Towards a Sustainable Smart e-Marketplace
A Stable, Efficient and Responsive Smart Exchange with Strategic Conduct

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Abstract: The landscapes of e-marketplaces are changing profoundly, evident in the phenomenal growth and potential of online services, consumers, and enabling mobile technologies. However, it is unleashing grave concerns about sustainability due to the fierce competitions, fuzzy dynamics and rapidly shifting powers. While it is attributed to the game-theoretic economics and computation complexities of the decentralized combinatorial allocation problem, this work establishes, denying e-traders expressing fair strategic choice is unfounded of adverse strategic risk. In fact, free market dynamics realize impact of smart learning on strategic conduct. The fact strategic rules enable faster consumer-to-market bidding lifecycle is another compelling factor. Hence, the work introduces the novel rule-based bidding language and GSPM double auction for the smart exchange that facilitates expressions of strategic rules, while uniquely exploits forward and reverse GSP auctions for efficient, tractable, stable, and budget balanced e-marketplace. The e-marketplace deliberates on rules for effective preference elicitation, while bringing self-prosperity in socially efficient ecosystem.

1 INTRODUCTION

Emerging e-marketplaces as in online advertising are undergoing seismic changes, quite evident in the phenomenal growth and potential of online services, engaged e-users, and enabling mobile technologies. However, it is unleashing serious concerns about its sustainability due to the fierce competitions, fuzzy dynamics and rapidly shifting powers. In fact, the striking impact of digital markets is stirring industry to diligently fetch more viable service delivery and revenue models that thrive in a e-market ecosystem (Moore, 1996). Hence, the enduring power struggle amongst rivals is polarizing towards fetching more efficient and sustainable ecosystem friendly dynamic mechanisms for trading of services and information liquidity. While it is attributed to the game-theoretic economics and computational complexities of the decentralized combinatorial allocation problem (CAP) of services amongst self-interest rational e-traders (i.e. agents), who may strategize on private preferences, this work establishes, denying e-traders expressing fair strategic conduct is unsubstantiated of adverse strategic risk. In fact, the emerging trend of real-time bidding on user attentions increases the complexity of economically inspired decentralized CAPs. While this work investigates and realizes the complexities of e-marketplaces, formally, it reveals and examines, also, few strategic overlooked issues.

The first issue relates to the fact present e-marketplaces restrain scope of strategic conduct thru mechanisms that grant incentives for non-strategic acts or, rather, penalize levies to be paid to losing bidders due to strategizing. For instance, the VCG (Vickrey, 1961) (Clarke, 1971) (Groves, 1973) mechanisms, penalize for strategizing, by reporting non truthful preferences to align payoffs with social welfare, rather than the desirable self-prosperity. Ironically, truthful mechanisms often benefit the revenue maximizing intermediaries (marketplaces), rather than their alleged computation efficiency. In fact, trading restrictions, often, promote adverse strategic natural reactions of rational smart agents that may extend to incomplete or false information revelation, given higher expected payoffs. Adverse strategies may be manifested by fraud, deception, collusion, shilling, free riding, shading, snipping or hidden actions. In fact, e-marketplaces are more vulnerable to adverse strategies than classic markets. Software agents might collude by submitting untruthful reduced bids for false partial requirements or form coalitions that benefit from super-agent

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power. Traders may, also, unleash several agents with multiple identities for false name bidding. Hence, this work establishes, denying e-traders (e-buyers and e-sellers) expressing strategic conduct, allegedly, to improve computation efficiency as in Google DoubleClick, Microsoft AdECN, Yahoo Right Media, and Facebook FBX, is unsubstantiated of dire business impact, given modern enabling hi-tech is transforming computation into commodity.

Indeed, the flexible expressions of fair strategic conduct that bring self-prosperity would, ultimately, mitigate adverse strategies that may defy markets, considering, often, higher risks and lower expected returns (Fair vs. adverse strategies to be examined in a coming work), given the dynamics of smart learning thru social interactions and repetitive trades. In fact, Adam Smith envisions traders interacting in free markets act as if guided by "invisible hand" that leads to desirable outcomes (i.e. efficiency and stability) due to markets' inherent flexibility of natural free choice and smart interaction. In fact, free market dynamics promote realizing impact of continuous learning on strategic conduct. However, free market efficiency would, often be realized with market thickness, uncongested interaction, and safe privacy (Roth, 2007). This work extends it, also, to applying fair rules of game-theoretic encounter (i.e. no enforced monopolistic rules). However, while online services gold rush and thriving technologies have tilted trader tactics to conceding to e-market restrictions, apparently, at the expense of strategic benefits, for the direct gains of easy access to the wealth of inventories and information liquidity, sustainability would be exposed, at which priorities align with the natural expression of strategic conduct higher returns, and better quality of service.

