



Sequential distributed predictive control of a 3D tower crane

Šandor Ilaš*, Jadranko Matuško, Fetah Kolonić

University of Zagreb Faculty of Electrical Engineering and Computing, Unska 3, 10000 Zagreb, Croatia



ARTICLE INFO

Keywords:

Rotary crane
Predictive control
Distributed control
Parameter varying systems
Stability

ABSTRACT

An asymptotically stabilizing sequential distributed model predictive control (MPC) of a 3D tower crane is proposed. Stability is ensured by employing three locally stabilizing MPC control laws. In the case of Lipschitz continuous local MPC control laws, a terminal cost and a terminal set constraint are used as stabilizing ingredients while robust control invariant feasible set is used as an additional constraint to guarantee recursive feasibility. On the other hand, in the case of an arbitrary cost function, switching to a robust dual-mode local control law is used inside of the terminal set to guarantee asymptotic stability.

1. Introduction

The primary role of a crane control system is to ensure the quick and safe transfer of a payload, while at the same time respecting various operational and technical constraints. During the transfer of the payload, an oscillatory motion is triggered by the crane's inertial forces or by external excitation. Suppression of this oscillatory payload motion is necessary to ensure a safe load transfer, but also to reduce dynamic loads on the crane structure. In general, this can be achieved by employing either open-loop or closed-loop solutions (Abdel-Rahman, Nayfeh, & Masoud, 2003).

Open-loop solutions are still widely used for suppressing the oscillations caused by the crane's inertial forces since they do not require a swing sensor and they are relatively simple to implement.

As a typical representative of the open-loop solutions, the input shaping approach modifies the operator command to reduce the payload oscillations using information about the crane's natural frequency and damping ratio. Despite being an open-loop solution, it allows for introducing a certain level of robustness to uncertainty in natural frequency (Blackburn et al., 2010; Kuo & Kang, 2014; Singhose, 2009). Another open-loop solution is open-loop optimal control, which is used not only to suppress crane oscillations but also for optimal motion planning in the sense of tracking error, minimum time, energy efficiency, or safety, subject to constraints (Wu & Xia, 2014; Zhang, Fang, & Sun, 2014). Common to all of the open-loop solutions is their ineffectiveness at suppressing externally induced oscillations.

On the other hand, closed-loop solutions are proven to be effective at suppressing both the oscillations caused by the inertial forces and by external sources. Closed-loop solutions may be in the form of a simple

linear control which assumes non-simultaneous sequential movements of the payload along multiple axes (e.g. payload hoisting/lowering, horizontal linear/rotary motion) (Sorensen, Singhose, & Dickerson, 2007) and sometimes combined with artificial intelligence techniques to compensate for model uncertainties (Yu, Li, & Panuncio, 2014).

Advanced approaches to closed-loop crane control include feedback linearization (Lee, Dang, Moon, Kim, et al., 2013) as well as adaptive and nonlinear control algorithms which can deal with the simultaneous movement of the payload along multiple axes and model uncertainties while guaranteeing closed-loop stability (Sun, Fang, Chen, & He, 2015; Sun, Fang, Chen, Lu, & Fu, 2016; Xi & Hesketh, 2010).

In some cases, a hybrid solution is used, combining an open-loop generated crane trajectory as a reference signal and closed-loop controller for handling external disturbances (Kolar, Rams, & Schlacher, 2017).

However, most of the classical closed-loop solutions for crane control suffer from the same problem, which is the inability to account for system constraints stemming from technical limitations and safety requirements in a systematic way. By systematically taking into account its technical constraints, a crane can be fully utilized, which results in improved performance and may result in a prolonged lifetime. Model Predictive Control (MPC) is a commonly used methodology that allows optimizing the control system performance while at the same time respecting system constraints. At each time instant, a finite-horizon optimal control problem is solved subject to constraints on the control input and states, with the current state used as an initial condition. The result of the optimization is an optimal finite-horizon control sequence. The first input from the sequence is applied to the plant. The procedure is then repeated in a receding horizon manner. The

* Corresponding author.

