Optimizing Project Resources Using the Hybrid Multi-objective Algorithm and Decision-Making Method

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Abstract. Schedule, cost, quality control, and rational use of labor and resources are key factors that project management aims to achieve, and these factors have a complex relationship with each other. However, almost all existing trade-off analysis models have only focused on addressing the time-cost issue without simultaneously considering the impact of collision activities on quality costs. Moreover, the results will be influenced by several external elements that are uncertain and hard to identify, such as weather conditions, machine and equipment capability, and labor efficiency, among others. Therefore, this research aims to develop an optimal model of project resource balance with quality considerations (TCQT) by applying fuzzy logic, the multi-objective social group optimization (MOSGO) algorithm, and the multi-criteria decision-making method (MCDM), while also considering the uncertainty of input variables. In this paper, fuzzy logic is used to select input and defuzzification to filter the results according to various factors. Additionally, the MOSGO algorithm is applied to determine a set of Pareto-optimal time-cost-quality curves, and multi-criteria decision-making methods are used to obtain the best outcome. The expected research outcome is the introduction of an optimization model that combines SGO, fuzzy techniques, and MCDM to optimize problems requiring resources along with quality control (TCQT) and integrate uncertainty that occurs in actual large-scale projects.

Keywords: Fuzzy logic · Hybrid multi-objective · Social group optimization · Time—cost—quality trade-off · Uncertainty

1 Introduction

In the contemporary economy, the construction industry faces a plethora of challenges, notwithstanding its exciting growth phase. To optimize profitability, construction corporations must enhance their technical and managerial competencies. Project management

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is a pivotal aspect in balancing progress, cost, quality, and resources to achieve organizational objectives, which have complex interdependencies [3]. Depending on the organization's perspective, goals may include minimizing costs and time or optimizing quality control. However, to reduce project duration, the organization must relinquish human resources, raw materials, machinery, and equipment, impacting overall costs and project quality, which can be positive or negative, depending on the activity's nature [11]. Hence, project managers must allocate resources efficiently to accomplish time-cost-resource utilization optimization goals. Nonetheless, traditional methodologies, such as the Metra potential method (MPM), Critical path method (CPM), and Program evaluation and review techniques (PERT), lack realism, heavily relying on assumptions and estimates, thus hindering accurate project outcome predictions. To surmount these limitations, advanced approaches to resource allocation are imperative, involving optimal resource utilization while minimizing waste.

Time-cost-resource optimization (TCRO) is a commonly used approach that categorizes optimization methods into three groups: heuristic-based, linear program-based, and meta-heuristic-based. However, each methodology has its advantages and disadvantages. While the advantages of a particular approach may make it the most suitable option, the disadvantages include an imbalance between time and cost (TCT) for large-scale projects [2]. On the other hand, previous studies have successfully applied fuzzy logic to introduce uncertainty into the time-cost optimization model [1]. However, there is still a lack of research that uses fuzzy logic to optimize project resources and a need for a time-cost trade-off model that considers collision activities' impact on quality costs. To address research gaps, this study aims to develop an optimal project resource balance model that considers quality and inherent uncertainty using fuzzy logic and MOSGO combined with a multi-criteria decision-making method. By taking this approach, the proposed model can account for uncertainties related to external factors that impact the project's resource allocation and quality.

2 Proposal Model for Uncertain Resource Tradeoff

This proposed study aims at building an optimal model of project resource balance with consideration of the uncertainty of input variables by applying fuzzy algorithm logic and multi-objective SGO to generalized construction projects [6]. Figure 1 depicts a schematic diagram of the entire proposed structural model incorporating MOSGO, fuzzy logic, and MCDM which were implemented in MATLAB software for the TCQT concern.

