Proceedings of the Seventh International Conference on
Artificial Intelligence, Soft Computing, Machine Learning and Optimization,
in Civil, Structural and Environmental Engineering
Edited by: P. Iványi, J. Kruis and B.H.V. Topping
Civil-Comp Conferences, Volume 11, Paper 2.1
Civil-Comp Press, Edinburgh, United Kingdom, 2025
ISSN: 2753-3239, doi: 10.4203/ccc.11.2.1

Construction Planning Based on Lagrange Optimization With Artificial Neural Network

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Abstract

One of the biggest obstacles in optimization is finding explicit objective functions that describe target outcomes. However, the need to explicitly define complex objective functions and constraints with respect to design variables can be eliminated through the use of Artificial Neural Network (ANN)-based optimization. This method enables the optimization of discontinuous, nonlinear design problems with multiple variables, objective functions, and constraints. In this study, a scheduling simulation is established to generate big data for construction planning of a warehouse project. The complex construction process scheduling is formulated into an objective function derived from ANNs, which is trained on the generated data to map zoning areas and manpower to costs. Jacobian and Hessian matrices of the ANN-based functions are formulated to implement the Newton-Raphson iteration for finding stationary points of the Lagrange functions. The optimization can consider planning constraints such as site capacity, concreting capacity, etc., while providing solutions for minimizing costs. Results show that cost predicted by ANN-based optimization is located at the minimum of big data ranges, indicating a potential of the proposed method to aid construction engineers in establishing optimized construction strategies.

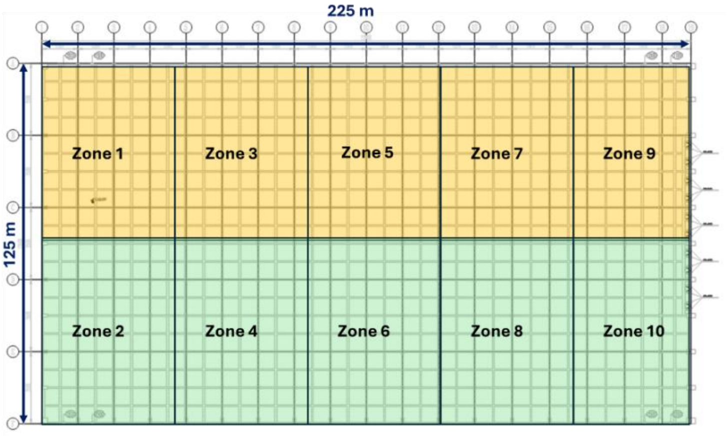
Keywords: ANNs, Lagrange, optimization, construction planning, construction scheduling, big data in construction.

1 Introduction

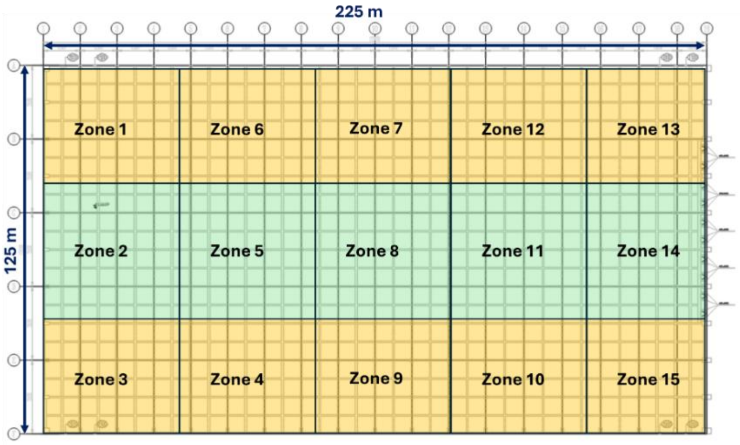
Construction planning is a complex process that involves considering multiple aspects of a project. Employing a large number of workers and hiring equipment intensively can reduce construction time but significantly increase operational and financial costs. On the other hand, reducing resource allocation can prolong the schedule, resulting in penalties for failing to meet deadlines. Traditionally, the optimization of construction schedules has relied heavily on trial-and-error methods and the experience of engineers, leading to inconsistent scheduling effectiveness. Recently, artificial intelligence (AI) has been successfully applied in many fields such as structural health monitoring, design optimization, quality control, and more. However, research on applying AI to optimize construction planning remains limited. Some notable studies include those by Raymond E. Levitt [1], Wei Lin [2], and Jude et al. [3]. The early mention of AI in construction planning was in 1988 by Raymond E. Levitt [1], who summarized early attempts at using AI-based techniques to generate construction project plans. These studies proposed generating construction plans using ANNs trained on stored engineering knowledge. However, their efficiency was limited by the quantity and consistency of available data. In 2021, Wei Yin [2] proposed an AI-based approach for construction schedule optimization. Resource allocation during construction phases was determined using fuzzy single-objective linear programming, demonstrating reduced resource intensity compared to the initial tender. In 2023, a study by Jude et al. [3] explored the application of ANN and neuro-fuzzy models in construction scheduling, where the networks were trained on data extracted from documents related to a two-storey reinforced concrete (RC) frame structure. The results indicated relatively good accuracy in ANN-based predictions.

