Optimal sliding mode controller design based on
dynamic differential evolutionary algorithm for
under-actuated crane systems

Zhe Sun, Yunrui Bi, Xuejian Zhao, Zhixin Sun, Chun Ying and Shuhua Tan

Abstract—In this paper, aiming at the payload residual vibration problem, a dynamic differential evolutionary algorithm based sliding mode controller (DDE-SMC) is designed for under-actuated crane systems. According to under-actuated crane systems mechanism of action, a fusion sliding function combined with position and angle sliding function is firstly given, and the corresponding control law by incorporating switching and equivalent control law is designed during control process. Moreover, in order to configure the control parameter efficiently, a dynamic DE algorithm is proposed and utilized for improving the anti-swing control performance. Through computer simulation and comparisons under different operation conditions, the proposed DDE-SMC demonstrates the effectiveness in damping the payload oscillations of under-actuated crane system.

Index Terms—Dynamic DE algorithm, Sliding mode controller, Parameter optimization, under-actuated crane.

I. INTRODUCTION

A

S one of the most important transportation facility, under-actuated cranes are widely applied in harbours, construction site and industrial factories for the heavy cargoes transportation. According to the structural difference, under-actuated crane can be classified overhead crane, boom crane and tower crane. Among these kinds of cranes, overhead crane is the most representative and commonly used crane. According to the overhead crane operation feature, the trolley should carry the payload rapidly and do not causing any excessive movement at the appointed position. Besides, the swing of the payload should keep small as possible for avoiding the unnecessary collision or accident. However, the high speed trolley movement easily causes payload swing in large amplitude so as to give rise to the potential safety hazard. Meanwhile, the under-actuated crane is a kind of typical under-actuated system, i.e., the degrees of freedom are more than the independent control inputs, which this intrinsic characteristic brings enormous challenges in anti-swing control. Hence, it is significant to design anti-swing controller for overhead crane.

Over the last decades, extensive researches have been studied for the anti-swing control of under-actuated cranes. At the early research stage, the input shaping [1], [2] and optimal control [3] have widely used for overhead cranes anti-swing control to reduce the residual vibration owing to the advantages of the easy designing difficulty and low hardware cost. However, the control performance might be degraded badly when the model parameter are inaccurate. In order to solve the adverse effect from the tiny variation of system parameter or external disturbances, various close-loop feedback control methods are gradually developed to make up for the deficiency of open-loop control. In literature [4], [5], researchers adopt PID control method and dual-state observer method for suppressing vibrations. The linear control method can better adapt to the change of system parameters, and has the merits of simple structure and easy design. However, this kind of method is based on the linearized model, which inevitably ignored the nonlinear characteristics of the overhead crane, and thereby leading to an unsatisfied anti-swing control performance in actual overhead crane control. For figuring out the nonlinear characteristic of overhead crane, numerous nonlinear control methods [6]–[9] are proposed for overhead crane systems. Generally, the aforementioned nonlinear control methods fully consider the nonlinear and under-actuated characteristic of the overhead crane, and make the control performance has a lot of ascension in oscillation elimination aspect.

Sliding mode control [10]–[18] is a commonly used variable structure control scheme owing to the merits of the simplicity and robustness against disturbances. Such as, in literature [10], authors developed a sliding mode anti sway control method for offshore container crane. By designing the sliding surface and incorporating the trolley dynamics, the sway of payload has been damped effectively. Researchers proposed a self-adaptive sliding mode controller for crane system when the priori knowledge of the payload mass and damped elements are unknown [11]. An integral sliding mode controller is designed for overhead crane systems, and suboptimal integral sliding mode is determined by using the proposed extended Theta-D method [12]. In literature [13], for vanishing oscillation of overhead crane, researchers proposed a novel non-linear control scheme by incorporating the partial feedback linearization and sliding mode technique for the cargo anti-swing control and trolley tracking control. In order to cope with system uncertainties, a fuzzy logic uncertainty observer based sliding-mode anti-swing control law was developed for overhead crane [14]. In literature [15], the authors proposed a Sugeno fuzzy algorithm based sliding mode controller for coping with the overhead crane dynamic characteristic.

