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STRATEGIC BEHAVIOR IN SERVICE NETWORKS UNDER PRICE AND SERVICE LEVEL COMPETITION

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Abstract
Decentralized service providers specialize on contributing their core competency to an overall goal. This paper focuses on the strategic behavior of service providers within Service Value Networks. We present an abstract model as a formalization of a service value network. The model comprehends an auction-based mechanism design to allocate multiattribute service offers within the network and to determine prices for complex services. Furthermore we study the mechanism theoretically as well as on a simulation basis in order to analyze strategic behavior of service providers within service value networks.

1. Introduction

A novel service-oriented economy following strategies such as differentiation, customer-centricity and flexible business is observed in today's service markets. Previous ideas of static value chains are giving way to highly dynamic service value networks formed by many services from different specialized service providers. Companies employ differentiation strategies by shifting resources to focus on their core business. An example is Xignite[3] that specializes on providing a broad catalog of financial Web services. Other companies such as Jamcracker[4] provide platforms to foster a demand and supply match between service providers and service resellers that offer value added services to customers. In theory, the complex products or services could be produced by a single vertically integrated company. But in this case the company could not focus on its core competencies, having to cover the whole spectrum of the value chain. Additionally, it would have to burden all the risks in a complex, changing and uncertain environment by itself. This is why companies tend to engage in networked value creation which allows participants to focus on their strengths. At the same time rapid innovation in the ICT sector enabled promising opportunities in B2B communication supporting this trend. However, especially in complex and highly dynamic industries, forming value networks – especially business webs with their open structure – is more than an attractive strategic alternative. Prominent advocates of this new paradigm are [19, 12, 21, 18]. Business webs bring together mutually networked, permanently changing legally independent

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3 http://xignite.com
4 http://www.jamcracker.com/
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actors in customer centric, mostly heterarchical organizational forms in order to create (joint) value for customers. Specialized firms co-opetitively contribute modules to an overall value proposition under the presence of network externalities.

In our work we present an abstract model as a formalization of a Service Value Network. The model comprehends an incentive compatible auction-based mechanism design to allocate multi-attribute service offers within the network and to determine prices for complex services. Incentive compatibility makes revealing the true type (service configuration and internal costs) a weakly dominant strategy for all service providers. Since incentive compatibility only holds for a one shot game, we study strategic behavior that might improve the SP payoffs. The strategic behavior is studied by means of a simulation-based analysis of two different strategies for service providers within Service Value Networks. We analyze two environmental settings, a price competitive environment as well as competition on basis of service levels. Based on our results we discuss strategic recommendations for service providers depending on how they are situated within the network.

The paper is structured as follows: The next section provides a literature overview on path-based procurement auctions and mechanism design in general as well as concepts for trading different kind of services specifically. Subsequently, we proceed with the introduction of a formal model and a mechanism design for allocating and pricing of complex services. The strategic behavior regarding the two strategies deviating from the weak dominant strategy is then analyzed using a simulation approach. We conclude the paper with a summary and an outlook to ongoing research and open questions.

2. Related Work

The principles of mechanism design to coordinate self-interested participants in perusing an overall goal are introduced in [16]. These mechanisms mainly apply to auctions of one or multiple units of one good. Thus, the basic auction mechanisms are not suited for auctioning heterogeneous combined services such as complex services. Heterogeneous goods and bundles are usually traded in combinatorial auctions. Nevertheless, combinatorial auctions yield major drawbacks regarding computational feasibility that result from an NP-hard complexity. Computational feasibility implies a trade-off between optimality and valuable mechanism properties such as incentive compatibility. [1, 17] propose approximate solutions for incentive compatible mechanisms to overcome issues of computational complexity. Path auctions as a subset of combinatorial auctions reduce complexity through predefining all feasible service combinations in an underlying graph topology [4]. As a subset of combinatorial auctions, path auctions are introduced in [8, 13] and [2]. In their work, path auctions are utilized for pricing and routing in networks of resources such as computation or electricity. Application-related issues of auctions to optimal routing are examined in [6, 9] and [15]. All of these approaches deal with the *utility services* layer according to the service classification in [3, 5] and hence do not cover the problems related to *elementary services* and *complex services*.

