is biased to reward those agents which had issued "better" bids (according to the mediator's criteria). Though it is not possible to know, with a one-shot negotiation, whether agents are issuing "better" bids due to a socially-oriented strategy or to a more correlated utility space, the expected effect is that agents will have an incentive to select the bids they send not only according to their own utility, but also to the mediator's criteria, which would be set to favor social welfare.

5.2 Stability analysis

Stability analysis is oriented to determine the possibility of an agent manipulating the negotiation to its own benefit. In the model we are dealing with, this manipulation may occur when an agent deviates from the socially optimal strategy taking a more selfish approach. To evaluate this empirically, we have performed experiments comparing the utility obtained by an *individualist* agent (or, more appropriately, a *selfish* agent, since it seeks to maximize its own payoff), using its individually optimal strategy $\alpha_i = 1$, against the utility obtained by the agent when using the corresponding socially optimal strategy α_s, assuming the rest of the agents are using α_s. Experiments have been made for utility spaces with different correlation lengths. Furthermore, since the model is designed for multi agent negotiations, experiments have been performed for different number of selfish agents, thus studying the effect of possible coalitions or coincidences.

Figures 8 and 9 show the experiment results for SA-Q and MWIS-Q, respectively, for six agents and six issues. Since the aim of the experiment is to study the stability of the proposed protocol, none of the weighted metrics proposed in the previous section has been used, and social welfare is computed at the mediator using Nash product. In addition, the mediator performs deal identification using the bid quality factors declared by the agents (i.e. there is no α_m). The figures show the ratio between the utilities obtained by selfish agents and the utilities obtained when there are no selfish agents for different correlation lengths and different number of selfish agents, for scenarios of different complexity. The horizontal axis represents the number of individualist or selfish agents, while in the vertical axis we have represented the ratio between utilities as notched box and whisker plots. In each figure, column labelled as "0" represents the dispersion of utility gains when there are no selfish agents. We can see that there are only significative gains for selfish agents in medium complexity scenarios. In high-complexity scenarios (Figs. 8a and 9a), the presence of selfish agents makes the negotiations fail, and thus there is no incentive to deviate from the socially optimal strategy. When utility space complexity decreases (Figs. 8b and 9b), we can see that a selfish agent may obtain gains over 40% for SA-Q and 200% for MWIS-Q. Increasing the number of selfish agents makes negotiations fail, thus making unlikely that coalitions will happen. For medium-low complexity scenarios (Figs. 8c and 9c) there is still a significant gain for selfish agents, and this gain increases with the number of selfish agents up to a number of three (coalitions between more agents make negotiations fail). Finally, for the less-complex scenarios (Figs. 8d and 9d), a selfish attitude does not imply a significant gain in utility, since all agents achieve high utility values using the socially optimal strategy. Tables 3 and 4 summarize the results for SA-Q and MWIS-Q, respectively, showing the medians and the 95% confidence intervals for 100 runs of each experiment. From these results we can conclude that the model is stable in low complexity and high complexity scenarios, and that the scenarios of medium complexity make stability problems arise, because of the existing incentive for agents to deviate from the social optimal strategy to their individually optimal one ($\alpha = 1.0$). As we have seen in Sect. 4.2.2, having all agents deviating to their individually optimal strategy makes the negotiations fail, and thus this situation is the worst

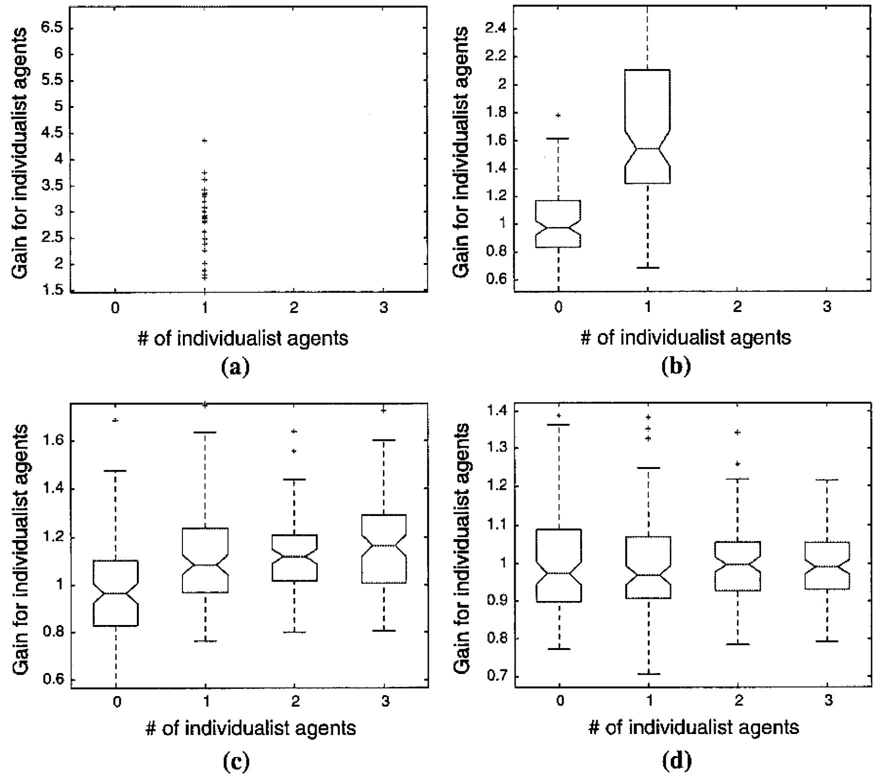

Fig. 8 Stability analysis of the protocol using SA-Q for scenarios with different correlation lengths. **a** $\psi = 2.8$, **b** $\psi = 4$, **c** $\psi = 4.3$, **d** $\psi = 5.9$

scenario induced by individually rational combinations of strategies, yielding zero utility for all agents, which imply an infinite expected price of anarchy (EPoA). This is an undesirable property of the model, and requires the application of additional mechanisms.

