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Personnel selection using analytic network process and fuzzy data envelopment analysis approaches ☆

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ABSTRACT

This paper develops a decision support tool using an integrated analytic network process (ANP) and fuzzy data envelopment analysis (DEA) approach to effectively deal with the personnel selection problem drawn from an electric and machinery company in Taiwan. The current personnel selection procedure is a separate two-stage method. The administration practice shows that the separation between stages 1 and 2 reduces the administration quality and may incur both the top manager's displeasure and the decision-makers' depression. An illustrative example by a simulated application demonstrates the implementation of the proposed approach. This example demonstrates how this approach can avoid the main drawback of the current method, and more importantly, can deal with the personnel selection problem more convincingly and persuasively. This study supports the applications of ANP and fuzzy DEA as decision support tools in personnel selection.

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1. Introduction

Human resources are one of the core competences for an organization to enhance its competitive advantage in a knowledge economy. Among the functions of human resource management, personnel selection significantly affects the character of employees and quality of administration, and hence it has attracted intensive attention and is an important topic for organizations. An effective personnel selection method should be able to assist the organization in selecting an appropriate person for a given job. Many studies have been conducted to help organizations make effective selection decisions. Further applications of effective techniques in the personnel selection field are still being developed. The personnel selection problem generally concerns with important and complex issues such as: (i) How to properly set the importance weights of criteria to reflect the situations in which not all personnel attributes/characteristics are equally important? (ii) How to use linguistic and/or numerical scales to evaluate the applicants under multiple criteria? (iii) How to aggregate the evaluation results and then rank the applicants? The inherent importance and complexity of the personnel selection problem require effective analytical methods to provide an operational/tactical decision framework.

The personnel selection problem drawn from an electric and machinery company in Taiwan is addressed in this study. A decision support tool using an integrated ANP and fuzzy DEA approach with three phases is developed to effectively deal with the current problem. The rest of this paper is organized as follows. Section 2 provides the relevant literature review. Section 3 describes the current method. In Section 4, the proposed approach is presented. Section 5 provides an illustrative example by a simulated application. Section 6 discusses the results. Finally, conclusions are given in Section 7.

2. Literature review

Researchers (e.g., Beckers & Bsat, 2002; Hough & Oswald, 2000; Liao, 2003; Robertson & Smith, 2001) have pointed out that many issues influence personnel selection practices, including change in personnel, change in work behavior, change in work, change in society, change of laws, advancements in information technology, and others. From a practical viewpoint of personnel selection, the rating biases are a common problem in the selection process (Arvey & Campion, 1982). Rothstein and Goffin (2006) argued that using personality measures appropriately may add value to personnel selection practices. Due to advancements in information technology, many studies have emphasized the development of decision support systems or expert systems to assist personnel selection (e.g., Hooper, Galvin, Kilmer, & Liebowitz, 1998; Mehrabad & Brojeny, 2007; Shih, Huang, & Shyur, 2005).

For the application of operation research related techniques in the personnel selection field, Chien and Chen (2008) proposed a data mining framework based on a decision tree and association rules to generate 30 meaningful rules for recruitment strategies. The personnel profile data and long-term work behavior records

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are collected to support this method. Kelemenis and Askounis (2010) developed a Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) based multi-criteria approach which incorporates the veto threshold for the ranking of the alternatives. In their approach, the ultimate decision criterion is not the similarity to the ideal solution but the distance of the alternatives from the veto set by the decision-makers. Dursun and Karsak (2010) argued that many individual attributes considered for personnel selection such as organizing ability, creativity, personality, and leadership exhibit vagueness and imprecision. Therefore, they developed a fuzzy multi-criteria decision-making algorithm, which uses the principles of fusion of fuzzy information, 2-tuple linguistic representation model and technique for order preference by similarity to the ideal solution, to tackle the assessment using both linguistic and numerical scales in a decision-making problem with multiple information sources. Gibney and Shang (2007) studied an application of the analytic hierarchy process (AHP) (Saaty, 1980) for the dean selection process of a business school. After the candidate finally selected by the Provost was different from the best one ranked by the search committee, the authors determined the reason for this difference, arguing that the root cause of the difference was a variation in emphasis on certain criteria. In fact, causing the differences in the evaluation results of the dean selection case are very likely to occur since AHP must satisfy the property of independence among the criteria in the decision-making process. Since dependence and feedback relationships will usually be generated among the criteria in actual practice, the analytic network process (ANP) (Saaty, 1996) is a more suitable technique for avoiding differences or errors in the evaluation results. In recent studies, many researchers have applied ANP to decision-making problems (e.g., Bernhard, Vacik, & Lexer, 2005; Chen, Lee, & Wu, 2008; Chung, Lee, Amy, & Pearn, 2005; Hsieh, Lin, & Lin, 2008; Jharkharia & Shankar, 2007). Regarding the characteristics of the AHP and ANP methods, a problem is decomposed into several levels to construct a hierarchy in the AHP scheme. The basic assumptions of AHP are that it can be used in functional independence of an upper part, or cluster, of the hierarchy from all its lower parts and from the criteria or items in each level (Lee & Kim, 2000). Saaty (1996) argued that many decision problems cannot be structured hierarchically because of the interaction and dependence of higher-level elements on a lower-level element. Then, he proposed the ANP method to deal with such problems. The ANP generalizes the AHP as a widely used technique by replacing a hierarchy with a network. With respect to the uses of AHP and ANP methods, Saaty suggested that AHP is used to solve the problem of independence on alternatives or criteria and ANP is used to deal with the problem of dependence among alternatives or criteria.