Although recent advances in AI technology offer promising opportunities for optimizing construction planning, a convenient and practical algorithm for resource allocation and scheduling has yet to be established. A commonly encountered challenge in planning reinforced concrete structures is to determine the optimal area for a single concreting zone and the corresponding number of workers required. This paper proposes a Lagrange-based approach to address this issue. A simulation algorithm was developed to generate scheduling-related big data, estimating formwork and labour costs based on the construction sequence of reinforced concrete elements, while accounting for financial expenses and penalties for deadline overruns. Instead of deriving objective functions through explicit mathematical expressions, ANN-based models were trained on the generated data. These trained functions were then optimized using Lagrange multipliers in combination with Newton-Raphson iterations, yielding an optimized plan that minimizes costs.

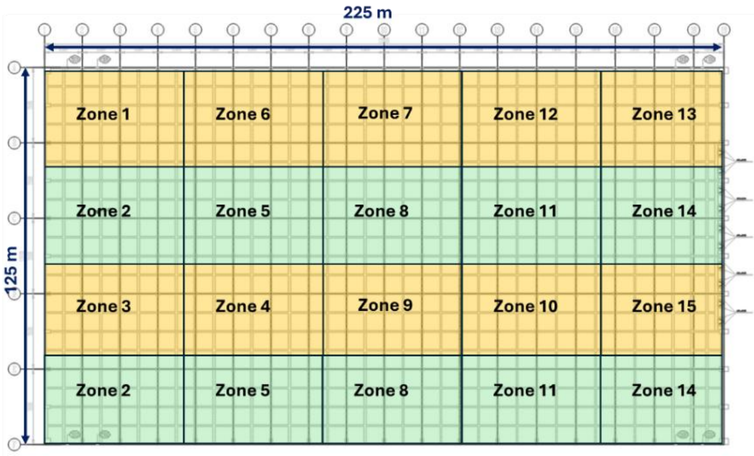
The present paper investigates a case study involving the construction of a large-scale reinforced concrete warehouse with dimensions of 125 m × 225 m, totalling 28,125 m^2. Based on typical concreting capacities per batch, which range from 1,500 m^2 to 3,000 m^2, the construction plan can be divided into 10 to 29 concreting zones. Figures 1(a), 1(b), and 1(c) illustrate examples of three among 20 options for dividing the plan, and the three examples in Figure 1 divide the plan into 10, 15, and 20 zones, respectively.



(a) Plan divided into 10 zones.



(b) Plan divided into 15 zones.



(c) Plan divided into 20 zones.

Figure 1: Master plan of the case study project.

The site management board decided to deploy three teams working simultaneously, allowing construction of three zones at a time. Each team consists of a formwork crew, a rebar crew, and a concreting crew, enabling them to operate independently. In terms of equipment, each team is assigned a set of formworks sufficient for one zone. Figure 2 illustrates the construction sequence of the RC floor with three zones constructed at the same time. It should be noted that the time required for formwork installation, rebar assembly, and formwork removal depends on the number of workers allocated to each team. In contrast, the curing period—from concrete pouring to formwork removal—is fixed at eight days, corresponding to the estimated time at which the floor can support its self-weight.

