World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:2, No:2, 2008

A New Approach for Controlling Overhead Traveling Crane Using Rough Controller

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Abstract**—** This paper presents the idea of a rough controller with application to control the overhead traveling crane system. The structure of such a controller is based on a suggested concept of a fuzzy logic controller. A measure of fuzziness in rough sets is introduced. A comparison between fuzzy logic controller and rough controller has been demonstrated. The results of a simulation comparing the performance of both controllers are shown. From these results we infer that the performance of the proposed rough controller is satisfactory.

Keywords**—**Accuracy measure, Fuzzy Logic Controller (FLC), Overhead Traveling Crane (OTC), Rough Set Theory (RST), Roughness measure

I. Introduction

THE crane can be considered as one of the most important tools used in industry to transfer loads from one desired position to another. Usually cranes have very strong structures in order to lift heavy payloads in factories, in building construction, on ships, and in harbors. Until recently, cranes were manually operated. But when cranes became larger and they are being moved at high speeds, their manual operation became difficult. Consequently, methods of automating their operation are being sought. Two special inference engines (two rule-base) FLC had been done with [1-2]. Many researchers [1-3] deal with the fuzzy controller, some of researchers took one FLC only to control two system's variables like [3]. In many real processes, control relies heavily upon human experience. Skilled human operators can control such processes quite successfully without any qualitative models. The control strategy of human operator is mainly based on linguistic qualitative knowledge concerning the behaviour of an ill-defined process. In order to cope with this difficulty, the human mind using intuitive and subjective thinking is realized as fuzzy logic An alternative approach to manipulating incomplete or imprecise information was presented by Pawlak in (1982) as a rough set theory [4]. The essence of this approach relies on the approximation of incomplete or imprecise information by means of completely and precisely known pieces of information. As a natural need, Dubois and Prade, [5] combined fuzzy sets and rough sets in a fruitful way by defining rough fuzzy sets and fuzzy rough sets. By analogy with the concept of a fuzzy controller, the idea of a rough controller based on the notion of a rough set theory will be introduced in the next section.

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II. Rough Set Theory

Rough Set Theory (RST) is a mathematical tool to deal with vagueness and uncertainty in the areas of machine learning. It is a recent development in the area of data mining and knowledge discovery. Let U be a set called universe and let R be an equivalence relation on U; called an in discredibility relation. The pair S= (U, R) is called an approximation space. Then for any non-null subset X of U;

$$\underline{A}(X) = \{x \in U : [x]_R \subseteq X\} \tag{1}$$

$$\overline{A}(X) = \{x \in U : [x]_R \cap X \neq \phi\} \tag{2}$$

The sets $A(X) = (\underline{A}(X), \overline{A}(X))$, are respectively, called the lower and the upper approximation of x in S; where [x]R denotes the equivalence class of the relation (R) containing the element x. Below are the fundamental notions of the RST [6-7].

Definition: Let A=($\underline{A}, \overline{A}$) and B=($\underline{B}, \overline{B}$) be any two rough sets in the approximation space S=(U,R) then;

(I) A U B= $(\underline{A} \cup \underline{B},\ \overline{A} \cup \overline{B})$.

(II) $A \cap B = (\underline{A} \cap \underline{B},\ \overline{A} \cap \overline{B})$.

(III) $A \subset B \Leftrightarrow A \cap B$.

