

Multi-agent negotiation in the Prestige oil spill response scenario: a conflict resolution mechanism design and simulations

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Abstract

Contingency management facing an imminent oil spill is often a difficult task as the long-term consequences of decisions generally affect the interests of different stakeholder groups - including the broad public. We suggest here that a balanced response scheme can be achieved by integrating various interests within a virtual negotiation process. This paper designs a hybrid negotiation protocol where multiple issues including money compensation are traded by parties. Aiming to examine appropriate designs of this process in multi-agent systems, we simulate negotiations based on the Prestige oil spill response scenario. Experiment results show that this designed protocol may work as a robust conflict resolution mechanism for deriving a multi-agent consensus. Finally, by comparing two different rational strategies taken by agents, we add support to the view that learning techniques help agents to improve their payoffs in negotiations.

Keywords: oil spill, negotiation, multiagent system, decision making.

1 Introduction

One of the major episodic threats for near-shore and coastal ecosystem and the human use of coastal areas arise from large oil or chemical spills. Contingency management thus aims to simply keep the drifting oil away from sensible coastal areas, depending on the weather situation and available combat facilities. This goal is mostly only partially achieved in real time operations. Given the complex dynamics of the physical system in the coastal zone and the different environmental and economic values of coastal areas under risk, decision making during



the oil spill response planning then becomes a politically sensitive task. If not in the process itself, at least in the aftermath and during the political evaluation of the combat strategy, various interested groups such as commercial organizations, NGOs, scientific institutions and local stakeholders are involved [1, 2].

This was also apparent after the disastrous consequences of the crude oil released by the tanker *Prestige* in autumn 2002 along the Spanish coast and with some delay also the French Atlantic coast. In an early phase of the accident, the only available response option was to tow the ship into different directions as shown in Figure 1. By using simulation techniques together with a multi-criteria analysis [3, 4], it is suggested that to tow the spilling vessel to a harbor or to drag it offshore into a northwestern direction would lead to a minimal overall ecological and economic damage. This result, of course, and the final choice between the two favorable towing directions depend on how the integrated damage is calculated. One basic element is the relative importance given to various stakeholder groups having different, often contradictory, interests and understandings of the problems and their solutions [5]. The still ongoing discussions on the appropriateness of the response taken by the Spanish authorities demonstrate that the lack of participation of social groups in environmental conflict decision making often leads to undesired results including social unrest and rejections of reasonable compromises [6].

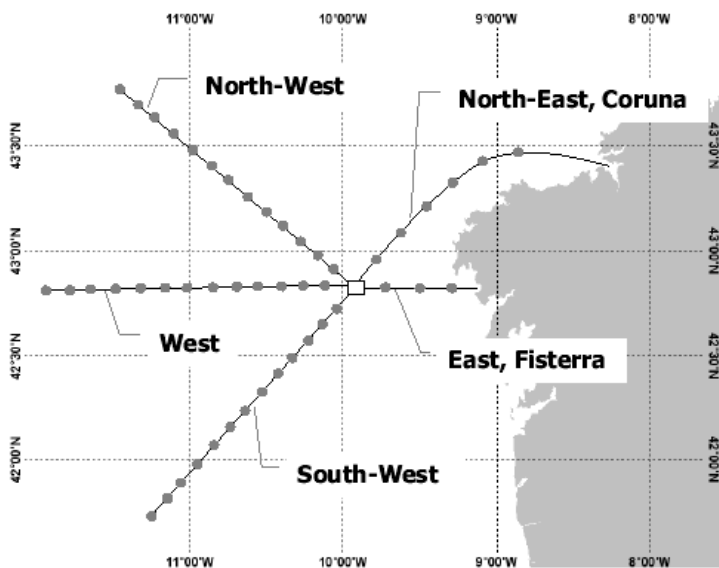


Figure 1: Towing routes. Two inshore strategies: North-East and East. Three off-shore strategies: North-West, West and South-West.

