Prioritization of Domain Dependent KR Techniques Using the Combined AHP

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Abstract

To provide an appropriate knowledge representation technique dependent on a particular domain, we consider the combined analytic hierarchy process (CAHP). This is an extended method of the conventional AHP which is useful when two different expert groups are involved. Our problem domain is confined to human resource management including such major activities as planning, selection, placement, compensations, performance evaluation, training, and labor-management relations. We prioritize rules, frames, semantic nets, and predicate logic representation techniques best suited to each and all domains through an exploratory study.

Introduction

In the development of expert systems (ES), it is not enough to evaluate and select a knowledge representation techniques (KRT) which is best suited to a particular domain [1]. A matter of concern is that a lack of framework for guidance still exists. The most important current KRT are logical representations, semantic nets, procedural representations, frame-based representations, production system architectures, and representation languages [4]. Human resource management (HRM) domain is a key part of management [3,7]. We propose a new methodology called the combined analytic hierarchy process (CAHP) which is able to overcome the limitations of the conventional AHP [10,11] when two groups are involved with a separate hierarchy. The judgments accomplished by a group can be applied to those of the other model. Another focus is to select confident decision makers in addition to including their estimated importance.

Evaluation Criteria and Preference Ordering

Many of KRT have a number of important advantages and disadvantages, respectively [1,2,8,9]. Based on the literature, the primary strength of predicate logic is its expressive power. A basic strength of semantic nets is its natural ability to represent deep knowledge. Although semantic nets and frames are often equivalent representations,

the concept of slots in a frame is more expressive than links in a semantic net. The form IF <situation> THEN <action> is not well suited to non-procedural knowledge compared with other KRT. Therefore a preference ordering is conceptually derived where the expression T1 > T2 is interpreted as T1 is preferred to T2, i.e., expressibility (EXPR): PL > FR > SN > RU. With regard to search efficiency (SEAR) which denotes amount time to manipulate the knowledge, the summarized table [1] is adapted with the following ordering: FR > SN > RU > PL.

Predicate logic is based on the form of wellformed formulas can infer all conclusions that logically follow from premises. The rules of inference are sound and complete. Semantic nets and frames can completely infer conclusions through the arc or slot relationship without timeconsuming for binding of each fact in a rule. So, completeness (COMP) is as follows: PL > SN/FR > RU. Certainty factors are supported in rules and frames can support guessing and default reasoning. Predicate logic cannot represent formulas that are not true or false. So, probabilistic reasoning (PROB) is as follows: FR/RU > SN/PL. The advantage of production rules results from their ability to represent modular knowledge in terms of chunking the knowledge. Objects are grouped into a frame. Structuring rules is often easier than making individual frames as a metaclass. Decomposing well-formed formulas into individual predicates is to be a task to change the problem definition. Therefore modularity (MODU) is as follows: RU > FR > SN > PL. The ISA relationship in a frame as well as a semantic net guarantees the following ordering of reusability (REUS): FR/SN > RU/PL. The pictorial representation of information is easier to understand (UNDE) than textual and the mathematical representation like rules and logic. We assume such ordering as SN > FR > RU > PL.

The CAHP Model

Two different goals should be combined in the CAHP model. The first goal, Goal1 focuses on accomplishing the priority of the evaluation criteria. But the second goal, Goal2 focuses on accomplishing the priority of the KRT. Goal3 as a

final goal is to select the best KRT for use in all HRM domains and each domain. Here our consideration is about how to combine levels of the decision. final models to make a Conventionally there are four ways that the inherent AHP can be applied to group decision-making [5]. Our approach is similar to the method of combining results from individual models or parts of a model. In the case that group members have significantly different goals or cannot meet to discuss the decision, it is useful that each group member should make judgments separately. The CAHP method is concerned with combining individual judgments effectively in terms of constructing a new hierarchy where the group members are the players at the top level of the tree. The Expert Choice software package is very efficient and effective as an implementation tool for the CAHP like the AHP. Numerous applications of the AHP have been made in industry by using Expert Choice.

Data Collection

Two types of questionnaires were designed. For the first group, the mailing list was compiled from a dictionary of the Korean Listing Companies with a recent hiring announcement from newspapers. For the second group, the mailing list was compiled from professors who are serving in the department of computer sciences and fifty committees who are the members of the Korea Expert Systems Society. They are regarded as knowledge engineers who have expertise with various KRT.

