A Negotiation Style Recommender Based on Computational Ecology in Open Negotiation Environments

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Abstract — **The system described herein represents the first example of a recommender system in digital ecosystems where agents negotiate services on behalf of small companies. The small companies compete not only with price or quality, but with a wider service-by-service composition by subcontracting with other companies. The final result of these offerings depends on negotiations at the scale of millions of small companies. This scale requires new platforms for supporting digital business ecosystems, as well as related services like open-id, trust management, monitors and recommenders. This is done in the Open Negotiation Environment (ONE), which is an open-source platform that allows agents, on behalf of small companies, to negotiate and use the ecosystem services, and enables the development of new agent technologies. The methods and tools of cyber engineering are necessary to build up Open Negotiation Environments that are stable, a basic condition for predictable business and reliable business environments. Aiming to build stable digital business ecosystems by means of improved collective intelligence, we introduce a model of negotiation style dynamics from the point of view of computational ecology. This model inspires an ecosystem monitor as well as a novel negotiation style recommender. The ecosystem monitor provides hints to the negotiation style recommender to achieve greater stability of an open negotiation environment in a digital business ecosystem. The greater stability provides the small companies with higher predictability, and therefore better business results. The negotiation style recommender is implemented with a simulated annealing algorithm at a constant temperature, and its impact is shown by applying it to a real case of an open negotiation environment populated by Italian companies.**

Index Terms — Recommender Systems, Agents,

I. INTRODUCTION

OPEN Negotiation Environments are platforms where agents, on behalf of small companies, negotiate contracts, terms and conditions for services. These platforms must provide tools for trust and open-id, since new agents can continuously come in and out of the negotiation environments. Furthermore, these platforms must be reliable when working with potentially millions of agents. Cyber-engineering methods inspired by computational ecologies will provide new services that agents may use in a collective way to produce more intelligent and robust behavior. Negotiation environments, as well as distributed manufacturing facilities and the distributed provision of services, require a strong web-based IT infrastructure that is cost effective and flexible. [1] This environment should be developed in open source [20] to reduce bugs, increase security and boost cyber-engineering innovation.

The goal is to introduce high-level knowledge about a business ecosystem so that slightly modified agent negotiation behavior can have a big impact on the global ecosystem. This could lead to benefits for all of the participating agents on behalf of small companies.

It is not only a matter of service composition, but of price, reliability and quality. These particular negotiation environments are not yet focused on delivering industrial, holonic manufacturing systems [12] to adapt to changing demand, but are instead focused on helping to reduce the enormous effort that companies invest in getting profitable contracts. Thus, there is not yet a connection between contract negotiations and Industrial Manufacturing Systems. However, establishing this connection, though out of the scope of this paper, is considered to be the next major research issue concerning Holistic Industrial Ecosystems [13].

Negotiation can be defined as an interaction of influences. Examples of such interactions include the process of resolving disputes, agreeing upon courses of action, bargaining for individual or collective advantage, or crafting outcomes to satisfy various interests. Negotiation involves three basic elements: process, behavior, and substance. Process refers to how parties negotiate: the context of the negotiations, the parties to the negotiations, the tactics used by the parties, and the sequence and stages in which all of these play out. Behavior governs the relationships among these parties, the communication between them, and the styles they adopt. Substance refers to what the parties negotiate over: agenda, issues (positions and, more helpfully, interests), options, and the agreement(s) reached at the end.

An essential element of ecosystems is the negotiation of alliances, which enable companies to join competencies as well as services and products into a complex offering. Given this, Business Ecosystems should be empowered with a tool to support tactical negotiation and agreement processes among

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participants. This environment should support the creation of Virtual Organizations [27] with a common business goal, and should facilitate the building, stabilization, and improvement of the ecosystem performance on a shorter time frame.

This aspect is also highlighted in [5], which states, "...The dynamic networking of the organizations … drives to the dynamic co-operation of the players," and "This will dramatically affect the ways enterprises are constructed and business is conducted in the future, and the actual slowly changing organizations will be replaced by more, fluid, amorphous and, often, transitory structures based on alliances, partnerships and collaboration."

However, in most commercial negotiation environments where some negotiation feature is implemented, the network of intermediaries/suppliers is static and centrally regulated. New entrants must strictly adhere to the centrally-defined business rules and data formats of the technological infrastructure. In fact, current solutions (like the "marketplace") are proprietary, managed, and pushed by strong intermediaries or big suppliers, typically squeezing out small independent players. The small suppliers cannot enter the network as full members and are faced with a severe digital divide: they are basically left out of large markets.

It is very common that one big company copes with big contracts from governments and other big companies by offering services at a large scale. It is also common that this company then subcontracts the services to smaller companies, which provide parts of the services at a local level. The big company thus starts negotiations with hundreds, or possibly thousands, of smaller companies. This scenario results in a population of small companies gathered around one big company. The big companies have the money the little companies search for. There is fierce competition to take shares of that money. On the other hand, the little companies not only have the services the big company needs, but can also serve other companies that offer money for their services. In a certain way, main contractors also have to compete to hire the best providers. The global picture is a sort of ecosystem of companies offering money for services. The whole set of populations around big companies turns into an ecosystem that has a dynamic behavior with respect to the number of companies that compete for contracts from the big companies. Today, enormous competition can exist for earning the contracts of one big company, and tomorrow, perhaps there will be no competition. The oscillations of high-low competition change the negotiation power of small and big companies and affect the terms of contracts and the benefits to the participating companies. Though competition is good for the main companies, small companies have the right to look for other opportunities, and that is why any type of recommender system for the business ecosystem would be very welcome. Thus, big companies would also compete. Small companies love the predictability of markets, specifically knowable prices and predictable, stable competition. In this paper, we design recommenders to provide stability to business ecosystems. In section VII, we will see a concrete case of the dynamics of one big Italian company, Coopservices, and a population of small companies that are negotiating with it, in a sort of negotiation of alliances, as well as the benefit of negotiation recommenders for them.

Predictability gives power to informed negotiators. A common negotiation adage is to be prepared to walk away; that is, be prepared to abort a negotiation or to have an exit strategy [10]. If one knows there is low competition, he can expect counteroffers with better terms. This paper will further develop this idea, and will formulate it in section III in terms of an agent that negotiates on behalf of small companies, choosing deadlines and exit conditions, and helping agents to decide whether to close a deal or make a counteroffer.

