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Multi-Objective Optimization Model for Thermal-Mechanical Treatment of Recycled Concrete Aggregate

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Abstract: Efficient use of recycled concrete aggregates (RCA) produced using construction and demolition (C&D) waste can help solve many of the problems, such as reducing the consumption of huge amounts of natural aggregate and the generation of construction waste. Thermal-mechanical treatment is becoming a convenient method for recycling old concrete, but research to determine its implementation parameters is almost always conducted through experimental methods. In this paper, the MOO model, which takes heating temperature and mechanical treatment time as input variables and apparent density and water absorption rate as output variables, is derived to determine the experimental conditions for obtaining high-quality RCA and suggests a multi-objective optimization model for the thermal-mechanical treatment of recycled concrete aggregates. When using this mathematical model, under the same basic conditions (heating method, parameters of the treatment machine, etc.), the optimal thermal-mechanical treatment working parameters (heating temperature and mechanical treatment time) can be predicted in advance only by changing the boundary condition values without a large number of experiments. Although the experiment to prove the results of optimization modeling established in this paper has not been carried out, a mathematical method has been proposed to predict the experimental conditions which will help reduce the cost of high-quality RCA production or provide a scientific guarantee for the experiment.

Keywords: Recycled Concrete Aggregate, Thermal-Mechanical Treatment, Apparent Density, Water Absorption Rate, Back Propagation Neural Network, Multi-Objective Optimization

1. Introduction

In recent years, with the acceleration of urbanization, excessive demolition work and construction activities have resulted in the generation of a large amount of construction and demolition (C&D) waste, especially concrete waste, which has caused serious consequences and is also harmful to the environment significant impact on society [1]. Worldwide, it is reported that around 48 billion metric tons of aggregate are consumed in the construction industry [2], and the total annual C&D waste generation exceeds about 3 billion tons [3]. Concrete development using recycled concrete is attracting wide attention as the demand for sustainability in the construction industry increases [4, 5]. Efficient use of recycled concrete aggregate (RCA) produced using C&D waste can help solve many of the problems such as the consumption of huge amounts of natural aggregate and the generation of construction waste [6-8]. For example, the production of 1ton RCAs could reduce carbon emission by 23%-28% and construction cost by 34%-4% respectively compared with the exploitation of natural aggregates (NAs) [9]. Thus, the incorporation of RCAs in concrete is beneficial for sustainable development of the construction industry.

RCA is an aggregate type composed of two main components: adhesive mortar and NA, with approximately 65-70% by volume of aggregate and the remaining 30-35% of cement paste [10]. The high-content cement paste of RCA can greatly affect the properties of RCA, increase porosity and water absorption rate, and lower abrasion resistance [10]. Therefore, the overall properties of RCA are not as good as NA which may lead to poor engineering performances of concrete materials incorporating RCA, especially asphalt concrete [11, 12].

To remove the mortar adhered with weak adhesion to the surface of RCA, many researchers focused on researching the physical surface treatment method.

Conventional heating and microwave heating methods use thermal stress generated by high temperatures to affect the mortar-aggregate interface, so that mortar, which is easy to peel off, can be separated from the NA [13-16]. Mechanical treatment is a general treatment method for producing high-quality RCA by separating the attached mortar from the NA using mechanical equipment [17-22]. However, the mechanical treatment method is a quick processing method that removes the mortar attached to the RCA by an external force but inconveniently achieves the goal of peeling and separation [23].

To improve the quality of RCA, some methods such as thermo-mechanical treatment are still under development [24-27]. Thermo-mechanical treatment is a convenient method for recycling old concrete. Reducing the heat treatment temperature and using simply designed equipment will help to improve the applicability of this method in field application [24].

But, in not only the heating treatment and mechanical treatment but also the thermal-mechanical treatment of which the effect is recognized as very high [24], all researchers have experimentally determined the heating treatment temperature and mechanical treatment time to obtain the target value of RCA (apparent density and water absorption rate, etc.).

Although numerous studies have been carried out on the thermal-mechanical treatment of RCA, most of them are mainly conducted by experimental methods, and no research has been undertaken using the mathematical model method. If the mathematical model is combined with the experiment in solving this problem, it will not only save a lot of cost and time but also have the advantage of using mathematical methods to calculate and design the optimizing point.

