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## A Free Exchange e-Marketplace for Digital Services

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A thesis submitted in partial fulfillment of the requirements for the degree in Doctor of Philosophy

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# **A FREE EXCHANGE E-MARKETPLACE FOR DIGITAL SERVICES**

(Thesis format: Monograph)

by

**Wafa Ghonaim**

Graduate Program in Electrical and Computer Engineering

A thesis submitted in partial fulfillment  
of the requirements for the degree of  
Doctor of Philosophy

The School of Graduate and Postdoctoral Studies  
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London, Ontario, Canada

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## Abstract

The digital era is witnessing a remarkable evolution of digital services. While the prospects are countless, the e-marketplaces of digital services are encountering inherent game-theoretic and computational challenges that restrict the rational choices of bidders. Our work examines the limited bidding scope and the inefficiencies of present exchange e-marketplaces. To meet challenges, a free exchange e-marketplace is proposed that follows the free market economy. The free exchange model includes a new bidding language and a double auction mechanism. The rule-based bidding language enables the flexible expression of preferences and strategic conduct. The bidding message holds the attribute-valuations and bidding rules of the selected services. The free exchange deliberates on attributes and logical bidding rules for automatic deduction and formation of elicited services and bids that result in a more rapid self-managed multiple exchange trades. The double auction uses forward and reverse generalized second price auctions for the symmetric matching of multiple digital services of identical attributes and different quality levels. The proposed double auction uses tractable heuristics that secure exchange profitability, improve truthful bidding and deliver stable social efficiency. While the strongest properties of symmetric exchanges are unfeasible game-theoretically, the free exchange converges rapidly to the social efficiency, Nash truthful stability, and weak budget balance by multiple quality-levels cross-matching, constant learning and informs at repetitive thick trades. The empirical findings validate the soundness and viability of the free exchange.

## Keywords

rule-based bidding, bidding lifecycle, market economy, free exchange, preference deduction, bid formation, double auction, quality levels, stable efficiency, market profitability.

# Table of Contents

Abstract .....	ii
Table of Contents .....	iii
List of Tables .....	vi
List of Figures .....	vii
List of Appendices .....	x
Chapter 1 .....	1
1 Introduction .....	1
1.1 Exchange e-Marketplaces: Potential Issues .....	1
1.2 Towards Free Symmetric Exchange of Market Economy .....	4
1.3 Problem Definition Statement .....	6
1.4 Thesis Organization .....	8
Chapter 2 .....	9
2 Problem Modeling, Analysis, and Issues .....	9
2.1 Combinatorial Allocation Problem Description .....	10
2.2 Formal Combinatorial Allocation Problem Model .....	12
2.3 Combinatorial Allocation Problem Complexity Analysis .....	15
2.4 Research Issues .....	17
Chapter 3 .....	20
3 Literature Review .....	20
3.1 Bidding Languages .....	20
3.2 Game-Theoretic Concepts .....	24
3.3 Equilibrium Solution Concepts .....	28
3.4 Direct Revelation and Incentive Compatibility .....	31
3.5 Vickrey-Clarke-Groves (VCG) Mechanisms .....	33
3.6 Impossibility and Possibility Results .....	37

3.7 Economic Based Mechanisms .....	38
3.8 Double Auction Mechanisms.....	44
3.9 Preference Elicitation Models.....	45
3.10 Winner Determination Models .....	47
3.11 Digital Advertising e-Marketplaces .....	50
Chapter 4 .....	54
4 RBBL: Rule Based Bidding Language .....	54
4.1 Market Economy: Insights from Microeconomics Theory.....	54
4.2 Strategic Impact of Constant Learning .....	56
4.3 Bidding Lifecycle: Bidding Automation for Rapid Trades .....	59
4.4 Rule Based Biding Language (RBBL) Model .....	61
4.5 RBBL Theoretical and Computational Properties .....	67
Chapter 5 .....	71
5 GSPM Double Auction Mechanism .....	71
5.1 Exchange Mechanisms.....	72
5.2 GSPM and EM Double Auction Mechanisms .....	73
5.2.1 Single Q-level GSPM Double Auction Mechanism .....	73
5.2.2 Multiple Q-levels GSPM Double Auction Mechanism .....	74
5.2.3 Single Q-level EM Double Auction Mechanism .....	76
5.2.4 Multiple Q-level $M^{\text{th}}$ EM Double Auction Mechanism.....	77
5.3 GSPM Economic and Computational Properties.....	78
5.4 GSPM and EM Algorithmic Structure.....	84
Chapter 6 .....	88
6 Experimental Results and Analysis.....	88
6.1 RBBL Rule-based Bidding Experimental Model .....	88
6.2 GSPM and EM Experimental Matching Models .....	92

6.3	Bounded GSPM Double auction Mechanisms .....	93
6.3.1	Experimental Bounded GSPM Description .....	94
6.3.2	Analysis of Bounded GSPM Trades .....	95
6.3.3	Analysis of Bounded GSPM Metrics.....	97
6.4	Unbounded GSPM Double Auction Mechanisms .....	100
6.4.1	Experimental Unbounded GSPM Description.....	100
6.4.2	Analysis of Unbounded GSPM Trades.....	101
6.4.3	Analysis of Unbounded GSPM Metrics .....	101
6.5	Bounded M <sup>th</sup> EM Double Auction Mechanisms.....	104
6.5.1	Bounded M <sup>th</sup> EM DA Description .....	104
6.5.2	Analysis of Bounded M <sup>th</sup> EM DA Trades .....	105
6.5.3	Analysis of Bounded M <sup>th</sup> EM DA Metrics .....	107
6.6	Unbounded M <sup>th</sup> EM Double Auction Mechanisms .....	109
6.6.1	Unbounded M <sup>th</sup> EM DA Description.....	109
6.6.2	Analysis of Unbounded M <sup>th</sup> EM DA Trades .....	110
6.6.3	Analysis of Unbounded M <sup>th</sup> EM DA Metrics .....	111
6.7	The GSPM and EM Comparative Analysis .....	113
6.7.1	Single and Multiple Q-level(s) Bounded GSPM and EM DAs .....	114
6.7.2	Single and Multiple Q-level(s) Unbounded GSPM and EM DAs.....	118
6.8	Complexity Analysis of the GSPM and EM Mechanisms.....	122
Chapter 7	.....	124
7	Conclusions and Future work .....	124
7.1	Experimental Findings and Comparative Analysis.....	126
7.2	Future Outlook .....	128
Bibliography	.....	130
Appendices	.....	139

## List of Tables

Table 1: Sample results of first and twentieth single Q-level (left set) and multiple Q-levels (right set) bounded GSPM repetitive trades of twenty request and ask bidders .....	95
Table 2: Sample results of first and twentieth single Q-level (left set) and multiple Q-levels (right set) unbounded GSPM trades of twenty request and ask bidders .....	100
Table 3: Sample results of first and twentieth single Q-level (left set) and multiple Q-levels (right set) unbounded EM trades of twenty request and ask bidders .....	105
Table 4: Sample results of first and twentieth single Q-level (left set) and multiple Q-levels (right set) unbounded EM trades of twenty request and ask bidders .....	110

## List of Figures

Figure 1: Google DoubleClick ad exchange OSP auction.....	4
Figure 2: Combinatorial allocation problem environment of digital services .....	12
Figure 3: An OR*, LGB and TBBL bidding instance .....	23
Figure 4: Requirement bidding model for job shop scheduling problem .....	24
Figure 5: GSPM DA in comparison with other DA models.....	45
Figure 6: A TBBL matching allocation instance of two bidders .....	48
Figure 7: Ad Networks and ad Exchanges.....	51
Figure 8: First price auction cyclic behaviors.....	59
Figure 9: Iterative bidding .....	60
Figure 10: Proxy iterative bidding .....	60
Figure 11: Bidding programs .....	61
Figure 12: One shot bidding .....	61
Figure 13: RBBL bid symmetric DAG structure .....	64
Figure 14: Rule based bidding .....	65
Figure 15: A sample instance of a RBBL bid structure and preference deduction.....	67
Figure 16: RBBL bid instance for IP analysis .....	70
Figure 17: Single Q-level GSPM DA mechanism.....	74
Figure 18: Multiple Q-level GSPM double auction.....	76
Figure 19: Single Q-level $M^{\text{th}}$ EM double auction .....	77

Figure 20: Multiple Q-level $M^{\text{th}}$ EM double auction.....	78
Figure 21: Attribute-values and rational rules of the RBBL validation.....	89
Figure 22: Rules processing times of twenty repetitive trades using the bounded and unbounded multiple Q-level GSPM and EM for two thousand bidders.....	90
Figure 23: Rules processing times vs. number of bidders for the bounded and unbounded multiple Q-levels GSPM and EM trades .....	91
Figure 24: Traded vs. initial true matched pairs of the first and twentieth trades of the bounded single Q-level (upper set) and multiple Q-levels (lower set) GSPM .....	96
Figure 25: Metrics of the bounded single Q-level (upper set) and multiple Q-level (lower set) GSPM of 200 and 1000 request and ask bidders .....	99
Figure 26: Traded vs. initial true matched pairs of the first and twentieth trades of the unbounded single Q-level (upper set) and multiple Q-levels (lower set) GSPM .....	102
Figure 27: Metrics of unbounded single Q-level (upper set) and multiple Q-level (lower set) GSPM of 200 and 1000 request and ask bidders .....	103
Figure 28: Traded vs. initial true matched pairs of the first and twentieth trades of the bounded single Q-level (upper set) and multiple Q-levels (lower set) EM DA .....	106
Figure 29: Metrics of bounded single Q-level (upper set) and multiple Q-level, (lower set) EM DA, of 200 and 1000 request and ask bidders .....	108
Figure 30: : Traded vs. initial true matched pairs of the first and twentieth trades of the unbounded single Q-level (upper set) and multiple Q-levels (lower set) EM DA .....	111
Figure 31: Metrics of the unbounded single Q-level (upper set) and multiple Q-level, (lower set) EM DA of 200 and 1000 request and ask bidders .....	113
Figure 32: Single Q-level (lefts set) and multiple Q-levels (right set) bounded GSPM and EM DA matching patterns at first and twentieth trades.....	115

Figure 33: Sample metrics of the bounded multiple Q-level GSPM DA and EM DA for two thousand request and ask bidders during twenty repetitive trades.....	117
Figure 34: Single Q-level (left set) and multiple Q-levels (right set) unbounded GSPM and EM DA matching patterns at first and twentieth trades.....	119
Figure 35: Sample metrics of the unbounded multiple Q-level, GSPM DA vs. EM DA for two thousand request and ask bidders during twenty repetitive trades.....	121
Figure 36 Complexity analysis of GSPM and EM algorithms .....	123
Figure 37: Free exchange e-marketplace trading platform .....	129

## List of Appendices

Appendix A: GSPM and EM MATLAB Simulation Algorithms .....	139
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## Chapter 1

### 1 Introduction

The phenomenal evolution of digital services and smart interactions is empowering a new culture that is transforming social lifestyles into commodities. The dynamics of mobile influence, digital engagement, constant learning, smart conduct, and real-time immediacy are rather disruptive for e-marketplaces. While it reveals massive opportunists, it raises concerns about restricted bidding choices, inflexible strategic conduct and inefficiencies of online trading mechanisms. Our work identifies and examines some potential issues of current exchange e-marketplaces from microeconomic, game-theoretic and computational perspectives. The work here reflects on our bias to free market economy practices and presents briefly the proposed free exchange e-marketplace model that follows free market economy. The problem definition statement outlines the desired exchange e-marketplace properties with respect to an expressive and flexible rule-based bidding language and truthfully stable, socially efficient and profitable double auction matching mechanism.

#### 1.1 Exchange e-Marketplaces: Potential Issues

The digital era trends are manifested by the thriving digital services (referred to as e-services) as mobile apps, online advertising (ad), and interactive digital marketing. While the prospects are countless, the e-marketplaces are encountering inherent game-theoretic and computational challenges that restrict the rational choices, preferences and strategic conduct of bidders. The remarkable evolution of interactive digital services is, in fact, inciting the industry to diligently fetch more viable delivery and revenue trading models that thrive in the market ecosystem (Moore, 1996). The game-theoretic complexity, however, impacts the strategic stability of trading mechanisms that dictate the rules of encounter. At stable equilibrium, a mechanism  $\mathcal{M}$  implements a social welfare function with solution concepts that predict strategies rational bidders select with assumptions about rationality of bidders and knowledge bidders have about other bidders. The computational complexity, otherwise, relates to the tractable algorithmic efficiency that

drive  $\mathcal{M}$  to compute, in polynomial time, a combinatorial allocation problem (CAP) where number of possible bids is exponential in number of e-services.

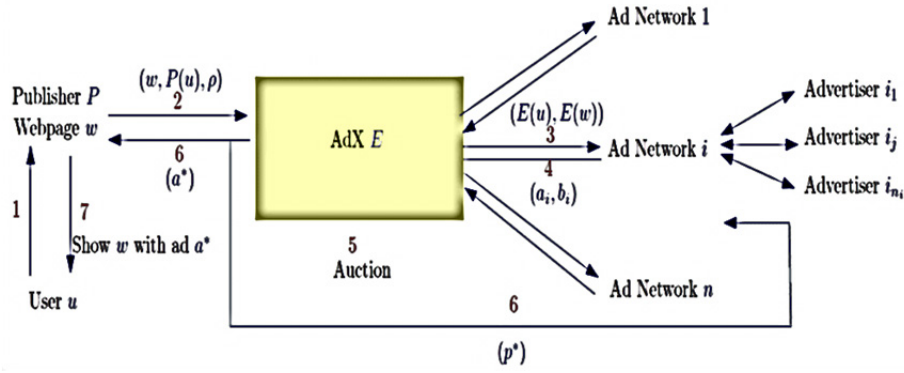
Our work identifies and examines, particularly, the potential challenges that initiate from the restricted bidding conduct and the inefficiencies of present exchange e-marketplaces. While complexities may justify the restrictive bidding practices, the de facto auctions are often designed for the strategic benefit of revenue maximizing e-marketplaces. For instance, in Google AdWords and DoubleClick exchange (Mansour et al., 2012; Google, 2013), the advertisers often bid with restricted number of keyword choices. Bidders submit single bids that do not adequately convey preferences for various ad positions while paying for, perhaps, no-sale cost-per-clicks. Google applies, otherwise, a rather fuzzy cost-per-acquisition pricing model at real conversions. The Facebook FBX exchange breaches the privacy of online users by using intruding cookies. The cookies collect and trade user personal profiles on the real-time-bidding exchange and charge using the revenue-per-page-view pricing rule. The restrictive bidding practices, however, provokes adverse strategies of bidders that may lead to digital market (referred to as e-market) failures. For instance, bidder agents (referred to as agents) may collude by submitting untruthful reduced bids for false partial requirements and form coalitions that act as super-agents to benefit from reduction in competition that harm social welfare. Collusion can be, even, more problematic in computational settings as bidders unleash several agents and adopt multiple identities name (i.e., false name bidding).

The inefficiencies of present exchange mechanisms, on the other hand, is understood in the context of Hurwicz impossibility theorem (Hurwicz, 1975) that states it is impossible to implement an allocative efficient (AE), strategy proof (SP) and budget balance (BB) social welfare function in dominant strategy equilibrium (DSE) in a simple exchange e-market and quasi-linear preferences even without requiring individual rationality (IR). (Green & Laffont, 1977) , demonstrates no AE and SP mechanism can be safe from manipulation by coalitions, even in quasi-linear environments. A *simple exchange* is one in which there are buyers and sellers selling single units of the same good (Parkes, 2001).

It is useful at this point to briefly define some of the related economic and computational concepts. The elaborate definitions are found in later chapters. A *mechanism*  $\mathcal{M} = (\Sigma, g)$  holds the rules of interaction that define strategies  $\Sigma_i$  of each agent and the outcome rule  $g: \Sigma_1 \times \dots \times \Sigma_l \rightarrow \mathcal{O}$ . The *social choice function* maps the profile of preferences to an outcome, while the *social welfare function* maps preferences to an efficient outcome. The *social allocative efficiency* (AE) maximizes the sum of utilities or valuations of bidders. An *incentive compatible* (IC) mechanism  $\mathcal{M}$  is the one in which agent best max utilities is at truthful (direct) revelation of private information. A direct-revelation mechanism (DRM)  $\mathcal{M}$  is *strategy-proof* if its truth-revelation is a DSE, a useful game-theoretic and computational property. A stronger solution concept is DSE at which every agent has the same utility-maximizing strategy, for all strategies of other agents. A Strategy  $s_i$  is a *dominant strategy* if it (weakly) maximizes the agent's expected utility  $u_i$  for all possible strategies of other agents  $s_{-i}$ ,  $u_i(s_i, s_{-i}, \theta_i) \geq u_i(s'_i, s_{-i}, \theta_i), \forall s'_i \neq s_i, s_{-i} \in \Sigma_{-i}$ . Agent can compute its optimal strategy without modeling the preferences and strategies of other agents. At weak *budget balance* (BB) the  $\mathcal{M}$  total utility transfers is positive (No deficit). The BB propriety maps to e-marketplace profitability. The *individual rationality* (IR) relates to voluntary participation in a trade at which an agent can achieve as much expected utility from participation using  $\mathcal{M}$  as without participation. The *computational efficiency* means that,  $\mathcal{M}$  is computed in polynomial time (i.e., tractable algorithms). The strategic (*game-theoretic*) *stability* means that  $\mathcal{M}$  implement a social welfare function at equilibrium with solution concepts that predict strategies agents will select with diverse assumptions about rationality of agents and knowledge agents have about other agents. The quasi-linear preferences simplify the utility transfer across agents, via side-payments.

The exchange challenges to achieving desirable properties for full symmetric exchange mechanisms influences industry exchange e-marketplaces. This is evident in the famous e-marketplaces as Google, e-Bay, Facebook and Amazon that utilize asymmetric auctions (i.e., single auction mechanisms) with reserve value of sellers. For instance, in (Mansour et al., 2012) Google DoubleClick ad exchange uses generalized second price (GSP) and

optional second price (OSP) auctions for matching (see Figure 1, source: (Mansour et al., 2012)). The OSP enables advertiser  $i$  submits mandatory bid  $b_i$  and optional bid  $0_i \leq b_i$  for  $\rho$  reserve price to mitigate exposure. The OSP, charges  $\max \{ \max_{j \neq i} b_j, 0_i, \rho \}$ .



**Figure 1: Google DoubleClick ad exchange OSP auction**

## 1.2 Towards Free Symmetric Exchange of Market Economy

Our work examines the restrictive bidding conduct and inefficiencies of present exchange e-marketplaces. In that vein, Adam Smith, remarkably, observed that bidders interacting in free market economy act as if guided by “invisible hand” that leads to desirable market outcomes. The *market economy* is the free market in which resources allocated by bidder buying and selling free decision making, as primarily governed by the opportunity cost, and influenced by the society (Hall & Lieberman, 2010). The invisible hand aligns the dynamics of the dual self-interests and essential needs of bidders that allocate the scarce assets efficiently and works best in economy of perfect competition. The dual dynamics promote collaborative strategies while discouraging monopolies. In this context, strategic practices would be the truthful rational reactions to constant learning of e-market disruptions, particularly, at repetitive trades that must be freely expressed. The flexible bidding language that is adequate for the free expression of rational conduct would facilitate, hence, the truthful revelation of the strategic reactions. Following the microeconomic perspective of free market economy, our work advocate, hence, an adequate e-marketplace allows for symmetric bidding with flexible expression of free choices and strategic conduct. The e-marketplace should have, also, an exchange

mechanism that enables fully symmetric matching trades between e-service providers and consumers. The exchange e-marketplaces should maintain its position as bidders most preferred trading platform by providing endlessly growing inventory and information liquidity with reliable visibility, metrics, and focus targeting. The exchange model should deliver, also, adequate desirable game-theoretic and computational properties as stable social efficiency, exchange profitability, and computational efficiency (i.e., tractability). The fully symmetric exchange would deliver a fair and equal trading flexibility and free bidding conduct for both buyers, who are currently enjoying much of the allowed trading flexibility, and sellers, who are most often confined with the reserve value model.

Our work advocates the flexible bidding conduct by introducing the free exchange (FX) e-marketplace that follows the free market economy (Hall & Lieberman, 2010). The free market economy has proved to be effective in organizing the economic activities for the social well-being, despite the self-interested decision making (Mankiw, 2012). The FX includes a flexible RBBL that empowers bidders to expressing free conduct. Our work endow the free exchange, also, with a double auction mechanism that improve stable efficiency. The rule-based bidding language (RBBL) enables free, flexible and concise expressions of preferences and strategic conduct by bidders using logical rules. The RBBL message includes distinct attribute-values of e-services and logical rules formulae that the FX deliberates on for automatic deduction and formation of the e-services and bids. The FX automatic bidding allows for least preference elicitation and multiple rapid trades. The RBBL is completely symmetric that enables the rule-based bidding not only for buyers but also for sellers, often, confined with their reserved values model.

The double auction (DA) exploits the forward and reverse generalized second price (GSP) auctions for a class of multiple e-services of identical attributes and different quality levels (Q-levels). The multiple Q-levels GSP based DA matching (GSPM) motivates truthful bidding and deliver symmetric social efficiency and strategic stability with constant learning at repetitive trades that deliver the truthful best response strategies of bidders. The DA heuristics are computationally tractable and secures, also, the FX

profitability. However, the GSPM social efficiency and e-market profitability is better realized with market thickness (Roth, 2007). Realizing perfect stable efficiency in profitable exchanges, however, is unfeasible game-theoretically (Hurwicz, 1975). Our work establishes, though, that the FX converges to the stable efficiency of the full information setting with constant learning at repetitive trades. The FX exploits the GSPM DA to achieving strategic equilibrium of self-interested rational bidders of private independent information and free strategic conduct. The GSPM takes advantage of the successes of the efficient, yet simple de facto GSP (Edelman et al., 2007) (Varian, 2007), and the repeated best response auction (Nisan et al., 2011). The proposed multiple Q-levels, GSPM DA enables tractable and IC exchange that delivers stable efficiency and profitability. This is evident in the rapid stable convergence of thick e-markets, i.e., large number bidders and transactions. The desirable properties of the FX free exchange RBBL rules bidding and GSPM DA is thoroughly verified through experimental analysis.

### 1.3 Problem Definition Statement

Our work examines the status quo of the restricted bidding conduct and inefficiencies of present exchange e-marketplaces. An adequate market economy exchange must allow for symmetric bidding with flexible expression of free choices and strategic conduct. The exchange should, also, have a symmetric double auction mechanism that enables for fully matching trades between e-service providers and consumers. The exchange model should deliver adequate desirable game-theoretic and computational properties like stable social efficiency, exchange profitability, and computational efficiency (i.e., tractability). Our work, hence, targets the realization of the following desirable properties in the bidding language: (1) Expressiveness: ability to flexibly, correctly and completely, represent the semantics and structure of the bidding preferences and strategic conduct ; (2) Ease-of-use: ability to express the semantics and structure of the bidding preferences and strategic conduct in direct and easy manner; (3) Conciseness: ability to express the semantics and structure of the bidding preferences and strategic conduct compactly with the least use of notations and structure; (4) Flexibility: ability to extend the bid semantics and structure to incorporate diverse logical rules formulae; (5) Symmetry: ability to express attributes and

logical rules formulae of any e-service and request and ask bids in the same bidding message; (6) Computational efficiency: ability to compute a tractable polynomial time preference deduction, bid formation and winner determination; (7) Rapid automation: ability to have command on the bidding lifecycle to delivering to more rapid trades, and (8) Distributed computation: ability to distribute the computational workload between the software agents of bidders and exchange for best resource utilization. Our work proposes that the strategic conduct may be exhibited by logical rule and operator formulae. The rule-based expressions allow bidders to share part of their problem constraints without full exposure. Another compelling aspect, is the fact the rule-based expressions expedite the trades with faster bidding lifecycle due to the automatic deduction and aggregation of rules of action that. Hence, our work introduces the rule-based bidding language (RBBL) for the free exchange e-marketplace that enables the flexible expression of strategic rules of conduct as logical rule and operator formulae in the bidding structure. The RBBL is fully symmetric that enables a simultaneous rule-based bidding, not only for buyers but also for sellers and those of mixed roles. The RBBL empowers the free exchange to deliberate on the logical rules and operators for automatic preference and service deduction and bid formation that secures rapid trades.

Furthermore, the strategic and computational complexities of the exchange impossibility theorem (Hurwicz, 1975) have motivated our work to target some relaxed (weaker) desirable properties for an adequate fully symmetric DA. While Hurwicz strong budget-balance is often not necessary, we can achieve adequate truthfulness, efficiency and weak budget balance using market economy settings: (1) Allocative Efficiency (AE): that maximizes the social utility welfare; the aggregate valuations of all buyers and sellers. The e-services are allocated to the bidders who value them most highly (2) Incentive Compatibility (IC): in which bidders maximize their utilities when they truthfully reveal private information. The truthful attitude of bidders is based on their *ex ante* expectations, given the mechanism outcome and their *ex-post* expectations, given their constant learning at repetitive trades. In (McAfee, 1992) and (Wurman et al., 1998), however, there is no DA that is both AE and IC; (3) Weak Budget Balance (BB): in which the total

payment that bidder agents make is positive so the exchange doesn't run at deficit, but secures sufficient profits; The weak BB guarantee a fairly positive e-market profit, at which no outside subsidy inwards or transfers outwards are required for a deal to be reached (4) Individuals rationality (IR): in which the agent's expected utility from using exchange is more than that of other choices given prior beliefs about preferences of other agents; The exchange matching do not make any bidder worse off than has the bidder not participates, (5) Strategic equilibrium: a mechanism implement a social welfare function at equilibrium with solution concepts that predict strategies agents will select with diverse assumptions about rationality of agents and knowledge agents have about other agents.; and (6) Computational tractability: extends to the polynomial time tractable performance of the RBBL bidding, exchange deduction, bid formation and winner matching heuristics. Generally, given bidders' preferences, an AE matching is *NP*-hard (Sandholm, 2008).

In summary, our work targets the stable and socially efficient matching allocation of a class of decentralized CAP of multiple units of e-services that share identical attributes at different Q-levels. Our work develops an expressive free exchange e-marketplace using the RBBL rules bidding that enables the flexible expression of bidding strategic conduct. Our work empowers the free exchange, also, with the GSPM GSP based multiple Q-level double auctions that facilitates fully symmetric exchange trades, while delivering social efficiency, strategic stability, computational tractability and e-market profitability.

## 1.4 Thesis Organization

Chapter 2 presents the formal description, and analysis of the combinatorial allocation problem. Chapter 3 expands on the related work and fundamentals. Chapter 4 introduces, describes and analyzes the formal modelling of the rule based bidding language (RBBL) and the inherent properties, while Chapter 5 introduces and investigates the GSPM, generalised second price based matching double auction and the inherent economic and computational properties. Chapter 6 describes, examines, and analyses the experimental simulation environment and empirical findings. Chapter 7 concludes with a summary of general research issues, contributions, empirical analysis, limitations, and future outlook.

## Chapter 2

### 2 Problem Modeling, Analysis, and Issues

Our work in this chapter targets the formal problem modeling and analysis of a special decentralized CAP of e-services that target the socially efficient symmetric allocation matching of request and ask e-service assets between self-interested rational bidders. The bidders may have conflicting goals that motivate their strategic conduct as manifested by their varying preferences for, indeed, maximizing expected utilities, given their beliefs about other bidder preferences. The decentralised CAP social efficiency optimizes the aggregate valuations and utilities of request and ask bidders for any discriminatory DA clearing prices. As the proposed DA matching mechanism is anticipated to incite the truthful revelation of request and ask bidders as will be proven later on in our work, the formal described and decentralized CAP assumes a truthful state of choices and rules of conduct of bidders. Hence, the decentralized CAP may be formally reduced and modeled as centralized CAP integer program (IP) for the winner determination problem (WDP). In fact, the DA mechanism selects the payment rule that motivates the IC of IR bidders with free disposal in which bidders have increasing values for e-services. The DA secures, also, BB for e-market profitability. The CAP IP is limited, however, by constraints (i.e., bids, budgets), local objectives, and the proposed DA rules of encounter.

The modeled CAP targets the efficient matching of multiple units of a particular e-service that shares identical attributes of varied attribute values and, essentially, different quality levels (Q-levels). For instance, the e-service commodity of the digital advertising (ad) CAP is the ad impression, that is a user single viewing of single ad, while the bidders are the publishers and advertisers. For mobile apps, the e-service is a software application that delivers certain functionality that run on buyers (consumers) who navigate app stores for a required app using mobile devices, smart phones or tablet computers. The seller (provider), however, is typically the application distribution platform such as Apple App Store, Google Play, and BlackBerry World. With larger number of Q-levels, however, the

CAP class may also be extended to the matching of multiple units of rather multiple different e-services. In fact, the multiple Q-levels concept is suites e-services that often comprise distinct attributes. While there are many e-services that share identical functionality, it may differ in some functional or nonfunctional (i.e., software quality) attributes. For instance, similar e-services from multiple sources would differ in their quality of services or user acceptance or reputation score. Otherwise, some games may differ in their functional complexity levels. In fact, the more the number of presented Q-levels, the narrower the tactical maneuverability of bidders with a Q-level solution space that, eventually, incites a rather truthful revelations.

## 2.1 Combinatorial Allocation Problem Description

Considering the time horizon as a set of discrete decision periods  $\tau_t, t = \{1, \dots, T\}$  during which the exchange e-marketplace collects the seller and buyer RBBL messages (i.e., e-service attributes, values, and rules), deduces the request and ask bids of the targeted multiple e-services to be traded. The FX ranks and sorts the request and ask bids of the selected e-services based on their valuations and Q-levels. The FX computes, the, the efficient matching for the multiple winners. Our work assumes bidders act exclusively as either e-service sellers or buyers, while the CAP allocation and pricing decisions are taken off-line at the end of decision periods  $\tau_t, t = \{1, \dots, T\}$ ,  $T$  is number of decision periods. The following is a formal description of the CAP at  $\tau_t$  that manifests a sequence of events (Mansour et al., 2012) as shown in the matching CAP environment of Figure 2:

- 1)  $m$  e-service providers  $P = \{P_1, \dots, P_j, \dots, P_m\}$  construct ask bids  $\mathbb{I}\langle f_p^j, v_p^j, r_p^j, Q_p^j, t_p^j \rangle$  that include: (1) feature-group attributes set  $f_p^j$  of provider  $P_j$  that form the e-service combinations:  $f_p^j = \{(f_1, g_1), \dots, (f_l, g_l), \dots, (f_f, g_f)\}$ , (2) initial true costs set  $v_p^j = \{v_1, \dots, v_l, \dots, v_f\}$  of attributes set  $f_p^j$  (i.e., value of  $(f_l, g_l)$  is  $v_l$ ) (3) rational rules  $r_p^j$  of provider  $P_j$  that direct the exchange deduction of various e-services and net valuations of asks, (4) assigned Q-levels  $Q_p^j$  set of the FX deduced ask e-services,

and (5) expiry times  $t_p^j$  of the conveyed logical rules. The logical rule formulae  $r_p^j$  represent the rational rules of action/reaction to the e-market anticipated disruptions.

- 2) Simultaneously,  $n$  e-service consumers  $C = \{C_1, \dots, C_k, \dots, C_n\}$  construct  $m$  request bids  $\coprod \langle f_c^i, v_c^i, r_c^i, Q_c^i, t_c^i \rangle$  to request e-services that include: (1)  $f_c^i$  attribute-group attributes of requested e-services  $f_c^i \subseteq f_p^j$ ; (2) initial true valuations  $v_c^i$  of the e-service attributes  $f_c^i$ ; (3) rational rules  $r_c^i$  that direct the exchange deduction and aggregation of e-services and their bids; (4) assigned Q-level  $Q_c^i$  set of the FX deduced request e-services; and (5) the expiry times  $t_c^i$  of the logical rules.
- 3) The exchange collects the bidding message requests and asks and exploits the rational rules  $r_p^j, r_c^i$  to deduce the offered and requested e-services. Eventually, the FX produces  $jp$  number of e-services for provider  $P_j$   $e_p^j = \{e_p^{j1}, \dots, e_p^{jq}, \dots, e_p^{jp}\}$  with related Q-levels  $Q_p^j = \{Q_p^{j1}, \dots, Q_p^{jq}, \dots, Q_p^{jp}\}$  and ask bids  $b_p^j = \{b_p^{j1}, \dots, b_p^{jq}, \dots, b_p^{je}\}$  and  $ic$  number of request e-services in set  $e_c^i = \{e_c^{i1}, \dots, e_c^{ik}, \dots, e_c^{ic}\}$  with related Q-levels set  $Q_c^i = \{Q_c^{i1}, \dots, Q_c^{ik}, \dots, Q_c^{ic}\}$  and request bids set  $b_c^j = \{b_c^{i1}, \dots, b_c^{ik}, \dots, b_c^{ic}\}$ . The e-services  $e_p^{jq} \subseteq f_p^j$ , is a combination of provider feature-group attributes, while  $e_c^{ik} \subseteq f_p^j$  a combination of consumer attributes that are induced by the stored logical rules, while the ask bid and request bids are the sum of the selected attribute values and the revised valuation of the FOL active rules. That is, for the deduced request e-service  $e_c^{ik} \in e_c^i$ , the request bid net value  $b_c^{ik} = \sum_k v(f_c^i) + v(r_c^i)$ , i.e., the sum of values of eligible attributes and the value adjustments of the FOL rules. Similarly, for eligible ask e-services  $e_p^{jq} \in b_c^j$  the ask bid values  $b_p^{jq} = \sum_q v(f_p^j) + v(r_p^j)$ .
- 4) The exchange e-marketplace announces the requested e-services with Q-levels  $Q_c^i$  and the time horizon  $\tau_t$ :  $\coprod \langle e_c^i, Q_c^i, \tau_t \rangle$  to the provider bidders  $P$ . The exchange also announces the offered e-services with  $Q_p^j$  set and the time horizon  $\tau_t$ :  $\coprod \langle e_p^j, Q_p^j, \tau_t \rangle$  to consumers  $C = \{C_1, \dots, C_i, \dots, C_n\}$ . The exchange stores the bidding attribute-values, FOL rules  $r_p^j$  and  $r_c^i$  and their expiry times  $t_p^j, t_c^i$  while hiding the request and ask

valuations  $b_p^j, b_c^i$  to mitigate the impact of exposure problem. The exchange signals consumers and providers, while collecting RBBL messages during  $\tau_t$ .

- 5) At expiry of  $\tau_t$ , the exchange: (1) deduces all ask  $b_p^{jq}$  and request bids  $b_c^{ik}$  using the RBBL attribute-values, Q-levels, logical rules and other constraints; (2) ranks all request and ask bids based on the Q-levels; (3) sorts all request (ask) bids in descending (ascending) orders based on their net values; and (4) computes the AE matching allocations and pricing rules for clearing the exchange.
- 6) Finally, the exchange e-marketplace returns  $\Pi(e_c^{ik}, Q_c^{ik}, \pi_c^{ik})$  and  $\Pi(e_p^{jq}, Q_p^{jq}, \pi_p^{jq})$  to winning bidders such that  $e_c^{ik} = e_p^{jq} \wedge \min Q_c^{ik} \geq Q_p^{jq}$ . The costs and payments  $\pi_c^*, \pi_p^*$  are the prices for the matched pairs.

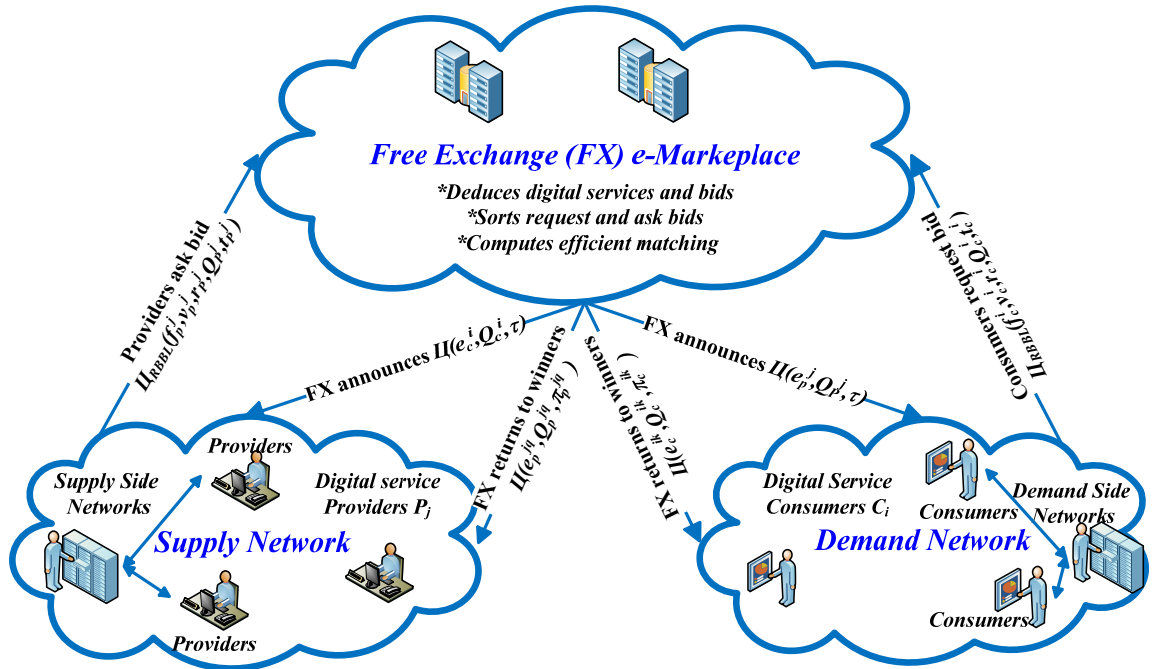


Figure 2: Combinatorial allocation problem environment of digital services

## 2.2 Formal Combinatorial Allocation Problem Model

Considering the time horizon as a set of discrete decision periods during which multiple e-services with the same attributes and different Q- levels are allocated to multiple

winners, our work assumes the matching allocation and pricing decisions are taken off-line at the end of a decision period  $\tau_t, t = \{1, \dots, T\}$ . Generally, the objective of the FX is to implement a trade  $\lambda^*_t$  for the CAP at period  $\tau_t$  that delivers social efficiency. Our work defines the social AE as the objective that maximizes the total request and asks valuations of bidders while securing e-market profitability. Formally, let  $\lambda^Q_{tijkq} \in \lambda^Q_t = 1$  if  $e_c^{ik} = e_p^{jq} \wedge \min Q_c^{ik} \geq Q_p^{jq}$  and  $\lambda^Q_{tijkq} = 0$ , otherwise. For  $(e_c^{ik}, e_p^{jq})$  matched pairs, the bidders have a quasi-linear utility:  $u_c^{ik}(\lambda^Q_t) = b_c^{ik}(\lambda^Q_t) - p_c^{ik}(\lambda^Q_t)$  for consumers who buy the e-services  $e_c^{ik}$  and  $u_p^{jq}(\lambda^Q_t) = c_p^{jq}(\lambda^Q_t) - b_p^{jq}(\lambda^Q_t)$  for the providers who sell the e-services  $e_p^{jq}$ ,  $\forall p_c^{ik}, c_p^{jq} \in \mathbb{R}_+$  (i.e., payments and costs). Bidders are assumed risk neutral in the formal model below, who pay as much as expected of an e-service with budget bounds  $(B_c^i)$ . Given instance  $FX(b, Q, \lambda, \tau_t)$  at period  $\tau_t$ , then, the CAP AE trade  $\lambda^Q_t = \lambda^*_t$  maximizes the aggregate values of bids (i.e.,  $v(e_c^{ik}) = b_c^{ik}$ ) and minimizes the aggregate values of asks (i.e.,  $v(e_p^{jq}) = b_p^{jq}$ ) given the multiple Q-levels. That is:

$$\max_{\lambda^Q_t} \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^{ic} \sum_{q=1}^{jp} \lambda^Q_{tijkq} b_c^{ik} + \min_{\lambda^Q_t} \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^{ic} \sum_{q=1}^{jp} \lambda^Q_{tijkq} b_p^{jq}$$

That is equivalent to

$$\begin{aligned} & \max_{\lambda^Q_t} \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^{ic} \sum_{q=1}^{jp} \lambda^Q_{tijkq} b_c^{ik} - \max_{\lambda^Q_t} \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^{ic} \sum_{q=1}^{jp} \lambda^Q_{tijkq} b_p^{jq} \\ & \max_{\lambda^Q_t} \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^{ic} \sum_{q=1}^{jp} \lambda^Q_{tijkq} \cdot (b_c^{ik} - b_p^{jq}) \end{aligned} \quad (1)$$

Given quasi linear utilities of request and ask bidders :  $u_c^{ik}(\lambda^Q_t) = b_c^{ik}(\lambda^Q_t) - p_c^{ik}(\lambda^Q_t) \geq 0$  and  $u_p^{jq}(\lambda^Q_t) = c_p^{jq}(\lambda^Q_t) - b_p^{jq}(\lambda^Q_t) \geq 0$ , then (1) becomes:

$$\max_{\lambda_t^Q} \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^{ic} \sum_{q=1}^{jp} \lambda_{tijkq}^Q (u_c^{ik} + u_p^{jq}) + \max_{\lambda_t^Q} \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^{ic} \sum_{q=1}^{jp} \lambda_{tijkq}^Q (p_c^{ik} - c_p^{jq}) \quad (2)$$

Hence, the social welfare objective of the CAP in formula (1) transforms to formula (2) that maximizes the aggregate utilities of the request and ask bidders and maximizes, also, the net FX e-market profit that should be of a positive value at all situations. In fact, the eligible criteria of the GSPM matching (i.e.,  $e_c^{ik} = e_p^{jq} \wedge \min Q_c^{ik} \geq Q_p^{jq}$ ) is that  $b_c^{ik} \geq b_p^{jq}$ . However, as per the GSPM forward GSP for buyers and reverse GSP for sellers the pricing rules,  $b_c^{ik} \geq p_c^{ik}(b_c^{ik+1})$  for the second bid in rank and  $p_c^{ik}(b_c^{ik+1}) \geq c_p^{jq}(b_p^{jq+1})$  for matching condition, then  $p_c^{ik} \geq c_p^{jq}$ . Hence, the GSPM realizes AE while maximizing the FX profitability that grows with the thick e-market. For an instance  $FX(b, Q, \lambda, \tau_t)$  of at  $\tau_t, t = \{1, \dots, T\}$ ,  $\lambda_{tijkq}^Q = 1$  if  $e_c^{ik} = e_p^{jq} \wedge \min Q_c^{ik} \geq Q_p^{jq}$ ,  $\lambda_{tijkq}^Q = 0$  otherwise:

$$\begin{aligned} b_c^{ik} &= \sum_k v(f_c^i) + v(r_c^i); b_p^{jq} = \sum_q v(f_p^j) + v(r_p^j) \forall b_c^{ik}, b_p^{jq} \\ &\geq 0 \text{ (RBBL valuation model)} \end{aligned}$$

$$p_c^{ik} = b_c^{ik+1}; c_p^{jq} = b_p^{jq+1}; \forall p_c^{ik}, \forall c_p^{jq} \in \{\mathbb{R}_+, 0\} \text{ (GSPM DA pricing rule)}$$

$\lambda_Q^*$ , solves the following IP model of the FX CAP with an objective similar to (1) and (2):

$$\max_{\lambda_t^Q} \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^{ic} \sum_{q=1}^{jp} \lambda_{tijkq}^Q \cdot (b_c^{ik} - b_p^{jq}) \quad \forall \tau_t \quad (\text{AE, IC}) \quad (3)$$

$$s. t. \sum_{i=1}^n \sum_{k=1}^{ic} \lambda_{tijkq}^Q \leq 1, \forall P_j, e_p^{jq}, \forall Q_p^{jq} \quad (\text{Unique Matching}) \quad (4)$$

$$\sum_{j=1}^m \sum_{q=1}^{jp} \lambda_{tijkq}^Q \leq 1, \forall C_i, e_c^{ik} \forall Q_c^{ik} \quad (\text{Unique Matching}) \quad (5)$$

$$\sum_Q \sum_{k=1}^{ic} \lambda_{tijkq}^Q \cdot b_c^{ik} \leq B_c^i \quad \forall i, C_i, b_c^{ik} \quad (\text{Max Budget}) \quad (6)$$

$$\sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^{ic} \sum_{q=1}^{jp} \lambda_{tijkq}^Q \cdot (p_c^{ik} - c_p^{jq}) \geq 0 \quad \forall Q_c^{ik}, Q_p^{jq} \quad (\text{Weak BB}) \quad (7)$$

$$\sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^{ic} \sum_{q=1}^{jp} \lambda_{tijkq}^Q \leq \min \left\{ \sum_i |e_c^i|, \sum_j |e_p^j| \right\} \quad (\text{Cardinality}) \quad (8)$$

$$\lambda_{tijkq} (e_c^{ik}, e_p^{jq}, Q_c^{ik}, Q_p^{jq}) \in \{0,1\} \quad \forall e_c^{ik}, e_p^{jq} \quad (\text{Integrality}) \quad (9)$$

Constraint (9) ensures integrality, while constraints (4) and (5) restrict any winning request-bid to be assigned at most to one ask-bid of the same unique e-service attributes, and restrict any winning ask-bid to be assigned at most one request-bid of the same attributes. Hence, the CAP turns into the generalized assignment problem known to be *NP*-Hard; constraints (6) and (7) ensure the weak budget balance that secures the e-marketplace profitability, while restricting the budget boundaries (i.e.,  $B_c^i$ ). Constraint (8) imposes the multiple Q-level cardinality balance of the offered and requested (supply and demand) of particular e-services by free disposal.

