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Applying Case-Based Reasoning in Supporting Strategy Decisions

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***Abstract*—**Globalization and therefore increasing tight competition among companies, have resulted to increase the importance of making well-timed decision. Devising and employing effective strategies, that are flexible and adaptive to changing market, stand a greater chance of being effective in the long-term. In other side, a clear focus on managing the entire product lifecycle has emerged as critical areas for investment. Therefore, applying well-organized tools to employ past experience in new case, helps to make proper and managerial decisions. Case based reasoning (CBR) is based on a means of solving a new problem by using or adapting solutions to old problems. In this paper, an adapted CBR model with k-nearest neighbor (K-NN) is employed to provide suggestions for better decision making which are adopted for a given product in the middle of life phase. The set of solutions are weighted by CBR in the principle of group decision making. Wrapper approach of genetic algorithm is employed to generate optimal feature subsets. The dataset of the department store, including various products which are collected among two years, have been used. K-fold approach is used to evaluate the classification accuracy rate. Empirical results are compared with classical case based reasoning algorithm which has no special process for feature selection, CBR-PCA algorithm based on filter approach feature selection, and Artificial Neural Network. The results indicate that the predictive performance of the model, compare with two CBR algorithms, in specific case is more effective.

***Keywords*—**Case based reasoning, Genetic algorithm, Group decision making, Product management.

I. INTRODUCTION

IN the actual globally changing business environment, companies are seeking new ways of providing additional value to customers and gain a competitive edge over their competitors. Product design and a clear focus on managing the entire product lifecycle have emerged as critical areas for investment. Companies are focusing on total management of product lifecycles because today's worldwide economic conditions demand they make process changes to remain competitive [1]. Product life cycle management (PLM) vision represents in fact the need to manage a large amount of product data that are generated in the various phases of life cycle, for supporting efficiency, flexibility and efficacy in the business processes applying innovative approaches [2]. This concept centered around the need to produce a coherent framework that could account for the relative success or failure of an individual product introduced onto the market, when best to change strategies such as pricing, or product manufacture, and determining when a product should be discontinued [3].

Therefore management of the product lifecycle is critical to meet customer needs throughout its entire life cycle and often multifaceted segment of running a successful enterprise. Devising and employing effective strategies that are flexible and adaptive to changing market circumstances stand a greater chance of being effective in the long-term. Products and consumer perceptions are variable, so changes in strategy may be required to better address customer needs, technological developments, new laws and regulations, and the overall product life-cycle. By monitoring external conditions and shifting product development accordingly, a company can better target its consumers and learn to react to their needs. In the other side, the practice of strategic management proves that when the management board is strongly limited in its capacity to take rational actions, specifically in the context of great decision complexity and uncertainty, it is good practice to refer to experience through reasoning by analogy [4]. Complexity of analogy-based reasoning has its roots in an attempt to solve new problems basing on past cases from a different domain, while we will focus on case-based approach for a single domain [5]. Facing a novel opportunity or predicament, strategists think back to some similar situation they have faced or heard about, and they apply the lessons from that previous experience [6]. In situations of true ambiguity, analogies and reference cases are able to support strategy decisions [4].

Case Based Reasoning (CBR) is a reasoning methodology that reuses past cases to find a solution to the new problem and is preferred for ill-structured managerial decisions [7]. A case based reasoner uses remembered cases to suggest a means of solving a new problem, to suggest how to adapt a solution that doesn't quick work, to warn of possible failures, to interpret a new situation, to critique a solution in progress, or to focus attention on some part of a situation or problem [8]. As CBR just refers to specific knowledge of previously experienced situations, it fits with complex and unstructured problems, and it is easy and convenient to update the knowledge base [9]. For these reasons, CBR has been popularly applied to management and engineering areas. CBR systems have been used in a wide variety of fields and applications [10]. "Reference [11] listed research areas and topics related to CBR, including cognitive psychology, pattern recognition, machine learning, cognitive science, information

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retrieval, statistics/ robotics, data structures, software engineering, and process planning". Furthermore, "Reference [12] suggested a classification method of CBR applications". According to this classification scheme, CBR applications can be classified into two main categories, Classification and Synthesis tasks. In classification tasks, a new case is assigned to a specific class in the case-base from which a solution can be derived. Maintenance systems [13], engineering applications such as detecting locomotive faults [14], Legal and medical knowledge management and diagnosis [15], Product recommendation in ecommerce [16] and efficient helpdesks and customer support systems [17] are some examples of this category. Synthesis tasks, such as configuration, planning, and designing, attempt to get a new solution by combining previous solutions [12]. There are a variety of constraints during this process. Comparatively, they are harder to implement. CBR systems that perform synthesis tasks must make use of adaptation and are usually hybrid systems [18].

