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Design and implementation of a case-based reasoning system for marketing plans

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Abstract

Unstructured intangible experiences and knowledge are usually difficult to represent and instantiate, which engenders the hardship of knowledge transfer and sharing. Past marketing plans are such valuable documents containing strategic planning knowledge and experiences.

Case-Based Reasoning (CBR), which consists of retrieving, reusing, revising, and retaining cases, has been proved effective in retrieving information and knowledge from prior situations and being widely researched and applied in a great variety of problem territories.

This paper targets at designing a CBR architecture and a method that facilitate the sharing and retrieving of cases of great concern to the marketing personnel. After an intensive survey of CBR methods and applications, a CBR system embedding multi-attribute decision making method, which provides both overall similarity level and similarity level of each selected attribute, is proposed to enhance the adaptation of a new marketing plan. In addition, a multi-attribute gap analysis diagram is developed to visualize the similarity along with the gap between candidate and target cases, so as to better support interaction and group decision making in the process of strategically formulating a new marketing plan. The CBR system was implemented and successfully demonstrated on case retrieval of a telecommunication company.

Keywords: CBR; AHP; Marketing plan; XML

1. Introduction

In the knowledge economy, intellectual capitals are vital for a company to compete and survive. Although intangible experiences and knowledge are hard to transfer and instantiate, enterprise databases contain precious data resources, which can be analyzed to reveal treasure knowledge of an enterprise. Knowledge is reasoning about information and data to actively enable performance, problem-solving, decision-making, learning, and teaching, defined Beckman (1997). Attributed to the advancement of data mining and knowledge discovery techniques, a portion of enterprise knowledge can be unearthed. However, while some knowledge is easier to discover because it occurs in structured data format repetitively, some is hard to retrieve or conceptualize because it is extremely creative and exists sometimes only once in the enterprise databases or unstructured documents. Past marketing plans are such valuable documents containing strategic planning knowledge and experiences. Marketing plans are developed and executed by different marketing managers. Although the experiences can be shared through oral communication and presentation after the associated activities are completed, the important knowledge cannot be fully leveraged because knowledge is useful only when it is provided at the right time in the right occasion to the right person. Therefore, how to systematically keep the past cases in a computer system, provide a mechanism to efficiently retrieve the most suitable cases, and facilitate adaptation is very compulsory and beneficial to marketing managers, which is one of the most important steps in implementing marketing knowledge management.

This paper aims at a case-based reasoning system for marketing plans so that plans can be represented and stored in the case base, precisely retrieved,

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disseminated, and adapted to leverage the power of knowledge sharing.

2. Case-based reasoning (CBR)

CBR, rooted in early 1980s, is to solve a new problem by remembering a previous similar situation and by reusing information and knowledge of that situation (Aamodt & Plaza, 1994). Terms related to CBR include exemplar-based reasoning, instance-based reasoning, memory-based reasoning, case-based reasoning, and analogy-based reasoning. The above definition describes what CBR means, while the CBR cycle delineates how it does, which consists of retrieving, reusing, revising, and retaining cases (Watson, 1999). In the subsequent sections, a review of CBR methods/techniques and applications are summarized.

2.1. Case representation

In designing a CBR system, case representation is the first step. A case should contain both content and context, typically composed of the problem, solution, and outcome (Shin & Han, 2001). Case representation can take different kinds of forms such as topological structure, tree structure, relational schema, attribute-value pairs, frames, objects, predicates, semantic nets, rules, etc. depending on the structure and content of the case and the developer's preference (Liao, Zhang, & Mount, 2000; Shin & Han, 2001).

2.2. Case retrieval

The case retrieval consists of subtasks, referred to as identify features, initial match, search, and select (Aamodt & Plaza, 1994). Choosing indices, critical to CBR system, is to facilitate the efficient organization and accurate retrieval of cases. Shin and Han (2001) categorized case indexing into three types: nearest-neighbor, which retrieves matched cases in memory based on a weighted sum of features between cases; inductive, which indexes past cases based on the most important features affecting the outcome as induced from the data itself; and knowledge-guided, which applies existing domain and experimental knowledge to locate relevant cases. Major automated indexing methods comprise difference-based, feature- and dimension-based or checklist-based, inductive learning-based, and similarity-based indexing (Liao et al., 2000). Guidelines suggested for selecting indexing features include predictiveness, abstractness, concreteness, and usefulness (Kolodner, 1993).

Jeng and Liang (1995) separated attributes into two types: qualitative and quantitative case attributes and performed direct indexing on qualitative attributes, but fuzzy indexing on quantitative attributes. In Kim and Han's cluster-indexing method for CBR (2001), training cases were indexed with the centroid values of clusters from SOM (Self-Organizing Maps) having minimum distance calculated by

$$D = \sqrt{\sum_{i=1}^{n} |C_{\mathrm{ref},i} - P_{\mathrm{ref},i}|^2},$$

where n is the number of features, C_{ref} are training cases, and P_{ref} are the centroid values of clusters from training cases, and with the centroid values of clusters from Learning Vector Quantization (LVQ). Shin and Han (2001) used inductive technique for case indexing by building a decision tree. Besides, feature-based indexing was adopted by researchers and applied in various domain areas (Chang, Dong, Liu, Lu, Changchien, & Shen, 2000; Montani, Bellazzi, Portinale, d'Annunzio, Fiocchi, & Stefanelli, 2000; Yang, Han, & Kim, 2004).

The determination of weight for each feature has a significant influence on the efficiency and accuracy of case retrieval. In many cases, the subjective weighting values are given by the user, and thus the retrieved solutions cannot always be guaranteed. Therefore, different methods have been proposed such as Genetic Algorithms (GA, Chiu, 2002), Artificial Neural Networks (ANN, Hui, Fong, & Jha, 2001; Shin & Han, 1999), Analytic Hierarchy Processing (AHP, Park & Han, 2002; Chang, Cheng, & Su, 2004), induction (Kibler & Aha, 1987), information gain (Wettschereck & Aha, 1995), statistical methods (Stanfill & Waltz, 1986; Mohri & Tanaka, 1994).