## 2.3 Combinatorial Allocation Problem Complexity Analysis

The CAP problem at period  $\tau_t$ , as formulated above is an instance (i.e., reduction) of a set-packing problem (SPP) (deVries & Vohra, 2003). Given a set of  $M$  elements and a collection  $V$  of subsets with non-negative weights, find the largest weight collection of subsets that are pairwise disjoint. Formally: let  $\lambda_j = 1$  if  $j^{th}$  subset of  $V$  with weight  $v_j$  is selected,  $\lambda_j = 0$ , otherwise. Let  $m_{ij} = 1$  if  $j^{th}$  subset of  $V$  contains  $i \in M$ ,  $m_{ij} = 0$ , otherwise. Then the SPP model is formulated as followed:

$$\max_{j \in V} \sum \lambda_j \cdot v_j \quad (\text{AE, IC}) \quad (1\text{spp})$$

$$\text{s.t. } \sum_{j \in V} \lambda_j \cdot m_{ij} \leq 1, \forall i \in M; \quad (\text{Unique Matching}) \quad (2\text{spp})$$

$$\lambda_j \in \{0,1\} \forall V \quad (\text{Integrality}) \quad (3\text{spp})$$

The SPP is equivalent to the IP in equations (3), (4), (5) and (9) of the exchange CAP IP with fewer constraints. Hence, the SPP is a functional reduction of exchange CAP and could be reduced or transformed in polynomial time (i.e.,  $\text{SPP} \leq_p \text{CAP}$ ). Indeed, the exchange CAP is an instance of SPP, as noted in (Rothkopf et al., 1998) and (Sandholm, 2002). However, the SPP is, generally, *NP*-Hard with fairly large number of bidders, while the recognition version is *NP*-complete (deVries & Vohra, 2003). Hence, the exchange CAP is generally *NP*-hard, in which the computation demanded for solving practical size problems is usually prohibitive. Hence, the exchange CAP would be computationally intractable for thicker e-market trades of practical size of bidders and cannot be solved using the exact approaches like Branch and Bound, Cutting planes, or Branch and Cut. In addition, the decentralized CAP has other inherent game-theoretic and computational challenges pertinent to the decentralized distribution of knowledge and control, quite evident in the bidder's rationality, strategic conduct, self-interest, decision making autonomy, and private information and actions. The *NP*-hard complexity of our CAP IP model motivates our work, hence, to adopt the rather more natural economic based approaches for rational bidders. Our proposed mechanism has to motivate, first, the truthful revelation of preferences and strategic rules of bidders, then computes socially efficient matching allocations and pricing out of the modeled CAP IP based on the truthful revelations as detailed in the next chapters. In that vein, our work investigates how to attract bidders to be strategically truthful, not tactically manipulative, how to develop a flexible, concise and expressive bidding messaging model that enables the free expressions of choices and strategic conduct, and how to reach tractable closure with rapid, efficient and stable allocations, while delivering profitability to the e-marketplace.

## 2.4 Research Issues

While the prospects of the digital era are enormous, e-marketplaces are encountering inherent and persistent game-theoretic and computational complexities that challenge the strategic and computational efficiencies of the matching mechanisms. In addition to the computational complexity of the centralized CAP, the distributed knowledge and control of the decentralized CAP imposes a rather further coordination and mechanism design complexities. The work in (Kalagnanam & Parkes, 2004) identified four areas of computational constraints that restrict the solution space of feasible mechanisms, including strategic, communication, valuation, and winner determination complexities. In the context of communication complexity, our work examines the limited bidding scope and trading conduct of e-market mechanisms that often provoke adverse strategies and lead to e-market failures. In the context of strategic, valuation and winner determination complexities, our work investigates, also, the inefficiencies of the symmetric exchange mechanisms with respect to allocation and revenue models. A fundamental challenge is the fact symmetric exchange models are hard to implement, as per Hurwicz impossibility theorem (Hurwicz, 1975). In fact, most present exchange e-marketplaces implement a rather single reserve price auction mechanism with the fixed reserve values of sellers. The design of an adequate exchange, though, promotes flexible and efficient symmetric interactions between rational bidders. In that vein, our work presents a realistic view of a symmetric exchange that delivers stable efficiency while facilitating the flexible choices and strategic tolerance of rational bidders. The decentralized CAP reveals, however, some hard game-theoretic and computational complexities as the following explains:

*Limited bidding conduct and language complexity:* Our work identifies and examines the potential challenges that initiate from the restricted bidding conduct and trading practices. While complexities may justify the restrictive bidding practices, the de facto auctions are often designed for the strategic benefit of revenue maximizing e-marketplaces. The restrictive bidding practices, however, provokes adverse strategies of bidders that may lead to digital market failures. Given the complex semantics and structure of interactions in open systems, preference formation becomes a hard problem, especially if preferences

are uncorrelated (Dash et al., 2003). The design of flexible bidding language that promote free strategic conduct has to deliver expressiveness, ease of use, conciseness, flexibility, and computational efficiency. Generally, the bidding model often confines agents express preferences that impact the computational e-market model. In (Nisan, 2000), a trade-off between the compactness and simplicity is analyzed, in which, at one extreme, there are the bidding programs that provide methods to compute valuations, while at the other far extreme, there are myopic bids used in iterative auction. A concise and expressive bidding language mitigates preference elicitation and lets agents convey their valuations compactly. The CAP would require an agent to specify  $2^{|N|} - 1$  bids, while few may be of interest. The proposed rules bidding would allow for expressing the logical and operators rule formula in the bidding structure with distinct attribute level valuations which exposes new challenges to the bidding complexity. Our work proposes the first order logic (FOL) for modeling the logical rules formulae. The free exchange smart preference deliberation, deduction, aggregation and bid formation are other emerging challenges.

*Mechanism design (MD) complexity:* The inefficiencies of present exchange mechanisms is understood in the context of *Hurwicz impossibility theorem* (Hurwicz, 1975) that states it is impossible to implement an AE, SP and BB social welfare function in DSE in a simple exchange and quasi-linear preferences. There are limitations related to developing tractable mechanism design (MD), game-theoretically and computationally, that delivers stable efficiency. For instance, while GVA is an AE SP mechanism, it is computationally intractable as it has to solve a complex optimization problem multiple times: once to determine the optimal matching allocation and once for each agent with its bid removed to determine the residual payment (Wellman et al., 2001). The agents compute solution concepts as Nash equilibrium (NE) or DSE, given information about the mechanism and beliefs about preferences, rationality, and beliefs of other agents. A NE or DSE MD mitigate the strategy selection problem that results in minimal agent computation (Varian, 1995), however, with limited choice of desired properties. Otherwise, an iterative-MD (Parkes, 2001) enables bounded agents to play myopic best-response strategy and reason about one round of the game at a time. Another approach is to select MD with

polynomial-time computable equilibrium (Nisan & Ronen, 2000) best-response that restricts strategies an agent in computing its best-response to a knowledge subset of the strategy space. While our work targets the stable social efficiency as adequacy objectives for the exchange DA design, our work realizes the particular game-theoretic complexity of o symmetric exchange in the context of *Hurwicz impossibility theorem*. In (McAfee, 1992) and (Wurman et al., 1998), there is no DA that is both efficient and IC.

*Computational complexity*: bounded computational resources impose challenges on the software agents and the MD that may necessitate explicit approximations and restrictions. However, approximations can change economic properties. For instance, approximating VCG auction payment and matching allocation rules break SP. Agents, for instance, are computationally bounded-rational when resolving the combinatorial complexity of computing their preferences on all outcomes given other agents strategists. In fact, solving even typical centralized CAP problems, where the number of possible bids is exponential as the number of items is most often *NP*-hard (Sandholm, 2008). Agents may use indirect iterative mechanisms (Wellman, 1993) (Parkes, 2001) and computing, rather, a myopic best-response bundle set. Direct MD one-shot agents, however, act in a game-theoretic sense, modeling the expected effect of their actions on other agents' actions. Another approach formulates queries about agent valuations that relieve agents from formulating preferences for all outcomes (Hudson & Sandholm, 2002).

In summary, our work targets a market economy based solution approach for a special class of decentralised CAP for the matching of multiple units of e-services that may share identical attributes and differs in quality levels. The game-theoretic and *NP*-hard computational complexities of the decentralised CAP between rational self-interested bidders in addition to the symmetric exchange inherent inefficiencies motivate selecting the economic based solution approach. Our work targets a fully symmetric exchange e-marketplace for the double auction matching of e-services that deliver fairly adequate properties like truthfulness, social efficiency, strategic stability and market profitability in a rather weaker sense to relax the symmetric exchange game-theoretic challenges.

## Chapter 3

### 3 Literature Review

Our approaches to designing adequate free exchange e-marketplace are multidisciplinary that draw concepts from microeconomics theory that studies impact of market allocations and pricing decision rules on bidder preferences and rational strategic conducts. Game theory is an essential mathematical framework for studying the models of conflict and cooperation among rational bidders. Our work exploits, also, the mechanism design theory that examines game-theoretic solution concepts for private information settings. The mechanism design theory uses the framework of non-cooperative games and incentive engineering to determine how the private preferences can be elicited. The combinatorial optimization and operation research analyze the problem computationally and help developing tractable algorithms for the matching CAP. Software engineering is crucial in the development and implementation of the multiagent based approaches for the decentralized rationality and interaction. It is a natural framework for realizing agent collaboration, rational self-interest and autonomy (Jennings, 2001) that map state history to actions and translate strategies into outcomes. The work in this chapter reviews aspects of the above mentioned disciplines that are relevant to the proposed free exchange model.

#### 3.1 Bidding Languages

The bidding language relates to the efficient CAP across multiple bidders that requires the determination of their preferences over the matching allocations and then choosing an allocation that satisfies certain criteria. Bidders may consider bundles of substitutes or complements or express complex preferences over combinations of items. Bidders provide  $2^{|N|} - 1$  bid valuations on  $N$  items over bundles that make it a computationally *NP*-hard problem (Sandholm, 2000) (Parkes, 2006). Furthermore, the complex semantics and syntactic structure of the interactions in combinatorial open systems, turn preference formation into a hard problem especially if preferences are uncorrelated (Dash et al., 2003). However, combinatorial bids eliminate the “exposure problem” as in SAA

(Milgrom, 2004). A bid defines values for matching allocations that constrain the spaces of acceptable matching allocations. However, the bidding language often, confine agents express preferences that impact properties of the computational e-market model. In fact, the structure of bids, and the rules specified, often, restricts the choice of bids by bidders. Bid structure relates closely to e-market structure. Some common bid structures are found in (Kalagnanam & Parkes, 2004), like divisible and indivisible bids with price-quantity pairs, divisible bids with price schedule, , bundled bids with price-quantity pairs and configurable bids for multifactor items.

The e-market model has a crucial impact on the bidding language complexity. Agents trading with iterative mechanism (Parkes, 2001) compute myopic best-response bundles using simple bidding structure. Another approach is to formulate queries about agent valuations (Hudson & Sandholm, 2002). Agents act in game-theoretic sense and require a complex form of bidding to formulate preferences. A concise and expressive bidding language mitigates preference elicitation problems and let agents communicate their valuations compactly. The work in (Boutilier & Hoos, 2001) (Boutilier, 2002), introduced two forms of logical bidding,  $\mathbb{L}_G$  and  $\mathbb{L}_{GB}$  that allow for logical formulae of requests and asks where goods present atomic propositions (i.e., substitutes), combined using logical connective, with a price of formulae. The  $\mathbb{L}_B$  logical bidding (Nisan, 2000) (Sandholm, 2000) uses bundles with related prices as atomic propositions combined using logical connectives. The additive-or  $\mathbb{L}_B^{\text{OR}}$  has one or more disjoint bids, and the total bid price is the sum of the bidder bid prices.  $\mathbb{L}_B^{\text{OR}}$ , is compact for particular valuations, but not expressive for general valuations. In exclusive-or  $\mathbb{L}_B^{\text{XOR}}$  bids state that at most one bid can be accepted. The total bid price is the value of the maximal bid price across the bundles when multiple bundles are accepted. One can also consider nested languages, as OR-of-XORs and XOR-of-ORs, and a generalization,  $\mathbb{L}_B^{\text{OR}^*}$  (Nisan, 2006) that supports constraints using phantoms, dummy goods, within atomic bids to provide more expressiveness and compactness.

The TBBL, tree-based bidding language (Cavallo et al., 2005) is a concise and expressive tree-structured bidding language that uses the interval to choose (IC) logical operator for internal nodes to combine bundles, while the leafs represent single items, facilitating by which a symmetric bidding for buyers and sellers. The TBBL allows agents to specify bounds on their true values for trades, to be refined during bidding. Computationally, the TBBL can be captured, concisely, in IP for the matching allocation problem. The TBBL uses IC operators to provide more concise representations than  $OR^*$  or  $\mathbb{L}_{GB}$ . The  $IC_n^n(\beta)$  is equivalent to an  $AND$ ;  $IC_1^n(\beta)$  is equivalent to an  $OR$ , and  $IC_1^1(\beta)$  is equivalent to  $XOR$  operator. Computationally, the TBBL can be captured, concisely, in an integer program (IP) for the CAP. The TBBL has an IC logical operator on internal nodes coupled with semantics for propagating values within the tree. The TBBL uses IC operators to provide more concise representations than  $OR^*$  or  $\mathbb{L}_{GB}$  (Boutilier & Hoos, 2001) (Nisan, 2006) (see Figure 3). Leafs of the tree are annotated with traded items and all nodes are annotated with changes in values. For bid tree  $T_i$  from bidder  $i$ , let  $\beta \in T_i$  node in the tree, and  $v_i(\beta) \in \mathbb{R}$  the value specified at node  $\beta$ . Let  $Leaf(T_i) \subseteq T_i$  the subset of nodes representing leafs of  $T_i$  and  $Child(\beta) \subseteq T_i$  the children of  $\beta$ . All nodes are labeled with operator  $IC_x^y(\beta)$ . Each leaf  $\beta$  is labeled as a buy or sell, with units  $q_i(\beta, j) \in \mathbb{Z}$  for the impression  $j$  associated with leaf  $\beta$ , and  $q_i(\beta, j') = 0$  otherwise. Same impression  $j$  may simultaneously occur in multiple leafs of the tree, given the semantics of the tree.  $IC_x^y(\beta)$ , node ( $x$  and  $y$  are non-negative integers) indicates the bidder is willing to pay for the *satisfaction* of at least  $x$  and at most  $y$  of her children. An extended *TBBL* (i.e., multiple parents DAG or using  ${}_a^b IC_x^y$  operator) subsumes both  $OR^*$  and  $\mathbb{L}_{GB}$ , and is more expressive. *TBBL* can express  $XOR$ ,  $OR$  and  $XOR/OR$  languages (Nisan, 2006).  $IC_n^n(\beta)$  with  $n$  children is equivalent to an  $AND$  operator;  $IC_1^n(\beta)$  is equivalent to an  $OR$  operator; and  $IC_1^1(\beta)$  is equivalent to  $XOR$  operator.

Given a tree  $T_i$ , the (change in) value of a trade  $\lambda$  is defined as the sum of the values on all satisfied nodes, where the set of satisfied nodes is chosen to provide the *maximal* total value. Let  $sat_i(\beta) \in \{0, 1\}$  denote whether node  $\beta$  in tree  $T_i$  of bidder  $i$  is satisfied,

if  $sat_i = \{sat_i(\beta), \forall \beta \in T_i\}$ , is valid for  $T_i$  and trade  $\lambda_i$   $sat_i \in valid(T_i, \lambda_i)$ :

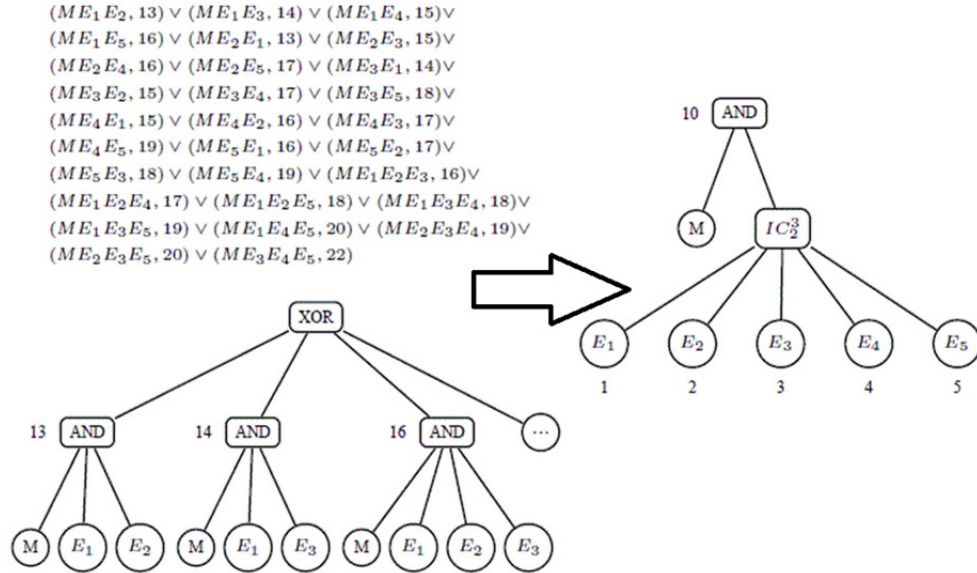
$$\forall \beta \in \{T_i \setminus Leaf(T_i)\} IC_x^y(\beta), x sat_i(\beta) \leq \sum_{\beta' \in Child(\beta)} sat_i(\beta') \leq y sat_i(\beta)$$

$sat_i \in valid(T_i, \lambda_i)$ , means the total number of units of each item requested across all satisfied leafs is no greater than the total number of units awarded in the trade, that is:

$$\sum_{\beta \in Leaf(T_i)} q_i(\beta, j) sat_i(\beta) \leq \lambda_{ij}, \quad \forall j \in G$$

Given the constraints formulated in above two equations, the total value of trade  $\lambda_i$  given bid-tree  $T_i$  from bidder  $i$ , is defined as the solution to an optimization problem:

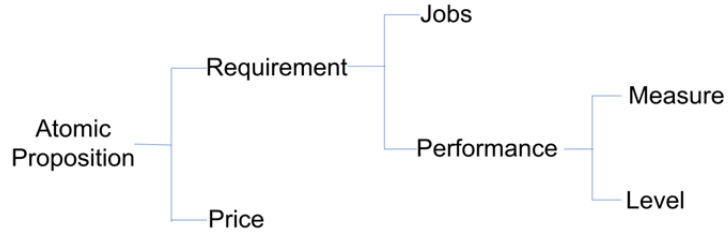
$$v_i(T_i, \lambda_i) = \max_{sat_i \in valid(T_i, \lambda_i)} \sum_{\beta \in T_i} v_i(\beta) sat_i(\beta)$$



**Figure 3: An OR\*, LGB and TBBL bidding instance**

In the  $\mathbb{L}_R$  requirement bidding (Wang et al., 2009) the atomic propositions attach value to the job scheduling problem, given a performance requirement is satisfied. With timeline discretization, agents can express time related scheduling requirements, such as release

times, due dates, indirectly by attaching values to various time units combinations, that could be NP-hard. As shown Figure 4, the  $\mathbb{L}_R$  Atomic proposition (root tree nodes) consists mainly of a requirement (level-1 node) for completing a set of Jobs (level-2 node) according to a Performance in SX (level-2 node) and a Price (level-1 node), an agent willing to pay for requirement. Performance is defined by a Measure (level-3 node) and Level (level-3 node). An Atomic proposition is represented by a 4-tuple leafs  $\langle \text{Jobs, Measure, Level, Price} \rangle$ .



**Figure 4: Requirement bidding model for job shop scheduling problem**

### 3.2 Game-Theoretic Concepts

Game theory (Von Neumann & Morgenstern, 1953) (Nash Jr., 1951) is the most reliable theoretical framework to investigating the states of the self-interested agents in conditions of strategic interaction. This is in comparison to many robust tools for analyzing decision making in decentralized systems with multiple autonomous agents. Blending these tools for computational settings, provide a basis for building multiagent systems (MAS) that exploits computational mechanism design by applying the microeconomic principles to computer systems design (Dash et al., 2003). Agents, often, represent distinct bidders with potentially conflicting goals that seek to maximize own gains, and leads, hence, to the strategic analysis of uncooperative games, through which a designer can impose only the protocols of a mechanism but can't control which strategies agents will implement.

The game theoretic analysis considers the following basic concepts and assumptions: An agent  $i \in N$  holds private information about its preferences of type  $\theta_i \in \Theta_i$  of possible types set, determines preference (i.e., agent's value) for an outcome  $o \in \mathcal{O}$  over a set of

different outcomes of a game. The *preferences*  $\theta_i$  are general when they provide a complete and transitive preference ordering  $\succ$  on outcomes. An *ordering is complete* if for all  $o_1, o_2 \in \mathcal{O}$ , we have  $o_1 \succ o_2$  or  $o_2 \succ o_1$  (or both). An ordering is *transitive* if for all  $o_1, o_2, o_3 \in \mathcal{O}$ , if  $o_1 \succ o_2$  and  $o_2 \succ o_3$  then  $o_1 \succ o_3$ . A *general environment* is one in which there is a discrete set of possible outcomes  $\mathcal{O}$  and agents have general preferences. The agent's *utility*  $u_i(\cdot)$  determines preferences over own strategy and other agent strategies, given its type  $\theta_i$ , and expresses *utility* as  $u_i(o, \theta_i)$  for outcome  $o \in \mathcal{O}$ ,  $\mathcal{O}$  of the set of possible outcomes that define *payments or costs* and *matching allocations*. Agent  $i$  prefers outcome  $o_1 \succ o_2$  iff  $u_i(o_1, \theta_i) > u_i(o_2, \theta_i)$ . The *strategy* of agent  $i$   $s_i(\theta_i) \in \Sigma_i$  (i.e.,  $s_i : \Theta_i \rightarrow \Sigma_i$ ) of agent's  $i$  possible strategies set given  $\theta_i$ , is a contingent plan or decision rule(s) that defines actions an agent will chose for every state of the world. In addition to pure strategy, an agent can have mixed or stochastic strategy  $\sigma_i \in \Delta(\Sigma_i)$ , a probability distribution over pure strategies. The *game* (i.e., auction) is a set of actions (i.e., bids) available to an agent and a mapping from agent strategies to an outcome. An agent's utility  $u_i(s_1 \dots s_l, \theta_i) = u_i(o, \theta_i)$  depends on agent strategies that realize strategic interdependence. The agent *rationality* relates to expected utility maximizing at which an agent selects a strategy that maximizes its expected utility, given the preferences  $\theta_i$  over outcomes, beliefs about strategies of other agents, and the structure of the game.

The *mechanism*  $\mathcal{M} = (\Sigma_1, \dots, \Sigma_l, g(\cdot)) = (\Sigma, g)$ , is a protocol of social interactions that defines set of strategies  $\Sigma_i$  available to each agent, an *outcome rule*  $g: \Sigma_1 \times \dots \times \Sigma_l \rightarrow \mathcal{O}$  and *payment rule*  $t: \Sigma_1 \times \dots \times \Sigma_l \rightarrow \mathfrak{R}$ , such that  $g(s)$  is the outcome implemented by the mechanism for strategy profile  $s = (s_1 \dots s_l)$ . The mechanism  $\mathcal{M}$  implements a *social choice function* (SCF)  $f(\theta)$  if the outcome computed with equilibrium agent strategies is a solution to the SCF for all possible agent preferences i.e.,  $g(s_1^*(\theta_1), \dots, s_l^*(\theta_l)) = f(\theta), \forall (\theta_1, \dots, \theta_l) \in \Theta_1 \times \dots \times \Theta_l$ , where strategy profile  $(s_1^*, \dots, s_l^*)$  is an *equilibrium solution* to the game induced by  $\mathcal{M}$ . The mechanism, together with the agent types, defines a game. Agents are assumed autonomous and *economically rational* that selects a best-response strategy to maximize their expected utility in equilibrium with other agents,

means no agent benefit from unilateral deviation. The *mechanism design* (MD) problem is to design a set of possible agent strategies (e.g. bid at least the ask price) and an outcome rule (e.g. match highest bid with lowest ask) to implement a SCF with desirable properties based on agent's strategies. A *desirable property* is a solution concept as strong as possible. Dominance is preferred to Bayesian-Nash as it makes less assumption about agents. *Game theory analyzes the outcome of a mechanism*. Generally, in auction theory and MD, agents are *risk neutral* and have *quasi-linear utility functions*.

The *quasi-linear utility* function for agent  $i$  of type  $\theta_i$  is  $u_i(o, \theta_i) = v_i(x, \theta_i) - t_i$ . Outcome  $o \in \mathcal{O}$  defines a choice  $x \in \mathcal{K}$  from a discrete choice set and a *transfer payment*  $t_i$  by the agent. The type  $\theta_i$  defines valuation function  $v_i(x)$  for choice  $x \in \mathcal{K}$ . In fact,  $x \in \mathcal{K}$  represent *matching allocations* (outcomes), and  $t_i$  transfer *payments* to the auctioneer. *Risk neutrality* states an expected utility maximizing agent pay as much as the expected value of an item. With quasi-linear preferences, the outcome of a SCF is divided into a choice  $x(\theta) \in \mathcal{K}$  and a transfer  $t_i(\theta) \forall$  agent  $i$ , i.e.,  $f(\theta) = (x(\theta), p_1(\theta) \dots p_l(\theta)) \forall \theta = (\theta_1, \dots, \theta_l)$ . The outcome rule,  $g(s)$ , in a mechanism with quasi-linear agent preferences, has a selected choice rule,  $k(s)$  from the choice set given strategy profile  $s$ , and selected payment rule  $t_i(s)$  for agent  $i$  given strategy profile  $s$ . Hence, a *quasi-linear mechanism*  $\mathcal{M} = (\Sigma_1, \dots, \Sigma_l, g(\cdot)) = (\Sigma_1, \dots, \Sigma_l, k(\cdot), t_1(\cdot), \dots, t_l(\cdot))$  defines strategy set  $\Sigma_i$  available to each agent; a choice rule  $k: \Sigma_1 \times \dots \times \Sigma_l \rightarrow \mathcal{K}$ , such that  $k(s)$  is the choice implemented for strategy profile  $s = (s_1, \dots, s_l)$ ; and transfer rules  $t_i: \Sigma_1 \times \dots \times \Sigma_l \rightarrow \mathbb{R}$ , for each agent  $i$ , to compute her payment  $t_i(s)$ . Properties of SCFs implemented by a mechanism can be stated separately, for both the choice selected and the payments.

The SCF  $f(\theta) = (x(\theta), p(\theta))$  is *Allocative-efficient (AE)* if  $\forall \theta_i \in \theta = (\theta_1, \dots, \theta_l)$ , an efficient matching allocation maximizes total value of all agents  $\sum_{i=1}^l v_i(x(\theta), \theta_i) \geq \sum_i v_i(x', \theta_i)$ ,  $\forall x' \in \mathcal{K}$ . A Mechanism  $\mathcal{M}$  is AE if it implements an AE SCF  $f(\theta)$ . The mechanism selects the choice  $x(\theta) \in \mathcal{K}$  that maximizes total agents value. Computationally, achieving AE is a *hard computational problem* (NP-complete). Yet, there are efficient algorithms that approximate maximum social welfare that gives a SCF

that approximates social welfare maximization, however, is different from it. A SCF  $f(\theta)$  is *Budget-balanced* (BB) if  $\forall \theta_i \in \theta = (\theta_1, \dots, \theta_l)$ , there are no net transfers out of the system or into the system, i.e.,  $\sum_{i=1}^l p_i(\theta) = 0$ . A SCF  $f(\theta)$  is *weakly BB* if  $\forall \theta_i \in \theta = (\theta_1, \dots, \theta_l)$ , a net payment can be made from agents to the mechanism, but no net payment from the mechanism to the agents, i.e.,  $\sum_{i=1}^l p_i(\theta) \geq 0$ . A Mechanism  $\mathcal{M}$  is *ex post* BB if the equilibrium net transfers to the mechanism are non-negative for all agent preferences, while  $\mathcal{M}$  is *ex ante* BB if the equilibrium net transfers to the mechanism are balanced *in expectation* for a distribution over agent preferences. An *AE* and *BB* imply *Pareto optimality* or *Pareto efficiency*. Given an initial matching allocation of items among a set of agents, a change to a different *matching allocation* that makes at least one agent better off without making any other agent worse off is a *Pareto improvement*. An matching allocation is *Pareto efficient* or *Pareto optimal* if no further Pareto improvements can be made. In other words, a SCF  $f(\theta)$  is *Pareto optimal* if it implements outcomes for which no alternative outcome is strongly preferred by at least one agent, and weakly preferred by other agents  $\forall o' \neq f(\theta), u_i(o', \theta_i) \geq u_i(o, \theta_i) \Rightarrow \exists j \in \mathcal{I} u_j(o', \theta_j) < u_j(o, \theta_j)$ . A *Pareto optimal mechanism* implements a Pareto optimal SCF  $f(\theta)$ . This is *ex post Pareto optimality*; i.e., the outcome is Pareto optimal for the specific agent types. At *ex ante* Pareto optimality is, there is no outcome that at least one agent strictly prefers and all other agents weakly prefer in expectation.

*The Individual-rationality* (IR), or “voluntary participation” constraints, allows an agent, to decide whether or not to participate. It places constraints on the level of expected utility that an agent receives from participation. A mechanism  $\mathcal{M}$  is *interim IR* if  $\forall$  preferences  $\theta_i$  it implements a SCF  $f(\theta)$  with  $u_i(f(\theta_i, \theta_{-i})) \geq \bar{u}_i(\theta_i)$ , where  $u_i(f(\theta_i, \theta_{-i}))$  is the expected utility for agent  $i$  at the outcome, given distributional information about the preferences  $\theta_{-i}$  of other agents, and  $\bar{u}_i(\theta_i)$  is the expected utility for non-participation. A mechanism  $\mathcal{M}$ , is *ex post IR* if agent's expected utility from participation is at least its best outside utility  $\forall \theta_i$  possible agent types, given prior beliefs about the preferences of other agents, a more suitable mechanism if agent can withdraw

once learns the outcome. A mechanism  $\mathcal{M}$ , is *ex ante IR* if agent chooses to participate before it even knows its own preferences; states that agent's expected utility in the mechanism, averaged over all possible preferences, must be at least its expected utility without participating, also averaged over all possible preferences (Parkes, 2001).

*Weak Monotonicity (WMON)*: A SCF  $f$  satisfies *WMON* if  $\forall i, \forall v_{-i} \rightarrow f(v_i, v_{-i}) = a \neq b = f(v'_i, v_{-i})$  implies that  $v_i(a) - v_i(b) \geq v'_i(a) - v'_i(b)$ . If the social choice changes when a player changes valuation, then player must have increased more his value relative to his value of the old choice. If a mechanism  $(f, p_1 \dots p_n)$ , is IC then  $f$  satisfies WMON. If all domains of preferences  $V_i$  are convex sets then for every SCF that satisfies WMON  $\exists p_1 \dots p_n$  such that  $(f, p_1 \dots p_n)$  is IC. The WMON condition is a local condition for each player separately and for each  $v_{-i}$  separately. For global characterisation, there are two extreme cases: when  $V_i$  is unrestricted and when severely restricted as to be essentially single dimensional. The intermediate range where the  $V_i$ 's are somewhat restricted, a range in which most computationally interesting problems lie, is still wide open.

### 3.3 Equilibrium Solution Concepts

A major objective of implementing, economic based MD techniques is to mitigate the computational limitations. In fact, economics and computations, often, intertwined, in a way, that facilitates resolving mutual problems. For instance, an economic equilibrium strategy may lead to intractable computational solution approach. Similarly, an economic truth-revealing equilibrium MD, may lead to optimal computationally tractable solution. In fact, the blend of MD economic and computing techniques to developing efficient mechanisms (Conitzer & Sandholm, 2002) is a potential research space. In that vein, the game theoretic MD investigates solution concepts for private information games, and often solved by a truth revealing strategy. A mechanism  $M = (\Sigma, g)$  may implement a SCF in equilibrium with diverse solution concepts that predicts strategies an agent select. Each solution concept differs in assumptions about agents' rationality and knowledge agents have about other agents. The main solution concepts may be tabled as followed:

*Dominant Strategy Equilibrium (DSE)*: Each agent has a best-response strategy no matter what other agent strategies  $S_i^*(\theta_i) = \arg \max_{s_i} u_i(\theta_i, g(s_i(\theta_i), s_{-i}(\theta_{-i})))$ ,  $\forall s_{-i}, \forall \theta_{-i}, \forall \theta_i \in \Theta_i$ . For  $s_i$  and  $s'_i$  strategies of player  $i$ ,  $\forall s_{-i}$  domination is classified as (1) strict, if  $u_i(s_i, s_{-i}) > u_i(s'_i, s_{-i})$ ; (2) weak if  $u_i(s_i, s_{-i}) \geq u_i(s'_i, s_{-i})$  and for at least one  $s_{-i}$ ,  $u_i(s_i, s_{-i}) > u_i(s'_i, s_{-i})$ ; and (3) very weakly if  $u_i(s_i, s_{-i}) \geq u_i(s'_i, s_{-i})$ . If a strategy dominates all others, then it is (strongly, weakly or very weakly) *dominant*. The DSE provides a robust solution concept as agents don't form beliefs about other agents' rationality or distribution over other agent types. The single item second price auction is a DSE implementation, as agents truthfully reveal bid values.

*Nash equilibrium (NE)*: (Nash Jr., 1951): A strategy profile  $s = (s_i, s_{-i})$  is at NE if, for all agents  $i$ ,  $s_i$  is a best response strategy to other agents, given their types and strategies  $s_{-i}$ :  $S_i^*(\theta_i) = \arg \max_{s_i} u_i(\theta_i, g(s_i(\theta_i), S_{-i}^*(\theta_{-i})))$ ,  $\forall \theta_{-i}, \forall \theta_i \in \Theta_i, \forall s_i$ .

Nash equilibrium is a stable strategy profile: no agent would want to change his strategy if she knew what strategies the other agents were following.  $\forall i, \forall s, s'_i \neq s_i$ , a *strict Nash strategy* profile occurs if,  $u_i(s_i, s_{-i}) > u_i(s'_i, s_{-i})$  and a *weak Nash strategy* profile occurs if  $u_i(s_i, s_{-i}) \geq u_i(s'_i, s_{-i})$ , and  $s$  is not a strict Nash equilibrium. Mixed-strategy Nash equilibrium is necessarily always weak, while pure-strategy Nash equilibrium can be either strict or weak, depending on the game.

*Ex post Nash equilibrium*: requires common knowledge about the agents' rationality but doesn't require any knowledge about type distributions. In this sense, ex post Nash has a no-regret property and an agent doesn't want to deviate from its strategy even once it knows the other agents' types. English auction is an example of ex post Nash implementation (McAfee & McMillan, 1987), with direct bidding IC strategy of ask price  $p$  whenever  $p \leq v_i$  for value  $v_i$ , as long as other IC agents are direct. However, direct bidding is not DSE (e.g. with jump bids). Formally, a profile of strategies  $s_1 \dots s_n$  is at *ex-post-Nash equilibrium* if  $\forall \theta_1 \dots \theta_n, s_1(\theta_1) \dots s_n(\theta_n)$  are in Nash equilibrium in the full information game.  $\forall i, \theta_1 \dots \theta_n, s'_i: (u_i(\theta_i, s_i(\theta_i), s_{-i}(\theta_{-i})) \geq u_i(\theta_i, s'_i, s_{-i}(\theta_{-i})))$ . Ex-post Nash requires  $s_i(\theta_i)$  be a best response to  $s_i(\theta_{-i}) \forall \theta_{-i}$ , without knowing

$\theta_{-i}$  but only knowing the forms of the other players' strategies  $s_{-i}$  as functions. Let  $s_1 \dots s_n$  be an *ex-post-Nash equilibrium* of game  $(\Sigma_1 \dots \Sigma_n; \theta_1 \dots \theta_n; u_1 \dots u_n)$ . If  $g'_i = \{s_i(\theta_i) | \theta_i \in \Theta_i\}$ ,  $s_1 \dots s_n$  is DSE in game  $(\Sigma'_1 \dots \Sigma'_n; \theta_1 \dots \theta_n; u_1 \dots u_n)$ .

*Bayesian Nash equilibrium (BNE)*: Agents select best-response strategies and announce types  $\hat{\theta}_i \in \Theta_i$  to maximize their expected utility given their beliefs about the common prior about distributional information of other agent types, and assuming other agents are following expected-utility best-response maximizing strategies, announced type  $\hat{\theta}_i$  need not equal true type:  $S_i^*(\theta_i) = \arg \max_{s_i} E_{\theta_{-i}} [u_i(\hat{\theta}_i, g(s_i(\theta_i), S_{-i}^*(\theta_{-i})))], \forall \theta_i \in \Theta_i$ . *BNE* is the weakest solution concept adopted in MD. In a *BNE*, every agent must hold both beliefs about other agents' rationality and correct beliefs about the distribution on types of other agents. An example of *BNE* implementation is the first price sealed-bid auction. Comparing *BNE* with *NE*, the key difference is that agent  $i$ 's strategy  $s_i(\theta_i)$  must be a best response to the distribution over strategies of other agents. A refined solution concept is *perfect BNE* as applied to dynamic games of incomplete information (Fudenberg & Tirole, 1991). Strict incomplete information means no probabilistic information captured in the model, called also "*pre-Bayesian*".

*Pareto optimality*: Strategy profile  $s$  is Pareto optimal, or strictly Pareto efficient, if there does not exist another strategy profile  $s' \in S$  that Pareto dominates  $s$ . A Strategy profile  $s$  Pareto dominates strategy profile (not action profile)  $s'$  if  $\forall i \in N, u_i(s) \geq u_i(s')$ , and there exists some  $j \in N$  for which  $u_j(s) > u_j(s')$ , means in a given Pareto-dominated strategy profile some player can be made better without making any other player worse off. Every game must have at least one optimum.

*Other Solution Concepts* (Leyton-Brown & Shoham, 2008): (a) *Maxmin*: a strategy of player  $i$  in an  $n$ -player, general-sum game that maximizes  $i$ 's worst-case payoff in hostile situations where all other players play the strategies that cause the greatest harm to  $i$ . The maxmin value or security level of the game for player  $i$  is  $\max_{s_i} \min_{s_{-i}} u_i(s_i, s_{-i})$ , that minimum amount of payoff guaranteed by a maxmin strategy, while the maxmin strategy

is  $\arg \max_{s_i} \min_{s_{-i}} u_i(s_i, s_{-i})$ ; (b) *Minmax*: A useful strategy when we want to consider the amount that one player can punish another without regard to his own payoff. the minmax strategy for player  $i$  against player  $j \neq i$  is is a mixed-strategy profile  $s_{-j}$  in the  $\arg \min_{s_{-j}} \max_{s_j} u_j(s_j, s_{-j})$ , where  $-j$  denotes the set players other than  $j$ . The minmax value for player  $j$  is  $\min_{s_{-j}} \max_{s_j} u_j(s_j, s_{-j})$ ; (c) *Minimax Regret*: In settings in which the other agent is not believed to be malicious, but is entirely unpredictable, it makes sense for agents to care about minimizing their worst-case loss, rather than maximizing their worst-case payoff; (d)  $\epsilon$ -*Nash*; reflects the idea that players might not care about changing their strategies to a best response when the amount of utility that they could gain by doing so is very small. This leads us to the idea of  $\epsilon$ -Nash equilibrium: Fix  $\epsilon > 0$ . A strategy profile  $s$  is an  $\epsilon$ -Nash equilibrium if, for all agents  $i$  and for all strategies  $s'_i \neq s_i$ ,  $u_i(s_i, s_{-i}) \geq u_i(s'_i, s_{-i}) - \epsilon$ ; and (e) *Evolutionarily stable strategy*: Roughly, a mixed strategy that resists invasion by new strategies.

### 3.4 Direct Revelation and Incentive Compatibility

The *direct revelation* makes direct claims about preferences (i.e., reporting types). A *direct-revelation mechanism* (DRM) is a mechanism in which the only strategic action of an agent is to make direct claim  $\hat{\theta}$  about preferences. Formally, the DRM  $\mathcal{M} = (\Sigma_1 \dots \Sigma_l, g(\cdot))$ , coordinates amongst agents with strategy sets  $\Sigma_i = \Theta_i \forall i$ , and delivers outcome rule  $g: \Sigma_1 \times \dots \times \Sigma_l \rightarrow \mathcal{O}$ , which selects an outcome  $g(\hat{\theta})$  given reported types  $\hat{\theta} = (\hat{\theta}_1, \dots, \hat{\theta}_l)$ . The *revelation principle* stated under weak conditions any mechanism  $\mathcal{M}$  can be transformed into an equivalent incentive-compatible (IC) DRM (i.e., the SCF is IC if it cannot be manipulated), such that it implements the same SCF, a theoretic key concept for analysis of *impossibility and possibility results* (Mas-Colell et al., 1995). The revelation principle for DSE implementation states any SCF that is implementable in DSE is implementable in *strategy proof* (SP) mechanism, which focuses attention at DRMs. If  $\mathcal{M}$  implements SCF  $f(\cdot)$  in *dominant strategy equilibrium* (DSE) then  $f(\cdot)$  is *truthfully implementable* in DSE, i.e., SP mechanism (i.e., the SCF is SP if it never

rewards agents for pretending preferences other than true ones). An *IC-DRM*  $\mathcal{M}$  is *strategy-proof (SP)* if truth-revelation is *DSE*. A mechanism  $\mathcal{M}$  is *coalition-proof if truth revelation is a DSE for any coalition of agents*, where a coalition is able to make side payments and re-distribute items after the mechanism terminates. An SP-DRM satisfies conditions : (1)  $\forall i, \forall v_{-i}, p_i$  does not depend on  $v_i$ , but only on chosen outcome  $f(v_i, v_{-i})$ ,  $\exists p_o \in \mathfrak{R}, \forall o \in \mathcal{O}$ , such that  $\forall v_i$  with  $f(v_i, v_{-i}) = o \rightarrow p(v_i, v_{-i}) = p_o$  (2) *optimal for each player*,  $\forall v_i, f(v_i, v_{-i}) \in \operatorname{argmax}_o (v_i(o) - p_o)$ . An IC-DRM  $\mathcal{M}$  implements SCF  $f(\theta) = g(\theta)$ , where  $g(\theta)$ , is the outcome rule of a mechanism. The preference of each agent  $i$  is modeled by a valuation function  $v_i: A \rightarrow \mathfrak{R}$ , where  $v_i \in V_i$ .  $V_i \subseteq \mathfrak{R}^A$  is set of possible valuation functions for agent  $i$ . A DRM  $\mathcal{M}$  is Bayesian-Nash IC (*BNE-IC*) if truth-revelation is *BNE*. If a DRM  $\mathcal{M}$  implements the SCF  $f(\cdot)$  in BNE, then  $f(\cdot)$  is truthfully implementable in a *BNE-IC DRM*. In *BNE* implementation, though, the distribution over agent types is common knowledge to the DRM, and agents.

The revelation principle was, initially, formulated for DSE (Gibbard, 1973), and later extended by (Green & Laffont, 1977) (Myerson, 1981). The outcome rule in the SP mechanism,  $g: \theta_1 \times \dots \times \theta_l \rightarrow \mathcal{O}$ , equal to the SCF  $f(\cdot)$ . DSE revelation principle suggests that to identify which SCFs are implementable in DSEs, just identify functions  $f(\cdot)$  for which truth-revelation is a DSE for agents in a DRM with outcome rule  $g(\cdot) = f(\cdot)$ . In the absence of dummy bidders (i.e., false naming) or collusion, the second-price sealed-bid (Vickrey) auction is an SP DRM for the single-item matching allocation problem. The revelation principle states what can be achieved and what cannot, without stating the computational structure to achieve a particular set of properties. The *IC* captures the essence of *MD*, to minimizing the impact of agents' rationality, learning, tactical and strategic self-interest in order to achieving a stable efficiency at economic and computational levels, given the bounded-computation and combinatorial complexity.

The *SP* is a useful game-theoretic and computation property, at which DSE is robust to assumptions about information and rationality of agents. An agent, also, computes optimal strategy without modeling preferences and strategies of other agents. The *SP*-

*DRM* Vickrey Clarke Groves (VCG) mechanism is a possibility that maximizes social welfare. However, the SP-DRMs are often expensive for agents because they place high demands on information revelation. In fact complete information revelation must be avoided in solving the combinatorial allocation problem (CAP), because agents often have hard combinatorial valuation problems to compute their value for any single outcome, and there are an exponential number of possible outcomes (deVries & Vohra, 2003). Iterative mechanism can sometimes implement DRM but with less information revelation and agent computation. In fact, computing *NE* in a game is difficult. It is even more difficult for *BNE* across games in which agents, owing to their continuous types, can play an infinite number of strategies (Nisan, 2000) (Reeves & Wellman, 2003). Designing IC mechanisms can mitigate strategy selection problem, especially, using DSE implementations. Other approaches include designing mechanisms using models of computationally limited agents. In the former model, the DSE MD require minimal agent computation (Varian, 1995). However, would be a non-realistic solution concept, given challenges, as rationality, self-interest, strategic qualities.

