

# A Negotiation Model for Collaborative Decision Making in Large-Scale Multi-Agent Systems

Tom Wanyama

Department of Networks and Software Engineering  
Faculty of Computing and Information Technology  
Makerere University, P. O. Box 7062  
Kampala, Uganda

wanyama@cit.mak.ac.ug

**Abstract** - Modeling agent negotiation is of key importance in building multi-agent system, because negotiation is one of the most important types of agent interaction. Negotiation provides the basis for managing the expectations of the individual negotiating agents, and it enables selecting solutions that satisfy all the agents as much as possible. Thus far, most negotiation models have serious limitation and weakness when employed in large-scale multi-agent systems. Yet, large-scale multi-agent systems find their use in major domains of human development such as space exploration, military technology, disaster response systems, and health technology. This paper presents an agent negotiation model which extends the capabilities of the model associated with the Agent Negotiation Engine for Collaborative Decision Making, to address the negotiation issues associated with large-scale multi-agents systems. The model utilizes Qualitative Reasoning and Game Theory algorithms to track the negotiation process, and a similarity criteria algorithm to manage the large amount of negotiation information associated with large-scale multi-agent systems. For completeness sake, the paper also presents the negotiation models from which the negotiation model for large-scale multi-agent systems evolved, as well as how and why the modifications were made.

## I. INTRODUCTION

Negotiation is a form of agent interaction that aims at identifying agreement solution options through an iterative process of making proposals (offers). In Group-Choice Decision Making (GCDM) process, the attributes of these proposals depend heavily on the preference models of the concern agents, and on the knowledge that the agents have about the preference models of their negotiation opponents. Consequently, apposite negotiation models should be able to assist agents to collect preference information of their negotiation opponents, and to integrate this information with their own preferences models in order

to identify and make proposals that are most likely to be accepted as the agreement solution options.

Although many negotiation models have been reported in literature, they all fall under two distinctive categories, namely: analytic based models [2, 7] and knowledge based models [1, 3]. In the context of Group-Choice problems in Large-Scale Multi-Agent Systems (LSMAS), negotiation models in literature have the following shortfalls:

- Both categories of negotiation models are developed with an implicitly assumption that agents are always

available during the entire negotiation period. This is not realistic in large-scale distributed multi-agents systems, because in such systems agents are terminated or crash without warning.

- Most analytic based agent negotiation models employ techniques that are naturally centralized; this is against the principle of decentralization, which is fundamental to the concept of Multi-Agent Systems (MAS). Moreover, analytic based models require the central processor to have complete information about the preferences of all the negotiating agents. This is impractical for LSMAS.
- Most knowledge based negotiation models result in random behavior (luck of mechanism to track the negotiation process) of the negotiating agents. This behavior results in unnecessary deadlocks in LSMAS. The few knowledge based negotiation models that track negotiation processes are invariably feasible for negotiations involving two agents, such as in the buyer seller negotiation problem.

This paper presents a negotiation model for solving group-choice problems in LSMAS. The model extends the capabilities of the agent negotiation model associated with the Agent Negotiation Engine for Collaborative Decision Making (ANE-CODEM) (see Wanyama and Far [10]). It is based on categorizing negotiation opponents of agents according to the similarity of their preferences. Since the agents focus on making proposal that are acceptable to classes of opponents, instead of dealing with each of the opponents individually, the model presented in this paper enables the agents to address issues associated with many negotiation opponents. This makes the model to be practical for both small and large-scale MAS. Furthermore, the model allows the agents to seamlessly join or leave the negotiation process, which addresses the issue of agents crashing, or being started and terminated without warning.

This paper is arranged as follows: Section 2 presents the related work, and Section 3 described how our negotiation model for LSMAS evolved. Section 4 presents a simulation example that illustrates the capabilities of our negotiation model for LSMAS. Finally, conclusions are given in Section 5.

## II. RELATED WORK

Negotiation is a very extensive subject that spans from pre-negotiation to post-negotiation analysis, both at the local and social level. Consequently, considerable amount of work on negotiation is available in literature from different domains, such as operational research, economics, and decision theory [4, 5]. In this section, we present the work that is directly related to our negotiation model.

