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Anti-swing and positioning control of overhead traveling crane

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Abstract

A new fuzzy controller for anti-swing and position control of an overhead traveling crane is proposed based on the Single Input Rule Modules (SIRMs) dynamically connected fuzzy inference model. The trolley position and velocity, the rope swing angle and angular velocity are selected as the input items, and the trolley acceleration as the output item. Each input item is given with a SIRM and a dynamic importance degree. The control system is proved to be asymptotically stable to the destination. The controller is robust to different rope lengths and has generalization ability for different initial positions. Control simulation results show that by using the fuzzy controller, the crane is smoothly driven to the destination in short time with small swing angle and almost no overshoot.

Keywords: Crane; Dynamic importance degree; Fuzzy control; Single input rule module; Stability analysis

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1. Introduction

Overhead traveling crane plays an important role in many factories, which transports a load from one place to another. Because high positioning accuracy, small swing angle, short transportation time, and high safety are required, operating an overhead traveling crane is a hard work and automation of operation is desirable.

Mita and Kanai [12] applied optimal control theory to generate a target speed pattern for fixed length crane on the assumption that there existed no swing angles at initial position and destination. Song et al. [17] showed a model reference adaptive control system with a fuzzy adaptation rule base, which reference model was essentially a target speed pattern. Because the target speed pattern approach did not consider the swing angle, Itoh et al. [8] added a fuzzy reasoning module into the deceleration section of the target speed pattern for both preventing big swing angle and positioning. Besides the target speed pattern based positioning, Hakamada and Nomura [5] further designed a feedback controller to control the swing angle through the whole process. Based on energy optimal speed reference, Hamalainen et al. [6] gave an optimal path planning approach for a trolley crane. For a given path with hoisting and lowering, Bartolini et al. [2] addressed a second-order sliding-mode crane controller and Moon and Vanlandingham [14] suggested a fuzzy approach for minimum time crane operation. However, the target speed pattern had to be regenerated for different rope length and different destination distance, and positioning accuracy was easily affected by disturbance.

Ishide et al. [7] trained a fuzzy neural network to control an overhead traveling crane by back-propagation method. Because trolley speed still kept big even when the trolley arrived at destination, however, this would result in big residual swing, low safety, and bad positioning accuracy. Kang et al. [10] proposed an adaptive switching control scheme, which had to design a set of fixed-length controllers based on different fixed-length nominal crane models and then selected one fixed-length controller according to control situations by an observer-based supervisor. Ohbayashi et al. [16] investigated robust control of an overhead traveling crane to different load mass by using second order derivative of universal learning network, but the maximum swing angle was larger than 10.0°. Other approaches like gain-scheduling controller [3], observer-controller [4], and variable structure control scheme [11] all need precise mathematical model and complicated calculation.

As Kang and Bien [9] pointed out, controlling a crane system is a multi-objective satisfactory problem. The system has two objectives: positioning of the trolley and anti-swing of the payload. Apparently, the two objectives contradict each other. For each objective, Nalley and Trabia [15] separately designed one fuzzy rule set and took the summation of the reference results of the two fuzzy rule sets as control input.

In this paper, a new fuzzy controller for anti-swing and position control of an overhead traveling crane is proposed. The trolley position and velocity, the rope swing angle and angular velocity are selected as the input items, and the trolley acceleration is selected as the output item. The Single Input Rule Modules (SIRMs) dynamically connected fuzzy inference model [18,19] is used to design the fuzzy controller. The fuzzy controller has a simple structure and needs no target speed pattern. Stability analysis is given and the fuzzy system is proved to be asymptotically stable to destination. The fuzzy controller is robust to different rope lengths and has generalization ability for different initial positions. Control simulation results demonstrate that by using the fuzzy controller, the overhead traveling crane smoothly moves to the destination in short time internal with small swing angle and almost no overshoot.

2. SIRMs dynamically connected fuzzy inference model

Let's begin with the SIRMs dynamically connected fuzzy inference model (shortened as the SIRMs model) [18,19] briefly for systems of n input items and one output item. The SIRMs model first sets up a SIRM separately for each input item as

$$\text{SIRM-}i : \left\{R_i^j : \text{if } x_i = A_i^j \text{ then } f_i = C_i^j\right\}_{j=1}^{m_i}. \tag{1}$$

Here, SIRM-i denotes the SIRM of the ith input item, and R_i^j is the jth rule in the SIRM-i. The ith input item x_i is the only variable in the antecedent part, and the consequent variable f_i is an intermediate variable corresponding to the output item f. In the jth rule of the SIRM-i, A_i^j is a fuzzy subset of x_i, and C_i^j is a fuzzy subset or singleton real number of f_i. Further, $i = 1, 2, \ldots, n$ is the index number of the SIRMs, and $j = 1, 2, \ldots, m_i$ is the index number of the rules in the SIRM-i.

To express clearly the different role of each input item on system performance, the SIRMs model further defines a dynamic importance degree w_i^{D} independently for each input item x_i $(i = 1, 2, \ldots, n)$ as

$$w_i^{\mathrm{D}} = w_i + B_i \Delta w_i. \tag{2}$$

The base value w_i guarantees the minimum weight of the corresponding input item for a control process. The dynamic value, defined as the product of the breadth B_i and the inference result of the dynamic variable Δw_i, plays a role in tuning the degree of the influence of the input item on system performance according to control situations. The base value and the breadth are control parameters, and the dynamic variable is described by fuzzy rules.

Suppose that each dynamic importance degree and the fuzzy inference result of each SIRM are already calculated. Then, the SIRMs model obtains the value of the output item f by

$$f = \sum_{i=1}^{n} w_i^{\mathrm{D}} f_i, \tag{3}$$

as the summation of the products of the fuzzy inference result of each SIRM and its dynamic importance degree for all the input items. By using the SIRMs, the input items can be processed dispersedly and the total number of fuzzy rules can be reduced much. By using the dynamic importance degrees, the control priority order of each input item can be represented definitely. Therefore, the SIRMs model makes designing of fuzzy controllers possible even for complicated control objects.

Since each SIRM can have only several fuzzy rules, it is easy to set such fuzzy rules just according to the relation of the input item with system performance. For simple problem, the parameters of the dynamic importance degrees may be selected by trial and error. But for complex problems, the parameters have to be tuned by some systematic approach like GA or other optimal searching methods. Although the SIRMs have no relationship with each other, Eq. (3) aggregates them with their dynamic importance degrees. Therefore, each input item takes its role in system performance according to its proportion in Eq. (3). If the output of each SIRM equals to its input and each importance degree is a constant, then Eq. (3) essentially becomes a linear state feedback controller. If the output of each SIRM equals to its input and each importance degree changes dynamically, then Eq. (3) corresponds to a gain scheduling controller. If the SIRMs and the importance degrees are given with nonlinearity, then Eq. (3) becomes nonlinear controller. Therefore, fuzzy controllers based on the SIRMs model can solve difficult control problem.

