Case-Based Reasoning Approach in Bid Decision Making

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Abstract: Since contractors' bidding behaviors are affected by numerous factors related both to the specific features of the project and dynamically changed situations, bidding decision problems are highly unstructured. No clear rules can be found in delivering a bidding decision. In this problem domain, decisions are commonly made based upon intuition and past experience. Case-based reasoning (CBR) is a subbranch of artificial intelligence. It solves new problems by matching against similar problems that have been encountered and resolved in the past. It is a useful tool in dealing with complex and unstructured problems, which are difficult if not impossible to be theoretically modeled. This paper presents a case-based reasoning bidding system that helps contractors with the dynamic information varying with the specific features of the job and the new situation. In this system, bid cases are represented by sets of attributes derived from a preliminary survey of several experienced bidders, focusing, respectively, on two reasoning subgoals: (1) Risk; and (2) competition. Through the system, similar cases can be retrieved to assess the possible level of competition and risk margin. A hypothetical example is explained and evaluated to demonstrate the feasibility of the method. The effectiveness of this system is tested by a Monte Carlo simulation in comparison to the conventional statistical method.

INTRODUCTION

Bidding is a very complex decision requiring simultaneous assessment of a large number of highly interrelated variables to arrive at a decision. These interrelationships are complex and intractable so that management expertise is mostly implicit and very difficult to be extracted and modeled. On the other hand, a decision maker can hardly consider all of the relevant variables due to one's bounded rationality and limited capacity of information processing (Deng 1994). Thus, the markup decision is so highly unstructured that it is very difficult to be analyzed and formulated in any rigid solution process. As observed by Hegazy and Moselhi (1994), the solutions for bidding devised in practice are primarily based on analogy with previous cases coupled with a mixture of intuition and experience.

Case-based reasoning (CBR) is a method of solving a current problem by analogizing the solutions to previous similar problems (Kolodner 1993). A CBR system draws its knowledge from a reasonably large set of cases contained in the case library of past problems rather than only from a set of rules. It solves new problems by adapting solutions that were used to solve old problems. Instead of relying solely on general knowledge of a problem domain, or making associations along generalized relationships between problem descriptors and conclusions, the CBR approach collects information about previous cases, and then retrieves this information for similar cases. By adopting this approach, it is able to utilize the specific knowledge of previously experienced, actual situations (cases) (Aamodt and Plaza 1994). Subsequently, the previous solutions may be adapted so that they more closely match the current problem and situation. Thus, such a reasoning method is very suitable for decision making in construction bidding —a complex, dynamically changing, and highly unstructured problem domain.

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BIDDING MODEL

Numerous research has been done on bidding models. Traditional bidding models, such as Friedman's (1956) model, Gates's (1967) model, and Carr's (1982) model, are based on statistical and probability theory. However, the bidding decision is a complex decision-making process affected by numerous factors. Each job has its unique characteristic and is bid in a specific economic and work situation. These models are unable to reflect the interaction of these factors. As Gates (1983) commented, these models are good for academics but not for practitioners.

Recently, some bidding decision support systems based on the artificial intelligence (AI) technique were introduced with the consideration of various determining factors. These systems included the expert systems developed by Tavakoli and Utomo (1989) and Ahmad (1990), and neural network systems developed by Moselhi et al. (1993), Hegazy and Moselhi (1994), and Dias and Weerasinghe (1996). Expert systems are rule-based systems. On the other hand, the bid decision is dynamically changing and highly unstructured, and is characterized by a significant degree of uncertainty and subjectivity. It is too complicated for any set of clear rules to be defined that will work in each new instance. A neural network system learns from cases. In this sense it is similar to the case-based reasoning. However, its reasoning process is concealed from the decision maker, operating like a black box. The decision maker cannot trace the reasoning process. For this reason, conclusions derived from the neural network are not very convincing to the decision maker. On the other hand, case-based reasoning system derives its recommendation from concrete past cases. The reasoning process can be more discernible to the decision maker. He can also interact with and review the reasoning process and even perform heuristic adjustments on the derived result where necessary.

Furthermore, the bidding issues are only generally addressed in the past systems. No deep reasoning has been made about the bidding process itself. Actually, a bidding decision is the product derived after evaluating the risk elements and potential competition together with an assessment of the company's competitive status. Chua and Li (2000) proposed a bid reasoning model along this line. As shown in Fig. 1, the reasoning is based on four subgoals, namely: (1) competition; (2) risk; (3) need for work; and (4) company's position in bidding.

The level of competition is commonly reflected by the number and competitiveness of competitors. For a given project and level of risk, the keener the competition, the lower the markup level of the winning bid tends to be. On the other hand, risk is reflected by the possible variation in cost. The

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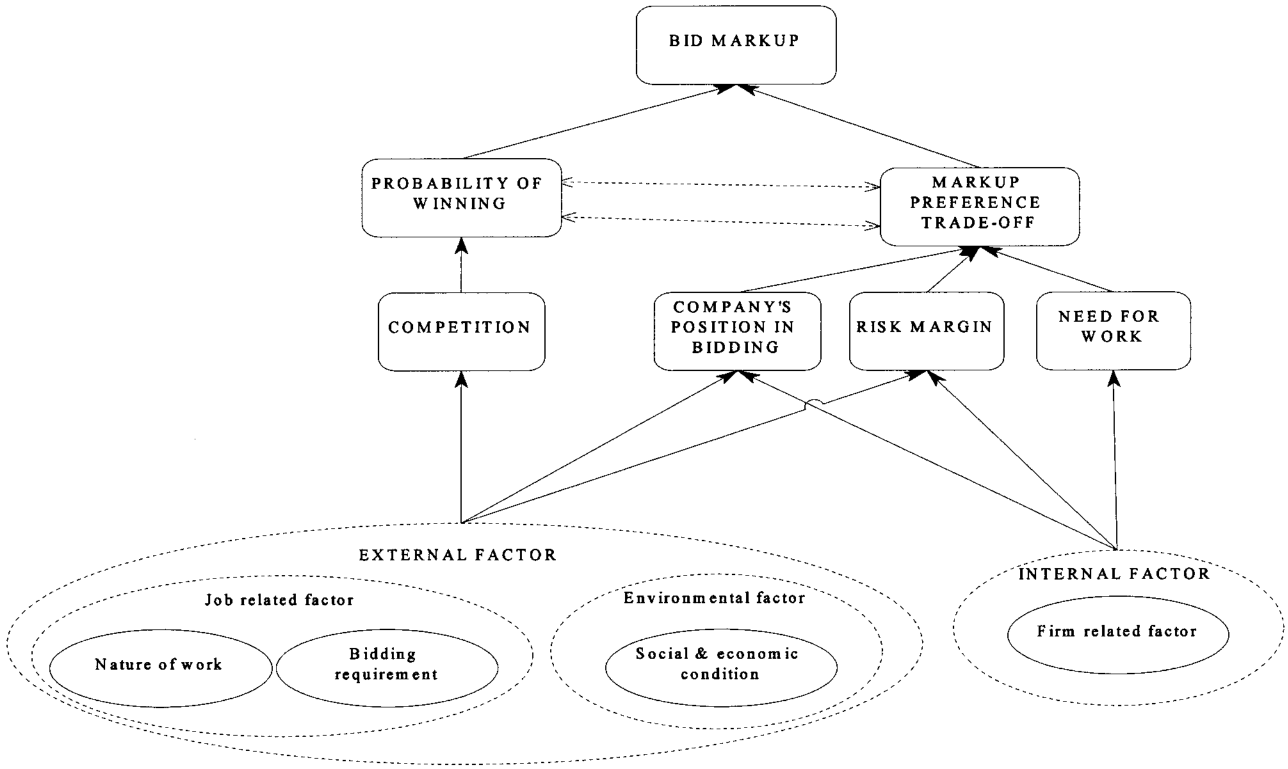