Computational Procedures

Unlike the AHP, the CAHP focuses primarily on how to determine the group's priorities and to merge several models into a single new model through all reflecting the group's judgments. Without respect to detailed procedures for AHP computations, the CAHP is performed by the following steps:

Let $X_{iik} \equiv$ the priority of the attribute X_j with respect to level k for Model i. If k = g, then goal node, where

D = HRM domainM = decision makerC =evaluation criterion T = KR technique d = number of domains m = number of consistent decision makers r_1 = number of HR managers responded r_2 = number of knowledge engineers responded c = number of evaluation criteria t = number of KR techniques CR_{ii} = the consistency ratio of decision maker j for model i T_k^* = the best KR technique for domain k T^* = the best KR technique for all domains

- Step 1: Select m such that $CR_{11} < CR_{12} < ... <$ $CR_{lm} < 0.2$ where $m \le 7$ and $m = 1, \dots, r_l$.
- Step 2: Let $M_{ljg} = 1/CR_{lj}$, j = 1, ..., m; $D_{ljg} =$ $1/d, j=1,\ldots,d.$
- Step 3: Calculate C_{1ik} for j = 1, ..., c, k = 1, ...
- Step 4: Synthesize C_{lig} for j = 1, ..., c.
- Step 5: Eliminate m from the Model 2 such that $CR_{2m} > 0.2$ for $m = 1, ..., r_2$.
- Step 6: Let N = total number of criteriamatched with the preference orderings for each $T_{2jk}, j = 1, ..., t, k = 1, ..., m.$ Let $M_{2jk} =$ N/CR_{2i} for j = 1, ..., m.
- Step 7: Select m such that $M_{21g} < M_{22g} < \ldots <$ M_{2ig} for $j = 1, \ldots, m$ and $m \leq 7$.
- Step 8: Let $C_{2jk} = 1/c$ for j = 1, ..., c, k = 1, ...
- Step 9: Let $C_{2jk} = C_{1jg}$ for j = 1, ..., c, k = 1,, m. Calculate T_{2jg} for $j=1,\ldots,t$. Step 10: Let $T_{3jg}=T_{2jg}$ for $j=1,\ldots,t$. Find T^*
- = $Max_{(j=1,...,t)}\{T_{3jg}\}$; Stop.
- Step 11: Let $M_{3jg} = M_{1jg}$ for j = 1, ..., m; $D_{3jk} =$ D_{ljg} for j = 1, ..., d, k = 1, ..., m.
- Step 12: For each domain, calculate C_{3jk} using C_{1jk} (Step 3) for j = 1, ..., c, k = 1, ..., dwhere $\sum_{j} \sum_{k} C_{3jk} = 1$.
- Step 13: Let $C_{2jk} = C_{3jk}$ for j = 1, ..., c, k = 1, ...
- Step 14: Calculate T_{2jk} again. Then $T_{3jk} = T_{2jk}$, for j = 1, ..., t, k = 1, ..., d.

• Step 15: $T_k^* = Max_{(j=1,\ldots,t)} \{T_{3jk}\}$ for $k=1,\ldots,d$.

Results

Twelve HR managers responded. For computations, five managers are included in Model 1 by the rule in Step 1. The strongest preference is shown for the PROB faraway followed by the MODU regarding no weights for each decision maker and for the reusability faraway followed by the modularity regarding weights for each decision maker by Step 2 (Table 1).

TABLE 1: Comparison of Synthesized Priorities of Evaluation Criteria in Model 1

	NW		ww	·
Alternatives	G.P	Rank	G.P	Rank
EXPR	.109	7	.069	7
SEAR	.125	5	.117	5
COMP	.138	4	.088	6
PROB	.211	1	.163	3
MODU	.158	2	.177	2
REUS	.140	3	.246	1
UNDE	.119	6	.140	4

NW: Without weights for manager WW: With weight for manager

Table 2 represents a check table to examine the match of the preference orderings and the computations of weight factor for each decision maker or knowledge engineer. For each pairwise comparison matrix, if the ordering of priority is matched with the defined general preference orderings of KRT, then it is a correct answer for each criterion denoted by 'o' else it is an incorrect answer, denoted by 'x'. The sum of each correct answer divided by the CR equals the weight of each decision maker (refer to Step 6). On the basis of the implementation limitation of the Expert Choice [6], the decision makers should be included in Model 2 and their weights are shown in Table 3 (refer to Step 7).

Using the weights of the evaluation criteria regarding the weights of decision makers, the overall priority weights for each KRT are shown in Table 4. Frames and semantic nets obtained the highest priorities for all cases with different weighting types in Model 2. Case IV as our goal means T_{2jg} in Step 9. Here the reason for involving three cases in addition to Case IV is to explain a

kind of sensitivity analysis. Table 5 summarizes the synthesized priorities of evaluation criteria for each domain regarding the weight of decision makers, i.e. C_{3jk} in Step 12. Note that each column sums to 0.143 which is equal to 1/d. Returning to Model 2 and using the priority of evaluation criteria derived in Step 12, the priority weight of each KRT for each domain are derived (Table 6). FR obtains the highest rank and PL obtains the lowest rank.

