

Raw Material Cost Prediction Planning and Ready-Mix Product Sales Using Adaptive Linear Neural Network Method

Ranti Hidayawanti¹, Yusuf Latief², Rossa Nur Hayati^{1*}

¹ Institut Teknologi PLN, Indonesia

² University of Indonesia, Indonesia

Received : January 26, 2024

Revised : January 29, 2024

Accepted : February 2, 2024

Online : March 13, 2024

Abstract

An important thing that needs to be considered to ensure the successful implementation of the project is planning. The current problem with RMC is the non-achievement of the target, which causes the company's condition to be not optimal. Stable production cost projections on construction projects have been a problem and a serious concern, especially for project contractors. Often, there is a deviation between the projected initial costs and the actual ones at the construction site. Production predictions need to be made to determine the accuracy of these needs. This study aims to predict the needs of production and raw materials in an industry and can accommodate the calculation of estimated profits. Prediction of an industry's production and raw material needs can be used as a reference in calculating profit estimates. The ADALINE method is a neural system consisting of several nodes. A node requires several input processes to produce one output, which can be used as a predictive model. The results show that the actual and simulation data results using the ADALINE model have 100% conformity. This shows that the ADALINE model on the neural network can also function as one of the prediction model choices in addition to performing a prediction function. Prediction results using neural networks are one of the alternative solutions for utilizing prediction models other than other prediction models.

Keywords *Neural Network, Ready Mix, Manufactured Sand, Supply Chain Management, Raw Material*

INTRODUCTION

The batching plant's inspection procedure aims to control product quality, reduce production costs, optimize administrative tasks, and reduce raw materials with damage. There are still some problems in predictions of product receipt in relation to process expenses. Cost overruns resulting from inaccurate prediction costs are the source of the current weakness. This frequently takes place, wasting booking expenses and reducing profit margins. By reducing the difference between the raw materials ordered and received, prediction level acceptance of raw materials with the inspection can manage the selection of raw material suppliers and optimize the production process (Mani et al., 2021). Currently, the estimation process has not utilized a neural network approach and still accommodates parameters that are not based on booking cost and profit data patterns. Cost estimation is an assessment of the expected costs of each construction project. The accuracy of these cost estimates will have a significant impact on the expected profits of the construction contractor. Therefore, a special contingency premium should be added to the initial forecast to increase the confidence level statistically.

Stable cost projections in construction projects are still a problem and a serious concern, especially for project contractors. Cost deviations from the initial cost plan often occur at construction sites. Therefore, a predictive assessment of the main factors affecting construction project costs is needed to improve the procurement and delivery of construction projects (Yadav & Swamy, 2018). An important factor in each industry is production management. The number of

Copyright Holder:

© Ranti, Yusuf, & Rossa. (2024)

Corresponding author's email: rossahaya@gmail.com

This Article is Licensed Under:



raw materials required is closely related to industrial activities, and the availability of these raw resources significantly impacts the ease of production activities. The available stock of raw materials greatly affects the number of products to be produced. Calculating the number of raw materials available must be carefully considered. In addition, predicting timelines for the presence of raw materials is very important for ready-mix production needs. Production predictions and prediction management must be completed to determine how quickly these requirements will be required. In order to produce the basic reference in the target marketing input required for this system include variables that affect the amount of production, and its output is a prediction of the amount of production, the amount of production and raw material required in an industry will be used as a reference in calculating profit estimates (Muzayyanah et al., 2014).

In this study, alternative solutions will be offered utilizing neural networks to solve the above problems. The solution uses an ANN adaptive linear (Adaline) model to generate projected costs for ordering and selling products. The difference that occurs between the projected order and product sales becomes an estimate of the profit margin obtained.

LITERATURE REVIEW

Raw Material

Ready Mix Concrete Plant (RMC) mixes cement, sand, aggregate and water to produce ready mix materials (Saleh & Mohammed, 2021). Optimal RMC management is difficult to achieve, so this causes a decrease in RMC quality management and productivity. Therefore, optimal RMC planning management is needed (Lee et al., 2022). Planning with accurate predictions will improve the performance ratio of the concrete batch plant by using the analysis of the amount of data collected in order to determine the most effective factors that have a large impact on the performance ratio of the concrete batch plant (Aziz, 2018).