3. Fuzzy controller for overhead traveling crane

As shown in Fig. 1, the overhead traveling crane consists of a trolley, a rope, and a load. The load is regarded as a material particle with a mass of m. The rope is considered as an inflexible rod with a length of l, which mass is ignored compared with the load mass. Having a mass of M, the trolley moves on a straight rail. Supposing no friction exists in the system, then the dynamic equations [10] of the overhead traveling crane are given by

$$\cos(\theta)\ddot{x} + l\ddot{\theta} + g\sin(\theta) = 0, \tag{4}$$

$$(M + m)\ddot{x} + ml\cos(\theta)\ddot{\theta} - ml\dot{\theta}^2\sin(\theta) = F, \tag{5}$$

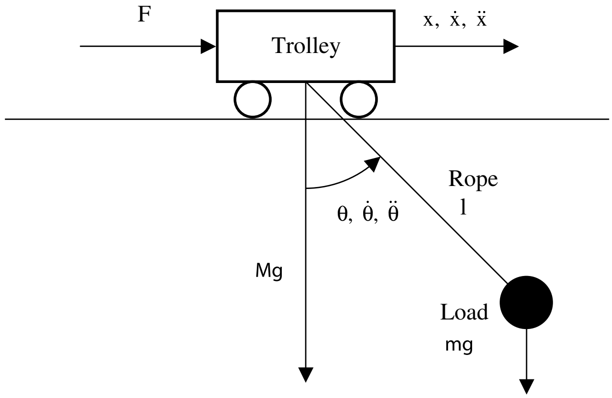


Fig. 1. Overhead traveling crane model.

by means of the Lagrange's equation of motion. Here, parameter $g = 9.81$ m/s^2 is the gravity acceleration. Variables x, θ, F separately denote the trolley position, the rope swing angle, and the driving force applied to the trolley. The trolley position is positive if the trolley locates at the right side of the rail origin. The rope swing angle is positive if the rope rotates counterclockwise from pendent position. The driving force toward right direction is positive.

Without loss of generality, the rail origin is taken as the desired position (the destination) of the trolley and the load. The control objective is to drive the trolley to transport the load safely from an initial position to the destination in short time without residual swing. This requires that the four state variables (trolley position x, trolley velocity $\dot{x}$, rope swing angle θ, and rope swing angular velocity $\dot{\theta}$) have to converge to zero.

Here, the four state variables after normalization are chosen in order as the input items x_i ($i = 1, 2, 3, 4$), and the trolley acceleration $\ddot{x}$ is selected as the output item. The scaling factors items s_i ($i = 1, 2, 3, 4$) of the four input items are fixed to 1.0 m, 1.0 m/s, 10.0°, and 10.0°/s, respectively. From Eq. (4), it can be seen that the load mass and the trolley mass have no direct influence on the swing angular acceleration if the trolley acceleration is known. After the trolley acceleration and the swing angular acceleration are obtained, the driving force F can be calculated according to Eq. (5).

Since there are four input items, the conventional fuzzy inference model, which puts all the input items into the antecedent part of each fuzzy rule, is confronted with problems such as difficulty of rule setting and exponential increase of fuzzy rules. Furthermore, it is intuitively understood that both the trolley velocity and the swing angle must be controlled to small with priority in order to achieve high safety. However, the conventional fuzzy inference model treats all the four input items equally and cannot give control priority to a specific input item. On the other hand, the SIRMs model solves the problems of the conventional fuzzy inference model by introducing the SIRMs and the dynamic importance degrees. Each SIRM can be considered to determine mainly the direction of the contribution of the corresponding input item in the model output of Eq. (3), and each dynamic importance degree can be considered to determine the magnitude of the contribution of the corresponding input item in Eq. (3). By adjusting the dynamic importance degrees according to control situations, the SIRMs together give reasonable value to the model output with competition and cooperation. Therefore, the SIRMs model is used to construct the fuzzy controller for anti-swing and position control of the overhead traveling crane. The design process includes the setting of the SIRMs, the setting of the fuzzy rules for the dynamic variables, and the setting of the control parameters of the dynamic importance degrees.

3.1. Setting the SIRMs

If the trolley position is positive, negative acceleration is needed so that the trolley moves negatively toward the destination. If the trolley position is negative, positive acceleration is needed so that the trolley moves positively toward the destination. Resultantly, the trolley position tends to approach to the destination.

If the trolley velocity is positive, negative acceleration is necessary such that the trolley velocity decreases from positive to zero. If the trolley velocity is negative, positive acceleration is necessary such that the trolley velocity increases from negative to zero. In this way, the swing angle will be small.

Therefore, the SIRMs of the two input items x_1 and x_2 corresponding to the trolley position and velocity can be set up both to Table 1.

If the swing angle is positive, the trolley should accelerate. Because of the inertia of the load, the rope will rotate clockwise and make the swing angle decrease toward zero. If the swing angle is negative, the trolley should decelerate so that the rope rotates counterclockwise and causes the swing angle to increase toward zero.

If the swing angular velocity is positive, the trolley should accelerate such that the swing angular acceleration becomes negative. If the swing angular velocity is negative, the trolley should decelerate such that the swing angular

Table 1
SIRMs of the trolley position and velocity

Antecedent variable x_i ($i = 1, 2$)	Consequent variable $\ddot{x}_i$ ($i = 1, 2$)
NB	1.0
ZO	0.0
PB	−1.0

Table 2
SIRMs of the swing angle and angular velocity

Antecedent variable x_i ($i = 3, 4$)	Consequent variable $\ddot{x}_i$ ($i = 3, 4$)
NB	−1.0
ZO	0.0
PB	1.0

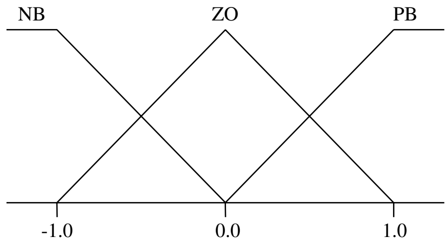


Fig. 2. Membership functions for the SIRMs.

acceleration becomes positive. Consequently, the swing angular velocity tends to become small.

Therefore, the SIRMs of the two input items x_3 and x_4 corresponding to the swing angle and angular velocity of the rope are both set up to Table 2.

In Tables 1 and 2, the membership functions NB, ZO, PB of each antecedent variable are defined in Fig. 2 as triangle or trapezoids. The consequent variables $\ddot{x}_i$ ($i = 1, 2, 3, 4$) are intermediate variables, all corresponding to the output item $\ddot{x}$ of the fuzzy controller, and their outputs are assigned with singleton real numbers.

