Proceedings of the 19th World Congress
The International Federation of Automatic Control
Cape Town, South Africa. August 24-29, 2014

Interactive Multiobjective Optimization for a Grab-Shift Unloader Crane

Johan Sjöberg [⋆,†], **Simon Lindkvist** [⋆], **Jonas Linder** [†], **Jonas Öhr** [‡],

[⋆] *ABB Corporate Research, Sweden*
[†] *Division of Automatic Control, Linköpings University, Sweden*
[‡] *ABB Crane Systems, Sweden*

Abstract: In this paper, multiobjective optimization (MOO) is applied to an optimal control problem for a grab-shift unloader crane. The crane is modeled as a cart-pendulum system with varying rope length and the trajectory of the grab is limited by the ship, the quay, and the crane structure. The objectives to minimize are chosen as time, energy and maximal instantaneous power. The optimal control problem is solved using a direct simultaneous optimal control method. The study shows that MOO can be an efficient tool when choosing a good compromise between conflicting objectives such as time and energy. Furthermore, navigation among the Pareto optimal solutions has proven to be very useful when a user wants to learn how the control variables interact with the process.

Keywords: Optimal Control, Crane control, multiobjective optimization

1. INTRODUCTION

Grab-shift unloader cranes are used to move bulk material from a ship to a hopper at shore. This type of cranes are today normally operated by an operator controlling the motion of the trolley and the grab so that fast and efficient trajectories are obtained. In order to improve the operation even more, the idea in this paper, is to determine the trajectories using optimal control instead. The optimal trajectories and control signals can then be used in many ways to improve the operation, for instance, to teach the operators or to run the crane autonomously. The formulation and solution of optimal control problems for cranes have been studied in several earlier references, see for instance, Al-Garni et al. (1995); Auernig and Troger (1987); Hu and Teo (2004).

It is important that the cost function reflects the desired behavior of the crane since the achieved trajectory and control signals are chosen to make the cost function as good as possible. Often the desired behavior is a compromise between different objectives such as speed, energy efficiency, control utilization etc. The objectives are commonly conflicting which means that depending on how the different objectives are prioritized, different trajectories and control signals will be optimal. Here optimal means that there is no way to improve one objective without deteriorating another (Miettinen, 1999). A solution that satisfies this property is denoted Pareto optimal and the set of all Pareto optimal points is the Pareto set. The image of the Pareto set in the objective space is denoted the Pareto frontier. An optimal control problem with many objectives is denoted a multiobjective optimal control problem.

The multiobjective optimal control problem is in this paper reformulated as a nonlinear program and the result is a multiobjective optimization problem (MOO) which can be written as

$$\begin{aligned} &\underset{\mathbf{x}}{\text{minimize}}\ \{f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})\} \\ &\text{subject to } \mathbf{x} \in X \end{aligned} \tag{1}$$

There are many algorithms to "solve" a MOO. One class is scalarization methods and another is vector optimization methods, see Miettinen (1999). The first class combines the objectives to form scalar objective functions that are solved as single-objective problems to yield one point in the Pareto set at a time. The second class treats the objectives independently and solves the MOO as a vector-valued optimization problem where many points in the Pareto set are obtained at once. In this work, the scalarization approach has been used.

In addition to how the Pareto optimal points are computed, another choice is at which time the decision maker (DM), *i.e.*, the person who decides which solution is "best", makes the decision. In this paper, an interactive method has been chosen where the DM is able to iteratively choose between different Pareto optimal solutions. In this way, the DM can control the search for a final solution depending on how the objective values and design variables vary in the Pareto set. The process of choosing the preferred solution is also often a good way to learn about the optimization problem and the plant. For large-scale problems, such as the optimal control problem for cranes, it can take substantial amount of time to find a single Pareto optimal solution using the scalarization method and an interactive process can then be slow and tedious for the DM. In recent research two-phase methods have been introduced. In these methods, the Pareto frontier is first sparsely sampled and the DM is then able to continuously "navigate" on an approximation of the frontier in real-time, see Eskelinen et al. (2010); Hartikainen et al. (2011); Monz et al. (2008). However, the approaches in these papers either require a convex Pareto frontier to yield good approximations (which is not always the case for industrial processes) or the computation of the approximation can be tedious. In this paper, an approach introduced by Linder et al. (2012) is used instead. By sampling the Pareto frontier in a specific manner and decomposing the set of sampled points into convex sets, it is possible to compute an approximate Pareto frontier fast even for non-convex Pareto frontiers, see Linder et al. (2012) for details.

There are also other papers that have studied MOO applied to optimal control problems for cranes, see for instance, Deb and Gupta (2004), Logist et al. (2010), and Sakawa and Shindo (1982).

The remainder of this paper is organized as follows: In Section 2 the model of the grab-shift unloader crane is presented. Section 3 shows how the MOO problem is stated from the optimal control problem. Section 4 introduces the developed MOO framework with a short description of how it can be used to investigate the Pareto frontier. In Section 5 the framework is applied to the crane optimal control problem. Finally, some conclusions are presented in Section 6.