2.1 Initialization

The model inputs comprise relationships and duration among tasks, the cost of each activity, and the corresponding quality. In this study, fuzzy numbers in time comprising the system have been converted to three numbers, which reflect the optimistic, most likely, and pessimistic conditions to demonstrate the uncertainty. When the execution time is measured by ambiguous numbers or uncertain lingual definitions, the solitary utility functions and the synthetic utility functions will include fuzzy mathematical

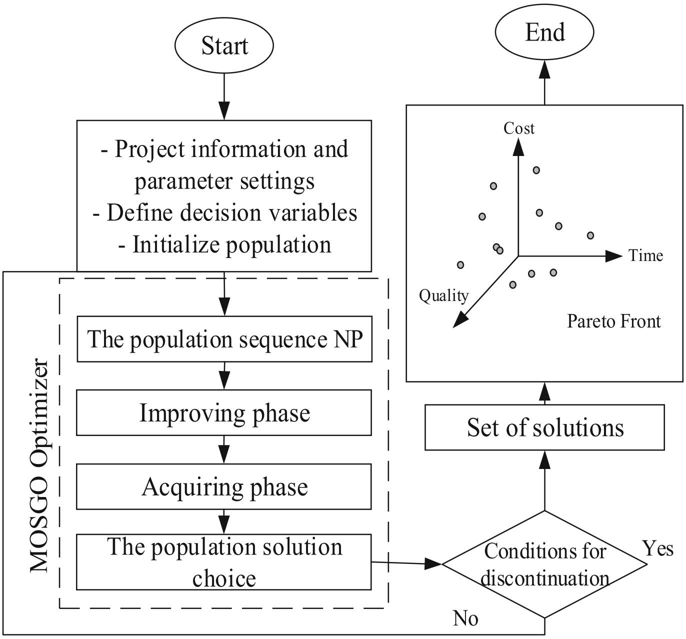

Fig. 1. MOSGO flowchart for the TCQT problem

operations and thus generate outcome fuzzy utility values [8, 12]. For the moment in (Fig. 2), the time is described by triangular fuzzy numbers, such as T = (153 154, 155).

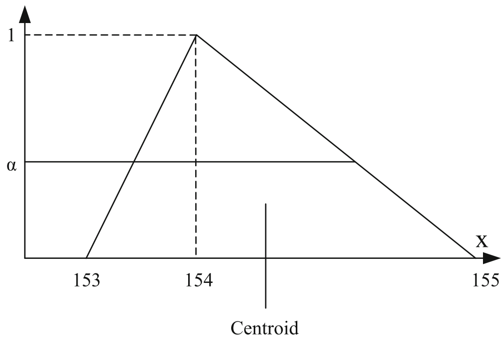

Fig. 2. Centroid method of defuzzification

Following, the operator needs to provide the metrics for the MOSGO issue. MOSGO utilizes a typical arbitrary technique to create the first NP individual of the population with $x_{ij} \in [0, 1]$ as defined in Eq. (1).

$$X_{i,j}^{G=0} = LB_i + x_{i,j} * (UB_i - LB_i);\ i = \overline{1, NP};\ j = \overline{1, D} \tag{1}$$

where LB and UB are the lower and upper bounds of decision variables. NP is the number of member in a social group; D is the decision variable number.

2.2 Decision Variables

Because the tasks in the project have much more than one realistic choice, one option would be selected randomly to be executed for each activity. As a result, we have a potential solution to the TCQT issue in construction projects depicted by the vector D.

$$X = [X_{i,1}, X_{I,2}, \ldots, X_{i,j}, .., X_{i,D}] \tag{2}$$

$X_{i,j}$ denotes an integer value in the intermission from 1 to M_j where M_j is the total feasible avenue for implementing activity j.

To optimize project schedule and expenses, evaluate Gantt chart works to shorten construction and select tasks to accelerate the schedule based on specific time and cost. Evaluating time for each task after identifying all project activities determines the total period necessary for project completion and specific activities [10].

$$T_p = min(\underset{i=1,..,M}{Max}(FT_i)) = min(\underset{i=1,..,M}{Max}(ST_i + D_i)) \tag{3}$$

where ST_i, FT_i are the beginning and end times of activity (i). The duration of each activity i is indicated by $D_{i.}$

Transforming the quality of construction activities into a functional value of the use of various resources is challenging due to the hard to measure the impact of these performance measures on the quality of the activity. The defined quality values are inferred from performance-based models that relate the long-term performance of the finished product of each operation with its quality values [7].

$$Q = \sum_{i=1}^{N} w_i Q_i \tag{4}$$

where N is the number of activities and w_i is the weight for activity i.