According to the literature [2][4], business negotiations can be classified into two types: auctions and negotiations (which can also be considered reverse auctions). Auctions primarily focus on price negotiation and follow a clearly structured procedure. Compared to auctions, negotiations are not exclusively based on the competitive approach, but are based on a more unstructured dealing and bargaining negotiation process. Business negotiations are based on specific legal documents and follow a specific workflow, which can vary in the number of iterations or steps necessary to reach an agreement [4]. There are several types of negotiations; the most general is the multi-bilateral, multiparty negotiation. A multi-bilateral negotiation consists of several negotiations, as shown in Fig. 1. The negotiations are complementary and have one or several common constraints regarding a certain issue. For example, a negotiation for a trip can consist of a negotiation for a flight and a negotiation for a hotel and a rental car. Potential issues that might be common constraints include the total price of travel and the starting and ending date. Dependency is related to the negotiation issues that are defined during the set-up phase of a negotiation. Each of the involved negotiations might be of a different type. For example, the negotiation of the flight might be an auction (price) and the negotiation of the hotel might be a negotiation for whether breakfast and wireless internet are included once the price is agreed upon. Since each negotiation can itself consist of another negotiation (Fig. 1), a participant in a negotiation on one level can be the owner of a different (and nested) negotiation on a lower level. Issues and timing from higher-level negotiations can be inherited by lower-level ones. The case study of section VII represents a nested negotiation over two levels. On the first level, there is a bilateral negotiation with a main contractor. On the second level, the main contractor uses a multi-party negotiation to negotiate the required service or products. This model can be applicable to any industrial-provider model. For example, any big project for a new factory requires the integration of architecture, mechanical engineering, automation, security, energy, materials supply, transportation, and cleaning. These services can be further decomposed and bundled, so that providers can deal with larger or smaller parts of the project. For example, the main contractor could tackle several of the industrial services, including security, transportation and cleaning, but may have no experience in industrial automation, nor would this contractor be able to subcontract it. Then, the main contractor would subcontract part of the security, transportation and cleaning services to other local providers. It is a sort of negotiation of alliances where the owner of the negotiation is the one who creates the group of companies that are going to work together. There are many options, and companies should choose their own negotiation style to adapt in their particular negotiation environment.

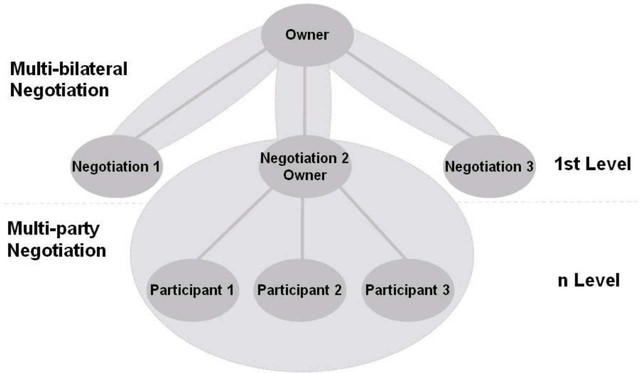

Fig. 1. Multi-bilateral multi-party negotiations.

There is no negotiation style recommender in either state-of-the-art recommender systems [6] or in recommender agents on the internet [14]. Therefore, there is an opportunity to create a new category of services devoted to the recommendation of a negotiation style for agents that negotiate in an open negotiation environment (ONE). This new category of services would act in a similar fashion to those agents who deliver their opinion to other agents when they have to provide a recommendation to their users, as described previously [15].

This study is interested in the dynamics of a ONE within a digital business ecosystem (DBE), studied within a cluster of digital business ecosystems, www.digital-ecosystems.org, as part of a project of the same name (http://one-project.eu). This paper is structured as follows. Section II further explains the concept of negotiation styles; section III presents a negotiation style model and its dynamics; section IV describes a negotiation style recommender based on a simple one-dimension monitor; section V shows a bi-dimensional monitor; section VI contains the negotiation style recommender implemented with a simulated annealing algorithm; section VII is a real case study; and section VIII concludes with final remarks and future work.

II. About Negotiation Styles

A negotiation can start with a published tender (by a tenderee) that invites interested companies to provide offers (offerers). A rejected or missing answer ends the contract negotiation. Contract negotiation continues with a counter invitation or a counter-offer.

We will focus on the number of counter-offers in a negotiation. We will name them "steps" in a negotiation, and they can also be referred to as "interactions," as shown in Fig 2. We will decide the agents' negotiation styles by means of the number of counter-offers.

Blake and Mouton [3] explains four types of opposing styles: cooperative vs. competitive and passive vs. active. The existing literature does not classify the number of steps in negotiations using the aforementioned negotiation styles. This paper suggests a classification of panic vs. confidence, wherein a panicked negotiator settles immediately and a confident negotiator settles over the long run. By considering that the pace of negotiation differs from country to country, and that the pace of negotiations in the United States is faster than in most other cultures [10], we may infer that this behavior (being fast) must have an impact on the outcome of negotiations. Generally speaking, for successful negotiations, a shorter negotiation is worse for the offerer and better for the tenderee if the tenderee had the power of negotiation. Having very few negotiation steps spread out over very long time windows (the Chinese style) is much worse for the offerer and much better for the tenderee. Long negotiations, despite aiming for a better outcome, suffer from a greater risk of deadlocks that may break the negotiations, with the corresponding risk of no outcome. In the long term, if one never settles, then there is no benefit at all.

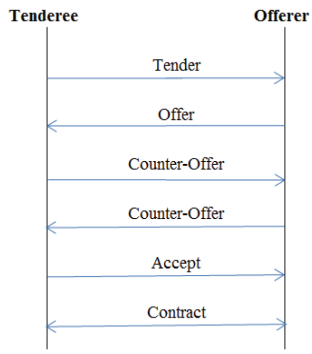

Fig. 2. Interactions in a negotiation. A counter-offer can be repeated many times. These are the **steps** used to settle a deal.

It seems that the optimal outcome is in the middle, meaning not settling immediately but not waiting a very long time to reach an agreement. Although some studies [4][10] have suggested saying "no" a final time when the deal seems close, whenever two agents apply this "say 'no' one more time" algorithm, it becomes heuristically better if they have a different pattern of saying "no." Thus, diversity in negotiation styles could have a positive impact on populations of negotiating agents.

We will adopt the Negotiation Styles approach of Blake and Mouton [3] and Karrass [10] in a narrow sense: one can be cooperative or aggressive in one dimension, as well as aggressive or passive in another dimension. The combination of the two dimensions provides four separate negotiation styles: accommodating, avoiding, collaborative, and competitive.

Let us think the negotiation as taking pieces of a pie. In the first dimension, one is aggressive if one seeks to take as large a "piece of the pie" as one can in a win-lose manner, by keeping all of the pie for oneself and leaving nothing for the opponent. On the other hand, one is being cooperative when making "the pie bigger," so that there is more room for negotiation. Even if one takes the larger piece of pie, the remaining pie is still big enough for the "loser" in a win-win or both-win [10] manner.

In the second dimension, being active tends to refer to thinking of many options and being very careful, which tends to increase the number of offers and counter-offers, the number of steps, and the time to close a deal. This approach could include being more entrepreneurial and more flexible and imaginative in trying to satisfy the demands of the counterparty. On the other hand, being passive means being inflexible to demands or not caring about the particulars of the deal, and this tends to result in a fast closing with few steps.

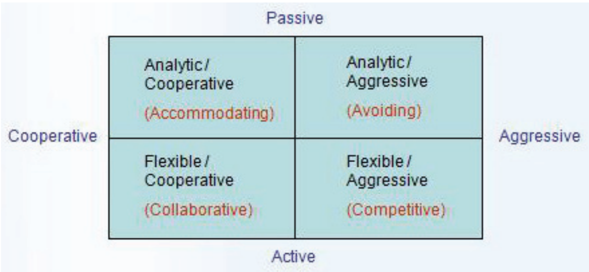

Fig. 3. A classification of Negotiation Styles.