Continuing the work done by [3], we here address the problem of finding a politically balanced relevance scheme with a multi-agent negotiation technique. The

underlying idea is that a computerized negotiation technique will also stimulate social participation and lead to a better account of their interests by responsible authorities during and already before accidents. In the case study used here we focus on the problem of choosing an appropriate towing direction. When technically building an autonomous agent, which is capable of representing a realistic argumentation behavior in a negotiation process, the main components that should be considered comprise [7]: (i) a negotiation protocol (ii) negotiation issues, and (iii) a reasoning model of the trading agents. In this paper, we firstly present a hybrid negotiation protocol, which consists of two principal stages and a negotiation center (NegCen) as a neutral organizer. This protocol is appropriate for deriving a multi-agent consensus in a dynamic oil spill response environment, as it supports, for example, the pareto efficiency, individual rationality, telling truth as essential prerequisites, from the economic point view. In terms of negotiation issues, it is apparently more realistic that agents trade over multiple attributes instead of a single attribute (e.g. the towing direction). Thus, compensations in money terms are provided to the agents who compromised an agreement that is unfavorable.

2 Negotiation issues

A central element of the approach we adopted is a negotiation over two attributes that was described as the multi-issue negotiation by [8]. Negotiation issues can be a number of quantitative and qualitative items. In our work, one response action, i.e. the option of towing the spilling vessel into one of five predefined directions and a compensation in money terms are considered. The money compensation allows a utility transfer within multi-agents, which ultimately leads to findings of individually rational and globally optimal solutions [9]. In our case study of oil spill abatement, different towing directions result in different amount of oil stranded on coastal sub-areas with their specific ecological and/or economic value. Thus, each agent prefers a response action, which induces a minimal impact to the coastal area of his or her interest. In order to persuade other agents to agree with his preferred response action, agents intend to compensate other agents, which are forced to make disadvantageous agreements on the selection of response actions. Both issues contribute to the utility of agents. If the function $u_j^A(a_j) \in [0, 1]$ describes the utility value of attribute a_j for agent A , the total utility (U_A) over all issues is calculated through a weighted sum:

$$U_A = \sum_{j=1}^2 w_j^A u_j^A \quad (1)$$

where w_j^A describes the relative importance that agent A assigns to issue a_j (with $\sum_{j=1}^2 w_j^A = 1$). Each agent evaluates the five towing options and assigns a maximum willingness to pay ($M_{ax}WTP$) and a minimum willingness to accept ($M_{in}WTA$) in money terms for its most and least preferred towing option, respectively. Therefore, an agent's reserved utility base line is constructed on the basis of



these items:

$$\begin{cases} base_A = w_1^A u_1^A(TO_{most}) + w_2^A u_2^A(-M_{ax}WTP) \\ base_A = w_1^A u_1^A(TO_{least}) + w_2^A u_2^A(+M_{in}WTA) \end{cases} \quad (2)$$

where the most preferred towing option (TO_{most}) together with its $-M_{ax}WTP$ contributes to agent A 's utility base line $base_A$, and the same definition is applied to the least preferred towing direction and its $M_{in}WTA$. There exists an agreement zone, if one agent's $M_{ax}WTP$ for a specific towing option (TO_j) is not less than its opponent's $M_{in}WTA$ (e.g. $M_{ax}WTP_{TO_j}^{ag.A} \geq M_{in}WTA_{TO_j}^{ag.B}$ or $M_{ax}WTP_{TO_j}^{ag.B} \geq M_{in}WTA_{TO_j}^{ag.A}$). Otherwise, the agreement zone does not exist and a consensus can not be reached during the course of play, which leads to a failure of negotiation.

