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Short Paper

Utilization of Multi Attribute Decision Making Techniques to Integrate Automatic and Manual Ranking of Options

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An information fusion system with local sensors sometimes requires the capability to represent the temporal changes of uncertain sensory information in dynamic and uncertain situation to access to a hypothesis node which cannot be observed directly. One of the central issue and challenging problem is the decision of what combination and order of sensors allocation should be selected between sensors, in order to maximize the global gain in the flow of information, when the data association is limited. In this area, Bayesian Networks (BNs) can constitute a coherent fusion structure and introduce different options (the combination of sensors allocation) for achieving to the hypothesis node through a number of intermediate nodes that are interrelated by cause and effect. BNs can rank the options in terms of their probabilities from Bayes' theorem calculation. But, decision making based on probabilities and numerical representations might not be appropriate. Thus, re-ranking the set of options based on multiple criteria such as those of multi-criteria decision aid (MCDA) should be ideally considered. Re-ranking and selecting the appropriate options are considered as a multi-attribute decision making (MADM) problem by user interaction as semi-automatically decision support. In this paper, Multi Attribute Decision Making (MADM) techniques as TOPSIS, SAW, and Mixed (Rank Average) for decision-making as well as AHP and Entropy for obtaining the weights of attributes have been used. Since MADM techniques give most probably different results according to different approaches and assumptions in the same problem, statistical analysis done on them. According to the results, the correlation between compared techniques for re-ranking BN options is strong and positive because of the close proximity of weights suggested by AHP and Entropy. Mixed method as compared to TOPSIS and SAW is the preferred technique when there is no historical (real) decision-making case; moreover, AHP is more acceptable than Entropy for weighting.

Keywords: Bayesian networks, sensor allocation, TOPSIS, SAW, AHP, entropy

1. INTRODUCTION

There are different definitions of information fusion. One is that [1] "Information fusion is the study of efficient methods for automatically or semi-automatically transforming information from different sources and different points in time into a representation that provides effective support for human or automated decision making." One

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technique for information fusion is Bayesian Networks (BNs) [2] which present knowledge about domain variables in uncertain and unpredictable environments through numerical and graphical representation. Moreover, a Bayesian Network can constitute a coherent fusion structure with the hypothesis node which cannot be observed directly and sensors through a number of intermediate nodes that are interrelated by cause and effect. To be able to handle the uncertainty of sensor readings, information variables may add an additional layer of variables which connects sensors to hypothesis variables. In a target tracking case with the set of stationary sensors for observation of a hypothesis variable (node), number of participated sensors and select the appropriate option (different combination of sensors allocation) in the decision-making is a challenging problem [2]. Thus, it is important to present the better picture of sensor configuration options (both ranking and selecting) which are more useful in order to help decision makers for their decisions making [3]. Bayesian Networks provide important support for decision-making by ranking the set of options according to probabilities and numerical representations. But in some situations we need to make decision and rank or re-rank the set of options based on multiple criteria such as those of multi-criteria decision aid (MCDA) [4]. Bayesian theory provides inference mechanisms through subsets of evidence from intermediate variables to observe hypothesis (goal) nodes which are not directly observed [5]. Hence, the BN tool assists the intelligence analyst with analyzing incoming observations. But in order to improve the results of the BN, we need to control sensors (to control the flow of information into the system) and for that purpose we consider sensor (configuration) options. Obviously, by user interaction, we can manage different possible options based on multi-criteria as semi-automatically Decision Support System (DSS). Multi-criteria analysis tries to incorporate multiple and different types of information and human experience into a DSS. Integration of human expertise with a fusion-based DSS can enable suggestions and recommendations for actions through understanding of problems and problem solving skills within a specific domain [6]. Hence, re-ranking of options in Bayesian Network-based systems for achieving to a hypothesis/unobserved variable in terms of qualitative and quantitative criteria is one of the decision-making problems.

In recent decades, for complex decisions in terms of the consideration of multiple factors, researchers have been focused on Multi Attribute Decision Making (MADM) techniques [7]. In MADM, several options according to some criteria are ranked and selected. Ranking and selecting will be made among decision alternatives described by some criteria (factors) through decision-maker knowledge and experience [8]. To our best knowledge, utilization of MADM techniques on re-ranking of BNs options have not yet been thoroughly studied. In this research, we have utilized and compared MADM techniques to integrate automatic and manual ranking of options in a Bayesian Network to find suitable ranking mehotd. Applied decision-making techniques include TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), SAW (Simple Additive Weighting), and Mixed (Rank Average) methods as well as AHP (Analytical Hierarchy Process) and Entropy methods for defining importance of weights of the attributes. Since MADM techniques have different approaches and assumptions for ranking and selecting in the same problem, they are more likely to have different results [9]. Therefore, we employ statistical tests if these differences are significant. Finally, the results of the applied MADM techniques will be compared and analyzed.