### 3.5 Vickrey-Clarke-Groves (VCG) Mechanisms

The VCG mechanisms (Vickrey, 1961) (Clarke, 1971) (Groves, 1973) are one-shot DRMs that provide DSE solutions to the CAP. The mechanism aligns the incentives of bidder agents with the system-wide objective of computing an efficient allocation. In fact, VCG mechanisms are, also, the only AE and SP mechanisms for agents with quasi-linear preferences and general valuation functions, amongst DRMs (Green & Laffont, 1977). The VCG mechanisms however, are not BB and often clear with deficit. In fact, one impossibility result, the Myerson-Satterthwaite theorem (Mas-Colell et al., 1995), shows no AE and BB mechanism can exist in many settings, including simple exchange. In special cases, however, VCG mechanisms are IR and satisfy weak BB, as in VCG for CA. Often, BB is compromised with efficiency loss. Approaches to addressing the BB problem include adjusting payments to get close to VCG payments but retain BB (Parkes et al., 2001) and *IC*. However, the explicit clearing of exchanges sub-optimally sacrifices some of AE in return for BB (McAfee, 1992). The revelation principle extends this

uniqueness to general mechanisms, direct or indirect (i.e., iterative). This uniqueness extends to GSP to achieve AE in DSE implementation must implement a VCG outcome. Consider a set of possible allocations,  $\mathcal{K}$  and agents with quasi-linear utility functions  $u_i(k, p_i, \theta_i) = v_i(k, \theta_i) - p_i$ ,  $v_i(k, \theta_i)$  agent's  $i$  value for matching allocation  $k \in \mathcal{K}$ , and  $p_i$  is her payment given type  $\theta_i \in \Theta_i$  that express her valuation function. In a DRM for quasi-linear preferences, the *outcome rule*  $g(\hat{\theta})$  is presented in terms of *choice rule*  $k : \Theta_1 \times \dots \times \Theta_l \rightarrow \mathcal{K}$ , and *payment rule*  $p_i : \Theta_1 \times \dots \times \Theta_l \rightarrow \mathbb{R}, \forall i$ . In VCG, agent  $i$  reports type  $\hat{\theta}_i = s_i(\theta_i)$ ;  $\hat{\theta} = (\hat{\theta}_1, \dots, \hat{\theta}_l)$ . The *VCG choice rule*  $k^*(\hat{\theta}) = \arg \max_{k \in \mathcal{K}} \sum_i v_i(k, \hat{\theta}_i)$  maximizes total reported value over all agents. The *VCG payment rule* is defined as  $p_i(\hat{\theta}) = h_i(\hat{\theta}_{-i}) - \sum_{j \neq i} v_i(k^*, \hat{\theta}_j)$ ,  $h_i : \Theta_{-i} \rightarrow \mathbb{R}$  is arbitrary function on the reported types of every agent except  $i$ . In fact, different choices of arbitrary function  $h_i$  make different tradeoffs across BB and IR.

VCG mechanisms are AE and SP for agents with quasi-linear preferences. SP insures DSE truth-revelation, from which AE follows with  $k^*(\hat{\theta}) = \arg \max_{k \in \mathcal{K}} \sum_i v_i(k, \hat{\theta}_i)$ . Then

$$u_i(\hat{\theta}_i) = v_i(k^*(\hat{\theta}), \theta_i) - p_i(\hat{\theta}) = v_i(k^*(\hat{\theta}), \theta_i) + \sum_{j \neq i} v_i(k^*, \hat{\theta}_j) - h_i(\hat{\theta}_{-i})$$

Since  $h_i(\hat{\theta}_{-i})$  is independent of agent  $i$ 's reported type; truth-revelation  $\hat{\theta} = \theta_i$  solves:  $\max_{\hat{\theta}_i \in \Theta_i} [v_i(x, \theta_i) + \sum_{j \neq i} v_i(x, \hat{\theta}_j)]$ ;  $x = k^*(\hat{\theta}_i, \hat{\theta}_{-i})$  the outcome selected by DRM. The only effect of the agent's announced type  $\hat{\theta}_i$  is on  $x$ , and the agent can maximize  $v_i(x, \theta_i) + \sum_{j \neq i} v_i(x, \hat{\theta}_j)$  by announcing  $\hat{\theta}_i = \theta_i$  as then the mechanism computes  $k^*(\hat{\theta}_i, \hat{\theta}_{-i})$  to explicitly solve:  $\max_{k \in \mathcal{K}} [v_i(k, \theta_i) + \sum_{j \neq i} v_j(k, \hat{\theta}_j)]$ . Truth-revelation is the DSE of agent  $i$ , whatever reported types  $\hat{\theta}_{-i}$  by other agents. The effect of payment  $p_i(\hat{\theta}) = (\cdot) - \sum_{j \neq i} v_i(k^*, \hat{\theta}_j)$  is to “internalize the externality” placed on other agents by reported preferences of agent  $i$ , hence aligns incentives with system-wide goal for AE;

*The Pivotal, or Clarke, mechanism* (Clarke, 1971) is a VCG mechanism in which the payment rule  $h_i(\hat{\theta}_{-i})$  is set to achieve (ex post) IR, and weak BB in an AE SP mechanism, when choice-set monotonicity, no negative externalities, and no single-agent effect hold with quasi-linear agent preferences. In fact, the payment rule  $h_i(\hat{\theta}_{-i}) = \sum_{j \neq i} v_j(k_{-i}^*(\hat{\theta}_{-i}), \hat{\theta}_j) - \max_{k \in \mathcal{K}} [\sum_{j \neq i} v_j(k, \hat{\theta}_j)]$  delivers *optimal social choice* without agent  $i$ . Then each agent makes payment  $p_i(\hat{\theta}_i) = v_i(k, \hat{\theta}_i) - (V(N) - V(N \setminus i))$ ,  $V(N)$  is total reported value of  $k^*$  and  $V(N \setminus i)$  is total reported value  $k_{-i}^*$  without agent  $i$ . The first two terms of the payment align an agent's incentives with VCG and make truth-revelation a *DSE*. In equilibrium, each agent receives as utility the marginal value it contributes to the system. The Clarke mechanism is *Ex post IR* when two (sufficient) conditions hold on agent preferences: (1) Choice set monotonicity: feasible choice set  $\mathcal{K}$  (weakly) increases as additional agents are introduced to the system; means an agent cannot "block" a selection, and (2) No negative externalities: Agent  $i$  has non-negative value, i.e.,  $v_i(k_{-i}^*, \theta_j) \geq 0$  for any optimal solution choice,  $k_{-i}^*(\hat{\theta}_{-i})$  without agent  $i$ ,  $\forall i$  and all  $\theta_i$ , means any choice not involving an agent has neutral (or positive) effect on that agent. Assume truth-revelation in equilibrium, and prove the total transfers are non-negative, such that the mechanism does not require a subsidy, i.e.,  $\sum_i t_i(\theta) \geq 0 \forall \theta \in \Theta$ :  $u_i(\theta_i, \theta_{-i}) = v_i(k^*(\theta), \theta_i) - (\sum_{j \neq i} v_j(k_{-i}^*(\theta_{-i}), \theta_j) - \sum_{j \neq i} v_j(k^*(\theta), \theta_j)) = \sum_i v_i(k^*(\theta), \theta_i) - \sum_{j \neq i} v_j(k_{-i}^*(\theta_{-i}), \theta_j) \geq 0$  is non-negative  $\forall i$ , because any choice with agents  $j \neq i$  is also feasible with all agents (monotonicity), and has just as much total value (no negative externalities). The Clarke mechanism also achieves weak budget-balance in special-cases. A sufficient condition is the *no single-agent effect*: For any collective choice  $k'$  that is optimal in some scenario with all agents, i.e.,  $k' = \max_{k \in \mathcal{K}} [\sum_i v_i(k, \theta_i)]$ , for some  $\theta \in \Theta$  then for all  $i$  there must exist another choice  $k_{-i}$  that is feasible without  $i$  and has as much value to the remaining agents  $j \neq i$ . In words, the no single-agent effect condition states that any one agent can be removed from an optimal system-wide solution without having a negative effect on the best choice available to the remaining agents. As soon as there are buyers and sellers in a market, we

very quickly lose even weak BB with Groves-Clarke mechanisms. The BB problem in a combinatorial exchange is addressed in (Parkes et al., 2001) including a number of methods to trade-off strategy-proofness and allocative efficiency for budget balance.

*The Generalized Vickrey Auction (GVA)* applies the Pivotal mechanism on the CAP. Let's allocate set  $\mathcal{G}$  of to  $\mathfrak{T}$  agents. The set of choices  $\mathcal{K} = \{ (S_1, \dots, S_I)^*: S_i \cap S_j = \emptyset, S_i \subseteq \mathcal{G} \}$  where  $S_i$  is an allocation of a bundle to agent  $i$ . Given type  $\theta_i$ , each agent  $i$  has *quasi-linear* utility function,  $u_i(S, p_i, \theta_i) = v_i(S, \theta_i) - p_i$  for bundle  $S$  and payment  $p_i$ . Let  $v_i(S, \theta_i) = v_i(S)$ . The AE maximize the total value:  $S^* = \arg \max_{S=(S_1 \dots S_I)} \sum_{i \in I} v_i(S_i)$  s.t.  $S_i \cap S_j = \emptyset, \forall i \neq j$ . The Pivotal mechanism applied to this problem is a sealed-bid CA, often called the *GVA*. *The GVA is AE, SP, IR, and weak BB for agents with quasi-linear preferences in the CAP*. Each agent  $i \in \mathfrak{T}$  submits a (possibly untruthful) valuation function,  $\hat{v}_i(S)$  to the auctioneer. The outcome rule computes  $k^*(\theta)$ , the allocation that maximizes reported value over all agents. In the GVA, this is equivalent to the auctioneer solving a winner determination problem (WDP) to solving the CAP with reported values and computing allocation  $S^* = (S_1^* \dots S_I^*)$  to maximize reported value. Let  $V^*$  denote the total value of this allocation. Allocation  $S^*$  is the allocation implemented by the auctioneer. The payment rule in the Pivotal mechanism also requires the auctioneer solve the CAP with each agent  $i$  taken out in turn to compute  $k_{-i}^*(\theta_{-i})$ , the best allocation without agent  $i$ . Let  $(S_{-i})^*$  denote this second-best allocation, and  $(V_{-i})^*$  denote its value. Finally, from Groves-Clarke payment rule  $p_i(\hat{\theta}) = p_{vick}(i) = h_i(\hat{\theta}_{-i}) - \sum_{j \neq i} v_i(k^*, \hat{\theta}_j)$ ;  $h_i(\hat{\theta}_{-i}) = \sum_{j \neq i} v_i(k_{-i}^*(\hat{\theta}_{-i}), \hat{\theta}_j) = (V_{-i})^*$ , the auctioneer compute agent  $i$ 's payment:  $p_{vick}(i) = (V_{-i})^* - \sum_{j \neq i} \hat{v}_j(S_j^*)$ . An agent pays the marginal negative effect that its participation has on the (reported) value of the other agents. Equivalently, the Vickrey payment can be formulated as a discount  $\Delta_{vick}(i)$  from its bid price,  $\hat{v}_i(S_i^*)$  i.e.,  $p_{vick}(i) = \hat{v}_i(S_i^*) - \Delta_{vick}(i)$  for Vickrey discount  $\Delta_{vick}(i) = V^* - (V_{-i})^*$ ; ( $V^* = \hat{v}_i(S_i^*) + \sum_{j \neq i} \hat{v}_j(S_j^*)$ ). *AE and SP* follow from the properties of the Groves mechanism. *Weak BB* holds; given all agents

pay non-negative amounts to the auctioneer, while *IR* holds as agents pay no more than their values for bundles they receive; Alternatively, one can verify that conditions *choice-set monotonicity*, *no negative externalities*, and *no single-agent effect* hold for the CAP.

### 3.6 Impossibility and Possibility Results

Impossibility theorems sketch the properties that no mechanism can achieve with rational agents in certain environments. The *Gibbard-Satterthwaite impossibility theorem* (Gibbard, 1973) (Satterthwaite, 1975) shows for adequate rich preferences on outcomes, it is impossible to implement a satisfactory non-dictatorial SCF in DSE. A SCF is *dictatorial* if one (or more) agents always receive one of its most-preferred outcomes. In fact, all dictatorial SCFs are SP (Mas-Colell et al., 1995). However, the impossibility theorem may not hold if there are: (1) additional constraints that relax agent preferences (e.g. quasi-linear) and reduce the onto (one to one) preference mapping to the outcomes, or (2) weaker implementation concept as the practical Bayesian Nash implementation. In fact, the e-market settings make implementation easier.

The *Hurwicz impossibility theorem* (Hurwicz, 1975) states it is impossible to implement an AE SP and BB SCF in DSE e-market settings of simple exchange economy with quasi-linear preferences, even without requiring IR. (Green & Laffont, 1977) demonstrate no AE and SP mechanism can be safe from manipulation by coalitions, even in quasi-linear environments. The general impossibility result follows from (Green & Laffont, 1977) (Hurwicz, 1975) established no member of the Groves family of mechanisms has BB, and that the Groves family is the unique set of SP implementation rules in a simple exchange economy. The *Myerson-Satterthwaite impossibility theorem* (Myerson, 1983) strengthens Hurwicz impossibility to include Bayesian-Nash implementation, if interim IR is required. It states that it is *impossible to achieve AE, BB and IR in a BN IC mechanism*, even with quasi-linear utility functions. An immediate consequence of this result is that we can only hope to achieve at most two of AE, IR and BB in a e-market with quasi-linear agent preferences, even if we look for BN implementation.

A positive result is the VCG mechanisms, which are AE (but not BB) SP mechanisms in quasi-linear domains that clearly exhibit it is possible to implement non-dictatorial SCFs in more restricted domains of preferences. However, they are not efficient and strong BB. The possibility results are outlined by agent preferences, the equilibrium solution concept and the environment or problem domain. Contrary to impossibility results, for *possibility results* a strong implementation concept is more useful than a weak implementation, e.g. dominant is preferred to Bayesian-Nash, and a general environment such as an exchange is preferred to a more restricted environment such as a combinatorial auction. Groves mechanisms are consistent with the Gibbard-Satterthwaite impossibility theorem because agent preferences are not general but quasi-linear; and Groves mechanisms are consistent with the Hurwicz/Myerson-Satterthwaite impossibility theorems because strong BB does not hold. Groves' mechanisms are not strong BB. This failure of strong BB is acceptable in some domains; e.g., in one-sided combinatorial auctions with single seller and multiple buyers it may be acceptable to achieve weak BB and transfer net payments to the seller.

### 3.7 Economic Based Mechanisms

The economic based e-market mechanisms are well rooted in the microeconomics theory, particularly in general equilibrium theory and mechanism design. The economic activity takes place in a setting of institutions that range from relatively simple arrangements, to complex structures (i.e., mechanisms). A mechanism models the institutions (market rules of encounter) that govern economic activities amongst rational agents with, often, private information to achieve the desired social goals. In fact, the economic based mechanisms are natural to respecting autonomy and information decentralization in open systems. Inherently, while mechanisms of interaction can be imposed from the society, agents have control over their own actions and chose their own strategies in response to the mechanism imposed. Hence, the economic theory addresses the strategic implications of agent's distributed private information, often manipulated for private advantage, where a mechanism is modeled as a game form. The desired outcome is given by a social goal function (SCF). A game form (i.e., mechanism) implements a SCF "rules of a game" if its equilibrium coincides with outcome (i.e., optimal system-wide solution) specified by

the SCF in the specified game theoretic solution concept, given the risk of the strategic manipulation of private information. Theoretically, in microeconomics, there are two approaches to modeling agent behavior: (1) *Game-theoretic mechanism design (MD)*, in which agents' *best-response strategy* to each other drives equilibrium state, at which agents cannot benefit from unilateral deviations to alternative strategies. Generally, the *game theoretical MD* investigates solution concepts for private information games, in which the game structure directs the game's outcome. The mechanism design theory uses the framework of non-cooperative games with incomplete information and investigates how the private preference information can be elicited. In fact, mechanism design can be viewed as reverse engineering of games or equivalently as the art of designing the rules of a game to achieve specific desired outcome. (2) *Price-taking-CE*, in which agents' myopic best-response to the current price drives equilibrium state, without modeling either the strategies of other agents or the effect of its own actions on the future states.

The *computational MD (CMD)*, however, resolves the challenge between game-theoretic and computational approaches. For instance, some best game-theoretic solutions provide computational benefits, as in DSE implementation. However, every agent must compute and reveal its complete preferences over all possible outcomes. While DSE is useful game-theoretically, it is intractable computationally (Parkes, 2001). In fact, the economic MD for decentralized optimization problem exposes number of computational problems. Costly computations at network and distributed processing and inherent combinatorial complexity can burden implemented game-theoretic mechanisms. Yet, self-interest and computation interact in non-obvious ways, while approximate solutions can destroy IC properties of a mechanism, software agent bounded rationality affect MDs that cannot be manipulated without agent solving an intractable problem (Parkes, 2001). An efficient mechanism must control the computational costs of the mechanism infrastructure and the computational costs of the agents, while retaining useful game-theoretic properties that handle agent self-interest. In (Kalagnanam & Parkes, 2004) the exchange should consider resources, market structure, preference structure; bid structure matching supply to demand e-market clearing and information feedback for direct or an indirect mechanisms.

In (Wellman et al., 2001), for instance, e-market mechanisms solve distributed resource allocation problems as in *market-oriented programming* (MOP (Wellman, 1995)). Agents require and produce resources, for which their decision problem is to evaluate the trade-offs of acquiring different resources using e-market prices. CMD specifies configuration of resources traded, and the mechanism that decides prices. Message of *bids* and *prices* are, also, concise between agents and the e-market mechanism. In fact, price systems can minimize the number of messages required to determine Pareto optimal allocations. Some mechanisms, furthermore, can elicit the information necessary to achieve Pareto optima in well-characterized situations, though. For instance, while first and second welfare theorems (Mas-Colell et al., 1995) secure strong performance of market mechanisms, results are formally restricted to special cases. Also, scheduling problems often exhibit complementarities, which violate conditions for welfare theorems or e-market protocols.

The MD sets incentives to induce the actions that deliver specific performance and economize on resources that operate the institutions (i.e., informationally efficient mechanisms) (Hurwicz & Reiter, 2006). The incentive theory tackles the private information problem, either of unobserved agent action, the case of moral hazard or hidden action; or ignored agent private knowledge, the case of adverse selection or hidden knowledge (Laffont & Martimort, 2002). The MD determines the economic incentives to encouraging agent truthful response that leads to best social solutions. The MD elicits the private information to select a desirable system wide outcome, despite the self-interested agents, through providing enough structure to enable strong theoretical claims about strategies agents will select and the optimality properties of final solutions. In fact, microeconomics, computer science and game theory empower research design of algorithmic solutions that optimize agent utilities in decentralised strategic settings. The following is a brief description of some well-known economic based mechanisms:

*The Combinatorial Auctions (CA)* determine the efficient allocations in settings with multiple items and agents that wish to express complements and substitutes across items (i.e., “I only want A if I can also get B” or “I only want AB or CD”). CA is implemented

in many settings, including wireless spectrum rights allocation, takeoff and landing slots at airports, and multiagent planning (deVries & Vohra, 2003). For allocative efficiency, the VCG mechanism provides an economic solution to the CA problem (CAP). The agents must submit bids on all item combinations. The central controller solves, then, a winner-determination problem (WDP) to determine the allocation that maximizes the reported value given agent bids. Buyers pay their bid prices for the bundles they receive in the efficient allocation, minus the Vickrey discount. However, the VCG mechanism for the CAP has several undesirable computational characteristics. The WDP in CA is NP-hard and difficult to approximate i.e., equivalent to weighted set-packing problem (deVries & Vohra, 2003). Furthermore, it is totally centralized, with all agents reporting their complete and exact valuations to the auctioneer center and the center-solving  $|N| + 1$  WDPs to determine the allocation and payments.

*The Double Auction (DA)* is, often, used for the exchange mechanisms, in application such as stock markets (i.e., NYSE), commodity markets (i.e., CME), etc. The DA allows multiple buyers and sellers to trade simultaneously or sequentially at either continuous (CDA) or periodic (Call) clear e-market (Shubik, 2005). Given the supply and demand of sellers and buyers, A DA matches request and ask bids and determines a clearing price. While our work targets desirable e-market adequacy objectives for the DA design of the FX such as, IC, AE, IR, it is almost impossible for a DA to have them all as per impossibility results. In (McAfee, 1992) and (Wurman et al., 1998), there is no DA mechanism that is both efficient and IC. The adoption of exchange DA institution, however, can be traced to its operational simplicity, efficiency, and agility to varying e-market conditions. Yet, the DA challenge is how to reach e-market equilibrium with AE, given bidders' self-interest, rationality, private information, knowledge, strategic choice and repetitive learning.

*The Combinatorial Exchange (CX)*: combines and the DA and CA mechanisms. While in DA, multiple buyers and sellers trade units of identical items (McAfee, 1992), in CA, a single seller has multiple heterogeneous items up for sale (deVries & Vohra, 2003)

(Cramton et al., 2006). Buyers in CA may have complementarities or substitutabilities between items, and use expressive bidding languages to describe these preferences. A common goal in the design of DAs and CAs is to implement efficient matching allocations that maximize total social welfare. The CX in (Parkes et al., 2001) is a combinatorial DA (DA) of multiple buyers and sellers trade multiple heterogeneous items. CXs have been use in many applications like wireless spectrum matching allocation (Kwerel & Williams, 2002), and airport takeoff and landing slot matching allocation (Rassenti et al., 1982). CX is used, also, for expressive sourcing by multiple bid-takers (Sandholm, 2008) for expressive sourcing using one-sided CAs. The work in (Lubin et al., 2008) introduced the *iterative combinatorial exchange* (ICE) that leverage their proposed tree-based bidding language (*TBBL*) to support simultaneously buy and sell bidders using valuation bounds and interval connect operators. The ICE converges to efficient trade with truthful bidders using duality theory (i.e., primal-dual) when prices are sufficiently accurate. Bidders annotate TBBL trees with initial lower and upper bounds on values of different trades. ICE, then, identifies provisional trade and payments in each round, and generates provisional clearing price on each item. In each round of ICE, each bidder tighten bounds on bid to make precise which trade is most preferred given current prices. When ICE terminates, a payment rule is used to determine the payments made, and received, by each participant. Since AE together with BB is not possible in CX due to Myerson-Satterthwaite impossibility, our work (Parkes et al., 2001) developed the *threshold payment* rule for defining final payments, which minimizes the ***ex post regret*** for truthful bidding across BB payment rules, when holding bids from other participants fixed; see (Milgrom, 2007). That allows ICE to inherit truthful bidding (i.e., revising *TBBL* bounds to remain consistent with a bidder's true valuation) in an *ex post* Nash equilibrium, just as can be achieved in *iterative Generalized Vickrey* auctions (Mishra & Parkes, 2007). DAs in which truthful bidding is in DSE are known for unit demand settings (McAfee, 1992) and also for expressive domains (Chu & Shen, 2008).

*The Dynamic Mechanisms* handles the coordinated decision making with regard to both dynamics of internal agent preferences and the external uncertainty about the world, The

*external uncertainties* describe decision problems in which uncertain events occur in the environment. The *internal uncertainties*, though, describe a decision problem in which the uncertain events occur within the scope of an bidder agent's view of the world. The dynamic mechanisms are quite realistic in their ability to embrace both uncertainty occurs outside and within bidder agents and coordinate self-learning and deliberation processes (Parkes, 2007). The IC constraints, however, must hold in every period, so that The dynamic mechanisms continually provide incentives for the bidders to share their private type information with the mechanism. The dynamics include arrival and departure of agents with respect a mechanism's outcome space, as well as changes to the outcomes that are available to a mechanism. An agent that arrives must have fixed type, and be able to report type, truthfully upon arrival. The dynamics are those of information acquisition, learning, and updates to local goals or preferences, all which trigger changes to an agent's preferences. For external uncertainty where agent's type is static, it is sufficient to align incentives only until the period in which an agent makes a claim about its type. Internal and external uncertainty could be combined, as well, (Cavallo et al., 2010). In fact, a various generalization of second price auction may deliver IC for uncertain environments with dynamic agents' population and where agents have general valuation functions on sequences of actions. In dynamic VCG mechanism, for instance, payments are defined so agents expected total payment from every period is the expected externality imposed by agents on the other agents. With external uncertainty, this property on payments needs to hold at agent's arrival. For internal uncertainty, this property must hold in *every* period.

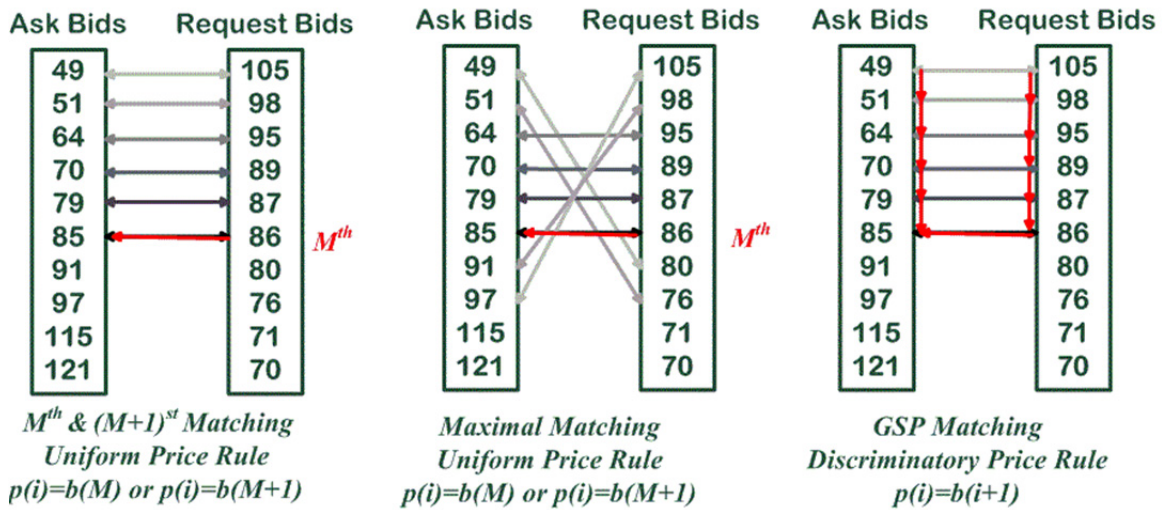
*The Dynamic VCG Mechanism* is a generalization of the VCG mechanism to dynamic environments (Parkes, 2003). Payments are collected so each agent's expected payment is exactly the expected externality imposed by the agent on other agents upon its arrival. The expected externality is the difference between the total expected discounted value to the other agents under optimal policy without agent  $i$ , and the total expected discounted value to other agents under the optimal policy with agent  $i$ . The digital VCG mechanism aligns incentives of agents with the social objective of following a decision policy that maximizes the expected total discounted value to all participants. The kind of IC

achieved by VCG mechanism is weaker than the DSE achieved in the static VCG mechanism. Rather, truthful reporting is an agent's best response in expectation, as long as the probabilistic model of the mechanism is correct and agents in the current and future periods are truthful. This is a refinement on a BNE, referred to as a within period *ex post NE*, because an agent's best strategy is to report its true type whatever the reports of other agents up to and including the current period, just as long as other agents follow the truthful equilibrium in future periods. It is equivalent to DSE in the final period of a dynamic problem, when digital VCG is equivalent to the static VCG mechanism.

### 3.8 Double Auction Mechanisms

The double two-sided double auction (DA) is often used for the exchange mechanisms in applications like stock markets (i.e., NYSE) and commodity markets (i.e., CME). The DA allows multiple buyers and sellers to trade simultaneously or sequentially at either continuous (CDA) or periodic (Call) clear e-market (Shubik, 2005). Given the supply and demand of sellers and buyers, a DA matches request and ask bids and determines a clearing price. A commonly used sealed bid DA matching method is equilibrium matching (EM) (Wurman et al., 1998) sealed-bid DA that is IC, in which the clearing price does not depend on the matching bidding prices, but rather externalities. The EM finds a uniform equilibrium price  $p^*$  that balances request-bids and ask-bids so that all eligible requests with price  $p \geq p^*$  and asks with  $p \leq p^*$  are matched (Friedman, March 1993). The 4-Heap EM algorithm (Wurman et al., 1998) implements the incentive compatible IC  $M^{th}$  Price auction clearing rule that sets the matching price at the  $M^{th}$  highest among all bids and the  $(M + 1)^{st}$  price rule at the  $(M + 1)$  highest among all bids. However, IC cannot extend to multi-unit bids, or simultaneously to buyers and sellers. A *uniform price* is normally determined by the last matchable or the first unmatchable pair w.r.t. the matching order. The EM DA, however, can be IC or AE, but not both, with some special pricing policies (McAfee, 1992) (Wurman et al., 1998). The adoption of DA, though, can be traced to its operational simplicity, efficiency, and high agility to varying e-market conditions.

Delivering AE as the uniform clearing price, however, might prohibit some matchable bids from being matched. However, IC cannot extend to multi-unit bids, or simultaneously to buyers and sellers. To maximize the number of matches, it is essential to allow different matches to be cleared at different prices (i.e., price discrimination). In fact, IC is not compatible with most desirable properties and is also hard to achieve, especially in dynamic/digital double auction (e.g. stock exchanges), where bids are entering or leaving over time and there is more than one matching to search sequentially (Blum, 2006) (Parkes, 2007). The work in (Zhao et al., 2010), introduced a maximal matching (MM) DA algorithm that maximizes market liquidity, share and auctioneer profit. However, while it delivers social efficiency it cannot guarantee IC. Figure 5 depicts, for visual comparison of matching and pricing, an instance of the EM, MM and proposed single Q-level GSPM DA models. The GSPM DA is described in chapter 5.



**Figure 5: GSPM DA in comparison with other DA models**

### 3.9 Preference Elicitation Models

Privacy is a concern that impact information revelation. Ascending CAs (Wurman & Wellman, 2000) (Ausubel et al., 2006) (Parkes, 2006) (Ausubel & Milgrom, 2006), minimize information requirements by posting prices on all bundles for asking bidders to reveal their demands at the current prices. An *elicitor model* proposed in (Conen &

Sandholm, 2001), a *preference elicitation model (PEM)* alternative, in which bidders asked for limited, and *relevant*, information. The PEM in CAs refers to the process, by which an auctioneer (elicitor) queries bidders for specific valuations, and may decide to ask further queries, given the sequence of responses to previous queries, or stops to determine a feasible matching allocation and payments. Using *incremental querying*, the auctioneer gradually builds up a partial model of bidder valuations, one that becomes more refined with each query, until an optimal matching allocation can be determined. An attribute that distinguishes the PEM is the fact specific information about preferences of the bidder may be relevant, given preferences of others. Thus, interleaving of queries among bidders offers potential reduction in elicited information (Conen & Sandholm, 2001). The PEM in CA exploits the general elicitation framework (GEF) (Sandholm & Boutilier, 2006) in which forms of incremental elicitation can be casted (Conen & Sandholm, 2001). The GEF for PEM includes: (1) *Query types* (i.e., Rank, order, bound, value or demand); (2) *Queried information models*: relate to query types and structural assumptions elicitor makes about valuations, since different queries impose different constraints; and (3) *Termination*: a critical process at which an elicitor requires enough information and a certificate to reach effective closure that require IC properties. The algorithmic GEF for PEM may be described as followed: (1) Let  $C_t$  the updated elicitor information regarding bidder valuations after iteration  $t$ .  $C_0$ , reflects any prior information available to the auctioneer; (2) Given  $C_t$ , either (a) terminate the process, and determine an matching allocation and payments; or (b) choose a set of queries  $Q_t$  to ask bidders; and (3) Update  $C_t$  given response(s) to query set  $Q_t$  to form  $C_{t+1}$ , and repeat.

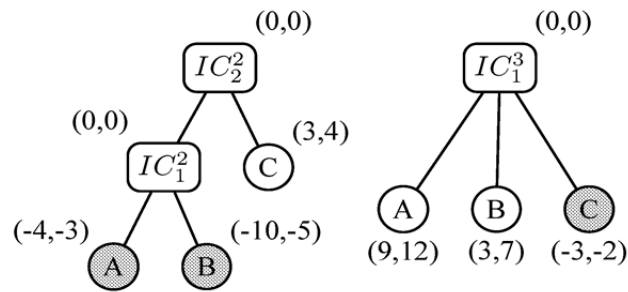
Preference elicitation in ICE is performed by combining two activity rules: (1) modified *revealed preference activity rule* (MRPAR) that requires each bidder decide which trade is most preferred in each round; and (2) *delta improvement activity rule* (DIAR) that requires each bidder refine his bid to improve price accuracy or prove no improvement is possible. ICE mitigates elicitation costs by directing bidders using price discovery and activity rules. As bidders prefer to reveal information as required to avoid leaks to competitors, ICE allows bidders specify lower and upper bounds on valuations and refine

bounds across rounds. Bounds allow price discovery, useful preference elicitation, and termination with efficient trade despite iterative valuations. ICE proxy model of revealed-preference activity rule, coupled with linear prices, ensures incremental progress. Activity rules are important in practice as they mitigate opportunities for strategic behavior. In (Milgrom, 2004), the *Milgrom-Wilson activity rule* requires a bidder to be active on a minimum percentage of the quantity of the spectrum for which it is eligible to bid, is critical component of the auction rules used by FCC for wireless spectrum auctions. ICE adopts a variation on the clock-proxy auction's RPAR.

### 3.10 Winner Determination Models

The winner determination problem (WDP) is, typically, solved by the central exchange e-marketplace from the agents' reported valuations (bids). The FX e-market computes the stable socially efficient matching of the denaturalized CAP that, often, involves solving an NP-hard combinatorial optimization problem (Sandholm, 2008). Some solution approaches include: (1) Identify and exploit one shot models through identifying polynomially solvable matched cases of the WDP (deVries & Vohra, 2003) (Nisan, 2000), that are rare to qualify, (2) Use approximations close to the optimal, but easier to compute that requires validation of the conservation of IC properties; or (3) Use an indirect iterative mechanisms, however, risk desired economic properties as SP and AE. Indirect mechanisms requires more time to converge to competitive equilibrium (CE) for e-market clearing due to the multiple round ascending auction model, though saving in processing time due to balanced distributed computing. The combinatorial nature of the problem, however, makes it difficult for two reasons. First, a bidder in an auction has an exponential number of choices' combinations that he can express bids on. Consequently, a bidder may need to submit an exponential number of bids. Second, the WDP is NP-hard (Sandholm, 2008); meaning rapid solution of large-scale problems is difficult. The WDP is the problem of determining an efficient trade given bids. The WDP in CAs and CEs is NP-hard (Rothkopf et al., 1998).

The work in (Lubin et al., 2008) formulates the ICE WDP as IP, and solve with branch-and-cut algorithms (Nemhauser & Wolsey, 1999). A similar approach has proved successful for solving the WDP in CAs (deVries & Vohra, 2003) (Sandholm & Boutilier, 2006). The work in (Lubin et al., 2008) allow bidder  $i$  report a lower and upper bound  $(\underline{v}_i(\beta), \bar{v}_i(\beta))$  on the value of each node  $\beta \in T_i$ , and refine these bounds across rounds. That in turn induces valuation functions  $\underline{v}_i(T_i, \lambda_i)$  and  $\bar{v}_i(T_i, \lambda_i)$ . The exact value, and thus true willingness-to-pay, remains unknown except when  $\underline{v}_i(\beta) = \bar{v}_i(\beta)$  on all nodes. The bid-tree  $T_i$  is *well-formed* if  $\underline{v}_i(\beta) \leq \bar{v}_i(\beta) \forall \beta \in T_i$ . In this case we have  $\underline{v}_i(T_i, \lambda_i) \leq \bar{v}_i(T_i, \lambda_i) \forall \lambda_i$ .  $\bar{v}_i(\beta) - \underline{v}_i(\beta)$ , is the *value uncertainty* on node  $\beta$ . For instance, Figure 6 portrays a matching allocation problem of two bidder agents, Bidder1 sells one of his items  $A$  or  $B$  if he gets Bidder2's item  $C$  at the right price. Bidder2 is interested in buying either of Bidder 1's items or selling his own items, with no structural constraints. Efficient trade assumes  $A$ , transfers to Bidder2, and  $C$  to Bidder1. While transferring  $C$  from Bidder2 to Bidder1 may not hurt, and since that trade is a prerequisite for Bidder1 to sell one of his items, it should execute. Bidders can begin with loose bounds on valuations, and gradually tighten them in response to pricing information provided by the mechanism. An interpretation of a revealed-preference activity rule, coupled with simple linear prices, ensures progress across rounds.



**Figure 6: A TBBL matching allocation instance of two bidders**

The WDP model ICE in (Lubin et al., 2008), may be modeled as followed: Given a bid tree  $T_i \in T = (T_1 \dots T_n)$ ,  $\beta \in T_i$  a node that satisfies trade  $\lambda_i$ . Then, the WDP for bids tree  $T$  and matching allocation  $x^0$ :

$$WD(T, x^0) = \max_{(\lambda_1, \dots, \lambda_n)} \sum_i v_i(\lambda_i) = \max_{\lambda, sat} \sum_i \sum_{\beta \in T_i} v_i(\beta) sat_i(\beta)$$

$$s.t. \lambda_{ij} + x_{ij}^0 \geq 0, \forall i, \forall j$$

$$\sum_i \lambda_{ij} = 0, \forall j$$

$$sat_i \in \text{valid}(T_i, \lambda_i), \forall i; sat = (sat_1, \dots, sat_n).$$

$$sat_i(\beta) \in \{0, 1\}, \lambda_{ij} \in \mathbb{Z}$$

The decision variables represent the satisfaction of nodes and capture the logic of the bidding language through linear constraints; a related approach has been considered in application to  $\mathbb{L}_{GB}$  (Boutilier, 2002). The formation determines the trade  $\lambda$  while in parallel determining the value to all bidders by activating nodes in the bid trees. Given reported valuation functions  $\hat{v} = (\hat{v}_1 \dots \hat{v}_n)$  the VCG collects the following payments:

$$p_{vcg,i} = \hat{v}_i(\lambda_i^*) - (V(\hat{v}) - V_{-i}(\hat{v})),$$

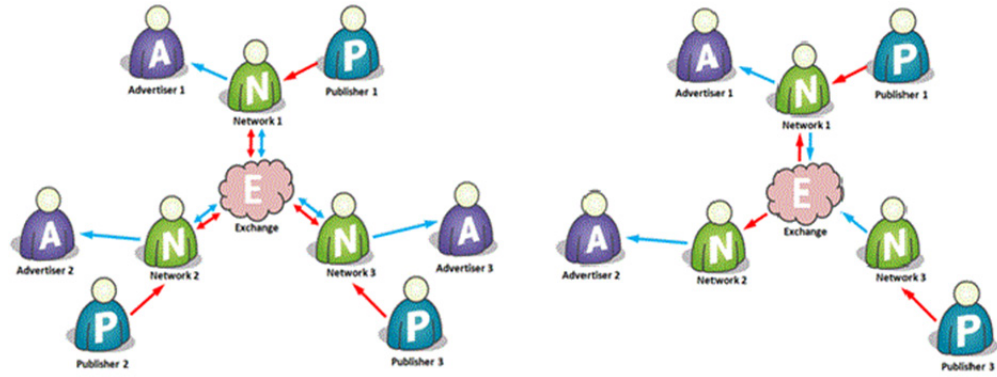
$\lambda^*$ , is the efficient trade,  $V(\hat{v})$  is the reported value of this trade and  $V_{-i}(\hat{v})$  is the reported value of the efficient trade in the economy without bidder  $i$ . Let's refer to  $\Delta_{vcg,i} = (V(\hat{v}) - V_{-i}(\hat{v}))$ , as the VCG discount. The problem with the VCG mechanism in the context of a CE is that *it may run at a budget deficit* with the total payments negative. An alternative payment method is the *Threshold rule* of (Parkes et al., 2001):  $p_{thresh,i} = \hat{v}_i(\lambda_i^*) - \Delta_{thresh,i}$ ,  $\Delta_{thresh,i}$ , is selected to minmax regret  $\max_i (\Delta_{vcg,i} - \Delta_{thresh,i})$  subject to  $\Delta_{thresh,i} \leq \Delta_{vcg,i} \forall i$  and  $\sum_i \Delta_{thresh,i} \leq V(\hat{v})$ . Threshold payments are BB and minimize the max deviation from VCG outcome across all balanced rules.

**Example** Consider possible trade of the two bidders in Figure 2: If Bidder 1 trades A for C he gets \$2 and Bidder 2 gets \$7. If Bidder 1 trades B for C he gets -\$2 and Bidder 2 gets \$2. If no trade occurs both bidders get \$0 value. Therefore the efficient trade is to swap A for C. Because the efficient trade creates a surplus of \$9 and removing either bidder results in the null trade, both bidders have a *Vickrey discount* of \$9. Thus if we use

*VCG payments*, Bidder 1 pays  $\$2 - \$9 = \$-7$  and Bidder 2 pays  $\$7 - \$9 = \$-2$  and the exchange runs at a deficit. The *Threshold payment* rule chooses payments that minimally deviate from VCG while maintaining *BB*. This minimization reduces the discounts to \$4.50, and thus Bidder 1 pays  $\$2 - \$4.50 = \$-2.50$  and Bidder 2 pays  $\$7 - \$4.50 = \$2.50$ .

### 3.11 Digital Advertising e-Marketplaces

The digital advertising (ad) online and mobile e-markets are a bold manifestation of the digital era. The ad value chain (Thomas, 2008) includes advertisers, publishers, media agencies, ad networks (adnet) of demand and supply side platforms, and ad exchanges (adx). The ad inventory is the supply of potential impressions to display to the right users at the right times in the right digital medium. As many publishers can't afford to maintain sales force, they sell ad inventory through adnets or adxs. Publishers maximize revenues by selling inventory at highest average price possible, due to the fact that ad inventory is perishable and finite. The adnet e-marketplaces create efficiency by providing targeting capabilities. There are vertical adnets which focus on a particular industry and contextual adnets that provide e-marketplace for selling keyword-based ads (i.e., Google AdSense). As it is complex for Adnets to forge many cross relationships, to manage the supply-demand unbalances, the ad adx would be the right answer, where adnets would have just one trading relationship, and one 'hop' away from each other (see Figure 7). In fact, adxs bring more transparency and simplify trading Ads. Nevertheless, the adx is poised to have a transformative effect on the digital era. While adnets will likely see better margins by going through the adx for inventory they can't clear themselves; the adx will level the playing field in terms of inventory access.



**Figure 7: Ad Networks and ad Exchanges**

The digital ad auction serves various forms like web TV ads (i.e., Google TV), contextual ads on search engine results pages (i.e., Google AdWords) banner ads, social networking Ads (i.e., Facebook Ads). The Google TV (Google, 2013) is an open smart platform that extends the computing capabilities and interactive user experience of any TV. In (N. Nisan et al., 2009), the Google TV uses simultaneous ascending auction (SAA) subject to over demand (Demange et al., 1986) (Cramton et al., 2006) (Milgrom, 2004) for *Walrasian* competitive equilibrium (CE) price and efficient matching allocation of TV ad spots. Advertisers bid their max daily budget and cost-per-view ads on target attributes that influence bid valuation. Pursuing tradeoff among cost minimizing advertisers and revenue maximizing publishers, the work in (N. Nisan et al., 2009) proposed an auction matching allocation at *Walrasian* minimum CE prices that is Pareto optimal and IC. While auction increases publisher revenues by exhausting winner budgets, advertisers are efficiently allocated set of ads at minimum price to win with little strategic incentive to reduce bids. However, while IC is realized for trivial case of *Walrasian* CE (Demange et al., 1986), no Pareto optimal auction is IC with budget limits (Dobzinski et al., 2008). Computing demand and matching allocations is also *NP-hard* (i.e., knapsack problem).

The AdWords (Google, 2013) utilizes the GSP auction. Every time a user searches on Google, AdWords run GSP auction and ads of relevant keywords are shown as sponsored links on search result page. Advertisers select keywords that trigger their ads, bid and PPC, however, the pay value of advertiser below them in ranking. To meet requirements,

the quality score (QS) measures the relevance of keywords to ad text and to a search query. Ads, ultimately, are ranked by  $\max \text{CPC-Bids} \times \text{QS}$ ; the minimum advertisers pay to hold position  $p^{(j)} \text{QS}^{(j)} \geq b^{(j+1)} \text{QS}^{(j+1)} \Rightarrow p^{(j)} = b^{(j+1)} \left( \frac{\text{QS}^{(j+1)}}{\text{QS}^{(j)}} \right) + \delta$  ( $\delta=0$  min payment). Furthermore, the higher the QS, the higher ad rank is, the lower CPC payment is and the better ad position. However, in the GSP auction, advertisers do not necessarily fare best when they truthfully reveal any private information asked for by the ad auction. Hence, Google's suggested CPC bidding strategies (i.e., cost per acquisition (CPA)).

Compared to VCG, the GSP is not proof efficient and has no equilibrium in DSE. The equivalent one-shot complete information game, however, proved to converge to “*locally envy-free*” equilibrium, at which the payoffs of the players are the same as in DSE of VCG auction, even though bids and payment rules are different. (Edelman et al., 2007), analyzed the generalized English auction (GEA) that depicts GSP to capture convergence of bidding behavior to static equilibrium. GEA is similar to English auction except bidders are assigned to slots in the order they drop out of the auction. Let  $\alpha_i$  known  $\forall i$ , valuations drawn from a continuous distribution  $F(\cdot)$ . The user knows own valuation and  $F(\cdot)$ . Let  $p^{(k,h,v^{(i)})} = v^{(i)} - \frac{\alpha_k}{\alpha_{k-1}} (v^{(i)} - b^{(k+1)})$ , the price at which user  $i$  drops out, where  $k$ , is no. of remaining bidders  $h = (b^{(k+1)}, \dots, b^{(k)})$  is the history of bidders. For dynamic GSP, if bids can change iteratively, agents eventually learn information about other agents that implies equilibrium is robust independent of the underlying distribution an *ex post* BNE strategy profiles for any set of distributions of advertisers' private values.

(Varian, 2007), analyzed the ad position auction with complete information, based on the two-sided matching assignment game (Shapley & Shubik, 1972) (Demange et al., 1986), and (Roth & Sotomayor, 1992). The work of (Shapley & Shubik, 1972) showed properties of the two-sided markets are robust to generalizations of the two-sided labour markets model. The ad positions (i.e., slot-s) in a web page are traded amongst advertisers (i.e., agent  $a$ ) of valuations  $v_{as} = v_a x_s$ ,  $v_a$  is expected profit PPC and  $x_s$ , is CTR. Ad agents simultaneously decide bids  $b_a$ , while each agent charged, if users click

on an ad slot, the bid value of agent below him in the ranking. The auction settles with Nash equilibrium. that is  $u_{as} \geq u_{at} \rightarrow (v_a - p_s)x_s \geq (v_a - p_t)x_t \forall t$ , other slots.