However, so far there has been no thorough research on applying case-based reasoning to support strategy decision making for product management. There has also been no reliable empirical research conducted to verify this approach and assess how useful it actually is in business practice [4]. At the same time global consulting companies have been building systems of databases containing information on the projects they have carried out with a view to adapting them for new clients. First applications of this class of systems in management include ORCA– a system supporting company restructuring processes during acquisitions and mergers, and ESAS– a system supporting business strategy planning processes. Both approaches mentioned above were promising prototypes [4].

For these reasons, the development of a strategy solution provider where it is possible to retrieve, use, manage data and information to obtain knowledge useful for supporting and taking decisions along the product life cycle is one important issue. Therefore case-based reasoning has been chosen as a suitable decision making paradigm to weight and rank available strategies, which focus on middle of life phase of products, and make decision based on them. Whereas CBR is truly sensitive to optimal feature subsets and if a true optimal feature subset is used in CBR-based prediction systems, it could produce acceptable predictive accuracy [19], the wrapper approach of Genetic Algorithm (GA) is applied. Meanwhile, for each case, a set of definite solutions are weighted with performing the proper analysis in Group Decision Making (GDM) environments.

This article is composed of 5 main sections. After the introduction, the second section is dedicated to a general presentation of the CBR method and feature selection. Section 3 then describes in detail the developed CBR approach for proposing weights for a set of solutions in order of preference in a given case. In the next section, the real-world dataset, experiment and results are described. Conclusions are finally drawn in section 5.

II. BASIC CONCEPT

A. *Case-Based Reasoning*

CBR is an important paradigm of artificial intelligence mainly used for problem-solving [18]. It tends to apply efficient methods to define descriptive patterns and explanations within an enormous amount of data. The basic idea behind CBR is to solve a new problem by remembering and reusing information from a previous similar experience. When given a new case to be classified, a case-based reasoner searches from case base for similar cases and composes predictive result on the basis of class labels of similar cases to the current case. Numerous CBR model exists, however one of the more used is the cyclic process [20], known as the R4 model but it can be extended to the R5model (if the preliminary step, case representation is included) (Fig.1)

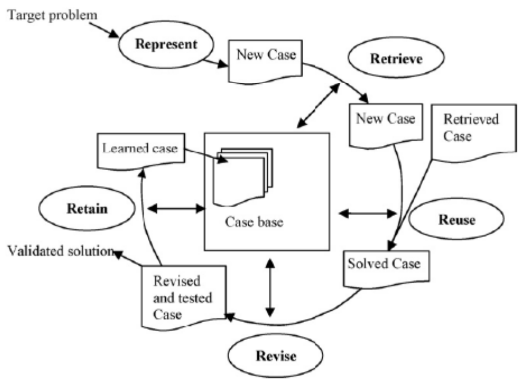

Fig. 1 The CBR process cycle [20]

The preliminary step consists in representing the past experiences contained in cases for the reasoning purpose. Many ways for case representations are possible, but the more used is a vector of feature–value pairs for the problem and solution descriptions. The initial step before applying the CBR process is to find relevant features for the problem and solution descriptions. After the filling of the target problem features, the next step in the cycle consists in retrieving the case or a subset of cases, stored in the case base, that are relevant to solve the target problem. Among well known methods, there are two chief methods to carry out case retrieval, i.e. nearest neighbor retrieval, and inductive approach, which the former is more widely used [21]. The system matches a new problem against cases in the case base using a specific retrieval method, and finds the most similar cases in this step. This method is called nearest neighbor (NN) matching [22]. The matching is realized with a similarity function. In NN matching, similar cases that are found affect the quality of the solution significantly, thus it is very important to design an effective retrieval method. The similarity between an input case and stored cases can be determined in many ways. It depends on the type of feature values. When cases are represented as feature vectors, calculating the weighted sum of feature distances is a common approach. The typical numerical function for NN matching is shown in (1) [22]:

$$sim(f^{l}, f^{R}) = \frac{\sum_{i=1}^{n} w_i \times sim(f_i^{l}, f_i^{R})}{\sum_{i=1}^{n} w_i} \qquad (1)$$