In the second issue, the work establishes the lack of rapid consumer-to-marketplace automation during bidding lifecycles is another compelling challenge to expressing strategic conduct. In fact, the time wasted in bidding processes at e-marketplaces like eBay, Amazon, etc. is an irritating engagement experience. For instance, a bidding lifecycle may take days, for an e-Bay auction, with rather manual configurations. Hence, the work introduces the concept of "bidding lifecycle", examine it effectiveness in divers trades and establishes, the flexible expressions of strategic rules (i.e. sub-programs) during the bidding process that are collected, stored and exploited by the smart exchange (SX), to deliver rapid bidding lifecycles.

The third challenge relates to the mounting combinatorial complexity of online ad problem evident in the emerging real-time bidding (RTB) of single users' attentions. RTB allows advertisers bid for single impressions, using user profiles, cost thresholds, and campaign goals to optimally assign bid values at real-time. RTB provides more liquidity, visibility, and competitive bidding, essential for the sustainable growth. In fact, contemporary e-markets are exploiting the complex multichannel engagement user experiences of online services that facilitate better market openness, and transparency. However, the combinatorial complexity (i.e. cherry-picking) of user level trades lack of efficient control, massive growth, and fierce competition are main concerns

Finally, a common issue in the decentralized e-markets relates to the implemented computation mechanism design for SX-CAP. The game-theoretic economics and computation complexities of the SX-CAP are observed in the GSP auction (Varian, 2007) (Edelman, Ostrovsky, & Schwartz, 2007), while it is allocative efficient (AE), it is not incentive compatible (IC) and often, maximizes auctioneer's revenue, rather than traders'. Conversely, while VCG auction is efficient and stable it is, often, intractable and runs at deficit. The iterative models (Ausubel & Milgrom, 2006) (Parkes, 2006), take longer time to converge with no guarantees of either AE or stability, an issue tackled, for instance, by iterative VCG (Parkes, 2001).The work, hence, targets a SX model that delivers an efficient, stable and tractable e-trading allocation for self-interested rational traders with independent private information and strategic conduct of rather conflicting goals.

This work examines and reflected on overlooked issues and, ultimately, develops a novel "rule-based" bidding language (RBBL) for smart exchange (SX) that allows for flexible expressions of smart strategic rules formulae. The RBBL is fully symmetric that enables flexible and rapid e-trading while unlocking the natural expressions of strategic conduct, not only for e-buyers, but, also, for e-sellers, often, confined with the reserved values. The RBBL empowers the SX to deliberate smart rules for rapid preference elicitations and valuations that ultimately, delivers rapid bidding lifecycle. The inherent game-theoretic economics and computation complexities of SX and the emerging combinatorial complexity of e-trading of user attentions, inspire designing the GSP based double auction (DA) matching (GSPM) that uniquely blends forward and reverse GSP auctions to achieving self-prosperity (i.e. max utility), social efficiency, strategic stability and computational tractability. The GSPM exploits the recent business successes and endorsements of the efficient, yet simple GSP auction (Edelman, Ostrovsky, & Schwartz, 2007) (Varian, 2007) and the theoretical Nash stability of GSP repeated best response auction (Nisan, Schapira, Valiant, & Aviv, 2011). The RBBL and GSPM, ultimately, empower bidders and SX with flexible expressions of smart rules and interaction pattern, smart preferences elicitation and efficient winner determination. The SX would, eventually, provide a timely seamless access to the ever growing inventory and information liquidly with stability self-prosperity, and social efficiency, while reducing friction and refining transparency. Thus, sustainability is secured the win-win dynamics of the naturally free e-market ecosystem. Section 2 presents a formal model of online ad problem and pertaining issues. Section 3 introduces the rule based bidding language, while the formal GSPM double auction model is investigated in section 4. Section 5 concludes with a remark on the ongoing work.

2 ONLINE PROBLEM MODEL

2.1 The Online Problem Description

This work targets a class of multiple-unit, multiple-attribute CAP of online services (i.e. impressions) amongst self-interest rational e-trader agents with conflicting goals that motivate strategic conduct, expressed as smart rules for, indeed, maximizing their expected utilities, given their belief about other trader preferences. The GSPM DA for SX-CAP assumes, however, truthful states of choices for a sound mixed integer program (MIP) and winners' determination (WD) matching problem. For online ad problem, the commodity of the e-marketplace is ad impression, (i.e. a single viewing of single ad by a single user). The SX allows symmetric bidding of both e-buyers and e-sellers with rather expressions of smart rules on factor-groups (FG). FG may, for instance, be an age group, location, interest, etc. Hence, an ad impression is designated by specific factors (i.e. webpage, user profile, service content, etc.) within a time period. Considering time is a set of discrete decision periods during which multiple e-services are allocated to multiple winners, the work assumes allocation and pricing decisions are taken off-line at the end of any decision period τ. The SX-CAP manifests sequence of events, as fairly tabled in (Mansour, Muthukrishnan, & Nisan, 2012) for ad exchange. Followed is a formal description of the online ad problem in the ad SX during period τ:

