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Improving AHP for construction with an adaptive AHP approach (A^3)

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Abstract

The Analytic Hierarchy Process (AHP) approach is widely used for multiple criteria decision-making in construction management. However, the traditional AHP requires that decision makers remain consistent in making pairwise comparisons among numerous decision criteria. Accurate expression of relative preferences on the criteria is difficult for decision makers due to the limitations of the 9-value scale of Saaty. Although Saaty proposed a method to assess the consistency of pairwise comparisons, no automatic mechanism exists for improving the consistency for AHP. This work proposes an adaptive AHP approach (A^3) that uses a soft computing scheme, Genetic Algorithms, to recover the real number weightings of the various criteria in AHP and provides a function for automatically improving the consistency ratio of pairwise comparisons. A real world construction management example for determining the weightings of the multiple criteria for a best-value bid is chosen as a case study to demonstrate the applicability of the proposed A^3. The application results show that the proposed A^3 is superior to the traditional AHP in terms of cost effectiveness, timeliness, and improved decision quality.

Keywords: Multiple criteria analysis; Analytic hierarchy process; Soft computing; Genetic Algorithms; Construction

1. Introduction

Construction management involves numerous multi-criteria decision-making (MCDM) problems. Correctly weighting various criteria is the key issue in a MCDM problem. The use of the Analytic Hierarchy Process (AHP) approach [1,2] to assess the criterion weightings in MCDM recently has become popular in different areas of construction management, such as project management [3,4], contractor selection [5–8], procurement [9], facility location determination [10], construction safety management [11], project/proposal evaluation [12,13], green building evaluation [14], and technology/equipment/material selection [15–17].

The AHP method can be used to construct the additive value functions for preferentially independent MCDM problems [18,19] and to determine the membership values of the elements in a fuzzy set [20]. However, several researchers, including Triantaphyllou and Mann [21] and Lakoff [22], have pointed out the weakness of AHP in assessing the relative importance weights of various criteria. This weakness results primarily from two limitations: (1) the difficulty of using Saaty's discrete 9-value scale to reflect the belief of decision makers in the relative importance relationship among the various criteria; (2) the difficulty of identifying the in-between numbers of fuzzy sets. Saaty's discrete 9-value scale method forces decision makers (DMs) to select numbers from the finite set {1/9, 1/8, 1/7, …, 1, 2, 3, …, 7, 8, 9}, contradicting the real world fuzzy memberships of elements in a fuzzy set. In most real world problems, the membership values in a fuzzy set take on continuous values (namely real numbers) rather than discrete numbers [21]. Triantaphyllou and Mann [21] found that this limitation can cause extremely high failure rates for AHP. Furthermore, the ability of humans to accurately express their knowledge decreases with increasing problem complexity. Thus, as the number of criteria in AHP increases, DMs are likely to make inconsistent judgments during pairwise comparison. The above two limitations are sources of the high Consistency Ratio (CR), that is the high inconsistency, when adopting the AHP method.

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Saaty devised a method of measuring CR (see Saaty [2]). If CR exceeds 0.10, the pairwise comparison needs to be reassessed. The reassessment process is tedious and does not guarantee the consistency of pairwise comparisons. Thus, another reassessment is necessary if the resulting CR remains unsatisfactory. The reassessment process is impractical in situations where time is crucial for DMs who are top managers of a company or for urgent MCDM problems that must be solved rapidly. Reassessment is simply too expensive for sorting out inconsistencies [23]. Tam et al. [23] proposed a tool that aids AHP decision-making that changes the consistency checking from a 1–9 value scale to a 1–3 value scale, thereby reducing the time required to handle inconsistency in decision-making for construction problems. Alternatively, the development of a method that automatically improves the CR of pairwise comparisons and recovers the continuous relative importance weights of various criteria is extremely attractive.

This investigation develops an Adaptive AHP Approach (in brief A^3) using Genetic Algorithm (GA) to recover the continuous relative importance weights of the various criteria based on two objective values: (1) CR, and (2) the difference of the derived pairwise weighting matrix (PWM) from the initial PWM. Since the search process of GA is guided by minimizing CR, it results in an adapted PWM with lower CR, which is acceptable in terms of the consistency requirements of AHP. The search process is also guided by minimizing the difference from the initial PWM. Thus, the resulting PWM reserves the original beliefs of the DM regarding the relative importance relationship among the criteria. The proposed A^3 also provides an automatic mechanism for improving CR, and thus eliminates the reassessment process of AHP.