It says that A is a rough subset of B or B is a rough superset of A. Thus, in the case of rough sets A and B, $A \subset B$ if and only if $\underline{A} \subset \underline{B}$ and $\overline{A} \subset \overline{B}$. This property of rough inclusion has all the properties of set inclusion. The natural inverse rough set of A denoted by (–A) is defined by:

(IV) $-A = (U - \overline{A}, U - \underline{A})$

(V) $A - B = A \cap (-B) = (\underline{A} - \overline{B}, \overline{A} - \underline{B})$

A) *Amount of Fuzziness Present in Rough Set*

Let (U,R) be an approximation space and suppose X⊆U. In the partition domain U/R, the rough set of X is, say, $R(X) = (\underline{X}, \overline{X})$. Thus in the approximation space (U,R) the set X is approximated by two approximations. One from the inner side called the lower approximation of X and the other is from the outer side called the upper approximation of X. If a set is approximated by X itself, then there is no roughness in this approximation. Otherwise, there exists some amount of roughness due to rough boundary. In order to express, numerically how a set can be approximated using all equivalence classes of R, the accuracy of approximation of X in S (accuracy measure) will be used [6].

$$\alpha_R(X) = \frac{\mathrm{card}\underline{R}X}{\mathrm{card}\overline{R}X} \tag{3}$$

Where X ≠0. As we can see, if X is R-exactly approximated in A_R then $\alpha_R(X) = 1$. If X is R-roughly approximated in S the $0<\alpha_R(X)<1$. Below we use another measure related $\alpha_R(X)$ defined as;

$$\alpha_R(X) = 1 - \alpha_R(X) \tag{4}$$

In addition, it is referred to as R-roughness of X. Roughness, as opposed to accuracy, represents the degree of inexact approximation of X in S. Additional numerical characteristics of imprecision, e.g., the rough membership function of the set X is defined as:

$$\mu_X^R(x) = \frac{\mathrm{card}([x]_R \cap X)}{\mathrm{card}([x]_R)} \tag{5}$$

The coefficient characterizing the uncertainty of membership of the element to the set with respect to the possessed knowledge is:

$$\mu_x(x) = \frac{\mathrm{card}([x]_R \cap X)}{\mathrm{card}(x)} \tag{11}$$

The above mentioned measures may be used in rough controller synthesis.

III. Rough Controller Structures

The main disadvantages of FLCs are the necessity of acquisition and preprocessing of the human operator's knowledge about the controlled process, sequential search rule bases, and time-consuming defuzzifcation methods. The following preliminaries are required in the sequel work and hence presented in brief [6-7]: For simplicity of the proposed methods, only (25-rule) as shown in the look-up table I was created using an ordinary fuzzy logic and was designed for the swing angle of the OTC. The corresponding knowledge base for a rough controller was created in the following way. At the beginning, a decision table was made, where the condition attributes {e, de/dt} corresponded to the decision attribute Uc={u}. In such a decision table an indiscernibility relation with respect to both condition and decision attributes has the same values. As we can see, the indiscernibility relation divides all rows of the decision table into equivalence classes. Accuracy measures were calculated. So, U={25-actions} and the upper rough set $\overline{R}X = \{25\}$, while the equivalence classes are as follows: PL={6}, PS={4}, Z={5}, NS ={4}, NL={6}.

TABLE I
LOOK-UP OF CONVENTIONAL FLC FOR SWING ANGLE OF OTC

θ \ dθ/dt	NL	NS	Z	PS	PL
NL	PL	PL	PL	PS	Z
NS	PL	PL	PS	Z	NS
Z	PL	PS	Z	NS	NL
PS	PS	Z	NS	NL	NL
PL	Z	NS	NL	NL	NL

The division of the universum U with respect to the indiscernibility relation is: X1=PL, X2=PS, X3=Z, X4=NS, X5=NL. In order to express, numerically how a set can be approximated using all equivalence classes of R the accuracy of approximation of X in S (accuracy measure) equation (3) will be used.

$\alpha_R(X1) = 1/6 = 0.167$
$\alpha_R(X2) = 0/4 = 0$
$\alpha_R(X3) = 1/5 = 0.2$
$\alpha_R(X4) = 0/4 = 0$
$\alpha_R(X5) = 1/6 = 0.167$

Therefore, the whole number rules become nine as given in the look up table II. Which divides the input space into three parts and obtaining the (two inputs and one output) rough controller block diagram is shown in Fig. 1. The main procedures of this controller are illustrated in Fig. 2.