Concrete

The main ingredient of concrete is a construction building material consisting of a mixture of water and minerals, cement additives, and chemicals in appropriate and below-standard proportions. In making concrete materials, a cement mixture needs to be designed and mixed with mortar according to the standardized proportions. Next, aggregates are added to the mortar to form concrete building materials. In this process, the most important thing is the mixing, which needs to be stirred completely to make the concrete performance meet the construction requirements (Han et al., 2021). The use of concrete in the wider world is often used in high-rise buildings (Hidayawanti et al., 2019).

Mixed aggregates (fine and coarse) can be determined in two ways: firstly, the composition of the mixed aggregate grains for concrete with K125 quality and higher quality must be checked by conducting a sieve analysis. Then, based on research (Hidayawanti et al., 2020), the method used to pass the screening is the fine modulus and the calculation of the mixed aggregate using a statistical formula calculation, which is a linear regression method to find the percentage ratio between coarse and fine aggregate in the design of a mixture that can be used in the manufacture of concrete.

Cost Prediction and Production

Ready-mix concrete manufacturers are always trying to improve the performance ratio of concrete batch plants in order to serve the construction market to high-quality standards while saving costs and time. Ready-mix concrete (RMC) is a mixture of different materials delivered to the customer, undamaged and freshly mixed (Aziz, 2018). Construction cost prediction to reduce time risk assessment is an indispensable step in a manager's decision-making process. Neural

network techniques require adequate data set sizes to model and estimate project costs (Hashemi et al., 2020).

The ability of each company to produce concrete is very different, depending on the foresight in calculating material costs, prudence in material waste management, buying materials at low prices, using the right tools, optimizing the operation of the equipment, choosing a factory location, and placing human resources to manage the production process whose ultimate goal is to get the lowest cost (production cost) in producing concrete (Hanun et al., 2018).

RESEARCH METHOD

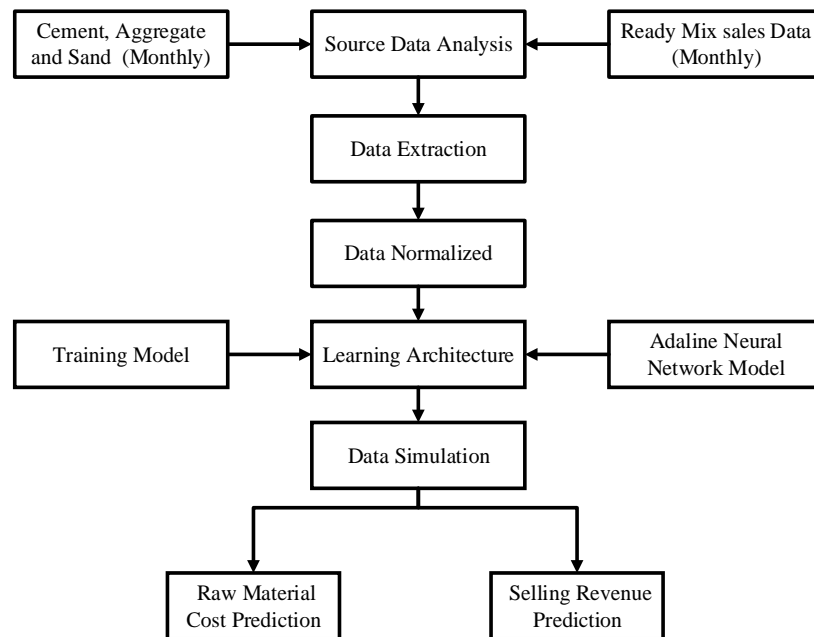


Figure 1. Research Flow Diagram

Source Data

The data source comes from 2 (two) ready-mix concrete company data, namely:

- Monthly raw material receipts data (January – December) during 2020 include the following data: Cement, aggregate and sand in m3 and the total purchase cost.
- Monthly ready-mix sales data (January – December) in 2020 from all production for all levels of concrete quality.

