Collaborative Agent System Using Fuzzy Logic

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Abstract. Collaborative agents are able to find global solutions to complex systems using local knowledge rather than a complete global knowledge set. The complexity, on the other hand, brings uncertainty. Global optimisation in a uncertain environment can be undertaken using fuzzy collaborative agents. Negotiation, involving generating, evaluating and modifying action plans, under fuzzy circumstance is a key to construct fuzzy collaborative agents and fuzzy multi-agent systems. This paper presents an approach of negotiation using fuzzy reasoning, in particular *fuzzy backward reasoning*. A fuzzy collaborative agent has local knowledge in the form of a fuzzy model. Fuzzy backward reasoning is performed based on the fuzzy model to generate and modify an action plan in each agent.

1 Introduction

Global knowledge representing the behaviours of a complex system is often hard to acquire and therefore incomplete in practice. This makes it difficult to perform global optimisation for the system. Collaborative agents, each of which has sufficient local knowledge, have been developed for the global optimisation without using a global knowledge set. The collaboration is often achieved through negotiation which involves generating, evaluating and revising action plans (Wangermann and Stengel, 1998; Moree and et al, 2000; Dospisil, 2001). The complexity of such a system can also mean uncertainty. Knowledge about the system contains ambiguity and vagueness. It is convenient to represent the knowledge using fuzzy sets and fuzzy implications. The collaborative agents in this situation, then, must be able to produce, evaluate and modify fuzzy action plans.

Negotiation between agents requires two categories of fuzzy implications. Those used to produce a plan reflect knowledge about decision-making, as the plan is a sequence of actions an agent may take. These implications are mappings from the state and auxiliary variables to the actions. Whilst, because an agent is committed to a task which associates to a part of a system, called a sub system, fuzzy implications used to evaluate an action plan should describe the behaviours of the sub-system. They are mappings from the actions and the auxiliary variables to the state variables of the sub-system. The fuzzy implications regarding decision-making are difficult to acquire. As a fuzzy system in general is the mimic of an existing system, the fuzzy implications regarding decision-making have to be developed based upon a successful decision-making mechanism. This requires the existence of such a successful mechanism in the first place. The fuzzy mappings will not be able to construct when the successful mechanism is not available.

To revise a fuzzy action plan, an agent must possess the ability to perform constrained optimisation in a fuzzy domain where both the cost function and constraints are fuzzy. The fuzzy constrained optimisation aims to find an intersection between the cost function and the constraints (Bellman and Zadeh, 1970; Wang, 1983; Zimmermann, 1990). The intersection is then used to modify the action plan. In the case where the intersection cannot be found, a new method is required for the purpose of reversing.

In this paper, an approach of producing a fuzzy action plan was presented. This approach applies *fuzzy backward reasoning* to the fuzzy implications that describe the behaviours of a sub-system. Hence, it avoids the problem of the lack of decision-making knowledge. A method of revising an action plan for the situation where an intersection cannot be found was also proposed in the paper.

This paper is organised in the following way. Section 2 defines the collaborative agents, including variables reflecting its state, functions being able to provide and knowledge which sustains the functions. Section 3 introduces the concept of fuzzy backward reasoning and its usage to the negotiation between the collaborative agents. Section 4 discusses the negotiation process. Section 5 shows the construction of a collaborative agent system for controlling liquid levels in a three-tank system and discusses experimental results.

2 Model of fuzzy collaborative agents

A collaborative agent is self-interest, has its own commitment and is able to negotiate with other agents. The negotiation procedure contains generating action plans, evaluating and revising these plans and finally forming a plan that is acceptable by all involved agents.

Definition 1:
An action plan $\mathbf{u}_i = [(u_i^1, u_i^2, \Lambda\ , u_i^n), (\mathbf{x}_i^1, \mathbf{x}_i^2, \Lambda\ \mathbf{x}_i^n)]$ consists of a sequence of actions an agent A_i may take as well as its effects on auxiliary variables, where u_i^j stands for the j^{th} action in the sequence of actions and $\mathbf{x}_i^j$ is a set of auxiliary variables influenced by u_i^j.