E-mail addresses: sandor.iles@fer.hr (Š. Ilaš), jadranko.matusko@fer.hr (J. Matuško), fetah.kolonic@fer.hr (F. Kolonić).

MPC methodology is already used to optimize tracking performance and/or energy efficiency, subject to constraints, of gantry cranes (Su et al., 2010), overhead cranes (Chen, Fang, & Sun, 2016; Käpernick & Graichen, 2013; Schindele & Aschemann, 2011; Vukov et al., 2012; Wu, Xia, & Zhu, 2015), and rotary cranes (Arnold, Sawodny, Hildebrandt, & Schneider, 2003; Bariša et al., 2014; Böck & Kugi, 2014; Egretzberger, Graichen, & Kugi, 2012; Graichen, Egretzberger, & Kugi, 2010).

Due to the finiteness of the horizon, MPC does not necessarily guarantee stability, nor recursive feasibility (Mayne, Rawlings, Rao, & Scokaert, 2000), which may compromise the system's safety as the existence of the solution to the optimization problem is not guaranteed.

In general, guaranteeing stability and recursive feasibility may negatively impact the overall system performance and result in a conservative control law. Arnold, Sawodny, Neupert, and Schneider (2005) and Neupert, Arnold, Schneider, and Sawodny (2010) were among the first who recognized this problem and provided such guarantees using the zero state terminal constraint.

On the other hand, a nonlinear suboptimal MPC approach to crane control is presented in Böck and Kugi (2014), Egretzberger et al. (2012), Graichen et al. (2010) and Käpernick and Graichen (2013), without an explicit stability analysis but suggesting that stability without terminal constraint can be guaranteed using the approach proposed in Graichen and Kugi (2010), which provides guarantees only for the input constraints.

Input constraints are also handled in Bariša et al. (2014), where MPC is used to generate the optimal reference signal for the underlying position controllers. To guarantee that the generated reference signal will converge to the desired reference, a decaying stage cost is used.

A different approach to guaranteeing the stability in the presence of both state and input constraints for a 3D tower crane has been proposed in Ileš (2015) and Ileš, Matuško, and Kolonić (2014). A dual-mode MPC with a nonzero terminal constraint is used for controlling a tower crane with the crane modeled in a cascaded form, where the motions of a tower crane are considered separately, with the couplings between them treated as a variation of the individual system's parameters. Such a model form enables a sequential solving of three local but coupled finite-horizon optimal control problems. As such, the proposed solution belongs to the class of a so-called sequential distributed model predictive control (Christofides, Scattolini, de la Pena, & Liu, 2013). In Ileš et al. (2014), closed-loop stability is ensured by using a worst case terminal set and an associated terminal cost. The recursive feasibility is guaranteed by keeping the system states in a worst case control invariant feasible set while the asymptotic stability is ensured by switching to a robustly stabilizing control law inside of the terminal set. However, only a sketch of the proof of stability and recursive feasibility of the proposed method has been given and the proposed method is limited to a quadratic cost function and a polytopic linear parameter varying (LPV) model of the crane.

Although sequential distributed model predictive crane control might be suboptimal, it enables efficient solving and guarantees the stability of each local MPC problem subject to constraints on both the control input and the states. By using a quadratic cost function and linear time-varying dynamics subject to convex constraints on the control input and states, each local optimization problem can be written as a convex quadratic program.

