Trust Evaluation for Reliable Electronic Transactions between Business Partners

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In the digital economy era, commercial relationships between business partners are increasing in flexibility, and temporary business binds tend to be created whenever a business opportunity arises. Moreover, the instability in demand increases the need for enterprises to procure new partners and the associate risk of inter-operating with partners that might be unknown beforehand. Therefore, enterprises need mechanisms that allow to evaluate the confidence they have on actual or potential partners, and to monitor this confidence in a continuous and automatic way. This paper evaluates a computational trust and reputation (CTR) system that provides estimated values of confidence on target partners. This system asymmetrically aggregates positive and negative evaluations of partners' behaviour, and introduces the percentage of successful contracts in the last t units of time as a first step to implement contextual factors in the partner's selection decision. The model was evaluated in an agent-mediated simulated textile virtual market, also described in this paper. We compare our approach with two other strategies of trust aggregation and present preliminary results that show that the asymmetric aggregation of evaluations and the introduction of the successful/violated contracts measure can improve the efficiency of the automatic selection of reliable partners in certain population scenarios.

1. Introduction

In the new era of digital economy, commercial relationships between business partners are increasing in flexibility, and business binds tend to be created whenever a business opportunity arises. The emergent need for new products and services, with increased quality, shorten time to market, and low price, and the instability in product demand, is forcing enterprises to risk new, sometimes unknown, suppliers, possibly spread all over the world. This new reality brings new technological, social, ethical, and economical challenges and risks to the industry.

Moreover, the desired automation of business inter-organizational relationships encounters some barriers in key stages, such as the selection of partners, negotiation and contract elaboration, particularly when there might be a large number of partners in the play (e.g. textile industry) that are unknown beforehand. The construction of reliable and broader accepted mechanisms of trust and reputation will allow organizations to continuously update their confidence level on actual and potential partners, in face of contextual changes. The benefits of such mechanisms are two-folded: i) allow for a broader selection of partners, as it would be possible to infer confidence values for a major number of partners (both from reputation transmission and definition of contextual similarities/profiling); ii) make it safer for an organization to increment the degree of tasks that could be automated, both in the partner selection process and in the automated negotiation of contracts, based on trust and reputation mechanisms. These mechanisms are, in fact, getting great attention from different research areas, from social science and psychology to economics and computer science, particularly in the multi-agent and the service oriented architecture communities.

Our current research work focuses on the automation of inter-organizational interactions in two different but yet complementary tasks: the partners' selection and the negotiation of contracts in dynamic environments, taken as input confidence knowledge derived from trust and reputation. In this paper, we present our model of computational trust and reputation (CTR); particularly, we describe its aggregation engine that computes confidence values in a non-linear, asymmetric like way (i.e. confidence generally grows slower and declines faster), using properties of the shape of a hysteresis curve. In order to better understand the role of CTR systems in the process of selecting partners, we developed the simulated textile virtual marketplace (STexVM), a multi-agent system where buyers and suppliers of textile fabrics worldwide have the chance to conduct business. The aim of this system is three-folded: to study the dynamics of automated partner selection in an environment with different types of buyers and suppliers; to evaluate our model of aggregation of trust based on the shape of an hysteresis' curve, already implemented; and to evaluate the model of contextual fitness we are currently developing, which would bring organizational and business context as extra knowledge to the computation of confidence scores.

The structure of this document is as follows: section 1 introduces the paper and presents a brief revision on current research on trust and reputation. Section 2 presents STexVM, an agent-mediated simulated textile virtual market that we build to evaluate our approach. Section 3 presents our CTR system, and section 4 evaluates the model and compares it with two other different strategies. Finally, section 5 concludes the paper.

