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RAW MATERIAL OPTIMIZATION WITH NEURAL NETWORK METHOD IN CONCRETE PRODUCTION ON PRECAST INDUSTRY

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ABSTRACT: The development of construction is presently experiencing rapid growth in Indonesia, leading to the requirement of the right materials for infrastructural enhancements. From the existing infrastructure, concrete innovations such as precasts are needed with good quality materials, for the quick completion of construction. This is because the need for good quality and smooth material helps to determine the success of a building project, with the use of technology through precast being a problem-solving process. Therefore, this study aims to analyze the patterns by which inventory procurement predictions produce precasts with good quality, using the e-readiness framework concept of the neural network through appropriate decision-making processes. It also focuses on innovating technological products used in the Indonesian precast industry. The Methodology Neural Network was used to produce the best target quality time and precast commodities. The result indicated two outputs from 2 neural network models, using five similar input-value variables. Based on the Adaline neural network, the outputs were observed as the highest sales-cost predictions for precast products, which often occurred in 1, 5, 6 and 9 months. Besides this, production activities were also normally operated at level (1), with profit optimization being highly considered before months 1, 5, 6 and 9. For the LVQ neural network, the result was a predictive classification of class intensity levels, where fast decision-making processes occurred in months 1, 6 and 9. Cost optimization was also carried out by ordering raw materials several months in advance, considering the trend in material prices and logistics.

Keywords: Raw material, Neural network, Concrete, Precast

1. INTRODUCTION

Concrete is formed by raw material components, namely cement, aggregates, sand and admixture [1]. In its development, concrete technology continues to innovate and develop. The use of cast concrete in place is common, along with its development concrete can be cast elsewhere and when it is formed it is used in buildings according to their needs or what is better known as precast. According to the 2847:2019 standard [2], precast concrete is a structural concrete element that is cast elsewhere from its final position in the structure. In other words, precast is a concrete component with reinforcement that has been printed in a factory and the assembly is carried out at the project site. The use of precast concrete can reduce the duration of work 3,94% - 72,97%, the number of workers 51,33% - 87,45%, budget plan 3,05% - 37,57%, the use of wood as formwork and scaffolding 90,11% -98,81% [3]. Examples of using precast are spunpile used for high-rise building foundations, girders for bridges, facades used for building walls, lining used for retaining walls in rivers. U-Ditch is used for drainage or irrigation channels and Box Culvert is used in waterway construction, so it is often refered to as a sewer.

Currently, precast is needed to speed up the execution time, so it doesn't affect the weather factors, this usage is also eco-friendly.

Fig. 1 Precast Product Spunpile

The figure above is an example of a precast product, namely a spunpile which is used as a foundation for high-rise buildings. There is also a spunpile type that is in a box form depending on the designation needed in a construction project.

The Indonesian government has been undergoing massive infrastructural development since 2019, with an effect observed in the significant increase in precast product demand in 2022. Based on these data, precast production was carried out by 76 registered factories, which were distributed throughout the country. Each factory had an increase in production, which varied between 210,000-500,000 tons yearly, to serve the increasing demand. This indicated that the average monthly production of each organization needs to reach 45,000 tons.

In Indonesia, efficiency is often measured from a cost and time perspective, showing that the use of precast concrete is more efficient than conventional methods [4]. Although this utilization is more efficient, technology-based precast supply chain parameters still need to become effective support. This supply chain is classified into various phases, namely planning, designing, manufacturing, transportation, installation, and construction. To achieve an integrated construction, the parties in these phases need to have efficient communication and effective collaboration in providing accurate and up-to-date information. According to the governmental data, the main problems in the precast supply chain phases began from the following, (1) poor planning, (2) ineffective communication between designers and manufacturers, (3) incompetent employees/workers, (4) damage to raw materials, and (5) large sizes and heavy precast components and coordination in the bad project site. Besides these conditions, the key issues also contributed to negative consequences on the efficiency, productivity and effectiveness of precast delivery [5]. After procurement, the damages to raw materials are often found to affect the quality of the process and precast production during the inventory phase (initial stage). This explains that the procurement division needs to be able to provide the certainty of scheduling receipts for efficient project completion when ordering raw materials. Irrespective of these conditions, practical raw material orders and assembly time have still not been highly considered, leading to the probable effects and implications of excess inventory occurrences and additional project-financing increment, respectively. Therefore, a methodology should be determined for the effective, efficient, and economical control of precast plants' inventory management [6].