Z. Sun, X.J. Zhao and Z.X. Sun are with the School of Modern Posts, Institute of Modern Posts, Nanjing University of Posts and Telecommunications, Nanjing, China, 210003. E-mail: zhesunny@njupt.edu.cn.

C.Ying and S.H.Tan are with the YuanTong Express, Shanghai, China, 201705

Y.R. Bi is with the school of automation, Nanjing Institute of Technology, Nanjing, China, 211167.

To configure the control parameters and mode parameters are vitally important for eliminating the chattering and improving robustness. However, the conventional search algorithm such as gradient decent algorithm, Levenberg–Marquardt algorithm, genetic algorithm, etc. are easily trap into local optima for those complex parameter optimization problem. Hence, it is significant to adopt a powerful evolutionary algorithm for solving the parameter configuration problem. Comparing with other heuristic evolutionary algorithms, differential evolution (DE) algorithm is a certified and efficient optimizing algorithm and has been widely and successfully applied to various engineering optimization fields due to its excellent global search efficiency. [19]–[27]. However, the search performance is easily affected due to the parametric sensitivity problem. Therefore, aiming at this problem, a dynamic DE algorithm is adopted to the sliding mode controller optimization process to strengthen the anti-swing control performance.

This paper is organized as follows. The brief description of overhead crane is stated in Section 2; Section 3 states the dynamic DE algorithm; The sliding mode controller and parameter optimization is addressed in Section 4; The experimental simulation results and comparisons are discussed in Section 5; The conclusions are summarized in the final section of this paper.

II. THE DESCRIPTION OF OVERHEAD CRANE SYSTEMS

Overhead crane systems is regarded as a nonlinear dynamic systems, and the intrinsic under-actuated characteristic also give rise to the difficulties for damping payload oscillation. As show in Fig.1, the overhead crane systems is composed of trolley and payload subsystems. Note that, the trolley will move at the horizontal direction by the driving force, and then, the payload will swing along with the trolley movement. In order understand the dynamic characteristic of overhead crane systems easily, we assume that the rope is inflexible and the rope weight is not consider, the payload swing along with x-y surface, and the friction between trolley and rail is ignored.

By adopting Lagrangian method, the corresponding equation of the generalized coordinate $q_i$ is described as

$$\frac{d}{dt} \left( \frac{\partial L_a}{\partial \dot{q}_i} \right) - \frac{\partial L_a}{\partial q_i} = T_i$$  \hspace{0.5cm} (1)

where $i = 1, 2$, $L_a = K - P$ ($K$ and $P$ represent the system kinetic energy and potential energy respectively), $q_i$ denotes the generalized coordination ($q_1$ and $q_2$ are $x$ and $\theta$, respectively), and $T_i$ is the external applied force.

Here, we assume that the payload is considered as a material particle, then, the system kinetic energy is acquired as follows

$$K = \frac{1}{2} M \dot{x}^2 + \frac{1}{2} m v^2$$  \hspace{0.5cm} (2)

where $v$ is a vector and it denotes the payload velocity, defined as

$$v = v_x + v_y$$  \hspace{0.5cm} (3)

where $v_x = \dot{x} + l \dot{\theta} \cos \theta$ and $v_y = -l \dot{\theta} \sin \theta$. Here, we assume the payload as a particle, then the moment of inertia can be ignore in equation (2).