There is normally a time constraint t associated with a task, in which an agent must complete the task. That is the corresponding sub-system should immediately enter into its steady-state after t. This time constraint applies a limitation onto the length of an action plan. Let T be the period of time when an action is applied to the sub-system and feedback is obtained from it. The length of the action plan n should satisfy $n \le t / T$.

Definition 2:
A plan **U** is the conjunction of revised action plans.

Actions and their effects on auxiliary variables form two subsets of an action plan, whilst $\mathbf{u}_i$ (i = 1, 2, Λ) are themselves the subsets of the plan **U**. The subsets of actions of different action plans may have intersection if two or more agents share the same facility to fulfil their commitments. The subsets of effects may also have intersections.

Definition 3:
A fuzzy collaborative agent A is a triple $A = \{\mathbf{V}_A, \mathbf{F}_A, K_A\}$, where $\mathbf{V}_A$ is a set of variables, $\mathbf{F}_A$ is a set of functions and K_A stands for local knowledge.

The model of a collaborative is shown in Fig. 1. In $\mathbf{V}_A$, there are two types of variables, namely *state variables* and *auxiliary variables*. The former is the state of the task an agent is committed to. These variables reflect the extent to which the agent pursues its commitment. The agent will make an action plan according to the values of these variables. The latter represents environment that surrounds the agent. Changes in the environment may be caused by disturbances and by other agents when they take actions for their own commitments. The environment changes may have a potential influence on the state of the task the agent committed to. As the collaborative agent is self-interest, it must be able to perceive the environment changes and make decision on whether or not to response to the environment changes. The auxiliary variables enable an agent to capture these changes.

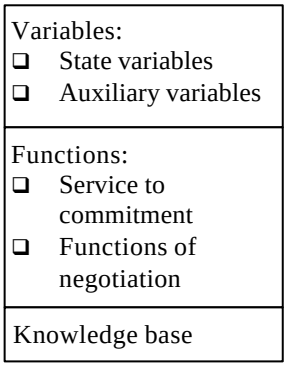


Fig. 1. Model of a collaborative agent

$\mathbf{F}_A$ contains functions of making an action plan $\mathbf{u}_i$, evaluating action plans received from other agents and revising its own action plan. These functions are supported by the local knowledge K_A stored in the agent. As K_A is formed with a set of fuzzy implications, various fuzzy reasoning methods are used to implement these functions.

Local knowledge K_A within an agent is actually a fuzzy local model that describes the dynamics of a sub-system of a complex system. A system usually contains measured variables, manipulated variables and external disturbances. The measured variables reflect the state and the output of the system. The manipulated variables are the inputs of the system. Giving values to the inputs, the system responses to the stimuli according to its dynamics. The input-output relationship represents the dynamics of

the system. A local model is the mathematical description of this relationship of a sub-system. A local fuzzy model is employed when uncertainty exists in the dynamics of a sub-system. In a fuzzy model, the values of input and out variables are fuzzy sets and the relationship is represented using a collection of fuzzy implications. The local fuzzy model also contains fuzzy implications representing changes on the auxiliary variables because of the stimuli.

3 Action plan generation and evaluation using fuzzy reasoning

3.1 Fuzzy reasoning

Fuzzy reasoning is performed based on fuzzy implications either to find a logical consequence for a given condition or to deduce a sufficient condition for a specified conclusion, called a given goal.

Definition 4:
Giving a fuzzy implication "if x is A then y is B" and a condition "x is A'", the procedure of searching for a logical consequence of the given condition is called fuzzy forward reasoning. That is

$$\begin{array}{ll} premise\,1: & x \text{ is } A' \\ \underline{premise\,2:} & \underline{\text{if } x \text{ is } A \text{ then } y \text{ is } B} \\ consequence: & y \text{ is } B' \end{array} \tag{1}$$

The performance of fuzzy forward reasoning is straightforward because the fuzzy implication implies that "y is B" is a necessary condition of "x is A". The most commonly used method is the composition rule of inference.