The remainder of this paper is organized as follows: Section 2 reviews the traditional AHP approach and its application in determining the fuzzy weightings of the various criteria in the MCDM; Section 3 then presents the proposed A^3; next, Section 4 analyzes the proposed A^3 for a real world best-value-bid MCDM problem to demonstrate the applicability of the proposed A^3; finally, advantages, limitations, and future research directions are discussed and conclusions presented.

2. The traditional AHP approach for MCDM problems

A typical multi-criterion decision problem can be expressed in the following equation:

$$\text{Optimize}\{Z_1(x), Z_2(x), \cdots, Z_n(x)\} \quad \text{s.t.} \quad x \in X, \tag{1}$$

where $Z_k(x)$ is the kth objective, x is the vector of solution attributes, and X is the solution space. Here we assume there are n objectives to be optimized. The goal of the DM is to optimize all of the n objectives. However, in the real world, the DM is usually encountered with a common dilemma where the improvement of one objective will cause the others to become worse. Thus, an aggregation of the performance on all objectives of an alternative is required to determine the best alternative.

Let's assume that the utility (or value) functions of all objectives are monotonically increasing (such as monetary utility, i.e., more is better). Then, the MCDP becomes

$$\text{Max } \{Z_1(x), Z_2(x), \cdots, Z_n(x)\} \quad \text{s.t.} \quad x \in X, \tag{2}$$

For some utility functions, which are monotonically decreasing, can be multiplied by -1 so that they become monotonically increasing. This formulation does not solve the problem since, in MCDM, there usually does not exist an optimal solution that optimizes all objectives. Tradeoffs are inevitable among the multiple objectives. A popular approach to solving MCDM is summing the weighed objectives to give a scalar value. That is,

$$\text{Max} \left\{ \sum_j w_j Z_j(x) \right\} \quad \text{s.t.} \quad x \in X,$$
$$\sum_j w_j = 1, \text{ and } w_j \geq 0 \text{ for } j = 1, \cdots, n; \tag{3}$$

where w_j is the weight for the jth objective. The solution x which gives the maximum value of Eq. (3) is considered as the optimal solution. However, this approach assumes that there exists an additive utility (or value) function. The necessary condition for the additive utility function is that the criteria should be *preferentially independent* [19,24]. Should the *preferentially independent* assumption hold in MCDP, the remaining work is to determine the weights in Eq. (3). A basic concern is that the weights should reflect the DM's belief in the relative importance of the various objectives. Here is where AHP can be helpful. The AHP method determines weights in Eq. (3) by pairwise comparison between each pair of objectives (or criteria). Each comparison is transformed into a numerical value of the Saaty's discrete 9-value scale (see Table 1).

The comparison results are then composed into a positive reciprocal matrix (i.e., PWM) $A=\{a_{ij}\}$, where $a_{ij}=a_{ik}\times a_{kj}$ (see Fig. 1).

Compared with the PWM in Fig. 1, it is obtained that $a_{ij} = \frac{wi}{wj}$,where w_i is the weight of the ith objective (i.e., Z_i). By multiplying A with the transpose of the vector $w^T=(w_1, w_2,\ldots, w_n)$, it gives nw. The problem becomes a linear equation as follows:

$$Aw = nw \tag{4}$$

By principle of linear algebra, the only way to obtain the nontrivial solution for the vector w is to solve $(A-n\mathrm{I})w=0$, where $\det(A-n\mathrm{I})=0$. This is a well known eigenvalue problem,

Table 1
Saaty's discrete 9-value scale

Numerical value	Linguistic definition
1	Equal importance
3	Weak importance of one over another
5	Essential or strong importance
7	Demonstrated importance
9	Absolute importance
2,4,6,8	Intermediate judgments between two adjacent judgments

$$
\begin{array}{c|cccc}
 & Z_1 & Z_2 & & Z_n \\
\hline
Z_1 & \frac{w_1}{w_1} & \frac{w_1}{w_2} & \cdots & \frac{w_1}{w_n} \\
Z_2 & \frac{w_2}{w_1} & \frac{w_2}{w_2} & \cdots & \frac{w_2}{w_n} \\
\vdots & \vdots & \vdots & & \vdots \\
Z_n & \frac{w_n}{w_1} & \frac{w_n}{w_2} & \cdots & \frac{w_n}{w_n}
\end{array}
$$