In the paper, firstly, to study the thermal-mechanical treatment of RCA, establish the functional relationship between input data (heating treatment temperature and mechanical treatment time) and out data (apparent density and water absorption rate) by using an artificial neural network based on the experimental data in the reference [25]. Secondly, a multi-objective optimization model with density and absorptivity as objective functions is established to calculate the optimal point in the given boundary condition interval.

2. The Basic Theories for Mathematical Modeling

2.1. Back Propagation Neural Network (BPNN)

In the thermal-mechanical treatment of RCA, the relationship between the working parameters is complex, so, when the heating temperature and mechanical treatment time each change, it is difficult to determine the functional relationship between them and the apparent density and absorptivity of RCA. ANN has the advantages of fast processing speed, simple calculation, and no need to assume the exact relationship between input and output variables, so it is an effective method to estimate complex processes [28]. Many artificial neural network models are used to estimate complex nonlinear problems [29-33]. Among them, BPNN is widely used because it has strong nonlinear mapping ability [34].

Figure 1 shows the structure of BPNN.

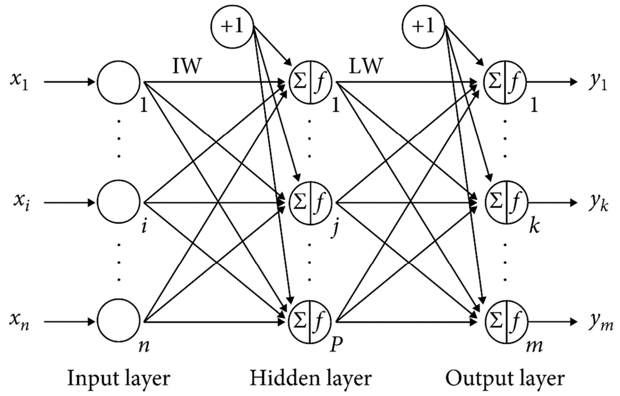

Figure 1. *Back propagation neural network (BPNN).*

The number of neurons in the hidden layer of BPNN is calculated by Eq. (1) [31, 35].

$$P = \sqrt{n+m} + \alpha \tag{1}$$

where u is the neuron number of the hidden layer, n is the neuron number of input layer, m is the neuron number of output layer, α is an adjusting constant, the range of α is the integer between 1 and 10.

The output model of the hidden layer neuron is computed as

$$Q_j = f(\sum W_{ij} X_i - b_j) \tag{2}$$

where W_{ij} is the weight between the ith neuron of the input layer and the jth neuron of the hidden layer, b_j is the threshold matrix, X_i is the vector of input variables, and f is the neuron transfer function between the input layer and hidden layer. Logsig and tansig functions are widely used in the transfer function.

The output model of the output layer neuron is computed as

$$G_k = f(\sum W_{jk} Q_j - b_k) \tag{3}$$

where W_{jk} is the weight between the jth neuron of the hidden layer and the kth neuron of the output layer, b_k is the threshold matrix, and f is the neuron transfer function between the hidden layer and output layer. Purelin function is widely using in the transfer function. If the training error of the neural network does not meet the allowable conditions, its threshold and weight shall be readjusted until the error is less than the expected value.

2.2. Multi-Objective Optimization (MOO)

Multi-objective optimization (also known as multi-objective programming, vector optimization, multicriteria optimization, multi-attribute optimization, or Pareto optimization) is a field of multicriteria decision-making, involving mathematical optimization problems involving simultaneous optimization of multiple objective functions. Multi-objective optimization has been applied to many scientific fields, including engineering, in which optimal decisions need to be made under the condition of the trade-off between two or more potentially conflicting objectives. In fact, in many practical engineering applications, designers make decisions between conflicting goals. In these cases, a multi-objective optimization study should be conducted, which provides multiple solutions that represent trade-offs between objective functions [36].

The mathematical expression of multi-objective optimization is as follows.

$$\left.\begin{array}{r} \min\ f(X) = \sum_{i=1}^{m_1} \sigma_i f_i(X) \\ s.t. Y_j(X) \geq 0\ (j = 1, 2, \dots, m_2) \\ g_k(X) = 0\ (k = 1, 2, \dots, m_3) \end{array}\right\} \tag{4}$$

where $[x_1, x_2, \dots, x_n]^T$ is the design parameters, $f(X)$ is the target function, $Y_j(X)$ and $g_k(X)$ are the constraint function, σ_i is the weighting factor of $f_i(X)$, and can be expressed as