Total project costs include direct costs and indirect costs to carry out all completion of the project. Direct costs for the project include expenses for materials, human labor, equipment, and for the work of subcontractors. Direct costs are directly attributable to the object, and it is financially feasible to do so. Indirect costs are not the direct cost component of performing construction work, but nevertheless, without this cost component, there would have been no direct costs. Indirect costs are an essential component of total project costs, and they include expenses such as rent, utilities, insurance, administrative salaries, and other overhead costs that are not directly attributable to the project's physical construction work. These costs are necessary to support the project's operations and ensure its successful completion [9].

$$C = \sum_{i \in A} dc_i^{(k)} x_i^{(k)} + T \times c_i^{(k)} \tag{5}$$

2.3 Improving Phase

In this stage, the new solution X_i of individual is generated based on the best individual G^{best}, taken directly from the set with the best individuals (first rank) of the population. The technique of quick filtration of non-outstanding values will sort out the ranks and the process of the improvement phase is revised by the formula:

$$X_{i,j}^{new} = \frac{\sum F\left(X_{i,j}\right)}{\sum F\left(G^{best}\right)} X_{i,j}^{old} + \beta\left(G^{best} - X_{i,j}^{old}\right); j = 1, 2, \ldots, D \tag{6}$$

The optimization pathway just advances when the new individuals are better than the old individuals so $X_{i.j}^{new}$ is accepted if it gives better compatibility than $X_{i.j}^{old}$.

2.4 Acquiring Phase

During the acquiring phase, an individual in a social group interacts with the best candidate G_{best}^{i} of that group and may also seemingly at random contact anyone else in the group to gain new knowledge. An individual acquires new understanding if he comes in direct contact with anyone who has more knowledge than himself. The one with the best knowledge (here called G_{best}^{i}) has the greatest potential impact above others. An individual will also acquire fresh information from others when they possess more knowledge than himself [9].

$$Xi, jnew = \begin{cases} X_{i,j}^{old} + \beta_1\left(X_{i,j} - X_{k,j}\right) + \beta_2\left(G_i^{best} - X_{k,j}\right), f\left(X_i\right) < f\left(X_k\right) \\ X_{i,:}^{old} + \beta 1\left(X_{k,:} - X_{i,:}\right) + \beta_2\left(G_i^{best} - X_{i,j}\right), f\left(X_i\right) \geq f\left(X_k\right) \end{cases} \tag{7}$$

where X_k is a random person in the current group ($i \neq k$); β_1 and β_2 are two independent random values.

2.5 The Population Solution Selection

Throughout the optimization process, the population size remains constant at *NP*. To identify the *NP* best outcomes from the cumulative population for the next generation, this research utilized a fast non-dominated sorting technique and crowding entropy method. Non-dominated sorting is the operation of arranging the individuals according to their objective function values. Initially, the fast non-dominated sorting method is used to separate the population into non-dominant subsets $\{F_1, \ldots, F_n\}$ the population numbers are considered from F_1 to F_k, respectively, with F_k is assumed to be the last selected subset. Typically, the size of subsets $\{F_1, \ldots, F_k\}$ is greater than *NP*.

Multiple-criteria decision-making (MCDM) is used to evaluate and compare options when there are multiple criteria to consider in TCQT problem. Multi-objective optimization problems involve conflicting objectives and result in a Pareto set—a set of solutions that aren't dominated by any other solution in terms of all objectives. ER method is commonly used to rank the Pareto set of non-dominated solutions in terms of project performance [4]. This process involves several steps, as described by Monghasemi et al. [5]: Step 1: Evaluate the non-dominated set of solutions to select each solution and determine the values of three attributes time, cost, and quality; Step 2: Compute the normalized weights for each attribute by Using the Shannon entropy approach; Step 3: Determine the normalized weights ω_j for each basic attribute (objective); Step 4: Combine the degree of belief; Step 5: Determine the utility score of the selected solution.