As shown in Fig.1, the system potential energy can be expressed by the potential energy of the payload subsystem because the potential energy of the trolley subsystem is irrevocable. The corresponding expression is depicted as

$$P = mg l (1 - \cos \theta)$$  \hspace{0.5cm} (4)

where $g$ represents the gravitational acceleration. According to the equation (2) and equation (4), $L_a$ is described as

$$L_a = K - P = \frac{1}{2} M \dot{x}^2 + \frac{1}{2} m v^2 - m g l (1 - \cos \theta)$$  \hspace{0.5cm} (5)

Considering the partial differential $L_a$ as for $x$ and letting

$$\frac{\partial L_a}{\partial x} = 0$$  \hspace{0.5cm} (6)

Partial differential $L_a$ with regard to $\dot{x}$ in equation (5) lets

$$\frac{\partial L_a}{\partial \dot{x}} = M \ddot{x} + m(\dot{x} + l \dot{\theta} \cos \theta)$$  \hspace{0.5cm} (7)

Further, differentiating (7) for time $t$, the corresponding expression is depicted as

$$\frac{d}{dt} \left( \frac{\partial L_a}{\partial \dot{x}} \right) = M \dddot{x} + m(\ddot{x} + l \dot{\theta} \cos \theta - \dot{\theta}^2 \sin \theta)$$  \hspace{0.5cm} (8)

The final Lagrangian expression as for $\dot{x}$ can be stated as

$$\frac{d}{dt} \left( \frac{\partial L_a}{\partial \dot{x}} \right) - \frac{\partial L_a}{\partial x} = (m + M) \dddot{x} + m(l \dot{\theta} \cos \theta - \dot{\theta}^2 \sin \theta) = F$$  \hspace{0.5cm} (9)

Considering the partial differential $L_a$ as for $\theta$ in equation (5) and letting

$$\frac{\partial L_a}{\partial \theta} = m[(\dot{x} + l \dot{\theta} \cos \theta)(-l \dot{\theta} \sin \theta) + (l \dot{\theta} \sin \theta)(l \dot{\theta} \cos \theta)] - m g l \sin \theta$$

$$= -m l \dot{\theta} \dot{\theta} \sin \theta - m g l \sin \theta$$

Differentiating $L_a$ for $\dot{\theta}$ in (5) yields

$$\frac{\partial L_a}{\partial \dot{\theta}} = m[(\dot{x} + l \dot{\theta} \cos \theta)(\dot{\theta} \cos \theta) + (\dot{\theta} \sin \theta)(l \dot{\theta} \cos \theta)] - m l \cos \theta + m l^2 \ddot{\theta}$$

$$= m l \cos \theta + m l^2 \ddot{\theta}$$
Further, differentiating the equation (11) as for time $t$, the form is described as

$$\frac{d}{dt}(\frac{\partial La}{\partial \theta}) = ml\ddot{x}\cos \theta - ml\dot{\theta}\sin \theta + ml^2\dot{\theta}$$

(12)

The final Lagrangian expression as for the $\theta$ can be stated as

$$\frac{d}{dt}(\frac{\partial La}{\partial \theta}) - \frac{\partial La}{\partial \theta} = ml\ddot{x}\cos \theta + ml^2\dot{\theta} + mg\sin \theta = 0$$

(13)

From equation (9) and equation (13), the mechanism model of overhead crane systems for $x$ and $\theta$ is acquired as follows

$$(M + m)\ddot{x} + ml(\dot{\theta}\cos \theta - \dot{\theta}^2\sin \theta) = F$$

(14)

$$\cos \theta + l\ddot{\theta} + g\sin \theta = 0$$

(15)

Here, $\theta$ and $x$ represent swing angle and the displacement respectively; $m$ and $M$ are denoted as payload and trolley mass respectively, $l$ is the length of rope; $F$ denotes the driving force.

Finally, the corresponding state space model expression can be described as

$$\begin{align*}
\dot{x}_1 &= x_2 \\
\dot{x}_2 &= f_1(x) + g_1(x)u \\
\dot{x}_3 &= x_4 \\
\dot{x}_4 &= f_2(x) + g_2(x)u
\end{align*}$$

(16)

where, $x = [x_1, x_2, x_3, x_4]^T$, $x_1 = x, x_3 = \theta$, $x_2$ and $x_4$ are respectively denoted as trolley and payload angular velocity; $u$ is the driving force coming from controller; $f_1, f_2, g_1$ and $g_2$ are described as

$$f_1(x) = \frac{ml^2\sin x_3 + mgsin x_3\cos x_3}{M + m\sin^2 x_3}$$

(17)

$$g_1(x) = \frac{1}{M + m\sin^2 x_3}$$

(18)

$$f_2(x) = \frac{(M + m)gsin x_3 + ml^2\sin x_3\cos x_3}{(M + m\sin^2 x_3)l}$$

(19)

$$g_2(x) = \frac{\cos x_3}{(M + m\sin^2 x_3)l}$$

(20)