FIG. 1. Bid Reasoning Model

TABLE 1. Key Factors Identified from Survey with Respect to Competition

ID (1)	Factors (2)	Weights: Unit rate contract (3)	Weights: Lump sum contract (4)	Weights: Design-build contract (5)
1	Availability of other projects	0.071	0.091	0.073
2	Availability of qualified staffs			0.042
3	Bid method (open/close)	0.051		0.115
4	Cashflow requirement		0.051	
5	Degree of technological difficulty	0.230	0.208	0.212
6	Identity of owner/consultant	0.149	0.148	0.091
7	Project public exposure and prestige	0.105	0.095	0.091
8	Project timescale and penalty for noncompletion	0.088	0.086	0.075
9	Safety hazards	0.052	0.051	0.050
10	Size of project	0.160	0.171	0.136
11	Time allowed for bid preparation	0.093	0.098	0.114

actual construction cost deviates from the estimate in the bid due to the uncontrolled risk elements. One main task in bidding is to assess the possible level of competition and potential risk so as to be able to assign a proper markup value for the bid price. This will be the focus of the present paper for the proposed case-based reasoning bidding system. Need for work will determine the contractor's keenness to get the job. The company's position in bidding reflects the strength of the company in comparison to industry competitors. These two reasoning subgoals are closely associated with the company's current status and specialty and affect the contractor's attitude toward risk.

The determining factors contributing to these four reasoning subgoals cover two broad groups of factors: (1) Internal factors; and (2) external factors. The internal factors are those inherently related to the company such as its expertise, experience, financial ability, resource, and current workload. They demonstrate the company's ability and advantage in bidding and performing the work.

The external factors relate to the nature of the work, bidding requirement, and the social and economic environment. Factors relating to the nature of work, such as size of project, degree of technological difficulty, resource demands, and prestige reflect the pertinent features of the project. Bidding requirement is the client's prerequisite for bidders' compliance in bidding such as prequalification, bidding method, and time allowed for bid preparation. Environmental factors reflect the social and economic conditions, such as the current bidding market, resource market, and government regulations.

Although internal (firm-related) factors do affect the bid markup decisions of individual contractors, such information is usually not accessible to the other bidders, so that they generally cannot be used to reason on the level of competition. The level of competition has to be reasoned from the external factors. Table 1 shows the key factors determining the level of competition with respect to different contract types that were identified from a survey conducted by Chua and Li (2000). The importance weightings shown in the table have been normalized to sum up to 1.

On the other hand, the level of risk would be ascertained from both the internal and external factors. Uncertainty during bid preparation generally arises from two sources: (1) Accuracy in estimating; and (2) adequacy and clarity of required information. The risk elements during project execution can

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TABLE 2. Key Factors Identified from Survey with Respect to Risk

ID (1)	Factors (2)	Weights: Unit rate contract (3)	Weights: Lump sum contract (4)	Weights: Design-build contract (5)
1	Adequacy of resource market price information			0.053
2	Competence of estimators	0.092	0.222	0.325
3	Completeness of drawing and specification	0.089	0.115	
4	Consultants' interpretation of specification	0.201	0.173	0.068
5	Current workload in bid preparation			0.104
6	Degree of technological difficulty	0.135	0.107	0.083
7	Delay or shortage on payment	0.064		
8	Expertise in management and coordination	0.067	0.061	0.057
9	Project timescale and penalty for noncompletion	0.213	0.158	0.116
10	Resource price fluctuation		0.059	
11	Similar experience	0.139	0.105	0.101
12	Time allowed for bid preparation			0.093

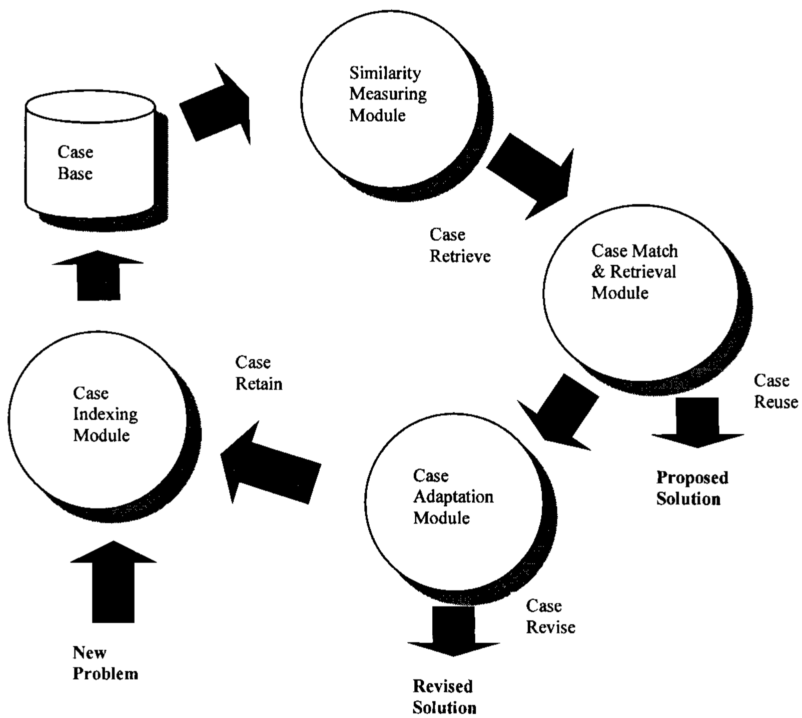

FIG. 2. Process of CBR

be classified under four categories, namely: (1) nature of work-related risk; (2) firm-inherent risk; (3) client- and consultant-posed risk; and (social and economic) (4) environment- (social and economic) related risk. Table 2 (Chua and Li 2000) shows the key factors determining the level of risk with respect to different contract types together with normalized importance weightings.

