Bidding strategy for agents in multi-attribute combinatorial double auction

Faria Nassiri-Mofakham a,*, Mohammad Ali Nemathbakhsh b, Ahmad Baraani-Dastjerdi b, Nasser Ghasem-Aghaee b, Ryszard Kowalczyk c, d

a Department of Information Technology Engineering, University of Isfahan, P.O. Code 81746-73441, Hezaj Jerib Avenue, Isfahan, Iran
b Department of Computer Engineering, University of Isfahan, P.O. Code 81746-73441, Hezaj Jerib Avenue, Isfahan, Iran

ABSTRACT

In a multi-attribute combinatorial double auction (MACDA), sellers and buyers’ preferences over multiple synergetic goods are best satisfied. In recent studies in MACDA, it is typically assumed that bidders must know the desired combination (and quantity) of items and the bundle price. They do not address a package combination which is the most desirable to a bidder. This study presents a new packaging model called multi-attribute combinatorial bidding (MACBID) strategy and it is used for an agent in either sellers or buyers side of MACDA. To find the combination (and quantities) of the items and the total price which best satisfy the bidder’s need, the model considers bidder’s personality, multi-unit trading item set, and preferences as well as market condition. The proposed strategy is an extension to Markowitz Modern Portfolio Theory (MPT) and Five Factor Model (FFM) of Personality. We use mkNN learning algorithm and Multi-Attribute Utility Theory (MAUT) to devise a personality-based multi-attribute combinatorial bid. A test-bed (MACDATS) is developed for evaluating MACBID. This test suite provides algorithms for generating stereotypical artificial market data as well as personality, preferences and item sets of bidders. Simulation results show that the success probability of the MACBID’s proposed bundle for selling and buying item sets are on average 50% higher and error in valuation of package attributes is 5% lower than other strategies.

1 Introduction

Combinatorial auction (CA) is one of the best suited mechanisms for trading a bundle of different synergetic items (services) in comparison to sequential or parallel auctions. When the items are substitutes, the bidder desires to acquire at most one of them. However, for the complementary items, the bidder’s valuation for the whole bundle is super-additive; therefore, the more complement the items, the more valuable the bundles (Cramton, Shoham, & Steinberg, 2006; De Vries & Vohra, 2003; Milgrom, 2004; Rothkopf, Peke, & Harstad, 1998). Multi-attribute combinatorial double auction (MACDA) is the most general but complex auction. This combinatorial auction considers other attributes than only price and better satisfies bidder’s preferences compared to auctions where the bidder is uncertain about or uninterested in attribute values that will later be settled during the contract phase (Bichler, Shabalin, & Pikovsky, 2009). In addition, while single-side auctions are of interest to the sellers in the forward and to the buyers in the reverse auctions', double auction clears with fairer outcomes and is of interest to both the buyers and the sellers. A seller can use CA for promotional offers to customers, since procuring a bundle of items rather than individual items can lead to savings in logistics costs.
time, payment and the overall cost savings for the customers, while the seller provides packages, which bring him the highest returns. A buyer can benefit in CA from efficient allocations when she has some preferences over combinations of items or a limited budget. Therefore, ‘‘multi-attribute combinatorial double auction’’ can better attribute multi-attribute preferences of both buyers and sellers where fair outcomes satisfy synergies among goods that bidders’ desire. MACDA has two prominent problems to be addressed: Winner determination (WDP) and bid generation (BGP). Similar to WDP, BGP is also an NP-Hard problem (Park & Rothkopf, 2005; Parkes, 2000; Triki, Oprea, Beraldii, & Crainic, 2014). Bidders would like to benefit for winning the goods. That is, not only a bidder likes to be a winner, but to prevent a winners’ curse she/he also prefers to gain rather than lose if she/he wins. Bidding is an important issue which also affects WDP (Rothkopf & Harstad, 1994; Rothkopf et al., 1998).

In recent years, several bidding strategies have been proposed by studies in combinatorial auctions (An, Elmaghraby, & Keskinocak, 2005; Leyton-Brown & Shoham, 2006; Parkes & Ungar, 2000; Pikovsky, 2008; Triki et al., 2014; Wilenius, 2009). However, none of the existing solutions addresses a multiple-attribute, double sided, and multiple-unit bidding scenario together (see Section 2). It is also worth noting that previous studies typically do not model bidder’s willingness to trade a bundle among many combinations that can be defined. Some works let the bidders to prioritize combinations (Park & Rothkopf, 2005). However, they do not show how the provided packages could be the best package of bundles a specific bidder most prefers. In other words, these studies assume that the bidders must know the desired bundles and priorities. Moreover, all the bidders in a market are not willing to be a profit maximizer so that they behave differently and prefer different packages. Market history is another source of information that a bidder needs to consider in devising a bid. This need for considering the history of the market and the bidder’s decision making model for prioritizing the packages makes efficient bidding in one-shot MACDA mechanism a very complex task.

The complexity of bidding a package among an exponential number of potential bundles of items with synergies comes back to the fact that besides the above mentioned requirements, bidders in MACDA should also address several important issues such as (1) size of the package, (2) items to place in the package, (3) quantities of each item in the package, (4) attribute values of each item in the package, (5) attribute values of the package, (6) price of the package, (7) limitations regarding items’ quantities for sellers, and (8) limitations regarding bidder’s budget for buyers (Leyton-Brown & Shoham, 2006; Vinyls, Giovannucci, Cerquides, Meseguer, & Rodriguez-Aguilar, 2008). Moreover, real markets do not necessarily reveal pricing made by all the bidders. The market exposes the bundles along with the prices at which the bundles traded. That is, the market hides individual valuations which each participant assumes for each individual item. The bidder faces the problem of which combination (and quantity) of items and in what values for the package price and attributes is the best combination regarding information resources (market history and policy) and his/her item set and bidding behavior. The bidder’s decision-making would depend on the winning/losing price of the bundles and his/her risk and cooperation attitudes towards the market.

This paper addresses the sellers and buyers’ bidding in MACDA. It proposes a strategy for the bidders in order to provide a multi-attribute combinatorial bid (MACBID) that addresses different behaviors of the bidders in a market. We model a bidder as a personality agent that interacts with MACDA by observing a history of the previous trades in the market and submitting her/his own bids (ask bids or sell bids) to MACDA in one-shot, where only traded bundles (not all the proposed bids) are revealed to the bidders. The traded bundle in the history consists of only quantities of each item in the bundle, values of each package attribute, and the package price. A bidder can make personality-based decisions different from the other bidders—with even the same item set and valuations—that observe the same market trades history. This strategy employs the bidder’s personality, multi-unit item set, and preferences as well as market situation. To be informed of the prices of the items and finding the most synergistic and desirable package for devising a personality-based and market-based multi-attribute combinatorial bid, we extend Markowitz Modern Portfolio Theory (Markowitz, 1952; Prigent, 2007), Five Factor Model of Personality (Liebert & Speigler, 1998; McCrae & Costa Jr, 1999; Nassiri-Mofakham et al., 2009; Norman, 1963; Oren & Chases-Aghaei, 2003), mKNN learning algorithm (Nassiri-Mofakham et al., 2009), and Multi-Attribute Utility Theory (Fasli, 2007; Lewicki, Saunders, & Barry, 2006; Nassiri-Mofakham, Chasem-Aghaei, Ali Nematbakhsh, & Baraani-Dastjerdi, 2008; Raiffa, 1982; Wooldridge, 2009). Markowitz MPT and FFN of personality help the bidder in bundling multi-unit complementary goods by considering market data as well as the bidder’s item set and personality, while FFN of personality, combinatorial mKNN learning, and MAUT are employed for selecting the best MACBID among substitutes of the devised bundle.

As we focus on the bidding process, issues regarding WDP to design a complete MACDA mechanism are outside the scope of this study. Therefore, we evaluate the proposed MACBID using benchmarking in a test suite. The study develops a multi-attribute combinatorial double auction test suite called MACDATS. This test suite provides algorithms for generating realistic artificial market data, personality, preferences, and multi-unit item sets of bidders. MACDATS which also operates as a support tool in helping humans in efficiently devising bids in the complex market, benchmarks efficiency, validation, and confidence of MACBID against other strategies.

The remainder of the paper is organized as follows. We overview related works in Section 2. In Section 3, we describe the MACDA market design space. Section 4 details MACBID strategy and presents the architecture of bidding agents. MACDATS and evaluation of MACBID is presented in Section 5. Section 6 concludes the paper by summarizing the contributions of the study and outlining future avenues of this research.

2. Related work

After the Smith’s seminal work on modeling the market behavior in 1962 (Smith, 1962) and reconsidering the importance of bidding by Rothkopf and Harstad in 1994 (Rothkopf & Harstad, 1994), several studies have significantly advanced bidding strategies in double auctions (Gjerstad & Dickhaut, 1998; He, Leung, & Jennings, 2003; Rapti, Karageorgos, & Ntalos, 2014; Vytelingum, Cliff, & Jennings, 2008). In ZI strategy (MacKin-Mason & Wellman, 2006) buyer/seller propose a random offer between the best bid/ask and the current value. In FM strategy (Tan, 2007) the best bid/ask added with a positive/negative value is proposed. GD strategy (Gjerstad & Dickhaut, 1998) records all bids/asks history and propose a bid/ask by cubic-spline extrapolation for.

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2 In this study, from now on, “she/her” and “he/his” refer to the “buyer” and “seller”, respectively.
In recent years, combinatorial auctions (CAs) have attracted significant interests in many disciplines, especially in computer science, economics, transportation, and electrical engineering. CAs offer a market mechanism for selling or buying combinations of synergistic goods. Despite of single-good auctions with straightforward mechanisms, determining the winners in CAs is a hard optimization problem (Blumrosen & Nisan, 2007; Cranton et al., 2006; Nisan, Roughgarden, Tardos, & Vazirani, 2007; Peke & Rothkopf, 2003; Rothkopf et al., 1998; Sandholm, 2000; Schwind, 2007). Nonetheless, many studies have proposed approximate algorithms for solving the winner determination problem (WDP) in single- and double-sided CAs (Dang & Jennings, 2003; Fukuta & Ito, 2008; Köksalan, Leskela, Wallenius, & Wallenius, 2009; Özer & Özurtan, 2009; Rastegari, Condon, & Leyton-Brown, 2010; Sandholm, 2002; Schellhorn, 2009; Sureka & Wurman, 2005; Tennenholtz, 2002; Wu & Hao, 2015; Xia, Staella, & Whinston, 2005). On the other hand, the bidding problem in CAs has recently emerged as a focus of attention in many studies as it affects the best response strategy (An et al., 2005; Bhargava, 2014; Ittekhar, Hallu, & Lindner, 2014; Triki et al., 2014; Wang & Xia, 2005; Wilenius, 2006). Studies proposed for bidding in CAs focus typically on either bid representation (Boutilier & Hoos, 2001; Cerquides, Endriss, Giovannucci, & Rodrı́guez-Aguilar, 2007; Day & Raghavan, 2009; Goossens, Muller, & Spieksma, 2009; Nisan, 2000; Nisan et al., 2007) or bidding strategies. It is worth noting that this study focuses on bidding strategies and does not consider winner determination and bid representation problems in CAs. Nonetheless, in the studies in WDP, bids are simply a bundle of random quantity of each item along with a price which is assumed as the maximum price the bidder wish to pay. Utility-maximizing and risk-neutrality are the features which have been considered for the bidders in the applications that employ single-side combinatorial auctions (Miyashita, 2014; Satunin & Babkin, 2014; Zhong, Huang, Wu, & Chen, 2013).

In works on the bidding problem, some studies consider it jointly with WDP so that the bidders are involved in solving the problem of determining winners by submitting and revising tentative bids as part of the global solution (Köksalan et al., 2009; Mendoza & Vidal, 2007). Those solutions are typically derived under strong (and often unrealistic) assumptions regarding the availability of information related to all bidders such as private valuations of other bidders or tentative solutions. Some other works on bidding in CA propose an adaptive approach for setting the profit margin for bundles of bids in the history of bids of a bidder (Sui & Leung, 2008). However, they do not consider which bundle to choose or in other words how to choose the items and their quantities for bundling.

The works proposed by Parkes and Ungar (2000), Leyton-Brown, Pearson, and Shoham (2000), Leyton-Brown and Shoham (2006), An et al. (2005), Wang and Xia (2005), Hualong and Fang (2010), Vinyals et al. (2008), Wilenius (2006), Pikovsky (2008), Bichler et al. (2009), address the bidding strategy as a problem isolated from solving WDP. The works presented by Wang and Xia (2005) and Wilenius (2009) considerably emphasize on the importance of bidding in CAs. Wilenius analytically shows that a bid on random synergetic combination is a best response strategy for bidders rather than bids on all combinations. There are two good studies tailored to transportation service procurement which do not match with our e-marketplace, but they relate regarding considering combinatorial bid generation. Wang and Xia propose two heuristic approaches for solving the combinatorial bid generation in transportation using integer programming under constraints regarding the bundle of lanes. A similar work by Triki et al. (2014) solves the same problem in transportation by considering the competitors’ prices on bundles and using two heuristics for sequential descending or ascending generation of a bundle based on approximated pairwise synergy values. It generates stochastic bids, assigns probabilistic prices, and assigns risks regarding the degree of uncertainty of the bid as to be a winning bundle. This study not only consider a single side of the market history (the competitors’ prices which may not be revealed in realistic markets), but also it model bids using distribution probabilistic functions and do not address how a price and by each different bidder is actually set in the same market.

Most of the works on combinatorial bid generation employs a few computational models which are listed below.

The best response strategy in a game-theoretically analysis for iterative combinatorial auctions is proposed by Parkes and Ungar (2000; Parkes & Ungar, 2000; Pikovsky, 2008; Wu & Hao, 2015). In that strategy, the bidder bids for all combinations that could maximize his/her surplus given the current prices. Therefore, the enumeration determines the bundle.