III. DYNAMIC DIFFERENTIAL EVOLUTION ALGORITHM

As one of the heuristic algorithm, differential evolution algorithm has been widely various practical applications for systems optimization, parameter identification, scheduling solving and so on. Firstly, DE algorithm randomly generated NP individuals $x = \{x_1, x_2, \ldots, x_N\}$ at start stage. Thereinto, the $i$th potential solution is denoted by the D-dimensional vector $x_i = [x_{i1}, x_{i2}, \ldots, x_{iD}]$. In order to improve the dynamic performance, a dynamic scaling factor is designed for overcoming the parameter sensitivity of DE algorithm and improving the search efficiency.

A. Mutation

There are three individuals $x_{i1}, x_{i2}, x_{i3}(x_{i1} \neq x_{i2} \neq x_{i3})$ need to be picked out at random. And these selected objective vectors must unconformity. The new mutant individual is produced based on the formula.

$$v_i = x_1 + F_m \cdot (x_2 - x_3)$$

(21)

where $F_m$ is denoted as scaling parameter which controls the amplification of $v_i(i \neq j = 1, 2, \ldots, NP)$. The value of the factor $F_m$ plays an important role in optimization process. If we assign a big value to $F_m$, that means, it will have more opportunities to jump out the local optimal, but it also may cause to badly global convergence performance. Similarly, the small value for it has, the local search performance will be improve, but the premature convergence also will be appeared.

According to the genetic strategy, the dynamic scaling factor is adopted in different evolution stages for getting better convergence performance. The dynamic value of $F_m$ can be calculated based on the formula as follows.

$$F_{dm} = \begin{cases}
F_{m}^{ini}; & g \leq a \\
F_{m}^{ini} - 2 \cdot \left(\frac{g - a}{b - a}\right)^2; & a < g \leq \frac{a + b}{2} \\
F_{m}^{ini} + 2 \cdot \left(\frac{g - b}{b - a}\right)^2 - 1; & \frac{a + b}{2} < g \leq b \\
F_{m}^{ini} - 1; & g < b
\end{cases}$$

(22)

where $F_{m}^{ini}$ is the initial scaling factor, $a$ and $b$ are the adjustable coefficient, $g$ is defined as current iteration number.

B. Crossover

After finishing the differential mutation operation, DE algorithm then carry out the crossover operation to improve the diversity of population. The new individual $u_i = \{u_{i1}, u_{i2}, \ldots, u_{iD}\}$ is created to mate the mutated individual $v_i$ with $x_i$ by using the following formula.

$$u_{i,j} = \begin{cases}
v_{i,j}; & \text{if } (rand_j \leq p_c \text{ or } j = rand_D) \\
x_{i,j}; & \text{if } (rand_j > p_c \text{ and } j \neq rand_D)
\end{cases}$$

(23)

where $rand_j$ denotes the $j$th arbitrary number between 0 and 1. $p_c \in [0, 1]$ is a constant crossover probability. The $rand_D \in [1, D]$ ensure the $u_{i,j}$ element be obtained.

C. Selection

In order to determine the target or the trial vector which can survive to the next generation, in this section, we adopt greedy selection strategy to pick out the new individual from $u_i$ and $x_i$, if the cost function value of $u_i$ is superior to the $x_i$, the $u_i$ will be selected, otherwise, the target individual $x_i$ is reserved. Given minimum optimization problem $\min f(x)$, the select operation is expressed as follows:

$$x_i^{t+1} = \begin{cases}
u_i; & f(u_i) < f(x_i) \\
x_i; & f(u_i) \geq f(x_i)
\end{cases}$$

