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Manpower Allocation of Work Activities for Producing Precast Components: Empirical Study in Taiwan

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Abstract: The production of precast components in the construction industry is a labor-intensive process. The objectives of this study are to prove the feasibility of using rough set theory to classify and weigh impact attributes, and to develop a model to assess the total quantities of labor needed for precast structural elements using a rough set enhanced K-Nearest Neighbor (KNN). Three main building components (beams, girders, and columns) were collected from the production of precast elements in Taiwan. After trimming and analyzing the basic data, the rough set approach is used to classify and weight the attributes into three levels of impact based on their frequency. A rough set enhanced KNN is accordingly developed, yielding an accuracy rate of 92.36%, which is 8.09% higher than the result obtained when using the KNN algorithm. A practical and effective prediction model would assist managers to estimate the manpower requirement of precast projects.

Keywords: construction management; precast component; K-Nearest Neighbor; rough set; manpower allocation

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1. Introduction

Construction industry is a highly experience-oriented field. Engineering construction relies mainly on manpower supplemented by equipment. In recent years, the size of the working population has been shrinking gradually, workers are aging, and the cost of construction materials is on the rise [1–4]. Meanwhile, people attach increasing importance to the quality of life and environmental resources. The construction industry needs to enhance its automation technology and review the construction management process so that production resources and cost control can be optimized.

Precast method adopts the concept of modularization for construction. Its automatic features make it possible for construction workers to be unrestrained by age and effectively solve the abovementioned problems. Due to the short construction periods, low cost, less environmental impact, and less likelihood of tiles falling off and wall cracking after an earthquake compared to external concrete walls cast in situ, the precast method is widely used around the world. It is also widely favored by people in the construction industry because of its unique durability and aesthetical appearance. According to a survey form Research and Markets (2021) [5], the market for precast construction is expected to grow from USD 130.6 billion in 2020 to USD 174.1 billion in 2025, with an estimated compound annual growth rate of 5.9%. Most of the structural components can be manufactured in a factory with the precast method. This reduces construction time and the uncertainty that often arose in the construction site in the past. Nzabonimpa and Hong noted that the production process of components in the precast factory is more flexible [3]. Benjaoran and Dawood proposed a production planning system for the management of precast concrete production to optimize the allocation of factory resources [6]. Insufficiency of human resources and skill shortages are identified as the principal causes of the uneven allocation of human resources in the precast concrete industry [7–13]. In addition, certain research findings propose the necessity for additional comparative investigations to establish the most suitable forecasting approach for anticipating the human resource demand in the precast concrete sector [11,14,15].

The main research aim in this study is to identify the factors that affect production time in precast concrete production and determine whether to adjust manpower schedules or provide additional work shift support. The study also aims to analyze the main structural components manufactured for construction projects, such as beams, girders, and columns, and to collect production data through field sampling work. In this research, precast production data over the past 10 years were collected to identify the production work items that affected the time of the precast production. To collect data, the researchers went to the precast factory to conduct field sampling work. For instance, production time for each production item was observed and every minute was recorded through CCTV for further analysis. However, due to Taiwan's personal information protection law, only total production time and labor hours can be disclosed. Further analysis of detailed personal information such as the gender and age of the employee is prohibited. The objectives of the study are to (1) prove the feasibility of using rough set theory to classify and (2) classify and weight impact attributes as well as (3) to develop a model using rough set enhanced K-Nearest Neighbor (KNN) to evaluate the total manpower quantities needed for precast structural elements. The hypothesis states that it is possible to improve the practicability by allowing the frequency of set theory intersections from rough set reduction to be used as factor weights. Therefore, the results of this study are expected to apply the rough set theory as a feature classifier and weighting recognizer to improve the overall production manpower allocation.