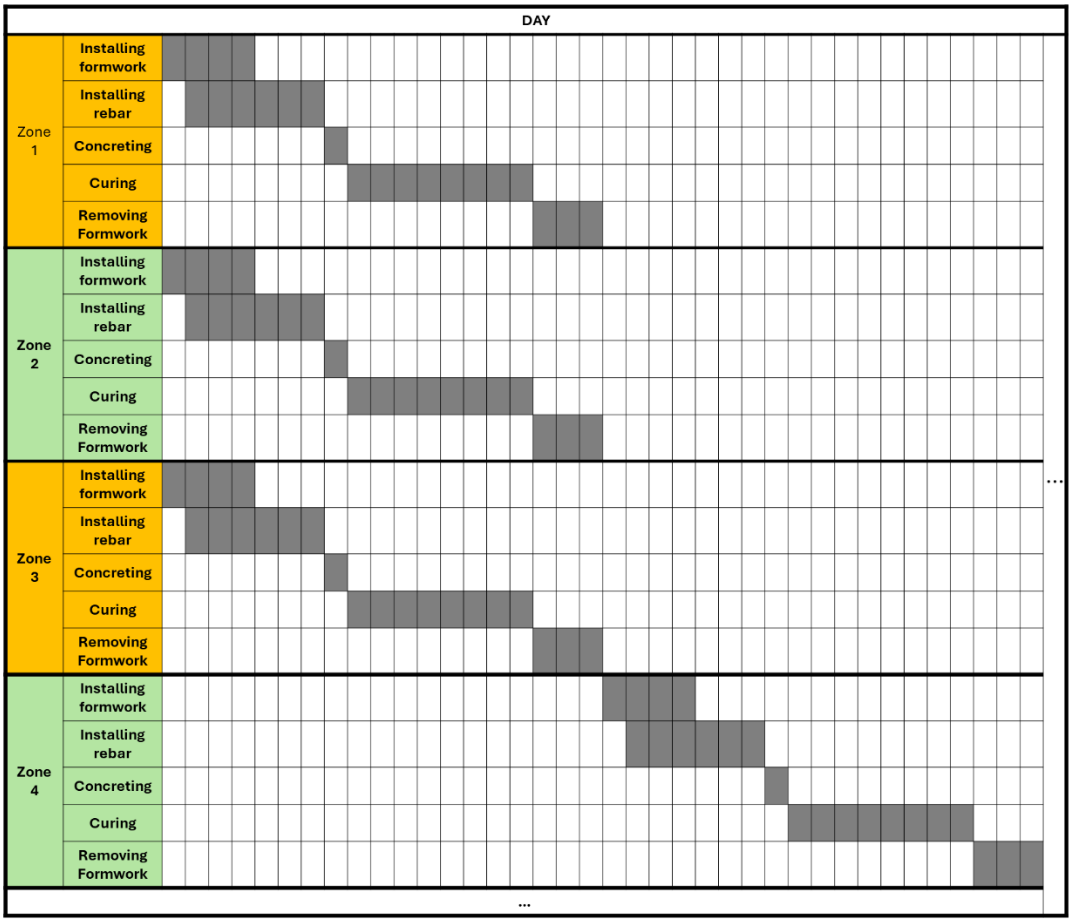


Figure 2: Construction sequence of the RC floor with three zones constructed simultaneously.

The target was to complete the structural work at a minimal cost. The overall cost includes formwork rental fees, salaries for steel and formwork workers, financial costs, transportation expenses, machine and equipment usage (e.g., cranes, trucks, concrete pumps), and material costs, etc. It is important to note that most expenses—such as material costs—were nearly fixed before the construction phase. Therefore, the focus of optimization was placed on formwork rental fees, labour wages, and financial costs, as these are highly influenced by construction planning. Financial costs were calculated based on the bank interest rate and the total expenditure. Table 1 shows fixed parameters and Table 2 lists input and output variables for the optimization.

Table 1: Fixed input parameters.

Fixed parameter	**Symbol**	**Value**	
Total area	A_T	28,125 m^2	
Number of zones to be constructed at the same time	n	3	
Formwork labor cost (installing and removing)	M_f	0.275 work shift/m^2	Based on Vietnamese norm
Rebar labor cost	M_s	0.897 work shift/m^2	
Labor cost for concrete curing	M_c	0.001 work shift/m^2	
Number of operations shifts per day	N_{s1}	3 shifts	Based on 8 hours-shift
Number of shifts a worker can do a day	N_{s2}	2 shifts	
Maximum number of workers on site	N_{max}	0.5/m^2	
Labor cost	L_1	30$ / shift	Based on Vietnamese market
	L_2	5$ / shift	
Cost of hiring formwork	M_h	0.0822$/ day	
Concrete curing time	T_c	8 days	Based on Vietnamese condition
Bank interest	E	5%/ year	

Table 2: Input and output variables for the optimization.