The digital ad auction model is evolving to an exchange matching model that cross trade e-market visibility intelligence and liquidity for the efficient matching allocation of digital media assets. The combinatorial exchange (CX) matching trade problem is tackled, for instance, in the ICE proxy architecture of (Cavallo et al., 2005), in which bidders submit and refine bounds on TBBL bids directly to the CX that drive price dynamics and ultimately clear the CX. The TBBL leads to a concise formation of the efficient trade problem as an IP. In fact, linear prices  $\pi$  are CE prices for the CX problem, if there is a feasible trade  $\lambda \in \mathcal{F}(x^0)$  with prices  $\pi: v_i(\lambda_i) - p^\pi(\lambda_i) \geq v_i(\lambda'_i) - p^\pi(\lambda'_i) \forall \lambda'_i \in \mathcal{F}_i(x^0), \forall i$  that makes  $\lambda$  of CE  $\pi$  prices an efficient trade (Bikhchandani & Ostroy, 2002). Algorithmically, the bid tree and TBBL calculate, iteratively, based on myopic best response iterative auction an optimal primal and optimal dual solution to solve for efficient matching allocation and price  $\langle x, p \rangle$  in a CX. The ICE iterative model, however, would enforce activity rules to guide preference elicitation in each round, ensure incremental progress and prevent *free-riding* that reduce the CX to a sealed-bid auction and lose desirable properties. The ICE allows bidders specify lower and upper bounds on valuations and refine bounds across rounds that allow price discovery, useful preference elicitation, and termination with efficient trade despite iterative model. While there are no truthful MD solutions for AE, and BB sealed bid CXs due to impossibility results (Myerson & Satterthwaite, 1983), any payment rule can be leveraged and would allow ICE to inherit truthful bidding in an *ex post* Nash equilibrium, just as can be achieved in iterative GVA (Mishra & Parkes, 2007). The DAs in which truthful bidding is in DSE are known for unit demand settings (McAfee, 1992) and also for more expressive domains (Chu & Shen, 2008). The free exchange (FX) secures AE and IC best response trade as based on the GSP matching and pricing models that maximizes the FX exchange revenue, rather than leaving it on deficit; as in Parkes, iterative GVA (Parkes, 2001) that adds further steps to enforce IC, while applying payment rules as *Threshold payment* rule on final payments to resolve BB problem (Parkes et al., 2001).

## Chapter 4

### 4 RBBL: Rule Based Bidding Language

An inspiring motivation to conveying the rule-based bidding strategies with the attribute-values of e-services is to facilitating the free market economy natural conduct of bidders. Our work follows this inherent microeconomic market concept based on the shared facts below. As a matter of fact, the constant learning of rational bidders at repetitive trades is what motivates realizing the truthful strategic behaviour of bidders using the rule-based bidding language. The RBBL would, also, facilitates multiple trading transactions of rather rapid response without scarifying privacy. This is due to the automatic deduction and aggregation of bidding rules and attribute-values of elicited e-services that facilitates bid formation by the free exchange platform for rather multiple automatic transactions of more rapid trades. In that vein, our work presents and examines the concept of bidding lifecycle in the current trading mechanisms. Our work facilitates the flexible bidding strategic conduct using the logical rules formula as presented in the RBBL model. An example elaborates on the application of the RBBL messaging by bidders and the free exchange deliberation and formation of elicited e-services and related bids. The desirable properties of the RBBL is examined and theoretically verified at the end of this chapter.

#### 4.1 Market Economy: Insights from Microeconomics Theory

Generally, the resource matching allocation problem amongst societies relied, primarily, on three institutional economies (mechanisms) (Hall & Lieberman, 2010): (1) *Traditional economy*: A *fair e-market* that allocates resources according to traditional practices that govern the fair distribution of goods and e-services. Though, predictable and stable; *traditional markets*, often, lack innovation and growth, hence, likely converge to stagnant economies; (2) *Command economy*: a central authority that plans and allocates resources according to explicit enforced rules; and (3) *Market economy*: A *free market* in which resources allocated by bidder buying and selling decision making, primarily governed by *opportunity cost*, as influenced, most often, by the society. Adam Smith, remarkably,

observed bidders interacting in free markets act as if guided by “invisible hand” that leads to desirable e-market outcomes: “[The trader] *neither intends to promote the public interest, nor knows how much he is promoting it... he intends only his own gain, and he is in this... led by an invisible hand to promote an end which was not part of his intention*”. Prices are the instrument of invisible hand in directing economic activities, reflecting both value of goods to a society and cost to society of making goods that, in many cases, maximize the welfare of society. The invisible hand, though, is less able to ensure economic prosperity is distributed fairly (Mankiw, 2012). Free markets reward people as per their ability to produce goods other people are willing to pay for. While public policies, as welfare, attempt to achieve fair distribution of economic well-being, the invisible hand leads free markets to allocate resources efficiently, works best in economy of perfect competition. The invisible hand is, also, not invincible to e-market failure due to either externalities or monopolistic power. Nevertheless, Smith’s insight ensures free market invisible hand of competition is better than fair e-market regulation or government ruled economy. The activities of buyers and sellers automatically push e-market price for a good towards equilibrium at which buyers and sellers are satisfied, and there is no upward or downward pressure on prices as supply and demand for the good is in balance (i.e., law of supply and demand).

Economists often advocate free markets as the best way to organize economic activities. After all, in free market economy, no one is looking out for the economic well-being of society as a whole. Despite the decentralized and self-interested decision making, the free market economies have proven remarkably successful in organizing economic activities in a way that promotes overall economic well-being (Mankiw, 2012). However, caution must be taken at microeconomic and computational levels to realizing and eradicating the adverse strategies of e-market participants as fraud, deception, adverse selection (of buyers of partial information) and hidden actions (i.e., moral hazard), that often, harm the social welfare efficiency and result in e-market failures. The mechanism design (MD) theory perceives an agent might unilaterally seek to manipulate an outcome. For instance, in Vickrey auction, if agents having the highest and second-highest valuations collude,

then these agents can benefit. Also, there might be bidding across mechanisms, making collusion harder to detect. Other strategic behaviors are snipping (submitting bids near to auction closing) and free riding (submitting overvalued bids with no financial shield) and shading. Our work advocates free e-market economy and establishes that free strategic conduct would eradicate, eventually, the adverse strategies driven by restrictions.

## 4.2 Strategic Impact of Constant Learning

The rationale of advocating free strategic conduct is particularly inspired by the impact of constant learning at repetitive trades. The learning process motivates bidders to deliberate about e-market disruptions and, hence, change their preferences and strategies. This type of strategic adjustment is perceived as a truthful and rational reaction due to learning new facts. The truthful strategic reaction is also driven by the invisible dynamics of the free market economy that stabilize the self-interest and essential needs of bidders to scarce assets. The free market economy draws, eventually, a rationally collaborative bidders response that delivers stable efficiency. The free expression of rational conduct would, hence, facilitate the truthful revelation of strategic conduct. Another compelling by-product is that the bidding automation allow for more rapid trades. The restricted bidding conduct would, otherwise, provoke deceitful tactics and adverse strategies that result in e-market failures. Our work proposes, hence, the free exchange that follows the free market economy that proved effective in organizing economic activities for the social well-being despite the self-interest of bidders. However, the free exchange stable efficiency would, often be better realized with thicker e-markets, uncongested interaction, and safe privacy (Roth, 2007). Another crucial factor is implementing fair mechanisms of no monopolies.

The limited bidding scope to free choices may be traced to the Vickrey–Clarke–Groves (VCG) mechanisms (Vickrey, 1961) (Clarke, 1971) (Groves, 1973) that penalize (internalize) bidders externality levies for reporting untrue strategic preferences, to align payoffs with the social welfare, rather than the desirable self-prosperity. Evidently, the fact e-markets penalize or inhibit strategizing incites adverse reactions that lead to e-market failure due to incomplete or false information revelation. The adverse strategies

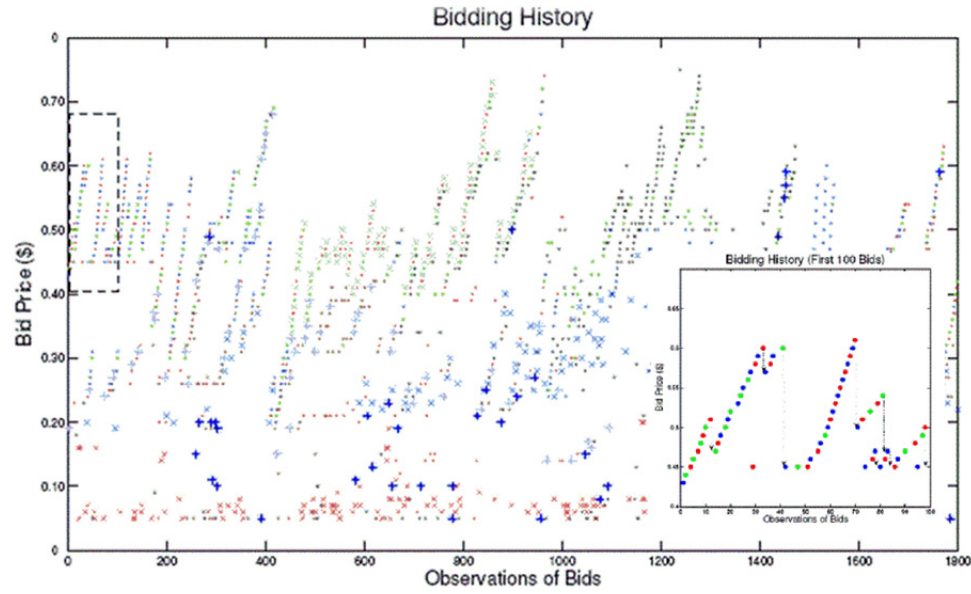
may be manifested by fraud, deception, collusion, shilling, free riding, shading, snipping or hidden actions. The e-markets are, mostly, more vulnerable to adverse strategies than classic markets. The virtual bidders may use agents to collude, form coalitions or unleash agents of multiple identities for false name bidding.

The strategic aspect of natural interactions in mechanisms has an incident in the Boston public school (BPS) choice under “Boston Mechanism” (Abdulkadiroglu et al., 2011), where smart parents strategized and gained preferred seats, the reason why it switched to a deferred acceptance, Stagey Proof (SP) mechanism that, literally, disables the strategic choices, through less intense preference elicitation, in this case, for a better social welfare outcome and, of course, to avoid lawsuits by unsatisfied parents. While equity is justified at school choice level, e-market fairness is not a natural attribute of the decentralized matching allocation problem. In fact, our work takes notice, not of the solution, but a comment by one affected parent “I’m troubled that you’re considering a system that takes away the little power that parents have to prioritize... what you call this strategizing as if strategizing is a dirty word...” (Recording from BPS Public Hearing; 05-11-04).

The strategic impact of the repeated trades and constant learning is empirically observed in the first-price auction as examined by (Edelman & Ostrovsky, 2007) on Yahoo!. The first price auction is found unstable as bidders shade true valuations and adjust bids frequently in response to others in a cycling behavior strategy as shown in Figure 8 (source: (Zhang, 2005)). The cyclic behaviour often results in slower trades and a potential revenue loss. The empirical evidence of bid and ranking fluctuations in the generalized second price auction (GSP) auction established history dependent strategies motivate such fluctuations. The work of (Zeithammer, 2006) analyzed eBay auctions using real data and observed that forward-looking bidders change strategies and actions once having information about future auctions. Zeithammer argued bidding true valuation would be too high, as it exposes the bidder to winning immediately, while losing the opportunity for a better price for the same item on future trades. Instead, bidders bid less than their valuations, a strategy referred to as “shading”. The key prediction of the theory

of “forward-looking” bidders should shade more when there are more items coming up for auction and when more of those items are desirable to the bidders. Such findings would impact, also, seller strategies, raising the question of whether eBay auction limits the potential of trading institutions. In fact, allowing strategic selling may change the bidder’s strategy. That, of course, raises the question whether current auction models are strategically sustainable

In (Nisan et al., 2011), the convergence of the GSP to VCG AE outcome is due to best response strategies that transform partial information to complete information models at repeated trades. Incidentally, our work takes note of Nisan’s remark *“It is quite an embarrassment that the pricing rule used in ad auctions, almost universally is GSP, rather than the more theoretically motivated VCG which mechanism design (MD) theory would suggest”*. While (Nisan et al., 2011) recognized the value of GSP cognitive and computational simplicity over VCG, yet, the theoretical analysis relate GSP stable efficiency to the fact GSP auction converges from uncompleted information trading model a complete information IC trading by implementing repeated best response truthful direct strategies with, indeed, continuously repeated trades. In particular, showing that VCG prices are equilibrium of GSP auction does not address the question of *how* the bidders may reach equilibrium without having the required information. This issue was also addressed by (Cary et al., 2007), who show that the GSP auction of bidders with repeated best response strategies, would converge to the VCG equilibrium. The work in (Varian, 2007) empirically analyzed the GSP data of Google and reported similar results to (Edelman et al., 2007) where the complete information locally envy-free equilibrium of the simultaneous-move game is observed in Google ad auction fairly accurately. The GSP, however, limits bidder choices. For any keyword, advertisers submit single bids; given different ad positions that may not sufficiently convey preferences of bidders..



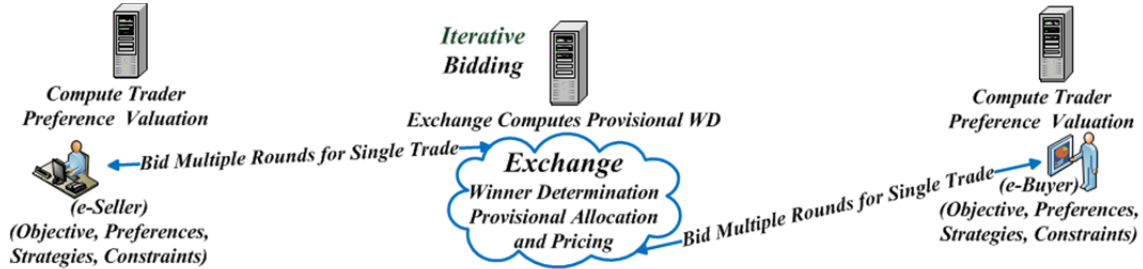
**Figure 8: First price auction cyclic behaviors**

### 4.3 Bidding Lifecycle: Bidding Automation for Rapid Trades

The time wasted in the bidding processes at de facto e-marketplaces is rather an annoying user experience. For instance, a bidding process may take hours or days for an e-Bay or Amazon auction. Our work examines the “bidding lifecycle” that relates to the processes of creation, dispatch, and expiry of the bidding process. While the bidder agents manage their local problems and the formation of their RBBL messages, the FX deduces and aggregates the bidding rules to elicit preferences, generate the requests and asks and computes winning matches. Hence, the bidding lifecycle would have substantial influence on designing mechanisms. The following is an analysis of the bidding lifecycles in various e-trading mechanisms:

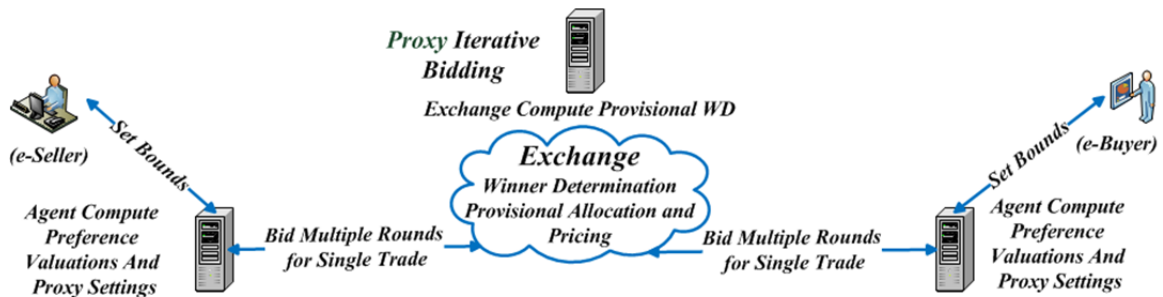
**Iterative Bidding:** commonly used in partial revelation indirect mechanisms (i.e., English auction, Dutch clock auction, SAA (Cramton, 2006), iBundle (Parkes, 2006)) and has a simple bidding structure and semantics. The bidding lifecycle expires at every round of a single trade and requires manual setups and bid formations. The iterative biddings and indirect mechanisms distribute the computational workload between agents and the exchange. The manual updates, however, require excessive setup times. The

clock auction reduces the bidding delays by enforcing a timeout constraint to promoting faster trades. Figure 9 depicts the iterative bidding for the free exchange e-marketplace.



**Figure 9: Iterative bidding**

**Proxy Iterative Bidding:** extends bidding lifecycle until e-market clears in the price taking model for a single trade as shown Figure 10, using proxy agents (i.e., *iBundle Tree based bidding language (TBBL)* (Parkes, 2006), *Ascending proxy auction* (Ausubel & Milgrom, 2006)) with valuation bounds (i.e., budget constraints) and provisional allocation. The proxy iterative bidding is computationally distributed with extended bidding lifecycle, however, for single trades. The bidders must set the valuation bounds at each trade and update proxy agents.



**Figure 10: Proxy iterative bidding**

**Bidding programs:** the complete problem model is sent to the exchange (see Figure 11) in the form of complex bid structure that includes the formal local problem objectives and constrains (Nisan, 2000). In fact, it is the other extreme of information revelation bidding compared to the simple iterative bidding in which the bidding lifecycle extends until the

problem is fully solved. However, there are inherent critical issues as found in (Parkes, 2001) like the privacy exposure problem that makes the bidding model impractical.

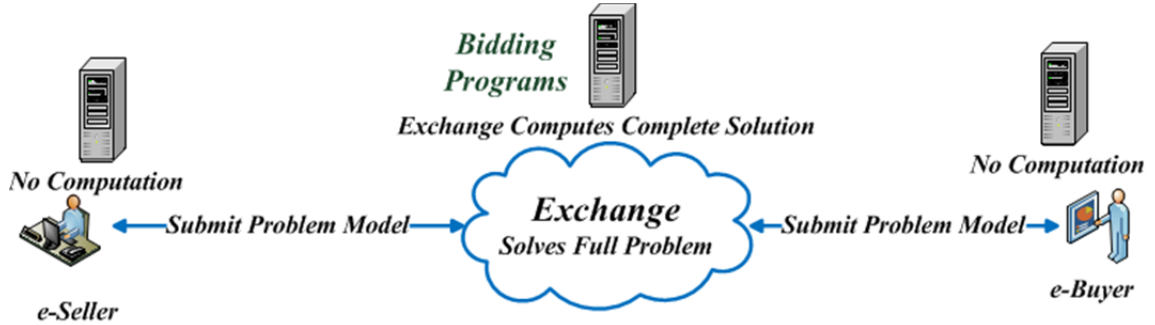


Figure 11: Bidding programs

**One Shot Bidding:** commonly used for complete information direct mechanisms (i.e., *First and Second sealed bid auctions, GSP, VCG*). The auctioneer collects single shot bids in sealed auction, and computes the winner determination. The bidding lifecycle is rapid for single trades. However, it requires setup at each trade. The computation model is distributed. Agents work on valuation and bid formation; while exchange computes winner determination allocation and pricing outcomes (see Figure 12).



Figure 12: One shot bidding

#### 4.4 Rule Based Biding Language (RBBL) Model

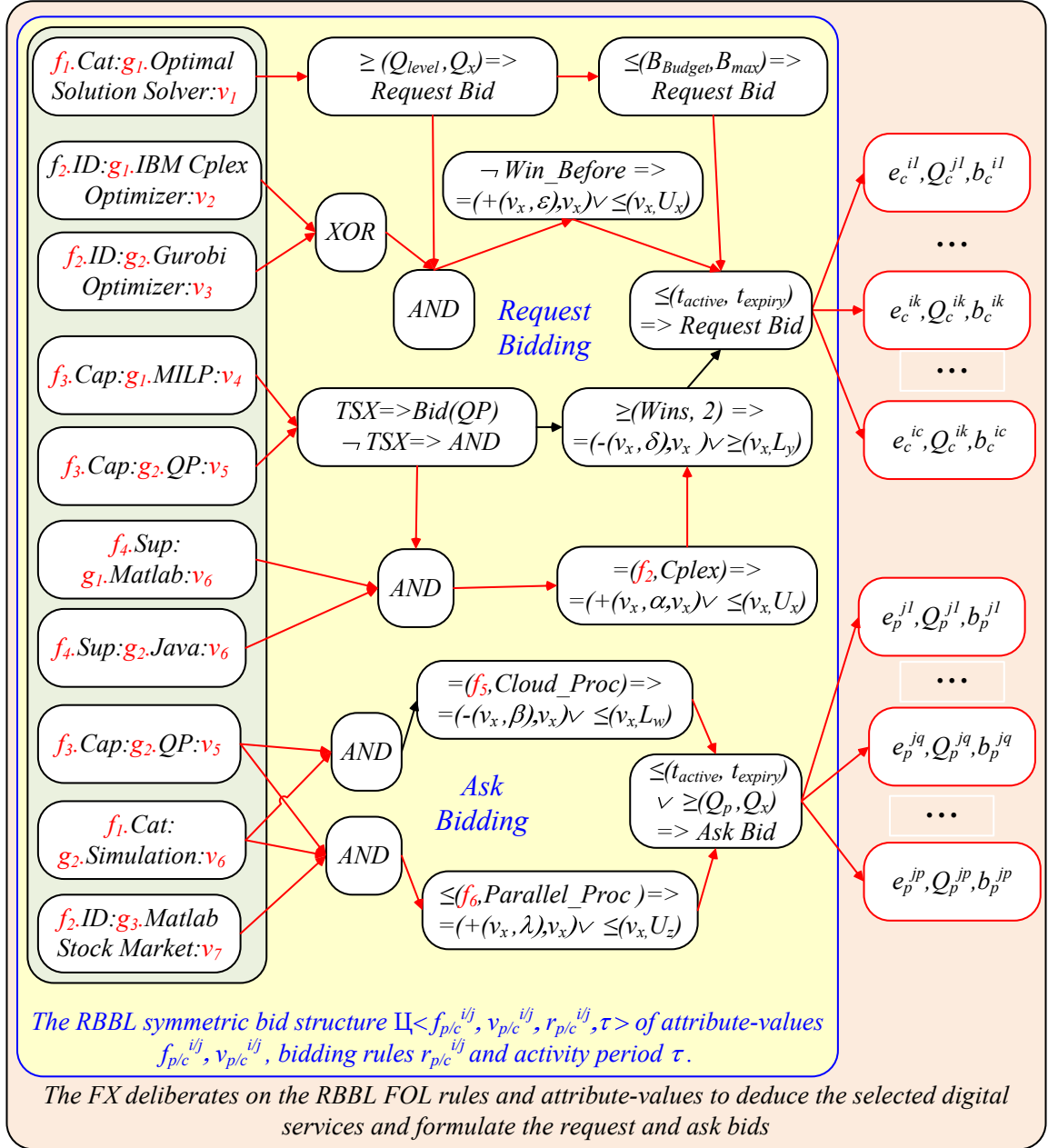
The RBBL is an expressive bidding language that has a directed acyclic graph (DAG) structure. Our work combines the expressive and structural attributes of the tree based bidding language (TBBL) in (Cavallo et al., 2005) with those of logical languages  $\mathbb{L}_G$

and  $\mathbb{L}_B$  in (Boutilier & Hoos, 2001) that include  $\mathbb{L}_B^{OR}$ ,  $\mathbb{L}_B^{XOR}$ ,  $\mathbb{L}_{GB}$  and  $\mathbb{L}_B^{OR*}$ . In fact, the RBBL subsumes the expressive and structural attributes of the TBBL in (Cavallo et al., 2005) and the logical languages  $\mathbb{L}_G$ ,  $\mathbb{L}_B$ ,  $\mathbb{L}_B^{OR}$ ,  $\mathbb{L}_B^{XOR}$ ,  $\mathbb{L}_{GB}$  and  $\mathbb{L}_B^{OR*}$  in (Boutilier & Hoos, 2001) using the logical rule and operators formulae in the bid DAG structure and semantics. Our work exploits the FOL to model the rules, formulae and other attributes like Q-levels and budget bounds. As shown in Figure 13, the RBBL symmetric DAG bidding structure consists of two segments, the attribute-values segment and the logical rules segment. The iconic attribute of the RBBL, however, is the addition of the logical rule formulae to the bid DAG message, which are simple rules that attribute to the local constraints of bidders, while preserving their privacy, contrary to the exposure problem of the bidding programs in (Nisan, 2000). The RBBL enables the repetitive adjustments of the preferences in response to constant learning at repetitive trade disruptions. The RBBL logical rule formulae enable bidders to expressing their free strategic conduct. The RBBL is symmetric model that allows for bidding requests and asks in a single DAG structure that may exploit diverse models of the rule formulae. For instance, our work uses the first FOL to model rule formulae and other bounding attributes like Q-levels and budget.

The RBBL semantics and structure outlines the blueprint for the deduction and formation of diverse e-services and bid combinations by the free exchange. The RBBL message comprises (1) the attribute-value segment of factor-group-value leafs. The attribute-value includes the attribute short description, the group identifier and initial values of attributes. For instance, as shown in Figure 13 the attribute-value leaf ( $f_3$ .Cap:  $g_2$ :QP,  $v_5$ ) designates  $f_3$ : capability feature of, particular group  $g_2$ : optimization solver of a quadratic programming problem with assigned value  $v_5$  by the bidder; (2) the logical rules internal control nodes that may include logical operator and logical rule formulae (i.e., FOL rules). The rules presents the control nodes of the RBBL DAG structure with often no values but rules applied on values. The FOL logical rules often update the values of the attributes or combinations following strategic aspects of bidders and the outcome of the constant learning at repeated trades. For instance, the FOL rule ( $\neg \text{Win\_Before} \Rightarrow = (+ (v_x, \varepsilon), v_x) \vee \leq (v_x, U_x)$ ) means, if the bidder has not won before, increase the value

$v_x$  that is the sum of the selected combined attributes by factor  $\varepsilon$  for next trade, as long as  $v_x \leq U_x$ . Evidently, the node rules often change the initial true attribute or combined attributes values. The selected Q-levels and max budgets may be presented explicitly as an attribute or implicitly as a rule.

As shown in Figure 13, the RBBL symmetric DAG bidding structure consists of two segments, the attributes segment and the logical rules segment. The RBBL model outlines the blueprint for inferring the diverse bid combinations by the exchange e-market: (1) the attributes segment comprises the feature-group-value leafs of the DAG structure. The attributes include the attribute short description, group identifier and initial true values of the feature. For instant, the feature leave  $(f_3.Cap: g_2:QP, v_5)$  evaluates the capability feature  $f_3$  of the optimization solver to compute a quadratic programming problem  $g_2$  for value  $v_5$ ; (2) the logical rules internal control nodes that may include logical operator and logical rule formulae (i.e., FOL rules). The rules presents the control nodes of the RBBL DAG structure with, often, no values but rules applied on values. The rules often update the values of the attributes or combinations following some strategic aspects being the outcome of constant learning and repeated trade disruptions. For instance, the FOL rule  $(\neg Win\_Before \Rightarrow = (+ (v_x, \varepsilon), v_x) \vee \leq (v_x, U_x))$  means if the bidder has not won before, increase the value  $v_x$  that is the sum of the selected combined attributes by factor  $\varepsilon$  for next trade, as long as  $v_x \leq U_x$ . Evidently, the node rules, often, change the initial true attribute or combined attributes values. The selected Q-levels and maximums budgets may be presented explicitly as an attribute or implicitly as rules.

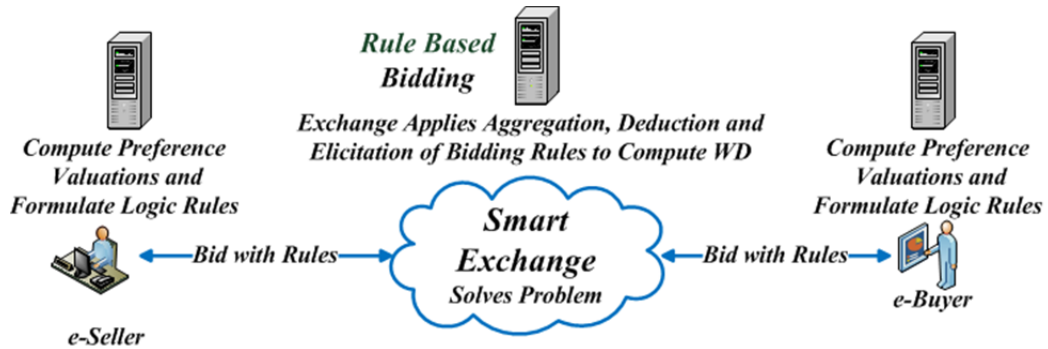


**Figure 13: RBBL bid symmetric DAG structure**

The FX collects the RBBL DAG messages and implements the automatic preference deduction algorithms (not covered) on rules and attributes sets to generate the combinations of requests and asks rather than solving a bidding program (Nisan, 2000). In fact, the rules act as filters (i.e., bid constraints) to reducing the complexity of the

feasible solution space. The RBBL internal logical rule formulae nodes compute the new attribute valuations and propagate the updated values within the DAG. The logical operators (i.e., *OR*, *AND*, *XOR*, etc.), otherwise, combine the attributes and their current values for the next stage. The RBBL is expressive with more flexibility and conciseness that reduces the complexity of preferences to sets of attributes and rules.

Compared with the bidding lifecycles of other mechanisms presented in literature review, the RBBL enables more rapid bidding lifecycle for multiple trades and hence expedites trades. The free exchange collects the bidding attribute-values and logical rules formulae to automatically deduce preferences, form bids, and computes winner determination with minimal preference elicitation. The RBBL facilitates, also, distributed computation, in which the request and ask bidders as well as the free exchange e-marketplace contribute, equally, in the computation and fulfillment of the social objective (see Figure 14).



**Figure 14: Rule based bidding**

The RBBL exploits the logical rule and operator formulae, concisely, while delivering the expressive semantics and structural attributes of other logical bidding languages. i.e.,  $\mathbb{L}_G$ ,  $\mathbb{L}_B$ ,  $\mathbb{L}_B^{OR}$ ,  $\mathbb{L}_B^{XOR}$ ,  $\mathbb{L}_{GB}$ , OR- of- XORs, XOR- of- ORs, and  $\mathbb{L}_B^{OR*}$ . and TBBL languages.

**The RBBL bidding process:** This example illustrates the process of RBBL flexible bidding and the free exchange deduction and aggregation of attribute-values and logical rules to forming targeted e-services and associated bids. As shown in Figure 15, there are two levels in the automatic construction of request and ask bids by the free exchange:

- 1) **Bidder action:** A consumer works on mathematical modeling and simulation wishes to bid for any commercial optimization solver e-service with a particular preference to either Gurobi or IBM Cplex Optimiser solutions. For simplicity, consider the part of the RBBL message instance in Figure 15 that includes only two attribute-values of the e-service: (1) category feature ( $Cat: f_1$ ) and (2) Source ID feature ( $ID: f_2$ ). The consumer would pay  $v_1$  for any solver: ( $f_1.Cat: g_1: Optimal Solution Solver: v_1$ ) and would add more  $v_2$  if the solver is a component of IBM Cplex or  $v_3$  if it is part of Gurobi Optimizer that is ( $f_2.ID: g_1: Gurobi Optimizer: v_3$ ). The bidder is looking for a Q-level  $\geq Q_x$  for any solver with limited budget  $B_{Budget} \leq B_{max}$ . The bidder has a strategy, if he couldn't win a specific trade then he would increase the bid valuation  $v_x$  by  $\varepsilon$  in the next repetitive trade on the same e-service subject to a limited upper bound  $v_x \leq U_x \in \mathbb{R}_+$ ,  $v_x$  is total attribute values that fan-in to the FOL rule. The bidder forms flexibly and concisely the RBBL message that include his preferences on requested e-services in the form of attribute-values and his bidding strategies in the form of FOL rules as shown in a part of Figure 15 then send it to the free exchange.
- 2) **FX action:** The FX receives the bidder RBBL message and stores it in the database. The FX and bidders share common semantics repository of feature-group attributes. The FX identifies an offer from Gurobi for a solver. The FX searches for request matches and identifies our consumer as an eligible buyer. The FX aggregation might consider, for instance, the matching of max budgets and min costs for qualifying eligibility before constructing bids. The FX then, automatically deliberates on the RBBL message and examines ( $f_1: g_1: v_1$ ) and ( $f_2: g_1: v_3$ ) attributes-values to form the requested e-services and bids. As shown in Figure 15, the red arrows indicate the transition state and activity flow of the logical operators on the attributes. The FX queries the attribute-value ( $f_1: g_1: v_1$ ) being offered by seller(s) and tags it as true to indicate eligibility. The ( $f_1: g_1: v_1$ ) attribute-value state transitions next to the Q-level FOL rule ( $\geq (Q_{level}, Q_x) \Rightarrow Bid$ ) that inspect the min required Q-level. If  $Q_{level} \geq Q_x$  true, the active flow branches to the max budget FOL ( $\leq (B_{Budget}, B_{max}) \Rightarrow Bid$ ) and also to bidding path of attribute ( $f_3, g_2, v_3$ ). For the first bidding path, if  $B_{Budget} \leq$

$B_{max}$  the “true” flow, steps to the bidding expiry rule:  $(\leq (t_{active}, t_{expiry}) \Rightarrow Request\_Bid)$ . If  $t_{active} \leq t_{expiry}$  the FX forms  $(e_c^1(f_1, g_1): Q_c^1(Q_{level}): b_c^1(v_1))$  request bid for e-service  $e_c^1$ . The FX inspects the FOL rule  $(\neg Win\_Before \Rightarrow = (+ (v_x, \varepsilon), v_x) \vee \leq (v_x, U_x))$  in the other bidding path that combines attribute-value  $(f_1, g_1: Q_c: v_1)$  with attribute  $(f_3: g_2: Q_c: v_3)$ . The FOL rule inspects the bidder winning status at repetitive trades and implements reactive strategy. The FOL rule increases the bid valuation  $v_x$  by  $\varepsilon$  in the next trade subject to upper bound  $v_x \leq U_x \in \mathbb{R}_+$  (i.e.,  $v_x = v_1 + v_3 + \varepsilon$ ) is total attribute values that fan-in to the FOL rule. The FX constructs, then, a second request bid  $(e_c^2(f_1, g_1, f_2, g_2): Q_c^1(Q_{level}): b_c^1(v_1 + v_3 + \varepsilon))$  after validating  $t_{active} \leq t_{expiry}$  as shown above. The FX generates, eventually, two request bids for the e-services  $e_c^1$  and  $e_c^1$  :  $(e_c^1(f_1, g_1): Q_c^1(Q_{level}): b_c^1(v_1))$  and  $(e_c^2(f_1, g_1, f_2, g_2): Q_c^1(Q_{level}): b_c^1(v_1 + v_3 + \varepsilon))$ .

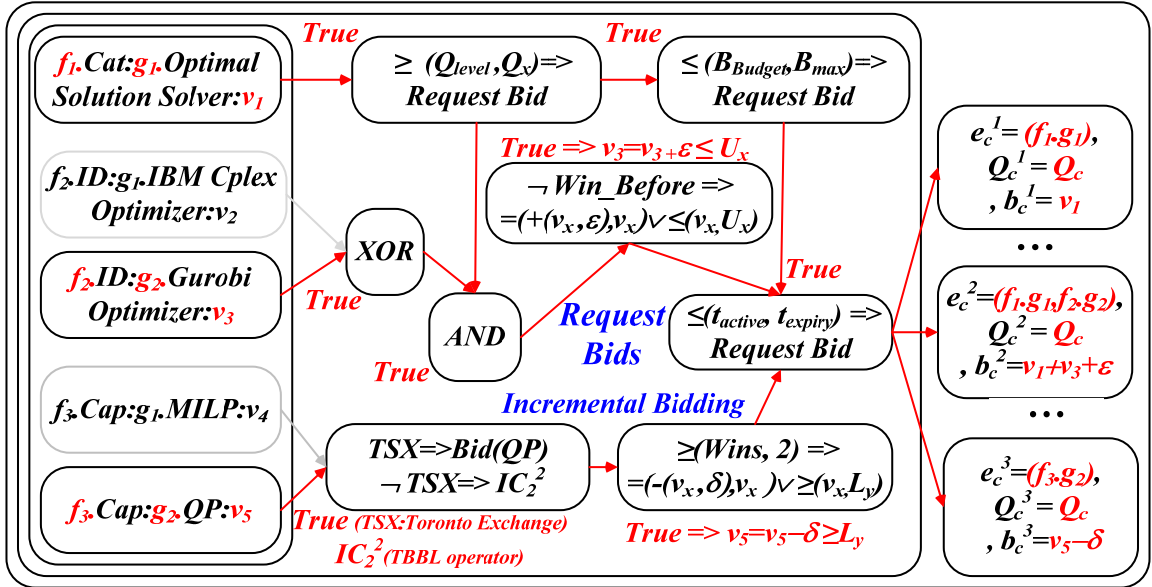


Figure 15: A sample instance of a RBBL bid structure and preference deduction

## 4.5 RBBL Theoretical and Computational Properties

**Proposition 1:** The RBBL logical rules and operator formulae expedites e-market trades.

Our work introduced and analyzed the bidding lifecycle concept that relates to the processes of creation (i.e., bidding), dispatch (i.e., execution) and termination (i.e., expiry) of bids. The bidding lifecycle captures the flow and duration of the trades. The RBBL logical rules and operators expedite the bidding lifecycle for multiple trades due to the automatic deduction and aggregation of logical rules and operators and the formation of the request and ask bids inside the FX system. Our work demonstrates empirically the performance benefits of the rules aggregation in the experimental analysis.

**Proposition 2:** The RBBL subsumes the logical bidding languages (i.e.,  $\mathbb{L}_G, \mathbb{L}_B, \mathbb{L}_{GB}$   $\mathbb{L}_B^{OR}, \mathbb{L}_B^{XOR}, \mathbb{L}_B^{OR*}$ ) and the tree based bidding languages (i.e., TBBL).

The RBBL exploits the DAG model and enables  $\mathbb{L}_{GB}, \mathbb{L}_B^{OR}, \mathbb{L}_B^{XOR}, \mathbb{L}_B^{OR*}$  and TBBL (Cavallo et al., 2005) semantics. For instance, the TBBL  $IC_y^x$  operator is presented as an RBBL rule (i.e.,  $R1: \leq (\text{Active\_Attributes}, y) \vee \geq (\text{Active\_Attribute}, x) \Rightarrow \text{Bid}$ ). The RBBL, otherwise, subsumes  $\mathbb{L}_{GB}, \mathbb{L}_B^{OR}, \mathbb{L}_B^{XOR}, \mathbb{L}_B^{OR*}$ , as shown Figure 13, where the logical operators are utilized concisely. As for the bidding lifecycle, the RBBL lifecycle extend to multiple trades. The TBBL works for single trade; once  $IC_x^y$  is selected for a choice with bounds (Lubin et al., 2008) it cannot change unless reconfigured for new trade.

**Proposition 3:** The RBBL facilitates direct and indirect mechanisms in a single message structure.

The RBBL logical rule formulae may serve for single shot bidding, otherwise for rule-based iterative or incremental. Both scenarios are shown in a single RBBL bidding instance in Figure 13. For the iterative bidding, the bid value is incremented or decremented subject to diverse rule-based inspected situations.

**Proposition 4:** The RBBL allows for capturing the CAP as an integer program (IP).

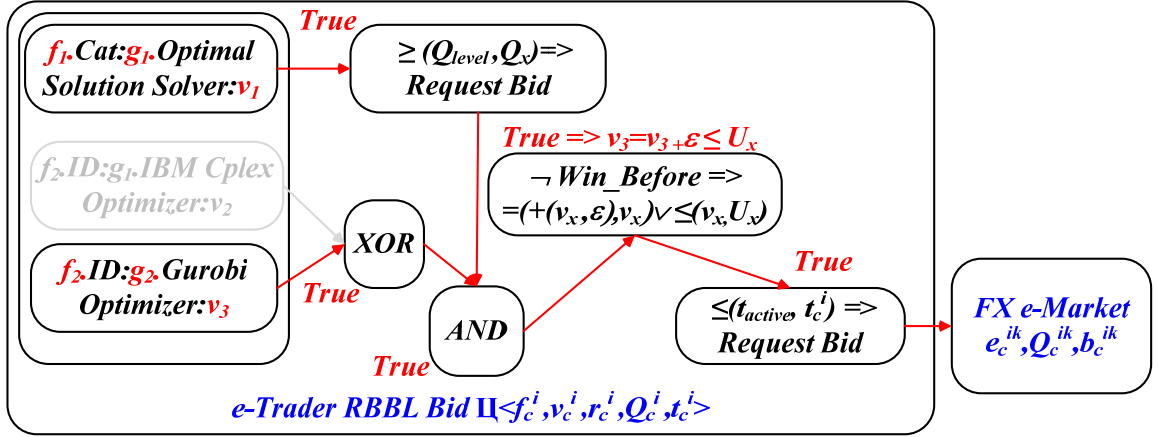
**Proof:** The work in (Boutilier, 2002) defines an IP formation for winner determination using  $\mathbb{L}_{GB}$  and provides positive empirical performance results using a commercial solver. The RBBL enable the free exchange to deliberate on the FOL bidding rules and attribute-

values of the e-services to deduce the e-services and preferences and formulate the request and ask bids. The FX problem model would then reduce to a form that is similar to the  $\mathbb{L}_{GB}$  IP in (Boutilier, 2002) as shown in Figure 13 and Figure 15. Chapter 2 expands on the IP formal modeling. Hence, the computational feasibility translates to the RBBL. Formally, given a request bid RBBL instance  $i$  of consumer  $c$  as shown in Figure 15, the RBBL bid model is  $\prod_c^i \langle f_c^i, v_c^i, r_c^i, Q_c^i, t_c^i \rangle$  where the notations are defined in the problem description. The FX may then deduce the  $(e_c^{ik}, Q_c^{ik}, b_c^{ik})$  for a selected e-service  $e_c^{ik}$  of a particular Q-level  $Q_c^{ik}$  and compute the total bid value  $b_c^{ik}$  of a trade  $\lambda_{tijkq}$  that is the true sum of attribute value RBBL leafs  $(f_c^i, v_c^i)$  and bid value revisions as applied by the active rules of the RBBL internal control nodes  $(r_c^i)$  before expiry  $t_c^i$  (i.e.,  $b_c^{ik} = \sum_k v(f_c^i) + v(r_c^i)$ ). The AE allocative efficiency indicates the set of selected satisfied attribute and control rules provide a max true total bid valuation. Given an RBBL message,  $\prod_c^i \langle \cdot \rangle$  and a bid-value  $b_c^{ik}(e_c^{ik})$  for e-service  $e_c^{ik}$  in trade  $\lambda_{tijkq}$ , let  $sat_c^i(n) \in \{0, 1\}$  denote if the attribute-value leaf or the active rule internal control node  $n$  in the RBBL bid  $i$  of consumer  $c$  (i.e.,  $\prod_c^i \langle \cdot \rangle$ ) is satisfied with if  $sat_c^i = \{sat_c^i(n), \forall n \in \prod_c^i \langle \cdot \rangle\}$ . For  $sat_c^i$  to be eligible for bid,  $\forall \prod_c^i \langle \cdot \rangle, \forall \lambda_{tijkq} \Rightarrow sat_c^i \in valid(\prod_c^i \langle \cdot \rangle, \lambda_{tijkq})$  means a given request (ask) is matched. The total value is the solution to the IP problem:

$$b_c^{ik}(e_c^{ik}) = v_c^{ik} \left( \prod_c^i \langle \cdot \rangle, \lambda_{tijkq} \right) = \max_{sat_c^i \in valid(\prod_c^i \langle \cdot \rangle, \lambda_{tijkq})} \sum_{n \in \prod_c^i \langle \cdot \rangle} v_c^{ik}(n) sat_c^i(n)$$

$$b_p^{jq}(e_p^{jq}) = v_p^{jq} \left( \prod_p^j \langle \cdot \rangle, \lambda_{tijkq} \right) = \min_{sat_p^j \in valid(\prod_p^j \langle \cdot \rangle, \lambda_{tijkq})} \sum_{n \in \prod_p^j \langle \cdot \rangle} v_p^{jq}(n) sat_p^j(n)$$

This formation is equivalent to the IP mode of the original problem model in chapter 2 ■.



**Figure 16: RBBL bid instance for IP analysis**

This chapter presents the RBBL modeling and analysis. The RBBL model exploits the logical rules and operators formulae on the internal control nodes coupled with the semantics for propagating attribute-values leaves within the RBBL DAG structure. The RBBL is inspired by the constant learning of rational bidders throughout their repetitive e-trades. The RBBL facilitates conveying the free bidding strategic conduct using the logical rules and operators formulae. The logical rules expedite e-market trades due to automatic deduction of the rules, operators and attribute-values to construct the selected e-services and to form the relevant request and ask bids. The RBBL allows for symmetric bidding of consumers and providers with unique valuations of factor-group e-service attributes that include multiple Q-levels. For an ad problem, the attribute may be an age group, location or interest. For a software app, the attribute can be e-service ID, capability, category, etc. The RBBL subsumes other logical bidding languages and is suitable for direct and indirect mechanisms. It allows, also, for capturing the CAP as an integer program (IP) for winner determination problem.

## Chapter 5

### 5 GSPM Double Auction Mechanism

Our work targets a tractable GSP based DA approach that delivers truthful, efficient and stable matching with the proposed free exchange e-marketplace profitability. The GSPM DA exploits the multiple Q-levels cross-matching heuristics for a class of decentralised CAP of multiple units of a single e-service of distinct attribute-values and multiple Q-levels. The RBBL allows for a unique valuation of each attribute while conveying the logical rules in the bidding structure. The free exchange employs the rules deduction, aggregation and formation on the stored attribute-value attributes of the RBBL to generate the multiple request and ask bids for a specific trade. Our work is motivated by the fact while GSP is not IC, the GSP repeated best response strategies (BBS) always converge to NE with VCG AE IC outcomes and payments, as analyzed and validated in (Edelman & Ostrovsky, 2007) (Varian, 2007) and (Nisan et al., 2011). The GSPM exploits the efficient GSP auction and the Nash stability of GSP repeated best response auction. The GSPM is tractable of polynomial time complexity. In fact, the best response strategy is, evidently, the rational strategic reaction to constant learning at repetitive trades that transform private settings to complete information stability.