A great number of various case retrieval methods have been proposed. Watson (1999) surveyed four types of CBR: nearest neighbour, induction, fuzzy logic, and database technology, where nearest neighbour is the most commonly used approach (Burke, MacCarthy, Petrovic, & Qu, 2000; Gardingen & Watson, 1999; Garrell & Guiu, 1999; Gupta & Montazemi, 1997; Haque, Belecheanu, Barson, Pawar, & Shaque, 2000; Shin & Han, 1999). Other approaches include Rough set theory (Huang & Tseng, 2004), Kernel methods (Fyfe & Corchado, 2002), similarity flooding algorithm (Madhusudan, Zhao, & Marshall, 2004), and other similarity indices (Chang et al., 2000; Slonim & Schneider, 2001).

2.3. Case adaptation

Once the best fit cases are retrieved, they are reused or adapted. Effective adaptation relies on adaptation knowledge and the fitness of the retrieved case for the target problem, but successful adaptation is based on the knowledge that in general is not readily available. Recognizing that practical retrieval technologies are available, but the general adaptation problem remains extremely difficult for CBR systems, experts in both CBR research and applications agree that the best use of CBR is as advisory systems that rely on the user to perform evaluation and adaptation (Haque et al., 2000). To learn the adaptation knowledge, there are some methods such as other domain knowledge, expert user, and the case base under consideration (Virkki-Hatakka, Kraslawski, Koiranen, & Nystrom, 1997).

2.4. CBR systems and applications

A complete task-method hierarchy of CBR has been proposed by Aamodt and Plaza (1994). The flourishing of CBR has successfully contributed to different domain areas and industries in the past decade. Aha (1998) listed research areas and topics related to CBR, including cognitive psychology, pattern recognition, machine learning, cognitive science, information retrieval, statistics/robotics, data structures, software engineering, and process planning.

Owing to the advantages of being able to deal with data with noise, missing data, and unstructured data, and closer to human decision making process than rule-based systems, CBR has been applied in medical diagnosis (Varma & Roddy, 1999), bankruptcy prediction (Park & Han, 2002), scheduling and process planning (Schmidt, 1998; Chang et al., 2000; Sadek, Smith, & Demetsky, 2001), customer classification (Chiu, 2002), fault diagnosis (Liao et al., 2000; Yang et al., 2004), prediction of information system outsourcing success (Hsu, Chiu, & Hsu, 2004), concurrent product design (Haque et al., 2000), risk analysis (Jung, Han, & Suh, 1999), knowledge management (Noh, Lee, Kim, Lee, & Kim, 2000), military control (Liao, 2000), and so on.

Aha (1998) listed categories of tasks where CBR has been successfully applied, including interactive troubleshooting, recommenders, and Internet commerce, and the failures concerning applying CBR, including corporate support, knowledge acquisition, and scope of applicability.

In addition, researchers also integrate agent technology with CBR, such as multi-agent intelligent system (Kwon & Sadeh, 2004), adaptive agent (Montazemi & Gupta, 1996), and active CBR (Li & Yang, 2001). While researchers focused on the methodology development of case reasoning and retrieval, Gonzalez, Xu, and Gupta (1998) developed a validation technique for CBR systems.

In summary of the review, CBR methods developed focused much on the retrieval mechanisms, and the associated case representation and indexing were also designed to facilitate the retrieval, while weighting and adaptation are more related to subjective decision making and expert knowledge and experiences. Furthermore, in the past few years, the number of CBR applications has grown rapidly, especially in the areas of engineering, and some in medical science, finance, and knowledge management. The methodologies of CBR are similar in the aspect of CBR cycle, but are domain problem and application specific. Therefore, the integration of domain problem and knowledge into the CBR system is essential.

Due to the creativity and diversity of strategic marketing planning and the lack of marketing knowledge retrieving and sharing system, this paper aims at the design and implementation of a CBR system for marketing plans.

3. Proposed CBR system for marketing plans

3.1. System architecture

Due to the difficulty of exchanging and sharing the marketing experiences and knowledge, a cased-based reasoning system is proposed. The agent-based marketing plans management and development architecture is shown in Fig. 1. The architecture supports the exchange and management of marketing plans among distributed case bases and the sharing, retrieval, and adaptation of marketing plans. The proposed CBR method facilitates the representation of the content of marketing plans, and thus the similarity index is designed accordingly. Since the focus of this research is on the case representation and retrieval of the CBR system, the implementation of mobile intelligent agents is beyond the scope and hence is omitted. The reasoning process of the proposed CBR system depicted in Fig. 2 shows that marketing plans are represented and stored in the case base as eXtensible Markup Language (XML) documents, and that an XML parser and an Multi-Attribute Decision Making (MADM) retrieval method are designed to search for the most similar existing cases in the case base. The development of the new marketing plan then can be elaborated by adapting or referencing the most similar cases. The case based reasoning method is further described next.

3.2. Case representation

The operations of a marketing plan consist of four steps: information, analysis, decision, and action, where information refers to financial parameters, marketing audit, and omnibus research facilities; analysis includes brand feasibility studies, market analysis, and product mix; decision concerns marketing targets, marketing mix, and budgets; and action indicates the execution of the plan (Stapleton & Thomas, 1998). Baker (2000) lists the essential components of a short-term marketing plan as:

1. Executive summary
2. Situation analysis (or market overview):

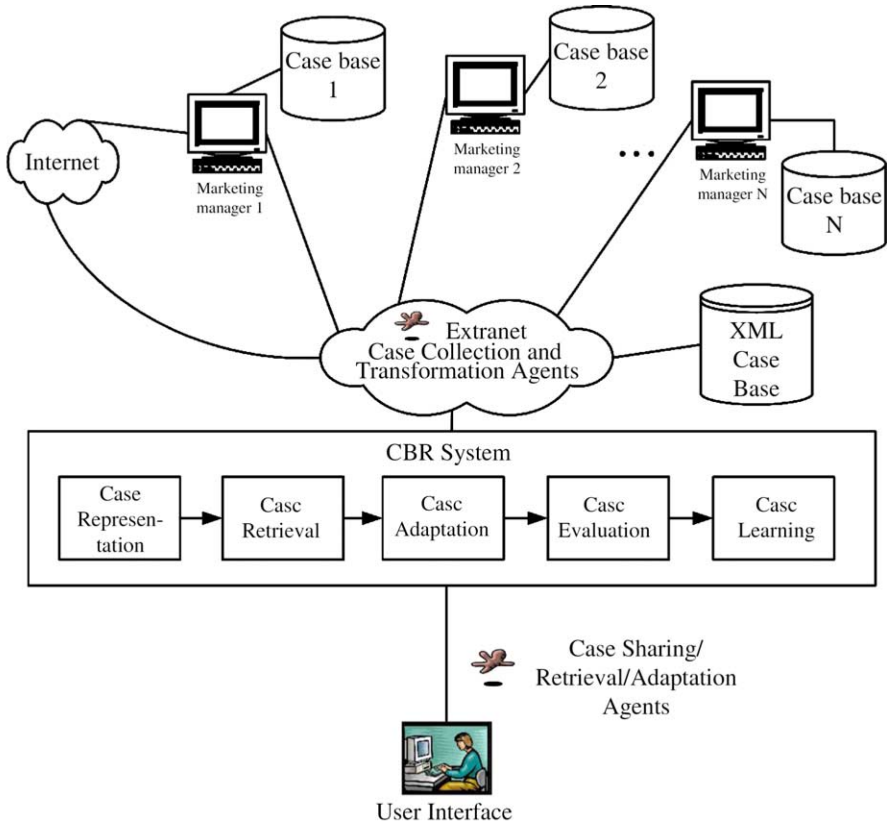


Fig. 1. Agent based architecture for the proposed CBR system for marketing plans.

(1) External environmental audit
(2) Industry audit
(3) Customer audit
(4) Internal evaluation (market audit)
3. Conclusions and key assumptions
4. Objectives
5. Core strategy
6. Key policies
(1) Product
(2) Price
(3) Place
(4) Promotion
7. Administration and control
8. Communication
9. Timing

XML is a meta-language for describing markup languages. By defining tags and the structural relationships between them, marketing plans can be generated as XML documents. With the elements (tags) and relationships, case exchange and retrieval can be better facilitated. This research bases on the real short-term marketing plans of a telecommunication company in Taiwan and develops the content elements of a marketing plan. The developed DTD (Document Type Definition) for indexing attributes of a marketing plan is shown as

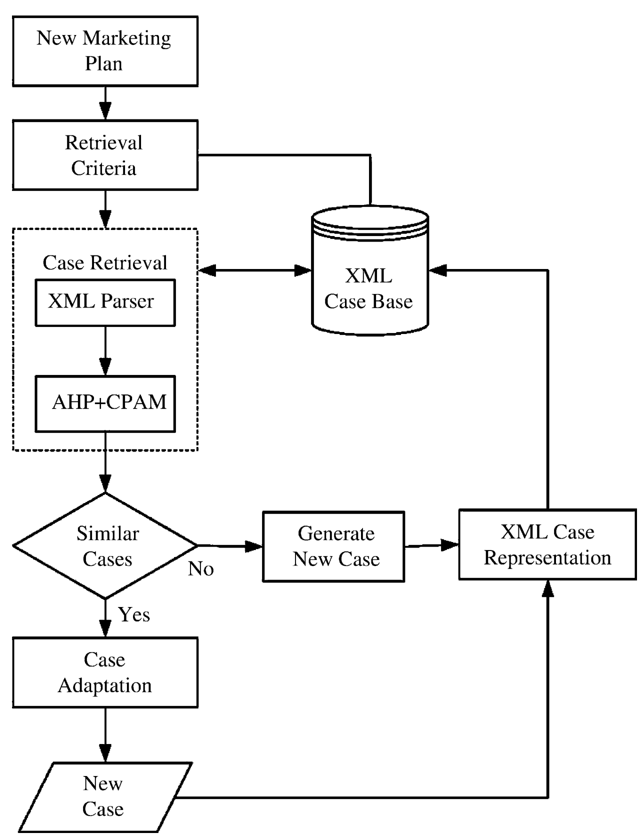


Fig. 2. The development procedure of a new marketing plan.

follows:

```
<?XML VERSION="1.0" ENCODING="BIG5"?>
  <!ELEMENT case_standard
(case_ID,case_name,case_company*,status_analysis*,SWOT* ,
objective*,goal*,strategy*,marketing_mix*,result*,others*)>
    <!ELEMENT case_ID (#PCDATA)>
    <!ELEMENT case_name (#PCDATA)>
    <!ELEMENT case_company (company_name,business_target,market_position)>
      <!ELEMENT company_name (#PCDATA)>
      <!ELEMENT business_target (#PCDATA)>
      <!ELEMENT market_position (#PCDATA)>
    <!ELEMENT status_analysis (political_economic_environment,
technical_development,industry_analysis,customer_analysis,competitor_analysis)>
      <!ELEMENT political_economic_environment (#PCDATA)>
      <!ELEMENT technical_development (#PCDATA)>
      <!ELEMENT industry_analysis (#PCDATA)>
      <!ELEMENT customer_analysis (#PCDATA)>
      <!ELEMENT competitor_analysis (#PCDATA)>
    <!ELEMENT SWOT (strength,weakness,opportunity,threat)>
      <!ELEMENT strength (#PCDATA)>
      <!ELEMENT weakness (#PCDATA)>
      <!ELEMENT opportunity (#PCDATA)>
      <!ELEMENT threat (#PCDATA)>
    <!ELEMENT objective (#PCDATA)>
    <!ELEMENT goal (#PCDATA)>
    <!ELEMENT strategy (#PCDATA)>
    <!ELEMENT marketing_mix (price,product,channel,promotion)>
      <!ELEMENT price (tariff,communication_charge)>
        <!ELEMENT tariff (#PCDATA)>
        <!ELEMENT communication_charge (#PCDATA)>
      <!ELEMENT product (main_product,sub_product,brand)>
        <!ELEMENT main_product (#PCDATA)>
        <!ELEMENT sub_product (#PCDATA)>
        <!ELEMENT brand (#PCDATA)>
      <!ELEMENT channel (franchisee,strategic_alliance,place)>
        <!ELEMENT franchisee (#PCDATA)>
        <!ELEMENT strategic_alliance (#PCDATA)>
        <!ELEMENT place (#PCDATA)>
      <!ELEMENT promotion (activity_objective,activity_goal,activity_period,
content,advertisement_media,employee)>
        <!ELEMENT activity_objective (#PCDATA)>
        <!ELEMENT activity_goal (#PCDATA)>
        <!ELEMENT activity_period (#PCDATA)>
        <!ELEMENT content (#PCDATA)>
        <!ELEMENT advertisement_media (#PCDATA)>
        <!ELEMENT employee (#PCDATA)>
    <!ELEMENT result (#PCDATA)>
    <!ELEMENT others (attachment*)>
  <!ELEMENT attachment (#PCDATA)>
```

