Water Resources Systems Operations via Multiagent Negotiation

(Extended Abstract)

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ABSTRACT

The operations of water resources infrastructures, like dams and diversions, often involve multiple conflicting interests and stakeholders. Agent-based approaches have recently attracted an increasing attention to design optimal operating policies for these systems. In this paper we contribute a general monotonic concession negotiation protocol that allows the stakeholders-agents of a regulated lake to reach agreements on the amount of water to release daily, balancing control of lake floods and water supply to agricultural districts downstream.

Keywords

Water resources systems; Negotiation

1. INTRODUCTION

Agent-based approaches have been recently proposed to represent the variety of stakeholders and decision makers in the operations of water resources infrastructures. To better capture the conflicting nature of the stakeholders' interactions, few works have attempted to model such interactions as negotiations [1, 6]. Yet, they introduce strong and somehow unrealistic assumptions, like the necessity for each agent to know the preferences of all other agents.

In this paper, we propose to use a general *monotonic concession negotiation* framework that allows the stakeholders-agents of a regulated lake to periodically reach agreements on the lake operating policy that determines the amount of water to release daily. The agreements mimic the outcomes of the decision-making process of the lake regulator, who has to balance different goals. In our approach, a mediator coordinates the negotiation process, without the need for agents (including the mediator) to know all their preferences.

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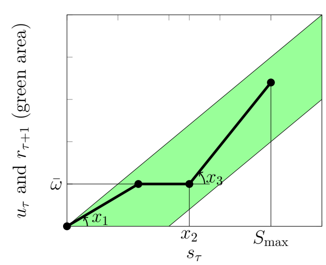

Figure 1: The control law and the feasible regulation region.

2. THE CASE STUDY

We consider a realistic test case inspired by a real world context, the Lake Como system, in Northern Italy, which is a regulated lake dammed on the outlet. The lake dam is operated to supply water downstream mostly for irrigation and to control floods on the lake shores.

The dam is operated with a control law $\pi()$ mapping the lake storage s_τ (expressed in m^3) at day τ into the release decision u_τ (expressed in m^3/day): $u_\tau = \pi(s_\tau)$. When actuated, u_τ produces the actual release $r_{\tau+1}$ (expressed in m^3/day) according to the physical constraints over the actuation (see green area in Fig. 1). As a control law $\pi()$, we consider the piecewise linear function of Fig. 1, known as the Standard Operating Policy, which depends on three parameters: x_1, x_2, and x_3. Note that $\bar{\omega}$ is the (constant) water request for irrigation and $S_{\max}$ is the maximum storage the lake can reach.

We consider the conflicting interests of the lake regulator that operates the dam as two agents. The *city agent* represents the communities living on the lake shores, who are worried about floods that happen when the water level is above a given threshold. The *irr agent* represents the farmers in the downstream irrigation districts that need $\bar{\omega}$ water supply to grow their crops. Different agents have different preferences on the values of the parameters x_1, x_2, and x_3 of the release policy. While the city agent prefers to maximize the release at every water level, the irr agent wants the release to satisfy the fixed demand and to not waste water that can be used in the future. Hence, values of x_1, x_2, and x_3 are the issues that are negotiated with the protocols illustrated below.

3. THE NEGOTIATION PROTOCOLS

We assume n agents that negotiate over m variables that can take real values (in our application, $n = 2$ and $m = 3$). An agent i makes its best proposal (that maximizes its utility function $\mathcal{U}_i : \mathbb{R}^m \mapsto \mathbb{R}$)[1] p_i^0 at the first negotiation step $t = 0$. It then proposes $p_i^{t+1} = \mathcal{F}_i(p_i^t, a^t)$ at later steps according to its strategy function that takes into account the counter-proposal a^t of mediator at step t. The mediator receives the proposals of the agents, calculates the counter-proposal according to its agreement function $a^t = \mathcal{A}(\{p_1^t, p_2^t, \ldots, p_n^t\})$, and sends it to the agents. The negotiation process can terminate with an agreement over the values of the m variables or with a *conflict deal*.