3.2. Setting the dynamic variables

For the dynamic variable of the trolley position, the absolute value of the trolley position can be selected as the antecedent variable. If the trolley is far from the destination, the dynamic variable of the trolley position should take big value so that the dynamic importance degree of the trolley position increases. As a result, the control of the trolley position is emphasized and the trolley is driven strongly toward the destination.

For the dynamic variable of the trolley velocity, the absolute value of the trolley velocity is used as the antecedent variable. If the trolley moves fast, the dynamic variable of the trolley velocity should become big so that the dynamic importance degree of the trolley velocity goes up. As a result, the trolley velocity takes control priority. From the SIRM setting of the trolley velocity, the trolley velocity will then be suppressed.

For the dynamic variable of the swing angle, the absolute value of the swing angle is chosen as the antecedent variable. If the swing angle is big, the dynamic variable of the swing angle should show big value such that the dynamic importance degree of the swing angle increases. Then, the control of the swing angle is strengthened and the swing angle tends to get small.

For the dynamic variable of the swing angular velocity, the absolute value of the swing angular velocity is taken as the antecedent variable. If the swing angular velocity is big, the dynamic variable of the swing angular velocity should get big such that the dynamic importance degree of the swing angular velocity goes up. Resultantly, the control of the swing angular velocity is emphasized and the swing angular velocity becomes small from the SIRM setting.

Therefore, the fuzzy rules for the four dynamic variables can all be set up in Table 3. Here, the membership functions DS, DM, DB are defined in Fig. 3. From Table 3, it is clear that if the absolute value of one input item is small, the corresponding dynamic variable will take small value. If the absolute value of one input item is big, the corresponding dynamic variable will take big value.

3.3. Setting the control parameters

To tune automatically the control parameters, i.e., the base values and the breadths of the four dynamic importance degrees, the random optimization search method [1] is used.

Table 3
Fuzzy rules of each dynamic variable

Antecedent variable $\lvert x_i \rvert$	Consequent variable Δw_i
DS	0.0
DM	0.5
DB	1.0

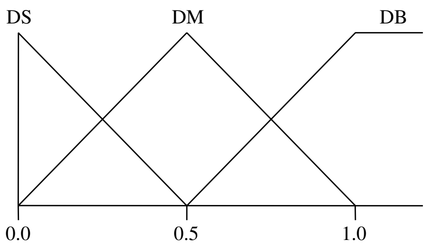


Fig. 3. Membership functions for the dynamic variables.

Here, the rope length, the trolley maximum velocity, and the trolley maximum acceleration are set up to, 1.0 m, 1.0 m/s and 1.0 m/s^2, respectively. The initial trolley position is set up to -1.0 m, while the initial values of the other state variables are set up to zero. The base values and the breadths of the dynamic importance degrees are initially set up to zero. In each trial of the random optimization search, the sampling period is fixed to 0.01 s, and the total control time is fixed to 25.0 s which is long enough for the trolley to arrive at the destination. The performance index is defined as

$$\Phi = T + \sum_{t \geqslant T}^{T+10} (|x| + |\dot{x}| + |\theta| + |\dot{\theta}|), \tag{6}$$

where the first term T is the transportation time when the trolley first arrives at the destination from each trial beginning. The second term means the total absolute error of the four state variables for 10 s after the trolley arrives at the destination. Apparently, the smaller the first term is, the shorter the transportation time becomes. The smaller the second term is, the faster the convergence of the four state variables is. Therefore, small performance index insures short transportation time, small swing angle, and small overshoot.

The random optimization search is run for 1000 trials along such a direction that the performance index decreases. The base values and the breadths after the random optimization search are listed in Table 4. As it can be seen from Table 4, the sum of the base value and the breadth of the dynamic importance degree of the trolley velocity is the biggest among the four input items. Moreover, the sum of the base value and the breadth of the dynamic importance degree of the swing angle is bigger than that of the other two input items. As a result, the dynamic importance degree of the trolley velocity will be the biggest when the trolley velocity is big, and the dynamic importance degree of the swing angle will be significant if the swing angle is big.

3.4. Control mechanism

The block diagram of the proposed fuzzy controller is shown in Fig. 4. The four state variables of the overhead traveling crane are first normalized by their scaling factors separately to generate the input items x_i ($i = 1, 2, 3, 4$). Each

Table 4
Control parameters

Input item	Base value	Breadth
Trolley position	2.0095	0.4890
Trolley velocity	3.3873	2.2554
Swing angle	2.5474	1.2201
Angular velocity	0.8262	1.6815

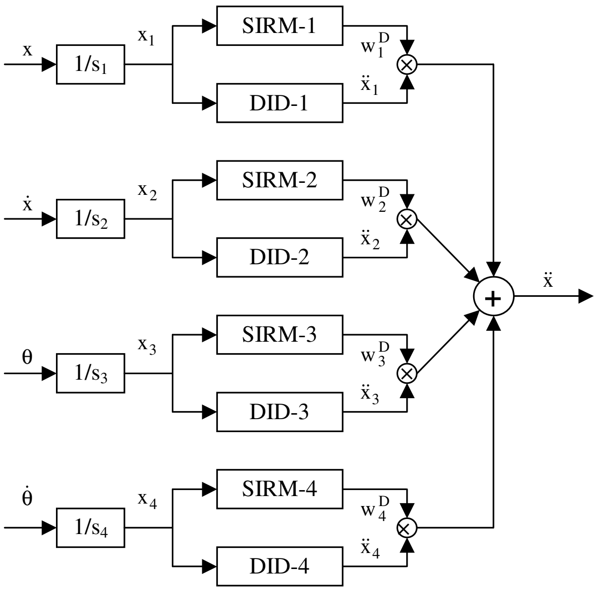


Fig. 4. Block diagram of the fuzzy controller.

input item x_i is then sent to the corresponding SIRM block and dynamic importance degree (DID) block. Based on the simplified inference method [13], the SIRM-i block performs the fuzzy inference of the SIRM corresponding to the input item x_i. Taking the absolute value of the input item x_i as the antecedent variable, the DID-i block calculates the value of the corresponding dynamic importance degree. After the output of each SIRM-i block is multiplied by the output of the DID-i block, the sum total for all the input items becomes the output of the fuzzy controller, i.e., the trolley acceleration $\ddot{x}$.

If the trolley locates far from the destination and the other state variables are nearly zero, the dynamic importance degree of the trolley position becomes almost as big as the others from Tables 3 and 4. Because only the SIRM of the trolley position is significant in this case, the contribution of the trolley position makes up the main part of the output item. According to the SIRM of the trolley position, the trolley will then be driven to move toward the destination.

If the trolley velocity becomes big, its SIRM and dynamic variable will both strongly get fired. In this case, the dynamic importance degree of the trolley velocity becomes the biggest and the inference result of the SIRM is also big. Consequently, the trolley velocity takes the control priority over the others. According to the SIRM of the trolley velocity, the trolley will then be controlled to move slowly so that no big swing angle occurs.

