree of disparity between data points. Clustering methods are commonly applied in fields such as bioinformatics (Glauber & Claro, 2018), data mining (Won et al., 2014), web searching (Ma et al., 2018b), image classification (Bandyopadhyay & Maulik, 2002; Omran et al., 2005), business strategy, social analysis, scientific exploration, and medical research (Ji et al., 2018). The two most commonly used clustering algorithms are the Partitioning Clustering Algorithm (PCA) and Hierarchical Clustering Algorithm (HCA) (Gautam & Chaudhuri, 2004). Both approaches assess data differences based on distance measures and are considered unsupervised learning methods in the field of data mining. They rely on the similarity index of objects as the basis for grouping, clustering similar items within the same population. By defining a criterion function, different populations are delineated, with objects within populations sharing higher similarities, while those between populations exhibit greater dissimilarities.

Clustering algorithms play a crucial role in data mining. Each data point is defined by a set of attributes, with the number of attributes referred to as dimensions. These algorithms group data into subsets based on their attributes, ensuring that data points within the same subset share a high degree of similarity, while data points between subsets are as distinct as possible (Bu, 2018; Su et al., 2009). The data used in clustering often involve multiple terms and belong to high-dimensional information, which cannot be easily visualized using standard methods. To address this, self-organizing maps (SOM) or Kohonen maps are used to project high-dimensional data into a lower-dimensional space, making it easier to interpret visually (Han & Kamber, 2000). Swarm intelligence clustering is one of the optimization algorithms frequently used in academia, as it effectively represents the distribution of data within clusters. It is widely applied in solving both continuous and discrete optimization problems, making it a versatile, multi-functional method. This approach is inspired by the collective behavior of animals or insects, such as the flocking patterns of birds. For example, Reynolds studied the flight behavior of flocking birds (Reynolds, 1987), observing that birds maintain specific formations during flight, sometimes dispersing and other times flocking together.

Research has offered explanations regarding the behavior of raised fish, suggesting that they gain valuable experience and foraging direction from other fish shoals during their search for food. These experiences enable the shoals to make better choices during food competition. Their behavior illustrates how information sharing among individuals benefits both the individual and the group. The algorithm based on this concept has been tested on several datasets, including the iris dataset, breast cancer dataset, chromosome dataset, dual-elliptical dataset, and a 20-dimensional non-overlapping dataset. When the results were compared to those of the K-means and Fuzzy C-means (FCM) algorithms, the SIP algorithm was found to provide the best clustering outcomes for four of the case studies. However, for the breast cancer dataset, the FCM algorithm achieved the highest clustering similarity, likely due to the dataset's characteristics, which do not display clear clustering patterns.

Some literature explains that the SIP algorithm is modeled after the foraging patterns of pigeons, a process divided into three stages: (1) Establish uniformly distributed points in space and treat them as pigeon locations. (2) Treat each data point as pigeon feed and distribute it to the pigeons. (3) Observe the foraging behavior of individuals as they migrate toward neighboring areas with more abundant food sources. Without specific assumptions, the SIP algorithm tends to produce better clustering results (Bu, 2018). Based on these studies, the SIP algorithm has proven to be highly accurate when a dataset exhibits significant clustering characteristics, and its accuracy remains stable even as dimensionality increases. Therefore, this study has selected the SIP algorithm for clustering operations.

4. Data collection and analysis

For more than a decade, this study engaged with the largest precast concrete plants in Taiwan to deeply investigate and understand its production system. The aim was to participate in and comprehensively examine the operations of precast plants through extensive field research. Personnel conducted thorough observations, measurements, and data collection to understand the characteristics and durations of each manufacturing process in the field. The data collection focused on the primary production times of three types of structural components: main beams, minor beams, and columns. This study gathered and analyzed data on precast structural components from over 90% of precast construction projects in Taiwan spanning the past decade. The data were sourced from orders placed by both public and private sectors, each order detailing quantities of precast components, dimensions, and client specifications. The projects encompassed various types such as collective residences, schools, office buildings, large shopping malls, technology and biotech factories, as well as collective townhouses and compound malls. As a result, the investigated precast concrete plant recorded time production in minutes for all 14 steps shown in Figure 1 as well as the data source for the study. Missing values are referred to the empty fields in each data or the misplaced data during data import or manual input. Extreme value is the value which has extremely large difference from other values of the same field within the same database. This study adopted standardized residual check and defined data that is above 2 times the standard deviation as extreme value (outliers). These two conditions often caused the deviation and invalidity of outcomes during clustering and statistical analysis. SPSS statistical software is hence utilized to filter and remove values with missing or extreme fields to prevent analysis error. The threshold of the extremums was set to ±2 standard deviation (4.6% of the total) away from the mean value for each attribute (process name) because the threshold has not only statistical but practical evidence support. Any orders falling into the extremum category are customized, tiny, or insignificant. Due to their insignificance in terms of volume, the decision and the following analysis are not affected even if extremums are considered. The original database gathered in this study had 72,560 components with a total of 1,015,840 production information. The database containing main beam, minor beam and column precast components was consolidated and processed using SPSS version 19.0 to remove invalid data as shown in Tables 2 to 4.