In the following section, we will take the 2nd dimension of the passive-active negotiation style, namely, the one that is most linked to the number of offers and counter-offers in the negotiation.

III. A Negotiation Styles Model Inspired by Computational Ecologies

First, we analyze general properties of computational ecologies to understand their potential link to negotiation styles. Perceptions and expectations concerning the current and future behavior of (eco)systems in many economic and social systems play an important role in determining the actions of an individual agent. Kephart et al. [11] closely investigated the dynamics of a model that captures the essential features of computational ecosystems, and analyzed these systems with computer simulations to gain insight into the effects of time delays, cooperation, multiple resources, and heterogeneity. They showed that a system performance can be improved if agents correctly predict the current state of the system. Furthermore, reference [7] considered a procedure for controlling chaotic behavior in systems composed of interacting agents making decisions based on imperfect and delayed information. Their procedure used a reward mechanism, whereby the relative number of agents following effective strategies is increased at the expense of others. This is known as the Hogg-Huberman model (or simply as the Hogg model). References [9] and [16] have investigated the dynamic properties of a discrete-time Hogg model.

Hogg [7] proposed a computational ecology model of the interaction of a large number of agents and their competition for resources. Agents in a computational environment appraise the computational power that they will receive when they choose one resource over another (it is the amount of CPU share). Unfortunately, they do not have instant access to information about the available computational power at every source, and thus the real computational power differs from the expected power, and worse, tends to be lower because of resource competition.

We begin by proposing a one-dimensional model, the one of being passive (close deals quickly) or active (close deals slowly). We propose a new model for negotiation styles, refining the Hogg Model. We refer to this model as the de la Rosa model of multiple agents' negotiation styles dynamics. This model consists of the interaction between a large number of agents and their competition in negotiating and settling deals with tenderees. The negotiating agents (offerer agents, or simply offerers) appraise the wealth, benefit, profit, or income they could obtain after choosing one tenderee over others. Although they may have instant access to information about tenderees' wealth and information about the benefits of previous negotiations with any of the negotiation agents, offerers do not know the real benefits (if any) available at the moment they will set a deal. This is because many factors affect the progress of any negotiation, and thus, the actual benefits will diverge from the expected benefits. The benefits also tend to be lower than expected due to the considerable competition for the healthiest tenderees.

Let us demonstrate the de la Rosa model in regard to the dynamic behavior of a community of offerers negotiating with two tenderees within a ONE instance. This gives us two sources of business opportunities (the resources in business ecosystems) with which offerers must negotiate. We define $f_r(t)$ as the fraction of the offerer agents negotiating with tenderee r at time t. An interaction can occur in a two-tenderee ecosystem, wherein offerer agents re-evaluate the tenderees' wealth as they continue to negotiate with them, attempting to maximize the benefit of contracts with those tenderees. The offerer choice is modeled by the following equation:

$$\frac{df_r}{dt} = \alpha\left(\rho_r - f_r\right) \tag{1}$$

where α is the rate at which agents re-evaluate their tenderee choice (whether it is fruitful or not) and ρ is the probability that an agent will prefer Tenderee 1 over 2. f_1 and f_2 are the fractions of the offerer agents negotiating with tenderees 1 and 2, respectively.

The number of agents using the same fruitful tenderee as a resource for business contracts increases until too many agents are negotiating with this tenderee, while the payback from the offerer diminishes because of the increasing competition, with the result that prices decrease and benefits drop. Thus, the uncertainty (σ) is modeled as a typical deviation on performance to decide when tenderee 1 clearly drove an offerer agent to a more profitable contract (higher payoff) than tenderee 2. *erf* is the Gaussian error function.

$$\rho = \frac{1}{2}\cdot\left(1 + erf\left(\frac{G_1(F(f_1)) - G_2(F(f_2))}{2\sigma}\right)\right) \tag{2}$$

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When working with fast (no) negotiation, that is, closing the deal very quickly and receiving the profit of the contract as soon as possible, the offerer agents' choice of tenderee stabilizes after a transient period, as shown in Fig. 4 (left), which shows the stabilized population of agents negotiating with tenderee 1. When the settlement is postponed (delayed), the offerer agents have access to the contract's profit by *k* sample times ago, and the ecosystem shows a chaotic behavior, as shown with the same tenderee in Fig. 4 (middle). The introduction of heterogeneity of agents with several delays introduces stability to the system as shown in Fig. 4 (right).

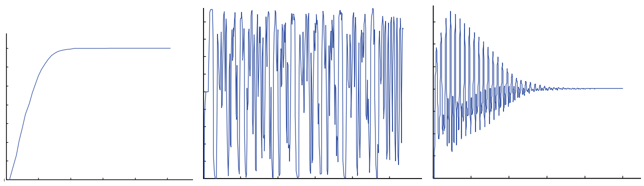


Fig. 4. (Left) Offerer agents with no negotiation, and instant access to profit; (middle) Offerer agents with delayed access to profit because of a long negotiation process; (right) Stabilization of tenderee usage in a group of heterogeneous (diverse) offerers.

The de la Rosa model is analogous to the Hogg model, as the following map in Table I shows:

Table I. Mapping of Hogg computational ecology to de la Rosa negotiation style models.

Hogg (1)	**de la Rosa (2)**
Computational capacity of a CPU	A tenderee's wealth or available money or room for tenders
Agents' appraisal of CPU	Offerers' appraisal of tenderee wealth
Delayed CPU information	Delayed settlement (of negotiations)
Delay: a number of time steps	Delay: a number of negotiation steps (indirect relation with time steps)
Payoff $G(t,\ d_a(F(t\text{-}nT))$	Payoff $G(t{+}nT,\ d_a(F(t)))$

The difference between the two models is that in the Hogg model, when an agent *a* makes a decision d_a by appraising at time *t* with *n* steps of delayed information $F(t\text{-}nT)$, it immediately obtains the payoff $G(t,\ d_a\ (F(t\text{-}nT)))$ in the form of the computational capacity of the selected resource, while in the de la Rosa model, the agent makes a decision by using current information to appraise the payoff it will obtain in the future (after *n* negotiation steps) from the wealth of the selected resource.

With $G(t,\ d_a(F(t\text{-}nT))$ as the payoff of the Hogg model and $G(t{+}nT,\ d_a(F(t)))$ the payoff of the de la Rosa model for the passive-active dimension of negotiation style, they become equal at $t'{=}t{+}nT$, where the payoff of de la Rosa model becomes $G(t',\ d_a(F(t'\text{-}nT)))$.

Therefore, some of the results obtained by Hogg can be mapped to the de la Rosa negotiation style model. In his paper [7], Hogg shows how 40 heterogeneous types of offerer agents stabilize an ecosystem (Fig. 4 – right). In our work, each individual agent has a different delay for settling and accessing the profit/benefit. The delay, therefore, defines the negotiation style. This approach presents some interesting features:

- The entire system benefits from heterogeneity, allowing the whole ecosystem to stabilize the tenderee preference for negotiation. That is, the size of the offerer agents' community stabilizes around each tenderee.
- The stability of a system is determined by the behavior of a perturbation around equilibrium. Since heterogeneous systems are more stable than homogeneous systems [11], the important issue is to calculate how much diversity ("the mix") is needed to stabilize the ecosystem. In our case, the diversity is represented by the set of different delays that offerer agents can use when performing their negotiations.
- This approach represents an interesting and simple mechanism to deal with heterogeneity in multi-agent systems, by means of a reward mechanism that introduces competition among the offerer agents through the "negotiation style" recommender, which will be introduced after the one dimension monitor in the following section.