The GSPM DA follows the EM for single Q-level matching allocation while it applies the GSP discriminatory DA price matching model that exploits the forward and reverse GSP auctions as described in later sections. The GSPM pricing model narrows down the valuation preferencing space of request (ask) bidders to the second price in descending (ascending) order that results in AE, particularly, in thick e-market repetitive trades, while securing e-market profitability. However, while the single Q-level GSPM DA is AE, it might not be IC for multiple units of single items (McAfee, 1992) (Wurman et al., 1998). The IC challenge of single Q-level GSPM DA inspires designing the multiple Q-level mechanism that motivates the IC of bidders through their desire to be winners in the

narrower, more competitive Q-levels, in addition to the prospect that their true valuations might win them a higher Q-level e-service item in the multiple Q-level cross-matching.

This chapter presents the different single Q-level and multiple Q-levels GSPM and EM DA algorithms. The chapter covers also the game-theoretic and computational properties of the GSPM DA mechanisms as well as the simulation algorithmic structure.

## 5.1 Exchange Mechanisms

The exchange mechanisms are emerging e-trading models for e-marketplaces that enable consumers to target potential users for, often, spontaneous impact throughout interactive user engagement and rational configuration. The exchange brings efficiency by eliciting prices, aggregating information, matching trades, and generating capital. The Facebook FBX, Google DoubleClick, Yahoo RMX, and Microsoft ad Exchange are few examples of the exchange e-marketplaces. The objective of the exchange mechanism is the stable and socially efficient matching allocation and pricing of the e-services. That, often, involves the rational self-interested agents of both providers and consumers (bidders). The bidders interact and collaborate probably at real-time given, often, their competitive local objectives to accept at equilibrium a system-wide outcome that satisfies them. The decentralized collaboration cannot, however, be modeled and implemented using the centralized models. This is due to the inherent challenges that tackle the decentralized and often conflicting local objectives of rational bidders, their constraints, preferences and valuations, decision making, self-interest, truth revelation and strategic conduct.

Building an efficient exchange, hence, is a daunting task. The large number of e-service providers and consumers that bid for the e-services at real-time by interacting with is a key challenge that strains, considerably, the computational resources of e-marketplaces. The present exchange e-marketplaces would, often, tackle those challenges, for bounded rational agents in rather constrained non-strategic settings. However, the e-marketplaces are typically challenged with issues related to the decentralized game-theoretic stability and social efficiency amongst rational bidders on top of the computational efficiency.

## 5.2 GSPM and EM Double Auction Mechanisms

As shown Figure 17 and Figure 18, the GSPM DA allocation rule follows the Equilibrium Matching (EM) (Wurman et al., 1998) for single Q-level and multiple Q-levels settings. Hence, our work examines the single Q-level EM DA (see Figure 19). The proposed Single Q-level GSPM DA pricing rule exploits the GSP forward auction for buyers (Varian, 2007) (Edelman et al., 2007) and reverse-GSP auction for sellers. The forward and reverse GSP DA narrows down the pricing tolerance of request and ask bidders to the second price in rank that improves stable efficiency, particularly, in thicker e-markets, while securing e-market profitability. The fact while the single Q-level GSPM and EM DA mechanisms are AE, it might not be IC for multiple units of single items, inspires designing the multiple Q-level GSPM and EM DA mechanisms for the class of multiple units of multiple Q-level items that motivates IC. The bidders IC is motivated by their desire to be winners in the narrower Q-level category, in addition to the prospect their true valuations might win bidders even a higher Q-level item in the cross-matching phase. Our work maintains, though, that the partial information revelation of bidders converge to complete information settings at best response strategist to repetitive trades that translates eventually, to a stable efficiency for all mechanisms subject to the best rational reaction of bidders to their dynamic states. This is formally analyzed in (Nisan et al., 2011). It is, also, validated through our experimental analysis. Figure 18 and Figure 20 presents the multiple Q-level GSPM and EM DA mechanisms.

### 5.2.1 Single Q-level GSPM Double Auction Mechanism

The single Q-level GSPM DA follows the EM DA (Wurman et al., 1998) in computing the matching allocations. However, our work proposes a forward-GSP auction pricing rule for buyers, and a reverse-GSP auction pricing rule for sellers for the multiple units of a single-item of multiple attributes as shown in Figure 17, steps are as follows:

- 1) Qualify request and ask bids' eligibility by fetching and grouping bids of identical e-service attributes (i.e.,  $e_c^{ik} = e_p^{jq}$ ).
- 2) Sort the eligible asks  $b_p^{jq}$  in ascending order for forward-GSP auction and sort the

- eligible bids  $b_c^{ik}$  in descending order for reverse-GSP auction with respect to request and ask values.
- 3) Matching: start at the top, add ask-request pairs to the matched list, if request-bid price  $b_c^{ik} \geq b_p^{jq}$  ask-bid price.
  - 4) Compute the GSPM allocations and assign matched pairs  $(e_c^{ik}, e_p^{jq})$  to the winning buyers  $C_i$  and sellers  $P_j$ .
  - 5) Assign prices such that  $p_c^{ik} = b_c^{ik+1}, c_p^{jq} = b_p^{jq+1} \forall p_c^{ik}, c_p^{jq} \in \{\mathbb{R}_+, 0\}$ . Every bid winner pays the second price below him in the bids ordered list, while every ask winner collects the second price below him in ordered list. For the last pair, if matched:  $p_c^{in} = b_c^{in}, c_p^{jn} = b_p^{jn}$ . Ask or bid bidders pays his bid or collects his ask.

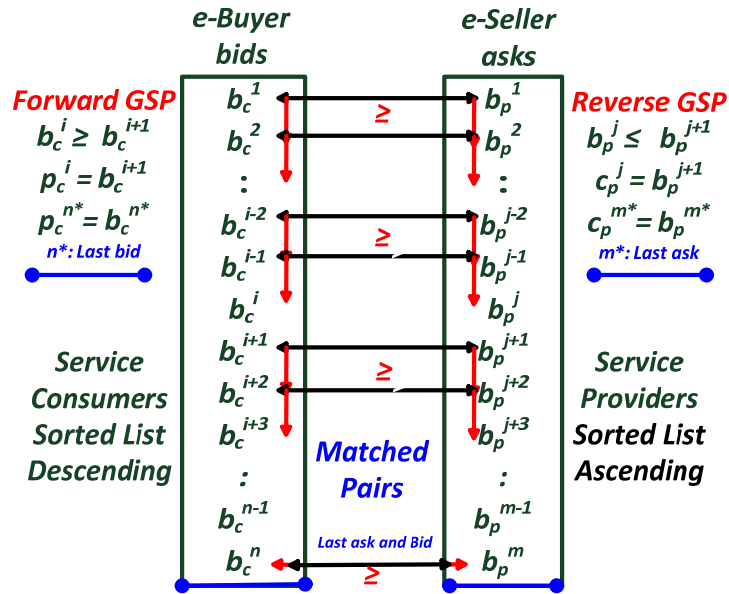


Figure 17: Single Q-level GSPM DA mechanism

### 5.2.2 Multiple Q-levels GSPM Double Auction Mechanism

The multiple Q-levels GSPM DA computes the allocation and pricing rules for multiple units of a single-item of multiple attributes, and multiple Q-levels. While the ask bidders offers the same particular e-service item, items are distinct in the assigned Q-levels. The bid bidders request the same e-service item, however, they are different in their minimum

requested Q-levels. The multiple Q-level GSPM sorts the Q-levels and applies a *multilevel cross-matching allocation* as shown Figure 18:

- 1) Sort Q-levels in descending order starting with the highest.
- 2) Group the request and ask bids based on sorted Q-levels such that  $\forall e_c^{ik} = e_p^{jq}, \min Q_c^{ik} = Q_p^{jq} = Q_m; \forall Q - level = Q_m$ .
- 3) For each Q-level, qualify the item eligibility by identifying and grouping the eligible requests and asks of identical e-service item attributes (i.e.,  $e_c^{ik} = e_p^{jq}$ ).
- 4) For each Q-level, sort the eligible asks  $b_p^{jq}$  in ascending order for forward-GSP auction and the eligible bids  $b_c^{ik}$  in descending order for reverse-GSP auction.
- 5) Start at the top of first highest Q-level list in rank (i.e.,  $Q - level = Q_{max}$ ). Add the ask-bid pairs to the matched list if  $b_c^{ik} \geq b_p^{jq} \wedge \min Q_c^{ik} = Q_p^{jq} = Q_m$ .
- 6) Step to the next lowest Q-level in rank  $Q - level = Q_{m-1}$ . Consider the unmatched asks  $\overline{b_p^{jq}}$  of the same or higher Q-levels from previous steps (i.e.,  $\overline{Q_p^{jq}} \geq Q_{m-1}$ ). Add the ask-bid pairs to the matched list if  $b_c^{ik} \geq \overline{b_p^{jq}} \wedge \min Q_c^{ik} \leq \overline{Q_p^{jq}}$ .
- 7) The chance of winning higher Q-level e-services motivates the IC truthful revelation of the consumers. The providers' IC is driven by getting more prospective consumers.
- 8) Compute the matching allocations and assign the matched pairs  $(e_c^{ik}, e_p^{jq})$  to the winning buyers  $C_i$  sellers  $P_j$ .
- 9) At each Q-level, apply the GSPM pricing rule, as in single Q-level  $p_c^{ik} = b_c^{ik+1}, c_p^{jq} = b_p^{jq+1} \forall p_c^{ik}, c_p^{jq} \in \{\mathbb{R}_+, 0\}, \forall Q$ . For the last pair in each Q-level, if matched, then  $p_c^{in} = b_c^{in}, c_p^{jn} = b_p^{jn}$ . every bidder pays his bid or collects his ask.

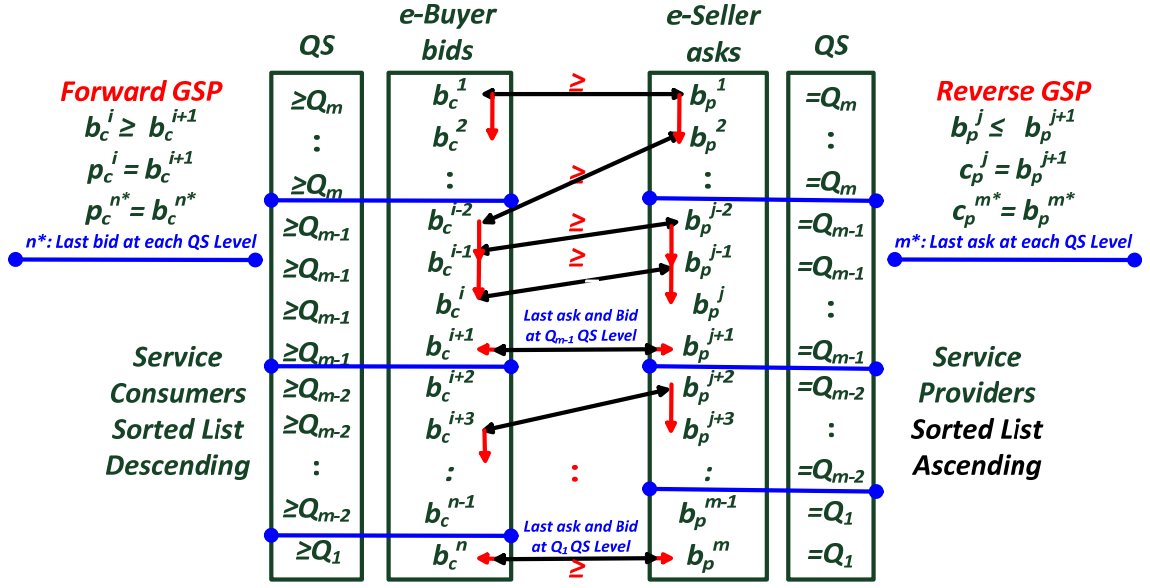


Figure 18: Multiple Q-level GSPM double auction

### 5.2.3 Single Q-level EM Double Auction Mechanism

The single Q-level  $M^{\text{th}}$  EM DA follows (Wurman et al., 1998) in computing the matching allocation and the  $M^{\text{th}}$  pricing (last matched ask price) rule (see Figure 19) for multiple units of a single-item of multiple attributes of a single Q-level. The work use this base models for the proposed multiple Q-level, EM DA. The following steps describe the single Q-level  $M^{\text{th}}$  EM DA:

- 1) Qualify the eligibility by identifying and grouping the request and ask of identical e-service item attributes (i.e.,  $e_c^{ik} = e_p^{jq}$ ).
- 2) Sort the eligible asks  $b_p^{jq}$  in ascending order and sort bids  $b_c^{ik}$  in descending order.
- 3) Process the matching: start at the top, add the ask-request pairs to the matched list, if the bid price  $b_c^{ik} \geq b_p^{jq}$  more or equal the ask price for the eligible pairs.
- 4) Compute the matching allocation list and assign matched pairs  $(e_c^{ik}, e_p^{jq})$  to the winning buyers  $C_i$  and sellers  $P_j$ .
- 5) Compute the EM  $M^{\text{th}}$  equilibrium pricing rule  $b_p^M$  as the last matched ask price (i.e.,  $b_p^M = b_p^{j+3}$ ). Assign prices such that  $p_c^{ik} = c_p^{jq} = b_p^M \forall p_c^{ik}, \forall c_p^{jq} \in \{\mathbb{R}_+, 0\}$ .

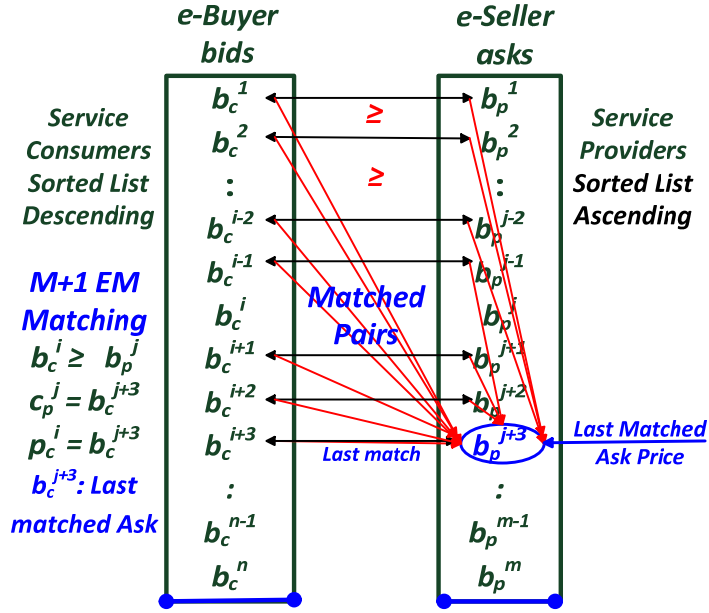


Figure 19: Single Q-level  $M^{\text{th}}$  EM double auction

#### 5.2.4 Multiple Q-level $M^{\text{th}}$ EM Double Auction Mechanism

Our work extends the single Q-level  $M^{\text{th}}$  EM and proposes a multiple Q-level EM DA that exploits a multiple EM points for the multiple Q-levels in computing the allocations and the pricing. The multiple Q-level,  $M^{\text{th}}$  EM DA follows the matching allocation of the multiple Q-level, GSPM DA. The multiple Q-level  $M^{\text{th}}$  EM DA applies a multiple cross-level matching allocation as described below and shown in Figure 20. The following steps describe the subject multiple Q-level  $M^{\text{th}}$  EM DA mechanism:

- 1) Sort the Q-levels in descending order.
- 2) Group all request and ask bids based on the sorted Q-levels such that  $\forall e_c^{ik} = e_p^{jq}, \min Q_c^{ik} = Q_p^{jq} = Q_m; \forall Q - \text{level} = Q_m$ .
- 3) For each Q-level, qualify the eligibility by identifying and grouping the eligible requests and asks of identical e-service item attributes (i.e.,  $e_c^{ik} = e_p^{jq}$ ).
- 4) For each Q-level, sort the eligible asks  $b_p^{jq}$  in an ascending order and the eligible bids  $b_c^{ik}$  in a descending order.
- 5) Start at the top of the highest Q-level in rank ( $Q = Q_{\max}$ ). Add the ask-bid pairs to the matched list if  $b_c^{ik} \geq b_p^{jq} \wedge \min Q_c^{ik} = Q_p^{jq} = Q_m$ .

- 6) Step to the next lower Q-level in rank ( $Q = Q_{m-1}$ ). Consider all unmatched asks  $\overline{b_p^{jq}}$  of the same or higher Q-levels (from pervious steps) (i.e.,  $\overline{Q_p^{jq}} \geq Q_{m-1}$ ). Add the ask-bid pairs to the matched list if  $b_c^{ik} \geq \overline{b_p^{jq}} \wedge \min Q_c^{ik} \leq \overline{Q_p^{jq}}$ .
- 7) Compute the matching allocations and assign the matched pairs  $(e_c^{ik}, e_p^{jq})$  to the winning buyers  $C_i$  and sellers  $P_j$ .
- 8) Within each  $Q = Q_m$  level, apply the  $M^{\text{th}}$  price rule (last matched ask price) such that  $p_c^{ik} = c_p^{jq} = b_p^M \forall p_c^{ik}, \forall c_p^{jq} \in \{\mathbb{R}_+, 0\}, \forall \min Q_c^{ik} = Q_p^{jq} = Q_m$ . The  $M^{\text{th}}$  price  $b_p^M$ , is the last matched ask price. For instance, as shown in Figure 20, there are multiple EM points (i.e.,  $(b_p^2, Q_m), (b_p^{j+1}, Q_{m-1}), (b_p^{j+2}, Q_{m-2}), (b_p^m, Q_1)$ ). In the case that the matching occurs at multiple Q-levels (i.e.,  $(b_c^{i-2}, Q_{m-1})$  and  $(b_p^2, Q_m)$ ), then apply the multiple Q-level cross matching allocation (i.e.,  $p_c^{i-2} = b_p^2$ ) that is the  $M^{\text{th}}$  matching price of  $Q_m$  level.

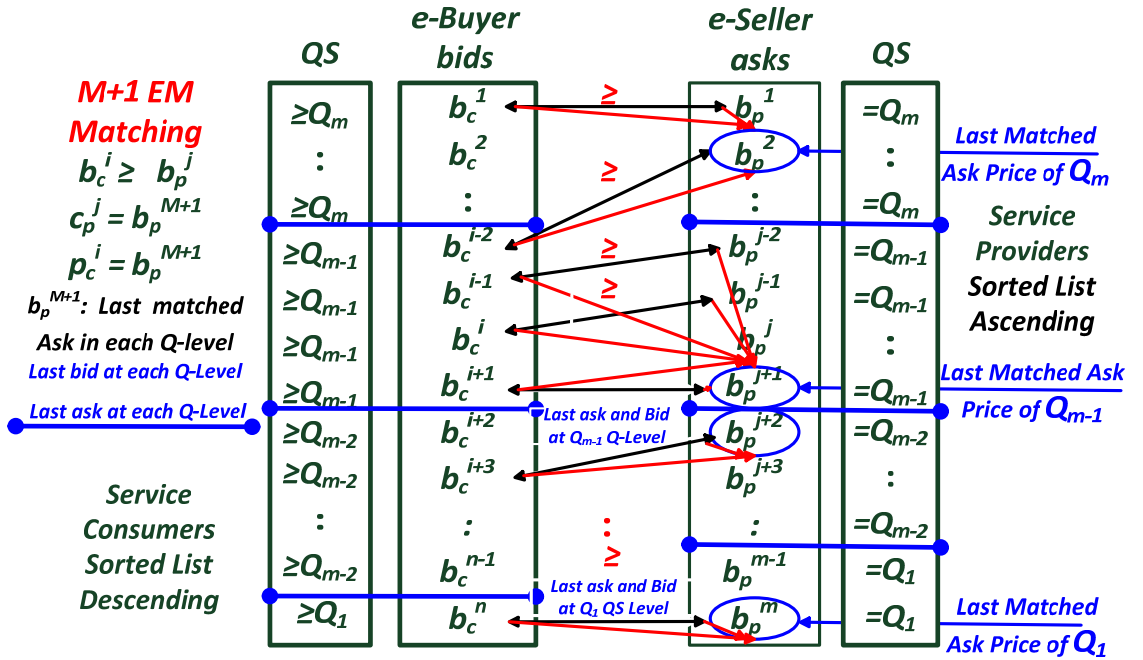


Figure 20: Multiple Q-level  $M^{\text{th}}$  EM double auction

### 5.3 GSPM Economic and Computational Properties

**Definition 1:** [GSPM and EM allocation rule]: Let  $P \cup C$ , the set of exclusive request and ask bidders  $P \cap C = \emptyset$  as per the problem model assumption. Let  $\mathfrak{B} = \mathfrak{B}_P \cup \mathfrak{B}_C$  the

set of eligible provider asks  $b_p^{jq} \in \mathfrak{B}_p$  and consumer bids  $b_c^{ik} \in \mathfrak{B}_c$  of the same offered and requested e-service (i.e.,  $e_c^{ik} = e_p^{jq}$ ) except for their Q-levels. Sort Q-levels in descending order and group bids  $b_p^{jq}$  and asks  $b_c^{ik}$  based on the sorted Q-levels such that,  $\forall e_c^{ik} = e_p^{jq}$ ,  $\min Q_c^{ik} = Q_p^{jq} \forall Q = Q_m$  (i.e.,  $\min Q_c^{ik} = Q_p^{jq} = Q_m$ ). Then sort bids (asks) in descending (ascending) order within each Q-level. Start at the top of the list of the highest Q-level (i.e.,  $Q_m = Q_{max}$ ). Add the ask-bid pairs to a particular Q-level matched list  $\mathfrak{M}_m$  if  $b_c^{ik} \geq b_p^{jq} \wedge \min Q_c^{ik} = Q_p^{jq} = Q_m$ . Step to the next Q-level (i.e.,  $Q = Q_{m-1}$ ). Consider unmatched asks  $\overline{b_p^{jq}}$  of the same or higher Q-levels (i.e.,  $\overline{Q_p^{jq}} \geq Q_{m-1}$ ). Add the ask-bid pairs to the matched list  $\mathfrak{M}_{m-1}$  if  $b_c^{ik} \geq \overline{b_p^{jq}} \wedge \min Q_c^{ik} \leq \overline{Q_p^{jq}}$  and so on until all eligible bids are matched.

**Definition 2:** [GSPM pricing rule]: the seller ask price for  $m \in \{1 \dots M - 1\} < M$  matched pair within any particular Q-level is  $p_p(b_p^m, b_c^m) = b_p(b_p^{m+1})$ , the price of the second lower seller ask in rank ( $b_p^{m+1}$ ). The buyer bid price for a matched pair is  $p_c(b_p^m, b_c^m) = p_c(b_c^{m+1})$ , the price of second lower buyer bid in rank ( $b_c^{m+1}$ ). For the last match in a particular Q-level  $m = M$ , buyers and sellers pay their exact request and ask  $p_p(b_p^M, b_c^M) = p_p(b_c^M)$ ; and  $p_c(b_p^M, b_c^M) = p_c(b_c^M)$ .

**Definition 3:** [Single Q-Levels EM  $M^{\text{th}}$  Pricing Rule]: the ask-bidder price for  $m \in \{1 \dots M\}$  matched pair within a particular Q-level is  $p_p(b_p^m, b_c^m) = p_p(b_p^M)$ , the ask price of the last matched pair ( $b_p^M$ ) within the Q-level. The request-bidder price for a matched pair is  $p_c(b_p^m, b_c^m) = p_c(b_p^M)$ , the ask-price of the last matched pair ( $b_p^M$ ) within the Q-level.

**Definition 4:** [Multiple Q-Levels EM  $M^{\text{th}}$  Pricing Rule]: the ask-bidder price for  $m \in \{1 \dots M\}$  matched pair within a particular Q-level (i.e.,  $Q_p^m = Q_c^m$ ) is  $p_p(b_p^m, b_c^m) = p_p(b_p^M)$ , the ask price of the last matched pair ( $b_p^M$ ) within  $Q_p^m = Q_c^m$  Q-level. The request-bidder price for a matched pair is  $p_c(b_p^m, b_c^m) = p_c(b_p^M)$ , the ask-price of the last matched pair ( $b_p^M$ ) within  $Q_p^m = Q_c^m$  Q-level. For the multiple Q-levels cross-matching

cases (i.e.,  $((b_p^m, Q_p^{m+r}) (b_c^m, Q_c^m))$ ,  $m, r$  are integers.  $p_p(b_p^m, b_c^m) = p_c(b_p^m, b_c^m) = p_p(b_p^{M'})$  the ask price of the last matched pairs of the higher Q-level  $Q_p^{m+r}$  for requests and asks.

**Theorem 1:** The VCG mechanisms (Vickrey, 1961) (Clarke, 1971) (Groves, 1973) are the only AE and SP mechanisms for bidder agents with quasi-linear preferences and general valuation functions amongst direct revelation mechanisms.

**Theorem 2:** The GSPM DA mechanism is allocative efficient (AE). The GSPM DA maximizes the aggregate utilities of request and ask bidders by maximizing the aggregate bid values of buyers and minimizing the aggregate ask values of sellers.

*Proof:* Consider a set of matching allocations  $\mathcal{K}$  for buyer agents  $j$  of quasi-linear utility  $u_j(k, p_j, \theta_j) = v_j(k, \theta_j) - p_j \geq 0; \forall v_j(\cdot)$  is buyer  $j$  bid value for the matching allocation  $k \in \mathcal{K}; \forall p_j$  is buyer  $j$  payment given type  $\theta_j \in \Theta_j$ . Let seller agents  $i$  utility  $u_i(k, c_i, \theta_i) = c_i - v_i(k, \theta_i) \geq 0; \forall v_i(\cdot)$  is seller  $i$  ask value for allocation  $k \in \mathcal{K}, \forall c_i$  is seller  $i$  collection given type  $\theta_i \in \Theta_i$ . Then, the social choice exchange mechanism outcome  $g(\hat{\theta}) = (k(\hat{\theta}), p(\hat{\theta}))$  is AE,  $\forall$  matching rule  $k: \Theta_1 \times \dots \times \Theta_l \rightarrow \mathcal{K}, \forall$  pricing rule  $p_i, c_j: \Theta_1 \times \dots \times \Theta_l \rightarrow \mathbb{R}$ , and reported types  $\hat{\theta} = (\hat{\theta}_1 \dots \hat{\theta}_l)$  iff:

$$k^*(\hat{\theta}) = \arg \max_{k \in \mathcal{K}} \sum_j v_j(k, \hat{\theta}_j) + \arg \min_{k \in \mathcal{K}} \sum_i v_i(k, \hat{\theta}_i) \quad \forall k \in \mathcal{K}$$

$$k^*(\hat{\theta}) = \arg \max_{k \in \mathcal{K}} \left( \sum_j v_j(k, \hat{\theta}_j) - \sum_i v_i(k, \hat{\theta}_i) \right), \forall k \in \mathcal{K}$$

Following the above analysis, and as presented in chapter 2, given an instance  $FX(b, Q, \lambda, \tau_t)$  at period  $\tau_t$ , then the GSPM AE  $\lambda_t^*$  trade maximizes the collective bid values of buyers (i.e.,  $v(e_c^{ik}) = b_c^{ik}$ ), and minimizes the collective ask values of sellers (i.e.,  $v(e_p^{jq}) = b_p^{jq}$ ) at multiple Q-levels. The above equations are equivalent to

equation (2) as shown in chapter 2. The AE social welfare objective of the CAP in (2) maps, hence, to maximizing the total utilities the net FX e-market profit.

**Forward-GSP auction max bid valuations:** A max buyer bid is her true value for a matching allocation. The buyer often strategizes by shading (lowering) her true bid value to increase utility. Consider the case of a unit-demand forward-GSP auction of a single Q-level e-service (i.e., similar factor-groups, from multiple sellers), then under the GSP auction rule, the best-response strategies of bidders converge to VCG efficient outcome, which is the only AE SP for agents with quasi-linear preferences (Edelman et al., 2007) (Varian, 2007) (Nisan et al., 2011)(see Theorem 1). The best-response true bids guarantee higher positions in the matched list that allow for the best winning chance while paying a lower second bid price in order. Also, bidders may risk losing possible matching allocation if they lower prices below the lowest matched pair. Furthermore, in the multiple Q-level matching, bidders would have a chance to win a better e-service item of higher Q-level using the multiple Q-levels cross-matching. In Definition 2, the  $m^{th}$  highest buyer bid  $b_c^m$  and charged  $p_c^m = b_c^{m+1}$  for a winning match. Her utility  $u^*(m) = b_c^m - p_c^m = b_c^m - b_c^{m+1} \geq 0$  since  $b_c^m \geq b_c^{m+1}$ . There is also no incentive if the  $m^{th}$  bidder switches bids with the one above her in rank  $u(m) = b_c^m - p_c^{m-1} = b_c^m - b_c^m = 0 \leq b_c^m - b_c^{m+1}$ . Hence, the GSPM achieves maximum (max) true bids for buyers at best response strategies.

**Reverse GSP auction minimum ask valuations:** a min seller ask is her true cost for a matching allocation. The seller often strategizes by shading (rising) her true cost value to increase utility. The AE Reverse GSP auction of the min ask bidders is equivalent to the AE Forward GSP auction of the max bid bidders as presented in chapter 2. hence the same argument of the forward GSP auction is applied. The best-response true asks guarantee higher positions in the matched list that allow for best winning chance, while collecting a higher second ask price in order. Also, the ask sellers may risk losing possible matching allocation if they raise prices higher than the highest matched pair. Moreover, in the multiple Q-level matching, the sellers would have a better chance to win a buyer from the lower Q-levels using the multiple Q-levels cross-matching■.

**Definition 5:** [Nash Equilibrium (NE)]: the NE “Symmetric NE (Varian, 2007)” of the simultaneous move game induced by the GSP auction is locally envy-free if an ask or bid bidder cannot improve her payoff by exchanging bids or asks with the bidder ranked one position above her” (Edelman et al., 2007).

**Theorem 3:** The GSPM DA has NE with VCG AE outcomes in IC manner with repeated best response.

**Proof:** consider the forward and reverse unit-demand GSP auctions for AE max bid buyers and min ask sellers. Using the analysis of (Edelman et al., 2007) for envy-free Nash equilibrium that is equivalent to the “Symmetric NE” (Varian, 2007) and the analysis in (Nisan et al., 2011), though IC is not dominant strategy under GSP, the full information GSP auction of the locally envy-free bidders and repeated best response strategies converges to NE with VCG AE outcomes in IC manner. In the GSP auction, there is no strategy profile from which all players but one do not wish to deviate and that strictly prefers to NE reached if all players follow the repeated best-response strategies, a necessary argument to establish the IC of best-response GSP auctions (i.e.,  $\nexists$  state  $s = (s_1, \dots, s_n) \in S$ , and player  $i \in [m]$  such that  $\forall j \neq i$ ,  $s_j$  is a best-response to  $s$  and  $u_i(s) > u_i(NE)$ ). In fact, unstable bidders would pay a price as high as the payment of the bidder who gets it in the VCG outcome, and thus, the unstable bidder would prefer to be allocated it in the VCG outcomes that require the IC of players. In GSPM DA if any buyer or seller agent  $i$  maximizes expected utility with strategy  $s_i$ , given its preferences and strategy of other agents then the strategy profile  $s = (s_1, \dots, s_l)$  is at NE state (Nash Jr., 1951), at which  $u_i(s_i(\theta_i), s_{-i}(\theta_{-i}), \theta_i) \geq u_i(s'_i(\theta_i), s_{-i}(\theta_{-i}), \theta_i), \forall s'_i \neq s_i$ . NE in GSPM requires every agent have perfect information about preferences of every other agent, agent rationality, and agents must all select the same Nash equilibrium ■.

**Definition 6:** [budget-balance (BB)] A social choice matching function  $g(\hat{\theta}) = (k(\hat{\theta}), p(\hat{\theta}))$  is FX *post* BB if  $\forall$  preferences  $\hat{\theta} = (\hat{\theta}_1 \dots \hat{\theta}_l): \sum_{i=1}^l p_i(\hat{\theta}) = 0$ ; no into or out transfers to the exchange. The AE and BB imply Pareto optimality. The  $g(\hat{\theta})$  is FX *post* weak BB if  $\forall \hat{\theta}: \sum_{i=1}^l p_i(\hat{\theta}) \geq 0$ ;

**Theorem 4:** The GSPM DA is *weak BB* that secures e-market profitability and grows with thick trades.

**Proof:** In theorem 1, the AE social matching objective of the GSPM DA in of equation (2) maps to maximizing the net FX e-market profit  $\max_{\lambda_t^Q} \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^{ic} \sum_{q=1}^{jp} \lambda_{tijkq}^Q (p_c^{ik} - c_p^{jq}) \geq 0$  that is always positive, as the GSPM DA requires that  $p_c^{ik} \geq c_p^{jq}$  as a condition for matching. As per Definition 1, the eligible criteria of the GSPM matching (i.e.,  $e_c^{ik} = e_p^{jq} \wedge Q_c^{ik} \geq Q_p^{jq}$ ) is that  $b_c^{ik} \geq b_p^{jq}$ . However, as per the GSPM pricing rules of Definition 2:  $b_c^{ik} \geq p_c^{ik}(= b_c^{ik+1})$  for second bid in rank and  $p_c^{ik}(= b_c^{ik+1}) \geq c_p^{jq}(= b_p^{jq+1})$  for matching state, then  $p_c^{ik} \geq c_p^{jq}$ . Hence, the GSPM DA maximizes the e-market profitability that grows thicker e-market trades. As  $b_p^{m+1} \geq b_c^{m+1}$  based on the matching rule requirement, the e-market profit is  $\sum_{i=m} p_i(\hat{\theta}) = b_p^{m+1} - b_c^{m+1} \geq 0, \forall m$ . For the last match  $M$ , the buyer (seller) pays (collects) his bid (ask). ■

**Definition 6 [Bidder Rationality (IR)]:** A mechanism  $\mathcal{M}$  is IR if for all preferences  $\theta_i$  it implements a SCF  $f(\theta)$  with  $u_i(f(\theta_i, \theta_{-i})) \geq \bar{u}_i(\theta_i)$ ,  $u_i(f(\theta_i, \theta_{-i}))$ , is the expected utility for agent  $i$  at outcome, given prior beliefs about others preferences distribution  $\theta_{-i}$  and  $\bar{u}_i(\theta_i)$  is the expected utility for non-participation.  $\mathcal{M}$  is ex post IR if an agent can withdraw once learns the outcome, in which expected utility from participation must be at least its best outside utility for all possible types of agent.

**Theorem 5:** The GSPM DA is ex-post Bidder Rational (IR), VCG AE and SP with quasi-linear agent preferences monotonic choice-set and no negative externalities.

**Proof:** The GSPM, VCG based exchange is IR when two sufficient conditions hold on agent preferences (Parkes, 2001): (1) Choice set monotonicity: feasible choice set  $\mathcal{K}$  increases as more agents introduced; means an agent cannot “block” a selection, and (2) No negative externalities: Agent  $i$  has non-negative value, i.e.,  $v_i(k_{-i}^*, \theta_j) \geq 0$ , means any choice not involving an agent has a neutral (or positive) effect on that agent. To show ex post IR, the utility to agent  $i$  in the VCG equilibrium outcome of the GSPM must always be non-negative, given IC in equilibrium. The utility to agent  $i$  with type  $\theta_i$  is:

$$u_i(\theta_i, \theta_{-i}) = v_i(k^*(\theta), \theta_i) - \left( \sum_{j \neq i} v_i(k_{-i}^*(\theta_{-i}), \theta_j) - \sum_{j \neq i} v_j(k^*(\theta), \theta_j) \right)$$

$$u_i(\theta_i, \theta_{-i}) = \sum_i v_i(k^*(\theta), \theta_i) - \sum_{j \neq i} v_i(k_{-i}^*(\theta_{-i}), \theta_j) = V^* - (V_{-i})^*$$

$V^* - (V_{-i})^*$  is non-negative because the value of the AE solution without agent  $i$ ,  $V_{-i}$  cannot be greater than the value of the AE solution with agent  $i$   $V^*$ , as any choice with agents  $j \neq i$  is also feasible with all agents (monotonicity), and has just as much total value (no negative externalities). ■

## 5.4 GSPM and EM Algorithmic Structure

The GSPM Algorithms follow the free market economy model and compute different cost or payment prices for the matched winners. The multiple Q-levels e-services CAP extends the complexity of the multiple-unit auction, as the cross-matching are dependent. The bidders might be assigned an e-service of the same Q-level or higher contrary to the independent multiple unit demand auctions. The simulation model allows for repetitive trades, in which the FX applies the stored RBBL logical rules and operators for preference deduction and request and ask bid formation at each trade to capture the bidder dynamic reactions to disruptions at constant learning. Request and ask bids are either bounded by the min/max true attribute valuations or unbounded.

The implemented algorithms and the activity flow structure of the simulated GSPM and EM double auction mechanisms includes: (1) initial non repetitive setting stage that instantiates the simulation code variables, generates the random true and first traded requests and asks with random Q-levels, and implements the GSPM/EM e-trading algorithms for the non-repetitive stage, and (2) repetitive e-trading stage that reevaluates the requests and asks based on the same instance of logical bidding rules of bidders. The rules examine the current and previous win and lose states of all bidders and compute accordingly the next move of request and ask revaluation. The stage implements, then,

the GSPM/ EM e-trading algorithms, repetitively until the last preset trades (i.e., twenty trades). The outline of the algorithmic flow model of the two stages is tabled as followed:

### **I. The Initial Settings Stage**

- Generate the initial true ask and request bid valuations. *(All Algorithms)*
- Generate the initial random traded bids. *(All Algorithms)*
- Generate the random Q-levels for all bids. *(Multiple Q-level Algorithms)*
- Generate the random Q-levels for all bids. *(Single Q-level Algorithms)*
- Sort Q-levels in descend order. Group, then, the true and traded requests and asks of each Q-level according to the sorted Q-levels. *(All Algorithms)*
- Sort the true and traded requests and asks of each Q-level group. *(All Algorithms)*
- Matching allocation for true and traded requests and asks. *(All Algorithms)*
- GSPM Pricing and Metrics of true bids without learning.
- EM Pricing and metrics for true bids without learning.

### **II. The Repetitive e-Trading Stage with RBBL and GSPM Simulated Dynamics:**

- GSPM Pricing and Metrics of Single/Multiple Q-level bids and Learning.
- EM M Pricing and Metrics of Single/Multiple Q-level bids and Learning.
- Scenario#1: local rules inside FX update bids. *(Unbounded Algorithms)*
- Scenario#1: local rules inside FX update bids. *(Bounded Algorithms)*
- Scenario#2: bidders' remote rules update bids. *(Unbounded Algorithms)*
- Scenario#2: bidders' remote rules update bids. *(Bounded Algorithms)*
- Scenario#3: FX aggregated rules update bids. *(Unbounded Algorithms)*
- Scenario#3: FX aggregated rules update bids. *(Bounded Algorithms)*
- Sort Request and ask of each Q-level Group. *(All Algorithms)*
- Matching allocation algorithm for true and traded bids. *(All Algorithms)*
- Table winners and losers status change for next trades. *(All Algorithms)*

The GSPM DA implements the SORT() algorithm in Appendix A on randomly generated true initial requests and asks and randomly generated traded requests and asks, derived from the true requests and asks. There are also the related randomly generated Q-levels. The SORT() algorithm: (1) sort Q-levels in descending order, (2) group true and traded requests and asks based on sorted Q-levels, and (3) sort true and traded bids (asks) within each Q-level in ascending (descending) orders. While the Q-levels is not effective in the single Q-level models, the SORT () algorithm, however, applies all GSPM and EM DA.

The MATCHING-ALLOCATION-RULE () algorithm in Appendix A, applies to all GSPM and EM DA mechanisms. All GSPM and EM matching allocations apply definition 1 for the matching allocations. The single Q-level GSPM pricing rule applies the GSPM-PRICING-RULE () algorithm in Appendix A. The pricing rule works for all GSPM DA mechanisms. All GSPM mechanisms apply definition 2 for the pricing rule of the winning bidders of the matched pairs of request and ask. The bounded GSPM, applies the BOUNDED-RULES-UPDATE () algorithm in Appendix A that models the constant learning reaction at repetitive trades. The algorithm inspects the win and loses states of all bidders at the current and previous trades and computes then the request and asks adjustments for next repetitive trade based on the conveyed RBBL bounded revaluation rules. The BOUNDED-RULES-UPDATE () constrains the revaluation bounds to a maximum of the true initial bid valuations and to a minimum of the true initial ask valuations. This reactive learning scheme is applied to all Bounded GSPM and EM mechanisms. The EXAMINE-CHANGE-OF-STATES () algorithm examines the winning and losing change of states of all bidders at the current and previous trades.

The single Q-level unbounded GSPM DA mechanism follows the bounded GSPM in applying the same algorithms of the matching allocation and pricing rules. However, the unbounded GSPM and EM apply the UNBOUNDED-RULES-UPDATE () algorithm in Appendix A that liberates the bounds of the rule-based adjustments due constant learning at repetitive trades. The UNBOUNDED-RULES-UPDATE () frees all rule-based bounds. This reactive learning scheme works for all unbounded mechanisms. The single Q-level

$M^{\text{th}}$  EM pricing rule applies the EM-PRICING-SINGLE-Q () algorithm shown in Appendix A. The pricing rule works for only single Q-level bounded and unbounded EM mechanisms. It is presented for demonstration, analysis and comparison. The multiple Q-level  $M^{\text{th}}$  EM pricing rule applies the EM-PRICING-MULTIPLE-Q () algorithm shown in Appendix A. The pricing rule works for multiple Q-level bounded and unbounded EM mechanisms. It follows definition 4.

This chapter covers the modeling and analysis of the proposed multiple Q-level GSPM DA mechanism. Our work presents the single Q-level GSPM and EM DA mechanisms as a reference DA mechanisms for developing the matching allocation and pricing rules of the multiple Q-level GSPM and EM DA mechanisms. In that vein, the work introduces the multiple Q-levels EM DA mechanism that extends the single Q-level EM to multiple equilibrium price points for rather multiple trades. The multiple Q-levels of the EM DA work as multiple EM trades that clear at different EM prices. While the single Q-level GSPM and EM DA are AE they are not IC. Hence, the multiple Q-level GSPM and EM DA is introduced to improve IC using the multiple Q-levels cross-matching. The multiple Q-level, EM DA is compared with the multiple Q-level, GSPM DA for the game-theoretic and computational properties, as presented in the experimental analysis of next chapter. The GSPM DA heuristics are polynomial time tractable and deliver social efficiency, strategic stability and weak budget balance that secures exchange profitability.

## Chapter 6

### 6 Experimental Results and Analysis

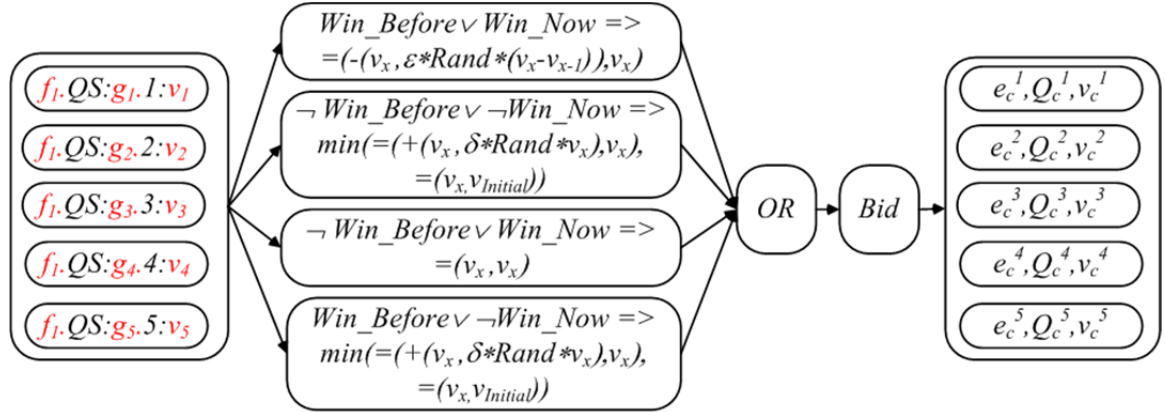
The work here analyses the experimental findings of implementing the RBBL, rules-based bidding language and the GSPM DA matching heuristics for the FX e-marketplace. The FX targets, particularly, the stable and efficient matching allocation of the request and ask bids on the e-services that the FX deduces and form out of the RBBL conveyed attribute-values, logical rules formulae, and multiple e-service Q-levels. This chapter tables the experimental simulation models and the implemented DA heuristics. The work derives, also the experimental findings and the conclusions out of the empirical analysis.