Leyton-Brown et al. (2000), Leyton-Brown and Shoham (2006) and Wu and Hao (2015) propose a combinatorial auction test suite (CATS) that attempts to model realistic bidding behavior and addresses the bidding problem in four domains: Paths in Space Problem, Proximity in Space Problem, Arbitrary Relationships Problem, and Temporal Matching Problem. The third problem, CATS-3, fits into our e-marketplace scenario and is used as one of the benchmark strategies for evaluating our MACBID in Section 6. CATS-3 develops algorithms for generating bundles of single-unit goods based on the degree of their synergy relationships.

INT strategy (An et al., 2005), which is called best Chain by Pikovsky (2008) and Bichler et al. (2009), enumerates the most profitable bundle given current prices while the goods have synergetic relationships.

Nonetheless, the best Response, CATS-3 and best Chain strategies are designed for a single-unit single-sided combinatorial auction. Vinyals et al. (2008) propose a MMUCA test suite adapting CATS for a special mixed multi-unit combinatorial auction. They do not assume goods in synergy but belonging to different levels in a supply chain. MMUCA also considers discounts regarding multiplicity of items in the bundle. MMUCA is a mixed of reverse and forward (but not a double-side) multi-unit combinatorial auction, while it is designed for a specific multi-level purpose.

However, none of the existing approaches (summarized in Table 1) has addressed a multiple-attribute, double-side, and multi-unit bidding solution all together. In addition, they do not consider bidders’ behavior and market information in formulating a bid. Therefore, the main aim of our research is to develop an efficient bidding strategy in a multi-attribute combinatorial double auction which considers trading set, bidder personality and market situation in a single-shot, sealed bid multi-attribute multi-unit combinatorial double auction under MACDA policy (Section 3.2) where the participants do not have any information about individual valuation of each participant for each item but the traded package prices.

3. Multi-attribute combinatorial double auction

As a solution for bidding in multi-attribute combinatorial double auction, we propose MACBID strategy by considering the bidder’s item set and personality as well as market situation in a single-shot, sealed bid auction so that no sell bid or buy bid, but only the trades are revealed to bidders. We consider a bidder as a personalized emotion-free agent who interacts with the market.

by observing the history of the previous trades and proposing her/ 
his own bid to the mechanism. However, we do not consider cul- 
tural differences among the bidders, emotional and commit- 
tion issues. We detail our MACBID strategy in the next section. In 
this section, we provide descriptions of the market space.

3.1. MACDA specifications

3.2. MACDA policies

In MACDA mechanism, that stands for multi-attribute combina-
torial double auction, many buyers and many sellers propose 
several multi-attribute combinatorial bids for trading multiple 
items. There are two types of bids based on multiple trade 
criteria, that is, a multi-attribute bundle bid or a multi-
attribute goods. There are two types of bids based on multiple 
and one for packages, namely item-based and package-based attributes. Item-based attributes of 
which describes its features, while package-based attributes reflect 
the criteria related to trading a package of the goods. This multi-
goods marketplace is also lawful so that in addition to bidding to 
the policies of the mechanism (see Section3.2), all participants know 
the permissible interval of each good attribute value announced by a 
legal party, e.g., the market maker.

Let \( n_a, n_b, n_c, \) and \( n_g \) are the number of goods, 
and package’s attributes in MACDA. Suppose \( B = \{ b_1, b_2, \ldots, b_n \} \) and \( S = \{ s_1, s_2, \ldots, s_m \} \) are sets of buyers and sellers, respectively. \( C = \{ c_1, c_2, \ldots, c_n \} \) represents package-based attributes (see 
Section 3.2.1). Let \( G = \{ g_1, g_2, \ldots, g_n \} \) is the set of goods in the 
market. MACDA lets different goods to have a different number of attributes 
which again may or may not be the same in types or orders.

For a good \( g \in G, A^g = \{ a_1^g, a_2^g, \ldots, a_k^g \} \) describes the attributes of 
g where \( n_k^g \) is the numbers of \( g \)’s attributes. Adopting Nassiri-
Mofakham, Nemathakhs, Ghasem-Aghaei, and Barama-Dastjerdi 
(2006, 2008, 2009a), the value intervals \( \{ \text{Min}_v, \text{Max}_v \} \), 
\( \{ \text{Min}_v, \text{Max}_v \}, \ldots, \) and \( \{ \text{Min}_v, \text{Max}_v \} \) are 
respectively defined for the attributes \( i \) through \( n_k^g \). In 
addition, \( \{ \text{Min}_v, \text{Max}_v \}, \{ \text{Min}_v, \text{Max}_v \}, \ldots, \) and 
\( \{ \text{Min}_v, \text{Max}_v \} \) represent the value intervals for 
package-based attributes. For the quantitative attributes, we assume 
\( n_1^g, \ldots, n_k^g \) and \( n_1^g, \ldots, n_k^g \) represent the number of values for 
goods and package attributes, respectively.

3.2. MACDA policies

MACDA governs several policies regarding bid representation, 
information revelation, and winner determination. Designing a 
comprehensive MACDA mechanism (specially, winner determina-
tion) is beyond the scope of this study. Nonetheless, in the following 
we describe these policies on a level required for bidders in design-
ing their bids.

\[ A \text{ Bundle of Multi-Unit Goods} \]

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Bundle size</th>
<th>Bundle goods</th>
<th>Goods quantities</th>
<th>Bundle price</th>
<th>Attribute values</th>
<th>Double-sided</th>
</tr>
</thead>
<tbody>
<tr>
<td>BestResponse</td>
<td>Enumeration-based</td>
<td>Bundles with max total surplus</td>
<td>–</td>
<td>Current price</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>CATS-3</td>
<td>Random</td>
<td>Random but Synergetically</td>
<td>–</td>
<td>Superadditive sum of values</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>INT</td>
<td>Enumeration-based</td>
<td>Those making the highest (private) Synergetic</td>
<td>–</td>
<td>Synergetic sum of values</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>MMUCA</td>
<td>Random</td>
<td>Random from available combinations</td>
<td>–</td>
<td>Discount-based superadditive</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

\[ \text{A Bundle of Multi-Unit Goods} \]

Fig. 1. Bid representation in MACDA.

3.2.1. Bid representation policy

A multi-attribute combinatorial bid \( D \) is an ordered set \( (d, e) \), so that

\[ d = (I_g, g \in G), I_p = (g, q_g) \text{ and } e = (p(c_1), p(c_2), \ldots, p(c_n)) \]

where, \( q_g \) and \( p(c_k) \) are quantity of good \( g \) and the value of \( k \)th attribute of the package \( (k = 1, \ldots, n_c) \), respectively. The first element of \( D \) is a set itself containing a combination of multi-unit goods.

In this study, we consider goods with two attributes, namely 
price and quantity. Several quantities can be proposed for goods 
in a bundle. All quantities are supposed to be as "all-or-nothing".

That is, a trade happens when all quantities offered for goods in 
a buy-bid and a sell-bid are matched. It is worth noting that there 
is no item-based attribute 'Price' in the bid structure. Price only 
appears for the package representing the synergetic total price of all 
goods in this package.

Item-based attributes are not necessarily the same among 
different goods. However, the same attributes have been defined 
for all packages. For example, suppose a university bookshop in which 
a buyer bids for a book and a bag. Item-based attributes for a 'Bag' 
can be 'Size', 'Color', 'Model', and so on, while for a 'Book', they 
can be 'Title', 'Author', 'Publisher', and so on. However, in addition to 
package 'Price', there are common attributes which are important 
in any trade such as 'Delivery', 'Payment Method', 'Shipping Style', 
'Packaging Style', 'Reputation of the Counterpart', and so on. Since 
goods are traded in a single package, there is no need for negotiat-
over these package-based attributes per each good but the package. 
For each good, the same template of attributes is used 
among all participants. However, all attribute values, of either 
item-based or packaged-based, can be freely different among 
several buyers' bids and sellers' asks.

A bid in MACDA is represented as in Fig. 1 together with the 
bidder's identification. When bids are submitted to MACDA, they 
are time-stamped.

\[ \text{A Bundle of Multi-Unit Goods} \]

<table>
<thead>
<tr>
<th>Goods attributes</th>
<th>Package attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good 1</td>
<td>Good 1’s Quantity</td>
</tr>
<tr>
<td>Good 2</td>
<td>Good 2’s Quantity</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Good j</td>
<td>Good j’s Quantity</td>
</tr>
</tbody>
</table>

\[ \text{A Bundle of Multi-Unit Goods} \]

5 In the literature, sometimes buy-bid and sell-bid are called bid and ask, 
respectively. A ‘bid’ is an offer for buying something, while an ‘ask’ is a propose for 
selling.

6 It is obvious that other attributes are also required for establishing any trade, such 
as destination address, account/check/card information, and so on. However, this 
information will then be exchanged between corresponding parties, if their bids are 
matched in MACDA. Therefore, there is no need for negotiating such attribute values 
and proposing in the bid.

3.2.2. Information revelation policy

MACDA policy is Partial Information Revelation. Participants propose sealed bids. MACDA exposes all participants only market history. That is, participants do have information about previous trades but not all offers. This hides asks and bids submitted to MACDA but trades happened among successful asks and bids. Therefore, all participants, either a buyer or a seller, see a sequence of timestamped trades represented with the same representation and structure shown in Fig. 1 and Eq. (1). The only difference between the representation of bids in the market and of trades in a transaction in the history is that no identification information regarding parties who exchanged those bids is included in the trade archiving. According to Section 3.2.1, trades also include no information regarding individual good prices but traded package prices. It is worth noting that traded packages in the market history do not necessarily include the same number and types of goods.

Therefore, MACDA trade history (HMACDA) is an ordered list of multi-attribute combinatorial anonymous trades, \( D^s = (t, d^s, e^s) \) where

\[
d^s = \left( f^s_g, \ g \in G \right), \quad e^s = (v^s(c_1), v^s(c_2), \ldots, v^s(c_n))
\]

In Eq. (2), \( v^s(\cdot) \) is the value of \( k \)th attribute of the package \((k = 1, \ldots, n)\) and \( d^s \) is a set of multi-unit goods \( f^s_g \) as

\[
f^s_g = (g, q^s_g)
\]

where, \( q^s_g \) is quantity of good \( g \) exchanged in \( s \)th trade. That is, \( D^s \) is a ternary vector of time of the trade, a combination of multi-unit traded goods, and the trade criteria values.

3.2.3. Winner determination policy

MACDA is running in one-shots. We assume that it follows an all-or-nothing method (and based on a time stamp) for determining winners and arbitraging (pricing). When one ask and one bid match completely, their corresponding bidders win and can trade. If several asks (bids) can match a bid (ask), the earliest ask (bid) wins. Bids and asks continuously are submitted to MACDA. At the end of each shot, MACDA clears those bids and asks which are matched. Designing MACDA winner determination policy as a subject of another stream of the research in CAs is beyond the scope of this study. However, an upper bound for an agent so that his/her bid to be supposed as a winning candidate is

\[
price^e \geq price^i, \quad \forall g \in G, \ q^e_g \geq q^i_g, \text{if } i \in S
\]

\[
price^e \leq price^i, \quad \forall g \in G, \ q^e_g \leq q^i_g, \text{if } i \in B
\]

where, \( price^i \) and \( q^i_g \) are the package’s price and quantities of goods \( g \) in bid \( i \) in the market, respectively. Similarly, \( price^e \) and \( q^e_g \) are the price of the package and quantities of goods in the agent \( e \)'s bid. If the agent’s bid for selling (buying) can satisfy another one’s bid for buying (selling) according to the condition described in Eq. (4), they then may be supposed as candidate winners.

4. The MACBID strategy

As reviewed in Section 2, none of the existing researches in combinatorial auction has addressed a general solution for multiple-attribute, double sided, and multiple-unit bidding. In addition, they do not model bidder’s willingness to trade a bundle among many combinations and are unable to show how their provided packages could be the best package of bundles a bidder prefers most. It is obvious that such an agent needs to consider bidder’s preferences and behaviors along with observing the market history and bidder’s item set in devising a bid.

We deal with bidding process in a market that is not multinational. Therefore, we do not consider cultural differences among bidders as well as emotional and commitment issues. The proposed architecture for a personified emotion-free bidding agent considers bidder’s personality, item set, and preferences as well as marketsituation. When a personified bidder who are endowed with an item set (for selling or buying) participate in MACDA, he/she is being informed of MACDA trades history and goods specifications. A bidder agent faces the problem of which combination of goods and in what total price is the best for the bidder to achieve his/her goals by considering information resources (i.e., market specifications, bidder’s item set, MACDA history and policies) and bidder’s behavior. A bidder not only wants to be a winner in MACDA, but also he/she prefers to make a profitable deal. In addition to the market parameters, his/her decision-making depends on the personality of the bidder to be a winner. Risk attitude of a bidder will determine how profitable his/her bid may be devised.

Adopting the personality-based bargaining model (Nassiri-Mofakham et al., 2009b) and portfolio optimization (Prigent, 2007), we extends Markowitz Modern Portfolio Theory (Markowitz, 1952; Prigent, 2007), Five Factor Model of Personality (Liebiet & Speigler, 1998; McCrae & Costa, 1999; McCrae & Costa, 1985, 1987; Nassiri-Mofakham et al., 2008; Nassiri-Mofakham et al., 2009b; Norman, 1963; Oren & Ghasem-Aghaei, 2003), a combinatorial version of mkNN learning algorithm (Nassiri-Mofakham, Nematbakhsh, Baraani-Dastjerdi, & Ghasem-Aghaei, 2007; Nassiri-Mofakham et al., 2009a), and Multi-Attribute Utility Theory (Fasli, 2007; Nassiri-Mofakham et al., 2009b; Raiffa, 1982) equip agent with decision-making capabilities toward devising a personality-based and market-based multi-attribute combinatorial bid.

Using MAUT, a bidder’s choice for a single object is based on the bidder’s preferences represented by a utility function over weights and values of multiple attributes of the object. According to Nassiri-Mofakham et al. (2008) and Nassiri-Mofakham et al. (2009b), this individual choice is best represented by personality-based parameters such as the bidder’s risk and cooperation. In a double auction, where many buyers and many sellers participate in the market, another type of risk is also raised. This later risk relates to the valuations of other bidders on the object that causes an uncertainty in their expected returns. When this market is combinatorial, the uncertainty is increased regarding the complexities that exist in valuations of bidders on different synergistic combinations of goods.

