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Research Article

Multiobjective Construction Optimization Model Based on Quantum Genetic Algorithm

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It is critical for the construction party to meet the established economic and social demand for the construction project with the shortest construction period and the lowest cost. In this study, the construction characteristics of the project were analyzed. In addition, the multiconstraint and multitarget construction optimization model with minimum period and cost was established based on the quantum genetic algorithm. In order to improve the adaptability of the quantum genetic algorithm for the multiobjective model, the encoding form, quantum revolving door, and genetic flow of the algorithm were reconstructed. MATLAB 2016b was used as the simulation platform, and the implementation of the algorithm was improved according to the characteristics of the variables in the construction project, including period and cost. Finally, the optimization of the algorithm was verified and analyzed by an engineering example. The results showed that using the multiobjective quantum genetic algorithm, the optimal duration/cost can be achieved and the most reasonable and effective control decision scheme for the construction management can be provided through the Pareto solution set.

1. Introduction

With the development of the world economy, more and more attention has been paid to the duration and cost of projects [1]. Large construction projects have large capital investment and long construction cycle [2]. In order to minimize the duration and cost of the project, it is critical to design an effective construction organization plan [3]. The purpose of the construction plan is to obtain a short construction period and a low cost. Researchers have focused on the studies to optimize the period and cost of construction. However, in the optimization algorithm, there is an inevitable conflict between schedule and cost [4]. Therefore, optimization is also known as striking a balance between duration and cost [5]. The optimization balance means that, under the constraints of personnel, machinery, and materials, managers can reasonably allocate resources to achieve the minimum combination of time and cost by appropriately increasing the cost/time of subprojects under the same circumstances [6].

Traditional balance strategy includes the critical path method, integer programming method, and enumeration method. However, due to the expansion of the construction project scale nowadays, the computational complexity has been growing exponentially [7]. Thus, it is difficult for these methods to meet the computing requirements of large-scale construction projects [8]. It is very urgent to find an algorithm that can find a quick, accurate, and effective optimization balance of period and cost, i.e., shortened construction period and reduced cost, without breaking the architectural design and function. In recent years, the heuristic algorithm with global search ability has been used to solve optimization problems, including the Jaya algorithm [9, 10], particle swarm algorithm [11], colony algorithm [12], simulated annealing algorithm [13], harmony search algorithm logic [14], and other hybrid algorithms [15, 16]. In general, the balance between duration and cost, which is the focus of long-term research in project management, can be investigated using these existing methods. Based on the results by Boussad et al. [17], in terms of

design ability and application effect, genetic algorithm was undoubtedly the best solution among many complex heuristic algorithms. Based on the in-depth studies of genetic algorithm, the combination of genetic algorithm and other methods has also been developed. Gulbin [18] considered the influence of environmental factors on the operation of the algorithm and designed the genetic algorithm for nondominant sequencing. Jia et al. [19] applied the fuzzy set theory based on the operation of genetic algorithm, considered the uncertain conditions of construction, and proposed a multiobjective method to optimize the duration, cost, and quality of the construction project. Mungle et al. [20] designed the fuzzy clustering genetic algorithm to solve the problem of multiobjective optimization for highway projects. Xie et al. [21] used the pretreatment method and cost improvement process to the genetic algorithm and established the optimization model of multimode resource-limited projects under variant constraints. However, these methods have inevitable limitations for large-scale projects with the requirements of high precision and high timeliness. Therefore, the computational model and algorithm for the optimization of large-scale construction projects need to be improved.

In theory, the problems which are solvable with genetic algorithm can also be solved by quantum genetic algorithm (QGA) [22, 23]. Thus, the QGA should be feasible in the field of genetic algorithm, such as the multiobjective optimization of both period and cost. In addition, as an alternative calculation method [24], quantum computing has a strong data analysis and processing ability for the large dataset [25–28]. Therefore, in this study, the QGA was used to solve the period/cost trade-off problems and developed an optimization model. In the optimization model, the genetic algorithm was used as the basis, the parallelism of quantum computing was integrated with the genetic algorithm, the quantum vector state expression was introduced into the genetic coding, and the chromosome evolution and renewal were achieved through the quantum revolving door. In this paper, the construction period-cost optimization model with the quantum genetic algorithm was established to improve the search efficiency on the basis of global search and reduce the application error of the Pareto solution. The experimental results proved that the proposed method had a better performance ratio than the traditional genetic algorithm.

