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Novel control method for overhead crane's load stability

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Abstract

Nowadays, cranes are widely employed in many fields of the industry and its utilization represents a large financial influence. The investment on cranes, for example, on docks are mainly associated with the time required for the positioning of the cargos. The objective in this experiment was to develop the control of a system to minimize the stabilization time of a load swinging due to crane movement using a controller created from a Lyapunov function. A metal structure was used with a pendulum, attached to a linear motor. After the controller was designed and implemented a series of experiments were done in varied conditions of mass and signal input. The system can be moved at high speed with the joystick and a trigger is pressed to quickly stabilize the pendulum. This, compared to the traditional methods of controlling this payload oscillation has made evident that the control method associated to the use of a joystick can reduce the loading time and also eliminate the need of a highly experienced driver operating the crane.

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1. Introduction

Cranes are essential machinery on modern world and are used to perform tasks which require the movement of heavy loads in different fields of industry such as construction, transportation or in manufacturing for the assembly of heavy components. There are several types of cranes which are selected according to the specific task to be performed. These cranes can be divided in overhead, fixed or mobile cranes. In the categories of fixed or mobile categories there are also lots of subdivisions, for example, fixed cranes can be tower cranes, telescopic cranes,

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gantry cranes, etc. Mobile cranes can be truck-mounted crane, carry deck crane, floating crane among many others. The main focus in this project is the study of the overhead cranes [1].

The fields in which overhead cranes are more useful are mainly inside factories to move heavy machinery or to assembly heavy equipment. This kind of crane is also used for moving containers on harbors [1]. The objective when operating a crane is to move an object from one place to another avoiding collision with other objects and placing it with the best possible accuracy. However, due to the inertia on the movement of the load, the object being moved is subject to oscillation and this is a problem that must be always avoided [2], [3], [4].

Many different approaches have been taken in order to mitigate the effects of the sway. A predictive approach was used by Singer et al. [12] by input shaping to prevent the load from ever swinging in 1997. A position and swinging compensation method was proposed with a proportional-derivative control by Fang et al. [13]. Wen Yu proposed a similar controller adding an uncertainty compensation neural network [14]. An observer based control was design and tested in a real bridge crane by Aschemann et al. [15]. Ahmad used delayed feedback signal and PD-type fuzzy logic controllers in a two-dimensional model of a gantry crane [16]. William Singhose et al. developed and implemented sway reduction by an input shaping controller compensating the motion induced oscillations [11].

The goal in this work is to design a control system that minimizes swinging of the load carried by the crane. A Lyapunov-based approach was taken in this research. Since stability can be a crucial factor in any control application that was decided to be the starting point for the stabilization of the load. For this a linear motor model Siemens 1FN3150 2WC0 (located in LUT's Laboratory of Intelligent Machines) was used with a metal structure attached to it. In this metal structure a pendulum is held and oscillates simulating the crane movement. The used equipment is shown in figure 1 (a). Also, the aim is to optimize the process making the movement and stabilization of the pendulum as fast and swiftly as possible.

Nomenclature

m	mass of the pendulum
R	length of the pendulum rod
x	horizontal position of the system
θ	angle of the rod
$\vec{r}$	position vector
$\vec{v}$	velocity vector
T	kinetic energy
V	potential energy
Q_θ	friction force
μ	friction coefficient
e	error
$V(\theta)$	lyapunov function

2. Control method

This section describes how the system was modeled into equations which were then used to design and implement the controller. Stability is analyzed and ensured introducing the necessary background regarding Lyapunov.

2.1. Mathematical model

The system can be modeled as shown in Figure 1 (b). A moving cart plays the part of the motor while a mass m hanging from a rigid bar of length R simulates the pendulum. The moving motor can be assumed to have no friction with the ground.

The generalized coordinate x is given to the position of the motor whileθ is used for the angle formed by the hanging masswith respect to the reference point.Therefore the equation of the position of the centre of mass can be written as shown in (1) and its time derivative as shown in (2) to express velocity.