The seminal mean–variance analysis introduced by Markowitz (1952) in quantitative finance shows that investors must take care not only the returns but also the risk of the portfolio of financial products, which is the standard deviation of their portfolio return than summation of the products’ risks. Extending the works of Markowitz (1952) and Nassiri-Mofakham et al. (2008); Nassiri-Mofakham et al. (2009b) lead us to a personality-based combination selection that considers risks of both the bidder and combination.

When the bidder is recommended by multi-attribute alternatives of a combination of goods, a combinatorial version of mkNN learning algorithm (mkNN-Com) is developed to show the bidder high frequency combination of the attribute values of that combination in the market. Markowitz MPT and FFM of personality help the bidder in bundling complement goods by considering market data as well as bidder’s item set and personality. For making multi-attribute substitute packages from the devised bundle, mkNN-Com learning is employed. FFM of personality and MAUT then help the bidder for selecting MACBID among these substitutes.

4.1. Architecture of the bidding agent

Fig. 2 depicts the proposed architecture for the bidding agent. The agent has two layers, namely: Perception and Bidding. Through

Perception layer the agent is being informed of the market as well as bidder's endowments and preferences. Bidding is the layer describing core of the agent's bidding strategy. Perception layer consists of three modules: (1) Information, (2) Preference, and (3) Market Processing. Preference module models the bidder's behavior, while Market Processing module brings the agent more detailed information about goods traded in the market. These modules are presented in Sections 4.2–4.4.

By detailed information of the market, the Bidding layer provides the agent with abilities in devising a multi-attribute combinatorial bid by considering both market information and bidder's preferences via three modules, namely: (1) Bundling, (2) Packaging, and (3) Bid Generation. Bundling and Packaging modules provide the bidder agent with an optimal multi-attribute package based on market situation as well as his/her item set and preferences. Finally, Bid Generation module determines the best multi-attribute combinatorial bid prescribed for this typical bidder agent. Sections 4.5–4.7 propose these three core modules.

4.2. Information module

This module contains the information resources that the agent's bidding is based on, namely: the goods and trade specifications, the market trades history, and the bidder's item set.

4.2.1. Goods and trade specification

The bidder is informed of the set of goods, the attributes of the goods (item-based attributes), the valid value intervals for each
good’s attribute, the package-based attributes, and the valid value intervals for each package attribute according to Section 3.1.

4.2.2. Market trades history

The history contains useful information such as the collective trading behavior of the participants regarding multi-attribute combinations of goods as well as the degrees of correlation among the goods in any arbitrary packages. Traded packages anonymously are revealed to the participants through the information revelation policy. HMACDA (MACDA trade history) is an ordered list of multi-attribute combinatorial trades \( HMACDA = \{(\mathbb{D}^j : t \in \mathbb{N}\) where,

\[
D_t = \{t, \langle \langle g_1^t, q_1^t \rangle, \langle g_2^t, q_2^t \rangle, \ldots \langle g_n^t, q_n^t \rangle \} \}
\]

is defined by MACDA according to Eq. (2). The trades include no information regarding the individual good prices but the traded package prices.

4.2.3. Bidder’s item set

In every shot, the bidder agent \( i \) trades a package of goods based on his/her endowments as a set of items. A seller agent sells the goods available in his stock while a buyer agent buys the goods that the bidder needs. Each good in the item set is assigned with the attributes values. Both agents consider their own bidder’s reservation value and other limitations as endowed by them by

\[
ItemSet^i = \{I^i_g : I^i_g = \langle g, RV^i_g \rangle, g \in G \}
\]

where, \( Min\_valid^i_g \leq RV^i_g \leq Max\_valid^i_g \).

Bidder’s reservation value is the minimum (maximum) price that a seller (buyer) agent is able to submit for the good. A seller agent has another limitation regarding the maximum available quantities of the good, while a buyer agent should consider trades in her budget limit. That is,

\[
Limitations^i = \{< Q^i_g, g \in G > \quad if \ i \in S
\]

Budget^i \quad if \ i \in B \}
\]

4.3. Preference modeling module

The agent’s preferences include the bidder personality data as well as her/his decision-making parameters, valuations and desire with respect to his/her item set. By observing history of the previous trades in the market, the bidder makes personality-based decisions that can be different from the other bidder’s who observes the same market trades history and considers the same item set and valuations.

This module consists of three components that model agent’s preferences regarding the bidder’s valuations for goods, decision-making parameters and objectives.

4.3.1. Bidder’s valuation

This component is for evaluating the value of a package and is applied in Section 4.7.1. In evaluating the value of a bundle of goods along with the corresponding trade attributes, we employ Multi-Attribute Utility Theory by adopting Nassiri-Mofakham et al. (2008), Nassiri-Mofakham et al. (2006) and Nassiri-Mofakham et al. (2009b), We suppose the bidder has private utility function based on different weighting on each package attribute (criterion).

A typical agent \( i, i \in B \cup S \), has two sets containing \( n \) criteria value intervals and their respective \( W^i_c \) weights, that are \( \{[\min^i_c, \max^i_c], \ldots, [\min^n_i_c, \max^n_i_c] \} \), and \( \{W^i_1, \ldots, W^i_n\} \), respectively, which satisfy \( \sum_{c=1}^n W^c = 1 \) as well as \( \min \_valid \leq \min^i_c \) and \( \max^i_c \leq \max \_valid \), for all criterion \( C \) (see Section 3.1).

Assuming \( AV^c_i \) and \( RV^c_i \) are respectively the agent’s aspiration and reservation values for any criterion \( C \) of the package and \( e^i_{c}(\text{package}) \) as it’s evaluated score of the value related to criterion \( C \), utility of a package for the agent \( i \) is a multi-attribute linear function

\[
u^i(\text{package}) = \sum_{c=1}^n W^i_c E^i_c(\text{package})
\]

where,

\[
E^i_c(\text{package}) = \begin{cases} \frac{e^i_{c}(\text{package}) - RV^i_c}{AV^i_c - RV^i_c}, & AV^i_c \neq RV^i_c \\ 1, & AV^i_c = RV^i_c \end{cases}
\]

4.3.2. Bidder’s behavioral parameters

In this study, we suppose the participants with stable personalities. We formalize the behavioral parameters for decision-making among emotion-free agents using Five Factor Model of Personality also referred to as OCEAN clustered in five groups, namely: Openness, Conscientiousness, Extraversion, Agreeableness, and Negative emotions. Personality of a bidder \( i \) is then represented as

\[
Personality^i = \langle O^i, C^i, E^i, A^i, N^i \rangle
\]

so that each personality factor consists six Fuzzy facets as shown in Fig. 3. Once the values of the six facets of a personality trait are specified, the corresponding personality type can be determined and entered in the personality template in Eq. (10).

The value of a trait is the value of the highest weighted value of the six facets, which constitute it. We define the bidder’s Risk factor \( R^i(0 \leq R^i \leq 1) \) and Cooperation factor \( CP^i(0 \leq CP^i \leq 1) \) using Fuzzy Inference Engines adapting the rules defined in Nassiri-Mofakham et al. (2008) and the six facets:

<table>
<thead>
<tr>
<th>Openness</th>
<th>Conscientiousness</th>
<th>Extraversion</th>
<th>Agreeableness</th>
<th>Negative emotions</th>
</tr>
</thead>
<tbody>
<tr>
<td>O1</td>
<td>C1</td>
<td>E1</td>
<td>A1</td>
<td>N1</td>
</tr>
<tr>
<td>O2</td>
<td>C2</td>
<td>E2</td>
<td>A2</td>
<td>N2</td>
</tr>
<tr>
<td>O3</td>
<td>C3</td>
<td>E3</td>
<td>A3</td>
<td>N3</td>
</tr>
<tr>
<td>O4</td>
<td>C4</td>
<td>E4</td>
<td>A4</td>
<td>N4</td>
</tr>
<tr>
<td>O5</td>
<td>C5</td>
<td>E5</td>
<td>A5</td>
<td>N5</td>
</tr>
<tr>
<td>O6</td>
<td>C6</td>
<td>E6</td>
<td>A6</td>
<td>N6</td>
</tr>
</tbody>
</table>

Fig. 3. Big-five personality template.
Mofakham et al. (2008) and Nassiri-Mofakham et al. (2009b) as shown in Fig. 4. Sections 4.5.1 and 4.7.2 employ this component.

4.3.3. Bidder’s objective function
In the previous work on personality-based bargaining model (Nassiri-Mofakham et al., 2009b), proposing the best initial offer in the bilateral negotiation (where the agent has not yet received any information from his/her counterpart) is according to the bidder’s risk-based boundary utility values. However, in this market, the bidder agent is informed of the market trades history and he/she makes his/her best decision regarding both the risk- and cooperation-based values in single-shot.

Different bidders may prefer different combinations with respect to their personalities. That is, besides maximizing the return and minimizing the risk, maximizing return-risk or any other varieties are the objective functions a bidder can employ in selecting an optimal combination. Therefore, by adapting (Rom & Ferguson, 1994) we define the goal and objective of the bidder toward selecting a bundle of goods by introducing an RL’ factor (0 < RL’ < 1) as

\[ RL’ = d(R^i, CP^i, \lambda) \]  

where,

\[ d(R^i, CP^i, \lambda) = \frac{R^i + \lambda CP^i}{1 + \lambda} \]  

is the decision function and 0 < \lambda < 1 is a concentration parameter that determines the weight of the bidder’s Risk and Cooperation factors. R^i, CP^i and \lambda influence the interval that RL’ falls in, its position in the interval, and the length of the intervals, respectively. The smaller is the \lambda, the shorter are the intervals, and vice versa. RL’ plays a role in the bidder’s decision-making based on the return and risk of a combination of goods (see Introduction of Sections 4.4 and 4.5.3) as formulated below:

\[ f^i(combination) = RL’(\text{return}_{\text{Combination}} - (1 - RL’)(\text{risk}_{\text{Combination}}) \]  

RL’ represents the bidder’s degree of rationality regarding a combination. A purely rational bidder agent with the minimum RL’ follows the maximum return combination (Rom & Ferguson, 1994), while the most risk-averse agent who has the maximum RL’ follows a combination with a minimum risk (Rom & Ferguson, 1994).

Then after, the bidder \( i \) solves the problem using Simplex method for the objective function that is then defined as

\[ \max f^i(combination) \]  

s.t. CONSTRAINTS’ are satisfied

where, CONSTRAINTS’ are defined as Sections 4.5.3 and 4.5.4. This component is applied in Sections 4.5.3 and 4.7.2.7

Fig. 4. The agent component for inferring Risk (R) and Cooperation (CP) of the bidder based on his/her personality (Nassiri-Mofakham et al., 2008, 2009a).

4.4. Market processing module
Through Information module, the bidder is informed of the goods and the values of their attributes along with a total package price traded previously in the market based on related package attribute values. In proposing a bid, the bidder needs to find which goods and in what quantities he/she should place in the bundle and in what a total price and attribute values propose to the market. However, for generating and pricing such a bundle, the bidder first needs to price goods in his/her item set. As described in Sections 3 and 4.2, the bidder has no information regarding individual values of the goods from the synergetic packages traded in the market. By using Market Processing module, the bidder gains an estimation of these unit prices.

4.4.1. Filtering HMACDA
For calculating an optimal multi-attribute combinatorial bid, a bidder agent solely considers transactions that include at least one good from his/her ItemSet (see Eq. (6)). The agent vertically filters MACDA trade history (HMACDA) using an association of all goods in his/her ItemSet. In this way, the bidder agent processes MACDA (filtered HMACDA) containing a sequence of limited amount of data logs in a period of time. That is,

\[ \text{HMACDA} = \{d^i[d^i + (t, d^i, c^i) \in \text{HMACDA}, \exists g \in I(g, f_g \in I(f_g) \} \]  

where, \( d^i \) and \( I(f_g) \) are defined as Eqs. (2) and (3), respectively.

The bidder agent then horizontally extracts random transactions from HMACDA. This extraction is based on a partitioning parameter \( \rho \) that determines which percentage of HMACDA transactions is used as the training set for the agent. This sampling generates MACDA and HMACDA. MACDA is used for the agent bidding purposes. In Section 5.3, we then employ VMACDA for testing and validation of the agent’s bid.

4.4.2. Predicting individual goods’ prices
For a bidder agent who only knows the individual reservation value of the goods in his/her ItemSet, it is not easy to precisely assign a synergetic value to their combinations, however. It is useful to find how the other participants have valued synergies of a combination. Individual prices for the goods along with the package price can give the agent a good idea for evaluating the synergy. However, MACDA provides the agent with information related to the traded packages rather than prices of the individual goods (see bid representation and information revelation policies in Sections 3.2.1 and 3.2.2).

The bidder considers the prices of packages and the goods’ quantities. For finding the best combination of the goods that the bidder has in his/her ItemSet, the agent makes a decision based on the trading situation of the prices of individual goods traded previously. However, these are hidden information revealed to no participants. From Section 3.2, it is remembered that participants...
To predict these hidden individual prices, suppose $\hat{p}_g$'s by an average of $p_M$  is the price of goods equilibrium prices, $\langle g \rangle$. In this method, we iteratively

$$q_{11}p_{11} + q_{12}p_{12} + \cdots + q_{1N}p_{1N} = \pi_1$$
$$q_{21}p_{21} + q_{22}p_{22} + \cdots + q_{2N}p_{2N} = \pi_2$$
$$\vdots$$
$$q_{MN}p_{M1} + q_{M2}p_{M2} + \cdots + q_{MN}p_{MN} = \pi_M$$

(16)

where $p_g(r = 1, \ldots, M, g = 1, \ldots, N)$ is the hidden single-item price supposed for good $g$ in transaction package $r$ and $\pi_r$ is the price of the package traded in this transaction. By getting a slice of quantities of the goods traded in each package, the seller should solve a system of Mequations and $M \times N$ variables as

Since $M \gg N$. Therefore, by considering only the package price and quantities of the goods traded in each package, the seller should solve a system of $N$ equations and $N$ variables as

$$p_M = \langle g \rangle p_M$$

where $p_M$ is the price of goods equilibrium prices, $\langle g \rangle$. In this method, we iteratively

\[ p_M = \frac{\sum_{g=1}^{N} (M - N + 1) \cdot (M - N + 2) / 2}{2} = \frac{385,003 \text{ solutions (price combinations)}}{2} \]

It is worth noting that not all these systems has valid solutions. However, for employing Markowitz Portfolio Theory (Markowitz, 1952) described in the introduction of Section 4, we need a full history rather than a single (average price) solution. This also helps for increasing the accuracy of the result and taking into account the price variances. We present an Iterative Sliding Window method to solve this problem as described below.