	Variable	Sym--bol	Range	Remark
Input variables (input variable for ANN training)	Zone area	A_z	1500 m^2 ~ 3000 m^2	To be generated within ranges assigned by engineers
	Number of formwork worker	W_f	300~500 manpower	
	Number of rebar worker	W_s	300~500 manpower	
Intermediate calculated variable (not being trained)	Number of zones	n_0	$n_0 = A_T / A_z$	To be calculated based on input variables
	Formwork area to be hired	A_{f0}	$A_f = nA_z$	
	Occupied formwork area	A_{f1}	To be calculated based on schedule	
	Free formwork area	A_{f2}	$A_{f2} = A_f - A_{f1}$	
Output variables (objective functions)	Construction time	T		To be calculated based on input variables
	Total cost of formwork rental fees, labour wages, financial costs	M		

2 Methods

The optimization procedure consists of three steps, as shown in Figure 3: generating big data, training ANNs, optimizing ANN-based objective functions.

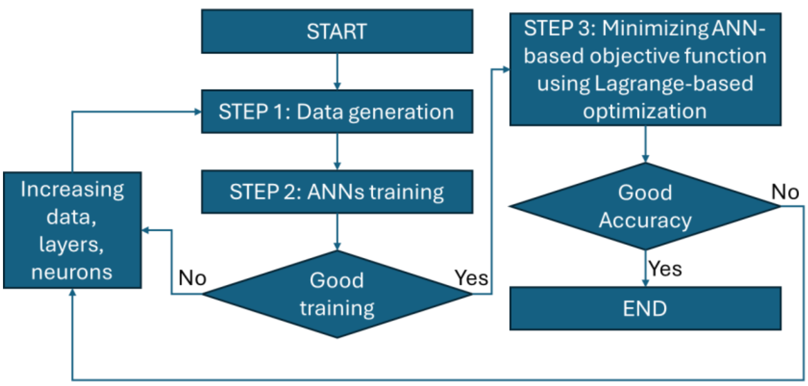


Figure 3: Three steps of ANN based Lagrange optimization

In Step 1, an algorithm, shown in Figure 4, is developed to simulate the construction sequence of RC structures and to calculate the schedule and costs based on zone areas and the number of workers. It estimates the daily work progress using the parameters listed in Table 3. A proper number of large datasets needed for training ANNs should be selected discreetly based on a level of complexity for a problem under consideration. Acceptable training accuracy based on two million datasets are yielded for construction schedule. Bigger datasets need to be regenerated, or training parameters need to be revised when training accuracies are not acceptable. Datasets are normalized between -1 and 1.

Table 3: Daily parameters showing work progress for data generator.

Variable	**Symbol**
Day	i
Zone number	j
Area of Zone j	Z_j
Area of Zone j at the end of Day i where formwork installation is finished	$P_{f\_i\_j}$
Area of Zone j at the end of Day i where rebar assembling is finished	$P_{s\_i\_j}$
Curing time of concrete at Zone j at the end of Day i	$P_{c\_i\_j}$
Area of Zone j at the end of Day i where formwork removal is finished	$P_{r\_i\_j}$
Number of zones where formwork installation or removal are being processed at the time of consideration	n_f
Number of zones where rebar installation is being processed at the time of consideration	n_s