The strategy an agent follows when placing bids in an auction is induced by the mechanism's properties. In incentive compatible auctions agents are incentivized to choose the strategy of revealing their true type. Incentive compatible mechanisms are firstly introduced and extensively investigated by [10, 11, 20]. Most of the research has been done with respect to truth-telling of prices and valuations. In the field of designing incentive compatible mechanisms, that induce truth-telling of non-functional properties of goods or services in multiattribute auctions, a lot of investigation is still missing. Traditional approaches in the area of multiattribute combinatorial auctions are not quite suitable to enable the trade of composite services. Auctions for composite services are much more complex than simple procuring auctions, where the suppliers themselves offer a full solution to the procurer. In composite services, this is not the case, as a flawless service execution and therefore the requester's valuation highly depends on the accurate sequence of its functional parts, meaning that in contrary to service bundles, composite services only generate value through a valid order of their components.

3. Abstract Model & Mechanism Design

The abstract model is a formalization of a service value network containing a *service requester*, *service providers* and *service offers*. It captures the networks characteristics using a formal notation. The model comprehends an auction-based mechanism design to allocate service providers within the network and to determine prices for complex services.

3.1. Service Value Network

A Service Value Network is represented by an k-partite, directed and acyclic graph $G=(V,E)$. Each partition $y_1,\ldots,y_K$ of the graph represents a functionality cluster that entails services that provide the same functionality. The topology information is public knowledge. The set of N nodes $V=\{v_1,\ldots,v_N\}$ represents the set of Service Offers with v is an arbitrary service offer. Services are offered by a set of Q Service Providers $S=\{s_1,\ldots,s_Q\}$ with s is an arbitrary service provider.

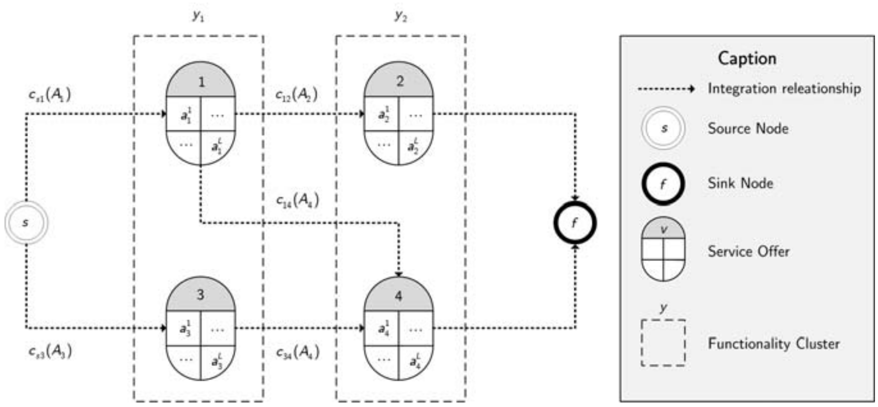

Figure 1 Service Value Network Model

The ownership information $\sigma: S \to V$ that reveals which service provider owns which service within the network is public knowledge. There are two designated nodes v_s and v_f that stand for source and sink in the network. The set of M edges $E=\{e_1,\ldots,e_M\}$ denotes service invocations such that e_{ij} represents an invocation of service j by service i. A service configuration A_j of service j is fully characterized by a set of attributes $A_j=\{a_j^1,\ldots,a_j^L\}$ where a_j^l is an attribute value of attribute type l of service j's configuration. Let furthermore $c_{ij}(A_j)$ denote a cost function that maps service j's configuration to corresponding costs that occur for invocation by service i such that $c: A \to R$. Let F denote the set of all feasible paths from source to sink. Every $f \in F$ represents a possible instantiation of the complex service. F_{-i} represents the set of all feasible paths from source to sink without node i and its incoming and outgoing edges. Let F_i be the set of all feasible paths from source to sink that entail node i such that $F = F_i \cap F_{-i}$. For illustration purpose, Figure shows a formalization of a Service Value Network with service offers $V=\{v_1,\ldots,v_4\}$. Every feasible path from source to sink represents a possible realization of the overall complex service.

3.2. Mechanism Design

The goal of the service requester is to maximize her utility U. Therefore she has to solve the problem of allocating a path f^* within the complex service network that yields the highest overall utility. Let U_f denote the overall utility of path f.

(1) $$o := \operatorname{argmax}_{f \in F} \mathrm{U}_f$$

Let U^* denote the utility of the winning path meaning the utility of a path f^* that maximizes the requesters utility U. Let U^*_{-s} denote the utility of a path f^*_{-s} that yields a maximum utility for the service requester in the reduced graph without every service owned by service provider s and its incoming and outgoing edges.

