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A Multi-Attribute Auction Mechanism based on Conditional Constraints and Conditional Qualitative Preferences

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Abstract

Auctioning multi-dimensional items is a key challenge, which requires rigorous tools. This study proposes a multi-round, first-score, semi-sealed multi-attribute reverse auction system. A fundamental concern in multi-attribute auctions is acquiring a useful description of the buyers' individuated requirements: hard constraints and qualitative preferences. To consider real requirements, we express dependencies among attributes. Indeed, our system enables buyers eliciting conditional constraints as well as conditional preferences. However, determining the winner with diverse criteria may be very time consuming. Therefore, it is more useful for our auction to process quantitative data. A challenge here is to satisfy buyers with more facilities, and at the same time keep the auctions efficient. To meet this challenge, our system maps the qualitative preferences into a multi-criteria decision rule. It also completely automates the winner determination since it is a very difficult task for buyers to estimate quantitatively the attribute weights and define attributes value functions. Our procurement auction looks for the outcome that satisfies all the constraints and best matches the preferences. We demonstrate the feasibility and measure the time performance of the proposed system through a 10-attribute auction. Finally, we assess the user acceptance of our requirements specification and winner selection tool.

Keywords: Constraint specification, Qualitative preference specification, Winner determination, Multi-attribute and reverse auctions, Multi-Attribute Utility Theory (MAUT), Mechanism design, Multi-criteria decision making (MCDM)

1 Introduction

In this section we first highlight the benefits of reverse and multi-attribute auctions. Then we present the motivations of our research work and its valuable contributions.

1.1 Scope

Over the past decade, a considerable number of procurement departments from different domains of industry embraced online reverse auctions [8], [30], [53]. In addition, numerous providers of reverse auction services are available, including Priceline, Bidz, AuctionAnything, Freemarkets, eBreviate, FrictionLess and Procuri. Reverse e-auctions are becoming very widespread in both small and large organizations because they offer significant advantages, such as an easier access to global and qualified suppliers, a better trading and market transparency, a lower purchasing cost, access to more variety of products, and an increased efficiency [6] , [30], [44]. For instance, a survey reports that corporate buyers in reverse auctions achieved 15% in cost savings and up to 90% in time reduction of the purchasing process [48]. This latter is generally completed in three to eight hours [30]. So both buyers and suppliers will reach their needs in a shorter time. According to [45], the price of the products can be reduced by as much as 20%, and by an average of 5% to 12%. This is the major factor attracting purchasing companies to reverse auctions [45]. On the sellers' side, online reverse auctions create larger client bases, secure new businesses, lower production costs, reduce excess inventories, and improve sales [44], [53].

Nowadays, there is a great demand to process multi-attribute contracts since real-world procurement scenarios, such as in business-to-business sector, are complex and involve multiple dimensions of the items (goods or services), [29]. Multi-attribute auctions are one of the most valuable procurement mechanisms [46]. In our research work, we focus on Multi-Attribute Reverse Auctions (that we call MARAs) for single-unit procurements. MARAs allow negotiation over the price along with other attributes, e.g. warranty, quality grade, payment and delivery terms for goods; response time, security and usability for service providers. We may note that multi-unit auctions can be represented with single-unit auctions where the quantity of items is specified as an attribute [49]. It has been shown that under the assumption that the buyer's utility function and the scoring rule are the same, MARAs produce much higher profits for buyers and sellers than traditional price-only auctions because MARAs offer more bidding flexibility [7], [8]. This auction type is becoming essential in e-commerce as a large number of modern day enterprises are developing their markets using e-procurement in order to cut on costs [55]. In 2011, e-procurement market achieved $5 billion with an annual prediction rate of 8% to 12% [4].

1.2 Motivations

Auctions are the most studied economic mechanisms because they are complex and of "considerable empirical significance" [54]. In this paper, we focus on the buyer and our design goal is to optimize his expected payoff. Auction mechanisms differ in terms of preference representation (through utility functions), preference revelation (truthful or not, full or partial), state of the competition (current best bid, ranking of bids, scores of bids, etc.), allocation and payment rules, bidding strategies, bid increment, and winner determination (additive or quasi-additive aggregation models, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [5], [7], [14], [47], [54], [55]. A fundamental concern in MARAs is how to obtain a useful description of the items, especially when they are complex and multidimensional. [50] evaluates several industrial organizations and identifies conditions that are vital for the success of reverse auctions, including: a proper specification of the auctioned items, a strong competition among suppliers, and procurement of complex and strategic items. Competition pressure may motivate sellers to provide better offers.

In our work, we are interested in two types of buyer's requirements: hard constraints and qualitative preferences (soft constraints), which have not been addressed in the context of MARAs. Items may require some constraints that are useful to reduce a large set of sell bids because bid allocation may be very time consuming. In auctions, preferences are commonly represented and measured quantitatively through additive utility functions. Qualitative and conditional preferences are beneficial features for MARAs [21], [39]. Buyers are more comfortable in expressing their preferences qualitatively rather than quantitatively [21]. For example, it is often more intuitive to say *I prefer Sony laptop to Toshiba* rather than *My preference for Sony is 0.75 and for Toshiba 0.25*. The former does not require a careful estimation of the preference values. Also, buyers may have some conditional preferences, e.g. the preference of the brand of a laptop depends on the price: *I prefer to buy a Sony if the price is more than $800*. This attribute dependency is lacking in additive utility functions [18]. According to [18], this dependency increases the economic efficiency of multi-attribute auctions. Nevertheless, often buyers do not know how to explicitly express their constraints and qualitative preferences over various attributes. Acquiring individuated preferences is a well-known bottleneck for negotiation and decision support systems [11], [41]. Consequently, it is necessary to provide buyers with a rigorous requirements elicitation approach [39]. Moreover, [47] shows that MARAs that fully reveal buyer's information have higher allocation efficiency than auctions with restricted requirements. This disclosure successfully helps bidders to identify the items that best satisfy the buyer's valuation [47]. With the increasing number of bidders, the expected pay-off of the buyer increases. This motivates the buyer to announce his true preferences i.e. the actual utility function [16]. In addition to the negotiable attributes of the auctioned item, other relevant factors (non-negotiable attributes) may be included to better determine the best supplier, such as reputation, cooperation or customer rating of sellers in the market [29]. This is what the buyer wants: purchasing from well trusted sellers in the market. [50] states that these factors can positively impact the long-term relationship of buyer-supplier.

Another problem faced by MARAs is defining methods to determine the bidder that best matches the buyer's specific preferences. However, determining the winner with diverse criteria is a computationally hard problem [8]. Hence, for the sake of efficiency, it is more suitable for MARAs to process quantitative data. For instance, additive utility functions are easily evaluated by sellers and very efficient even when the number of bidders is very large in some domains [16]. Nevertheless, in multi-criteria problems, the attribute weight determination is a crucial issue [14]. So, there is a remaining challenge to provide buyers with more features and comfort in one hand, and keep MARAs efficient on the other hand [39].

1.3 Contributions

We develop a multi-round, first-score (first-preference), semi-sealed MARA for single sourcing. We establish our auction mechanism with the following features:

1.3.1 Constraint and Preference Specification

We propose a procurement system where the buyer may elicit constraints and qualitative preferences over an arbitrary number of attributes (including one non-negotiable attribute). Real auction requirements are rarely unconditional [18]. Consequently, to express dependencies among attributes, our system enables the buyer specifying conditional constraints as well as conditional qualitative preferences. Also, the buyer has to submit constraints on the bidding process. The constraint and preference statements are well structured and easy to use, and our system provides friendly Graphical User Interfaces (GUIs) to assist step by step the bid taker in collecting in a precise and convenient way his personal requirements. MARAs should provide all these facilities to the buyer so that the system satisfies his requirements at the maximum, and therefore ensures a better outcome.

1.3.2 Winner Determination

Our system looks for the optimal outcome that completely satisfies all the constraints and best matches the preferences (the most preferred configuration). In this paper, the winner selection is a multi-criteria decision problem. Our MARA maps the qualitative preferences into the utility function MAUT [39], a widely used technique for multi-attribute decision-making problems [8]. MARA takes advantage of the efficiency of MAUT by transforming the qualitative requirements into quantitative ones. In this paper, the winner selection is performed according to the submitted bid and one non-negotiable attribute. But to establish the scoring rule, there are two difficult issues that we need to address: determining the weights as well as the value functions of all the attributes. This is really a challenging task for the buyer, especially when there are lots of attributes. So, another major contribution of our work is the complete automation of the seller selection. Indeed, our MARA generates automatically the weights and utility values directly from the bid-taker's qualitative preference information. According to the attribute type, quantitative or qualitative, we define the individual value functions differently.

1.3.3 Mechanism Design

We design our MARA protocol as follows: (1) the buyer's utility function, attribute weights and bidding constraints are fully revealed to sellers prior to negotiation in order to maximize his expected payoff (the overall seller utility should be optimized, preferably nearest to 1). Full revelation increases the likelihood of allocation efficiency [47], and Pareto optimality [5]. Truthful revelation achieves the optimal payoff [5], [54]; (2) semi-sealed bid protocol, sealed in each round and open after that, to benefit sellers of the bid privacy, and at the same time only the final scores and statuses of bidders are disclosed at the end of each round. This announcement is sufficient for sellers to make progressive offers for subsequent rounds; (3) first-score protocol where the highest score bidder wins; (4) multi-rounds to give sellers a chance to improve their bids by providing better configurations.

1.3.4 MARA Evaluation

We first set up an experiment to demonstrate the feasibility of our procurement system through a 10-attribute reverse auction involving a good number of constraints, preferences and sellers. Moreover, we assess the performance of MARA by conducting several experiments to measure the processing time of checking the constraints and determining the winner by varying the number and types of constraints and preferences. Based on the results, we can conclude that our MARA system is able to find the best seller within a very reasonable time. We also assess the user acceptance of our tool based on three criteria: ease of use, usefulness and satisfaction.

2 Related Works

Here we review prior research on user's constraints and preferences in different application areas, the additive aggregation method MAUT, and preference accuracy and stability.

2.1 User's Preferences and Constraints

Preference elicitation plays an essential role in negotiation systems such as automated market places, bilateral bargaining, auctions and shopping websites. Maximizing the satisfaction of buyers may be achieved by considering precisely their preferences. [27] proposes a personalized matchmaking system that determines the best offer by evaluating and sorting the sellers' offerings according to the buyer's specific interests. This system is based on a neural-network technology, self-organizing map, and the economics model MultiNomial Logit. [41] discusses and evaluates different methods, such as Self Explicated Approach, Full Profile Conjoint, Hybrid Conjoint, and Analytic Hierarchy Process, to elicit and represent preferences in negotiation support systems. Based on a multi-attribute utility theoretic model of user preferences, [23] introduces an algorithm that learns an overall utility function with flexibility to accept several types of information, such as the attribute weights and utility functions. It combines evolutionary learning with the external knowledge and local search. By conducting some experiments, the authors show that their algorithm of utility elicitation in an agent-based negotiation system provides a good learning performance and thus can be used in a wide variety of applications. [19] exposes a general interactive tool to obtain users' preferences about concrete outcomes, and to learn utility functions automatically based on users' feedback. In [57], the authors propose a preference elicitation framework as well as a linear programming model to infer the appropriate preference model w.r.t the user's preference statements. They implement the framework based on an agent intermediary architecture consisting of several components: the semantic analyzer, preference elicitation, bid evaluation, model base and database. [22] identifies five crucial factors in the context of real-world preference elicitation problems such as real-time, multi-attribute, low cognitive load, robust to noise and scalable. Based on these requirements, this paper suggests a framework that facilitates the efficient evaluation of value of information heuristics. This framework performs effectively with all the five factors for both real-world and synthetic datasets. In [22], preferences are expressed as additive value functions. Formalizing users' preferences accurately is also very important in most decision support systems [14]. These systems rely on preferences to produce effective user models. [28] develops a variant of the fully probabilistic design of decision-making strategies. In [28], the elicitation of preferences is based on quantitative data and the solving method on Bayes rules. In [36], the authors are concerned about the preference elicitation models of several domains such as decision support systems and recommender systems. They perform three experiments: the first one is to let the user express preferences through various models the second one is to analyze the trade-off between user's feedback and effort, and the third one is to study the influence of interfaces on users. This work uses ranking, ordering and navigational techniques to represent preferences. Furthermore, the acquisition of high quality users' preferences is significant in interactive web services [26]. The quality of the returned results depends on the capability of the services to acquire the preferences. [26] examines the adaptation and personalization strategies during the elicitation process for web services. This paper describes preference elicitation techniques in ADVISOR SUITE, a domain-independent software tool used in e-commerce.