Where $w_i \in [0,1]$, is the weight of the ith feature and $\sum_{i=1}^{n} w_i = 1$, f_i^l is the value of the ith feature for the input case, f_i^R is the value of the ith feature for the retrieved case, and sim( ) is the similarity function (usually, Euclidean distance) for f_i^R and f_i^l. If various similar cases are found, the global similarity function ranks them. 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 [23]. 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 [24]. In the next step, the solution is tested to verify its adequacy (by simulation, experimental validation for example). After the tests, the solution may need some adjustments to fit more specifically the target problem. Consequently, the user revises the solution generated in the previous step to withdraw the discrepancies between the desired and the adapted solution. Finally in retain step, the solution of current problem is evaluated and stored in the case base as a new case in order to realize the system's self-learning ability. If a new case is too similar to another one in the case base, it is not stored because it increases the case base without bringing added value. Therefore, CBR can learn from old knowledge and information to solve new similar problem.

B. Feature Selection

In a CBR system, attributes are the key features used to classify cases and develop a basis for the similarity criterion [18]. Since case-based classifiers and nearest-neighbor algorithms are very sensitive to their input features, irrelevant attributes may cause an increase in the classification error. Therefore feature selection, a process to find the optimal subset of attributes that satisfy a given criteria, can serve as a preprocessing tool of great importance before solving the problem [25]. There are many studies on feature selection. They can be categorized, based on whether feature selection is performed independently of the learning algorithm, into two models, one model is the filters and the other one is the wrappers [26]. Statistical approaches, such as factor analysis (FA), independent component analysis (ICA), principal component analysis (PCA), F-score and discriminant analysis (DA), which use general characteristics of the data to evaluate attributes and operate independently of any learning algorithm, can be adopted in filter based feature selection. Even though the filter model is fast, the resulting feature subset may not be optimal [26]. The wrapper model [27], applies a target learning algorithm to estimate the worth of attribute subsets. Some researchers have concluded that if the purpose of the model is to minimize the classifier error rate, and the measurement cost for all the features is equal, then the classifier's predictive accuracy is the most important factor. In other words, the classifier should be constructed to achieve the highest classification accuracy. The features adopted by the classifier are then chosen as the optimal features. In the wrapper model, the meta-heuristic approaches are commonly employed to help in looking for the best feature subset. Although meta-heuristic approaches are slow, they obtain the (near) best feature subset [19].

III. Proposed CBR

This study applies an adapted CBR model which performs the principle of the group decision making to propose weighs of solutions in order of preference in the target case. Genetic algorithm is used as a wrapper approach to select a proper subset of features. The information encoded about the past experiences, depends on the domain of application as well as on the goal for which the cases are used. For our purpose, the cases are composed of two parts: the problem and the solution one. This problem is expressed by a limited set of features, P={$p_1, p_2, \ldots, p_n$}. P is a n-dimentional vector space, which means a decision making problem and p_i (i=1,2, …, n) means an evaluation criterion of problem solution. S={$s_1, s_2, \ldots, s_m$} is also a limited set, representing the solution set of case. S is an m-dimentional vector space which s_j (j=1,2, …, m) ∈ [0,1] and $\sum_{j=1}^{m} s_j = 1$. For each problem, which is stored in the case base, solutions are compared and weighted in order the suitability for the given problem. For a new problem, the best cases will be retrieved from the case base. In this step, CBR use the k-nearest neighbor algorithm for total holdout data set. Generally, the technique of the nearest neighbor uses Euclidean distance, as follows:

$$DIS_{xy} = \sqrt{\sum_{i=1}^{n} w_i (p_{xi} - p_{yi})^2} \qquad i=1,2,\ldots, k \qquad (2)$$

Where DIS_{xy} is a distance between x and y, p_{xi} and p_{yi} are the values of case x and y on the ith feature, n is the number of features and w_i is the importance weighting of features x, y. By using the weighted distance defined in (3), a similarity measure between two cases, SM_{xy}, can be defined as follows:

$$SM_{xy} = \frac{1}{1 + DIS_{XY}} \qquad (3)$$

After calculating the similarity of each candidate case with the new case, k cases with the highest similarity are selected and returned to the user.