Every service provider s receives a payment or transfer $t^s = \sum_{i \in \tau(j), j \in \sigma(s), e_{ij} \in f^*} t^s_j$ for all services she owns which are on the winning path. A payment t^s_j for service j corresponds to the monetary equivalent of the *utility gap* Δu_j between the winning path and second best path. In other words a monetary equivalent to the utility service j contributes to the overall utility of the complex service. This monetary equivalent represents the price that service provider s could have charged without losing her participation in the winning allocation.

(2) $$t^s_j := p_{ij} + (\mathrm{U}^* - \mathrm{U}^*_{-s})$$

Consequently the payment function t^s for service provider s is defined as

(3) $$t^s := \begin{cases} \sum_{j \in \sigma(s)} \sum_{i \in \tau(j)} p_{ij} + (\mathrm{U}^* - \mathrm{U}^*_{-s}), & \text{if } e_{ij} \in o \\ 0, & \text{otherwise} \end{cases}$$

Costs c^s that service provider s has to bear for performing offered and allocated services result accordingly:

(4) $$c^s := \begin{cases} \sum_{j \in \sigma(s)} \sum_{i \in \tau(j)} c_{ij}(A_j), & \text{if } e_{ij} \in o \\ 0, & \text{otherwise} \end{cases}$$

3.3. Bidding Language

As a formalization of information objects which are exchanged during auction conduction we introduce a bidding language for requesters and providers. Our formalization assures compliance with the WS-Agreement specification in order to enable realization in decentralized environments such as the Web. A service requester wants to purchase a complex service f which is characterized by a configuration A_f. The importance of certain attributes and prices of a requested complex service is idiosyncratic and depends on the preferences of the requester. The requester's preferences are represented by a utility function U of the form:

(5) $$\mathrm{U}_f(\alpha, \Lambda, \mathrm{A}, \mathrm{P}) = \alpha S\left(\mathrm{A}_f\right) - \mathrm{T}_f$$

T_f denotes the sum of all transfer payments the requester has to transact to service providers that contribute to the complex service such that $\mathrm{T}_f = \sum_{e_{ij} \in f} t_j$. The configuration A_f of the complex service is the aggregation of all attribute values of contributing services on the path f such that $\mathrm{A}_f = (\mathrm{A}_f^1, \ldots, \mathrm{A}_f^L)$ with $\mathrm{A}_f^l = \oplus_{e_{ij} \in f} a_j^l$. The aggregation of attributes values depends on their type (i.e. encryption can be aggregated by an AND operator whereas response time is aggregated by a sum operator). The scoring rule $S(\mathrm{A}_f) = \left(\sum_{l=1}^{L} \lambda_l \left\| \mathrm{A}_f{}^l \right\| \right)$ represents the requester's valuation for a configuration A_f of the complex service represented by path f. The scoring rule is specified by a set of weights $\Lambda = \{\lambda_1, \ldots, \lambda_L\}$ with $\sum_{l=1}^{L} \lambda_l = 1$ that defines the requester's preferences of each attribute type. To assure comparability of attribute values from different attribute types the aggregated attribute values $\mathrm{A}_f{}^l$ are mapped on an interval $[0;1]$. T_f represents the overall price of the complex service. α can be interpreted as the willingness to pay for a optimal configuration $S(\mathrm{A}_f) = 1$ based on the requester's score. In other words α defines the substitution rate between configuration and price based on the requester's preferences.

Definition 1. **MULTIATTRIBUTE SERVICE REQUEST**

A request for a complex service is a triple of the form

(6) $$R := (G, F, \alpha, \Lambda, \Gamma)$$

with G represents a complex service network, F represents all feasible paths from source to sink that form a possible instantiation of a complex service, Λ the requester's preferences and α the willingness to pay. Γ denotes the set of lower and upper boundaries for each attribute type.

A service offer consists of an announced service configuration A_j and a corresponding price bid p_{ij} that a service provider wants to charge for service j being invoked depending on the predecessor service i such that $b_{ij}(e_{ij}) = (A_j, p_{ij})$ is a service offer bid for invocation of service j which interoperable with a predecessor service i with $b : E \rightarrow A \times R$. A service provider s bids for all incoming edges to every service she owns.

Definition 2. **MULTIATTRIBUTE SERVICE OFFER**

A multiattribute service offer is a set of bids of the form

(7) $$B^s := \begin{cases} b_{ij}(e_{ij}) = (A_j, p_{ij}), & i \in \tau(j), j \in \sigma(s) \\ 0, & \text{otherwise} \end{cases}$$

with $\tau(v)$ denotes the set of all predecessor services to service v with $\tau : V \rightarrow V$ and $\sigma(s)$ the set of all services owned by service provider s.