2. MODELING OF A HARBOR CRANE

2.1 The Trolley and the Grab

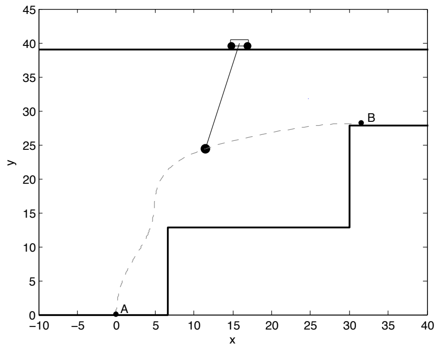

Fig. 1. The crane system including the trolley, the grab and the ship, quay and hopper profile.

In principle, the crane can be described as a cart-pendulum system, see Figure 1. The trolley and the hoist (the drum that controls the rope length) are driven by electric motors and it is assumed that there are inner feedback loops so that the optimal control formulation can use the trolley and the hoist accelerations as control inputs. With these control inputs the model can be written as

$$\dot{p}_t = v_t \tag{2a}$$
$$\dot{v}_t = a_t \tag{2b}$$
$$\dot{l}_r = v_r \tag{2c}$$
$$\dot{v}_r = a_r \tag{2d}$$
$$\dot{\theta} = \omega \tag{2e}$$
$$\dot{\omega} = \frac{1}{l_r}\Big(-2v_r\omega - \cos(\theta)a_t - g\sin(\theta)\Big) \tag{2f}$$

where p_t is the trolley position, v_t is the trolley speed, l_r is the rope length, v_r is the hoist speed (the first derivative of the rope length), θ is the pendulum angle, ω is the pendulum angular velocity, a_t is the trolley acceleration, and a_r is the hoist acceleration (the second derivative of the rope length).

The grab position can be expressed as

$$x_{pl} = p_t + l_r\sin(\theta) \tag{3a}$$
$$y_{pl} = h - l_r\cos(\theta) \tag{3b}$$

where y_{pl} and x_{pl} are the grab position vertically and horizontally, respectively, and h is the height of the crane. The forces on the trolley and in the rope are given by

$$\frac{F_t}{m_l} = \frac{m_l + m_t}{m_l}a_t + l_r\cos(\theta)\dot{\omega}$$
$$+ \sin(\theta)a_r - l_r\omega^2\sin(\theta) + 2v_r\cos(\theta)\omega \tag{4a}$$
$$\frac{F_r}{m_l} = -\sin(\theta)a_t - a_r + l_r\omega^2 + g\cos(\theta) \tag{4b}$$

where F_t is the force acting on the trolley, F_r is the force acting in the rope, m_l is the mass of the load and m_t is the mass of the trolley. Based on (4), the power required by the trolley and hoist motors can be written as

$$\frac{P_t}{m_l} = \frac{F_t}{m_l}v_t, \quad \frac{P_l}{m_l} = \frac{F_r}{m_l}v_r \tag{5}$$

The model described by (2) – (5) has 14 variables. However, in order to improve convergence and speed of the optimizations extra variables and equations are introduced to split complicated expressions into parts. This is denoted lifting and is inspired by Albersmeyer and Diehl (2010). Because of the lifting, the dynamical model used in the optimization has 22 variables. Throughout the paper, these 22 variables except the control signals (a_t and a_r) are concatenated to a vector denoted $x(t)$ while the control signals are concatenated to a vector denoted $u(t)$.

2.2 Obstacles and Limitations

The motion and the control inputs are also subject to limitations. The states and the controls are constrained by simple bound constraints

$$-10 \le p_t \le 50$$
$$-4.33 \le v_t \le 4.33$$
$$0 \le l_r \le 60$$
$$-2.33 \le v_r \le 3.17$$
$$-\frac{\pi}{2} \le \theta \le \frac{\pi}{2}$$
$$-5 \le \omega \le 5$$
$$-1.5 \le a_t \le 1$$
$$-1 \le a_r \le 2$$

The grab must also avoid obstacles such as the crane structure, the ship and the quay. The height profile for these obstacles is described the black solid line in Figure 2.

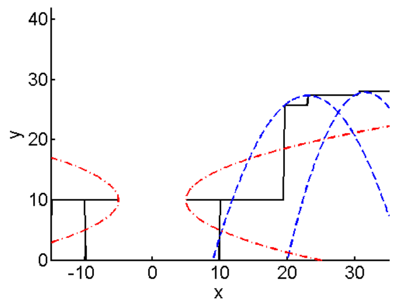

Fig. 2. The height profile of the crane, quay and ship (black solid), and the quadratic approximations horizontally (blue dashed) and vertically (red dash-dotted).

In order to obtain a smooth NLP, it is desired that the constraints are differentiable. Therefore, a smooth approximation of the obstacles parameterized in the grab position is derived. The limitation of this approach is of course that it could be hard to find good smooth approximations of rectangular obstacles. However, the approximation need not be accurate for all positions but