3 A hybrid negotiation protocol

Three widely used protocols in negotiations are (i) the one shot, (ii) the ultimatum and (iii) the alternating offer. Their efficiencies have been assessed in [10]. They provided two arguments. Firstly, when applied to the Prestige response decision making, the alternating offer is approved to be the most effective negotiation method, since it works efficiently in a complex environment where completely contrary interests of agents exist. Secondly, in the situation where no strongly different demands exist, the straightforward mechanism of the one-shot performs well. It carries the benefit to be quite fair and less time consuming. Thus, a hybrid negotiation protocol is created by combining the one-shot and the alternating offer, consisting of two principal stages as shown in Figure 2. The first stage is the one-shot like mechanism where a negotiation center (NegCen) as a neutral organization helps to identify both agents' preferences. The two agents A and B simultaneously sent their preferences (e.g. the towing direction) to NegCen without any knowledge of the opponent's demand. If their preferences are identical, the negotiation is ended successfully with equally distributed payoffs to the agents. Otherwise, the negotiation comes to the second stage, which includes several negotiation rounds. Firstly, one of the agents is randomly selected as a starter to send an initial proposal to the opponent. After evaluating the incoming offer, the opponent may accept or reject it with a counter proposal. This process is repeated until the negotiation is ended with an agreement or a time limit is met. Agents will receive nothing if the negotiation is not ended with an agreement. The designed protocol ensures pareto efficiency, individual rationality, maximal social welfare, fairness, telling truth and partial revelation of preferences.

Pareto efficiency: all potential solutions build up an agreement space of agents (see Figure 3 left). During a negotiation, it enables agents to compare alternative solutions and find an optimal solution as close to the pareto optimal frontier as possible. The pareto optimal solutions are efficient in the sense that no other solution exists where some individuals are better off and no individual worse off.



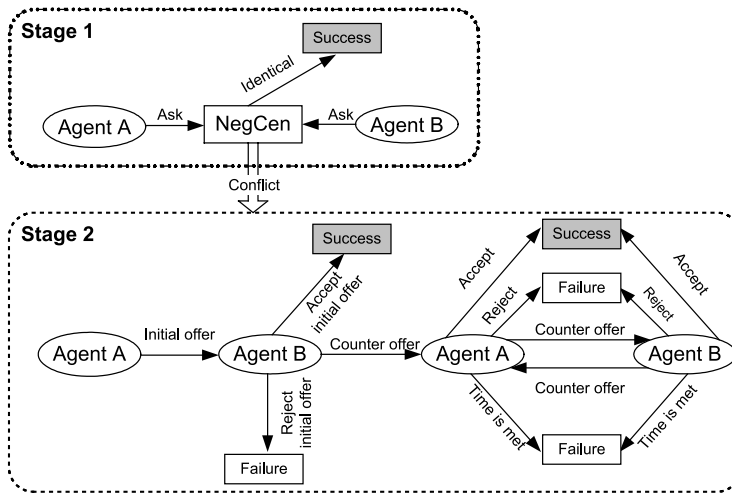


Figure 2: A detailed scheme of the hybrid negotiation protocol.

Individual rationality: negotiating agents are rational at several principal aspects. Firstly, by participating the agent's payoff increased with respect to a non-participation. Secondly, they prefer making an agreement, if the suggested proposal has a better utility payoff than its utility base line. Thirdly, their actions such as presenting an initial offer, evaluating an incoming offer and proposing a counter offer are based on a personal multi-attribute utility function and conservative utility.

Maximal social welfare: if the social welfare is defined as a set of indifference curves shown in the right diagram of Figure 3, the pareto optimal choice which reaches the local maximal social welfare indifference curve S_3 at a single point G defines the best solution. Here the social welfare focuses on the combined product of all individual utilities as described in [11]. Thus, solution G presents an equity for both of agents. In a real negotiation, agents intend to avoid an agreement which benefits one agent too much and make the other suffer a big loss. Such a case like choice H , although it is at pareto optimal frontier, is prevented by using the utility base line as a constraint.