**Iterative Sliding Window Method.** In this method, we iteratively slide a window of $N$ equations toward the end of $\text{TMACDA}$, as shown in Fig. 5. Among all \( \left( \begin{array}{c} M \\ N \end{array} \right) \) systems of size $N$, that is, we get at most \( (M - N + 1) \cdot (M - N + 2) / 2 \) solutions (i.e., products’ price combinations)\(^9\).

It is worth noting that not all these systems has valid solutions. Solutions containing positive prices for all $N$ goods build $\text{PMACDA}$ composed of a new stream of transactions based on these individual goods’ prices. Windows containing newer transactions create newer price combinations while those including older transactions compose older combination of prices. Therefore,

\[ \text{ESWA 9731 No. of Pages 28, Model 5G} \]

\[ \text{19 December 2014} \]

\[ \text{Q1} \]

\[ \text{F. Nassiri-Mofakham et al./Expert Systems with Applications xxx (2014) xxx–xxx} \]


\[ \text{Q1} \]

\[ \text{Q1} \]

\[ \text{Q1} \]
PMACDA = \{ (r, \{p^i_g \colon g = 1, \ldots, N \} \colon r \in \mathbb{R}) \}.
\tag{17}

4.4.3. Reducing price dispersions

In predicting the prices using Iterative Sliding Window Price Prediction method (Fig. 5), PMACDA contains all non-negative solutions. PMACDA is used as a stream of the goods’ prices traded over a period of time. With respect to real private prices for the goods traded in packages in double-sided mechanism experiments, although PMACDA provides pretty good average information regarding goods prices, these prices may contain huge dispersions.

Filtering PMACDA throws out dispersed data and improves STD of the predicted values. We carry out this filtering using an ε-Test by adapting to F-test over data. F-test says that if by eliminating a transaction we get $F = \frac{\text{std}_{\text{new}}^2}{\text{std}_{\text{old}}^2}$ close to 1, then removing that transaction is useful; however, if $F$ gets larger than 1, then the transaction should not be removed. In the following, we present our ε-Test method.

ε-Test method

We first compute $\mu_g$, the mean of the variables $p_g$ (prices of good $g$) as $\mu_g = \frac{1}{N} \sum_{i}p_i$, where $K = |\text{PMACDA}|$ is the number of transactions created in PMACDA. Following Section 4.4.2, $N \leq n$, is the maximum single-item number of the goods (item types) traded in PMACDA. It is worth noting that vectors representing transactions in PMACDA contains the same number of goods as TMAcDA. However, PMACDA and TMAcDA differ in the number of transactions either.

We assume $\varepsilon$ is the error rate tolerated in predicting $p_g$’s. We iteratively test each transaction in PMACDA to throw out transactions with large dispersions in the predicted prices. In this filtering, we eliminate a transaction if the deviation of at least one $p_g$ in the transaction exceeds $\varepsilon$ percent from its $\mu_g$. That is, if for any $p_g$ in a transaction in PMACDA we observe $\frac{p_g - \mu_g}{\mu_g} \geq \varepsilon$, then this transaction is not entered into FPMACDA (filtered PMACDA). Fig. 5 depicts this filtering method.

Using this filtering, the bidder agent now has a good estimation of the market prices in FPMACDA. These prices have been predicted only based on traded quantities of the products in combinatorial transactions in a total package price. The method interestingly resulted in predictions close to real prices regarding their standard deviation $\sigma_g$. These values are bidder-independent so that all bidders observing the same period of the market history estimate the same averages and standard deviations for the same goods.

4.4.4. Squeezing

Generated FPMACDA now contains prices of all goods in transactions addressing trades that consist at least one good in the agent’s ItemSet. However, the agent only needs prices related to those goods in his/her ItemSet’. Therefore, the agent squeezes FPMACDA by throwing out unrelated prices to produce SMACDA as

\[
\text{SMACDA} = \{ (r, \{p^i_g \colon g \in \text{ItemSet‘} \} \colon r \in \mathbb{R}) \}.
\tag{18}
\]

This squeezed FPMACDA, has the same number of transactions as FPMACDA and with the same number of goods in ItemSet’.

4.5. Bundling module

As explained in Section 4.1, Bundling, Packaging, and Bid Generation are the core modules for the bidder agent in devising a bid. In this section, we detail Bundling module by proposing four components for pricing the goods in ItemSet, interpreting the utilization of the market for the prices set by the agent, finding optimal bundle of goods and their quantity percentages in the bundle, and finally quantifying the goods’ quantities and the bundle price.

4.5.1. Preference- and market-based unit-pricing model

The bidder agent now should set a price for each good as if it is for trading individually than in a combination. The agent should compute these individual prices according to the bidder’s preferences as well as the market situation. By employing Market Pricing module in Section 4.4., the bidder agent has found an estimation through average $\mu_g$ and standard deviation $\sigma_g$ of market prices for each good $g$ in his/her ItemSet. In Section 4.3.2, we formulated behavior of the agent toward risk and cooperation in the market using the bidder’s personality factors. In addition, through Section 4.2.3, the agent is informed of the bidder’s reservation values for each good.

In our previous work (Nassiri-Mofakham et al., 2009b), proposing the best initial offer in bilateral negotiation in a single-good e-marketplace where the agent has not yet received any information from his/her counterpart is according to the bidder’s risk-based boundary utility values. However, in MACDA, the agent is informed of previous transactions in the market. Therefore, his/her decision-making in single-shot is based on both risk- and cooperation-based values. Hence, we extend that approach (Nassiri-Mofakham et al., 2009b) to a wider range of behaviors for the bidders interacting the market by considering Risk ($R_i$) and Cooperation ($CP_i$) of each bidder $i$ and his/her reservation values ($RV^i$) as well as average $\mu_g$ and standard deviation $\sigma_g$ of market prices for each good $g$. The bidder agent $i$ generates a price set for all goods $g$ in his/her ItemSet’ as

\[
\text{PRICING} = \{ g, p_{g}^i \colon g \in \text{ItemSet‘} \}
\tag{19}
\]

where,

\[
p_{g}^i = \phi(i)Y^i_g + (\phi(i) + (-1)^{\phi(i)}e^{-(\sigma_g^i)^2})X^i_g
\tag{20}
\]

and

\[
X^i_g = F\left(\Delta X^i_g, \Delta Y^i_g \right), \quad Y^i_g = F\left(\Delta Y^i_g, \Delta Y^i_g \right), \quad \beta = \ln \left(\frac{X^i_g}{Y^i_g} \right)
\tag{21}
\]

so that,

\[
F^i() = \begin{cases} 
\text{Max} & \text{if } i \in S \\
\text{Min} & \text{if } i \in B 
\end{cases}
\tag{22}
\]

while, $\Delta X^i_g, \Delta Y^i_g$ and $\Delta Y^i_g, \Delta Y^i_g$ are computed using $r^i$

\[
r^i = (-1)^{\phi(i)}(R^i - \phi(i))
\tag{23}
\]

where,

\[
\phi(i) = \begin{cases} 
0 & \text{if } i \in S \\
1 & \text{if } i \in B 
\end{cases}
\tag{24}
\]

We also employed

\[
d^i_g = (-1)^{\phi(i)}\sigma_g^i
\tag{25}
\]

that aggregates the seller and buyer agents’ pricing formula. Fig. 7 presents this pricing method for both seller and buyer agents in MACDA. In this pricing, a unit price $p^i_g$ is proposed with respect to the distance of $CP^i$ and $R^i$ with those of extreme behaviors. These extreme prices $X^i_g$ and $Y^i_g$ are first determined through $R^i$ and then adjusted by $CP^i$. Without any regard to the degree of risk and cooperation of a bidder agent, seller and buyer agents prefer higher and lower prices, respectively. Accordingly, they employ Max and Min functions in setting a price by considering both the bidder’s $RV^i$ and market prices, respectively.

It is worth mentioning that the approach presented in Fig. 7 encapsulates 10 class of scenarios regarding $RV^i$ of a bidder $i$ for good $g$ with respect to its $\mu_g$ and $\sigma_g$ in the market. Five classes represent scenarios for pricing by a seller agent whose $R^i$ value varies between 0 and 1. In each class, $CP^i$ value of the seller agent belongs...
to a region for values between 0 and 1 (as shown in the first column of Fig. 8). Similarly, five classes of scenarios represent the buyer agent’s pricing method. When the seller agent’s $R_i$ falls into the interval $[0.45,0.55]$, different pricing with respect to his/her $CP_i$ are as shown in Fig. 8.

We explain the approach using Fig. 9 and assuming that bidder $i$ is a seller agent. This seller agent considers different values in his decision-making. For example, in Scenario 9(b), these values corresponding points 1–7 are as follows:

Point 1: $\mu_g + \sigma_g$ and $\max(\mu_g - \sigma_g, RV_i)$

Point 2: $\frac{\mu_g + \sigma_g}{2}, \frac{RV_i}{2}$

Point 3: $\mu_g$ and $\max(\mu_g, RV_i)$

Point 4: $\frac{\mu_g + RV_i}{2}$

Point 5: $\max(\mu_g - \sigma_g, RV_i)$

Point 6: $\frac{\mu_g - \sigma_g}{2}, \frac{RV_i}{2}$

Point 7: $\mu_g - \sigma_g$

Therefore, for a seller agent with this $RV_i$, when $R_i = 0.50$ and $CP_i = 0.85$, two extreme prices affecting his pricing are $X_i' = \frac{\mu_g + \sigma_g}{2}$ at point 4 and $Y_i' = \frac{RV_i}{2}$ at point 3 that correspond to $CP_i = 0$ and $CP_i = 1$ for sellers with $0.45 \leq R_i \leq 0.55$, respectively (See ComputeExtremePrices in Fig. 7 where this seller agent with $R_i = 0.50$ falls in the third case $0.45 \leq R_i \leq 0.55$). Hence, this seller agent assigns $\text{pricing}_i = \frac{\mu_g + \sigma_g}{2}$ to good $g$. 

### Figure 7
The preference- and market-based pricing algorithm.

### Figure 8
Scenarios for pricing a good $g$ by seller agents with $0.45 \leq R_i \leq 0.55$.

![Figure 7](image_url)

![Figure 8](image_url)
Example 1. As a more detailed example, suppose seller agent 1 with \( R^1 = 0.50 \) and \( CP^1 = 0.85 \) would like to price a shirt whose reservation value is \( RV^1_{shirt} = 45 \) while \( \mu_{shirt} = 52.38 \) and \( \sigma_{shirt} = 8.02 \). Therefore, he proposes \( pricing^1_{shirt} = \text{Avg}(52.38, 45) - 0.85 \ln(0.5238/45) = 45.54 \). However, seller agent 2 who has endowed shirts with the same reservation value \( RV^2_{shirt} = 45 \) but with \( R^2 = 0.83 \) and \( CP^2 = 0.85 \), prices his shirts differently and higher than of seller agent 1 as \( pricing^2_{shirt} = \text{Max}(52.38, \text{Avg}(60.40, 45)) - 0.85 \ln(0.5238/45) = 49.27 \). Table 2, shows the pricing of only eight different agents (among all) for selling shirt in this market.

It is worth noting that, for the same endowments of ItemSets, these buyer agents (among all) assign to their required shirt.

Example 2. It is obvious that a buyer’s reservation value (the maximum value that she can pay for a good) may or may not be higher than a seller’s reservation value (the minimum value that he can sell the good at). However, for comparing the approach presented in Fig. 7 and showing that different roles may cause different pricing, we suppose eight buyer agents with the same values of the seller agents in Example 1. Table 3 shows prices that these buyer agents (among all) assign to their required shirt.

4.5.2 Interpreting the market

The bidder agent \( i \) now has priced goods \( g, g \in \text{ItemSet}^i \) using Eq. (20). To bid optimally, the bidder needs to explore how profitable the market situation is regarding the prices he/she assigned for his/her ItemSet compared to prices of the goods traded in the market. To find high return products, the bidder interprets returns that could gain from the market history per estimated transaction prices.

Suppose that the bidder desires to trade a good \( g \) in \( pricing^g \). By observing transaction \( r \) in the market history, where the good \( g \) has been traded at price \( p^g_r \), we define

\[
\text{return}^g_r(p^g, pricing^g_r) = \left(1 - \phi(i)\right) \frac{(p^g_r - pricing^g_r)}{pricing^g_r} \tag{26}
\]

where \( \phi(i) \) is defined as Eq. (23).

Now, the bidder can interpret SMACDA transactions (See Section 4.4, Eq. (16), Fig. 6, and Section 4.4.4) into IMACDA based on the return percentages that he may gain by trading his/her goods at those transaction prices. IMACDA is then represented as

\[
\text{IMACDA}^1(i, \text{RETURN}^g_r : r \in \mathbb{N}) = \left\langle \text{return}^g_r(p^g, pricing^g_r) : g \in \text{ItemSet}^i \right\rangle \tag{27}
\]

where,

\[
\text{RETURN}^g_r = \left\langle \text{return}^g_r(p^g, pricing^g_r) : g \in \text{ItemSet}^i \right\rangle \tag{28}
\]

and \( r \) is the sequence number of IMACDA transactions.