1. Upon online users browsing of m publishers P (e-sellers) webpages, $\forall P_j \in P = \{P_1 \dots P_j \dots P_m\}$, forms m_P impressions, $I_P^j = \{\, I_P^{j1} \dots I_P^{jq} \dots I_P^{jm_P}\}$ of user, publisher and webpage profiles. $I_P^{jq} = \left\{(f_1^{P_{jq}}, g_1^{P_{jq}}) \dots (f_l^{P_{jq}}, g_l^{P_{jq}}) \dots (f_{m_j}^{P_{jq}}, g_{m_j}^{P_{jq}})\right\}$, ad asset has m_j distinct FG attributes $\forall\, I_P^{jq} \in\, I_P^j$.
2. P_j, bids $\cup\left(\left(I_P^j, v_P^j, r_P^j\right), \tau\right)$"asks" on impression assets I_P^j . $\left(I_P^j, v_P^j, r_P^j\right)$, is sets of P_j ask-bids, $I_P^j \ni I_P^{jk}$ is impressions set, $v_p^j \ni v_P^{jq}$ is associated ask-prices set and $r_p^j \ni r_P^{jq}$ is smart rules set. An ask-bid price is sum of factor-group values of I_P^{jq}impression asset in I_P^j: Let $\left\{v_1^{P_{jq}} \dots v_l^{P_{jq}} \dots v_{m_j}^{P_{jq}}\right\}$ask values of I_P^{jq}; then I_P^{jq}ask-bid price is $v_P^{jq} = v\left(\, I_P^{jq}\right) = \sum_{l=1}^{m_j} v_l^{P_{jq}}$. The pricing model may exploit cost per-factor (cpf), per-group (cpg) or per-impression (cpi).
3. The SX announces impressions contextual info and quality scores$\cup\left(QS_x^j(.), I_P^j, \tau\right)$ to advertisers $A = \{A_1 \dots A_i \dots A_n\} \forall P_j\; QS_x^j\left(w_{P_j}, QS_p^j, QS_u^j, \tau\right)$, is SX quality scores (QS) on webpage publisher and user at τ as derived by SX intelligence and deliberation. The SX stores bidding rules r_P^j of publishers while hiding prices v_P^j to mitigate strategic impact of exposure problem., $I_P^\tau = \left\{I_P^1 \dots I_P^j \dots I_P^m\right\}$ is publishers' impression assets, while $QS_x = \left\{Q_x^1 \dots Q_x^{S_j} \dots\; Q_x^{S_m}\right\}$is SX QS set.
4. Advertisers,$A_i \in A$, collect $SX(QS_x,\, I_P^\tau, \tau)$ info and returns request-bids that target either user attentions or segment $\cup\left(\,(I_A^i, b_A^i, r_A^i), B_A^i, Ad_A^i, \tau\right)$ for Ad_A^i asset. B_A^i, is allocated budget.(I_A^i, b_A^i, r_A^i) is request bid with b_A^i, bid values and r_A^i, the associated rules of $I_A^i = \{\, I_A^{i1} \dots I_A^{ik} \dots I_A^{im_A}\} \ni I_A^{ik}$ $=\{(f_1^{A_{ik}}, g_1^{A_{ik}}) \dots (f_l^{A_{ik}}, g_l^{A_{ik}}) \dots (f_{m_r}^{A_{ik}}, g_{m_r}^{A_{ik}})\}$; $I_A^i \in I_A^\tau = \{I_A^1 \dots I_A^i \dots I_A^m\}$.$b_A^i = \{v_A^{i1} \dots v_A^{ik} \dots v_A^{jn}\}$, is the pricing set of $I_A^{ik} \in I_A^i$. $\forall\, I_A^{ik}$, let $\{v_1^{A_{ik}} \dots v_l^{A_{ik}} \dots v_{m_i}^{A_{ik}}\}$ set of best bid-price values on I_A^{ik} FGs, the total offered-price on I_A^{ik} is $v_A^{ik} = v(I_A^{ik}) = \sum_{l=1}^{m_i} v_l^{A_{ik}}$, A_i bid for, given $v_A^{ik} \geq v_p^{jk}$ if matched else no bid returned. RBBL is used for bid choices, valuations and smart rules.
5. The SX applies GSPM double auction (DA) matching allocations and payments for winners using forward and reverse GSP auctions, fter collecting all request and ask bids. The SX computes efficient allocations and payments. It returns $\left(I_P^{jq}, \pi_{P_j}^*, B_A^i, Ad_{A_i}^*\right)$ to wining P_j, $\forall P_j$ and $\left(I_A^{ik}, \pi_{A_i}^*, Ad_{A_i}^*\right)$ to wining $A_i, \forall A_i\; I_P^{jq} = I_A^{ik}$. $\pi_{P_j}^*, \pi_{A_i}^*$, are SX pricings for matched (P_j, A_i) pair on $I_P^{jq} = I_A^{ik}$, while $Ad_{A_i}^*$, is media asset to be dispatched and B_A^i is A_i budget.
6. Publisher P_j serves webpage w_{P_j} with winning ad $Ad_{A_i}^*$ at τ for ad impression I_P^{jq}. P_j, allocates the dispatched $Ad_{A_i}^*$ to a specific location that fulfils the impression- request as matched with impression-asset.