As previously mentioned, the goal of case reuse is to propose a solution to the target case, derived from solution(s) of the retrieved case(s).various methods to adapt a case exist. But in our study, source solutions of the k most similar problems are used to build and propose a solution to the target problem. The adaption method consists in taking a weighting majority vote to select the most likely solution to the target problem, as follows [28]:

$$class = \arg\max_v \sum_{j=1}^{|E'|} w'_i \times I(v, c'_j) \tag{4}$$

Where v is one of the class labels, $|E'|$ is the set of closest cases to the target case (z), c'_j is the class label of one of the nearest neighbors, I(p,q) is a function that returns the value 1 if p=q and 0 otherwise, and w'_i, which is used to penalize neighbors that are located far away from the target case, is defined as follows:

$$w' = 1 \big/ DIS_{xz}^2 \quad ; \ (x \in |E'|) \tag{5}$$

Thus w', weighted vector of the k most similar cases to the target case is expressed as follows:

$$w' = [w'_1 \quad w'_2 \quad \dots \quad w'_k] \tag{6}$$

Each of the k most similar problems (cases) has a set of solutions, which must be reused to the target problem. Different values have been assigned to every solution in the solution sets of the k similar problems. Therefore, for the target problem, there are k similar cases and each of them has m solutions' value, which has been determined by the expert. The weighted solution matrix is defined as follows:

$$\begin{bmatrix} w_{11} & w_{12} & \dots & w_{1m} \\ w_{21} & w_{22} & \dots & w_{2m} \\ \dots & \dots & \dots & \dots \\ w_{k1} & w_{k2} & \dots & w_{km} \end{bmatrix} \tag{7}$$

Where w_{ij} (i=1,2, … k; j=1,2, … m, 0< w_{ij} <1) is the value of solution ith in the case jth among the k most cases to the target case and $\sum_{j=1}^{m} w_{ij} = 1$. In this step the principles of group decision making method and weighting majority vote are applied in order to evaluate and adapt the solutions developed in selected cases. Therefore, ith solution's value of the target problem, W_i, is a group integrated value of solution i among k similar cases, which has a general form:

$$W_i = \sum_{j=1}^{k} w'_j \times w_{ji} \qquad (i = 1,2,\dots,m) \tag{8}$$

Consequently, the set of proposed solution to the target problem, which is acquired by group integrated value of solutions of the k-most similar cases is:

$$W = [W_1 \quad W_2 \quad \dots \quad W_m] = \left[\sum_{j=1}^{k} w'_j \times w_{j1} \quad \sum_{j=1}^{k} w'_j \times w_{j2} \quad \dots \quad \sum_{j=1}^{k} w'_j \times w_{jm}\right] \tag{9}$$

The solution generated is then evaluated for validity. Finally, the completed new case is retained in the case base. The flowchart of the model is shown in Fig. 2. The detailed explanation for each step is presented as follows.

Step1: The collected data is first input to the system and scaling is applied to prevent feature values in greater numeric ranges and to prevent numerical difficulties in the calculation. The scaled data is divided into two disjoint sets, known as the training set and test set, respectively.

Step 2: Initial population, which individually is comprised selected features, is generated.

Step 3: For each individual population, the training data is randomly splited into the train and validation using cross validation, k-fold cross validation is conducted on the training set. Then the average validation accuracy of the k-fold cross validation, the fitness value, is calculated.

Step 4: if the termination criteria are satisfied, the process reruns CBR on the largest set to measure classification accuracy on the test set with selected features. Otherwise, the next iteration, forming a new population by genetic operation, occurs.

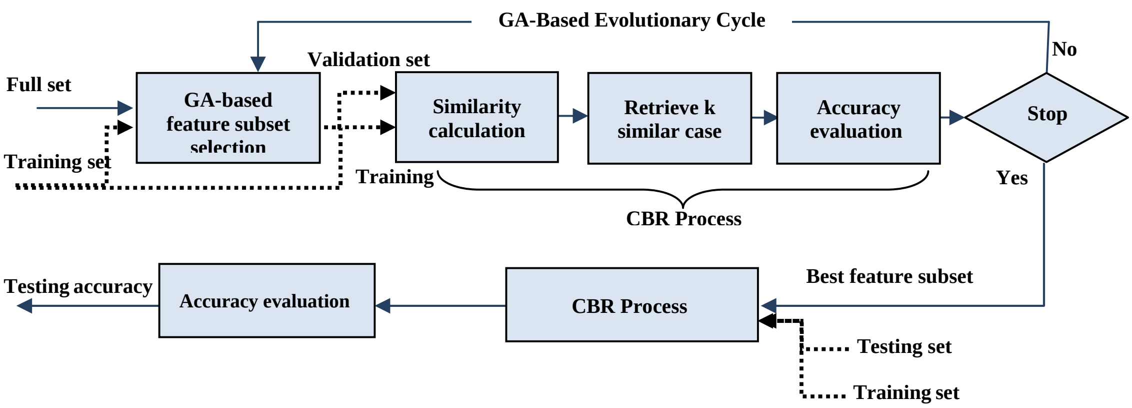

Fig. 2 Flowchart of CBR-GA modified from[29]