In the previous section, a set of alternative mechanisms for deal identification at the mediator were proposed. Those mechanisms were intended to incentivize agents to social behavior, and thus solve the stability problems of the model. To evaluate the effect of the proposed mechanisms on the stability of the protocol, we have repeated the experiments for the different approaches discussed in Sect. 5.1:

- *Nash:* Reference approach, using Nash product.
- *Average_V*: Product weighted by average bid volume (Eq. 4).
- *Average_$Q_{0.5}$*: Product weighted by average quality factor (Eq. 5), with $\alpha_m = 0.5$, corresponding to the theoretical socially optimal strategy. This α_m is also used for deal identification at the mediator, as described in Sect. 5.1.
- *Average_Q_0*: Product weighted by average quality factor, with $\alpha_m = 0$, corresponding to a deal identification strategy totally decoupled from agent utility (the mediator only considers bid volume). This α_m is also used for deal identification at the mediator.

Figures 10 and 11 present the results of the experiments for SA-Q and MWIS-Q, respectively. The figures show the results for 6 agents and 6 issues with utility spaces of correlation

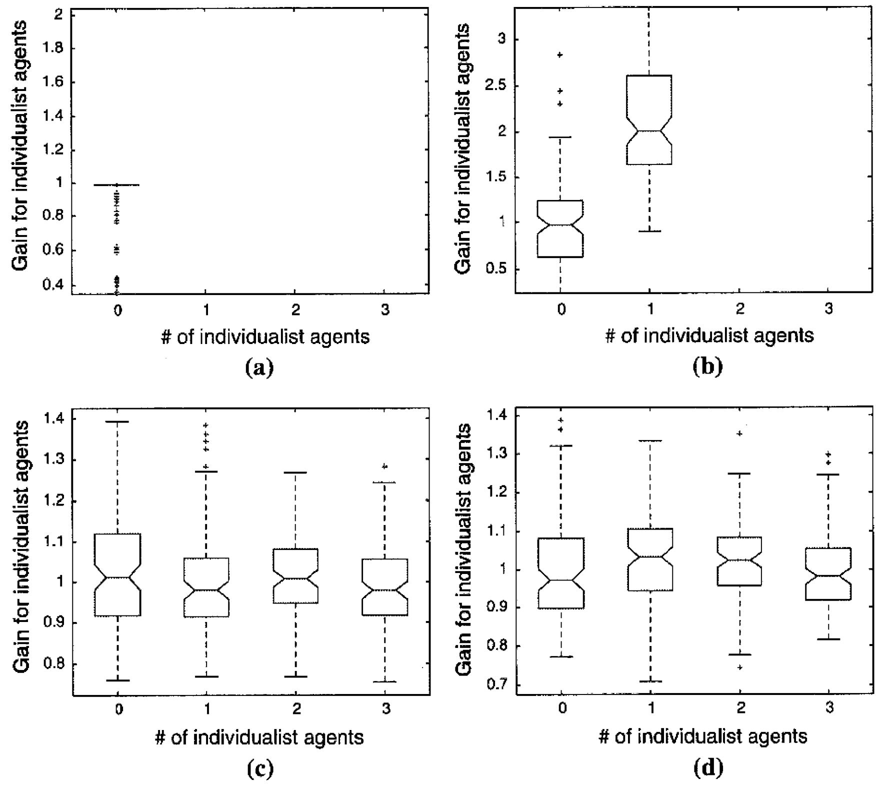

Fig. 9 Stability analysis of the protocol using MWIS-Q for scenarios with different correlation lengths. **a** $\psi = 2.8$, **b** $\psi = 4$, **c** $\psi = 4.3$, **d** $\psi = 5.9$

Table 3 Stability analysis for SA-Q with six agents and six issues: gain for individualist agents against social agents

ψ	Number of individualist agents					
	1		2		3	
	median	conf. interval	median	conf. interval	median	conf. interval
2.8	–	–	–	–	–	–
3.1	–	–	–	–	–	
4.0	1.5440	[1.4170, 1.6710]	–	–	–	–
4.3	1.0861	[1.0436, 1.1286]	1.1203	[1.0902, 1.1503]	1.1648	[1.1207, 1.2090]
4.6	0.9993	[0.9663, 1.0322]	1.0208	[0.9981, 1.0435]	1.001	[0.9796, 1.0224]
5.9	0.9693	[0.9438, 0.9949]	0.9976	[0.9775, 1.0177]	0.9907	[0.9715, 1.0100]

lengths $\psi = 4$ and $\psi = 4.3$, which were identified in the previous experiment as the most critical scenarios regarding stability. Each graphic presents a box-plot for the final outcomes of 100 runs of the experiment. The horizontal axis represents the approach under evaluation, while in the vertical axis we have represented the gain for individualist agents in each

Table 4 Stability analysis for MWIS-Q with six agents and six issues: gain for individualist agents against social agents

ψ	Number of individualist agents					
	1		2		3	
	median	conf. interval	median	conf. interval	median	conf. interval
2.8	–	–	–	–	–	–
3.1	–	–	–	–	–	
4.0	2.0086	[1.8574, 2.1598]	–	–	–	–
4.3	1.1066	[1.0610, 1.1522]	1.1986	[1.1431, 1.2541]	–	–
4.6	0.9795	[0.9567, 1.0024]	1.0081	[0.9870, 1.0292]	0.9785	[0.9567, 1.0003]
5.9	1.0336	[1.0081, 1.0591]	1.0243	[1.0043, 1.0443]	0.9811	[0.9598, 1.0024]

