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RESEARCH ARTICLE

A Novel Parsimonious Best Worst Method for Evaluating Travel Mode Choice

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ABSTRACT There is an obvious trade-off between the amount of information obtained from user surveys and low-cost and time-efficient survey. In this study, we propose a Parsimonious Best Worst Method (P-BWM) to unburden the evaluators from the extensive number of pairwise comparisons required originated by numerous factors and alternatives required by the Best Worst Method (BWM) in the complex decision problems. The new Parsimonious BWM model assigns priorities to many elements by contrasting pair wisely some reference elements, also it combines the straightforwardness of direct evaluations with the dependability and stability of the BWM approach. The developed Parsimonious BWM technique has been experimented and validated in a real-world problem of Mersin city in Turkey, to evaluate travel mode alternatives. Moreover, a comparative analysis has been applied to the correlation of the adopted outcomes between BWM and P-BWM.

INDEX TERMS Multiple criteria analysis, best worst method, parsimonious preference information, pairwise comparison matrix, travel mode choice.

I. INTRODUCTION

In general, the scholars are confronted by the riddle in preference surveys, where several complicated questions are asked to get precious data as much as possible, or in other cases, they construct unsophisticated evaluations to get a large number of responses through the high response rate.

The Analytic Hierarchy Process (AHP) is the most applied approach for scaling performances taking into consideration factors and alternatives and their significance [1]. For scrutinizing the main advancement of AHP approach, see [2], [3], [4], [5], [6], and [7]. However, the evaluators spend enormous time and effort for evaluating even small decision problems. Despite the many advantages of AHP, the recently created Best Worst Method (BWM) has quickly become the second favored choice application to evaluate the complex decision issues after the Analytic Hierarchy Process (AHP). Owing to the required efforts from the decision-makers, the questionnaire of BWM considers a fewer number of pairwise comparisons (PCs) comparing to other complex matrix-based Multi Criteria Decision Making (MCDM) methodologies. For instance, in AHP, the estimation process requires (n(n-1)/2) comparisons while BWM requires only (2n-3) comparisons, where n is the number of the evaluated elements [8]. More comparisons lead to a long time for estimation process and vigorous effort from the evaluator side. The other unique characteristic of BWM is represented by the high reliability degree of the derived weights, which comes from the consistency of the obtained results, because the consistency check in BWM is for testing reliability degree for evaluating the comparisons, on the opposite of other MCDM methodologies, the consistency check is for testing whether the comparisons are reliable or not, reduces efficiently the risk of getting a confusing or uncertain evaluation. The further advantage of BWM is using merely the integer numbers and which makes it simpler and more comprehensive for participants than other MCDM methodologies, for instance, AHP. The BWM has a precise conspicuous advantage in comparison to any other survey methodologies [9].

The Parsimonious Best Worst Method (P-BWM) allows to employ the methodology for estimating complex decision

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problems dealing with a big number of factors and alternatives. The model is proposed for reducing the cognitive effort of the evaluator to supply data. In our paper, the minimizing process for PCs numbers is compared with BWM. The P-BWM model is saving the time and efforts efficiently, which interns pacify the evaluator during the evaluation process. For instance, if we have 10 alternatives it would be necessary following the rules of the conventional BWM to ask (2×10-$3 = 17$) 17 PCs, while in the P-BWM model only 3 PCs evaluations are required. If we suppose that for evaluating each PC, in average, the evaluators would spend 30 seconds, then they should take ($17 \times 30 = 510$) 8.5 minutes for evaluating 17 PCs by using BWM, however, they would spend only ($3 \times 30 = 90$) 1.5 minutes for evaluating 3 PCs by using P-BWM. Even if we considered the time of direct evaluation, the proposed model still reduces evaluation time. For instance, 10 alternatives would consume about 2 minutes to be rated and the total evaluation time would be $2 + 1.5 = 3.5$ minutes which still shorter than 8.5 minutes. So, the proposed model reduces the time of pairwise comparisons for evaluators, even if we consider the time of direct evaluations. In fact, we cannot limit the time for evaluators, we just spot the light on the actual efforts and time that the evaluators spend for conducting the evaluation process. This small example reflects the tremendous difference between BWM and the proposed P-BWM model.