$$\begin{cases} \sigma_1 = \dfrac{f_{m_1}(X^{*1}) - f_{m_1}(X^{*m_1})}{[f_1(X^{*m_1}) - f_1(X^{*1})] + [f_2(X^{*(m_1-1)}) - f_2(X^{*2})] + \cdots + [f_{m_1}(X^{*1}) - f_{m_1}(X^{*m_1})]} \\ \sigma_2 = \dfrac{f_{m_1-1}(X^{*2}) - f_{m_1-1}(X^{*(m_1-1)})}{[f_1(X^{*m_1}) - f_1(X^{*1})] + [f_2(X^{*(m_1-1)}) - f_2(X^{*2})] + \cdots + [f_{m_1}(X^{*1}) - f_{m_1}(X^{*m_1})]} \\ \qquad \vdots \\ \sigma_{m_1} = \dfrac{f_1(X^{*m_1}) - f_1(X^{*1})}{[f_1(X^{*m_1}) - f_1(X^{*1})] + [f_2(X^{*(m_1-1)}) - f_2(X^{*2})] + \cdots + [f_{m_1}(X^{*1}) - f_{m_1}(X^{*m_1})]} \end{cases} \tag{5}$$

where $f_i(X)$ is the i th sub-objective function, X^{*i} is the optimum solution of the ith sub-objective function, $f_i(X^{*i})$ is the ith sub-objective function value obtained using X^{*i}. The optimization toolbox of the MATLAB is used to solve the MOO problem.

3. Numerical Results

In this paper, firstly, the experimental value of particle size 8/16mm in the reference [25] is used as the training sample to train the BPNN described in section 2.1, and on this basis, the functional relationship of heating temperature T, mechanical treatment time t and apparent density ρ, water absorption rate W is derived. In this case, the BP model includes one hidden layer, an input layer, and an output layer, in which T and t are used for input data, and the ρ and W are used for output data.

The results of BPNN training are as follows.

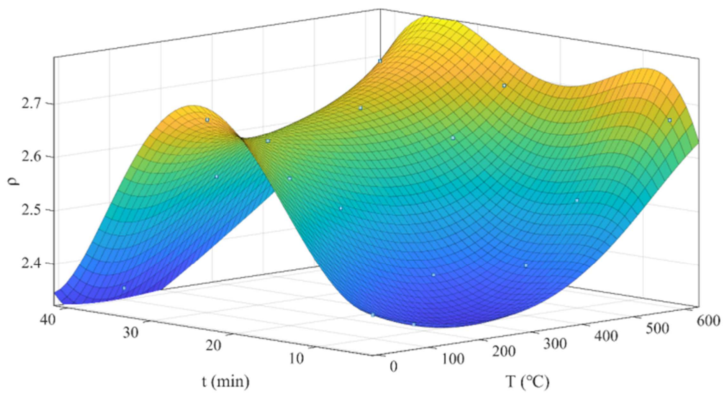

Figure 2. *Functional relationship of heating temperature T, mechanical treatment time t and apparent density ρ.*

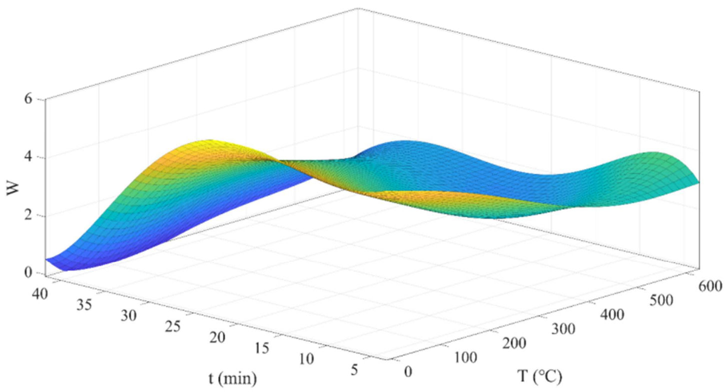

Figure 3. *Functional relationship of heating temperature T, mechanical treatment time t and water absorption rate W.*

$$\rho = p_1 + p_2T + p_3t + p_4T^2 + p_5Tt + p_6t^2 + p_7T^3 + p_8T^2t + p_9Tt^2 + p_{10}t^3 + p_{11}T^4 + p_{12}T^3t + p_{13}T^2t^2 + p_{14}Tt^3 + p_{15}t^4 + p_{16}T^5 + p_{17}T^4t + p_{18}T^3t^2 + p_{19}T^2t^3 + p_{20}Tt^4 + p_{21}t^5 \quad (6)$$

$$W = q_1 + q_2T + q_3t + q_4T^2 + q_5Tt + q_6t^2 + q_7T^3 + q_8T^2t + q_9Tt^2 + q_{10}t^3 + q_{11}T^4 + q_{12}T^3t + q_{13}T^2t^2 + q_{14}Tt^3 + q_{15}t^4 + q_{16}T^5 + q_{17}T^4t + q_{18}T^3t^2 + q_{19}T^2t^3 + q_{20}Tt^4 + q_{21}t^5 \quad (7)$$

where p_i, q_j are coefficients, as shown in Tables 1 and 2.

