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SOFT-CONSTRAINED PREDICTIVE CONTROL FOR AN OVERHEAD CRANE

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Abstract

Reduction of transient and residual payload swing in crane systems is a key control objective to guarantee the safety and efficiency requirements. The fast and accurate payload positioning with swing suppression within the acceptable range to avoid accidents is the challenging problem due to the underactuated nature of crane systems. Since the actuated motion causes undesirable payload swing, the efficient control method should be developed to ensure fast and precise payload positioning and meet the safety requirements. The standard model predictive control method is not suitable for underactuated mechanical systems. In this article the two, soft and hard-constrained anti-sway predictive control strategies are compared in experiments carried out on a laboratory scaled overhead travelling crane. The both control schemes are developed based on the linear parameter-varying model of a planar crane system. The recursive least square algorithm with parameter projection is used to estimate the model parameters. The soft-constrained optimization problem is solved using the particle swarm optimization algorithm with the inertia weight linearly decreasing during iteration. The metaheuristic optimizer is applied to determine the sequence of optimal control increments subject to the hard constraint of the control input and soft constraint of the payload swing. The comparison of hard and soft-constrained predictive controllers is carried out on a laboratory stand for different payload deflection constraints.

Keywords: *overhead crane, predictive control, recursive least square estimation, particle swarm optimization*

1. Introduction

The safety and efficiency for cranes operations require solving different types of constructional and technological problems, as well as problems related to automation of crane operations [5-7, 11, 17, 18]. Cranes, which are used in material handling systems of many industrial sectors, are the examples of underactuated mechanical systems due to the fact that the position of a rope suspended payload is indirectly controlled through controlling the actuated mechanisms of a crane. Since the actuated motion causes undesirable payload swing, the efficient control method should be developed to ensure fast and precise payload positioning and meet the safety requirements. These involve reduction of transient and residual payload swing within the acceptable range.

The problem under consideration is attractive for researchers, and either open loop or feedback-based control solutions are reported in many previous papers. A thorough review of various methods reported in the literature for crane modelling and control is presented in [1, 13]. The most of these control techniques focuses on suppressing the residual vibration, while the transient oscillations are frequently neglected. The model predictive control (MPC) has been recently applied in different crane control applications, such as hydraulic forestry crane [8], boom crane [2], gantry crane [16] and overhead crane [9]. The predictive control approaches reported in the literature show effectiveness in suppressing the residual vibration; however, they consider mainly the constraints of input signal, acceleration and velocity of a crane without limiting the transient payload deflection. The hard-constrained MPC solutions for payload swing limitation are presented in [3, 14]. The GPC-based approach with the particle swarm optimization (PSO) algorithm is developed in [15] for the soft constraint of payload swing.

In this article, the hard and soft-constrained predictive approaches developed in [14, 15] are compared in experiments carried out on a laboratory scaled overhead travelling crane. In both cases, the predictive control scheme is developed using the generalized predictive control (GPC) procedure based on the discrete-time linear parameter varying (LPV) model of a crane dynamic. The parameters of a model are on-line estimated using the recursive least square (RLS) algorithm with parameter projection. In the second approach, the PSO algorithm is applied to determine the sequence of optimal control increments over the control horizon subject to hard constraint of the control input and soft constraint of the payload swing. The GPC-PSO controller is successfully verified during the experiments carried out on a laboratory stand and compared with the hard-constrained predictive control strategy developed in [14].

The rest of the article is organized as follows. Section two presents the LPV model of an overhead crane taken into consideration. The predictive controller with the PSO algorithm is presented in section three. Section four exhibits and discusses the results of experiments. The work is summarized in section five.

2. LPV model of an overhead crane

A 2-D crane system is considered as a spherical pendulum moved by a cart (Fig. 1). A payload is a point-mass suspended at the end of a massless rigid cable. Neglecting the influence of the pendulum motion on the cart motion, the dynamic of the actuated cart and the unactuated pendulum is simplified to the first-order (1) and second-order (2) discrete-time LPV models, respectively.

