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Distributed constraint optimization for addressing vessel rotation planning problems

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ABSTRACT

A distributed constraint optimization problem (DCOP) is a description of constraint optimization problem where variables and constraints are distributed among a group of agents, and where each agent can only interact with agents that share constraints. Even though DCOPs have been studied since the 1990s, there are only a few attempts to address real world problems using this formalism, mainly because of the complexity of the solution algorithms. In this paper, we compare 4 state-of-the-art DCOP approaches to solve the vessel rotation planning problem (VRPP), which concerns deciding on the optimal sequence of vessel visits to different terminals in a large seaport. We hereby also consider two agent structures: a single layer and a multi-layer structure. For each of the structures, we compare the four different algorithms for solving DCOPs, aiming at studying how the algorithms perform in VRPPs of increasing sizes. We assess the methods based on the size and quantity of messages exchanged, computation time, and quality of solutions.

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1. Introduction

The distributed constraint optimization problem (DCOP) is a theoretical model framework representing several agents that jointly have to make decisions on values of variables so as to minimize the sum of constraint costs, or to maximize the sum of utility values (Weiss, 2013). A DCOP is defined as consisting of a set of agents, variables and constraints between variables that reflect the costs/utilities of assignments to variables. Control of values of variables in DCOPs is distributed, with agents only able to assign values to variables that they hold. Furthermore, agents are assumed to know only the constraints involving variables that they hold. In order to find a solution to a DCOP, agents need to communicate with each other through message exchange. It is commonly assumed that agents can only communicate with agents that hold variables constrained with their own variables. These agents with which an agent can communicate are called their neighbors (Modi et al., 2005; Pearce and Tambe, 2007). The DCOP formalism has been mainly applied in meeting scheduling (Maheswaran et al., 2004; Petcu and Faltings, 2005; Greenstadt et al., 2007), coordination of sensors in networks (Hosseini et al., 2013; Zivan et al., 2009; Lesser et al., 2003), resource allocation in disaster evacuation (Lass et al., 2008; Carpenter et al., 2007), synchronization of traffic lights (Junges and Bazzan, 2008), and management of power distribution networks (Kumar et al., 2009). Distributed constraint optimization is well suited for formulating those problems since they are distributed by nature.

A vessel rotation is the sequence in which a vessel visits different terminals in a large port. The vessel rotation planning problem (VRPP) concerns the problem of assigning rotations to a number of vessels. The decision makers involved are vessel operators and terminal operators. Vessel operators are responsible for the voyage plan of vessels and for coordinating inland shipping activities, while terminal operators are responsible for the transshipment of containers between deep sea vessels, trains, trucks, and inland vessels as well as the temporary storage of containers. An example of terminals in the port of Rotterdam is presented in Fig. 1. As we can see, there are several clusters of terminals in a port. Each vessel considered will unload or load containers at different terminals. On a typical day, around 25 inland vessels visit the port of Rotterdam, with each vessel visiting on average 8 different container terminals (Moonen et al., 2007).

Nowadays, vessel operators and terminal operators communicate with each other through telephone, fax and e-mail for making appointments. Vessel operators each have their own preferences regarding when to visit particular terminals. However, in practice, the appointments made often cannot be met (Melis et al., 2003). In the port of Rotterdam, the average rotation time for an

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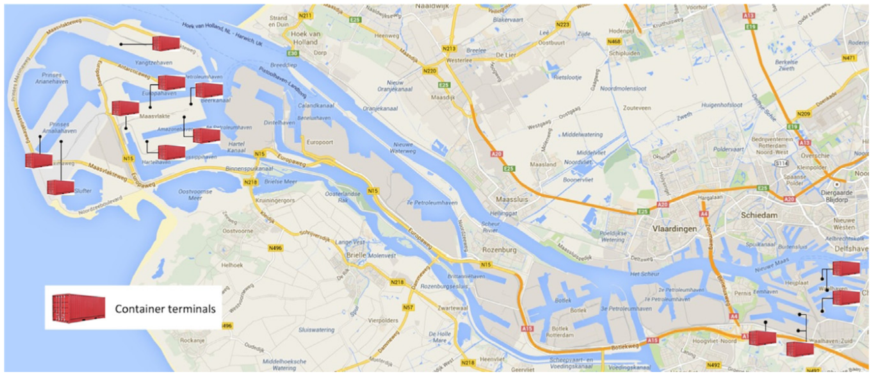

Fig. 1. Container terminals in Port of Rotterdam (adapted from Port of Rotterdam Authority, 2011).

inland vessel is approximately 22.5 h, of which only 7.5 h are used for loading and unloading, the rest of the time vessels are waiting and traveling (Moonen et al., 2007). Typically, vessels need to visit multiple terminals, which creates dependencies between the activities performed at the terminals. This means that a disturbance at one terminal can lead to the interruption of the operations of a vessel and terminal operators elsewhere. This makes it very difficult for vessel operators to stick to the appointments made with terminal operators. Vessel operators therefore will have longer waiting times at terminals, and terminals have to cope with uncertain arrival times of vessels and underutilization of capacity than desired (Douma, 2008).