The rest of this paper is organized as follows. Section 2 presents related works. Multi-attribute decision-making (MADM) techniques are described in section 3. In section 4, Bayesian Networks and sensor allocation are reviewed. Experimental results are in detail in section 5. Finally, a conclusion is given in section 6.

2. RELATED WORKS

Using MADM techniques for improving decision making results are not a novel idea. There are several researches using MADM such as, TOPSIS [8, 29, 30], SAW [14, 29, 30], AHP [7, 10, 19, 31], and Entropy [20]. To the best of the author's knowledge, there is no any applied MADM techniques for ranking and selecting the different combination of sensors allocation. Bayesian Network models are powerful tools for reasoning and decision-making under uncertainty, but BNs can provide different options of sensors allocation in terms of their probabilities from Bayes' theorem calculation in order to estimate state of a hypothesis node through informational (intermediate) nodes [5]. However, (re-)ranking the different combination of sensors allocation can be considered as a MADM problem.

There are significant specifications of SAW and TOPSIS methods which include applicability for large-scale decision problems, simplicity in concept and computation, and applicability for hierarchical multi-level attributes. Moreover, AHP method is suitable when an attribute hierarchy has more than three levels [10]. This means that the overall goal of the problem is on the top level, multiple criteria which define alternatives in the middle level, and competing alternatives in the bottom level. So, in this study, two techniques as SAW and TOPSIS according to their ideal characteristics have been selected. Since different methods provide different results, decision-makers use more than one technique in important decisions. In order to overcome this problem, we have utilized Mixed (Rank Average) method which obtained from average of applied techniques results [11]. Likewise, AHP and Entropy are two important weight methods which we have used for them. By three different techniques and two weight methods, we are faced with five different re-rankings as TOPSIS with AHP, TOPSIS with Entropy, SAW with AHP, SAW with Entropy, and Mixed method. Since MADM methods have different approaches and assumptions for ranking/selecting options in the same problem, it is likely that they yield different results [9]. Therefore, applied MADM methods have investigated by statistical tests if these differences are significant. We have used Kendall's tau-b factor, Spearman correlation coefficient, and Pearson correlation coefficient (because our study is about ranking data and data are quantitative). All statistical tests are implemented by SPSS software.

3. MULTI-ATTRIBUTE DECISION-MAKING TECHNIQUES

Multi-attribute decision-making (MADM) is the well-known branch of decision making which deals with decision problems through a number of qualitative and quantitative criteria [8]. Ranking and selecting of limited number of decision alternatives are made by some attributes. The multiple attribute-based decision problems should be solved with one of the many methods; moreover, the availability to the large number of

MADM problem-solving techniques provides a paradox between selections of MADM methods [12]. These contradictions may come from differences in use of weights, the selection approach of the 'best' solution, objectives scaling and introduction of additional parameters [13].

3.1 SAW (Simple Additive Weighting)

SAW model or Scoring Method (SM) is most often used in multi-attribute decision-making techniques. To do this, the normalized value of the criteria for the alternatives must be multiplied with the weight of the criteria. Then, the best alternative with highest score is selected as the preferred alternative [14]. The analytical structure of the SAW method for *N* options and M attributes can be summarized as:

$$s_i = \sum_{j=1}^{M} w_j r_{ij} \qquad i = 1, 2, \ldots, N. \tag{1}$$

s_i: is the overall score of the *i*th alternative; r_{ij}: is the normalized rating of the *i*th alternative for the *j*th criterion which: $r_{ij} = \frac{x_{ij}}{\max_i x_{ij}}$ for the benefit and $r_{ij} = \frac{1/x_{ij}}{\max_i (1/x_{ij})}$ for the cost criterion representing an element for the normalized matrix; x_{ij}: is an element of the decision matrix, which represents the original value of the *j*th criterion of the *i*th alternative; w_j: is the importance (weight) of the *j*th criterion; *N* and *M* are the number of alternatives and criteria, respectively.