2. Problem Description

In the engineering construction management, the period and the cost of the construction project are two main objectives to be controlled. However, there is a restrictive relationship between both objectives; that is, gaining one objective is at the expense of another. For example, the reduction of time leads to an inevitable increase of cost [29, 30]. Thus, the time/cost optimization of the construction project is also considered a multiconstraint hybrid optimization problem [31]. On the contrary, the network plan of a project is composed of several subprocesses which are logically arranged, and there are several alternatives for each of the subprocesses. Different labor and construction machinery schemes can lead to different time and cost of the process. For instance, the project duration, direct cost, and indirect cost can be affected by different schemes. Thus, the time/cost optimization problem is also considered a multivariable problem. In general, before solving the multiobjective optimization problem [32], functional expressions are needed to show the relationship between each objective. Table 1 lists the symbol interpretation.

2.1. Objective 01: Time. The total time of the project is calculated by summing up the duration of each subprocess. The duration of the subproject is marked with an intermediate variable "x." The selected subprocess requires that the work can and must start immediately when the previous work is finished, without restrictions of resources or other processes. The restrictions on the time parameter of each process satisfy the logical relationship between processes. The calculation equation and constraint conditions of the control period of the construction project are defined as follows:

$$T = \sum D_j^i, \tag{1}$$

$$D_i^e \le D_i^{(j)} \le D_i^n, \tag{2}$$

$$T \le T_{\max}. \tag{3}$$

2.2. Objective 02: Cost. The cost includes direct cost and indirect cost. Both costs have different changing rules and need to be calculated separately. Direct cost is the sum of the costs of personnel, construction machinery, and materials, which are directly used in the construction process and the measures of the project. At the same time, the cost is increased in the emergency construction due to the increase in the dispatched resources and the construction difficulty and the extension of working hours of both personnel and machinery. Indirect costs are not directly included in the project. Instead, they refer to other expenses that must be paid for the preparation, organization, and management of construction and production, including enterprise management fees and policy fees. The value of the indirect costs can be estimated by contract documents or experts. The calculation equation and constraint conditions of the control cost of the construction project are defined as follows:

$$C = \min \sum_{i=1}^{n} \left\{ \alpha_i^{(j)} C_{(1,i)}^{(j)} + \alpha_i^{(j)} \Delta t C_{(2,i)}^{(j)} \right\}, \tag{4}$$

$$\sum_{j=1}^{m} \alpha_i^{(j)} = 1, \tag{5}$$

$$C \le C_{\max}, \tag{6}$$

$$\left\{ \alpha_i^{(j)} \right\} \subseteq \{0, 1\}, \tag{7}$$

where $C_{(1,i)}$ is the sum of the product of the unit price and the work quantity of the process and the measure cost.

Table 1: Notations.

Notations	Meanings
D_j^i	Duration of the jth procedure of the ith subitem
$D_i^e(D_i^n)$	Emergency (normal) construction time of available construction plan for the ith subitem
T	Total project time
C	Total project cost
$C_{(1,i)}$	Direct cost of activity i
$C_{(2,i)}$	Indirect cost of activity i
Δt	Duration of alternatives
$\alpha_i^{(j)}$	Probability of selecting plan j in the ith procedure

3. Optimization Model Based on QGA

3.1. QGA. QGA is a new evolutionary optimization algorithm which integrates quantum computation with genetic algorithm. The QGA has obvious performance advantages due to the introduction of quantum concepts such as quantum state, quantum revolving gate, and probability amplitude in quantum computation. The QGA has few iterations, high search efficiency, and wide applicability. Besides, one chromosome can express the superposition of multiple states and thus has a large storage capacity. Even when the population is very small, the global optimization of the algorithm is not affected. Thus, the possibility of the algorithm to fall into a local search is greatly avoided. Compared to the traditional genetic algorithm (GA), the QGA does not rely on the gene updates by genetic operators such as crossover and mutation to achieve the evolution of the population. Although these genetic operators can change the probability amplitude to some extent, the quantum chromosome already exhibits the population diversity due to the use of quantum superposition. Instead, the introduction of genetic operators such as crossover and mutation will reduce the computing speed and performance of the QGA.