3.3. Case retrieval

In designing the case retrieval method, the main issues concerned in marketing strategy development tools and models should be contemplated and considered. Jain (1993) introduced seven models that exhibit direct application to marketing strategies: the experience curve concept, the Profit Impact of Market Strategy (PIMS) model, value-based planning, the delphi technique, trend-impact analysis, cross-impact analysis, and scenario building. In the analytic frameworks for strategic marketing planning proposed by Baker (2000), there are several issues addressed: downward sloping demanding curves, the concept of product life-cycle (PLC), diffusion theory, using PLC as a planning tool, portfolio analysis, growth-share matrix, directional policy matrix, Baker's box, gap analysis, scenario planning, and SWOT. Apparently, the marketing planning is highly interactive, requires the flexibility to move backwards and forwards from the general to the specific, and consists of stages to be dealt with concurrently. The formulation of a marketing plan relies heavily on marketing personnel's strategic planning capability and experiences about both internal factors and external environment. Therefore the proposed case retrieval method will emphasize on the subjective weighting of attributes and the incorporation of internal performance compared with the external competitors into the similarity index.

Since every marketing plan is unique and it is hard to accurately define the similarity index without content based elements, the proposed CBR method focuses on the retrieval accuracy, rather than the automatic retrieval efficiency.

There are two steps in the proposed case retrieval method: parser with key content elements and retrieval by similarity index. With XML elements and structure defined for marketing plans, users can apply the parser to preliminarily search for matched cases with the required keywords as criteria. Fig. 3 is the structure of such a parser for marketing plans. After matched cases are found, the second step of retrieval by similarity index can proceed. In order to interpret the multi-attribute measurement of case similarity, a visualization aid is necessary and presented next.

3.3.1. Multi-attribute gap analysis diagram (MAGA diagram)

A new marketing plan consists of multiple components as indicated in the DTD design in Section 3.2, such as goal, strategy, marketing mix, etc. In order to retrieve the most desiderative case, the components of great importance all need to match the user's target specification. In the proposed CBR method, the similarity of each important component can be measured quantitatively. However, since the old marketing plans might not be developed directly based on the same components and each component has different level of importance to the user when retrieving the cases, the final similarity level of each component (attribute) is obtained through a series of evaluation, weighting, transformation, and computation processes.

As the illustrative MAGA diagram (Fig. 4) shows, there might be an angle of deviation from the orientation of each component being compared for each candidate case because of the different situation and goal when it was developed. The projection of each case onto each