2. Literature Review

2.1. Precast Production Management Research

In the recent years, more and more researchers have started to adapt manufacturing resource planning theories in the precast production (PP) field. The standards for automated production and production procedures of precast components have been investigated to evaluate the best combination of production cost and time [1,10]. In addition, genetic algorithms have been used to analyze the multi-objective plan of PP work and provide a decision-making application for precast factory production. The time for PP process was optimized, and the relationship with the production processes was confirmed [16,17]. Some researchers studied the optimization of profit and logistics in PP. To evaluate the optimization of PP, in their research, Leu and Hwang studied the impact of equipment and skilled labor on the production program under limited resources. A mixed production model that was subjected to resource constraints was established [7]. The overall production efficiency and performance of a precast factory was improved through process reengineering models and actual production examples were used from the precast factory to verify that idle resources or waiting time could be minimized [18]. The optimization of the production process confirmed the relationship between the production processes [19]. Kim et al. used laser scanning and building information modeling to conduct automatic quality assessment and assurance of precast concrete panels [20,21].

2.2. Human Resource Management in Precast Research

Human resource management (HRM)-related study is an extremely important part of research in the precast industry. The results of the study are not an innovation issue, but may be helpful to precast companies [22]. In recent years, there have been a growing number of cases discussing HRM issues related to precast projects [11,12,19,22]. These findings show that the cost of production workers accounts for a high proportion of budget. The relevant research topic is finding a way to explore advanced tools to allocate manpower.

3. Data Collection and Selection

During data collection for this research, the production time of beams, girders, and columns of the precast building structure was identified as the target for analysis. This research was funded by the Ministry of Science and Technology of Taiwan to collect data on the production time of the components in the last 10 years (2008–2019). The project types for which precast component data were collected in this research included high-tech plants, residential buildings, shopping malls, and schools, categorized according to the types of sites (Table 1).

Table 1. Number of precast building projects.

Project Type	Beams		Girders		Columns	
	Project Quantity	Components Quantity	Project Quantity	Components Quantity	Project Quantity	Components Quantity
High-tech plant	17	10,701	20	10,532	19	10,532
Residential building	4	2759	2	778	4	778
Shopping mall	4	2855	5	2672	4	2672
School and Office building	8	3243	8	2749	7	2749
Total	33	19,558	35	16,731	34	18,868

The database containing beam, girder and column precast components was consolidated and processed using SPSS version 19.0 to remove invalid data such as shape of components and number of production repetitiveness, etc. Based on component types, data were collected for 19,558 beams, 16,731 girders, and 18,868 columns, which added up to a total of 55,157 components across all three component types. According to the research outcome [18] on the construction process of the three components, including beams, girders, and columns, 14 attributes that influence manpower allocation for precast production projects. Figure 1 shows a flowchart of the precast component production process according to this sequence. The process includes cleaning the steel mold (removing any residual contaminants, concrete debris, or welding slags in the mold) (attr1), assembling modules (installing the bottom and side molds and placing steel molds) (attr2), lofting (surveying the installed steel mold components against the setting-out reference lines) (attr3), dipping the steel rod cage (putting the steel rod cage in the steel mold and adjusting the length of all reserved steel pipes) (attr4), placing the wooden panels (typically involves positioning them into the mold where the precast concrete will be poured and cured) (attr5), checking before pouring (confirming that steel reinforcement and other cast-in components were installed in the correct position, and whether the dimensions of all components were correct) (attr6), concrete pouring (attr7), fixture removal (attr8), concrete maintenance operations (normal maintenance time was 8–10 h) (attr9), removing the mold (removing all related molds) (attr10), stripping (the operation of removing the steel mold from the finished component) (attr11), component repair (any defects on the concrete surfaces and sides greater than 5 mm had to be repaired) (attr12), inspection of finished components (labeling, numbering and checking the size of finished components) (attr13), warehouse storage (placing the components in a storage warehouse for stacking and storage) (attr14). The ranges of the selected production time data are shown in Table 2.