As being a new model, there are no previous applications of it and this leads to several open questions in terms of the conditions and limitations related to conducting P-BWM. The proposed model permits to use the logic of the BWM, nevertheless reducing the number of preference comparisons asked from the evaluators. The new model consists of four main steps: (I) direct evaluation of the factors with respect to the considered alternative, (II) choosing reference evaluations; (III) application of BWM to reference evaluations; (IV) revision of the direct evaluation on the basis of the prioritization supplied by BWM on reference evaluations.

This paper proposes a novel Parsimonious Best Worst Method (P-BWM) model for travel mode choice evaluation and have been applied in a real case. Compared with the conservative BWM model, it is acknowledged that this P-BWM method can reduce the number of pairwise comparisons. In a certain extent, this study can save the time and efforts in decision making process.

To validate the new P-BWM model we conducted the real-world survey with experts from engineering departments in Mersin University, whom were asked to estimate the travel mode in Mersin city. The rest of the work is structured as follows; In the Methodology section both BWM and P-BWM are presented. The Results section introduces expert surveys applied by BWM and P-BWM, which illustrate the merits of the new model. Finally, conclusions are drawn related to the application of the created model.

II. METHODOLOGY FOR THE PROPOSED RESEARCH

In this section, the basic Best Worst Method is presented, then the novel parsimonious extension is illustrated.

A. THE BEST WORST METHOD (BWM)

The Best-Worst Method (BWM) approach has been created recently for evaluating complex decisions, when there are multiple factors or alternatives involved. Because it is more convenient than other MCDM approaches, it has been conducted for evaluating a large number of different complex problems since its creation [10], [11], [12], [13], [14]. Additionally, many modified BWMs have been introduced recently by relevant scholars to improve the performance of the classical BWM [15], [16], [17], [18], [19], [20]. The reliability and efficiency of BWM is quite high with respect to the amount of data needed (see [13] for a general review on the main improvements of BWM and [12], [21], [22], [23] for some recent contributions related to BWM). Similarly, to the AHP approach, BWM uses PCs to compute the weight scores of factors and alternatives. However, the BWM approach requires fewer comparisons ($2n - 3$) compared to the AHP approach ($n(n-1)/2$) [9]. Moreover, BWM approach is easy to apply and more reliable compared to other methodologies [9]. The main steps of BWM approach for deriving scores are depicted in Figure 1.

To provide an overview on all stages, we define the phases in the following order:

Step 1: Identifying the problem and the set of alternatives. In the first step, the decision maker defines n alternatives $(A_1, A_2, \ldots, A_n)$ that are used to make the judgment.

Step 2: Defining the best and worst alternative by simple scoring of the participant experts.

Step 3: Evaluating PCs between the best alternative to other types by using a scale of 1 to 9, where 1 means "equal importance" and 9 means "extremely more important". The result of this step is represented by the following best to others vector:

$$V_B = (v_{B1}, v_{B2}, \ldots, v_{Bn}) \tag{1}$$

where v_{Bj} is the preference of alternative B (the most important or the best) over the alternative j and $v_{BB} = 1$.

Step 4: Conducting the PCs between the worst mobility type and all other types by using a scale of 1 to 9. The result of this step is represented by the following vector:

$$V_j = (v_{1W}, v_{2W}, \ldots, v_{nW}) \tag{2}$$

where v_{jD} is the preference of alternative j (the most important or the best) over the alternative W and $v_{WW} = 1$.

Step 5: Calculating the final optimal weights ($D_1^*, D_2^*, \ldots, D_n^*$) of the alternatives, and the indicator of the optimal consistency of comparisons ξ^*.