Example: An advertiser wish to bid ad impressions at *Segment level* $I_A^1 = \{\left(f_1^{A_1}\!: ID\; g_1^{A_1}\!: CNN\right)$, $\left(f_2^{A_1}\!: Cat\; g_2^{A_1}\!: sport\right)\}$ or at *user level* $I_A^2 = I_A^1 \cup$

$\{(f_4^A$: Loc, g_4^A: California), (f_5^A:Ag, g_5^A: Gen X)}, or $I_A^4 = I_A^2 \cup \{(f_3^{A_1}$: Day part, $g_3^{A_1}$: Morning), ($f_4^{A_1}$: Content, $g_4^{A_1}$: Super Bowl)},etc. of possible factor-group values $\{v_1^{A_{ik}} \dots v_l^{A_{ik}} \dots v_{m_i}^{A_{ik}}\}$ and total $v_A^{ik} = v(I_A^{ik}) = \sum_{l=1}^{m_i} v_l^{A_{ik}}$. Figure 1, depicts the online ad problem model in smart exchange.

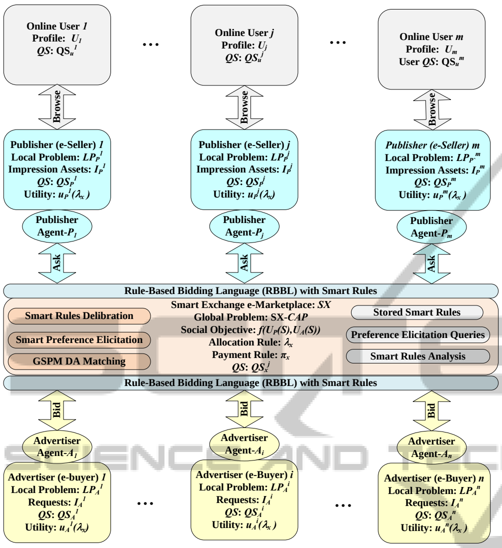

Figure 1: The Online ad problem Model in Smart Exchange.

2.2 The SXCAP AE Matching Problem

The SX computes an efficient-trade rather than optimal- revenue-trade, as there are many competing e-traders and networks, so it is unfeasible to exercise monopoly power. The work assumes e-trader agents act exclusively as either service providers or service consumers. The SX computes an efficient outcome allocations and payments from agents' reported valuations, or smart rules preference elicitation that usually, involve solving an NP-hard CAP. In fact, the WDP in CAs (and thus also in CEs) is NP-hard (Rothkopf, Pekec, & Harsrad, 1998). Generally, the objective of the SX is to implement a trade λ^* for the SX-CAP at period τ that delivers social efficiency. The SX selects then payment rule that drives IC, individual rationality (IR) (i.e. agent expected payoff > payoff of non-participating), with budget balance (BB) (i.e. total cross SX payments =0, or non-negative). Formally, assume $v(\emptyset) = 0$ with free disposal (i.e. agents have weakly increasing values for services $v(I_A^{ik}) \le v(I_A^{ik'}) \forall I_A^{ik'} \supset I_A^{ik}$). Let e-trade $\lambda(I_A^{ik}, I_P^{jq}) = \lambda_{ijkq} = 1$, points to impressions I_A^{ik} and I_P^{jq} are matched (i.e. $I_A^{ik} = I_P^{jq}$) for same FG attributes, and the request-bid on I_A^{ik} and ask-bid on I_P^{jq} are eligible for trade; $\lambda(I_A^{ik}, I_P^{jq}) = \lambda_{ijkq} = 0$, otherwise. $\forall$ e-trader agents of quasi-linear utilities $u_{i(j)}(\lambda_{ijkq}, p_{ijkq}) = v_{i(j)}(\lambda_{ijkq}) - p_{ijkq} \forall \lambda_{ijkq} \in \lambda$ $\forall$clearing price, $p_{ijkq} \in \mathbb{R}$. p_{ijkq}, is negative, if bidder receives a payment for the trade. Bidders are modeled as being risk neutral (i.e. agent pays as much as the expected value of an item) with budget constraints (i.e. B_A^i) for ad campaign (e.g. frequency of playback of ad Ad_A^i). The SX-CAP is limited by constraints (bids and budgets), rules, objectives, and mechanism. Given instance $SX(v, \lambda, \tau)$ at period τ, the efficient λ^* is, then, given as follows:

Definition 1: Given instance $SX(v, \lambda, \tau)$ of true bids at τ, $\lambda_{ijkq} = 1$ if $I_A^{ik} = I_P^{jq}$, $\lambda_{ijkq} = 0$ otherwise, then efficient trade λ^* solves:

$$\max_{\lambda} \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{m_A} \sum_{q=1}^{m_P} \lambda_{ijkq} \cdot \left(v_A^{ik} - v_P^{jq}\right) \ \forall \tau \ (AE, IC) \quad (1)$$

$$v_A^{ik} = \sum_{l=1}^{m_i} v_l^{A_{ik}}\ ;\ v_P^{jq} = \sum_{l=1}^{m_j} v_l^{P_{jq}} \quad \forall v_A^{ik}, \forall v_P^{jq} \in \{\mathbb{R}_+, 0\}$$

$$s.t. \sum_{i=1}^{n} \sum_{k=1}^{m_A} \lambda_{ijkq} \le 1, \forall P_j, \forall I_P^{jq} \ (Unique\ Maching) \quad (2)$$

$$\sum_{j=1}^{m} \sum_{q=1}^{m_P} \lambda_{ijkq} \le 1, \forall A_i, I_A^{ik} \quad (Unique\ Maching) \quad (3)$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{m_A} \sum_{q=1}^{m_P} \lambda_{ijkq} \cdot v_A^{ik} \le B_A^i \ \forall A_i, I_A^{ik} (Max\ Budget) (4)$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{m_A} \sum_{q=1}^{m_P} \lambda_{ijkq} \cdot \left(v_A^{ik} + v_P^{jq}\right) \ge 0 \quad (BB) \ (5)$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{m_A} \sum_{q=1}^{m_P} \lambda_{ijkq} \le min\{\sum_{i} |I_A^i|, \sum_{j} |I_P^j|\} \quad (6)$$

$$\lambda_{ijkq}(I_A^{ik}, I_P^{jq}) \in \{0,1\} \ \forall I_A^{ik}, I_P^{jq} \quad (Integrality) \ (7)$$

Constraint (C7) ensures integrality, while (C2, C3) restrict a request-bid on specific unique impression to be assigned at most to one ask bid of the same unique ad impression, and restrict an ask-bid on an offered unique impression to be assigned at most one request- bid of the same. The SX-CAP, hence, turns into the generalized assignment problem known to be NP-Hard; (C4, C5) ensure budget balance (BB), and restricts budget boundaries (i.e. B_A^i), while (C6) impose strict balance in items' supply-demand by free disposal. The above SXCAP problem is an instance (i.e. reduction) of set-packing problem (SPP) (deVries & Vohra, 2003). In fact, the SPP is a functional reduction of the SXCAP transformed in polynomial time (i.e. SPP $\le_p$ SXCAP). The SPP is *NP*-Hard, but the recognition version is *NP*-complete (deVries & Vohra, 2003). Thus, the SXCAP is *NP*-complete and can't be solved using exact approaches (i.e. branch and bound, Cutting planes etc.). Due to the decentralized nature of the problem, however, this work adopts an economic based approach for SX-CAP modeling.

3 THE RBBL SMART BIDDING

3.1 Expressing Strategic Conduct

Economists often advocate free markets as the right way to organize economic activities, in which economic social welfare is not a priority, but rather self-prosperity. However, free markets have proven successful in organizing economic activities for the social well-being (Mankiw, 2012), despite their inherent flexibility that enables traders to exploiting strategic conduct. However, present e-marketplaces restrain scope of strategic conducts, due to alleged computation limitations. This work argues, denying users expressing their natural strategic conduct, while limiting preference space would have a dire impact on business sustainability. In fact, the tight restrictions on strategic behaviour and e-trading practices, often, promote adverse strategic reactions that disrupt social efficiency. Hence, this work envisions a sustainable SX e-marketplace empowers consumers with strategic conduct on e-trading and interaction patterns using a flexibly expressive bidding language (BL). The SX should deliberate on smart rules for effective preference elicitation, while computing efficient allocations and payments. The SX, should, eventually, provide a seamless access to the ever increasing online services, inventories and information liquidly, for the benefit of consumers and e-marketplaces, the result of win-win dynamics in naturally free markets ecosystem.