Fig.1. Pairwise weighting matrix (PWM) of AHP.

where n is a root of the characteristic equation of A. Saaty [1] has shown that A has unit rank (since every row is a constant multiple of the first row) and the components of eigenvector corresponding to maximum eigenvalue of A give the real weights associated with the objectives (i.e., $w_1, w_2,\ldots, w_n$). With these weights, we can solve Eq. (3) to obtain the solution x. AHP method consists of multiple levels for decomposition of decision-making process. For each sub-objective in each level, there is an associated A matrix. Saaty also provided the method for aggregating the weight matrices of various levels. Before aggregation, the weight vector obtained from the eigenvector of Eq. (4) should be normalized so that the summation of all components in the vector is equal to unit. The aggregation process of two adjacent levels is simply the multiplication of weight values of the lower level with the associated weight value of the higher level. Thus, the contribution of a considered objective in the lowest level is the accumulative multiplication of all weights along the path from the top objective to the considered objective in the hierarchy.

The AHP method described above is a structured, systematic, and effective approach for determining the relative importance weights in MCDM. However, due to the limitation of Saaty's discrete 9-value scale and the inconsistency of human's judgments while the weights are assessed during the pairwise comparison process, the aggregation weight vector might be invalid. Saaty described this inconsistency as perturbations in the coefficients of the A matrix. Thus, the problem $Aw=nw$ becomes $Aw'=\lambda_{\max}w'$. The inconsistency can be represented as the difference between number of criteria (n) and $\lambda_{\max}$. It turns out that a reciprocal matrix A with positive entries is consistent if and only if $n=\lambda_{\max}$. Saaty [2] proposed a method to measure the inconsistency by first estimating the consistency index (CI). The CI is defined in Eq. (5).

$$
\mathrm{CI} = \frac{\lambda\max - n}{n-1}, \tag{5}
$$

where n and $\lambda_{\max}$ are defined as above. Then, the CI is divided by the random consistency index (see Table 2) to obtain the consistency ratio (CR). If the CR is greater than 0.10, the pairwise comparison results should be rejected. Another cycle of reassessment for the relative importance weightings of the criteria is required until CR is falling below 0.10. Although guidelines can be followed to develop a better pairwise comparison, some drawbacks (such as the limitations of discrete 9-value scale as described in section one and the lack of automatic mechanism for improving the CR) can make AHP impractical or impossible for MCDM when the time is crucial.

3. Proposed adaptive AHP approach (A^3)

3.1. Selection of soft computing scheme

Late decision-making in construction management MCDM problems generally implies increased costs and sometimes even causes project failure. The omnipresence of inconsistency in MCDM makes reassessment inevitable. When decision makers are top managers, the costs (i.e., required man hours) of reassessment are increased. In many situations, reassessment is simply impossible for top managers because of the time constraints involved. Soft computing techniques can be very useful in solving such problems.

In contrast to the use of traditional hard computing methods (where achieving precision, certainty, and rigor in calculation are the primary goals), a soft computing paradigm (where tolerance of imprecision, uncertainty, and approximate reasoning is permitted) should be exploited (whenever possible) to yield a low-cost but acceptable solution [25]. Several soft computational schemes exist, including fuzzy set [26], Artificial Neural Networks (ANNs) [27], rough sets [28], and GAs [29]. Technique selection is case sensitive, and depends on the characteristics of the problem domain. Fuzzy set is most suitable approach for structured problems, ANN is suitable for application to semi-structured problems, and GA is the best choice for non-structured problems.

As described above, the PWM of AHP can be accepted only when CR is below 0.10. The reasons for causing a high CR include Saaty's discrete 9-value scale for relative weight assessment and human inconsistency for identifying the in-between numbers of fuzzy sets, particularly given an increasing number of criteria. Thus, a continuous (instead of discrete) value weighting scheme and an adaptive algorithm to determine the real number weights automatically are desired. It is observed that the relationship between the values of elements in PWM and the matrix eigenvalue is non-structured, GA are thus more suitable for the adapting process than other learning schemes (e.g. gradient descent in back-propagation ANN) that require explicit relationship between the objective function and the parameters. The GAs, first proposed by Holland [29], are algorithms based on the observation of the natural selection in the evolution of nature lives. The basic GA mechanism consists of three basic operations: (1) reproduction; (2) crossover; and (3) mutation. For detailed description of GA operations, please

Table 2
Random consistency index (*RC*)

Number of criteria	1	2	3	4	5	6	7	8	9
RC	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

refer to Goldberg [30]. To apply GAs for the proposed A^3, the objective functions and coding scheme must be determined. This determination is detailed below.