IV. EXPERIMENTAL RESULT

The data set is derived from the data of real department store in Iran over two years and has 95 records. Each record, representing information of a product, is composed of 24 features. The features fall into the three categories; customer information, product information and purchasing information. Customer information includes gender, marital status, children, yearly income, education, occupation and house status. Characteristics of the product itself, such as weight, volume, shelf width and height are included in the product information category. Also price, cost, units sales, frequency of sales and customers are associated to the category of purchasing information. Based on critical factors that are considered in each product, various strategies should be defined to manage products in the middle of life phase. Three strategies including more advertisement, changing prices and discontinuing of product selling, are selected to be considered as a solution set of each problem. The values of solutions, which are determined by the expert, reflect the importance of them in past problems. Therefore, there are 24 input variables, that describe product situation and 3 output variables, which are weighted to express the preference of each strategy in special product. The range of each feature value is scaled to the range of [-1, +1]. The k-fold approach is used to evaluate the classification accuracy rate [25]. This study set k as 4; that is, the data is divided into four portions. The data from each portion is formed based on the ratio of each category (classification) in the original data. Three portions of data are retrieved as training data and left one portion for testing each time. Since each portion is used as testing data once, four accuracy rates can be obtained. The final accuracy rate is the average of the four accuracy rates. The results obtained by the model are shown in Table.1 , that the accuracies of the model under 1NN-11NN are listed.

TABLE I
PREDICTIVE ACCURACY OF CBR-GA IN THE SEARCH OF NN

NO. of Nearest Neighbor	NO. of Selected feature	Accuracy (%)
1	10	0.78760
3	11	0.80715
5	9	0.86655
7	9	0.83925
9	13	0.80315
11	16	0.77605

It is found that the accuracy the model does best in 5NN, which nine features are selected as input features, and the corresponding predictive accuracy is 0.86655 %.

In order to verify the performance of the model, 3 models are experimented for the same data set. The first model, CBR, does not have any special process of feature selection. CBR-PCA adopted the filter approach feature selection based on Principal Component Analysis (PCA). And the last one is Artificial Neural Network (ANN), a Multi-Layer Perceptron (MLP) neural network. Table II shows the performance of mentioned models. The paired t-test is used to examine whether the differences of predictive accuracy between CBR-GA and other models are statistically significant.

The results show that there are significantly different predictive performances between CBR-GA and two CBR algorithms (CBR, CBR-PCA) at least at the level of 1%. It is also found that there is no significant difference in predictive accuracy between CBR-GA and ANN. It can be interpreted that CBR-GA may improve the prediction accuracy of conventional CBR up to the accuracy of ANN.

TABLE II
PREDICTIVE PERFORMANCE OF VARIOUS MODELS

Model	Minimum	Maximum	Minimum
CBR	0.713	0.7574	0.73272
CBR-PCA	0.7085	0.7594	0.73971
CBR-GA	0.7981	0.8907	0.84376
ANN	0.797	0.8735	0.84098

V. CONCLUSIONS

Business today is becoming more of a knowledge-based (KB) activity. PLM is widely recognized as a business necessity in current time. PLM enables companies to leverage their investments in product related intellectual and physical assets and is the vehicles to reduce cost, provide solid return on investment, and enable product and process innovation. Many of these activities involve making decisions by using past experience to select the appropriate choice from a set of possibilities. However, businesses would not automate their decision processes unless they could have enough confidence in the correctness of the solution produced. Case Based Reasoning (CBR) is a reasoning methodology that solves new problems by adapting previously successful solutions to similar problems. This paper applies CBR to provide suggestions for managing strategies of a given product for the middle of life phase. The set of solutions, as available strategies, are weighted by CBR in the principle of group decision making and reflect the importance of implementing each strategy in the product. The dataset of a department store are used to experiment the model. 24 features under 3 categories are selected to evaluate 95 products. The K-fold crossvalidation is utilized to assess model and genetic algorithm is used to select features. Compared to other models such as Basic CBR and CBR-PCA, CBR-GA has the highest prediction accuracy with the dataset.

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