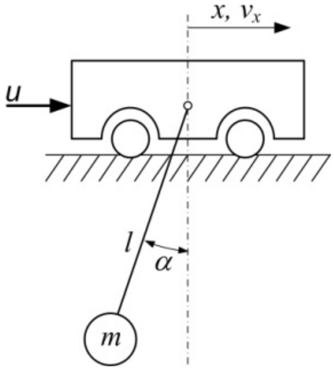

Fig. 1. Planar model of a crane, where x, v_x, m, l, u and α are position and velocity of a cart, mass of a payload, rope length, controlling signal corresponding to control force acting on a crane, and sway angle of a payload, respectively

$$A(z^{-1})v_x(t) = B(z^{-1})u(t-1)\,, \tag{1}$$

$$C(z^{-1})\alpha(t) = D(z^{-1})v_x(t)\,, \tag{2}$$

where $A(z^{-1}) = 1 + a_1z^{-1}$, $B(z^{-1}) = b_0$, $C(z^{-1}) = 1 + c_1z^{-1} + c_2\, z^{-2}$, and $D(z^{-1}) = d_0 + d_1z^{-1}$ are the polynomials in the backward shift operator z^{-1}.

Since the parameters of models (1) and (2) vary with operating conditions, the RLS algorithm is applied for online estimation according to:

$$\hat{\theta}_i(t) = \hat{\theta}_i(t-1) + \mathbf{P}_i(t)\varphi_i e_i\,,\ i = 1, 2 \tag{3}$$

$$\mathbf{P}_i(t) = \frac{1}{\mu}\left(\mathbf{P}_i(t-1) - \frac{\mathbf{P}_i(t-1)\varphi_i\varphi_i^{\,T}\mathbf{P}_i(t-1)}{\mu + \varphi_i^{\,T}\mathbf{P}_i(t-1)\varphi_i}\right),\ i = 1, 2, \tag{4}$$

where:

$\varphi_1 = [u(t-1), -v_x(t-1)]^T$,

$\varphi_2 = [v_x(t), v_x(t-1), -\alpha(t), -\alpha(t-1)]^T$,

$\hat{\theta}_1(t) = [\hat{b}_0, \hat{a}_1]^T$,

$\hat{\theta}_2(t) = [\hat{d}_0, \hat{d}_1, \hat{c}_1, \hat{c}_2]^T$,

$e_1 = v_x(t) - \varphi_1 \hat{\theta}_1(t-1)$,

$e_2 = \alpha(t) - \varphi_2 \hat{\theta}_2(t-1)$

and $\mu \in (0,1]$ is the forgetting factor.

The parameter projection can be used to ensure that the parameter estimates converge to feasible and stable solutions. In practice, the parameters are bounded within the range of operating conditions, which can be specified by the lower and upper limits of the rope length, mass of a hook assembly and a rated load. Thus, for the a priori known bounds $\hat{\theta}_{i,\min}$, and $\hat{\theta}_{i,\max}$ the parameter estimates should satisfy

$$\hat{\theta}_{i,\min} \le \hat{\theta}_i(t) \le \hat{\theta}_{i,msx},\ i = 1, 2. \tag{5}$$

3. Predictive controller with PSO algorithm

3.1. Unconstrained predictive controller

To determine the sequence of the optimal control increments over the control horizon N_u, the objective function is formulated as:

$$\min J = \sum_{j=1}^{N_p} \left(\hat{x}(t+j) - x_r(t+j)\right)^2 + \sum_{j=1}^{N_p} \lambda_{1,j} \left(\hat{\alpha}(t+j)\right)^2 + \sum_{j=1}^{N_u} \lambda_{2,j} \left(\Delta u(t+j-1)\right)^2, \tag{6}$$

where x_r is the reference signal, λ_1 and λ_2 are the weighting coefficients, N_p is the prediction horizon.

