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EXPERTISE-BASED EXPERTS IMPORTANCE WEIGHTS IN ADVERSE JUDGMENT

Evy Herowati[1,2], Udisubakti Ciptomulyono[1], Joniarto Parung[2] and Suparno[1]
[1]Industrial Engineering, Institute of Technology Sepuluh Nopember, Surabaya, Indonesia
[2]Industrial Engineering, University of Surabaya, Surabaya, Indonesia
E-Mail: evy@ubaya.ac.id

ABSTRACT

The objective of this research was to propose the use of expertise levels of experts to determine the experts' importance weights since there has been no research that determines the 'importance weight' using the expertise level as a whole. The significance of this research was the integration of three concepts, namely: the *expert's expertise level*, FPR's *Additive Consistency* and *the Induced-OWA operator* to obtain the expert's importance weight in adverse judgment situation. The Expertise level of an expert in adverse judgment situation is determined by his/her own assessment on a set of alternatives and defined as 'the ability to differentiate consistently' and expressed as the ratio between Discrimination and Inconsistency. The experts provided their preferences using FPR (Fuzzy Preference Relations) since FPR has Additive Consistency property to replicate each element of FPR matrix. Experts were sorted according to their expertise level and the experts' importance weights followed the OWA (Ordered Weighted Averaging) operator's weights which were determined by parameterization using Basic Unit-Interval Increasing Monotonic functions. The experts' importance weights model illustrated by a numerical example, and it concluded that the higher the expert's expertise level, the higher his/her importance weight.

Keywords: additive consistency, expertise, fuzzy preference relations, importance weight, induced OWA operator.

INTRODUCTION

The expertise level of decision maker greatly affects the quality of the resulting decision [1]. The decision quality made by the experts presumed better than decision quality made by the non-experts as an expert have the ability to think differently [1-3]. This is because the inherent ability of the experts enables them to understand problems in more detail and depth so that the experts can distinguish the various aspects of the situation that is usually overlooked by the non-expert [4].

Related to decision that requires the Decision Maker (DM) expertise in Group Decision Making (Decision Making with more than one DM), the DM individual assessment needs to be explored and group decision is taken based on the integration of individual assessments into the group assessment, by performing aggregation of DM assessments mathematically [5]. One important factor that must be considered in the aggregation process is the importance weight of each DM. The magnitude of the DM's importance weight influence decisions. If a DM assessing an alternative with a high score and this DM gets a high importance weight, then this alternative would get a high total score and most likely has a high opportunity to be selected as the best alternative. Therefore, to improve the decision quality, the DMs' importance weights should be determined based on their expertise level.

Some researchers defined the expertise level as "the ability to differentiate consistently" through the evaluation of his/her assessment level on alternatives [6-7]. The level assessment on alternatives is called *the adverse judgment* [8]. Shanteau (2002) stated the experts as those who can differentiate between similar but not exactly the same, cases and repeat their assessments consistently. They formulated the expertise level as the ratio between Discrimination ability and Inconsistency [6-7]. The drawback of this formulation found in the Inconsistency measurement [9]. Measuring Inconsistency required repetition; consequently the experts need to assess the same cases more than once. Assessing the same cases more than once is very difficult to do independently without being influenced by previous assessments. This is the reason of the need for adjustment to the formula implementation in determining the expertise level.

A number of researches have been proposed in determining the DMs importance weights and can be categorized into 2 groups: direct evaluation to DMs and evaluation to the DMs' assessment level. The DMs' importance weights determination through direct evaluation to DMs consists of a 'supra DM' who assessed the DM then gave weight to each DM [10-12] and 'a group of DM' who assessed each member in the DM group [13-15]. The direct evaluation methods could potentially lead to decision bias due to the assessors' subjectivity, the assessors' difficulty in assessing other DM and popularity effect (a person who has been recognized by peers usually assumed more expert; but it is possible that the 'assumed less expert' would be the creator of new knowledge [6]). While the determination of the DMs' importance weight through evaluation of their assessment on a set of alternatives can be classified into the determination of importance weights based on maximum consensus that could be achieved in the group [16-18], minimum deviation of DM individual opinion to the group opinion [19-21], minimum distance from the DM individual opinion to group opinion [22-27] and consistency of DM assessment on alternatives [8, 28-30]. In general, the methods of determining the DM importance weights in the