3.2 TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)

TOPSIS technique is suggested by Yoon & Hwang in 1981 [15]. Based on the idea that the best alternative should have the shortest geometric distance from a positive ideal solution (the best possible) and the longest geometric distance from a negative ideal solution (the worst possible), TOPSIS method consists of the following steps:

(1) Normalize the decision matrix: the normalization of the decision matrix is done using the below transformation for each n_{ij}:

$$n_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \tag{2}$$

Then, weights should be multiplied to normalized matrix.

(2) Determine the positive and negative ideal alternatives:

$$A^+ = \{v_1^+, v_2^+, \ldots, v_n^+\} = \{(\max_i V_{ij} | j \in J), (\min_i V_{ij} | j \in J' | i = 1, 2, \ldots, m)\} \tag{3}$$

Positive attribute: the one which has the best attribute values (more is better).

$$A^- = \{v_1^-, v_2^-, \ldots, v_n^-\} = \{(\min_i V_{ij} | j \in J), (\max_i V_{ij} | j \in J' | i = 1, 2, \ldots, m)\} \tag{4}$$

Negative attribute: the one which has the worst attribute values (less is better).

$J = \{j = 1, 2, ..., n \mid j$ for posistive attributes$\}$
$J' = \{j = 1, 2, ..., n \mid j$ for posistive attributes$\}$

V_{ij} is the weighted normalized matrix.

(3) Obtain the separation measure (based on Euclidean distance) of the existing alternatives from ideal and negative one [16]:

$$d_{i^+} = \left\{ \sum_{j=1}^{n} (V_{ij} - V_j^+)^2 \right\}^{0.5}; \; i = 1, \; 2, \; ..., \; m; \; d_{i^-} = \left\{ \sum_{j=1}^{n} (V_{ij} - V_j^-)^2 \right\}^{0.5}; \; i = 1, \; 2, \; ..., \; m. \quad (5)$$

(4) Calculate the relative closeness to the ideal alternatives:

$$cl_{i^+} = \frac{d_{i^-}}{(d_{i^+} + d_{i^-})}; 0 \le cl_{i^+} \le 1; \; i - 1, \; 2, \; ..., \; m. \quad (6)$$

(5) Rank the alternatives: based on the relative closeness to the ideal alternative, the higher cl_{i^+}, the better is the alternative A_i.

3.3 AHP (Analytical Hierarchy Process)

AHP was proposed by Thomas L. Saaty in 1995 [17]. It is a popular MADM technique and widely used, especially in military problems [18]. AHP reflects the natural behavior of human thinking. This technique examines the complex problems based on their interaction effects. The details of AHP procedure are described in [17, 19].

3.4 Mixed Method

Decision-makers usually use more than one decision-making technique in important decisions. Different decision-making techniques may provide different results according to their approaches and assumptions. In order to overcome to this problem, Mixed method as Rank Average Method is used. Since the Mixed method involves average of methods results and their specifications, it can be an ideal method in some problems [11].

3.5 Entropy

Entropy is the one of the most important concepts in social science, physics, and information theory. Shannon's entropy method is suitable for finding the appropriate weight for each criterion in MADM problems [20]. According to this method, whatever dispersion in the index is greater, the index is more important. Entropy steps are as follow:

Step 1: Calculate P_{ij} to eliminate anomalies with different measurement units and scales.

$$P_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}}; \forall j \quad (7)$$

Step 2: Calculate the entropy of E_j

$$E_j = \left(\frac{-1}{\ln(m)}\right)\sum_{i=1}^{m}[P_{ij} \ln P_{ij}]; \forall j. \tag{8}$$

Step 3: Calculate of uncertainty d_j as the degree of diversification

$$d_j = 1 - E_j; \forall j. \tag{9}$$

Step 4: Calculate of weights (W_j) as the degree of importance of attribute j

$$W_j = \frac{d_j}{\sum_{j=1}^{n} d_j}; \forall j. \tag{10}$$

Where a_{ij} is value of ith option (entry) for jth index; P_{ij} is the value-scale of jth index for ith option (entry).

4. BAYESIAN NETWORKS AND SENSOR ALLOCATION

The sensor allocation problem has been considerably investigated in recent years. Two research issues of sensor allocation include deciding where to physically deploy sensors, and decide which physical parameters should be measured by sensors. Also, optimal sensor allocation is where to allocate sensor, which is closely related to decision-making objectives. To do this, a Bayesian Network is built to represent the causal relationships between the observable variables in order to determine which observable variables should be sensed [21, 22]. Moreover, Bayesian Networks are used to find the prioritization of sensor options through value of obtained information from domain [23].