Substituting output variables $x_1 = x$ and $x_2 = \alpha$, the relations (1) and (2) can be rewritten to the CARIMA (Controlled Auto-Regressive and Integrated Moving-Average) models:

$$A_i(z^{-1}) x_i(t) = B_i(z^{-1}) u(t-1) + \xi_i(t)/\Delta,\ i = 1, 2, \tag{7}$$

where $A_1(z^{-1}) = \Delta A(z^{-1})$, $A_2(z^{-1}) = A(z^{-1})C(z^{-1})$, $B_1(z^{-1}) = T_s B(z^{-1})$, $B_2(z^{-1}) = B(z^{-1})D(z^{-1})$ are the polynomials in the backward shift operator related to (1) and (2), $x_1(t) = T_s v_x(t)/\Delta$, $\Delta = 1 - z^{-1}$, T_s is a sample time, ξ_1 and ξ_2 are the uncorrelated random sequences.

According to [4], the j-step ahead predictors are derived from:

$$\hat{x}_i(t+j) = G_{i,j}(z^{-1}) \Delta u(t+j-1) + F_{i,j}(z^{-1}) x_i(t),\ i = 1, 2, \tag{8}$$

where $G_1(z^{-1})$, $G_2(z^{-1})$, $F_1(z^{-1})$ and $F_2(z^{-1})$ are the polynomials recalculated through recursion of the Diophantine equations [4].

The cost function to be minimized can be rewritten as

$$\min\ J = \left(\mathbf{G}_1 \tilde{\mathbf{u}} + \mathbf{f}_1 - \mathbf{x}_r\right)^T \left(\mathbf{G}_1 \tilde{\mathbf{u}} + \mathbf{f}_1 - \mathbf{x}_r\right) + \boldsymbol{\lambda}_1 \left(\mathbf{G}_2 \tilde{\mathbf{u}} + \mathbf{f}_2\right)^T \left(\mathbf{G}_2 \tilde{\mathbf{u}} + \mathbf{f}_2\right) + \boldsymbol{\lambda}_2 \tilde{\mathbf{u}}^T \tilde{\mathbf{u}}, \tag{9}$$

where:

$\mathbf{f}_i = [f_{i,1}(t+1), f_{i,1}(t+2), \dots, f_{i,1}(t+N_p)]^T$,

$$\mathbf{G}_i = \begin{bmatrix} g_{i,0} & 0 & \cdots & 0 \\ g_{i,1} & g_{i,0} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & g_{i,0} \\ \cdots & \cdots & \cdots & \cdots \\ g_{i,Np-1} & g_{i,Np-2} & \cdots & g_{i,Np-Nu-1} \end{bmatrix}, i = 1, 2.$$

3.2. PSO algorithm

To find the optimal sequence of control increments over the control horizon the cost function (9) should be minimized subject to constraints of control input and payload swing. PSO [10] is utilized to solve this problem, since the effectiveness of this concept has been proven in recent works [12, 19] reporting on the PSO-based MPC. The PSO optimizer is computationally efficient and easy to implement and hybridize with other heuristic algorithms in order to ensure efficient balancing between the global and local search.

The future control increments represents coordinates of *i*th particle's position. At each *k*th iteration, the particle changes position searching the appropriate solution in the N_u-dimensional search space. The velocity and position coordinates, denoted $v_{i,j}$ and $\tilde{u}_{i,j}$, respectively, are updated based on the previous best solution of the particle (personal best solution) and the global best solution in the population denoted $\tilde{u}^p_{i,j}$ and $\tilde{u}^g_j$, respectively. The coordinates of particles velocity and position are updated as follows:

$$\begin{aligned} v_{i,j} &= wv^{k-1}_{i,j} + c_1 r_1\left(\tilde{u}^p_{i,j} - \tilde{u}^{k-1}_{i,j}\right) + c_2 r_2\left(\tilde{u}^g_j - \tilde{u}^{k-1}_{i,j}\right) \\ \tilde{u}^k_{i,j} &= \tilde{u}^{k-1}_{i,j} + v^k_{i,j} \end{aligned}, \tag{10}$$

subject to:

$$\tilde{u}_{\min} \le \tilde{u}_{i,j} \le \tilde{u}_{\min}$$

$$v_{\min} \le v_{i,j} \le v_{\max} \,.$$

where $k = 1, 2, ..., m$, w is called inertia weight linearly decreasing from 0.9 to 0.4 during iteration, c_1 and c_2 are positive constants called acceleration coefficients, and r_1 and r_2 are the scalars randomly chosen between 0 and 1.