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adverse judgment situation are more objective than direct evaluation to the DMs. These methods had certain property: the closer the DM's individual opinion on group average opinion, the greater his/her importance weight regardless of his/her expertise level. In particular, there were methods of importance weight determination based on the DM's consistency evaluation in pairwise comparison FPR (Fuzzy Preference Relation). These methods assumed that the more consistent the DM preferences, the more relevant the DM opinion and resulting the higher the DM importance weight. These consistency-based methods are more objective compared with the other methods, but these methods have not considered the expertise level as a whole.

In this paper, the DM importance weight is determined based on the expertise level as a whole as the ability to differentiate consistently and expressed by the ratio between Discrimination and Inconsistency and the difficulty in repetition is replaced by estimation using Additive Consistency (AC) of FPR. The DM provides preference in the form of pairwise comparisons FPR where FPR has the Additive Consistency (AC) properties that used to estimate repetition. The experts then sorted by their expertise level and the experts' importance weights are associated with the OWA (Ordered Weighted Averaging) operator's weights which are determined by parameterization using Basic Unit-Interval Increasing Monotonic functions (BUM).

To do this, this paper is organised as follows. Following the first Section, it is discussed the concepts used to obtain the DM's Importance weight, namely the expertise level of expert, the AC property of FPR and the Induced OWA Operator. Next, the methodology to obtain the *expertise-based experts importance weights* is discussed and followed by the applicability test of the methodology using a numerical example. Finally, in the last Section we drew our conclusions.

LITERATURE REVIEWS

There are three important concepts used in this research to obtain the DM's Importance weight, namely the experts' expertise level, the AC property of FPR and the Induced OWA Operator.

The Expertise Level of Experts

An expert usually has some backgrounds in certain fields and recognized by his/her peers [31]. Shanteau *et al*. (2002) determine the expertise level of an expert based on his/her assessment level (adverse judgment). They argued that only people who can differentiate between similar but not exactly the same, cases and repeat their judgment consistently, considered as an expert [6]. Therefore there are two requirements necessary for determining the expertise level, namely the Discrimination ability and the Inconsistency and expressed in CWS - Index as shown in eqn (1), (2) and (3):

$$\text{CWS-Index} = \frac{\text{Discrimination}}{\text{Inconsistensy}} = \frac{\text{standard deviation of different alternatives' values}}{\text{standard deviation of the same alternative's values}} \quad (1)$$

$$\text{Discrimination} = \sqrt{\frac{\sum_{j=1}^{n} r(M_j - GM)^2}{n-1}} \quad (2)$$

$$\text{Inconsistency} = \sqrt{\frac{\sum_{j=1}^{n}\sum_{i=1}^{r} (M_{ij} - M_j)^2}{n(r-1)}} \quad (3)$$

Where

r	:	The number of replications
M_j	:	The average of individual values for case-j
GM	:	Grand mean of all individual values
n	:	The number of different cases
M_{ij}	:	The individual value for replication-i case-j

In order to measure the expertise level of the experts, the evaluated experts were asked to elicitate their evaluation more than once. Only those who have a high level of Discrimination ability and low level of Inconsistency can be clasified as expert and obtain a high value of CWS-Index. Unfortunately, this method required repetition and this repetition are very hard to do independently without being affected by previous evaluation.

The Additive Consistency of FPR

The Decision Makers could use a variety of evaluation formats, among others, is FPR. FPR is one of the most widely used evaluation format to provide evaluation in Group Decision Making (GDM) [16, 32-33] since FPR can be used as tools on aggregating individual opinions into a group opinion [34].

Suppose that a group of Decision Makers $E = \{e_1, e_2, ...e_m\}$, $m \geq 2$ evaluate a finite set of alternatives $X = \{x_1, x_2, ...x_n\}$, $n \geq 2$ by using pairwise comparisons FPR $P \subset XxX$ having a membership function $\mu_p : XxX \rightarrow [0,1]$ and represented by means of the n x n matrix $P = (p_{ij})$ [35]. p_{ij} is the preference degree of alternative x_i over x_j. $p_{ij} = 1/2$ means indifference between x_i and x_j, $p_{ij} > 1/2$ means x_i is preferred to x_j.