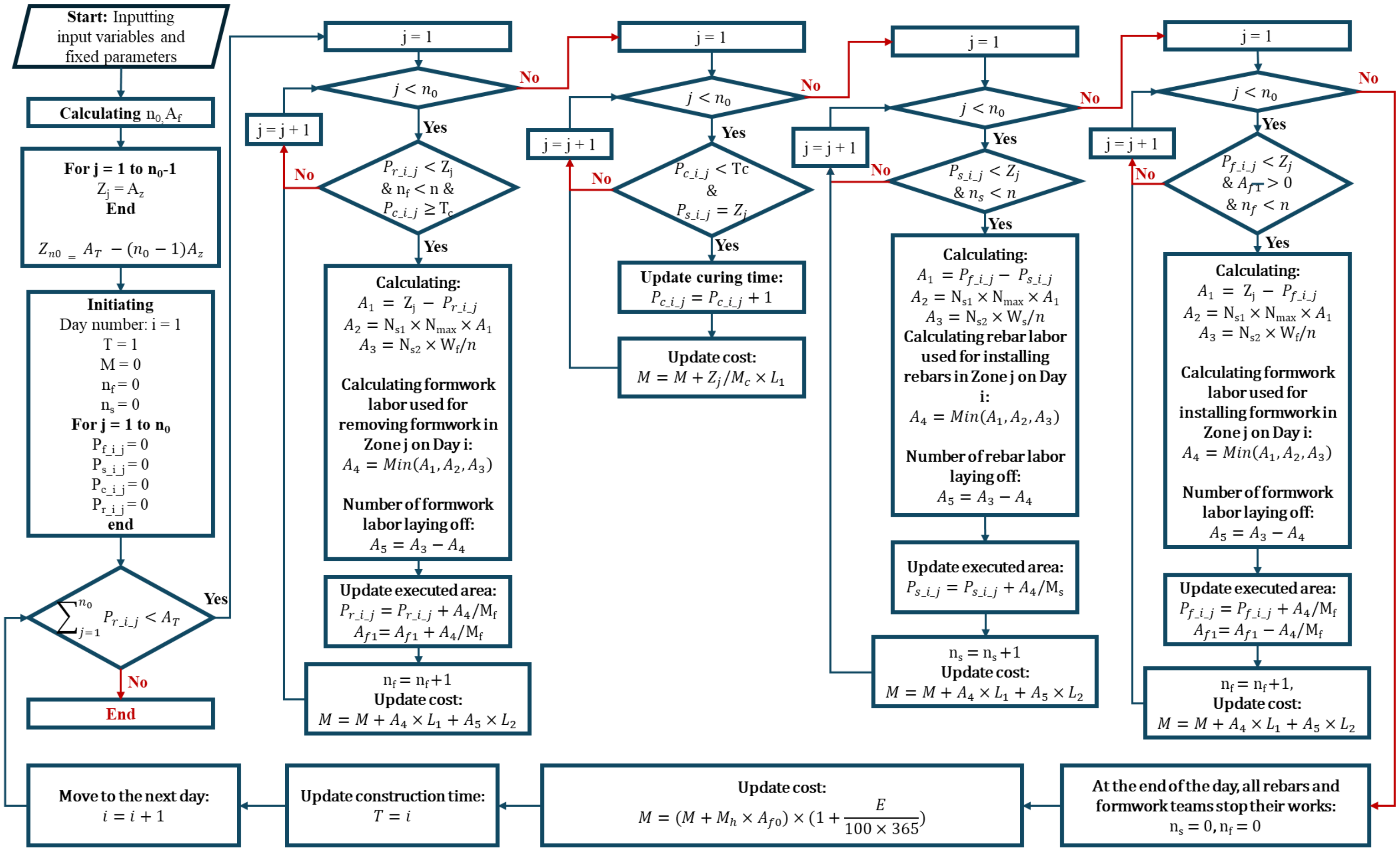


Figure 4: Algorithm developed to simulate the construction sequence of RC structures for generating big data

In Step 2, MATLAB deep learning toolbox (MATLAB 2024b) [4] is used to train ANNs-based generalized functions based on large datasets generated from Step 1 to calculate weight and bias matrices. A number of large datasets and training parameters selected to train ANNs affects accuracies of weight and bias matrices. Good training parameters for ANNs should be used in achieving good training results. Training parameters include a number of hidden layers, neurons, validations, and required epochs, etc. The ANN-based objective functions and constraining functions are, then, derived using weight and bias matrices found from training.

In Step 3, explicitly obtained objective functions are replaced by ANN-based objective functions to apply Lagrange multiplier method for the optimization of ANN-based objective functions with KKT conditions. SQP algorithm of MATLAB global optimization toolbox [4] is used for solving for maxima and minima of each objective function after ANN-based objective functions, equalities, and inequalities are substituted into MATLAB global optimization toolbox [4]. Further explanation of ANN-based Lagrange optimization can be found on the Books [5] - [12].