This paper builds on the results presented in Ileš (2015), Ileš et al. (2014) and provides more general and less conservative stabilizing ingredients for sequential distributed model predictive control of a 3D tower crane, with a formal proof for two different cases. In the first case, Lipschitz continuous local MPC control laws are assumed. In this case, a terminal set, a terminal cost, and a robust control invariant initial feasible set are proposed as stabilizing ingredients. However, unlike in Ileš (2015) and Ileš et al. (2014), in the proposed approach switching to a robustly stabilizing control law is not needed in the case of Lipschitz continuous MPC, which results in a less conservative control law for the local subsystem. For the case of an arbitrary cost

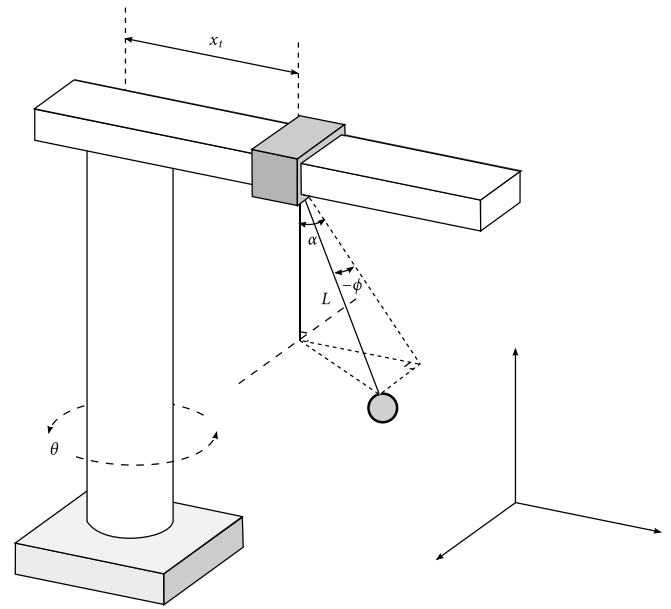


Fig. 1. Model of a tower crane.

function, local MPC controllers are not necessarily Lipschitz continuous. In that case, asymptotic stability is ensured by switching to a robust stabilizing control law inside of the terminal set. This second case is a generalization of the results presented in Ileš et al. (2014) which enables using more complex models of the crane and an arbitrary cost function.

This paper is organized as follows. In Section 2 a simplified mathematical model of a 3D tower crane model in a cascaded form is given. The proposed sequential distributed MPC based control approach is presented in Section 3. In Section 4 implementation details are given. In Section 5 simulation and experimental results are presented. Section 6 concludes the paper.

2. Mathematical model of a tower crane

By far the most widely used control oriented crane model is the so-called lumped mass model (Abdel-Rahman et al., 2003). It assumes that the tower crane, shown in Fig. 1, consists of a massless hoisting line and a trolley–jib support mechanism, while the payload is modeled as a point mass. The jib rotates in a horizontal plane, while the trolley moves along the jib. Together with the hoisting mechanism, the tower crane enables three degrees of freedom.

The nonlinear mathematical model of the crane's motion can be derived via Lagrange's equations, by defining the total potential and kinetic energy of the system as functions of generalized coordinates: jib angular position θ , swing angle ϕ , trolley position x , swing angle α , and cable length L . In this paper the simplified control oriented model presented in Altaf (2010) and Omar (2003), which was derived from the full nonlinear model using a small-angle approximation and the assumption that the rates of change of the cable length, trolley position and jib position have the same order of magnitude as the swing angles and their rates of change, ($\dot{\theta} \approx 0, \dot{x}_t \approx 0, \dot{L} \approx 0$), is adopted. As a result, the crane model is represented in a cascaded form consisting of three separate subsystems, with the coupling between them treated as a variation in system parameters. The presented model simplification is the Taylor-series linearization of each subsystem around a steady state with constant positions of the other subsystems.

The hoisting dynamics is represented by a linear time-invariant model as follows:

$$\ddot{L} + \left(\frac{1}{\tau_L} \right) \dot{L} + mg = \frac{K_L}{\tau_L} u_L. \quad (1)$$

Download English Version:

<https://daneshyari.com/en/article/7110150>

Download Persian Version:

<https://daneshyari.com/article/7110150>

[Daneshyari.com](https://daneshyari.com)