1.1 Literature Revision on Trust and Reputation

Current work on trust and reputation has diversified in multiple subfields. In the theoretical domain, there is important work on trust and reputation as elements of social intelligence. [1] addresses the theoretical issues related to reputation and image[1] in artificial societies and social simulation, and the authors extended recently their cognitive model of reputation in order to more thoroughly address the transmission of reputation ([2]). Probably the area where more research effort has been put, namely, in the multi-agents community, is the representation and aggregation of social evaluations into trust and/or reputation scores, which would serve as input to partner's selection in B2B scenarios. Some models have been proposed, from the simple eBay reputation

[1] The authors consider both image and reputation as social objects, as they concern shared information about the target "presumed attitude towards socially desirable behaviour". However, image is described as an evaluation belief, while reputation is a meta-belief, i.e., it is a belief about other agents' evaluations of a given target agent.

system that sums up integer values, to approaches that aggregates classifications using means and weighted means [3][4][5], Beta distributions [6], Dirichlet distributions [7], Bayesian approaches [8][9], and trust learning approaches [10] [11] [12]. Some of these models are implemented using complex beliefs, desires and intentions (BDI) architectures [5] [13]. A new trend of investigation on this area is the exploration of the business context to improve the decision making, raising significantly the number and type of information that the evaluator has in order to compute the trust. I.e., along with social evaluations given by direct experience or through witnesses, a plethora of new information related to the context of the business and of the organizations involved can improve the prediction of behavior of partners in a very significant way. However, few proposals have been made on this specific area [14], opening an enormous world of research.

2. The STexVM System

The STexVM is a simulated virtual marketplace for trading textile goods that ensures (as much as possible) reliable transactions, in a sense that it is able to detect business partners that in some moment start behaving in a defective way. The simulated environment is based on existent online virtual marketplaces where buyers and sellers in the textile and fashion industry can post buying and selling leads (e.g. the Fibre2Fashion marketplace).[2]

The STexVM follows the multi-agent paradigm, and is implemented over Jade platform[3], using the standard behaviours of Jade and FIPA[4] performative and interaction protocols. The key agents in this environment are buyers and suppliers. Buyers' agents represent companies that periodically need to buy a given amount of fabric (e.g. cotton, chiffon, voile) to textile suppliers. The type and quantity of fabric the buyer needs to purchase in a period of time (round period) are defined at its time of creation. At each negotiation round, a buyer can buy to one or more suppliers, until it reaches the defined quantity for the round. Based on these requirements, we can stipulate that a buyer agent has two main objectives: i) to periodically buy the needed quantity of the designated goods, in order to supply its operational activity; and ii) to maximize the utility it gets from the acquired material. In our simulated environment, the utility is related to the quantity and quality of the purchased goods it is able to buy at every negotiation round. Therefore, the choice of a reputable partner is essential to the lifecycle of the buyer.

Supplier agents represent textile companies that periodically need to sell a given amount of fabric (e.g. cotton, chiffon, voile) to buyers. Each supplier shall provide two different types of fabric, and the exact type and quantities of fabric the supplier needs to sell in a period of time (round period) are defined at its time of creation. The supplier agent was purposely designed to be simple, and its main objective is to periodically sell a determinate amount of the goods it has to sell, emulating a real world manufacturer and exporter of textile fabrics. The remaining agents of the STexVM

[2] http://www.fibre2fashion.com/
[3] http://jade.tilab.com/
[4] http://www.fipa.org/

system are the Agent Simulation Manager, who manages the configuration parameters related with buyers and suppliers; the Agent DF, which registers competences of buyers and suppliers; and the Agent CTR, which gathers information about the performance of suppliers and computes their confidence scores on-demand, when requested by the buyers. Figure 1 illustrates the relation between these agents.

2.1 Initial Configuration of Suppliers and Buyers

Each buyer and supplier that enters the simulated virtual marketplace gets a random configuration over a predefined set of values. In order to perform our simulations in a scenario that would approach a real textile environment, we picked and mangled real data from online virtual marketplaces.