3.2. Definition of objective functions

In selection of objective functions, the CR is definitely a primary objective value to be minimized, since the basic requirement for AHP results to be accepted is that CR should be less than 0.10. However, if the CR is the only objective to be considered, it might result in a PWM that satisfies the CR requirement but sacrifices the DM's original preferences on criterion weightings. Thus, the other objective is required to guide the search toward the direction that reserves the DM's original belief in the relative importance of the various criteria. In the proposed A^3, a difference measurement between the adapted PWM and the original PWM is considered as the second objective.

3.3. Determination of coding scheme

While considering the coding scheme for GA, three important concerns are: (1) the coding scheme should guarantee global search; (2) the coding should be compact; and (3) similar numbers should be coded similarly. By global search, it means that all possible values of the parameters should be able to be coded. By compact, it means that the coded numbers should not be too large (in digit number), otherwise it will cause memory problem while implementing in computer programs. The binary coding scheme is qualified for the first two requirements. However, it does not satisfy the third requirement. That is, similar numbers might be coded differently. For example, "7" is coded as 0111 in a 4-digit binary format, "8" is coded as 1000 in a 4-digit binary format. Even though "7" is very close to "8", the Hamming distance between "7" and "8" in the binary coding is 4 (the maximum error in a 4-digit code). In order to improve this drawback, the Gray Code (GC) scheme is adopted instead of the binary code. The GC can be obtained from a binary code by performing XOR operations. Let an n-digit binary code be $[b_n\ b_{n-1} \ldots\ b_1]$. An GC for $[b_n\ b_{n-1} \ldots\ b_1]$ is represented as $[g_n\ g_{n-1} \ldots\ g_1]$, where $g_n = b_n$, $g_k = b_k \oplus b_{k-1}$. The GC guarantees global search, as compact as the binary code, and similar number coded similarly. For example, "7" is coded in GC as 0100 and "8" is coded in GC as 1100. The Hamming distance between 7 and 8 in GC scheme is only 1. As a result, the similarity is significantly improved.

3.4. Formulation of GA for A^3

Before developing the formulation of GA for A^3, the considered parameters should be defined first. Since the goal is to determine the values of elements in PWM so that the eigenvector (the final weights for the various criteria) of the matrix can be found, the considered parameters include all of the elements of PWM. As described before, the PWM is a positive reciprocal matrix. Thus, only the elements in the upper triangular of PWM are required. The elements on the reciprocal positions can be obtained by the following equation:

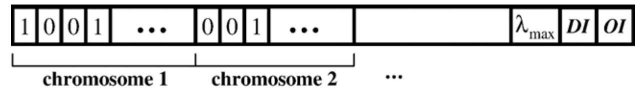

Fig. 2. Data structure of a GA genotype for AHP.

$$a_{ji} = \frac{1}{a_{ij}}, \tag{6}$$

where a_{ij} is the element of row i and column j in PWM. Therefore only $\frac{n^2-n}{2}$ elements are required for constructing PWM. Thus, we can consider the $\frac{n^2-n}{2}$ elements as the parameters in GA. Then, an individual gene called *genotype* in GA for A^3 is constructed. Each parameter is a chromosome on the genotype. The values of the $\frac{n^2-n}{2}$ elements in PWM are coded into GCs. For example, a 3-digit real number can be expressed as a 10-digit GC. Each digit in GC is either 0 or 1.