Saaty (1996) conceptually expressed the hierarchy and network structures as Fig. 1. The following super-matrix representation of the hierarchy shown in Fig. 1a is given by him:

$$W_h = \begin{bmatrix} 0 & 0 & 0 \\ W_{21} & 0 & 0 \\ 0 & W_{32} & I \end{bmatrix}$$

In the super-matrix W_h, W_{21} is a vector that represents the impact of the goal on the criteria and W_{32} is a matrix which represents the impact of the criteria on each of the alternatives. The identity matrix I is used to show that each element depends only on itself. This is a necessary aspect of a hierarchy when viewed within the context of the super-matrix. The zero entries correspond to those elements having no influence (Yuksel & Dagdeviren, 2007). If the criteria are dependent among themselves, the hierarchy is replaced by the network shown in Fig. 1b. The interdependency is expressed by the presence of matrix W_{22} in the $(2, 2)$ entry of super-matrix, which yields W_n as follows (Saaty, 1996):

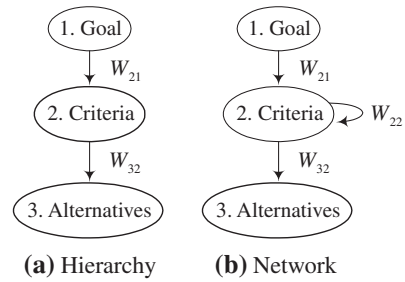

Fig. 1. Hierarchy and network structures (Saaty, 1996).

$$W_n = \begin{bmatrix} 0 & 0 & 0 \\ W_{21} & W_{22} & 0 \\ 0 & W_{32} & I \end{bmatrix}$$

Any zero entry in the super-matrix W_n can be replaced by a matrix if there is an interrelationship of the elements within a cluster or between two clusters (Yuksel & Dagdeviren, 2007).

In addition to interdependences among multiple criteria, personnel selection problems also involve decision-making in uncertain and vague situations, which requires an appropriate approach, such as fuzzy method, to deal with them. To obtain the final ranking values of candidates, Liang and Wang (1994) developed a fuzzy method to combine subjective assessments from interviews and objective assessments from tests. In their rating scheme, triangular fuzzy numbers (TFNs) were used to quantify the linguistic assessments of criteria weights and ratings. Yaakob and Kawata (1999) also used a fuzzy method to deal with workers' placement problem, and relationships among workers were included in the workers' assignment to make an adequate decision.

From the viewpoint of an employer, all applicants can be viewed as homogenous units. The evaluation results as well as ranking of applicants are substantially based on their relative performance. Thereby, data envelopment analysis (DEA) (Charnes, Cooper, & Rhodes, 1978) is a suitable technique for assessing the performance of applicants. DEA is a non-statistical and non-parametric technique for evaluating the relative efficiencies of a set of homogenous decision-making units (DMUs) that use multiple inputs to produce multiple outputs. Conceptually, the efficiency score of a DMU is measured by using the ratio of its weighted sum of outputs to its weighted sum of inputs. One of the characteristics of DEA is that each DMU determines a set of weights so as to reflect its best efficiency relative to all others. However, to prevent unfavorable factors from being ignored in the evaluation by setting a weight of zero to them, Charnes, Cooper, and Rhodes (1979) claimed that all weights should be greater than a small non-Archimedean number. In addition to this traditional way of assigning weights, the idea for weight restriction has been used in the relevant studies. One of the weight restriction methods is assurance region (AR) (e.g., Kao & Hung, 2008; Sun, 2004). Through the ARs obtained by prior information, DEA models can handle the cases in which the weights are subjected to predetermined relationship. When management is concerned with the degree to which the goals are met, then by setting the inputs of each DMU as one to neglect the difference and influence of inputs, the measurement result obtained is referred to as relative effectiveness (Chang, Hwang, & Cheng, 1995; Kao, Hwang, & Sueyoshi, 2003).

In conventional DEA, input and output data are treated as exact values on a ratio scale. In recent years, many researchers have developed DEA models to tackle the uncertain situations where some of the input or output data are not known exactly. Imprecise data can be expressed as fuzzy numbers, rank order data or bounded intervals.

DEA with exact values or imprecise data is a powerful technique and has been extensively applied to evaluate the relative efficiencies of a set of DMUs in real-world management cases (e.g., Chen & Lu, 2007; Cook & Zhu, 2006; Johnes, 2006; Kao & Hung, 2008; Lertworasirikul, Fang, Joines, & Nuttle, 2003; Wang, Greatbanks, & Yang, 2005; Yang, 2006). Besides, DEA has been applied to select the best one from the experimental data set. For example, Ertay and Ruan (2005) applied DEA to an experimental data set consisting of 48 simulation scenarios, which are referred to as 48 DMUs, for determining the most efficient number of operators and the efficient measurement of labor assignment in cellular manufacturing system. Gutierrez and Lozano (2010) proposed a three-step approach to find the optimal parameter combination in robust design. In their approach, neural networks were used to estimate the performance measure for all possible combinations of factor levels. After that, DEA was used first to select the efficient factor level combinations and then for choosing among them the one which leads to a most robust quality loss penalization.