This means that the Bayesian Network constructs an influence diagram to user incorporate with information of each sensor node in order to select appropriate ones. There is multitude of sensors which are deployed in an array to cover a large area under surveillance. In a decision-making process, these sensors need to be networked and configured for exchange of raw measurement or some decisions results from processing the data for the detection, discrimination, localization, and tracking the target of interest. Improving performance by sensor fusion and minimizing network latency in sensor configuration management are challenging problems [2]. Moreover, the problem in the sensor planning include which appropriate sensor configuration must be selected in order to have a proper recognition [24]. With the hypothesis and sensors, a coherent fusion structure by a Bayesian Network can be constructed. The root node of such a network would contain the hypothesis variable and the sensors are in the lowest level without any children. The hypothesis node is causally linked to the sensor nodes through intermediate nodes which are interrelated by cause and effect. In the real world, a fusion system may receive incorrect information from sensors according to different reasons such as sensor noise and imprecise acquisition devices. Therefore, sensor readings include uncertainties which may reduce the reliability of a fusion system. To handle the measurement uncertainty of sensor readings in a Bayesian network, we can add an additional layer of variables as 'information variables' which connect intermediate variables to sensors [2].

5. EXPERIMENTAL RESULTS

5.1 Identification of General Decision-Making Criteria

We have used literature review and recent experiences of some specialists in order to identify some general decision-making attributes (criteria) for re-ranking the BN options. Most criteria depend on three factors: *Characteristics of the choice* (*e.g.*, uncertainty, complexity, and instability), *Environment* (*e.g.*, time and resource available, irreversibility of the choice, and possibility of failure), and *decision maker* (*e.g.*, knowledge, strategies, expertise, and motivation). In a Bayesian Network model, experts with different knowledge in a same project may have different solutions and opinions for identifying the causal relationship among variables, quantifying graphical models, and ranking on the set of options in terms of numerical probabilities [25]. Moreover, a combination of contextual and informational decision factors will have effect on decision making [26]. These factors are politics, power structure, trust, and time pressure for rapid decisions. In addition, tangible factors include cost, risk, adherence to organizational technology standards and strategies, and informal external information sources with their relationship. In order to final identification of general attributes, we have used Delphi method as a structured communication technique which relies on a panel of experts. Ten experts that were familiar with sensor allocation and Decision Support Systems concepts were chosen. After this procedure, the ten attributes as final general attributes were selected in Table 1.

5.2 Results and Discussion

We conducted two experiments using two real scenarios (drawn with the GeNIe tool). We constructed 1st scenario of a fusion structure with a Bayesian Network from [27]. This BN (Fig. 1) includes a hypothesis variable (corresponding to a knowledge request issued by an intelligence analyst and not directly observable) and information variables. In this BN example, only "will to attack", "capability to attack", "increased air movements", "increased radio", and "increased presence of friendly" can be observed. The hypothesis variable as "planning to attack X-town" can normally not be observed. The variable "increased presence of MIDA" also has not been considered. In the 2nd scenario (Fig. 2)[1], there is a mobile robot acting as a night guard on the entrance floor of a small business building to find an intruder. In this example, "Motion Detected", "Sound Received By Robot" (information variables), "Sound Detected", "Train Passing" (mediating variables) can be observed, and the hypothesis variable is "Intruder".

One method for acquiring information in general Bayesian Networks with uncertain observations has been proposed in [27]. They have enumerated all possible options (allocation of sensing resources to Bayesian Network variables) and evaluated them according to their expected impact if an option was implemented. The details of expected performance calculation are also described in [27].

[1] Informatics Research Centre, Information Fusion course, University of Skövde, Sweden, January, 2011.

Table 1. General decision-making attributes.

No.	Attribute	Description
C1	User Knowledge	User understanding and opinion of a situation based on user's experience or education according to previous decisions made in real (historical) cases can effect on current decision making process.
C2	User Strategy	An action plan for each contingent state of the situation.
C3	Time Pressure	Before time shortage, a task must be finished or executed. Time pressure might lead to an inappropriate situation that the option is not implemented in time or being fail.
C4	Resource Availability	It states that how many resources are available at any time to do a job. This means that, is there sufficient resources for implementation of an option or not?
C5	External Information Source	Extra information from environment and related objects.
C6	Risk of Failure	A condition or fact that being unsuccessful, insufficient or disappointing. It can estimate the likelihood of occurrence of a hazardous event.
C7	Trust	Confident expectation of selecting a variable.
C8	Complexity	The state or quality of a choice (option) can be complex or intricate. It is likely that state of an option becomes more complex or less complex for different reasons, *e.g.*, lack of information for sensor controlling or lack of information about impact of observable variables.
C9	Cost	The estimation of the amount of money, effort, time, risk or material that have to be paid.
C10	Expected Performance	It is calculated according to [27] which will mention in the next section.