If the trolley velocity is small and the swing angle is big, the dynamic importance degree of the swing angle becomes bigger than that of the trolley velocity. Further, the inference result of the SIRM of the swing angle is also bigger than that of the trolley velocity. In this case, the contribution of the swing angle to the output item exceeds that of the trolley velocity and the swing angle instead has the control priority over the others. From the SIRM setting of the swing angle, the swing angle will then be forced to decrease.

If the swing angular velocity gets big while the others are small, the dynamic importance degree of the swing angular velocity becomes nearly as big as the others. Because only the inference result of the SIRM of the swing angular velocity is big in this case, however, the contribution of the swing angular velocity forms the major part of the output item. Then the control of the swing angular velocity becomes activated and the swing angular velocity will be reduced based on its SIRM.

In this way, anti-swing and position control of the overhead traveling crane is realized by using the SIRMs and adjusting the values of the dynamic importance degrees automatically according to control situations.

3.5. Stability analysis

To guarantee the performance of a control system, stability analysis is necessary. As well known, however, stability analysis of a non-TK type fuzzy control system is not an easy task. To make stability analysis possible, here discussion is first limited in a small neighbor of the destination, that is, the values of the four state variables are all supposed to be very small.

In the neighbor of the destination, the inference results of the two SIRMs of the trolley reversely equal to the corresponding input items and the inference results of the two SIRMs of the load completely equal to the corresponding input items according to the SIRMs and the membership functions of Fig. 2. Because the inference result of each dynamic variable becomes almost zero in the neighbor of the destination from the fuzzy rules of Table 3 and the membership functions of Fig. 3, each dynamic importance degree can be approximated by its base value. According to Eq. (3) and Table 4, therefore, the output item of the fuzzy controller, i.e., the trolley acceleration is then obtained by

$$\ddot{x} = -2.0095x_1 - 3.3873x_2 + 2.5474x_3 + 0.8262x_4. \tag{7}$$

Substituting the state variables for the input items, Eq. (7) further becomes

$$\ddot{x} = -2.0095x - 3.3873\dot{x} + 14.5955\theta + 4.7338\dot{\theta}. \tag{8}$$

Compared with the well-known linear state feedback controller, it is evident that Eq. (8) is essentially a linear state feedback controller. Therefore, the stability analysis problem of the fuzzy control system is transformed into the stability analysis problem of a usual linear state feedback control system when the values of the four state variables are small enough. In order to identify the stability of the designed control system, the well-known linear state feedback control theories are available.

First, Eq. (4) is linearized for small swing angle and a linear state equation of the four state variables is established. Then, Eq. (8) is substituted into the state equation and a closed-loop system matrix is obtained. After the system matrix is solved, the four eigenvalues of the system matrix are found to be $-3.190+1.927i$, $-3.190-1.927i$, $-0.870+0.814i$, $-0.870-0.814i$, where i is the imaginary unit. Because the real parts of the eigenvalues are all negative, the designed control system proves to be asymptotically stable to the destination.

Furthermore, if the trolley is far from the destination, the trolley will be forced to move toward the destination according to its SIRM setting. If the trolley velocity is big, the SIRM of the trolley velocity will make the trolley velocity decrease. If the swing angle becomes big, the SIRM setting will cause the swing angle to get small. If the swing angular velocity gets big, the SIRM setting will reduce the swing angular velocity. Therefore, global stability of the control system is guaranteed.

4. Control simulations

In order to verify the performance of the proposed fuzzy controller, several control simulations are done in this section. Moreover, the control results are compared with those of the linear state feedback controller of Eq. (8).

In Fig. 5, time responses of the trolley position and the swing angle are depicted. Fig. 5(a) is obtained by the proposed fuzzy controller, while Fig. 5(b) is obtained by the linear state feedback controller. The initial position of the trolley is −1.0 m, and the initial values of the other state variables are all zero. The maximum swing angle is 3.307° in Fig. 5(a) and 3.572° in Fig. 5(b). The transportation time, that the four state variables of the overhead traveling crane converge from the control beginning to 0.01 m, 0.01 m/s, 0.10°, and 0.10°/s, is 4.66 s in Fig. 5(a) and 6.46 s in Fig. 5(b). As it can be seen from the time responses, the linear state feedback controller further causes some overshoot (0.030 m) besides the long transportation time.

In Fig. 6, another control simulation example is shown where the initial position of the trolley is set up to −2.0 m. Because the initial position is out of the scaling factor of the trolley position, the SIRM of the trolley position works at its saturation domain and the trolley acceleration is suppressed by the fuzzy controller. As a result, in Fig. 6(a) the trolley moves at a moderate speed without overshoot, and the transportation time and the maximum swing angle are separately 7.26 s and 3.554°. On the other hand, because the linear state feedback controller determines the control input in proportional to each state variable, big trolley acceleration is generated for big trolley position. Consequently, in Fig. 6(b) the trolley moves at a high speed and the maximum swing

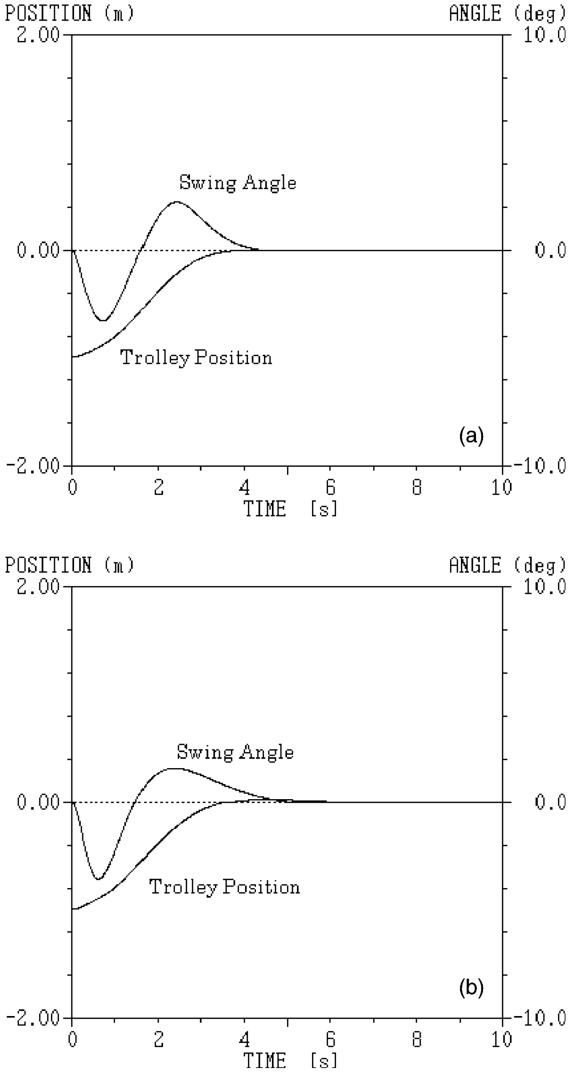
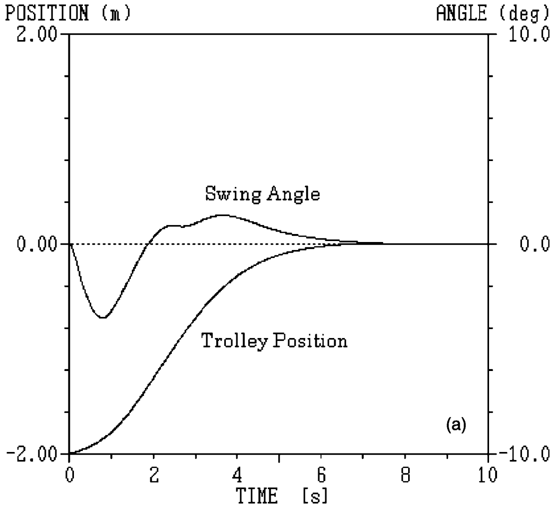