Data Extraction Raw material receipt data file. The existing data is extracted by filtering the file. The filtering results are in the form of monthly data (January – December) detailed receipts of cement, aggregate and sand in cubic units (m3) and their respective purchase costs. Methodology explains what research method was used and how the data was collected and analyzed quantitatively or qualitatively to get more explanation in the result and discussion.

$$X_{Map} = \frac{X_{Original} - X_{Min}}{X_{Max} - X_{Min}} \quad (1)$$

Where,

X_{Map} = Normalized Value

$X_{Original}$ = Original Value

X_{max} = Max Value Registered
 X_{Min} = Min Value Available

Learning Architecture

Learning architecture consists of a single neuron that accumulates inputs in normalized sand, cement, and aggregate values. The process is carried out with a decision boundary indicated by the input vector. The outputs of the architecture are Raw Material Cost Prediction and Selling Revenue Prediction.

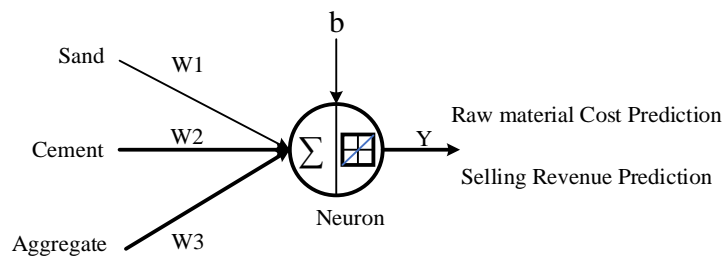


Figure 2. Learning Architecture

Data Simulation

Controlling production costs is essential for increasing industry competitiveness (Phitthayanon & Rungreunganun, 2019). By dividing the whole amount of the original price into equal units, the prediction of raw material costs is a calculation that determines the cost of the raw materials required to manufacture a material (product). Sand, cement, and aggregate are examples of the raw materials for precast construction that are being discussed here. Estimating future sales is crucial for a firm and essential for corporate success (Mohanapriya & Saranya, 2020). Profit from expected product sales is known as forecasted sales revenue. The data pattern on the annual sales of precast items is the source of the prediction data. Here is an example of actual data collected from material receipts over the course of a year.

Neural Network

Artificial Neural Networks (ANN) is a major side-by-side collaboration of simple processing units that acquire knowledge from the environment through the learning process and store knowledge in its connections (Guresen & Kayakutlu, 2011). ADALINE Neural Network can be described as a nervous system divided into several nodes. Each node requires several input processes and produces one output. ADALINE began as a single-neuron structure developed by Bernard Widrow in 1959. This method can be utilized to incorporate an artificial nervous system model into a system (Siswipraptini et al., 2020). The training algorithm for ADALINE is as follows:

- a. Initialization of weight
- b. Learning rate (α)
 - Usually, a value of around 0.1 is utilized.
 - The process of learning does not converge if the value is too high.
 - A figure that is excessively small will result in an extremely slow learning algorithm.
 - Practically, the value of the learning rate is determined between $0.1 \leq n \leq 1.0$, where n is the number of input units.
- c. Continue repeating so until the stop criteria are reached.

For each pair of s, t do:

- Set input activation: $XI = Si$
- Calculate

$$y = b + \sum X_i W_i \quad (2)$$

where:

y = output

b = biased value

X_i = input data

W_i = weight value

- Update bias (b) and weight W_i

$$b' = b + \alpha (t - y) \quad (3)$$

where:

b' = new biased value

b = old, biased value

α = learning rate

t = target

y = output

$$W'_i = W_i + \alpha (t - y) X_i \quad (4)$$

where:

W'_i = new weight value

W_i = old weight value

α = learning rate

t = target

y = output

X_i = input data

Meanwhile, the testing algorithm for ADALINE is:

- a. Weight Initialization (v). Obtain the weight from the learning process.
- b. For each bipolar input in x vector:
 - Set activation of the input unit x_i ($i = 1, \dots, n$)
 - Calculate the network value (net) from input to output

$$net = b + \sum X_i W_i \quad (5)$$

where:

net = network value

b = biased value

X_i = input data

W_i = weight value

- Apply activation function:

$$y = f(net) \begin{cases} 1 & \text{if } net \geq 0 \\ -1 & \text{if } net < 0 \end{cases} \quad (6)$$

where:

y = output

net = network value

Table 1. Example of Annual Material Receipt Data

No.	Receive data	Purchase Order	Materials	Vendors	Volume	Qty	Price	Total
1	31-01-2020 23:46:05	PO/RMC/12-2019/15430	Cement Type 1	INDOCEMENT TUNGGAL PRAKARSA	31,64	Ton	713.636,00	22.579.443,04
2	31-01-2020 15:32:49	PO/RMC/12-2019/15430	Cement Type 1	INDOCEMENT TUNGGAL PRAKARSA	32,86	Ton	713.636,00	23.450.078,96
3	31-01-2020 08:59:57	PO/RMC/12-2019/15430	Cement Type 1	INDOCEMENT TUNGGAL PRAKARSA	34,24	Ton	713.636,00	24.434.896,64
4	31-01-2020 00:47:31	PO/RMC/12-2019/15430	Cement Type 1	INDOCEMENT TUNGGAL PRAKARSA	37,32	Ton	713.636,00	26.632.895,52
5	30-01-2020 17:26:44	PO/RMC/12-2019/15430	Cement Type 1	INDOCEMENT TUNGGAL PRAKARSA	36,12	Ton	713.636,00	25.776.532,32
6	28-01-2020 17:39:46	PO/RMC/12-2019/15436	Aggregate 10-25	MITRA ABADI KARYA UTAMA	26,03	m ³	202.000,00	5.258.060,00
7	27-01-2020 17:39:44	PO/RMC/12-2019/15436	Aggregate 10-25	MITRA ABADI KARYA UTAMA	26,26	m ³	202.000,00	5.304.520,00
8	27-01-2020 16:36:57	PO/RMC/12-2019/15436	Aggregate 10-25	MITRA ABADI KARYA UTAMA	26,01	m ³	202.000,00	5.254.020,00
9	26-01-2020 16:19:41	PO/RMC/12-2019/15436	Aggregate 10-25	MITRA ABADI KARYA UTAMA	26,21	m ³	202.000,00	5.294.420,00
10	26-01-2020 16:18:40	PO/RMC/12-2019/15436	Aggregate 10-25	MITRA ABADI KARYA UTAMA	26,00	m ³	202.000,00	5.252.000,00
11	26-01-2020 12:32:16	PO/RMC/12-2019/15436	Aggregate 10-25	MITRA ABADI KARYA UTAMA	25,94	m ³	202.000,00	5.239.880,00
12	08-01-2020 01:56:11	PO/RMC/12-2019/15439	Sand	KORDON PUTRA. CV	24,14	m ³	193.000,00	4.659.020,00
13	08-01-2020 01:54:38	PO/RMC/12-2019/15439	Sand	KORDON PUTRA. CV	24,15	m ³	193.000,00	4.660.950,00
14	08-01-2020 01:52:51	PO/RMC/12-2019/15439	Sand	KORDON PUTRA. CV	24,10	m ³	193.000,00	4.651.300,00
15	08-01-2020 01:51:47	PO/RMC/12-2019/15439	Sand	KORDON PUTRA. CV	24,27	m ³	193.000,00	4.684.110,00

FINDINGS AND DISCUSSION

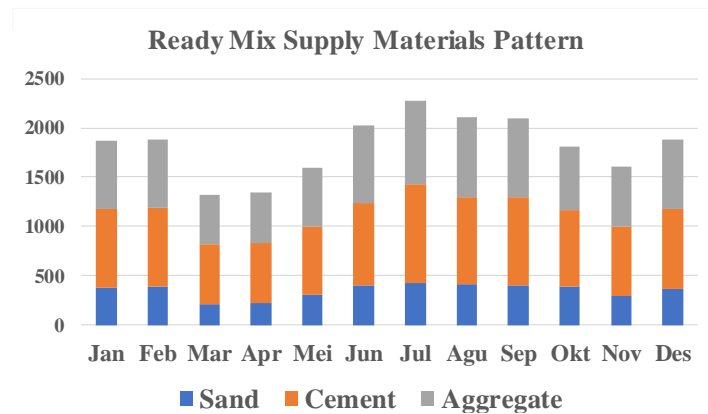


Figure 3. Precast Supply Materials Patterns

Figure 3 explains the pattern of acceptance of cement, aggregate and sand materials. In the figure, the x-axis depicts the 12 months, while the y-axis describes the weight of each material in tons. It can be seen that cement dominates the weight of the material, where the weight is higher than other materials. The pattern of receiving or ordering materials has a low value occurring in months 3, 4 and 11.