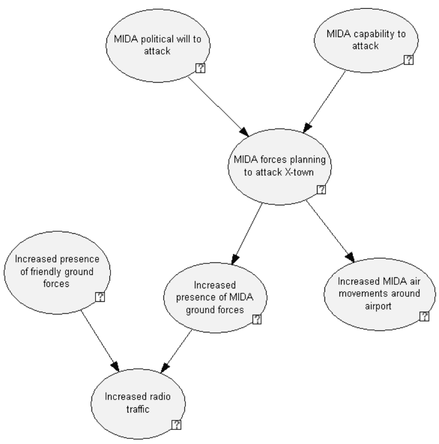

Fig. 1. MIDA scenario [27].

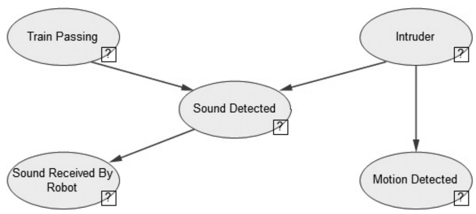

Fig. 2. Mobile robot scenario.

The results of these scenarios are a set of options (sensor allocation) in seventy different possible allocations. We have utilized the first best twenty options in terms of the high expected performance in order to better possibility of filling decision matrix by expert users as well as analysis and comparison. The reason of using the expected performance is that, it was the only appreciable and available criterion from investigated options. In the first scenario, the structure of every option is, *e.g.*, ((2, 1, 1, 0, 0), 0.9939219115):

- 1st Number: 2 sensors/resources were assigned to the attack_will variable,
- 2nd Number: 1 sensor to attack_capability,
- 3rd Number: 1 sensor to air_movements,
- 4th Number: 0 sensor to presence_friendly,
- 5th Number: 0 sensor to radio_traffic, and
- 6th Number: 0. 9939219115 is expected performance.

In the second scenario, the structure of every option is, *e.g.*, ((3, 1, 0, 1), 0.9949520805):
- 1st Number: 3 sensors/resources were assigned to the MotionDetected variable,
- 2nd Number: 1 sensor to SoundReceivedByRobot,
- 3rd Number: 0 sensor to SoundDetected,
- 4th Number: 1 sensor to TrainPassing, and
- 5th Number: 0. 9949520805 is expected performance.

As main problem is re-ranking of these generated options (different combination of sensors allocation), we are going to re-rank these options via Multi Attribute Decision Making (MADM) techniques by user interaction. For filling the decision matrix with 20 options and 10 attributes (criteria), we employ the experiences of three expert users in military sections (meaning with extended experience in the application of information fusion and Bayesian Networks systems) in two scenarios (Figs. 1 and 2).

Analysis of decision matrix should be included quantitative values, but some criteria were qualitative. Hence, Odd Bipolar Scaling is used to convert qualitative variables to quantitative. Since scales of attributes measurement are different, they should be expressed as non-scaling values. To do this, linear non-scaling method used as follow:

For positive attributes: $\dfrac{r_{ij}}{\max_i r_{ij}}$ and for negative attributes: $\dfrac{1/r_{ij}}{\max_i (1/r_{ij})}$ where, r_{ij} is the value of ith row and jth column and $\max_i$ is maximum value of ith column.

Due to the lack of space in this paper, we only present analysis of TOPSIS technique with AHP for the first scenario. To do AHP, for constructing a pair-wise comparison matrix to determine important factors of each attribute, an expert user idea has been used. One important issue is comparisons compatibility. This means that the inconsistent expert judgment can be a factor when using the pair-wise comparison method. We applied Expert Choice 2000 software for AHP implementation and display the Inconsistency Ratio (IR) of the AHP technique in order to solve inconsistent expert judgment. The IR provides a measure of the logical rationality of the pair-wise comparisons, and IR value less than 0.10 is generally considered acceptable [28]. The weight of each attribute has been sorted from more important to less important in Table 2 (IR = 0.09).

Table 2. Attributes weight by AHP technique.

