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Development of Hybrid Model for Estimating Construction Waste for Multifamily Residential Buildings Using Artificial Neural Networks and Ant Colony Optimization

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Abstract: Due to the increasing costs of construction waste disposal, an accurate estimation of the amount of construction waste is a key factor in a project's success. Korea has been burdened by increasing construction waste as a consequence of the growing number of construction projects and a lack of construction waste management (CWM) strategies. One of the problems associated with predicting the amount of waste is that there are no suitable estimation strategies currently available. Therefore, we developed a hybrid estimation model to predict the quantity and cost of waste in the early stage of construction. The proposed approach can be used to address cost overruns and improve CWM in the subsequent stages of construction. The proposed hybrid model uses artificial neural networks (ANNs) and ant colony optimization (ACO). It is expected to provide an accurate waste estimate by applying historical data from multifamily residential buildings.

Keywords: ant colony optimization; artificial neural network; construction waste; multifamily house; multifamily building

1. Introduction

The amount of construction waste has been increasing yearly and accounts for 10% to 30% of landfill use worldwide [1]. This large volume is due to the fact that construction waste can be generated during any building project, including apartments, detached houses, villas, studios, and infrastructure, even during the clearance of remaining materials, demolished or defective materials, and waste from construction sites [2,3]. Another reason for such a high volume of waste is that contractors might exceed their equipment and labor capability for cleaning up waste and materials, which negatively affects project performance in terms of cost overruns [4]. South Korea has also had problems linked to the growing amount of construction waste due to an increasing number of construction projects and the lack of a construction waste management (CWM) strategy. According to the "Nation's Waste Generation and Disposal, 2013" published by the Ministry of Environment (MOE) of the government of South Korea, the amount of construction waste generated in 2013 was 186,629 tons per day, which accounts for 48.9% of the total domestic waste [5]. As a consequence of the negative effects of the high rate of construction waste, most stakeholders are seeking effective methods for improved disposal cost predictions and the procurement of recyclable materials during the early project stages, which can prevent cost overruns. In particular, concrete waste accounts for approximately 80% to 90% of all waste when some projects are constructed or demolished, which is a relatively high rate [5].

If contractors cannot predict the quantity of waste exactly, the disposal costs are likely to increase and affect a project's budget considerably. The estimation of construction waste amounts is determined using a trial and error process, thereby causing uncertainty. Skoyles [6] suggested that bills related to the quantity of waste during the early stages of a project only provide a fundamental measure of the construction waste which, due to the lack of a reliable estimation method, often leads to an increase of between 15 and 20 times the original estimate during the construction process. Hence, an accurate estimation strategy for construction waste is needed in order to address these issues. In most cases, contractors have only a minimum amount of estimation information at the beginning of a project, which often leads to cost overruns. An accurate estimation strategy is one way to avoid exceeding the budget and leads to economic benefits through the minimizing and recycling of waste.

Several prediction models have been developed for estimating quantity and costs in the construction field, including methods based on regression analysis (RA), case-based reasoning (CBR), and support vector machines (SVMs) [7–10]. Since the 1970s, RA has improved as a method of estimating quantity and cost, and is a very powerful model in construction projects for early stage economic feasibility analysis [9]. However, RA has certain limitations, including the lack of a specific approach for selecting the most suitable model of historical data when predicting construction costs [11,12]. Furthermore, input variables that affect such estimations must be considered beforehand, and it is difficult to manage a large number of variables [12,13]. CBR has been widely used since the 1980s and uses past cases that are similar to the current situation, thereby attempting to modify past cases to adapt to the current problem parameters [14]. CBR has its own inherent problems. For example, it requires a large database to ensure the accuracy of the analysis [15]. Moreover, CBR requires constant updates because it mainly uses the previous experience of an event, circumstance, or simulation [16]. SVM has been used for cost estimations because of its high performance and self-learning capabilities [10]. However, SVM requires a trial and error methodology to determine both a proper core function and the related parameters [17].