Until recently, very rare DEA research has been applied in personnel selection issues, although it has been widely applied to other management problems. In this study, a decision support tool using an integrated ANP and fuzzy DEA approach is developed for an electric and machinery company in Taiwan to support personnel selection. An illustrative example elaborates the implementation of the proposed approach.

3. Current method

The current personnel selection procedure is a separate two-stage method. In stage 1, the company establishes a decision-making group consisting of five members, denoted by D_1–D_5, from functional and human resource divisions to perform the evaluation mechanism. Group decision-making is used to avoid the biases of a decision-maker towards a particular object. A ranking list of the applicants is suggested to the top manager. In stage 2, the top manager makes a final selection decision or returns the suggestion by taking into account his staffing philosophy and the evaluation results submitted by the decision-making group.

The procedure conducted in the summer of year 2009 for selecting a senior electrical engineer is used to illustrate the current method. In stage 1, three criteria consisting of professional knowledge and expertise (C_1), previous professional career and educational background as well as achievements (C_2) and personality and potential (C_3) were used to assess the candidate applicants. These criteria correspond largely to the functional criteria and individual job criteria suggested by Lewis (1985). To evaluate how an applicant can satisfy the requirements of this job, the selection process used application forms, tests and interviews. A formulated grading list containing ten attributes for each criterion was used by the decision-makers to evaluate the applicants. Each applicant was appraised by the job supervisor (D_1) under C_1, by division manager of the job (D_2) and director of human resource division (D_3) under C_2, and by D_1–D_5 under C_3. For each attribute, a crisp point (up to 10) was graded by the decision-maker according to the grading guides. For C_2 and C_3, the mean of the points appraised by the decision-makers was used as the aggregate point of the applicant. Thus, the grading point under each criterion is 100 at most, which is so-called a quantified 100-point system.

Regarding the criteria weights, the AHP weighting method (Saaty, 1980) was employed to determine the preference weights of criteria. The five decision-makers respectively conducted a series of pairwise comparisons in terms of their contribution to the objective (i.e., selecting the best personnel). The relative importance was judged with Saaty's 1–9 scale. The method of geometric mean suggested by Dyer and Forman (1992) was used to include the judgments of five decision-makers. The determined aggregate importance weights of C_1, C_2 and C_3 are 0.473, 0.269 and 0.258, respectively, with consistency ratio (CR) of 0.033 (<0.1).

Eight applicants, denoted by A_j, $j = 1, \ldots, 8$, submitted their application forms and took part in the tests and interviews administered by this company. The points of A_1, for example, graded by the decision-makers under C_1, C_2 and C_3 are 71, 61 and 67.2, respectively. By incorporating the importance weights of criteria, the weighted point of A_1 is calculated as $71 \times 0.473 + 61 \times 0.269 + 67.2 \times 0.258 = 67.33$. The ranking list of eight applicants is $A_5 \succ A_1 \succ A_6 \succ A_4 \succ A_8 \succ A_7 \succ A_3 \succ A_2$ according to the weighted points obtained, in which an applicant with a higher weighted point is ranked higher. The decision-making group recommended this ranking list to the top manager for making a selection decision.

In stage 2, the top manager considers the staffing philosophy with different aspects and priorities. The staffing philosophy contains three aspects: inclination and potential to follow and transmit the organization culture (T_1), to accomplish the organization mission (T_2) and to be a successor to the superintendent (T_3). These three aspects correspond to the organizational criteria suggested by Lewis (1985) and are actually applied as the staffing policy of this company. By considering the priorities of these aspects and the relationships between the aspects and criteria, the top manager returned the suggested ranking list because he thought the weight of C_1 is too high, while that of C_3 is too low.

The decision-makers reconsidered their respective pairwise comparisons and recalculated the weights of C_1, C_2 and C_3 as 0.406, 0.223 and 0.371, respectively, with CR of 0.007 (<0.1). Then, they recalculated the weighted points of applicants and resubmitted a new ranking list of $A_1 \succ A_5 \succ A_4 \succ A_6 \succ A_8 \succ A_7 \succ A_3 \succ A_2$ to the top manager. Finally, A_1 was selected as the senior electrical engineer and A_5 was the first one on the waiting list.

The drawback of this current method comes from the adoption of AHP method to determine the preference weights of criteria. Under the AHP scheme, the relationships of interdependence among criteria and interaction between staffing philosophy aspects and criteria were neglected. Thus the top manager's staffing philosophy and priorities were not incorporated in the evaluation procedure, although the decision-makers may know the staffing philosophy aspects in advance. The decision-making group indeed appraised the applicants according to the local criteria weights which were determined by the group's judgment. This caused the separation between stages 1 and 2. This drawback clearly reduced the administration quality and may incur both the top manager's displeasure and the decision-makers' depression. In the study for dean selection (Gibney & Shang, 2007), the separation between evaluation and selection stages brings up a discordant outcome where the adopted person is different from the best one recommended by the search committee. In this study, the ANP method, which takes into account the interdependent and feedback relationships, is used to determine the weights of criteria to avert the shortcoming of separation between stages 1 and 2.