3.1.1. Quantum Bits. Bit is the unit of information in binary number. In traditional calculation, there are only two basic states, i.e., "0" and "1." After the introduction of the quantum concept, the bit state becomes a vector unit in a two-dimensional complex coordinate. Besides 0 and 1, the quantum bit state can also be the linear superposition of the basic states [33], which is called the superposition state of quantum bits:

$$|\phi\rangle = \alpha|0\rangle + \beta|1\rangle. \tag{8}$$

Among them, "$|\cdot\rangle$" is the Dirac notation to indicate the state. The parameters α and β are the probability of the corresponding states, respectively. The probability of $|0\rangle$ is $|\alpha|^2$, while the probability of $|1\rangle$ is $|\beta|^2$. Both probabilities satisfy the normalization condition:

$$|\alpha|^2 + |\beta|^2 = 1. \tag{9}$$

On the basis of binary coding in the genetic algorithm, the quantum bit state $|\phi\rangle$ is used to code the target and the initial value. The coding rules can be expressed as follows: through the expression of the quantum superposition state, a gene can express any quantum bit information. In addition, the genome sequence can be formed by the composition of chromosomes. The mth chromosome of the scheme can be represented as follows:

$$P_m^n = \left[\begin{array}{c|c|c|c|c} \alpha_1^n & \alpha_2^n & \cdots & \alpha_{j-1}^n & \alpha_j^n \\ \beta_1^n & \beta_2^n & \cdots & \beta_{j-1}^n & \beta_j^n \end{array}\right], \tag{10}$$

where n is the number of iterations and j is the quantum number (length of the chromosome). The complete quantum population containing all the modern chromosomes can be expressed as

$$P(t) = \left\{p_1^t, p_2^t, \ldots, p_m^t, \ldots, p_T^t\right\}. \tag{11}$$

3.1.2. Quantum Gate. The renewal and evolution of the quantum population are conducted through a quantum gate, which is a quantum device that can realize logical transformation within a certain time interval. The quantum gate ACTS is used for the superposition of the quantum and results in the phase change of the gene position in the chromosome. Finally, the probability converges to 0 or 1 within a shortest time and the optimal searching solution is achieved. The only requirement for quantum gates is

$$U^+ * U = I, \tag{12}$$

where U is the matrix representation of the quantum gate, U^+ is the conjugate transpose, and I is the identity matrix. Quantum gates have many forms. In this algorithm design, the method of quantum rotation is defined as follows:

$$U(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}, \tag{13}$$

where θ is the rotation angle. The chromosome renewal process can be expressed as follows:

$$\begin{bmatrix} \alpha_k^{n+1} \\ \beta_k^{n+1} \end{bmatrix} = \begin{bmatrix} \cos\theta_i & -\sin\theta_i \\ \sin\theta_i & \cos\theta_i \end{bmatrix} \begin{bmatrix} \alpha_k^n \\ \beta_k^n \end{bmatrix}, \tag{14}$$

where $[\alpha_k^n, \beta_k^n]^{\mathrm{T}}$ is the Kth quantum bit of the Nth generation of the chromosome:

$$\theta_i = \Delta\theta \times \text{sig}, \tag{15}$$

where $\Delta\theta$ determines the convergence speed and the search accuracy of the algorithm. If the amplitude of $\Delta\theta$ is too small, the search time is increased or even "stagnates." If the amplitude is too large, premature convergence can occur, and it is difficult to obtain the optimal solution. sig is the coefficient sign of the rotation angle, namely, the rotation direction, whose value determines the direction of convergence to the optimal solution. When ibin (current individual quantum bit value) is equal to ibbest (optimal individual quantum bit value), sig is $1/\sqrt{2^m}$; when ibin and ibbest are different, the values of sig are shown in Table 2.