Table 2. The datasets of the girders' product process

Progress name	Total items	Average	Standard Deviation	Missing Value		Extremum items[a]	
				Items	Percentage	Minimum	Maximum
Cleaning the steel mold	26608	23.652	3.472	138	0.52%	48	432
Assembling modules	26608	18.5072	4.26724	267	1.00%	43	158
Lofting (positioning of iron components)	26608	10.1519	4.21608	169	0.64%	26	881
Dipping the steel rod cage	26608	22.0891	3.98388	367	1.38%	31	126
Laying of embedded parts	26608	34.8589	12.50582	152	0.57%	11	963
Checking before pouring and Concrete pouring	26608	13.3943	3.65394	125	0.47%	72	71
Concrete placement	26608	15.5814	2.60231	163	0.61%	13	39
Concrete surface whitewashing	26608	40.1912	3.59262	89	0.33%	7	120
Concrete curing works and curing time	26608	10.8656	18.3966	71	0.27%	18	55
Removal of all related molds	26608	17.5553	5.38304	39	0.15%	46	102
Mold removal	26608	14.0378	2.87126	76	0.29%	33	178
Component repair	26608	40.2499	14.75031	155	0.58%	28	733
Inspection of finished components	26608	15.6986	3.33023	331	1.24%	25	102
Warehouse storage	26608	19.664	2.57596	376	1.41%	23	147

Note: [a] – Extremum (Average-2*SD, Average+2*SD).

Table 3. The datasets of the beams' product process

Progress name	Total items	Average	Standard Deviation	Missing Value		Extremum items[a]	
				Items	Percentage	Items	Percentage
Cleaning the steel mold	21480	22.9457	2.7968	208	0.97%	111	26%
Assembling modules	21480	19.8923	3.98912	19	0.09%	62	288%
Lofting (positioning of iron components)	21480	10.3241	4.71305	71	0.33%	13	302%
Dipping the steel rod cage	21480	21.6775	3.24493	80	0.37%	75	102%
Laying of embedded parts	21480	35.9386	12.99222	85	0.40%	4	358%
Checking before pouring and Concrete pouring	21480	16.1241	3.8073	199	0.93%	5	70%
Concrete placement	21480	15.1905	1.91026	158	0.74%	0	169%
Concrete surface whitewashing	21480	31.4543	4.37761	63	0.29%	2	109%
Concrete curing works and curing time	21480	11.2678	1.61068	61	0.28%	18	66%
Removal of all related molds	21480	16.9319	3.97995	107	0.50%	22	56%
Mold removal	21480	12.9149	2.94961	71	0.33%	17	123%
Component repair	21480	40.4221	15.85232	269	1.25%	37	375%
Inspection of finished components	21480	12.0435	3.35277	93	0.43%	198	112%
Warehouse storage	21480	19.1983	3.25813	266	1.24%	98	181%

Note: [a] – Extremum (Average-2*SD, Average+2*SD).

Table 4. The datasets of the columns' product process

Progress name	Total items	Average	Standard Deviation	Missing Value		Extremum items[a]	
				Items	Percentage	Items	Percentage
Cleaning the steel mold	24472	23.2738	2.95224	285	1.16%	160	36%
Assembling modules	24472	18.8229	3.46196	110	0.45%	36	443%
Lofting (positioning of iron components)	24472	7.4614	3.98143	90	0.37%	12	178%
Dipping the steel rod cage	24472	32.9428	7.68624	116	0.47%	5	64%
Laying of embedded parts	24472	40.7658	33.52384	93	0.38%	10	501%
Checking before pouring and Concrete pouring	24472	14.8983	5.99388	201	0.82%	103	363%
Concrete placement	24472	27.6775	4.89601	107	0.44%	2	139%
Concrete surface whitewashing	24472	52.654	8.63711	66	0.27%	31	308%
Concrete curing works and curing time	24472	13.1075	2.83263	3	0.01%	74	271%
Removal of all related molds	24472	7.862	2.90099	52	0.21%	16	13%
Mold removal	24472	16.1487	3.79836	45	0.18%	66	162%
Component repair	24472	69.8593	13.94626	36	0.15%	171	562%
Inspection of finished components	24472	14.3553	3.61085	20	0.08%	196	105%
Warehouse storage	24472	20.43492	4.72846	188	0.77%	147	18%

Note: [a] – Extremum (Average-2*SD, Average+2*SD).

Based on the information in Tables 2 to 4, the typical duration for producing girders, beams, and columns falls within the ranges of 10.15 to 40.24 minutes, 10.32 to 40.42 minutes, and 7.46 to 69.85 minutes, respectively. An initial statistical analysis does not reveal any discernible data clustering patterns. There is a pressing need for an effective data analysis tool to handle the vast amount of data in order to better understand the production complexities associated with these precast components.

5. Proposed model

After summarizing the literature review on efficient clustering methods, the SIP algorithm was selected. Subsequently, the database was normalized by assigning a maximum value of 1 and a minimum value of 0 to each characteristic. All values are transformed into value ranging from 0 to 1 through the following equations, by substituting the original data to be converted and the maximum and minimum values of the specific characteristics. After the normalization of all characteristic fields, the grade gap between different fields would diminish while maintaining relative high-low positions for all data within the same field, further analysis is next conducted.