2.6 Stopping Conditions

The optimization process cycle is discontinued when the halting requirements are satisfied, as indicated by the system administrator. This study utilizes the highest limit of loops to be run as the halting condition. After the methodology halts, a set of non-superior solutions (called Pareto) is generated. The meaning of the Pareto solutions, representing the average quality of the non-superior solutions, can then be calculated, and used to evaluate the performance of the optimization process (Table 1).

Table 1. Data of case study 1

No	Logical	Option 1					Option 2					Option 3				
		T1	T2	T3	C	Q	T1	T2	T3	C	Q	T1	T2	T3	C	Q
1		4	5	6	2030	90	2	4	5	2300	97	_	_	_	_	_
2	1FS-3 days	7	8	10	1020	91	6	7	8	1280	96	5	6	7	1510	91
3	1,2	7	8	9	1700	96	5	7	8	1850	92	5	6	8	2090	90
…							…									
28	27FS-3 days	9	10	12	320	88	8	9	12	440	97	7	8	10	610	89
29	28	1	3	4	50	87	–	–	–	–	–	–	–	–	–	–

3 Case Study

The utilization and capability of the proposed model for solving the TCQT issue are evidenced by using two real case studies. The first case is a road and bridge engineering project derived from previous research intended to illustrate the application of solving the trade-off TCQ trade-off issue [10]. The above project aims to upgrade the existing two-lane highway into a four-lane highway with a length of 100 m with a total of 29 activities for a brief application in this study. The second case—a typical case in Vietnam is Spun pile of package Construction of the Test Pile and Mass Pile of "Manufacturing Facility—The Sai Gon Hi-Tech (SHTP) collected from Central Construction Joint Stock Company. The second case project consists of 46 activities with 4400 nos D600 and 360 nos D300 units on a total area of 2 zones (GFA 233000 m^2). The characteristics and types of data are quantifiable and precisely defined. Tables 2 and 3 illustrate two project data, including activity logical precedence relationships, activity durations, costs, and quantities for each execution option. These cases highlight the complexities involved in large-scale construction projects and underscore the need for careful planning, precise execution, and effective project management to ensure successful project completion within the given constraints.

The MOSGO algorithm operates without any user-defined inputs except for two control variables, established using a trial-and-error technique. Case study 1 used a population size of 100 and ran for 50 generations, while case study 2 used a population size of 300 and ran for 100 generations. Tables 3 show the optimal solutions for case studies 1 and 2, respectively, while Fig. 3a, b present a 3D view of all the optimal solutions, highlighting trade-offs that must be considered. The model employed in case study 1 considers project quality and uncertainties related to project duration, making it superior to earlier methods of analysis. Case study 2 showcases the need to consider multiple objectives and trade-offs when making decisions. S2 offers the shortest duration, S4 is the most cost-effective option, S6 prioritizes quality, and S8 provides a balanced solution.

The data shows that project duration and total project cost have an inverse relationship in both case studies. This means that as the project duration decreases, the total project cost tends to increase, and vice versa. Project duration also has an impact on project quality, as excessively short or long durations can have negative effects on quality outcomes. Higher project costs are often associated with lower-quality results, which is closely tied to the correlation between project duration and cost. Proceeding to set alpha 0.5 in a fuzzy uncertainty problem means that you are assuming equal membership and non-membership to the fuzzy set. This implies that all values in the problem are given equal consideration in terms of their membership of the fuzzy set. This could be appropriate in some cases where there is no strong preference or bias toward any particular value. Notably, when incorporating uncertainty (at a probability of 0.5) into the solution approach, the resulting findings can be intriguing and informative.