Each individual is evaluated based on the objective function (9) taking into account the soft constraint of the payload swing:

$$\lambda_{1,j} = \begin{cases} \lambda_1, & if \ \left|\hat{\alpha}(t+j)\right| \le \alpha_{\max} \\ p\lambda_1, & if \ \left|\hat{\alpha}(t+j)\right| > \alpha_{\max} \end{cases}, \tag{11}$$

where $p > 1$ is the penalty factor applied when predicted payload deviation exceeds an allowed value.

4. Results of experiments

The predictive control technique with the PSO-based optimizer was tested on a laboratory scaled overhead crane equipped with DC motors, and incremental encoders used for sensing the position of crane and sway angle of a payload. The measurement and control system was based on a PC (2 GB RAM, CPU Intel Core2 Quad Q6600 2.4 GHz) with the PCI-1710HG multi I/O board installed. The control algorithm was implemented using the C-MEX S-function incorporated into the MATLAB/Simulink (Version 7.0) running on Windows XP.

The objective of the control was positioning the crane to x_r = 1 m and reducing the payload deflection within the tolerance ± 0.02 m, where the payload deflection was approximated as a product of rope length and sway angle of a payload ($l\alpha$). The GPC-PSO strategy with the RLS estimation was tested for sample time T_s = 0.1 s, forgetting factor μ = 0.99, and for the control input signal range $-10 \le u(t) \le 10$ V. The parameters of the control scheme were empirically chosen as N_p = 30, N_u = 8, λ_1 = 3.7, λ_2 = 0.008, c_1 = c_2 = 1.5, swarm size n = 30, and maximum number of iterations m = 100.

Figures from 2 to 4 present the results of experiments carried out for the rope length l = 2.2 m and mass of a payload m = 10 kg, and for different constraints of the payload deviation selected as $l\alpha_{max}$ = {+/- 0.08, +/- 0.07, +/- 0.06} m. The error of crane position and residual vibration are within the tolerance +/- 0.02 m after the settling time 5.4 s, 5.9 s and 6.3 s for the payload deflection limits +/- 0.08 m, +/- 0.07 m and +/- 0.06 m, respectively. The maximum value of payload deflection is 0.0755 m, 0.0697 m and 0.0545 m for constraints of +/- 0.08 m, +/- 0.07 m and +/- 0.06 m, respectively. So, the safety requirement is satisfied for different payload deviation constraints. Those results are compared with the GPC-KT strategy developed in [14] where the Kuhn-Tucker complementarily conditions have been applied in the GPC-based procedure to solve an optimal control problem for the two-step ahead prediction of sway angle of a payload. The GPC-KT strategy satisfies the control objectives and constraints of the payload deflections, however, results in worse settling time compared to the GPC-PSO: 6.7 s, 7.3 s and 7.8 s for the payload deviation constraints +/- 0.08 m, +/- 0.07 m and +/- 0.06 m, respectively. For the same constraints the pendulum oscillations are reduced more smoothly using the GPC-PSO strategy with prediction horizon N_p = 30.