SIP is inspired by the foraging behavior of doves. In this method, each data pattern x in a dataset is treated as an artificial crumb. These artificial crumbs, representing data patterns, are sequentially scattered onto a two-dimensional artificial ground, encouraging the flock of doves to adjust their movements in search of them. Individual doves benefit from the discoveries of others since each is influenced by the success of the best-performing member, leading to an instinctive desire to imitate the most successful individual. Over time, the flock divides into groups based on the distribution of the artificial crumbs. These groups, representing financial variables, form clusters within the dataset, exhibiting similarities within each cluster and differences from neighboring clusters. The arrangement on the two-dimensional ground allows for a quick estimation of the number of clusters inherent in the dataset (Su et al., 2009; Chen et al., 2016a):

$$Y = \frac{\chi - \min}{\max - \min}.$$

The procedures of SIP algorithm are performed as follows.

The definition of notations used in SIP algorithm is elaborated as follows:
x – Data mode/pattern in database;
w – Multidimensional sensory organ vector of pigeons;
p – 2D location vector of pigeon;
e – Epoch number;
k – Time index;
f^{e}_{j} – The degree of satiate for j-th pigeon at epoch e;
b_f – Pigeon with closest distance to feed;
b_s – Pigeon with highest satiety;
$M \times N$ – Pigeon amount.

The SIP Algorithm procedures are listed as follows.

Step 1: Determine the amount of pigeons, assuming the amount of $M \times N$ and randomly distributed around an imaginary artificial plane.

Step 2: Define epoch number to $e = 0$ and set satiety degree to $f_j^e = 0$, for $j = 1, \ldots, M \times N$. Initialized multidimensional sensory organ, w_j, for $j = 1, \ldots, M \times N$. There are three methods to initialize this term, one of the simplest way is to initialize the multidimensional sensory organ randomly into small valued vectors. The second way is to randomly select from the data and the data mode with the same amount of data and randomly allocate them as the initial sensory organ vector, while the third way is based on basic instinct. Through adopting the special initialization method, the location vector of the pigeon group would be assigned to corresponding multidimensional sensory organ vector.

Step 3: Calculate the total satiety of the pigeon group:

$$T(e) = \sum_{j=1}^{M\times N} f_j^e. \quad (1)$$

Step 4: Place the artificial feeds x_k to the artificial plane.

Step 5: Use the smallest distance method to determine the pigeon b_f that are the closest to the feed.

$$b_f = \arg\min_j x_k - w_j(k), \text{ for } j = 1,\dots,M\times N. \quad (2)$$

Step 6: Use the following equation to add in the satiety degree of each pigeons:

$$f_j^e(\text{new}) = \frac{x_k - w_{bf}(k)}{x_k - w_j(k)} + \lambda f_j^e(\text{old}). \quad (3)$$

Step 7: Pigeon with the highest satiety is selected using the following equation:

$$b_s = \arg\max_{1\le j\le M\times N} f_j^e. \quad (4)$$

Step 8: The sensory organ vector and location vector p_j of the pigeons is updated with the equation below, including the learning rate of η_w and η_p:

$$w_j(k+1) = \begin{cases} w_{bf}(k) + \eta_w\left(x_k - w_{bf}(k)\right), & \text{for } j = b_f, \\ w_j(k), & \text{for } j \ne b_f; \end{cases} \quad (5)$$

$$p_j(k+1) = p_j(k) + \eta_p\beta\left(p_{bs}(k) - p_j(k)\right) \text{ for } j = 1,\dots,M\times N, \quad (6)$$

where

$$\beta = \left(\frac{f_{bs}^e - f_j^e}{f_{bs}^e}\right)\frac{x_k - w_{bf}(k)}{x_k - w_j(k)}\left(1 - \frac{p_j(k) - p_{bs}(k)}{L}\right),$$

$$L = \sqrt{M^2 + N^2}. \quad (7)$$

Step 9: Proceed back to Step 4 and reiterate this operation until all data are completed.

Step 10: If $\left|\sum_{j=1}^{N\times M} f_j^e(\text{new}) - T(e)\right| \le \varepsilon$ criterion is met, this loop would be terminated, otherwise, increase the epoch number and return to Step 3.

The source code can be seen at http://140.115.51.174:5000/fbsharing/qLs1i1lP (Chen et al., 2016b). Upon the completion of clustering method, this study studies the clustering outcomes of the resulting populations, which mainly presented two characteristics. (1) There is certain difference in characteristics between populations. (2) There are certain similar features for data within the same population. These two characteristics are the ultimate target of this study through the implementation of clustering algorithm and automated clustering approach, in order to reveal the difference between various production works. The difference between different orientations should be obvious while the dissimilarity between the same orientation should be small.