In the setting of auctions, very few papers take into account hard constraints. The auctioneer can consider constraints on different types of objects, such as attributes, bids, and auction termination. In [32], [49], constraints represent trivial information, such as the quantity of the auctioned item (e.g. quantity <= 2000). In [31], the authors propose a constraint-based negotiation framework where offers and counter-offers are based on constraints (such as budget and time constraints) and arguments. [8] defines constraints by linear inequalities in a multi-dimensional auction platform. Preferences and constraints can co-exist together in many domains [1], [37], and it is of great benefit to handle them together in many real-world applications. For instance, [21] employs MAUT to process quantitative preferences, and Conditional Preference networks (CP-nets) to formalize qualitative preferences. [37] describes constraints as a weighted Constraint Satisfaction Problem (CSP), conditional and qualitative preferences as CP-nets. [2] introduces an online shopping system that provides the buyers with the ability to specify in an interactive way constraints and preferences where the latter can be quantitative, qualitative or both. This work employs C-semiring to describe quantitative preferences, CP-nets for qualitative ones, CSP for constraints. This paper utilizes branch and bound method to provide the users with a list of outcomes. [1] introduces a new algorithm to determine the best outcome based on the arc consistency propagation technique. It performs several experiments to show that the proposed approach is able to save substantial amount of time to generate the optimal solutions.

As pointed out by previous researches, acquiring individuated preferences is a well-known bottleneck for decision support systems (like auctions, negotiation and recommenders) [11], [41]. In our study, we provide a formal and an explicit description of the auctioneer's requirements. In the literature on users' preferences, the elicitation models are represented either graphically or with quantitative utility functions. Both allow a compact expression of preferences. The graphical models generate a set of incomparable optimal outcomes, and users have to analyze the outcome space in order to select a solution that best fits their preferences. We believe this is a burden on auction buyers. Moreover, with the quantitative utility functions, users have to estimate the attributes weights and individual utilities. This is also a time consuming task. The goal of our work is to facilitate buyer's purchasing decision by allowing them to enter qualitative requirements, and also to completely automate the scoring function, such as MAUT which produces a raking of the outcomes. To the best of our knowledge, our constraint and preference formalisms are unique.

2.2 Additive Aggregation Methods

In our paper, the winner selection is a Multi-Criteria Decision Making (MCDM) problem. MAUT is the most successful technique in multi-criteria decision-making systems [8]. It is used to tackle complex problems involving a large number of decision variables. This scoring function compares and ranks the set of feasible alternatives to reflect the decision makers' interests [8]. In MAUT, the weights and individual utility functions of all the variables should be specified quantitatively [58]. This is a very challenging task. However, given the individual utility functions and weights, determining the winner is straightforward and efficient. MAUT has been applied to several domains, like negotiation science, engineering applications, and e-commerce including multi-attribute auctions and shopping [51]. Bichler et al. advocate the utilization of MAUT in the setting of multi-attribute auctions in order to evaluate seller’s offers in single sourcing [8]. [49] develops a MAUT-based trading system for multiple sourcing. [20] summarizes the applications of MAUT in e-commerce area. Perfect and Frictionless employ MAUT for bid analysis in their commercial sourcing software packages [9]. Our auction system converts the qualitative preferences into the additive measure MAUT. [13] points out that the additive aggregation approaches in MCDM have very low performance cost and are easy to use by the decision makers. However, in some real-world cases, there may be some correlation among the item attributes and the non-additive functions, such as the fuzzy-based model [56] and the interval-based Choquet integral [13], are the most suitable to deal with these dependencies. The issue with the non-additive functions is their exponential complexity [13]. Additionally, identifying the interdependencies between attributes may be tedious.

2.3 Preference Accuracy and Stability

In order to determine the best solution for any decision support systems, several papers confirm that the accuracy and even the completeness of users' preferences are essential when looking for multi-attribute items. [38] argues that this accuracy is important for users to understand the produced outcome and agree with it. For instance, in recommendation systems, there is a compromise between the amount of effort spent in the elicitation process and the accuracy of the returned items [25]. As reported by a very recent work [33], Europe has adopted an official directive specifically for MARAs: buyers should provide their scoring functions (representing their preferences) as well as the attribute weights or their order. [33] affirms that preference elicitation is crucial in online MARAs and also states that *It is difficult to elicit one’s preference in a form which can be converted into an accurate utility or value function*. Another paper [18] proposes a preference tool for multi-attribute auctions that allows users to represent non-additive preferences based on preference structures as well as on the Generalized Additive Independence (GAI), a graphical formalism that handles attribute dependencies. The experiment demonstrates the benefits of expressing those dependencies. [50] evaluates several industrial organizations and identifies conditions that are vital for the success of reverse auctions, such as a proper specification of the auctioned items. In our research, we tackle this issue of preference accuracy. In our point of view, it is important to provide auction buyers with a high quality decision process.

In the context of users' preference construction, preference stability has attracted attention from many researchers. Through a laboratory experiment, [24] explores the influence of effort, choice and experience on preference stability. The experiment shows that participants in the easy choice environments had instable preferences while those with difficult decisions had very stable preferences. When a consumer deals with difficult choices, it helps him stabilize his preferences. This paper recommends to marketers to aid consumers think deeply about the trade-offs among the item attributes. This will help them understand their preferences and accept the outcomes. The preference stability is also highly impacted by the experience the user gains on the item domain. Often a buyer builds his preferences when he is new to an item category, and then develops stable preferences as he gains more experience [24]. [15] reports that a consumer can precisely learn his true preferences via the repeated decision tasks. Nevertheless, according to [42], most of the previous research testifies that preferences are not so stable and all depends on individuals and item categories. Another paper [3] argues that as soon the decision context changes, the consumers’ preferences change too. In the future, it will be beneficial to study preference stability in MARAs.

3 The Proposed MARA Mechanism

When a buyer posts a request to purchase an item our system first provides him with all the possible item attributes. The buyer then selects the attributes he is interested in. Subsequently, a reverse auction based on the buyer's attributes is launched in order to obtain the best possible offer from suppliers.

3.1 Buyer’s Requirements Specification Process

The auctioneer specifies his requirements through four phases. It’s up to him to elicit simple or complex constraints/preferences depending on his expertise about the item and on the item complexity as well.

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3.1.1 Phase 1: Specifying Constraints on Attributes

The buyer has an option to elicit hard constraints on the attributes of his choice. Constraints are represented with the following structure and syntax:

$$(condition_{a_1})and/or,...,and/or(condition_{a_i}) \Rightarrow constraint_{a_j} \quad (1)$$

where *condition* and *constraint* both denote a relation between an attribute and its values: $rel(a_i, value(s) of a_i)$ such that $rel \in \{=, \neq, <, >, \leq, \geq\}$, and *value(s)* may be discrete or continuous. These values are generated from the item database. When the condition clause in (1) is empty, the constraint is non-conditional i.e. the attribute of interest has no dependencies on other attributes.

3.1.2 Phase 2: Specifying Qualitative Preferences on Attributes

Next the buyer should submit the qualitative preferences for all the attributes, called importance levels, as shown in Table 1. This will provide a ranking of all the attributes.

Table 1: Attribute importance levels in MARA

Qualitative Importance Level	Quantitative Importance Level	Rank
Extremely Important	1	M + 1
Very Important	0.75	M
Important	0.5	M - 1
Not Very Important	0.25	M - 2

3.1.3 Phase 3: Specifying Qualitative Preferences on Attribute Values

The bid-taker may also specify qualitative preferences on the values of some attributes, called likings, using the following format:

$$(condition_{a_1})and/or,...,and/or(condition_{a_j}) \Rightarrow preference_{a_j} \quad (2)$$

where

$$condition_{a_i} = rel(a_i, value(s) of a_i) / rel \in \{=, \neq, <, >, \leq, \geq\}$$

$$preference_{a_j} = a_j(value_{a_{j1}}(liking),..., value_{a_{jN}}(liking))$$

If the condition clause in (2) is empty, then the preference is non-conditional. Often the value of one attribute depends on the values of some other attributes. Attributes can be of two types: quantitative (numeric) or qualitative (string). Table 2 presents the possible qualitative likings for these two types. For those attributes of high importance levels, we recommend to the buyer to input his likings, and for those of less importance, the buyer has a choice. We may note that through likings, the buyer is able to decide which quantitative attributes to maximize (i.e. large values are better) and those to minimize (i.e. small values are better).

Table 2: Attribute value liking in MARA

Attribute Type	Qualitative Liking	Quantitative Liking	Rank
Qualitative	Highest (H)	1	N
	Above Average (AA)	0.8	N - 1
	Average (A)	0.6	N – 2
	Below Average (BA)	0.4	N - 3
	Lowest (L)	0.2	N – 4
Quantitative	Highest (H)	1	
	Lowest (L)	0.2	

3.1.4 Phase 4: Specifying Constraints on Bidding

The buyer must also set values for three thresholds regarding the seller admissibility and auction termination: (1) the minimum seller utility that the buyer will consider for the first round. Each bidder should respect this minimum utility, otherwise it will be disqualified; (2) the number of rounds when the buyer does not have that much time; (3) the satisfactory seller utility to be considered as a potential winner. For example, if this value has been set to 0.8, this means the buyer will be happy enough to buy the product from the winner whose configuration satisfies his preferences at least 80%, and the auction will end. The target of the auction is to maximize the overall seller utility value, preferably to this threshold value.