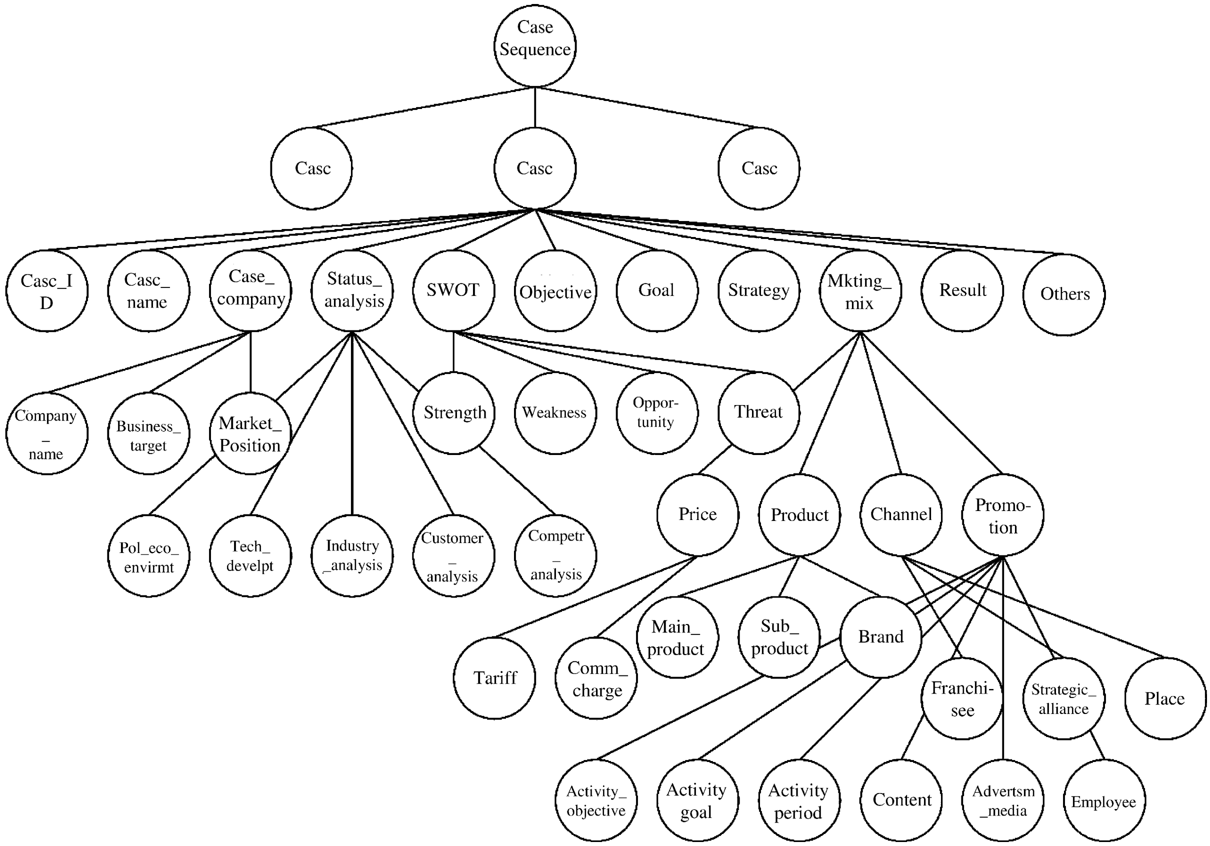


Fig. 3. Structure of the parser for marketing plans.

component indicates the final quantitative measure of the similarity level in the component. Since multiple components are compared, it therefore becomes an MADM problem. It is quite possible that a case outperforms another case in some attributes, but with the rest of attributes inferior. Apparently, a MADM method for ranking the candidate cases is essential, which will be introduced in the next section. In addition, Fig. 4 also shows the gap between the candidate case and the target value in each attribute, which along with attribute weight provide very helpful information in adapting an old marketing plan into a new one.

3.3.2. *Ranking of candidate cases' similarity levels to target case in terms of multiple attributes*

By integrating AHP and Core Process Analysis Matrix (CPAM, Changchien & Shen, 2002) methods, a multi-attribute similarity ranking method for marketing plans retrieval is proposed as shown in Fig. 5. After the first step of the proposed CBR, parser with key content elements, only a few candidate cases are retrieved. To further rank the relative similarity levels of the candidate cases to the user's target specification, a quick browse through the cases is necessary for the sake of quantification of the similarity levels. The notations and procedure of implementing the multi-attribute similarity ranking method is introduced as follows:

Take the six attributes concerned in Fig. 4 for illustration, which are product, campaign, SWOT, customer, advertisement, and goal. For each attribute i, the similarity function is defined as $f_i(T_i, S_i)$, where T_i and S_i are the ith attributes for target case T and candidate case S, respectively. $f_i(T_i, S_i)$ is indicated as the projected arrow (level) on attribute i in Fig. 4. Assume there are n attributes, then the similarity

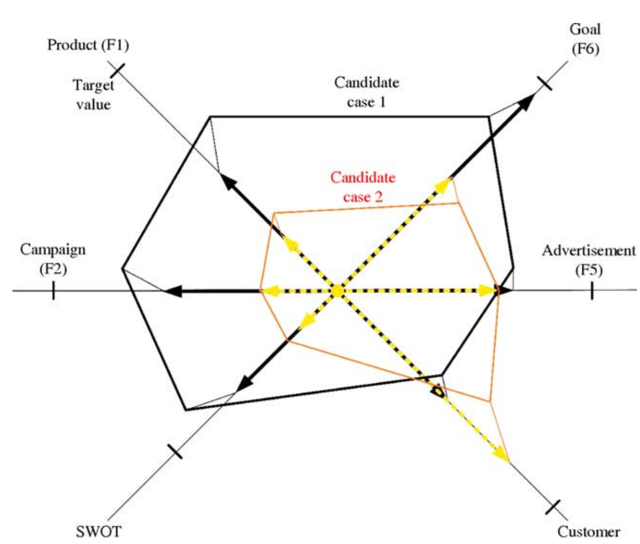


Fig. 4. An illustrative MAGA diagram.

	Cases $j=1\sim m$									
Criteria $i=1\sim n$	Case 1	Case 2	…	Case m	W_i	CP_i^{us}	CP_i^{comp}	RCP_i	AW_i	NAW_i
Attribute 1										
Attribute 2										
…										
Attribute n										
RS_j										
S_j										
Ranking										

Fig. 5. A proposed multi-attribute ranking method for marketing plans retrieval.

measure between T and S is defined as:

$$\text{Similarity}\ (T,S) = \sum_{i=1}^{n} f_i(T_i, S_i) \times w_i,$$

where w_i is the weight for attribute i.In the proposed multi-attribute similarity ranking method, AHP method is incorporated to obtain the relative similarity levels of $f_i(T_i, S_i)$ of all the m candidate cases to the target case and w_i for attribute i. AHP requires the user to perform pairwise comparisons (after a quick browse of the contents) of the similarity levels of the m candidate cases with respect to the target case, so as to systematically generate the relative similarity level of each candidate case to the target case. Pairwise comparisons are rated based on a scale of 1–9, where 1 means equally similar and 9 means absolutely similar. Here follows is the procedure of calculating the relative similarity levels of candidate cases to the target case in terms of attribute i.

1. Obtain the m candidate cases: CandidateSet = {case$_1$, case$_2$, …,case$_m$}.
2. Select the n attributes to be evaluated: AttributeSet = {att$_1$, att$_2$, …,att$_n$}.
3. Give relative similarity level (1–9) with respect to the target case by comparing every two candidate cases selected from the CandidateSet for each att$_i$ selected from AttributeSet. Follow the procedure of AHP method and calculate the similarity score (V_{ij}, similarity score of case j for attribute i) and perform consistency check. Repeat for $i=1$ to n and fill in the relative similarity scores into the shaded area in Fig. 5.