6. Results

This study processed a sum of 55,158 effective production components, totaling in 772,212 data. The data of produced components were separated into main beam, minor beam and column, and they were input into SIP algorithm for automated clustering. For determining the number of clusters in cluster analysis, this study uses the two criteria mentioned in the previous section. In the scatter plots shown in Figure 2a, the positions of the doves represent data points, helping to reveal the underlying structure of the data. Observing the data, one can see that the updating rules cause the doves to gather around their respective food sources, which correspond to the data's inherent structure. By the end of this process, the final positions of the doves are reflected in a scatter plot. From this image, the number of clusters can be visually identified, with each cluster representing a food source. Figure 2b illustrates that the process resulted in four distinct clusters. As the data amount increased, no matter which production data of precast components, their corresponding research

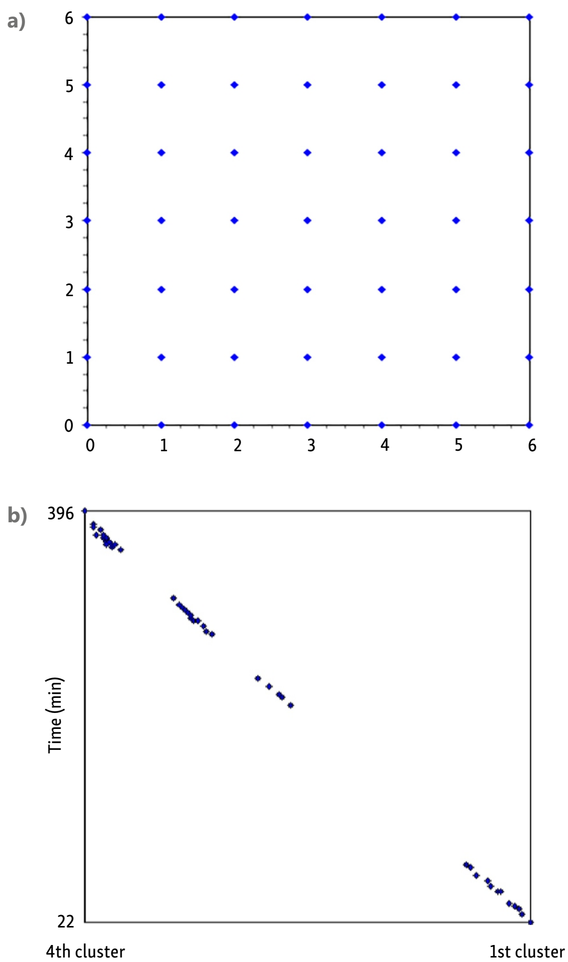

Figure 2. SIP Girder clustering

modes would gradually form into populations with different characteristics. Data of all three components were clustered into four populations with significant characteristics. This study presented the SIP clustering result for each component type as shown in Figure 2b.

(1) Component production complexity classification of precast main beam component

This study gathered 19,559 production data of main beam and clustered through SIP algorithm. The manufacturing information of the main beam components within the gathered database would cluster automatically according to their characteristics. Table 5 displays the clustering outcome of SIP for the production complexity of each component type. Based on the clustering results, the component production complexity of the main beam's precast component was clearly clustered into four populations, this study therefore defined them into four grades. For grade one component production complexity of the main beam, 6,054 components were clustered and their average production time was 239.91 minutes, where the minimum and maximum production time were 227.22 and 252.74 minutes respectively. 7,276 components were clustered for grade two component production complexity with a mean production time of 295.45 minutes, while the minimum and maximum production time were 274.90 and 311.94 minutes respectively. Grade three component production complexity clusters had 3,996 components with average manufacturing duration of 338.79 minutes, ranging from 321.96 minutes to 358.56 minutes. The last cluster of grade four component production complexity had 2,233 components with production time averaged at 382.68 minutes and lies between 364.19 minutes to 396.18 minutes.

(2) Component production complexity classification of precast minor beam component

As for the production information of minor beams, this study analyzed 16,731 components and clustered through SIP algorithm, where the production data of the precast components of the minor beams would automatically cluster together according to data characteristics. Clustered classification of the precast components of minor beam is shown in Table 5. According to the clustered outcome, the component production complexity of the minor beam components was classified into four populations, so this study defines these populations into four grades. Population rated grade one component production complexity of the minor beam had 4,532 components in cluster with an average production time of 216.24 minutes per component, while the minimum and maximum production time were 202.75 and 231.17 minutes respectively. 4,643 components were clustered for grade two component production complexity with a mean production time of 273.19 minutes, ranging from 258.98 to 289.81 minutes per beam. Grade three component production complexity clusters had 4,788 components with average manufacturing duration of 318.26 minutes, ranging from 302.97 minutes to 333.96 minutes. The last cluster of grade four component production complexity had 2,768 components with production time averaged at 367.82 minutes, with a minimum and maximum production time of 350.69 and 383.49 minutes per components.