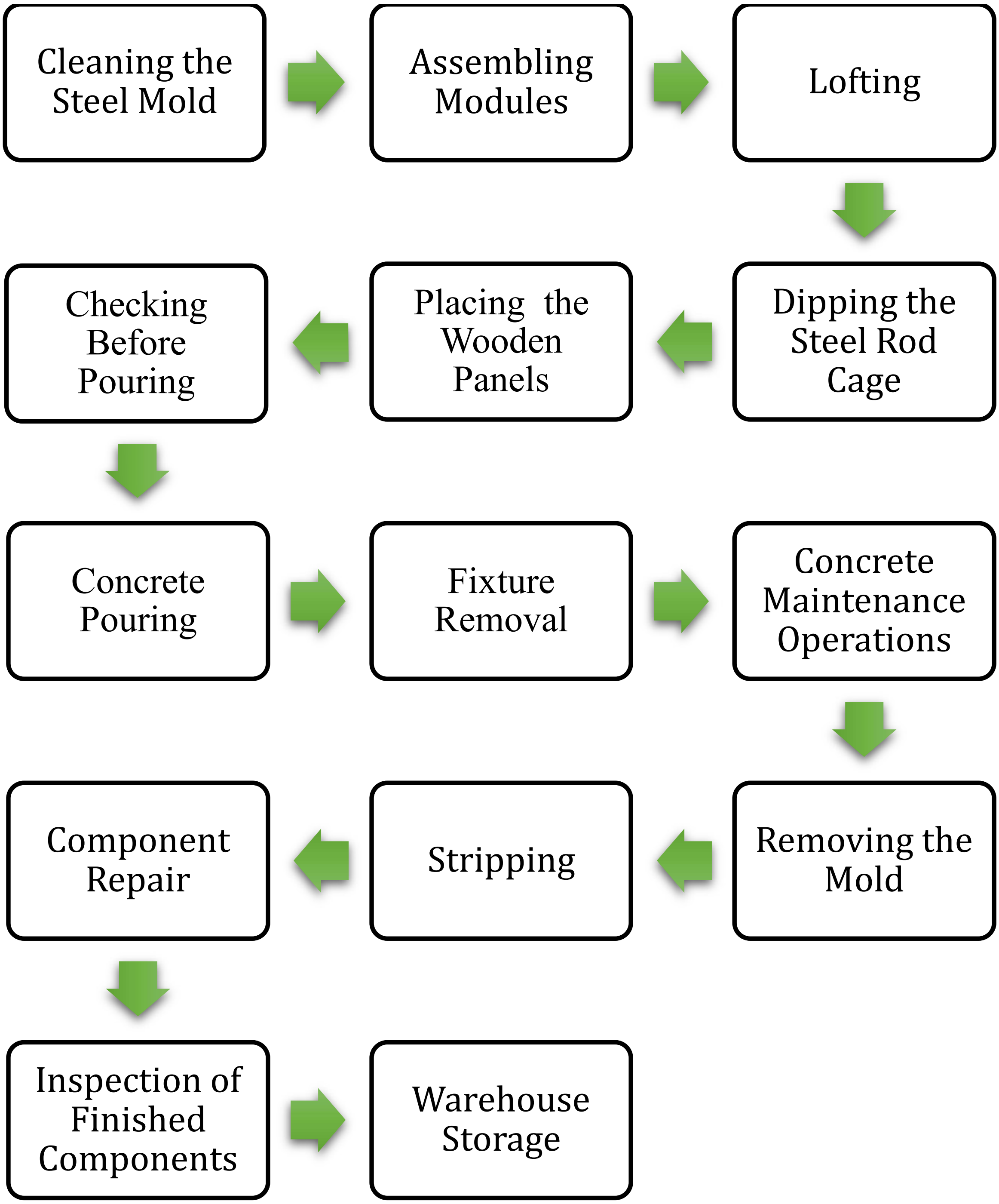

Figure 1. The procedure for production of precast components [18].

Table 2. Ranges of the selected production time data (Unit: minutes).

