A review of the artificial intelligence applications in construction dispute resolution

D. Ilter & A. Dikbas
Istanbul Technical University, Istanbul, Turkey

ABSTRACT: It is generally acknowledged that construction disputes are inevitable, highly complicated and may become destructive in construction projects. Artificial Intelligence (AI) applications have been developed recently with the aim of facilitating dispute resolution processes in construction as AI have become more specialized. In this paper, contemporary AI applications in construction dispute resolution field are analyzed and categorized into three groups as settlement oriented systems, method selection oriented systems and dispute evaluation oriented systems, reviewing the tools used in each category so far. This analysis is expected to contribute to the further development of the subject, by providing a holistic perspective and determining the trends and neglected areas in the field.

1 INTRODUCTION

Almost all researchers in the field of dispute resolution agree that disputes are inevitable and may become destructive in the construction projects. Ellis & Baiden (2008) state that disputes between project participants have been identified as the principal causes of poor performance in construction projects and that disputes very often lead to prolonged delays in implementation, interruptions and sometimes suspensions. This poses a serious risk for all parties to a construction project if the disputes are not resolved before going to a court since litigation is a long, expensive and acrimonious process.

In order to avoid litigation in dispute resolution, a range of Alternative Dispute Resolution (ADR) methods are widely used in the construction industry and have become an important issue of construction research and literature in the last decades (Ilter et al., 2007). ADR is a non-adversarial technique which is aimed at resolving disputes without resorting to the traditional forms of either litigation or arbitration (Ashworth 2005). According to Katsh & Rifkin (2001), the trend toward non-legalistic systems of settling dispute is pushing ADR methods to the foreground and litigation into the background. The use of Artificial Intelligence (AI) in dispute resolution is extending this trend at the double, by contributing to a more efficient use of ADR methods.

AI is defined as the study and design of intelligent agents, where an intelligent agent is a system that perceives its environment and takes actions which maximizes its chances of success (Russell & Norvig, 2003). McCarthy (1955) who coined the term for the first time, defines AI as the science and engineering of making intelligent machines. In the last decade, AI research has become highly specialized and today applications of AI can be seen in diversified fields including medical diagnosis, stock trading, law, military, web search engines, entertainment and many more.

In this paper, AI applications in construction dispute resolution are analyzed and categorized, reviewing the tools used in each category. This analysis is expected to contribute to the further development of AI applications in dispute resolution, by providing a holistic perspective and determining the trends and neglected areas in the field.

2 ARTIFICIAL INTELLIGENCE

Coppin (2004) defines AI as the study of systems that act in a way that to any observer would appear to be intelligent. AI involves using tools based on the intelligent behavior of humans and other animals to solve complex problems.

According to Nilsson (2002), AI is concerned with intelligent behavior in artifacts, which involves perception, reasoning, learning, communicating and acting in complex environments. Ultimate goal of AI is generally perceived as the development of machines that can do what humans can, or possibly even better. Another goal of AI can be defined as understanding this kind of behavior whether it occurs in machines or in humans. Thus, AI has both scientific and engineering goals.

The wide range of the applications required further categorizations of AI. The problems of AI have been divided into subgroups such as deduction, reasoning, problem-solving, knowledge representation, planning, learning, natural language processing, motion and manipulation, perception, social intelligence, creativity and general intelligence. Approaches to AI, on the other hand, have been grouped as cybernetics and brain simulation, cognitive simulation, logical AI, symbolic AI, knowledge based AI, sub-symbolic AI and statistical AI. However, because of the diversified applications of AI, these sub-groups are still to general.

There are diversified tools used in AI research as well. The most frequently used tools in AI are search and optimization, propositional logic, first-order logic, fuzzy logic, default logics, case-based reasoning, probabilistic methods for uncertain reasoning, classifiers and learning methods, neural networks and genetic algorithms. These tools at the same time constitute the methods used in the applications and determine the approach to the problem at hand.

3 AI APPLICATIONS IN DISPUTE RESOLUTION

Notwithstanding the trend of applying AI techniques in construction, the use of AI in construction dispute resolution has not attracted too great attention despite the fact that dispute resolution is an important component of project management. (Cheung et al., 2004). As a result of his comprehensive literature review, Chau (2007) also found that AI techniques are not common and are rarely applied in legal field.

After an analysis of the aims and methodologies used, existing research on AI applications in construction dispute resolution were classified into three groups by the authors. These are:

1. Settlement oriented systems which generally deal with negotiation support
2. Method selection oriented systems which generally deal with selection of the appropriate dispute resolution method
3. Dispute evaluation oriented systems which generally deal with identifying the causes of construction dispute, the likelihood of occurrence or the impact of the dispute

Below, is the brief explanations and the reviews of applications in each category.