The first protocol is called *point-based*, has been originally presented in [2], and considers proposals as vectors of m elements: $p_i^t = [x_1, x_2, \ldots, x_m] \in \mathbb{R}^m$, with the meaning that p_i^t contains the values that agent i would like to assign to the m variables at step t (in our application, a proposal is the release policy that agent i would like to adopt). The strategy function of agent i is:

$$p_i^{t+1} = \mathcal{F}_i(p_i^t, a^t) = p_i^t + \alpha_i \cdot (a^t - p_i^t)$$

where $\alpha_i \in (0, 1]$ is called *concession coefficient* and represents the rigidity of agent i to move toward the counter-proposal received from the mediator. The agreement function $\mathcal{A}(\{p_1^t, p_2^t, \ldots, p_n^t\})$ averages the proposals p_i^t of the n agents and, in a way, expresses the aggregated preferences of all agents. If, at some t, all p_i^t are equal to the same value $\bar{p}$, then the final agreement is reached.

The second protocol is called *set-based* and has been originally introduced in [4]. Let call $\mathcal{P}_i(\Gamma_i^t) = \{x \in \mathbb{R}^m \mid \mathcal{U}_i(x) \geq \Gamma_i^t\}$ the set of proposals that agent i accepts given an *acceptability threshold* Γ_i^t. Namely, $\mathcal{P}_i(\Gamma_i^t)$ contains all the combinations of values for the m variables that give agent i an utility that is at least Γ_i^t. In the set-based protocol the proposals are defined as: $p_i^t = \mathcal{P}_i(\Gamma_i^t)$, namely agent i, at each step t of the negotiation, proposes the set of *all* the combinations of values for the m variables that it can accept (in our application, a proposal is the set of release policies that agent i can adopt). The strategy function of agent i updates the acceptability threshold Γ_i^t in order to concede, namely in order to have $\Gamma_i^{t+1} < \Gamma_i^t$, for example: $\Gamma_i^{t+1} = \Gamma_i^t - c_i$, where $c_i > 0$ is called *concession step*. The agreement function $\mathcal{A}(\{p_1^t, p_2^t, \ldots, p_n^t\})$ used by the mediator is:

$$a^t = \bigcap_{i=1}^{n} p_i^t = \bigcap_{i=1}^{n} \mathcal{P}_i(\Gamma_i^t)$$

If, at some step t, $a^t \neq \emptyset$, then an agreement is found.

[1] Note that the negotiation protocols are presented referring to utility functions $\mathcal{U}_i$ for uniformity with relevant literature, but in our application we consider cost functions. The two representations are trivially related.

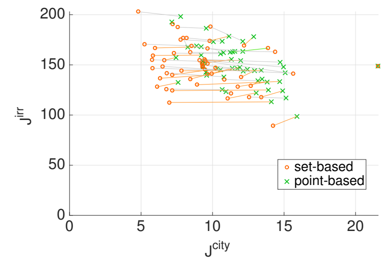

Figure 2: Actual costs incurred by the agents.

4. SIMULATIONS

We have implemented the two protocols in MATLAB. We assume a linear relation between inflow q_τ and water storage: $s_{\tau+1} = s_\tau + q_{\tau+1} - r_{\tau+1}$. Values for q_τ are stochastically generated from a normal distribution $q_\tau \sim N(\mu_q, \sigma_q)$ with $\mu_q = 40$ m^3/day and $\sigma_q = 10$ m^3/day. We generate time series of $5,000$ samples (one sample per day) and divide them in blocks $B_1, B_2, \ldots, B_j, \ldots$ of $b = 90$ days each. A negotiation is performed every b days. Cost functions of the city and irr agents are derived from [3, 5]. For the negotiation relative to block B_{j+1}, the cost functions of agents are calculated by considering the cost incurred by the agents over block B_j.

We report experiments showing that the set-based protocol consistently produces Pareto optimal agreements, which are not reached in many cases when using the point-based protocol. Fig. 2 shows the *actual* costs incurred by the two agents for the policies corresponding to the agreements found over all the blocks with the point-based (green) and the set-based (orange) protocols. Agreements relative to the same block are connected with a line segment that is orange if the policy found by the set-based protocol dominates that found by the point-based protocol, green if the opposite happens, and grey if the the two policies are not dominated.

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