4. Proposed approach

The conceptual flow of the proposed approach is depicted in Fig. 2 with three phases. In phase 1, fuzzy technique is utilized for evaluating applicants. Since the assessment results for personnel attributes/characteristics have inherent vagueness and ambiguity, it is difficult to measure them precisely. Furthermore, Tsaur, Chang, and Yen (2002) argued that the evaluation outcomes obtained from decision-making problems of diverse intensity may be misleading if the fuzziness of subjective judgment is not considered. Therefore, the ratings of applicants are considered as linguistic variables to express the evaluation results more rationally. TFN

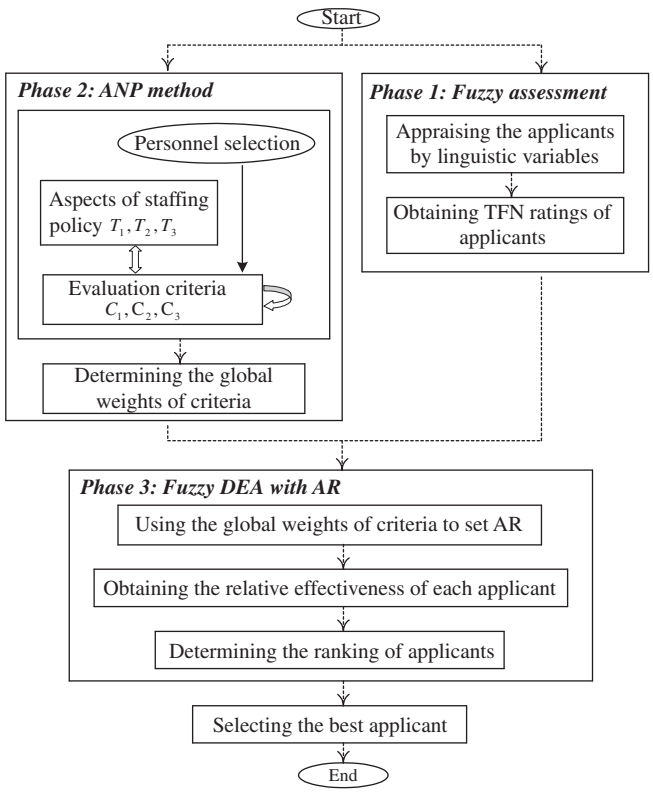

Fig. 2. Conceptual flow of the proposed approach.

is then used to quantify the judgment value of linguistic data because TFN is intuitively easy to use (Liang & Wang, 1994). Moreover, TFN has the advantages of representing the most general situation by the center and reflecting some possibilities by the spreads. The linguistic variable scheme in the rating set (Cochran & Chen, 2005; Liang & Wang, 1994) is modified a little bit, as shown in Table 1, and then used in this study to assess applicants with respect to different criteria.

In phase 2, the interdependent and feedback relationships are taken into account in the determination of criteria weights by using the ANP method. To avert shortcoming of current method, in addition to evaluating how an applicant can satisfy the requirements implicit in each of the criteria, the aspects of staffing policy and their priorities should be confirmed for selecting the appropriate person. In practice, the aspects of staffing policy and the evaluation criteria interact with each other. The priorities of the aspects affect the weighting on criteria for assessing the applicants. On the other hand, determining the weights of criteria also influences the priorities of the aspects. A two-way arrow is used to represent this outer dependence. In addition, a relationship of interdependence may arise among criteria, and this inner dependence of criteria is represented by a looped arc. Since there are outer and inner dependence relationships existing in the current problem, the ANP technique is employed to deal with the weighting process. If the weights of criteria are determined and the original priorities of the aspects are retained, the criteria weights are referred to as global weights and then can be used to evaluate the candidate applicants; otherwise, the weighting process should be reconsidered and measured again so as to avoid using the unsuitable weights. Denoting the global weights of criteria p and q by u_p^* and u_q^*, respectively. The ratio of $\pi_{pq}^* = u_p^*/u_q^*$ is used in the following DEA model to set AR for u_p and u_q (see Eq. (3.4) later).

Table 1
Linguistic variables and quantified TFNs.

Linguistic data	TFN
Very good (VG)	(8, 10, 10)
Good (G)	(6, 8, 10)
Fair (F)	(3, 5, 7)
Poor (P)	(0, 2, 4)
Very poor (VP)	(0, 0, 2)

In phase 3, a suitable fuzzy DEA with AR is developed for evaluating and ranking the applicants. By employing the output-oriented DEA based on CCR model (e.g., Martic & Savic, 2001; Sun, 2004), the relative efficiency of DMU k, denoted by h_k, is measured as follows:

$$\begin{aligned} \frac{1}{h_k} &= \text{Min} \sum_{i=1}^{m} v_i X_{ik} \\ \text{s.t.} \quad & \sum_{r=1}^{s} u_r Y_{rk} = 1 \\ & \sum_{i=1}^{m} v_i X_{ij} - \sum_{r=1}^{s} u_r Y_{rj} \geqslant 0, \quad j = 1, \ldots, n, \\ & v_i, u_r \geqslant \varepsilon, r = 1, \ldots, s, i = 1, \ldots, m, \end{aligned} \tag{1}$$

where X_{ij} denotes the input amount of X_i for DMU j, and Y_{rj} is the output amount of Y_r for DMU j; v_i and u_r are weights attached to X_i and Y_r, respectively, and ε is a small non-Archimedean number.