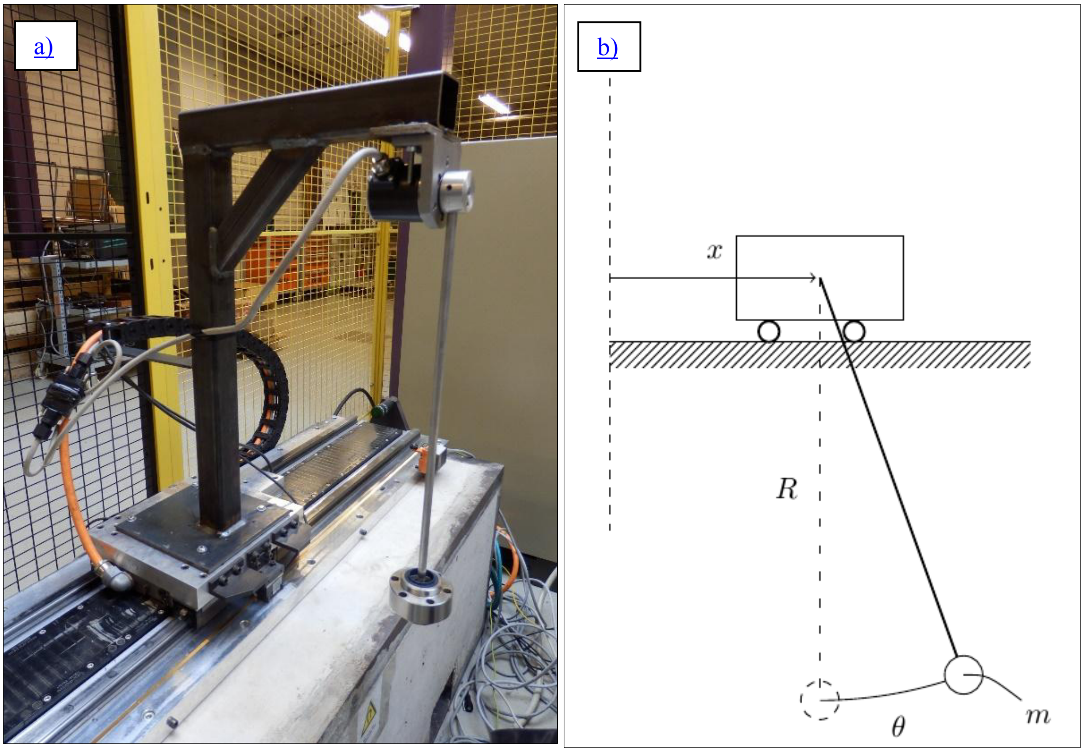

Fig. 1. (a) crane model; (b) mechanical model .

$$\vec{r} = x \cdot \vec{\imath} + R \cdot (sin\theta \cdot \vec{\imath} - cos\theta \cdot \vec{\jmath}) \quad (1)$$

$$\vec{v} = \dot{x} \cdot \vec{\imath} + R \cdot \dot{\theta} \cdot (cos\theta \cdot \vec{\imath} + sin\theta \cdot \vec{\jmath}) \quad (2)$$

In order to obtain the equation of motion using Lagrange's method we express the kinetic and potential energy as shown respectively in (3) and (4) in function of the generalized coordinates. Angular friction is taken into consideration by the addition of (5) expressing angular friction force [5].

$$T = \frac{1}{2}mv^2 = \frac{1}{2}m(\dot{x}^2 + R^2\dot{\theta}^2 + 2 \cdot R \cdot \dot{\theta} \cdot \dot{x} \cdot cos\theta) \quad (3)$$

$$V = -m \cdot g \cdot r = -m \cdot g \cdot cos\theta \quad (4)$$

$$Q_\theta = -\mu \cdot \dot{\theta} \quad (5)$$

The Lagrangian is built with (6) and put together with the friction force (5) in Lagrange's equation (7). The final form of the equation of motion is shown (8) [6].

$$L = T - V \quad (6)$$

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\theta}}\right) - \frac{\partial L}{\partial \theta} = Q_\theta \quad (7)$$

$$R^2\ddot{\theta} + Rg \cdot sin\theta + R \cdot x \cdot cos\theta + 2\frac{\mu}{m}\dot{\theta} = 0 \quad (8)$$

2.2. Lyapunov controller

Necessary theoretical background is introduced in this section regarding different kinds of stability related to lyapunov and definitiveness of functions. The design of the controller itself will be carried out in this section as well obtaining the mathematical expression of the control law.