Fig. 5. Control simulation example (1). (a) Proposed fuzzy controller, (b) linear state feedback controller.

angle increases almost double to 6.913°. Although the trolley transits the destination in less than 4.0 s, an overshoot amount of 0.060 m appears in the time response of the trolley position and the transportation time finally becomes 7.19 s.

Fig. 7 shows the control results of the overhead traveling crane, where the rope length is 0.5 m long and the initial position is −2.0 m. Although the initial



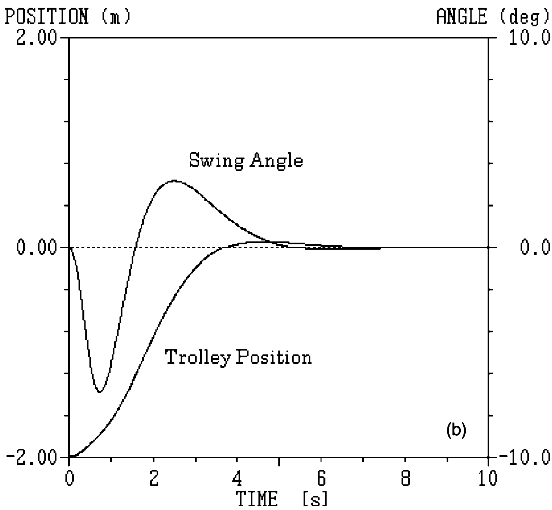
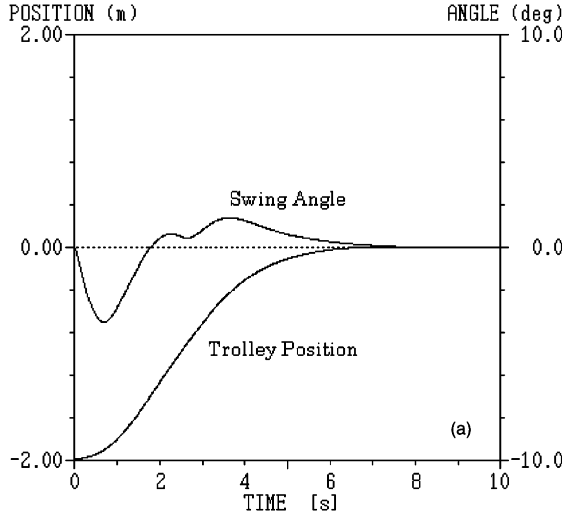


Fig. 6. Control simulation example (2). (a) Proposed fuzzy controller, (b) linear state feedback controller.

position and the rope length are both different from those used in the random optimization search, the fuzzy controller can robustly drive the crane to the destination in 7.37 s with an overshoot amount of only 0.002 m. On the other hand, the linear state feedback controller generates big trolley acceleration from the control beginning and shortens the transportation time to 7.25 s with an overshoot amount of 0.052 m. Further because the rope is shorter, the natural frequency of the rope increases. For the same trolley acceleration,



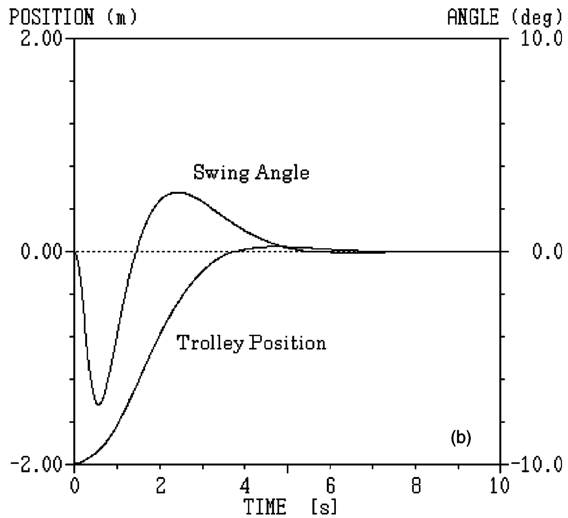


Fig. 7. Control simulation example (3). (a) Proposed fuzzy controller, (b) linear state feedback controller.

shorter rope is easier to swing. As a result, the maximum swing angle (3.558°) in Fig. 7(a) gets a little bigger than that of Fig. 6(a), and the maximum swing angle in Fig. 7(b) becomes even bigger to 7.221°.

The control results of the overhead traveling crane, where the rope length is 2.0 m long and the initial position is −2.0 m, are indicated in Fig. 8. Even though the rope length is doubled compared with Fig. 6, the fuzzy controller can still smoothly control the crane to the destination in 7.36 s without

