A Decision Support System for Market Mechanism Choice in e-Procurement

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1. Introduction

Since the rise of the Internet electronic markets have become an important component of e-procurement by bringing together demand and supply. E-markets are meeting venues for component suppliers and purchasers, who use exchange mechanisms to electronically support the procurement process. Exchange mechanisms can be conceived as market institutions providing sets of rules, which determine the functioning of the market and the permissible actions such as bidding deadlines, non-disclosure rules or bid-revocation constraints. In nowadays procurement landscape, mechanisms vary from electronic procurement catalogues, where requests and offers are publicly announced, to e-negotiations[1], where the participants bargain over the conditions of a trade using electronic message exchange and / or decision support platforms, to auctions, where one or two sides automate the process during which participants from the other side compete against each other (Kersten, Neumann, Vahidov, & Chen, 2006). The variety of procurement solutions already suggests that there is no single best solution for all imaginable sourcing activities. Instead, some mechanisms like e.g. an auction might be advantageous in certain situations while others are not (and vice versa).

In this paper we present a knowledge-based system (KMS) aimed at supporting procurement staff in their decision making on which mechanism to choose best for a specific sourcing scenario.

The remainder of this paper is organized as follows: In Section 2 we describe the acquisition and storage of mechanism and procurement knowledge. Section 3 explains the system design and implementation of the KMS before we conclude this paper with a summary and an outlook.

2. Knowledge Acquisition and Storage

As with all knowledge based systems, the most crucial task is the acquisition, adaptation, verification and maintenance of the underlying knowledge base. Especially challenging in this context is the fact that theoretical literature on mechanism design could be a possible source for providing knowledge on which procurement mechanism to choose (Bichler, 2001; Hurwicz, 1973; Krishna, 1997; Maskin, 1989), as can be empirical literature (Beall, 2003; Jap, 2002; Millet, 2004), structured interviews e.g. with procurement experts from industry, or even common sense.

For the acquisition of knowledge we followed a twofold approach: On the one hand we took recommendations from existing literature, identified their respective prerequisites, condensed them into a parametric format and stored them into the knowledge base. On the other hand we conducted interviews with procurement experts from several different industries trying to confirm that the findings from literature are in line with business practice in nowadays industry sourcing. In the latter case a specific feature of the knowledge base became especially valuable

[1] Procurement negotiations are oftentimes called RFQ (Request for Quotations).

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when storing the results into KMS: In some cases, experts were unable to give a definite recommendation on which mechanism to choose while they were quite clear on which mechanism not to choose. E.g. in a case where strong bidder asymmetries occur, it is easy to predict that an English auction will lead to an outcome that is more favorable for the supplier than for the buyer, while it is not clear if e.g. a Dutch auction or an electronic negotiation might be the more favorable alternatives instead. In such a case a procurement officer on the buyer side might still receive a warning or a hint that an English auction will lead to an outcome that is more expensive and thus potentially undesirable for him than alternative procurement mechanisms like e.g. a Dutch auction. Thus, though it might not be possible to give a definite mechanism recommendation in this case, at least the awareness of the respective KMS user on potential pitfalls in mechanism choice could be increased.

3. System Design and Implementation

For the implementation of a knowledge based system several different approaches are known from literature. The first group of mechanisms rely on rule engines that basically store knowledge in IF…THEN conditions. In this area RETE (Forgy, 1982) is still the reference algorithm for matching many patterns on many objects. Many alternatives have been proposed since then, the most notable ones being TREAT (Miranker, 1987) and LEAPS (Batory, 1994) but the main problem with this group of algorithms is of a technical nature: Existing implementations of these rule engines rely on proprietary storage formats for the rules (and thus for the knowledge) that do not cope well with traditional DBMS. To the author's knowledge only one (quite complex) approach exist that adapts the RETE algorithm to directly work on a database (Jin et al., 2005).

For our system a database for storage and retrieval of recommendations was more advantageous as it provides a convenient way to store verbal recommendations along with structured information and allows easy manipulation of the stored data. Thus we adapted an alternative approach for the knowledge storage and the recommendation retrieval which stems from the research on recommender-systems. In this area, case-based reasoning is oftentimes used to compute similarities between a new case and existing (historic) cases (Chi, 1991; Porter, 1993).