For applying DEA to the current problem, A_j is referred to as DMU j and the assessment result of A_j under C_r is referred to as Y_{rj}. In this study, the input amount is not considered, the measurement result is so-called effectiveness. According to the argument of Kao et al. (2003), model (1) can be modified as model (2) to measure the relative effectiveness of DMU k, denoted by E_k, by considering one input and setting its amount as one for each DMU. Chang et al. (1995) used the dual form of model (2) to measure the relative effectiveness for evaluating the relative achievement of regional developments in 23 administrative regions of Taiwan.

$$\begin{aligned} \frac{1}{E_k} &= \text{Min } v_1 \\ \text{s.t.} \quad & \sum_{r=1}^{s} u_r Y_{rk} = 1, \\ & v_1 - \sum_{r=1}^{s} u_r Y_{rj} \geqslant 0, \quad j = 1, \ldots, n, \\ & u_r, v_1 \geqslant \varepsilon, r = 1, \ldots, s. \end{aligned} \tag{2}$$

Since the output measures are expressed as TFNs in this study, the fuzzy DEA based on a possibility DEA model (PCCR1) (Lertworasirikul et al., 2003) is employed to develop a suitable model for the current problem. Besides, the global weights of criteria, say u_p^* and u_q^*, obtained in phase 2 are used to set the AR for u_p and u_q. Denoting the TFN measure of Y_{rj} by $\tilde{y}_{rj}$ and employing the possibility level α, the possibility DEA–CCR model with AR for measuring the relative effectiveness of DMU k is proposed as follows:

$$\frac{1}{E_k} = \text{Min } v_1 \tag{3.0}$$

$$\text{s.t.} \quad \sum_{r=1}^{s} u_r (\tilde{y}_{rk})_\alpha^U \geqslant 1, \tag{3.1}$$

$$\sum_{r=1}^{s} u_r (\tilde{y}_{rk})_\alpha^L \leqslant 1, \tag{3.2}$$

$$v_1 - \sum_{r=1}^{s} u_r (\tilde{y}_{rj})_\alpha^U \geqslant 0, \quad j = 1, \ldots, n, \tag{3.3}$$

$$\frac{u_p}{u_q} = \pi_{pq}^*, \quad p = 1, \ldots, s-1, \quad q = 2, \ldots, s, \quad p < q, \tag{3.4}$$

$$u_r, v_1 \geqslant \varepsilon, \quad r = 1, \ldots, s. \tag{3.5}$$

Regarding the meaning of possibility level, a high possibility level means that precise results are obtained, whereas a low possibility level means there is high confidence in the outcome (Wang et al., 2005). According to the judgment guide of PCCR1 model (Lertworasirikul et al., 2003), DMU k is α-possibilistic effective if its E_k value at the α possibility level is greater than or equal to one; otherwise, it is α-possibilistic ineffective.

In model (3), the fourth constraint (Eq. (3.4)) represents the ARs of output weights, where the ratio of u_p to u_q is equal to π^*_{pq}. According to the ARs, each DMU can select a set of weights to reflect its best relative effectiveness under the restriction that the weights should comply with the predetermined relationships. This approach is organized into the homogeneous weight restriction method (Charnes, Cooper, Huang, & Sun, 1990; Thompson, Langemeier, Lee, Lee, & Thrall, 1990). Since the three output measures are comparable by using the same rating scheme of Table 1, this ratio relationship of AR is meaningful.

5. Illustrative example

A simulated application of the proposed approach in the selection of electrical engineer of the case company illustrates its implementation.

5.1. Fuzzy assessments of applicants

By using the rating scheme in Table 1 to appraise the applicants, the assessment results of A_1 under C_2, for example, are shown in Table 2. The TFN ratings assessed by D_2 and D_3 total to $(59, 79, 91)$ and $(55, 75, 85)$, respectively. Thus, the aggregate TFN rating of A_1 under C_2 is obtained as $((59 + 55)/2,\ (79 + 75)/2,\ (91 + 85)/2) = (57, 77, 88)$ and then used as $\tilde{y}_{21} = (57, 77, 88)$ in following DEA model. The center of 77 represents the most general situation and the left spread of 20(=77–57) and right spread of 11(=88–77) reflect some possibilities. Table 3 shows the aggregate TFN ratings of the eight applicants under three criteria.