TABLE II
THE LOOK-UP TABLE OF ROUGH CONTROLLER

e \ de/dt	P	Z	N
N	$\alpha_R(X3)$	$\alpha_R(X2)$	$\alpha_R(X1)$
Z	$\alpha_R(X4)$	$\alpha_R(X3)$	$\alpha_R(X2)$
P	$\alpha_R(X5)$	$\alpha_R(X4)$	$\alpha_R(X3)$

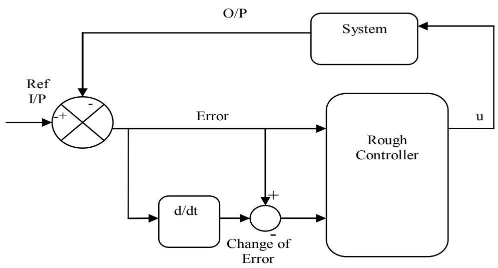


Fig. 1 Block diagram of Rough Controller For OTC

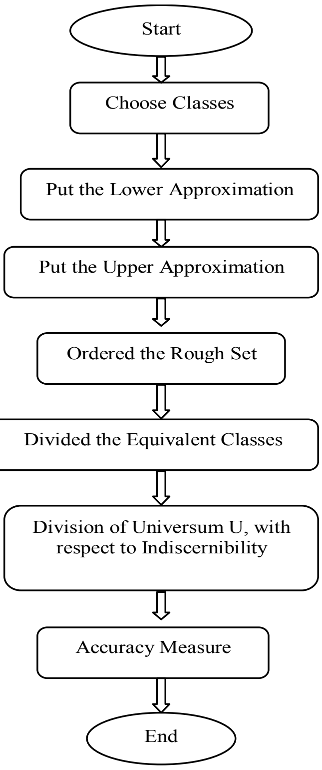


Fig. 2 The main structure of Rough Controller

IV. The Mathematical Model of the OTC

This section presents a nonlinear dynamic model. It is derived based on a two degree-of-freedom swing angle, for a three-dimensional overhead crane. The dynamic model for a three-dimensional overhead crane has the following features: XYZ is the fixed coordinate system and ($X_T Y_T Z_T$) is the trolley coordinate system, which moves with the trolley. The origin of the trolley coordinate system is (x, y, 0) in the fixed coordinate system. Each axis of the trolley coordinate system is parallel to the counterpart of the fixed coordinate system. Fig. 3 shows the coordinate systems of a three-dimensional overhead crane and its load [[8]].

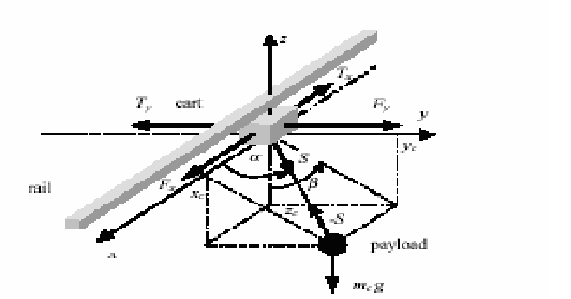


Fig. 3 Coordinate systems of a three-dimensional overhead crane and its load

The equations of the trolley–load system are associated with the generalized coordinates x, θ_x, y, θ_y and L, respectively, by used Lagrange's equations.

$$(M_x + m)\ddot{x} + mL\cos\theta_x\ddot{\theta}_x + m\sin\theta_x\ddot{L} + D_x\dot{x} + 2m\cos_x\theta_x\dot{L}\theta_x - mL\sin\theta_x\dot{\theta}_x = f_x \quad (7)$$

$$mL^2\ddot{\theta}_x + mL\cos_x\dot{x} + 2mL\dot{L}\theta_x + mgL\sin\theta_x = 0 \quad (8)$$