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3.2 Automated Winner Determination Process

Our auction system evaluates the submitted bids by using MAUT*, an enhancement of MAUT, to consider (conditional) constraints and (conditional) qualitative preferences. In MAUT, each negotiable attribute *na* in a bid has a value denoted by v_{na}, and is evaluated through an attribute value function $U_{na}(v_{na})$ [8]. An attribute has a weight that scales its importance degree to the buyer. The MAUT score of a bid is calculated as the aggregation of all the individual weighted utilities of the attributes [8]:

$$MAUT(bid_{seller}) = \sum_{na=1}^{M} Weight_{na} \times U_{na}(v_{na}) \,/\, bid_{seller} = (v_1, \ldots, v_M) \tag{3}$$

We improve the scoring function MAUT to take into account one non-negotiable attribute, called *nna*:

$$MAUT(seller) = MAUT(bid_{seller}) + MAUT(nonNegAtt_{seller}) \tag{4}$$

$$MAUT(nonNegAtt_{seller}) = Weight_{nna} \times U_{nna}(v_{nna})$$

$$seller = (bid_{seller}, v_{nna})$$

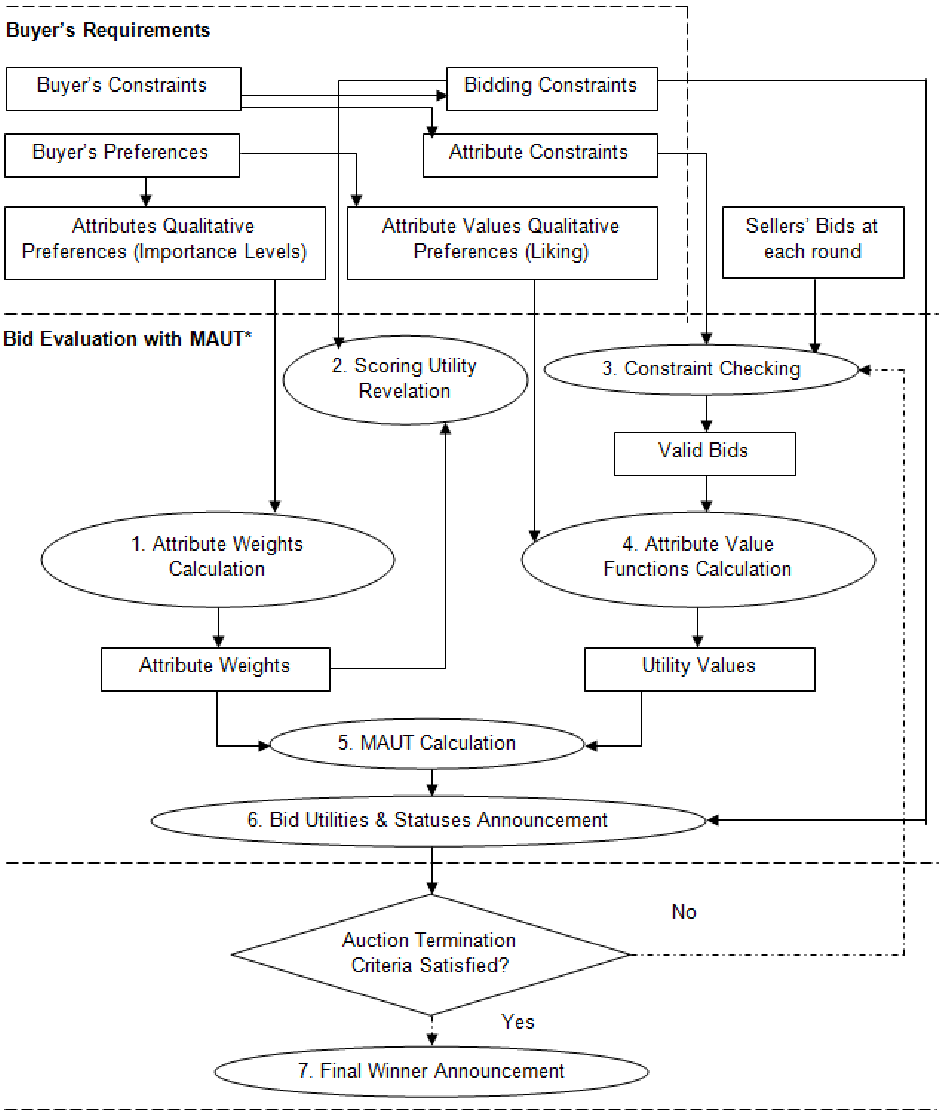

Figure 1: Winner selection in MARA

The non-negotiable attribute represents the past history of the seller in the market, such as reputation, feedback ratings, fairness or cooperation. Its value v_{nna} is not submitted by the seller but collected from a third party. This

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attribute will help the buyer purchase from well-trusted sellers. In this document, the winner selection is performed according to the submitted bid and the non-negotiable attribute.

In MAUT, there are two difficult issues that we need to address: determining the weights as well as the value functions of all the attributes. As depicted in Figure 1, MAUT* generates automatically the weights based on the bid-taker's qualitative importance levels, and the value functions based on his qualitative likings.

3.2.1 Phase 1: Calculating the Attribute Weights

The buyer may know the preferences over the attributes but not their precise weights. It is a challenging task to give numerical estimates of the weights, especially when there are many attributes. Here the weights are calculated automatically based on the importance levels of the attributes (a can be negotiable or non-negotiable attribute):

$$Weight_a = QuanImpLevel_a \times Rank_a \times WeightRate \qquad (5)$$

$$/\,Weight_a \in [0,1] \text{ and } \sum_{a=1}^{M} Weight_a = 1$$

where

- QuanImpLevela is the equivalent quantitative importance level of attribute a (cf. Table 1)
- Ranka, a relative value of a, is calculated w.r.t the buyer's importance level and number of attributes, M +1 (cf. Table 1)
- WeightRate is the step value of weights of attributes

3.2.2 Phase 2: Revealing the Scoring Rule and Submitting Bids

We consider a truthful buyer i.e. his true utility function (which is here equal to the scoring rule MAUT), is fully revealed to sellers at the beginning of the auction in order to maximize the buyer's expected payoff [16], [47]. More precisely, the generated attribute weights and their ranking, the attribute value functions (defined in phase 4 of subsection 3.2), and bidding constraints are all made public to bidders. We may note that the constraint and preference statements given by the buyer in phases 1, 2 and 3 of subsection 3.1 are not announced to the sellers as it will be time consuming to analyze them.

The sellers will now decide which optimal bids (the best configuration of values) they should provide with respect to the buyer's utility function. In each round, each seller submits one full bid (by selecting a value from the allowable attribute values) only on the negotiable attributes. The value of the non-negotiable attribute is shown to the seller. If his past history is not remarkable, this will motivate him to compete better to win the auction. A round closes when all the bids have been submitted. Before bid submission, our tool calculates and displays the overall score (including the non-negotiable attribute) to aid the bidder in his decision process. In the first round, sellers should respect the minimum utility threshold. Regarding the bidding strategies of sellers, usually auctions are designed under the assumption of symmetric independent private-value model and risk neutrality [7], [55].

Table 3: Constraint checking of bids

```
flag = Φ;
for i = 1 to nbCond do
    {  // nbCond is the number of conditions in const
       if (value(a, seller) == value(a, cond_i) or value(a, seller) ∈ value(a, cond_i)) then
          // value(a, seller) is the value of the attribute a in seller
          // value(a, cond_i) is the value of attribute a in condition i of const
          flag_i = TRUE;
       else flag_i = FALSE;
       flag = flag ∪ {flag_i};
     }
conditionClause = evaluateConditionClause(flag, op_c);
// op_c is the set of operators in condition clause of const
if (conditionClause == TRUE) then
    if (value(a, seller) == value(a, const) or value(a, seller) ∈ value(a, const)) then
       // value(a, const) is the value of the attribute a in const
       flag_const = TRUE;
    else flag_const = FALSE;
if (flag_const == TRUE) then return FALSE;
else return TRUE;
```

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3.2.3 Phase 3: Checking the Constraint Consistency of Sellers

As illustrated in Figure 1, the system deletes from the running auction those sellers that violate any constraint. In fact, a bidder is deleted as soon as it violets the first constraint in order to save some processing time. Constraints are useful to reduce a large set of suppliers since their evaluation can be time consuming. The algorithm (cf. Table 3) that we propose checks whether or not a given seller violates a constraint const of an attribute a.

3.2.4 Phase 4: Defining the Attribute Value Functions

The individual utility values are produced from the buyer's likings but only for the admissible bidders (cf. Table 4). We may note that if the buyer does not include a liking for an attribute, then the system assigns 0 to the quantitative liking of the values. In the case of a conditional preference, if a seller does not satisfy the condition(s), then the system assigns 0 to the quantitative liking of the attribute values for that seller. According to the type of the attributes, quantitative or qualitative, we propose two different linear attribute value functions: $U_a() \in [0,1]$ where 0 is the worst seller and 1 the best one. If a seller does not satisfy the condition clause of a preference of attribute *a*, then the system assigns 0 to $U_a(v_a)$ such that v_a is submitted by the seller. The condition clause of a preference is extracted in the same way as in the constraint of (cf. algorithm of phase 3).

Table 4: Attribute value function definition

Qualitative Type

if (*conditionClause* == TRUE) **then**
  for each $v_a \in$ seller **do**
      $U_a(v_a) = QuanLiking_{va} \times Rank_{va} \times UtilityRate$
else $U_a(v_a) = 0$

where • $QuanLiking_{va}$ is the equivalent quantitative liking of attribute value v_a (cf. Table 2). • $Rank_{va}$, a relative value of v_a, is calculated w.r.t the buyer's liking and number of attribute values, *N* (cf. Table 2). • *UtilityRate* is the step value of attribute values.
Quantitative Type

• v_{aH} is the value of *a* which has the highest liking
• v_{aL} is the value of *a* which has the lowest liking
• v_{aL} /v_{aH} /v_a is a value or an average value in case of a range of values of *a*
 	
if (*conditionClause* == TRUE) **then**
{
 $U_a(v_{aH}) = 1$ // utility value of v_{aH}
  for each $v_a \in$ seller **do**
    if $v_a \in [v_{aL}, v_{aH}]$ **then**
      $U_a(v_a) = (v_{aH} - v_a) / (v_{aH} - v_{aL})$
    else $U_a(v_a) = 0$ // $v_a > v_{aH}$ or $v_a < v_{aL}$
  $U_a(v_{aL}) = lowest(U_a(v_a))/N$
}
else $U_a(v_a) = 0$

3.2.5 Phase 5: Generating Partial Feedback Information about Sellers

Finally, MARA announces the MAUT utilities only of the admissible sellers (but not the bid contents) as well as statuses (disqualified, challenged or winner) of all participating bidders. Each seller is assigned a randomly generated ID (to remain anonymous). The seller with the most preferable item specification, i.e. with the highest overall utility, wins in the current round. In the next round, each bidder should beat (i.e. satisfy more preferences) the previous winner (ascending auction). Our protocol is semi-sealed, sealed in each round and open after that, because the bidders' offers are kept private during the auction, but at the end of each round, MARA reveals only the final scores of the qualified sellers. This announcement is sufficient for bidders to submit competitive bids in the next round. It is important not to show other sellers' offerings as they are in a long-term competition. According to [5], the more information is revealed about the bids, the more the likelihood of achieving allocation efficiency.

We may also note that our system can handle multiple rounds to give sellers a chance to improve their bids and compete better in the next rounds. The auction closes when the number of rounds has been reached, or when the overall utility of the best seller is greater than or equal to the satisfactory utility threshold. The winner of the auction should then produce an item with the exact configuration of his bid. In case our system returns several winners, the buyer can: 1) choose one among them (which supplier he likes the best), or 2) update his preferences but only these winners will compete in the next round.