In addition to the digits for the $\frac{n^2-n}{2}$ elements in PWM, three real number parameters should be recorded on each genotype: (1) the maximum eigenvalue of the relative importance weight matrix, (2) the difference index (DI) between the original genotype and the derived genotype, (3) the overall index (OI) combining the performance of CR and DI. The maximum eigenvalue represents the first objective (i.e., consistency), since the lower eigenvalue achieves the lower CR. The DI represents the second objective (i.e., difference from the original genotype). There are many ways to measure DI, such as the Hamming distance between the two genotypes or the summation of square differences of all elements between the two genotypes. In the proposed A^3, the DI is defined in Eq. (7).

$$\mathrm{DI} = \frac{|G./G^*| + |G^*./G|}{n^2 - n}, \tag{7}$$

where G and G^* are row vectors of the original and derived genotypes in real number format. In Eq. (7), "./" means *element-to-element division*. That is, the division is performed for each pair of elements at the same position in the two genotypes. As G is equivalent to G^*, the DI in Eq. (7) gives 1. The reason why Eq. (7) is adopted for defining the DI rather than Hamming distance is that Hamming distance does not reflect the real difference between the same gene values in the two genotypes. Additionally, the summation of the square difference suffers from a similar problem to the Hamming distance.

The last parameter in the genotype is an overall evaluation of the two objectives. It is obvious that the goal of A^3 should be to reduce the values of both of DI and OI. The lower value of the first objective means the better consistency. The lower value of the second objective means better conformity between the derived PWM and DM's original belief. Thus, a straightforward definition for OI is simply the summation of λ_{max} and DI. Since the lowest value of λ_{max} is n (number of criteria) and the lowest value of DI is *unit* (when two genotypes are identical), it is intuitive to define OI as shown in Eq. (8).

$$\mathrm{OI} = (\lambda_{max} - n) + (DI - 1) \tag{8}$$

With the definitions of all parameters, the data structure of a genotype can be constructed as shown in Fig. 2. In the data structure of a genotype, there are totally $\left(\frac{n^2-n}{2}+3\right)$ elements. The first $\frac{n^2-n}{2}$ elements are in GC format (i.e., 0 or 1). The last three elements are real numbers.

3.5. GA operations in A^3

The first step of GA process in A^3 is to build the initial population of GA. A *population* in GA is the collection of a group of genotypes, and a *generation* is defined as a population performing a cycle of GA operations (i.e., reproduction, crossover, and mutation). In the evolution process of GA, only the genotypes with good objective performance will be selected from the parent generation to the next generation. Notably, a DM has only to perform one round of pairwise comparisons, resulting in an initial PWM. A primary genotype is created from the upper-right triangle of the initial PWM. The primary genotype is reproduced 20 times to generate 20 identical genotypes. Next, mutation is applied to all genotypes except 1. This mutation results in an initial population with only 1 genotype that is identical to the original genotype; the other 19 genotypes are slightly different from the original genotype.

During the second step, the initial population is crossed over with itself to generate 400 (=20×20) off-springs. Only 1 off-spring is identical to the original genotype and 399 new genotypes are produced. All 400 genotypes are evaluated, and the best 20 genotypes are selected for further evolution. The evolution process stops when all genotypes are the same or the objective performances do not improve any more. Then, the genotype with the best objective performance is selected as the final genotype. The PWM is then constructed based on the final genotype, and the eigenvector of the PWM is found to be the final weights for the various criteria. It will be demonstrated in the next section that no matter how many criteria are considered, the proposed A^3 is able to derive an PWM that can reflect the DM's original belief and achieve a CR much lower than the requirement (i.e., CR = 0.10). If the number of criteria is large, it will be very difficult for the DM to achieve the required CR even if the reassessment process is performed repeatedly. This is because that human's ability to accurately express his/her knowledge decreases as the problem is getting complicated.

4. Demonstrated case study

A real world MCDM problem in selecting a best-value bid (BVB) for a case project (National Laboratory Animal Center construction project) is adopted as a case study. In this MCDM problem, both the traditional AHP approach and the proposed A^3 are applied for weighting the MCDM criteria.

4.1. Description of case background

The case project comprises three main components: (1) civil and building construction (Civil and Building); (2) mechanical, electrical and plumbing (MEP) works; and (3) specific pathogen free (SPF) facility. The total project duration is 450 days, and the project budget is around USD 2.8 billion. The case project was performed under a design/build contract. A general contract should be awarded via a BVB evaluation process.

BVB contractor selection is a MCDM problem. The project owner (National Applied Research Laboratories, NARL) organized a BVB evaluation committee according to Taiwanese Government Procurement Law. This committee consisted of 17 members (that is, DMs) from three domains: (1) five members from the Civil and Building domain; (2) six from the MEP domain; and (3) six from the SPF domain. These members were selected from either academia or government agencies.