The maximum absolute difference has to be minimized by:

$$\min \ max_j \left\{ \left| \frac{D_B}{D_j} - v_{Bj} \right|, \left| \frac{D_j}{D_W} - v_{jW} \right| \right\}$$
$$\sum_j^{s.t.} D_j = 1, D_j \geq 0, \text{for all } j \tag{3}$$

TABLE 1. The consistency index values for computing the consistency ratio.

v_{BD}	1	2	3	4	5	6	7	8	9
CI	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

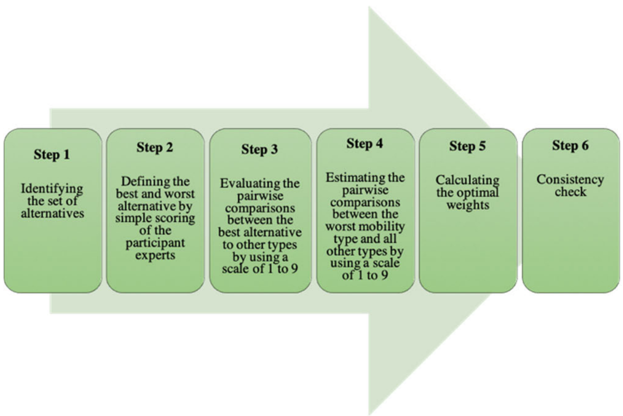

FIGURE 1. The main steps of the BWM approach.

After that the solution could be obtained by solving the following linear programing problem:

$$
\begin{aligned}
&\min \xi^* \\
&s.t. \\
&\quad \left|\frac{D_B}{D_j} - v_{Bj}\right| \le \xi^*, \text{ for } all\ j \\
&\quad \left|\frac{D_j}{D_W} - v_{jW}\right| \le \xi^*, \text{ for } all\ j \\
&\quad \sum_j D_j = 1 \\
&\quad D_j \ge 0, \text{ for all } j
\end{aligned} \tag{4}
$$

Step 6: The Consistency Check

The following formula computes the Consistency Ratio to check the tolerable inconsistent of the PCs [16].

$$\text{Consistency Ratio} = {\xi^*}/{\text{Consistency Index}} \tag{5}$$

where the Consistency Index (CI) is given in Table 1 [16] gained by random experiments for different number of comparisons.

B. THE PARSIMONIOUS BEST WORST METHOD (P-BWM)

Despite the unique advantages of BWM, it still suffers from handling with high number of elements and to overcome this bottleneck, the new Parsimonious BWM model has been invented.

The prevalent steps of the proposed new P-BWM model for F_m factors and a alternatives can be summarized in the following:

1) Direct rate evaluation of the factor F_m with respect to alternative a;
2) Choosing a number of reference factors. Let us remark the reference alternatives by s, and the number of reference factors by t_m;
3) The participated evaluators are asked to conduct BWM to the set composed of the reference evaluations (let us denote γ_{ms} the direct evaluation of the s reference element by the evaluators) defined on Step 2 adopting the normalized evaluations $u(\gamma_{ms})$, for all $m = 1, \ldots, n$ and for all $s = 1, \ldots, t_m$;
4) The following items have to be checked and discussed with the evaluators: the consistency of the PCs has to calculated by the consistency ratio, the normalized evaluations $u(\gamma_{ms})$, for all $m = 1, \ldots, n$ and for all $s = 1, \ldots, t_m$, have to be compared with the corresponding ratings $rm(\gamma_{ms})$ controlling that the monotonicity is satisfied, that is verifying that $rm(\gamma_{ms1}) > rm(\gamma_{ms2})$ if $u(\gamma_{ms1}) > u(\gamma_{ms2})$,
5) The rating of the evaluations provided by evaluators (which are not the reference evaluations) are adopted by linear interpolation for the normalized evaluations which have to be computed in the previous step. Let us donate: $u(r_m(a))$ the normalized evaluation score of the factor m with respect to alternative a, which is calculated from the interpolation of the values adopted by the reference BWM in the 3. and 4. Steps, $u(\gamma_{ms})$ the normalized BWM score of $s+1$ reference factor gained from the PC, γ_{ms} the direct evaluation of the s reference factor by the evaluators, γ_{ms+1} the direct evaluation of the $s+1$ reference element by the evaluators, $r_m(a)$ the direct corresponding rating provided by the evaluator to the alternative a, For each $rm(a) \in [\gamma_{ms}, \gamma_{ms+1}]$, the following value has to be computed, which avoids the rank reversal issue:

$$
\begin{aligned}
u(r_m(a)) = {} & u(\gamma_{ms}) \\
& + \frac{u(\gamma_{ms+1}) - u(\gamma_{ms})}{\gamma_{ms+1} - \gamma_{ms}}(r_m(a) - \gamma_{ms})
\end{aligned} \tag{6}
$$

Basically, in P-BWM we have a monotonic increasing order of the factors, determined by direct evaluation on a factor level. From this order we select t_m reference factors and conduct the PCs on them. Their increasing order has to be kept and consistency to be checked. Afterwards, we substitute their weight values with the direct ratings and get back to the original monotonic increasing order. In this order normalizing any r_j elements mean to find its low (γ_{ms}) and high (γ_{ms+1}) neighbor out of the reference factors. Their monotonic order cannot be changed, which is assured by formula (6).

III. A CASE STUDY FOR TESTING P-BWM MODEL FOR TRAVEL MODE ANALYSIS

In order to validate the proposed P-BWM model we applied a real survey with 7 evaluators from engineering departments in Mersin University, they were asked to evaluate the travel

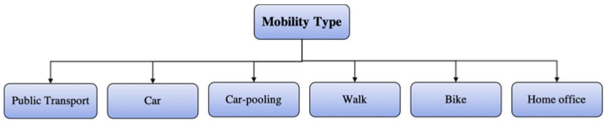

FIGURE 2. The travel types.

TABLE 2. The aggregated scores for travel mode alternatives by using BWM approach.

Travel Mode	Public Transport	Car	Car-Pooling	Walk	Bike	Home-Office
Final weight	0.081	0.389	0.039	0.108	0.141	0.242
Rank	5	1	6	4	3	2

mode problem in Mersin city. In this case study, no factors have been adopted, only the alternatives (the transport modes themselves) were estimated, since we relied on expert considerations and did not strive to influence their decisions by any factor selection. In the applied survey six mobility types were utilized as listed in Figure 2 (Public transport, Car, Car-pooling, Walk, Bike and Home office).

In the real-world case study, two user surveys were applied by BWM and P-BWM in a Turkish city, Mersin in December, 2021, seven answers from the academic stuff members in engineering departments have been received., the survey process has been started with BWM survey (each person evaluated 9 PCs).

Having selected the commuting alternatives and implemented the BWM logic, the following short questionnaire was created.

- "Please select the best and worst mobility type for commuting!"
- "Please evaluate other mobility types with respect to the best type using a scale of 1 to 9"
- "Please evaluate other mobility types with respect to the worst type using a scale of 1 to 9"

After computing weights of mobility alternatives for every evaluator in all group, and calculating the consistency, we aggregated the weights for each group by utilizing the geometric mean to get the final weight vectors.

The total number of PCs for the evaluators is 2n-3 = 9, where n = 6. After aggregating 7 score vectors which were generated from 7 responses, the results are presented in Table 2.

A. P-BWM MODEL FOR EVALUATING TRAVEL MODE

The experiments, they were done face to face with 7 academic experts in the engineering field, before filling up the survey, we explained the target of the survey and main steps of the application. The meeting was in same day for each expert. The P-BWM process has a unique difference point from BWM, which is the direct rating for the alternatives, in this point we ensure that the evaluator would not be impacted by the traditional steps of the BWM.