The utilization of technology has reportedly been implemented widely, to support the management of raw materials during the inventory processes. This was in line with the raw material control for precast tunnelling projects in China [7], where many businesses were leveraging historical sales and demand data to implement intelligent inventory management systems. Demand forecasting involves predicting/ensuring the consumption/collection of precast raw materials. This plays an important role in the area of inventory control and supply chain, due to enabling production and distribution planning. It is also conditioned to reduce raw material delivery times and optimize decisions on the supply chain [8]. This is to help the developers and operators of inventory management systems in improving efficiency, maximizing productivity, and minimizing material losses [9].

Many studies have also evaluated smart inventory implementation, namely the dynamic brick-and-mortar supply chain analysis. This evaluated the benefits of implementing smart applications and systems to improve Vendor Managed Inventory (VMI) efficiency. In the supply chain mechanism, the manufacturer configured the production level and replenished the inventory at the retailer's store, where prices were set up to affect sales and inventory. In this condition, the company also shared the revenue and inventory costs through an agreement. This condition was very dynamic when inventory increased and decreased at production and sales levels respectively, with periodical variations observed according to several stochastic errors [10]. In this case, the need for accurate predictions led to a more effective and cheap supply chain, as well as allowed companies to provide quality, quantity, periodical, and low-production cost products [11]. Many studies also used other machine learning approaches to map prediction patterns, such as fuzzy subtractive clustering [12].Therefore, this study aims to analyze the patterns by which inventory procurement predictions produce precast products with good quality, using the e-readiness framework concept of the neural network method through appropriate decision-making processes. In this condition, prediction modelling was prepared as part of the application of e-readiness in raw material management. The pattern of obtaining these materials was also used as the best test data, to assess the management model in smart inventory.

2. RESEARCH SIGNIFICANCE

Integration and utilization in the field of precast manufacturing is still not widely found. Integration requires redefining for adjustments in corporate culture in precast companies. The redefinition was carried out for reasons of planning the preparation of raw materials as precast making materials. Optimal material ordering must match the project schedule, raw material repository and technology. Order optimization is carried out with strict monitoring supported by customized e-readiness technology selection. Customize technology selection by implementing 2 neural network models namely; adaptive linear (Adaline) and linear vector quantization (LVQ) are still not common.

3. LITERATURE REVIEW

3.1 E-Readiness

Technology Readiness Index (TRI) 1.0 is constructed based on four-dimensional aspects, namely Optimism, Innovation, Discomfort, and Insecurity [13], as shown in Fig. 1. This is often applied to a company with the Strategic Alignment Maturity Model (SAMM), to determine the utilization level of information systems in all business operations [14]. It is also one of the innovative references used in managing highly efficient logistics. In addition, TRI is related to the Global Competitiveness and Logistics Performance Indexes (GCI & LPI), as well as other similar supportive dimensions.

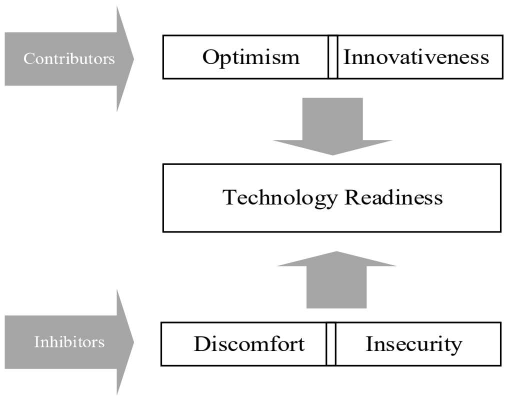

Fig. 2 E-Readiness Technology

In precast manufacturing companies, technology is also used in raw material management by arranging and using a very suitable procedural schedule and method, respectively. Using linear programming methods, Markov models, and genetic algorithms, scheduling often emphasizes the management of time to handle and obtain raw materials [15]–[17].