It is worth noting that this interpretation of SMACDA transactions is carried out only for those goods that are exist in ItemSet. That is, IMACDA has the same number of transactions as SMACDA but contains less number of goods as equal as of goods in ItemSet.

Fig. 9. Four scenarios of \( RV_i^g \) of bidder \( i \) for good \( g \) with respect to its \( \mu_i \) and \( \sigma_i \) in the market.

Table 2

<table>
<thead>
<tr>
<th>Seller agent ( i )</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>( g^i )</td>
<td>0.50</td>
<td>0.83</td>
<td>0.50</td>
<td>0.83</td>
<td>0.50</td>
<td>0.83</td>
<td>0.50</td>
<td>0.83</td>
</tr>
<tr>
<td>( CP^i )</td>
<td>0.85</td>
<td>0.85</td>
<td>0.15</td>
<td>0.15</td>
<td>0.85</td>
<td>0.85</td>
<td>0.15</td>
<td>0.15</td>
</tr>
<tr>
<td>( RV_{shirt}^i )</td>
<td>45</td>
<td>45</td>
<td>45</td>
<td>45</td>
<td>55</td>
<td>55</td>
<td>55</td>
<td>55</td>
</tr>
<tr>
<td>( pricing^i_{shirt} )</td>
<td>45.54</td>
<td>49.27</td>
<td>48.12</td>
<td>52.10</td>
<td>53.00</td>
<td>55.40</td>
<td>55.00</td>
<td>57.29</td>
</tr>
</tbody>
</table>

Table 3

<table>
<thead>
<tr>
<th>Buyer agent ( i )</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>( g^i )</td>
<td>0.50</td>
<td>0.83</td>
<td>0.50</td>
<td>0.83</td>
<td>0.50</td>
<td>0.83</td>
<td>0.50</td>
<td>0.83</td>
</tr>
<tr>
<td>( CP^i )</td>
<td>0.85</td>
<td>0.85</td>
<td>0.15</td>
<td>0.15</td>
<td>0.85</td>
<td>0.85</td>
<td>0.15</td>
<td>0.15</td>
</tr>
<tr>
<td>( RV^i_{shirt} )</td>
<td>45</td>
<td>45</td>
<td>45</td>
<td>45</td>
<td>55</td>
<td>55</td>
<td>55</td>
<td>55</td>
</tr>
<tr>
<td>( pricing^i_{shirt} )</td>
<td>45.00</td>
<td>45.00</td>
<td>45.00</td>
<td>45.00</td>
<td>53.89</td>
<td>55.00</td>
<td>54.81</td>
<td>55.00</td>
</tr>
</tbody>
</table>
4.5.3. Devising optimal combination of goods

Following Sections 4.4.1–4.4.4, 4.5, 4.5.1 and 4.5.2, the bidder now has individual return values regarding predicted individual goods prices. Based on these return values, we design a combination, which is the most profitable one for the seller. To do that, we can now employ an approach based on Markowitz Portfolio Theory (Elton & Gruber, 1997; Fama, 1971; Goebel, 2007; Markowitz, 1952; Müller, 1988; Prigent, 2007), as follows.

For each good $g$, $g \in \text{ItemSet}^i$, the expected return of the good for the bidder $i$ is

$$E_g^i = \frac{1}{K'} \sum_{k=1}^{K'} \text{return}^i_{k,g} \cdot \text{pricing}_{k,g}^i, \quad K' = |\text{IMACDA}|$$

where, variable $\text{return}^i_{k,g}$ is defined as Eq. (26). We suppose non-negative $\text{q}^i_k$'s initialized equally as quantity percentages corresponding goods $g$ in a combination for bidder $i$, so that $\sum_{k=1}^{K'} \text{q}^i_k = 100$ where, $N^i$ is the number of goods in the bidder's ItemSet. Return of a combination of goods is then defined as the sum of weighted expected returns of goods as

$$\text{return}^i_{g, \text{combination}} = \sum_{g \in \text{combination}^i} \text{WE}_{g}^i, \quad g \in \text{combination}^i$$

where,

$$\text{WE}^i_g = E_g^i \cdot \text{q}^i_g$$

is the weighted expected return of good $g$ and

$$\text{combination}^i = \{ (\text{q}^i_g: g = 1, \ldots, N^i), \text{return}^i_{g, \text{combination}}, \text{risk}^i_{g, \text{combination}} \}$$

includes quantity percentages corresponding goods composing the combination as well as return and risk of combination as defined in Eqs. (30) and (34), respectively.

Now, using a Simplex optimization the bidder finds which goods and in what quantity percentages maximize his/her objective function\(^{10}\) (e.g., with maximum return in a minimum risk. See also Eq. (11) in Section 4.3.3) regarding a combination.

Several constraints are applied in the optimization with respect to quantity percentages weighted returns of goods, as follows. Constraint 4 is considered in Section 4.5.4.

**Constraint 1.** All quantity percentages must be non-negative:
\[ \forall g \in \text{ItemSet}^i, \text{q}^i_g \geq 0. \]

**Constraint 2.** Summation of all quantity percentages must be 100:
\[ \sum_{g=1}^{N^i} \text{q}^i_g = 100. \]

**Constraint 3.** Weighted returns of goods must be non-negative:
\[ \forall g \in \text{ItemSet}^i, \text{WE}^i_g \geq 0. \]

For the most profitable bid, the bidder likes to choose a combination, which maximizes his/her objective function (see Section 4.3.3). For example, a bidder may prefer a combination, which gives him/her the highest return with a minimum variance compared to any other combinations. Variance of a combination is calculated from the weighted individual goods variances and their covariance from (predicted) historical price data in IMACDA. Goods' variance/covariance matrix is defined as

$$\text{VCV}^i = \begin{bmatrix} \text{var}^i_1 & \text{cov}^i_{1,2} & \cdots & \text{cov}^i_{1,N} \\ \text{cov}^i_{2,1} & \text{var}^i_2 & \cdots & \text{cov}^i_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ \text{cov}^i_{N,1} & \text{cov}^i_{N,2} & \cdots & \text{var}^i_N \end{bmatrix}$$

in which, variance and covariance of goods $g$ and $h$ are

$$\text{var}^i_g = \frac{1}{K'} \sum_{k=1}^{K'} \left( \text{return}^i_{k,g} - E^i_g \right)^2, \quad K' = |\text{IMACDA}|$$

and

$$\text{cov}^i_{g,h} = \frac{1}{K'} \sum_{k=1}^{K'} \left( \text{return}^i_{k,g} - E^i_g \right) \left( \text{return}^i_{k,h} - E^i_h \right), \quad \text{var}^i_g \text{var}^i_h$$

respectively. Therefore, variance of combination is defined as

$$\text{risk}^i_{\text{combination}} = \frac{1}{\sum_{g=1}^{N^i} \sum_{h=1}^{N^i} \text{WE}^i_g \text{WE}^i_h \text{q}^i_g \text{q}^i_h} \times \sqrt{\sum_{g=1}^{N^i} \sum_{h=1}^{N^i} \text{WE}^i_g \text{WE}^i_h \text{q}^i_g \text{q}^i_h \text{cov}^i_{g,h}}$$

(34)

Variance of a combination is equated with risk, measuring how much worse than average the combination return is likely to be. Optimal portfolio then decreases this uncertainty in gaining higher levels of returns by minimizing volatility in combination return. By combining higher return goods in a smart way, their fluctuations cancel each other out. This gives the bidder high average rate of return, with less of fluctuations.

When the market growth situation is unknown, it is rational to select a combination composing goods less correlated with respect to their returns. It is useful for participants in devising their initial bids for entering the market. Next, when the bidder explores the efficiency of the market, he/she can focus on combinations containing high correlated goods, which yield higher returns though in higher risks. This issue is considered in Section 7.2 for further research.

4.5.4. Optimal bundle generation

By optimization presented in Section 4.5.3, the bidder does now have an optimal combination\(^{10}\) as defined in Eq. (32). This section introduces a component that converts values of quantity percentages and rate of return to values of goods quantities and package price to provide the bidder with an optimal bundle of goods. To do that, the bidder agent first needs to have a look at his/her ItemSet Limitations\(^{10}\). In the following, we quantify the values from the seller and buyer agent points of view.

(a) Bundling for the seller agent

For converting values of quantity percentages to values of goods quantities, suppose $q^i$ is the total number of quantities in the bundle. Therefore, quantity $q^i_g$ corresponding goods $g$ in the bundle is

$$\text{quantity}^i_g = q^i \cdot \text{q}^i_g$$

(35)

where $q^i_g$, defined through Eq. (32), are quantities corresponding goods $g$ in combination\(^{10}\). However, according to Eq. (7), a seller agent should consider the maximum available quantities corresponding goods $g$ in the his ItemSet, $Q^i_g, \ldots, Q^i_N$, where $Q^i_g > 0, g = 1, \ldots, N^i$ ($N^i$ is the number of goods in the bidder's ItemSet).

**Constraint 4S.** The seller agent $i$ should obviously consider quantity $q^i_g$ for goods $g$ that $q^i_g < Q^i_g$. To be attainable for existing goods, therefore the seller agent must have

…

Footnotes:

10. In this study, each bidder solves his/her optimization problem using his/her fixed objective function to provide a single combination which is later enlarged to a package of multi-attribute bundles in Section 4.6. However, if the bidder changes the value of $a$ for more concentrating his/her goal toward either return or risk in Eq. (13), he/she can gain a list of combinations sorted by their objective values. Some of these combinations may be iso-variance while the others may be iso-return. Iso-variance combinations are substitutable for a bidder who employs max(return) as his/her objective function. Similarly, a bidder that would like to choose a combination with the greatest possible rate of return, are indifferent among iso-return combinations.
\[ q^i = \min \left\{ \frac{Q_k^i}{q_k^i} : g = 1, \ldots, N^i, \quad q_k^i \neq 0 \right\}. \]

Therefore, the bundle costs

\[ \text{price}^i = \sum_{g=1}^{N^i} \text{quantity}^g q^g \text{pricing}^g \]

where \( \text{pricing}^g \) are defined as Eq. (20) in Section 4.5.1.

Therefore, the combinatorial bundle of multi-unit goods prescribed for the seller agent \( i \) is

\[ CBundle^i = \{ \text{quantity}^g : g = 1, \ldots, N^i, \text{price}^i \} \]

where \( \text{quantity}^g \) and \( \text{price}^i \) are defined as Eqs. (35) and (36), respectively.

(b) Bundling for the buyer agent

Similar to a seller agent, a buyer agent applies Eq. (35) for converting values of quantity percentages \( q^g \) corresponding goods \( g \) to goods quantities values \( \text{quantity}^g \) assuming \( q^g \) is the total number of quantities in the bundle. Therefore, the bundle should cost less than or equal to her budget. That is,

\[ \text{price}^i = \sum_{g=1}^{N^i} \text{quantity}^g \cdot \text{pricing}^g \leq \text{Budget}^i \]

which is reduced to

\[ q^g \leq \frac{\text{Budget}^i}{100\sum_{g=1}^{N^i} \text{pricing}^g}. \]

However, the buyer agent now should consider Constraint 4B for \( \text{price}^i \).

Constraint 4B. It is obvious that the buyer agent \( i \) should consider a bundle whose \( \text{price}^i \) satisfies \( \text{price}^i \leq \text{Budget}^i \).

Therefore, \( \text{quantity}^g \) \( (g = 1, \ldots, N^i) \) are defined using Eqs. (35) and (36), \( \text{price}^i \) is then determined through Eq. (38). This leads the buyer agent \( i \) to a combinatorial bundle of multi-unit goods \( CBundle^i \) as defined in Eq. (37).

4.6. Packaging module

Four components of Bundling module provided the bidder agent with \( CBundle^i \), a combinatorial bundle of multi-unit goods. By this end, this optimal combinatorial bundle is a single-attribute package only considering the price attribute of the package.

Packaging module now assigns values of other package-based attributes for wrapping a bid. This wrapping is based on market data to generate substitute packages. Section 4.7 then filters these substitutes using bidder’s preferences.

For this packaging, we consider two cases. First, we consider 2-attribute packages, where the second attribute is for example only one of ‘Delivery’, ‘Payment Method’, ‘Shipping Style’, ‘Packaging Style’, ‘After Sale Services’, ‘Reputation of the Counterpart’ attributes. This case utilizes Multi-Valued \( k \)-Nearest Neighbor Learning algorithm (Nassiri-Mofakham et al., 2009a). Next, we present an algorithm for packaging multi-attribute packages where any number of package-based attributes can be considered.

To do that, the bidder agent first does a \( c \)-Test on TMACDA to reduce it to a CFMACDA that contains confident transactions.

4.6.1. Filtering confident history trades

In order to have an accurate prediction of package-based attributes values for the recommended \( CBundle^i \), we limit the bidder agent to confident historical transactions in TMACDA using a \( c \)-Test. A confident transaction is a transaction that is exactly matched with the \( CBundle^i \) template. That is, it contains exactly the same items as \( CBundle^i \). Note that TMACDA consists transactions that contain at least one good \( g, g \in \text{ItemSet}^i \).

\( c \)-Test. For this filtering test, \( \text{quantity}^g \) in \( CBundle^i \) are XOR-ed with quantities of goods in each of \( K \) transactions in TMACDA \( (K = |TMACDA|) \). If \( \text{quantity}^g > 0 \) and no quantity of good \( g \) has been traded in transaction \( t \) or if \( \text{quantity}^g = 0 \) and transaction \( t \) has traded good \( g \), then transaction \( t \) is not entered into CTMACDA.

Fig. 10 depicts this filtering method for generating confident transactions.

4.6.2. Packaging in multi-attribute combinatorial e-marketplace

This section provides the bidder agent with a package of bundles. This package contains substitutable attribute values highly co-occurred in the market trades history regarding the bundle. We first introduce this packaging in 2-attribute combinatorial e-marketplace. The multi-attribute case is then presented by proposing a combinatorial multi-valued \( k \)-nearest neighbor learning algorithm.