Definition 5:
Giving a fuzzy implication "if x is A then y is B" and a goal "y is B'", the procedure of searching for a sufficient condition that will logically lead to the given goal is called fuzzy backward reasoning. That is

$$\begin{array}{ll} premise\,1: & y \text{ is } B' \\ \underline{premise\,2:} & \underline{\text{if } x \text{ is } A \text{ then } y \text{ is } B} \\ consequence: & x \text{ is } A' \end{array} \tag{2}$$

Performing fuzzy backward reasoning involves solving a fuzzy relational equation. This will give all sufficient conditions for the given goal (Pham and Li, 2001). The fuzzy relational equation is formed with fuzzy implications, the given goal and unknown variables and has the following form

$$X \circ R = Y_d \tag{3}$$

where X stands for a set of unknown sufficient conditions, R is a collection of fuzzy implications and Y_d is the given goal.

3.2 Action plan making using fuzzy backward reasoning

As being formed with a set of fuzzy implications, a local fuzzy model can be represented as the following:

$$\begin{cases} R_1 : \{U, X\} \rightarrow Y \\ R_2 : U \rightarrow X \end{cases} \tag{4}$$

where U stands for manipulated variables, X is a group of auxiliary variables and Y is a group of state variables. R_1 describes the dynamics of the sub-system and R_2 represents the effects that U applies on X.

Formula (4) is equivalent to the following fuzzy relational equations

$$\{U, X\} \circ R_1 = Y \tag{5a}$$

$$U \circ R_2 = X \tag{5b}$$

That an agent is committed to a sub-system means that the agent must achieve a desired output of the sub-system. When this value, denoted y_d is given and is represented as fuzzy sets Y_d, Equation (5a) becomes $\{U, X\} \circ R_1 = Y_d$. Fuzzy backward reasoning can then be applied to it and action U can be deduced. By substituting U into Equation (5b), the effects of this action on X will then be obtained.

Note that U satisfies Y_d in fuzzy domain does not necessarily mean that u, U's counterpart in a non-fuzzy domain, can satisfy y_d. The reason of this is the physical constraints on the action in the non-fuzzy domain. In fuzzy domain, an extreme fuzzy set has an extreme linguistic meaning, e.g. "very big". A non-zero value of this extreme fuzzy set logically means an extreme action is required. However, the non-fuzzy value of this logical extreme action is limited by what can be achieved physically when this action is converted to the non-fuzzy domain. Thus, although an extreme non-fuzzy value is obtained through the conversion, it might be not as extreme as specified.

This leads to the fact that y_d cannot be achieved in one go. The above procedure of producing an action and its effects on auxiliary variables X needs to be repeated several times until y_d is achieved. The iteration will produce a sequence of actions and their effects on X. An action plan is therefore formed.

3.3 Action plan evaluating using fuzzy forward reasoning

When an agent A_j perceives the change in environment caused by the actions of agent A_i ($i \neq j$), it will ask for the action plan of A_i and then examines the influences of these actions and of the environmental changes on its own commitment. If the influence is negative, it will make its own action plan $\mathbf{u}_j$ aiming to reduce the influences. This action plan will then be sent to the agent A_i for its evaluation.

In both agent A_i and agent A_j, the evaluation is carried out using fuzzy forward reasoning. In the case where these two agents share the same facility to fulfil their

commitments, both the subset of actions and that of effects in an action plan will substitute into Equation (5a). In the case where they do not share the same facility, only the subset of effects will be used in Equation (5a). When fuzzy forward reasoning is performed, Equation (5a) yields a sequence of Y', the sub-system's output. If this sequence of output is far from the one generated by its own action plan, the action plan received from the other agent is unacceptable.

4 Negotiation

4.1 Profit function

In the case where agents A_i and A_j ($i \neq j$) apply actions to the same facility, if the intersection of the actions can be found, the intersections can be taken as a plan and global optimisation will be achieved. In the case where the intersections do not exist, a new method is needed for the purpose of global optimisation.

Definition 6:
A profit function of an agent is the inverse proportional to the abstract error between the desired output and actual output of a sub-system to which the agent is committed in a certain period of time. That is

$$p = \frac{1}{1+|\frac{y_d - y}{y_d}|} \tag{6}$$

When $y = y_d$ within the certain period of time, $p = 1$, otherwise p takes a value between 0 and 1.