Table 2. Data of case study 2

No	Logical	Option 1				
		T1	T2	T3	C	Q
1		153	154	155	221300	90
2		1	2	5	2000	91
3	2	6	7	8	5100	88
4	2SS + 2 days	1	2	4	9285	86
5	4SS + 5 days	21	22	25	49700	88
6	5	27	28	31	37600	86
7	5SS + 10 days	4	5	7	4200	90
8	7SS	6	7	9	6300	86
9	3SS	20	21	25	78500	89
10	5SS + 10 days	16	17	19	73500	88
11	3SS + 3 days	41	42	43	278400	84
12	2SS + 3 days	8	9	11	17300	84
13	8	11	12	14	1850	88

(*continued*)

Table 2. (*continued*)

No	Logical	Option 1				
		T1	T2	T3	C	Q
14	13SS	10	11	13	4060	87
15	14FF	5	6	8	7350	89
16	14FF	2	3	5	4550	84
17	14	16	17	20	39850	89
18	17SS + 3 days	12	13	16	90	88
19	6SS + 7 days	4	5	7	7050	85
20	2SS + 3 days	8	9	12	17400	85
21	19	10	11	13	2160	89
22	21SS	10	11	14	4230	87
23	23FF	2	3	5	4550	90
24	23	15	16	19	42500	85
25	24SS + 3 days	15	16	17	85	84
26	14	101	102	103	2059000	85
27	24SS + 10 days	104	106	109	73800	88

(*continued*)

Table 2. *(continued)*

No	Logical	Option 1				
		T1	T2	T3	C	Q
28	27SS	104	105	108	388000	87
29	28	1	2	5	9350	85
30	22	110	112	115	2260000	89
31	25FS + 2 days	115	117	118	81900	90
32	31	113	116	117	428440	89
33	2SS + 3 days	7	8	10	1580	89
34	5	6	7	9	125	89
35	34SS	6	7	8	540	88
36	35FF	5	6	9	7420	85
37	35FF	2	3	5	4650	90
38	35	15	16	17	6950	89
39	38SS + 3 days	15	16	19	90	88
40	35	91	92	95	91740	89
41	40SS	7	8	10	7860	88
42	40	92	93	98	7560	90
43	42SS	90	91	93	32500	88
44	28SS + 10 days, 32SS + 10 days	103	104	107	92000	86
45	44SS + 3 days	100	102	106	1450	88

(continued)

Table 2. (*continued*)

No	Logical	Option 1				
		T1	T2	T3	C	Q
46	44SS + 20 days	20	21	25	26000	89

Option 2					Option 3				
T1	T2	T3	C	Q	T1	T2	T3	C	Q
152	153	154	223300	94	148	150	151	228300	90
–	–	–	–	–	–	–	–	–	–
4	5	6	6400	95	1	3	4	10800	89
–	–	–	–	–	–	–	–	–	–
18	19	21	53320	90	16	17	18	61000	93
19	20	21	53300	96	17	18	19	69000	91
2	3	4	8285	90	1	2	3	11000	89
4	5	6	8685	90	1	4	5	10500	92
17	18	19	83840	93	15	16	18	85000	91
14	15	16	85100	95	11	12	14	99000	91
39	40	41	294400	91	34	36	40	305000	91
6	7	8	25020	90	2	4	5	28800	89
9	10	11	2320	97	6	7	8	2510	88
8	10	11	4510	92	5	6	8	6600	88
2	3	4	9200	94	1	2	3	11000	90

(*continued*)

Table 2. (*continued*)

Option 2					Option 3				
T1	T2	T3	C	Q	T1	T2	T3	C	Q
1	2	3	9100	92	–	–	–	–	–
14	15	16	45950	96	12	13	14	48800	92
10	11	12	110	90	7	10	11	150	92
3	4	5	9400	96	1	3	4	11600	89
5	7	8	24000	95	2	4	5	28600	89
8	10	11	2400	94	5	7	8	2880	91
7	10	11	4700	95	4	5	6	7310	92
1	2	3	9100	90	–	–	–	–	–
–	–	–	–	–	–	–	–	–	–
12	15	16	95	95	10	13	14	105	90
98	99	100	2110700	94	95	96	98	2150000	93
101	102	103	76130	93	97	99	100	79600	91
102	103	104	395600	95	95	96	98	412500	89
–	–	–	–	–	–	–	–	–	–
108	110	111	2301900	93	103	105	106	2450000	90
114	115	116	83350	95	110	113	114	88300	88
112	114	116	432200	91	108	112	113	436000	89
6	7	8	1925	94	4	6	7	2100	89

(*continued*)