IV. One Dimension Monitor

A monitor will measure the distribution of the offerer agents' population in terms of negotiation styles. The monitor will try to measure the stability of the populations of offerer agents negotiating with the tenderees in the ecosystem. A recommender might use the information from the monitor to stabilize the population of the open negotiation environment by balancing the population of different types of offerer agents that negotiate with the tenderees. This will be achieved by recommending changes in the offerer agents' negotiation style, affecting the number of steps to reach a settlement, or altering the fulfillment percentage on the object of the negotiation.

Now we present some examples of the stabilization effect of introducing a diversity of negotiation styles only in the aggressive-passive dimension.

A. Example with Two Tenderees and Three Negotiation Styles

The three negotiation styles are: $s = 0$ (always accept, or **passive**), $s = 1$ (accept after at least one counteroffer), $s = 2$ (say "no" one more time, or **aggressive**).

A and *B* represent the two tenderees, and all three scenarios are run under the same conditions:

- Contracts with tenderee *A* have doubled the benefit of those with tenderee *B*.
- Initial conditions $f^A = f^B$, that is, the same number of offerers are negotiating with tenderee *A* and tenderee *B*. f^A denotes the total number of offerers of any type negotiating with *A*, that is, $f^A = f_0^A + f_1^A + f_2^A$. Analogously, the total number of offerers of one type *s* is $f_s = f_s^A + f_s^B$. The total number of offerer agents is 20.
- $\alpha = 1$, $\rho = \mathrm{I}$, and no agents are allowed to type change/shift.

- A maximum of 1 agent from any population changes tenderee at each step.

Scenario 1. There are 20 offerers of type 0, $f_0 = 20$ ($f_1 = 0$). This means that all agents immediately settle with a "no" counteroffer. The run proceeds along 14 steps as follows:

Time t stamp	1	2	3	4	5	6	7	8	9	10	11	12	13	14
f^A	10	11	12	13	14	13	14	13	14	13	14	13	14	13
f^B	10	9	8	7	6	7	6	7	6	7	6	7	6	7
Profit from A	1/5	1/5	1/6	1/6	1/7	1/6	1/7	1/6	1/7	1/6	1/7	1/6	1/7	1/6
Profit from B	0	1/9	1/8	1/7	1/6	1/7	1/6	1/7	1/6	1/7	1/6	1/7	1/6	1/7
More Profit from	A	A	A	A	B	A	B	A	B	A	B	A	B	A

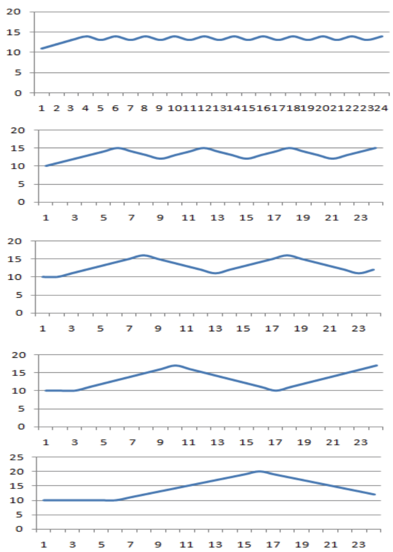
One can see that there is a cycle every two time steps, that is, a frequency of 0.5.

Scenario 2. There are 20 offerers of type 1, $f_0 = 0$, $f_1 = 20$. That is, all agents settle with delay 1, after 1 counteroffer. The run proceeds along 15 steps as follows:

Time t stamp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
f^A	10	10	11	12	13	14	15	14	13	12	13	14	15	14	13
f^B	10	10	9	8	7	6	5	6	7	8	7	6	5	6	7
Profit from A	1/5	1/5	1/5	1/6	1/6	1/7	1/7	1/7	1/6	1/6	1/6	1/7	1/7	1/7	1/6
Profit from B	0	0	1/9	1/8	1/7	1/6	1/5	1/6	1/7	1/8	1/7	1/6	1/5	1/6	1/7
More Profit from	A	A	A	A	A	B	B	B	A	A	A	B	B	B	A

One can see there a cycle at six time steps in length, that is, a frequency of 0.167. Experimenting with populations with different delays shows that *average*(f^A) $\approx 2 \cdot$*average*(f^B).

One can easily observe in the following runs that as delay increases (the type of agents), variability also increases (increasing σ^2). A higher variability made he decisions become more difficult, and the population went toward chaotic behavior, as predicted by the Hogg model.



Type 0, no delay, freq=0.5, σ^2 =0.8

Type 1, 1 step, freq=0.17, σ^2 =1.1

Type 2, 2 steps, freq=0.13, σ^2 =1.6

Type 3, 3 steps, freq=0.07, σ^2 =2.1

Type 7, 7 steps, freq= ?, σ^2 =2.7

Scenario 3. This scenario introduces diversity (heterogeneity) into Scenario 2 by letting two agents be of type 0, while the remaining eighteen are of type 1 ($f_0 = 2$, $f_1 = 18$); t= 1, …, 10. This does not change the initial conditions of $f^A = f^B = 10$.

Time t stamp	1		2		3		4		5		6		7		8		9		10	
	f0	f1	f0	f1	f0	f1	f0	f1	f0	f1	f0	f1	f0	f1	f0	f1	f0	f1	f0	f1
f^A	1	9	2	9	2	10	2	11	2	12	1	13	0	12	1	11	2	12	1	13
f^B	1	9	0	9	0	8	0	7	0	6	1	5	2	6	1	7	0	6	1	5
Profit from A	1/5	1/5	1/5	1/5	1/6	1/6	1/6	1/6	1/7	1/7	1/7	1/7	1/6	1/6	1/6	1/6	1/7	1/7	1/7	1/7
Profit from B	0	0	1/9	1/9	1/8	1/8	1/7	1/7	1/6	1/6	1/6	1/6	1/8	1/8	1/8	1/8	1/6	1/6	1/6	1/6
More Profit from	A		A		A		A		B		B		A		A		B		B	

As it can be observed in the following plots (Fig. 5), the oscillation bands in Scenario 3 with the heterogeneous populations of two negotiation styles (0 and 1) is narrower than those of Scenario 2 (smaller typical deviation of 1.0 compared to 1.1 from Scenario 2), and has lower frequency than Scenario 1 (frequency of 0.25, twice as small as the 0.5 from Scenario 1). This was achieved simply by introducing two agents of type 0.

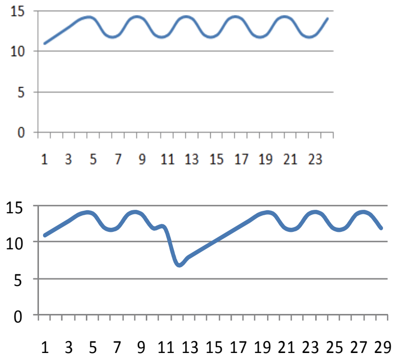


Fig. 5. Few agents of type 0 stabilize a mixed population of agents. Disturbances at time step 13 are rejected.