Attributes	Weight	Attributes	Weight
(1) User strategy	0.234	(6) Trust	0.066
(2) Cost	0.196	(7) Expected Performance	0.046
(3) Resource Availability	0.128	(8) External Information Sources	0.044
(4) User Knowledge	0.124	(9) Possibility of Failure	0.027
(5) Time Pressure	0.109	(10) Complexity	0.026

To do TOPSIS, after multiplying weights (from AHP) to normalized matrix (Eq. (2)), we should determine the positive and negative ideal alternatives (Eqs. (3) and (4)):

Table 3. Positive and negative ideal alternatives with TOPSIS-AHP.

A+	0.04838	0.04083	0.00690	0.02084	0.01297	0.01637	0.07700	0.00298	0.00208	0.01609
A-	0.00537	0.00453	0.06211	0.00231	0.00144	0.14736	0.00855	0.00894	0.01875	0.00566

Then, we should calculate Euclidean distance of alternatives (Eq. (5)):

Table 4. Euclidean distance in TOPSIS-AHP.

Options	d_{i^+}	d_{i^-}	Options	d_{i^+}	d_{i^-}
O1	0.04568	0.14525	**O11**	0.07268	0.14783
O2	0.04217	0.14850	**O12**	0.07095	0.12059
O3	0.08483	0.12064	**O13**	0.07061	0.11896
O4	0.03237	0.14987	**O14**	0.04781	0.14424
O5	0.05150	0.15497	**O15**	0.08032	0.11885
O6	0.05426	0.14488	**O16**	0.04481	0.15295
O7	0.13919	0.07335	**O17**	0.03895	0.15750
O8	0.04344	0.15558	**O18**	0.08343	0.13857
O9	0.03882	0.15292	**O19**	0.03913	0.15032
O10	0.04740	0.13778	**O20**	0.08815	0.13851

Finally, calculating the relative closeness to the ideal alternatives and ranking the alternatives based on cl_{i^+} (Eq. (6)):

Table 5. Rank the alternatives with TOPSIS-AHP.

Options	cl_{i^+}	Re-ranking	Options	cl_{i^+}	Re-ranking
O1	0.76073	**8**	**O11**	0.67040	**13**
O2	0.77885	**6**	**O12**	0.62957	**14**
O3	0.58715	**19**	**O13**	0.62753	**15**
O4	0.82239	**1**	**O14**	0.75106	**9**
O5	0.75055	**10**	**O15**	0.59674	**18**
O6	0.72751	**12**	**O16**	0.77339	**7**
O7	0.34511	**20**	**O17**	0.80172	**2**
O8	0.78173	**5**	**O18**	0.62418	**16**
O9	0.79755	**3**	**O19**	0.79347	**4**
O10	0.74403	**11**	**O20**	0.61108	**17**

Re-ranking results from applied methods are shown in Figs. 3 and 4. The obtained re-ranking results from five different techniques are very different as compared to ranking only based on the expected performance. This means that, by user interaction we could evaluate every twenty options with ten criteria as semi-automatically decision support. For example in Fig. 3, first, second, third, and fourth options in initial ranking have been changed to seventh, eleventh, fifteenth, and sixth ranked in average re-ranking. Hence, the first five best options regarding to user interaction are ninth, nineteenth, seventeenth, eighth, and fifth options. In Fig. 4, 1^{st}, 2^{nd}, 3^{rd}, and 4^{th} options in first ranking have changed to 14^{th}, 8^{th}, 15^{th}, and 5^{th} in average re-ranking, respectively. In contrast, first four options in average re-ranking have become options of 17^{th}, 9^{th}, 19^{th}, and 8^{th}, respectively. In spite of obtained different results from five techniques, we cannot conclude which one is better and more acceptable than others. Because we need to investigate and evaluate these results with some historical real cases. Obviously, previous decisions made are helpful to evaluate which techniques are more close to real decisions and which ones are not. In the duration of the evaluation of experimental results, it was difficult to get real cases (either the military is not willing to share or they do not have time). In order to do the evaluation properly, we would have to set up practical experiments with domain experts and show that the joint decision making (fusion system and human-based MADM) is more efficient than either of the two independently. Hence, in the absence of historical decisions made, analysis of the integration (or usage) of MADM with BNs results can improve decision-making performance by incorporating experiences and knowledge of decision makers (experts) as a semi-automatically decision-making system. According to Fig. 3, trend of variations in five applied techniques are similar. For instance, fourth option as the highest variation is ranked to 1^{st}, 5^{th}, 6^{th}, 9^{th}, and 11^{th} from TOPSIS (AHP), SAW (AHP), Mixed, TOPSIS (Entropy), and SAW (Entropy), respectively. In contrast, ninth option as one of the lowest variation is ranked to 3^{rd} from TOPSIS (AHP) and 1^{st} from four other techniques. Moreover, in Fig. 4, first option as the highest variation is ranked to 11^{th}, 7^{th}, 13^{th}, 9^{th}, and 14^{th} from SAW (AHP), SAW (Entropy), TOPSIS (AHP), TOPSIS (Entropy), and Mixed, respectively. In contrast, fourth option as one of the lowest variation is ranked to 11^{th} from SAW (AHP), 9^{th} from SAW (Entropy), and 5^{th} from three other techniques. Comparison of results via statistical tests can be helpful in order to define which method can be preferred among others, when there is no any historical case (decision made). Because statistical tests can be employed for obtaining the strong correlation and relationship between different results in applied techniques.