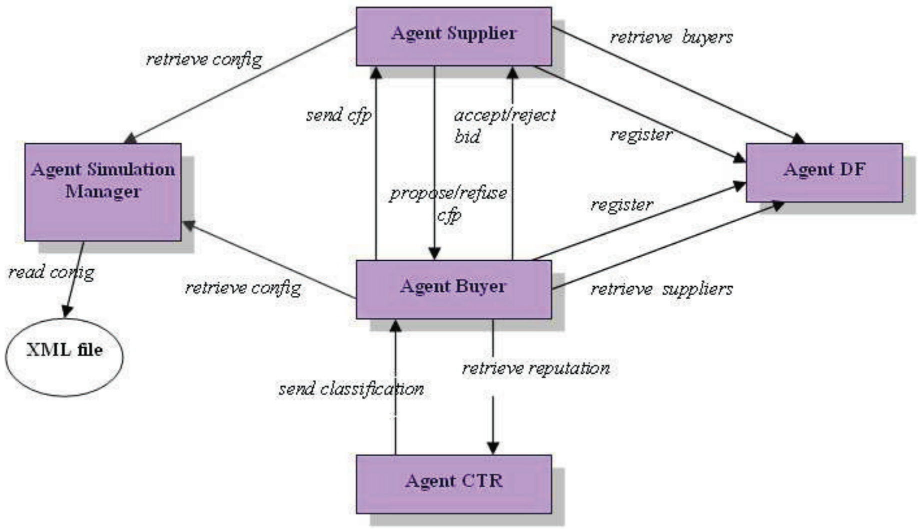

Fig. 1. Interactions between agents in the STexVM system

All suppliers in the STexM system assume the role of *manufacturer & exporter*, for simplicity. Suppliers are characterized by a set of properties that are setup when a new instance of a supplier is created; for each new supplier, two different fabrics are chosen from the values presented in Table 1 (left), and they are associated to a quantity randomly picked up from the values on the table (right). Each supplier also gets a country of registration, a year of establishment, and the total number of staff and annual sales. The latter three values are taken from real data collected from a virtual marketplace in the textile domain. Finally, each supplier is initially assigned an estimated “behaviour” from three possible values: “good”, “fair” and “bad”.

Buyers are characterized by their *buying characteristics*, related to the good they need to buy periodically (number and type) and respective range of quantities. Again, these values must be randomly picked up from the values in Table 1, every time a new instance of the buyer agent is created.

Table 1. Type of fabrics (left) and quantities (right) that can be transacted in the virtual marketplace

Type of Fabric (Good)	Quantities (meters)
Blended, Chiffon, Cotton, Crepe, Denim, Dyed, Embroidery, Fibre Waste, Fleece, Grey, Interlock, Jersey, Knitted, Lycra, Nylon, Polyester, Silk, Spandex, Terry Cloth, Velour, Velvet, Viscose, Voile, Wool, Woven	500; 5,000; 25,000; 50,000; 80,000; 120,000; 180,000; 240,000; 500,000; 1,000,000

2.2 Selection of Partners

At every negotiation round, each buyer issues a call for proposals (cfp) that sends to all registered sellers of the good in cause. A contract-net like negotiation occurs, and the buyer selects a number $n > 0$ of partners that optimizes the expected utility in the round, using equation (1).

$$E(u) = \arg \max_i \mathit{for\ each\ i} \sum_j util_j * trust_j \quad (1)$$

In the equation above, i stands for the possible combinations of suppliers' proposals that fit the quantity specified in the current cfp, not exceeding it; j represents the suppliers considered in each of these combinations, and $trust_j$ is the confidence score computed for supplier j at selection time Finally, $util_j$ is the quantity proposed by each supplier j in the round, normalized by the quantity specified in the cfp, i.e., $quant_j/Quant$. In our system, a buyer can order less quantity than the maximum quantity ($Quant$) defined in the cfp, but it cannot exceed $Quant$. Also, a buyer cannot accept partial quantities of the received bids.