For the other two reasoning subgoals, the contractor's keenness to bid or need for work would be determined by the contractor's own internal factors, while the company's position in bidding with respect to its competitors would be determined by the interaction of both internal and external factors.

CASE-BASED REASONING

As a fairly new subbranch of artificial intelligence, CBR is a computational method that employs past experience of similar problems in current problem solving (Riesbeck and Shank 1989). Under the traditional point of view, reasoning is a process of composing, decomposing, and recomposing. Founded on the psychological theory of human reasoning, CBR recognizes that humans often solve a new problem by comparing it with similar ones that they had already resolved in the past. To emulate this, CBR comprises essentially 3 tasks:

1. Retrieves one or a small set of the most similar cases
2. Solves the new situation by reusing or revising former solutions
3. Retains the new case and solution as part of past cases for future retrievals

A CBR system typically consists of a case library, which is a repository of past cases, and several interrelated components or modules to achieve the above tasks, as shown in Fig. 2. The case indexing module allows a case to be uniquely represented, indexed, and partitioned in the case library. The similarity measuring module computes the similarity between the new case and the cases in the case library. The case match and retrieval module ensures that the cases with higher similarity value are retrieved when required. Solutions of the similar cases can be used as inspiration for solving the new problem. Since a new situation rarely matches old ones exactly, old solutions must be adjusted to fit the new case. The case adaptation module performs the reasoning over the most similar case or a set of similar cases retrieved and carries out the necessary data analysis to adapt the case(s) for a proper solution.

Since its origination, the basic idea of CBR and its under-

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lying theories have spread very fast. Over the last few years, CBR has grown from a rather specific and isolated research area to a field of widespread interest. Activities are rapidly growing, as seen by the increased rate of research papers, the commercially and academically available CBR development tools, and also the applications in various areas. Its applications in architecture design (Schmitt 1993), decision support (Deng 1994), progress scheduling (Sycara and Miyashita 1994), construction negotiation (Li 1996), and structure diagnoses (Roddis and Bocox 1997) have shown its great potential in the field of engineering and management.

FRAMEWORK FOR CASEBID

The framework for the proposed bid decision support system, CASEBID, is depicted in Fig. 3. A CBR development shell, ReCall (Isoft 1996), has been used to develop the system. The TCL (tool command language) scripting language (Ousterhout 1994) has been used to automate the procedures.

The objective of the system is to propose a bid markup level to the decision maker on the basis of past experience. Past bid cases are stored in the case base or case library. Factors that the decision maker considers to be significant determinants of the bid markup are built into the system as the domain knowledge. Weights 1 and 2 are the sets of relative importance weightings of the determining factors with respect to competition and risk, respectively. The case base coupled with the domain knowledge constitute the knowledge base of the system.

The decision process begins when the user presents a new case to the system. A set of cases relevant to the new episode according to an index tree structure will be extracted from the case base. These cases are deemed in the neighborhood of the new case. The similarity values of these cases are then computed and those that match the new episode better (with higher similarity values) with respect to the two subgoals of competition and risk will be presented to the case adaptation module. The case adaptation module either proposes a markup level based on the criterion of maximized expected profit after assessing the level of competition and risk as presented by the similar cases, or it takes the analysis further and derives an alternative markup level based on the criterion of maximized utility value by taking into consideration the decision-maker's risk preference as judged from the company's need for work and position in the industry. In this paper, only the first method is discussed. The outcome of the new bid case, whether a failure or success, needs to be recorded into the case base so as to provide a lesson for future situations.

CASE REPRESENTATION

A case can be defined as a contextualized piece of knowledge representing an experience that teaches a lesson fundamental to achieving the goals of the reasoner (Kolodner 1993). A collection of cases forms a case base.

The biggest issue in CBR is the retrieval of appropriate cases. It is important to ensure that the right cases can be recalled at the right times. This is known as the indexing problem in CBR, which has two aspects. One is the vocabulary problem that requires appropriate labels be assigned to the case

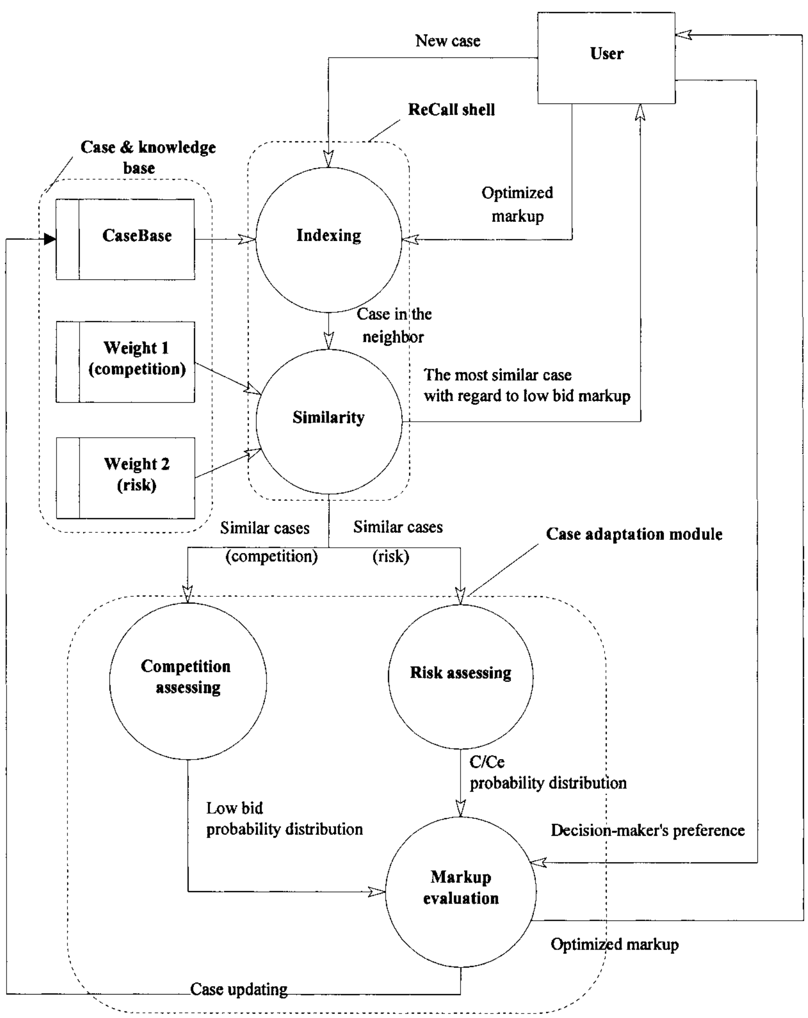

FIG. 3. Context Diagram of Case-Based Reasoning Bidding System

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so that it can be easily referenced in the case library during retrieval. The other problem is that of organizing the cases so that searching through the case library can be efficient and accurate. The case organization aspect will be addressed later.