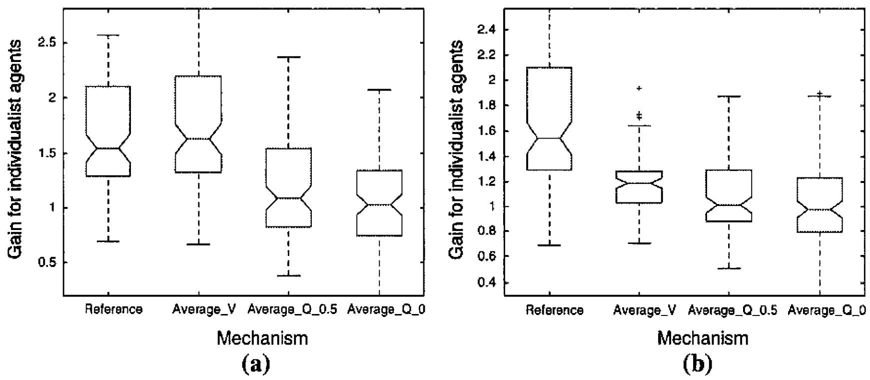

Fig. 10 Effect of the different mechanisms on the stability of the protocol for SA-Q in the most critical scenarios. **a** $\psi = 4.0$, **b** $\psi = 4.3$

negotiation. We can see that the mechanism based on average volume provides not enough improvement in stability, since for all cases median utility results are higher for selfish agents, thus maintaining the incentive for agents to deviate from the socially optimal strategy. The mechanism based on average quality factor, however, significantly mitigates the gain for selfish agents, removing the incentive to choose the previously individually optimal strategy ($\alpha = 1$). Due to the effect of this mechanism, the situation where all agents take selfish strategies is no longer induced by individually rationality, thus avoiding the infinite Expected Price of Anarchy values. This adequately improves the stability of the protocol, and this improvement is greater for $\alpha_m = 0$. From these results we can conclude that decoupling deal identification from the attitudes of the negotiating agents by making the mediator calculate its own quality factor improves the strategic stability of the negotiation process, significantly decreasing Expected Price of Anarchy.

Since the techniques give preference to socially oriented offers against higher utility offers, this may make final deals to be further from the theoretical optimum. To evaluate this, as discussed in Sect. 2.1.3, we can consider the Price of Stability (PoS) imposed by the proposed mechanisms. As it occurred with PoA, we cannot use Price of Stability definition directly,

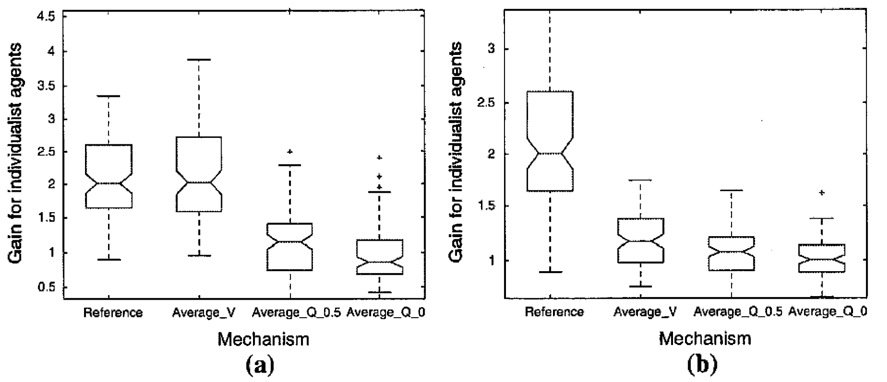

Fig. 11 Effect of the different mechanisms on the stability of the protocol for MWIS-Q in the most critical scenarios. **a** $\psi = 4.0$, **b** $\psi = 4.3$

Table 5 Effect of the different mechanisms over social optimality rate (and thus, over expected price of stability) for SA-Q

ψ	Mechanism							
	Reference		Average_V		Average_Q_0.5		Average_Q_0	
	Med.	Conf. interval	Med.	Conf. interval	Med.	Conf. interval	Med.	Conf. interval
2.8	0.326	[0.305, 0.347]	0.633	[0.608, 0.658]	0.614	[0.587, 0.641]	0.632	[0.609, 0.655]
3.1	0.530	[0.511, 0.549]	0.588	[0.562, 0.614]	0.572	[0.546, 0.598]	0.571	[0.545, 0.597]
4.0	0.769	[0.740, 0.798]	0.620	[0.583, 0.657]	0.600	[0.566, 0.634]	0.625	[0.594, 0.656]
4.3	0.960	[0.951, 0.969]	0.734	[0.696, 0.771]	0.756	[0.715, 0.797]	0.727	[0.688, 0.767]
4.6	1.000	[1.000, 1.000]	0.836	[0.811, 0.860]	0.856	[0.831, 0.881]	0.847	[0.826, 0.869]
5.9	1.000	[1.000, 1.000]	0.939	[0.922, 0.956]	0.953	[0.938, 0.967]	0.967	[0.953, 0.981]

since it relies on Nash equilibrium conditions. We can, however, define *Expected Price of Stability (EPoS)* in an analogous way as we defined EPoA in the previous section:

Definition 15 *Expected Price of Stability (EPoS)* The *Expected Price of Stability* in a non-deterministic game is the ratio between the maximum expected social welfare achievable by means of a feasible agent strategy combination and the maximum expected social welfare achievable by means of an *individually rational* agent strategy combination.

$$EPoS = \frac{\max_{s \in S} E\left[sw(s)\right]}{\max_{s \in S_{i.r.}} E\left[sw(s)\right]},$$

where S is the set of all feasible strategy combinations of the game, $S_{i.r.} \subseteq S$ is the set of all strategic combinations which are individually-rational for the negotiating agents, and $E\left[sw(s)\right]$ is the expected social welfare for a given strategy combination s.

Tables 5 and 6 present the median social optimality rates for SA-Q and MWIS-Q, respectively, using the different mechanisms proposed, when all negotiating agents choose the socially optimal strategy. The statistic on this ratio is analogous the inverse of the Expected Price of Stability defined above. As a reference, the results obtained when no asymmetrical

Table 6 Effect of the different mechanisms over Social Optimality Rate (and thus, over Expected Price of Stability) for MWIS-Q

ψ	Mechanism							
	Reference		Average_V		Average_Q_0.5		Average_Q_0	
	Med.	Conf. interval	Med.	Conf. interval	Med.	Conf. interval	Med.	Conf. interval
2.8	0.553	[0.521, 0.585]	0.503	[0.470, 0.536]	0.536	[0.504, 0.567]	0.520	[0.489, 0.550]
3.1	0.681	[0.652, 0.710]	0.583	[0.555, 0.611]	0.606	[0.578, 0.634]	0.596	[0.573, 0.620]
4.0	0.949	[0.925, 0.973]	0.838	[0.809, 0.867]	0.773	[0.751, 0.795]	0.814	[0.790, 0.838]
4.3	0.975	[0.952, 0.981]	0.964	[0.958, 0.970]	0.962	[0.954, 0.969]	0.973	[0.966, 0.981]
4.6	1.000	[1.000, 1.000]	1.000	[0.995, 1.000]	1.000	[0.995, 1.000]	1.000	[0.994, 1.000]
5.9	1.000	[1.000, 1.000]	1.000	[1.000, 1.000]	1.000	[1.000, 1.000]	1.000	[1.000, 1.000]

social welfare metric is used have been included. Results show that, for SA-Q, the approaches which improve stability suffer a significant decrement in optimality for the most correlated scenarios, and an increment in optimality for the most uncorrelated ones (due to the decrement in failure rate). For MWIS-Q a similar trend is observed, though the optimality loss is lower. We can conclude that, though it is possible to stabilize the model to a great extent by having the mediator compute its own quality factor Q, this stability has a price, which is the loss of social optimality.