(3) Component production complexity classification of precast column component

This study analyzed a grand total of 18,868 components for precast column production data. These data are also analyzed through SIP algorithm and they would automatically cluster into several populations based on data characteristics. Clustered classification of the precast components of the column is shown in Table 5. According to the clustered outcome, the component production complexity of the column components was classified into four populations, so this study rated these populations into four grades. Grade one component production complexity of the column clustered 5,073 data with an average production time of 282.90 minutes per component, ranging from 265.31 minutes to 299.61 minutes. As for grade two component production complexity, 7,011 components were included in this cluster with a mean production time

Table 5. The manufacturing complexity of each type components (unit: min)

Component name	Measure item	Unit	Grade one manufacturing complexity	Grade two manufacturing complexity	Grade three manufacturing complexity	Grade four manufacturing complexity
Girders	Quantity	set	6,054	7,276	3,996	2,233
	min process time	min	227.22	274.90	321.96	364.19
	max process time	min	252.74	311.94	358.56	396.18
	average time	min	239.91	295.45	338.79	382.68
Beams	Quantity	set	4,523	4,643	4,788	2,768
	min process time	min	202.75	258.98	302.97	350.69
	max process time	min	231.17	289.81	333.96	383.49
	average time	min	216.24	273.19	318.26	367.87
Columns	Quantity	set	5,073	7,011	2,486	4,298
	min process time	min	265.31	320.94	359.69	461.56
	max process time	min	299.61	345.67	389.68	506.98
	average time	min	282.90	334.44	373.60	485.99

of 334.44 minutes while the minimum and maximum production time were 320.94 and 345.67 minutes respectively. Grade three component production complexity clusters had 2,486 components with production time averaged at 373.60 minutes per components, ranging from 359.69 minutes to 389.68 minutes. The last cluster of grade four component production complexity had 4,298 components with average component production duration of 485.99 minutes, whereas their minimum and maximum production time were 461.56 and 506.98 minutes per components.

(4) Integrated cluster analysis on the component production complexity of three types of precast components

Integrated analysis outcome of all the component production particulars of main beam, minor beam and column components are shown in Table 6. The total production duration of main beam components of the first and second grade has average production time difference of 55.54 minutes, requiring an extra 23.15% workload. The difference between the first and the third grade population is 98.88 minutes and a workload increment of 41.22% is required. Whereas the difference between the first and the fourth-grade clusters is 142.77 minutes gap and require an additional 59.51% workload. Each component production complexity clustering was obvious. The difference of total production duration between the second and the third grade is 43.34 minutes and required 14.67% more workload, while the difference between the second and the fourth grade is 87.23 minutes and involved 29.52% extra workload. The gap of the total production time between the third and the fourth grade population is 43.89 minutes and an additional of 12.95% workload, which the complexity grade gap was quite apparent. As for the total production time for the minor beam components, its first and second grade had an average production time difference of 56.95 minutes, requiring an extra 26.34% workload. The difference between the first and the third grade is 102.02 minutes and a workload increment of 47.18% is required. Whereas the difference between the first and the fourth grade clusters is 151.63 minutes gap and require an additional 70.12% workload. Each component production complexity clustering of the average production time was obvious. The difference of the total production time of the minor beam between the second and the third grade is 45.07 minutes and required 16.50% additional workload, whereas the gap between the second and the fourth grade is 94.68 minutes and involved 34.66% extra workload. The gap of the total production time between the third and the fourth grade population is 49.61 minutes and an additional of 15.59% workload, indicating that the complexity grade gap was quite apparent. Average production time for the column components had 51.54 minutes difference between its first and second grade, which involved an additional 18.22% workload. The differences between the first and third population grade is 90.71 minutes of average production time, demanding an extra 32.06% workload. While the gap between the first and the last population cluster was 203.09 minutes and require an extra 71.79% workload, all of which indicated the dissimilarity between component production complexity clusters was clear. For the total production time of column components, the second grade differs with the third grade by 39.16 minutes and required 11.71% more workload; differs with the fourth grade by 151.55 minutes and increased 45.31% workload. The third grade differs with the fourth grade by 112.39 minutes and required an additional 30.08% workload, which again suggested that the complexity grade gap was apparent. In summary, the gaps between these 4 levels are significant and the workload increases between Level 1 and 2, Lever 2 and 3, Level 3 and 4 are 18.22%, 11.71%, and 30.08%, respectively.

Table 6. The difference between the manufacturing complexity of each type components (unit: min)

Component name	Measure item	Grade one manufacturing complexity		Grade two manufacturing complexity		Grade three manufacturing complexity		Grade four manufacturing complexity	
Girder	Average process time	239.91		295.45		338.79		382.68	
	Difference from grade one	0	0	55.54	23.15%	98.88	41.22%	142.77	59.51%
	Difference from grade two	–55.54	–23.15%	0	0	43.34	14.67%	87.23	29.52%
	Difference from grade three	–98.88	–41.22%	–43.34	–14.67%	0	0	43.89	12.95%
	Difference from grade four	–142.77	–59.51%	–87.23	–29.52%	–43.89	–12.95%	0	0
Beam	Average process time	216.24		273.19		318.26		367.87	
	Difference from grade one	0	0	56.95	26.34%	102.02	47.18%	151.63	70.12%
	Difference from grade two	–56.95	–26.34%	0	0	45.07	16.50%	94.68	34.66%
	Difference from grade three	–102.02	–47.18%	–45.07	–16.50%	0	0	49.61	15.59%
	Difference from grade four	–151.63	–70.12%	–94.68	–34.66%	–49.61	–15.59%	0	0
Column	Average process time	282.90		334.44		373.60		485.99	
	Difference from grade one	0	0	51.54	18.22%	90.70	32.06%	203.09	71.79%
	Difference from grade two	–51.54	–18.22%	0	0	39.16	11.71%	151.55	45.31%
	Difference from grade three	–90.70	–32.06%	–39.16	–11.71%	0	0	112.39	30.08%
	Difference from grade four	–203.09	–71.79%	–151.55	–45.31%	–112.39	–30.08%	0	0