Table 2. *(continued)*

Option 2					Option 3				
T1	T2	T3	C	Q	T1	T2	T3	C	Q
5	6	7	152	96	3	5	6	175	90
4	6	7	650	89	1	4	5	970	91
4	5	6	9285	92	2	3	4	11500	93
1	2	3	6285	96	–	–	–	–	–
13	14	15	7750	97	10	12	13	8700	91
14	15	16	100	90	11	12	13	120	89
90	91	91	93830	89	84	85	89	95900	90
6	7	8	8785	95	4	6	7	10800	92
89	90	91	7830	91	85	87	88	7980	88
88	90	91	32930	92	84	88	89	35600	91
99	100	101	100745	96	93	94	95	103500	91
98	100	101	1600	94	96	97	98	1900	92
18	19	20	27500	92	16	18	19	28500	92

Table 3. Optimum solutions of both cases

Solution	Storted by	Execution option combination	Time	Cost	Quality	Case Study
S1	Time	2.3.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.3.1.1	71,07	35,82	0.8986	1
S2	Time	1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.2.1.3.1.1.1.1.1.3.3.1.1.1.1.1.1.1.1.1.3.1.1.1.1	242,2	6,518,400	0.8767	2
S3	Cost	1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.3.1.1	86,45	32,01	0.8959	1
S4	Cost	1.1.1.1.2.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1	256,2	6,499,860	0.8758	2
S5	Quality	2.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.3.1.1	71,9	34,60	0.9014	1
S6	Quality	1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.2.1.3.1.1.1.1.1.3.3.1.1.1.1.1.1.1.1.1.1.1.1.1.1	249,6	6,505,000	0.8787	2
S7	Compromised	2.3.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1	77,45	33,21	0.9	1
S8	Compromised	1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.3.1.1.1.1.1.3.1.1.1.1.1.1.1.1.1.1.3.1.1.1.1	248	6,507,440	0.8781	2

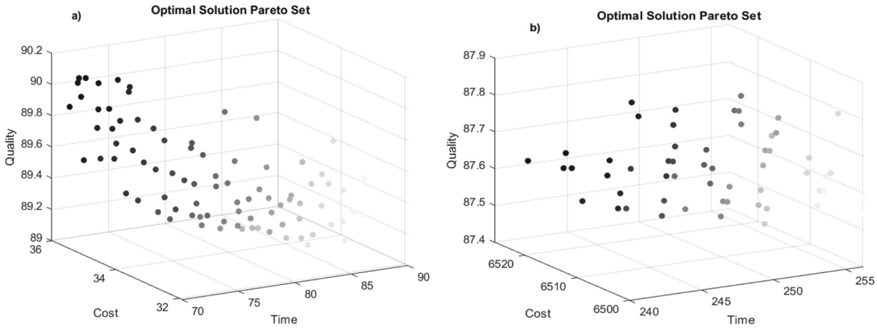

Fig. 3. **a**, **b** Time-cost-quality of the optimum solutions in case study 1 and case study 2

4 Conclusion

This study presented a new hybrid multi-objective algorithm that combines social group optimization, fuzzy logic, and multiple-criteria decision-making methods to solve the optimization problem requiring resources along with quality control in construction with the integration of uncertainty about the time that occurs in the actual large-scale project. The MOSGO algorithm has been updated to an unrestricted version that promotes harmony between development and optimization procedures in comparison to the existing version. The first case study's operational model demonstrates remarkable stability and yields superior outcomes compared to previous studies, particularly when optimization incorporates a novel quality objective that had not been addressed previously. In the second case study, the model's proficiency in problem-solving for realistic large-scale projects is demonstrated, underscoring its potential to effectively manage complex and expansive projects. The practical implementation of the hybrid algorithm in actual construction scenarios further substantiates the model's efficacy in significantly enhancing project outcomes.

The above-proposed MOSGO-TCQT model is adaptable, easily updatable, and can be digitized and incorporated into computer programming. Its versatility and effectiveness make it a promising tool for addressing complex and expansive problems in the primary objective of this research is to address the complex interdependence among the three critical factors of project management: time, cost, and quality.

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