6 Incentive compatibility analysis

As we have seen in Sect. 2.1.3, incentive-compatibility is defined as the property of a negotiation mechanism which makes telling the truth the best strategy for any agent, assuming the rest of the agents also tell the truth. Though there are negotiation models where incentive compatibility can be proved analytically [11], these proofs are difficult to derive in the nonlinear domain. This is specially true for heuristics approaches with a great degree of variability, such as the model we are dealing with. In these cases, experimental evaluations may be conducted to assess the possible influence of insincere revelation of information over the stability of the negotiations. This is the approach we have taken to study incentive-compatibility in our model.

6.1 Experimental settings

Incentive compatibility analysis is oriented to evaluate the possibility for negotiating agents to manipulate the negotiation to their own benefit by means of revealing insincere information. In the negotiation model we are dealing with, information revealed to the mediator is the set of agents' bids. These bids represent regions within the solution space. Each offer has an associated utility value, a volume, and an associated quality factor value. Since bid volume is directly related to the region represented by the bid, it does not seem feasible to fake it, since it can be easily checked by the mediator. Quality factor may be faked, but since the mediator is very likely to recompute it using its own α parameter, this strategy is also harmless. Finally, agents may fake bid utility. Insincere information revelation about bid utility may generally occur in two ways: exaggerating upward or downward the utility values of *all* bids, or exaggerating the utility values of *some* bids with respect to the others. Exaggerating all bids is not profitable with the proposed deal identification mechanisms, since bid selection at the mediator is performed independently for each agent. This means that the bids from different agents do not compete among each other to be selected as part of a solution. In contrast, the different bids of a single agent compete among themselves. Taking this into account, an agent could try to exaggerate the utility value of its preferred bids, thus trying to increase the probability of the mediator choosing those preferred bids to form deals. As far as social welfare is concerned, this is a problem if the set of exaggerated bids is small with respect to the total set of bids, since that would reduce the number of effective bids considered by the mediator, thus reducing deal probability.

To study the effect of utility exaggerations over the negotiations, we have conducted experiments comparing the utility obtained by an *insincere agent* with the utility obtained being sincere, assuming the rest of the agents are sincere. The behavior of the insincere agent is modeled by exaggerating the utility of a portion of the agent's highest utility bids. We have considered different degrees of exaggeration for the insincere agent.

- *Reference:* There are no insincere agents.
- *75%:* The insincere agent exaggerates 75% of its bids.
- *50%:* The insincere agent exaggerates half of its bids.
- *25%:* The insincere agent exaggerates one quarter of its bids.
- *12.5%:* The insincere agent exaggerates one eigth of its bids.

In all cases, exaggerated bids are the ones which yield better utility for the agents before exaggeration. Bid exaggeration is performed by multiplying the affected bids by a constant. The constant has been chosen to be higher than the average utility for agent bids, in order to make more likely that exaggeration could significantly impact the mediator's choice. In these experiments, the value for this constant is 10000. Again, experiments have been repeated for utility spaces with different values for the correlation length ψ.

6.2 Experimental results

Experiment results for SA-Q y MWIS-Q for six agents and six issues are shown, respectively, in Tables 7 and 8. Each table represents the median ratios between the utilities obtained by insincere and truthful agents. The results are statistically significant for $P < 0.05$. We can see that there are only significative gains for the insincere agents in medium complexity scenarios. In high-complexity scenarios, the presence of the insincere agent makes the negotiations fail, and thus there is no incentive to deviate from the socially optimal strategy. When utility space complexity decreases, we can see that an insincere agent may obtain gains over 40% for both SA-Q and MWIS-Q depending on the degree of exaggeration. Finally, for the less-complex scenarios, insincere revelation of information does not imply a significant gain in utility, since all agents achieve high utility values by being sincere.

Figure 12a and b show the box plots of the results for 100 runs of the experiments for SA-Q and MWIS-Q, in the most critical scenarios identified above (i.e. $\psi = 4.0$ for SA-Q and $\psi = 4.3$ for MWIS-Q). We can see a different evolution in the gain for the insincere agent as the degree of exaggeration varies. For SA-Q, this gain increases as the proportion of exaggerated bids decreases, which is reasonable taking into account that, if the mediator is successfully tricked into choosing bids only from the exaggerated set, the average utility of the bids in the set is higher (they are its better n bids). Exaggerating too much, however, can excessively reduce the selected bid set, thus impacting deal probability and making negotiations fail, which happens for a 12.5% degree of exaggeration. For MWIS-Q the maximum

Table 7 Incentive-compatibility analysis for SA-Q

ψ	Degree of exaggeration				
	Reference	75%	50%	25%	12.5%
2.8	0.9875	1.0061	–	–	–
3.1	0.9903	1.0107	–	–	–
4.0	0.9904	1.2708	1.4464	1.5071	–
4.3	0.9882	0.9662	1.0042	0.9727	0.9981
4.6	1.0015	1.0037	0.9858	0.9866	0.9974
5.9	1.0042	1.0107	1.0010	0.9840	1.0040

Table 8 Incentive-compatibility analysis for MWIS-Q

ψ	Degree of exaggeration				
	Reference	75%	50%	25%	12.5%
2.8	1.0022	0.9656	–	–	–
3.1	0.9783	0.9777	–	–	–
4.0	1.0035	1.0051	–	–	–
4.3	0.9763	1.1459	1.4785	1.3523	1.1614
4.6	0.9882	0.9463	0.9991	0.9672	0.9968
5.9	1.0091	1.0145	1.0054	0.9544	1.0139

gain is achieved for 50% degree of exaggeration, and further narrowing of the exaggerated bid set makes the gain for the insincere agent decrease, but it does not make negotiations fail. This is an effect of the higher correlation in the MWIS-Q selected scenario ($\psi = 4.3$), which makes deal probability higher. Finally, we can observe that exaggeration of the 75% of the bids has no significant effect, since most agent bids are included in the exaggerated set in this case. From these results we can conclude that there are incentives for the agents to behave insincerely in those scenarios, and therefore additional mechanisms should be introduced in the model to make it incentive-compatible.