Artificial neural networks (ANNs), which imitate the learning process of the human brain, have been applied widely to cost estimation in the construction field [13,14]. Previous studies have described ANNs as being superior to RA, CBR, and SVM for estimating construction quantities and costs [13–15,18–20]. One of the most common ANN algorithms is back propagation (BP), which provides training for the parameter settings to the ANNs. BP does not have a clearly defined theory for the search of suitable parameter settings [7]. Parameters have been determined by trial and error, as well as empirically, which is tedious and time consuming [21]. Previously, a genetic algorithm (GA) was incorporated with ANNs to overcome the problems inherent in BP [14]. However, a GA requires complicated encoding and a decoding operator [22]. In addition, a GA requires a long processing time to generate solutions when the structure of the ANN is complex and there are many training samples [22,23]. As a result, the low convergence speed affects the accuracy of the parameters. To overcome the limitation of previous methods, ant colony optimization (ACO) has been applied to optimize the number of nodes in the hidden layer, the momentum, and the learning rate. ACO mimics the behavior of real ants in a colony. The ants find the shortest way between their nest and a food source using their swarm intelligence and abilities [24]. Ashena and Moghadasi [25] state that ACO is better than GA for finding parameters. Consequently, ACO is the preferred means of optimizing an ANN.

Based on the aforementioned problems, the aim of this research is to predict the exact quantity and cost of construction waste during the early stages of a project in order to address cost overruns in the subsequent stages, and to overcome the limitations of existing models, through the development of a hybrid model. To apply this hybrid model, we focused on the estimation of waste concrete, which accounts for 80% to 90% of all waste when multifamily residential buildings are demolished.

2. Methodology

Figure 1 illustrates our strategy to optimize the ANNs to achieve the goals of the study. The methodology includes the following: (1) an overall review of CWM, including quantity and costs, and an assessment of the verification capabilities of ANNs and ACO; (2) a collection of historical data on multifamily residential buildings and an investigation of the factors that affect the amount of construction waste; (3) selection of the most suitable technical factors as input variables, and the quantity of waste concrete as an output variable; (4) determination of training parameters such as the number of nodes in the hidden layer, the momentum, and the learning rate of BP using ACO and simple ANNs, wherein the weights are automatically adjusted during training; (5) the application of input (distinguishable variables) in a developed system to obtain an output of the quantity of waste concrete using data on actual multifamily residential building projects; (6) budget confirmation by calculating standard costs; and (7) a comparison of the results of the proposed hybrid model with results from simple ANNs.

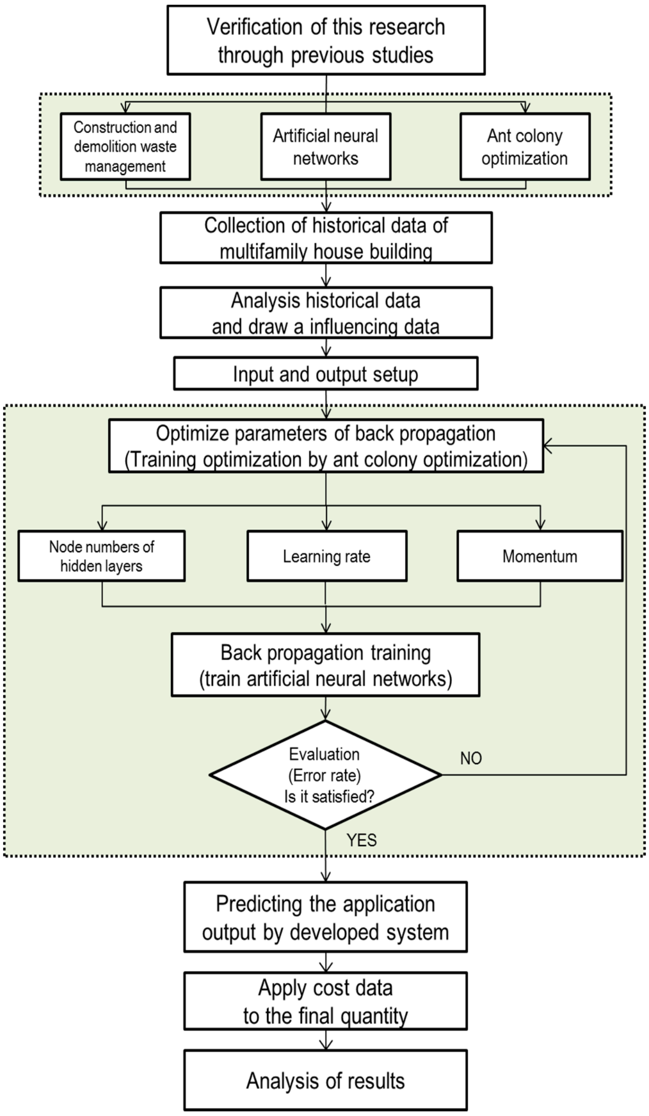

Figure 1. Procedure of the research strategy.