3. The Proposed CTR Model

3.1 Aggregation using Non-Linear Curves

We developed an aggregation model that allows for the expression of non linearity in the process of trust constructing. On one hand, it captures an important feature of the dynamics of trust as defined in [1], the *asymmetry*, where trust is hard to gain and easy to lose. On the other hand, our model extends the non-linearity concept to distinct phases on the process of trust construction. In this context, Melaye and Demazeau (2005) address the asymmetry question in [15], but focus their approach on direct observations and do not consider different phases in the trust construction process. At the extent of our knowledge, none of the existent CTR models addresses the non-linearity of trust dynamics in a practical way.

In order to model the non-linear behaviour of our aggregation engine, we were intuitively influenced by the physical phenomena of hysteresis, and developed simple heuristics based on the hysteresis curve to pre-validate our assumptions, as described above. Figure 2 shows a hysteresis curve obtained from the application of Rostilav Lapshin formula [16] depicted in equation 2.

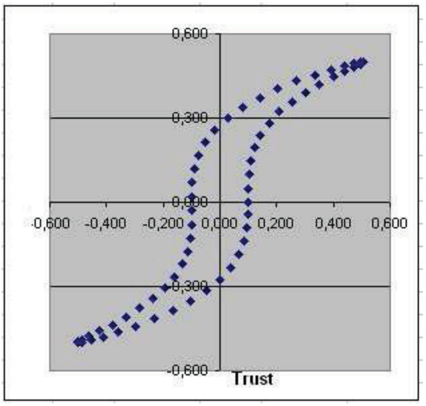

Fig. 2. The shape of a hysteresis curve with parameters a=0.1, b_x=0.5, b_y=0.5, n=1 and m=3. In the formula, *a* represents the coersitivity parameter, *m* and *n* are integers used to fit the curve and b_x and b_y are the saturation parameters.

$$x(\alpha) = a.\cos^m \alpha + b_x.\sin^n \alpha \qquad (2)$$
$$y(\alpha) = b_y \sin \alpha$$

In our model, the trust of a given supplier is captured in the OX axe (see picture above). We use the rightmost plot of the curve to aggregate positive results (e.g. evaluations, contract results), and the leftmost plot to aggregate negative results. This signifies that the model captures sudden changes in the behaviour of the suppliers, and that the impact of negative results is weaker when the confidence value of the supplier is rather low or rather high, and stronger when the supplier is in the process of acquiring trust, following here common sense about confidence construction.

3.2 Contextual Fitness

Social evaluations help the selector to predict how well a given candidate partner will execute a task and to compare between several candidate partners. However, there are some questions a selector would pose before making a decision that cannot be answered by simply aggregating available classifications in the form of trust and reputation values. These questions involve somehow a certain level of *intuition*. As an exemplificative case, consider a high tech company that fears to select a partner from a country of origin without high technology tradition, even though this partner has proved high quality work in the desired task in the recent past. This is the type of contextual knowledge we intend to incorporate in our CTR model, and we name it *contextual fitness*, as it will provide extra decision information to the selector by computing a value of *how well the candidate partner fits in the selector current needs*, as defined in the issued cfp. Additionally, the selector can also provide additional preferential conditions, such as:

C1. *DeliveryTime ≥ Price ≥ Quality;* ***C2.*** *OriginCountry !=p {countryA, countryB}*

In C1, the selector expresses an order of preference among attributes of the CFP, using the operator ≥, and in C2 the selector indicates that it preferentially would not deal with candidate partners for a list of origin of countries. The contextual fitness component, not yet formally described, is then an inference engine that analyses the *profile* of the actual business, supported by the cfp and by conditions defined by the selector, and the *profile* of the candidate partners, and infer how well they adapt. The profile of the partners is given taking into account historical relevant classifications stored at the CTR system and financial and organizational characteristics of the partners stored in a registry service. We use again an example to help clarifying the value of the contextual fitness component: let us imagine that an entity pretends to explore a business opportunity in the fashion market and creates a virtual enterprise for the fabrication of fashionable t-shirts. This entity starts to look for partners in the fashion/textile industry, including designers, garment manufacturers, fabrics suppliers, accessories' dealer, etc. Now, for the sake of simplicity, consider that the selector initiates the selection of partners' process and issues this (rather simplistic) description of component "zipper", included in the cfp:[5]

material: <cotton; nylon>; quantity: [10000-7500]; weight: <150; 200>; color: <red; purple>; delivery time: 2 weeks