In summary, the three scenarios demonstrate how delayed settlements destabilize the negotiation ecosystem, and how stability can be reestablished by introducing diversity. These observations suggest that a recommender will tell agents to shift their delays in settlement in order to gain global stability, and further predictability for business.

V. The Bidimensional Monitor

We now introduce a second dimension to the monitor negotiation style: competition vs. collaboration. This negotiation style dimension is deducible by measuring the % *fulfillment* as the percentage of the negotiated object or negotiation target. We heuristically propose that less than 50% fulfillment means that the agent is being cooperative, while greater than 50% fulfillment means the agent is being aggressive. Let us use the common analogy of "pieces of pie" to talk about the object of negotiation. If the "pie" grows, then the fulfillment tends to reach 50% in pieces. In contrast, when the pie remains the original size, fulfillment tends toward 0% or 100% of the pie. With this simple assumption, we can also create a linear classification of the agent's a_i negotiation style in this dimension by applying the measure:

$$D_i = || 0.5 - R_i || \in [0, 1],$$

where $R_i \in [0, 1]$ is the fulfillment of agent a_i with respect to his earnings target.

This dimension can be split into d divisions. Lower values of D_i mean that the agent is being cooperative, and higher values mean that the agent is being competitive. Since this dimension is ordered by this measure, and it is countable by means of divisions $d \in [1, 2, ..., d_{max}]$, the de la Rosa model is also applicable to this negotiation style dimension in the following way. If an agent makes the decision to close a deal at a certain fulfillment, he will receive the benefit d divisions apart from the target, and $d_a(F(t)) = F(t)*d/d_{max}$. Now, $F(t)$ is more precise than its formulation in section II; it provides not only information about the potential wealth of the tenderee, but information or guesses about his object of negotiation, his margin, and his negotiating room.

$$G\ (t+nT,\ F(t)*d/d_{max}) \tag{3}$$

Adding the second dimension is a refinement of $d_a(F(t))$. The properties of the de la Rosa model studied for the first dimension stand for both dimensions, although only when they are taken into account together. The Ecosystem Monitor is one of the pieces of the recommender that considers only the cooperative-competitive dimension unless it is reduced again.

Now, we are ready to define a bidimensional monitor M of negotiation styles in an open negotiation environment as:

$$M\ (n_{max},\ d_{max}),$$

where n_{max} is the maximum number of steps to close deals (the higher the steps, the more active), and d_{max} is the maximum number of divisions in closing deals (the higher the values, the more competitive).

$M\ (n, d)$ counts the number of agents at every negotiation style located at (n, d), so that every agent a_i is defined by the negotiation style $s_i = (n_i, d_i)$. M acts as a distribution of agents in the space of negotiation styles.

Once the agents are properly classified at every moment by the monitor, the negotiation style recommender can work with recommendations targeted to every negotiation style.

VI. A Negotiation Style Recommender

A recommender might use the information from the monitor to stabilize the ONE within a digital business ecosystem (DBE) by balancing the size of the population of different types of offerer agents that negotiate with the tenderees. This might be achieved by recommending changes in the offerer agents' negotiation style, by affecting the number of steps to settle or the number of divisions for their negotiating room. The recommender suggests shifting by α steps the type s that defines the style of negotiation of an offerer agent towards another type, $s+\alpha$, where α is a tuple of integers.

Therefore, the monitor will take care of balancing the population of agents, conveniently parameterized by s negotiation styles. The idea is as follows:

- $\#s := n_{max} \cdot d_{max}$ is the number of negotiation styles
- T_1 and T_2 are two different time windows (T)
- O is an instance of a ONE
- f_s , $f_r \subseteq$ O are subsets of negotiating offerer agents of types s and r
- ε , $\theta \in \Re$
- $H\ (O, \#s, T)$ measures the offerers' population stability in O, with $\#s$ types of agents, in a time window T. The higher the stability, the better. Direct or indirect measures of stability include typical deviation, entropy, and the Shannon information measure [18].

The recommender will balance the offerer agents' population of every type s (negotiation style), and informs agents of in-use negotiation styles so that agents change from using a style with a relatively large population to using a style with a relatively small population. The actions are as follows:

1. If `H(f`$_s$`,s,T) < H(f`$_r$`,s,T)`, then recommend agents of type s to change/shift to type r.
2. If `H(O,s,T`$_1$`) < ε` (unstable), then `#s := #s+1` (the number of negotiation styles is increased).

Any population of negotiation style s that stays small ($f_s < \theta$) during T_2 will disappear by making `#s := #s - 1` (the number of negotiation styles is decreased), and the recommender then tries to extinguish the population f_s by distributing/recommending to agents of this population to join other populations with different negotiation styles.

A. A Simplification of the Negotiation Style Recommender

The former algorithm requires a measure of the stability of the business ecosystem, and it is a type of greedy algorithm. By considering that the de la Rosa model guarantees, from the point of view of diversity, the stability of the ecosystem, it might be necessary to rethink the recommender task of simply redistributing agents across the space of negotiation styles.

To do so, we apply [17], a Simulated Annealing-inspired algorithm to obtain a distribution of agents as flat as possible. Simulated Annealing is a type of learning, adaptive and evolutionary algorithms [25], specially adapted for search. So far, there is no reported previous application to the field of recommender systems though it has had several industrial applications in forecast [26]. It may behave similarly to collaborative filtering [6]: classify the agents according to their behavior and then make them have uniform behavior. The heuristics is that the monitor represents a surface with mountains as piles of agents at a grid on a surface; one then begins shaking the surface, and some agents fall from their piles to lower piles. If the shaking is strong, the agents may abruptly jump from one style to another, but if the shaking is moderate, the agents will tend to form a flat surface. Flatness refers to uniformity, high heterogeneity, and high entropy. This can also be obtained by a series of greedy algorithms, sorting out the proper place for agents from many random starting points.

The following pseudo code implements the simulated annealing heuristic, starting from state `s0` (style s0) and continuing to a maximum of `kmax(s)` steps (the maximal number of neighbors for `s`), or until a state with energy `Mmax` or less is found. The call `neighbor(s)` should generate a randomly chosen neighbor of a given state `s`; the call `random()` should return a random value in the range [0,1). The annealing temperature `TEMP` should yield the temperature to use, in a range of temperatures (0, 1]. The state (s, s0) is a tuple indexing on `M[n,d]`, which is the monitor of Negotiation Styles in a matrix of `n` steps (active-passive dimension) and d divisions (collaborative-aggressive dimension). `P(e,en,TEMP)` should return a value in the range [0,1] and is implemented as `(e+1)/(en+1)*TEMP`, which follows the definition of `P` for simulated annealing. The recommendation Rec is another bidimensional matrix [n, d] of tuples (x, y) reflecting the recommended shift in both dimensions for every agent of style s0.

```
for all s0 ∊ [n , d]
  Rec (s0) = Simulated Annealing (s0, M)
endfor
```

```
Algorithm: Simulated Annealing (s0, E)
                       // SA with fixed temperature
  s := s0; e := M(s) // Initial state, energy
  k := 0             // Energy evaluation count
  while k < kmax(s) and e > Mmax
        // While time remains & err not good enough
    sn := neighbor(s)//   Pick some neighbor
    en := M(sn)      //   Compute its energy
    if P(e, en, TEMP ) > random()
       //Should we move to it if it is the next best?
    then   s := sn; e := en  // Yes, change state
    k := k + 1       //   One more evaluation done
  endwhile
return s0-s       //The best movement direction
```

The dynamic behavior of the whole population of offerer agents is a confluence of the results of their negotiations as well as the decisions they make while observing the recommendations. That is, an agent may try to follow the recommendations, but the negotiation output might be different than expected. For example, the recommendation could be to reduce the time to close a deal, but the agent, even if it tries, may not be able to; the time might even increase. The important fact is that in the mid and long term, the recommendation effect might prevail, and its beneficial effects will be seen at a global level. Sometimes, the recommendation can lead agents into trouble and cause them to lose money, but the global impact will be good.

