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Model Predictive Control of Gantry Crane with Input Nonlinearity Compensation

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***Abstract*—**This paper proposed a nonlinear model predictive control (MPC) method for the control of gantry crane. One of the main motivations to apply MPC to control gantry crane is based on its ability to handle control constraints for multivariable systems. A pre-compensator is constructed to compensate the input nonlinearity (nonsymmetric dead zone with saturation) by using its inverse function. By well tuning the weighting function matrices, the control system can properly compromise the control between crane position and swing angle. The proposed control algorithm was implemented for the control of gantry crane system in System Control Lab of University of Technology, Sydney (UTS), and achieved desired experimental results.

***Keywords*—**Model Predictive Control, Control constraints, Input nonlinearity compensation, Overhead gantry crane.

I. Introduction

GANTRY cranes are widely used in factories to transport heavy loads and hazardous materials. The operation of cranes can be divided into five steps: gripping, lifting, moving the load from point to point, lowering, and ungripping. Moving the load from point to point is the most time-consuming task in the process and requires a skilful operator to accomplish it [8]. In most of the applications, the transfer has to be performed as fast as possible. Such fast motion would induce undesirable swing, which may cause load damage and other types of hazards, and hence reduces the operation efficiency. The goal of control of gantry crane in this study is to automatically move the crane to a particular position as quickly as possible, while trying to keep the swing of the mass to a minimum.

For the control of gantry crane, various approaches can be found in literature. One of the most popular techniques in use is to separate the controller design into an anti-swing part and a tracking part. Each one is designed separately and then combined to ensure the performance and stability of the overall system [8]. For example, Yu et. al. [15] developed a nonlinear feedback control approach based on inner (anti-swing) outloop (tracking) structure. Yang et. al. [14] developed a parameter adaptive nonlinear controller for gantry position tracking and sway angle stabilization [7]. The second technique is based on the feedback of the position and the swing angle [8]. For example, Ridout [9] [10] developed controllers, which feed back the trolley position and speed and the load swing angle. The feedback gains are calculated either by trial and error based on the root-locus technique or by adjusting the trolley-velocity gain according to the error signal. Recently, Omar and Nayfeh [8] developed a gain scheduling feedback control approach with friction compensation and obtained good control results.

In this study, these two approaches were combined implicitly based on multivariable model predictive control (MPC). The main advantages of MPC is that it allows us to use the detailed knowledge of a process, in the form of a dynamic model, as an aid to control the process within required constraints [4]. Arnold et al. applied the MPC strategy in boom crane control [1]. However the structure of boom crane is quite different with the gantry crane. Nonlinear fuzzy MPC has been adopted in gantry crane control in [6], where the controller is based on the searching of the optimal solution in a discretized control space. In this paper, we developed a different MPC algorithm, which implement both tracking and anti-swing by tuning weighting matrices, where the control space needs not to be discretized. Hence this optimal solution is more accurate in the sense of quantization error.

Dead zone type phenomena occurs in various components of control systems including sensors, amplifiers and actuators, especially in electric servo motors [2] encountered in this study. It has a number of possible effects on control systems and the most common effect is to decrease the control accuracy and possibly lead to limit cycles or system instability. Tao et. al. [13], Bai [2] and Selmic et. al. [12] developed the adaptive dead zone inverse (ADI) approaches to deal with unknown dead zones. The idea is to cancel completely the effect of the dead zone so that linear analysis and design can be applied.

In this paper, the dead zone inverse strategy is also adopted in order to cancel nonlinear behaviour so that linear MPC is applicable. It should be emphasized that the special dead zone type nonlinearity (non symmetric dead zone with saturation) encountered in this study is theoretically non-invertible. However, as saturation can be treated as a constraint of the MPC controller, it is only required to inverse the dead zone in non saturation range.

This paper is organized as follows. The modelling of the system is given in Section 2. Section 3 introduces the proposed model predictive controller with input nonlinearity compensation. The experimental results and its discussions are also provided in this section. Conclusion is given in Section 4.

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II. MODELLING OF GANTRY CRANE SYSTEM

The overhead gantry crane system consists of a small crane that is driven by a DC motor in a horizontal direction along on I-beam that is approximately three meters long (See Figures 1 and 2). Attached to the bottom of the crane is a hanging mass, which is suspended 0.82m below the crane. Essentially, the hanging mass acts as a simple pendulum. As the crane moves along the I-beam, the acceleration of the crane affects the momentum of the mass, and as such, causes it to swing. The higher the acceleration of the moving crane, the further the mass will swing from its stationary position.