In this BVB evaluation process, the committee must determine the MCDM criteria. Fig. 3 illustrates the three-level hierarchy of the criteria determined by the committee for this case project. This MCDM hierarchy contained four level-one criteria, including price, organization, technical score, and question and answer (Q&A). Moreover, two level-one criteria

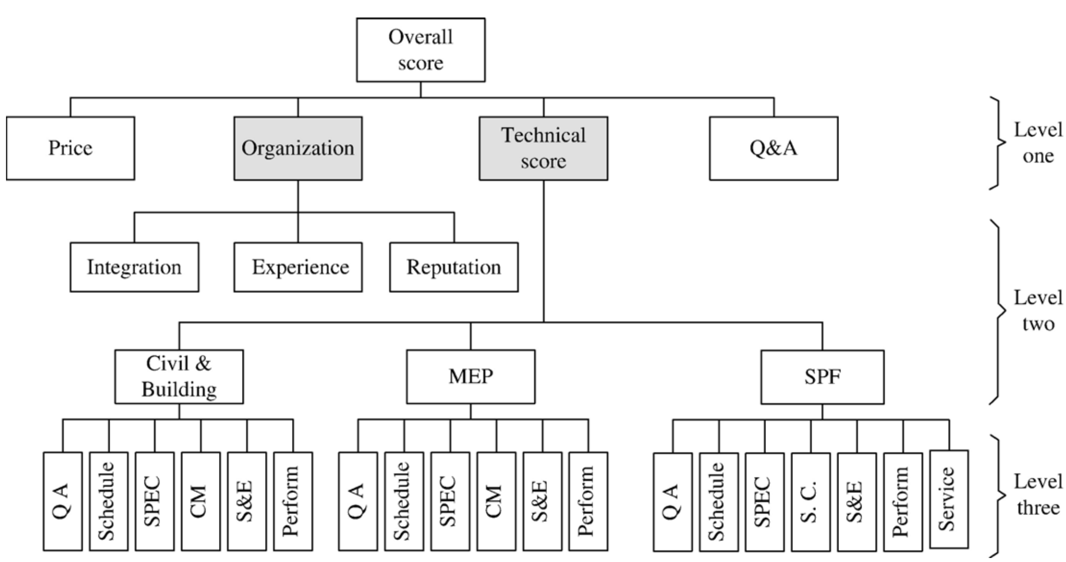

Fig. 3. MCDM hierarchy for the case study.

Table 3
The average *AHP and A^3 weightings* of the MCDM hierarchy for the case study

Criteria	Average weightings of criteria					
	AHP			A^3		
	Level one	Level two	Level three	Level one	Level two	Level three
Price	0.113			0.105		
Organization	0.234			0.235		
Integration		0.095			0.100	
Experience		0.040			0.035	
Reputation		0.098			0.100	
Technical score	0.588			0.597		
Civil and Building		0.128			0.118	
QA			0.026			0.025
Schedule			0.029			0.028
SPEC			0.025			0.024
CM			0.024			0.020
S&E			0.010			0.007
Perform			0.014			0.014
MEP		0.225			0.200	
QA			0.054			0.046
Schedule			0.047			0.041
SPEC			0.063			0.054
CM			0.025			0.024
S&E			0.017			0.015
Perform			0.019			0.020
SPF		0.235			0.279	
QA			0.047			0.052
Schedule			0.030			0.039
SPEC			0.061			0.082
S. C.			0.016			0.016
S&E			0.021			0.026
Perform			0.028			0.033
Service			0.032			0.031
Q&A	0.065			0.063		

were further broken down into sub-criteria. The *organization* level-one criterion is broken down into three level-two criteria, including integration ability (*integration*), joint contract experience (*experience*), and (3) team member reputation (*reputation*).

The *technical score* level-one criterion was also broken down into three level-two criteria, namely: *Civil and Building*, *MEP*, and *SPF*. Moreover, the *Civil and Building* and *MEP* level-two criteria consist of six level-three criteria, namely: quality assurance (QA), schedule planning and control capabilities (*schedule*), product specification (SPEC), construction management capability (CM), safety and environmental protection (S&E), and previous performance (*perform*). Furthermore, the *SPF* level-two criterion includes seven level-three criteria: QA, schedule, SPEC, S&E, perform, subcontractor management capability (S. C.), and service post installation (*service*).