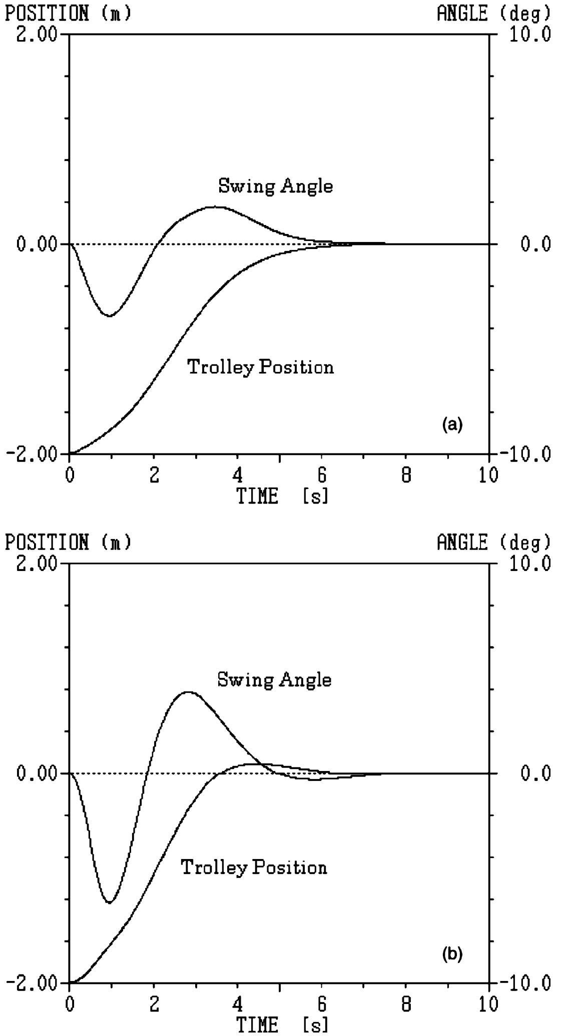


Fig. 8. Control simulation example (4). (a) Proposed fuzzy controller, (b) linear state feedback controller.

overshoot. Because of big overshoot amount of 0.096 m, however, the linear state feedback controller takes 7.75 s to finish the control. Further because the natural frequency of the rope becomes smaller in this example, the rope is slow to swing. Resultantly, the maximum swing angle decreases to 3.449° in Fig. 8(a) and 6.190° in Fig. 8(b) compared with Fig. 6. Apparently the maximum swing angle by the linear state feedback controller is still much bigger than that by the fuzzy controller.

Fig. 9 displays the transportation time necessary for the fuzzy controller and the linear state feedback controller under different rope lengths and different initial positions. The rope length (vertical axis) is selected every 0.1 m from 0.1 to 2.0 m. Because the results are symmetric with respect to positive and negative trolley positions, the trolley initial position (horizontal axis) is chosen every 0.1 m from 0.1 to 2.0 m. The symbols ●, ○, ■, □ mean separately that the transportation time is within 3.5, or 5.0, or 6.5, or 8.0 s. By using the fuzzy controller, the transportation time is within 5.0 s in most of the cases that the rope length is shorter than 1.3 m and the initial position is smaller than 1.3 m, and is within 6.5 s if the rope length is shorter than 1.6 m and the initial position is smaller than 1.6 m. By using the linear state feedback controller, on the other hand, the transportation time is over 5.0 s if the initial position is bigger than 0.4 m, and is over 6.5 s if the initial position is bigger than 1.0 m.

Fig. 10 depicts the maximum swing angles resulting from the fuzzy controller and the linear state feedback controller under different conditions. The symbols ●, ○, ■, □ specify separately that the maximum swing angle is within 2.0°, or 4.0°, or 6.0°, or 8.0°. As it can be seen from Fig. 10, the maximum swing angle is within 4.0° for all the conditions when the fuzzy controller is used. By using the linear state feedback controller, however, the maximum swing angle is almost bigger than 4.0° if the initial position is bigger than 1.1 m. In most of the cases that the initial position exceeds 1.7 m, the maximum swing angle becomes even bigger than 6.0°.

Fig. 11 shows the overshoot amounts arising under different conditions. The symbols ●, ○, ■, □ denote separately that the overshoot amount is within 0.01, or 0.04, or 0.07, or 0.10 m. It is clear from Fig. 11 that in almost all the cases the overshoot amount is within 0.01 m when the fuzzy controller is used. However, the overshoot amount gets large with the increasing of the initial position and the rope length under the linear state feedback controller. And the overshoot amount exceeds 0.04 m in most of the cases that the initial position is bigger than 1.0 m.

5. Discussions

No need to say, the linear state feedback controller of Eq. (8) has constant feedback gains. Although the maximum trolley acceleration is given, the actual trolley acceleration determined by Eq. (8) is proportional to the value of each state variable if the trolley acceleration is still smaller than the maximum. When the trolley is far from the destination, the linear state feedback controller will then generate big trolley acceleration. Consequently, the trolley moves fast toward the destination and causes the rope to swing largely. When the trolley approaches to the destination, the trolley velocity decays slowly because of the constant feedback gains. As a result, big overshoot occurs, big residual swing

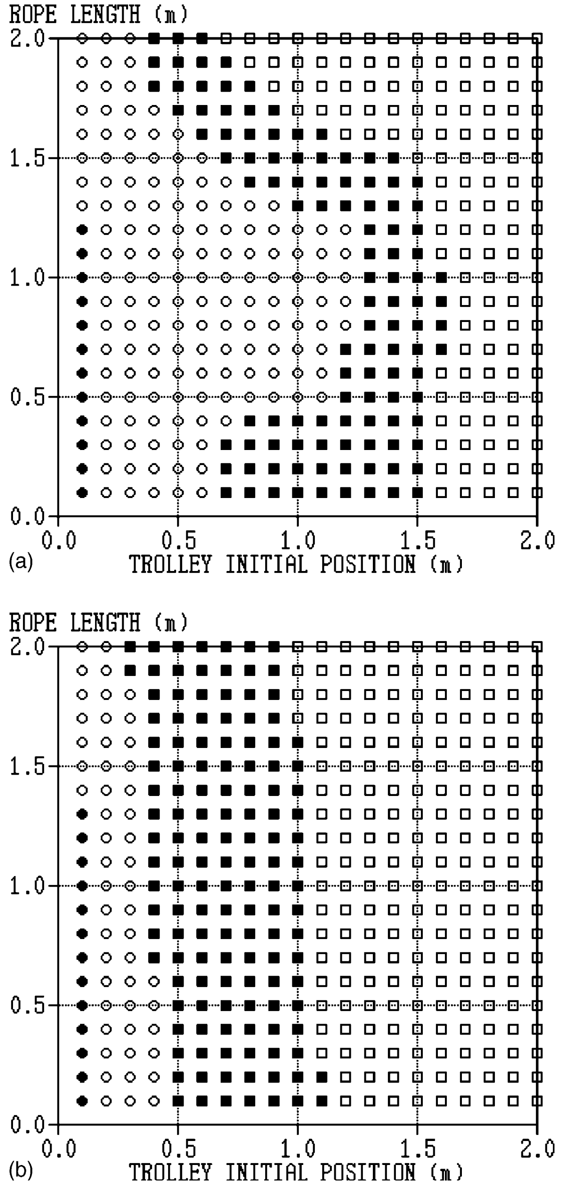


Fig. 9. Comparison of transportation time. (a) Proposed fuzzy controller, (b) linear state feedback controller.

appears, and the transportation time becomes long although the trolley transits the destination in short time interval.