(24)
D. Numerical test

In this section, shown in TABLE I, nine typical benchmark functions, namely Rosenbrock, Sphere, Hyper Ellipsoid, Schwefel ridge, Griewank, Ackley, Rastrigin, Schwefel, Salomon, are utilized to confirm the effectiveness of the proposed algorithm. The first four functions ($f_1$-$f_4$) are typical unconstrained uni-modal function. The rest of five test functions are commonly used constrained multi-modal function with large search space, numerous local optimum and fraudulence. All of test functions are simulated for high dimensional search space ($D = 30$). The standard genetic algorithm (GA), particle swarm optimization (PSO) and DE algorithm are respectively tested for demonstrating the validity of improved DE algorithm. The parameter configuration are listed in TABLE II. And to be fair, every mentioned algorithm implement thirty times for each test function.

If the inequality $|O_b - O^*| \leq \varepsilon = 10^{-10}$ is satisfied, then the optimization process will be ended. Here $O_b$ represents the final optimized value by using optimizing algorithm, $O^*$ represents the intrinsic optimal value, and $\varepsilon$ is the precision requirement. The $\bar{F}_w$, $\bar{F}_b$ and $\bar{F}_{av}$ represent the worst, best, average objective function value respectively, the $Iter_{av}$ is the average iteration number. The final average results are summarized in TABLE III.

For the uni-modal functions ($f_1 \sim f_4$), comparing with standard GA, PSO and DE algorithm, the dynamic DE algorithm gives better results in convergent accuracy. In $f_5$ and $f_6$ functions testing, dynamic DE algorithm can satisfy the testing terminated condition in limited iteration. For $f_7$ and $f_8$ functions, dynamic DE algorithm still exhibits good results in convergence accuracy.

For the multi-modal functions ($f_7 \sim f_9$), it is obvious that the better optimal value are acquired by dynamic DE algorithm. For $f_7$, $f_8$, $f_9$, and $f_{10}$ functions, the dynamic DE algorithm shows better convergent performance. Interestingly, in function $f_7$ testing, standard DE algorithm acquired the worse optimized results to compare with GA and PSO. The main reason is the fixed algorithm parameters lead to the standard DE algorithm trampled into local optimal in some more complex optimizing problems. Through various benchmark functions testing, the dynamic DE algorithm exhibits superior convergent speed and accuracy, which the search capability is more suitable for the high dimension complex parameter identification problem other than other algorithms.

IV. THE SLIDING MODE CONTROLLER AND PARAMETER OPTIMIZATION

The sliding mode control method is regarded as a variable structure systems, in which the sliding modes are induced by disruptive control forces. It has been studied extensively and successfully adopted in complex nonlinear systems owing to outstanding robustness against disturbances.

A. The designing of sliding mode controller (SMC)

Without loss of generality, considering the following nonlinear dynamic systems

$$\dot{x} = f(x, t) + g(x, t)u + d(t)$$  (25)
Here, \( f \) and \( g \) represent the nonlinear functions of the dynamic systems; \( \mathbf{x} = [x, \dot{x}, \cdots, x^{(n)}]^T \) denote the system state variables; \( u \) represents the input force; \( d(t) \) denotes uncertain disturbance.

Here, we denote the \( x_d \) as the reference position, the corresponding error between the reference point and system states is depicted as follows.

\[
e(t) = \mathbf{x}_d(t) - \mathbf{x}(t) \tag{26}
\]

Let sliding surface \( s(e) = 0 \), and sliding surface can be defined as follows.

\[
s(e) = \mathbf{C}e \tag{27}
\]

where \( \mathbf{C} = [c_1, c_2, \cdots, c_{n-1}, 1] \). According to the sliding mode control theory, the control law must force error vector \( e(t) \) close to the sliding surface and move along with the sliding surface to the origin. Then, the control process can be divide into the approaching phase (letting \( s(e) \neq 0 \)) and the sliding phase (letting \( s(e) = 0 \)). For the approaching phase, the control law must satisfy the following condition \( s(e)\dot{s}(e) < 0 \) to drive the error \( e \) toward the sliding surface.