The algorithm works with TEMP as a parameter that has to be set heuristically at a moderate level. In contrast to the original simulated annealing, our implementation needs to keep the temperature constant, continually shaking the surface of agents' negotiation styles.

Finally, if TEMP = 0, then the method works as a greedy algorithm.

VII. CASE STUDY: A MONITORING AND NEGOTIATION STYLE RECOMMENDER EXEMPLIFIED WITH 4 POPULATIONS

As mentioned earlier, an essential element of digital business ecosystems is the negotiation of alliances, which enable companies to join competencies as well as services and products into a complex offering. James Moore's[2] vision of Business Ecosystems [28] has been partially supported by Web 2.0, and more recently by the achievements in B2B networking systems that have enabled enterprises to efficiently cooperate [20]. Given this fact, the case study is of a Business Ecosystem that is empowered by a tool supporting tactical negotiation and agreement processes among participants, especially small companies. This environment supports the creation of Virtual Organizations with a common business goal, and facilitates the building, stabilization, and improvement of the ecosystem performance on a shorter time frame.

A first and prime implementation is the Digital Business Ecosystem Project (DBE), which has been defined by the project team [5] as "...an open-source distributed environment that can support the spontaneous evolution and composition of software services..." [20]. The ONE project[3] aims to provide organizations (especially small and medium enterprises - SMEs) with a sophisticated negotiation mechanism that will help SMEs to extend their portfolio of services, thus increasing their ability to fulfill more complex customer demands at a faster pace.

For our experiments, we use a negotiation environment that has no central governance cockpit or console with which to administer negotiation models and ongoing processes. The execution of the negotiation process will be hosted on each participant's hardware, not in a central node, thus reducing concerns about privacy. This also avoids susceptibility to a single point of failure.

The ONE platform [20] offers many information services for Open Negotiation Environments, one of which is the recommender for SMEs. Here, we consider the case of one of the users of the ONE platform, Coopservices (CS), an Italian company that provides a large number of services, from cleaning, security, porterage, reception and catering, to logistics, transportation and public lighting management. Its principal value is that it can compose any subset of its services in a package with a bid. Normally, CS subcontracts local Italian providers to complete its package and bids. In this paper we focus on cleaning and security bundles.

The CS national service referent and the local suppliers can be considered as an informal ecosystem as defined by Moore [19] [28]. The companies cooperating together with CS in order to provide complete cleaning and maintenance services can be competitors or cooperators, as they provide complementary services. Furthermore, most of the companies involved in cooperation with CS are known to each other and have experience in cooperating with each other. During the cooperation, a common language is developed in areas relating to product and service description, so that communication becomes easier. In all, CS counts an average of **one thousand negotiations per year**. Every negotiation has an average of three companies participating, with a minimum of one and a maximum of ten. The negotiation process can last from **one month to one year**, taking, on

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average, six months for public contractors and one month for private ones. Referring to the negotiated volume per year, CS manages from 1 to 20 M€, with an average of 7 M€.

Considering the many possible negotiation approaches, CS uses both on-line and secret auctions, and open and on-invitation tenders. Auctions involve a public or highly structured contractor like a multinational company, and are adopted in 60% of cases. Tender is adopted in 40% of cases, usually involving less-structured contractors. During 2006, 20% of the negotiations (200 out of 1,000) were successful. The main reasons for negotiation failures were related to pricing or technical inadequacies. The national negotiation process uses many technologies: telephone calls, fax, and standard and certified emails. Today, they use the ONE platform on the internet. Internally, CS manages the negotiation through an information system with entries on the commercial and technical-planning sides. Internally and externally, the service proposal is constructed by circulating a standard model (Italian, *Attività di Progettazione*) that evolves during the process. The IT equipment of negotiation partners varies, but CS generally requires a standard profile composed of telephones, computers, the internet, and Microsoft Office.

Fig. 6 depicts the current negotiation situation at CS. The process is accomplished by filling a standard model, internally with a dedicated section of the commercial IT system, and externally via emails.

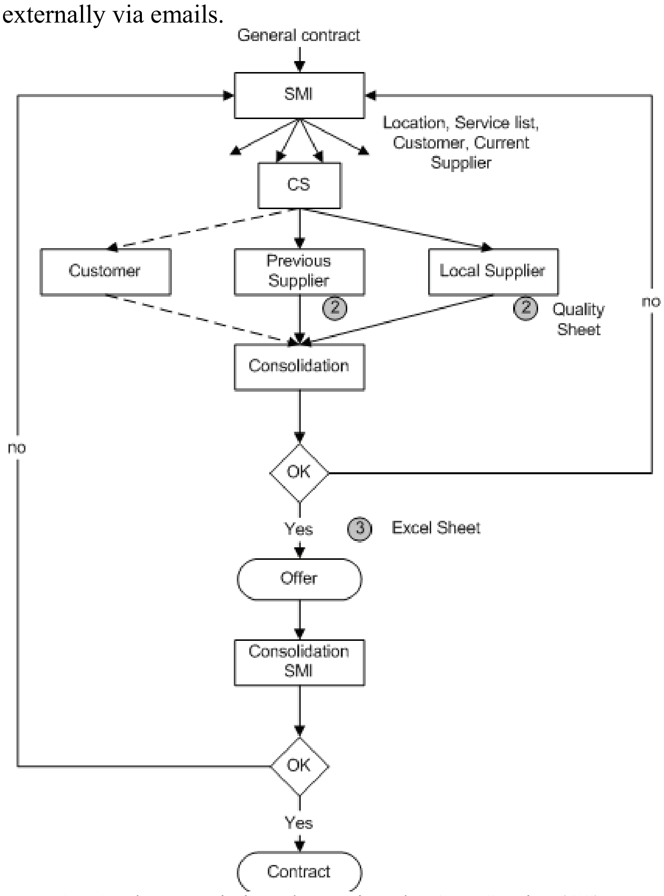

Fig. 6. The Negotiation Flow Driven by CoopService (CS).

A. Selection of the Negotiation Approach

By the term negotiation, CS means the circular and incremental verification of requests, involving both technical and economic constraints. CS also understands the auction negotiation process where the answer is provided in a more direct way. Usually, CS decides to use auction or tender types of negotiation upon the request of the manager, and mostly depending on the outside requirements, but never under a company policy.