The dynamic model of a three-dimensional overhead crane is reduced to that of a two-dimensional overhead crane moving along the x-axis (Traveling). When $\dot{y} = \ddot{y} = \theta_y = \dot{\theta}_y = \ddot{\theta}_y = 0$, the equations of motions for the crane system become as below:

$$(M_x + m)\ddot{x} + mL\cos\theta_x\ddot{\theta}_x + D_x\dot{x} - mL\sin\theta_x\dot{\theta}_x = f_x \quad (9)$$

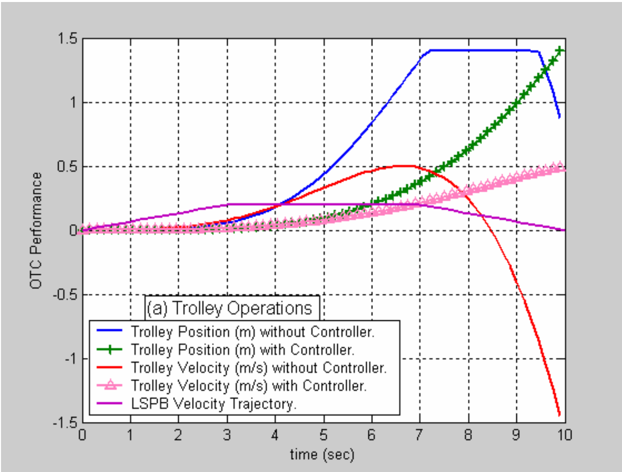
$$mL^2\ddot{\theta}_x + mL\cos_x\dot{x} + mgL\sin\theta_x = 0 \quad (10)$$

Where D_x, D_y, and D_L denote the viscous damping coefficients associated with the x, y, and L motions, respectively. M_x is the trolley mass, while m is the load mass, and L is the length of the load cable.

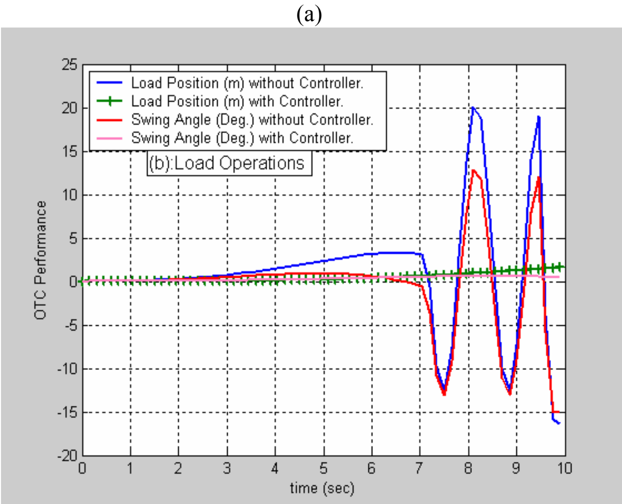
V. Simulation Results

Numerical results obtained by simulating the control of the OTC will be presented here. A knowledge base of table I and table II represents the knowledge base for a rough controller. Fuzzy and rough controllers have been tested on OTC model. In essence, the goal of the procedure in designing a rough controller, capable of reducing time consumption of computation also, to get high system performance in terms of swing damping while providing fast travel and zero final velocity, as will be seen below. In the first test, different inputs have been used and a specific trajectory command (LSPB, Linear Segment Parabolic Blend) on the system. The output's results of the rough controller are shown in Fig. (4, a, b). All measurements responded well, the controller generate a control action to track the load to the desired position damping the oscillation and at the same time reducing the payload travel time. As an exception, the trolley velocity continuously increased until the trolley was stopped by the limit switch (mechanical constraint). The FLC was implemented to obtain the minimum angle within limited values (±15°) within a specified time, Fig. (5, a, b). Table III shows a competition among these controllers (Fuzzy and rough). In these experiments the tracking ability was tested. A sinusoidal input was applied with two different frequencies for both controllers, as illustrated in Figs. [(6, a, b) and (7, a, b)]. When frequency is decreased with the same amplitude, the performance of OTC system with FLC has improved the swing damping, while the movement of the trolley is slower.