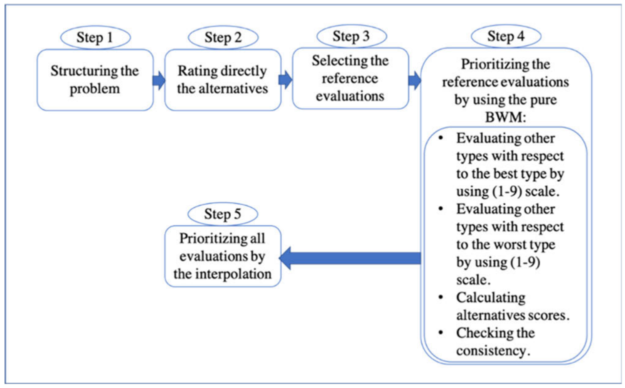

FIGURE 3. The framework of the proposed P-BWM model.

The main five steps of P-BWM model for our case are illustrated as follows (Figure 3):

Step 1: Constructing the structure: six alternatives were selected for estimating travel mode, the selection process was done with decision makers in the related field;

Step 2: Direct rating for the six alternatives: the evaluators did the estimation process with respect to the goal, then we aggregated the normalized ratings for all of them;

Step 3: Choosing the reference evaluations: the evaluator defined 3 reference elements [31], [32].

Step 4: Evaluating the reference evaluations: The PC evaluation of the reference elements done by employing BWM. The evaluator asked to compare the best reference element with the other and compare the worst reference element with the others. Then the consistency of the PC was tested to detect the reliability [8];

Step 5: Prioritizing all evaluations by interpolation: the scores for all other alternative have been computed by interpolation taking in consider the adopted priority values from the previous step (Formula 6).

The main difference here is that in BWM approach the evaluator asked to highlight the best and the worst alternatives and conduct PC for all alternatives with respect to the best alternative and with the worst alternative, however, in our P-BWM model, firstly the direct rate is asked to be conducted which provides at the same time the best alternative and worst alternative, then conduct BWM on the reference elements. The original idea is minimizing the time and effort for evaluators.

Before starting the evaluation process, we explained the process for each evaluator, since the surveys have been done face to face with each evaluator alone and we guided them during conducting the evaluations.

Step 1: The six alternatives in our case are directly evaluated by evaluators based on (0- 100) scale. The gained ratings were aggregate by employing the geometric mean technique [26]. The final rate score for each alternative was as follow (Table 3): a_1 "Public transport" (0.087); a_2 "Car" (0.0362); a_3 "Car-Pooling" (0.027); a_4 Walk (0.099); a_5 Bike (0.149) and a_6 Home-Office (0.276).

TABLE 3. The direct evaluation for travel mode alternatives the final parsimonious scores.

Travel Mode	Public Transport	Car	Car-Pooling	Walk	Bike	Home-Office
Aggregated direct rate (0-100)	13	53	4	14	22	40
Normalized direct rate	0.087	0.362	0.027	0.099	0.149	0.276
Rank	5	1	6	4	3	2

TABLE 4. The obtained scores from BWM approach for the reference elements.

Reference elements	Car	Bike	Car-Pooling
Scores	0.694	0.223	0.083

Step 2: Following that, suitable reference alternatives have to be selected out of the total alternatives. For our case the following reference elements have been selected considering their position in the direct evaluation (highest value; middle value and lowest value), "Car" ($\gamma_1 = 0.362$); "Bike" ($\gamma_2 = 0.149$) and "Car-Pooling" ($\gamma_3 = 0.027$). Keeping in mind avoiding big number of references, which can lead to several PC evolutions. Abastante et al. [24] selected 4 references for 13 elements, while Duleba [25] and Duleba and Moslem [7] selected 3 references for 11 elements. Till now, the optimal number of reference elements is exposed to debates and it needs further research for clarification.

Step 3: Choosing the reference evaluations: the evaluator defined 3 reference elements;

In our case, we selected Car, Bike and Car-Pooling.

Step 4: Evaluating the reference evaluations: The PC evaluation of the reference elements done by employing BWM (Table 4). The evaluator asked to compare the best reference element with the other and compare the worst reference element with the others. Then the consistency of the PC was tested to detect the reliability [8] Rezaei.