7. Model comparison and evaluation

The primary goals in evaluating the proposed model are to assess (1) its convergence efficiency and (2) computation time. The results of the proposed model are recommended to be compared with widely used clustering algorithms such as k-means and hierarchical clustering (Chen et al., 2023). The k-means algorithm, a fundamental clustering technique, selects initial centroids randomly and assigns data points to the nearest centroid, while hierarchical clustering creates a tree-like structure where each data point starts as its own cluster, progressively merging similar clusters. Using the same dataset of 772,212 entries divided into 10 subgroups with 10-fold cross-validation, and visualizing the high-dimensional results via the Sammon projection method in a two-dimensional plot, Figure 3 presents the clustering outcomes from both k-means and hierarchical algorithms. Notably, the results from k-means and hierarchical clustering show no signs of convergence, with data points visibly scattered. Additionally, their computation times are significantly longer compared to the proposed model, as shown in Figure 2b. Specifically, neither k-means nor hierarchical clustering successfully converged the data points into distinct clusters, even with nearly double the processing time: 396 minutes for SIP vs. 815 minutes for k-means and 902 minutes for hierarchical clustering.

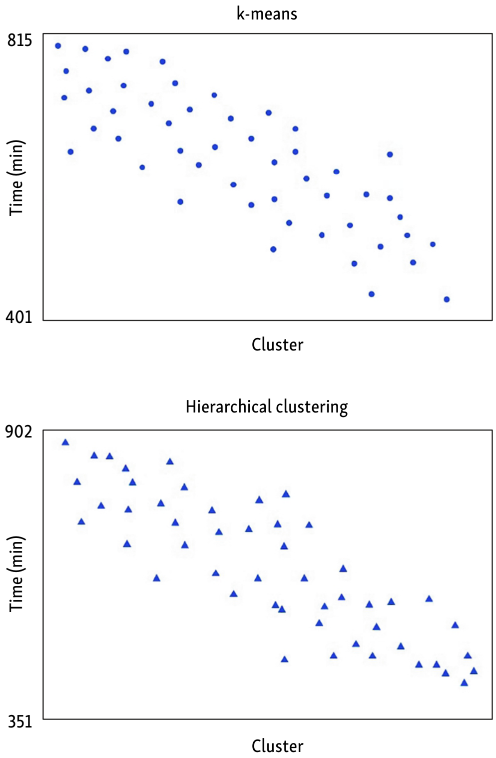

Figure 3. Girder clustering results by k-means and hierarchical clustering algorithms

8. Implementation and discussion

This study based on the aforementioned outcomes of the grading, type and amount of precast components clusters, and constructed spreadsheet to compute the total component production duration for each precast components using Office Excel software. This enabled us to estimate the total production time of each structural body components in the precast concrete plant, which allowed the rapid computation of total production duration of each project by inputting the planned embedded type, amount, dimension, and component amount of each structural modules.

Based on the convenient sampling concept, the case selected for the implementation is an actual order from the Taiwan construction industry which is then processed by the largest precast concrete plant in Taiwan. The project site is located in northern Taiwan with a base area or 8,166 m^2, which is a large compound business building consisted of 3 basement floors below ground and 15 floors above ground. The produced amounts of main beam, minor beam and column are 477, 231 and 414 components respectively, which totaled in 1,122 components. This study based on the graphic information of the project site and initially compiled the production type information of the main beams as shown in Table 7. There were 6 types of component dimensions, which all have 4 embedded parts for hoisting. Other component types have embedded parts quantity ranging from 1 to 6 parts, in which main beam of 60×65×789 and 80×70×889 dimension had the highest amount of 8 parts. As for beam tubing, dimensions of 60×62.4×789 had the largest amount. Whereas in terms of component quantity, beam dimension of 60×62.4×789 had the largest quantity of 108 components, 70×65×800 had the smallest quantity of 63 members.

Table 8 shows the production type information of minor beam components. There are five component dimensions, all of which had 4 embedded hoisting parts. Other types of embedded parts had quantity ranging from 1 to 8 parts, in which the minor beam of 40×50×625 dimension had the most amount of 8 components. As for beam tubing, minor beam of 40×52.4×650 dimension had the most amount of 3 sets. For component quantity, beam dimension of 50×60×750 had the largest quantity of 80 components, 55*65*920 had the smallest quantity of 9 members. Production type data of column components are listed in Table 9. There are 5 types of column dimensions and all are designed with 4 embedded parts for hoisting. Other forms of embedded parts ranges between 2 to 6 components in precast columns, where column with dimensions of 100×100×450 and 110×110×350 had the most amount of 6 components. Power distribution box is designed into columns with dimensions of 100×100×250, 100×100×45, 110×110×250 and 110×110×650. As for component quantities, column with 100×100×250 dimension had the most components of 172 while column with 110×110×650 dimension had the least amount of 30 components.