AC property of FPR among three alternatives x_i, x_j and x_k [36] are as follows:

$$(p_{ij} - 0{,}5) + (p_{jk} - 0{,}5) = (p_{ik} - 0{,}5) \quad \forall\ i, j, k = 1,2,...,n \quad (4)$$

$$p_{ij} + p_{jk} + p_{ki} = 3/2 \quad \forall\ i, j, k = 1,2,...,n \quad (5)$$

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The AC property yields a relationship between the preferences and we can obtain estimated values by using 3 different formulas as follows [28]:

$$\varepsilon p_{ik}^{j1} = p_{ij} + p_{jk} - \tfrac{1}{2},\ j \neq i,k \tag{6}$$

$$\varepsilon p_{ik}^{j2} = p_{jk} - p_{ji} + \tfrac{1}{2},\ j \neq i,k \tag{7}$$

$$\varepsilon p_{ik}^{j3} = p_{ij} - p_{kj} + \tfrac{1}{2},\ j \neq i,k \tag{8}$$

in which:

εp_{ik}^{j1} : Estimation of p_{ik} using the first formula

εp_{ik}^{j2} : Estimation of p_{ik} using the second formula

εp_{ik}^{j3} : Estimation of p_{ik} using the third formula

For every element of the matrix FPR p_{ij} , these formulas produce as many as 3x (n-2) replications (since there are 3 formulas and $j \neq i,k$). These replications allow AC property be used to complete the incomplete FPR [28-29, 37-41] and measure someone's consistency level in providing assessment [28-29, 34, 39-40, 42] in which the consistency level then be used to determine the importance weight of each expert. The drawbacks are previous studies only considered the Consistency level, but not the Discrimination, thus have not covered the whole concept of expertise level as proposed by Shanteau *et al*., (2002).

The Induced OWA Operator

The OWA operator is an aggregation operator proposed by Yager (1988) in which the order of the arguments have primary role in the aggregation process [43]. An n-dimensional OWA Operator is a mapping $F: I^n \rightarrow I$ defined as $F_w(a_1, a_2, ..., a_n) = \sum_{j=1}^{n} w_j b_j$ where b_j is the jth largest element in the set of input arguments $(a_1, a_2, ..., a_n)$ and w_j is the order weights satisfy $w_j \geq 0$ and $\sum_{j=1}^{n} w_j = 1$ [43]. In this case the input arguments are ordered according to their own values.

In the Induced OWA Operator, the ordering of the input arguments are based upon the order inducing variable [44]. An n dimensional Induced OWA Operator Is a mapping $F: I^n \rightarrow I$ defined as $F_w(\langle u_1, a_1\rangle, \langle u_2, a_2\rangle, ..., \langle u_n, a_n\rangle) = \sum_{j=1}^{n} w_j b_j$ where u_i is called the order inducing variable and a_i is called input argument, w_j is the order weights and $w_j \geq 0$ and $\sum_{j=1}^{n} w_j = 1$ and b_j is the input argument value of the pair having the *j*-th largest value for the order inducing variable. An important issue in using the OWA operator or the Induced OWA operators in aggregation process is the issue of obtaining the OWA weights. Yager (1996) proposed that the OWA weights can be parameterized by BUM $Q: [0,1] \rightarrow [0,1]$ having the properties: $Q(0) = 0; Q(1) = 1; Q(x) \geq Q(y)\ \ if\ \ x \geq y$ and the OWA weights w_j are as follows [45-46]:

$$w_j = Q(R_j) - Q(R_{j-1}) \tag{9}$$

where $R_j > R_{j-1}$, and the obtained weights satisfy $w_j \geq 0$ and $\sum_{j=1}^{n} w_j = 1$. The BUM is associated with the accumulation of DM importance weight. Since BUM is an increasing Monotonic Function as illustrated in Figure-1, then the individual DM importance weight can't be negative or $w_j \geq 0$.

Another important property of this function is the maximum value of BUM is one, so the accumulation of the total DM importance weights also 1. Yager (1988) proposed a particular form of BUM Function as $Q(R) = R^{\alpha}$, α positive parameter [43].