4. Strategic Alternatives

The proposed mechanism is incentive compatible for a one shot, i.e. it is a weak dominant strategy to bid the true cost. We assume that participants cannot communicate directly in a non-iterated game. In contrast, the iterated game gives participants the opportunity to tacitly collude through their bidding behavior. Consider the following cases:

1. All service providers (SP) submit bids at 10% above their true cost. The allocation remains the same but the SPs receive a higher payment since the claimed costs are higher and the individual utility surplus remains equal. As such, at least the allocated SP wished that everyone submits higher bids.
2. For those SP that are not allocated it is beneficial to submit bids at their true cost in order to produce a higher utility, and as such, increase the likelihood of being allocated.
3. Let SP *i* being allocated at true cost and let SP *i* be the only SP submitting a bid above its true valuation. Due to the higher costs the utility the SP generates decreases and as such the likelihood of being allocated also decreases. If SP *i* is allocated anyway the payment decreases due to the smaller difference of the utility surplus. As such, it is not beneficial for SP *i* to submit cost above the true valuation. The situation changes if other SPs also submit cost above the true valuation since the utility difference might increase. In that case submitting higher costs can be beneficial.
4. Let SP *i* submit bid at true valuation and being allocated. Let SP *j* submit bids above the true valuation and being part of the second best allocation possibility. This bidding behavior will lead to a higher payment for SP *i*. As such, SP *i* prefers other SPs to submit bids above their true cost.

We investigate this strategic decision problem by means of simple agent-based simulations. Inspired by the work of [14] we implement two simple strategies, probe-and-adjust (PA) and adjust-dependent-on-own-and-cluster-return (AOCR). Both strategies are reactive and do not implement any sophisticated learning algorithm. In so far, we follow a pure agent-based approach [7].

4.1 Strategies

Each SP has four action alternatives. She can either bid the true cost or increase the bid up to four times by discrete steps at 0.03 currency units. In total each SP has five bid alternatives, true cost or true cost + i times 0.03 and $\{i=1,..,4\}$.

4.1.1 Probe and Adjust (PA)

The first reactive strategy is called Probe-and-Adjust. Those SP which are allocated increase the bid at one discrete step as long as they drop of the best path or they reach the upper cost limit (true cost + 0.12 currency units). All SP which are not allocated decrease the bid by one discrete cost step until they are either allocated or they bid their true cost.

4.1.2 Adjust Dependent on Own and Cluster Return (AOCR)

The second reactive strategy considers not only the individual return but also the market returns of the direct competitors in the same functional cluster. The aim is to maximize cluster return but not on own cost, i.e. we identify four cases, (1) actual cluster return is greater than the one the round earlier and SP *i* (a) is allocated and (b) SP is not allocated, as well as (2) the cluster payment is equal or lower than the one the round earlier and SP *i* (a) is allocated and (b) is not allocated respectively. Dependent on the described situation the SP take the following actions: (1a) SP *i* increases her bid by one discrete step, (1b) SP *i* does not change her bid, (2a) SP *i* does not change her bid, (2b) SP *i* decreases her bid by one discrete step.

4.2 Hypothesis development

We study the results of strategic behavior under two competitive situations, price competition (PC) and quality competition (QC). In the price competition scenario all SP of one cluster offer their services at the same quality level but different price levels, i.e. the true costs of the SP differ slightly. Since competition takes place not only on prices but also on quality the offered services differ additionally in quality of one service attribute in the quality competition scenario. Let all SP in the network follow the PA strategy in the PC scenario we expect that prices will reach the true valuation equilibrium (when all SP bid their true valuation). In contrast, we expect prices to reach a level between the true valuation equilibrium and the high bid equilibrium (when all SP submit bids at the highest possible level) while all SP follow the AOCR strategy in the PC scenario. We expect a different picture for the QC scenario. Since the quality level largely impacts the service requesters' utility we expect that SP can exploit their competitive advantage by submitting higher bids which will lead to higher payments on average. Thus, we derive the following hypothesis:

- **H1**: In the PC scenario with only PA strategies payments will converge to the true valuation equilibrium
- **H2**: In the PC scenario with only PA strategies the deviation from the weak dominant strategy will be low, i.e. submitting the true valuation is the most frequently chosen strategy.
- **H3**: In the QC scenario the diversification on the basis of service quality decreases competition, and as such, will lead to a higher number of deviators from the weak dominant strategy (truth telling).
- **H4**: In the QC scenario the deviation from truth telling leads to higher payments for allocated SP.
- **H5**: AOCR strategy leads to higher payments of the allocated services compared to the PA strategy.