3. Literature Review

3.1. Cost Estimation of Construction Waste

Previous studies have identified cost estimation at the early stage as a key element in determining and choosing appropriate construction waste management practices and technologies [26,27]. Flanagan and Tate [28] described the importance of estimation in the early stages for reducing costs, as shown in Figure 2. Specifically, the cost reduction potential curve shown in the figure reveals that significant cost savings can be achieved in the design and development stages, in contrast to the construction and maintenance stages. Flanagan and Tate [28] proposed that decision-making has a stronger influence on costs, and that the likelihood that contractors can remove unnecessary factors is greater during the early stages of construction. In the opinion of Wu et al. [27], an estimation model can prevent cost overruns by predicting the exact quantity of waste in a project. Therefore, they suggested the use of a computer-based forecast model to estimate construction waste in Hong Kong.

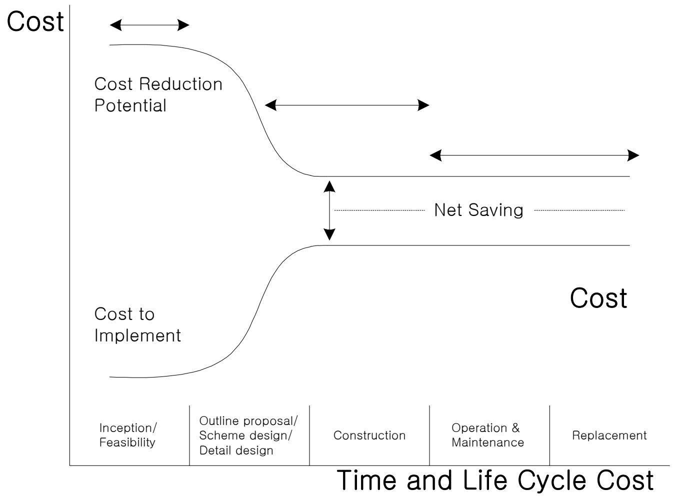

Figure 2. Importance of early stage estimation to reduce cost.

Wrap [29] stated that the accurate cost estimation of construction waste saves 66% in disposal costs. This is because managers can generate the best waste management plan by controlling the amount of labor and equipment, predicting the amount of recyclable materials, and reducing the amount of material waste. Consequently, the overall purpose of accurate cost estimation in terms of construction waste is to prevent cost overruns and reduce costs by improving CWM [26].

3.2. Construction Waste Management

CWM allows contractors to estimate the total amount of construction waste. Accurate estimations lead to improved budgets and the reuse, recycling, and reduction of waste throughout the entire construction process [4,30]. Ndihokubwayo and Haupt [4] stated that a much higher generation of waste than initially estimated occurs as a result of incorrect estimates, design changes, poor decision-making of stakeholders, the site conditions, and problems related to materials. For example, in variation orders, a change in the estimation, design, and scope of a project can result in a 9% cost overrun. Similarly, Gbekor [31] suggested that CWM includes the exact estimation, collection, treatment, and disposal of construction waste. It can be inferred from these research definitions that CWM is the practice of protecting building projects from incurring cost overruns and causing environmental problems. In addition, Mohd [32] categorized the benefits of CWM into three groups: creating environmental benefits, saving money, and improving the economy. Thus, CWM encourages sustainability within the economy by creating value through the recycling of construction waste materials. An excellent CWM strategy in the early stages of a project leads to a reduction in the cost of waste disposal, as well as to high rates of recycling, by reducing the procurement of resources. CWM also saves construction time by reducing the need for design changes, and augments the profits of clients [30]. Therefore, CWM has become necessary for a project's performance in terms of economic profit and sustainability.