Consider also that the selector has defined the following contextual condition:

C1. Delivery Time = ABSOLUTE

Now, let us imagine that a given candidate partner has proven to be reliable in the past in providing 150g red cotton zipper in two weeks, but he never traded more than 5000 units at a time. In this case, the inference engine can predict, based on the candidate profile, whether the candidate partner would be able to deliver such a quantity in the cfp terms. The mentioned profile can be build upon several parameters, such as the partner's tendency in negotiation over the time, organizational information (e.g. number of employees, country of origin, size of the industrial plants) and several financial figures.

4. Simulated Experiments

We developed a simple simulation scenario to evaluate the proposed non-linear model of trust aggregation and to compare it with other approaches. Therefore, we defined four different strategies to partner selection and tested each one of them in the STexVM system. The QUANT strategy orders candidate bids by decreasing quantity and then keeps selecting every proposal with quantity equal or less than the remaining quantity, until the quantity defined in the cfp is reached. This strategy does not take into consideration the trust values of the suppliers. In the remaining three strategies, the selection of partners is done taking into account the expected utility gain in select-

[5] In the above example, the tuples indicated the preferred order of values (e.g. the selector prefers zippers weighting 150g to 200g), and the first value in range parameters indicated the preference of the selector (e.g. he accepts to deal quantities from 7500 to 10000 units, although it prefers to buy as closed as the higher value possible).

ing one ore more suppliers in the current round, as specified in equation 1.[6] Therefore, strategy ASYM uses our non-linear aggregation engine to compute the trust component, while the WMEAN strategy uses an aggregation engine that computes the mean of the results weighted by the recency of the results (cf. [17]). As mentioned earlier, there are several CTR models that use weighted means to aggregate social evaluations, therefore the WMEAN strategy will allow us to compare our strategy with one that is disseminated in the trust and reputation community. Finally, strategy ASYM+ adds the percentage of successful contracts of the supplier in the last N transactions/units of time to the ASYM strategy, by multiplying this percentage with the confidence score returned by the ASYM aggregation engine.

For all the strategies, in the first rounds of each experiment the buyers start to explore the space of available candidate partners, by randomly selecting the partners, and after some rounds they progressively increase the exploitation by selecting partners based on the chosen strategy. The experiments are homogeneous, in the sense that in each simulation run we populated the simulated environment with buyers following the same strategy.

4.1 Experimental Methodology

In order to evaluate the four strategies described above, we used three different populations of suppliers' agents. We consider three types of behaviour for suppliers ("good", "fair", and "bad"), where the behaviour of a supplier is related to the results of the contracts it makes during it lifecycle with buyer agents. Each supplier was assigned a behaviour at its creation time, following a uniform distribution over the three possible values. We consider that the capacity of each type of suppliers in fulfilling the contract is modelled by a Markovian process with two states (1 and 0, standing for contract fulfilment and contract violation, respectively) and transition probabilities P11 (Fulfilment-to-Fulfilment) and P01 (Violation-to-Fulfilment). The values considered for populations A, B and C are defined at Table 2.

Table 2. Values of the transition probabilities used in the experiments. $P_0 = 0.50$ for all cases.

	Type "Good"		Type "Fair"		Type "Bad"	
	P11	P01	P11	P01	P11	P01
Popul. A	0.90	1.00	0.80	0.75	0.50	0.50
Popul. B	0.90	0.90	0.90	0.70	0.90	0.50
Popul. C	0.70	0.70	0.70	0.70	0.70	0.70

[6] We shall note that equation 1 takes into account three possible terms of inter-organizational business contracts, namely, the delivery of the contracted good, the partial delivery of it (e.g., supplier *x* succeeds to deliver the fabric but supplier *y* does not), and the quality of the supplied good, where 0 corresponds to an unacceptable quality good, and 1 corresponds to an excellent quality product; although we restrict the classification of the received value to a Boolean value, we intend it to be picked from a broader range of possible values, either discrete (e.g., labels as "good", "acceptable" and "not acceptable") or continuous (e.g. in the [0, 1] range), in a future version of the system.