In this condition, a good inventory receipt system is needed to provide more value during the prediction process, where efficient and periodical systematic performance is a function of operational activities. This helps to reduce time consumption in determining optimal operations in various parameters [18]. Additionally, process quality problems and production cost efficiency are adequately maintained [1], [19], [20].

3.2 Neural Network

The amount of inventory is often related to the company's profit and the entire supply chain's survival. This indicates that prediction processes need to increase the company's ability to prevent risks, improve profits, and reduce losses during the acquisition of inventory, using the backpropagation neural network (BP) method [21], [22]. Some reports were also observed based on the development of technology readiness, such as [23], [24]. This emphasized determining the optimization value of material handling, using a neural network with 2 algorithm methods, namely ADALINE (Adaptive Lenear Neuron) and LVQ (Linear Vector Quantization). ADALINE network functions to perform cost projection. LVQ model function led to the prediction of cost-benefit into 3 categorical levels, namely high, medium, and low demand, as shown in figure 3.

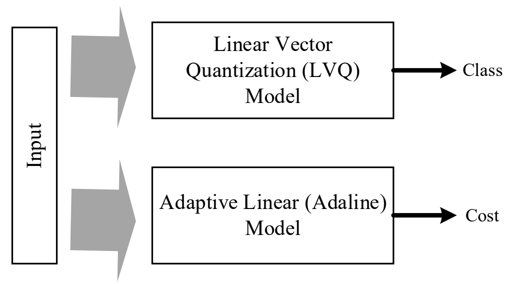

Fig. 3 Neural Network Model based on E Readiness

Based on the figure above, even though it uses 2 (two) models, namely the adaptive linear model and Linear vector quantization, both have the same input. Inputs come from Raw material receiving, vendor level and regional and enterprise technology infrastructure.

3.3 Adaline

ADALINE (Adaptive Linear Neuron or later Adaptive Linear Element) is an early single-layer artificial neural network, which is implemented as an algorithm to predict outputs with an automatic controller. Although the accuracy obtained is not satisfactory, the value still changes and becomes highly precise during more data analyses [25]. In the following equation, an input vector (K) is observed with the pattern.

$$X_k=[x_0, \quad x_{1k}, \quad x_{2k}, \quad \ldots, \quad x_{nk}]^T \tag{1}$$

Where X_k = the components of the weights and coefficients. Moreover, a weight vector (Wk) is observed in the Eq. (2) as follows,

$$W_k = [\mathrm{w}x_0, w_{1k}, w_{2k}, \ldots, w_{nk}]^T \tag{2}$$

where $y_K = W_K^T X_K$.

Output $y_k = \sum_{k=1}^{n} X_k W_k + \theta$

Adaptive learning rule

Learning is also known as the Least Mean Square (LMS), whose rules in this process are observed as follows,

$$W \leftarrow W + \eta(d - o)x \tag{3}$$

3.4 Linear Vector Equations Quantization (LVQ) Model

This is one of the widely used ANN models (Artificial Neural Network), which emphasizes the prototype of a supervised learning classification algorithm and its network. These are trained through a competitive method similar to the Self-Organizing

Map. The clustering technique is also used as a classifier to evaluate the deviations in the data sample through a random or specific density. This shows that performance remains the same with almost all combinations of training and testing [26]. Based on the following formula, learning is conducted by calculating the euclidian distance,

$$d(\vec{x},\vec{w}_k) = \min d(\vec{x},\vec{w}_k) \quad (4)$$

W_k (weight improvement) is also used to determine the weight (w) with the smallest distance value (d) as follows,

$\vec{w}_k \leftarrow \vec{w}_k + \eta.(\vec{x} - \vec{w}_k)$, when $c_m =/\neq y$, it is close to each other or part of the set, respectively.

4. METHODOLOGY

Research scenarios or methodologies must be carried out in order to achieve valid and accurate research results. In general, this research was conducted according to the methodology as shown in figure 4 below. Input from the system is in the form of monitoring data from e-readiness technology, processes and neural network learning carried out to achieve cost results and decision classes.