4.3 Simulation Model

We apply a simulation approach to study these questions. We model the problem as a n-person game in which each node represents a service offer. We assume that SPs only own a single service. As such, we use the terms node and SP synonymously. Each SP follows one of the reactive strategies which it is assigned at the beginning of the simulation run. Thus, in each period $t \in \{1, \ldots, T\}$ each node i observes the own payoff r as well as the payoff r^* of the best node in the cluster. The payoff r resulting from the action chosen is dependent on the topology of the network, the service requests, the offers of all nodes (including functionality and price). Regarding one topology all these factors are stochastic. As such, the node's action decision does not solely control the payoff. Thus, the decision problem of the nodes is comparable to an *n-armed bandit problem*. After having decided on an action, the best path is computed as well as the payoffs for all nodes on the path. The first action is chosen arbitrarily.

4.4 Simulation Settings

We conduct simulations with $N = 20$ nodes in 4 arbitrary chosen topologies with 5 functionality clusters and a density of 0.8. This results in 20 simulation runs. Each simulation run has T=50 periods. The cost per link are drawn from a uniform distribution in the interval [0.5, 0.7] and assigned for each simulation run. Attribute values for response time ($\in [0;1]$) and encryption ($\in [0;1]$) are assigned at a fix value of 0.5. Link costs and attribute values stay fix over all simulation periods but SP can decide to submit bids above their true cost. The service requester's preferences are also fixed for each of the simulation periods in a way that he weights attribute values and price equally. Furthermore total path prices, and consequently, overall path utilities are normalized to the interval $[0;1]$. We run simulations for four different scenarios: (1) all nodes offer the same service levels and use the PA strategy (PC-PA), (2) all nodes use PA but offer different service levels for the attribute “response time” (QC-PA), (3) all nodes follow the AOCR-strategy and offer the same service levels (PC-AOCR), and (4) the nodes offer different service levels for the attribute “response time” and all follow the AOCR-strategy (QC-AOCR).

4.5 Results and Assessment

First, we analyze descriptive parameters. Table 1 displays the average values of the sum of payments to the SP in the network. We compare the total-network payments for all SP submitting their true valuation and compare it to the total-network payments achieved by the SP which were also allowed to deviate from the true valuation. The received surplus (achieved payoffs – true valuation payoffs) is positive in all four scenarios which supports our assumption that collusion might be beneficial. Additionally, we observe that the total surplus is lower in the AOCR scenarios compared to PA scenarios. Besides the total networks payoffs it is also important to study the individual payments especially of those SP who would be allocated while playing the true valuation. Table 2 displays the average individual payoffs as well as the average individual payoff while playing the true valuation strategy.

Table 1 Aggregated Payments of all SPs in the Network

	PA-PC	PA-QC	AOCR-PC	AOCR-QC
mean payments total-network (truth-telling)	2,899	3,166	2,899	3,166
mean payments total-network (achieved)	2,971	3,309	2,943	3,203
mean surplus total-network (achieved)	0,072	0,142	0,043	0,037
surplus (%)	2,48%	4,49%	1,49%	1,16%

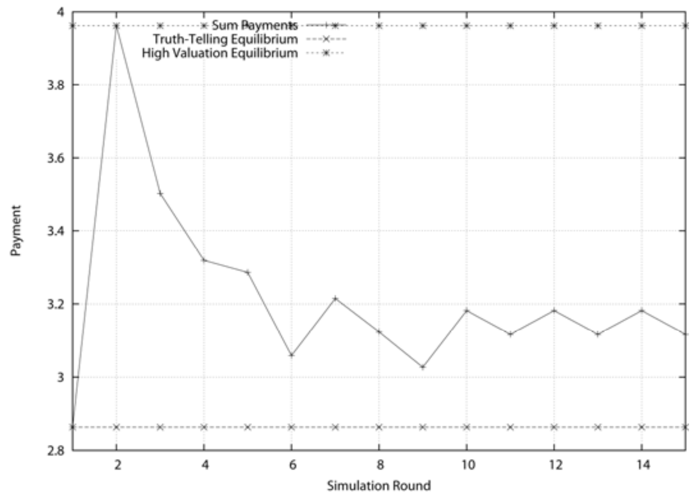

Figure 1 Development of Aggregated SP Payments (PA-PC Setting)