Case Attributes—Indexing Vocabulary

Tasks and domains must be analyzed to find the functionally relevant labels or descriptors. These labels or descriptors are referred to as the indexing vocabulary or case attribute. Any case vocabulary must be able to represent the specific and relevant features of a case. Each set of case vocabularies will center on a reasoning subgoal. Accordingly, two sets of case vocabularies are associated with the two corresponding subgoals: (1) Competition; and (2) risk.

The determining factors for bid markup should serve as good potential candidates for the case indexing vocabulary. Too many indices, however, can impair the efficiency of the case-based reasoner. Thus the index will comprise only the key determining factors as established in Tables 1 and 2 for competition and risk, respectively. [A broader list may be obtained from Chua and Li (2000).] They are classified in Table 3 according to the ''CONTENT'' (the components of the bid) and ''CONTEXT'' (the situation at the time of bidding) parts of the vocabulary. Job-related factors represent the specific features of a bid case and form the content of the bid case. Social and economic factors reflecting the external environment, and firm-related factors reflecting the company's status collectively set the context for the bid case. The context of a bid case describes the state of the world in which the episode takes place.

Some other attributes not included in Tables 1 and 2 are also added to the case structure. A set of these that include ''TypeOfContract'' (type of contract), ''TypeOfProject'' (type of project), ''ProjectName'' (project name), ''BiddingDate'' (date of bidding), record the general information of the bid. ''TypeOfContract'' and ''TypeOfProject'' will serve as filter attributes to narrow the search to a smaller neighborhood of the new case that will be discussed later. ''LowBidMarkup'' and ''C/Ce'' are two other attributes added to represent the level of competition and risk margin, respectively. ''LowBidMarkup'' is the markup value of the lowest bid of the other bidders based on the contractor's own estimate of construction cost. A low value is indicative of a high level of competition. ''C/Ce'' is the ratio of the actual construction cost to the estimated cost. A value greater than 1 means a cost overrun. ''CompetitorBid'' is another attribute added to track competitors' bids in past cases.

Case Attributes' Domain Values

There are three main categories of attributes and the domain values for each attribute are represented differently as follows.

Attribute Type with No Implied Logical Relationship among Domain Values

In this case, the domain values serve to classify the attribute into several categories. For instance, the domain of the attribute ''TypeOfContract'' contains values of ''Unit rate contract,'' ''Lump sum contract,'' and ''Design-build contract.'' Since there is no logical relationship between the values in the domain, they can be treated as discrete points.

Attribute Type with Implied Logical Relationship between Domain Values

For this type of data, a generality taxonomy is created to establish the relationship between the values of its definition domain. For example, Fig. 4 shows the taxonomy created for ''IdentityOfOwner'' (identity of owner). The reason for constructing the taxonomy tree is obvious. Without defining any taxonomy tree, such as in the previous type of attributes, all domain values are isolated discrete points. The taxonomy tree defines logical relationships between the values. The taxonomy structure enables a similarity value to be assessed for two different values of the attribute, otherwise they would have to be treated as dissimilar values if they were discrete points.

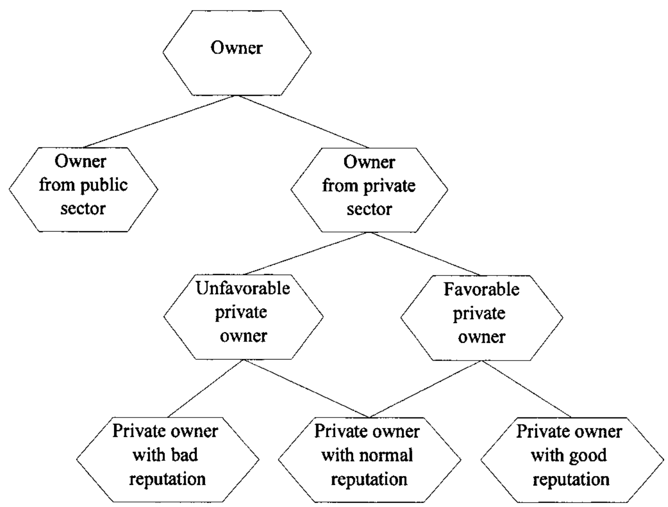

FIG. 4. Taxonomy for Attribute ''IdentityOfOwner''

TABLE 3. Case Indexing Vocabulary

Function (1)	Reasoning Goal: Competition (2)	Reasoning Goal: Risk (3)
Indexing vocabulary representing case ''CONTENT''	• Size of project • Degree of technological difficulty • Cash flow requirement • Project public exposure and prestige • Project timescale and penalty for noncompletion • Identity of owner/consultant • Safety hazards • Bidding method (open/close) • Time allowed for bid preparation	• Degree of technological difficulty • Project timescale and penalty for noncompletion • Consultants' interpretation of specification • Delay or shortage on payment • Time allowed for bid preparation • Completeness of drawing and specification
Indexing vocabulary representing case ''CONTEXT''	• Availability of other projects • Availability of qualified staffs	• Resource price fluctuation • Expertise in management and coordination • Similar experience • Current workload in bid preparation • Competence of estimators • Adequacy of resource market price information

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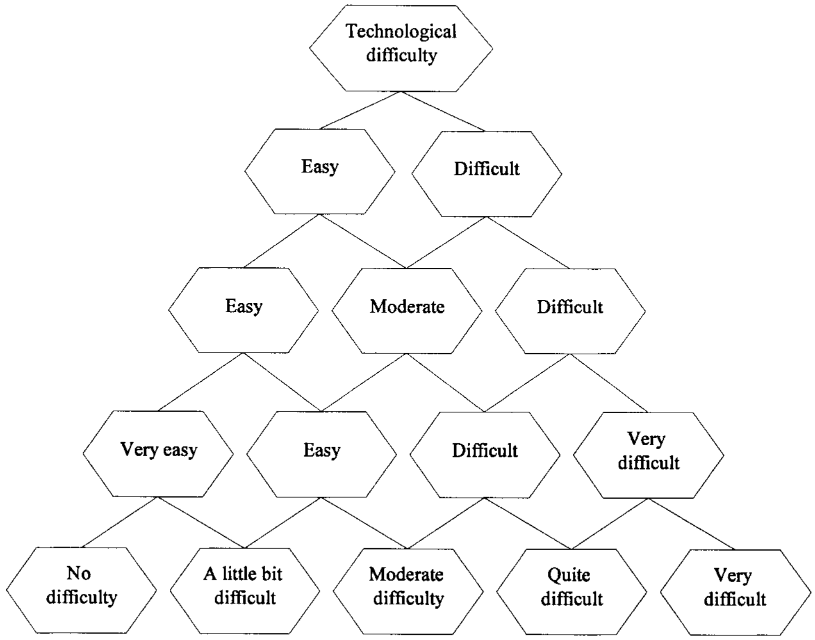