6.3 Incentivizing sincere behavior in the auction-based negotiation protocol

As we have seen, the proposed model is prone to manipulations by means of *exaggerations* made by the agents, and there is an incentive for agents to behave insincerely. This is an undesirable property in a negotiation model, and may lead to further stability problems. Therefore, we seek for mechanisms which counter this effect, incentivizing sincere revelation of information. A possibility to achieve this is to normalize the utility values assigned by the agents to their bids, thus lowering the absolute differences in utility. We propose three different possibilities regarding utility normalization:

- *Normalization to maximum utility* : obtained by dividing each agent's bid utility by the maximum utility value issued by that agent:

$$u_n(b_i) = \frac{u(b_i)}{\max_{b_j \in B} u(b_j)}. \tag{6}$$

  Using this normalization mechanism we can avoid the manipulation of the final deal by exaggerating upwards the utility values of the preferred offers. It does not prevent,

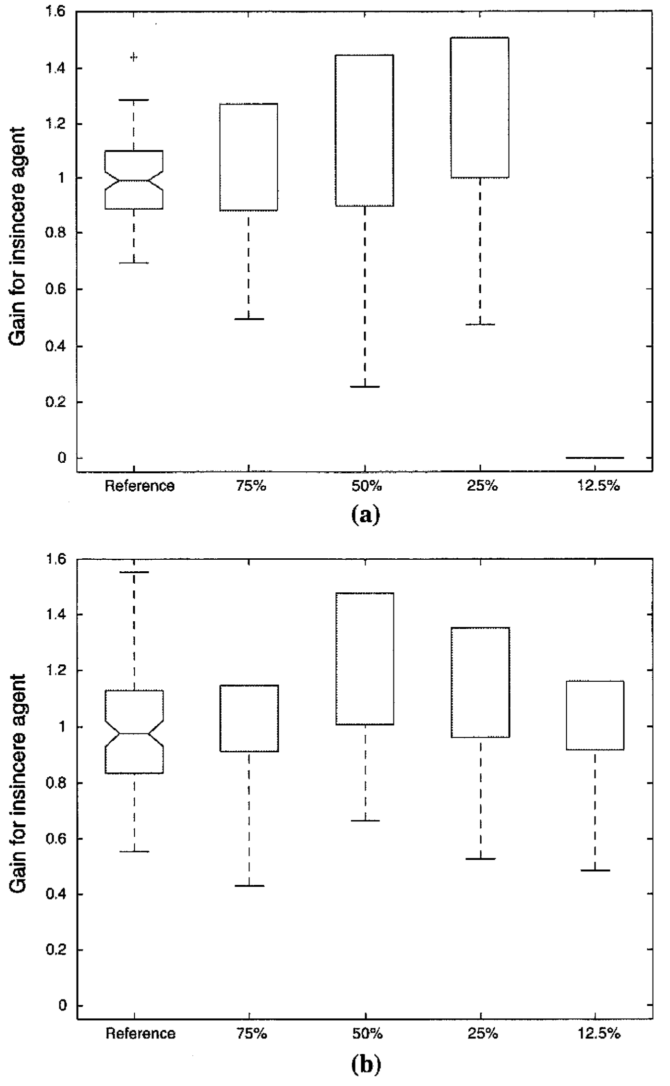

Fig. 12 Detail of the incentive-compatibility analysis for the most critical scenarios. **a** SA-Q $\psi = 4.0$, **b** MWIS-Q $\psi = 4.3$

however, downward exaggerations, that is, to assign an extremely low value to the bids which are less profitable for the agent.

- *Bounded maximum-minimum normalization*: Attempts to prevent the manipulation of the negotiation model through upwards or backwards exaggerations. It is given by the expression

$$u_n(b_i) = u'_{\min} + \frac{u(b_i) - u_{\min}}{u_{\max} - u_{\min}} \left(u'_{\max} - u'_{\min}\right), \tag{7}$$

where $u_{\max} = \max_{b_j \in B} u(b_j)$, $u_{\min} = \min_{b_j \in B} u(b_j)$ and $u'_{\min}$ and $u'_{\max}$ are parameters chosen by the mediator. In this way, a utility mapping from the interval $[u_{\min}, u_{\max}]$ to the interval $[u'_{\min}, u'_{\max}]$ is performed for all bids, putting an upper bound $\frac{u'_{\max}}{u'_{\min}}$ to the ratio between the utilities of an agent's bids.

- *Ordinal normalization:* obtained by ordering the different bids of an agent according to their utility or quality factor, and mapping this order to a monotonically increasing succession of utility values, regardless of the original utility values. For instance, if B is the set of bids for an agent, in ascendent order of utility, and taking the arithmetic succession $s = \{1, 2, \ldots, n_B\}$ as the mapping function, the normalized bid utility values would be of the form

$$u_n(b_i) = s_i = i.$$

Our hypothesis is that using these normalization methods may positively contribute to the incentive-compatibility of the model. To evaluate the effect of the proposed mechanisms over the incentive-compatibility of the model we have repeated the experiments performed above for the different normalization mechanisms proposed:

1. *Reference:* Utility values are not normalized.
2. *Umax:* Mediator uses *normalization to maximum utility* (Eq. 6).
3. *Bounded:* Mediator uses *bounded maximum-minimum normalization* (Eq. 7).
4. *Ordinal:* Mediator uses *ordinal normalization.*

Figure 13 a and b show the box plots of the results for 100 runs of the experiments for SA-Q and MWIS-Q in the most critical scenarios identified above, that is, $\psi = 4.0$ with a 25% degree of exaggeration for SA-Q and $\psi = 4.0$ with a 50% degree of exaggeration for SA-Q. We can see similar trends for both cases. Though all proposed normalization techniques reduce the incentive for the insincere agent to exaggerate, only bounded maximum-minimum normalization makes the expected gain for the insincere agent negligible, thus effectively removing the incentive to exaggerate, improving incentive-compatibility of the model.