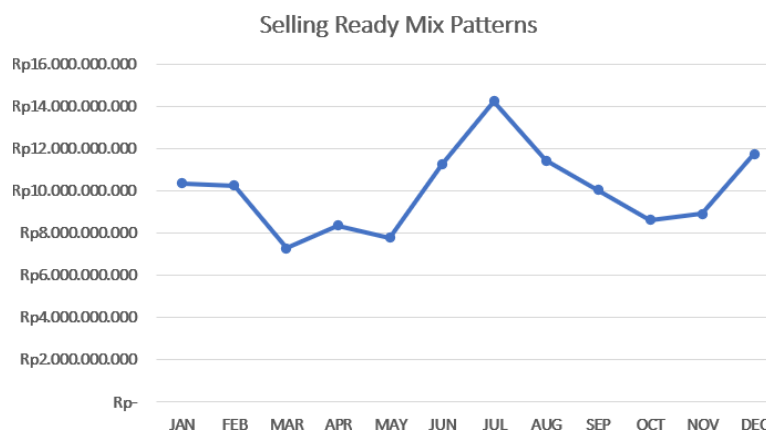


Figure 4. Selling Ready Mix Patterns

Figure 4 describes the ready-mix concrete sales pattern. In the figure, the x-axis depicts the 12 months of the year, while the y-axis describes the total sales price of ready-mix concrete. In the picture, it can be seen that the pattern of low sales occurred in March, May, and October. On the other hand, at the end of the year and the beginning of the year, as well as months 6, 7, 8 and 9, there was an increase in sales of ready-mix concrete. The highest cost amount generated is around 14 billion rupiahs in July. Based on Figure 3 and Figure 4, it can be seen that high orders for raw materials occurred in July, which strongly correlates with the value of ready-mix concrete sales in the same month. This indicates that orders for raw materials also increased due to the high demand for ready-mix products. The production process in the same month looks balanced between sales and orders for raw materials in the form of sand, cement and aggregate. The opposite also happens

if sales conditions are low, as in March.

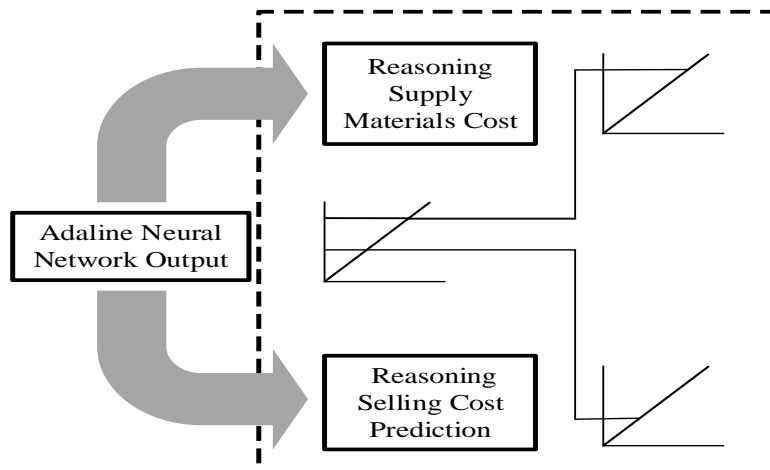


Figure 5. Prediction Output Reasoning

The system scenario process is carried out on the neural network architecture, as shown in Figure 2. As Figure 5 explains, the system input is in the form of units in weight (tons) of cement, aggregate and sand materials. The process is continued by the neural network model by normalizing the data values for cement, aggregate and sand materials as equation (6). The training process and value classification using the ADALINE method are carried out as equation (1) – (5). The output in the form of value results from the ADALINE method is then reasoned by mapping the classification based on the upper and lower limits of the value of the pattern of ordering raw materials and selling ready-mix products.