3.1 *Settlement Oriented Systems*

Settlement oriented systems usually focus on negotiation support. In recent years, negotiations are regarded as effective means of resolving disputes among parties (Han & Feng, 2005). Negotiations are a special class of group decision making problems that can be formulated as constrained optimization problems and are characterized by high degrees of conflict among the negotiation participants. A variety of negotiation support techniques have been used to help find solutions acceptable to all parties in a negotiation (Montano & Malaga, 2002). With the development of computer technologies, many negotiation support systems are developed. Current research in developing negotiation support systems generally uses AI applications.

The traditional approach, developed by Raiffa (1982), towards providing negotiation decision support has been to use game theory. Jennings et al. (2001) claimed that negotiation theory fits very well with many different approaches such as AI, social psychology, game theory and there is no universally best technique for negotiation decision support, given the wide variety of possibilities. However, Bellucci et al (2004) argued that there usually is a best technique in terms of properties and performance characteristics depending on the negotiation context.

Over the past decade, many systems have been developed which use AI techniques to provide decision support to negotiators. The earliest negotiation support system that used AI was LDS, developed by Waterman & Peterson (1980), which assisted legal experts in settling product liability cases. SAL, developed by Waterman et al (1986), helped insurance claims adjusters evaluate claims. These two systems represented the first steps in recognizing the virtue of settlement oriented decision support systems.

Today, strategies in negotiation support range from the use of AI tools, such as artificial neural networks (ANN), Genetic Algorithms (GA), case-based reasoning (CBR), fuzzy theory and other knowledge-based approaches to mathematical approaches encompassing game theory (GT) and other axiomatic approaches, as well as Multi Criteria Decision Making (MCDM).

GA, is based on the genetics theory and is useful if the decision variables can be encoded as strings of a chromosome, where each chromosome represents one of the possible solutions (Cheung at al., 2004). With an objective function to minimize or maximize a performance measure, GA works on an initial population consisting of solution candidates to derive the optimal solution by combining discrete options into many packages. It takes criteria (as given by users) and forms new solutions by introducing statistical theory, in particular combinatorial probability theory. Bellucci & Zeleznikow (1998) was the first to suggest that GA can limit the search space and hence maybe useful when building a negotiation support system.

Montano & Malaga (2002) developed an approach that employs GA for finding acceptable solutions for multiparty multi-objective negotiations. This approach is consistent with the complex nature of real world negotiations and therefore capable of addressing more realistic negotiation scenarios than other techniques. In addition to the traditional genetic operators of reproduction, cross-over and mutation, the search is enhanced with a new operator called trade, which stimulate concessions that might be made by parties during the negotiation process.

Bellucci & Zeleznikow (2001) integrated game theory (GT) and AI to advise upon structuring the mediation process and advising disputants upon possible trade offs. Lodder (1999) developed argumentation tools that support disputants to communicate about their conflict. The negotiation systems of Bellucci & Zeleznikow (2001) did not facilitate discussion, whereas the dialogue tools of Lodder (1999) did not suggest solutions. Therefore, Bellucci et al (2004) combined the dialogical reasoning of Lodder (1999) within the game theory based negotiation techniques of Bellucci & Zelenikow (2001), and constructed an ODR environment. In this environment, if the advice suggested by the negotiation support system is acceptable to the parties, then the dispute is resolved. Otherwise, the parties agree to those issues resolved through the use of the negotiation support system and then return the remaining issues in dispute to the dialogue system. This process continues until either all issues are resolved or a stalemate is reached. A stalemate occurs when no further issues are resolve on moving from the argumentation tool to the negotiation support system or vice versa (Bellucci et al, 2004). The following scenarios are reported to arise through the use of this system: (1) No issues are resolved after the use of either the argumentation tool or the negotiation support system and total failure is reported. (2) Some issues are resolved, but a stalemate occurs. One of the two scenarios then occur (a) Either the parties do not agree to accept the partial resolution of the issues resolved during the process and no progress is reported. (b) The parties agree to some or all of the issues resolved during the process and partial success is reported. (3) The dispute is resolved and success is reported.

Another AI tool used in negotiation support systems is CBR. CBR is one of most commonly used artificial intelligence techniques in recent years. In a typical CBR system, the problems will be presented by a user-interface or another program. The system will then search its case library and find a list of cases which are of greatest similarity with the presented case. The selected cases are listed in descending order of similarity scores. When a new case is input, the CBR system will retrieve the appropriate case in the case library. The CBR system will then use the information of the retrieved cases and suggest a way to solve the presented case. This reasoning generally involves both determining the differences between the retrieved cases and the current query case; and modifying the retrieved solution appropriately, reflecting their differences. Unless the retrieved case is a close match, the solution will probably have to be revised. Therefore, a confirmed solution will be produced and become a new case and that can be retained in the case library (Cheung et al., 2004).