There are some criteria inside CS that drive the choice of a potential business partner:

1. The partner is already under contract with CS (this is considered to imply the next two points)
2. Technical capacities
3. Economic convenience
4. Normative constraints: on the sub-contracts in the public sector (Italian *Legge Merloni*), on the administrative transparency and responsibility (Italian *Legge 231*), and on the liberalization of services (Italian, *Legge Bersani*).

External partners are listed and evaluated in an internal database. There is also a blacklist of companies that are not considered suitable for collaboration. Partners could be totally or partially owned companies, or external companies with whom CS has a trusted relationship. Partnership with companies that are territorially closed to contractor sites and are certified by CS is considered more suitable. Negotiations could be open and public or restricted and private, and sometimes partners also provide a public contest on their own. The IT infrastructure and knowledge are, in any case, not relevant for the selection and involvement of partners.

CS does not allow potential partners to subcontract with other suppliers. This means that the negotiations usually consider only the first level of suppliers.

CS works as a tenderee in the open negotiation environment, and it is one of the many tenderees that work at this main level of contracting in Italy. CS has to achieve good terms in their contracts in order to do competitive and sustainable business, but it also has to look after its local suppliers, the tenderees, which need an adequate profit margin to stay in business.

B. The Monitor and Open Loop Recommendation

CS and other tenderees already have sufficient information about the types of providers, and intuitively this promotes competition within all categories of local suppliers. The new monitor of this paper is devoted to offerers, the small and medium enterprises (SMEs) who work hard to win contracts, and a recommender system that supplies benefits for the whole ecosystem of offerers and tenderees. The monitor takes the negotiation logs from CS and other main contractors, and for every deal (contract), records the number of steps the deal takes to settle (sometimes it may take one year to settle) and the % fulfillment.

The ONE platform has a Centralized Log Management. This stores log data in a central repository though a Distributed Knowledge Base (DKB), which is a good solution for a log repository in both centralized and distributed (P2P) platforms. In this study, we focus on those negotiations related to the bundling of cleaning, security, porterage, and reception, where CS subcontracts at the local level. Some companies offer only cleaning, but others offer interesting bundles of porterage, reception and cleaning. The variety of bundles is surprisingly wide, as are the price and quality of the offerers.

Recall that the goal of the recommendation strategy is to achieve a balance between negotiation style populations. For the sake of simplicity, let us keep the one-dimensional monitor (the passive-active dimension) and four negotiation styles that range from a few weeks up to one year.

Primarily, the monitor will segment the *s* negotiation styles into *N* categories $f_i^{'};\ i = 1..N$, such that several populations will fit in a category; that is, the category will contain several negotiation styles, and therefore $f_i^{'} = f_{s_1} + \cdots + f_{s_{M_i}}$. The number of categories depends on the granularity we use for the negotiation styles, with the limits $N \leq \#s$, and the complexity we can reach with the recommendation strategy.

The goal is to obtain a uniform distribution of negotiation style types, that is $\forall i, M_i = \frac{\#s}{N}$. Let us take N = 2, $f_1^{'} = f_0 + f_1$ as the category with a low number of negotiation steps, and $f_2^{'} = f_2 + f_3$ as the one with a high number of negotiation steps. If we put the categories on a one-dimensional axis from a low to high number of steps, then the $f_1^{'}$ category will be on the left and the $f_2^{'}$ category will be on the right. Negotiations on the right can take up to one year. Negotiations on the left can be as fast as a few weeks.

As previously described, the monitor will then continuously count the number of steps that agents effectively use in their negotiations in every ONE instance, and will represent them in tables like Table II. The monitor will also calculate stability measures, such as the entropy H represented in Table II, at every time step t. At each time step, the recommender will decide what category shifts must take place. In our example, this is very simple: the recommender suggests agents shift from left to right, or vice versa. Since there are several categories, in the future, the recommendation should be much more sophisticated in terms of deciding how many populations to manage, how to classify agents into populations and what the temporal windows to back these decisions are.

Table II depicts an evolution of populations in our experiment with data obtained from CS, with a sample of ten companies selected from one thousand. At every time step of 6 months, the shifts of SMEs (the agents) can be seen from one type of negotiation style to another after measurement of their deal settling time. The shifts are spontaneous because agents vary the number of steps to settle for various reasons, including the tenderee changing the conditions, difficulties in fulfilling the tenderee conditions, a change of skills of the offerers, and simply because of their own decisions as agents. This is what we term the *natural evolution* or natural run of the population, spread across the four types, and showing a certain preference to be passive at the lower zero and one types of negotiation style (there are 7.8 agents on average at those types compared to 2.2 agents on average at the higher types). This preference is possibly a result of these companies possessing very low negotiation power compared to CS due to their difference in size (they are SMEs) or their financial situation, which makes them desperate for the CS business. To ensure statistical stability, the results of each experiment were averaged over 100 test runs over the logs, and the mean results are reported. Where necessary, a Student's t-test was used to confirm statistical significance at the 95% confidence level.

Table II. Original dynamics of the run of four populations of negotiation styles regarding tenderee CS and an open loop recommendation.

t	f_0	f_1	f_2	f_3	f'_1	f'_2	H	Open Loop Recommendation
0	10	0	0	0	10	0	0,00	**L-->R**
1	7	3	0	0	10	0	0,52	**L-->R**
2	5	3	2	0	8	2	0,99	**L-->R**
3	5	2	2	1	7	3	1,26	**--**
4	4	3	2	1	7	3	1,32	**L-->R**
5	4	3	1	2	7	3	1,32	**--**
6	3	3	1	3	6	4	1,37	**L<--R**
7	3	4	1	2	7	3	1,32	**L-->R**
8	4	4	1	1	8	2	1,19	**L-->R**
9	4	4	1	1	8	2	1,19	**--**
10	3	5	1	1	8	2	1,16	**L-->R**
	average				7,8	2,2	**1,18**	

C. Closing the Loop

Table III depicts the recommendations at every time step given by the simulated annealing-inspired algorithm. "L→R" indicates a recommendation that agents with lower (left) types are recommended to move to higher (right) types, and "L←R" indicates the inverse, while "--" indicates that there is no recommendation.

Table III. List of Recommendations in a closed loop – Greedy algorithm.

t	Recommendation	f_0	f_1	f_2	f_3	f'_1	f'_2	H
0	L-->R	10	0	0	0	10	0	0,00
1	L-->R	4	3	3	0	7	3	1,04
2	--	2	3	5	0	5	5	1,02
3	L<--R	2	2	5	1	4	6	1,30
4	L<--R	1	3	5	1	4	6	1,35
5	L<--R	1	3	4	2	4	6	1,51
6	L<--R	0	3	4	3	3	7	1,57
7	--	1	4	4	1	5	5	1,39
8	--	2	3	5	0	5	5	1,02
9	L<--R	2	2	6	0	4	6	0,91
10	L-->R	1	5	4	0	6	4	1,03
				average		5,2	4,8	**0,99**

The result after the recommendations is that some agents tried to modify their negotiation styles. Few succeeded because it is not straightforward to change, since the number of steps depends not only on the offerer agents, but also on the tenderees and competition. Table IV shows the impact of recommendations on the natural run of the population at every time step in a situation where there is feedback following each time step (Temperature (TEMP) = 0.5 in Table IV; compared to TEMP = 0.0 for the greedy algorithm in Table III).