Components		Beams				Girders				Columns			
Attribute No.	**Attribute**	**Maximum**	**Minimum**	**Average**	**Standard Deviation**	**Maximum**	**Minimum**	**Average**	**Standard Deviation**	**Maximum**	**Minimum**	**Average**	**Standard Deviation**
1	Cleaning the steel mold	31.9	19.02	24.652	2.472	25.97	17.76	22.246	1.893	27.95	18.05	23.274	2.352
2	Assembling modules	27.87	12.91	18.507	3.267	27.12	13.02	18.892	3.589	25.98	13.02	18.823	2.962
3	Lofting	17.95	2.01	9.152	4.616	19.32	2.04	10.324	4.713	13.91	2.01	6.461	3.481
4	Dipping the steel rod cage	32.14	15.48	23.089	2.984	29.86	14.82	21.678	3.145	44.95	22.02	32.943	5.686
5	Placing the wooden panels	55.68	21.95	35.859	9.106	54.70	19.05	27.939	9.992	105.91	17.05	40.766	29.524
6	Checking before pouring	19.93	8.89	13.394	2.654	20.50	8.83	14.124	3.007	22.94	8.06	13.898	3.994
7	Concrete pouring	19.97	14.01	16.081	1.202	20.46	12.06	15.191	1.41	35.97	20.08	27.678	3.696
8	Fixture removal	46.26	35.04	39.649	2.093	39.92	25.13	31.454	2.878	67.95	41.11	52.654	6.637
9	Concrete maintenance operations	14.95	8.04	10.866	1.34	15.15	9.02	11.268	1.311	16.95	10.02	13.108	1.633
10	Removing the mold	29.76	10.96	17.555	4.083	24.76	9.52	15.932	3.58	10.99	3.02	6.482	2.301
11	Stripping	19.12	9.17	13.438	2.071	17.84	8.71	12.915	1.95	21.99	13.04	17.149	1.798
12	Component repair	63.86	20.12	38.25	11.76	69.72	20.22	41.422	12.852	91.87	55.08	70.859	9.946
13	Inspection of finished components	24.18	9.75	15.599	2.93	18.82	8.04	12.044	2.253	19.95	9.05	14.355	2.411
14	Warehouse storage	23.02	15.69	19.664	1.276	22.89	14.71	19.394	1.258	24.98	16.01	20.796	2.028

4. Rough Set Enhanced K-Nearest Neighbor (KNN)

In the past few years, artificial neural network has become a commonly used and effective technology. Moreover, it provides a self-adjusting platform for the development of hybrid methods. Its application has become common and successful in construction or building related fields [23–28]. Hence, much research on the application of KNN can be found in the construction domain. KNN can be applied in areas such as cost estimation, contractor selection, programming, budgeting, quality control, image crack recognition and knowledge sharing [29–32]. The precise results produced by KNN enhancement methods help solve practical problems [33–35].

Rough set theory was introduced in 1982 [36]. Its combination with artificial neural network had been regarded as an ideal tool for nonlinear problem approximation. It is also a useful method for forecasting problems. This technology has been applied in the domain of knowledge discovery such as database, fault diagnosis, data mining, knowledge acquisition, machine learning, expert system, and decision-making support system [37,38].

The rough set theory is presented in form of an information system. A specific set of data was grouped together according to data characteristics. Hence, data were grouped into N sets of different categories. The four components of the information system may be represented by the symbols as shown in Formula (1):

$$\mathrm{S} = \{\mathrm{U}, \mathrm{A}, \mathrm{V}\}. \tag{1}$$

In the formula, S represents the information system. U is a universal set defined as $\mathrm{U} = \{x_1, x_2, \ldots, x_N\}$, which represents a finite set containing N objects. A is an attribute set. $\mathrm{A} = \{a_1, a_2, \ldots, a_M\}$ is a finite set of attributes from a_1 to a_M. V is a set composed of a values. $\mathrm{V} = \{v_1, v_2, \ldots, v_K\}$ is known as the characteristic range of a. Assuming that Object x and y $\in$ X in S are indiscernible from each other, we express X as

$$\mathrm{IND}\left(\mathrm{X}\right) = \{(\mathrm{x},\ \mathrm{y}) \in \mathrm{U} \times \mathrm{U} | \forall \mathrm{a} \in \mathrm{X},\ \mathrm{fa}(\mathrm{x}) = \mathrm{fa}(\mathrm{y})\}. \tag{2}$$