7 Concluding remarks

Situations of high price of anarchy, which imply that individual rationality drives the agents towards strategies which yield low individual and social welfares, should be avoided when designing negotiation mechanisms. This is specially important when dealing with complex negotiations involving highly rugged utility spaces, since in these cases "low individual and social welfare" often means that the negotiations fail. Therefore, an strategic analysis is paramount for any model intended to work for highly rugged utility spaces, in order to determine the strategic properties of the model and to allow to establish additional mechanisms for stability if needed.

In this paper we have performed a strategy analysis for the auction based negotiation protocol for highly rugged utility spaces we proposed in refs. [31,55]. This strategy analysis has started studying the existence of individual and social optimal strategy profiles. This has revealed the existence of an individual optimal strategy, which is different from the socially optimal strategy. A more in-depth stability analysis has shown that, for highly correlated or lowly correlated scenarios, there is no incentive for negotiating agents to deviate from the socially optimal strategy. However, for medium complexity scenarios a selfish agent may

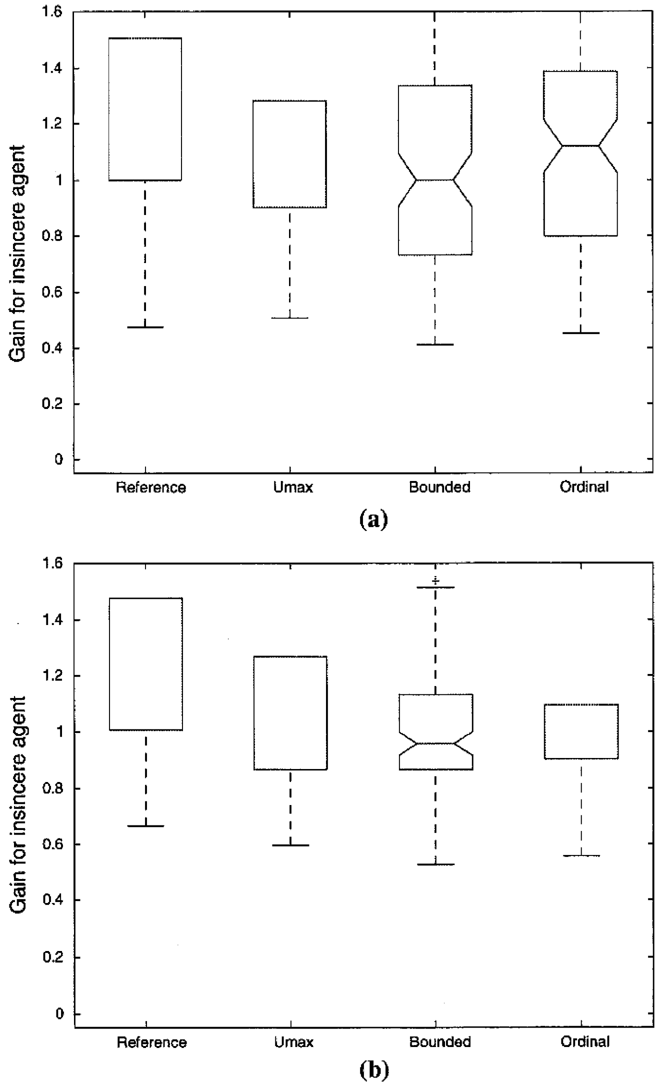

Fig. 13 Effect of the proposed normalization mechanisms for the most critical scenarios. **a** SA-Q, $\psi = 4.0$, 25% degree of exaggeration. **b** MWIS-Q, $\psi = 4.3$, 50% degree of exaggeration

benefit from using its individually optimal strategy, which raises stability concerns, leading the model to high expected price of anarchy values. To solve this, we have proposed a set of mechanisms intended to incentivize social behavior among negotiating agents. These mechanisms are based on biasing deal identification at the mediator towards those bids which are more socially oriented, thus decoupling the search for social welfare from the individual agents' goals. Experiments show that the proposed mechanisms successfully stabilize the protocol, avoiding the situations of infinite expected price of anarchy.

Finally, incentive compatibility issues in the protocol have been analyzed, showing that the model may be manipulated by agents which exaggerate the utility values of a subset of their bids, achieving significant gains for the insincere agents in medium correlated scenarios. To solve this, a set of normalization techniques have been proposed in order to incentivize sincere behavior. Experiments have shown that, though all proposed techniques reduce the incentive for an agent to exaggerate its bids, only the proposed bounded maximum-minimum normalization mechanism effectively removes the expected gain for being insincere, thus making the model incentive-compatible.

Though the experimental analysis performed has proven the effectiveness of the stability and incentive-compatibility mechanisms proposed, there is still plenty of research to be done in this area. We are interested on extending the strategy analysis presented in this work to an iterative version of the studied negotiation protocol, which would allow the agents to refine their bids in successive iterations of the protocol. This would raise very interesting additional considerations regarding agent and mediator strategies, since it would allow to develop adaptive measures. For the negotiation agents, this would mean, for instance, to be able to acquire a reasonable belief about the other agents' strategies during the negotiation, and to adapt its own strategy accordingly. This would drastically change the strategy analysis, since it would have to be conducted in a similar manner to a Bayes-Nash problem. The different results of the strategy analysis would probably impact the mechanisms needed at the mediator, and even more taking into account that the mediator could also take advantage of adaptive measures, trying to deduce agent strategies during the negotiation process, and to apply the different mechanisms as needed. In addition, the effect of the correlation between the utility functions of *different* agents (as opposed to the correlation length within each agent's utility function) should be analyzed. Finally, we are working on the generalization of these approaches for other negotiation protocols and utility function types.