TAI	BLE	2: A	Ch	eck 1	Tabl	e for	Pre	feren	ce Orderings	
KE	C1	C1	C3	C4	C5	C6	C7	N	M	Rank
1	О	O	X	О	О	О	О	6	200	5
2	О	\mathbf{X}	О	O	О	О	X	5	500	1
3	X	X	\mathbf{X}	X	X	X	X	1	50	11
4	\mathbf{X}	\mathbf{X}	O	O	X	O	O	4	400	2
6	O	O	О	O	О	O	O	7	175	7
7	X	X	X	X	\mathbf{X}	O	\mathbf{X}	1	50	11
8	X	O	О	X	О	o	X	4	133	8
9	X	X	X	X	X	O	X	1	33	15
13	X	O	X	O	X	O	O	4	44	14
14	O	X	O	O	\mathbf{X}	0	O	5	200	5
15	O	O	O	O	О	O	O	7	350	3
16	X	\mathbf{X}	X	O	X	O	X	2	100	10

O: match; X: mismatch; KE: knowledge engineers; C-n: nth criterion; N: total number of criteria matched with the preference orderings; M = N/CR, C1: EXPR; C2: SEAR; C3: COMP; C4: PROB; C5: MODU; C6: REUS; C7: UNDE

TABLE 3: Knowledge Engineers Selected and Their Normalized Weights

17 O X X O X O O

KE	2	4	15	12	14	1	6
Nor. WT	.235	.188	.165	.142	.094	.094	.082

TABLE 4: Comparison of Synthesized Priorities of Evaluation Criteria in Model 2

Alterna- tives	Case	I	Case	II	Case	Ш	Case	IV
	EK Pri.	EC Rank	EK Pri.	WC Rank		EC Rank	WK Pri.	WC Rank
RU	.212	4	.331	3	.224	4	.245	3
SN	.251	2	.258	2	.247	2	.252	2
FR	.304	1	.232	1	.299	1	.327	1
PL	.232	3	.179	4	.230	3	.177	4

EK: without weighting for each KE, EC: without weighting for each evaluation criterion; WK: weighting for each KE, WC: weighting for each evaluation criterion

TABLE 5: Synthesized Priorities of Evaluation Criteria for Each Domain in Model 1

Date II	MIANTE III IVLOREI S
	PLAN SELE PLAC COMP PERF TRAN LABO
EXPR	.00829 .00576 .00592 .01037 .01171 .01203 .01579
SEAR	.02142 .02374 .01565 .01319 .01032 .01678 .01413
COMP	.01461 .00935 .00785 .01579 .01298 .01105 .01637
PROB	.02175 .01887 .03755 .02361 .02034 .02113 .01979
MODU	.02904 .02666 .02800 .02517 .02709 .02423 .01730
REUS	.02954 .03732 .03034 .03943 .03865 .03088 .02677
UNDE	.01842 .02127 .01489 .01552 .02191 .01516 .03291

TABLE 6: Synthesized Priorities of KRT for Each Domain in Model 3

R	Ü	S	N	F	R	P	L
Pri.	Rank	Pri.	Rank	Pri.	Rank	Pri.	Rank
299	1	.259	3	.299	1	.142	4
240	3	.265	2	.339	1	.156	4
289	2	.235	3	.321	1	.155	4
240	3	.242	2	.328	1	.190	4
241	3	.250	2	.327	1	.182	4
	3	.251	2	.340	1	.180	4
225	3	.266	2	.310	1	.199	4
	Pri. 299 240 289 240 241 230	Pri. Rank 299 1 240 3 289 2 240 3 241 3 230 3	Pri. Rank Pri. 299 1 .259 240 3 .265 289 2 .235 240 3 .242 241 3 .250 230 3 .251	Pri. Rank Pri. Rank 299 1 .259 3 240 3 .265 2 289 2 .235 3 240 3 .242 2 241 3 .250 2 230 3 .251 2	Pri. Rank Pri. Rank Pri. 299 1 259 3 299 240 3 .265 2 .339 289 2 .235 3 .321 240 3 .242 2 .328 241 3 .250 2 .327 230 3 .251 2 .340	Pri. Rank Pri. Rank Pri. Rank 299 1 .259 3 .299 1 240 3 .265 2 .339 1 289 2 .235 3 .321 1 240 3 .242 2 .328 1 241 3 .250 2 .327 1 230 3 .251 2 .340 1	R U S Rank Pri. Rank Pri. Rank Pri. Rank Pri. Rank Pri. Rank Pri. Pri. Rank Pri. Rank Pri. Rank Pri. Rank Pri. Rank Pri. 1.42 240 3 .265 2 .339 1 .156 249 2 .235 3 .321 1 .155 240 3 .242 2 .328 1 .190 241 3 .250 2 .327 1 .182 230 3 .251 2 .340 1 .180

With the Spearman rank correlation test, accepting H_0 means that the ranks are either uncorrelated or negatively correlated, i.e., two KRT exhibit a insignificant level of agreement in their rankings for each domain. Rejecting H_0 means that the ranks are positively correlated. In comparison with the decision rules as described in the preliminary study, our strategy is to combine such KRT with highly correlated based on their rankings. As a result, RU and SN are positively correlated and should be combined.

Conclusion

In summary, to provide an appropriate ES development technique which is dependent on a particular domain, selection of KRT is regarded as one of the most important tasks. We evaluated and selected key KRT for use in HRM problem domains in terms of two exploratory phases. In the first phase, ranks of RU, FR, SN, and PL were obtained by computing the weighted sum of alternatives. In the second phase, they were prioritized using the CAHP which is an enhanced method of the AHP. It primarily focuses on how to combine the different group's judgments

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