The relationship between the lower and upper approximations of an attribute set is denoted by R. If it is assumed that set X is a subset of the universal set U and R is a specific characteristic set, the lower approximation (X) and upper approximation $\overline{R}(X)$ are defined as follows:

$$(X) = \{Y\} \in U/R : Y \subseteq X \tag{3}$$

$$\overline{R}(X) = \cup\{Y \in U/R : Y \cap X \neq \varnothing \tag{4}$$

If the objects contained in the universal set are used in the expressions, the lower approximation (X) and upper approximation $\overline{R}(X)$ may be defined as follows:

$$(X) = \{X \in U : [x]\ \mathrm{IND}\ (R) \subseteq X\}, \tag{5}$$

$$\overline{R}(X) = \{x \in U : [x]\ \mathrm{IND}\ (R) \cap X \neq \varnothing. \tag{6}$$

For all subsets in X, if there is a subset Q and Q $\subseteq$ X, which can represent the same result as X and IND (Q) = IND(X), Q is defined as a reduction set of X. Once the analysis results is simplified through the attribute set, the extraction of crucial factors can proceed. The importance of attribute extraction depends on the frequency of occurrence in the set theory. The rough set theory is employed to eliminate criteria indicators that do not influence the classification of the evaluation object, thereby guaranteeing that the index system post-screening has a notable influence on the evaluation outcomes.

The KNN algorithm is one of mature data mining techniques. Its main idea is that if KNN in the training set of the point to be predicted belongs to the same category, it can be inferred that the point also has the same features and attributes. In this study, rough set theory was used to extract the crucial factors that affect the production time of a precast factory. The model was developed by incorporating the rough set theory as a feature classifier and weighting recognizer, and KNN was adopted as the inference engine. Compared with the other engine, the use of KNN with certain rules as inputs for the deep learning approach can not only simplify the learning process, but also improve the prediction accuracy [39]. KNN was chosen because it has been shown in previous research to achieve satisfactory accuracy for prediction, and the built-in toolbox of Matlab was used to perform K-fold cross-validation to ensure the validity of the model.

The built-in toolbox of Matlab was used to perform K-fold cross-validation in this research. During K-fold cross-validation, all data were randomly allocated to K groups, where K was automatically set to ten groups. The value for k is fixed to 10 indicates that the size difference between the training set and the resampling subset is getting smaller. Previous research also indicated that satisfactory accuracy was achieved while using KNN for prediction [40,41]. Therefore, in this study, the KNN recommendation provided in Matlab toolbox is set to one hidden layer, 20 neurons, 0.4 learning rate and 0.9 alpha is the best, which matches the recommendations of previous studies [42,43].

5. Results and Discussion

In this research, rough set theory was implemented to simplify 14 decision production item attributes for beams, girders, and columns by eliminating redundant attributes and identifying core attributes. In Tables 3–5, the attribute column showed the number of attributes that each attribute set had. When the positive region (PR) was equal to 1, it indicated that the truncated data table was consistent with the original data of production time. The truncated stability coefficient (SC) indicated the stability of dynamic reduction. Maximum stability was achieved when SC was equal to 1. It could be seen that beams, girders, and columns had achieved good stability and consistency after analysis. The simplified attributes satisfied the classification defined. Any attribute with a frequency ≥80% (occurrence times 80% or above) is considered a core attribute, any attribute with a frequency ≤20% represents is considered an insignificant attribute, and any attribute with a frequency anywhere between 20% and 80% is a medium impact attribute [44].

Table 3. Beam Reduction results.