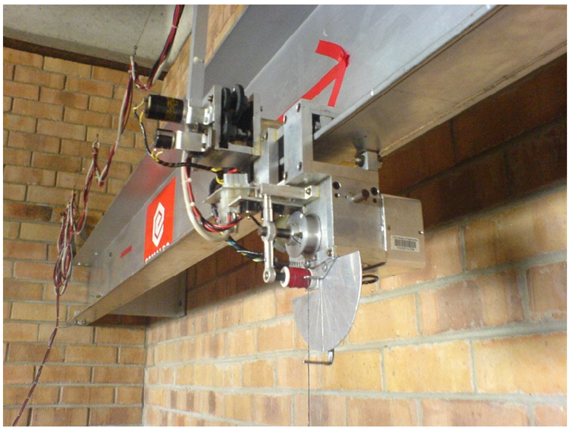

Fig. 1 Gantry crane system

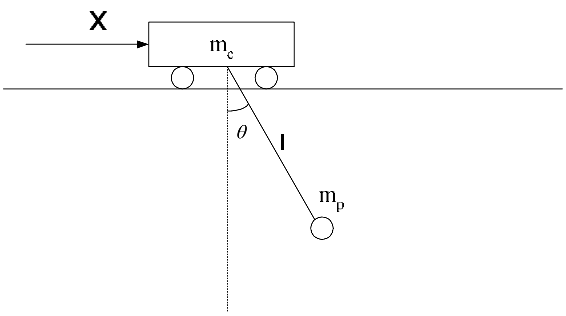

Fig. 2 Ideal gantry crane system

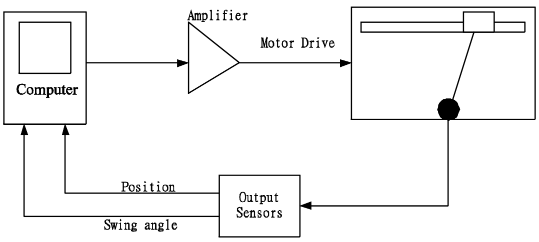

Fig. 3 The computer controlled gantry crane system

The overhead gantry crane system consists of a small crane that is driven by a DC motor in a horizontal direction along on I-beam that is approximately three meters long (See Figures 1 and 2). Attached to the bottom of the crane is a hanging mass, which is suspended 0.82m below the crane. Essentially, the hanging mass acts as a simple pendulum. As the crane moves along the I-beam, the acceleration of the crane affects the momentum of the mass, and as such, causes it to swing. The higher the acceleration of the moving crane, the further the mass will swing from its stationary position. The overhead gantry crane system has one control input and two controlled outputs (see Figure 3). The input is provided by the computer, and is passed to the crane motor, which drives the crane to a given velocity. The outputs of the system are the horizontal position of the crane and the swing angle of the hanging mass.

The input-output transfer function is modelled based on the Lagrangian approach [5]. In order to simplify the discussion, first we assume the friction between the track and crane is zero. Later, the inverse of the friction function will utilized to compensate it.

In Figure 2, we select the $q_1 = x$ and $q_2 = \theta$ as the generalized coordinates. Then, the Lagrangian of the system is

$$\begin{aligned} L &= T - U \\ &= \frac{1}{2}m_c\dot{q}_1^2 + \frac{1}{2}m_p[(\dot{q}_1 + \dot{q}_2 l cosq_2)^2 + (\dot{q}_2^2 l sinq_2)^2] \\ &- m_p g l(1 - cosq_2) \end{aligned} \tag{1}$$

Then, we derive two Lagrangian equations as follows:

$$\left\{ \frac{d}{dt}\left(\frac{\partial L}{\partial \dot{q}_i}\right) - \frac{\partial L}{\partial q_i} = F_i . i = 1,2 \right.$$

That is:

$$\left\{ \begin{array}{l} \ddot{q}_1(m_c + m_p) + m_p l(\ddot{q}_2 cosq_2 - \dot{q}_2^2 sinq_2) = F_x \\ m_p l(\ddot{q}_1 cosq_2 + l\ddot{q}_2 + g sinq_2) = 0 \end{array} \right. \tag{2}$$

If the controlled closed loop is well designed, it is reasonable to assume that θ is sufficiently small. Then, we can linearize equation (2) and obtain the following transfer functions:

$$\begin{bmatrix} X(s) \\ \Theta(s) \end{bmatrix} = \begin{bmatrix} \dfrac{s^2 l + g}{s^2(m_c l s^2 + m_c g + m_p g)} \\ -\dfrac{1}{m_c l s^2 + g(m_c + m_p)} \end{bmatrix} F(s) \tag{3}$$

The motor can be approximated by a first order system:

$$F(s) = \frac{k_m s}{\tau s + 1} U(s) \tag{4}$$

where $U(s)$ is the input voltage to the motor.