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A Appendix: Deduction of the expressions used in the probabilistic analysis

This section deduces these expression used in Sect. 4.1 for the probabilistic analysis of the auction based negotiation model. For ease of understanding, the deduction of the expressions is presented in a progressive manner. First of all, deal probability is calculated for an exchange between two agents of an *elemental* bid (a single unitary bid for each agent, for a single issue), and then it is shown how the expression varies when the number of issues and agents increase. Then, the resulting expression is generalized for an arbitrary number of bids per agent. Finally, given the expression for deal probability, expressions for expected utility and expected deal utility (defined as the expected utility conditioned to the event of a successful deal) are determined.

A.1 Deal probability

Considering the negotiation protocol described in Sect. 3.2, the probability of finding a deal is given by the probability of finding a common intersection of at least one bid of each agent. The simplest scenario we can devise is a bilateral, single issue negotiation where each agent makes a single, elemental bid, that is, a bid that represents a single point in the solution space.

Let a y b be the negotiating agents, and let $x^a, x^b \in D$ be their respective offers in a finite domain D with cardinality $|D|$. The probability P_{solution} of a deal or solution to the negotiation problem in this case is given by the probability of the coincidence of both bids. In this way,

$$P_{solution} = \bigcup_{x\in D} p\left[\left(x^a = x\right) \cap \left(x^b = x\right)\right] = \underbrace{\sum_{x\in D} p\left[\left(x^a = x\right) \cap \left(x^b = x\right)\right]}_{x^j = x \text{events are disjoint}}$$

$$= \underbrace{\sum_{x\in D} p\left(x^a = x\right) p\left(x^b = x\right)}_{x^a \text{ and } x^b \text{ are independent}} = \sum_{x\in D} \frac{1}{|D|}\frac{1}{|D|} = \frac{|D|}{|D|^2} = \frac{1}{|D|}, \qquad (8)$$

where we have assumed as the probability that a bid has a given value $p\left(x^a = x\right) = \frac{1}{|D|}$, which corresponds to a uniform bid distribution, for a maximum uncertainty scenario.

Extending the previous expression to a bilateral negotiation about n issues is straightforward. Again, let us consider the simplest case of a single elemental bid per agent. In this case, each bid will represent a point in an n-dimensional solution space, and the deal probability will be given by the probability of *all* issue values corresponding to one agent's bid matching the respective values of the issues corresponding to the other agent's bid.

Let a y b be the negotiating agents, and let $x^a, x^b \in D$ be their respective offers, such that the bid issued by agent j is given by $\bar{x}^j = \left\{x_i^j \mid i \in 1, \ldots, n\right\}$, and such that $x_i^j \in D\ \forall i, j$. The probability of a deal or solution to the negotiation problem in this case is given by the expression

$$P_{solution} = \bigcap_{1\leq i\leq n} \left\{\bigcup_{x\in D} p\left[\left(x_i^a = x\right) \cap \left(x_i^b = x\right)\right]\right\}$$

$$= \underbrace{\prod_{1\leq i\leq n} \left\{\bigcup_{x\in D} p\left[\left(x_i^a = x\right) \cap \left(x_i^b = x\right)\right]\right\}}_{\text{issue matches are independent events}} = \prod_{1\leq i\leq n} \frac{1}{|D|} = \frac{1}{|D|^n}. \qquad (9)$$

In a similar way, this expression may be generalized to the case of n_a agents, taking into account that deal probability in this case is given by the probability of a match between the respective values for *all* issues of *all* agents' bids, and that each agent bid is independent from the others'. In this way, the expression for the probability of finding a solution or deal in this case will be the following:

$$P_{solution} = \bigcap_{1\leq i\leq n} \left\{\bigcup_{x\in D} p\left[\bigcap_{1\leq j\leq n_a} \left(x_i^j = x\right)\right]\right\}$$

$$= \bigcap_{1\leq i\leq n} \left\{\bigcup_{x\in D} \left[\prod_{1\leq j\leq n_a} p\left(x_i^j = x\right)\right]\right\}$$

$$= \bigcap_{1\leq i\leq n} \left\{\sum_{x\in D} \left[\prod_{1\leq j\leq n_a} p\left(x_i^j = x\right)\right]\right\}$$

$$= \bigcap_{1 \le i \le n} \left\{ \sum_{x \in D} \left[\prod_{1 \le j \le n_a} \frac{1}{|D|} \right] \right\}$$
$$= \bigcap_{1 \le i \le n} \left\{ \frac{|D|}{|D|^{n^a}} \right\} = \prod_{1 \le i \le n} \left\{ \frac{1}{|D|^{n_a - 1}} \right\}$$
$$= \frac{1}{|D|^{n(n^a - 1)}}. \tag{10}$$

So far we have considered only single, elemental bids, that is, each agent issued a single bid representing a single point in the solution space. This assumption allowed us to ensure deal events were disjoint (there was only a possible deal), which allowed to compute probabilistic unions as sums of probabilities. Generalizing to the case of multiple bids makes multiple points of agreement possible, and thus makes necessary to take into account possible intersection among deal events to compute probabilistic unions.

Given a set of N events $E_1, \ldots, E_N$, with known probabilities $p(E_i)$, and not necessarily disjoint, the probability of the union $\bigcup_{i=1}^{N} E_i$ is given by

$$p\left(\bigcup_{i=1}^{N} E_i\right) = 1 - p\left(\bigcap_{j=1}^{N} \overline{E_i}\right).$$

If the events are independent and equiprobable, we have that $p(E_i) = p$, $p\left(\overline{E_i}\right) = 1 - p$, and the probability of the intersection above is given by $p\left(\bigcap_N \overline{E_i}\right) = (1-p)^N$. In this case, we can see that the above expression leads to the following:

$$p\left(\bigcup_{i=1}^{N} E_i\right) = 1 - (1-p)^N$$
$$= 1 - \sum_{j=0}^{N} \binom{N}{j} 1^{N-j} (-p)^j$$
$$= 1 - \sum_{j=0}^{N} \binom{N}{j} (-1)^j p^j$$
$$= \sum_{j=1}^{N} (-1)^{j+1} \binom{N}{j} p^j. \tag{11}$$