3.2 Bidding Lifecycle Analysis

An inspiring drive to developing the RBBL is to improving consumer-to-marketplace performance by extending the bidding "lifecycle" and exploiting distributed computing. The bidding lifecycle relates to the period bid can be active throughout diverse trades before it get expired and dropped off the trading platform. The work realizes the performance impact of frequent biddings that might require frequent manual setups (i.e. eBay, Amazon, etc.). While irrelevant in classic markets, it has a major impact on digital e-markets, considering the huge number of online transactions. Hence, minimizing bidding lifecycle would have a crucial impact on designing effective SXs another compelling for applying smart rules. For instance, iterative bidding of indirect mechanisms (i.e. English auction), has short multiple round bidding lifecycles to each trade and requires extra time for bid formulation. Hence, clock auction mitigates impact by enforcing time constraint for rapid response. The proxy iterative bidding shortens the bidding lifecycle using proxy agents (see (Parkes, 2006)) with valuation bounds and provisional allocation that works until market clears, for single e-trades. On the other extreme there are the bidding programs (Nisan, 2000), in which the complete formal problem model is sent to and solved by the e-marketplace. However, bidding programs are not feasible due to core computation, valuation and privacy problems. Direct mechanisms (i.e. GSP auction) use complex bidding, with short lifecycle that ends each e-trade with the execution of WD. This work develops, hence, the RBBL for distributed multiple trades. The RBBL enables rapid bidding lifecycle by using complex rules stored in the SX for smart preference elicitation on multiple e-trades that enables rapid performance. The RBBL enables, also, distributed computation between e-trader software agents and SX engine (see Figure 2).

Figure 2: Rule Based Bidding (Distributed for Multiple Trades).

3.3 The Rule Based Bidding Language

This work presents the SX computation model to managing online trading using an expressive bidding structure that empower consumers with complex rational interaction patterns, and flexible level of strategic freedom. In that vein, the work introduces the RBBL that generalizes and blends the TBBL in (Cavallo, et al., 2005), logical $\mathbb{L}_G$ and $\mathbb{L}_B$ (Boutilier & Hoos, 2001), that include $\mathbb{L}_B^{OR}$, $\mathbb{L}_B^{XOR}$, $\mathbb{L}_{GB}$, OR-of-XORs, XOR-of-ORs, and $\mathbb{L}_B^{OR*}$ with Nisan's bidding programs (Nisan, 2000), and various preference elicitation models in (Sandholm & Boutilier, 2006), while facilitating expressions of strategic conduct with flexibility, expressiveness, consciences for a computationally tractable, efficient and stable. The RBBL is symmetric that allows e-traders to bidding buys and sells in single tree structure that exploits "complex rule" operators (CR_0) for smart preference elicitation, formulation, and efficient WD.

An instant of the RBBL bid tree structure is shown Figure 3. The gray blocks refers to the CR_0's that may be expressed using propositional logic (PL), first order logic (FOL), temporal logic (TL), etc. (not shown in this work) that reflects the dynamic constraints applied to a given situation. The CR_0 may represents campaign duration, if "Ask bids

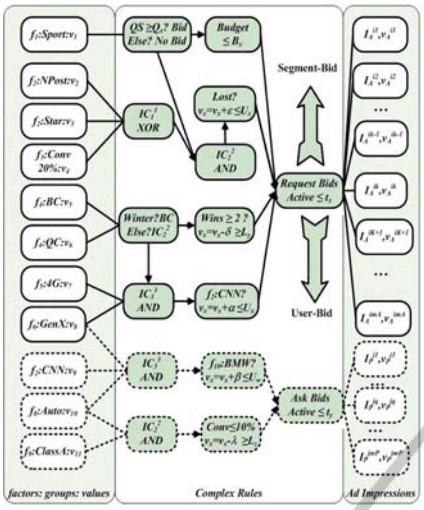

Figure 3: RBBL bid structure.

active time ≤ t_x"); *tactics*, "At lost trade, increase value of factor by ε for next trade, stop at upper bounds ≤ U_x "; "When number of win trades ≥ 2, reduce value by δ, stop at lower limit≥ L_x "; "CNN ad impressions? Increase value by α for next trade, stop at upper bound ≤ U_x"; *logic operators* "≥", "If, then, else" rule; IC_x^y TBBL, AND, OR, XOR, OR*, etc. $CR_0's$, reduce the complexity of dynamic choices. The SX stores $CR_0's$ for smart deliberation and effective preference elicitation, rather than solving complete bidding programs. The SX descripts $CR_0's$, then, rather than full enumeration; it deliberates $CR_0's$ to elicit preferences and valuations. In fact, the diverse types of $CR_0's$, add smart filters to reducing combinatorial complexity by narrowing down the feasible solution space. Bids are expressed as annotated bid trees of either e-sell or e-buy nodes. RBBL has $CR_0's$ on internal nodes for propagating values within the tree. Leaves of the tree are annotated with traded items and nodes are annotated with changes in values. RBBL facilitates direct (one-shot) and indirect (iterative) mechanisms and is captured as MIP, while facilitating effective rules deliberation and smart preference elicitation for efficient winner determination.