FIG. 5. Taxonomy for Attribute "TechnologicalDifficulty"

Quantitatively Measurable and Qualitatively Assessable Data Type

For attributes that can be quantitatively measured, their domain values are divided into some qualitative regions. For instance, the domain values for the attribute ''SizeOfProject'' (size of project) is divided into five regions: (1) ''Very small''; (2) ''small''; (3) ''average''; (4) ''large''; and (5) ''very large.'' Two values are considered equal if they lie within the same region, otherwise the distance between their qualitative regions provides a measure of their match or similarity score.

Some attributes can only be qualitatively assessed. In this case, a taxonomy tree is again built to relate the qualitative regions or values to each other. For example, the attribute ''TechnologicalDifficulty'' (technological difficulty) has five qualitative assessment values from ''no difficulty'' to ''very difficult.'' Fig. 5 defines the relationships between its domain values.

CASE-BASED ORGANIZATION

Structure

The case data and structure in CASEBID are represented in an object-oriented way so that a case instance is assigned as an object of a class and thus inherits all properties or attributes of the class. Classes are organized in a hierarchy of generalities where the most general concepts appear toward the roots of the hierarchy. Subclasses will inherit all properties and relationships defined in their superclasses. Different classes are linked through the ''link'' type of attribute.

The class structure in CASEBID is depicted in Fig. 6. One main class is ''Bid.'' For the same reasoning subgoal, an attribute that is important for one type of contract may not be important for the other types of contracts. To account for this, the main class is divided into three subclasses according to the types of contracts, namely: (1) ''UnitRateContract''; (2) ''LumpSumContract''; and (3) ''DesignBuildContract.'' The attributes in Table 4 are assigned in a way that class ''Bid'' possesses the common attributes that will be inherited by the three subclasses while each subclass will have its own direct attributes, as shown in Table 5. Consequently, a bid case is treated as an object of one of the subclasses according to the type of contract adopted in the bid.

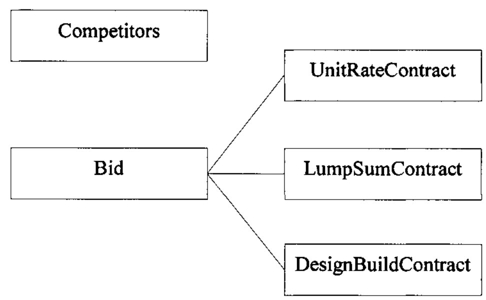

FIG. 6. Case-Based Structure

''Competitors'' is another class with two attributes: (1) ''BidMarkup''; and (2) ''Identity'' (competitor's markup and identity, respectively) to keep track of competitors' bidding behaviors. Objects in this class may be linked to corresponding objects or cases in the other classes through a link attribute ''CompetitorBid'' (Table 4). Depending on the availability of date, for each competitor bidding for the job, an object of the class ''Competitors'' will be defined to link to the case attribute ''CompetitorBid.''

Indexing Tree

An indexing tree has been incorporated in the case structure to enhance the search in the case base. Fig. 7 shows the indexing tree for the reasoning subgoal, competition. The nodes in the indexing tree for ''TypeOfContract'' and ''TypeOfProject'' correspond to the two most discriminating attributes with regard to the subgoal. Cases deposited under each of the lower level nodes represent very dissimilar bidding situations from the other nodes at the same level. When a new situation is presented, the similarity search is confined only to the node (or neighborhood) of the new case, instead of the entire case base. Effectively, the nodes other than the new case node are pruned away.

For the reasoning subgoal, risk, another set of indexing nodes corresponding to the attribute ''BidResult'' form the third level of nodes in the indexing tree. Since the contractor has no way to obtain the actual construction cost data for the jobs that the contractor has lost, these jobs cannot be employed to reason about risk. The additional level of nodes formed by

TABLE 4. Attributes of Class "Bid"

ID (1)	Attribute name (2)	Definition (3)	Domain value data type (4)	Reasoning goals focused on (5)
1	AvailabilityOfOtherProjects	Availability of other projects	Qualitatively assessable	Competition
2	BiddingDate	Date of bidding	Date	—
3	BidResult	Bid result	Categorical data with no logical relationship	—
4	C/Ce	Ratio of actual cost and estimated cost	Numerical	—
5	CompetenceOfEstimators	Competence of estimators	Qualitatively assessable	Risk
6	CompetitorBid	Competitor's bid	Link	—
7	ConsultantInterpretationOfSpecification	Consultant interpretation of specification	Qualitatively assessable	Risk
8	DegreeOfTechnologicalDifficulty	Degree of technological difficulty	Qualitatively assessable	Competition and risk
9	ExpertiseInManagementCoordination	Expertise in management and coordination	Qualitatively assessable	Risk
10	IdentityOfOwner	Identity of owner	Categorical data with implied logical relationship	Competition
11	LowBidMarkup	Low bid markup	Numerical	—
12	ProjectPublicExposurePrestige	Project public exposure and prestige	Qualitatively assessable	Competition
13	ProjectTimeScalePenaltyForNonCompletion	Project timescale and penalty for noncompletion	Qualitatively assessable	Competition and risk
14	SafetyHazards	Safety hazards	Qualitatively assessable	Competition
15	SimilarExperience	Similar experience	Qualitatively assessable	Risk
16	SizeOfProject	Size of project	Quantitatively measurable	Competition
17	TimeAllowedForBidPreparation	Time allowed for bid preparation	Qualitatively assessable	Competition
18	TypeOfContract	Type of contract	Categorical data with no logical relationship	—
19	TypeOfProject	Type of project	Categorical data with no logical relationship	—

TABLE 5. Attributes of Subclasses

ID (1)	Attribute name (2)	Definition (3)	Domain value data type (4)	Reasoning goals focused on (5)
		(a) Subclass "UnitRateContract"		
1	BidMethod	Bid method	Categorical data with no logical relationship	Competition
2	CompletenessOfDrawingSpecification	Completeness of drawing and specification	Qualitatively assessable	Risk
3	DelayShortageOnPayment	Delay or shortage on payment	Qualitatively assessable	Risk
		(b) Subclass "LumpSumContract"		
4	CashFlowRequirement	Cash flow requirement	Qualitatively assessable	Competition
5	CompletenessOfDrawingSpecification	Completeness of drawing and specification	Qualitatively assessable	Risk
6	ResourcePriceFluctuation	Resource price fluctuation	Qualitatively assessable	Risk
		(c) Subclass "DesignBuildContract"		
7	AdequacyOfResourcePriceInformation	Adequacy of resource market price information	Qualitatively assessable	Risk
8	AvailabilityOfQualifiedStaffs	Availability of qualified staffs	Qualitatively assessable	Competition
9	BidMethod	Bid method	Categorical data with no logical relationship	Competition
10	CurrentWorkLoadInBidPreparation	Current work load in bid preparation	Qualitatively assessable	Risk
11	TimeAllowedForBidPreparation	Time allowed for bid preparation	Qualitatively assessable	Risk

"BidResult" (with binary-type domain value) provides the necessary filter for this distinction.