Since marketing plan development is part of a business strategic plan, a CBR reasoning method for marketing plan ought to take into account the relative performance between the business and the main competitor. The rest of the procedure of generating the ranking of the candidate cases' similarity levels to the target case is described below:

1. Follow the procedure of AHP and compute the weight (w_i) for each attribute i.
2. Assign the current performance levels of the business ($\mathrm{CP}_i^{\mathrm{us}}$) and the main competitor ($\mathrm{CP}_i^{\mathrm{comp}}$) based on a scale of 1–9 (the larger, the better) for each attribute i. Calculate the business' relative current performance to the main competitor for each attribute i: $\mathrm{RCP}_i = \frac{\mathrm{CP}_i^{\mathrm{us}}}{\mathrm{CP}_i^{\mathrm{comp}}}$.
3. Compute adjusted weight for each attribute i: $\mathrm{AW}_i = \frac{w_i}{\mathrm{RCP}_i}$.
   Normalize the adjusted weight for each attribute i: $\mathrm{NAW}_i = \frac{\mathrm{AW}_i}{\sum_{i=1}^{n} \mathrm{AW}_i}$.
   Calculate the raw similarity level for each case j: $\mathrm{RS}_j = \sum_{i=1}^{n} \mathrm{NAW_i} \times V_{ij}$.
   Find the final relative similarity level of each case j: $S_j = \frac{\mathrm{RS}_j}{\max_j\ \mathrm{RS}_j}$, and rank the cases accordingly.

With the final overall similarity level and the individual similarity level of each attribute, along with the aid of MAGA diagram, case adaptation can proceed as the procedure described in the following section.

3.4. Case adaptation

With the aidance of MAGA diagram showing the similarities and gaps of top ranked cases, case adaptation can advance based on either the best case if the retrieved case and the target case are extremely similar to each other in terms of the main attributes, or the top few cases ranked since a marketing plan consists of a good number of components and it is very possible that each top ranked case is very similar to the target case only in some components, where a new marketing plan can be constructed by comprising the case components that best fit the target case extracted from different top ranked cases. However, the adaptation is still highly dependent on the marketing personnel's knowledge and experiences of strategic planning. Once an adapted case is constructed and executed,

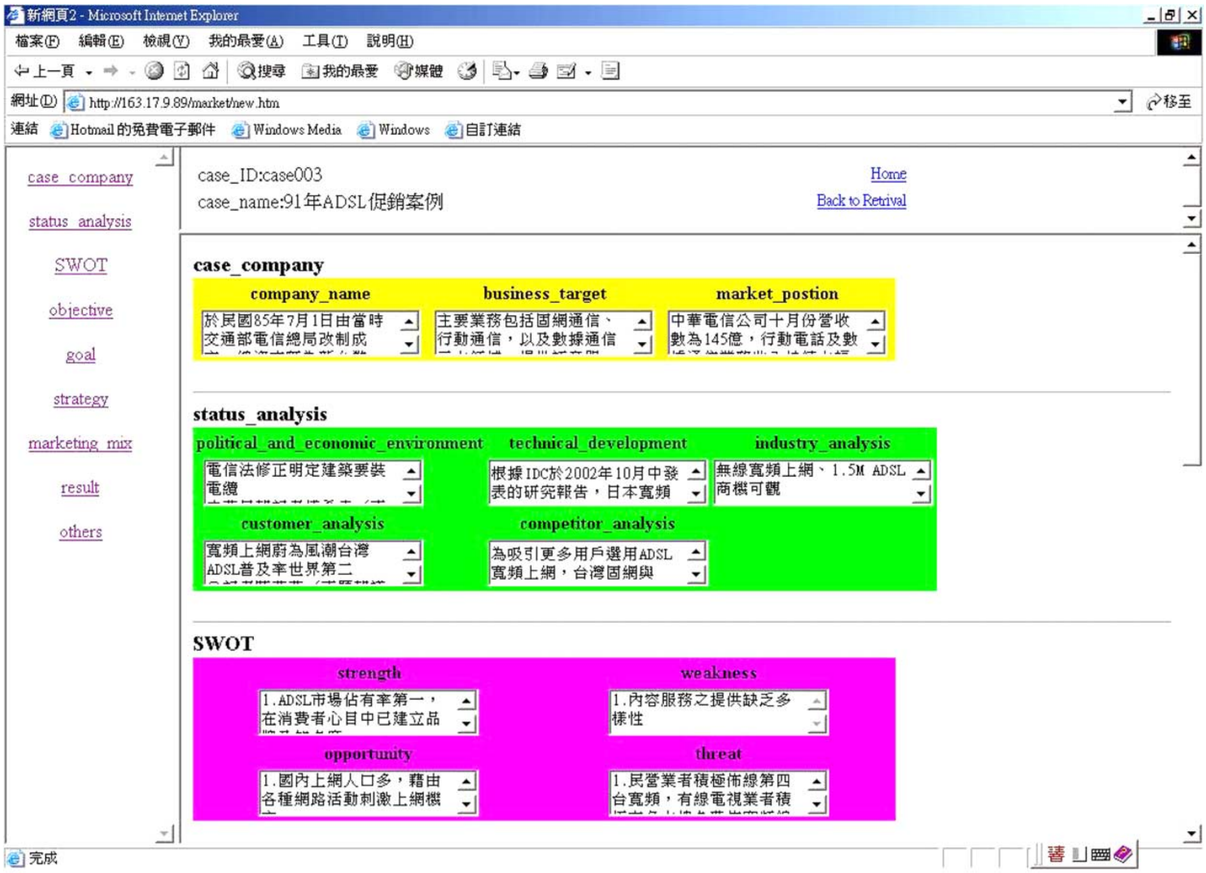


Fig. 6. The interface showing the querying result of an existing marketing plan.

the case and result can be saved by the CBR system for other to retrieve.

4. Implementation and evaluation

4.1. Case-based reasoning system for marketing plans

The proposed CBR system is developed using Java and XML languages. The main functions include create, modify, delete and retrieve cases. Some of the marketing plans of a telecommunication company in Taiwan between years 2001 and 2003 are collected. The marketing plans are those related to products like Asymmetric Digital Subscriber Line (ADSL), Wireless Local Area Network (WLAN), and marketing campaigns with events like annual Information Technology (IT) month and company anniversary, totally seven cases. These cases are represented based on the DTD defined earlier and saved into the CBR system. Fig. 6 is the interface showing an existing marketing plan created in the case base. Since the cases are lengthy and written in Chinese, they are not included in the paper.