Finally, as for the efficiency of the system performance, it is necessary to use four different performance indices (P.Is) criterion methods for this purpose. These performance indices are ISE (Integral Square Error), ITSE (Integral–of-Time-multiplied Square Error), IAE (Integral–Absolute Error), ITAE (Integral-of-Time multiplied Absolute Error) respectively. The best P.I would be obtained with sinusoidal (frequency=0.5 Hz and Amplitude=1.5 Vp-p), among the values of P.I the IAE is considered the best one.

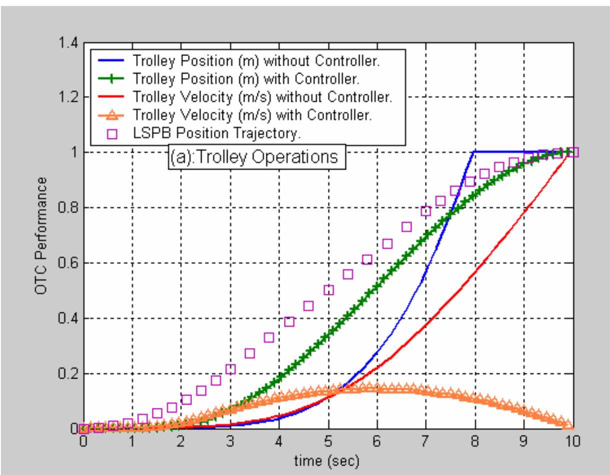


(a)

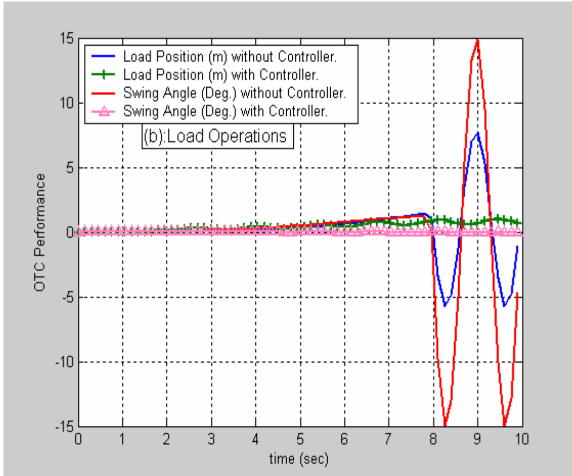


(b)

Fig. 4 (a, b) Rough controller with LSPB trajectory command

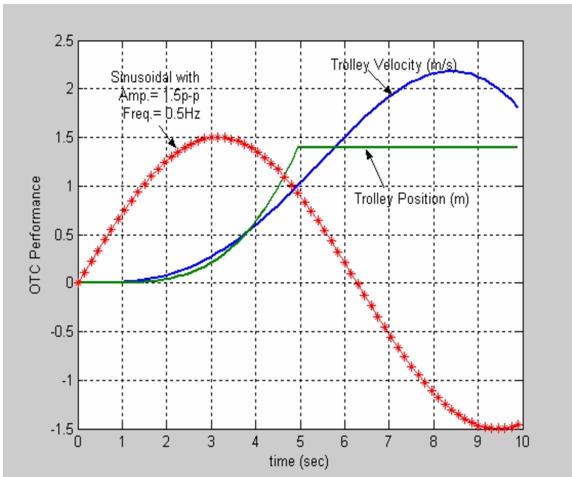


(a)