Fairness: all agents are treated equally important during the whole negotiation. No dominant or superior agent exists and equal opportunities to start a negotiation are shared.

Telling truth: the negotiation centre is neutral. Both agents have no information about the preferences of the opponent before the start of negotiation. Thus, telling the truth is a dominant strategy for both agents.

Partial revelation of preferences: Not all preferences of agents are revealed in the process of negotiation. For example, their reserved utility base line remains a completely private information.

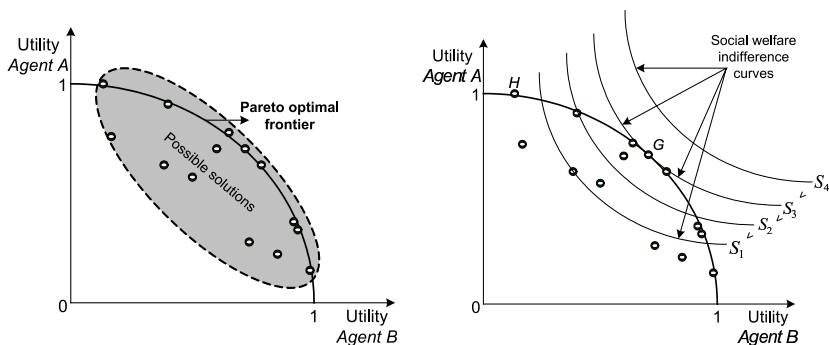


Figure 3: Pareto optimal and maximal social welfare. Left: possible solutions and Pareto optimal. Right: social welfare indifference curves.

4 Rational agents

As we mentioned before, negotiating agents are capable of a number of actions such as evaluating an incoming offer and proposing a counter offer. All these behaviours are based on their personal multi-attribute utility function and reserved utility base line,

$$action_A = \begin{cases} \text{accept} & U_A(\text{offer}_{inc})/base_A \geq c \\ \text{reject} & U_A(\text{offer}_{inc})/base_A \leq b \\ \text{offer}_{counter} & U_A(\text{offer}_{inc})/base_A \in (b, c) \end{cases} \quad (3)$$

where c and b are pre-designed constants. Through comparing the utility of an incoming offer with the base line, agent A selects one corresponding action on a rational basis. For example, agent A intends to accept the incoming offer, if its utility is 1.5 times ($c = 1.5$) as high as its utility base line ($base_A$). According to the way in which a counter offer is proposed, two different reasoning models are generated: the conservative model and the reinforcement learning model. In the conservative model, the counter offer is made randomly within the interval of $[base_A, 1]$,

$$\text{offer}_{counter}^A = \arg \{U_A(\text{offer}) \geq base_A\} \quad (4)$$

An agent with the conservative reasoning model is simply a rational agent, and in this paper, is called the conservative agent. Contrary, in the reinforcement learning model, the counter offer is suggested by a simple learning function,

$$\text{offer}_{n+1}^A = \text{offer}_n^A + \alpha(\text{offer}_n^B - \text{offer}_n^A) \quad (5)$$

where α is a learning rate ranging between 0 and 1. The counter offer of agent A in the next negotiation round $n + 1$ is a function of both offers given at a former negotiation round. A learning function brings the benefit of learning the preferences of opponents and adapting a strategy by which better payoffs are achieved

during the following plays. An agent being capable of such a learning function is taken as a learning agent. In the next section, in order to support a view that learning techniques help agents improve their payoffs in sequential negotiations, the performance of both types of negotiating agents are evaluated in the frame of a balanced contingency management.