Table 2 Individual Payoffs of Thruth-Telling SPs

	PA-PC	PA-QC	AOCR-PC	AOCR-QC
mean payments per allocated SP (true valuation)	0,580	0,633	0,580	0,633
mean payments allocated SP (achieved)	0,570	0,642	0,593	0,655
mean surplus allocated SP (achieved)	-0,009	0,009	0,014	0,022
surplus (%)	-1,60%	1,44%	2,35%	3,40%

The comparison of the average individual payoffs draws a different picture compared to the comparison of the aggregated payoffs. Following the PA-strategy in a price competition environment even leads to negative payoffs. Payoffs are larger for the AOCR-strategy. We also observe that the quality competition leads to higher individual payments on average compared to the price competition scenarios regardless of the strategy chosen. Unfortunately, the performed t-tests do not support this observation on a significant level. Consequently, we do not find significant support for Hypothesis H5. In contrast, we find support for Hypothesis H1 since the t-test does not support significant difference of the true-valuation payments and the PA-PC payments. Regarding H4 stating that it is beneficial in the AOCR-QC scenario to deviate from truth telling for those SP that would be allocated while submitting their true cost, we perform a single sided t-test and find significant support on a level of $p = 0.02$. Figure 2 shows exemplarily the course of one simulation run in the PA-PC setting. The payment sum converges already after a few repetitions close to the true-valuation-equilibrium as expected. We observe similar results in the simulation runs of the same setting with different network topologies. This additionally supports H1.

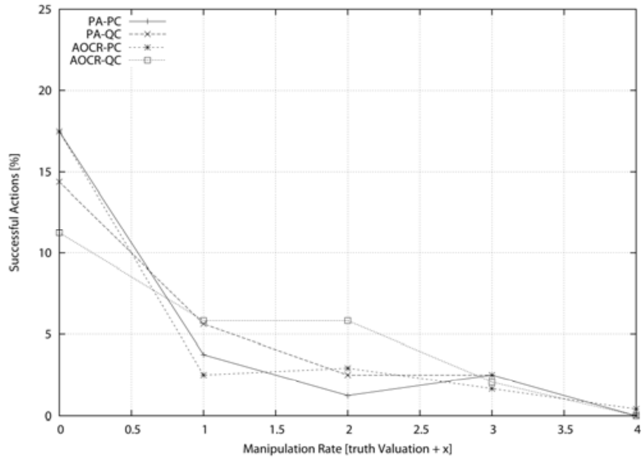

Figure 2 Frequency of Successful Actions Chosen by Allocated SPs

Regarding Hypothesis H2 and H3, we investigate both, the frequency of actions taken by all SP (incl. those SP that are not allocated) as well as the frequency of actions taken by the successful SPs. Figure 3 display the frequency of successful actions. Comparing the frequency of submitting true cost in the PA-PC vs. PA-QC we observe a decrease in the number of successful truth tellers. Unfortunately, we do not find significant statistical support since the t-test produces a p-value of 0.09, and thus, the null-Hypothesis cannot be rejected.

5 Conclusion

In the present paper we describe that the fundamental change from a product-oriented to a service-oriented economy fosters the formation of service value networks. Service providers offer their services within these networks. Service requesters combine different service offers to complex services best matching their preferences. The main question in service value networks is how to efficiently match service offers and complex service requests and dynamically determine prices. We propose an auction-based approach as a central allocation mechanism for multi-attribute services. Therefore, we introduce a formal model for service value networks as a *k*-partite, directed and acyclic graph, we specify the bidding language to define service offers and service requests, and we introduce the incentive compatible auction mechanism. In a repeated game incentive compatibility does not hold. We study two simple strategies to collude by means of an agent-based simulation approach. The simulation results show that deviating from truth telling might be beneficial especially for those SP who are in the allocation. The payments of SP can increase especially if the service quality offers are diverse and as such the difference in prices does not play a such important role as in a price competition regime. We are aware that the results are based on a simple model with relatively strict assumptions. We have just studied two simple strategies, but there certainly exist a couple of more sophisticated strategic alternatives. Additionally, we did not take varying preferences of service requesters into account. As such, the results are model-specific and a generalization is to be proven with additional simulations based on real-world data. During the model development a couple of ideas for future work came up. The most interesting aspect is to introduce additional strategies and also to study mixed strategy settings. We are also interested in using a learning mechanism in order to discover additional strategies. In the present model and simulation we have studied one proposed mechanism which we want to compare to alternative mechanisms, e.g. first-price auctions in which bidding strategies play a very important role.

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