CASE RETRIEVAL

Similar cases are retrieved from the case base on the basis of similarity value. The similarity value ranges from 0 to 1; a similarity value of 1 means exact matching and 0 means totally different. Its value is determined based on the local similarity value and importance weights of each attribute.

For attributes with data domain characterized by discrete values with no implied logical relationship, the local similarity value is either 1 when the two values are identical or 0, otherwise. If there is some implied logical relationship between data elements of the attribute's domain or the attribute can be qualitatively or quantitatively assessable, the local similarity value depends on the positions where the data value of the two cases appear in the taxonomy abstraction tree. The nearer the common index node they share, the closer they are and the higher the similarity value will be between them. For example, in Fig. 4, "Private owner with bad reputation" is very close to the value "Private owner with normal reputation" because they share the common index node "Unfavorable private owner" which is only one level away. The similarity value between "Private owner with bad reputation" and "Private owner with good reputation" is smaller since the common index node they share is two levels away.

The importance weights adopted in the study are the normalized weights depicted in Tables 2 and 3 for competition and risk, respectively. These weights can also be defined by contractor's experience, if available. Nevertheless, the global similarity value is determined as the sum of the product of the local similarity value and importance weights of all the attri-

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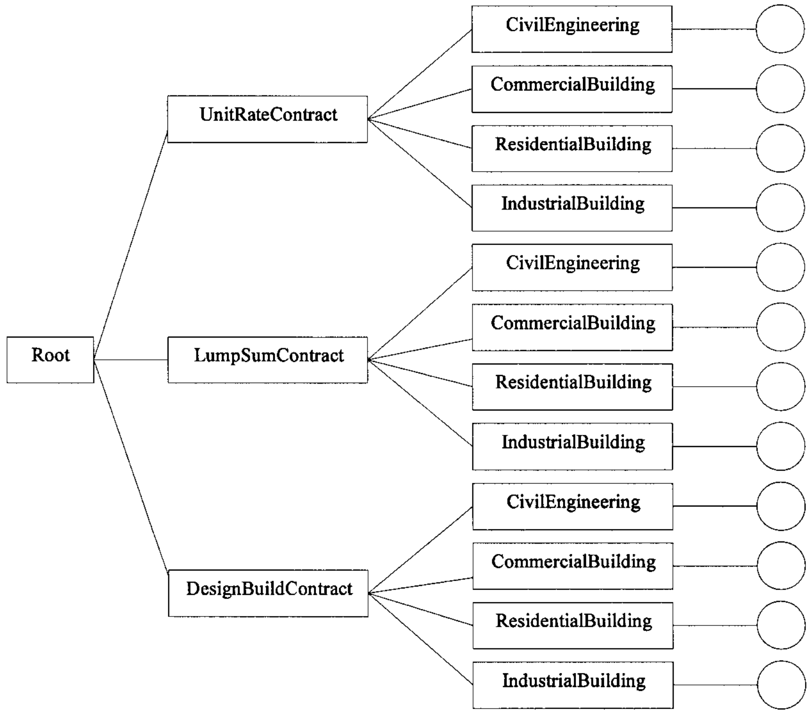

FIG. 7. Indexing Tree (Focusing on Competition)

TABLE 6. Design for Test Scenarios

Designed New Cases			
High-competition case (1)	Low-competition case (2)	High-risk case (3)	Low-risk case (4)
Select high value for attributes positively contributing to competition. Select low value for attributes negatively contributing to competition.	Select high value for attributes negatively contributing to competition. Select low value for attributes positively contributing to competition.	Select high value for attributes positively contributing to risk. Select low value for attributes negatively contributing to risk.	Select high value for attributes negatively contributing to risk. Select low value for attributes positively contributing to risk.

butes corresponding to the respective subgoals. In this way, two sets of similar cases will be retrieved. One set is focused on the subgoal of competition and the other on the subgoal of risk, providing the decision maker with the past experience to reason about the two subgoals in the present situation.

BID MARKUP OPTIMIZATION

In general, markup can be optimized under the criterion of expected profit maximization using two methods. The first method has been adopted by most bidding models [e.g., Friedman (1956) and Gates (1967). The optimal markup value was derived from the probability distribution of competitors' bid markups. On the other hand, the second method adopted by researchers such as Hansmann and Rivett (1959), Ackoff and Sasieni (1968), and Broemser (1968), optimizes the markup value based on the probability distribution of the low bid markup. CASEBID adopts the latter method to evaluate the probability of winning and optimizes the markup value.

Based on the retrieved cases for competition, a histogram of ''LowBidMarkup'' can be constructed. It is not difficult to determine the accumulative probability distribution of the winning chance (P_{wi}) for any given markup value (M_i)

$$P_{wi} = \frac{\xi_i}{\xi} \quad (1)$$

where ξ = total number of cases retrieved; and ξ_i = number of cases with the winning bid markups higher than M_i.

Assuming no bidding cost, the expected profit for any given markup value M_i can then be computed as

$$EP_i = P_{wi} \cdot (M_i - m_c) \quad (2)$$

where EP_i = expected profit at markup level M_i; and m_c = mean value of ''C/C_e'' from the retrieved cases for risk. The expression can be easily adjusted to account for bidding cost. The markup level corresponding to the maximum expected profit is the optimal markup value M_{opt}.

After adaptation the decision maker can review the proposed solution by recalling from the case library the case(s) with the most similar bid markup. He can compare the attributes of the retrieved case(s) with the new case to verify that the proposed solution is adequate for the current situation. If necessary, similar cases with respect to any attribute of the new case can be retrieved so that the decision maker can make heuristic adjustments to the system-proposed optimal markup. Furthermore, a distribution of past competitors in similar past bids can be built from ''Identity.'' If necessary, the ''LowBidMarkup'' of the likely competitors can be retrieved to assist in further adaptation.