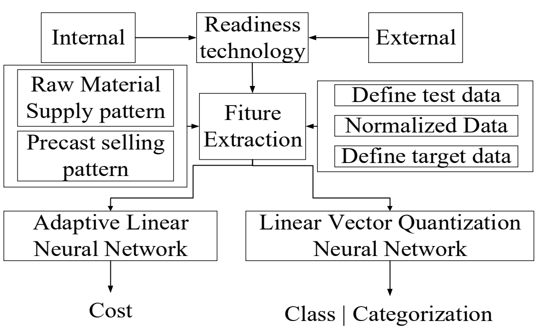

Fig. 4 Study Methodology

The e-readiness technology emphasized the following factors, (1) security, (2) technical issues, (3) software reliability, (4) digital operations for internet usage, and (5) technical skill utilization [27]. The concept of this technical influence also originated from internal and external organizations, as shown in figure 4. Feature Extraction serves to normalize raw material pattern data, precast selling pattern. In addition to also performing categories of data functions and training both neural network architecture models in used. Test data is used as inputs and targets based on monthly data patterns that occur. Internal data e readiness is an advantage to be achieved by making improvements by improving the quality and quantity of company resources. External e readiness is intended to look at competing companies that have the same core business and available infrastructure and can support company performance.

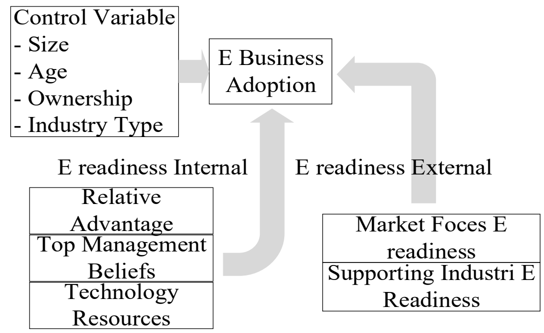

Fig. 5 The concept of e-readiness influence

Based on the external conditions, e-readiness emphasized many factors regarding the case perspective of each corporation in its respective business field. In this study, these factors were limited, including the IT technology infrastructure supporting the precast industry and the vendor market for raw materials. Meanwhile, the internal conditions of this technology focused on related technical improvements, using neural network methods for prediction processes.

4.1 Feature Extraction

The internal data sources were the direct measurement of the goods' receipts, regarding the yearly production of raw materials at precast organizations. In this condition, the raw material parameters included cement, sand, and aggregate. In preparation for the precast products, a value extraction was also observed for the contributions of the materials and costs, as shown in figure 6. This showed that the cement and aggregate costs and materials were the largest/lowest and smallest/highest contributions, respectively.

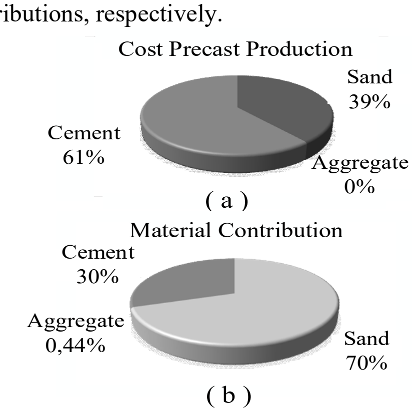

Fig. 6 Cost Contribution (a) production (m^3) and material contribution (b) precast product

The second parameter focused on the monthly-supply behaviour pattern of each raw material for a year, as shown in figure 7.

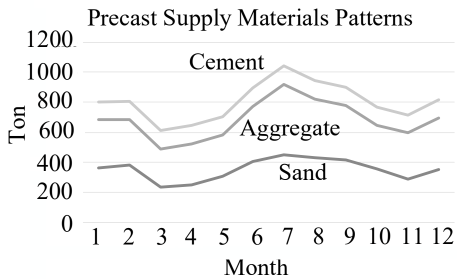

Fig. 7 Annual supply pattern of precast raw materials

Based on the pattern that occurs as can be seen in Figure 7, it can be seen that the pattern of each raw material (cement, aggregate and sand) has the same correlation even though it differs in the volume of orders. The data comes from ordering raw materials for a year (12 months). The highest order is cement, aggregate then sand.