In recent years, there have been several attempts at better aligning of vessel and terminal operations. In Schut et al. (2004), a multi-agent based planning system named APPROACH is introduced. In APPROACH, vessel operator and terminal operator align their operations once a day, at a fixed time, for the next 24 h. To determine a rotation, vessel operator agents can ask terminal operator agents repeatedly whether certain time slots are convenient, and terminal operator agents reply with yes or no. It is an intuitive and rather straightforward way to obtain agreement. However, the outcomes of the approach sometimes contain routes considered unlogical and with longer sailing times than needed (Moonen et al., 2007). In Douma et al. (2009) the same type of agents is used as in APPROACH, but with different interaction protocols and agent structures. The authors aim at improving the performance of the multi-agent systems by considering design choices that could influence the acceptance of the end users and the extent to which users can optimize their operations in Douma et al. (2012). In particular, a simulation game was developed to communicate and help future users get a clear picture of what the solution is about. However, this work does not apply any optimization algorithms, so the solutions obtained, though more efficient, are not guaranteed to be optimal solutions.

The fact that there is no automated way to generate rotation plans for vessels leads to significant and uncertain waiting times of vessels at terminals and causes idle time for terminal quay resources. Although inland vessel transportation is an attractive transportation mode, it is currently not used to its full potential. The problem considered in this paper consists of finding in an automated way an optimal solution to a VRPP using distributed constraint optimization. We proposed an initial approach for solving the VRPP with DCOP in Li et al. (2014). In that paper, the vessel operators are modeled as a single layer of agents in the DCOP framework. The agents have to communicate and negotiate with each other to get optimal solutions. However, the problem size that could be handled by the DCOP model and proposed algorithms was too limited. The contribution of this paper is in proposing a new multi-layer control architecture and assessment of a number of state-of-the-art DCOP solution methods. This will lead to a significant improvement over the approach proposed before.

This paper is organized as follows. In Section 2, the definitions for DCOP are given. Section 3 introduces the VRPP formally and proposes reduce computational complexity of the VRPP at a system structure level. For DCOP algorithms to solve the VRPPs are introduced in Section 4. Section 5 presents the experimental results of the four algorithms, used in either a single or multi-layer setting, with respect to solution quality, communication load and computation time. Conclusions and future work are given in Section 6.

2. DCOP background

In this section, we first introduce the general definition and framework of distributed constraint optimization. We adopt the DCOP formalism as defined in Petcu (2009). A DCOP is represented by a triple $\langle \mathcal{A}, \mathcal{COP}, \mathcal{R}^{\text{ia}} \rangle$, where:

- $\mathcal{A} = \{A_1, \dots, A_N\}$ is a set of N agents;
- $\mathcal{COP} = \{COP_1, \dots, COP_N\}$ is a set of disjoint, local Constraint Optimization Problems (COPs); COP_i is called the local subproblem of agent A_i; COP_i is defined by a triple $\langle \mathcal{X}_i, \mathcal{D}_i, \mathcal{R}_i \rangle$, where $\mathcal{X}_i = \{X_{i1}, \dots, X_{i|\mathcal{X}_i|}\}$ is a set of $|\mathcal{X}_i|$ variables that belong to A_i; $\mathcal{D}_i = \{d_{i1}, \dots, d_{i|\mathcal{X}_i|}\}$ is a set of finite variable domains of the variables in $\mathcal{X}_i$; $\mathcal{R}_i = \{r_{i1}, \dots, r_{i|\mathcal{R}_i|}\}$ is a set of $|\mathcal{R}_i|$ utility functions, where each utility function $r_{i|\mathcal{R}_i|}$ is with scope $\mathcal{X}_i$, $r_{i|\mathcal{R}_i|} : d_{i1} \times \dots \times d_{i|\mathcal{X}_i|} \rightarrow \mathbb{R} \cup \{-\infty\}$. The utility functions are used to represent objectives, as well as both hard and soft constraints. For hard constraints, the value of the utility function is 0 if the constraint is satisfied; otherwise the value is $-\infty$. For soft constraints, for different combinations of the values for variables, different values will be assigned to the utility functions.
- $\mathcal{R}^{\text{ia}} = \{r_1^{\text{ia}}, \dots, r_{|\mathcal{R}^{ia}|}^{\text{ia}}\}$ is a set of so-called inter-agent utility functions defined over variables of multiple agents. Each $r_l^{\text{ia}} : scope(r_l^{\text{ia}}) \rightarrow \mathbb{R}$ expresses the utility for a joint decision obtained by the agents that have variables involved in r_l^{ia}. The agents that have variables can decide on the values of these variables involved in r_l^{ia} and are called "responsible" for r_l^{ia}. Inter-agent utility functions are considered known to all agents involved, i.e, those agents of which the local variables are part of the inter-agent utility function.

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