Table 1. *Values of* p_i.

p_1	2.4	p_8	4.8×10^{-7}l	p_{15}	-5.3×10^{-6}
p_2	-1.7×10^{-4}	p_9	-8.5×10^{-6}	p_{16}	-9.9×10^{-15}
p_3	-7.6×10^{-3}	p_{10}	7.9×10^{-5}	p_{17}l	3.3×10^{-13}
p_4	9.3×10^{-8}	p_{11}	1.2×10^{-11}	p_{18}	-5.3×10^{-12}
p_5	-5.2×10^{-5}	p_{12}l	-2.3×10^{-10}	p_{19}	3.9×10^{-10}
p_6	1.1×10^{-3}	p_{13}	-2.2×10^{-8}	p_{20}	-8.9×10^{-9}
p_7	-3.8×10^{-9}	p_{14}	5.9×10^{-7}	p_{21}	6.9×10^{-8}

Table 2. *Values of* q_j.

q_1	6.3	q_8	5.1×10^{-6}	q_{15}	-4.6×10^{-5}
q_2l	-2.3×10^{-3}	q_9	-6.1×10^{-5}	q_{16}	-1.6×10^{-13}
q_3l	-0.2	q_{10}	6.9×10^{-4}	q_{17}	4.2×10^{-12}
q_4	-6.4×10^{-6}	q_{11}	2.2×10^{-10}	q_{18}	-5.8×10^{-11}
q_5	-7.2×10^{-4}	q_{12}	-4.0×10^{-9}	q_{19}	3.4×10^{-9}
q_6	9.9×10^{-3}	q_{13}	-1.8×10^{-7}	q_{20}	-7.3×10^{-8}
q_7	-8.4×10^{-8}	q_{14}	4.7×10^{-6}	q_{21}	5.9×10^{-7}

Then, based on the MOO theory described in section 2.2, the multi-objective optimization model has been established as follows.

$$\left.\begin{array}{c} min\, f(T,t) = \sigma_1/\rho + \sigma_2 W \\ s.t. \rho \geq 2.5 \\ W \leq 3 \\ 0 < T \leq 600 \\ 0 < t \leq 40 \end{array}\right\} \quad (8)$$

According to Eq. (5), the values of the weighting factors σ_1 and σ_2 are as follows.

$$\sigma_1 = 0.897 \quad (9)$$

$$\sigma_2 = 0.103 \quad (10)$$

The boundary values of ρ and W have been determined according to JIS A5021 [37], and the boundary values of T and t have been determined according to the experimental values [25].

Based on the model (Eq. (8)), solving the questions raised, then, the optimization was obtained when the heating temperature was 364°C and the mechanical treatment time was 40 min. At this time, the apparent density is 2.5g/cm^3, and the water absorption rate is 1.2%.

4. Conclusion

In this paper, the MOO model, which takes heating temperature and mechanical treatment time as input variables and apparent density and water absorption rate as output variables, is derived to determine the experimental conditions for obtaining high-quality RCA. When using this mathematical model, under the same basic conditions (heating method, parameters of treatment machine, etc.), the optimal working parameters (heating temperature and mechanical treatment time) can be predicted in advance only by changing the boundary condition values without a large number of experiments.

Although the experiment to prove the results of optimization modeling established in this paper has not been carried out. However, a mathematical method has been proposed to predict the experimental conditions that can achieve the goal, which will help reduce the cost of high-quality RCA production or provide a scientific guarantee for the experiment.

Highlight

1) Efficient use of recycled concrete aggregates produced using construction and demolition (C&D) waste can help solve many problems.
2) Thermal-mechanical treatment is a convenient method for recycling old concrete.
3) The research on the treatment of recycled concrete aggregates only depends on experimental methods.
4) A multi-objective optimization model for the thermal-mechanical treatment of recycled concrete aggregates was proposed.

Conflict of Interest Statement

All the authors do not have any possible conflicts of interest.

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