4.2 Data Test

This emphasized the data of sand, aggregate and cement, which were mixed based on the best quality standard of Indonesian concrete category K 500-K 600. These data were obtained according to the order for 12 months, as shown in table 1.

Table 1 Precast raw material cost

No	Materials	Cost IDR (m^3)
1	Sand	242,000
2	Aggregate	200,000
3	Cement	715,000

4.3 Normalized Data

The nominal unit of numeric data was normalized to facilitate data processing in the neural network architecture. This indicated that normalization was carried out by mapping into numbers between 0 and 1, as shown in the following formula,

$$X_{Map} = \frac{X_{Original} - X_{\min}}{X_{\max} - X_{\min}} \quad (4)$$

Where :
X_{map} = Normalization Value
$X_{Original}$ = Original Value
X_{max} = Maksimum Value
X_{Min} = Minimum Value

In 2021, the normalization of input variables were also carried out on the price of raw materials, frequency of intermediaries, and volume of transaction costs. Moreover, the target data originated from the average total sales of precast products in the same year.

4.4 Target Data

The target data contained three vectors, namely the minimum, maximum, and median sales values of the total cost, as shown in figure 8.

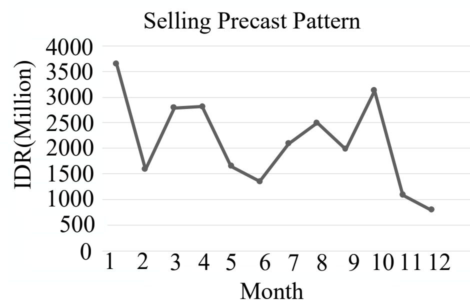

Fig. 8 Total precast unit cost for the year.

Based on figure 8, the optimization patterns of the raw material supply and sales profits were observed when the production target need to achieve 45,000 tons monthly with a minimum unit cost of IDR800 million.

5. DISCUSSION

Based on the external conditions, the system input parameters included the readiness of IT technology infrastructure, which supported the precast industry and market vendors providing raw materials. In this analysis, the final output was a value within a specified range. Meanwhile, the internal input factors included the monthly frequency of raw material supplies in a year (Tons). Table 2 shows the input and target variables of this analysis.

Table 2 Input Parameter Identification and Prediction

No	Input Parameter	Prediction Parameter	
		Adaline	LVQ
1.	IT Readiness Infrastructure	Monthly Precast Selling Patterns	Decision Classification Level
2.	Level Market Vendor		
3.	Cement Contributions (monthly)		
4.	Aggregate Contributions (monthly)		
5.	Sand Contributions (monthly)		

5.1 Architecture Neural Network Adaline

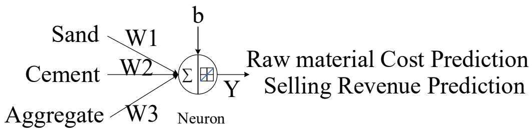

Fig. 9 Adaline Architecture

Based on figure 9, five defined input values were observed, indicating a linear activation function between 0 and 1. The figure describes the neural network architecture of the adaline model. This model uses a single layer of neurons and will carry out the learning process to achieve optimal architectural weights. The optimal architectural weight will produce a number that can be calibrated against the precast sales data pattern.

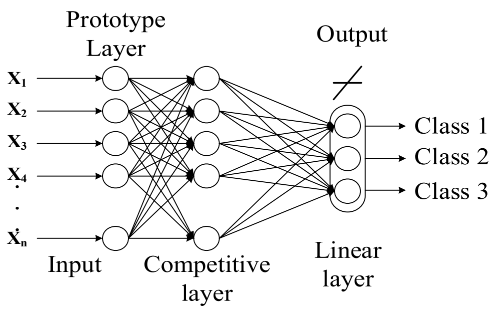

Fig. 10 Linear Vector Quantization Architecture

In figure 10 five defined input values were also observed, where a linear classification produced 3 cluster categories. The figure explains the neural network architecture of the Linear vector quantization model. This model uses competitive layer and linear layer neurons as its output. This architecture will carry out the learning process to achieve optimal architectural weight. Optimal architectural weight will result in a class classification of precast sales data patterns.