3 Results

Figure 5 presents the distributions of the generated data, including zone area, number of formwork workers, and number of steel workers—randomly generated within the ranges specified in Table 2—as well as the corresponding calculated costs. Table 4 summarizes the training results, with performance evaluated using the root mean square error (RMSE) calculated by Equation (1).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}} \quad \text{Equation (1)}$$

Where:

y_i - The ith test values

$\hat{y}_i$ - ANN-based value of the ith test

N - Number of tests

Table 4: Training quality

No.	Parameter	Layer	Neuron	Best epochs	RMSE
2	Cost	6	40	24057	3.077E-4

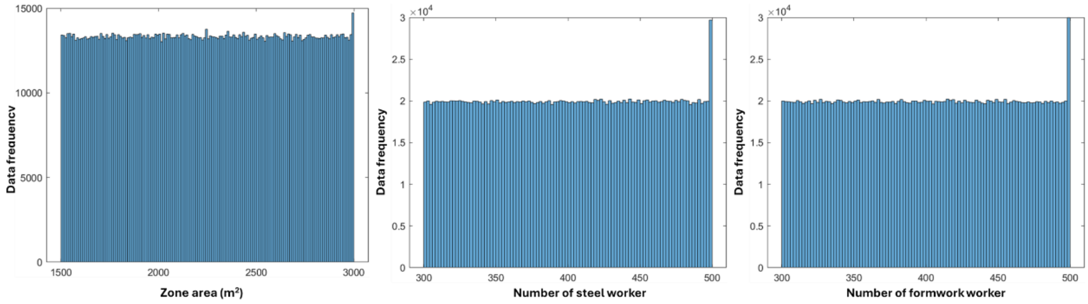


Figure 5: Distribution of big data

Table 4 shows the ANN-based construction plan for minimizing cost. The accuracy of the ANN-based functions is verified by substituting input variables into the data generator, demonstrating that the ANN-based optimized plans achieve considerable accuracy with deviation of 0.0443% between the ANN-based outputs and those calculated by the generator. Figure 6 shows that the cost-optimized plan provided by the proposed algorithm is located at the minimum of the distribution of big data for costs.

Table 4: Cost-optimized plan provided by ANN-based Lagrange algorithm

(1)	**Cost-optimized variables provided by ANN-based Lagrange algorithm**	Zone Area	**2359.1 m^2**
		Number of steel workers	321 men
		Number of formwork workers	300 men
(2)	**Cost predicted by ANNs**		1.680 million $
(3)	**Cost recalculated by construction sequence simulator**		1.681 million $
(4)	**Construction time**		96 days
(5)	**Cost deviation: [(2)-(3)]/(2)*100**		0.0443%