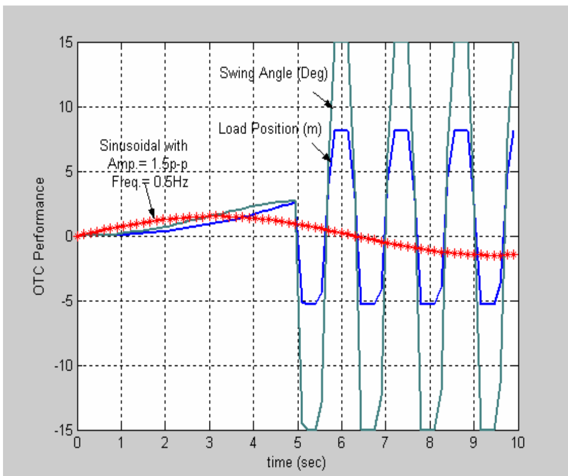


(b)

Fig. 5 (a, b) Fuzzy controller with a LSPB trajectory command

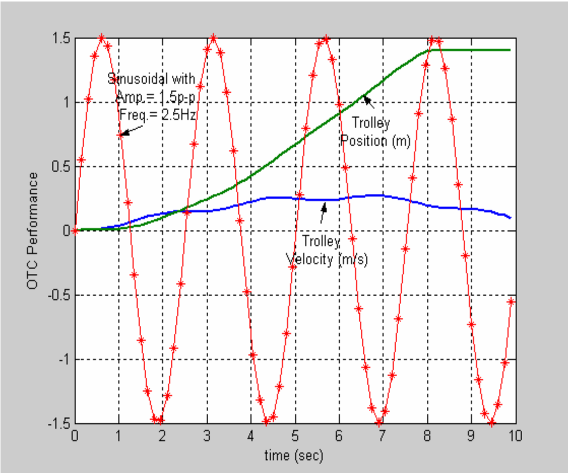


(a) Trolley Operation

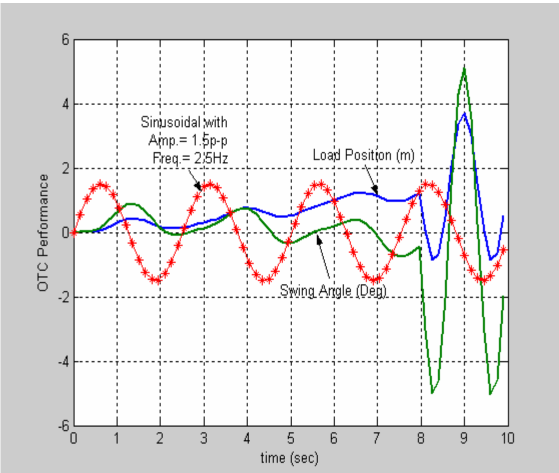


(b) Load Operation

Fig. 6 (a, b) Sinusoidal input with frequency=2.5Hz and Amplitude=1.5 Vp-p



(a) Trolley Operation



(b) Load Operation

Fig. 7 (a, b) Sinusoidal input with frequency=0.5 Hz and Amplitude=1.5 Vp-p

TABLE III
RESULTS OF OTC SYSTEM WITH (FUZZY AND ROUGH CONTROLLERS, WITH DIFFERENT INPUT SIGNALS

Type of controllers	Execution time (sec)	Performance Index			
		ITSE	ISE	IAE	ITAE
Fuzzy Controller	9	28.47	3.28	3.79	28.96
Fuzzy Controller Rough Controller	10	26.13	3.02	3.64	27.7
Rough Controller	5	16.73	1.89	2.78	20.71
Sinusoidal					
Sinusoidal with Freq.=2.5Hz, Amp.=1.5Vp-p	4	24.45	4.95	6.29	31.07
Sinusoidal with Freq=0.5Hz, Amp.=1.5Vp-p	6	26.2	5.17	6.317	31.5

VI. CONCLUSIONS

As a conclusion, a rough controller works much faster than a conventional FLC under the same operating conditions. While controlling the system can be observed by using an FLC get a smooth control value as a function of time; applying a rough controller to get a sharp function of time for the control value. Nevertheless, the quality index does not differ very much for both controllers. However, the best error criterion P.I was obtained with FLC. The quickest running time was recorded with the rough controller (5 sec).

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