2-Attribute combinatorial packaging. For 2-dimensional packages, Multi-Valued \( k \)-NN learning algorithm (Nassiri-Mofakham et al., 2007; Nassiri-Mofakham et al., 2009a) is applied for determining \( m \) substitute values highly occurred in the trades history (CTMACDA) based on the second attribute of the package (It is worth noting that the first attribute is price that was determined by Bundling module). These \( m \) \((m \text{ is variable})\) values of this package-based attribute have highly occurrences among the \( k \) nearest trades neighbor (Cover & Hart, 1967; Han & Kamber, 2006; Mitchell, 1997) to the queried package with respect to its item-based attributes. The mkNN algorithm presents multi-valued clas-
sification for an instance based on a single query (e.g., “payment
method” package attribute). In other words, a multi-dimensional
instance (multi-good bundle) is considered for classification in
another multi-dimensional space (multi-attribute space). There-
fore, the bidder agent is prescribed with

$$2A^i_{\text{CPACK}} = \langle \{\text{quantity}_i, \quad \text{g} = 1, \ldots, N\}, \text{price}_i, \{v_1, \ldots, v_m\} \rangle$$ (42)

where $v_1, \ldots, v_m$ are $m$ values of this package attribute that have
high occurrence rate among $k$ nearest (with respect to their Euclid-
ian distance) trades to $C^i_{\text{Bundle}}$. 

Example 3. Assume $C^i_{\text{Bundle}} = \langle 4 \text{ pairs of Shoes}, 4 \text{ Bags}, 8 \text{ Shirts, 8 Trousers}, 2000 \rangle$ is the optimal combinatorial multi-unit
bundle recommended to the bidder agent $i$ in a 2-tribute
combinatorial e-marketplace, where the package-based attributes
are Price and Payment Method. Among all transactions in
CTMACDA, suppose $m$NN learning (with $k = 9$) first explores nine
transactions shown in Table 4 as 9-nearest neighbors of $C^i_{\text{Bundle}}$. 

In determining appropriate values for package-based attributes of
the instance, first suppose we do two separate $m$-NNs for querying
“payment method” and “delivery”. The first $m$NN suggests both
“Credit” and “Cash” (among “Credit”, “Check”, and “Cash”) for pay-
ment method (both with the majority of 4/9) and the second one intro-
duces “1 Day” and “1 Week” (among “1 Day”, “1 Week”, “10 Days”,
and “1 Month”) for delivery (both with the majority of 3/9).

MACPACK$^i = \langle \{\text{pairs of Shoes}, 4 \text{ Bags}. 8 \text{ Shirts. 8 Trousers}, 2000\rangle, \{\langle \text{Credit}, 1 \text{ Day}), \langle \text{Credit, 1 Week}\rangle\} \rangle$. 

4.6.3. A combinatorial multi-valued $k$-nearest neighbor learning
algorithm

This algorithm first assigns a distance to each confidant transac-
tion $r$ in CTMACDA (see also Section 4.6.1). Euclidian distance is
computed among $C^i_{\text{Bundle}}$ quantities of goods and its price with
respect to quantities of goods and price of each transaction (as
shown in Distance(R, CBundle) in Fig. 11). CTMACDA transactions
are sorted based on their distance values in ascending order.

Example 4. Assume the same $C^i_{\text{Bundle}}$ of Example 3 is the optimal
combinatorial multi-unit bundle recommended to the bidder agent
$i$ in a 3-tribute combinatorial e-marketplace, where package-
based attributes are Price, Payment Method, and Delivery. Among
all transactions in TMACDA, again suppose $m$NN learning (with
$k = 9$) explores nine transactions shown in Table 5 as 9-nearest
neighbors of $C^i_{\text{Bundle}}$ based on quantities of its items and the
package price.

In determining appropriate values for package-based attributes of
the instance, first suppose we do two separate $m$-NNs for querying
“payment method” and “delivery”. The first $m$NN suggests both
“Credit” and “Cash” (among “Credit”, “Check”, and “Cash”) for pay-
ment method (both with the majority of 4/9) and the second one intro-
duces “1 Day” and “1 Week” (among “1 Day”, “1 Week”, “10 Days”,
and “1 Month”) for delivery (both with the majority of 3/9).

MACPACK$^i = \langle \{\text{pairs of Shoes}, 4 \text{ Bags}. 8 \text{ Shirts. 8 Trousers}, 2000\rangle, \{\langle \text{Credit, 1 Day}), \langle \text{Credit, 1 Week}\rangle\} \rangle$. 

4.7. Bid generation module

This module is the last among three core modules in prescribing
a multi-attribute combinatorial bid to a bidder. By this end, the
bidder agent has generated MACPACK, a package of multi-attribute
substitute optimal combinatorial bundles. We call each of these
candidate bundles a MACBUNDLE. In this module the bidder agent
first sorts these MACBUNDLES based on their utilities. Using the

In the worst case, the combination of attributes values may even consist of an
attribute value which is not individually highly occurred.
Table 5
Sample traded packages most similar to an optimal package (4 pairs of Shoes, 4 Bags, 8 Shirts, 8 Trousers, 2000) in a multi-attribute combinatorial e-marketplace.

<table>
<thead>
<tr>
<th>Package</th>
<th>Price</th>
<th>Payment</th>
<th>Delivery</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 pairs of Shoes</td>
<td>3 Bags</td>
<td>10 Shirts</td>
<td>6 Trousers</td>
</tr>
<tr>
<td>4 pairs of Shoes</td>
<td>3 Bags</td>
<td>10 Shirts</td>
<td>6 Trousers</td>
</tr>
<tr>
<td>4 pairs of Shoes</td>
<td>2 Bags</td>
<td>9 Shirts</td>
<td>8 Trousers</td>
</tr>
<tr>
<td>5 pairs of Shoes</td>
<td>3 Bags</td>
<td>10 Shirts</td>
<td>6 Trousers</td>
</tr>
<tr>
<td>5 pairs of Shoes</td>
<td>4 Bags</td>
<td>9 Shirts</td>
<td>5 Trousers</td>
</tr>
<tr>
<td>3 pairs of Shoes</td>
<td>4 Bags</td>
<td>10 Shirts</td>
<td>5 Trousers</td>
</tr>
<tr>
<td>5 pairs of Shoes</td>
<td>2 Bags</td>
<td>8 Shirts</td>
<td>7 Trousers</td>
</tr>
<tr>
<td>5 pairs of Shoes</td>
<td>4 Bags</td>
<td>10 Shirts</td>
<td>6 Trousers</td>
</tr>
<tr>
<td>4 pairs of Shoes</td>
<td>2 Bags</td>
<td>9 Shirts</td>
<td>5 Trousers</td>
</tr>
</tbody>
</table>

Algorithm mKNN-COM(Bundle, CTMACDA, TMACDA, k):
if CTMACDA has any transaction
  For each transaction r in CTMACDA
    distance = Distance(CTMACDA(r), Bundle)
  end for r
  Sort(CTMACDA, distance, Ascending)
  n = k * product of per-attribute number of values
  TOPN = attribute values of (at most) top n transactions from sorted CTMACDA
  MTOPVALCOM = Majority(TOPN)
else
  GenTopMACPack_atts(Bundle, TMACDA)
end if
return MTOPVALCOM
End

Majority(TOPN):
For each TOPN transaction t
  TOPN(t).support = Support(TOPN(t), TOPN)
end for t
X = max(TOPN, support)
for each TOPN transaction t
  IF TOPN(t).support == X
    For each package-based attribute c
      VALCOM(m,c) = TOPN(t).att(c).codeValue
    end for c
    m = m + 1
  end if
end for t
return VALCOM
End

Support(T, TOPN):
= Count(TOPN)
counter = 1
For each TOPN transaction t
  For each package-based attribute c
    count = 0
    IF T(c) == TOPN(t,c)
      count = count + 1
    else Break
  end if
  end for c
  IF count == number of packaged-based attributes (i.e., nc)
    counter = counter + 1
  end if
end for t
Sup = counter / n
return Sup
End

Distance(R, Bundle):
EuclidianDistance = sqrt(\sum_{i=1}^{nc} (R.Good(g).qty - CBundle.Good(g).qty)^2 + (R.price - CBundle.price)^2)
return EuclidianDistance
End

GenTopMACPack_atts(Bundle, TMACDA):
For each TMACDA transaction t
  Atts(t) = TMACDA(t).Atts
  MTOPVALCOM = Majority(Atts)
end for t
return MTOPVALCOM
End

Fig. 11. Finding promising combinations of package attributes using combinatorial multi-valued k-nearest neighbor algorithm.

bidders' preferences, it then recommends the best MACBUNDLE suite to the bidders' preferences for proposing as MACBID to MAC-DA. MACBID is devised from market trades data, the bidder's Item-Set, and his/her preferences.

4.7.1. Ranking MACBUNDLES

All MACBUNDLES in MACPACK have the same return rate. However, they differ in their attribute values\(^{12}\). Top attribute values recommended by the market may or may not be valuable for the agent as he/she may value an attribute value worthless or unavailable. The bidder agent then applies bidder’s valuations on the attributes for ranking multi-attribute combinatorial bundles recommended in MACPACK by Eq. (43). The agent assigns weighted multi-attribute utility value to each MACBUNDLE as described in Section 4.3.1 and then sorts all MACBUNDLES based on their utility values in descending order

\[
\text{OMACPACK} = \{<\text{quantity}_j, g, \text{price}_i, \langle \text{utility}_w, \text{delivery}_i, \text{payment}_j \rangle> \mid w = 1, ..., m \}
\]

where, \(m\) is the number of MACBUNDLES in MACPACK determined using \(mKNN\)-Com Learning in Section 4.6.2.

We explain the approach adapting Nassiri-Mofakham et al. (2008) and Nassiri-Mofakham et al. (2009b) in Example 5.

Example 5. Assume a 3-attribute e-marketplace where packages are traded based on Price, Delivery, and Payment Method. Suppose Delivery includes five methods, namely: 1 Day, 2 Days, 1 Week, 10 Days, and 1 Month. Payment Method denotes the three Cash, Credit, and Check methods. We suppose that the bidder agent scores all attributes to values between 0 and 100. Assume the agent weights Delivery and Payment Method to 0.7 and 0.3, respectively. Moreover, the bidder agent assigns the following values to each Delivery and Payment Method:

- Delivery value: 1 Day = 100, 2 Days = 70, 1 Week = 70, 10 Days = 40, 1 Month = 0
- Payment Method values: Cash = 60, Credit = 100, Check = 80.
- Therefore, \(\text{EV}_{\text{Delivery}} = 0\), \(\text{EV}_{\text{Delivery}} = 100\), and \(\text{EV}_{\text{Payment}} = 40\), \(\text{EV}_{\text{Payment}} = 100\).

Now, assume that the recommended MACPACK to this bidder agent is the following \(m = 4\) multi-attribute combinatorial bundles

\[
\text{MACPACK} = \{<4 \text{ pairs of Shoes}, 4 \text{ Bags}, 8 \text{ Shirts}, 8 \text{ Trousers}, 2000, \langle \text{Cash}, \text{ 1 Week}, \langle \text{Check}, \text{ 1 Month} \rangle \rangle> \}
\]

The agent then assigns utilities to MACBUNDLES using Eq. (1) and sorts them as shown in Table 6.

Table 6

<table>
<thead>
<tr>
<th>Bundle</th>
<th>Price</th>
<th>Payment</th>
<th>Delivery</th>
<th>Utility</th>
</tr>
</thead>
<tbody>
<tr>
<td>4 pairs of Shoes, 4 Bags, 8 Shirts, 8 Trousers</td>
<td>2000</td>
<td>Credit</td>
<td>1 Day</td>
<td>1.00</td>
</tr>
<tr>
<td>4 pairs of Shoes, 4 Bags, 8 Shirts, 8 Trousers</td>
<td>2000</td>
<td>Check</td>
<td>1 Day</td>
<td>0.90</td>
</tr>
<tr>
<td>4 pairs of Shoes, 4 Bags, 8 Shirts, 8 Trousers</td>
<td>2000</td>
<td>Cash</td>
<td>1 Week</td>
<td>0.59</td>
</tr>
<tr>
<td>4 pairs of Shoes, 4 Bags, 8 Shirts, 8 Trousers</td>
<td>2000</td>
<td>Check</td>
<td>1 Month</td>
<td>0.20</td>
</tr>
</tbody>
</table>

12 As shown in Eq. (43) each MACBUNDLE consists two parts: a combinatorial bundle of multi-unit goods and a combination of package-based attribute values.
on the above-mentioned parameters rather than prescribing the best roles for the sellers or buyers. Therefore, the true evaluation of MACBID could be against human bidders to determine if MACBID correctly model the bidders’ decision-making.

Nonetheless, for evaluating the strategy we employ CATS-similar data extended for multi-unit and multi-attributes markets. Although Combinatorial Auction Test Suite (Leyton-Brown et al., 2000; Leyton-Brown & Shoham, 2006) generates more realistic bids than distributions employed in previous studies in CAs, it does not model market realities such as multi-unit items and discounts which is considered in MMUCA test suite (Vinylas et al., 2008). MMUCA although deals with the latter, it is a test suite designed for specific mixed-unit combinatorial auctions where a procurement involves a mixture of forward and reverse combinatorial auctions.

We evaluate MACBID using MACDATS, a MACDA Test Suite which adapts required CATS and MMUCA features and more (e.g., realistic limited discounts, package attributes, and buyer and seller roles) for multi-attribute combinatorial double auction. MACDATS generates artificial but amenable data for trades history due to the synergetic relationships among goods and discounts for items and attributes of packages traded in multi-unit and multi-attribute scenario.

We benchmark MACBID by analyzing its efficiency against state-of-the-art bidding strategies in CAs.

5.1. Benchmark strategies

As shown in Table 1, bestResponse, INT, and CATS-3 strategies are designed for a single-unit and single-attribute market. To be com-

Table 7
MACBID’s prescribed for nine seller agents recommended with the same OMAKPACKi.