We implemented[2] a case-based reasoning algorithm that compares a new case (i.e. a parametric recommendation request from a user) to cases (i.e. previously entered recommendations) already stored in KMS. This approach reduces the task of finding a suitable mechanism recommendation to comparing parameter lists with each other and returning the results if the number of matches between the list elements exceeds a certain predefined threshold value.

The parameter list in Figure 1 could have been entered e.g. by a procurement officer via a graphical user interface to KMS. It consists of parameters that describe the procurement situation the officer seeks advice for. The second list (Figure 2) represents part of the "knowledge" stored in KMS. It contains parameters from the same parameter domain as the first list but in this case the parameters can be seen as prerequisites that must be fulfilled for the attached recommendation to be valid.

For the recommendation retrieval itself, the input parameter list is compared to all recommendation prerequisite lists stored in the KMS. In each comparison cycle the similarity between all list items from both compared lists is computed on a per attribute basis. If an attribute is found in the input parameter list but not in the respective recommendation

[2] An online demo is available on http://www.anegom.de

prerequisite list, the parameter is counted as a *relaxation*. If, on the other hand, a parameter is only found in the recommendation prerequisite list, it is counted as *restriction* as the parameter was not specified by the user but is required for the recommendation to be valid.

If a parameter is found in both lists, the similarity between both parameter values will be computed. If this similarity exceeds a predefined threshold, the parameter will be counted as a "matching parameter", otherwise it will be discarded as "non-matching". After having finished all comparisons between the lists, three measures are available indicating the overall matching quality of a recommendation: *No. of restrictions*, *No. of relaxations*, and *matching quality* (no. of matching parameters / total no. of parameters matched).

A recommendation is then returned to the user if (a) its matching quality exceeds a predefined threshold, (b) the number of restrictions does not exceed a predefined threshold, and (c) none of the "restriction" parameter was marked as a "knock-out" criterion. For convenience, the results are sorted by matching quality in descending order. The number of relaxations and the number of restrictions are also displayed to the user as further indicators.

Input Parameter List		
Name	Value	Type
Objective	Reduce buy price	String
Current Process	Manual orders	String
Prod. Type	Good	String
Prod. LC	Commodity	String
Prod. Quantity	100.000	Integer
# Negotiable Attributes	1	Integer
# Sellers	10	Integer
# qualified Sellers	3	Integer

Figure 1: Input Parameter List

Recommendation Prerequisite List

Recommendation Prerequisite List

Recommendation Prerequisite List			
Name	**Predicate**	**Value**	**Type**
Objective	=	Reduce buy price	String
Current Process	≠	Auctions	String
Prod. Type	=	Good	String
Prod. LC	=	Commodity	String
# Negotiable Attributes	=	1	Integer
# Sellers	near	7	Integer
Recommendation: Use English Reverse Auction			
Mechanism Parameter Name		**Value**	
Order visibility:		Best order only	
Allow Order Revocation		false	

Figure 2: Recommendation Prerequisite List

4. Conclusion and Outlook

The paper at hand proposes a decision support system for selecting procurement mechanisms. The reasoning component is realized by means of a case-based reasoning approach. In contrast to other approaches, such as (manual) mechanism design, the proposed knowledge based approach is capable of generating recommendations by combining several effects and patterns. An important feature of the implemented case based reasoning algorithm is that it can make recommendations even in cases that are hitherto not studied and where other sources are not available. A prototypical implementation servers as proof-of-concept and is available on http://www.anegom.de.

This paper is a step towards understanding the effect and strength of different procurement mechanisms in different scenarios. Contributions include the definition of an extensible default domain model and the integrated case based reasoning approach. The prototype KMS is intended to support procurement staff in their decision making on what sourcing tool to use by making reasonable recommendations.

Future research needs to further investigate possibilities for providing incentives to users to actively contribute knowledge to the system avoiding free rider phenomena known from p2p systems.

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