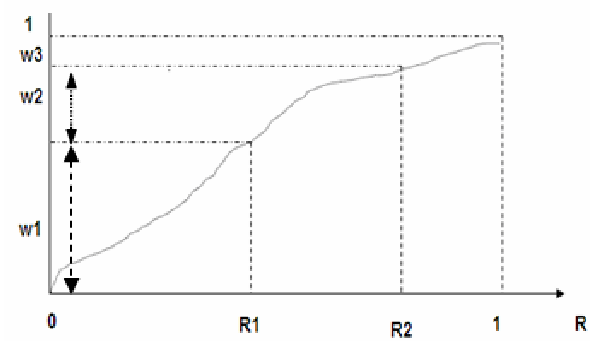

Figure-1. The OWA Weights from Basic Unit Interval Increasing Monotonic Function.

THE PROPOSED METHOD

This research uses expertise level as 'the ability to differentiate consistently' and expressed as ratio between Discrimination and Inconsistency and the experts provide evaluation using pairwise comparison FPR. AC property of FPR enables us to get the replications without asking the DMs to repeat their evaluation and the result of this step is CWS-Index. Based on this Index, we obtain the rank of the DMs based on their assessment level [9, 47]. The next step is obtaining the DMs importance weights based on the Induced OWA weights and BUM function as illustrated in Figure-2.

The expertise-level expressed by the CWS-Index in logarithmic function and used as the order inducing variable. The expertise-level are used as the R-variable in determined the importance weights.

NUMERICAL EXAMPLE

In order to show the applicability of the proposed methods, we provide a numerical example to illustrate

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Expertise-based experts' importance weight. Suppose there are 5 experts expressed in $E = \{e_1, e_2, e_3, e_4, e_5\}$ and asked to provide assessment on a set of 4 alternatives $X = \{x_1, x_2, x_3, x_4\}$.

The data of experts' assessment are as follows [47]:

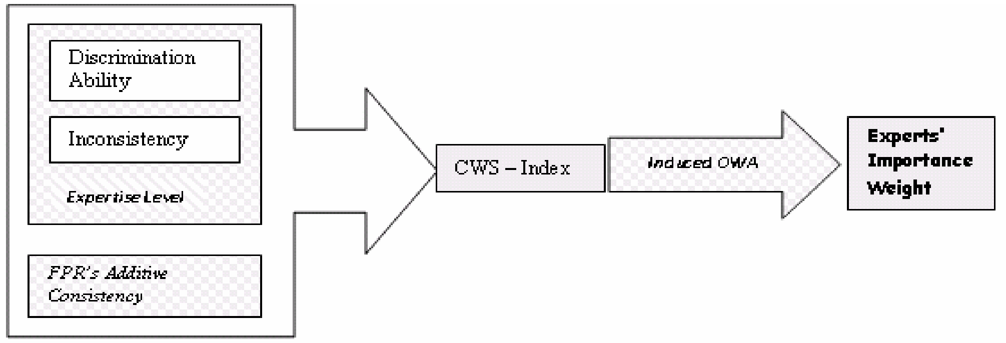

Figure-2. The Proposed Method.

$$P_1 = \begin{bmatrix} 0.5 & 0.4 & 0.4 & 0.4 \\ 0.6 & 0.5 & 0.4 & 0.7 \\ 0.6 & 0.6 & 0.5 & 0.7 \\ 0.6 & 0.3 & 0.3 & 0.5 \end{bmatrix}, \quad P_2 = \begin{bmatrix} 0.5 & 0.3 & 0.4 & 0.45 \\ 0.7 & 0.5 & 0.65 & 0.6 \\ 0.6 & 0.35 & 0.5 & 0.45 \\ 0.55 & 0.4 & 0.55 & 0.5 \end{bmatrix},$$

$$P_3 = \begin{bmatrix} 0.5 & 0.9 & 0.6 & 0.7 \\ 0.1 & 0.5 & 0.3 & 0.4 \\ 0.4 & 0.7 & 0.5 & 0.6 \\ 0.3 & 0.6 & 0.4 & 0.5 \end{bmatrix}, \quad P_4 = \begin{bmatrix} 0.5 & 0.43 & 0.64 & 0.71 \\ 0.57 & 0.5 & 0.43 & 0.36 \\ 0.36 & 0.57 & 0.5 & 0.21 \\ 0.29 & 0.64 & 0.79 & 0.5 \end{bmatrix},$$

$$P_5 = \begin{bmatrix} 0.5 & 0.7 & 0.8 & 0.6 \\ 0.3 & 0.5 & 0.65 & 0.55 \\ 0.2 & 0.35 & 0.5 & 0.4 \\ 0.4 & 0.45 & 0.6 & 0.5 \end{bmatrix}$$