This result can be used to generalize the expression for deal probability obtained in the previous section to the case of multiple offers. Let us consider again a set of n_a agents negotiating about n issues. In this case we will consider that each agent k sends n_{bp}^k elemental bids. We consider elemental bids without loss of generality, since any other kind of bids (e.g. hyper-rectangles) can be decomposed to elemental bids. There may be overlaps between the different bids of an agent (i.e. they may or may not be disjoint). The probability P_{solution} that there is a solution or deal to the negotiation problem will be given by the probability that *at least one* of the possible combinations of bids from the different agents results in a deal. If each agent k issues n_{bp}^k bids there are $\prod n_{bp}^k$ possible combinations of one offer of each agent. The event C_l denotes the fact that the combination l results in a deal. The different events C_l

are equiprobable, and their probability is given by Eq. 10, reproduced here for convenience:

$$p(C_l) = \frac{1}{|D|^{n(n^a-1)}}.$$

Taking this into account, and using Eq. 11 for the computation of the probability of a union of equiprobable events, deal probability for the set of bids is given by the expression

$$\begin{aligned} P_{\text{solution}} &= p\left(\bigcup_{l=1}^{\prod n_{bp}^k} C_l\right) = \sum_{j=1}^{\prod n_{bp}^k} (-1)^{j+1} \binom{\prod n_{bp}^k}{j} p(C_l)^j \\ &= \sum_{j=1}^{\prod n_{bp}^k} (-1)^{j+1} \binom{\prod n_{bp}^k}{j} \left(\frac{1}{|D|^{n(n^a-1)}}\right)^j. \end{aligned} \tag{12}$$

A.2 Expected utility and expected deal utility

Once deal probability has been determined, it is easy to compute expected utility. By definition, the expected value of a random variable X which takes values from a domain D is computed as the sum $\sum_{x \in D} x \cdot p(X = x)$ of the products of each possible value for the variable and the respective probability that the variable takes each value. For the case of the expected utility for an agent, the possible values of the variable are the utility values associated to the different bids, and the probability that the variable takes each value is the probability that each bid results in a deal. To compute this probability, we have to take into account that each elemental bid $\bar{x}_i^j$ of an agent j may be part of $\prod_{k \neq j} n_{bp}^k$ events $C\left(\bar{x}_i^j\right)_l$, representing the fact that the different combinations of this bid with the different elemental bids of the rest of the agents may result in a deal. In this way, the deal probability for a given elemental bid $\bar{x}_i^j$ is given by

$$p\left(\bar{x}_i^j\right) = p\left(\bigcup_{l=1}^{\prod_{k \neq j} n_{bp}^k} C\left(\bar{x}_i^j\right)_l\right) = \sum_{j=1}^{\prod_{k \neq j} n_{bp}^k} (-1)^{j+1} \binom{\prod_{k \neq j} n_{bp}^k}{j} \left(\frac{1}{|D|^{n(n^a-1)}}\right)^j.$$

From this expression, the expected utility for an agent j is computed as follows:

$$\begin{aligned} E\left[u^j\right] &= \sum_{i=1}^{n_{bp}^j} u\left(\bar{x}_i^j\right) p\left(\bar{x}_i^j\right) \\ &= \sum_{i=1}^{n_{bp}^j} \left[u\left(\bar{x}_i^j\right) \sum_{j=1}^{\prod_{k \neq j} n_{bp}^k} (-1)^{j+1} \binom{\prod_{k \neq j} n_{bp}^k}{j} \left(\frac{1}{|D|^{n(n^a-1)}}\right)^j \right] \\ &= \left[\sum_{i=1}^{n_{bp}^j} u\left(\bar{x}_i^j\right)\right] \left[\sum_{j=1}^{\prod_{k \neq j} n_{bp}^k} (-1)^{j+1} \binom{\prod_{k \neq j} n_{bp}^k}{j} \left(\frac{1}{|D|^{n(n^a-1)}}\right)^j \right], \end{aligned} \tag{13}$$

where $\sum_{i=1}^{n_{bp}^j} u\left(\bar{x}_i^j\right)$ is the sum of the utilities of all points issued as bids by the agent. For the case of non-elemental bids, we consider each agent j issues n_b^j bids. Each bid m of the agent represents an *iso-surface* of the agent's preference space (e.g, an hyperrectangle), and thus may be decomposed in v_m^j elemental bids of the same utility u_m^j, where v_m^j is the *volume* of the iso-surface represented by the bid m. In this case, we can establish the equivalence $\sum_{i=1}^{n_{bp}^j} u\left(\bar{x}_i^j\right) = \sum_{m=1}^{n_b^k} u_m^k \cdot v_m^k$, and the expression for the expected utility results as follows

$$E\left[u^j\right] = \left[\sum_{m=1}^{n_b^k} u_m^k \cdot v_m^k\right] \left[\sum_{j=1}^{\prod_{k\neq j} n_{bp}^k} (-1)^{j+1} \binom{\prod_{k\neq j} n_{bp}^k}{j} \left(\frac{1}{|D|^{n(n^a-1)}}\right)^j\right],$$

which is the expression we saw for Eq. 2.

Finally, expected deal utility for an agent may be obtained easily, since it only depends on the utility distribution within the set of bids issued by the agent. Assuming a deal have been reached, the probability for each elemental bid to be part of the deal will be $p\left(\bar{x}_i^j \,|deal\right) = \frac{1}{n_{bp}^j}$, assuming the different elemental bids are equiprobable (maximum uncertainty scenario). Taking this into account, expected deal utility is given by

$$E[u^j \,|deal] = \sum_{i=1}^{n_{bp}^j} u\left(\bar{x}_i^j\right) p\left(\bar{x}_i^j \,|\text{deal}\right) = \frac{1}{n_{bp}^j} \sum_{i=1}^{n_{bp}^j} u\left(\bar{x}_i^j\right),$$

which, for hyperrectangular bids, takes the form we saw in Eq. 3:

$$E[u^j \,|deal] = \frac{\sum_{m=1}^{n_b^j} u_m^j \cdot v_m^j}{n_{bp}^j}. \tag{14}$$

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