5.3 Comparison of Results

Three statistical tests as Pearson Correlation, Kendall's tau, and Spearman Rank Correlation have been employed. Pearson Correlation is widely used to measure the relationship degree between the two variables. It is same as the Spearman Rank Correlation which measures the strength of association of two variables. Kendall's Tau-b rank correlation states the strength of the dependence in paired observations. Kendall's tau provides a value between [−1 +1] which a positive correlation indicates that the ranks of both variables increase together while a negative correlation indicates that the rank of one variable increases and the other one decreases.

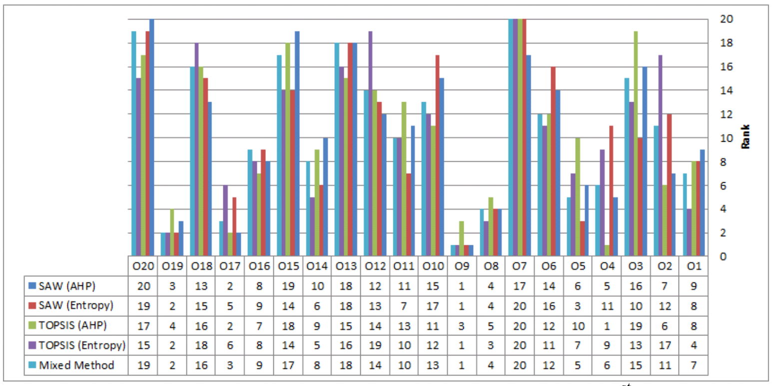

Fig. 3. Results of the rank from five applied techniques in 1st scenario.

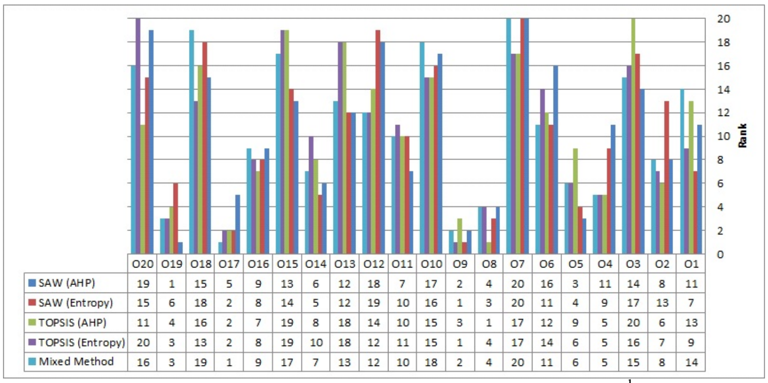

Fig. 4. Results of the rank from five applied techniques in 2nd scenario.

Table 6. Results of Pearson, Spearman and Kendall's TAU-B correlation.