To achieve CWM efficiency, it is crucial to know and improve the applied waste forecasting method. The "waste index" is the most popular method of forecasting the amount of construction waste is based on the waste generation rate per construction area and demolition area, and has been used in several studies [2,3,6,33]. Poon et al. [3] measured the amounts of 37 construction waste materials (e.g., cement, concrete, mortar, timber, and steel) based on tons (quantity) and cubic meters (volume) to find the causes of material waste at construction sites in Hong Kong. Bossink and Brouwers [33] weighed and classified the construction waste components at five residential construction sites. The most important finding in each case considered in these studies was that a maximum of 10% of the total material weight had become waste. Seo and Hwang [5] suggested the use of waste intensity units for 11 components of a demolished building. Based on these units, they converted these components into weights and then multiplied the results by the total floor area of demolished buildings in South Korea. As a result, they quantified the waste generation of buildings per square meter. Waste concrete and brick were shown to account for over 90% of CDW. Next, a classification model was presented to forecast a more detailed quantity based on the waste index method. Solis-Guzman et al. [30] clarified this model based on construction project budgets in Spain through the use of a database and spreadsheet that were prepared using site observations. This model can be used by many companies and countries, provided that they have their own classification system when generating a budget. However, these two methods are dependent on data from previous similar projects. Moreover, the accuracy of the results is low due to the different forecasting methods and standards. Kim and Shim [14] mentioned the importance of a hybrid model in preliminary stages and took notice of the necessary input data and their weight scale by verification of the developed hybrid model.

3.3. Artificial Neural Networks

One approach recommended by several academics and practitioners is the use of ANNs. Studies have verified that ANNs are superior to RA, CBR, and SVM for estimating waste amounts and costs. Garza and Rouhana [11] compared ANNs with a parametric estimation model based on RA in terms of carbon steel pipe costs. They used 110 samples with cost parameters, including elbows, flange ratings, and pipe diameters, which were applied to the ANN and RA as inputs. They concluded that ANNs provide better performance than RA, and show strong forecasting capabilities. ANNs do not have a limitation in the number of cost variables they can apply because they can organize and learn by themselves. However, RA has low accuracy (±50% to ±30%) due to its unsuitability for controlling large numbers of variables. Bode [12] suggested that ANNs can find hidden relationships in training data, which is helpful for a cost estimator. They verified their study using the mean absolute relative error (MARE) to measure the performance of each model. The MARE results were 0.623 for RA, 0.352 for ANNs, and 0.362 for CBR, which indicates that ANNs outperform the other two models. Similarly, Viharos and Mikó [15] proved that ANNs have lower error rates (12% on average) than CBR (13%) for estimating costs, and provided the most exact approach. They also suggest that ANNs are able to estimate costs in complex systems using a small amount of input data at the early stage. Kim et al. [20] compared the accuracy of the three estimation models: RA, ANNs, and SVM, for estimating costs in the early stage of a school construction project. This study obtained MARE results indicating that ANNs have better accuracy (5.27) than RA (5.68) and SVM (7.48) for estimating school construction projects.

In addition to the cost estimation of ANNs, some researchers have examined the quantity estimation capability of ANNs [18,19]. Jaliliet et al. [18] and Noori et al. [19] proposed a method for accurately predicting the amount of municipal solid waste, which is important for improving waste management. They compared ANNs to multivariable linear regression (MLR) using a correlation coefficient and the average absolute relative error (AARE). The results show that the ANN coefficient and AARE are 0.837 and 4.4%, respectively, and that the MLR model achieved values of 0.445 and 6.6%. This indicates that ANNs obtain better prediction results for an amount of municipal solid waste than traditional MLR. This research shows that ANNs are simple to use in the case of developing a model when significant information is lacking regarding the cause and effect relationships between the system variables [18,19]. Thus, ANNs are suitable and superior to the other models for quantity and cost estimations.

3.4. Ant Colony Optimization

Ant colony optimization (ACO) is one of the best new computational models for parameter optimization, and overcomes several disadvantages of ANNs [25]. ACO is quite effective and useful when the search space is large and complex, and requires a short computation time [25,34–37]. These studies show that ACO finds parameters (such as the weight, the number of nodes in a hidden layer, bias, and threshold) in less time. Previous studies have explained the need in various industries to optimize the performance of the ANNs by applying ACO. Li and Chung [34] developed computing software that is an improvement on previous algorithmic models for solving the specific optimization problems inherent in BP training. They compared a combination of ANNs and ACO with simple ANNs to verify their performance. The results show that the generalization errors in the learned and unlearned data of ACO-based ANNs (0.09, 0.11) are lower than those for simple ANNs (0.21, 0.36). Subsequently, Ashena and Moghadasi [25] used ACO to optimize the thresholds and weights of ANNs for bottom hole pressure estimations. They compared ACO with GA-based ANNs to examine the performance of ACO. The results show that ACO achieves better results; i.e., the mean square errors (MSEs) of ACO and GA are 0.0014 and 0.0018, respectively, and their efficiency coefficients are 0.9896 and 0.9109, respectively. The results of Hatampour et al. [37] also supported the aforementioned research, showing that the capability of optimized ANNs is greater than that of simple ANNs. They used ACO to optimize the numbers of hidden layers, weights, and biases in the proposed ANNs for predicting the permeability of petroleum reservoir rocks. These results demonstrate that ANNs optimized using ACO perform better than simple ANNs. Wang and Guo [36] verified that ACO, unlike other research approaches, can optimize the numbers of nodes in ANN hidden layers for a macroscopic water distribution system. They also compared ACO-based ANNs to an RA model, and showed that the hybrid model reduces the MSE by over 40% compared with RA.