3.3 An Illustrative Example

We assume a buyer wants to purchase a single TV with six attributes: Brand, Weight, Display Technology, Refresh Rate and Price. The buyer submits the following two constraints for this TV auction:

- (NCC_{Brand}) NULL ⇒ Brand ≠ {Panasonic, LG}
- (CC_{Price}) (Weight ≥ [5 - 5.9]) or (Display Technology = LED) and (Refresh Rate ≤ 120) ⇒ Price ≤ [1000 - 1499.99]

Here the non-conditional constraint (NCC_{Brand}) indicates that the TV brand must be neither Panasonic nor LG. The conditional constraint (CC_{Price}) means if the TV weight is greater than or equal to [5kg - 5.9kg] (i.e. not less than 5kg), or the display technology is LED, and the refresh rate is less than or equal to 120Hz, then the price must be less than or equal to [$1000 - $1499.99] (i.e. not greater than $1499.99).

Next the buyer provides the following importance levels for the five TV attributes: Brand as *Very Important*, Weight as *Important*, Display Technology as *Important*, Refresh Rate as *Not Very Important* and Price as *Extremely Important*. Since the two attributes, Brand and Price, are *Very Important'* and *Extremely Important* for the buyer, therefore he can provide likings for the values of these two attributes:

- (NCP_{Price}) NULL ⇒ Price([800 - 899.99] (H), [1000 - 1499.99] (L))
- (CP_{Brand}) (Refresh Rate > 120) ⇒ Brand (LG (BA), Panasonic (A), Sharp (-), Sony (-), Toshiba (H))

The non-conditional preference (NCP_{Price}) expresses that the interval [800 - 899.99] has the highest preference and [1000 - 1499.99] the lowest one; (CP_{Brand}) means if the value of Refresh Rate is greater than 120, then the qualitative liking of each value of Brand is given. The symbol - indicates that the buyer does not specify any liking for the value.

Table 5(a): Brand weight and utility value calculation

Weight Calculation		**Rank**	**Quantitative Importance Level**	**Weight**
		4	0.75	0.27
Attribute Value Function Calculation	**Attribute Value**	**Rank**	**Quantitative Liking**	**Utility Unit**
	LG	4	0.8	0.16
	Panasonic	3	0.6	0.36
	Sharp	0	0	0
	Sony	0	0	0
	Toshiba	5	1	1

In Tables 5(a) and 5(b), we show for example how the weights are produced by MARA respectively for the two attributes Brand and Price. Based on the importance levels given in Phase 2 of subsection 3.1 and Table 1, WeightRate can be calculated as follows: ((0.75 × 4) + (0.5 × 3) + (0.5 × 3) + (0.25 × 2) + (1 × 5)) × WeightRate = 1. So, WeightRate = 0.09.

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Table 5(b): Price weight and utility value calculation

Weight Calculation		**Rank**	**Quantitative Importance Level**	**Weight**
		5	1	0.45
Attribute Value Function calculation	**Attribute Value**	**Quantitative Liking**		**Utility Unit**
	[700 - 799.99]	0		0
	[800 - 899.99]	1		1
	[900 - 999.99]	-		0.25
	[1000 - 1499.99]	0.2		0.05
	[1500 - 2000]	0		0

Suppose now the following two sellers are competing in the TV auction:

- Seller1: Brand = Panasonic; Display Technology = LED; Price = 1500; Refresh Rate = 120; Weight = 4
- Seller2: Brand = Toshiba; Display Technology = Plasma; Price = 1200; Refresh Rate = 600; Weight = 4

The first seller does not satisfy the two constraints (NCC_{Brand}) and (CC_{Price}). On the other hand, the second one satisfies all the constraints. Table 5 gives the utility unit for each qualitative value of Brand, and each quantitative value range of Price. As we can see Toshiba received the highest liking for Brand. So, (1 × 5) × UtilityRate = 1, and therefore the UtilityRate = 0.2. The range [800 – 899.99] obtained the highest liking for Price, so, U([800 – 899.99]) = 1; since the two following ranges are out of interest, so U([700 – 799.99]) = 0 and U([1500 - 2000) = 0; U([900 – 999.99]) = (849.995 – 949.995) / (849.995 – 1249.995) = 0.25, and finally U([1000 – 1499.99]) = 0.25/5 = 0.05.

3.4 A Summary

After a buyer selects an item category, our auction tool provides important information like the legal attributes and their domains. The buyer has an option to express constraints on the attributes he is interested in as well as qualitative preferences on: 1) all the attributes by providing an importance order, and 2) the attribute values of his choice. Next, he has to specify three bidding thresholds. Subsequently, the system calculates the attribute weights directly from the qualitative preferences. A reverse auction is then initiated by revealing publically the scoring rule. Interested sellers can register to the auction. After deleting those bids that do not satisfy the constraints, our tool calculates the individual utilities and MAUT of the remaining bids and announces the round winner. The auction continues until the termination conditions are met. Our system provides a great flexibility for buyers who may post: 1) very simple requirements i.e. without any conditions, and 2) requirements on the attributes he has deep knowledge. For uncertain attributes and uncertain values, he has a choice to not enter any information. For example, if the buyer does not enter a preference on a certain value of an attribute (in Table 5(a), *Sharp* and *Sony* or the value is out of interest (in Table 5(b), [700-799.99] and [1500-2000]), our MARA assigns 0 to its quantitative liking. This means the buyer may always submits partial information on the attribute domain. In the future, we will improve our system to assign a value other than 0 by generating it from the buyer's history and feedback. This will require exploring the research area on preference stability.

4 A 10-Attribute Auction Experiment

For the purpose of simulation, we utilize Jadex [10], [34], an agent execution platform that provides services that are compliant to the Foundation for Intelligent Physical Agents (FIPA). Jadex incorporates the Belief-Desire-Intention model [12], [40]. We develop each agent with a set of beliefs (agent's knowledge about itself and its environment), goals (the desires an agent intends to achieve), plans (the assigned tasks an agent performs) and messages. In Jadex, an agent is described with an Agent Definition File (ADF) containing its beliefs and desires. ADFs are encoded in XML, and plans in pure Java classes. For the integrated development environment, we use Eclipse IDE 3.7.2 and Java SE Development. As illustrated in Figure 2, we design MARA as 3-layer software architecture. The presentation agent contains friendly GUIs to assist the buyer step by step in specifying accurately his (non) conditional constraints as well as (non) conditional qualitative preferences. It also aids the sellers to submit their bids. The business layer contains the winner determination agent which implements all the MAUT* algorithms, as well as Admin agent which controls the interaction between the data store and presentation layers to ensure security. Data layer stores all the information of auctions, items and participants. We may note that this architecture can be easily deployed as a Web-based distributed application. In the following case study, we show the feasibility of our MARA system.

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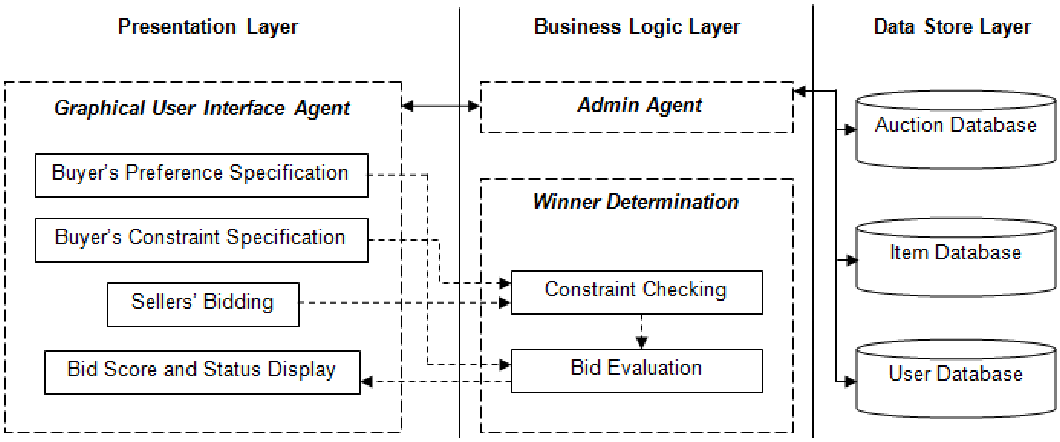
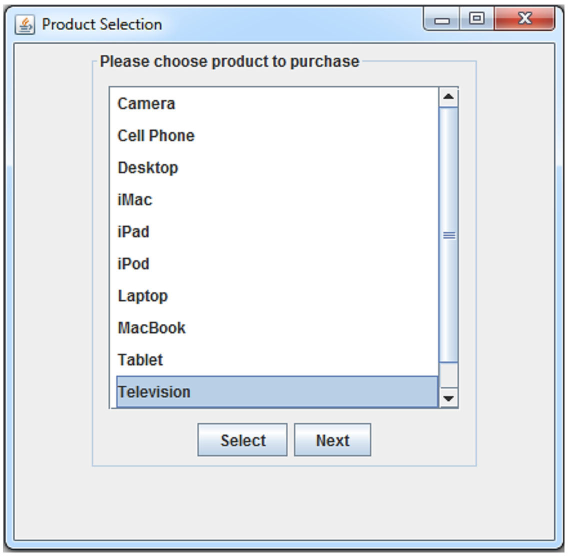
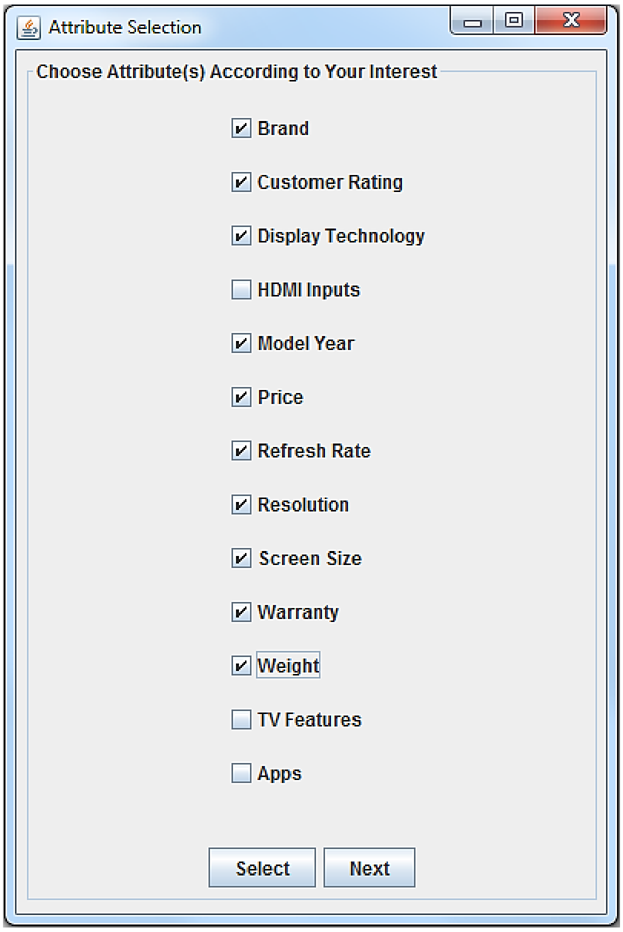


Figure 2: 3-Layer software architecture of MARA

4.1 Item Selection

First the buyer selects the item he would like to procure, e.g. a TV as shown in Figure 3(a). Our auction system extracts from the item DB, the TV attributes (here 13), and according to Figure 3(b), the buyer chooses 10 attributes (Customer rating is the non-negotiable attribute). Afterwards, our system generates the domain for each chosen attribute as depicted in Figure 3(c).