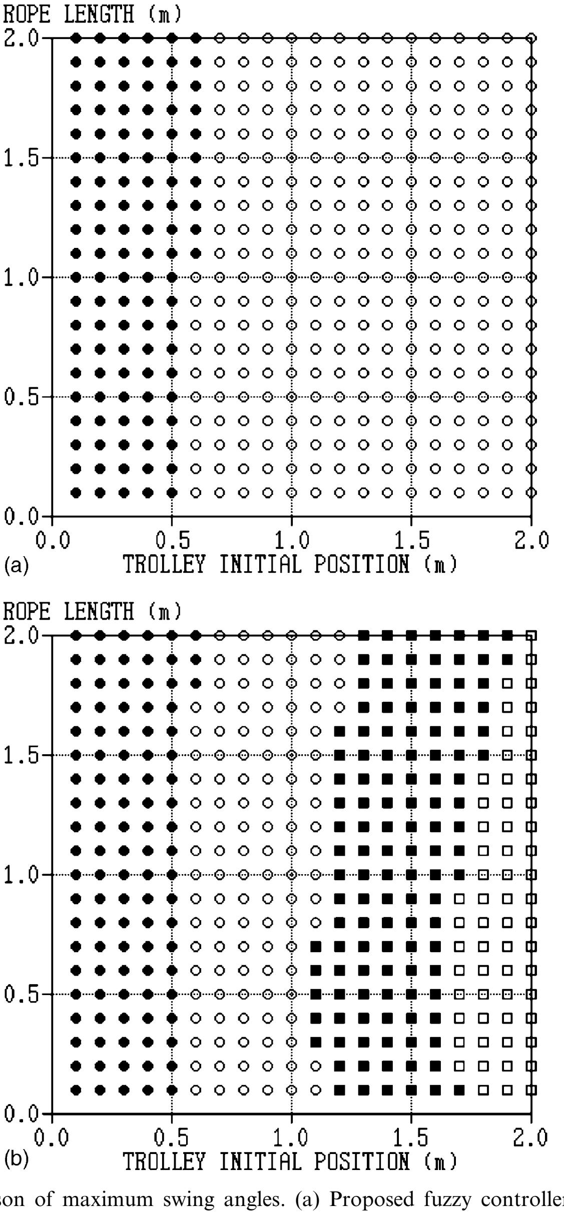
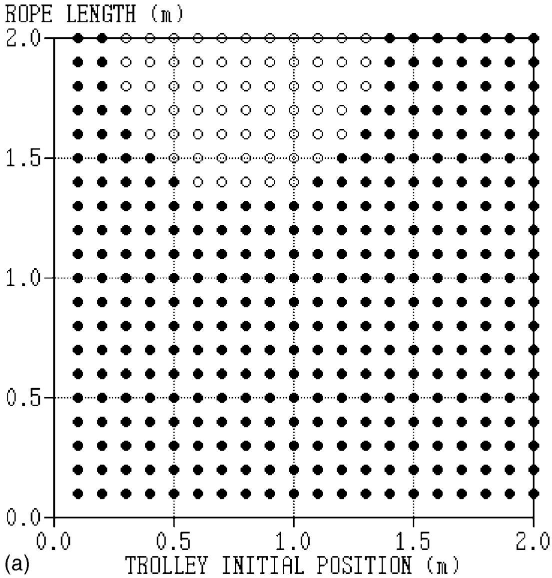


Fig. 10. Comparison of maximum swing angles. (a) Proposed fuzzy controller, (b) linear state feedback controller.

The proposed fuzzy controller, on the other hand, uses the SIRMs that have saturation features, and the dynamic importance degrees that change



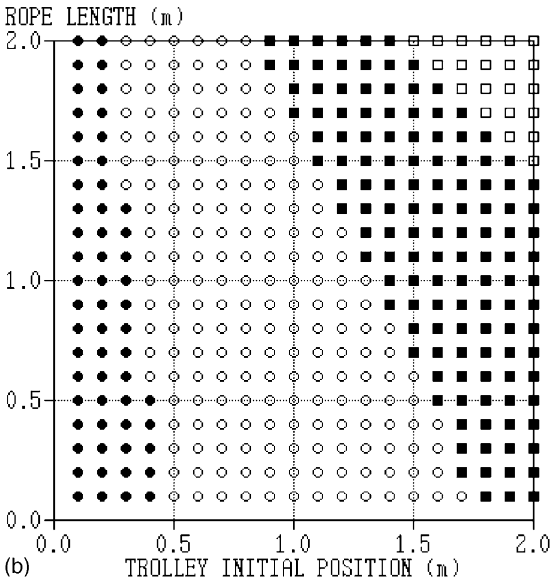


Fig. 11. Comparison of overshoot amounts. (a) Proposed fuzzy controller, (b) linear sate feedback controller.

automatically with control situations. Each dynamic importance degree has its minimum when the corresponding input item is zero and has its maximum after the corresponding input item reaches its scaling factor. Except the SIRM of the trolley position, the other three SIRMs are designed to essentially prevent the trolley velocity from getting big. The saturation feature of each SIRM limits the output of the SIRM. When the trolley is far from the destination, the SIRM of the trolley position will get saturated. After the trolley starts moving toward the destination, the dynamic importance degrees of the trolley velocity, the swing angle, and the angular velocity will increase so that the trolley velocity is strongly suppressed. Resultantly, the maximum swing angle is small and the trolley arrives at the destination almost without overshoot.

Since the fuzzy controller and the linear state feedback controller both guarantee the stability of the control system, high positioning accuracy is realized in both cases. From the above control results, however, the transportation time by the fuzzy controller is shorter than or nearly equal to that by the linear state feedback controller. During transportation, big swing angle will lead to low safety and even danger. When the trolley approaches to the destination, big overshoot amount and big residual swing angle may cause the load to bump against others locating in front of the destination. As indicated above, the control results by the fuzzy controller demonstrate small swing angles and almost no overshoot. Further in Figs. 5–8, the fuzzy controller causes almost no residual swing angle while the linear state feedback controller causes a residual swing angle of near or over 1.0° when the trolley first transits the destination. Compared with the linear state feedback controller, therefore, it can be said that the overhead traveling crane controlled by the fuzzy controller is transported to the destination safely in short time interval with high accuracy.

Unlike the target speed pattern approaches [5,6,8,12,17], the designed fuzzy controller is more flexible because no target speed pattern is necessary. From different initial positions, the desired fuzzy controller can achieve almost similar results while the target speed pattern approaches have to regenerate the target speed pattern each time. If disturbance appears during transportation, the proposed fuzzy controller can absorb the influence of disturbance and then perform as usual. In such situation, however, the target speed pattern approaches will lead to bad positioning accuracy.

Moreover, because the change of the rope length has little influence on the control performance of the fuzzy controller from the control simulations, the fuzzy controller is robust to different rope length. Different from the adaptive switching control scheme [10], therefore, there is no need to prepare several controllers for different rope lengths. Even though the rope length is different, the fuzzy controller can achieve almost the same good control results. As mentioned above, the trolley mass and the load mass do not affect the performance of the fuzzy controller. Compared with the universal learning network [16], therefore, the proposed fuzzy controller is more robust and performs better.