4.2. Plan retrieval

There are two steps in retrieving a case from the system. In the first step, keywords are provided by the user to the parser of the CBR system. Since the terminology might be different in different plans, the user can use the parser as a query engine, and perform ad hoc queries until the user is satisfied with the results. A result of matched cases by retrieving with parser is shown in Table 1. The qualified candidate cases should have the matched elements larger than or equal to a user defined support threshold. For example, In Table 1, 8 elements are being compared, and if the support threshold is set to 50%, that means at least 4 ($50\% \times 8 = 4$) elements should be matched to be qualified as a candidate case. In Table 1, cases 1, 4, and 5 are selected by the parser.

Once the candidate cases are selected, the relative similarity level of each candidate case to the target case should be calculated in order to locate the most suitable case for adaptation. Following the procedure in Section 3.3.2, the user has a quick browse through the three candidate cases, then gives a pairwise comparison on every two cases in terms of each attribute (Fig. 7). Given the AHP result along with weights and CP^{us} and CP^{comp} values, the final similarity levels of cases 1, 4, and 5 are computed as 0.4, 0.31, and 0.29, respectively (Fig. 8). Apparently, case 1 is the top ranked case to be selected and adapted to develop the new marketing plan. However, since the final similarity levels are small and very close for all the three candidate cases, the user may consider developing a new case based on the case

Table 1
A result of matched cases by retrieving with the parser

No	Element	Keywords	Cases						
			1	2	3	4	5	6	7
1	Customer_analysis	Online users		V		V			
2	Competr_analysis	Cable	V	V	V		V		V
3	Tech_develpt	Multimedia integrated	V				V		
4	Strategy	Exhibition participation	V			V			
5	goal	New users							
6	Activity_objective	Broadband connection			V	V	V		
7	Content	ADSL	V	V	V	V	V	V	V
8	Advertsm_media	Newspaper				V		V	
Attributes matched			4	3	3	5	4	2	2
Support (%)			50	37.5	37.5	62.5	50	25	25
Candidate cases selected			⊙			⊙	⊙		

components of the top ranked cases with highest attribute similarity levels.

4.3. Evaluation

In the application of the proposed CBR system to marketing plans of a telecommunication company, there are only seven cases saved in the case base for illustration due to the limited resource. The proposed CBR system, when compared with other existing CBR systems, has the following advantages:

1. The agent-based architecture and XML facilitate the integration and exchange of current isolated marketing plans of dissimilar formats and organization in different distributed computer systems.
2. Case representation incorporates the domain specific case indexing features.
3. MADM weighting and ranking provides not only overall similarity levels, but also the similarity level for each selected attribute, which allows user to decide to either adapt the best case or comprise the new case by few top