Step 5: Prioritizing all evaluations by interpolation: the scores for all other alternative have been computed by interpolation taking in consider the adopted priority values from the previous step (Formula 6).

$$
\begin{aligned}
u\,(\text{Home}-\text{Office}) &= 0.223 + \frac{0.694-0.223}{0.362-0.149} \times (0.362-0.276) \\
&= 0.223 + \frac{0.471}{0.213} \times (0.086) = 0.413 \\
u\,(\text{Walk}) &= 0.083 + \frac{0.223-0.083}{0.149-0.027} \times (0.099-0.027) \\
&= 0,083 + \frac{0.14}{0.122} \times (0.072) = 0.166 \\
u\,(\text{Publictransport}) &= 0.083 + \frac{0.223-0.083}{0.149-0.027} \times (0.087-0.027) \\
&= 0.083 + \frac{0.14}{0.122} \times (0.06) = 0.152
\end{aligned}
$$

TABLE 5. The final parsimonious scores for travel mode alternatives.

Travel Mode	Public Transport	Car	Car-Pooling	Walk	Bike	Home-Office
Final Parsimonious scores	0.152	0.694	0.083	0.166	0.223	0.413
Rank	5	1	6	4	3	2

TABLE 6. The final normalized parsimonious scores for travel mode alternatives.

Travel Mode	Public Transport	Car	Car-Pooling	Walk	Bike	Home-Office
Final Parsimonious scores	0.088	0.401	0.048	0.096	0.129	0.239
Rank	5	1	6	4	3	2

TABLE 7. Comparison of the reference conventional BWM survey and the new P-BWM survey.

	BWM survey	P-BWM survey
Location	Mersin. Turkey	Mersin. Turkey
Evaluators	Academic experts	Academic experts
Question technique	personal interviews	personal interviews
Number of evaluators	7	7
Number of questions	7 PCMs	direct evaluation + 3 PCMs
Type of questions	Pairwise comparisons	Direct evaluations and few pairwise comparisons
Average time of filling	250 seconds	160 seconds
Consistency	All PCMs were consistent	All PCMs were consistent

Table 5 presents the final parsimonious scores for travel mode alternatives and Table 6 presents the final normalized scores.

Table 7 illustrates the comparison of technical details of the conducted two methodologies.

IV. CONCLUDING REMARKS

This paper proposes a novel prioritization Parsimonious Best Worst Method (P-BWM) model using pairwise comparison matrices for travel mode choice evaluation, the proposed model have been applied in a real case. Compared with the conservative BWM model, it is acknowledged that this P-BWM method can reduce the number of pairwise comparisons, where the model employs the pairwise comparison matrices that is parsimonious with respect to the preference information asked to the decision maker. In a certain extent, this study can save the time and efforts in decision making process.

It permits to use BWM approach even if the considered decision problems present a high number of alternatives or factors. The new proposal is composed of 5 steps: (I) estimate of the performances of the considered alternatives on each factor; (II) definition of some reference evaluations in accordance with the analyst; (III) pairwise comparison of the reference evaluations by using the BWM method; (IV) control and discuss with the DM the consistency of the supplied PCs; (V) interpolation of the values obtained by BWM approach in the previous step in order to get the normalized evaluations of all alternative performances.

As limitation, the risk of information loss has to be emphasized. The reduction of comparisons is very useful from practical point of view, since the evaluation time of each questionnaire decreases significantly which possibly increases the response rate of the participants. On the other hand, however, the reduction means information loss on the relations of the missing pairs of the factors or alternatives in the decision problem. This risk should be considered and handled by the methodologists of the decision and the survey should balance between the evaluation time and information loss.

We would also like to underline that the proposed procedure permits to apply P-BWM in decision problems with a huge number of elements to be compared. For this reason, we believe that our proposal of a parsimonious version of BWM can be considered a relevant contribution for the basic theory and application of BWM. In future studies, Bayesian model can be integrated with P-BWM for evaluation and comparison of the complex problems in fuzzy environment [27].

COMPETING INTERESTS

All authors are here with confirm that there are no competing interests between them.

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