Based on equations (3) and (4), we have

$$\begin{bmatrix} X(s) \\ \Theta(s) \end{bmatrix} = \begin{bmatrix} \dfrac{k_m(s^2 l + g)}{s(\tau s + 1)(m_c l s^2 + m_c g + m_p g)} \\ -\dfrac{k_m s}{(\tau s + 1)[m_c l s^2 + g(m_c + m_p)]} \end{bmatrix} U(s) \tag{5}$$

As $m_c >> m_p$, equation (5) can be approximated as:

$$\begin{bmatrix} X(s) \\ \Theta(s) \end{bmatrix} = \begin{bmatrix} \dfrac{k_m}{m_c s(\tau s + 1)} \\ -\dfrac{k_m s}{[m_c l s^2 + g(m_c + m_p)](\tau s + 1)} \end{bmatrix} U(s) \tag{6}$$

Finally, the parameters of model (6) are determined based on physical measurements of the gantry crane and step response data obtained from the computer controlled gantry crane system (see Figure 3).

$$\begin{bmatrix} X(s) \\ \Theta(s) \end{bmatrix} = \begin{bmatrix} \dfrac{5.8}{s(s+2.4)} \\ -\dfrac{5s}{(s+2.4)(s^2+7.8)} \end{bmatrix} U(s) \qquad (7)$$

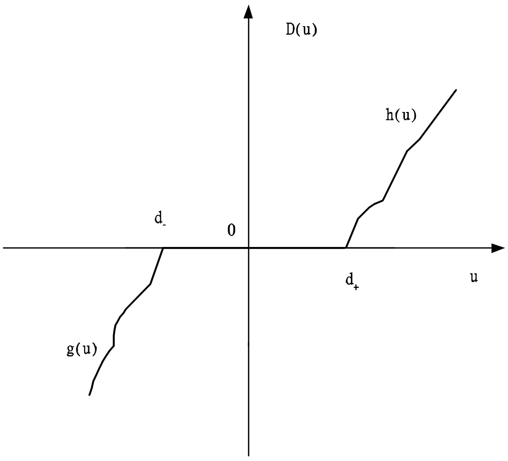

Fig. 4 Nonsymmetric deadzone nonlinearity

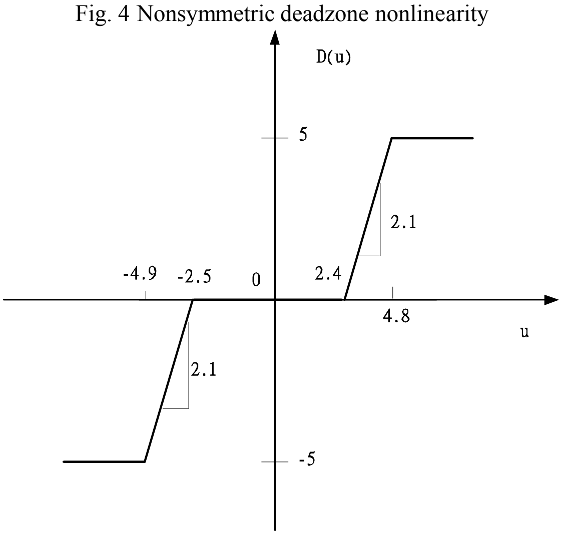

Fig. 5 Estimated nonlinearity

The dead zone was encountered when the voltage input is greater than -2.5 and less than 2.4. That is, the motor does not respond and hence does not move if a voltage is within this dead zone.