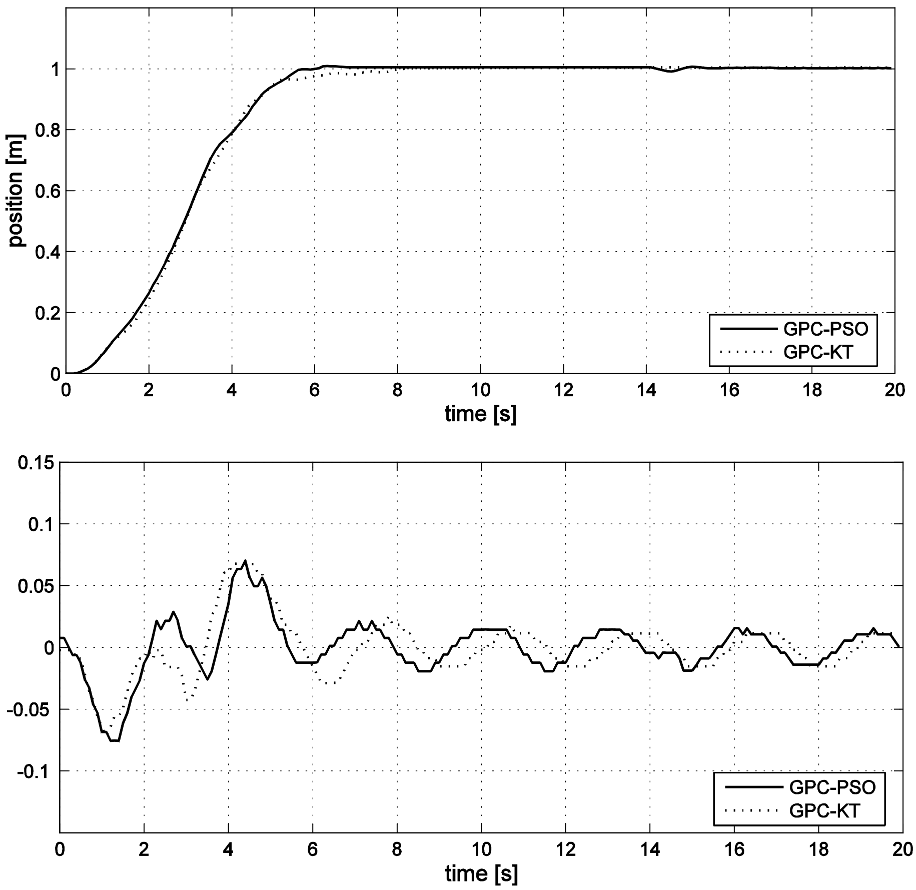

Fig. 2. Comparison of GPC-PSO and GPC-KT – experiment for l =2.2 m, m = 10 kg, payload deflection constraint +/- 0.08 m