#### 6.1 RBBL Rule-based Bidding Experimental Model

The RBBL is a promising flexible and concise expressive language model that may find applications in a wide scope of e-services, particularly, the e-marketplaces. The fact that the RBBL bidding messages convey the logical rules and operators with rather multiple attributes, attribute values, Q-levels and other constraining attributes, require that the FX e-market system to have functional units that describe the logical rule and operator formulae, deduce and aggregate the preferences of bidders out of the logical rules, and generate the attribute combinations of the requested bids and offered asks. Our work, however, doesn't cover the scope of reasoning and deduction of the rule and operator formulae. The presented experimental validation examines, nevertheless, the proof of concept and verifies the performance advantage of using rules aggregation. Our work uses MATLAB toolboxes to simulate the ask and request bidding behavior of a number of bidders with the assumption that bidders apply self-learning abilities at repetitive trades that translate to logical rules conveyed to the FX e-marketplace

The presented RBBL experimental validation examines the proof of concept and verifies the performance advantage of using the RBBL rules aggregation. Our work uses the MATLAB to simulate the RBBL bidding model and the rule-based dynamic behavior of

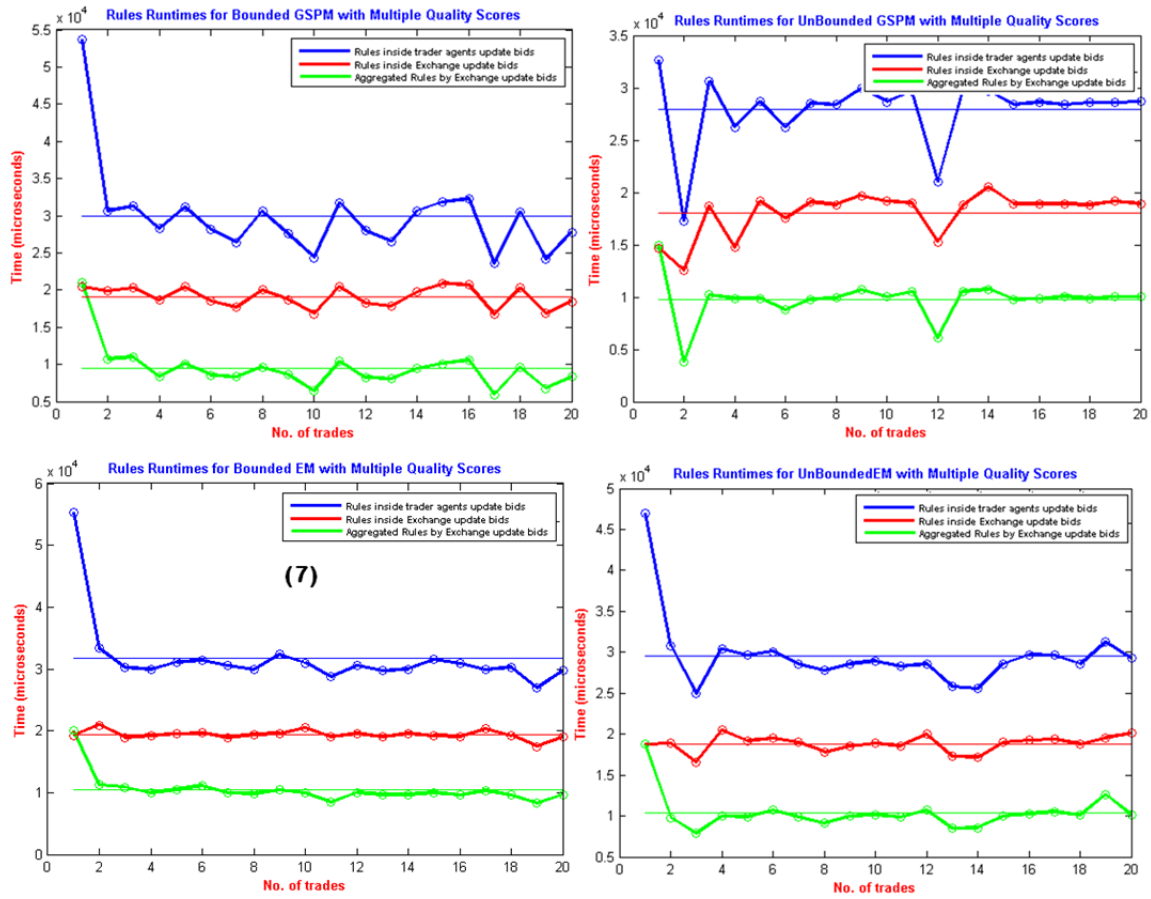
the number of bidders with at repetitive trades. The simulation creates multiple Q-levels as attributes (i.e.,  $Q_c^{ik}, Q_p^{jq}$ ) with random initial values for a e-service request or ask (i.e.,  $e_c^{ik}, e_p^{jq}$ ). The simulation correlates the attribute-values with the Q-level (i.e., generate higher random values for higher Q-level). The random request and ask bids are then deduced by the exchange out of the multiple Q-level attribute-values and logical rules formulae. There is also a random variation between bids and true values. The FX collects the multiple Q-level attribute-values and the FOL rational rule formulae as shown in Figure 21. The depicted RBBL FOL rules instruct the free exchange to increment the attribute-values or combinations (i.e.,  $v_x = v_x + \delta * \dots$ ) if the consumer is not a winner. Otherwise, at loss the request and ask bids stay as is or decrement attribute-values (i.e.,  $v_x = v_x - \varepsilon * \dots$ ).



**Figure 21: Attribute-values and rational rules of the RBBL validation**

The simulations work for three scenarios: (1) execute the RBBL rules inside the bidder agents; (2) execute the RBBL rule inside the FX with no aggregation to inspect the communication cost; and (3) execute the RBBL rule inside the FX with simple aggregation of bidder rules. The exchange applies two aggregation rules: (a) group and sort request and ask bids inside the FX according to the multiple Q-levels, rather than every trade inside the bidder agents; and (b) stop updating all request and ask bids that reach the upper or lower bounds for the next stage (i.e., for bounded mechanisms). For instance, the bounded GSPM applies a heuristic that inspects the win and lose states of all

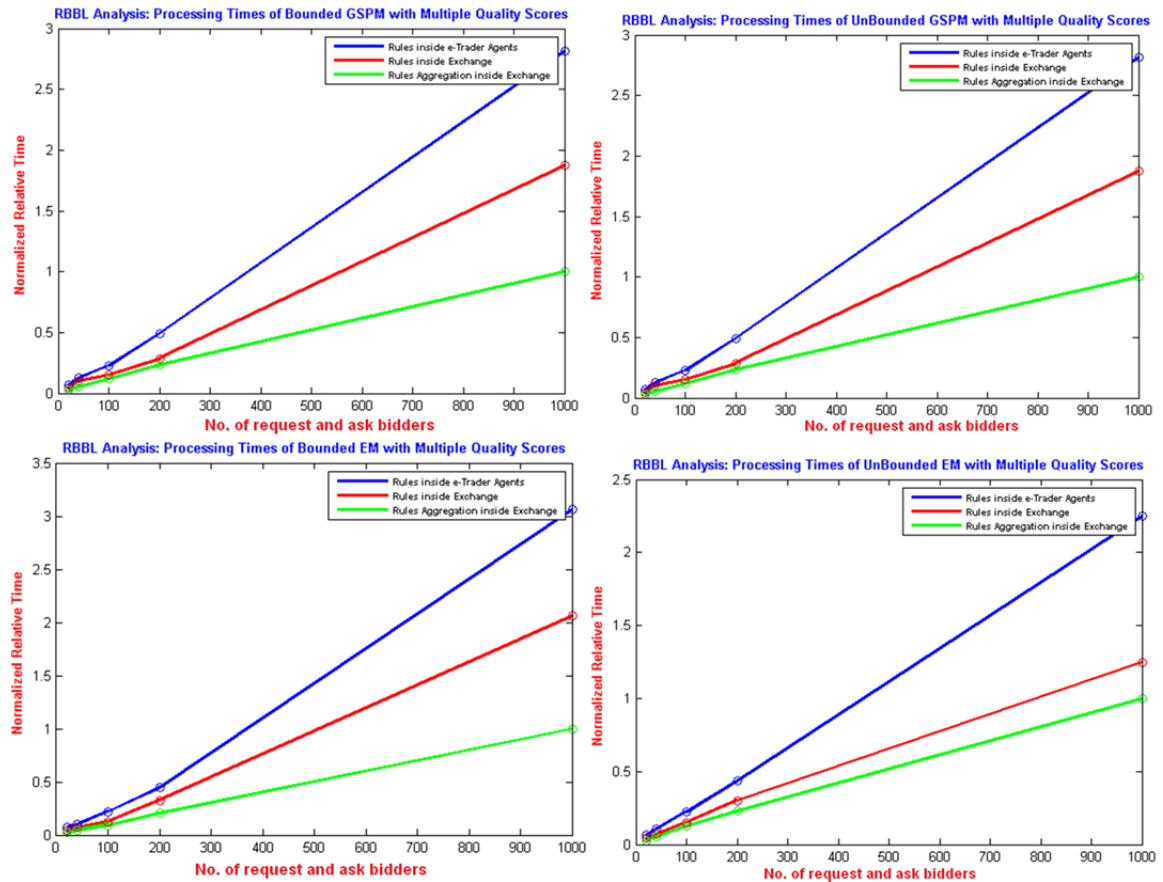
bidders at the current and previous trades and computes the bid value adjustments for the next repetitive trade based on the RBBL rules. Another heuristic constrains the request and ask bid adjustment bounds to the maximum of the true initial request values and to the minimum of the true initial ask values. Figure 22 shows the rules processing times of twenty repetitive trades that use the bounded and unbounded multiple Q-levels GSPM and EM heuristics for one thousand request and one thousand ask bidders. The simulation applies the three rule based update scenarios mentioned above. The results of repeated experiments show similar performance patterns for any number of bidders.



**Figure 22: Rules processing times of twenty repetitive trades using the bounded and unbounded multiple Q-level GSPM and EM for two thousand bidders.**

Figure 23 shows the rules processing times for different number of bidders. The rules aggregation inside the FX saved roughly half of the average relative processing times of

all bidder agents that are locally simulated inside the FX. Also, the rules aggregation inside the FX saved almost two third of the average processing times of remote bidder agents (i.e., over local network). The performance advantage would be significant with thicker e-market trades of much larger number of bidders and transactions over best effort internet due to high communication cost and effective aggregations. Obviously, even a simple aggregation of the RBBL rules inside e-exchange would deliver more rapid response and, hence, faster trades. It is also evident that the higher the number of bidders (i.e., thicker e-markets), the more effective the RBBL aggregation process. Of course, the communication cost would make the RBBL more desirable, particularly, in thicker e-markets with a large number of online bidders. Our work, anticipate, also the preference elicitation deduction (not implemented) would have a more substantial impact.



**Figure 23: Rules processing times vs. number of bidders for the bounded and unbounded multiple Q-levels GSPM and EM trades**

## 6.2 GSPM and EM Experimental Matching Models

The GSPM DA matching is another prospective venue for the FX e-marketplace. The FX applies the GSPM DA heuristics on the generated requests and asks to compute efficient and stable matching allocation and pricing outcomes. A key theme in the GSPM is the fact it motivates the strategic IC of bidders while narrowing down the tactical scope using the second price in rank without blocking the rational free choice. The FX achieves truthful interactions by implementing an AE DA matching that exploits both the GSP and reverse GSP for trading e-services of identical attributes and multiple Q-levels. For instance, a request bidder would be better off if she conveys a truthful valuation on an the e-service of particular Q-level, as it would minimize the risk of losing to others in the matched list at that Q-level, while having an incentive for a chance to be awarded an e-service of rather higher Q-level using the GSPM multiple Q-level cross-matching heuristics. Another key aspect is that GSPM DA guarantees e-market profitability that grows with the rapid stable convergence of the thick e-markets. The GSPM ensures, hence, the stable social efficiency of the FX e-marketplace, while securing sufficient e-market profitability that grow with number of satisfied bidders.

The simulation work in this section targets the comparative analysis between the GSPM and EM (Wurman et al., 1998) DAs. The reason for choosing the EM for comparison is due to the fact while the GSPM is discriminatory pricing for symmetric DA the EM is uniform clearing pricing for symmetric DA. The EM computes the market competitive equilibrium of supply and demand and work efficiently at perfect competition of free market economy. The EM is, also, desirable for its efficiency and tractability, hence, widely used in diverse market auctions (i.e., energy market auction). The simulation implements, examines and reports the experimental results and findings of the eight GSPM and EM double auction mechanisms that exploits the conveyed RBBL instance message of as described in the previous section, for up to 2000 request and ask bidders that dictates their constant learning and reactive model: (1) Single Q-level bounded GSPM DA, a base model for the multiple Q-levels GSPM DA, (2) Single Q-level unbounded GSPM DA for testing impact of free unconstrained strategies, (3) Multiple Q-

levels bounded GSPM DA, the core model, (4) Multiple Q-levels Unbounded GSPM DA, the core unbounded extension, (5) Single Q-level Bounded EM DA (Wurman et al., 1998), (6) Single Q-level Unbounded EM DA, (7) Multiple Q-levels bounded EM DA, a new proposed extension of (5) for comparative analysis, and (8) Multiple Q-levels unbounded EM DA. The simulation implements, examines and reports the experimental results and findings of the four comparative analysis between GSPM and EM DA mechanisms that exploits also the conveyed RBBL instance as described above for 2000 request and ask bidders that dictates the constant learning and reactive model.

### 6.3 Bounded GSPM Double auction Mechanisms

The matching allocation of the single Q-level and multiple Q-levels bounded GSPM DA mechanisms follow the GSPM matching allocation rule in definition 1. While definitions 1 exploits, to some extent, the equilibrium matching (EM) allocation (Wurman et al., 1998), it extends the matching allocations to the multiple Q-level cross-matching that motivates the IC. The pricing rules, however, follows our proposed GSPM pricing rule in definitions 2 for the requests and asks. One of the challenges that multiple Q-level GSPM mechanisms encounter is the instability of both AE and IC properties. This means there is no incentive for bidders to reveal their true valuations if they can reduce their traded bids and still win. As such our work extend the CAP model to include multiple Q-level items and introduce the multiple Q-level GSPM mechanisms that improve incentive compatible due to multiple Q-levels cross-matching. The cross-matching allows for matching bids of a particular Q-level and asks of the same or high Q-levels. The more the number of Q-levels, the narrower the tactical maneuverability space of bidders. A consumer may bid for an e-service of certain functionality at a minimum Q-level. The e-service providers may offer similar e-services of rather different Q-levels. Then the multiple Q-level GSPM DA implements the MATCHING-ALLOCATION-RULE () for cross- matching that allows winners to win an item of targeted Q-level or higher. Hence, the consumer would have an incentive to reveal truthful requests and asks to guarantee place in the winning list or increase chances to win an even higher Q-level e-service with the same bid. The same applies to ask bidders, where they increase also chances to win a place in

the matched list and give a higher chances to match with higher request bid bidders for lower Q-level e-services. This section describes and examines the main implemented algorithms and reports on the experimental findings.

### 6.3.1 Experimental Bounded GSPM Description

Table 1 depicts a GSPM requests and asks processing instance of twenty bidders at the first and twentieth repetitive trades with constant learning and strategic rule-based revaluations. The first two tables depicts the processing of the requests and asks through different algorithmic stages of the GSPM DA at first trade: (1) twenty sorted initial true requests and asks of single and multiple Q-level, (2) twenty generated random requests and asks that is purposely deviated at random from the initial true requests and asks (without learning and revaluation of rules), and (3) GSPM requests and asks matching allocations with applied GSPM pricing rule (i.e., payments and costs). The second table depicts the processing of the requests and asks through the algorithmic stages of the GSPM DA at the twentieth trade: (4) the same twenty sorted initial true requests and asks of single Q-level, (5) the twenty generated random requests and asks using RBBL logical rules, (6) the GSPM requests and asks matching with applied GSPM pricing rule. Apparently, the expected number of matched-pairs increases at repetitive trades due to the constant learning and rational reactions of bidders that adapts with the winning and losing states and prospects as described in the rules revaluation algorithms. The other observation relates to the constant fall of the variance between the requests and asks throughout the repetitive e-trading process until it reaches the stability of second prices or EM price or true setting bounds. In fact, this is a natural reaction of bid (ask) winners who attempt to lower (raise) valuations at constant learning of repetitive trade disruptions for achieving higher utilities. Bid (Ask) Losers, however, attempt to rise (lower) valuations for having a rather better chance to be in the winner matched list. The outcome as observed in the Table 1 and Figure 24 is an initial rapid drop of variance between requests and asks and an increasing number of matched pairs. Variance converges to stability as matched pairs converge to maximum matching or that of true settings. For multiple Q-level, it is observed that the matched list per Q-level grows with repetitive

trades with some requests and asks Q-level cross-matched. The allocation and pricing rules of single Q-level GSPM is applied for multiple Q-levels with rather cross-matching.

**Table 1: Sample results of first and twentieth single Q-level (left set) and multiple Q-levels (right set) bounded GSPM repetitive trades of twenty request and ask bidders**

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sorted True Bids	98	98	93	92	87	85	81	80	75	74	69	56	53	32	26	15	13	10	2	1
Sorted Bids	93	80	77	77	76	70	69	65	63	61	55	54	44	29	20	12	11	8	2	1
Matched Bids	93	80	77	77	76	70	69	65	0	0	0	0	0	0	0	0	0	0	0	0
Bid Payments	80	77	77	76	70	69	65	65	0	0	0	0	0	0	0	0	0	0	0	0
Ask Costs	19	34	41	45	50	54	54	54	0	0	0	0	0	0	0	0	0	0	0	0
Matched Asks	19	19	34	41	45	50	54	54	0	0	0	0	0	0	0	0	0	0	0	0
Sorted Asks	19	19	34	41	45	50	54	54	67	68	68	68	77	84	85	91	102	103	104	111
Sorted True A...	18	18	31	35	36	44	48	49	55	57	65	65	72	72	73	80	88	88	94	100
Sorted Ask QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	5	4	4	4	4	4	3	3	3	3	3	3	3	2	2	2	2	2	2	1
Sorted True Bids	68	96	86	70	57	41	58	53	48	45	39	27	44	43	25	18	10	10	17	17
Sorted Bids	59	94	75	70	50	38	50	39	34	34	28	21	37	37	21	16	9	8	14	13
Matched Bids	0	94	0	0	0	0	50	0	0	0	0	0	37	37	0	0	0	0	0	0
Bid Payments	0	75	0	0	0	0	39	0	0	0	0	0	37	21	0	0	0	0	0	0
Ask Costs	0	0	84	0	0	41	0	0	0	0	0	2	10	20	0	0	0	0	0	0
Matched Asks	0	0	73	0	0	33	0	0	0	0	0	1	2	10	0	0	0	0	0	0
Sorted Asks	110	110	73	84	125	33	41	65	72	76	81	1	2	10	20	28	41	42	53	55
Sorted True A...	94	97	66	69	98	31	38	52	60	62	76	1	2	9	19	24	38	41	45	48
Sorted Ask QS	5	5	4	4	4	3	3	3	3	3	3	2	2	2	2	2	2	2	2	2

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sorted True Bids	98	98	93	92	87	85	81	80	75	74	69	56	53	32	26	15	13	10	2	1
Sorted Bids	75	74	73	72	71	70	69	68	67	66	65	56	53	32	26	15	13	10	2	1
Matched Bids	75	74	73	72	71	70	69	68	67	66	65	0	0	0	0	0	0	0	0	0
Bid Payments	74	73	72	71	70	69	68	67	66	65	65	0	0	0	0	0	0	0	0	0
Ask Costs	56	57	58	59	60	61	62	63	64	65	65	0	0	0	0	0	0	0	0	0
Matched Asks	55	56	57	58	59	60	61	62	63	64	65	0	0	0	0	0	0	0	0	0
Sorted Asks	55	56	57	58	59	60	61	62	63	64	65	65	72	72	73	80	88	88	94	100
Sorted True A...	18	18	31	35	36	44	48	49	55	57	65	65	72	72	73	80	88	88	94	100
Sorted Ask QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

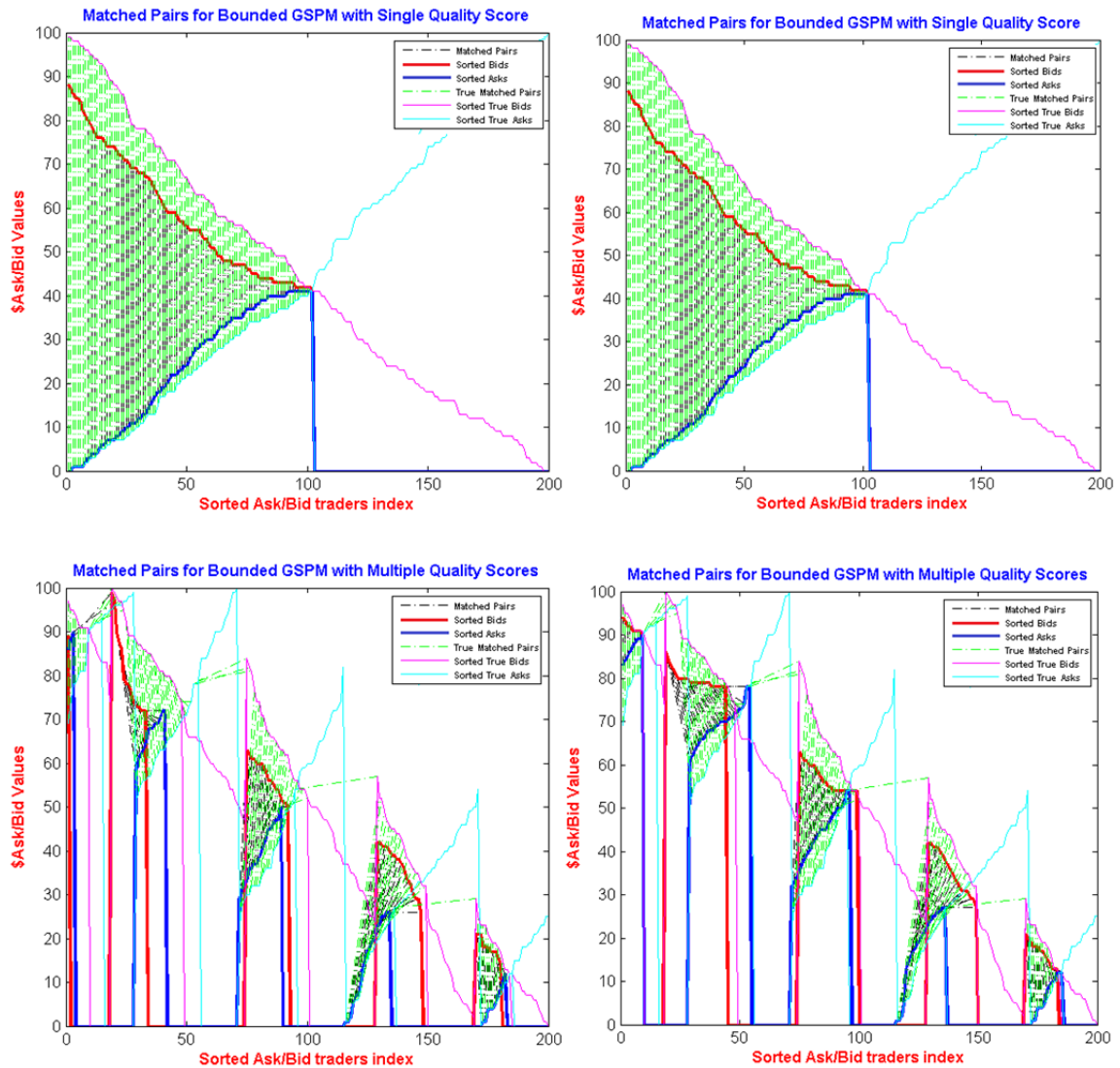
  

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	5	4	4	4	4	4	3	3	3	3	3	3	3	2	2	2	2	2	2	1
Sorted True Bids	68	96	86	70	57	41	58	53	48	45	39	27	44	43	25	18	10	10	17	17
Sorted Bids	68	86	86	70	57	41	48	48	48	45	39	27	20	19	18	18	10	10	17	17
Matched Bids	0	86	86	0	0	0	48	48	0	0	0	0	20	19	0	0	0	0	0	0
Bid Payments	0	86	70	0	0	0	48	48	0	0	0	0	19	18	0	0	0	0	0	0
Ask Costs	0	0	82	98	0	38	52	0	0	0	0	2	18	19	0	0	0	0	0	0
Matched Asks	0	0	76	82	0	37	38	0	0	0	0	1	2	18	0	0	0	0	0	0
Sorted Asks	94	97	76	82	98	37	38	52	60	62	76	1	2	18	19	24	38	41	45	48
Sorted True A...	94	97	66	69	98	31	38	52	60	62	76	1	2	9	19	24	38	41	45	48
Sorted Ask QS	5	5	4	4	4	3	3	3	3	3	3	2	2	2	2	2	2	2	2	2

### 6.3.2 Analysis of Bounded GSPM Trades

The first set of Figure 24 depicts the constant learning trend as exploited by the RBBL rule instance of 200 request and ask bidders in the first and twentieth trades. Obviously, the second graph of the first set shows the rapid fall of the variance between requests and asks and the growing size of the matched list. In fact the final matched list is similar to that the initial true matched list shown in light colors. The losing bidders demonstrate the bounded *aggressive corrective moves* to increasing (lowering) their bids (asks) for a better winning chance that results in a more matched pairs. However, the winning bidders demonstrate a *bounded conservative moves* to decreasing (increasing) their bids (asks) that increases their utilities within their bounds and results in the fast drop of bids/asks variance. The second set demonstrates the impact of thicker e-markets (i.e., 200 request

and ask bidders). Obviously, the more the thicker e-markets is the more stable and rapid it converges to social efficiency due the converging very small difference between bid/ask and payment/cost values being the second prices as realized by (Roth, 2007).



**Figure 24: Traded vs. initial true matched pairs of the first and twentieth trades of the bounded single Q-level (upper set) and multiple Q-levels (lower set) GSPM**

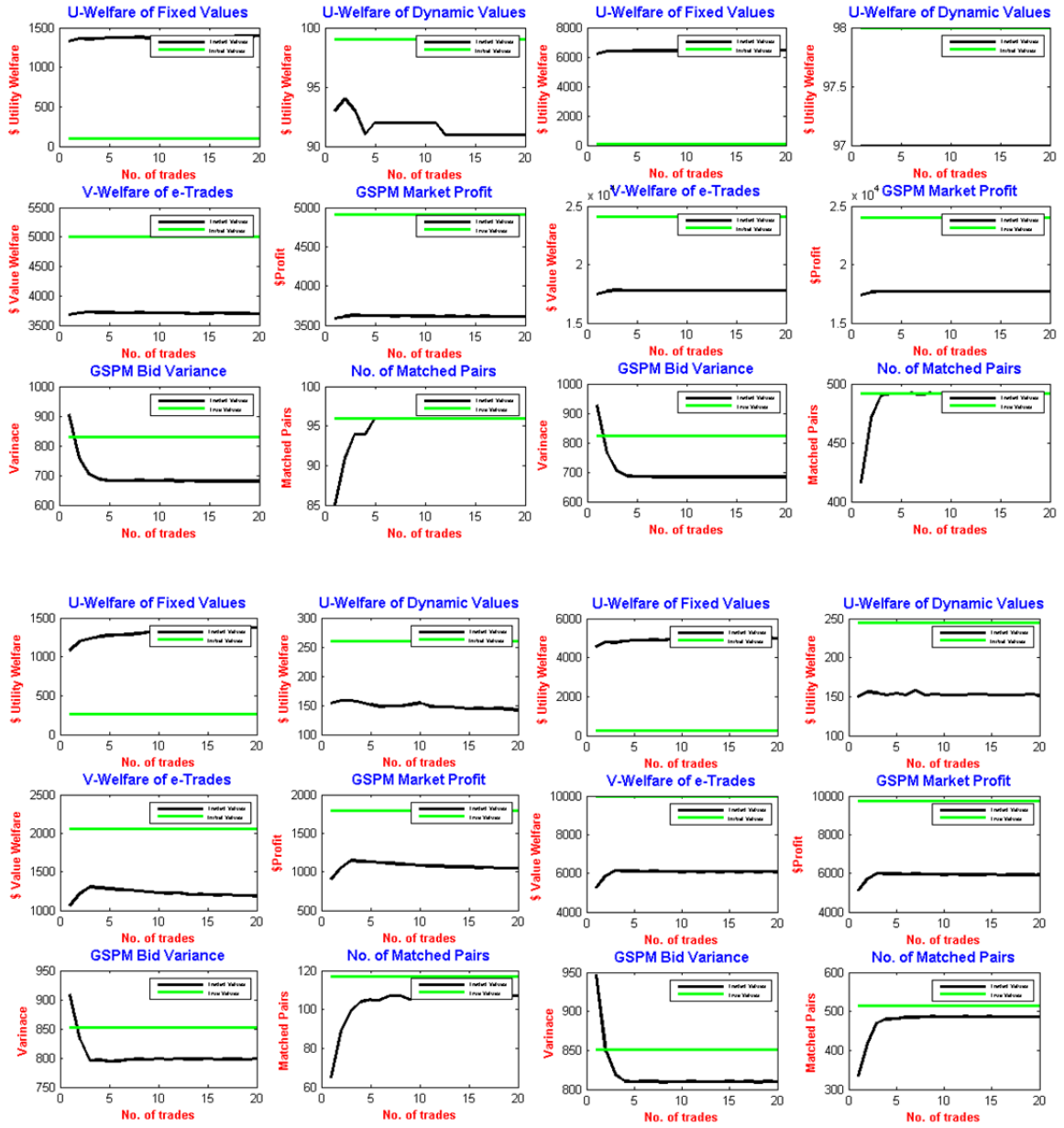
### 6.3.3 Analysis of Bounded GSPM Metrics

Figure 25 depicts the metrics of two instances of 200 and 1000 single Q-level and multiple Q-levels request and ask bidders in the bounded GSPM e-market. The following are the experimental findings:

1. The *U-Welfare of fixed initial values (fixed U-Welfare)* is the *utility social welfare* that aggregates the utilities of bidders in reference to their fixed initial true requests and asks (i.e.,  $\sum (\text{Initial true bids} - \text{current payments}) + \sum (\text{current costs} - \text{Initial true asks})$ ). The *fixed U-Welfare* converges rapidly to a *maximum stable AE bounds* compared to the initial true welfare (i.e., green line) as request and ask utilities increase due to the rule based adjustments driven by constant learning at repetitive trades. That results in a rising asks/costs and falling bids/payment until they reach the stable bounds of the second price limits. The thick e-market increases the *fixed U-Welfare* significantly in reference to the true initial settings at thicker e-market trades.
2. The *U-Welfare of dynamic (current) values (moving Welfare)* is the moving utility social welfare that aggregates the utilities of bidders in reference to the *current trade true* requests and asks (i.e.,  $\sum (\text{current bids} - \text{current payments}) + \sum (\text{current costs} - \text{current asks})$ ). The *moving U-Welfare* converges to a low stable utility welfare that is close to max item value. This is due to the sharp fall of differences between current bids (asks) and second price payments (costs) at repetitive trades. The thick e-markets have *no effect* on the converged utility value, but delivers instant convergence due to the faster stability of requests and asks at thicker repetitive trades.
3. The *V-Welfare* is the valuation social welfare that correlates with the *e-market profit*. The *V-Welfare* is equal to the *moving U-Welfare* and the *e-market profit*. Hence, the *V-Welfare* converges to the *e-market profit* as the *moving U-Welfare* converges to a stable low value at thicker trades. The *V-Welfare* totals the *maximum bid and minimum ask values* or equivalently the maximum bid minus maximum ask values which at thicker trades converges to the maximum payment

minus maximum cost values, or the FX e-market profit. The *V-Welfare* and *e-market profitability* of bounded GSPM converge to stable positive value that is lower than that of initial settings due to the rule based adjustment that direct the convergence to lower value bids and higher value asks at constant leaning of repetitive trades. In fact, the winners maintain a *bounded conservative moves* to increase utilities while losers takes a *bounded aggressive moves* to join in the matched list until they reach the bounded true values. This is the free natural reaction of bidders that directs the V-Welfare stability as it balances the rising asks and the falling bids and converge to the second prices payment/cost or true bounds. The thicker e-market deliver higher, stable and more rapid instant convergence as the variance drops considerably. The GSPM DA guarantees, also, the *e-market* converge rapidly to a stable *profitability* that grow, also, with the economy of scale of thicker e-market trades.

4. The bounded GSPM converges rapidly after few trades to the maximum number of the matched pairs of the true initial value settings shown in green line. This is due to the initial rapid and aggressive incremental fall of bids and rise of asks of the losing bidders to gain a winning seat in the matched list. The winners then takes a *conservative moves* close to the second prices to gain better utilities.
5. The variance of bounded GSPM drops rapidly at the first initial trades to optimizing the random initial settings with larger delta adjustments of the requests and asks then it stabilizes with smaller changes as values get closer to the second price bounds. The variance converges, then, to a stable low value outcome due rather to the narrowing differences between the rising asks and the falling bids.



**Figure 25: Metrics of the bounded single Q-level (upper set) and multiple Q-level (lower set) GSPM of 200 and 1000 request and ask bidders**

## 6.4 Unbounded GSPM Double Auction Mechanisms

### 6.4.1 Experimental Unbounded GSPM Description

The instance in Table 2: follows the same settings of the Table 1. However, it is obvious that the unbounded GSPM DA allows losers to play rather more aggressive corrective moves and *break risk neutrality* for better winning chance within and across the multiple Q-levels. Hence, the unbounded GSPM matched list converges to complete matched list at repetitive trades with most losers turn into winners while narrows down the bids/ asks variance. The violation of the risk neutrality of allows losers an *unbounded free choice and conduct*. The first and final trades in Table 2: demonstrate how unbounded losers converge to winners through aggressive lowering (raising) of their bids (asks) in a way that breach risk neutrality. Winners, however, apply conservative moves to narrow down variance between requests and ask to increase their utilities. The multiple Q-level unbounded GSPM motivation follows the one of bounded GSPM in the previous section.

**Table 2: Sample results of first and twentieth single Q-level (left set) and multiple Q-levels (right set) unbounded GSPM trades of twenty request and ask bidders**

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sorted True Bids	97	96	93	91	85	84	82	77	68	68	41	27	26	26	13	11	7	3	3	3
Sorted Bids	88	86	80	77	76	74	68	64	50	49	37	26	21	19	10	8	5	3	3	2
Matched Bids	88	86	80	77	76	74	68	64	50	49	0	0	0	0	0	0	0	0	0	0
Bid Payments	86	80	77	76	74	68	64	50	49	49	0	0	0	0	0	0	0	0	0	0
Ask Costs	6	8	11	24	28	36	43	47	48	48	0	0	0	0	0	0	0	0	0	0
Matched Asks	5	6	8	11	24	28	36	43	47	48	0	0	0	0	0	0	0	0	0	0
Sorted Asks	5	6	8	11	24	28	36	43	47	48	56	56	57	61	72	79	81	98	101	110
Sorted True A...	5	5	6	9	22	25	29	37	43	46	49	53	54	55	61	62	73	85	87	100
Sorted Ask QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	5	5	5	5	4	4	4	4	3	3	3	2	2	2	2	2	1	1	1	1
Sorted True Bids	98	93	91	75	95	84	79	70	68	58	44	43	47	47	44	10	1	21	16	14
Sorted Bids	90	87	81	75	90	77	65	64	51	43	43	41	42	42	37	8	1	19	15	14
Matched Bids	0	0	0	0	90	77	0	0	0	43	0	0	42	42	37	0	0	19	0	0
Bid Payments	0	0	0	0	77	65	0	0	0	43	0	0	42	37	8	0	0	15	0	0
Ask Costs	0	0	0	0	70	75	0	59	0	0	0	0	9	17	29	0	0	0	0	0
Matched Asks	0	0	0	0	69	70	0	43	0	0	0	0	1	9	17	0	0	0	0	4
Sorted Asks	91	97	102	118	69	70	75	43	59	60	71	79	1	9	17	29	36	43	49	4
Sorted True A...	71	89	95	99	62	63	69	41	49	52	60	65	1	7	16	25	35	38	41	4
Sorted Ask QS	5	5	5	5	4	4	4	3	3	3	3	3	2	2	2	2	2	2	2	1

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sorted True Bids	97	96	93	91	85	84	82	77	68	68	41	27	26	26	13	11	7	3	3	3
Sorted Bids	56	54	50	47	45	42	39	37	36	34	33	32	31	29	28	27	27	26	25	2
Matched Bids	56	54	50	47	45	42	39	37	36	34	33	32	31	29	28	27	27	26	25	0
Bid Payments	54	50	47	45	42	39	37	36	34	33	32	31	29	28	27	27	26	25	25	0
Ask Costs	19	19	19	20	20	20	21	21	21	21	21	21	21	22	22	22	22	22	22	0
Matched Asks	18	19	19	19	20	20	20	21	21	21	21	21	21	21	22	22	22	22	22	0
Sorted Asks	18	19	19	19	20	20	20	21	21	21	21	21	21	21	22	22	22	22	22	22
Sorted True A...	5	5	6	100	9	22	25	29	37	43	46	49	53	54	55	61	62	73	85	87
Sorted Ask QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	5	5	5	5	4	4	4	4	3	3	3	2	2	2	2	2	1	1	1	1
Sorted True Bids	98	93	91	75	88	95	70	84	79	58	44	43	47	47	44	10	1	21	14	16
Sorted Bids	92	91	90	89	257	252	249	245	239	52	51	51	11	10	8	8	1	8	8	7
Matched Bids	92	91	90	89	257	252	249	0	0	52	51	51	11	10	8	8	0	8	8	7
Bid Payments	91	90	89	89	252	249	245	0	0	51	51	51	10	8	8	1	0	8	7	7
Ask Costs	85	86	87	87	70	71	71	11	12	12	0	0	7	7	7	7	8	8	0	1
Matched Asks	84	85	86	87	69	70	71	11	11	12	0	0	7	7	7	7	7	8	0	1
Sorted Asks	84	85	86	87	69	70	71	11	11	12	12	13	7	7	7	7	7	8	8	1
Sorted True A...	71	89	95	99	62	63	69	41	60	49	52	65	1	7	16	35	38	25	41	4
Sorted Ask QS	5	5	5	5	4	4	4	3	3	3	3	3	2	2	2	2	2	2	2	1

### 6.4.2 Analysis of Unbounded GSPM Trades

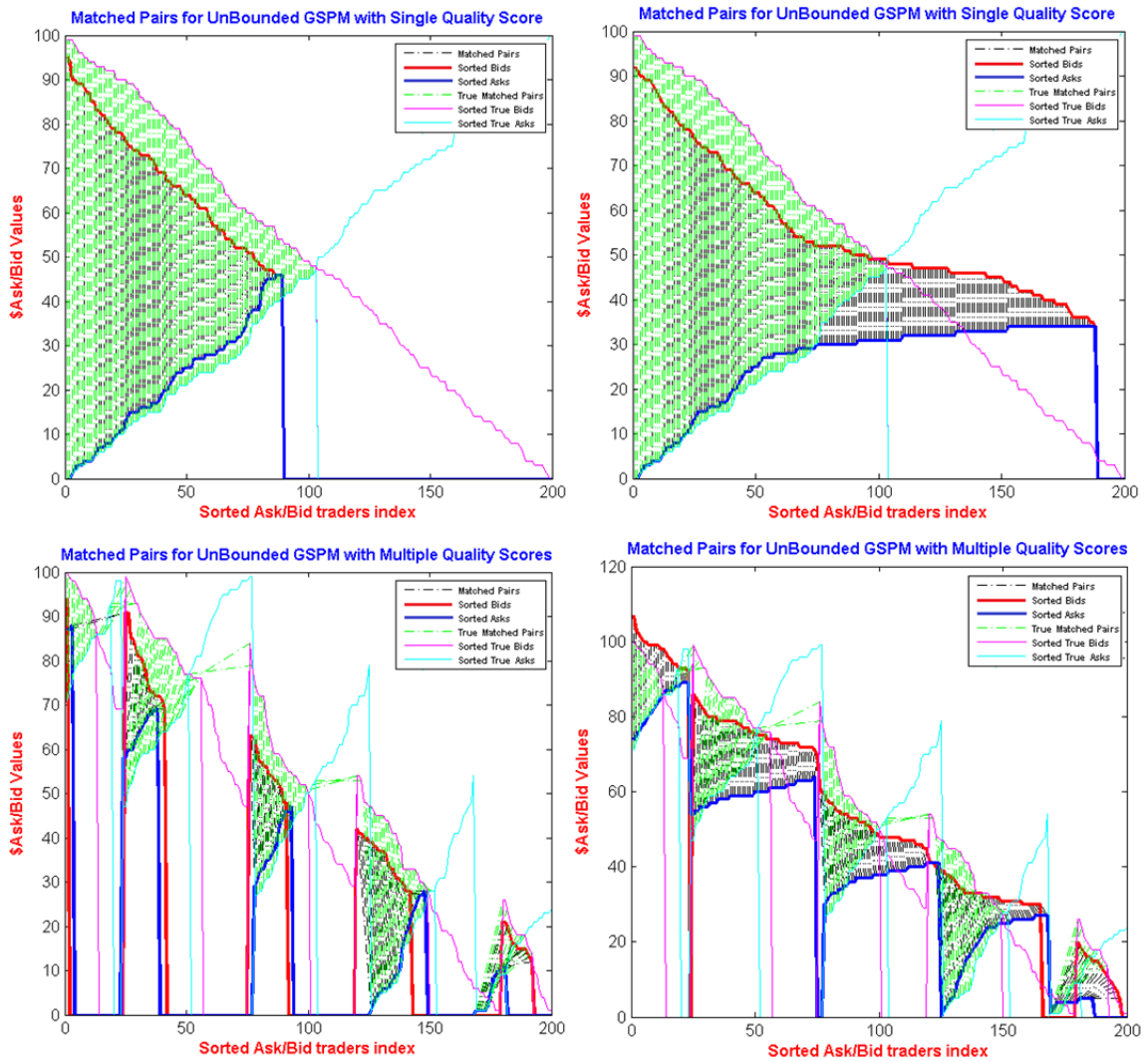
Figure 26 shows the constant learning trend of 200 request and ask bidders in the first and twentieth trades. The second graph show an almost complete matched list that include all bidders with constant drop of the bid/ask variance similar to the bounded GSPM. The lower graph set shows the multiple Q-level matched list with some cross-matched pairs. The narrowing gap between requests and asks (falling variance) at each Q-level is obvious, as well. In fact, the losers demonstrate a rather *unbounded aggressive corrective moves* by *breaching risk neutrality* for a winning chance (i.e., often found in classic markets for clearing of slow moving items) by increasing (lowering) bids(asks) beyond initial true bounds (i.e., see the curve extension into the losers zone). The results exhibits the rapid convergence of thick e-market *risk neutral winners* to stable efficiency at each Q-level while the unbounded *risk unneutral losers* become winners at repetitive trades with the *bounded conservative moves* of winners within the initial winning space and the *unbounded aggressive moves* of losing bidders beyond the initial winning space to become winners. That result is a complete cross-matched list and lower variance.

### 6.4.3 Analysis of Unbounded GSPM Metrics

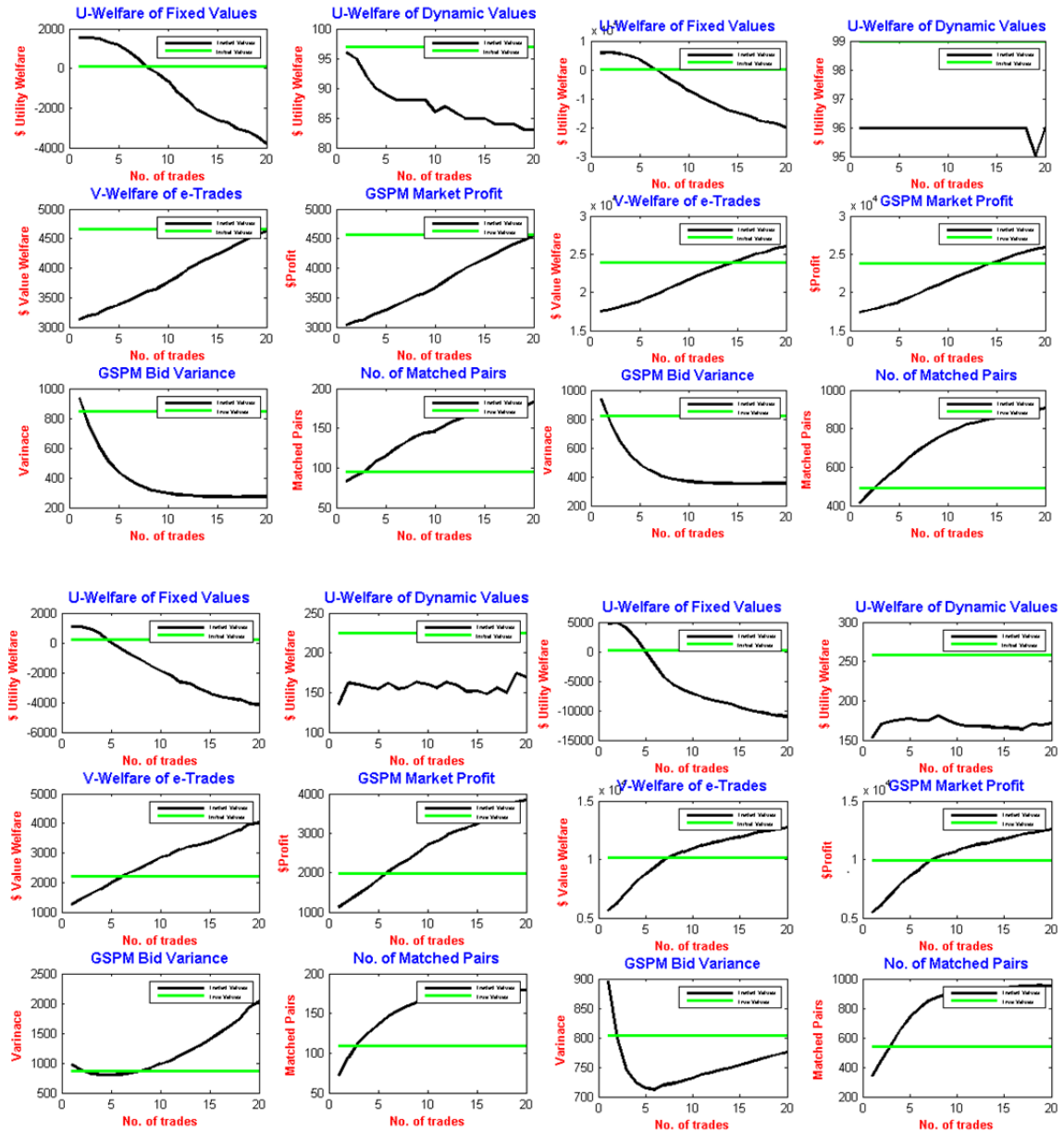
Figure 27 depicts the metrics of the Single Q-level and multiple Q-levels Unbounded GSPM DA mechanism. The analysis emphasizes the following experimental findings:

1. The *U-Welfare of fixed values* keeps falling to the negative quadrant at repetitive trades and also with thicker e-markets of more bidders compared to that of the initial true settings due to, primarily, the violation of risk neutrality of losers.
2. The *moving U-Welfare of dynamic values* converges to a stable low utility welfare that is close to max item value at thicker trades. This is due to the sharp fall of differences between current bids (asks) and second price payments (costs) at repetitive trades. The thick e-markets have *no effect* on the converged utility, but keep decreasing and converge to a stable low welfare at repetitive trades.
3. The *V-Welfare* and *e-market profitability* keep increasing to values beyond that of the initial true settings due to the rule-based *aggressive adjustments* that direct the

unbounded convergence of the *risk unneutral* higher value bids and lower value asks of the losing bidders at constant leaning of repetitive trades. In fact, the winners maintain *bounded conservative moves* to second prices to increase utilities while the losing bidders take *unbounded aggressive moves* to join in the matched list. The *V-Welfare* and *e-market profitability* converge to stability when all requests and asks of now all joining winners get closer to the second prices. The *V-Welfare* and *e-market profitability* grow for all trades and thicker markets.