In [12], Selmic et. al. discussed a general nonsymmetric deadzone nonlinearity $D(u)$ (see Figure 4). A mathematical model for this deadzone characteristic is as follows:

$$D(u) = \begin{cases} g(u) \le 0, & u \le d_- \\ 0, & d_- < u < d_+ \\ h(u) \ge 0, & u \ge d_+ \end{cases} \qquad (8)$$

Functions $h(u)$ and $g(u)$ are invertible. In this study, it is obvious $d_+ = 2.4$ and $d_- = -2.5$, but we need to determine functions $h(u)$ and $g(u)$. The nonsaturation parts of functions $h(u)$ and $g(u)$ in our study are approximated as linear functions: $h(u) = k_+(u - d_+)$ and $g(u) = k_-(u - d_-)$. Coefficients k_+ and k_- are identified as $k_+ \approx k_- \approx 2.1$. The overall input nonlinearity is shown in Figure 5, which is a nonsymmetric deadzone with saturation.

MPC for nonlinear system is much complicated because of the difficulties of nonlinear optimization. As mentioned in the introduction, the dead zone inverse strategy is adopted in this study in order to cancel nonlinear behaviour so that linear MPC is applicable.

In this study, functions $g(u)$ and $h(u)$ are noninvertible due to saturation. However, the functions are invertible in non-saturation range. According to [12], a pre-compensator (also called pre-load) within non-saturation range is drawn as in Figure 6. Saturation can be treated as input constraint for MPC controller.

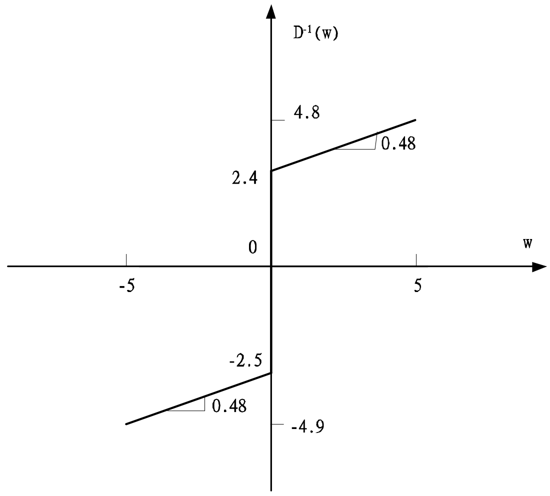

Fig. 6 Inverse of the estimated nonlinearity within non-saturation range

The experimental implementation of the inverse of the dead zone function is a simple logic statement. After experiments, it is found this pre-compensator introduces very sharp transient when the voltage goes through zero (similar to an ideal relay). The motor would jump accordingly and would pose a problem with the swing control due to the sudden velocities. In order to avoid the sharp transient, the following logic statements are served as pre-compensator:

- if ($OutputVoltage > 0.15$) and ($ABS(PositionError) < 0.2$)
  $OutputVoltage = 2.4 + 0.48 * OutputVoltage$;
- if ($OutputVoltage > -0.15$) and ($ABS(PositionError) < 0.2$)
  $OutputVoltage = -2.5 + 0.48 * OutputVoltage$.

From the above statements, it can be seen the pre-compensation action is confined by position tracking error ($|PositionError| > 0.2$) and output voltage of MPC controller ($|OutputVoltage| > 0.15$). Experiments proved the confined pre-compensation action can effectively compensate input nonlinearity and avoid sharp transient.

III. Model predictive control for gantry crane system

Based on the identified model, the model predictive controller is designed to implement both position tracking and anti-swing. The model predictive controller can handle saturation by simply imposing an input constraint. After the pre-compensator is employed, the gantry crane system can be treated as a linear dynamic system. Therefore, linear MPC can be applied to deal with this problem.

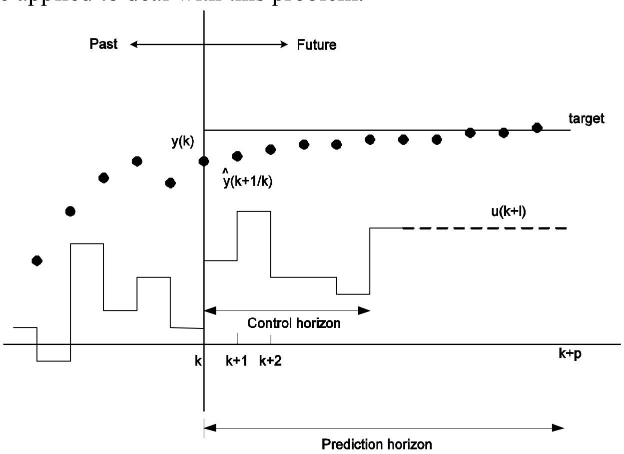

Fig. 7 Model predictive control algorithm description

Model predictive control predicts and optimize the future behaviour of the process based on a dynamic model of the process. At each control interval, the MPC algorithm calculates an open loop sequence of the manipulated variables in such a way to optimize the future behaviour of the plant [3]. The first value in this optimal sequence is injected into the plant. Figure 7 shows the state of a MPC system that has been operating for many sampling instants. Integer k represents the current instant. The latest measured output, y_k , and previous measurements, y_{k-1}, y_{k-2},..., are known.