Table IV. Impact of recommendation on the populations by means of simulated annealing.

t	Recommendation	f_0	f_1	f_2	f_3	f'_1	f'_2	H''
0	L-->R	10	0	0	0	10	0	0,00
1	L-->R	4	3	3	0	7	3	1,04
2	--	2	3	5	0	5	5	1,02
3	L<--R	2	2	5	1	4	6	1,30
4	--	1	4	4	1	5	5	1,39
5	--	1	4	3	2	5	5	1,51
6	L<--R	0	4	3	3	4	6	1,57
7	L-->R	1	5	3	1	6	4	1,35
8	L-->R	2	3	3	2	5	5	1,51
9	L<--R	2	2	4	2	4	6	1,46
10	L<--R	2	3	3	2	5	5	1,51
				average		5,5	4,5	**1,49**

Entropy in Tables II, III and IV is represented as the H, H' and H'' columns at every time step *t*. We calculate the steady state entropy as an average of the last three steps of every run to make the comparisons. The recommendation of negotiation style shifts in the simulated annealing produced substantial increases in entropy, H'' > H, which implies improved population balance and higher diversity: the populations are flat, more so than without any recommendation. As shown in Table V, the simulated annealing algorithm obtained the highest steady state entropy through the greedy algorithm, and better balanced the left f_1 and right f_2 populations.

Since the important fact is having a higher entropy, the simulated annealing is our suggested algorithm for negotiation style recommenders.

Table V. Comparison of the steady state entropies and balance of left and right populations.

Analysis	f'_1	f'_2	H
Original dynamics	7.8 ±0.17	2.2 ±0.17	1.18 ±0.05
Greedy	5.2 ±0.16	4.8 ±0.16	0.99 ±0.05
Simulated annealing	5.5 ±0.23	4.5 ±0.23	1.49 ±0.1

According to the de la Rosa negotiation dynamics model, higher diversity stabilizes the ONE, which improves the predictability and business opportunities of the whole digital business ecosystem, as shown in the examples of section III.

VIII. Final Remarks

This research proposes the negotiation style recommender as a new category of recommenders. Recommendations are executed by agents by increasing or decreasing the number of steps before settlement, and by increasing or decreasing their expected fulfillment.

The result is a recommender scheme that is conceptually simple yet powerful for large populations (thousands or millions of agents), and which operates with low computational complexity. This simplicity comes from the dynamics of the de la Rosa negotiation style model, inspired by the Hogg model of computational ecologies.

The scenarios presented here show that a greater diversity of offerer agents helps to stabilize the ecosystem of negotiating agents. This diversity is good according to the de la Rosa model, because wealth goes to a wider number of offerer agents, who work on behalf of small and medium companies – SMEs. Our experiments demonstrated how the monitor tracks homogeneous populations of offerers (those with lower entropies) and lets the recommender introduce increasing diversity of negotiation styles, so that those populations will then have higher entropy. Future versions of the recommender will reward agents for their change in negotiation style, perhaps in the same way that governments use taxes to induce changes in economic behavior. We suggest focusing on two axes, rewarding schemes and mining techniques, to back the classifications of agents into negotiation styles. If agents are not properly classified, the recommendation is simply impossible. It is therefore critical to solve this issue.

When having a powerful classification of agents into negotiation styles, a simple recommendation algorithm based on simulated annealing is proposed. It is not strictly necessary to measure the stability of a ONE Ecosystem, and the recommender merely needs to keep the population of agents as flat as possible in terms of their negotiation styles. The de la Rosa model forecasts the stability of the ecosystem, at least from this point of view. The results show that this approach is workable.

Concerning a wider picture of the future research on negotiation recommenders, let us have a look at Fig. 7. This is the architecture of a full recommender for a business ecosystem.

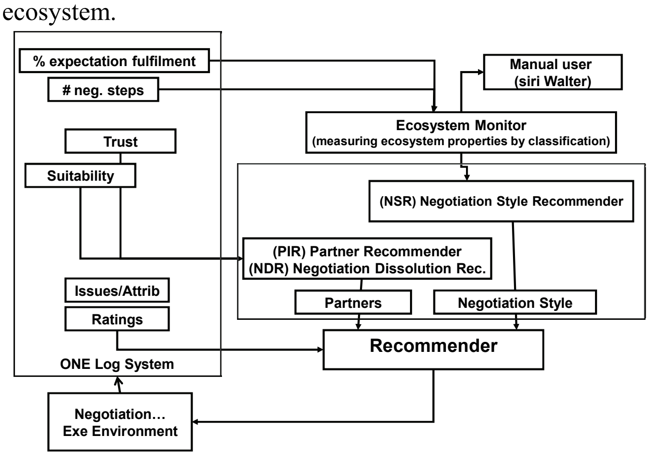

Fig. 7. The architecture of the full open negotiation environment recommender.

The Ecosystem Monitor is one of the pieces of the recommender. In the ONE platform, the ecosystem monitor keeps a log of the percentage (%) of expectation fulfillment and the number (#) of negotiation steps. This information is used to make recommendations on negotiation styles by the NSR (Negotiation Style Recommender). The recommendations are not sent directly to the agents, but instead pass through an Active Offer Shaping [23], which takes issues and ratings from the log and integrates the recommendations from a partner's recommender module [22], and a negotiation dissolution recommender module [24], which take information from the log such as trust and suitability. A user from the Tenderees' side (*Siri Walter* is the user of the negotiation platform from CS in the ONE project) can use the information from the ecosystem monitor for other manual uses. However, he has no access to the negotiation style recommender or other output of the recommender system, since it is only devoted to SME, the offerers. The practical results of this work on the ONE project are restricted to a one-dimensional recommendation. Future work could focus on practical experiences with wider (multidimensional) negotiation style recommendations. Following are possible areas of further research, from highest to lowest importance. First, data-mining methods for estimating the granularity in the classification of agents regarding their negotiation style, as well as the measurements obtained using business ecosystem monitors, need to be further investigated. Second, standard techniques, like collaborative and content-based filtering [6] [14], may be applied to negotiation styles, as well as to trust approaches for recommendation [14], not only to shaping offers [23]. Third, extensive research on partner recommenders to create virtual organizations that bid for contracts is necessary, since many small companies do not have partners when going to the tenderers. Fourth, further algorithms are necessary to estimate the proper moment to cut a negotiation off and walk away, so that agents know when to stop investing efforts in negotiations with low expected benefit. The main efforts should be put to have good data-mining methods to classify agents because this simplifies enormously the recommender algorithms.

The originality of our approach is that we are looking for global behaviors that will increase opportunities at an individual level. However, some recommendations may not be appropriate for an individual agent at certain moments or in certain situations. Since our system only provides recommendations, agents may decide to follow them or not, or they can ignore them in order to follow the behavior of the tenderee (many agents think that the customer, who pays, is the boss); thus, further research into designing the proper rewards for agents will be necessary.

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