ILLUSTRATIVE EXAMPLE

Several sets of hypothetical cases were created in the case library to demonstrate the feasibility of the proposed system. Some attributes were considered to contribute positively while others negatively to the bidding results. The relationships had been verified by an experienced bidding expert and found to be acceptable. The hypothetical cases were created with the above assumed relationships. In this way, each node in the indexing tree for the same contract and project type was pop-

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ulated with over 30 cases. Moreover, four new test cases were designed to simulate four possible scenarios, namely: (1) high-competition case; (2) low-competition case; (3) high-risk case; and (4) low-risk case. The design of these test cases are governed by the principles shown in Table 6.

Determining Optimal Markup

In deriving the optimal markup, the level of competition is first assessed. Altogether, the top 10 similar cases were retrieved for each test scenario. Fig. 8 shows the histograms of the low bid markups of the similar cases retrieved for the high-competition and low-competition test scenarios, respectively. The low bid markup distribution of the retrieved cases tends to be on the lower side for the relatively high-competition scenario than that for the low-competition scenario. The results conform with the assumptions made when building the example world represented by the hypothetical cases. It also agrees with what would be expected in practice since generally contractors would lower their markup margin when they expect keen competition. The normal distributions based on the means and standard deviations of the histograms are also depicted in the figure. Fig. 8 shows the corresponding probability of winning a bid P_{wi} for a given markup M_i.

The level of risk is assessed from the cost variation ratio C/C_e of the similar cases. Fig. 9 shows the histograms of C/C_e

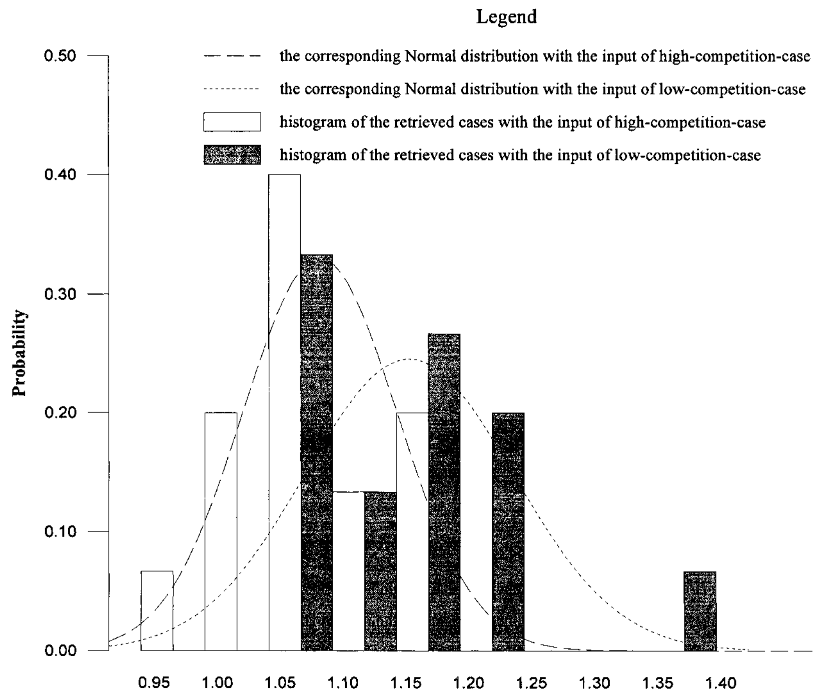

FIG. 8. Cases Retrieved with Different Inputs Focusing on Concept "Competition"

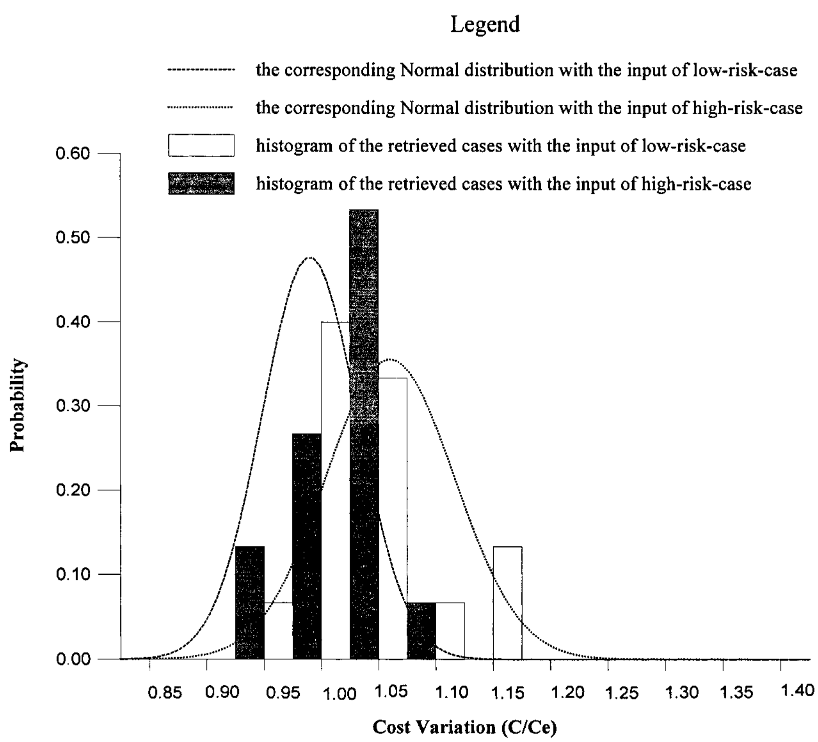

FIG. 9. Cases Retrieved with Different Inputs Focusing on Concept "Risk"

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of the top 10 similar cases for the high-risk and low-risk scenario, respectively. The C/C_e probability distribution of the retrieved cases for the low-risk scenario tends to have a lower mean with a smaller dispersion when compared with the high-risk scenario which can be expected in practice. The results again show a trend that agrees with the assumptions used in establishing the hypothetical cases. The model is thus able to retrieve the appropriate similar cases for different bidding situations, albeit in an example world. The global similarity value ranges from about 0.7 to 0.9 for the 10 most similar cases in each of the test scenarios. The lowest similarity value is about 0.4.

The expected profit for any given markup can then be computed according to (2) from Fig. 9 and the mean values of the retrieved C/C_e. Fig. 10 shows the expected profits for the four test situations. As can be expected, the expected profits in the case of low competition and low-risk situations are considerably higher than those corresponding to the higher competition and risk situations. For a given markup level the probability of winning P_{wi} is higher in the former situations. Although the suggested markup level in each situation is the one at which the expected profit is maximized, there is a broader range of markup levels that may be applicable so that further adaptation as suggested earlier is plausible.