To calculate its next move u_k, the controller operates in two phases [3]:

1. Estimation and prediction: In order to make an intelligent move, the controller needs to know the current state and any internal variables that influence the future trend. To accomplish estimation and prediction, the controller uses all past and current measurements and the models.

2. Optimization: Values of setpoints, measured disturbances, and constraints are specified over a finite horizon of future sampling instants, $k+1$, $k+2$, $\cdots$, $k+p$, where p is the prediction horizon. The controller computes m moves u_k, u_{k+1}, ... u_{k+m-1}, where m is the control horizon. The moves are the solution of a constrained optimization problem:

$$\min_{\Delta u_k \cdots \Delta u_{k+m-1}} \left(\sum_{l=1}^{p} \| \hat{y}_{k+l/k} - r_{k+l} \|^2_{\Gamma_l^y} + \sum_{l=1}^{m} \| \Delta u_{k+l-1} \|^2_{\Gamma_l^u}\right), \quad (9)$$

where,

- $\hat{y}_{k+l/k}$ is the predicted values of y at time $k+l$ based on information available at time k.
- p is prediction horizon which sets the number of control intervals over which the controller predicts its outputs when computing controller moves.
- m is control horizon which sets the number of moves computed. It must not exceed the prediction horizon. If less than the prediction horizon, the final computed move fills the remainder of the prediction horizon.
- $\Delta u_k = u_k - u_{k-1}$.
- $\| x \|^2_{\Gamma} = x^T \Gamma x.$
- Γ_l^y and Γ_l^u are weighting matrices for predicted errors and control moves ($\Gamma_l^y > 0$ and $\Gamma_l^u \geq 0$).

For details of the formulations, see [3] or [11].

Before control system implementation, the following issues should be addressed: the definition of system constraints, the selection of prediction and control horizons and weighting matrices.

As the inverse of the static nonlinearity has been identified and applied as a pre-compensator, the compensated system can be regarded as a linear dynamic system. Then, the optimization problem associated with the MPC controller design can be described as in (9). The constraint of this optimization problem is due to the saturation of the motor input voltage:

$$-5v \leq u \leq 5v \quad (10)$$

There are no specific rules for the selection of prediction horizon p and control horizon m. However, increasing p often results in less aggressive control action. Increasing m makes the controller more aggressive and increases computational effort. After extensive simulation and experimental studies, the value of prediction horizon p and control horizon m were selected as is 30 and 5 respectively.

The implementation of position tracking as well as anti-swing, the weighting matrices for predicted errors and control moves as Γ_l^y and Γ_l^u had been well tuned.

The overall digital control system is implemented by using a National Instrumentation (NI) Data Acquisition Card (DAQ 6062E). The core of model predictive control algorithm is Quadratic Programming (QP), which is realized by using Labview 8.0. Experimental results for two weighting functions

$$\begin{cases} \Gamma_l^y = diag([10]) \\ \Gamma_l^u = 0.2 \end{cases} and \begin{cases} \Gamma_l^y = diag([2.51]) \\ \Gamma_l^u = 0.2 \end{cases} \quad (11)$$

are shown in Figure 8. From the figure it can be seen that the proposed MPC based control strategy can well compromise between position tracking and anti-swing by properly selecting weighting matrices. Specifically, if select $\Gamma_l^y = diag([10])$ (weight for anti-swing control is zero), then good position tracking can be obtained, but the controller cannot reduce swing. On the other hand, if select a proper weight for anti-swing control ($\Gamma_l^y = diag([2.51])$), then the swing angle can be suppressed to a desired low level. No surprisingly, this will degrade position tracking. It should be also emphasized that this approach can also be applied for the accommodation of actuator failures as these failures can be easily handled by simply adding extra control constraints.