The advantages of ACO in the aforementioned studies are contributed computations, heuristic techniques, and positive feedback [35]. Contributed computations can efficiently avoid premature convergence, heuristic techniques can be used to find better potential solutions at the early stage, and positive feedback ensures the fast detection of better solutions [38]. Therefore, ANNs with ACO provide a good approach for solving several types of optimization problems.

4. Model Development

4.1. Artificial Neural Networks

ANNs imitate the learning process of the human brain. They are attracting the interest of researchers due to their good performance in the modeling of nonlinear relationships, and have been widely applied in the construction field to estimate costs [13,14]. Figure 3 shows a neural network structure in which $X_1, X_2, \ldots, X_n$ are input layers that accept information from the outside; W_{ij} and W_{jk} are weights of the connection strength between neurons; θ is the threshold; f is a nonlinear activation function; and Y is an output layer in which output information is processed in the neural network, which is represented by Equation (1) [39]. Basically, ANNs comprise more than one layer between the input and output layers; i.e., the connected input, hidden, and output layer directions.

$$Y = \sum_{i=0}^{n} W_i \cdot X_i - \theta_i \quad (1)$$

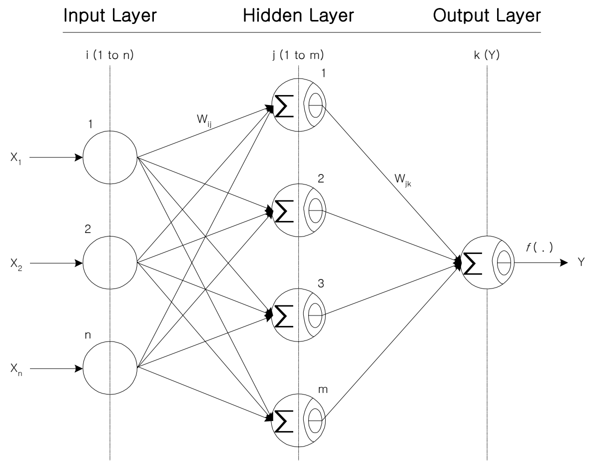

Figure 3. The structure of a neural network.

ANNs are divided into two work processes: training and testing. The network training process sets the training samples in the input and output models for training the network parameters. The most typical method applied in multilayer neural networks is BP, which manages the training algorithm [39]. BP usually contains a nonlinear sigmoid transfer function to compute the output. Equations (2) and (3) describe the output of each hidden neuron and the output of each output neuron, respectively. (Each variable is defined above.)

$$f\,(x_i) = 1\;/\;(\,1 + \exp(\,-(\,\textstyle\sum_1^n x_i{\cdot}w_{ij} - \theta_{ij}))) \quad (2)$$

$$f\,(x_j) = 1\;/\;(\,1 + \exp(\,-(\,\textstyle\sum_1^n x_j{\cdot}w_{ij} - \theta_{ij}))) \quad (3)$$

In contrast, the test run process can calculate the equivalent output from a new input [40]. Therefore, ANNs that actually simulate the mechanism of the human brain can automatically detect the regulations and output of the given environment.

$$P_i^k\,(t) = \begin{cases} \dfrac{[\tau_i(t)]^{\alpha}\cdot[\eta_i]^{\beta}}{\sum_{l\in J^k}[\tau_l(t)]^{\alpha}\cdot[\eta_l]^{\beta}}, & i\,f \in i\,J^k \\ 0 & \end{cases} \quad (4)$$

where η_i is a heuristic approach for selecting task i that is needed for high performance, and J^k is the set of possible characteristics. Two parameters (α and β) decide an ant's pheromone value and empirical information, and $\tau_l(t)$ is the amount of virtual pheromone for task i. The pheromones are updated as shown by Equation (5):

$$\tau_i\,(t+1) = (1-\rho)\cdot\tau_i\,(t) + \textstyle\sum_{k=1}^{m}\Delta_i^k\,(t) \quad (5)$$

In addition, ρ simulates the evaporation of pheromones to indicate decay. According to Equation (5), every ant can update its pheromone trail. There are many routes from the nest to the feeding area, but as time passes, the pheromones evaporate and their concentration is weakened. Consequently, the concentration of pheromones in a short path remains strong. Therefore, among the many paths possible, ants tend to choose a short path where the pheromones remain strong.