<table>
<thead>
<tr>
<th>i</th>
<th>Agent’s</th>
<th>CPi = 0.52, ax = 1, EVi = 0.24</th>
<th>Recommended utilityi = 0.39</th>
</tr>
</thead>
<tbody>
<tr>
<td>i</td>
<td>Agent’s</td>
<td>CPi = 1, ax = 1, EVi = 0,</td>
<td>Recommended utilityi = 0.20</td>
</tr>
<tr>
<td>i</td>
<td>Agent’s</td>
<td>CPi = 0.52, ax = 0.46, EVi = 0.25,</td>
<td>Recommended utilityi = 0.40</td>
</tr>
<tr>
<td>i</td>
<td>Agent’s</td>
<td>CPi = 0.46, EVi = 0.25,</td>
<td>Recommended utilityi = 0.62</td>
</tr>
<tr>
<td>i</td>
<td>Agent’s</td>
<td>CPi = 0.46, EVi = 0.25,</td>
<td>Recommended utilityi = 0.88</td>
</tr>
<tr>
<td>i</td>
<td>Agent’s</td>
<td>CPi = 0.46, EVi = 0.25,</td>
<td>Recommended utilityi = 0.94</td>
</tr>
<tr>
<td>i</td>
<td>Agent’s</td>
<td>CPi = 0.46, EVi = 0.25,</td>
<td>Recommended utilityi = 1</td>
</tr>
<tr>
<td>i</td>
<td>Agent’s</td>
<td>CPi = 0.46, EVi = 0.25,</td>
<td>Recommended utilityi = 0.75</td>
</tr>
<tr>
<td>i</td>
<td>Agent’s</td>
<td>CPi = 0.46, EVi = 0.25,</td>
<td>Recommended utilityi = 0.60</td>
</tr>
</tbody>
</table>
parable with MACBID, they are first extended for a multi-unit multi-attribute scenario. This comparison is presented in Section 5.3. We also note that these strategies consider only a self-interested agent, while MACBID models different behaviors human in exhibit a market.

5.1.1. Best response plus strategy

The bestResponse bid (Bichler et al., 2009; Parkes & Ungar, 2000; Pikovsky, 2008) maximizes the bidder’s surplus if he or she were to win it at current prices. As a bidder agent trading in MACDA, bestResponse bidder needs to employ Market Processing Module (as presented in MACBID, Section 4.4) to be informed of market prices $\mu_g$ of each good $g \in ItemSet$. The bidder agent determines the most profitable bundle $S$ so that $\mathcal{S} \subseteq ItemSet$, $\text{Surplus}(S) \geq \text{Surplus}(T), \forall T \subseteq ItemSet'$ where,
\[
\text{Surplus}(S) = \sum_{g \in S} \text{Surplus}(g), \quad \text{Surplus}(g) = \mu_g - RV^d_g.
\]

The agent then prices the bundle $S$ as
\[
\text{price}(S) = \sum_{g \in S} \mu_g.
\]

For each packaged-based attribute, he selects a value with the highest utility according to the bidder’s valuation (see Section 4.2.3). The greedy BR buyer agent needs to consider her budget regarding bundling and multi-unit goods. Among all goods with positive surplus, she iteratively adds $q^d_i$ units of the most profitable good $g \in ItemSet$, so that
\[
\text{Surplus}(g) = RV^d_g - \mu_g > 0 \quad \text{and} \quad q^d_i
\]

\[
= \min \left( \frac{\text{Max\_valid}^d_i \cdot \text{available\_budget}}{\mu_g} \right)
\]

where $\text{Max\_valid}^d_i$ is the maximum tradable quantities of good $g$ in the market. The price of the bundle $S$ is then
\[
\text{price}(S) = \sum_{g \in S} \mu_g q^d_i.
\]

For selecting attribute values, she acts similar to BRP seller agent.

5.1.2. INT Plus Strategy

Similar to BRP strategy, the INT bidder (An et al., 2005; Bichler et al., 2009; Pikovsky, 2008) also needs to find market prices $\mu^d_i$ of each good $g \in ItemSet'$ using MACBID’s Market Processing Module.

(a) The INTPlus Seller

An INTP bidder agent considers a matrix of pair-wise synergy values of goods and puts all available $Q^d_i, g \in ItemSet'$, into the bundle $S$, where it is a bundle with the highest average unit utility value. That is, he enumerates all bundles of goods $g \in ItemSet'$ to explore a bundle $S$ with the highest $\nu'(S)$ where,
\[
\nu'(S) = \sum_{g \in S} Q^d_i \text{Surplus}(g) + \frac{2}{\sum_{g \in S}} \sum_{h=g} \text{syn}(g, h)
\]

and
\[
\text{Surplus}(g) = \mu_g - RV^d_g.
\]

The agent then set price of $S$ as
\[
\text{price}(S) = \sum_{g \in S} \mu^d_i q^d_i.
\]

For attribute values, she behaves similar to INTP seller agent.

5.1.3. CATS-3 Plus Strategy

In CATS-3 strategy (Leyton-Brown et al., 2000; Leyton-Brown & Shoham, 2006), each agent knows the common value of each good. For that, the bidder agent in MACDA needs to employ MACBID’s Market Processing Module in MACDA. The agent also uses goods’ private values. To do that, we equip CATS3P bidder with MACBID’s UnitPricing component. Once the strategy generates the synergetic bundle, its price is determined using $\text{pricing}^d_i$ (which is determined according to common value $\mu^d_i$ and $g$’s private value). Selecting good $g \in ItemSet'$ is according to a normalized matrix of pair-wise synergy values of goods. For details of the strategy, please refer to (Leyton-Brown et al., 2000; Leyton-Brown & Shoham, 2006).

(a) The CATS3P Seller

The CATS3P seller then puts all available $Q^d_i$ of those goods into the bundle and prices the bundle as
\[
\text{price}(S) = \sum_{g \in S} \text{pricing}^d_i Q^d_i.
\]

For each packaged-based attribute, he selects a value with the highest utility according to the bidder’s valuation. (b) The CATS3P Buyer

Once a high synergetic good is selected, the CATS3P buyer agent also needs to consider to the bidder’s budget limit. She puts $q^d_i$ quantities of this good $g \in ItemSet'$ where
\[
q^d_i = \min \left( \frac{\text{Max\_valid}^d_i \cdot \text{available\_budget}}{\text{pricing}^d_i} \right)
\]

and prices the bundle as
\[
\text{price}(S) = \sum_{g \in S} \text{pricing}^d_i q^d_i.
\]

For selecting attribute values, she acts similar to CATS3P seller agent.

5.2. The MACDATS setup

The purpose of MACDA Test Suite is to generate market history of trades as well as sampling goods, selling and buying bidders. MACDATS consists eight main routines for modeling primitive assumptions for the market, sampling goods, sampling goods relationship, sampling trades attributes, sampling market history, sampling sellers, sampling buyers, and benchmarking MACBIDders.

5.2.1. Simulating the market

The market is simulated through setting up market primitives as well as trades history. We setup the market with \( n_v = 8 \) goods each with \( \text{Min}_\text{valid}_v = \text{Min}_\text{valid}_p = 1 \) and \( \text{Max}_\text{valid}_v = \text{Max}_\text{valid}_p = 100 \). In addition to package’s price, there are \( n_c = 3 \) packaged-based attributes, each with at most \( n_v \times n_c = 5 \) values.

Goods are in synergetic relationship using a pairwise synergy matrix. The history of the market is setup by 1000 package transactions, where each package is generated by synergetic goods using a multi-unit CATS-similar good selection method. We also employ a MMUCA-similar discounting method. However, to be discounted, a minimum required and up to an upper limit of the good’s quantity should be traded.

5.2.2. Simulating bidders

For evaluating MACBID, we test it using sampling sellers and buyers who employ MACBID strategy against sellers and buyers who bid under BRP, INTP, and CATS3P strategies. All bidders propose their bids according to their own item set. That is, they bid only for goods in their item set (stock/need) with respect to either type or quantity as well as trade attributes that they afford to consider. A bidder agent is now equipped with the following information: (1) a unique id + role (2) bidder’s risk factor, (2) bidder’s cooperation factor, (3) bidder’s item set, (4) budget limit (if a buyer), (5) maximum available quantity of each good (if a seller), (6) attributes value set for the bidder, (7) pair-wise synergy matrix of goods, (8) the strategy id, and (9) predicted prices of goods in the market.

In Section 5.3, we evaluate MACBID and multi-unit multi-attribute extensions on state-of-the-art bidding strategies in CAs (Section 5.1).

5.3. Evaluation and behavior of MACBID

We assign a bid two values: success rate and error rate. Winner determination policy (see Section 3.2.3) considers Eq. (4) that proposes an upper bound for a bid to be supposed as a candidate winner. This bound determines the bid’s success percentage. This can be done by enumerating bids of other participants in the other side of the market that may be satisfied with the bid. That is,

\[
\text{success}(\text{bid}) = \frac{\text{Avg dist}(\text{bid}, \text{trade})}{\text{Trade}/\text{MACDA}}
\]

where,

\[
\text{dist}(\text{bid}, \text{trade}) = \max \left\{ (-1)^{\phi(i)} \left( \frac{q_i - q_i^p}{q_i^p} \right) \mid q_i^p, q_i \text{ are the package's price and quantities of goods in bid } i, \phi(i) = \text{price} \right\}
\]

and \( \phi(i) \) is defined as Eq. (23). \( \text{price}^c \) and \( q_i^p \) are the package’s price and quantities of goods in bid \( i \), respectively. Similarly, \( \text{price}^v \) and \( q_i^v \) are respectively the package’s price and quantities of goods in the agent’s bid.

Error rate of a bid is defined as the average number of attributes in transactions whose attributes differ from those in the bid. That is,

\[
\text{aErr}(\text{bid}) = \frac{\text{Avg dist}(\text{bid}, \text{trade})}{\text{Trade}/\text{MACDA}}
\]

where, template of bid \( i \) is matched with bid \( i' \) and \( v^c \) and \( v^v \) are the values of the package attribute \( c \) in bid \( i' \) and bid \( i \), respectively.

It is worth noting that success rate of a bundle is a number between 0 and 1, while error rate of package attributes is described as a percentage.

5.3.1. MACBID evaluation

The true evaluation of MACBID could be against human bidders to compare if MACBID correctly model the bidders’ decision making. Nonetheless, in this section we show the measures for bidding under MACBID and extended benchmark strategies. To do that, we endow item sets to bidders that we generated in Section 5.2.2. Two twenty item sets are generated for selling and buying, respectively. Seller agents are simulated with reservation values and available quantities in goods in the item sets, while buyer agents need to consider their reservation values and budget limits.

To compare MACBID, BRP, INTP, and CATS3P per each item set, we generate different stereotypical behaviors through different values for \( k \) and \( C_p \) per each strategy. With values of 0, 0.25, 0.50, 0.75, and 1 for \( k \) and \( C_p \), twenty-five behaviors are considered for bidders using each strategy. We first compute RL for each agent using Eq. (11). Success rate of bundles and error rate of pack-

Table 8

<table>
<thead>
<tr>
<th>Constraint</th>
<th>Good 1</th>
<th>Good 2</th>
<th>Good 3</th>
<th>Good 4</th>
<th>Good 5</th>
<th>Good 6</th>
<th>Good 7</th>
<th>Good 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Q^v_8 )</td>
<td>43</td>
<td>20</td>
<td>8</td>
<td>19</td>
<td>3</td>
<td>13</td>
<td>14</td>
<td>3</td>
</tr>
<tr>
<td>( R^v_8 )</td>
<td>71.0281</td>
<td>37.0375</td>
<td>26.5414</td>
<td>40.5918</td>
<td>5.2859</td>
<td>17.5993</td>
<td>84.293</td>
<td>92.5985</td>
</tr>
<tr>
<td>( R^p_8 )</td>
<td>74.8269</td>
<td>44.1313</td>
<td>26.3501</td>
<td>39.069</td>
<td>22.0095</td>
<td>22.4322</td>
<td>79.875</td>
<td>83.4205</td>
</tr>
<tr>
<td>( \sigma_8 )</td>
<td>0.7526</td>
<td>0.6972</td>
<td>0.6423</td>
<td>0.6845</td>
<td>0.6923</td>
<td>0.6894</td>
<td>0.6824</td>
<td>0.6814</td>
</tr>
</tbody>
</table>

Table 9

<table>
<thead>
<tr>
<th>Constraint</th>
<th>Good 1</th>
<th>Good 2</th>
<th>Good 3</th>
<th>Good 4</th>
<th>Good 5</th>
<th>Good 6</th>
<th>Good 7</th>
<th>Good 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Q^v_8 )</td>
<td>49</td>
<td>20</td>
<td>0</td>
<td>23</td>
<td>4</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( R^v_8 )</td>
<td>77.5859</td>
<td>40.697</td>
<td>0</td>
<td>43.298</td>
<td>4.9123</td>
<td>17.5258</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( R^p_8 )</td>
<td>75.5624</td>
<td>40.4949</td>
<td>0</td>
<td>45.7081</td>
<td>22.716</td>
<td>19.1341</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( \mu_8 )</td>
<td>11.371</td>
<td>11.771</td>
<td>0</td>
<td>14.2598</td>
<td>8.4684</td>
<td>8.204</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( \sigma_8 )</td>
<td>0.7526</td>
<td>0.6972</td>
<td>0.6423</td>
<td>0.6845</td>
<td>0.6923</td>
<td>0.6894</td>
<td>0.6824</td>
<td>0.6814</td>
</tr>
</tbody>
</table>

age attributes of each bid are then computed through Eqs. (47) and (48).

Tables 8 and 9 show two different item sets endowed to two seller agents. The last two rows of each table depict the value and deviations of goods’ prices predicted by these seller agents.

Figs. 13 and 14 show that by increasing the rationality factor of agents, success rate of MACBID stands higher than other strategies. It is the same for MACBID’s attributes, where its error rate is lower than of other strategies when the rationality of the agent is increased. However, two greedy BRP and INTP strategies behave the same for all agents in a success rate of 0.25.