3.4 The RBBL Properties

Followed are propositions on the RBBL that briefly define related game-theoretic and computational properties. Analyses, formal proofs and verification of which, though, are found in another work:
Proposition 1: RBBL generalizes pervious bidding languages (i.e. $\mathbb{L}_R$, $\mathbb{L}_G$ and $\mathbb{L}_B$ $\mathbb{L}_B^{OR}, \mathbb{L}_B^{XOR}, \mathbb{L}_{GB}$, OR-of-XORs, XOR-of-ORs, and $\mathbb{L}_B^{OR*}$, TBBL, extended TBBL) and extends to complex rules, constrains and valuations for direct and indirect mechanismsis.
Proposition 2: RBBL facilitates direct (one-shot) and indirect (iterative price-taking) mechanisms.
Proposition 3: RBBL captured as MIP, facilitates effective preference formation and elicitation for efficient winner determination. The SX stores and descripts complex rules of all bids, then, rather than full enumeration; it applies smart learning heuristics to elicit dynamically preferences and valuations.
Proposition 4: RBBL is scalable, allows for sub-bids that can be analyzed by multiple processors. RBBL prevent the exposure problem by hiding budgets, using XOR like substitutable bids.

4 THE GSPM DOUBLE AUCTION

Double auctions are, often, used in exchange markets, such as stock exchange (i.e. NYSE), commodity markets (i.e. CME), etc. While the work targets desirable IC, AE, etc. for the DA design of SX, it is, often hard for a DA to have them all. In (McAfee, 1992) and (Wurman, Walsh, & Wellman, 1998) , for instance, there is no DA that is both AE and IC. This work , however, introduces a unique GSP based DA the exploits the fact while GSP is not IC, GSP repeated best response strategies converge to Nash equilibrium with VCG AE IC outcomes and payments, as analyzed and validated in (Edelman & Ostrovsky, 2007) (Varian, 2007) and (Nisan, Schapira, Valiant, & Aviv, 2011). Hence, the GSP based DA for SX achieves desired properties with repeated best repose strategies. While at IC, traders maximize their utilities with truthful revelation of private choices, AE assures maximizing aggregate valuations of buyers and sellers. Other desired proprieties are BB (i.e. total surplus generated equal available surplus at NE), SX profit maximization (i.e. max sum of differences between request and ask bid prices of all matched pairs) and IR, where the net benefit to each e-trader from using the DA is less than the net benefit of any alternative.

4.1 The GPM Double Auction Model

The DA equilibrium matching (EM) (Wurman, Walsh, & Wellman, 1998) is a common sealed-bid matching that is IC, in which clearing price does not depend on matching bid prices, but externalities. EM finds uniform equilibrium prices p^* that balances request and ask bids so all eligible requests with price $p \geq p^*$ and asks with $p \leq p^*$ are matched using 4-Heap algorithm that implements the IC last matched M^{th} auction for single-unit sellers and first unmatched $(M+1)^{st}$ auction for single-unit buyers.

However, EM IC is not applicable to multi-unit bids or symmetric buys and sells. In fact, EM DA can be IC or AE but not both (McAfee, 1992). To maximize matches, it is essential to allow price discrimination in which different matches cleared at different prices. IC is hard to achieve, also, in dynamic DA (e.g. stock exchange), where bids are entering or leaving over time and there is more than one matching to search sequentially (Parkes, 2007). The work in (Zhao, Zhang, & Perrusse, 2010), presented maximal matching (MM) DA that maximizes market liquidity, allocations, and profit, yet, is not IC.

As stated earlier, to tackle the combinatorial complexity of RTB, this work introduces the GSPM DA, GSP discriminatory pricing model. As shown Figure 4, GSPM exploits the GSP forward auction for e-buyers, while proposes a reverse-GSP auction for e-sellers. At time τ, given requests $I_A^i \in I_A^\tau$ and ask bids $I_P^j \in I_P^\tau$, the GSPM algorithm: (1) Qualifies eligibility by identifying and grouping eligible pair matches (i.e. $I_A^{ik} = I_P^{jq}$) w.r.t. factor-groups, (2) Sorts eligible ask (request) bids in ascending order of forward GSP (descending of reverse GSP) auction w.r.t. bid values; (3) Process Matching, start at the top, add ask-request pairs to the matching list, if ask-bid price ≤ request-bid price as per definition 2; (4) Computes Allocations, based on results, assign matched pair $\left(I_A^{ik}, I_P^{jq}\right)$to advertiser A_i and publisher P_j; and (5) Assigns prices, following definition 3.