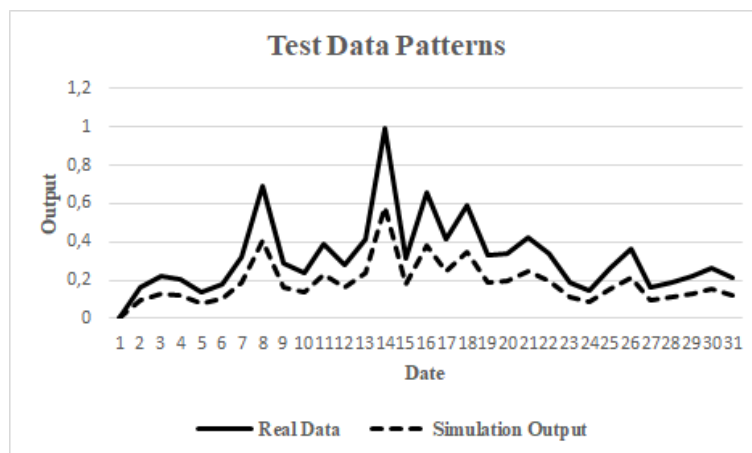


Figure 6. Test results of ordering ready mix raw materials

Figure 6 describes the test results of the ready-mix raw material ordering data model. The data is data on the cost of ordering raw materials for one month being tested. It can be seen that the pattern in the figure between the results of the ADALINE model and the actual data looks the same. This shows that the ADALINE model on the neural network used to predict the cost of ordering raw materials has functioned and can be used as an option for predicting the cost of ordering ready-mix

raw materials.

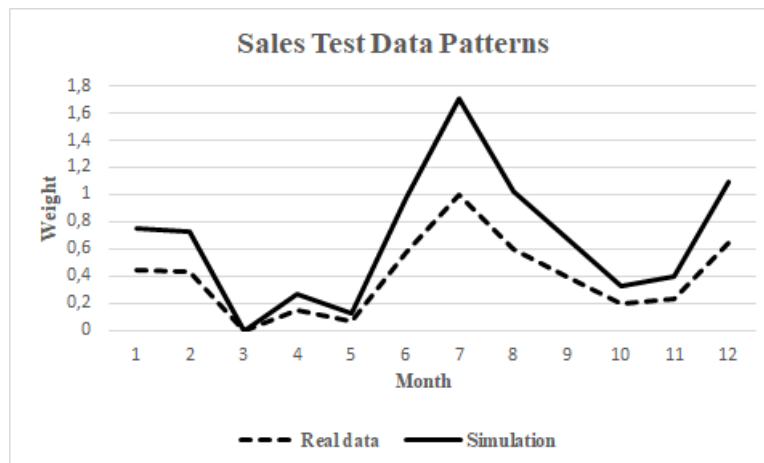


Figure 7. Sales Data Test

Figure 7 describes the test results of the ready-mix product sales data model for a year (12 months). The data is the monthly ready-mix concrete sales value for one year being tested. It can be seen that the actual data sales pattern and the results of the adaptive neural network model look the same. This shows that the ADALINE model on the neural network is already a good precision model to perform the prediction function and can also be used as one of the prediction model options.

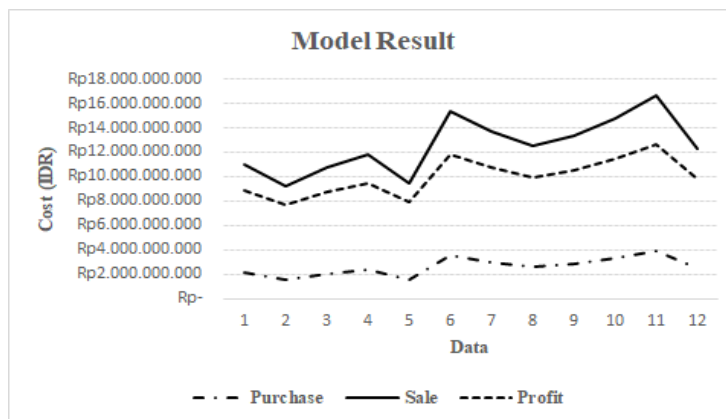


Figure 8. Sales Data

CONCLUSIONS AND FURTHER RESEARCH

Predictions of the adaptive neural network model are made using training data in the form of input derived from daily real transactions receiving raw materials in the form of sand, cement, and aggregate. The model's results will be reasoned with the model's output against the pattern of ordering costs and costs generated from ready-mix concrete sales transactions. Prediction results are in the form of the value of the cost of ordering goods (daily) and the total selling price (monthly). Profit is obtained from the difference in the selling price and the cost of ordering goods. The prediction results of the Adaptive Neural Network model follow the ordering pattern based on the volume of ready-mix raw materials in the form of sand, cement, and aggregate. It can be seen that

if there is a low order volume of raw materials, then this will also affect the selling value, which also tends to be low. If, on the other hand, the order for raw materials is low, the profit will also adjust accordingly to be high. The Adaptive Linear Neural network model with the implemented methodology has become a precise model in the function of predicting the cost of ordering raw materials, as well as predicting the sales value of ready-mix products.