According to the aforementioned approaching phase condition, here, we denote the switching control law \( u_{sw} \) as follows.

\[
u_{sw} = u_0 \text{sgn}(s(e)) \tag{28}
\]

where \( \text{sgn}(\cdot) \) is the sign function, \( u_0 \) is unknown constant.

In the sliding phase, we denote the equivalent control \( u_{eq} \) as follows so as to propel the system dynamics to stay on the sliding surface. And the equivalent control force \( u_{eq} \) is acquired by letting \( \dot{s}(e) = 0 \).

\[
\dot{s} = \mathbf{C} \dot{e} = \mathbf{C} \frac{\partial s}{\partial \mathbf{x}} (\dot{x}_d - \dot{x}) = \mathbf{C} \left( \frac{\partial s}{\partial \mathbf{x}} \dot{x}_d - \frac{\partial s}{\partial \mathbf{x}} \left( f(\mathbf{x}, t) + g(\mathbf{x}, t)u + d(t) \right) \right) = 0 \tag{29}
\]

Here, to assume \( \frac{\partial s}{\partial \mathbf{x}} g(\mathbf{x}, t) \) is non-singular. Then

\[
u_{eq} = \left( \frac{\partial s}{\partial \mathbf{x}} g(\mathbf{x}, t) \right)^{-1} \left( \frac{\partial s}{\partial \mathbf{x}} \dot{x}_d - \frac{\partial s}{\partial \mathbf{x}} \left( f(\mathbf{x}, t) + d(t) \right) \right) \tag{30}
\]

The corresponding control law is obtained as follows.

\[
u = u_{sw} + u_{eq} = u_0 \text{sgn}(s(e)) + \left( \frac{\partial s}{\partial \mathbf{x}} \dot{x}_d - \frac{\partial s}{\partial \mathbf{x}} \left( f(\mathbf{x}, t) + d(t) \right) \right)^{-1} \tag{31}
\]

**B. Parameter optimization of SMC**

For implementing the parameter optimization, the parameters of SMC need to be encoded by decimal firstly. According to the overhead crane systems feature, the amplitude and residual oscillation of payload should keep as small as possible so as to avoid the unexpected accident, and trolley should move smoothly so as to rapidly and accurately arrival the appointed position. The cost function can be denoted as follows.

\[
F_{cost} = \int_0^t |x| dt + 2 \int_0^t |\theta| dt \tag{32}
\]

where \( x \) and \( \theta \) respectively denote trolley displacement and payload swing angle.

The optimization procedure is summarized as follows.

Step 1: Set up the parameter range of sliding mode controller;

Step 2: Initialize dynamic DE algorithm parameter such as \( G = 500, \text{NP}=30, p_c = 0.5, F_{\text{mut}} = 1.2, a = 50, b = 450; \)

Step 3: Randomly generate \( NP \) groups sliding mode control parameter;

Step 4: Implement overhead crane systems control process for every group parameter and calculate the cost function value;

Step 5: Let \( t = t + 1 \) and \( i = 1; \)

Step 6: Calculate the dynamic scaling factor \( F_{\text{dom}} \) based on the eq.(22) and implement the mutation operation (eq.(21)) to acquire mutant individual \( \mathbf{v}_i; \)

Step 7: According to the eq.(23), carry out the crossover operation between \( \mathbf{x}_i \) and \( \mathbf{v}_i \) to acquire new individual \( \mathbf{u}_i; \)

Step 8: Let \( i = i + 1 \) and go to step 5 until \( i = NP; \)

Step 9: Perform overhead crane systems control process based on the new \( NP \) groups parameter and compute the cost function value;

Step 10: Implement selection operation to pick out the best \( NP \) groups parameter;

Step 11: Determine whether the best group parameter meets the iteration end condition. If it is met, then stop. Otherwise return to step 5.