4.2. Description of Data

The data collected for the development of the proposed model are based on the minimum 1st floor and maximum 17th floor of 118 multifamily residential building projects built by general contractors between 1959 and 1986 in South Korea. These projects were demolished between 1998 and 2010.

Skitmore [41] stated that the accuracy of estimation for a building project is generally associated with the amount of available project information such as the year, location, gross floor area, and number of stories. As shown in Table 1, data on the quantity estimation of waste concrete, which is one of the CDWs used in this study, were collected. Eight input variables and one output variable were easily obtained during an early project stage.

Table 1. Input and output variables.

Description		Min.	Max.	Average	Remark
Input	Location	Seoul, Gyeonggi, Incheon, Daegu, Busan, Gwangju			Categorical
	Stories	2	17	5	Numerical
	No. of buildings	1	56	7.1	
	Completion year	1959	1986	1976	
	Demolition year	1998	2010	2006	
	No. of houses	20	2260	254	
	Gross floor area	730	104,434.6	14,212	
	Lot area (m^2)	1015	934,597	23,638	
Output	Total quantity of construction waste				

Historical data are based on past information, and these values need to be revised. Thus, the years of completion and demolition were not used as input variables, but were used as a standard for converting extracted variables based on an index of average yearly fluctuation. The data collected from 118 projects were randomly divided into 15 test cases and 103 training cases. Moreover, the data collected for training were classified randomly into 85 training datasets and 18 cross-validation datasets. These were used for testing the ANNs during the training process. Specifically, BP requires cross-validation data to avoid over-training [42]. Over-training means that all new data are considered equal to the training data, making it difficult to explicitly describe the new data. Thus, ANNs require generalization by applying cross-validation to improve the description of new data, although such a generalization could lead to lower accuracy of the description of the training data.

4.3. Parameter Set-up

Setting the parameters of the ANNs and ACO is crucial for designing the model itself. The parameter values of the ANNs and ACO are used to determine the best architecture for some specific problems in order to generate the best prediction or pattern recognition results. For achieving optimized value, ACO is available to assist in conducting ANN computations. The parameters that affect the performance of the ACO are the number of ants, a pheromone decay parameter, an updated strength parameter of the local pheromone, and the generations. For the exploration of ants in this study, we used 5 to 20 ants to test the performance. A larger number of ants leads to an increase in the time consumed to reach a solution and decreases the error rate for testing the ANNs. Sivagaminathan and Ramakrishnan [43] suggested that a pheromone decay parameter of 0.9 and an updated strength parameter of 0.8 are suitable for future generation ants, which influenced how we determined the proper direction. The number of generations is crucial for the algorithm's performance in terms of time and error. This study used 5 to 20 generations. Consequently, eight ants and eight generations have the lowest error rates of 3% and 2%, respectively. Through the training of the ANNs using ACO, we optimized three parameters: the number of nodes in the hidden layer, the momentum, and the learning rate. The weights were automatically adjusted during the training session using MATLAB 7.0. ANNs were trained from 88 cases through the BP training processes using ACO. The training results of the developed model based on cross-validation data showed the smallest MSE with six hidden layer nodes, a learning rate of 0.8, and a momentum of 0.8. For a comparison with the hybrid model, simple ANNs were set to three hidden layer nodes, a learning rate of 0.6, and a momentum of 0.9.