2.2.1. Lyapunov Stability Analysis

Lyapunov stabili1y analysis plays an important role in the stability analysis of control systems described by state space equations. There are two methods of stability analysis due to Lyapunov, called the *first method* and the *second method;* both apply to the determination of the stability of dynamic systems described by ordinary differential or difference equations. The first method consists entirely of procedure in which the explicit forms of the solutions of the differential equations or difference equations are used for the analysis. The second method, on the other hand, does not require the solutions of the differential or difference equations. This is the reason the second method is so useful in practice [10].

Although there are many powerful stabili1y criteria available for control systems, such as the Jury stability criterion and the Routh-Hurwitz stability criteria, they are limited to linear time-invariant systems. The second method of Lyapunov, on the other hand, is not limited to linear time-invariant systems: it is applicable to both linear and nonlinear systems, time-invariant or time-varying.

In particular, we found that the second method of Lyapunov is indispensable for the stabili1y analysis of nonlinear systems for which exact solutions may be unobtainable. (It is cautioned, however, that although the second method of Lyapunov is applicable to any nonlinear system. obtaining successful result may not be easy task. Experience and imagination may be necessary to carry out the stability analysis of most nonlinear systems.) The second method of Lyapunov is also called the *direc1 method* of Lyapunov [6].

2.2.2. Second method of Lyapunov

From the classical theory of mechanics, we know that a vibratory system is stable if its total energy is continua1ly decreasing until an equilibrium state is reached.

The second method of Lyapunov is based on a generalization of this fact: If the system has an asymptotically stable equilibrium state, then the stored energy of the system displaced within a domain of attraction decays with increasing time until it finally assumes its minimum value at the equilibrium stale.

For purely mathematical systems, however there is no simple way of defining an "energy function." In order to circumvent this difficulty, Lyapunov introduced the so called Lyapunov function a fictitious energy function. This idea is, however, more general than that of energy and more widely applicable. In fact, any scalar function satisfying the hypotheses of Lyapunov stability theorems can serve as a Lyapunov function.

2.2.3. Positive definiteness of scalar function

A scalar function $V(x)$ is said to be *positive definite* in a region Ω (which includes the origin of the state spaces) if $V(x)>0$ for all nonzero states x in the region Ω and if $V(0)=0$.

A time varying function $V(x,t)$ is said to be positive definite in a region Ω (which includes the origin of the state space) if it is bounded from below by a time invariant positive definite function, that is , if there exists a positive definite function $V(x)$ such that:

$$V(x,t) > V(x) \qquad for\ all\ t \geq t_0$$

$$V(0,t) = 0 \qquad for\ all\ t \geq t_0$$

Negative definiteness of scalar functions: A scalar function V(x) is said to be negative definite if –V(x) is positive definite.

Positive semi definiteness of scalar functions: A scalar function V(x) is said to be positive semi definite if it is positive at all states in the region Ω except at the origin and at certain other states, where it is zero.

Negative semi definiteness of scalar functions: A scalar function V(x) is said to be negative semi definite if –V(x) is positive semi definite.

Indefiniteness of scalar functions: A scalar function V(x) is said to be indefinite if in the region Ω it assumes both positive and negative values, no matter how\v small the region Ω is [6].

2.2.4. Lyapunov functions

The Lyapunov function, scalar function, is a positive definite function, and it is continuous together with its first partial derivative (with respect to its arguments) in the region Ω about the origin and has a time derivative which, when taken along the trajectory, is negative definite (or negative semi definite).

Lyapunov functions involve $x_1, x_2, \dots, x_n$, and possibly t. We denote them by $V(x_1, x_2, \dots, x_n, t)$, or simply by $V(x,t)$. If Lyapunov functions do not include t explicitly, then we denote them by $V(x_1, x_2, \dots, x_n)$, or $V(x)$.

Notice that $\dot{V}(x, t)$ is actually the total derivative of $V(x, t)$ with respect to t along a solution of the system. Hence $\dot{V}(x,t) < 0$ implies that $V(x, t)$ is a decreasing function of t.

A Lyapunov function is not unique for a given system (For this reason, the second method of Lyapunov is a more powerful tool than conventional energy considerations. Note that a system whose energy E decreases on the average but not necessary at each instant is stable but that E is not a Lyapunov function.)