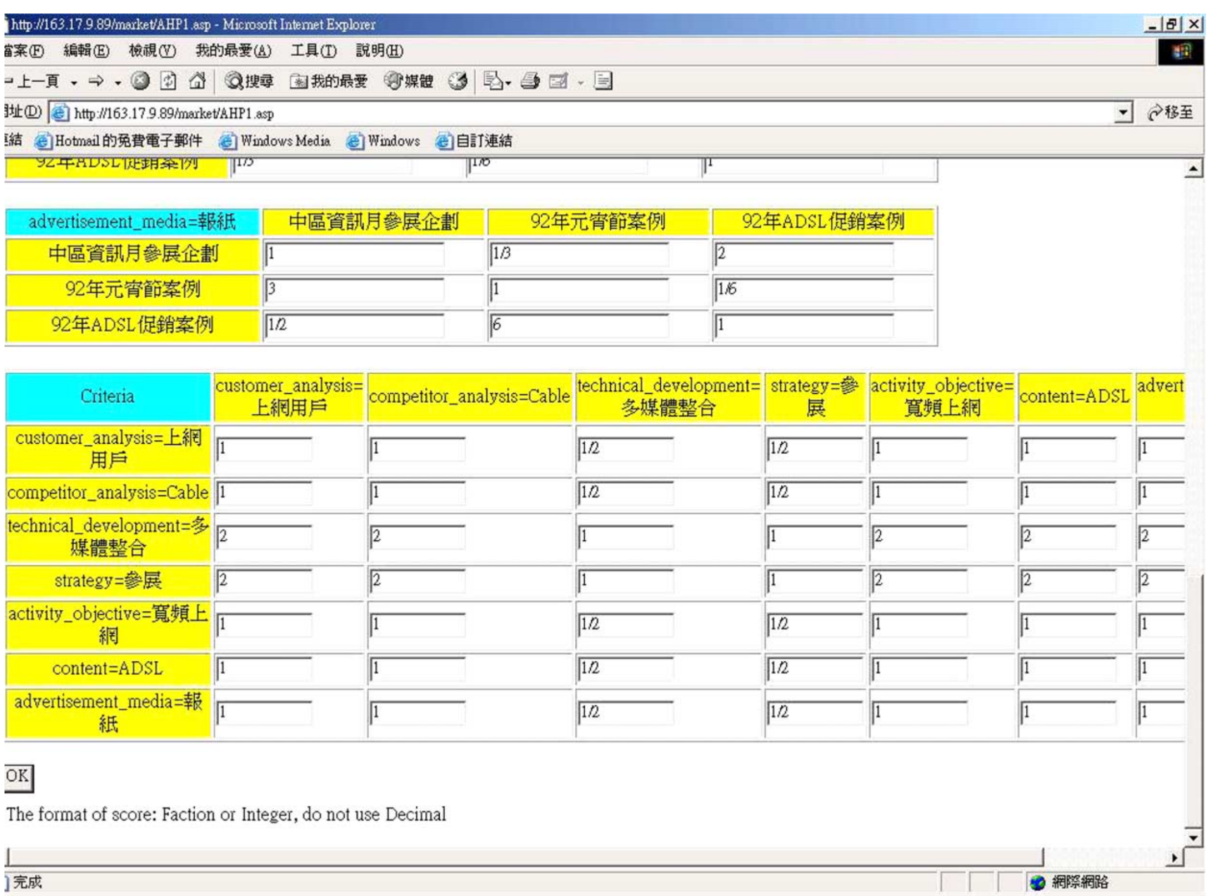
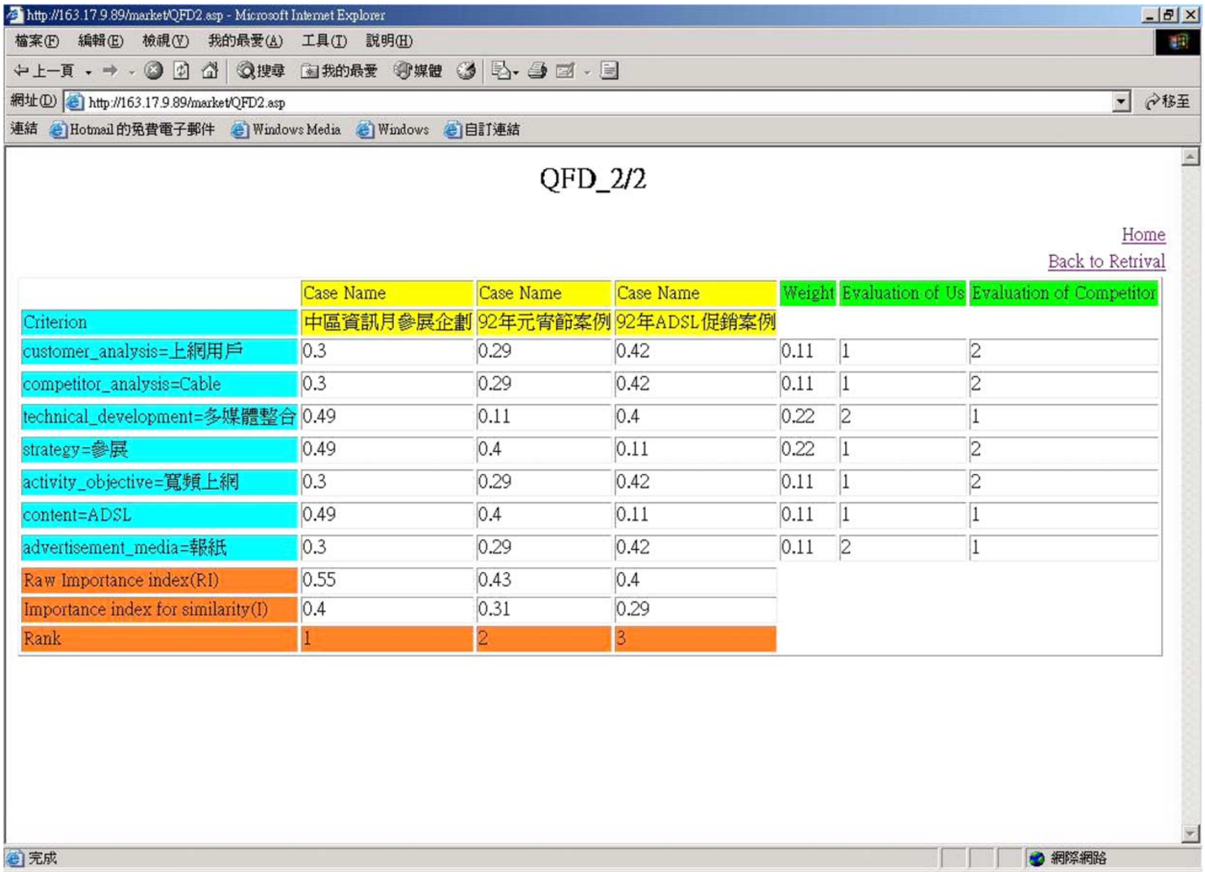


Fig. 7. The interface of 'ranking using AHP'.



	Case Name	Case Name	Case Name	Weight	Evaluation of Us	Evaluation of Competitor
Criterion	中區資訊月參展企劃	92年元宵節案例	92年ADSL促銷案例			
customer_analysis=上網用戶	0.3	0.29	0.42	0.11	1	2
competitor_analysis=Cable	0.3	0.29	0.42	0.11	1	2
technical_development=多媒體整合	0.49	0.11	0.4	0.22	2	1
strategy=參展	0.49	0.4	0.11	0.22	1	2
activity_objective=寬頻上網	0.3	0.29	0.42	0.11	1	2
content=ADSL	0.49	0.4	0.11	0.11	1	1
advertisement_media=報紙	0.3	0.29	0.42	0.11	2	1
Raw Importance index(RI)	0.55	0.43	0.4			
Importance index for similarity(I)	0.4	0.31	0.29			
Rank	1	2	3			

Fig. 8. The interface showing the final ranking of similarity levels.

ranked cases based on the similarity level of each attribute.

4. Internal evaluation and outside competitors' performances are considered in the measurement of similarity index for each attribute, which is important in strategic marketing planning.
5. Provide both Multi-Attribute similarity measurement (CBR) and visualization (MAGA diagram) support for case adaptation.

5. Summary and conclusions

This paper has conducted a survey of CBR researches. To facilitate the exchange, management, retrieval, and sharing of marketing plans, a CBR method is developed, which includes a visualization mechanism, a parser for preliminary qualification, and an MADM similarity level measure for precise retrieval. The CBR system is developed and applied to a telecommunication company. By representing the existing marketing plans as XML documents following the specific DTD defined in the research, several marketing plans are stored in the case base. Finally, a demonstration of the two step retrieval is presented.

According to the survey of the existing CBR methods, most methods, when applied to marketing plans, can not directly support well due to the complex multi-dimensional concerns considered, the content based retrieval, and difficulty in weighting and evaluating the similarity indices in developing a strategic marketing plan. Our proposed CBR system, unlike the other nearest neighbour methods which calculate the similarity by weighted sum of feature similarity levels, embeds AHP and CPAM methods into the procedure of case retrieval and ranking, leading to a more precise and detailed retrieval results for case adaptation. By plotting the top ranked cases on the MAGA diagram, along with the quantitative similarity levels of top ranked cases, case adaptation can be implemented, better facilitating interaction and group decision making, which is an important requirement for strategic planning.

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