(a) (b)

Figure 3: (a) Product selection (b) Attribute selection

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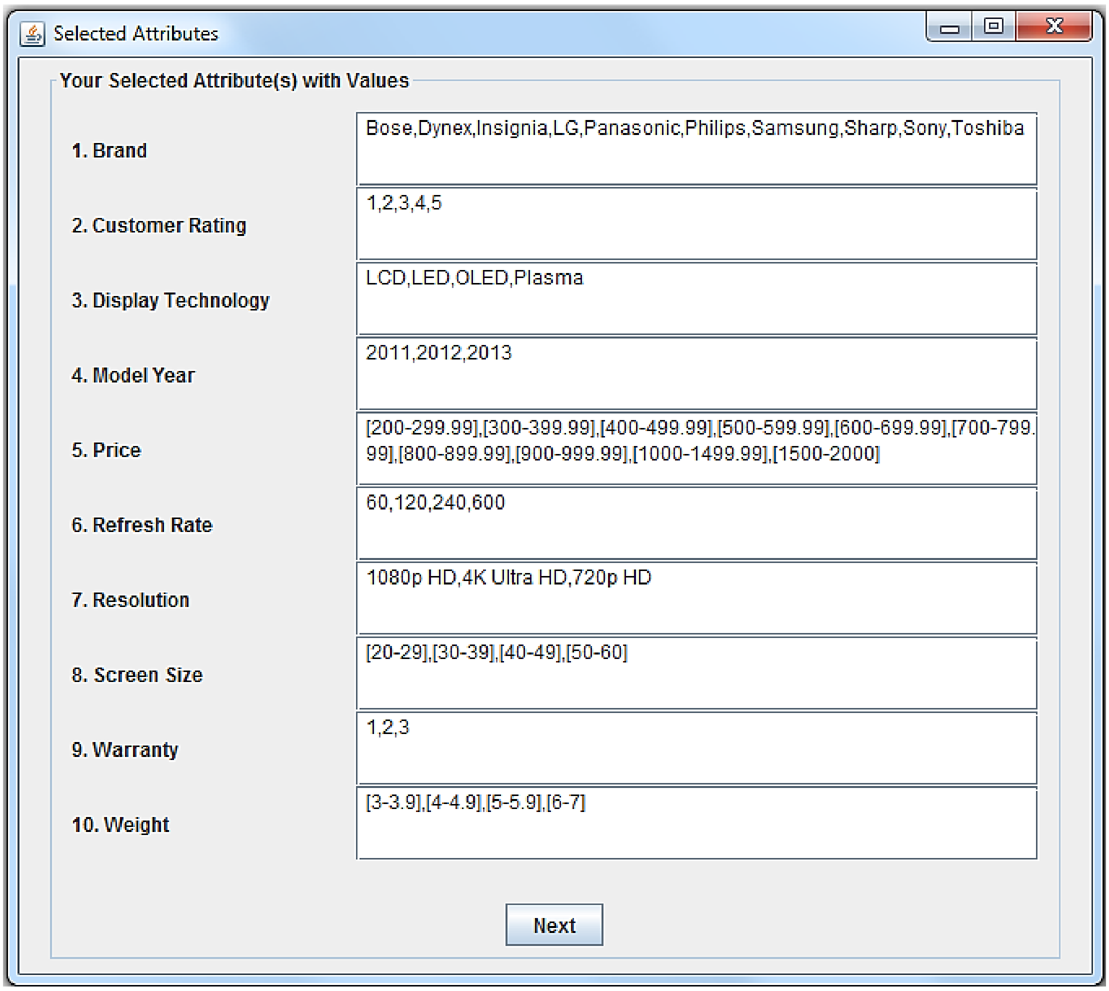

Figure 3(c): Attribute values generation

4.2 Constraint Specification

Through GUIs, the buyer is assisted step by step to submit the following examples of constraints:

- ($NCC_{ModelYear}$) NULL ⇒ Model Year ≠ 2011
- ($NCC_{Warranty}$) NULL ⇒ Warranty ≥ 2
- ($NCC_{RefreshRate}$) NULL ⇒ Refresh Rate ≥ 120
- ($NCC_{ScreenSize}$) NULL ⇒ Screen Size ≥ [30 - 39]
- (CC_{Price}) (Refresh Rate ≤ 240) ⇒ Price ≤ [900 - 999.99]
- (CC_{Weight}) (Brand = Panasonic) and (Resolution = 720p HD) ⇒ Weight ≤ [5 - 5.9]
- ($CC_{ScreenSize}$) (Brand = LG) or (Resolution = 1080p HD) ⇒ Screen Size ≤ [40 - 49]

For instance, Figure 4(a) and Figure 4(b) illustrate respectively a non-conditional and a conditional constraint.

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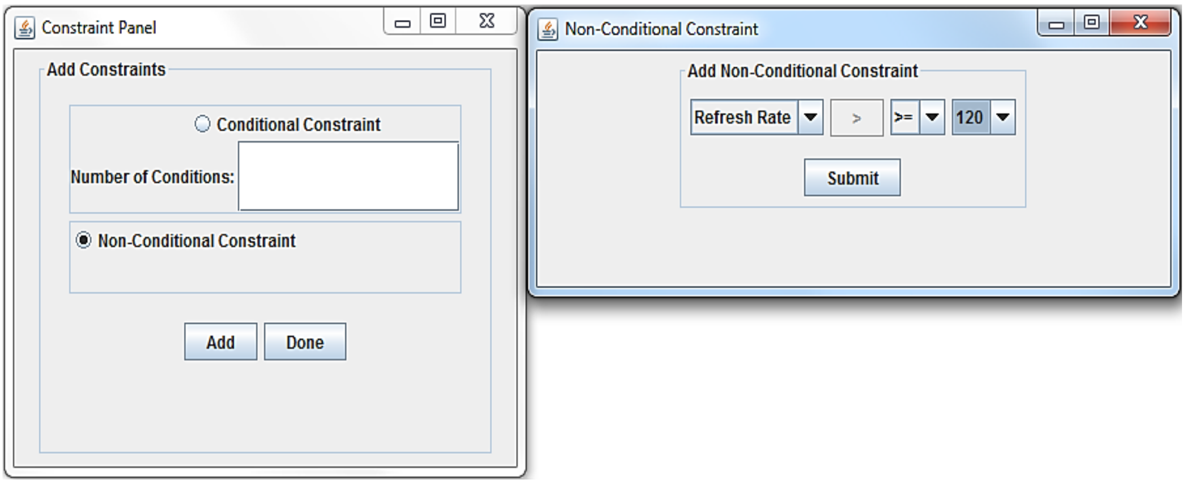

Figure 4(a): Non-Conditional constraint specification $NCC_{RefreshRate}$

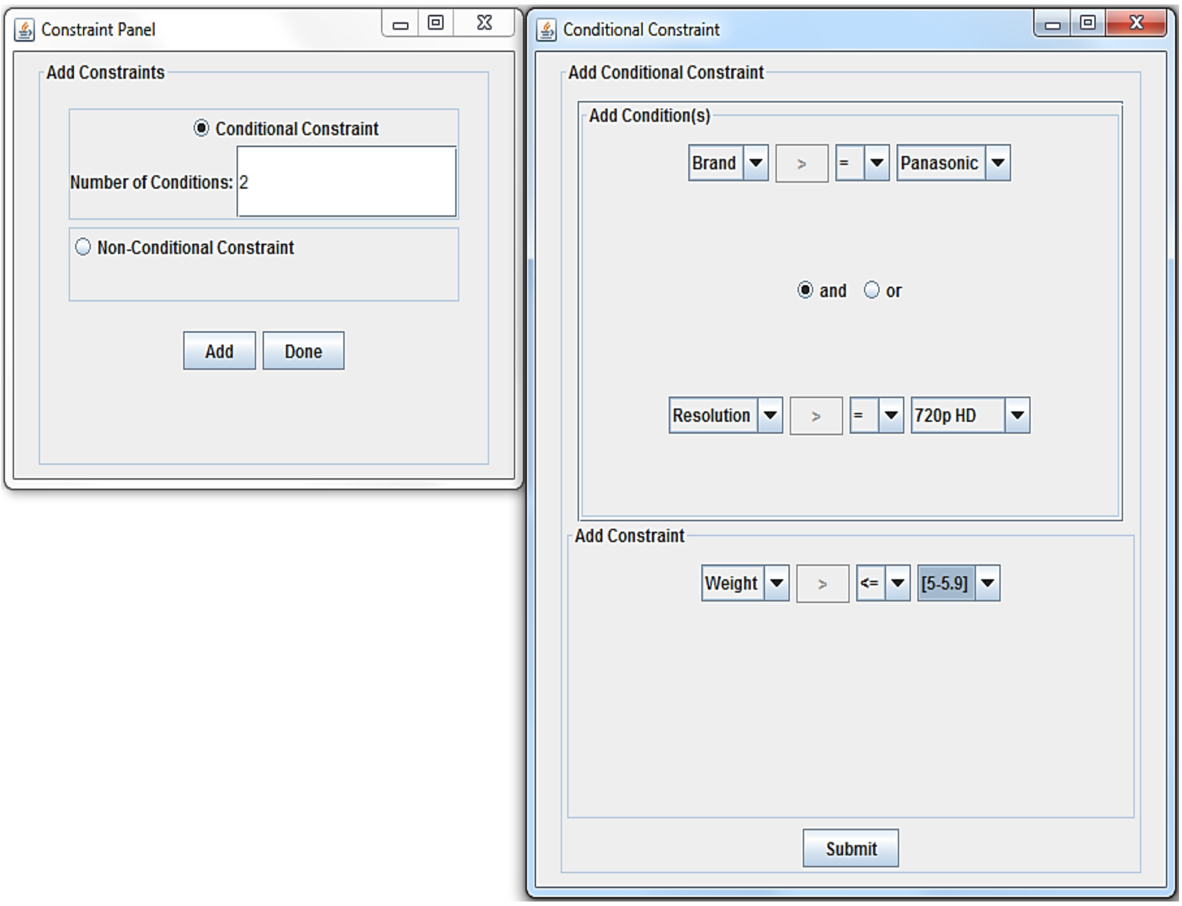

Figure 4(b): Conditional constraint specification CC_{Weight}

4.3 Attribute Importance Level Specification

The buyer qualitatively ranks the ten attributes w.r.t to their importance levels (cf. Figure 5).

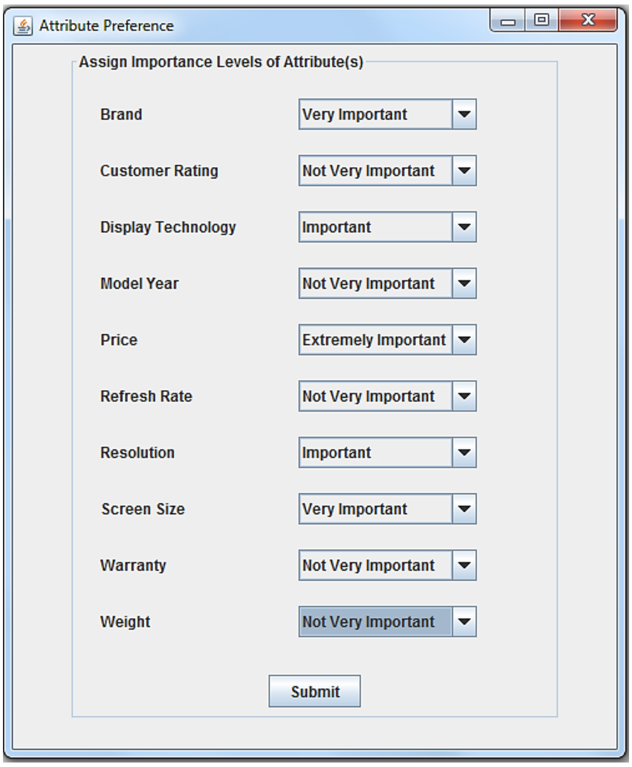

Figure 5: Qualitative preferences on TV attributes

4.4 Attribute Value Liking Specification

Now the buyer can judge the values of some attributes. He also knows which quantitative attributes to maximize (Model Year, Refresh Rate, Screen Size, Warranty and Customer Rating) and the ones to minimize (Price and Weight).