The analytic based agent negotiation models utilize analytic techniques such as *Game Theory* to determine the solutions that maximizes the social welfare of the negotiating agents [7]. These models minimize communication among the negotiating agents; however, besides the drawbacks associated with LSMAS presented in Section 1, these models invariably have the following general shortfalls:

- The agents have no control over the tradeoffs made during the negotiation process.
- The analytic based models do not follow the natural process of negotiation, where in between offers and counter offers, multiple negotiation decision variables are traded-off against one another, in order to identify the solution that maximizes the social welfare.

Kraus [8] presents a knowledge based agent negotiation model that implicitly depends on tradeoffs made by the negotiating agents to determine the agreement solution. In the model, the agents evaluate the solution options individually, and then start the process of making offers and counter offers. In between each negotiation round, the agents make tradeoffs aimed at identifying a solution option that is acceptable to all negotiating agents. This model has the following major shortfalls:

- It does not give any guarantees that the agreement solution maximizes the social welfare of the negotiating agents.
- It does not support learning from the offers made by the agent negotiation opponents in order to enable the agents to make offers that are more socially acceptable, as the negotiation progresses; resulting in a random behavior of the agents.
- The agents have no way of knowing whether the negotiation is converging or not.

To circumvent the shortfalls of the analytic models, as well as the shortfalls of the Kraus [8] model, Faratin et al [6] have proposed an agent negotiation model, which depends on utility, similar to the analytic models. Moreover, the model enables the agents to tradeoff during negotiation, like the knowledge-based models. The negotiating agents can utilize the model proposed by Faratin et al even if they have partial information about the solution, thus the model has the potential of enabling the agents to search a larger solution space. However, in the context of LSMAS, the model has the shortfall of being viable for only two negotiating agents such as in buyer-seller negotiation problems. Therefore, the

approach of Faratin et al may not be applicable to LSMAS in its current form.

Ray and Triantaphyllou [9] propose a negotiation model that is based on the possible number of agreements and conflicts on the relative importance of the decision variables. However, having different preference functions does not necessarily mean preferring different solution options. Therefore, this model is too inefficient to be utilized in LSMAS. The other shortfalls of this model are the assumptions that the clients of the agents have the same concerns, hence the same set of decision variables, and that the preference models of negotiating agents is public information. In practice, agent clients normally have different concerns, which lead to having different sets of decision variables, as well as preference value functions, and this information is usually private.

This paper presents an agent negotiation model that extends the capabilities of the model associated with ANE-CODEM, in respect of Group-Choice decision making in LSMAS. We call the model the **Universal Agent NEgotiation Model (UANEM)**, because it is applicable to both small and large-scale MAS. Moreover, the model can be used in a variety of negotiation problems such as Group-Choice negotiation, Seller-Buyer negotiation, and Auction problems. It should be noted that this paper focuses on the use of the model in the Group-Choice negotiation problems. Finally, it should be noted that UANEM is similar to the negotiation model of Faratin et al [6]; except, UANEM utilizes a Game Theory component of ANE-CODEM to support negotiation among  $n$ -agents.

## III. THE BACKGROUND TO THE DEVELOPMENT OF THE UANEM

The UANEM was developed as a result of an evolutionary process that began with the development of a Group-Choice Negotiation Model for Multi-Agent Systems (GCNM-MAS) that is presented in Wanyama and Far [11], and is shown in Figure 1. The capabilities of the model were extended, resulting in a new and more powerful agent negotiation model that is based on the ANE-CODEM (see Wanyama and Far [10]).

### A. The GCNM-MAS

We developed the GCNM-MAS for use in a Decision Support System (DSS) for the selection of Commercial-Off-The-Shelf (COTS) products, which we were working on [11]. The main objective of that project was to develop a DSS, which allows both the group and the individual stakeholder processes to be carried out concurrently. Therefore, our main concern was the provision of appropriate user agents for the various stakeholders of the COTS selection process, and the integration of the user information to automatically identify the 'best-fit' COTS products. The automatic negotiation was not met to replace the human decision makers, but to assist the stakeholders to carryout simulation based analysis and ask the 'what if'