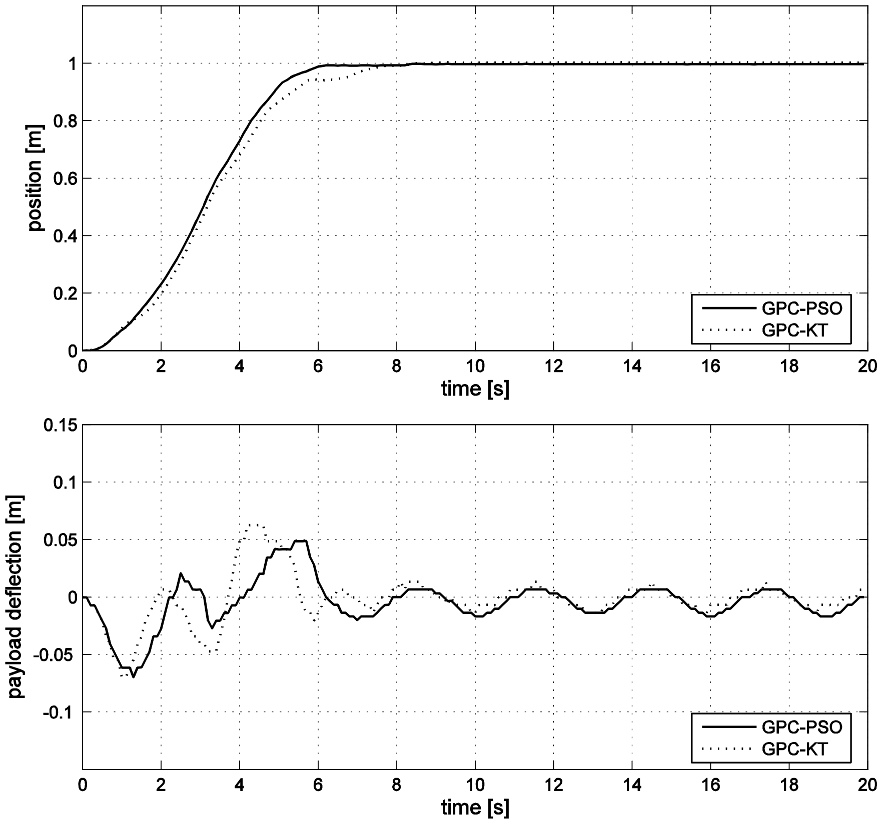

Fig. 3. Comparison of GPC-PSO and GPC-KT - experiment for l =2.2 m, m = 10 kg, payload deflection constraint +/- 0.07 m

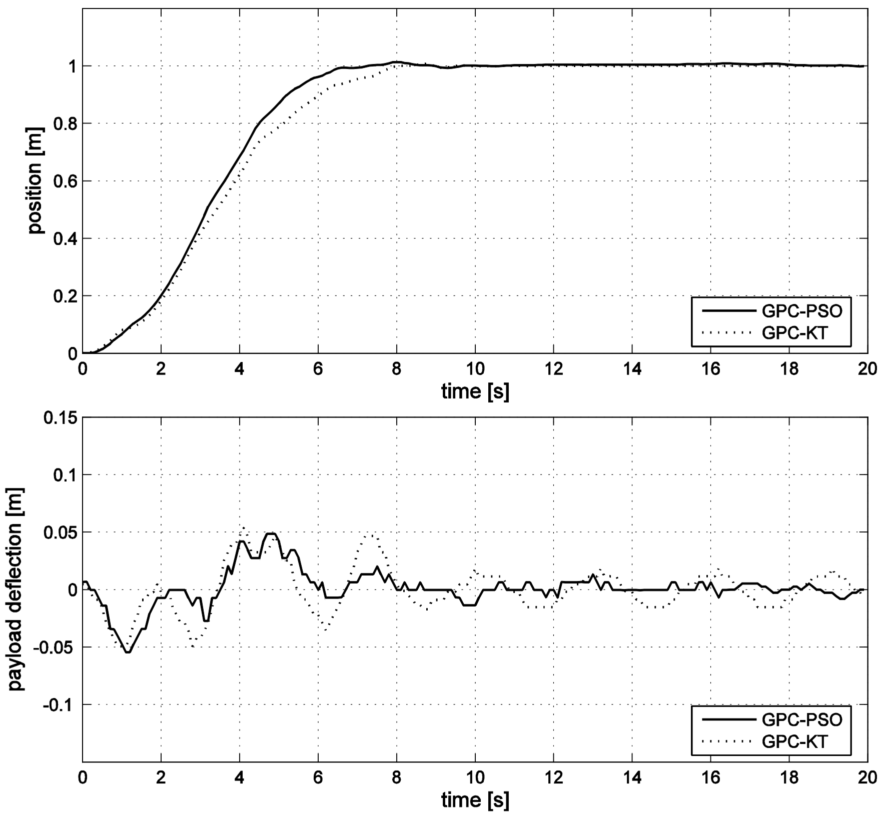

Fig. 4. Comparison of GPC-PSO and GPC-KT - experiment for l =2.2 m, m = 10 kg, payload deflection constraint +/- 0.06 m

5. Conclusions

The hard-constrained and soft-constrained predictive approaches developed are compared in experiments carried out on a laboratory scaled overhead travelling crane. The predictive control schemes are developed using the GPC procedure based on the discrete-time LPV model of a crane dynamic. The parameters estimations are performed using the RLS algorithm with parameter projection. The PSO algorithm is applied to determine the sequence of optimal control increments over the control horizon subject to hard constraint of the control input and soft constraint of the payload swing. The experimental results proved the effectiveness of the proposed predictive control strategy in terms of limiting the payload deflection in transient state and reducing the residual payload oscillation.

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