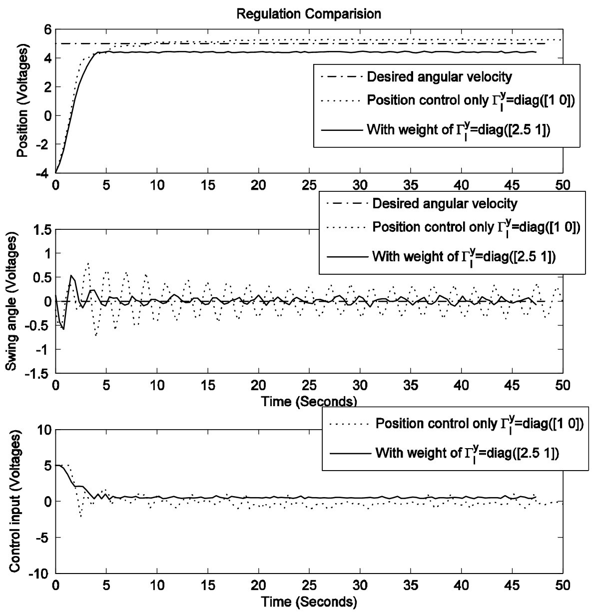

Fig. 8 Control of overhead gantry crane system with different weighting matrices. Top: Step response of position sensor output (One voltage approximately equals to 0.277 meter). Middle: Step response of angular sensor output (One voltage approximately equals to 15 degree). Bottom: Control output.

IV. CONCLUSION

This paper investigates the control of overhead gantry crane by using model predictive control. Firstly, the model of the gantry crane system is established, which includes a static input nonlinearity (deadzone with saturation). The saturation nonlinearity is treated as an input constraint of the designed MPC controller. The deadzone nonlinearity is compensated by using deadzone inverse approach. MPC controller is then designed for the pre-compensated system. By adjusting weighting matrices, we well compromise position tracking and anti-swing control. Real time experimental results demonstrated the efficiency of the proposed method.

REFERENCES

[1] E. Arnold, O. Sawodny, J. Neupert, and K. Schneider. Anti-sway system for boom cranes based on a model predictive control approach. *IEEE International Conference on Mechatronics and Automation; Piscataway, NJ*, 3:1533--1538, 2005.

[2] Er-Wei Bai. Adaptive dead zone inverses for possibly nonlinear control systems. In Gang Tao and Frank L. Lewis, editors, *Adaptive Control of Nonsmooth Dynamic Systems*, pages 31--47. Springer, 2001.

[3] Alberto Bemporad, Manfred Morari, and N. Lawrence Ricker. *Model Predictive Control Toolbox*. The MathWorks, Inc, 1994.

[4] C.E. Garcia, D.M. Prett, and M. Morari. Model predictive control: Theory and practice-a survey. *Automatica*, 25:335--348, 1989.

[5] A. MacFarlane. *Dynamical System Models*. Harrap, London, 1970.

[6] L.F. Mendonc, J.M. Sousa, and J.M.G. Sa da Costa. Optimization problems in multivariable fuzzy predictive control. *Int. J. Approximate Reasoning*, 36:199--221, 2004.

[7] H.T. Nguyen. State-variable feedback controller for an overhead crane. *Journal of Electrical and Electronics Engineering*, 14(2):75--84, 1994.

[8] H.M. Omar and A.H. Nayfeh. Gantry cranes gain scheduling feedback control with friction compensation. *Journal of Sound and Vibration*, 281:1--20, 2005.

[9] A.J. Ridout. Anti-swing control of the overhead crane using linear feedback. *Journal of Electrical and Electronics Engineering*, 9(1/2):17--26, 1989.

[10] A.J. Ridout. Variable damped control of the overhead crane. *IECON Proceedings, IEEE, Vol. 2, Los Alamitos, CA*, pages 263--269, 1989.

[11] J.A. Rossiter. *Model-based Predictive Control*. CRC PRESS, London, 2003.

[12] Rastko R. Selmic and Frank L. Lewis. Deadzone compensation in motion control systems using augmented multilayer neural networks. In Gang Tao and Frank L. Lewis, editors, *Adaptive Control of Nonsmooth Dynamic Systems*, pages 49--81. Springer, 2001.

[13] Gang Tao and Petar V. Kokotovic. *Adaptive control of systems with actuator and sensor nonlinearities*. Wiley, New York, 1996.

[14] Jung Hua Yang and Kuang Shine Yang. Adaptive coupling control for overhead crane systems. *Mechatronics*, 17(2-3):143--152, 2007.

[15] J. Yu, F.L. Lewis, and T. Huang. Nonlinear feedback control of a gantry crane. *Proc. American Control. Conf., Seattle*, pages 4310--4315, June 1995.