3.2. Optimization Process

3.2.1. Encoding and Population Initialization. There are three encoding methods in the quantum genetic algorithm.

Table 2: Values of sig.

ibin	ibbest	f (jfval) < f (best)	sig			
			$\alpha_i\beta_i > 0$	$\alpha_i\beta_i < 0$	$\alpha_i = 0$	$\beta_i = 0$
0	1	True	1	0	0	±1
0	1	False	−1	1	±1	0
1	0	True	−1	1	±1	0
1	0	False	1	−1	0	±1

The initial population encoding is quantum bit encoding, in which N is the length of the encoded quantum bits. The pseudocode is shown in Figure 1.

```
QGAChrom = zeros(P, N * 2);
for i = 1:P
for j = 1:N * 2
QGAChrom(i, j) = 1/sqrt(2);
end
end
```

Figure 1: Code in quantum bit encoding.

When the population is first measured, the quantum bit code is converted into the binary code, as shown in Figure 2. The binary is decoded into the decimal in the calculation of the adaptability of the population.

```
Chrombin = zeros(P, N);
for i = 1:P
    for j = 1:N
        pick = rand;
        if
pick > (QGAChrom(i, j)^2)
            Chrombit(i, j) = 1;
        else
            Chrombin(i, j) = 0;
        end
    end
end
```

Figure 2: Conversion of the quantum bit code to the binary code.

To optimize the construction period and cost of a project, the population can be defined as the set of chromosomes (Figure 3) that stores the duration of all sequential subitems, and the initial population can be expressed as $P(t = 0) = \{p_1^0, p_2^0, \ldots, p_m^0, \ldots, p_T^0\}$, where T is the population size. The probability amplitudes of the population $2jT$ are all $1/\sqrt{2}$, which means that, in the initial state, each chromosome is in a linear superposition state with the same probability of $1/\sqrt{2^m}$.

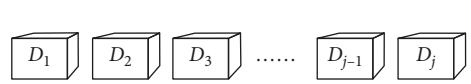

Figure 3: Diagram of the single chromosome structure.

3.2.2. Evaluation of Adaptability. The individuals in the population can be evaluated by adaptability. Higher adaptability indicates that the individual is better and has greater survival probability. On the contrary, the individuals with lower adaptability are easier to be eliminated. The adaptability evaluation function is generally consistent with the objective function. Since the two opposite subobjectives, i.e., duration and cost, seek for the minimum values in the optimization model, equations (1) and (4) can be changed as follows:

$$\text{Value 1} = \frac{1}{C}, \qquad \text{Value 2} = \frac{1}{T}. \tag{16}$$

Both the adaptability values in decimal and the nondominant solution (there was no other solution better than this one) were obtained from the calculation.

3.2.3. Quantum Genetic Operation. In the operation, the $Q(t)$ state of the population is observed and compared with the existing optimal solution, and then the population with the quantum revolving gate is updated to obtain $Q(t+1)$. The adaptability was calculated. If the optimal solution in $Q(t+1)$ is better than the currently stored solution, the stored solution is replaced. In the update process, the population number is always constant and the nondominant solution does not repeat.

3.2.4. Termination Judgment. If the termination condition is satisfied, the set of optimal solutions for the schedule and cost of the subprocess is the output. Otherwise, Steps 2 and 3 are repeated. The flowchart of the optimization process is shown in Figure 4.

3.3. Experimental Results and Analysis

3.3.1. Algorithm Instance. A high-rise building project was selected as the main project for optimization, the construction data (Table 3) were collected, and the feasibility of the experimental model was verified. Before optimization, according to the construction plan, the completion duration of the project was 380 days and the cost was 19.749 million yuan.

The parameters of the quantum genetic algorithm are shown in Table 4. This algorithm was implemented by MATLAB 2016b.

After running the optimization, the results were summarized as follows:

(1) The period/cost evolution of a project is recorded and shown in Figures 5 and 6. From the figures, it is noted that all the target curves are in a declining trend, which indicates that the evolution of the quantum genetic algorithm is effective. With the increase in the number of iterations, the iteration curve remains flat, which suggests that the algorithm is convergent and can achieve the optimal value in