4.2 The GSPM Properties

The development of GSPM model is inspired by the analysis of (Edelman, Ostrovsky, & Schwartz, 2007) for envy-free Nash equilibrium, (NE) that is equivalent to the "Symmetric NE" (Varian, 2007) as well as the findings in (Nisan, Schapira, Valiant, & Zohar, 2011), in which, while truth telling is not dominant strategy under GSP, the full information repeated best response strategy (BRS) GSP has NE with VCG AE IC outcomes. Followed are brief definitions and theorems that briefly define the GSPM game-theoretic economics and computation properties. However, the analyses, formal proofs and verification of which are detailed in another work:

Definition 2: [*GSPM DA Matching and Allocation Rules*]: Let $P \cup A$ the set of traders, and $P \cap A = \emptyset$, for exclusive trade, as per problem assumption. Let $\mathfrak{B} = \mathfrak{B}_p \cup \mathfrak{B}_A$set of request and ask bids. Let ask-bid $b_p^{jq}(I_P^{jq}, v_P^{jq})$=$b_p^m \in \mathfrak{B}_p$ and request bid $b_A^{ik}(I_A^{ik}, v_A^{ik})$ =$b_A^m \in \mathfrak{B}_A$. Sort eligible ask b_p^m (request b_A^m) bids in ascending order of forward GSP (descending of reverse GSP) auction w.r.t. bid values. Then, the ordered set of matched ask-request pairs $\mathfrak{M} = \{(b_p^1, b_A^1) \ldots (b_p^m, b_A^m) \ldots (b_p^M, b_A^M)\}$ is a GSPM DA matching set, if ∀ matched ordered pair$\left(b_p^m, b_A^m\right)$, prices $p(b_p^m) \le p(b_A^m)$, $\forall\, b_p^i \ne b_p^j,\ b_A^i \ne b_A^i, i \ne j$. Then $\mathfrak{M}$, is a GSPM list of eligible ordered pairs.

Definition 3 [*GSPM DA Pricing Rule*]: the ask-price for m≤M matched pair is $p_P(b_p^m, b_A^m) = p_P(b_p^{m+1})$, the ask price of 2nd matched pair $\left(b_p^{m+1}, b_A^{m+1}\right)$. The request-bidder price for $m < M$ matched pair is $p_A\left(b_p^m, b_A^m\right) = p_A(b_A^{m+1})$, the request-price of 2nd matched pair (b_p^{m+1}, b_A^{m+1}). For last match $m = M$, traders pay their request and ask bid values, $p_P\left(b_p^M, b_A^M\right) = p_P\left(b_p^M\right)$; $p_A(b_p^M, b_A^M) = p_A(b_A^M)$.

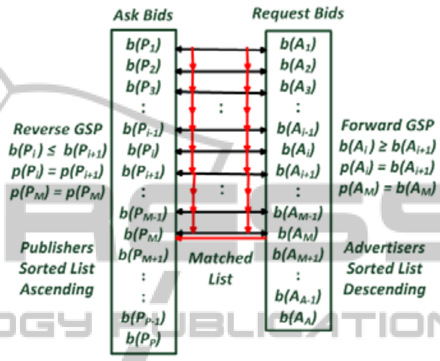

Figure 4: GSPM double auction model for ad impressions.

Proposition 5 [GPSM DA AE]: The GSPM DA mechanism that implements AE social choice (SC) function, maximizes total payoffs by maximizing total valuations of e-buyers, while minimizing total cost of e-sellers given IR e-trader agents, hence, maximizing the total profit the SX marketplace.

Theorem 1: The GSPM DA with BRS is AE

Theorem 2: The GSPM DA maximizes SX revenue.

Theorem 3: The GSPM with repeated BRS is IC.

Theorem 4: GSPM DA is *ex post* weak BB.

Theorem 5: GSPM DA is ex-post IR.

Definition 4 [locally envy-free NE]: Equilibrium ("Symmetric NE" (Varian, 2007)) of the GSP simultaneous-move game is locally envy-free if bidder cannot improve payoff by switching bids with the bidder ranked one position above her" (Edelman, Ostrovsky, & Schwartz, 2007)

Theorem 5: GSPM has NE with repeated BRS.

5 CONCLUSIONS

This work presents formal analysis and modeling of the GSPM, GSP based double auction and RBBL, rule-based bidding language for smart exchange. The work argues denying traders free expressions of fair strategic conduct, challenges sustainability and provokes adverse strategic reactions. This work establishes, also, lack of consumer-to-marketplace rapid bidding cycles is another compelling factor to realizing the strategic choice. The work examines the bidding lifecycle model and establishes strategic bidding delivers more efficiency, better automation and fairly distributed computing. Hence, the RBBL enables the flexible expressions of strategic conduct using smart rules. The smart exchange exploits the smart rules to deliberating on effective preference elicitation. The GSPM tackles inherent and evolving combinatorial complexities by uniquely exploiting both forward and reverse GSP auctions, for a truthful, efficient, stable and tractable matching that delivers rapid automation, self-prosperity, and social efficiency with a seamless access to the massively growing inventories and information liquidly. The smart exchange e-marketplace secures, ultimately, the business sustainability, by reducing friction and improving transparency, in the win-win dynamics of the naturally free e-markets ecosystem. The work is ongoing, however, on game-theoretic economics and computation efficiency of the GSPM and RBBL with focus on sound empirical validation and results.

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