- (NCP$_{Price}$) NULL ⇒ Price ([300 - 399.99] (H), [1000 - 1499.99] (L))
- (NCP$_{RefreshRate}$) NULL ⇒ Refresh Rate (600(H), 120(L))
- (NCP$_{Brand}$) NULL ⇒ Brand (Bose (BA), Dynex (L), Insignia (BA), LG (AA), Panasonic (A), Philips (A), Samsung (A), Sharp (BA), Sony (AA), Toshiba (H))
- (NCP$_{ScreenSize}$) NULL ⇒ Screen Size ([50 - 60] (H), [30 - 39] (L))
- (NCP$_{ModelYear}$) NULL ⇒ Model Year (2013(H), 2012(L))
- (NCP$_{Warranty}$) NULL ⇒ Warranty (3(H), 2(L))
- (NCP$_{CustomerRating}$) NULL ⇒ Customer Rating (5(H), 3(L))
- (CP$_{DisplayTechnology}$) (Price > [300 - 399.99]) and (Screen Size ≥ [40 - 49]) ⇒ Display Technology (LCD (BA), LED (A), OLED (AA), Plasma (H))
- (CP$_{Resolution}$) (Refresh Rate ≥ 120) ⇒ Resolution (1080p HD (H), 4K Ultra HD (AA), 720p HD (A))
- (CP$_{Weight}$) (Screen Size ≥ [30 - 39]) ⇒ Weight ([4 - 4.9] (H), [6 - 7] (L))

In Figures 6(a) and 6(b), we show the specification of a non-conditional and a conditional preference respectively.

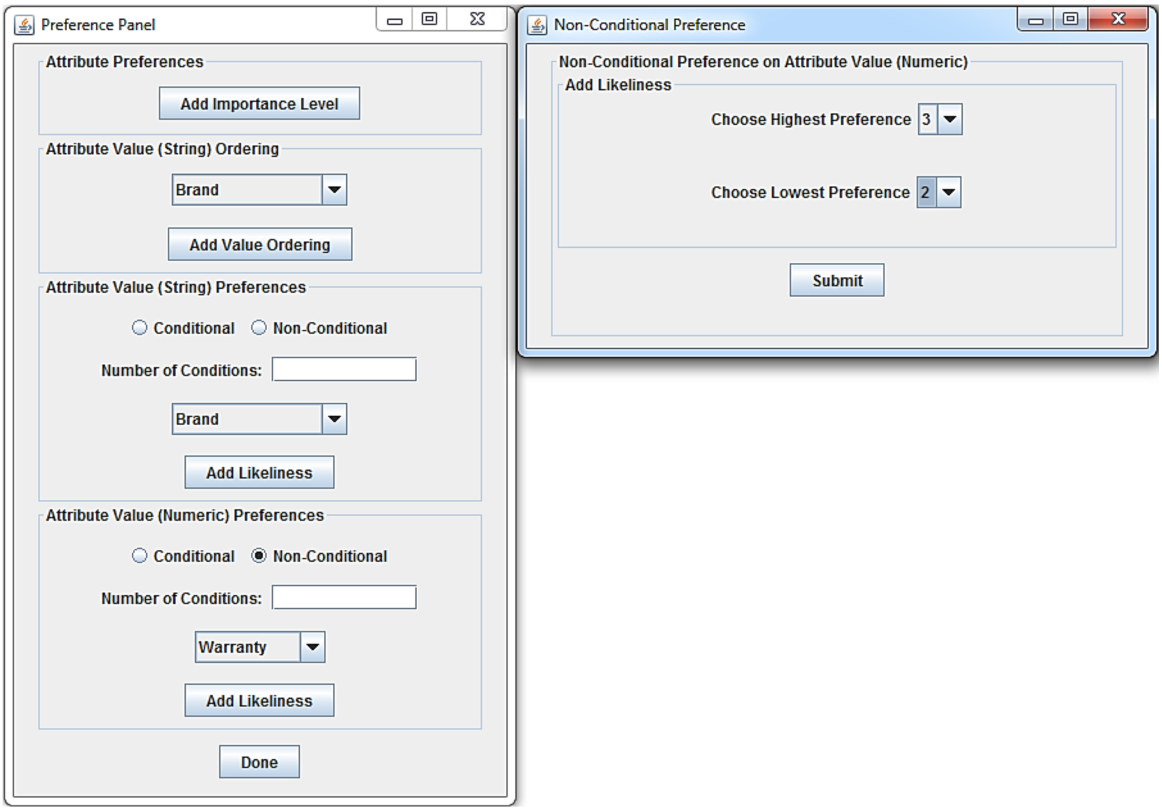

Figure 6(a): Non-Conditional preference specification $NCP_{Warranty}$

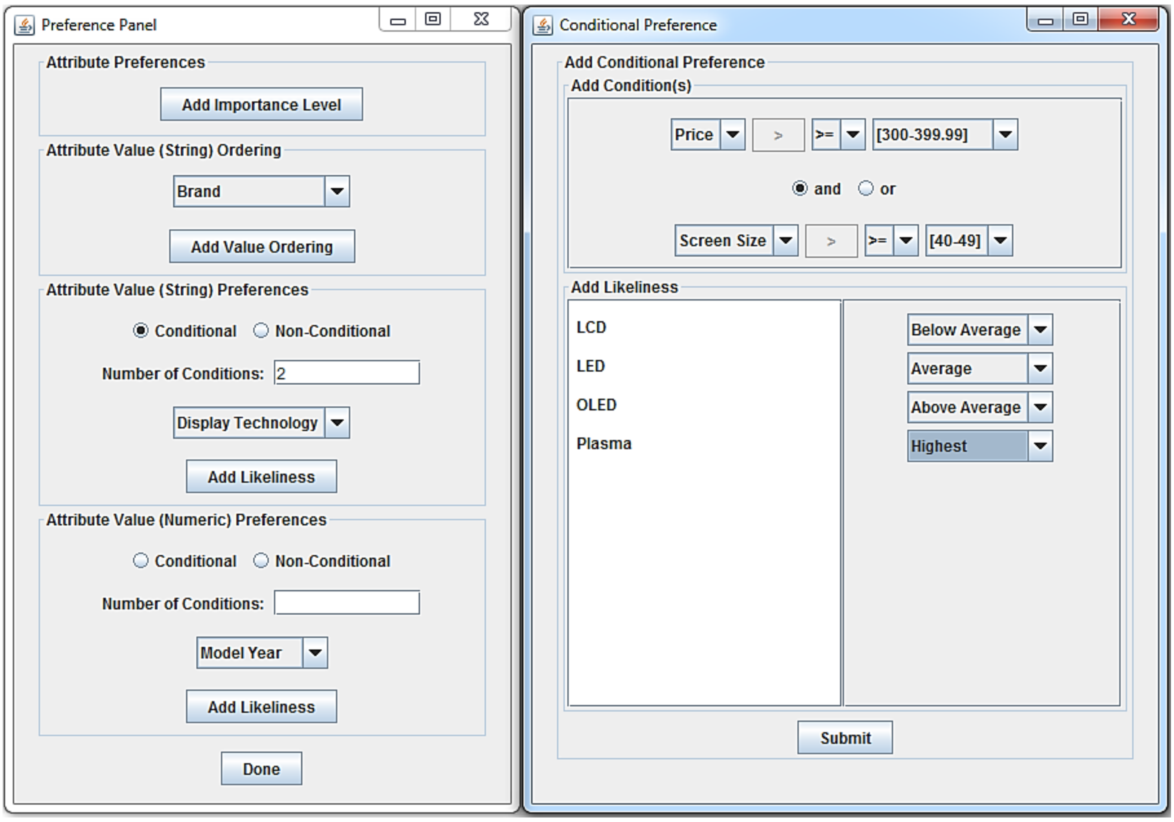

Figure 6(b): Conditional preference specification $CP_{DisplayTechnology}$

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4.5 Scoring Rule Revelation and Bid Submission

First the system displays the attribute weights to the registered bidders: Brand (0.188), Customer Rating (0.021), Display Technology (0.069), Model Year (0.007), Price (0.278), Refresh Rate (0.028), Resolution (0.083), Screen Size (0.167), Warranty (0.014), and Weight (0.146). Then, it posts the attribute ranking: Price > Brand > Screen Size > Weight > Resolution > Display Technology > Refresh Rate > Customer Rating > Warranty > Model Year.

Now the sellers know which attributes are the most important to the buyer. The MAUT utility, attribute value functions and bidding constraints are also revealed. We assume here the minimum seller utility threshold is set to 0.5, the number of rounds to 4, and the satisfactory utility threshold to 0.7. Figure 7(a) depicts the bid submission GUI of a seller on the nine negotiable attributes, whereas the value of the non-negotiable attribute, Customer Rating, is extracted from the user DB and then displayed to seller. In this TV auction, 30 sellers participate and their first sealed bids are given in Figure 7(b).

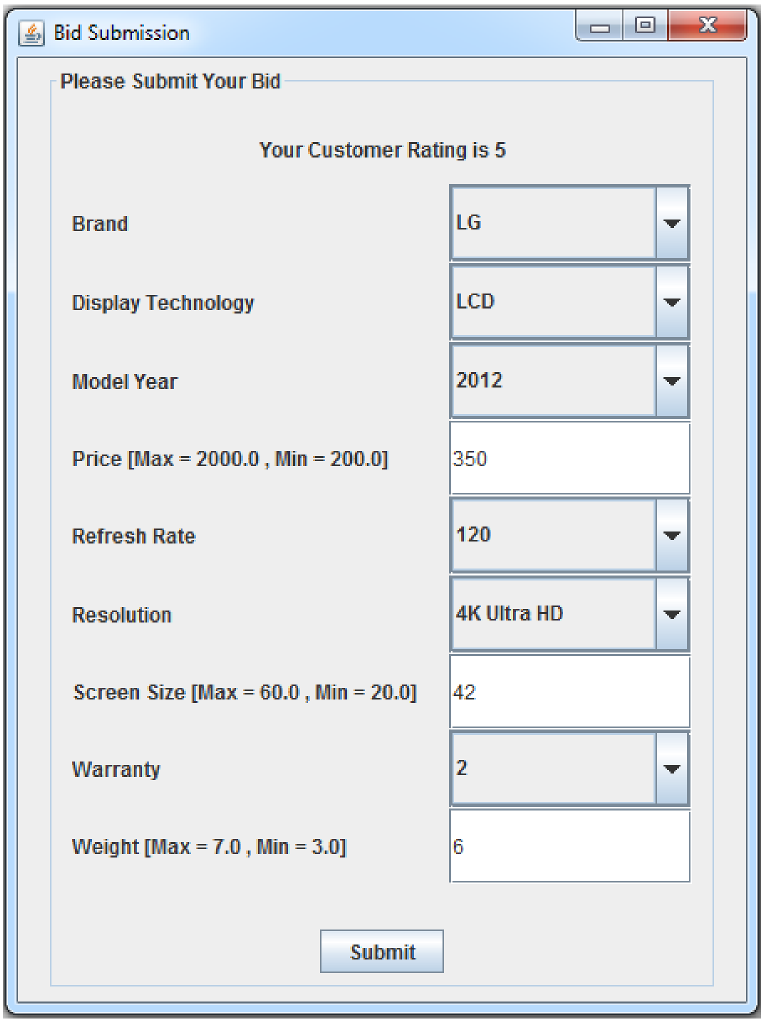

Figure 7(a): An example of bid submission

4.6 Winner Selection in Two Rounds

In the first round, Figure 8(a) ranks the 30 bidders and depicts S18 as the most preferred seller (here the winner satisfies only 65% of the buyer's preferences). 5 sellers are disqualified as they don't satisfy the minimum utility threshold, and 18 others are also removed from the TV auction since they violate some attribute constraints. The remaining 7 bidders are challenged for the next round since the auction termination criteria are not satisfied yet. At round 2 (cf. Figure 8(b)), all the remaining sellers improve their bids (all greater than S18 previous score). The winner's score, S18, passes the satisfactory utility threshold, and therefore the auction stops at the second round.