∩#	Pos.Reg.	SC	Attribute	Reductions
1	1	1	11	attr1, attr2, attr5, attr6, attr7, attr8, attr10, attr11, attr12, attr13, attr14
2	1	1	11	attr1, attr2, attr5, attr6, attr7, attr8, attr9, attr10, attr11, attr12, attr13
3	1	1	11	attr1, attr2, attr4, attr5, attr6, attr8, attr10, attr11, attr12, attr13, attr14
4	1	1	11	attr1, attr2, attr5, attr6, attr8, attr9, attr10, attr11, attr12, attr13, attr14
5	1	1	11	attr1, attr2, attr4, attr5, attr6, attr8, attr9, attr11, attr12, attr13, attr14
6	1	1	12	attr1, attr2, attr3, attr4, attr5, attr7, attr8, attr9, attr10, attr11, attr13, attr14
7	1	1	12	attr1, attr2, attr3, attr5, attr6, attr7, attr8, attr9, attr10, attr11, attr13, attr14
8	1	1	12	attr1, attr2, attr3, attr4, attr5, attr7, attr8, attr9, attr10, attr11, attr12, attr13
9	1	1	12	attr1, attr2, attr3, attr4, attr5, attr7, attr8, attr10, attr11, attr12, attr13, attr14
10	1	1	12	attr1, attr2, attr3, attr4, attr5, attr6, attr7, attr8, attr9, attr11, attr12, attr13
11	1	1	12	attr1, attr2, attr3, attr4, attr6, attr7, attr8, attr9, attr11, attr12, attr13, attr14
12	1	1	12	attr1, attr2, attr3, attr4, attr6, attr7, attr8, attr10, attr11, attr12, attr13, attr14
13	1	1	12	attr1, attr2, attr3, attr4, attr5, attr6, attr7, attr8, attr9, attr11, attr13, attr14
14	1	1	12	attr1, attr2, attr4, attr6, attr7, attr8, attr9, attr10, attr11, attr12, attr13, attr14
15	1	1	12	attr1, attr2, attr4, attr5, attr7, attr8, attr9, attr10, attr11, attr12, attr13, attr14

Table 4. Girders Reduction results.

∩#	Pos.Reg.	SC	Attribute	Reductions
1	1	1	12	attr1, attr2, attr3, attr4, attr5, attr7, attr8, attr10, attr11, attr12, attr13
2	1	1	13	attr1, attr2, attr3, attr4, attr5, attr6, attr7, attr8, attr9, attr10, attr11, attr13, attr14
3	1	1	12	attr1, attr2, attr3, attr4, attr5, attr7, attr8, attr9, attr10, attr12, attr13, attr14
4	1	1	11	attr1, attr2, attr4, attr5, attr8, attr9, attr10, attr11, attr12, attr13, attr14
5	1	1	12	attr1, attr3, attr4, attr5, attr7, attr8, attr9, attr10, attr11, attr12, attr13, attr14
6	1	1	12	attr1, attr4, attr5, attr6, attr7, attr8, attr9, attr10, attr11, attr12, attr13, attr14

Table 5. Columns Reduction results.

∩#	Pos.Reg.	SC	Attribute	Reductions
1	1	1	12	attr1, attr2, attr3, attr4, attr5, attr6, attr7, attr8, attr10, attr11, attr12, attr13
2	1	1	12	attr1, attr2, attr3, attr4, attr6, attr7, attr8, attr10, attr11, attr12, attr13, attr14
3	1	1	11	attr1, attr2, attr4, attr5, attr8, attr9, attr10, attr11, attr12, attr13, attr14
4	1	1	10	attr1, attr2, attr4, attr6, attr8, attr9, attr10, attr11, attr12, attr13
5	1	1	12	attr1, attr2, attr4, attr5, attr6, attr8, attr9, attr10, attr11, attr12, attr13, attr14
6	1	1	11	attr1, attr3, attr4, attr6, attr7, attr8, attr9, attr10, attr11, attr12, attr14
7	1	1	10	attr1, attr3, attr4, attr5, attr7, attr8, attr9, attr10, attr11, attr12
8	1	1	10	attr3, attr4, attr5, attr7, attr9, attr10, attr11, attr12, attr13, attr14

Tables 6–8 show the critical results of attributes. The importance of attributes depended on their occurrence frequency in the intersection of all sets under the set theory. There were five core influencing factors for beams: steel mold cleaning, assembling modules, fixture removal, stripping, and inspection of finished components. They indicated that more labor input was required for production, and shift workers were often required to accelerate the pace of work in order to finish production as soon as possible. Results of our analysis also proved that overtime production problems exist in the precast industry. There were seven core influencing factors that affected the production time of girders: cleaning the steel mold, dipping the steel rod cage, placing the wooden panels, fixture removal, concrete maintenance operations, removing the mold, and inspection of finished components. They indicated that the production time of the abovementioned components is quite different and has a significant impact. Both the allocation of manpower and the professional competence level of assigned shift workers should be improved to enhance production efficiency. There was one non-influencing factor, which was checking before pouring. The others were medium-influencing factors. There were three core influencing factors that affected column production efficiency: removing the mold, stripping, and component repair. The results indicated that attention should be paid to these three work items in a column production project. In regard to the production by shift workers, those shift workers who were responsible for removing the mold should not only be familiar with the details of their own workflow, but should also have an understanding of the stripping and component repair processes. This would allow the subsequent work items to be completed more expeditiously in order to increase production efficiency. This finding is consistent with those of other studies that have also highlighted the importance of assigning skilled workers to tasks that are critical to production processes. Skilled workers typically have the expertise and experience necessary to perform these tasks efficiently and effectively, which can help minimize the risk of delays and other production issues [13,45].