As can be seen from the table above, in population A, suppliers of type "Good" have high probability of success and never fail two contracts in a row (once P00 is zero). The remaining types correspond to worse behaviours. In population B, all suppliers have the same, high probability of fulfilling a contract (P11 is 0.90), but suppliers of type "Good" are less prone to fail more than one contract in a row than the remaining types of suppliers, being "Bad" the worst case. In population C, all suppliers have the same (rather low) probability of fulfilling their obligations. Although the proposed population modelling does not directly mirror reality, it allows us to study how the different strategies respond to the resulting patterns of contract violations.

For each one of the four strategies defined above, we run 4 experiments per suppliers' population, in a total of 12 experiments or runs per strategy. Also, at each run, we launched 15 buyers and 75 suppliers, and each buyer issued 50 cfp at corresponding negotiating rounds. At this point, it is convenient to remind that a cfp discriminates the fabric and the quantity of material that the buyer intends to purchase, and it is sent to all suppliers that sell the desired fabric; in response, every supplier that receives a cfp sends a proposal with, at maximum, the required quantity of the fabric material, or refuses to propose if it not able to satisfy the cfp requirements in the current round. Also, each supplier is able to replenish its stock at the start of each negotiation round.

Finally, the utility gained by each buyer at each negotiation round was recorded, and at the end of the experiments the average utility of a buyer and the corresponding standard deviation were evaluated for each one of the considered strategies. The average utility captures the capacity of the buyer in selecting good suppliers, and, this way, allows for the evaluation of the performance of each one of the four strategies. Table 3 presents compact data about the experiments.

Table 3. Values and parameters used in the experiments

Quantities	5000, 50000, 180000, 240000, 500000, 1000000
Fabrics	Chiffon, Cotton, Denim, Dyed, Jersey, Fleece
# buyers	15
# of sellers	75
Types of sellers	Chosen upon a uniform distribution over the types {"good", "fair", "bad"}
# issued CFP per buyer, per run	50
# runs per strategy and per population	4
# past results (Hyst+ strategy)	8
Exploit/Exploration formula	Uniform distribution over f(x), where f(x) = 100 – $round_i$ * 7 or 10, if (100 – $round_i$ * 7 < 10)
Hysteresis parameters	a = 0.1, b_x = 0.5, b_y = 0.5, m=1, and n=3; the parameter α increases/decreases in steps of $\Pi/12$units.

4.2 Results and Conclusions

Figure 3 shows the average utility of buyer agents obtained per strategy and per population, in percentage. In population A, the ASYM strategy outperforms the others three, with buyers buying, in average, 83.81% of the desired good in the desired quantity (ASYM+ reached 80.31%, QUANT 70.18% and WMEAN 79.67%). Concerning population B, the ASYM+ got 83.73% of average utility, outperforming the remaining three (ASYM: 81.81%, QUANT: 81.68%, and WMEAN: 82.27%). Finally, in population C, the obtained results were quite similar (ASYM: 67.63%, ASYM+: 68.21, QUANT: 68.72% and WMEAN: 68.17%).