**V. SIMULATION EXPERIMENT OF OVERHEAD CRANE SYSTEMS**

Based on the description of overhead crane systems, the overhead crane systems can be divided into trolley position subsystem and payload angle subsystem. The position sliding function and angle sliding function respectively are given as follows.

\[
s_1(x_1, x_2) = c_1 x_1 + x_2 \tag{33}
\]

\[
s_2(x_3, x_4) = c_2 x_3 + x_4 \tag{34}
\]

Then, the overall sliding function can be derived as:

\[
s(x_1, x_2, x_3, x_4) = \lambda_1 s_1 + \lambda_2 s_2 = \lambda_1 c_1 x_1 + \lambda_1 x_2 + \lambda_2 c_2 x_3 + \lambda_2 x_4 \tag{35}
\]

where \( \lambda_1, \lambda_2, c_1, c_2 \) are denoted as adjusted parameter of sliding function.

In order to verify the validity of the proposed method, the PID controller [4], optimized PID controller, sliding mode controller and optimized SMC are investigated and compared each other respectively. Without loss generality, these control methods are simulated under the following conditions.

Condition 1: payload weight \( m = 1 \text{kg} \), destination \( x_d = 3, x_d = 7. \)

Condition 2: payload weight \( m = 3 \text{kg} \), destination \( x_d = 3, x_d = 7. \)
TABLE IV
THE PARAMETERS OF PID AND SMC CONTROLLERS

<table>
<thead>
<tr>
<th>PID</th>
<th>$K_p = 60$</th>
<th>$K_i = 0$</th>
<th>$K_d = 60$</th>
<th>$k = 0.8$</th>
<th>(\lambda_1 = 0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimized PID</td>
<td>$c_1 = 0.9$</td>
<td>$c_2 = 5$</td>
<td>$\lambda_1 = 1$</td>
<td>$\lambda_2 = -0.6$</td>
<td>$u_{eq} = 200$</td>
</tr>
<tr>
<td>Optimized SMC</td>
<td>$c_1 = 0.79$</td>
<td>$c_2 = 9.67$</td>
<td>$\lambda_1 = 1$</td>
<td>$\lambda_2 = -0.36$</td>
<td>$u_{eq} = 100$</td>
</tr>
</tbody>
</table>

Condition 3: payload weight $m = 9kg$, destination $x_d = 3$, $x_d = 7$.

The Fig.2, Fig.3 and Fig.4 respectively illustrate the results of trolley position and swing angle with different appointed position of three conditions. The corresponding parameters are listed in Table II. In trolley position control aspect, the simulated control methods are enable to arrive at the appointed position accurately. Obviously, the PID control, optimized PID and optimized SMC drive the trolley to the destination more rapidly than unoptimized SMC. Note that, comparing with other three methods, the optimized SMC doesn’t need too much adjustments when the trolley arrived at the appointed position.

In payload angle control aspect, the PID controllers (un-optimized and optimized) exhibit unsatisfied performance in eliminating residual vibration. In addition, the oscillation amplitude of the unoptimized PID controller is much higher than SMCs, which the maximum amplitude is close to 1.8 radian for the first condition. From the results we can infer that the anti-sway control performance of the PID controllers have highly correlated with payload weight and appointed point. It means that the eliminating residual vibration is relative good when payload is heavy and the amplitude is relative low when the specify point is not far, vice versa. The main reason is that itself linear characteristic of the PID controller cannot handle the nonlinear system effectively. In contrast, the SMCs can damp the payload residual vibration effectively with short time. Besides, the performance of amplitude is much better than PID controllers. And the payload weight has not too much effect on anti-swing performance. Most important, the optimized SMC gives the best anti-swing performance in eliminating residual vibration and damping the oscillation amplitude, which it can avoid the unexpected accident effectively.

VI. CONCLUSIONS

For eliminating the payload residual vibration, we firstly design a sliding mode controller for under-actuated overhead crane systems. Moreover, for configuring the SMC parameter efficiently, we proposed a dynamic DE algorithm by introducing a dynamic scaling factor which is inspired by genetic scheme and utilize it to configure SMC parameters for solving the chattering problem. By simulating under three different operation conditions, the dynamic DE algorithm based SMC exhibits the best control performance in the trolley position and payload anti-swing control performance.
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