This study further consolidated the precast component production type information of the large compound business mall into the spreadsheet to estimate the total project duration as shown in Table 10. This information included the types and amount of the embedded parts type and the quantity and dimensions of the precast component, and so

Table 7. The production time of the girder component of Big Mall project

Component name	Section (cm)	Embedded component quan.	Other type embedded parts quan.	Quan. of the pipe penetration sleeve	Component quan.
Girder	60×62.4×789	4	1	0	58
	60×62.4×789	4	2	0	32
	60×62.4×789	4	2	1	8
	60×62.4×789	4	3	4	10
	60×65×789	4	6	0	42
	60×65×789	4	4	1	22
	60×65×789	4	4	2	16
	70×68×700	4	2	0	46
	70×68×700	4	2	1	20
	50×60×800	4	4	0	45
	50×60×800	4	4	1	20
	50×60×800	4	4	3	18
	70×65×800	4	2	0	36
	70×65×800	4	2	1	15
	70×65×800	4	4	2	12
	80×70×889	4	2	0	36
	80×70×889	4	6	0	25
	80×70×889	4	4	2	16
Section: width×depth×length.					

Table 8. The production time of the beam component of Big Mall project

Component	Section (cm)	Embedded component quan.	Other type embedded parts quan.	Quan. of the pipe penetration sleeve	Component quan.
beam	40×50×625	4	1	0	25
	40×50×625	4	2	0	26
	40×50×625	4	8	0	6
	40×50×625	4	4	1	4
	40×52.4×650	4	1	0	22
	40×52.4×650	4	4	0	18
	40×52.4×650	4	6	1	8
	40×52.4×650	4	2	3	10
	50×60×750	4	2	0	28
	50×60×750	4	4	0	28
	50×60×750	4	2	1	12
	50×60×750	4	4	2	12
	50×60×880	4	4	0	15
	50×60×880	4	6	1	4
	50×60×880	4	8	2	4
	55×65×920	4	2	1	5
	55×65×920	4	4	2	4
Section: width×depth×length					

forth. First of all, the production details regarding the main beam component are analyzed. According to the clustering results, component production complexity of Grade 1 has 208 components, which constitute around 43.61% and their production time is 49,901 minutes. Grade 2 has 88 components in clusters and take up 18.45% with production time of 26,004 minutes. Cluster of Grade 3 has 109 components and was 22.85% of all beams, with production time of 36,928 minutes. There are 72 components in the cluster of Grade 4, constituting 15.09% and their production time is 27,552 minutes. Summing up all main beam components above, the overall total production time for main beam is 140,386 minutes. For the production analysis of minor beam, the clustering outcome showed that Grade 1 has 101 components, which constitutes around 33.77% and requires 21,816 minutes of production time. Grade 2 has 78 components and approximately 18.45% of all beams, with production time of 21,309 minutes.

Table 9. The production time of the column component of Big Mall project

Component	Section (cm)	Embedded component quan.	Other type embedded parts quan.	Quan. of the pipe penetration sleeve	Component quan.
column	100×100×250	4	2	0	96
	100×100×250	4	4	0	56
	100×100×250	4	2	1	20
	100×100×450	4	2	0	62
	100×100×450	4	6	0	22
	100×100×450	4	3	1	12
	100×100×450	4	4	1	8
	110×110×250	4	2	0	36
	110×110×250	4	4	1	8
	110×110×350	4	2	0	38
	110×110×350	4	6	0	26
	110×110×650	4	2	0	24
	110×110×650	4	2	1	6
Section: width×depth×length					

There are 10 components in Grade 3, constituting 4.33% and their production time is 3183 minutes. Whereas Grade 4 has 42 components in clusters and take up 18.18% with production time of 15,451 minutes. Total production time of all minor beam components take up 61,760 minutes. As for the production data analysis of columns, Grade 1 has 132 components and was 31.88% of all columns, which took 37,342 minutes to produce. There were 94 components Grade 2, constituting 22.71% and their production time is 31,433 minutes. Grade 3 has 134 components and approximately 32.37% of all columns, with production time of 50,062 minutes. Whereas Grade 4 has 54 components in clusters and take up 13.04% with production time of 26,244 minutes. Total production time of the precast column components summed up to be 145,082 minutes.

In summary, Tables 7–9 show the details information for the case study. Tables 10 and 11 demonstrate how production complexity estimation works by plugging the data into SIP algorithm, indicating that, for example, 43.61% of girder components can be categorized Grade 1 with estimated production time of 49,901 minutes; 18.18% (5.19% + 8.66% + 4.33%) of beam components can be categorized as Grade 4 with estimated production time of 15,451 (4414 + 7358 + 3679) minutes. This case study of an actual project site is analyzed in this study, by inputting all precast component types into a grade-clustered total production time spreadsheet. Through this spreadsheet, the total production time and component production complexity of each components can be identified accurately and clearly. The decision making and management teams at the precast concrete plant can plan the detailed resources scheduling below according to the above-mentioned project duration.