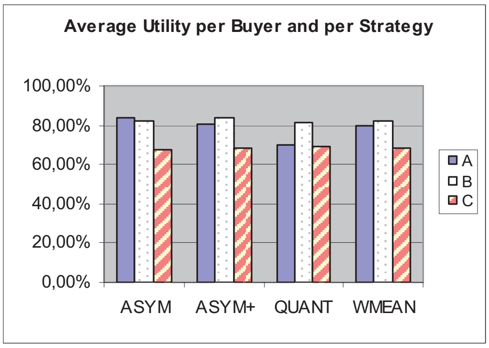

Fig. 3. Average utility per buyer, strategy and population (A, B and C)

While ASYM and ASYM+ performed a little better that WMEAN and QUANT, in reality we would expect that ASYM+ strategy would show greater advantage when compared to the others three strategies, because of its ability to asymmetrically aggregate trust and to take recency into account. Therefore, in order to understand the effect of random partner selection at the exploration rounds in the results, we traced the last 50 transactions of every run, for each strategy and for each population, and averaged the number of unsuccessful results (we remind here that at the last 50 transactions the probability of a random selection of partners is 10%). Figure 4 shows the results we obtained. In reality, we observed that the strategy ASYM+ outperformed the remaining strategies in population A (13% of violated contracts, against 14% of ASYM, 22.50% of QUANT and 15.50% in WMEAN) and in population B (9% of violated contracts, against 12.50% of ASYM, 16.50% of QUANT and 14% of WMEAN). Considering population C, the WMEAN strategy presented poorer results than the QUANT strategy (30% against 28.50%), and strategies ASYM and ASYM+ got an average of violated contracts of 24.50% and 25.50%, respectively.

In order to reduce the possibility of noise, we rerun the experiments for population A and strategies ASYM+ and WMEAN, considering 12 runs for each strategy. We observed that ASYM+ got an average of 12.17% of violated contracts in the last 50 transactions, outperforming once again WMEAN, which obtained 14.83% of contract violations. Also, we observed that 80.17% of the suppliers selected in the last 50 transactions were of type “Good”, for the ASYM+ strategy, while this number reduced to 69.83% for the WMEAN strategy.

Analysing this latter data, we can conclude that the non-linear aggregation of trust leads to a better estimate of the future behaviour of suppliers than the weighted mean with recency approach, allowing for the effective reduction of violated contracts. Moreover, the empirical analysis of the traces captured from the experiments shows that such a model that embeds the historical construction of trust is more effective in predicting patterns of behaviour than approaches that simply averages evaluations.

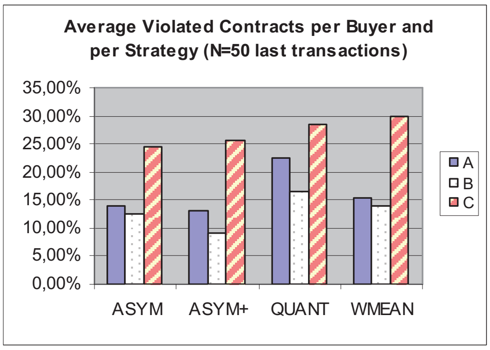

Fig. 4. Average number of violated contracts per buyer, strategy and population (last 50 transactions)

4. Conclusions and Future Work

This document presented the STexVM system, a simulated virtual marketplace that mirrors the posting of buying and selling leads of real textile virtual market, while adding up an important component of automation of the process of partner selection, essential to the interoperability concept. This system follows the multi-agent systems paradigm, and was implemented in Java over the Jade Platform. One important component of the developed prototype is it module of computational trust and reputation (CTR), an aggregation engine that computes confidence scores using a non-linear, hysteresis like approach.

We evaluated the performance of the non-linear strategy, measuring the number of successful contracts per buyer in the total number of cfp issued by the buyer in each experiment. Therefore, we measured the capacity of the buyer in selecting different types of suppliers based on the estimated trust. Then, we compared this approach with a trustless-based strategy that selects partners by the quantity they are available to supply, and to a strategy that estimates the trust of suppliers using a weighted average aggregator. The results obtained seem to validate our hypothesis that a non-linear strategy allows for a better detection of good suppliers, leading to a reduced number of broken contracts, when compared with strategies that aggregates evaluations based on average statistics. Based on these results, another formalization of non-linearity aside from the hysteresis approach might be explored. As future work, we will change the STexVM system in order to keep contractual information about suppliers between different experiments, avoiding the bootstrapping of the system and the associated noise derived from the initial strong exploration phase.

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