Table 5
Traditional fuzzy rule set

			$\theta = \text{NB}$			$\theta = \text{ZO}$			$\theta = \text{PB}$		
			x								
			NB	ZO	PB	NB	ZO	PB	NB	ZO	PB
$\dot{\theta} = \text{NB}$	$\dot{x}$	NB	−0.91	0.78	0.94	−0.22	0.01	−0.99	−1.15	−0.65	1.06
		ZO	−2.10	−1.92	−0.88	−0.07	−0.31	−0.78	−0.57	−1.40	−0.45
		PB	−2.43	1.45	−0.77	−1.12	−1.36	−1.37	−0.04	1.17	0.63
$\dot{\theta} = \text{ZO}$	$\dot{x}$	NB	−0.36	0.45	−0.10	1.53	−0.33	−0.63	−0.24	−0.46	−1.41
		ZO	1.11	0.16	0.53	0.51	0.00	−0.61	−2.20	−0.45	1.43
		PB	0.18	−0.41	−1.45	0.03	−1.14	1.69	0.46	−0.62	0.40
$\dot{\theta} = \text{PB}$	$\dot{x}$	NB	1.54	0.04	−0.78	0.10	1.12	1.65	0.00	−0.98	−1.67
		ZO	−2.43	−0.64	0.56	0.24	0.36	−0.58	0.24	0.84	−1.47
		PB	−1.09	1.59	−0.55	−0.08	0.60	−2.27	−1.20	−1.12	−2.01

To further compare with traditional fuzzy model, a four-input one-output fuzzy rule system for the overhead crane is constructed here (Table 5). Just like the controller designed in Section 3, the four input items are trolley position x, trolley velocity $\dot{x}$, rope swing angle θ, and rope swing angular velocity $\dot{\theta}$, and the output item is the trolley acceleration $\ddot{x}$. The input scaling factors are the same with the proposed controller, and Fig. 2 gives the membership functions for each input item. Because there are totally 81 fuzzy rules in the rule set and each fuzzy rule has four inputs to consider, it is not easy to set such a fuzzy rule set manually. Then the random optimization search method [1] is again used to tune automatically the fuzzy rules under the same conditions with Section 3.1. Table 4 shows the final fuzzy rule set. Fig. 12 depicts four control results based on the fuzzy controller. The control conditions of Fig. 12(a) correspond to that during tuning. As can be seen from these figures, the traditional fuzzy controller can control the swing angle to a rather small range and transport the payload to the destination. However, the payload swings sharply during transportation, and the transportation time becomes long. Furthermore, the control results change much with the control situations. When the rope length is shortened from 1.0 to 0.5 m and the trolley initial position is changed from −1.0 to −2.0 m, for example, Fig. 12(c) indicates that the swing angle of the payload becomes about 3.0° and it takes more than 15.0 s to converge to the destination. Therefore, compared with the traditional fuzzy controller, the proposed fuzzy controller is more robust and effective. In addition, the proposed fuzzy controller is easy to design and easy to understand because each SIRM and each dynamic variable have only several fuzzy rules, and the dynamic importance degrees directly adjust the influence of the corresponding input items.

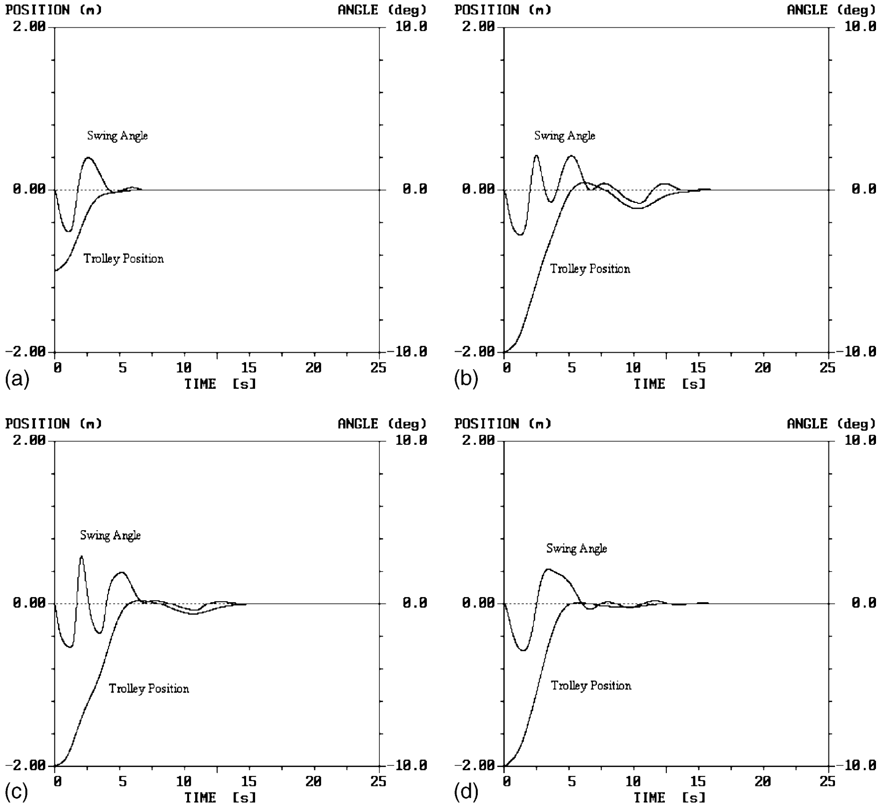


Fig. 12. Simulation results by traditional fuzzy controller. (a) Rope length 1.0 m and trolley initial position −1.0 m, (b) rope length 1.0 m and trolley initial position −2.0 m, (c) rope length 0.5 m and trolley initial position −2.0 m, (d) rope length 2.0 m and trolley initial position −2.0 m.

6. Conclusions

A new fuzzy controller based on the SIRMs dynamically connected fuzzy inference model is proposed for anti-swing and positioning control of the overhead traveling crane. The fuzzy controller takes the trolley position, the trolley velocity, the rope swing angle, and the swing angular velocity as the input items, and the trolley acceleration as the output item. Each input item has a SIRM and a dynamic importance degree. The dynamic variable of each dynamic importance degree uses the absolute of the corresponding input item as its antecedent variable. The fuzzy controller has a simple structure and the control system is proved to be asymptotically stable to the destination. Control simulation results show that the fuzzy controller is robust to the change of the rope length and has generalization ability for different initial positions.

Compared with the linear state feedback controller, the fuzzy controller realizes the anti-swing and positioning control of the overhead traveling crane in short time interval with high accuracy and small swing angle.

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