Table 10. The production time of the girder component of Big Mall project

Grading of the manufacturing complexity	Embedded components	Other type embedded parts quan.	Pipe penetration sleeve	Average production time	Quantity	Percentage	Production time (min)
Grade 1	4	< 2	0	239.91	208	43.61%	49,901
Grade 2	4	3~5	0	295.50	45	9.43%	13,297
	4	0	1	295.50	0	0%	0
	4	1~2	1	295.50	43	9.01%	12,706
Grade 3	4	6~8	0	338.79	67	14.05%	22,698
	4	0	2~3	338.79	0	0%	0
	4	3~5	1	338.79	42	8.81%	14,229
	4	1~2	2	338.79	0	0%	0
Grade 4	4	> 8	0	382.68	0	0%	0
	4	> 6	1	382.68	0	0%	0
	4	0	> 4	382.68	0	0%	0
	4	> 3	2	382.68	28	5.87%	10,715
	4	> 1	3	382.68	44	9.22%	16,837
Total					477	100%	140,386

Table 11. The production time of the beam component of Big Mall project

Grading of the manufacturing complexity	Embedded components	Other type embedded parts quan.	Pipe penetration sleeve	Average production time	Quantity	Percentage	Production time (min)
Grade 1	4	< 2	0	216.00	101	43.72%	21,816
Grade 2	4	3~5	0	273.20	61	26.41%	16,665
	4	0	1	273.20	0	0%	0
	4	1~2	1	273.20	17	7.36%	4,644
Grade 3	4	6~8	0	318.3	6	2.60%	1,909
	4	0	2~3	318.3	0	0%	0
	4	3~5	1	318.3	4	1.73%	1,273
	4	1~2	2	318.3	0	0%	0
Grade 4	4	> 8	0	367.9	0	0%	0
	4	> 6	1	367.9	12	5.19%	4,414
	4	0	> 4	367.9	0	0%	0
	4	> 3	2	367.9	20	8.66%	7,358
	4	> 1	3	367.9	10	4.33%	3,679
Total					231	100%	61,760

1. Manpower: (1) Demand and allocation of project engineers. (2) Related technical personnel allocation can be divided into common personnel and professional technicians. Common personnel: workforce targeted for mold cleaning and assembly, steel cage hoisting and so on. Professional technicians: workforce responsible for the layout of embedded parts, marking and layout of steel parts, component maintenance and so forth.
2. Planning of mechanical equipment and machineries: Bridge/overhead crane, cable crane, steel bending machines and others.
3. Material planning: (1) Total concrete amount is calculated and daily concrete demand is hence deduced. This enabled decision makers to identify if the concrete supplied within the concrete plant is sufficient. (2) Material amount related to production: the production scheduling of the embedded parts and manufacturing tools.
4. Factory area: Planning and setup of the production and storage areas.
5. Steel mold amount planning: Plan the steel mold quantity according to the progress demand of each project and the production area.

9. Conclusions

This study aimed at enhancing all related resources planning and utilization of precast concrete plants. The component production complexity clustering of the structural components in precast building was identified specifically for main beam, minor beam and column. This study first reviewed past literatures and gathered critical information of precast concrete plants in Taiwan over the last decade. These data included the operation duration for each production process involved for the structural components and the basic attributes of each projects. Through the clustering outcome from SIP algorithm, the structural components of precast structures, such as main beam, minor beam, column and other components, were significantly clustered into four populations in terms of component production complexity. The required production time and difference between each populations of the structural components are clearly presented in the tables above. Even though the use of SIP algorithm is an effective and successful application, we have considered it as a minor contribution compared with the major novelty contributions as follows. Therefore, the research major novelty and contributions lie in the elaboration associated with: (1) the component production complexity of precast structural body and difference in production time, reasonably beneficial to the management operation of precast concrete plants, such as the plant prearrangement prior to order acquisition, subsequent progress tracking, and management planning; (2) the real-life precast concrete plant industry that gives suggestions for manpower allocation, material planning, factory configuration, and steel mold planning; (3) rapid computation for precast component production time for entire structural components in the new project. This could serve as an important reference for the optimal allocation of manpower, machineries and equipment, in order to push the production process in to optimal operation mode. The research limitation and suggestions for future work are highlighted as follows. The study does not deal with labor cost control that has always been one of the key issues of precast concrete plant management. This can also be integrated with the clustering outcome of the component production complexity from this study. Through resource leveling assessment, the overtime issue of labors and the optimal model of manpower dispatch can be investigated in order to achieve labor cost control. The research also investigates only on beam, minor beam, and column components. It can be further extended to the component production complexity clustering investigation of wall panels, balcony panels, staircase, lattice beam and other structural forms, aiming to further improve the component production operation of the entire precast structure. For those extremums, follow-up studies are suggested working on this matter and tries to figure out the association between the orders and production processes. It could explore further useful information for the precast construction practice. To bolster the theoretical contributions, it is recommended to conduct thorough comparisons with other theories and algorithms. Such comparative analyses can provide more robust support for the research findings. Moreover, a holistic approach to comparison, encompassing not only precast product processes but also considering cost data and manpower allocation, would yield comprehensive insights. This multifaceted comparison has the potential to significantly enrich the study's value, benefiting both the academic community and practical practitioners in the field.

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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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