Effectiveness Test using Monte Carlo Simulation

A Monte Carlo experiment was conducted to test the effectiveness of CASEBID. One set of 30 cases of the same type of project and contract was taken as the sample for the experiment. In each iteration, one case was randomly selected to be the outcome for a new bid situation. Using CASEBID, the levels of competition and risk were assessed and the optimized markup for maximum expected profit determined. If the derived markup value was less than the bid markup for the new case (the low bid markup in the new case is based on the same estimated construction cost of the contractor), the contractor was considered to have won the job. Altogether, 100 iterations were made and the results are shown in Fig. 11. In summary, there were 55 wins yielding, on the average, 7.4% expected profit.

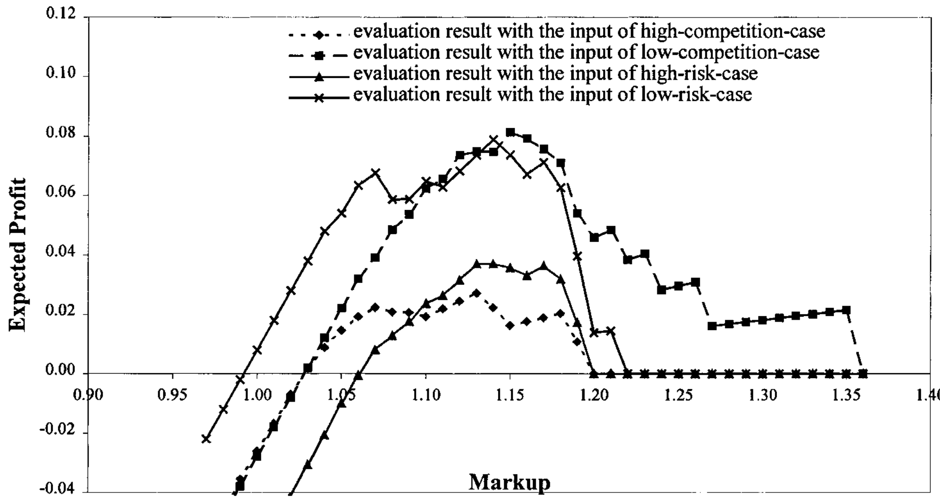

FIG. 10. Markup Optimization Based on Four Different Retrievals

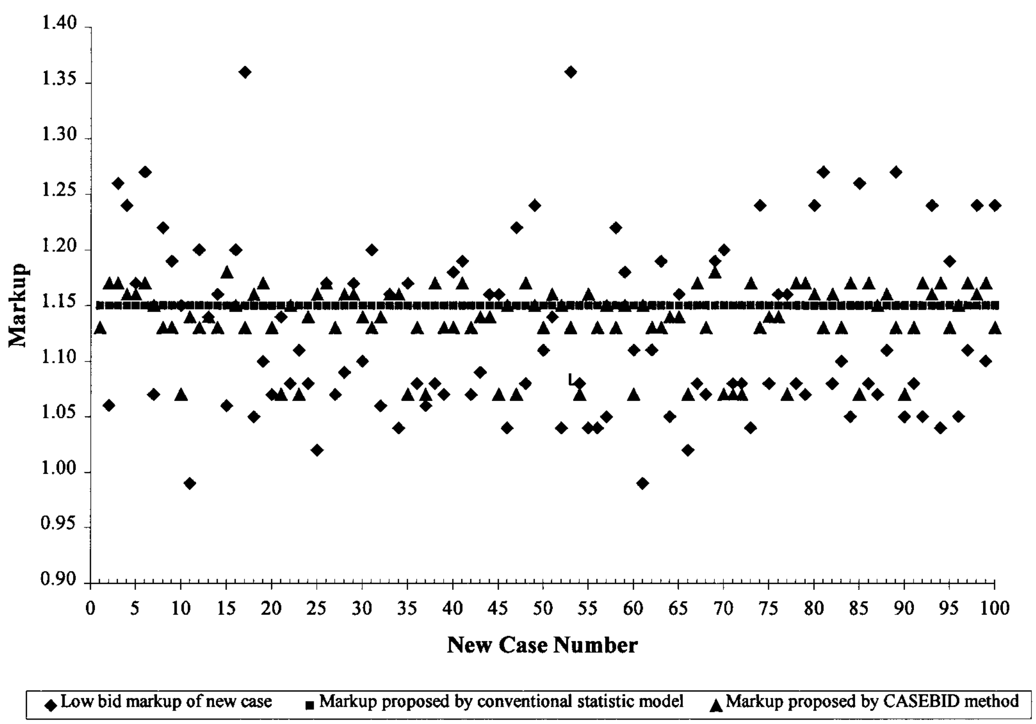

FIG. 11. Results of Monte Carlo Simulation

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In the conventional statistical bidding approach, the entire set of 30 cases was used to compute the optimal markup level. Regardless of which case was selected in the iterations, the set of record remained static so that the same optimal markup value of 15% was obtained. Using the static set of data, there were only 41 wins yielding an average 6.15% expected profit, which is far less than that produced using CASEBID. Although this has been verified for only a single set of data, the same trend should be achievable elsewhere, since using case-based reasoning, a more suitable set of cases was retrieved for the markup decision.

CONCLUSION

As far as highly unstructured bidding problems are concerned, the proposed CBR bidding system, CASEBID, has certain obvious advantages over the other bidding systems. It has been admitted that, in practice, humans resolve such unstructured problems primarily based on their experience with similar previous cases. CBR systems augment the memory of humans by recalling similar situations. The decision is then resolved by adapting the past solutions found in the recalled situations to suit the new situation.

Comparing with traditional expert systems, CASEBID draws its knowledge from both the general domain knowledge and the lessons that concrete cases provided. Essentially, CASEBID approaches the bidding problem by assessing the level of competition and risk from past similar cases to arrive at the optimal markup. It does not have to rely on well-formulated rules that are nonexistent or intractable in the bidding problem. On the other hand, CASEBID avoids the ''black box'' nature that is characteristic of neural network systems. The user reviews the suggested markup level, makes comparisons with other similar cases, and makes heuristic adjustments over the markup level, if necessary. He can also draw on likely competitor's bidding profiles to make further adaptation.

This paper has described the framework for CASEBID. An example has also been presented to demonstrate the feasibility of the system. Using Monte Carlo simulation, CASEBID has been shown to outperform the conventional statistical approach. It posed 55% bid wins, yielding an average 7.4% expected profit compared to 41% bid wins, yielding an average 6.15% expected profit in the case of the latter approach.

It must be pointed out, however, that the main problem with this system might be the collection of cases. The system must ensure enough numbers of cases in the case library for the statistical processing. Since the jobs for one company will usually fall into only a few categories, the problem should be resolved with the passage of time.

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