Table 6. Importance of attributes (Beams).

No.	Attribute	Frequency	Occurrence	Core Attribute	Medium Impact Attribute	Insignificant Attribute	Importance Rank
1	Cleaning the steel mold	80.6%	15	V			1
2	Assembling modules	80.6%	15	V			1
3	Lofting	40.6%	8		V		4
4	Dipping the steel rod cage	60.3%	11		V		3
5	Placing the wooden panels	60.9%	12		V		2
6	Checking before pouring	60.3%	11		V		3
7	Concrete pouring	60.9%	12		V		2
8	Fixture removal	80.6%	15	V			1
9	Concrete maintenance operations	60.3%	11		V		3
10	Removing the mold	60.3%	11		V		3
11	Stripping	80.6%	15	V			1
12	Component repair	60.9%	12		V		2
13	Inspection of finished components	80.6%	15	V			1
14	Warehouse storage	60.9%	12		V		2

Table 7. Importance of attributes (Griders).

No	Attribute	Frequency	Occurrence	Core Attribute	Medium Impact Attribute	Insignificant Attribute	Importance Rank
1	Cleaning the steel mold	80.3%	6	V			1
2	Assembling modules	50.6%	4		V		3
3	Lofting	50.6%	4		V		3
4	Dipping the steel rod cage	80.3%	6	V			1
5	Placing the wooden panels	80.3%	6	V			1
6	Checking before pouring	15.8%	2			V	4
7	Concrete pouring	60.9%	5		V		2
8	Fixture removal	80.3%	6	V			1
9	Concrete maintenance operations	80.3%	6	V			1
10	Removing the mold	80.3%	6	V			1
11	Stripping	60.9%	5		V		2
12	Component repair	60.9%	5		V		2
13	Inspection of finished components	80.3%	6	V			1
14	Warehouse storage	60.9%	5		V		2

Table 8. Importance of attributes (Columns).

No	Attribute	Frequency	Occurrence	Core Attribute	Medium Impact Attribute	Insignificant Attribute	Importance Rank
1	Cleaning the Steel mold	74.5%	7		v		2
2	Assembling Modules	70.3%	5		v		3
3	Lofting	32.6%	3		v		6
4	Dipping the steel rod cage	74.5%	7		v		2
5	Placing the wooden panels	60.9%	5		v		4
6	Checking before pouring	60.9%	5		v		4
7	Concrete pouring	52.3%	4		v		5
8	Fixture removal	74.5%	7		v		2
9	Concrete maintenance operations	60.9%	5		v		4
10	Removing the mold	80.5%	8	v			1
11	Stripping	80.5%	8	v			1
12	Component repair	80.5%	8	v			1
13	Inspection of finished components	60.9%	5		v		4
14	Warehouse storage	60.9%	5		v		4

Classification and weighted feasibility were performed through the KNN and the rough set enhanced KNN. Ten cross-validations were conducted on the weighting values of attributes for beams, girders, and columns. The forecast results in Table 9 show that an average accuracy of 92.36% was achieved with rough set enhanced KNN algorithm. This was 8.09% higher than the accuracy of KNN. Hence, this assumption was valid. The results demonstrated the practicability of adopting the rough set method as the content classifier, content weighting recognizer, and accuracy enhancer in an inference engine.

Table 9. Comparison between KNN and rough-set enhanced KNN.