5.2. Global weights of criteria

For determining the appropriate weights of criteria, the pairwise comparisons concerning the outer dependences between the aspects and criteria and the inner dependences among the criteria are conducted. Regarding outer dependences, the measurements include pairwise comparisons for criteria with respect to aspects and those for aspects with respect to criteria. Table 4 shows, for example, the pairwise comparison matrix conducted by D_1 for criteria under T_1. The question asked to the decision-makers for the pairwise comparison is: "What is the relative impact on T_1 by one criterion when compared to another criterion in selecting the best applicant?" It can be seen from Table 4 that the relative importance of C_1 when compared to C_2 with respect to T_1 in selecting the best applicant is three. The aggregate pairwise comparison matrix obtained by calculating the geometric mean of five decision-makers' judgments is shown in Table 5. The eigen-vector reveals that on controlling T_1 the relative weights of C_1, C_2 and C_3 are 0.450, 0.165 and 0.385, respectively. These values are listed in the bottom three cells of the first column of Table 6. Using a similar procedure, the relative weights of three criteria with respect to T_2 and T_3, respectively, can be obtained. These weights are shown in the bottom half of columns 2 and 3 of Table 6.

Regarding pairwise comparisons for aspects with respect to criteria, the top manager conducts the relevant measurements. Table 7 provides, for example, the pairwise comparison matrix conducted by the top manager for aspects under C_1. For the pairwise comparison, the top manager asks himself: "What is the relative impact on C_1 by one aspect when compared to another aspect in selecting the best applicant ?" The eigen-vector in Table 7 indicates that on controlling C_1 the relative importance weights of T_1, T_2 and T_3 are 0.123, 0.557 and 0.320, respectively. These values are listed in the top three cells of the fourth column of Table 6. Similarly, the relative weights of three aspects under C_2 and C_3, respectively, are obtained and listed in the top half of columns 5 and 6, respectively, of Table 6.

To detect the inner dependences among criteria, the pairwise comparisons for criteria are conducted by the decision-makers to examine the impacts of the criteria on each criterion. Table 8 shows, for example, the pairwise comparison matrix conducted by D_1 for C_2 and C_3 under C_1. The question asked to the decision-makers for the pairwise comparison is: "What is the relative importance of C_2 compared with C_3 on controlling C_1?" The aggregate pairwise comparison matrix obtained by calculating the geometric mean of the judgments of five decision-makers is shown in Table 9. The eigen-vector reveals that on controlling C_1 the relative weight of C_2 is 0.689 and that of C_3 is 0.311. These values are listed in the bottom two cells of the fourth column of Table 6. By a similar procedure, the relative weights of C_1 and C_3 under C_2 and those of C_1 and C_2 under C_3 are obtained and shown in the bottom half of last two columns of Table 6.

Table 6 is an unweighted super-matrix. For columns 4–6 of Table 6, the top half and bottom half yield two blocks. Since the components in the upper block and the lower block are equally important, we artificially weight the elements in the two blocks by 0.5 and then raise this super-matrix to powers. The super-matrix converges to a steady state after multiplying it 11 times. The limit super-matrix is shown in Table 10. All columns of Table 10 are identical; the top half shows the long-term converged weights of the aspects of staffing policy and the bottom half shows the converged weights of criteria. As can be seen, the converged weights, referred to as global weights, of C_1, C_2 and C_3 are as $u^*_1 = 0.258$, $u^*_2 = 0.191$ and $u^*_3 = 0.217$. These three values are amounted to 0.666. For adjusting these values to reach a total of one, they can

Table 2
Assessment results of A_1 under C_2.

Attribute	Decision-maker D_2		Decision-maker D_3	
	Linguistic data	Quantified TFN	Linguistic data	Quantified TFN
1	F	(3, 5, 7)	VG	(8, 10, 10)
2	VG	(8, 10, 10)	F	(3, 5, 7)
3	VG	(8, 10, 10)	VG	(8, 10, 10)
4	G	(6, 8, 10)	F	(3, 5, 7)
5	F	(3, 5, 7)	G	(6, 8, 10)
6	G	(6, 8, 10)	VG	(8, 10, 10)
7	VG	(8, 10, 10)	P	(0, 2, 4)
8	F	(3, 5, 7)	VG	(8, 10, 10)
9	VG	(8, 10, 10)	F	(3, 5, 7)
10	G	(6, 8, 10)	VG	(8, 10, 10)
Total		(59, 79, 91)		(55, 75, 85)
Aggregate		(57, 77, 88)		

Table 3
TFN ratings of eight applicants.

Applicant (A_j)	$\tilde{y}_{1j}$	$\tilde{y}_{2j}$	$\tilde{y}_{3j}$
A_1	(55, 75, 91)	(57, 77, 88)	(45.2, 64.4, 80)
A_2	(50, 70, 88)	(38, 58, 76)	(39, 57.8, 75.4)
A_3	(46, 64, 80)	(41.5, 61.5, 80.5)	(37.2, 56.4, 74)
A_4	(57, 77, 91)	(52.5, 72.5, 86.5)	(46, 65.6, 81.6)
A_5	(52, 72, 88)	(44, 64, 79)	(45.6, 65.2, 81.6)
A_6	(39, 59, 79)	(49, 69, 85)	(47, 66.2, 80.6)
A_7	(50, 70, 88)	(52, 72, 85)	(40.2, 59.4, 77)
A_8	(52, 72, 88)	(47.5, 67.5, 83.5)	(41, 60.6, 78.6)

Table 4
Pairwise comparison matrix for criteria under T_1 by D_1.