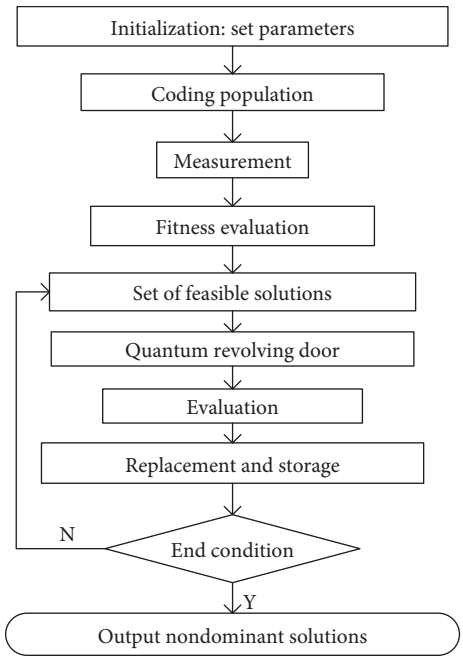

Figure 4: Optimization process of the quantum genetic algorithm.

Table 3: Construction data.

No.	Activity	Time (days)		Cost (ten thousand yuan)	
		Normal	Emergency	Normal	Emergency
1	Measurement and actinomycetes	3	1	0.1	0.3
2	Precipitation and support	15	10	46	65
3	Earthwork	5	2	9	14
4	Pile foundation	10	6	240	300
5	Earthwork backfilling	5	2	1.8	3
6	Structure of the first layer	12	7	63.5	70
7	Structure of the second or third layer	22	12	58	66
8	Structure of the fourth floor	10	5	56	64
...					
17	Structure of the 13th floor	10	5	56	64
18	Stage acceptance of the main project	3	1	0.5	1.5
19	Wall masonry and secondary structure	50	30	147	196
20	Structure of the 14th floor	10	5	56	64
...					
33	Structure of the 27th floor	10	5	56	64
34	Structure of the 28th floor	12	7	64	70
35	Structure acceptance	3	2	1	2
36	Wall masonry and secondary structure	50	30	147	196

Table 4: Parameter values of the QGA.

$\Delta\theta$	Population	Variable dimension	Max. iterations
0.01π	80	36	400

the process of evolution instead of getting into local optimum.

(2) Figure 7 shows the final solution of the QGA, i.e., the Pareto front under the dual constraints of both time limit and cost. According to the Pareto front of the optimization, the project manager can select a set of feasible processes with flexible activity arrangement under certain constraints of time or construction period (Table 4) to maximize the economic and social benefits. For example, when the total construction period is 280 days, the total cost is at least 22,882,600 yuan. The corresponding duration of the subprocess is shown in Figure 8, in which the 19th activity is concurrent engineering and does not increase the total construction period. At this time, no other combination method of the subprocesses can be superior to the scheme shown in Figure 8.

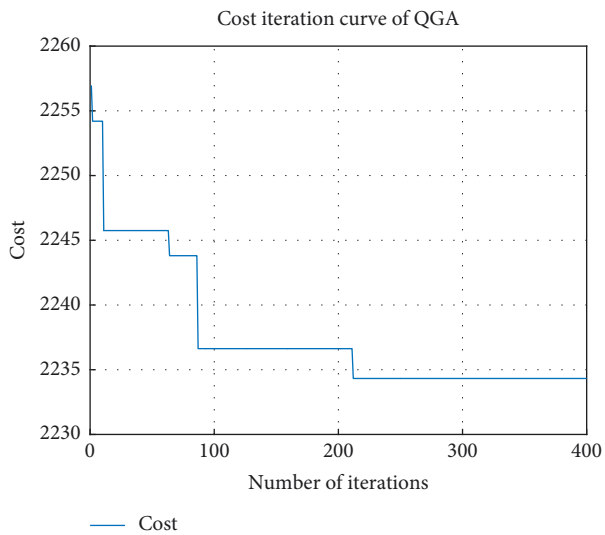

Figure 5: Iteration curve of the construction period in the multiobjective quantum genetic algorithm.