CBR have been adopted firstly in the settlement oriented systems. Two of the early CBR systems that have been developed in the area of conflict resolution are the MEDIATOR (Kolodner & Simpson, 1989) and PERSUADER (Sycara, 1990). The MEDIATOR was developed to provide common-sense advice in conflict situations involving resource disputes. The PERSUADER was developed as a mediator in labor negotiations. Both the MEDIATOR and the PERSUADER were developed to resolve conflicts within a limited problem domain.

Han & Feng (2005) developed a more comprehensive negotiation support system based on CBR. This system regards the information and computer technology as the means and uses decision and behavior theories. The improved nearest neighbor method is adopted in case retrieval, where all attributes of negotiation case are classified so that the retrieved case is more similar to current negotiation. Traditional negotiation support systems were, on the other hand, only confined to use the linear programming, the utility function, the partiality of interest, the exponent algorithm or AHP for modeling negotiation.

3.2 *Method Selection Oriented Systems*

Selecting a dispute resolution process is the first step to resolve a dispute and this is a very important decision because of the resource implications. There are successful applications of Multi-Criteria Decision Making (MCDM), cost based methods and the game theory in the problem of appropriate dispute resolution method selection. However, Cheung et al. (2004) suggested that the AI technique of CBR which draws information based on past cases may also fit nicely with this type of selection problem and developed CDRe (Case-Based Reasoning approach to Construction Dispute Resolution). CDRe seeks to provide a systematic method to assist construction professionals in dispute resolution method selection. In order to achieve the aforementioned objective, Cheung et al. (2004) first conducted a review of literature to identify the critical selection parameters. Project data sets were then collected for the case library. As a result, a total of 57 cases were collected, out of which 48 cases were used for model development and 9 cases were used for testing purposes. CDRe achieved seventy seven percent prediction accuracy for the testing set.

3.3 *Dispute Evaluation Oriented Systems*

Research on construction dispute resolution tend to focus on the identification of factors affecting the success of a resolution process. However, selection of an appropriate dispute resolution method is only possible if a dispute is thoroughly evaluated. Evaluation of a dispute involves identifying the causes of construction dispute, the likelihood of occurrence and the impact of the dispute. The likelihood and impact of dispute could be expressed in numerical terms through probabilistic analysis or mathematical models. However, project managers prefer interpreting the likelihood and impact of disputes in linguistic terms due to the natural way of human thinking and representation (Cheung et al., 2001).

This situation constitutes a suitable environment for the application of another AI tool, the fuzzy sets theory. According to Asai & Aschmann (1995), the fuzzy reasoning can be used for the identification of fuzzy relations between input and output, composition of output (decision) from input and the inverse operation to determine the input from the output.

The fuzzy construction dispute evaluation model developed by (Cheung et al., 2001) mainly focuses on composition and inverse operation functions. The relation of the fuzzy construction dispute evaluation model was devised by setting up a fuzzy algorithm for storing human experience, opinions and linguistic variables. The model consists of four components; dispute identification, dispute analysis, dispute evaluation and dispute control. Dispute identification is the input of the model, where causes of disputes and the characteristics of the project are evaluated based on twelve variables. The data entered into the system is then processed in dispute analysis part where the likelihood of occurrence and the impact of disputes is computed. The linguistic project characteristic information together with the results generated by the dispute analysis component forms a basis for the model. Through the fuzzy transformation, the model provides the users with the results of the dispute evaluation. Using the fuzzy sets theory allows the use of vague and linguistic information, which is normally inherent in the model.

CBR systems have also been developed to provide real time feedback to assist in the structuring and modeling of a dispute situation. Ross et al. (2002) developed a CBR system, GMCRCBR, for dispute situations that will integrate with existing analytical tools. This CBR system addresses a need to store dispute cases in a standardized format and to be able to retrieve this data in an efficient manner. This CBR system can also be utilized to help speed up the modeling process by filling in missing information for a dispute situation by retrieving information from similar archived cases. The issues such as case representation, case storage, case retrieval, and case reuse are considered. A large number of real-world disputes are documented and analyzed in GMCRCBR.

CBR utilizes the specific case information available as historical precedence for proposing solutions to current problems. The most important aspects of the existing cases are first stored and indexed. New dispute situations are then presented and similar, existing cases are identified from the knowledge base. Finally, the previous problem situations are adapted and the revised solutions are proposed for the current situation (Ross et al., 2002).