As mentioned in section 3, there is a time constraint t associated to a task and an agent should be able to complete the task within t. This is the commitment of this agent. The more the agent fulfils its commitment, the much profit it gains. When the agent makes the task complete within τ, it gains its maximum profit. The error $|y_d - y|$ at the end of period of t quantitatively indicates the degree to which the task is completed, or equivalently the extent to which the agent fulfils its commitment. If the system is still far away from its desired state at the end of t, the error is large, which means the completeness of the commitment is poor. One the other hand, if the system is very close to its desired state, the error will be very small, which shows that the agent fulfils its commitment very well.

4.2 Negotiation process

A negotiation process involves generating, evaluating and modifying action plans. An agent will generate its action plan according to the task to which it is committed. It will ask for and evaluate action plans from other agents if it perceives environmental changes. The agent will modify its action plan for compromise. The negotiation process between the collaborative agents is illustrated in Fig. 2.

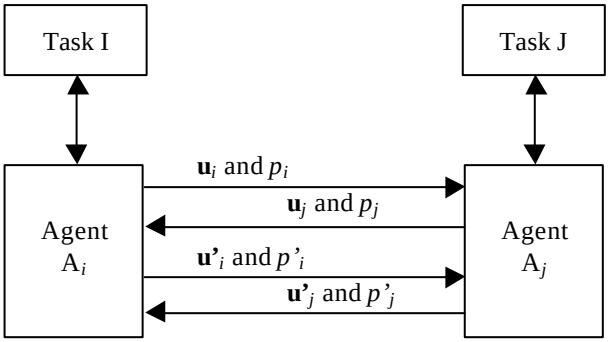


Fig. 2. Negotiation between collaborative agents

Agent A_i and agent A_j commit to Task I and Task J, respectively. A_i perceives the states of the sub-system Task I associates and generates an action plan, $\mathbf{u}_i$, for the task. Then, A_i calculates p_i that is the profit according to $\mathbf{u}_i$. At the same time, it applies the first action of the action plan to the sub-system, which causes the change in auxiliary variables. When A_j perceives the change, it will ask for the action plan from A_i and calculate profit p_j. If p_j is not satisfactory, A_j generates its own action plan $\mathbf{u}_j$, calculates $p_j^{'}$ and then sends it to A_i where the evaluation of $\mathbf{u}_j$ will take place. A_i calculates profit $p_i^{'}$. If the condition

$$p_i^{'} + p_j^{'} > p_i + p_j \tag{7}$$

holds true, $\mathbf{u}_j$ is accepted, otherwise, $\mathbf{u}_i$ will be revised and sent to A_j for evaluation. This process will be carried out iteratively until the revised $\mathbf{u}_i^{'}$ and $\mathbf{u}_j^{'}$ that hold Equation (7) are found.

4.3 Calculation of profit

An agent calculates its profit according to the profit function (Equation (6)) using its own action plan $\mathbf{u}_i$. In this situation, all u_is and $\mathbf{x}_i$s in the action plan are substituted into Equation (5a) to deduce a sequence of y which are used in Equation (6) to compute profit p. When evaluating an action plan of the other agent, It calculates the profit based on the action plan $\mathbf{u}_j$ received from another agent when evaluating the plan. If these two agents share the same facility for their commitments, both u_js and $\mathbf{x}_j$s are used, otherwise only $\mathbf{x}_i$s are taken into account.

4.4 Modification of action plan

The action plan that one agent, A_i, received from another agent, A_j, contains a sequence of values of auxiliary variables. These values should be used as constraints when A_i modifies the action plan proposed by itself. Local knowledge and fuzzy backward reasoning are once again used for this purpose. The values of the auxiliary variables will be substituted into Equation (5a) such as

$$\{U', X_j\} \circ R_1 = Y_{dj} \tag{8}$$

where, X_j takes the values x_j from the received action plan and U' stands for the new action in fuzzy domain. When fuzzy backward reasoning is performed, U' can be deduced. The non-fuzzy counterpart of U' is a sequence of new actions $(u_i^{1'}, u_i^{2'}, \Lambda, u_i^{n'})$. If the new actions exist, the sequence of actions will be replaced by the sequence of new actions and a revised plan forms as the following:

$$\mathbf{u}_i' = \{(u_i^{1'}, \Lambda, u_i^{n'}), (x_j^1, \Lambda, x_j^n)\} \tag{9}$$