T_1	C_1	C_2	C_3
C_1	1	3	2
C_2	0.333	1	0.5
C_3	0.5	2	1
			CR = 0.008

Table 5
Aggregate pairwise comparison matrix for criteria under T_1.

T_1	C_1	C_2	C_3	Eigen-vector
C_1	1	2.766	1.149	0.450
C_2	0.361	1	0.435	0.165
C_3	0.871	2.297	1	0.385
				CR ≅ 0

Table 6
Initial unweighted super-matrix.

	T_1	T_2	T_3	C_1	C_2	C_3
T_1				0.123	0.082	0.230
T_2				0.557	0.343	0.122
T_3				0.320	0.575	0.648
C_1	0.450	0.618	0.324	0	0.520	0.549
C_2	0.165	0.147	0.168	0.689	0	0.451
C_3	0.385	0.235	0.508	0.311	0.480	0

Table 7
Pairwise comparison matrix for aspects under C_1.

C_1	T_1	T_2	T_3	Eigen-vector
T_1	1	0.25	0.333	0.123
T_2	4	1	2	0.557
T_3	3	0.5	1	0.320
				CR = 0.018

Table 8
Pairwise comparison matrix for C_2 and C_3 under C_1 by D_1.

C_1	C_2	C_3
C_2	1	2
C_3	0.5	1
		CR = 0

Table 9
Aggregate pairwise comparison matrix for C_2 and C_3 under C_1.

C_1	C_2	C_3	Eigen-vector
C_2	1	2.215	0.689
C_3	0.451	1	0.311
			CR = 0

be further normalized by dividing them by 0.666. This causes $u_1^* = 0.387$, $u_2^* = 0.287$ and $u_3^* = 0.326$. This prior information provides that $\pi_{12}^* = 1.348(= 0.387/0.287)$, $\pi_{13}^* = 1.187(= 0.387/0.326)$ and $\pi_{23}^* = 0.880(= 0.287/0.326)$, which are used in Eq. (3.4). In theory, the relationship among these values is as $\pi_{13}^* = \pi_{12}^* \cdot \pi_{23}^*$.

5.3. Relative effectiveness and ranking of applicants

Model (3) is used in this study by setting $n = 8$ and $s = 3$ to calculate the relative effectiveness scores of the eight applicants with the data shown in Table 3. By using the prior information about global criteria weights obtained from Section 5.2, the ARs of Eq. (3.4) are set as $u_1/u_2 = \pi_{12}^* = 1.348, u_1/u_3 = \pi_{13}^* = 1.187$ and $u_2/u_3 = \pi_{23}^* = 0.880$. With these ARs, each applicant can select the values of u_1, and u_3 so as to reflect his/her best relative effectiveness under the restriction that the predetermined weight relationships remain unchanged. The possibility levels are set at six different values (α = 0, 0.2, 0.4, 0.6, 0.8, 1) according to the opinion of the top manager. The relative effectiveness scores are shown in Table 11. The numbers in parentheses shown in columns 2–4 of Table 11, for example, indicate the ranking of the applicants under the specific possibility levels. By using the average of six relative effectiveness scores, the aggregate ranking list of the applicants is $A_1 \succ A_4 \succ A_5 \succ A_7 \succ A_8 \succ A_6 \succ A_2 \succ A_3$, where A_1 is the best one to be recruited and A_4 is the first one on the waiting list.

Table 10
Super-matrix after convergence.

	T_1	T_2	T_3	C_1	C_2	C_3
T_1	0.049	0.049	0.049	0.049	0.049	0.049
T_2	0.118	0.118	0.118	0.118	0.118	0.118
T_3	0.167	0.167	0.167	0.167	0.167	0.167
C_1	0.258	0.258	0.258	0.258	0.258	0.258
C_2	0.191	0.191	0.191	0.191	0.191	0.191
C_3	0.217	0.217	0.217	0.217	0.217	0.217

6. Discussion

The ranking list of the applicants obtained by the proposed approach is not in complete agreement with that provided by current method. In comparison with the current method, the proposed approach has some advantages. Firstly, it adopts global criteria weights to incorporate the decision–makers' judgments about criteria with the top manager's opinion about the aspects of staffing policy. Thus the shortcoming of separation between decision–makers' judgments and top manager's opinion existing in the current method is overcome. Secondly, it takes into account the subjectiveness and vagueness of assessments by using the fuzzy scheme. Thus the possibility of obtaining the biased evaluation outcomes, which come from the use of current crisp 100-point system, is averted. Thirdly, it considers both precision and confidence of relative effectiveness by measuring them at different possibility levels. Thus the lack of consideration of precision and confidence under the current crisp data scheme is improved. Fourthly, by using the DEA with AR, each applicant shows his/her best relative effectiveness while the predetermined weight relationships remain unchanged. Thus the defect of obtaining evaluation results subject to the fixed criteria weights is reformed. The third and fourth advantages of the proposed approach are creative course of action which can especially advance the personnel selection quality.