5. Model Application

5.1. Evaluation

Although a considerable number of statistical parameters are used for performance comparisons, the MSE, mean absolute error rate (MAER), and standard deviation are the most appropriate according to Ashena and Moghadasi [25]. Thus, the training and testing performances were evaluated using MSE and MAER, respectively, as follows:

$$\text{MSE} = \frac{\sum_{i=1}^{n} (O_i - T_i)^2}{n} \tag{6}$$

$$\text{MAER} = \frac{\sum \left| \frac{Q_e - Q_a}{Q_a} 100 \right|}{n} \tag{7}$$

where Q_i is the historical value of the output for the ith sample, T_i is the expected value of Q_i, and n is the number of training cases in Equation (6). In addition, in Equation (7), Q_e is the quantity to be estimated when applying the model and Q_a is the historical amount of data collected. The performance of the simple ANNs and the developed model using 15 test datasets was evaluated using the MAER and standard accuracy, which is summarized in Table 2. The standard deviation of each model is shown in Table 3. Coulibaly and Baldwin [44] suggested that an efficiency coefficient of 0.9 shows the most suitable model performance, a range of 0.8 to 0.9 indicates good performance, and a value lower than 0.8 indicates inadequate model performance.

Table 2. Results of estimating quantity of each test set.

No.	Historical Quantity (m^3)	Simple ANNs			ANNs + ACO		
		Expect Quantity	Error Rate (%)	Accuracy (%)	Expect Quantity	Error Rate (%)	Accuracy (%)
1	9975	13,535	26.3	73.7	11,572	13.8	86.2
2	24,775	27,035	8.36	91.64	23,114	6.7	93.3
3	6300	7374	14.56	85.44	6304	0.06	99.94
4	8190	14,459	43.36	56.64	11,712	30.07	69.93
5	57,461	41,828	27.2	72.79	43,880	23.64	76.36
6	18,276	19,071	4.17	95.83	17,447	4.53	95.46
7	4725	6657	29.02	70.98	5392	12.37	87.63
8	12,650	11,278	10.85	89.15	9135	27.78	72.21
9	6310	4583	27.37	72.63	5331	15.52	84.48
10	55,666	59,786	6.89	93.11	56,498	1.47	98.53
11	145,432	125,760	13.52	86.47	128,843	11.41	88.59
12	89,373	86,029	3.74	96.26	92,137	2.99	97
13	63,517	55,578	12.49	87.5	59,524	6.29	93.71
14	10,334	12,877	19.75	80.25	13,791	25.06	74.93
15	30,415	38,620	21.25	78.75	41,362	26.47	73.53
MAERs			17.92			13.88	
Accuracy				82.08			86.12

Table 3. Descriptive analysis value of statistical parameters.

	Mean	Std. Deviation	Std. Error	Accuracy	Efficiency Coefficient
Simple ANNs	17.9231	10.7816	2.8815	82.0768	0.988757
ANNs + ACO	13.8788	10.0168	2.6771	86.1212	0.988914

5.2. Standardization of Cost Data

Before the standardization of cost data can be applied, the unit of output (m^3) needs to be converted into tons. One cubic meter can be converted into 1.65 tons according to standardized specifications in South Korea. We used the standard costs of the Korea Resource Association (KORAS) guidelines to build a budget, and compared the final results of the two models using 15 test cases, as shown in Table 4. The average disposal cost of waste concrete in South Korea is £9.22 (15,935 KRW) per ton, which includes indirect material costs including the use of equipment, direct and indirect labor costs, overhead costs, general management expenses (profit), and additional taxes (10% of the total cost) based on standardized specifications. Table 5 shows the disposal costs for waste concrete from 1998 to 2010.

Table 4. Results of estimating the cost of each test set.

No.	Historical Cost (1000 KRW)	Simple ANNs			ANNs + ACO		
		Quantity (Ton)	Unit Cost	Expect Cost	Quantity (Ton)	Unit Cost	Expect Cost
1	262,270	22,332.75	15,935	355,872	19,093.8	15,935	304,260
2	651,403	44,607.75	15,935	710,824	38,138.1	15,935	607,731
3	165,644	12,167.1	15,935	193,883	10,401.6	15,935	165,749
4	215,338	23,857.35	15,935	380,167	19,324.8	15,935	307,941
5	1,510,808	69,016.2	15,935	1,099,773	72,402	15,935	1,153,726
6	480,526	31,467.15	15,935	501,429	28,787.55	15,935	458,730
7	124,233	10,984.05	15,935	175,031	8896.8	15,935	141,771
8	332,603	18,608.7	15,935	296,530	15,072.75	15,935	240,184
9	165,907	7561.95	15,935	120,500	8796.15	15,935	140,167
10	1,463,612	98,646.9	15,935	1,571,938	9,3221.7	15,935	1,485,488
11	3,823,807	207,504	15,935	3,306,576	212,590.95	15,935	3,387,637
12	2,349,862	141,947.85	15,935	2,261,939	152,026.05	15,935	2,422,535
13	1,670,037	91,703.7	15,935	1,461,298	98,214.6	15,935	1,565,050
14	271,709	21,247.05	15,935	338,572	22,755.15	15,935	362,603
15	799,694	63,723	15,935	1,015,426	68,247.3	15,935	1,087,521