The estimation of each matrix element by using formula 1, 2 and 3 will generate 6 estimated values. For example the estimated value of all matrix P_4 elements is presented in Table-1. For each element of the matrix P_4 there are 7 values (r = 7), i.e. 6 estimated values and 1 real value and we can calculate Discrimination and Inconsistency value.

$$\text{Discrimination}=\sqrt{\frac{\sum_{j=1}^{n} r(M_j - GM)^2}{n-1}} = \sqrt{\frac{1.54057}{(12-1)}} = 0.3742 .$$

$$\text{Inconsistency} = \sqrt{\frac{\sum_{j=1}^{n}\sum_{i=1}^{r} (M_{ij} - M_j)^2}{n(r-1)}} = \sqrt{\frac{3.80029}{12x(7-1)}} = 0.2297$$

$$\text{CWS-Index for Expert} - 4 = \frac{0.3742}{0.2297} = 1.629$$

The CWS-index for all experts are represented in Table-2. CWS-Index for Expert-1, Expert-2, Expert-3, Expert-4 and Expert-5 subsequently is 3.580, 8.237, 12.610, 1.629 and 7.612. Based on these CWS-Indexes, the Expertise-based Experts ranking obtained is [47]: Expert 3 - 2 - 5 - 1 - 4.

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Table-1. The CWS-Index calculation for Expert-4.

Element Matrix	Original data	Formula-1		Formula-2		Formula-3		M_j	$r(M_j - GM)^2$	$\sum_{i=1}^{r}(M_{ij} - M_j)^2$
p_{12}	0.43	0.714	0.857	0.714	0.857	0.714	0.857	0.724	0.32655	0.13703
p_{13}	0.64	0.357	1	0.357	1	0.357	1	0.633	0.10789	0.72886
p_{14}	0.71	0.286	0.357	0.286	0.357	0.286	0.357	0.357	0.16037	0.16327
p_{21}	0.57	0.286	0.143	0.286	0.143	0.286	0.143	0.296	0.31635	0.16764
p_{23}	0.43	0.714	0.643	0.714	0.643	0.714	0.643	0.643	0.12636	0.11224
p_{24}	0.36	0.786	0.143	0.786	0.143	0.786	0.143	0.439	0.03403	0.77988
p_{31}	0.36	0.643	0	0.643	0	0.643	0	0.388	0.10206	0.68222
p_{32}	0.57	0.286	0.357	0.286	0.357	0.286	0.357	0.367	0.13948	0.05539
p_{34}	0.21	0.571	0.429	0.571	0.429	0.571	0.429	0.480	0.00585	0.11953
p_{41}	0.29	0.714	0.643	0.714	0.643	0.714	0.643	0.673	0.19050	0.13120
p_{42}	0.64	0.214	0.143	0.214	0.143	0.214	0.143	0.571	0.02772	0.63265
p_{43}	0.79	0.429	0.571	0.429	0.571	0.429	0.571	0.531	0.00342	0.09038
Total									1.54057	3.80029

Table-2. Discrimination, Inconsistency, CWS-Index and Experts Ranking.

	e_1	e_2	e_3	e_4	e_5
Discrimination	0.3703	0.3302	0.5835	0.3742	0.4662
Inconsistency	0.1035	0.0401	0.0463	0.2297	0.0612
CWS-Index	3.580	8.237	12.610	1.629	7.612
Rank	4	2	1	5	3

Table-3. The Importance Weights Calculation Using BUM $Q(R) = R^{\alpha}$.