**Figure 26: Traded vs. initial true matched pairs of the first and twentieth trades of the unbounded single Q-level (upper set) and multiple Q-levels (lower set) GSPM**



**Figure 27: Metrics of unbounded single Q-level (upper set) and multiple Q-level (lower set) GSPM of 200 and 1000 request and ask bidders**

4. The unbounded GSPM e-market converges to the maximum complete matched pair that covers almost all ask-bid pairs at repetitive trades. This is a result of the unbounded reactions of bidders that disregard risk neutrality for a winning seat.

5. The variance drops rapidly at the initial trades due to the large delta adjustments of the requests and asks of losers. The variance converges, then, to stable low value due to the narrowing difference between the rising asks and the falling bids.

## 6.5 Bounded $M^{\text{th}}$ EM Double Auction Mechanisms

The bounded  $M^{\text{th}}$  EM mechanism applies the matching allocation and  $M^{\text{th}}$  pricing rule of (Wurman et al., 1998), however, for single Q-level requests and asks. This  $M^{\text{th}}$  EM is described in chapter 4 while the pricing rule is based on definition 3.

### 6.5.1 Bounded $M^{\text{th}}$ EM DA Description

The data Table 3 depicts the EM requests and asks processing of twenty bidders at the first and twentieth repetitive trades with constant learning and rule-based adjustments. It follows data Table 1 in structure. As in other DA mechanisms the repetitive trades increase the number of matched pairs. The other observation relates to the converging of requests and asks to almost same valuation in the twentieth trade with rather a minor change in the EM equilibrium price. In fact, this is a natural reaction of bid (ask) winners who attempt to lower (raise) their valuation for achieving higher utilities. Bid (Ask) Losers, however, attempt to raise (lower) their valuations for better winning chances. As mentioned in chapter 4, our work, inspired by the theoretical model and the experimental finding of the multiple Q-level GSPM DA, proposes a generalized multiple Q-level  $M^{\text{th}}$  EM DA mechanism that exploits a multiple equilibrium matching points for the multiple Q-levels in computing the matching allocation and pricing rules for multiple units of a single-item of multiple attributes, and multiple Q-levels. The proposed multiple Q-level  $M^{\text{th}}$  EM DA follows the matching allocation of the proposed multiple Q-level GSPM mechanism. The multiple Q-level  $M^{\text{th}}$  EM DA sorts the Q-levels, with asks of same Q-levels and bids of same min Q-levels, and apply a multilevel cross- matching allocation as shown in Figure 20. The multiple Q-level  $M^{\text{th}}$  EM DA pricing rule, however, follows definition 4. The following steps describe the multiple Q-level  $M^{\text{th}}$  EM mechanism. The multiple Q-level cross-matching allows for matching between bids of a particular Q-level and asks from the same or high Q-levels. The multiple Q-level EM DA implements the

matching allocation algorithm#2 as d in definition 3 and the following multiple Q-level  $M^{\text{th}}$  EM pricing algorithm#8 as stated in definition 4.

**Table 3: Sample results of first and twentieth single Q-level (left set) and multiple Q-levels (right set) unbounded EM trades of twenty request and ask bidders**

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sorted True Bids	93	84	83	77	75	68	65	61	56	53	46	29	28	27	22	17	16	15	14	4
Sorted Bids	86	79	77	75	65	56	53	50	48	47	32	25	22	21	16	14	13	12	10	4
Matched Bids	86	79	77	75	65	56	53	50	0	0	0	0	0	0	0	0	0	0	0	0
Bid Payments	48	48	48	48	48	48	48	48	0	0	0	0	0	0	0	0	0	0	0	0
Ask Costs	48	48	48	48	48	48	48	48	0	0	0	0	0	0	0	0	0	0	0	0
Matched Asks	14	19	22	39	42	46	48	48	0	0	0	0	0	0	0	0	0	0	0	0
Sorted Asks	14	19	22	39	42	46	48	48	49	49	50	50	53	55	60	89	95	101	104	105
Sorted True A...	11	19	21	34	39	41	42	43	45	46	47	48	48	53	56	79	86	86	90	95
Sorted Ask QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	5	5	5	4	4	4	4	3	3	3	3	2	2	2	2	1	1	1	0	0
Sorted True Bids	96	88	81	87	80	62	53	63	54	37	21	33	29	7	1	8	6	5	0	0
Sorted Bids	92	73	59	74	64	45	42	55	40	28	20	29	21	7	1	6	5	4	0	0
Matched Bids	0	0	0	74	0	0	0	55	0	0	0	29	0	0	0	6	0	0	0	0
Bid Payments	0	0	0	59	0	0	0	37	0	0	0	19	0	0	0	1	0	0	0	0
Ask Costs	59	0	0	0	0	0	0	37	0	0	0	0	19	0	0	0	0	1	0	0
Matched Asks	59	0	0	0	0	0	0	37	0	0	0	0	19	0	0	0	0	1	0	0
Sorted Asks	59	76	69	98	98	118	37	44	47	58	68	72	19	25	31	39	42	1	10	25
Sorted True A...	50	70	76	77	86	94	33	37	44	55	57	65	16	21	25	32	36	1	8	22
Sorted Ask QS	4	4	4	4	4	4	4	3	3	3	3	3	2	2	2	2	2	1	1	1

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sorted True Bids	93	84	83	77	75	68	65	61	56	53	46	29	28	27	22	17	16	15	14	4
Sorted Bids	48	48	48	48	48	48	48	48	48	46	29	28	27	22	17	16	15	14	4	4
Matched Bids	48	48	48	48	48	48	48	48	48	0	0	0	0	0	0	0	0	0	0	0
Bid Payments	47	47	47	47	47	47	47	47	47	0	0	0	0	0	0	0	0	0	0	0
Ask Costs	47	47	47	47	47	47	47	47	47	0	0	0	0	0	0	0	0	0	0	0
Matched Asks	46	46	46	46	46	46	46	46	46	0	0	0	0	0	0	0	0	0	0	0
Sorted Asks	46	46	46	46	46	46	46	46	47	47	48	48	53	56	79	86	86	90	95	95
Sorted True A...	11	19	21	34	39	41	42	43	47	45	46	48	48	53	56	79	86	86	90	95
Sorted Ask QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

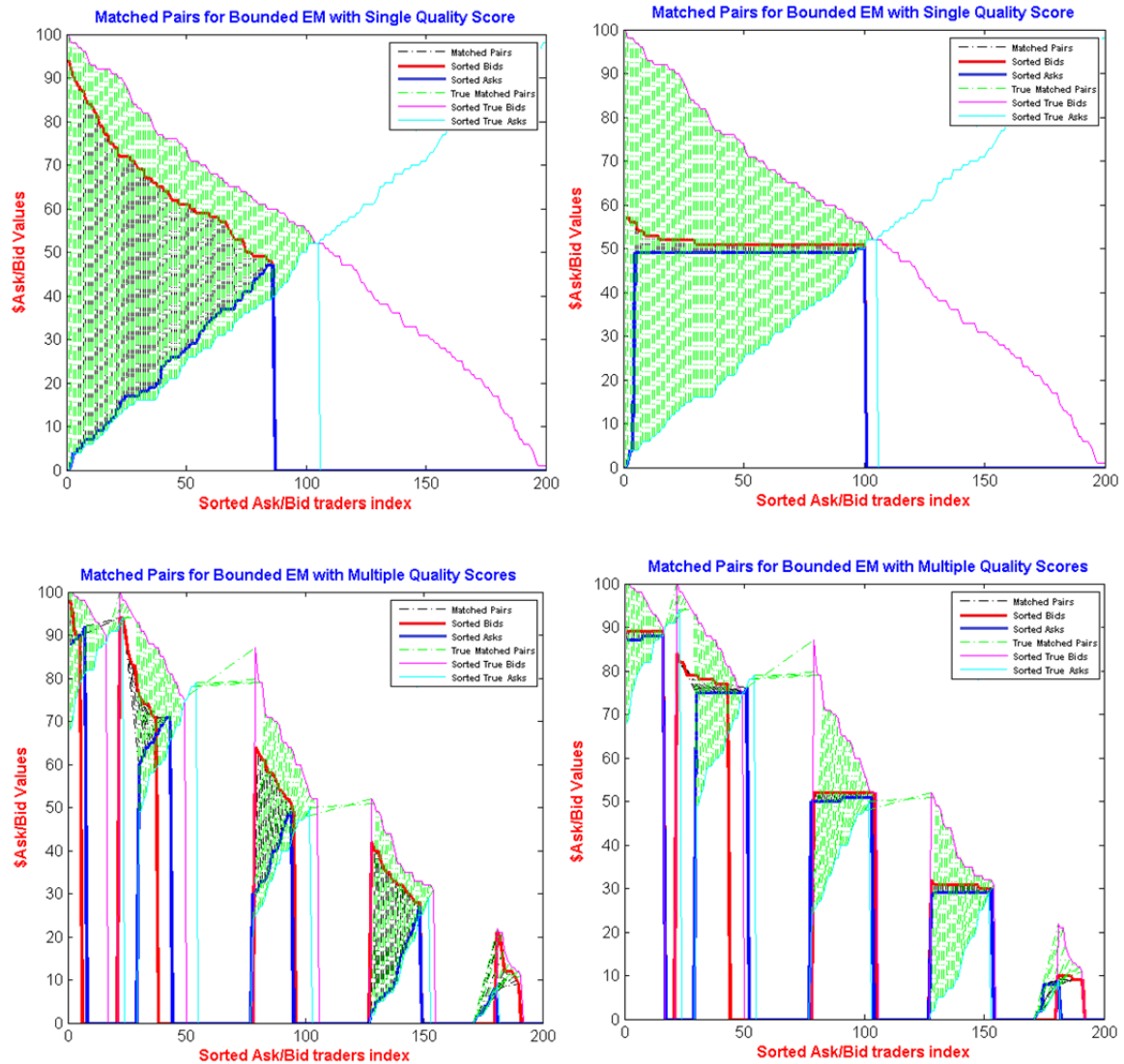
  

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	5	5	5	4	4	4	4	3	3	3	3	2	2	2	2	1	1	1	0	0
Sorted True Bids	96	88	81	87	80	62	53	63	54	37	21	33	29	7	1	8	6	5	0	0
Sorted Bids	96	88	81	71	71	62	53	42	42	37	21	23	22	7	1	5	5	3	0	0
Matched Bids	0	0	0	71	71	0	0	42	42	0	0	23	22	0	0	5	0	0	0	0
Bid Payments	0	0	0	70	70	0	0	41	41	0	0	22	22	0	0	1	0	0	0	0
Ask Costs	70	70	0	0	0	0	0	41	41	0	0	0	22	22	0	0	0	1	0	0
Matched Asks	69	70	0	0	0	0	0	40	41	0	0	0	21	22	0	0	0	1	0	0
Sorted Asks	69	70	76	77	86	94	40	41	44	55	57	65	21	22	25	32	36	1	8	22
Sorted True A...	50	70	76	77	86	94	33	37	44	55	57	65	16	21	25	32	36	1	8	22
Sorted Ask QS	4	4	4	4	4	4	4	3	3	3	3	3	2	2	2	2	2	1	1	1

### 6.5.2 Analysis of Bounded $M^{\text{th}}$ EM DA Trades

Figure 28 shows the constant learning trend as exploited by the RBBL rule instance of 200 bidders in the first and twentieth trades. Both repetitive trades converge each Q-level to the  $M^{\text{th}}$  equilibrium price (i.e., the last matched ask price in a Q-level) that bid (ask) winning bidders have to pay (collect). In fact the final matched list is quite similar to the initial true valuation matched list as shown in light colors of the second graph of both sets. The losers demonstrate a *bounded aggressive moves* to increasing (lowering) their bids (asks) for a winning chance while the winners demonstrate a *conservative moves* to decreasing (increasing) bids (asks) their utilities that narrows down bids/asks variance. The second set reveals the insignificant impact of the thicker e-market on EM contrary to the GSPM. The observed outcome of repetitive trades is the very low variance of the

converging requests and asks and also the no e-market profits. In fact, EM e-markets profit is most often equal to zero, in which the GSPM DA find an inherent competitive advantage over EM DA.



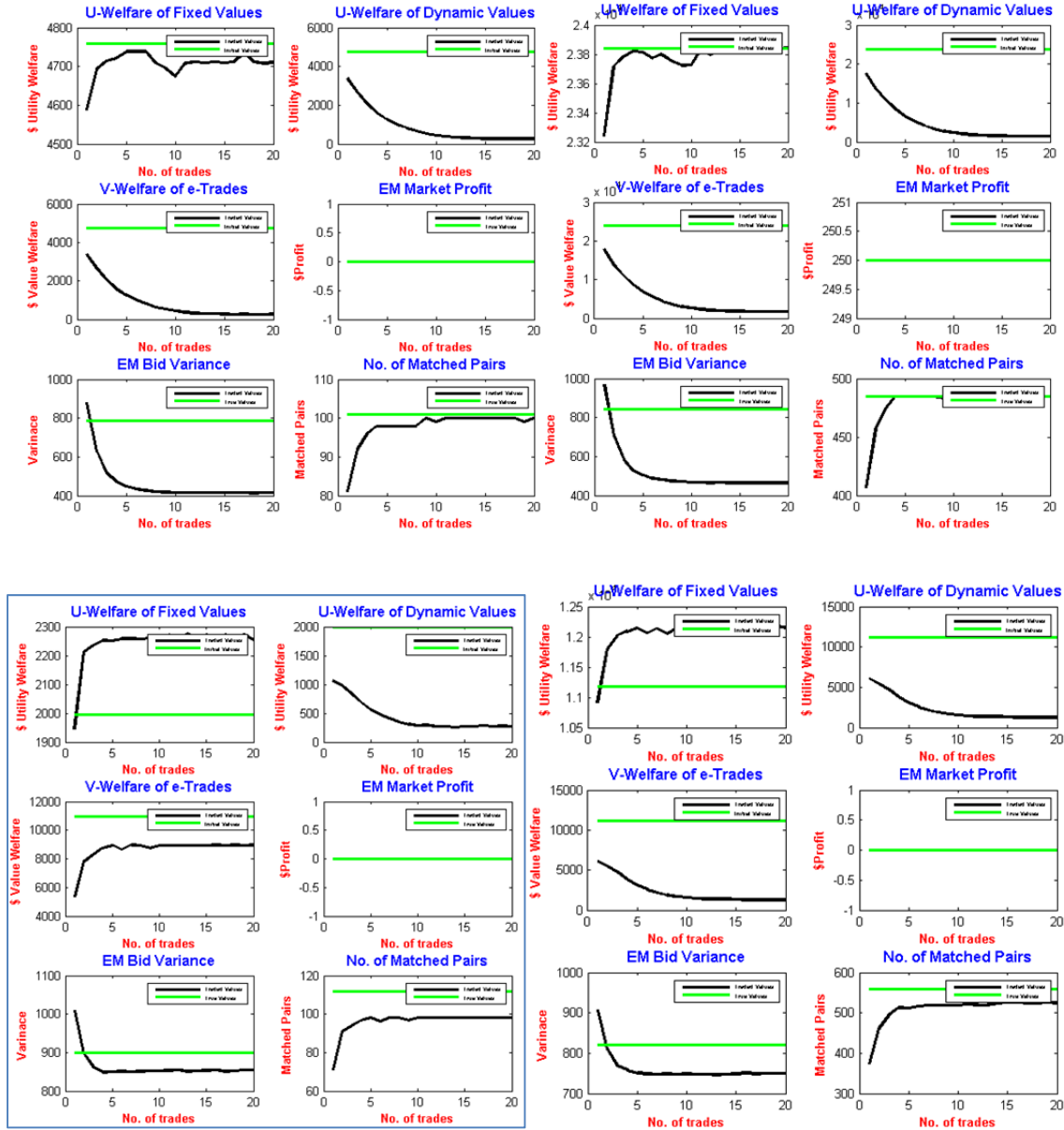
**Figure 28: Traded vs. initial true matched pairs of the first and twentieth trades of the bounded single Q-level (upper set) and multiple Q-levels (lower set) EM DA**

### 6.5.3 Analysis of Bounded $M^{\text{th}}$ EM DA Metrics

Figure 29, depicts the metrics of two instances of request and ask bidders in single and multiple Q-levels bounded EM DA. The following are the experimental findings:

1. The *fixed U-Welfare* converges rapidly to the stable bounds of initial U-Welfare values (i.e., green line) for single Q-level model as request and ask fixed utilities keep increasing and converges to the EM price at repetitive trades that is close the mean of initial EM prices as shown in Table 3. The *fixed U-Welfare* of multiple Q-levels EM converges to a higher stable bounds, however, with respect to initial U-Welfare based on the rather more fuzzy means of the initial multiple Q-level EM prices, as shown in Table 3. Another reason is the cross matching effect. The thick e-markets increase the U-Welfare significantly with respect initial settings due to increasing number of trades. This is due to the constant rising of asks/costs and falling of bids/payment until they reach the stable bound of initial true values.
2. The moving U-Welfare converges to a stable low utility welfare. This is due to the sharp fall of differences between current bids (asks) and  $M^{\text{th}}$  EM payments (costs) at repetitive trades. The thick e-markets, while it have no effect on the converged welfare value it delivers rapid convergence as the bids (asks) variance drops with thick e-market trades.
3. *moving U-Welfare* keeps decreasing and converges to small value at constant learning of repetitive trades as the current bids/payments and current asks/costs converge to the same EM e-market  $M^{\text{th}}$  equilibrium price value with low variance.
4. The *V-Welfare* falls rapidly and converges to stable low value with respect to the initial true V-Welfare. This is due to the large incremental valuation drops of initial winning bids and losing asks that stabilizes with smaller increments as requests and asks get closer to the EM pricing bounds. However, the losers keep bounded *aggressive moves* to join in the matched list, while winners maintain *conservative moves* to increase utility. The thicker e-market, while it increases the V-Welfare, it delivers instant convergence as the variance drops rapidly with

thicker trades. The *e-market profitability*, however, maintains a zero value for all trade as the ask/bid bidders collect/pay the same  $M^{\text{th}}$  EM price.



**Figure 29: Metrics of bounded single Q-level (upper set) and multiple Q-level, (lower set) EM DA, of 200 and 1000 request and ask bidders**

5. The bounded EM DA converges to the maximum number of true matched pairs at repetitive trades (i.e., light green) . This due to the fewer bidders at each Q-level and the corrective style of losers to join the matched list.
6. The variance drops rapidly at the initial trades due to the large delta adjustments of losers. The variance converges, then, to stable low value due to the narrowing difference between the rising asks and the falling bids close to the EM Mth price.

## 6.6 Unbounded $M^{\text{th}}$ EM Double Auction Mechanisms

The Single Q-level Unbounded EM DA mechanism follows the bounded Single Q-level EM in the matching allocation and pricing rules. However, the unbounded EM applies the UNBOUNDED-RULES-UPDATE () algorithm that liberates bounds of the constant learning reaction at repetitive trades. The UNBOUNDED-RULES-UPDATE frees all rule-based bounds. This reactive learning scheme works on unbounded DA mechanisms. The Multiple Q-level Unbounded EM DA model follows the Multiple Q-level Bounded EM model in previous section. This section examines the unbounded choices of bidders.

### 6.6.1 Unbounded $M^{\text{th}}$ EM DA Description

The data in Table 4 follows the same setting of the Table 3. However, it is obvious that the unbounded EM DA allows losers to play rather more aggressive corrective moves and *break risk neutrality* for better winning chance. Hence, the unbounded GSPM matching list converges to full list of all trades while reducing the bid/ask variance. The violation of the risk neutrality of allows bidders an *unbounded free choice and conduct*. The first and final trades demonstrate how unbounded losers may converge to be winners and impact the matched list through lowering (raising), freely, their bids (asks) and how winners narrow request and ask variance to increase their utilities.

**Table 4: Sample results of first and twentieth single Q-level (left set) and multiple Q-levels (right set) unbounded EM trades of twenty request and ask bidders**

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sorted True Bids	95	90	81	81	79	74	73	71	65	65	58	56	52	39	38	20	17	10	9	
Sorted Bids	86	81	73	71	70	63	59	57	56	55	53	50	48	43	32	31	17	13	8	7
Matched Bids	86	81	73	71	70	63	59	57	56	55	53	0	0	0	0	0	0	0	0	0
Bid Payments	50	50	50	50	50	50	50	50	50	50	50	0	0	0	0	0	0	0	0	0
Ask Costs	0	50	50	50	50	50	50	50	50	50	50	0	0	0	0	0	0	0	0	0
Matched Asks	0	2	7	9	11	15	27	31	41	42	50	0	0	0	0	0	0	0	0	0
Sorted Asks	0	2	7	9	11	15	27	31	41	42	50	70	76	82	91	97	101	111	114	120
Sorted True A..	0	2	7	7	9	13	25	29	37	40	41	65	66	72	72	78	85	89	97	97
Sorted Ask QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	4	4	4	4	4	4	3	3	3	3	3	2	2	2	2	2	2	2	1	1
Sorted True Bids	96	82	79	75	74	71	86	80	75	69	63	67	58	56	54	42	38	11	22	19
Sorted Bids	94	77	67	66	63	61	75	61	61	61	57	51	43	41	41	32	29	11	19	16
Matched Bids	94	0	0	0	0	0	75	61	61	61	0	51	43	41	41	32	0	0	0	0
Bid Payments	61	0	0	0	0	0	58	58	58	58	0	20	20	20	20	0	0	0	0	0
Ask Costs	0	61	0	0	0	0	0	58	58	58	58	0	20	20	20	20	0	0	0	0
Matched Asks	0	61	0	0	0	0	0	25	31	44	58	0	2	5	5	6	20	0	0	0
Sorted Asks	106	61	79	81	94	99	102	25	31	44	58	72	2	5	5	6	20	42	42	23
Sorted True A..	88	60	64	64	80	92	93	21	25	42	53	60	2	4	4	5	17	34	40	20
Sorted Ask QS	5	4	4	4	4	4	3	3	3	3	3	2	2	2	2	2	2	2	1	1

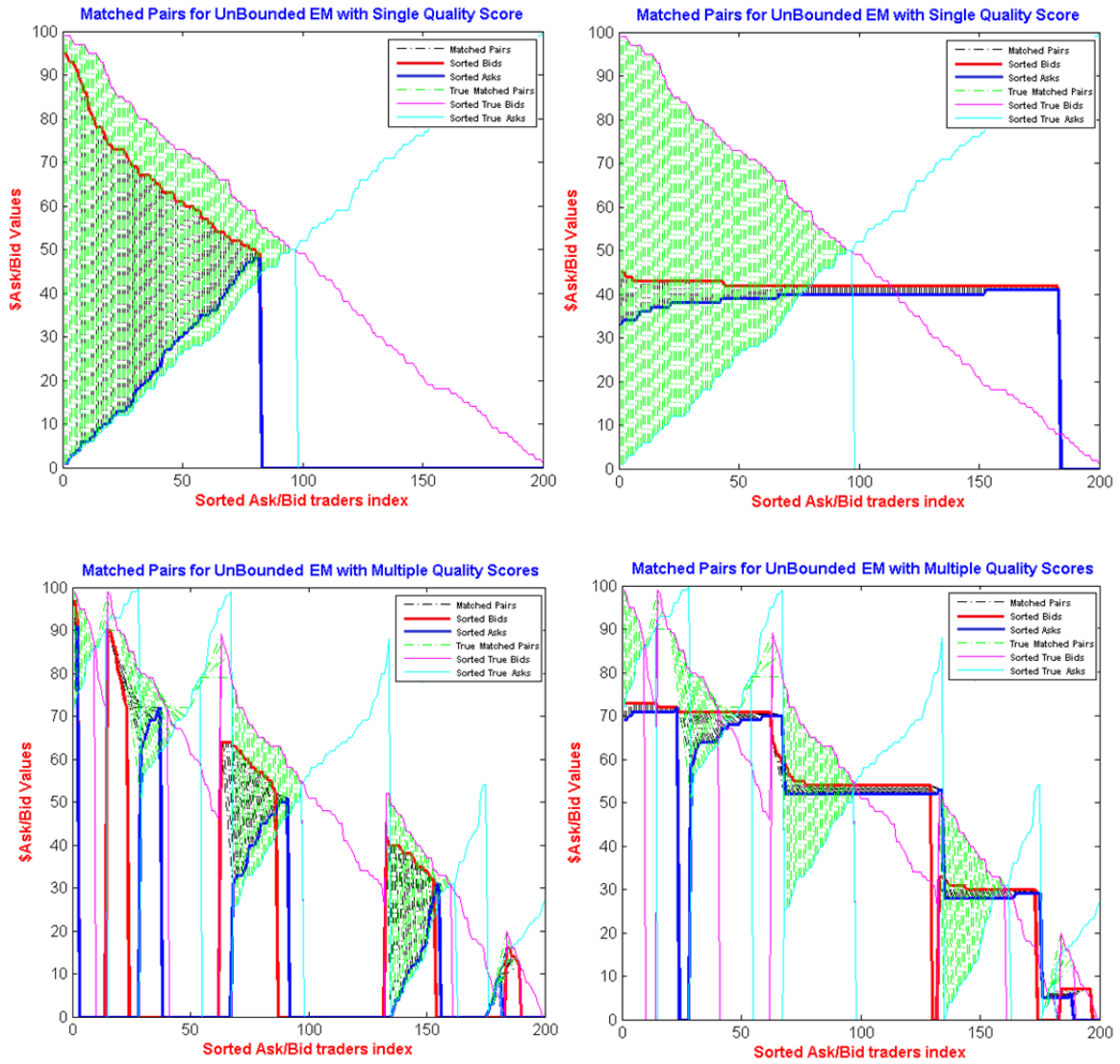
Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sorted True Bids	95	90	81	81	79	74	73	71	65	65	58	56	52	39	38	20	17	10	9	
Sorted Bids	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47
Matched Bids	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47
Bid Payments	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46
Ask Costs	0	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46
Matched Asks	0	45	45	45	45	45	46	46	46	46	46	46	46	46	46	46	46	46	46	46
Sorted Asks	0	45	45	45	45	45	46	46	46	46	46	46	46	46	46	46	46	46	46	46
Sorted True A..	0	2	7	7	9	13	25	29	37	40	41	65	66	72	72	78	85	89	97	97
Sorted Ask QS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Set/Trader No	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
Sorted Bid QS	4	4	4	4	4	4	3	3	3	3	3	2	2	2	2	2	2	2	1	1
Sorted True Bids	96	82	79	75	74	71	86	80	75	69	63	67	58	56	54	42	38	11	22	19
Sorted Bids	67	67	67	67	67	67	60	60	60	60	60	23	23	23	23	23	23	22	26	24
Matched Bids	67	67	67	67	67	67	60	60	60	60	60	23	23	23	23	23	23	22	26	0
Bid Payments	66	66	66	66	66	66	59	59	59	59	59	22	22	22	22	22	22	22	19	0
Ask Costs	66	66	66	66	66	66	0	59	59	59	59	22	22	22	22	22	22	22	22	19
Matched Asks	67	64	64	65	66	66	0	58	58	58	58	21	21	22	22	22	22	22	22	19
Sorted Asks	67	64	64	65	66	66	66	58	58	58	58	59	21	21	22	22	22	22	22	19
Sorted True A..	88	60	93	64	64	80	92	21	25	42	53	60	2	4	4	5	17	34	40	20
Sorted Ask QS	5	4	4	4	4	4	3	3	3	3	3	2	2	2	2	2	2	2	1	1

### 6.6.2 Analysis of Unbounded $M^{\text{th}}$ EM DA Trades

Figure 30 shows the constant learning trend of 200 request and ask bidders in the first and twentieth trades. The second right graphs show an almost full matched list that include all bidders with constant drop of the bid/ask variance. In fact, the losers demonstrate a rather *unbounded aggressive corrective moves* and *break risk neutrality* for a winning chance by increasing (lowering) bids(asks) beyond initial true bounds (i.e., see the curve extension into the losers zone). The loser/winning dynamics results in a full matching and reduction of bid/ask variance. The lower set exhibits the rapid convergence of thicker e-market to stable efficiency while unbounded losers become winner at repetitive trades. That attributes to the extension of the matching curve in the losers space as shown below.



**Figure 30: : Traded vs. initial true matched pairs of the first and twentieth trades of the unbounded single Q-level (upper set) and multiple Q-levels (lower set) EM DA**

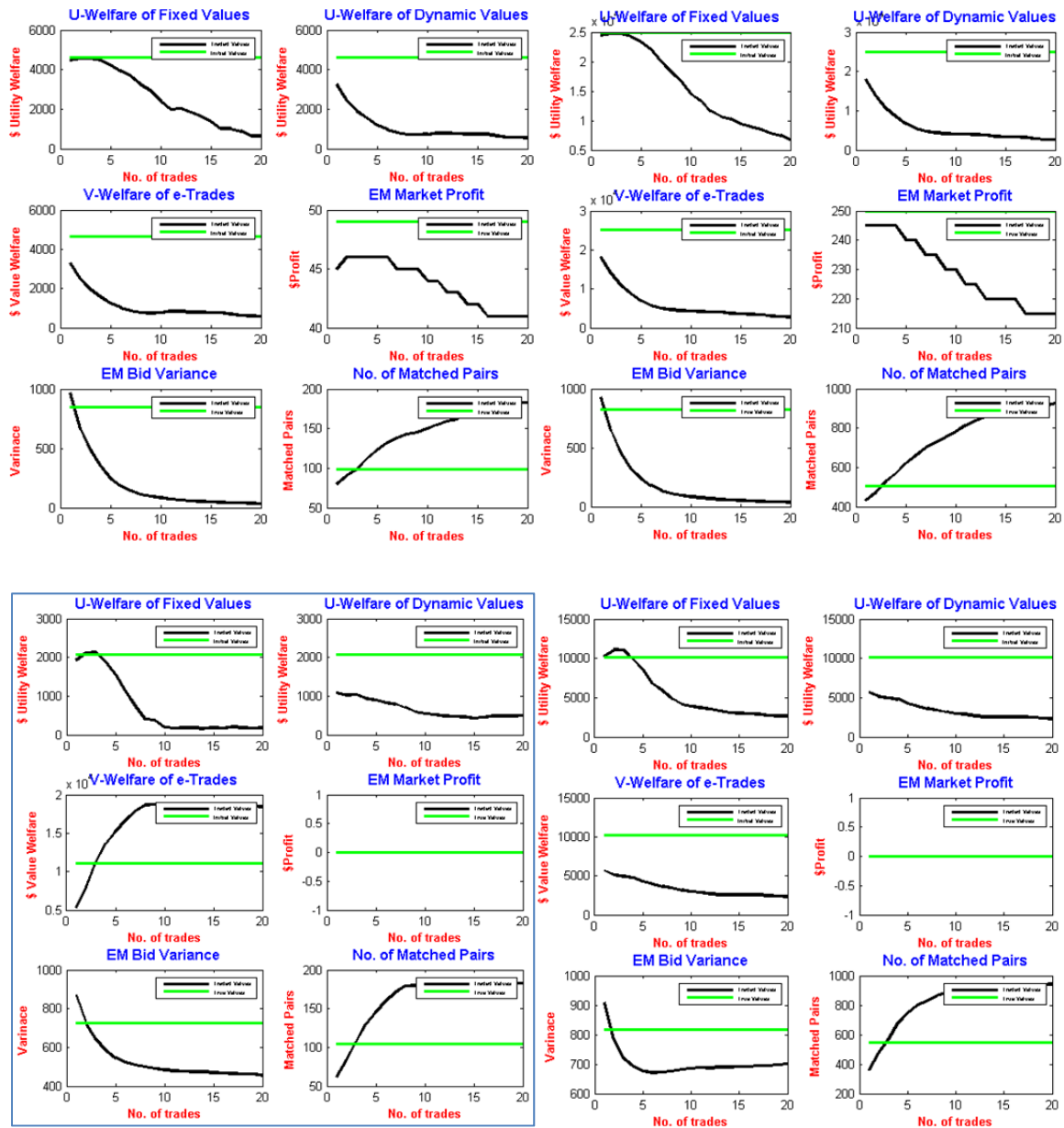
### 6.6.3 Analysis of Unbounded $M^{\text{th}}$ EM DA Metrics

Figure 31 depicts the metrics of the Single Q-level Unbounded EM DA mechanism. The analysis emphasizes the following experimental findings:

1. The *fixed U-Welfare* falls rapidly from values close to the initial true welfare value shown in light green to rather lower positive values that converge to zero U-

Welfare at repetitive trades. This is due to the violation of the risk neutrality that motivates losers to overbid by decreasing (increasing) their bids (asks) over true bounds that generates negatives utilities and force welfare to decrease gradually until all requests and asks matched at EM price and zero welfare.

2. The *moving U-Welfare* keeps decreasing and converges to stable lower values at repetitive trades as the current bids/payments and current asks/costs converge to the EM e-market  $M^{\text{th}}$  equilibrium price value.
3. The *V-Welfare* and *e-market profitability* falls rapidly and converges to stable lower value with respect to the initial true V-Welfare. This is due to the large incremental valuation drops of initial winning bids and losing asks that converges to more stable smaller increments as requests and asks get closer to EM pricing bounds. This V-Welfare stability is due the balancing effect of the rising asks and the falling bids that converge to the  $M^{\text{th}}$  pricings. The EM delivers almost no (i.e., zero) *e-market profitability* as the ask/bid bidders collect/pay the same EM price. Also, thick e-markets increase the V-Welfare and deliver instant convergence.
4. The EM e-market converges slowly to the a full matched pairs list for single and multiple Q-levels that include all bidders (i.e., initial winners and losers) after few trades (see the green line for initial requests and asks valuation matched list) at repetitive trades. This due to the fewer bidders at each Q-level and the aggressive corrective style of losers to join the matched list.
5. The variance drops slowly at the initial trades due to the large delta adjustments of losers. The variance converges, then, to stable low value due to the narrowing difference between the rising ask bids and the falling request bids close to the EM  $M^{\text{th}}$  price.



**Figure 31: Metrics of the unbounded single Q-level (upper set) and multiple Q-level, (lower set) EM DA of 200 and 1000 request and ask bidders**

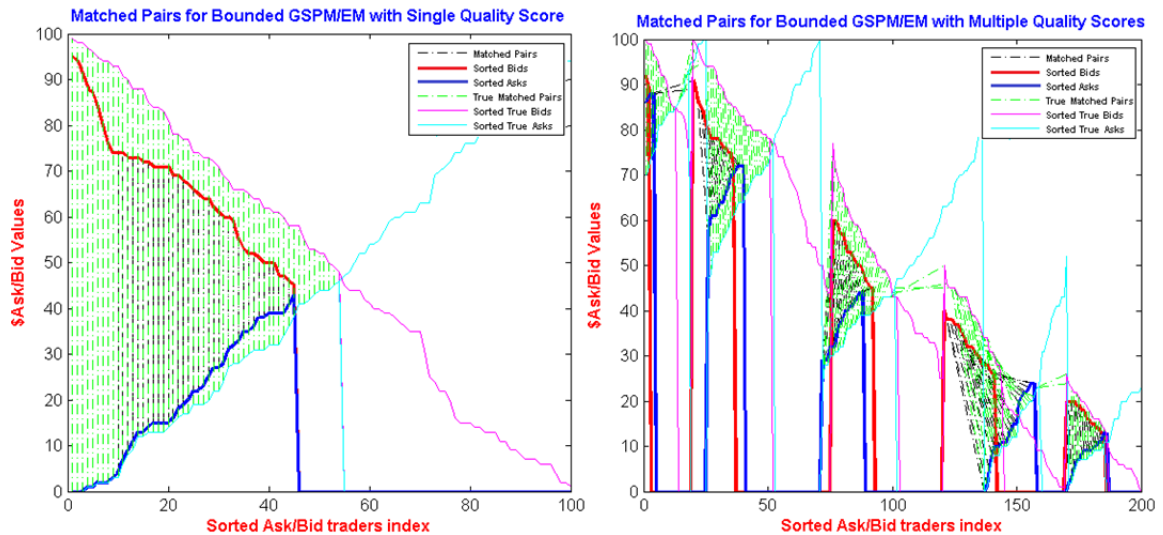
## 6.7 The GSPM and EM Comparative Analysis

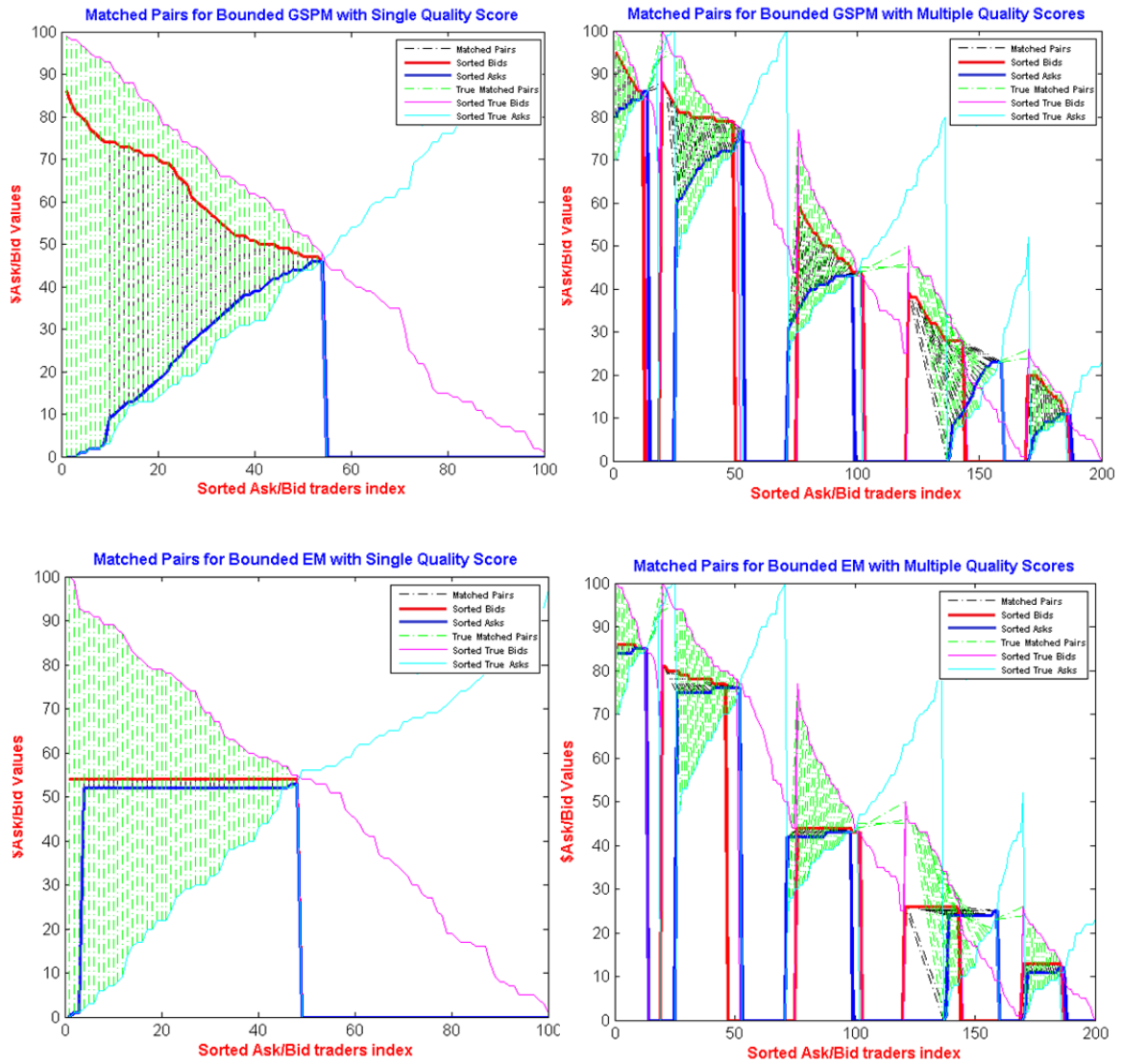
This section summarizes the comparative experimental findings between the GSPM and EM DA mechanisms for the single Q-level and multiple Q-levels requests and asks. Our

work here investigates, also, the bounded and unbounded bidder reactions due to their constant learning of e-market dynamics at repetitive trades.

### 6.7.1 Single and Multiple Q-level(s) Bounded GSPM and EM DAs

**Experimental Matching Behaviour:** Figure 32 depicts the matching patterns of the GSPM and EM DA mechanisms for bounded request and ask bidders of a single Q-level (left set) and multiple Q-levels (right set) e-service at the first and twentieth repetitive trades. The GSPM and EM DA exhibit a gradual reduction of the request/ask bids variance with the increasing matched list that converges to the initial true matched list. The GSPM thicker trades converge rapidly to stable efficiency as request and ask bids converge to the second prices. The  $M^{\text{th}}$  EM thick trades, however, have no effect. The losers demonstrates a bounded aggressive corrective actions by increasing (lowering) their request (ask) bids for a winning chance. The winners demonstrate conservative actions to improve their utilities. That results in reducing the request/ask bids variance. The EM repetitive trades converge to the  $M^{\text{th}}$  equilibrium prices.





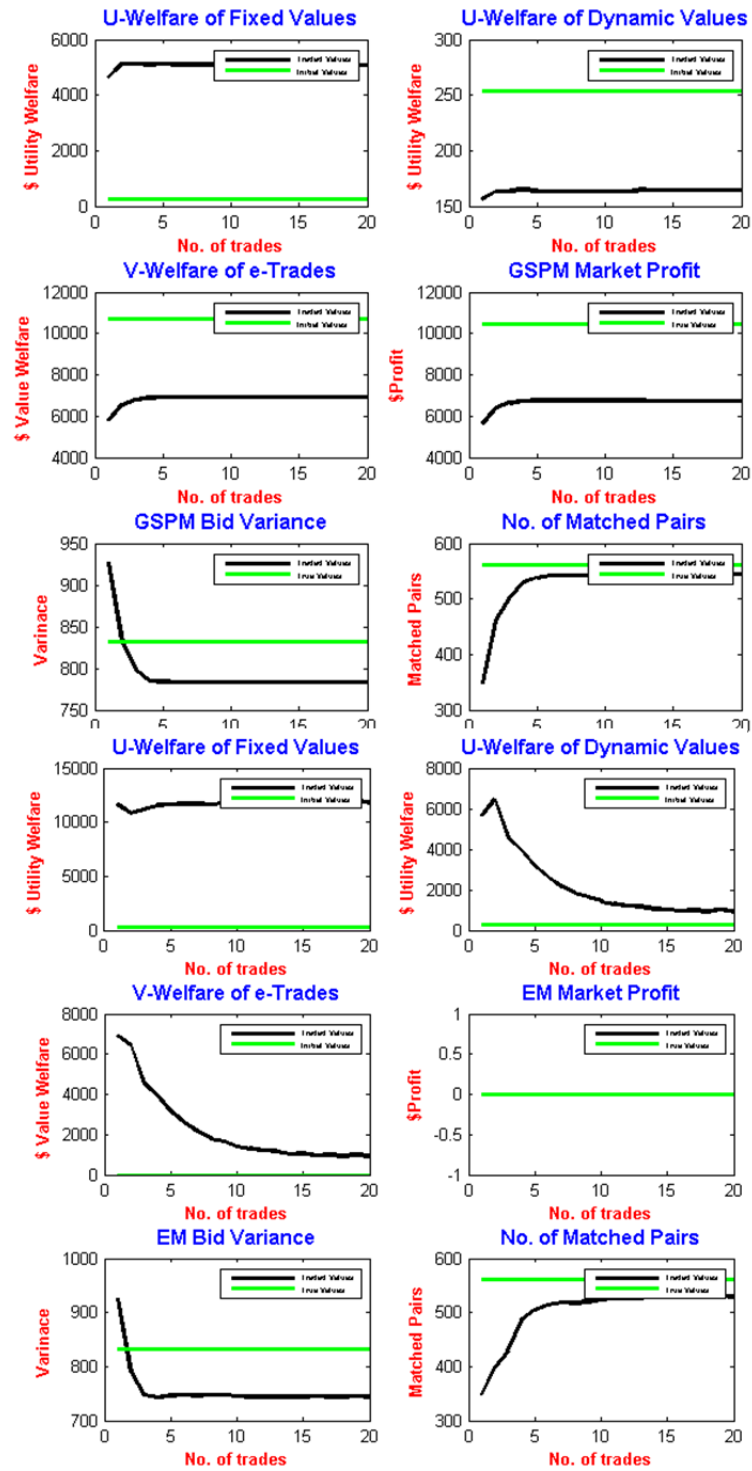
**Figure 32: Single Q-level (lefts set) and multiple Q-levels (right set) bounded GSPM and EM DA matching patterns at first and twentieth trades**

**Experimental Metrics:** Figure 33, depicts sample metrics of the GSPM and EM DA mechanisms of a two thousand bounded request and ask bidders of multiple Q-levels e-services during twenty repetitive trades. The analysis extends to single Q-level models.

- 1) The *fixed U-Welfare* of the GSPM or EM DA converges rapidly to a maximum stable AE bounds compared to the initial true welfare (i.e., green line) as ask and request bid utilities increase due to the rule adjustments driven by constant learning at repetitive

trades. The EM converges to higher welfare values compared to GSPM as the rising asks/costs and falling bids/payments of the GSPM converge to the stable bounds of the closer second prices, while the EM converges to the stable bounds of the rather distant EM price. Else, the thicker e-markets increase the fixed U-Welfare significantly.