The unit cost focuses only on pure waste concrete when apartments, commercial buildings, roads, or bridges are constructed or demolished. To obtain the expected cost, the quantity of each test set (tons) is multiplied by the unit cost, which is based on the average yearly demolition cost. These average results were then compared with the historical costs.

Table 5. Disposal cost of waste concrete from 1998 to 2010.

Year	Unit	Cost (KRW)
1998	Per ton	13,854
1999		14,524
2000–2001		15,066
2002–2003		15,767
2004–2007		15,896
2008–2009		17,921
2010		16,239
Average		15,935

6. Results

The results of the two estimation models were obtained by trial and error and through ACO using the 15 cases from testing. The average accuracy of the simple ANNs was 82.08%, and that of the developed model was 86.12%. The simple ANNs and the developed model with 15 test datasets provided average MAERs of 17.92 and 13.88, standard deviations of 10.78 and 10.02, and standard errors of 2.88 and 2.68, respectively. In terms of the efficiency coefficient, the two models showed similar results. Two values, 0.988757 and 0.988914, were evaluated as the most suitable model performances by Coulibaly and Baldwin [44]. Thus, the developed model had a higher accuracy, smaller MAER, and better standard deviation and error than the simple ANNs. In terms of performance, an ANN with ACO is the most reliable and exact model for estimating waste quantities.

7. Discussion

A total of 9 out of 15 (60%) of the test datasets are in the range of the normal distribution of errors in this result. Although the average deviation and error rates are verified within a statistical range, more than normal 60% data are recommended in order to expect a more reliable result. When we applied cost data to the converted output variables, ANNs incorporating ACO outperformed the simple ANNs in terms of budget accuracy. Notably, Table 4 shows that the costs of the six test sets (2, 3, 6, 10, 12, and 13) are almost similar to the historical cost data. Although the results of the simple ANNs in terms of quantity and cost for waste concrete also show a higher accuracy and efficiency coefficient, the results of the developed model are better than those of the simple ANNs. Therefore, we suggest that the developed model is a suitable estimation tool for solving the aforementioned problems. To summarize the advantages of this model, the difficulty in determining the ANN parameter is solved, and the time and effort required to obtain the ANN parameter are reduced.

8. Conclusions

Accurate quantity predictions and cost estimations of construction waste during the early stages of construction are key factors in securing a project's success. However, the increasing amount of construction waste and the lack of estimation strategies have complicated attempts to accurately estimate these quantities and costs. To address this problem, a new model is proposed that applies ANNs incorporated with an ACO. ANNs have a problem in finding the BP parameters. Therefore, ACO is employed to optimize the parameters (i.e., the number of hidden layer nodes, the momentum, and the learning rate). In this study, simple ANNs were compared with ANNs optimized using ACO. Our results show that the proposed hybrid model estimates more efficiently and accurately the amount of waste concrete during the early stages of a project because its error rates are lower and its accuracy is higher than in the case of simple ANNs. Thus, the hybrid model reduces the training time and calculation complexity, and improves the estimation accuracy. Having obtained ideal performance in terms of ANN optimization, we suggest that the proposed approach can facilitate the solution of similar problems associated with the use of ANNs. We suggest that our research results will help in the decision-making process for budget estimations by modeling the nonlinear relationships of technical factors, and by providing more convenient estimation models that are easier for the construction industry to use.

Further detailed study is necessary for practical applications, such as sensitivity analysis for investigating the effects of different ranges of model parameters on waste estimates. Also, in further research, three limitations should be considered in achieving higher performance. First, the use of waste concrete estimates to represent total construction waste should be considered because practical application of the ANNs + ACO model is necessary in order to determine the exact rate of considered materials. Second, the results from the proposed model were only compared to Korean residential projects. Therefore, more model validation with recent projects is recommended because the reliability of the developed model is generally high with a varied case set. Finally, additional input parameters should be used for total construction waste estimates—for example, the architectural style and the construction technology.

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