REFERENCES

- Aziz, R.F. (2018). Statistical model for predicting and improving ready mixed concrete batch plants. performance ratio under different influences. *Alexandria Engineering Journal*, 57(3). <https://doi.org/10.1016/j.aej.2017.06.016>.
- Guresen, E. & Kayakutlu, G. (2011). Definition of Artificial Neural Networks with comparison to other networks. *Procedia Computer Science*. <https://doi.org/10.1016/j.procs.2010.12.071>.
- Han, S., Ni, X. & Huang, R. (2021). Study on Quality Control of Concrete Raw Materials in Road and Bridge Construction. *Frontiers Research of Architecture and Engineering*, 4(1). <https://doi.org/10.30564/frac.v4i1.3118>.
- Hanun, Y., Alisjahbana, S. W., Ma'some, D. M., Setiawan, M. I., & Ahmar, A. S. (2018). Designing Cost Production of Concrete. *Journal of Physics: Conference Series*, 1028. <https://doi.org/10.1088/1742-6596/1028/1/012063>.
- Hashemi, S.T., Ebadati, O.M. & Kaur, H. (2020). Cost estimation and prediction in construction projects: a systematic review on machine learning techniques. *SN Applied Sciences*. <https://doi.org/10.1007/s42452-020-03497-1>.
- Hidayawanti, R., Legino, S., Sangadji, I., & Widodo, R. P. A. (2019). The efficiency of fly ash and cement slag to development building. *International Journal of GEOMATE*, 16(57). <https://doi.org/10.21660/2019.57.4857>.
- Hidayawanti, R., Purnama, D. D., Iduwin, T., Legino, S., & Wachid, F. I. (2020). The impact aggregate quality material as a linear regression study on mixture concrete. *International Journal of GEOMATE*, 18(70). <https://doi.org/10.21660/2020.70.5611>.
- Lee, S-J., Jung, K-T., Youn, J-Y., & Lee, D. (2022). Optimal management plan through ready-mix concrete placement and transportation time. *International Journal of Mechanical Engineering*, 6(3), 866-872.
- Mani, A., Bakar, S. A., Krishnan, P., & Yaacob, S. (2021). Markov Decision Process approach in the estimation of raw material quality in incoming inspection process. *Journal of Physics: Conference Series*, 2107, 012025. <https://doi.org/10.1088/1742-6596/2107/1/012025>.
- Mohanapriya, S. & Saranya, S.M. (2020). Sales prediction using machine learning algorithm. *International Journal of Advanced Science and Technology*, 29(3 Special Issue).
- Muzayyanah, I., Mahmudy, W. F. & Cholissodin, I. (2014). Penentuan Persediaan Bahan Baku dan Membantu Target Marketing Industri Dengan Metode Fuzzy Inference System Tsukamoto. *DORO: Repository Jurnal Mahasiswa PTIIK Universitas Brawijaya*, 4(2014).
- Phitthayanon, C. & Rungreunganun, V. (2019). Material cost prediction for jewelry production using deep learning technique. *Engineering Journal*, 23(6). <https://doi.org/10.4186/ej.2019.23.6.145>.
- Saleh, I.A. & Mohammed, A.M.F. (2021). Emission rates of pollutants from ready Mix Concrete plants in Cairo, Egypt. *Egyptian Journal of Chemistry*, 64(4). <https://doi.org/10.21608/EJCHEM.2021.47757.2976>.
- Siswipraptini, P.C., Aziza, R. N., Sangadji, I., & Indrianto, I. (2020). The design of a smart home controller based on ADALINE. *Telkomnika (Telecommunication Computing Electronics and Control)*, 18(4). <https://doi.org/10.12928/TELKOMNIKA.V18I4.14893>.

Yadav, A.R. & Swamy, R.M. (2018). Factors Affecting Cost and Inflation of a Project. *International Research Journal of Engineering and Technology (IRJET)*, 5(2).