If, for some reasons, new actions for some of x_j cannot be found, the original actions will be retained in the action plan. Suppose $u_i^{m'}$ is not exist, u_i^m will be retained and the revised plan will be in the form shown below:

$$\mathbf{u}_i' = \{(u_i^{1'}, \Lambda, u_i^{m'}, u_i^{m+1'}, \Lambda, u_i^{n'}), (x_j^1, \Lambda, x_i^m, x_j^{m+1}, \Lambda, x_j^n)\} \tag{10}$$

5 Control of a three-tank system using collaborative agents

5.1 Three-tank system

A three-tank plant is illustrated in Fig. 3. Three tanks, namely Tank-I, Tank-III and Tank-II from left to right, are installed on the top of a reservoir that is used to store liquid. The three tanks have the same cross section area and are coupled with connection pipes. Liquid levels in these tanks are regulated through manipulating the inlet flowrates. There are two inlets in this plant. One goes to Tank-I, and the other to Tank-II. Two pumps, P_1 and P_2, pump liquid into Tank-I and Tank-II with flowrates q_1 and q_2, respectively. Liquid in these two tanks can enter into Tank-III through connection pipes. The flowrates of the connection pipes are manipulated using ball valves V_1 and V_3. The plant has one outlet pipe located at the bottom of Tank-II. Ball valve V_2 is installed on the outlet pipe to control the outlet flowrate. It can only be manipulated manually. There are three other pipes installed at the bottom of each tank, with ball valves V_4, V_5 and V_6, respectively, to simulate disturbances. Three pressure sensors are used to measure liquid levels in the three tanks.

Global optimisation in this three-tank system is to find a sequence of optimal values of q_1 and q_2 that will drive h_1 and h_2 to their desired values hd1 and h_{d2}, respectively. As the tanks are coupled together, q_1 does not only change h_1 but also h_3, which adds an influence onto h_2. q_2 has the similar influence. The determination of q_1 and that of q_2, therefore, tangle together. Suppose that the complete and precise global knowledge such that

$$(\dot{h}_1, \dot{h}_2) = f(h_1, h_2, h_3, q_1, q_2) \tag{11}$$

is not available, the optimisation has to perform based on local knowledge.

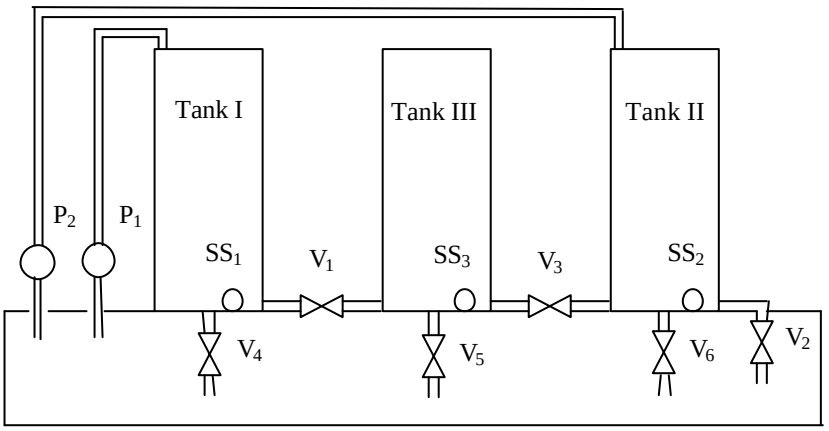


Fig. 3. A three-tank system

5.2 Collaborative agents

The global optimisation consists of two tasks. One is to decide a sequence of q_1 and the other to decide a sequence of q_2. Two agents, A_1 and A_2, are developed, each of which is committed to one of these tasks. These two agents have an identical structure. Agent A_i (i = 1, 2) has four variables, namely q_i, h_i, $\dot{h}_i$, and h_3. q_i is an action the agent will take, h_i and $\dot{h}_i$ represent the state of a task and h_3 is the auxiliary variable from which an agent can perceive the action taken by the other.

Agent A_i possesses local knowledge about the way of an action and changes in h_3 influencing $\dot{h}_i$ when h_i is in certain levels and about that of q_i altering h_3. This knowledge is imprecise and therefore is represented using fuzzy implications in the following form:

$$(Q_i, H_i, H_3) \rightarrow \dot{H}_i \tag{12a}$$

$$H_i \rightarrow H_3 \tag{12b}$$

where $Q_i, H_i, \dot{H}_i, H_3$ are the counterparts of $q_i, h_i, \dot{h}_i, h_3$ in fuzzy domain.