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Bid Evaluation

Seller Id	Brand	Display Technology	Model Year	Price	Refresh Rate	Resolution	Screen Size	Warranty	Weight
S1	LG	LCD	2012	350	120	4K Ultra HD	42	2	6
S2	Sony	LCD	2012	1200	120	1080p HD	42	2	4.5
S3	Bose	LED	2012	450	240	4K Ultra HD	55	1	5.2
S4	Sharp	Plasma	2012	950	120	4K Ultra HD	52	3	5.5
S5	Sony	LCD	2012	360	120	4K Ultra HD	22	3	3.3
S6	Bose	OLED	2013	540	600	4K Ultra HD	52	2	7
S7	Samsung	Plasma	2013	1300	600	4K Ultra HD	55	2	6
S8	Dynex	OLED	2012	620	120	720p HD	55	2	6.5
S9	Insignia	Plasma	2012	1200	600	1080p HD	35	2	6.2
S10	Samsung	Plasma	2012	1700	600	720p HD	32	2	3.6
S11	Panasonic	LCD	2012	770	120	720p HD	45	2	3.8
S12	Sony	LCD	2013	810	600	720p HD	58	2	4
S13	Samsung	LED	2011	910	60	1080p HD	30	1	5.2
S14	Toshiba	LED	2012	840	60	4K Ultra HD	20	3	6
S15	Philips	Plasma	2012	830	120	4K Ultra HD	35	3	5.5
S16	Samsung	Plasma	2012	780	240	4K Ultra HD	32	3	4
S17	Panasonic	Plasma	2012	990	240	4K Ultra HD	30	2	3.3
S18	Toshiba	OLED	2012	750	240	1080p HD	35	2	4.4
S19	LG	OLED	2012	950	240	1080p HD	40	3	5
S20	Panasonic	Plasma	2012	910	120	4K Ultra HD	40	2	7
S21	Bose	LCD	2011	1200	60	1080p HD	40	1	4
S22	Insignia	LCD	2011	1100	60	1080p HD	50	1	5
S23	Bose	OLED	2011	1800	60	1080p HD	55	1	6
S24	Bose	LCD	2012	1400	60	1080p HD	54	1	4
S25	Bose	LCD	2011	1300	240	1080p HD	45	1	6
S26	Sharp	Plasma	2012	950	120	4K Ultra HD	52	3	5.5
S27	Bose	OLED	2013	540	600	4K Ultra HD	52	2	7
S28	Samsung	Plasma	2013	1300	600	4K Ultra HD	55	2	6
S29	Dynex	OLED	2012	620	120	720p HD	55	2	6.5
S30	Insignia	Plasma	2012	1200	600	1080p HD	35	2	6.2

Constraint Checking | MAUT* | Bid Status

Figure 7(b): Bids values at first round

Bid Status

Seller ID	MAUT*	Bid Status
S18	*0.649*	*Winner*
S12	0.636	Challenged
S1	0.574	Challenged
S16	0.557	Challenged
S19	0.527	Challenged
S4	0.506	Challenged
S26	0.506	Challenged
S15	0.439	Disqualified
S7	0.427	Disqualified
S28	0.427	Disqualified
S17	0.318	Disqualified
S10	0.220	Disqualified
S22	0.000	Disqualified
S23	0.000	Disqualified
S5	0.000	Disqualified
S24	0.000	Disqualified
S25	0.000	Disqualified
S27	0.000	Disqualified
S29	0.000	Disqualified
S21	0.000	Disqualified
S20	0.000	Disqualified
S6	0.000	Disqualified
S8	0.000	Disqualified
S9	0.000	Disqualified
S11	0.000	Disqualified
S13	0.000	Disqualified
S14	0.000	Disqualified
S3	0.000	Disqualified
S2	0.000	Disqualified
S30	0.000	Disqualified

(a) First round

Bid Status

Seller ID	MAUT*	Bid Status
S18	*0.773*	*Winner*
S12	0.751	Challenged
S1	0.694	Challenged
S19	0.672	Challenged
S16	0.618	Disqualified
S4	0.000	Disqualified
S26	0.000	Disqualified

(b) Second round

Figure 8: Overall scores and statuses of sellers

5 Performance Evaluation

The execution time required by MAUT* to calculate the winner of an auction is a good measurement to assess the performance of our MARA system. Auctioning a complex product may involve a large number of attributes, constraints and preferences. So, if an auction takes several minutes to produce the results at each round, then the system will lose its market. In this paper, we conduct several experiments by varying the types and number of

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constraints and preferences. We utilize in total 10 attributes, 30 sellers, and the following 10 constraints and 10 preferences.

Non-Conditional Constraints:

- (ncc1) NULL ⇒ Model Year! = 2011
- (ncc2) NULL ⇒ Warranty ≥ 2
- (ncc3) NULL ⇒ Refresh Rate ≥ 120
- (ncc4) NULL ⇒ Screen Size ≥ [30 − 39]
- (ncc5) NULL ⇒ Brand!= Dynex

Conditional Constraints:

- (cc1) (Refresh Rate ≤ 240) ⇒ Price ≤ [900 − 999.99]
- (cc2) (Brand = Panasonic) and (Resolution = 4K Ultra HD) ⇒ Weight ≤ [5 − 5.9]
- (cc3) (Brand = LG) or (Resolution = 1080p HD) ⇒ Screen Size ≤ [40 − 49]
- (cc4) (Model Year = 2013) and (Warranty ≥ 2) ⇒ Brand! = Bose
- (cc5) (Customer Rating < 2) and (Model Year ≤ 2012) ⇒ Price ≤ [500 − 599.99]

Non-Conditional Preferences:

- (ncp1) NULL ⇒ Price ([300 − 399.99] (HS), [1000 − 1499.99](LS))
- (ncp2) NULL ⇒ Refresh Rate (600(HS), 120(LS))
- (ncp3) NULL ⇒ Brand (Bose(BA), Dynex(LS), Insignia(BA), LG(AA), Panasonic(A), Philips(A), Samsung(A), Sharp(BA), Sony(AA), Toshiba(HS))
- (ncp4) NULL ⇒ Screen Size ([50 − 60] (HS), [30 − 39](LS))
- (ncp5) NULL ⇒Model Year (2013(HS), 2012(LS))

Conditional Preferences:

- (cp1) (Price ≥ [300 − 399.99]) and (Screen Size ≥ [40 − 49]) ⇒ Display Technology (LCD (BA), LED (A), OLED (AA), Plasma (HS))
- (cp2) (Refresh Rate ≥ 120) ⇒ Resolution (1080p HD (HS), 4K Ultra HD (AA), 720p HD (A))
- (cp3) (Screen Size ≥ [30 − 39]) ⇒ Weight([4 − 4.9] (HS), [6 − 7] (LS))
- (cp4) (Price ≥ [800 − 899.99]) ⇒ Warranty(3(HS), 2(LS))
- (cp5) (Refresh Rate ≥ 240) or (Screen Size ≥ [30 − 39]) ⇒ Customer Rating (5(HS), 3(LS))

Figures 9(a) and 9(b) depict the processing time of MAUT* by varying the number of non-conditional and conditional constraints respectively (the latter is shown in Table 6 (a)). As the buyer adds more constraints, there may be two consequences: the execution time may decrease or remain the same. The increment of constraints creates more chances for the bidders to violet them, which results to their disqualification. Thus, the execution time decreases as it needs to evaluate fewer sellers. For example in Figure 9(b), we can see that it takes more running time when the number of conditional constraints is 1 than 2, because the two constraints cc1 and cc2 disqualify more bidders than cc1 alone. However, it takes the same running time when the number of conditional constraints are 2 and 3, because both (cc1, cc2) and (cc1, cc2, cc3) delete the same number of sellers. Similarly, Figure 10 illustrates the execution time by varying the number of non-conditional and conditional preferences (the latter is given in Table 6 (b)). As the buyer includes more preferences, the execution time of MAUT* to determine the winner increases.

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Table 6: (a) Varying number of conditional constraints (b) Varying number of conditional preferences

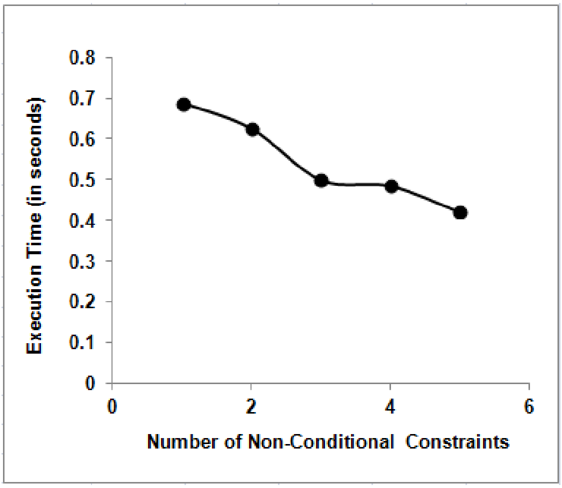
NCC	CC	NCP	CP
5	1(cc1)	5	5
5	2(cc1, cc2)	5	5
5	3(cc1, cc2, cc3)	5	5
5	4(cc1, cc2, cc3, cc4)	5	5
5	5	5	5

(a)

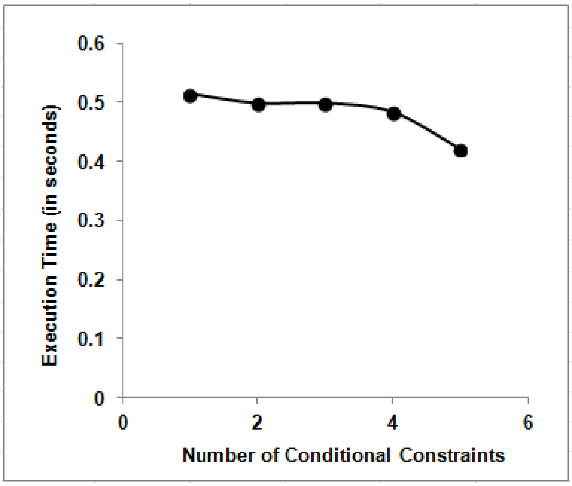
NCC	CC	NCP	CP
5	5	5	1(cp1)
5	5	5	2(cp1, cp2)
5	5	5	3(cp1, cp2, cp3)
5	5	5	4(cp1, cp2, cp3, cp4)
5	5	5	5

(b)

More precisely we show in Table 7 how the number of conditions, constraints and preferences impact the execution time of MAUT* and also the auction outcome (disqualified, challenged or winner). For example, when we increase the number of conditions from 2 to 7 in preferences, the execution time increases from 0.323 to 0.422. In some situations, almost all sellers respect many constraints, or few constraints might make almost every seller invalid. For these reasons, the execution time does not necessarily decrease linearly every time the number of constraints increases; it might decrease sharply or slowly or even sometimes remain the same. Also, the execution time increases from 0.323 to 0.688 with the increment of the number of preferences from 1 to 5. MAUT* returns the overall utilities for all the 30 sellers in a very reasonable time, for example in just 0.422 seconds when processing all the 10 constraints and 10 preferences. We can conclude that our MARA protocol is able to determine the winner efficiently. Depending on the number of preferences, the auction returns different results. In Table 7, for the qualified sellers, when varying the number of preferences and their conditions, the system returns three different winners: S1, S16 and S18. For instance, when there are one or two non-conditional preferences, the winning bidder is S16. But when there are three non-conditional preferences, S18 surpasses S16 because he scores a better overall utility for the third non-conditional preference.