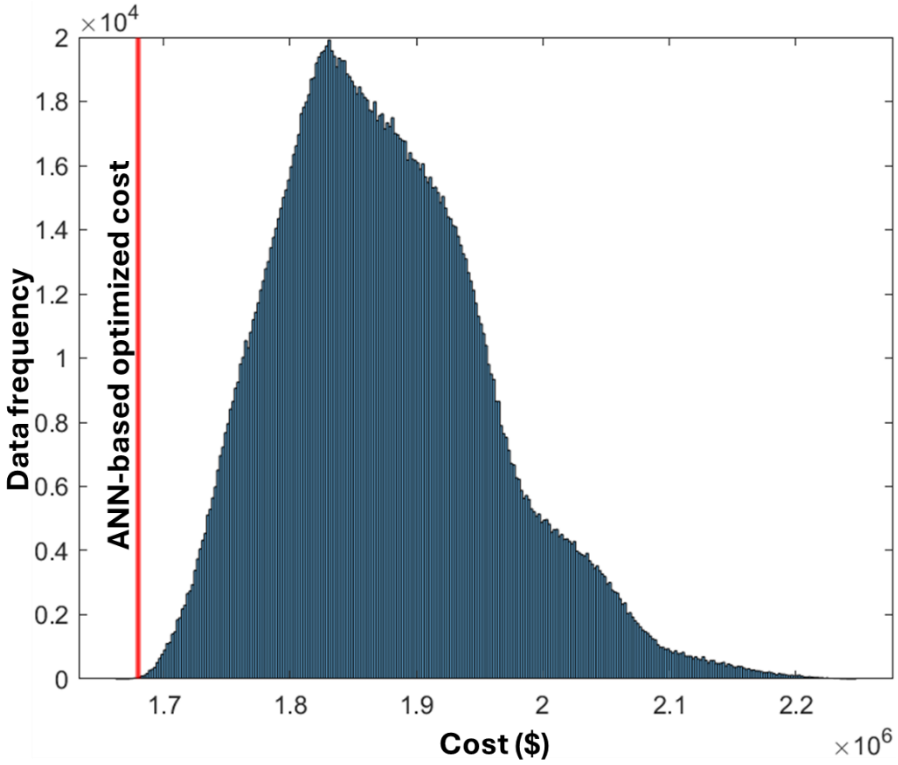


Figure 6: Distribution of big data for cost

4 Conclusions and Contributions

The present study presents a novel algorithm for generating large-scale construction data, enabling the estimation of costs based on the sequential activities of RC structures. The complex relationships between key input variables—zone area and workforce size—and cost are effectively captured using ANNs. A single-objective Lagrange-based optimization framework is then applied to the ANN-derived objective functions, yielding optimized construction plans. Comparisons show considerable accuracy (0.0443% deviation) in prediction and reductions in cost relative to baseline data, highlighting the efficacy and practical potential of the proposed ANN-integrated optimization approach in enhancing construction managing and decision-making.

Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT 2019R1A2C2004965).

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT; Ministry of Science and ICT) (RS-2025-00553289).

References

[1] R.E. Levitt, N.A. Kartam, and J.C. Kunz, "Artificial Intelligence Techniques for Generating Construction Project Plans", in Journal of Construction Engineering and Management, Vol. 114, No. 3, 329–343, 1988.

[2] W. Yin, "Multi-Objective Optimization of Construction Schedule Based on Artificial Intelligence Optimization Algorithm", in *Proceedings of the 2021 3rd International Conference on Artificial Intelligence and Advanced Manufacture*, 1621–1624, October 2021.

[3] J.I. Obianyo, R.C. Udeala, and G.U. Alaneme, "Application of Neural Networks and Neuro-Fuzzy Models in Construction Scheduling", in Scientific Reports, Vol. 13, No. 1, Article 8199, 2023.

[4] The MathWorks, Inc., MATLAB 2024b, in *MATLAB Software*, The MathWorks, Inc., Natick, Massachusetts, United States, Version 2024b, 2024.

[5] W.K. Hong, "Hybrid Composite Precast Systems: Numerical Investigation to Construction", in "Hybrid Composite Precast Systems", Woodhead Publishing, Elsevier, United Kingdom, 2019.

[6] W.K. Hong, "Artificial Intelligence-Based Design of Reinforced Concrete Structures; Artificial Neural-Networks for Engineering Applications", in "AI-Based Design for RC Structures", Woodhead Publishing, Elsevier, United Kingdom, 2023.

[7] W.K. Hong, "Artificial Neural Network-based Optimized Design of Reinforced Concrete Structures", in "Optimized Design of RC Structures", C.R.C. Press, Taylor & Francis, United Kingdom, 2023.

[8] W.K. Hong, "Artificial Neural Network-based Designs of Prestressed Concrete and Composite Structures", in "Optimized Design of Prestressed and Composite Structures", C.R.C. Press, Taylor & Francis, United Kingdom, 2023.

[9] W.K. Hong, "AI-Based Optimized Design of Structural Frames: With Application to Practical Building Designs", in "Optimized Design of Structural Frames", C.R.C. Press, Taylor & Francis, United Kingdom, 2024.

[10] W.K. Hong, "Artificial Intelligence-Based Design of Reinforced Concrete Structures", Daega Publishing, Republic of Korea, October 2021.

[11] W.K. Hong, "AI-based Data-centric Engineering (AIDE) using ANN-based Hong-Lagrange Optimizations", Daega Publishing, Republic of Korea, Chapter 1, October 2022.

[12] W.K. Hong, "AI-based Data-centric Engineering (AIDE) for Reinforced Concrete Columns and Beams using ANN-based Hong-Lagrange Optimization", Daega Publishing, Republic of Korea, December 2022.