	e_3	e_2	e_5	e_1	e_4
CWS- Index	12,6100	8,2370	7,6120	3,5800	1,6290
Log(CWS-Index)	1,1007	0,9158	0,8815	0,5539	0,2119
Accumulated(Log(CWS-Index))	1,1007	2,0165	2,8980	3,4519	3,6638
R=Normalized(Accumulated(Log(CWS-Index))	0,3004	0,5504	0,7910	0,9422	1,0000
$Q(R) = R^{\alpha} = R^{0.25}$	0,7403	0,8613	0,9431	0,9852	1,0000
Importance Weights for $\alpha = 0.25$ (in %)	74,03	12,10	8,17	4,22	1,48
$Q(R) = R^{\alpha} = R^{0.5}$	0,5481	0,7419	0,8894	0,9706	1,0000
Importance Weights for $\alpha = 0.5$ (in %)	54,81	19,38	14,75	8,13	2,94
$Q(R) = R^{\alpha} = R$	0,3004	0,5504	0,7910	0,9422	1,0000
Importance Weights for $\alpha = 1$ (in %)	30,04	25,00	24,06	15,12	5,78
$Q(R) = R^{\alpha} = R^2$	0,0903	0,3029	0,6256	0,8877	1,0000
Importance Weights for $\alpha = 2$ (in %)	9,03	21,27	32,27	26,20	11,23

Table-3 shows the importance weights calculation using BUM $Q(R) = R^{\alpha}$. After obtaining the rank, the experts are sorted by their expertise level. Expert-3 (e_3) is an expert with the highest rank and placed on the first order. Expert-2 (e_3) is in the second order. Then we calculate the logarithm of the CWS-Index and the accumulation of the logarithm of the CWS-Index. After normalized the accumulation of the logarithm of the CWS-Index, the maximum value of these logarithm is 1 in accordance with the BUM function which has a maximum value of 1 and the experts total Importance weights are 1. In Table-3, the BUM function will be determined by several values of the parameter α. For example, for the parameters $\alpha = 0.25$, $\alpha = 0.5$, $\alpha = 1$, $\alpha = 2$.

Suppose, we want to determine the importance weight of DMs for parameter $\alpha = 0.25$.

The CWS-Index for e_3 is 12,610
For e_3, Log(CWS-Index)=log(12,610) = 1,1007
For e_2, Log(CWS-Index)=log(8,2370 = 0,9158
For e_3, Acc((Log(CWS-Index)) =1,1007
For e_2 ,Acc((Log(CWS-Index)) =1,1007+0,9158=2,0165
For e_3 ,R=Norm(Acc(Log(CWS-Index)))=1,1007/3,6638= 0,3004
For e_2 ,R=Acc((Log(CWS-index))=2,0165/3,6638 = 0,5504
If parameter $\alpha = 0{,}25$, $Q(R) = R^{\alpha} = R^{0.25}$
For e_3, $Q(0{,}3004) = 0{,}3004^{0.25} = 0{,}7405$
For e_2, $Q(0{,}3004) = 0{,}5504^{0.25} = 0{,}8613$
The Importance weight for e_3 is 74, 05 %.
The Importance weight for e_2 is 86, 13% - 74, 05 % = 12, 10 %

If parameter $\alpha = 2$, mismatches occur since the expert with higher expertise level gained smaller importance weight, for example Expert-3 (e_3) as the expert with the highest expertise level, gets the smallest importance weight. If the parameter $\alpha = 1$, expert with higher level of expertise gained greater importance weight but not significantly. If the parameter $\alpha = 0.5$, expert with higher level of expertise gained greater importance weight significantly. Thus the parameter α should be less than 1 to obtain the expected result, the higher the expert's expertise level, the higher his/her importance weight.

CONCLUSIONS

An *expertise-based experts importance weight* method is proposed in order to develop the experts importance weight in adverse judgment situation in which every expert provides his/her judgment in pairwise comparisons FPR.

This model consists of 2 stages. The first stage, we obtain the experts' ranking by combining the experts' expertise level and Additive Consistency of FPR. In the second stage, we develop the experts' importance weight by using Basic Unit-Interval Increasing Monotonic Functions $Q(R) = R^{\alpha}$, $\alpha < 1$ to get the expected results, the higher the expert's expertise level, the higher his/her importance weight.

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