ANN is another AI technique used by Cheung et al., (2000) in developing dispute evaluation oriented systems. ANN is an adaptable system that can learn relationships through repeated presentation of data and is capable of generalizing to new and previously unseen data. It discovers relationships in the input data sets through iterative presentation of the data and the intrinsic mapping characteristics of neural topologies. ANN is highly distributed interconnections of adaptive nonlinear processing elements. The connection strengths, also called the network weights, can be adapted so that the network's output matches a desired response. Unlike more analytically based information processing tools, neural computation explores the information contained within input data, without further assumptions. ANN is used for both regression and classification. In regression, the outputs represent some desired, continuously valued transformation of the input patterns. In classification, the objective is to assign the input patterns to one of several categories or classes, usually represented by outputs restricted to lie in the range from 0 to 1, so that they present the probability of class membership. ANN is regarded as convenient and relatively easy to use as there are less modeling constraints. However, its major disadvantage is the lack of explanation or justification of the suggested solution (Cheung et al., 2000).

Chau (2007) suggested that ANN can be used to identify the hidden relationships among various interrelated factors and to predict decisions that will be made by the court, based on characteristics of cases and the corresponding past court decisions. A precise prediction of possible litigation outcomes would effectively help to significantly reduce the number of disputes that would need to be settled by the much more expensive litigation process. As a result, Chau (2007) presented a particle swarm optimization (PSO)-based neural network approach for prediction of the outcome of construction litigation, based on court decisions in the last 10 years. A key contribution of the presented research and the unique work done by the author is the adoption of the PSO-based AI techniques tailoring for the prediction of construction litigation outcomes, which is a field where new technological aids are rarely applied.

4 SYNTHESIS

Table 1. Categorization and tools used in AI applications.

Category	CBR	ANN	GA	FL	AI & GT
SOS	×		×		×
MSOS	×				
DEOS	×	×		×	

Table 1 shows the use of AI tools (Case-based reasoning, artificial neural networks, genetic algorithm, fuzzy logic and artificial intelligence integrated with game theory) in the categories defined by the authors, namely settlement oriented systems (SOS), method selection oriented systems (MSOS) and dispute evaluation oriented systems (DEOS). It can be seen that CBR is the most widely used AI tool with applications in all categories. GA and AI & GA is used in settlement oriented systems, whereas ANN and FL is used in dispute evaluation oriented systems. On the other hand, CBR is the only AI tool used in method selection oriented systems.

Settlement oriented systems are the oldest and most widespread applications of AI in construction dispute resolution. Research in this category began as early as 1980s and CBR, GA, AI & GT as well as some hybrid tools have been used in the applications developed.

Only very recently a research based on CBR (CDRe) is undertaken in method selection oriented systems category. CDRe works by comparing the dispute at hand with the disputes in the case library (a database) and proposes a dispute resolution method to the user based on this comparison. However, this comparison is made based on only eleven criteria. It is possible that inadequate number of criteria and the impossibility of assigning weights to this criteria may render the results obtained imprecise. Further research is needed for the development of AI applications in dispute resolution method selection.

CBR, ANN and fuzzy logic tools have been used in the applications developed in the dispute evaluation oriented sytems category. Among these, the possibility of dealing with the linguistic terms may render fuzzy logic a stronger alternative since project managers prefer interpreting the likelihood and impact of disputes in linguistic terms due to the natural way of human thinking and representation.

5 CONLUSION

AI research has become highly specialized and today, applications of AI can be seen in construction dispute resolution as well as many other areas. Although these applications are quite new and regarded as rare by many researchers, AI has already contributed to the field as more efficient use of ADR methods, more systematic approaches to dispute resolution method selection and more analytic appraisal of claims and disputes.

In this paper, the research on AI applications in construction dispute resolution was analyzed and categorized into three groups as settlement oriented systems, method selection oriented systems and dispute evaluation oriented systems, reviewing the tools used in each category so far.

The findings reveal that case-based reasoning (CBR), artificial neural networks (ANN), genetic algorithm (GA), fuzzy logic (FL) and AI integrated with game theory (AI & GT) are the most frequent AI tools used in the applications in construction dispute resolution field. Another noteworthy finding is the low number of AI applications developed in the method selection oriented systems category, compared to the diversified applications in settlement oriented systems category. It is also interesting that CBR is the most widespread AI tool with applications in all three of the categories.

Today, successful contract management and dispute resolution requires the use of accumulated knowledge and experience of dispute cases. Therefore, building adequate claim and dispute libraries may be one of the most important goals to be achieved through AI applications in the field. The widespread application of CBR tool constitutes a promising platform in achieving this goal.

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