Similarly, Tables 10 and 11 show two item sets of buying. The bids proposed by four bidding strategies for these item sets are depicted in Figs. 15 and 16, respectively. Again, it is observed that success rate of MACBID is increased by increasing the rationality factor of agents. It is the same for MACBID’s attributes, where its error rate is almost decreased by increasing the degree of rationality.

The average outcomes resulted from the four above mentioned strategies for all twenty selling items sets and twenty buying item sets each using 25 different behaviors for bidding agents are shown in Tables 12 and 13. It is observed that packages offered by both

![Fig. 13. Evaluating bids for selling the first item set based on (a) bundle’s success rate (b) error rate of package attributes.](image)

![Fig. 14. Evaluating bids for selling the second item set based on (a) bundle’s success rate (b) error rate of package attributes.](image)

<table>
<thead>
<tr>
<th>Table 10</th>
<th>First sample item set for buying with budget of 20,000.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constraint</td>
<td>Good 1</td>
</tr>
<tr>
<td>$RV_x^i$</td>
<td>0</td>
</tr>
<tr>
<td>$\mu_x$</td>
<td>0</td>
</tr>
<tr>
<td>$\sigma_x$</td>
<td>0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 11</th>
<th>Second sample item set for buying with budget of 20,000.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constraint</td>
<td>Good 1</td>
</tr>
<tr>
<td>$RV_x^i$</td>
<td>83.7896</td>
</tr>
<tr>
<td>$\mu_x$</td>
<td>76.218</td>
</tr>
<tr>
<td>$\sigma_x$</td>
<td>12.5476</td>
</tr>
</tbody>
</table>

sellers and buyers using MACBID have the highest success probability (0.38 for selling and 0.14 for buying). In addition, they own the lowest error percentage in valuation of package attributes (47% for selling and 46% for buying) with respect to benchmark strategies.

### 5.3.2. MACBID behavior

In Section 5.3.1, we compared four strategies by aggregating all bids based on the rationality factor of the agents. In this section, we analyze the behavior of MACBID by considering risk and cooperation factor of the agents. We show the success probabilities of bundles and percentages of error in package attribute values through 3D diagrams.

![Fig. 15. Evaluating bids for buying the first item set based on (a) bundle's success rate (b) error rate of package attributes.](image)

![Fig. 16. Evaluating bids for buying the second item set based on (a) bundle's success rate (b) error rate of package attributes.](image)

In Fig. 17, the highest success rate happens for an agent with $R^i = 1$ and $CP^i = 0$. For this item set (Table 8), agents with $R^i \in [0.75, 1]$ and any $CP^i$ have proposed the most successful bids. In addition, when $R^i \in [0.25, 1]$ and $CP^i \in [0.25, 1]$ the seller agent faces with the least rate of error in attribute values of his bid. Therefore, the agents with the higher degrees of risks have more concentrations toward return of the packages (see Eq. (13)) and propose bids that are more successful. Also, as shown in Fig. 18, the agents with $R^i = 0.75$ and $CP^i \in [0.50, 1]$ proposed bids with the highest success probabilities, while the minimum rate of error in attributes happens for the agents with $R^i = 1$ and $CP^i = 0.50$. For values $R^i \in [0.75, 1]$ and any $CP^i$, we observe the least rate of error for attribute values. Again, this agent with high degrees of risk is a successful seller for trading the item set.

#### Table 12
Average outcomes of four bidding strategies by twenty-five different selling agents.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>MACBID</th>
<th>CATS3P</th>
<th>INTP</th>
<th>BRP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average success probability of devised packages</td>
<td>0.378679</td>
<td>0.201213</td>
<td>0.290233</td>
<td>0.290233</td>
</tr>
<tr>
<td>Average error percentage of attributes' values</td>
<td>46.82008</td>
<td>49.05939</td>
<td>49.24563</td>
<td>49.24563</td>
</tr>
</tbody>
</table>

#### Table 13
Average outcomes of four bidding strategies by twenty-five different buying agents.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>MACBID</th>
<th>CATS3P</th>
<th>INTP</th>
<th>BRP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average success probability of devised packages</td>
<td>0.14196</td>
<td>0.07984</td>
<td>0.113698</td>
<td>0.111104</td>
</tr>
<tr>
<td>Average error percentage of attributes' values</td>
<td>45.6067</td>
<td>49.44674</td>
<td>47.36076</td>
<td>48.0008</td>
</tr>
</tbody>
</table>

Fig. 17. The 3D representation of MACBID behavior for sell bids in Fig. 13 with respect to the agents’ risk and cooperation factors and based on (a) bundle’s success rate (b) error rate of package attributes.

Fig. 18. The 3D representation of MACBID behavior for sell bids in Fig. 14 with respect to the agents’ risk and cooperation factors and based on (a) bundle’s success rate (b) error rate of package attributes.

Fig. 19. The 3D representation of MACBID behavior for buy bids in Fig. 15 with respect to the agents’ risk and cooperation factors and based on (a) bundle’s success rate (b) error rate of package attributes.
For buying item set of Table 10, as shown in Fig. 19, agents with $R^i = 0.50$ and $CP^i \in [0.75, 1]$ have the highest rates of success in bundling. The lowest rate of error in package attributes is observed for agents with $R^i \in [0.75, 1]$ and any $CP^i$. This lower rate happens for $R^i \in [0.50, 0.75]$ and $CP^i \in [0.0, 0.75]$. These successful agents represented negotiator behavior. In Fig. 20, a buyer agent with $R^i = 1$ and $CP^i = 0$ has faced with the highest rate of success in bundling and minimum rate of error in package attributes. The agents have successful bidding for $R^i \in [0.75, 1]$ and $CP^i \in [0.0, 0.25]$. For minimum rate of error in attribute values, the agents should avoid bidding with $R^i \in [0.0, 0.25]$ and $CP^i \in [0.75, 1]$.

5.4. Discussion and key findings

From Table 12, it is observed that the success probability of packages proposed by MACBID for selling is respectively 1.88, 1.33, and 1.31 times more than those of CATS3P, INTP, and BRP. For package attributes, MACBID error is 0.954, 0.951, and 0.951 times less than the errors by the above mentioned strategies, respectively. That is, the success probability of MACBID packages have an average superiority 1.5 times higher than benchmark strategies, while their attributes’ errors are 0.952 times of errors in these strategies.

Similarly, for packages proposed for buying, Table 13 shows that the probability for MACBID with respect to CATS3P, INTP, and BRP is 1.78, 1.25, and 1.28, respectively. MACBID’s error in attributes’ values is 0.92, 0.96, and 0.95 with respect to CATS3P, INTP, and BRP, respectively. That is, in average, the package proposed by MACBID has less error in valuation of attributes (0.94) and higher success probability (1.44) with respect to current strategies.

In addition, success probability of MACBIDs proposed by agents that are more rational is 1.37 and 1.05 times higher than bids of agents with $RL^i < 0.5$ for sellers and buyers, respectively. Agents that are more rational face with less error percentages that are 0.99 and 0.98 times less than bids of packages proposed by less rational agents for sellers and buyers, respectively.

Similarly, we consider the average success probability of packages and average error percentages of attribute values devised by MACBID with respect to risk and cooperation factors (Section 5.3.2) for twenty different selling and buying item sets using twenty-five different behaviors for bidding agents. Fig. 21 shows that increasing both risk and cooperation enhances the success probability of packages proposed by sellers. As Fig. 22 shows, less risk or average cooperation both increases error percentages in attribute values for their packages.

With respect to nine different behaviors related to combination of three fuzzy values low (L), medium (M), and high (H) for risk and cooperation factor of an agent (see Table 6 in (Nassiri-Mofakham et al., 2009b)), we evaluate packages regarding the seller and buyer agents’ behaviors. Fig. 23 shows that raising the seller’s risk increases his proposed package’s success probability and decreases its error percentages. For each risk value, cooperation factor has a positive effect on the success probability of proposed packages. The

![Fig. 20. The 3D representation of MACBID behavior for buy bids in Fig. 16 with respect to the agents’ risk and cooperation factors and based on (a) bundle’s success rate (b) error rate of package attributes.](image)

![Fig. 21. Bundle’s success rate for MACBID sell bids with respect to the agents’ (a) risk and (b) cooperation factors.](image)
Fig. 22. Error rate of package attributes for MACBID sell bids with respect to the agents' (a) risk and (b) cooperation factors.

Fig. 23. Depicting (a) bundle's success rate (b) error rate of package attributes of sell bids based on the MACBID agents' behavior.

Fig. 24. Bundle's success rate for MACBID buy bids with respect to the agents' (a) risk and (b) cooperation factors.

Fig. 25. Error rate of package attributes for MACBID buy bids with respect to the agents' (a) risk and (b) cooperation factors.
Similarly, we show the average of success probability and error percentages in buy bids proposed by MACBID buyer agents in Figs. 24 and 25.

It is observed that buyer agents with medium degrees of cooperation enjoy higher success probabilities and less error percentages in attribute values for their proposed packages. Medium and high risk values have respectively the same effects on increasing the success probability and decreasing error percentages in attribute values of the packages proposed by buyers. Fig. 26 depicts also that negotiator buyer agents (medium risk and medium cooperation) have proposed the most successful full packages.

6. Conclusions and future works

In this paper, we presented a novel strategy, MACBID, for bidding agents in a complex multi-attribute combinatorial double auction (MACDA). MACBID consists of two perception and bidding layers and are implemented in six modules. These modules model the market and the bidder, process the market, bundle complement multi-unit goods, package multi-attribute bundles, and finally propose the best tailored bid for the bidder.

We also presented a novel model for pricing goods and bundling in a multi-good e-marketplace. We considered seller and buyer roles, individual item set, valuations, personality-based features of the bidders and market data in pricing and bundling models. The simulation results show that average success probability of sell bids and buy bids using MACBID packages are about 50 percent higher and average error for attribute values was 5 percent lower than existing strategies.

MACBID strategy could be adopted and adapted as an automated bidder or a bidding support system in any problem in combinatorial markets with double side and multi-attribute and multi-unit combinatorial demands and supplies proposed or inspired by human beings. In addition to only profit-maximizer agents which are often considered in the literature, MACBID could well model different realistic human-like degrees of risk and cooperation attitudes related to the personality of the bidders and dynamic behavior of the market towards combinations of items. Section 6.1 gives more details on the theoretical contributions and practical implications of the paper. Future works are presented in Section 6.3.

6.1. Implications for theory

While the existing studies in auctions address truth-telling as the dominant strategy for the agents, it is not clear what the true valuation of each agent could be. By extending Markowitz Modern Portfolio Theory, the study proposed an algorithm for bidders to predict unit price of each good by observing just traded bundles in the history of the market where each traded package reveals no information regarding individual item prices but the package price. Although all the bidders sense the same market information, using the proposed pricing algorithm (Fig. 7) each bidder finds how much an item is worth to him/her based on the predicted unit prices (Fig. 5) and associated risks from the market, the bidder’s wish list (to buy or sell) as well as his/her cooperation and risk factor (adapted from the Five Factor Model of Personality). This causes two different agents who have the same item list could be simulated to assume different item prices and in turn bundle different quantities of items and with different total bundle prices. In addition, mkNN-Com algorithm (Fig. 11) finds the most appropriate package attribute values based on top $m$ values used for trading top $k$ bundles similar to the packaged items in the history of the market. Finally, each bidder again can choose a package (MACBID, Fig. 12) different from those proposed by the other agents based on different utilities they assign based on their risks and cooperation factors. This helps the research on WDP to use more meaningful bids than the bids generated using random distribution functions.

Briefly speaking, the main contribution of this paper is a novel bidding strategy for agents in a multi-attribute combinatorial double auction and summarized as follows:

- We proposed an extension to Markowitz Modern Portfolio Theory and Five Factor Model of Personality for a personality-based multi-attribute combinatorial bid.
- Adapting mkNN, multi-attribute substitutes of the devised bundle of complementary goods were packaged. The FFM of personality and MAUT were employed for selecting MACBID among substitute bundles in the package.
- We extended MPT by introducing a personality-based objective function and transformed price-based transactions to return-based transactions. For this transformation, we first predicted prices of individual goods in transactions; modeled agent’s pricing based on the role, item set and personality of the bidder; and then formalized the agent’s return.
- A test suite provided algorithms for generating stereotypical artificial market data as well as personality, preferences and item sets of the bidders.

6.2. Implications for practice

The study has important implications in growing practice in applications of combinatorial auctions, double auctions, and combinatorial double auctions in different fields. In addition to the scenarios similar to those employed in the paper, the practical implications of the study could be in existing and upcoming complex applications in multi-commodities industries that need proposing or requesting dynamic and personalized services. Stock exchange (Antweiler, 2014; Ausubel, Cramton, & Jones, 2014;...
6.3. Further research

In this study, we assumed packages are multi-attribute but the goods are determined by only quantity and price. For future research, MACBID could be extended for multi-attribute goods.

Moreover, for predicting the value of each unit item from the individual price of the bundles of multi-unit items traded before in the market, we assumed that the price of each traded item in the package should have a meaningful deviation from the quasi-equilibrium price of each item in the market (Section 4.4.2). Another study can solve this prediction problem by violating this assumption. In a full implementation of MACDA mechanism is an important subject for further development of the research on bidding strategies in MACDA as it helps to evaluate bids under a mechanism. By assuming the static behavioral parameters of bidding agent in single-shot MACDA, still another study could extend the research by proposing adaptive bidding in a multi-round or continuous MACDA and learning as well as modeling emotions affected from MACDA feedbacks on the previous bids of the agent and its peers or counterparts.

We defined a concentration factor $\alpha = 0.5$ (see Section 4.3.3) as a static parameter affecting the agent’s objectives for trading off between risk and return of a bundle. However, $\alpha$ could be a static or dynamic parameter depending on seasonal, cultural, continental, or international situations. Modeling $\alpha$ in a multi-national MACDA could be the subject of another research.

By considering ontological concepts for describing relationships among goods’ attributes, a study could propose another representation for bidder’s preferences and bid generation.

Finally, the models for price predictions, pricing, bundling, and packaging issues presented in this paper could be open and unfold interesting theoretical and practical space for a stream of further works.

References