1st Scenario				2nd Scenario			
Pearson and Spearman Correlation		Kendall's TAU-B Correlation		Pearson and Spearman Correlation		Kendall's TAU-B Correlation	
Paired Comparison	Correlation Coefficient	Paired Comparison	Correlation Coefficient	Paired Comparison	Correlation Coefficient	Paired Comparison	Correlation Coefficient
SAW (AHP) Mixed	0.950	SAW (AHP) Mixed	0.821	TOPSIS (AHP) Mixed	0.962	TOPSIS (AHP) Mixed	0.889
SAW (Ent.) Mixed	0.913	SAW (Ent.) Mixed	0.768	SAW (AHP) Mixed	0.933	TOPSIS (Ent.) Mixed	0.818
SAW (AHP) TOPSIS (AHP)	0.913	TOPSIS (Ent.) Mixed	0.758	SAW (AHP) TOPSIS (AHP)	0.911	SAW (Ent.) Mixed	0.775
TOPSIS (AHP) Mixed	0.899	TOPSIS (AHP) SAW (AHP)	0.747	SAW (Ent.) Mixed	0.901	TOPSIS (AHP) SAW (AHP)	0.755
TOPSIS (Ent.) Mixed	0.893	TOPSIS (AHP) Mixed	0.716	TOPSIS (Ent.) Mixed	0.90	SAW (AHP) Mixed	0.749
SAW (AHP) SAW (Ent.)	0.851	SAW (AHP) SAW (Ent.)	0.674	TOPSIS (AHP) SAW (Ent.)	0.882	SAW (AHP) TOPSIS (Ent.)	0.711
SAW (Ent.) TOPSIS (Ent.)	0.851	SAW (Ent.) TOPSIS (Ent.)	0.674	SAW (Ent.) TOPSIS (Ent.)	0.861	TOPSIS (AHP) SAW (Ent.)	0.694
SAW (AHP) TOPSIS (Ent.)	0.737	SAW (AHP) TOPSIS (Ent.)	0.579	TOPSIS (AHP) TOPSIS (Ent.)	0.802	SAW (AHP) SAW (Ent.)	0.621
TOPSIS (AHP) TOPSIS (Ent.)	0.735	TOPSIS (AHP) TOPSIS (Ent.)	0.537	SAW (AHP) TOPSIS (Ent.)	0.774	TOPSIS (AHP) TOPSIS (Ent.)	0.587
TOPSIS (AHP) SAW (Ent.)	0.687	TOPSIS (AHP) SAW (Ent.)	0.484	SAW (AHP) SAW (Ent.)	0.702	SAW (Ent.) TOPSIS (Ent.)	0.524

Since there is much data (20 entries), the results of Pearson and Spearman are convergent (Table 6). According to Table 6, the correlation between different applied techniques with 99% of confidence level is strong and positive which is statistically significant ($p < 0.01$). This very high confidence level comes from statistical tests output in SPSS software as 'correlation is significant at the 0.01 level (2-tailed)'. In both scenarios, the correlation between TOPSIS and SAW techniques with AHP method (0.913 and 0.911) is stronger than with Entropy method (0.851 and 0.861). Moreover, correlation between TOPSIS, SAW, and Mixed (0.899 and 0.95 in 1st scenario, 0.962 and 0.933 in 2nd scenario) with AHP are better than with Entropy (0.893 and 0.913 in 1st scenario, 0.9 and 0.901 in 2nd scenario). Significant statistical correlation between ranked options with five different techniques is because of the close proximity of weights by AHP and Entropy. In the Table 6, the highest relation is Mixed method with SAW and TOPSIS by both AHP and Entropy. Since the Mixed method involves average of methods results, it is expected to have a stronger correlation as compared to others. When there is no historical real case for investigation of correlation between real decisions made and applied techniques, Mixed method can be ideal technique among others. In contrast, the almost lowest relation is TOPSIS (AHP) with SAW (Entropy) and TOPSIS (Entropy) with SAW (AHP). Hence, Mixed method has provided better results with the most correlations among other paired comparisons. The values for concordance coefficient from Kendall's tau_b results are close to +1; as a result, there is a large agreement between the ranks. Also, concordance coefficient between applied techniques with AHP is better than Entropy.

6. CONCLUSION

In this study, we applied TOPSIS, SAW, and Rank Average (Mixed) method as decision-making techniques with AHP and Entropy as weighting methods to re-rank the Bayesian Network options. As we observed in the proposed practical experiments with domain experts, there is a significant correlation (relation) between ranked options and the five applied techniques because of the close proximity of weights by AHP and Entropy. The experimental results show that the joint decision making (fusion system and human-based MADM) by incorporating of domain experts is more efficient than either of the two independently for re-ranking Bayesian Network options. However, the concordance coefficient with AHP method is somewhat better than Entropy. In spite of simplicity of Entropy, AHP with usage of expert judgment is more reliable. As we found, relation between TOPSIS and SAW techniques with AHP is more acceptable than Entropy with stronger correlation. Relation between techniques of TOPSIS, SAW and Mixed with AHP are more acceptable than with Entropy. When there is no historical real case for investigation of correlation between real decisions made and applied techniques; Mixed method has provided better results with the most correlations among other paired comparisons. Obviously, the use of the previous decisions made in some real cases will be helpful to evaluate which techniques are more close to real decisions and which ones are not. According to advantages of applied techniques, it is expected that TOPSIS technique and AHP method can provide closer results to real decisions made.

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