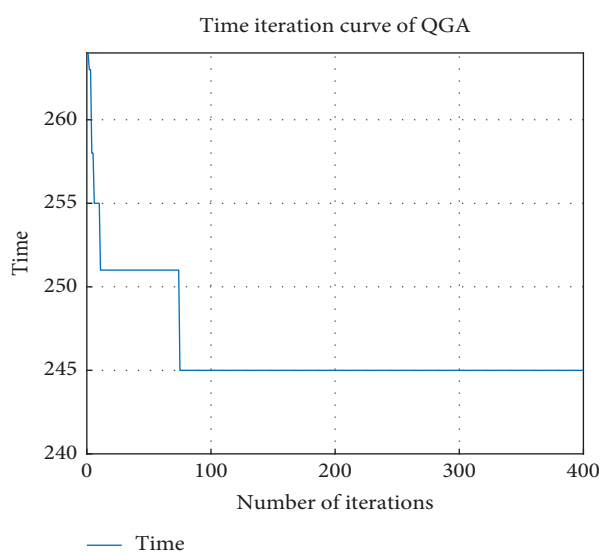

Figure 6: Iteration curve of cost in the multiobjective quantum genetic algorithm.

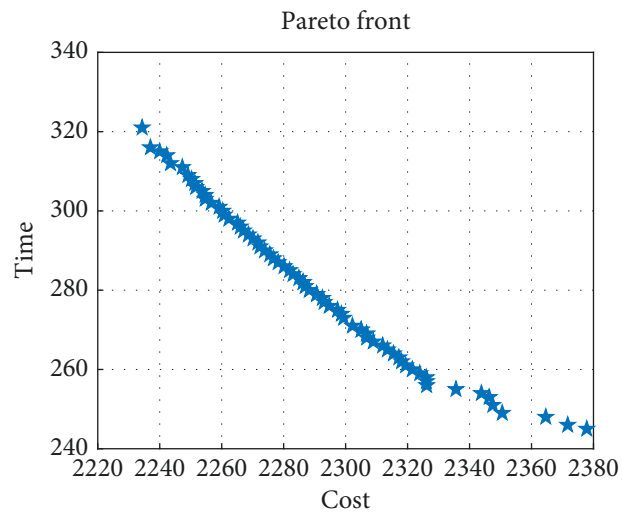

Figure 7: Pareto solution set of the multiobjective quantum genetic algorithm.

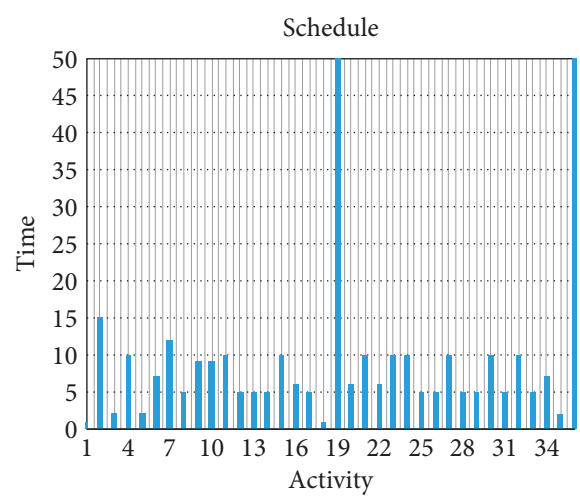

Figure 8: Process portfolio for 280 days.

4. Conclusions

The trade-off between period and cost in construction management is a classic problem in the multiobjective optimization with constraints. A new model based on the quantum genetic algorithm (QGA) was proposed in this study. Firstly, in the process of double-objective optimization, the conflict between the construction period and the practical cost was considered, and the direct and complex relationship between the two objectives was analyzed. Two main objective functions were established, which provided a mathematical basis for the application of the algorithm to the construction management. Secondly, a complete optimization concept and process of the quantum genetic algorithm were developed, the quantum coding mode was explained, the quantum revolving door was improved, and the computational efficiency of the algorithm was improved in large-scale projects. Through the construction example of a high-rise building project, the quantum genetic algorithm was proved to be able to obtain the optimization results under the condition of small population size and few iteration times. Thus, the quantum genetic algorithm had the advantages of short calculation time and strong global optimization ability. Finally, the developed model was applied to a practical construction project. The experimental results showed that the QGA can perform multiple optimization cycles and find the nonconflicting Pareto solution quickly and accurately to meet the requirements under different constraints in different projects with variant activity arrangements. In addition, the QGA can also provide owners and contractors with more realistic decision-making schemes conveniently and efficiently, which can maximize the economic benefits. In the future, the development of

intelligent algorithms with high efficiency in large-scale engineering optimization will become the research focus.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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