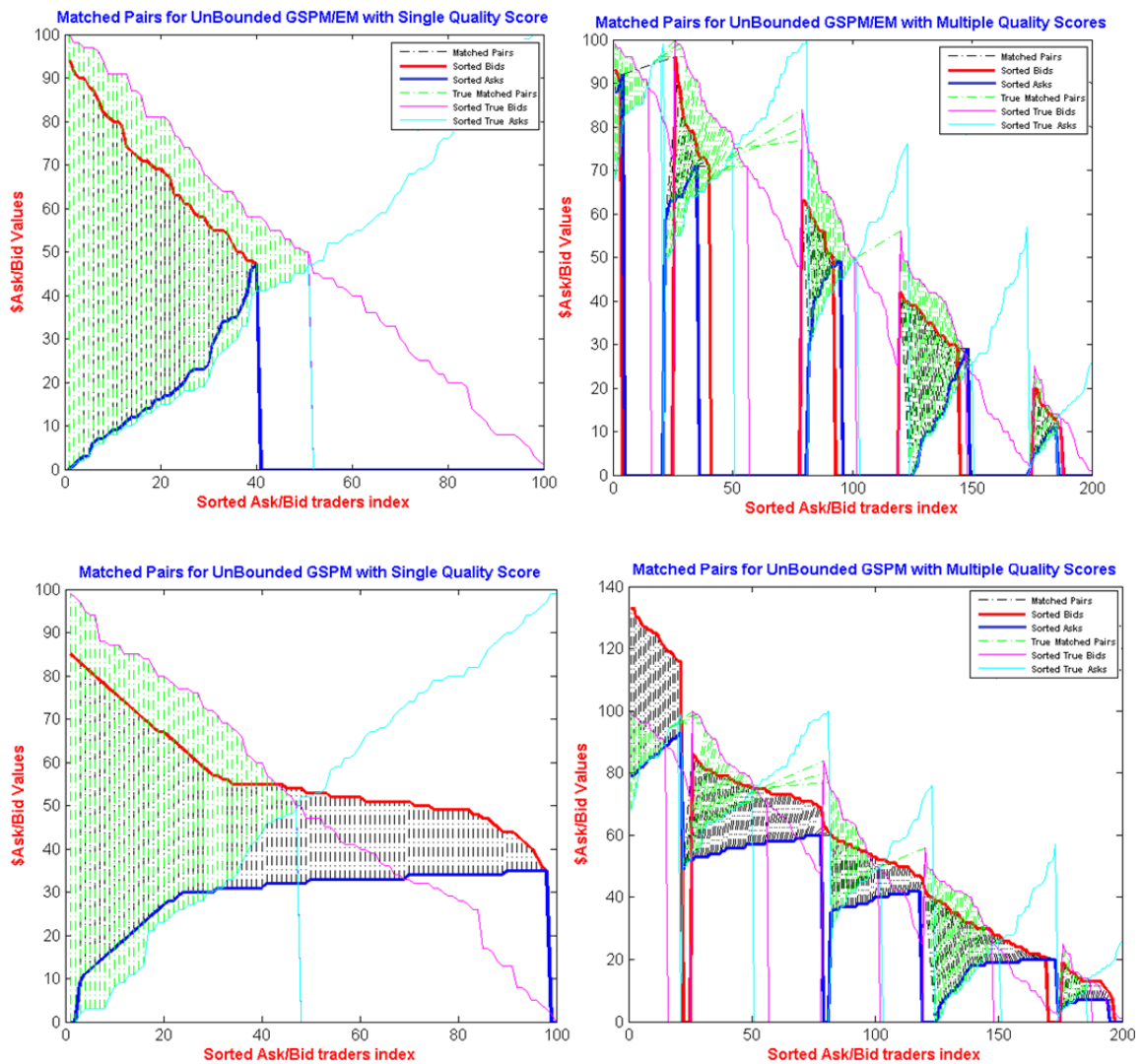
- 2) The *moving U-Welfare* of the GSPM and EM converge to a low stable utility. This is due to the rapid fall of differences between current request (ask) bids and GSPM second price payments (costs) or the  $M^{\text{th}}$  equilibrium price value at repetitive trades. The thick e-markets have no effect on the converged utility, but deliver instant GSPM convergence and faster EM convergence (slower in base) due to the faster converging stability of the bids and ask at thicker trades.
- 3) The *V-Welfare* and *e-market profitability* converge to stable positive value that is lower than that of initial settings due to the rule based adjustment that direct the convergence to lower value bids and higher value asks at constant leaning of repetitive trades. The winners maintain bounded conservative moves to increase utilities while losers take bounded aggressive moves to join in the matched list until they reach the bounded true values. The thicker e-market deliver higher, stable and more rapid instant. The GSPM DA guarantees, also, the *e-market* converge rapidly to a stable *profitability* close to the V-Welfare that grow, also, with the economy of scale of thicker e-market trades. The *V-Welfare* of the EM DA, however, falls rapidly and converges to stable low value close to zero with respect to the initial utility. This is due to the large increments of initial request and asks bids that stabilize with smaller increments as request and ask bids get closer to the EM pricing bounds. However, the EM *profitability* maintains a zero value as ask/bid bidders collect/pay the EM price.
- 4) The bounded GSPM and EM DA converge to the maximum number of *matched pairs* close to the true value matched pairs (shown in green). This is the natural matching progress of the bounded learners (bidders) at repetitive trades.
- 5) The *variance* of the GSPM and EM DA drops rapidly at the initial trades due to the large delta adjustments of the request and ask bids of the losers. The variance then converges with smaller adjustments to a stable low value as the falling bids and the rising asks get closer to the GSPM second price or the EM  $M^{\text{th}}$  price bounds.

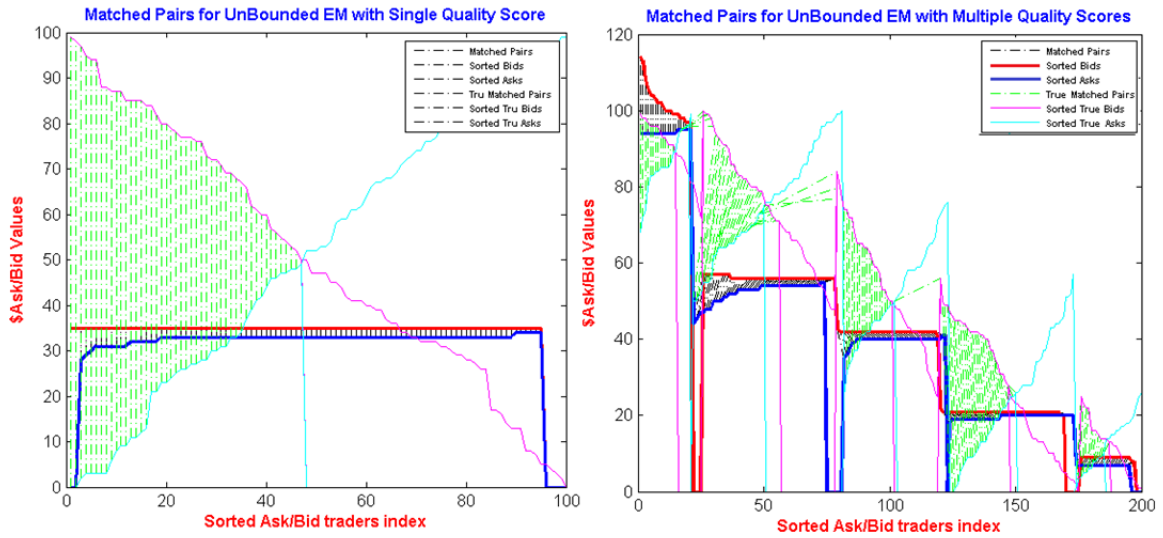


**Figure 33: Sample metrics of the bounded multiple Q-level GSPM DA and EM DA for two thousand request and ask bidders during twenty repetitive trades**

### 6.7.2 Single and Multiple Q-level(s) Unbounded GSPM and EM DAs

**Experimental Matching Behaviour:** Figure 34 depicts the matching patterns of the GSPM and EM DA of unbounded request and ask bidders of single Q-level and multiple Q-levels e-service at the first and twentieth repetitive trades. Both unbounded DA deliver a full matched list of all bidders (i.e., initial winners and losers). The losers demonstrate a rather unbounded aggressive corrective move and break risk neutrality for a winning seat by increasing (lowering) request (ask) bids beyond initial true bounds (i.e., see the curve extensions into the losers zone). The thicker DA e-market trades deliver a rapid stable efficiency of winners while losers join in winners at repetitive trades.



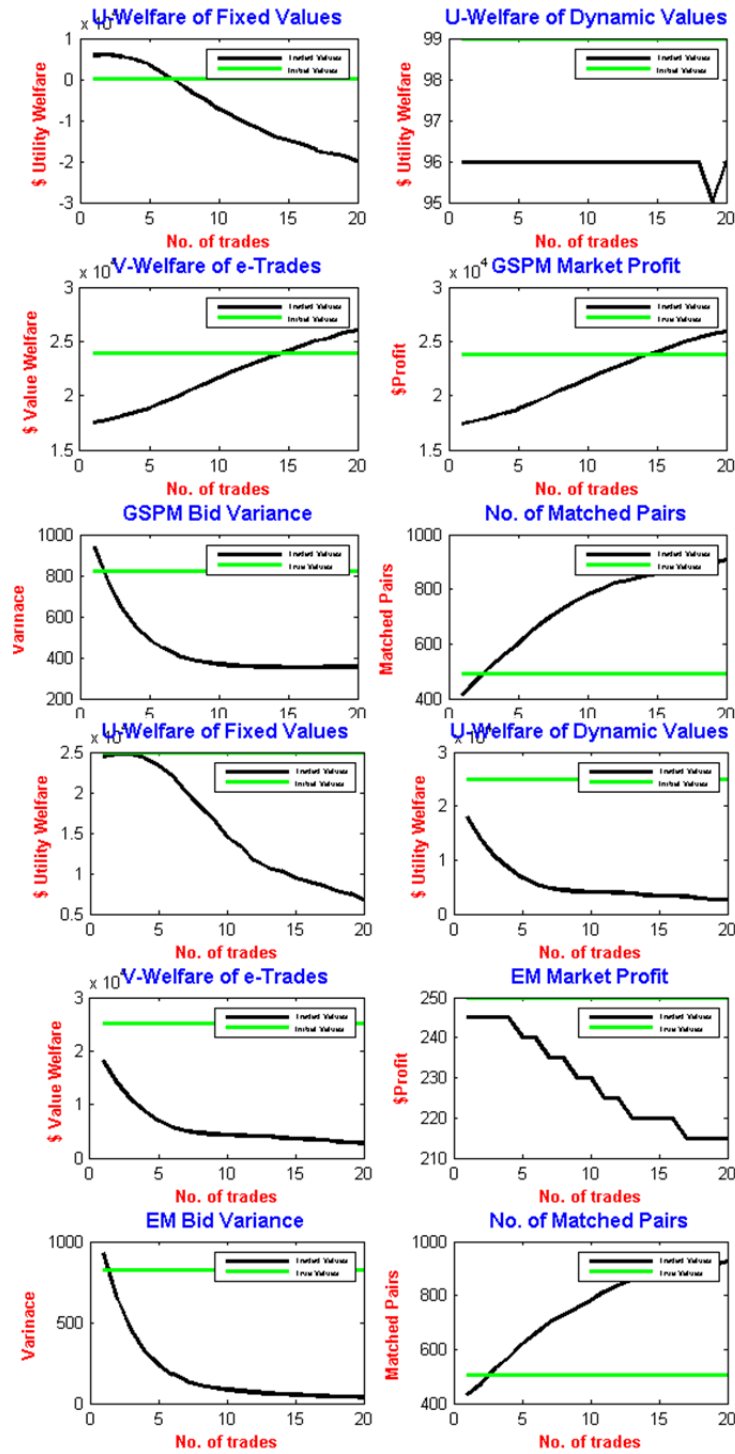


**Figure 34: Single Q-level (left set) and multiple Q-levels (right set) unbounded GSPM and EM DA matching patterns at first and twentieth trades**

**Experimental Metrics:** Figure 35 depicts sample metrics of the GSPM and EM DA mechanisms of two thousand unbounded request and ask bidders of multiple Q-levels e-services during twenty repetitive trades. The analysis extends to single Q-level models.

- 1) The *fixed U-Welfare* of the unbounded GSPM DA keeps falling to the negative quadrant at repetitive trades, while the *fixed U-Welfare* of the unbounded EM keeps falling to rather positive lower values. The thicker e-market trades intensify the impact. This is due to the violation of the risk neutrality that motivates losing bidders to overbid by decreasing (increasing) their bids (asks) over true bounds that generate negatives utilities. The GSPM *fixed U-Welfare* drops to a negative zone as its *bounded fixed U-Welfare* shown in previous section get overrun by the negative utilities. The EM *fixed U-Welfare* drops to lower positive value, though, due to its higher bounded EM fixed U-Welfare. This pattern of tactical trading actions is often found in conventional markets or e-market, where there are some bidders who are stuck with their non-moving or slow-moving items. It also observed in markets where bidders might need a critical item or tactically inspecting the e-market valuation for an items.

- 2) The *moving U-Welfare* of the unbounded GSPM and EM DA keep decreasing and converges to a stable low welfare at repetitive trades. This correlates with the constant fall of differences between the current bids (asks) and the GSPM second price payments (costs) or the EM  $M^{\text{th}}$  equilibrium price at repetitive trades. The thick e-markets have *no effect*, but delivers instant GSPM convergence, while keeps falling for EM until it converges to a stable low utility.
- 3) The *V-Welfare* and *e-market profitability* of GSPM DA keep increasing to values beyond that of the initial true setting due to the *unbounded aggressive adjustments* that direct the unbounded convergence of the *risk unneutral* higher value bids and lower asks of the losers at constant leaning of repetitive trades. However, the winners maintain bounded conservative moves to second prices to increase utilities. The GSPM *V-Welfare* and *e-market profitability* converge to stability when all request and ask bids of now all joining winners get closer to the second prices. The *V-Welfare* and *e-market profitability* grow for all trades and thicker markets. The *V-Welfare* and *e-market profitability* of the EM DA, however, keep falling and converge to stable lower value with respect to the initial true V-Welfare. These is due to the larger increments of request and ask bids that stabilize with smaller increments as request and ask bids get closer to the EM price. The EM delivers zero *profitability* as the request/ask bidders collect/pay the same EM price.
- 4) The unbounded GSPM and EM converge to the maximum full matched pairs that covers almost all request-ask pairs at repetitive trades. This is a result of the unbounded reactions of bidders that scarify risk neutrality for a wining match.
- 5) The variance drops rapidly at the initial trades due to the large delta adjustments of the request and ask bids of losers. The variance converges to stable low value due to the narrowing difference between the rising asks and falling bids.

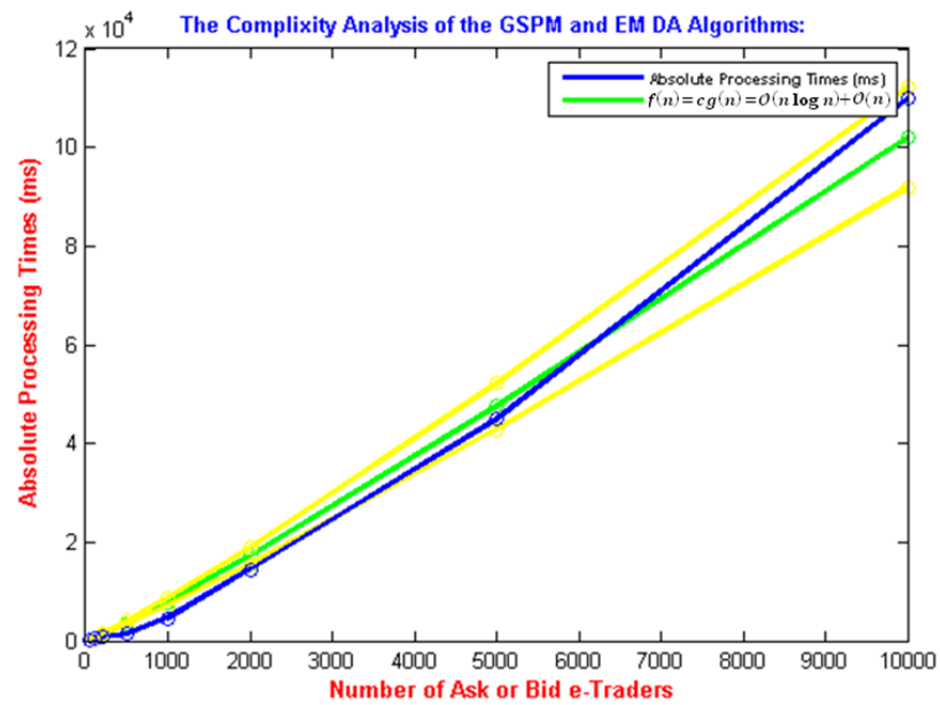


**Figure 35: Sample metrics of the unbounded multiple Q-level, GSPM DA vs. EM DA for two thousand request and ask bidders during twenty repetitive trades**

## 6.8 Complexity Analysis of the GSPM and EM Mechanisms

Our work examines the execution runtimes for all matching codes using the MATLAB tic-toc. A similar pattern of processing times is observed for GSPM and EM DAs at various trade settings. In fact, the most demanding function is the SORT () function that all DA mechanisms share for grouping, sorting and indexing. The blue curve in Figure 36 depicts the average absolute processing runtimes of all DA allocation and pricing algorithms for up to 10000 ask or request bidders. Figure 36 shows also the asymptotic  $g(n) = \mathcal{O}(n \log n) + \mathcal{O}(n)$  upper bound curve in green of the  $f(n)$  that our work derived for the complexity of the experimental data pattern of the processing runtimes at different trades. The experimental results pattern is common between all DA mechanisms. The yellow curves are sample functions (i.e.,  $f(n) = c(g(n))$ ) that present an upper and lower bounds for the experimental data results, It designates a tighter bounds  $g(n) = \Theta(n \log n) + \Theta(n)$ . However, our work maintains the upper bound complexity  $\mathcal{O}(n \log n) + \mathcal{O}(n)$  as the worst case runtime of all algorithms.

The GSPM DA is equivalent to finding a *maximum bipartite matching* in a bipartite graph  $G = (V = (b_c^{ik}, b_p^{jq}), E)$ , where  $E$  contains one edge for each pair of bid  $b_c^{ik}$  and ask  $b_p^{jq}$  if  $b_c^{ik} \geq b_p^{jq}$ .  $\forall e_c^{ik} = e_p^{jq}$ ,  $\min Q_c^{ik} = Q_p^{jq} \forall Q = Q_m$ . For  $n$  bidders, the GSPM and EM run in  $\mathcal{O}(n \log n)$  time for the sorting and in  $\mathcal{O}(n)$  time for the matching in the worst case. The  $\mathcal{O}(n \log n)$  term is the *worst case* complexity of the sorting as found in the case of the *merge sort*, while the  $\mathcal{O}(n)$  term, however, is for the allocation matching of the EM algorithms that is applied also to the GSPM algorithms. For the case of different  $n_c$  bid bidders and  $n_p$  ask trades the GSPM and EM algorithms would run at  $\mathcal{O}(\min(n_c, n_p) \log \min(n_c, n_p)) + \mathcal{O}(\min(n_c, n_p))$  times.



**Figure 36 Complexity analysis of GSPM and EM algorithms**

## Chapter 7

### 7 Conclusions and Future work

Our work contemplates on the profoundly changing landscapes of e-marketplaces due to the massive growth and interactive marketing of e-services. While the prospects of the digital era are enormous, e-marketplaces are encountering inherent and persistent game-theoretic and computational complexities that challenge the strategic and computational efficiencies of the matching mechanisms. In fact, the mounting complexities are inciting the industry to pursue more resilient delivery and revenue ecosystem friendly e-market mechanisms (Moore, 1996). Our work examines the limited bidding scope and strategic trading conduct of e-market mechanisms that often provoke adverse strategies and lead to e-market failures. The market economy of free rational conduct would, however, enable stable social efficiency by equalizing the dual self-interest and essential needs of bidders to the scarce assets. The dual dynamics inspire the collaborative strategies that discourage monopolies. The constant learning at repetitive trades motivates bidders to reason about e-market disruptions and adjusts preferences and strategic conduct in a rational manner. This type of strategic conduct is a truthful rational reaction that must be freely expressed. Our work targets the solution approach of a rather truthful, efficient and stable problem models of a class of CAP for multiple units of a single-item (i.e., e-service or app) of multiple-attributes, attribute-values and, particularly, multiple Q-levels that extend to the CAP of multiple units of multiple attribute items (i.e., multiple e-services).

Our work introduces the free exchange by endowing it with the RBBL that enables the flexible and symmetric expression of free choice and strategic conduct. The RBBL structure includes multiple distinct attribute-values of various digital and the logical rule formulae. The RBBL bidding model enables a graph-based expressions of the multiple distinct attribute-values of various e-services, and also the expressions of applied logical rule formulae. The RBBL enables the free exchange to reasoning about the attribute-values using logical rules deduction for a rapid automatic construction of e-services and

bid formations. Hence, the RBBL enables a rapid exchange clearing. Our work presents the formal model of the e-services CAP and expanded on how the RBBL allows for capturing the CAP as a formal IP for the stable and efficient winner matching allocation. However, our work does not expand on the smart aspect of the free exchange. Our work uses MATLAB to simulate the request and ask bidding behaviour and self-learning at repetitive trades that maps to logical rules conveyed to the exchange e-marketplace.

Our work investigates, also, the inefficiencies of the exchange mechanisms with respect to allocation and revenue models. A fundamental challenge is the fact exchange models are hard to implement, as per Hurwicz impossibility theorem (Hurwicz, 1975) that states it is impossible to implement an AE, IC and BB social welfare function in a DSE settings even for simple exchange (Parkes, 2001) and quasi-linear preferences. This is also the case even without requiring IR. The work in (Green & Laffont, 1977) demonstrates no DSE AE and IC mechanism can be safe from manipulation by coalitions, even in quasi-linear settings. Our work endows the free exchange, also, with the GSPM, GSP DA matching. The formal problem model captures the CAP as a IP for the socially efficient matching allocation. The free exchange deliberates on the logical rules for preference deduction and winner matching. The free exchange applies the GSPM matching on the induced request and ask-bids to compute an efficient and stable matching. The GSPM DA uniquely exploits the tractable forward and reverse-GSP auction heuristics that improve the truthful, efficient, stable, profitable, and tractable FX matching. The FX GSPM targets the symmetric, efficient and stable matching between multiple buyers and sellers of a class of multiple units of a particular e-service of multiple Q-levels.

The free exchange improves truthfulness by implementing a multiple Q-levels GSPM. The request bidder would be better off if it bid truthfully on a e-service of a particular Q-level, as it would minimize the risk of losing to others at that Q-level, while having an incentive to win a e-service of higher quality. The GSPM also secures e-market profitability that grows with thick trades and makes it lucrative to e-markets.

Given, the complexity of exchange impossibility theory (Hurwicz, 1975), our work proposes an exchange model that exploits the relaxed (weaker) properties of the e-services CAP that translates to the multiple unit-demand matching with multiple Q-levels to improve the symmetric DA properties. Our model suggest also the application of constant learning at repetitive trades in rather thicker markets that transform efficiently the private information model to full information settings using our proposed FX model.

## 7.1 Experimental Findings and Comparative Analysis

The experimental analysis targets the algorithmic simulation and comparison between the GSPM and EM for the matching allocation and pricing outcomes of the CAP class of multiple units DA of a single-item (i.e., e-service). The single items (e-services) may be constructed from multiple attributes and multiple Q-levels using the RBBL tree based bidding attribute-values and logical rule and operators formulae. The simulation allows for repetitive trades. Requests and asks bids are either bounded or unbounded by the Min/Max request and ask bid limits. The simulation implements, analyses and reports the algorithms and the experimental findings of the presented GSPM and EM DA mechanisms that serve either bounded or unbounded bidders of single or multiple Q-level request and ask bids. The DA mechanisms exploit the conveyed RBBL instance of the bidders that dictates their rational reactions at constant learning.

The experimental scenarios examines the performance advantage of using only the rules aggregation for a number of request and ask bidders with the assumption that bidders apply self-learning abilities at repetitive trades that maps to logical rules and conveyed to the FX. The RBBL rules aggregation inside the free exchange reduces the relative processing time of the remote (i.e., over local networks) bidder agents processing time in multiple folds. Furthermore, the reduction of processing time by the aggregation of rules increases significantly with thicker e-market trades over best effort internet. In addition, our work assumes that the smart deduction and minimal elicitation, that is to be explored in future work, would have a substantial performance improvement for more rapid trades.

The FX applies the GSPM matching on the induced and generated e-services and requests and asks bids to find an efficient and stable matching allocation and pricing outcomes. The FX e-marketplace facilitates truthful interactions by implementing the GSPM double auction matching that exploits the multiple Q-level forward and reverse GSP double auctions for e-trading e-services. The GSPM DA delivers stable social efficiency quite rapidly at the first trades with fairly thick e-market trades (i.e., more than 100 bidders). However, the EM DA keeps unstable social efficiency for most repetitive trades. The GSPM stable efficiency is due to the pricing rule that narrows down the tactical maneuverability, the multiple Q-level cross-matching and the best response at repetitive trades. In fact, the rational reaction of bidders at constant learning of the e-market dynamics drives both the GSPM and EM to converge to stable efficiency. The process transforms the exchange e-market from incomplete information to complete information truthful settings. However, there is no guarantee the EM DA would converge in a lower number of rounds due to the EM pricing model that allows for aggressive tactical moves of losers throughout repetitive trades until they converge to the EM prices.

The GSPM DA secures the e-market profitability that grows with thicker trades. This is an inherent attribute of the GSPM DA matching. However, the EM DA mechanism delivers no profitability. The e-market profitability is lucrative to e-marketplaces that deliver the liquidity and the computational e-services. The bounded GSPM and EM DA converge to the maximum number of matched pairs close to the true value matched pairs. This is the natural matching progress of the bounded bidders at repetitive trades. The unbounded GSPM and EM DA converge, however, to the maximum full matched pairs that cover almost all ask-bid pairs at repetitive trades. This is a result of the unbounded reactions of bidders that scarify risk neutrality for a wining match. The unbounded GSPM DA and EM DA allows for negative utilities due to the *unbounded aggressive adjustments* of losers that direct the convergence of the risk unneutral higher value request bids and lower ask bids of the losers until they turn into winners. This is due to the violation of the risk neutrality by the losers over true bounds. Otherwise, the bounded conservative conduct of winners targets utility maximization. Our work examines the

unbounded model to investigate bidder's behaviours at GSPM thicker and/or repetitive trades. An interesting observation is that GSPM DA delivers stable AE social efficiency for bidders of bounded GSPM trades and also for winners of unbounded GSPM trades. The losers of unbounded GSPM trades destabilises their allocation region due to their unbounded aggressive moves that breaks risk neutrality.

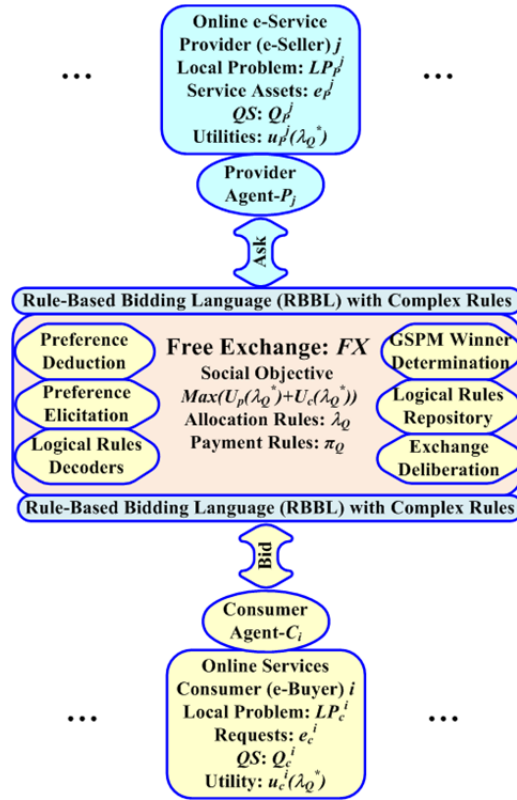
It is also observed the variance of both GSPM and EM DA requests and asks drops rapidly at the initial trades due to the bounded or unbounded large delta adjustments of the requests and asks of losers aggressive moves. The variance converges, then, with rather the smaller adjustments of winners conservative moves to a stable low value as bidders hit their true valuation bounds or as the difference between the falling bids and the rising asks narrows down until they get closer to the GSPM second prices in order or the EM  $M^{\text{th}}$  price bounds.

The complexity analysis of the diverse GSPM DA mechanisms examines the processing runtimes at diverse GSPM and EM trades. Our work observed there is at no extra computational cost in implementing the GSPM algorithmic heuristics compared to the EM DA counterpart. In fact, the GSPM mechanisms utilize the EM algorithms for the sorting, grouping, indexing and the allocation matching that often demands the highest computation cost while applying linear pricing models. Hence, the GSPM DA would deliver better economic properties such as stable efficiency and e-market profitability for the same computational cost.

## 7.2 Future Outlook

This is ongoing research with promising prospects. The free exchange is an attempt to liberalize the e-market mechanisms that would drive their resilience through free, rapid and stable trades, social efficiency, self-prosperity, and e-markets profitability. However, there are potential aspects to be furthered such as how the free exchange smart engine can be computationally effective for the automatic deduction of the bidding rules and the formation of request and ask bids. There is also the scalability impact of thick e-market

trades and real-time performance. Another issue has to do with how the bidders may effectively generate the suitable strategic rules that deliver to their local constraints and objectives without exposure. The solution approaches in this research are anticipated to open new horizons for ecosystem friendly and computationally tractable mechanisms. The proposed free exchange facilitates the free rational strategic conduct that equalizes the conflicting forces of the essential needs to the scarce resources and the self-interested local objectives and local feasibility constraints. The free exchange with the flexible strategic conduct of bidders would eventually deliver a socially efficient and strategically stable and profitable e-marketplace. In fact, the free rational conduct is still an overlooked encounter in the digital era and mobile influence where bidders are the targets and are the real-time commodity. The desirable properties of the FX e-market is verified through the experimental analysis of proposed FX model. Figure 37 outlines the FX trading platform with the proposed RBBL model and GSPM double auction mechanism.



**Figure 37: Free exchange e-marketplace trading platform**

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## Appendices

### Appendix A: GSPM and EM MATLAB Simulation Algorithms

```

SORT (Bids, Asks, BidQS, AskQS) % Sort Q-levels and Request and Ask Bids
% Bids is set of all request bids.
% BidQS is set of all Q-levels of request bids.
% Asks is set of all ask bids.
% AskQS is set of all Q-level of ask bids.
% (1) Sort all Q-levels in descend order.
% (2) Group request and ask bids according to Q-level ranks.
[sBidQS, sBidQSX] = sort (BidQS, 'descend');
[sAskQS, sAskQSX] = sort (AskQS, 'descend');
% sBidQS is set of sorted Q-levels of request bids. sBidQSX is sort index.
% sAskQS is set of sorted Q-levels of ask bidders. sAskQSX is sort index.
% (3) Group Request and ask bids based on the sorted Q-levels.
For j=1:1: buyers % Rearrange Request and ask based on sorted Q-levels
    QBid (j) = int16 (Bids (sBidQSX (j))); %group traded requests based on Q-level
    QTruBid (j) = BidTruVals (sBidQSX (j)); %group True request based on Q-levels
End
For j=1:1: sellers
    QAsk (j) = int16 (Asks (sAskQSX (j))); %group traded Asks based on Q-levels
    QTruAsk (j) = AskTruVals (sAskQSX (j)); % group True Asks based on Q-levels.
End
For i=1:1: QS
    For j=1:1: buyers % Count Number of Bids in each Q-level group
        If (i==sBidQS (j))
            BidQS_size (i) =BidQS_size (i) +1; % Number of request Bids in Q-level=i
        End
    End
End
For i=1:1: QS
    For j=1:1: sellers % Count Number of Asks in each Q-level group
        If (i==sAskQS (j))
            AskQS_size (i) =AskQS_size (i) +1; % Number of Ask Bids in Q-level=i
        End
    End
End
% (4) Sort the true and traded request and ask bids for each Q-level
% sQBid and sQAsk are the sorted Requests and asks bids based on Q-levels.
buyPointer =1; % Points to the start of each Q-level in bid list
sellPointer =1; % Points to the start of each Q-level in Ask list
For i=QS:-1:1
    [B,X]= sort (QBid (buyPointer: buyPointer +BidQS_size (i)-1), 'descend');
    Bt= sort (QTruBid (buyPointer: buyPointer +BidQS_size (i)-1), 'descend');
    sQBid (buyPointer: buyPointer +BidQS_size(i)-1) = B;% Sorted Bids in Q-level
    sQBidX (buyPointer: buyPointer +BidQS_size(i)-1)= X;% Sorted Index
    % Sort True item Bid valuations to follow sorted Bids
    sQTruBid (buyPointer :buyPointer +BidQS_size(i)-1) =Bt;
    [B, X]= sort (QAsk(sellPointer :sellPointer +AskQS_size(i)-1), 'ascend');
    Bt= sort (QTruAsk (sellPointer :sellPointer +AskQS_size(i)-1), 'ascend');
    sQAsk (sellPointer: sellPointer +AskQS_size (i)-1) =B;%Sorted Asks in Q-level
    sQAskX (sellPointer: sellPointer +AskQS_size (i)-1)=X; % Sorted Index
    % Sort True item Ask Valuations to follow sorted Asks
    sQTruAsk (sellPointer :sellPointer+ AskQS_size(i)-1)= Bt;
    buyPointer = buyPointer +BidQS_size(i);% Step to next Q-level Bid list
    sellPointer = sellPointer+ AskQS_size(i);% Step to next Q-level ask list
End

```

```

MATCHING-ALLOCATION-RULE (sQBid, sQAsk, BidQS_size, AskQS_size) % Match
Request and Ask Bids and Allocate Winners (Same for all DA mechanisms)
% sQBid/sQAsk: sorted request/ask bids.
% BidQS_size/AskQS_size: number of request/ask bids in each Q-level.
n = min (sQBid, sQAsk); % n is minimum size of sorted Requests and asks
matched = 0; % Initial number of qualified matches
msQBid = zeros(1,n); % Initial sorted match list of request bids.
msQAsk = zeros(1,n); % Initial sorted match list of ask bids.
sQAskT = sQAsk; %
buyPointer = 1; % Bid Start Pointer
sellPointerS = 1; % Ask start pointer
sellPointerE = 1;
For i =Q-level:-1:1 % Inspect matching allocation For each Q-level
    For j= buyPointer to buyPointer + BidQS_size(i)-1
        For k=sellPointerS:1:sellPointerE+AskQS_size(i)-1
            flag = 0;
            If (sQBid(j) >= sQAskT(k))% sorted bid is more of equal ask?
                msQBid(j) = sQBid(j); % Select sorted Bid for match list
                msQAsk(k) = sQAsk(k); % Select sorted ask for match list
                sQAskT(k) = Big-M;% Big-M is very high to drop matched ask
                matched = matched+1; % Set number of matches in Q-level =i
                flag= 1;
            End
            If (flag == 1)
                Break% Start with new bid and compare it with sQAskT asks
            End
        End
    End
    % Done with one Q-level? Then increment to next Q-level
    buyPointer= buyPointer + BidQS_size(i);%BidQS_size no of bids in Q-level=i
    sellPointerE=sellPointerE+ AskQS_size(i));%AskQS_size of asks in Q-level=i
End

```

```

GSPM-PRICING-RULE (msQBid, msQAsk, sBidQS, sAskQS, matched)%GSPM Pricing
Rule for any Q-level ( Same for all GSPM DA mechanisms).
% msQBid/ msQAsk: matched and sorted bid/ask sets,
% sBidQS/sAskQS: bid/ask Q-levels,
% matched: numbers matched bid/ask pairs for any Q-level.

n = min (sQBid, sQAsk); % n is minimum size of sorted Requests and asks
Cost = zeros (1, n);
Payment = zeros (1, n);
For i=1:1: matched-1;
    If and(msQAsk(i)> 0,sAskQS(i)== sAskQS(i+1)) % sQAsk has same Q-level?
        Cost (i) = sQAsk (i+1); % Ask value within Q-level group
    ElseIf and (msQAsk (i)> 0, sAskQS (i)> sAskQS (i+1))
        Cost (i) = sQAsk (i); % sQAsk is at the end of Q-level group
    End
    If and (msQBid (i)> 0, sBidQS (i) == sBidQS (i+1))
        Payment (i)= sQBid(i+1); % Bid Value within Q-level group
    ElseIf and (msQBid (i)> 0, sBidQS (i)> sBidQS (i+1))
        Payment (i) = sQBid (i); % Bid Value at the end of Q-level group
    End
End
If and (msQAsk (matched)> 0, msQBid (matched)> 0) % Matching of the last pair
    Cost (matched)= sQAsk(matched);
    Payment (matched) = sQBid (matched);
End

```

```

EM-PRICING-SINGLE-QS (msQBid, msQAsk, sQAsk, sBidQS, sAskQS, matched)%EM
Pricing Rule for Single Q-level EM DA Mechanism.
% msQBid/ msQAsk: matched and sorted bid/ask sets,
% sBidQS/sAskQS: bid/ask Q-levels,
% matched: numbers matched bid/ask pairs for single Q-level

n      = min (sQBid, sQAsk); %n is minimum size of sorted Requests and asks
Cost   = zeros (1,n);
Payment = zeros (1,n);
For i=1:1: matched-1;
    if and(msQAsk(i)> 0,sAskQS(i)== sAskQS(i+1)) % sQAsk has same Q-level?
        Cost (i) = sQAsk (matched); % Ask value within Q-level group
    ElseIf and (msQAsk (i)> 0, sAskQS (i)> sAskQS (i+1))
        Cost (i)= sQAsk(matched); % sQAsk is at the end of Q-level group
    End
    If and (msQBid (i)> 0, sBidQS (i) == sBidQS (i+1))
        Payment (i) = sQAsk (matched); % Bid Value within Q-level group
    ElseIf and (msQBid (i)> 0, sBidQS (i)> sBidQS (i+1))
        Payment (i) = sQAsk (matched); % Bid Value at the end if Q-level group
    End
End
If and(msQAsk(matched)> 0,msQBid(matched)> 0) % EM matching for last pair
    Cost (matched)= sQAsk(matched);
    Payment (matched) = sQAsk (matched);
End

```

```

EM-PRICING-Multiple-QS(msQBid, msQAsk, sQAsk, sBidQS, sAskQS,
AskQS_size, BidQS_size) %EM Pricing Rule for Multiple Q-levels EM DA.

% msQBid/ msQAsk: matched and sorted bid/ask sets,
% sBidQS/sAskQS: bid/ask Q-levels,
% matched: numbers matched bid/ask pairs for single Q-level
n      = min (sQBid, sQAsk); %n is minimum size of sorted Requests and asks
Cost   = zeros (1,n);
Payment = zeros (1,n);
sellPointer =1;
lastmsQAsk = zeros(QS);
For i=QS:-1:1 % Set M Equilibrium Pricing for each Q-level
    For k=sellPointer :1:sellPointer +AskQS_size(i)-1
        if (msQAsk(k)> 0) % Does sQAsk has same Q-level?
            lastmsQAsk (i) = k;
        End
    End
    sellPointer = sellPointer + AskQS_size(i);
End
buyPointer   = 1;
sellPointerS = 1; % Ask start pointer
sellPointerE = 1;
sQAskT = sQAsk;
For i=QS:-1:1
    For j=buyPointer :1: buyPointer+ BidQS_size(i)-1
        For k=sellPointerS:1:sellPointerE+AskQS_size(i)-1
            flag=0;
            if (msQBid(j) >= sQAskT(k))
                if(k<= lastmsQAsk(i))
                    Cost(k)= sQAsk(lastmsQAsk(i));% M-Pricing
                    Payment(j)= sQAsk(lastmsQAsk(i)); % Value within Q-level
                End
            End
        End
    End
End

```

```

        End
        sQAskT(k)= 99999;
        flag= 1;
    End
    if(flag == 1)
        break
    End
End
End
End
buyPointer = buyPointer + BidQS_size(i);
sellPointerE= sellPointerE+ AskQS_size(i);
End

```

```

BOUNDED-RULES-UPDATE (BidWinnersNow, AskWinnersNow, sQAsk, sQBid,
sQTruBid, sQTruAsk, delta_win, delta_loss, Bid_switch, Ask_switch)
% Bid_switch and Ask_switch hold change of state of bidders.
% Min and Max is for bounded adjustments of RBBL rules inside exchange
For j=1:1:n
    winnerNow = BidWinnersNew (j);% Recall current winners list
    If (sQBid (j) >= sQTruBid(j))% Stop bidders at true valuation threshold
        sQBid (j) = sQTruBid(j);
    Elseif and ( winnerNow, not(Bid_switch(j)))% Buyers wins and still wins
        sQBid (j) = sQBid(j)- delta_win*rand(1)*(sQBid(j)-Payment(j));
    Elseif and(not( winnerNow),not (Bid_switch(j)))% Buyer is still a loser
        sQBid (j) = min(sQBid(j)+ delta_loss*rand(1)*sQBid(j),sQTruBid(j));
    Elseif and( winnerNow, Bid_switch(j)) % Buyer wins after losing
        sQBid (j) = sQBid(j);
    Elseif and(not( winnerNow),Bid_switch(j))% Buyers loses after winning
        sQBid (j) = min(sQBid(j)+ delta_loss*rand(1)*sQBid(j),sQTruBid(j));
    End
    winnerNow =AskWinnersNew (j);
    If (sQAsk(j) <= sQTruAsk(j))
        sQAsk(j) = sQTruAsk(j);
    Elseif and( winnerNow, not(Ask_switch(j))) % Seller is still winner
        sQAsk(j) = sQAsk(j)+ delta_win*rand(1)*(Cost(j)-sQAsk(j));
    Elseif and(not( winnerNow),not (Ask_switch(j)))%Seller is still a loser
        sQAsk(j) = max(sQAsk(j)- delta_loss*rand(1)*sQAsk(j), sQTruAsk(j));
    Elseif and( winnerNow, Ask_switch(j)) )% Seller wins after losing
        sQAsk(j) = sQAsk(j);
    Elseif and(not(winnerNow),Ask_switch(j))% Seller loses after winning
        sQAsk(j) = max(sQAsk(j)- delta_loss*rand(1)*sQAsk(j),sQTruAsk(j));
    End
End
End

```

```

UNBOUNDED-RULES-UPDATE (BidWinnersNow, AskWinnersNow, sQAsk, sQBid,
sQTruBid, sQTruAsk, delta_win, delta_loss, Bid_switch, Ask_switch)
% Bid_switch and Ask_switch hold change of state of bidders.
% Min and Max is for unbounded adjustments of RBBL rules inside exchange
For j=1:1:n
    winnerNow = BidWinnersNow (j);% Recall current winners list
    If and( winnerNow, not(Bid_switch(j)))% Buyers wins and still wins
        sQBid(j) = sQBid(j)- delta_win*rand(1)*(sQBid(j)-Payment(j));
    Elseif and(not( winnerNow),not (Bid_switch(j)))% Buyers is still loser
        sQBid(j) = sQBid(j)+ delta_loss*rand(1)*sQBid(j);
    Elseif and( winnerNow, Bid_switch(j)) % Buyer wins after losing
        sQBid(j) = sQBid(j);
    Elseif and(not( winnerNow),Bid_switch(j))% Buyers loses after winning
        sQBid(j) = sQBid(j)+ delta_loss*rand(1)*sQBid(j);
    End
End

```

```

End
winnerNow =AskWinnersNow (j);
If and( winnerNow, not(Ask_switch(j))) % Seller is still winner
    sQAsk(j) = sQAsk(j)+ delta_win*rand(1)*(Cost(j)-sQAsk(j));
Elseif and(not( winnerNow),not (Ask_switch(j)))%Seller is still loser
    sQAsk(j) = sQAsk(j)- delta_loss*rand(1)*sQAsk(j);
Elseif and( winnerNow, Ask_switch(j)) % Seller wins after losing
    sQAsk (j) = sQAsk(j);
Elseif and(not(winnerNow),Ask_switch(j))% Seller loses after winning
    sQAsk (j) = sQAsk (j)- delta_loss*rand(1)*sQAsk(j);
End
End

```

```

EXAMINE-CHANGE-OF-STATES (BidWinnersOld, BidWinnersNow, AskWinnersOld,
AskWinnersNow) %Examine Request and ask bidders New/Old Winning States.
Status_changes = 0;
Bid_switch = zeros (1, buyers);
Ask_switch = zeros (1, sellers);
For j=1:1: n
    winner_before = BidWinnersOld (j); % Set win/lose state history
    If xor (winner_before, BidWinnersNow (j)) % Inspect win/lose switching
        Bid_switch (j) =1; % Set to one if state changes only.
        Status_changes = Status_changes +1; % Set number of state changes
        BidWinnersOld (j) = BidWinnersNow (j); % Save state for next trade
    End
    winner_before = AskWinnersOld (j);
    If xor (winner_before, AskWinnersNew (j))
        Ask_switch (j) =1;
        Status_changes = Status_changes +1;
        AskWinnersOld (j) = AskWinnersNew (j);
    End
End
End

```

## Curriculum Vitae

**Name:** Wafa Ghonaim

**Post-secondary Education and Degrees:** University of Kuwait, Kuwait  
1984 Bachelor of Science (BSC), Electrical Engineering.  
2002 Post Graduate Diploma (PGD) Electrical Engineering.

Western University, London, Ontario, Canada  
2005 Master of Engineering Science (MESC), Software Engineering  
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### **Publications:**

Ghonaim, W., Ghenniwa, H., & Shen, W. (2011). Towards an Agent Oriented Smart Manufacturing System. Proceedings of the 15th International Conference on Computer Supported Cooperative Work in Design (CSCWD 2011), (pp. 636-642). Switzerland.

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