(K = 10) Testing Subset No.	KNN	Rough-Set Enhanced KNN
1	85.59	91.01
2	85.56	91.85
3	85.77	91.51
4	85.22	91.94
5	85.78	93.77
6	85.41	91.82
7	85.86	91.88
8	80.71	95.82
9	85.59	91.87
10	77.23	92.17
Average	84.27	92.36

The proposed model combines rough set filters, KNN concepts and assumptions, K-fold cross-validation; any input model cases need to be compliant. Therefore, Step 1 is to extract data information from the cases that are trimmed according to Table 1. Step 2 is keying in the trimmed data and loading all 14 attributes into the model and database. Step 3 is an automated process. The proposed model produces results for predicting the number of manpower with the average accuracy of 92.36%. The predicted labor demand results all contain a value between 0 and 1, which can be converted to raw work hours from 2.01 (minimum) to 105.91 (maximum). The proposed model implementation is shown in Figure 2.

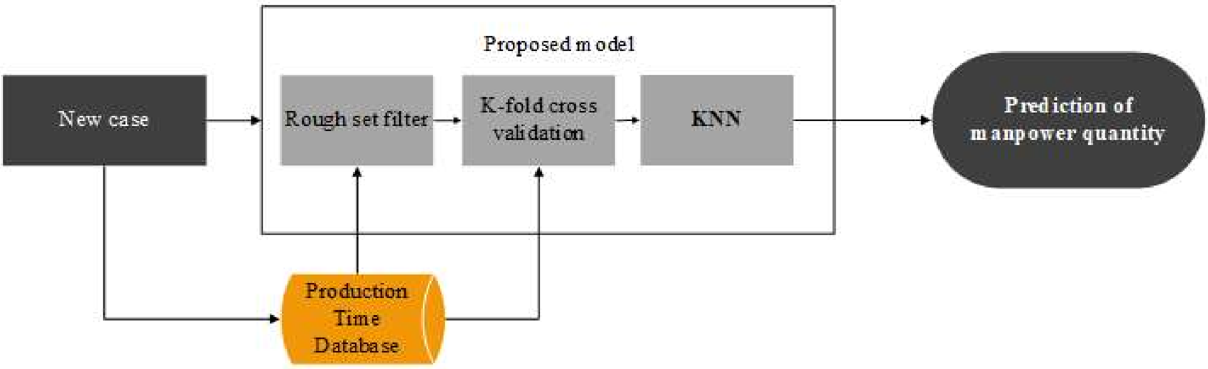

Figure 2. The proposed model structure.

6. Conclusions

Manufacturing precast concrete components in the Taiwan construction industry usually relies on personal experience and rule of thumb, as well as the project size as the basis for production scheduling and management. The findings demonstrate the significant contributions of various production procedures in precast concrete components to the overall production time. It was determined that there were five, seven, and three core factors that affect the production time of beams, girders, and columns, respectively. This finding has the potential to resolve corporate precast production distress and generate decision rules, providing users with a guideline to examine their corporate human resource allocation. For example, in the production of precast beams, factories with insufficiently experienced workers could assign skilled workers to perform steel mold cleaning, assembling modules, fixture removal, stripping, and inspection of finished components. As workers gain more experience, work shifts could be adjusted to better allocate human resources. Precast practitioners can benefit from establishing manpower allocation standards. This could save them time and allow them to target the most appropriate production work activities for assignments. This study not only provides a solution for accurate prediction of the on-site manpower quantities, but also introduces feasible attribute selection, weight identification and accuracy improvement using the rough-set approach. The use of existing tools through this model simplifies the prediction process for production manpower requirements and allocation. It reduces the influence of human factors and keeps the prediction accuracy within 10%. This study provides an important reference for precast industry practitioners by reducing the uneven distribution of resources through manpower allocation.

Although this paper contributes to exploration of the manpower requirement influential factors, there are still some research limitations. First, it is suggested that subsequent research should improve this model and make forecasts for other different types of components such as wall panel and staircase components. Once detailed data are obtained, input variables may be re-considered. Second, unforeseen disturbances such as machine breakdowns and precast element issues may occur during the actual production process of precast components, and the average number of workers assigned to each step is not taken into account. Third, the model developed in this study uses data on Taiwan precast construction firms only. Future studies should conduct similar research covering other industries and backgrounds.

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