Subsequently, the committee should determine the weightings of the criteria for each level of the MCDM hierarchy. The committee then should assign each bidder a score for each criterion. The overall score of a bidder is calculated by aggregating the weighted score of each criterion from the bottom level to the top level. A five-point Likert scale ranging from 1 to 5 is used to assess the scores at the bottom level. Two approaches were applied below to determine the criteria weightings: traditional AHP and proposed A^3.

4.2. Weighting approaches

4.2.1. Traditional AHP weightings (AHP weightings)

In *AHP weightings*, the relative importance among criteria at the same level is compared to obtain PWMs using the discrete 9-value scale of Saaty, as described above. Fourteen members (three Civil and Building members, five MEP members, and six SPF members) of the committee joined in assessing *AHP weightings* in the case study. Each member was required to complete six relative importance assessment tables, and thus generated six PWMs, including one level-one PWM, two level-two PWMs (*organization* and *technical score*), and three level-three PWMs (*Civil and Building*, *MEP*, and *SPF*). Totally, 84 ($=6\times14$) PWMs were obtained.

Among the 84 PWMs, only 35 PWMs were acceptable (i.e., $CR<0.10$) at the first assessment; the rest 49 PWMs required reassessment. Thirty-three (out of 49) PWMs were acceptable at the second assessment; the rest 16 PWMs needed reassessments. Meanwhile, 13 (out of 16) PWMs were acceptable on the third assessment, and the remaining three PWMs were acceptable on the fourth assessment. No PWMs needed fifth assessment.

To sum up, a total of 152 ($=84+33\times1+13\times2+3\times3=152$) PWMs were performed. An average 2.5 h (including the time of processing the input data and AHP assessment) was required to generate a PWM. Totally 380 ($=2.5\times152$) man hours were spent on the AHP weightings. The reassessment process took 18 days. The left of Table 3 shows the average criteria weightings using the *AHP weightings* (consisting of four cycles of AHP assessments). Additionally, the left of Table 4 illustrates the average CR, DI and OI values for each of the four cycles of the AHP assessments.

4.2.2. Proposed A^3 weightings (A^3 weightings)

In the *A^3 weightings*, the primitive PWMs obtained from the first assessment of the AHP weightings is automatically reassessed when CR exceeds 0.10. In the case study, 49 (out of 84) PWMs were unacceptable (that is, $CRs>0.10$). Thus, the proposed A^3 is applied to adjust the relative importance values of the criteria in the unacceptable PWMs to meet the consistency requirement.

A prototype computer program was designed with the Matlab® language for implementing the proposed A^3. Moreover, a personal computer with CPU of 1.5 MHz was adopted as

Table 4
The average CR, DI and OI values obtained using the AHP *and* A^3 approaches

Weighting approach	AHP				A^3	
Assessment cycle	Primitive	Second	Third	Fourth	Primitive	Final
No. of *PWM*	84	49	16	3	84	49
Average CR	0.142	0.101	0.085	0.063	0.142	0.073
Average DI	1.000	1.337	1.454	1.360	1.000	1.121
Average OI	0.639	0.795	0.898	0.606	0.639	0.479

Table 5
Overall score and weighted scores of bidders for the AHP *and* A^3 approaches

Weighting approach	Weighted scores			
	AHP		A^3	
Bidder	A	B	A	B
Price	10.70	10.25	10.78	10.34
Organization	21.26	22.14	20.04	20.98
Technical score	41.12	36.58	42.51	38.21
Q&A	5.03	4.58	4.96	4.54
Overall score	78.11	73.55	78.29	74.07

the platform for this case study. The adaptations of all 49 PWMs were finished within a day. Restated, the proposed A^3 was 17 (=18−1) days faster than the traditional AHP approach in completing the reassessment process. The right of Table 3 displays the average criteria weightings, and the right of Table 4 shows the average CR, DI and OI values using the A^3.

4.3. Evaluation results

Only two bidders, namely bidders A and B, bid for this case project. After reviewing the bidder submissions, auditing their oral presentations, and clarifying questions via Q&A, the 14 committee members scored the 24 criteria at the bottom level of the decision hierarchy for each bidder. Table 5 illustrates the level-one-criterion weighted scores and the overall score for each bidder when applying traditional AHP and the proposed A^3. Both approaches suggest the same, namely, bidder A is identified as the best-value bidder, although the overall and weighted scores differ slightly between the two approaches.