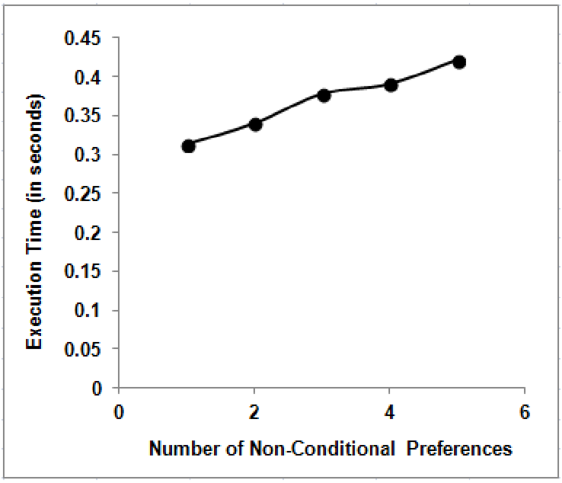


(a)

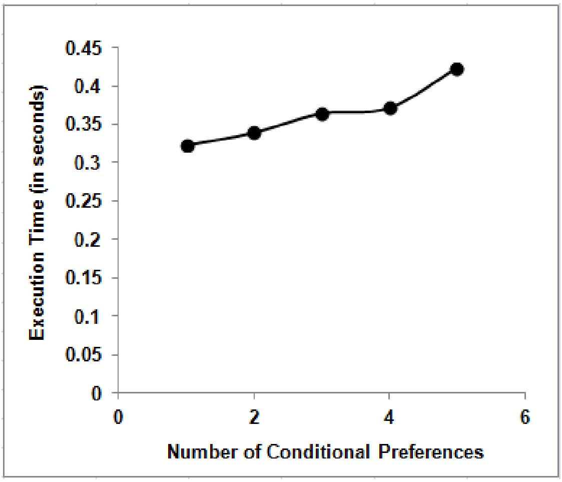


(b)

Figure 9: (a) Non-Conditional constraints vs execution time (b) Conditional constraints vs execution time



(a)



(b)

Figure 10: (a) Non-Conditional preferences vs execution time (b) Conditional preferences vs execution time

Table 7: Winner selection results

C1	C2	C3	C4	C5	C6	C7	C8	C9
1	5(9)	5(1, 4)	5(7, 2, 3)	13	17	0.688	0.649	S18
2	5(9)	5(1, 4)	5(7, 2, 3)	14	16	0.625	0.649	S18
3	5(9)	5(1, 4)	5(7, 2, 3)	15	15	0.500	0.649	S18
4	5(9)	5(1, 4)	5(7, 2, 3)	16	14	0.485	0.649	S18
5	1(1)	5(1, 4)	5(7, 2, 3)	12	18	0.516	0.649	S18
5	2(3)	5(1, 4)	5(7, 2, 3)	13	17	0.500	0.649	S18
5	3(5)	5(1, 4)	5(7, 2, 3)	13	17	0.500	0.649	S18
5	4(7)	5(1, 4)	5(7, 2, 3)	15	15	0.485	0.649	S18
5	5(9)	1(0, 1)	5(7, 2, 3)	18	12	0.313	0.449	S16
5	5(9)	2(0, 2)	5(7, 2, 3)	18	12	0.340	0.456	S16
5	5(9)	3(1, 2)	5(7, 2, 3)	18	12	0.378	0.626	S18
5	5(9)	4(1, 3)	5(7, 2, 3)	18	12	0.391	0.647	S18
5	5(9)	5(1, 4)	1(2, 1, 0)	18	12	0.323	0.490	S1
5	5(9)	5(1, 4)	2(3, 2, 0)	18	12	0.339	0.535	S1
5	5(9)	5(1, 4)	3(4, 2, 1)	18	12	0.364	0.642	S18
5	5(9)	5(1, 4)	4(5, 2, 2)	18	12	0.371	0.647	S18
5	5(9)	5(1, 4)	5(7, 2, 3)	18	12	0.422	0.649	S18

C1 = Number of non-conditional constraints
C2 = Number of conditional constraints (total number of conditions)
C3 = Number of non-conditional preferences (number of string type, number of numeric type)
C4 = Number of conditional preferences (total number of conditions, number of string types, number of numeric types)
C5 = Number of disqualified sellers
C6 = Number of challenged sellers including winner
C7 = Execution time of MAUT* (in seconds)
C8 = Overall utility value of winner
C9 = ID of winner

6 User Acceptance Evaluation

To assess the benefits and limits of our constraint/preference specification and winner determination tool, we conducted a small laboratory experiment with several graduate students from our Computer Science department. The evaluation is based on three user acceptance criteria given in Table 8. We employed in total 11 questions, most of them extracted from the article [17].

Table 8: User acceptance criteria

	Yes/ No	Comment
Ease of Use		
1. Is the system easy to use?		
2. Is the system user-friendly?		
3. Do you think the system is flexible?		
Usefulness		
4. Do you get the information you need in time?		
5. Does the system provide sufficient information?		
6. Is the information clear?		
7. Will you use it again?		
Satisfaction		
8. Do you think the GUIs are presented in a useful format?		
9. Do you think the output is presented in a useful format?		
10. Are you satisfied with the results?		
11. Are you satisfied with the overall system?		

In the following, we summarize the results and comments provided by the participants.

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6.1 Ease of Use

Specifying simple constraints and preferences, i.e. with 0 or 1 condition at the most, is relatively an easy task. However many auctioned items have complex requirements, so in this case expressing requirements with several conditions requires a lot of effort and time. The preference and constraint formalisms are easy to understand. The hardest part is the condition specification, which depends on the knowledge subjects have about the item domain. On the other hand, our system provides a great flexibility to buyers and gives them full control. In each phase of the requirements construction process, buyers have a chance to decide. Novice buyers may always submit simple requirements and also requirements only on the attributes they are familiar with. For uncertain attributes and uncertain values as well, they have a choice to not enter any preference or constraint.

6.2 Satisfaction

All the participants were satisfied with the system time performance. We let each buyer decides between the effort he would like to spend in the requirements construction and the accuracy of the produced results.

6.3 Usefulness

Although students expressed a good intention in using our auction tool again due to its flexibility, they provided us with suggestions to assist the buyers better. They proposed showing more information with every GUI, such as its purpose along with a concrete example, and also a progress bar to let the buyers know their positions (e.g. phase 2 out of 4) in the specification process. Some of them suggested developing a compact master interface.

In summary, the shortcoming of our tool is that it costs non-experienced users effort and time to comprehend the first time the item characteristics and hence construct their individual constraints and preferences. After several trials, subjects were more comfortable. The strengths are great flexibility and accuracy. Flexibility offers buyers a good user experience. In our tool, the specification process appears to be complicated but it is made convenient and feasible via an interactive and friendly approach. The latter comes with GUIs that are based on simple options and buttons.

7 Conclusion and Future Work

We proposed a multi-round, first-score, semi-sealed MARA mechanism for complex procurement scenarios. The elicitation of buyer's personal preferences for various attributes plays an essential role in performing a multi-dimensional auction. Our MARA provides buyers with choices and flexibility in the elicitation process. Through friendly GUIs, our system is able to aid the buyer specifying (non) conditional constraints as well as qualitative (non) conditional preferences. To determine the winner efficiently, it converts qualitative requirements into quantitative ones, and produces automatically the attribute weights and attributes utility values. Weights and individual utilities are generated from the buyer’s qualitative preferences. The buyer’s full utility function and some feedback information on the participants of the auction are made public. Moreover, we explored experimentally the feasibility and performance in time of MARA through a 10-attribute reverse auction involving a good number of constraints, preferences and sellers. We also evaluated the acceptance of our requirements specification and winner determination tool.

There are several promising future research directions on MARAs. To increase the acceptability of our auction system, the buyer can be provided with more options, such as eliciting qualitative preferences on some attributes and quantitative ones on others in the same auction. In this study, the preference of an attribute may depend on other attribute values. Thus, we would like to compare our formal preference specification technique with the GAI method (an interesting graphical representation model that handles attribute dependencies [11], [18]). Regarding the constraint specification, if it is over-constrained (the set of attribute constraints is too strong) and there are not enough qualified sellers to process, so in this situation, we can inform the buyer about the constraints that are mostly violated. The buyer can then revise these constraints.

We considered the case where attributes are utility independent. An interesting future work is to define the attribute utility function based on the dependent attributes. To determine the winner, we applied an additive aggregation function (MAUT) that assumes that the attributes are independent. Another research direction is to identify what is the most appropriate non-additive aggregation method for the auction winner evaluation. The issue here is how to map the buyer's qualitative preferences into the non-additive function. Also, we would like to apply heuristic techniques, such as genetic algorithms, to find the optimal winner within a given time constraint [43]. In real life, there might be a considerable number of suppliers, attributes, constraints and preferences, and exact algorithms may take a big amount of time to process all the bids. Still, heuristic algorithms may produce an optimal winner by saving a lot of processing time.

In this article, we focused mostly on auction buyers as well as on mechanism design. It would be interesting to automate the multi-attribute negotiation process by deploying intelligent software agents that will participate in the auctions on behalf of sellers. This will considerably reduce the burden on sellers and increase market efficiency as well. We will also investigate which trading strategies are the most appropriate for sellers in the setting of MARAs. An interesting work [16] explores bidder's strategies for three different protocols in the context of multi-attribute auctions: first-score sealed-bid, second-score sealed-bid and sequential full information revelation. These strategies help bidders to determine the best bid based on the optimal quality attributes and optimal price. [52] proposes two Bayes-Nash equilibrium strategies for bidders of multi-attribute auctions: one based on the expected profit and the other one on Cobb-Douglas utility function. Also, we would like to integrate game theory to examine the economic properties of the auction outcomes.

This paper is the first step of our research on users' constraints and preferences in the context of MARAs. We are interested in extending our work with a more advanced study on user interaction models and their acceptance. [35] reports that very few works have been done on user interaction models in the area of preference elicitation. Moreover, we would like to examine how MARAs are used in real-life e-markets and analyze the ones that succeed.

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