5 Trading the response to the Prestige accident in simulated experiments

By using the hybrid protocol, we let two different types of agents (e.g. the conservative agent and the learning agent) run negotiations on behalf of their owners (e.g. fishermen, environmentalists or policy-makers) for a suitable response to an imminent oil spill. As mentioned previously, the towing direction of the spilling vessel and the money compensation are considered. Totally 300 oil spill scenarios randomly generated are presented to the agents. This number is found to be sufficient to distinguish the different performances of agents). In each scenario, five different towing directions result in different damage distributions for coastal sub-areas. Both agents evaluate and rank towing options with regard to the damage level on their interest areas. Out of these 300 scenarios, only 117 cases can be successful traded. This is partly due to the lack of an agreement zone. Another reason derives from the nature of the conservative agent (e.g. randomly selection of the proposals in its possible action space), what may result in a failure in the negotiation under the time constraint, although in a few cases it promote a very fast joint agreement [12]. The average utility gain over all successful negotiations is taken as a measure to evaluate the performance of both agents. The development of the average utility for both agents is presented in Figure 4. Unsurprisingly, the learning agent does perform a little better than the conservative agent in terms of the average utility. Since the learning agent, unlike the conservative agent, adapts its strategy gradually by predicting the opponent's preference with a reinforcement learning method. It leads to a better payoff derived for the learning agent when an agreement is reached.

6 Conclusions and future works

The hybrid negotiation protocol here is demonstrated to robustly depict basic features of real conflict mitigation. It, thus, may assist parties involved in a dispute over environmental decision making problems. In particular, its test of the response to the Prestige oil spill, 2002 shows that the consensus is a win-win solution for parties, once the negotiation is terminated successfully, although sometimes this compromise consensus is not the best decision made by the multi-criteria analysis in [3]. Our main conclusions comprise: (i) The sequential negotiation with the designed negotiation protocol is demonstrated to yield reasonable results and, thus may serve as a useful tool for supporting environmental decision makings dealing with various stakeholder groups. (ii) Adding compensation as one of the important



negotiation issues into a multiple attribute utility function, more feasible solutions are generated. (iii) When simulation experiments are involved with different rational agents, the learning agent performs well as compared with the conservative agent. This outcome reinforces the view that learning techniques help agents to serve better on behalf of their owners by improving payoffs in sequential negotiations.

Above all, we aim to verify the usefulness of the approach in a real conflict situation in the future. In parallel to the trading of virtual agents, a web-based negotiation software will enable real stakeholders to interactively solve environmental decision making problems, for example regarding the allocation of offshore wind farms and an imminent oil spill response preparation and planning. This model presented here can then serve as a frame of reference for supervising the computer guided stakeholder interactions.

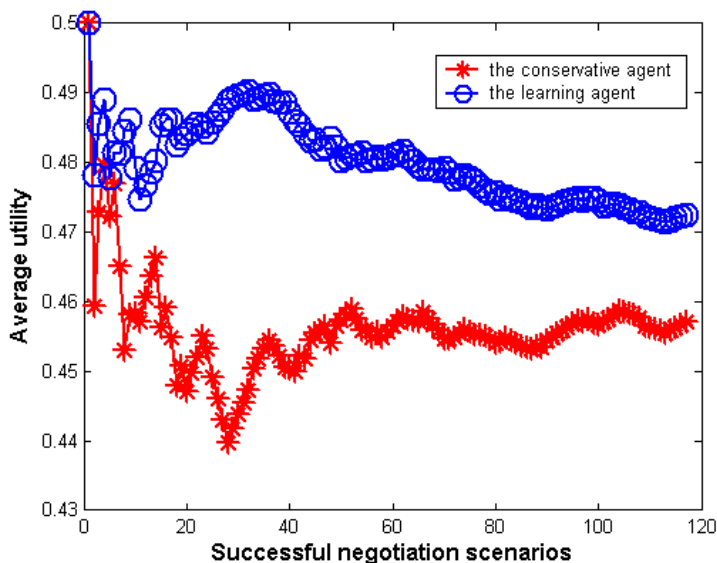


Figure 4: Comparisons of average utility outcomes for two different types of agents. The learning agent is marked with circles and the star line refers to the conservative agent.

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