Since the proposed approach has some advantages, it can not only avoid the drawbacks of current method but also deal with the current personnel selection problem more convincingly and persuasively. Thereby, the top manager could validly make the selection decision in accordance with the submitted ranking order. This is contributory for making a right selection decision and especially important when more than one applicant will be recruited. The proposed approach certainly requires somewhat of computational efforts, but these can be performed easily with the well-known powerful packages such as Excel and LINGO. Hence, the proposed approach is feasible and worthy to implement in practice. This approach can be modified for different industries or organizations by altering the linguistic variable scheme shown in Table 1, the number of applicant, the number and/or content of staffing policy aspects, the number and/or content of evaluation criteria.

Table 11
Relative effectiveness and ranking.

Applicant	$\alpha = 0$	$\alpha = 0.2$	$\alpha = 0.4$	$\alpha = 0.6$	$\alpha = 0.8$	$\alpha = 1$	Average	Aggregate ranking
A_1	0.9989	0.9994(2)[a]	0.9999(2)	1.0000(1)	1.0000	1.0000	0.9997	1
A_2	0.9285	0.9183(7)	0.9074(7)	0.8952(7)	0.8820	0.8677	0.8998	7
A_3	0.9024	0.8925(8)	0.8818(8)	0.8699(8)	0.8570	0.8431	0.8745	8
A_4	1.0000	1.0000(1)	1.0000(1)	0.9995(2)	0.9989	0.9982	0.9994	2
A_5	0.9618	0.9576(5)	0.9531(3)	0.9478(3)	0.9420	0.9358	0.9497	3
A_6	0.9377	0.9298(6)	0.9214(6)	0.9119(6)	0.9016	0.8905	0.9155	6
A_7	0.9643	0.9588(4)	0.9529(5)	0.9461(4)	0.9387	0.9307	0.9486	4
A_8	0.9654	0.9594(3)	0.9530(4)	0.9456(5)	0.9376	0.9289	0.9483	5

[a] The numbers in parentheses indicate the ranking of the applicants under a specific possibility level.

This causes different values of n and s in model (3). Note that, by considering the robustness of the evaluation results, the rule of thumb that the number of applicant should be at least two times the number of criteria, viz., $n \geqslant 2s$, (Kao et al., 2003) must be held.

The evaluation results reveal some phenomena. Firstly, both A_1 and A_4 are evaluated as effective candidates with three times out of the six possibility levels. Secondly, the higher the possibility level, the better the relative effectiveness score of A_1, while the changing tendencies of the other seven applicants are contrary to that of A_1. This condition may be caused by the different spreads of TFN ratings or by the ARs of weights. Thirdly, the ranking list under one possibility level may be different from that under another possibility level. As can be seen, for example, the ranking lists shown in columns 2–4 of Table 11 are different.

Instead of using the average of relative effectiveness scores, one may alternately wish to use the relative effectiveness scores under a preferred possibility level, say $\alpha = 0.6$, to rank the applicants. In case of a tie, the extended DEA-measure method (Andersen & Petersen, 1993), in which the reference set is changed by omitting the efficient DMU to be measured, can be used to calculate the so-called index number for breaking the tie. For example, the preferred possibility level is set at 0.42, then both A_1 and A_4 are effective at this level. To break this tie, the index number of A_1 is calculated as 1.000002 by restricting the 3rd constraint of model (3) (Eq. (3.3)) as $j \neq 1$, while A_4 is assigned the index 0.9999 by restricting the constraint as $j \neq 4$. As a result, A_1 is superior to A_4.

The top manager agreed that the proposed approach is a more effective technique, and it will be implemented to deal with personnel selection affair in the near future.

7. Conclusions

Personnel selection significantly affects the character of employees and quality of administration, and hence it has attracted intensive attention and has been an important topic for organizations. An effective personnel selection technique should be able to assist the organization to select the right person for a given job. Many studies have been conducted to help organizations make appropriate selection decisions. Since developing an effective approach to select the right person for a given job is very critical, further applications of effective techniques in the personnel selection field are still being developed.

The current procedure for selecting personnel of an electric and machinery company in Taiwan is a separate two-stage method. The administration practice shows that the separation between stages 1 and 2 reduces the administration quality and may incur both the top manager's displeasure and the decision-makers' depression. This paper develops a decision support tool using an integrated ANP and fuzzy DEA approach with three phases to effectively deal with the current problem. In phase 1, a fuzzy scheme is utilized to appraise the applicants for taking into account the subjectiveness and vagueness of assessments. In phase 2, ANP technique is employed to obtain the global criteria weights by incorporating the decision–makers' judgments about criteria with the top manager's opinion about the aspects of staffing philosophy. In phase 3, a possibility DEA-CCR model with AR is developed to measure the relative effectiveness of applicants at different possibility levels considering both precision and confidence of assessment outcomes. Furthermore, each applicant shows his/her best relative effectiveness when the predetermined weight relationships remain unchanged. A simulated application illustrates the implementation of the proposed approach.

The proposed approach can avoid the main drawback of the current method, and more importantly, can deal with the personnel selection problem more convincingly and persuasively. This study supports the applications of ANP and fuzzy DEA as decision support tools in personnel selection.

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