5.2 Simulation Result

The final stage of the process in a neural network model is to produce the final result. Simulations are carried out to measure whether the model is functioning as expected. The input parameters, the weights of the neural network learning outcomes to the output parameters will be tested according to their respective functions on the results. The model is declared good if several data scenarios until the output have been achieved.

Scenarios from the data will be tested according of the upper limit value and the lower limit value of the data pattern.

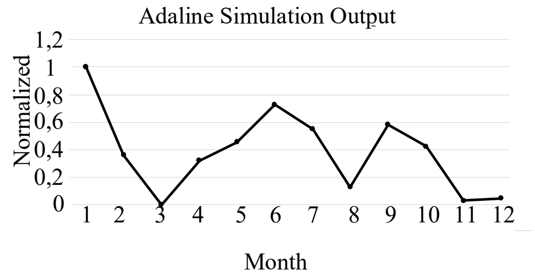

Fig. 11 Adaline Method simulation results

According to figure 11, the pattern of obtaining raw materials for precast products fluctuated based on the test data from 2021, through the Adaline method of learning for a year. In this condition, the lowest orders were in the 3rd, 8th, 11th, and 12th months when 5 parameters were inputted into this method.

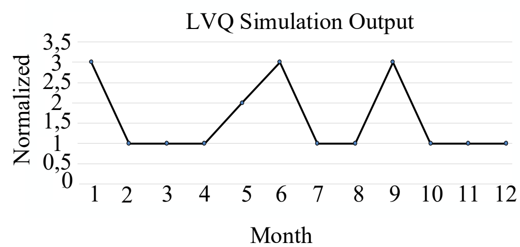

Fig. 12 LVQ Method Simulation Result

Based on figure 12, the pattern of obtaining raw materials for precast products also fluctuated regarding the test data from 2021, through the LVQ method learning for a year. This proved that the highest classes and the best values occurred in the 1st, 6th, and 9th months when 5 parameters were inputted into this method, with the lowest orders observed on the 2nd, 3rd, 4th, 7th, 8th, 10th, 11th, and 12th periods. In the 5th month, the values obtained were also found not to be very high or low. These actions emphasized the option of maintaining existing raw materials or placing orders regarding the increment of the previous month.

Table 3 Class and Cost Relation

No.	Month	Classes	Cost (IDR)
1	Jan	3	3,644,810
2	Feb	1	1,829,060
3	Mar	1	804,661
4	Apr	1	1,724,870
5	May	2	2,097,578
6	Jun	3	2,872,875
7	Jul	1	2,370,019

8	Aug	1	1,170,018
9	Sep	3	2,464,231
10	Oct	1	2,010,972
11	Nov	1	895,467
12	Dec	1	942,555

According to table 3, the second and third months had different advantages, although they were in class (1). This was in line with the eighth and eleventh months. The midpoint was also observed in class (2), which occurred in the 5th month. However, the 1st, 6th, and 9th months exhibited quite a large amount of transactions, leading to significant effects on the order of raw materials and logistics financing considerations.

6. CONCLUSION

Based on these results, cost optimization was conducted by accepting and creating new orders when the conditions were found in class (2). This action was often carried out by observing the trend of the previous month. Due to the high-order rate, the classes also showed that the level of operations need be accelerated and periodically limited when the conditions were categorized in class (3). For class (2), the order for raw materials was only performed by observing the Adaline method simulation, since a tendency was found for the market to absorb precast products in the following month. Furthermore, the application of the neural network method was appropriately implemented when supported by external e-readiness factors, including the which include infrastructure preparedness and many material vendor options. The implementation of this conceptual technology also used 2 neural network models for precast products. This involved the processing and production of similar input values and different decision model simulation, respectively. Irrespective of these differences, a strong correlation was still observed with the time efficiency of the decision-making process. Therefore, bother LVQ and Adaline contributed 50% to this decision approach.

7. ACKNOWLEDGMENTS

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