The agents have the capability of performing fuzzy forward reasoning and fuzzy backward reasoning and that of communicating to one another.

5.3 Negotiation

A typical situation where the two agents must collaborate is that A_1 lifts h_1 up to a new height hd1 ($h_{d1} > h_2$) (task 1) and meanwhile A_2 keeps h_2 at its original height (task 2). In this situation, when A_1 takes actions to fulfil task 1, h_3 increases as well. This will make h_2 go up. To prevent h_2 from being affected, A_2 has to act. In turn,

A_2's action may influence h_1 in the similar way. Therefore, the collaboration between A_1 and A_2 is required.

Simulation started from an initial condition where h_1 and h_2 are at their steady states, $h_1 = h_2 = 200$ (mm). When a new height for h_1, $h_{d1} = 300$ (mm) was set, A_1 made its action plan $\mathbf{u}_i$, as shown in below:

$$\mathbf{u}_1 = \{(15.0 \quad 15.0 \quad 15.0 \quad 5.4 \quad 4.5 \quad 3.7 \quad 2.9 \quad 2.1 \quad 1.3 \quad 0.3),$$
$$(198 \quad 210 \quad 227 \quad 245 \quad 260 \quad 274 \quad 284 \quad 292 \quad 297 \quad 299)\}$$

with a profit p = 1.00. A_1 took the first action immediately. As this affected h_2, A_2 joined the collaboration by starting negotiation with A_1. The negotiation process evolves.

- A_2 evaluated $\mathbf{u}_1$ by substituting the second part of $\mathbf{u}_1$ into its own fuzzy model and performing fuzzy forward reasoning. The profit with $\mathbf{u}_1$ is p_2 = 0.92.
- Having tried to increase its profit, A_2 made its own action plan $\mathbf{u}_2$ such that

  $$\mathbf{u}_2 = \{(5.7 \quad 2.6 \quad 1.3 \quad 0.3 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0),$$
  $$(198 \quad 210 \quad 227 \quad 245 \quad 250 \quad 250 \quad 250 \quad 250 \quad 250 \quad 250)\}$$

  by performing fuzzy backward reasoning as h_2 would be affected by $\mathbf{u}_1$. The profit increases to $p_2' = 1.00$.
- A_1 modified $\mathbf{u}_1$ through constrained optimisation by taking into account of the second part of $\mathbf{u}_2$. The revised action plan is shown in below:

  $$\mathbf{u}_1' = \{(15.0 \quad 9.0 \quad 5.1 \quad 4.0 \quad 2.9 \quad 2.5 \quad 2.1 \quad 1.3 \quad 0.3 \quad 0.3),$$
  $$(198 \quad 210 \quad 227 \quad 245 \quad 250 \quad 250 \quad 250 \quad 250 \quad 250 \quad 250)\}$$

  with the profit $p_1' = 1.00$. As $p_1' + p_2' > p_1 + p_2$, the negotiation stopped.

5.4 Discussion

The action plan $\mathbf{u}_1$ is able to raise h_1 to its new desired height h_{d1} = 300 (mm). However, when it was made, its influence to h_2 was not taken into account. As the increase of h_1 can make h_2 deviate from its desired height, A_2 had to make its action plan $\mathbf{u}_2$ in which h_3 was eliminated below 250 (mm). To keep $h_3 \leq 250$ (mm), $\mathbf{u}_1$ was revised. When A_1 modified $\mathbf{u}1$, h_3 was assumed taking a height above 250 (mm) to reduce q_1. Though h_1 would take longer time to reach hd_1, h_2 was not affected because the actual value of h_3 did not exceed 250 (mm).

6 Conclusion

A collaborative fuzzy agent was proposed in this paper for the purpose of performing global optimisation with incomplete and ambiguous knowledge. The agent has local knowledge which is a fuzzy model describing the behaviour of a sub-system. It generates and modifies action plans through, in particular, fuzzy backward reasoning. A profit function was presented as a criterion for promoting the negotiation between two agents. A multi-agent system developed for a three-tank system illustrated the effectiveness of the proposed approach.

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