5. Benefits and limitations

5.1. Benefits

The proposed A^3 is demonstrated to have three benefits for MCDM: (1) cost effectiveness; (2) timeliness; and (3) improved decision quality.

5.1.1. Cost effectiveness

Since the proposed A^3 does not require the DMs to perform the reassessment process, numerous man hours (that is, labor costs) can be saved. In this case study, 210 man hours were required for conducting the primitive (first) assessment of PWMs in the traditional AHP or the proposed A^3. However, the proposed A^3 needed only an additional 8.2 man hours for adaptation, as the traditional AHP required additional 170 man hours for reassessment. Namely, 161.8 (=170−8.2) man hours or approximately 42.6% (=161.8/(210+170)) of man hours can be reduced.

5.1.2. Timeliness

Numerous DMs were top managers and were not always free to participate in the assessment and reassessments. In the case study, it took seven days to collect the primitive PWMs from the DMs. When the traditional AHP approach was applied, the reassessments required a further 18 days for PWM collection. However, the adaptation of the proposed A^3 took just one day. Thus, 17 days or 68% (=17/(7+18)) of data-collection time was saved by applying the proposed A^3. Table 6 lists the abovementioned man hours and data-collection time with respect to the traditional AHP and A^3 in this case study.

5.1.3. Improved decision quality

The traditional AHP approach requires DMs to perform reassessments to meet required CRs. Such reassessments may force the DM to adjust their primitive PWM (representing their original beliefs regarding the relative importance relationships among the criteria) simply to meet the consistency requirements [31]. The DI defined in Eq. (7) can be employed to monitor this adjustment. Restated, DI is used to measure the difference in relative importance relationships between the primitive PWM and the modified (through reassessment or adaptation) PWM. Higher DI indicates a larger deviation (i.e., poor decision quality) from the primitive PWM (i.e., the original belief of the DM is assumed to be the truest one). A modified PWM is identical to the primitive one when its DI equals unit. As shown in Table 4, the average values of DI are 1.337, 1.454, and 1.360 for the second, third and fourth reassessments, respectively, when the AHP approach is applied. These DI values all exceed that (DI=1.121) of the adaptation when the proposed A^3 is employed. Thus, the proposed A^3 can improve the decision quality.

5.2. Limitations

Two limitations of the proposed A^3 were identified during the course of this study. First, the proposed A^3 adapts PWMs based on a primitive assessment. Consequently, no reductions can be achieved in the man hours (210 man hours in the case study) and time (7 days in the case study) for data collection required for the primitive assessment. Strategies for reducing the man hours required and data-collection time should be explored in future investigations.

Second, the proposed A^3 assumes that the DMs can asses the relative importance between criteria logically (namely, the DMs should be able to select the nearest numbers in the discrete 9-value scale of Saaty) despite the inevitability of inconsistency in the pairwise comparisons. If illogical judgments occur, the adapted PWM can be considered a compromised PWM that only meets the CR requirement. Therefore, notifying the DMs to carefully assess the pairwise comparisons of criteria to obtain

Table 6
Comparison of man hours and data-collection time for the AHP *and* A^3 approaches

	AHP		A^3	
Weighting approach	Primitive assessment	Reassessments	Primitive assessment	Adaptation
Man hours	210	170	210	8.2
Time for data collection (days)	7	18	7	1

the primitive PWM should be stressed when the proposed A^3 is used.

6. Conclusion

The work presents an adaptive AHP approach (A^3) to improve the traditional AHP method of solving MCDM problems from three perspectives: (1) cost effectiveness — the proposed A^3 eliminates the reassessment process required by the traditional AHP approach, saving numerous man hours (and thus associated costs) (42.6% savings in man hours were achieved in the case study); (2) timeliness — the proposed A^3 shortens the time required to gather the PWM reassessment data (a 68% reduction in data-collection time was achieved in the case study), allowing emergent MCDM problems to be solved in time; (3) improved decision quality — the proposed A^3 enhances the decision quality, which better reflects the original belief of the DM in the relative importance relationships of the criteria. Finally, besides the two limitations mentioned in Section 5.2 that need to be addressed, another important future research task is to develop an automated system for performing A^3 to accelerate data collection.

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