In the second method of Lyapunov, the sign behavior of $V(x,t)$ and that of its time derivative $\dot{V}(x,t)=dV(x,t)/dt$ give information about the stability of an equilibrium state without having solution.

Note that the simplest positive definite function is of a quadratic form as shown in equation (9):

$$V(x) = \sum_{i=1}^{n} \sum_{j=1}^{n} q_{ij} x_i x_j \quad i, j = 1,2, \dots, n \tag{9}$$

In general, Lyapunov functions may not be of a simple quadratic form. For any Lyapunov function, however, the lowest degree terms in V must be even. This can be seen as follows. If we define $\hat{x}_i$ as in equation (10) then in the neighborhood of the origin the lowest degree terms alone will become dominant and we can write V(x) as (11):

$$\frac{x_1}{x_n} = \hat{x}_1, \ \frac{x_2}{x_n} = \hat{x}_2, \ \dots \ , \ \frac{x_{n-1}}{x_n} = \hat{x}_{n-1}, \tag{10}$$

$$V(x) = x_n^p \, V(\hat{x}_1, \hat{x}_2, \dots, \hat{x}_{n-1}, 1) \tag{11}$$

If we keep the $\hat{x}_i$'s fixed, $V(x) = x_n^p \, V(\hat{x}_1, \hat{x}_2, \dots, \hat{x}_{n-1}, 1)$ is a fixed quantity, For p odd, x_i^p can assume both positive and negative values near the origin, which means that $V(x)$ is not positive definite. Hence p must be even.

2.2.5. System

The system we consider here is defined by $\dot{x} = f(x,t)$ where x is a state vector (an n-vector) and $f(x, t)$ is an n-vector whose elements are functions of $x_1, x_2, \dots, x_n$, and t. We assume that the system equation has a unique solution starting at the given initial condition. We shall denote the solution of system equation as $\phi(t; x_0, t_0)$, where $x=x_0$ at $t=t_0$ and t is observed time. Thus $\phi(t_0; x_0, t_0)=x_0$.[6]

2.2.6. Equilibrium State

In the system equation, a state x_e, where $f(x_e,t) = 0$, for all t is called an *equilibrium state* of the system. If the system is linear and time invariant, that is, if $f(x, t) = Ax$, then there exists only one equilibrium state if A is nonsingular, and there exist infinitely many equilibrium states if *A* is singular. For nonlinear systems, there may be one or more equilibrium states. These states correspond to the constant solutions of the system ($x = x_e$ for all *t*).

Determination of the equilibrium states does not involve the solution of the differential equation of the system equation, but only the solution any isolated equilibrium state (that is, where isolated from each other) can be shifted to the origin of the coordinates, or $f(0, 1) = 0$, by a translation of coordinates [6].

2.2.7. Controller design

The controller equation will be obtained assuming an angular feedback with θ_{ref} as reference resulting in (12) as error signal. As Lyapunov function (13) is used with r being explained as in (14) leaving α as a tuning parameter for future controller optimization.

$$e = \theta_{ref} - \theta \tag{12}$$

$$V(\theta) = \frac{1}{2} r^2 \tag{13}$$

$$r = \dot{e} + \alpha \cdot e \tag{14}$$

Equations (12) and (14) both ensure that V meets the requirements of a Control-Lyapunov function [5]. Constant κ is also left for future controller optimization.

$$\dot{V} = -\kappa V \tag{15}$$

The combination of (16) and (13) provides with (18) which is also combined with both (8) and (17) resulting in the final form of the controller equation using linear acceleration as input into the system as shown in (19).

$$\dot{V} = r \cdot \dot{r} = (\dot{e} + \alpha \cdot e)(\ddot{e} + \alpha \cdot \dot{e}) \tag{16}$$

$$\ddot{e} = \ddot{\theta}_d - \ddot{\theta} \tag{17}$$

$$\dot{V} = (\dot{e} + \alpha \cdot e)(\ddot{e} + \alpha \cdot \dot{e}) = -\frac{\kappa}{2}(\dot{e} + \alpha \cdot e)^2 \tag{18}$$

$$\ddot{x} = -\frac{R}{\cos\theta}\left\{ \begin{matrix} \ddot{\theta}_d + \frac{g}{R}\sin\theta + \frac{2\mu}{mR^2}\dot{\theta} + \left[\frac{\kappa}{2} + \alpha\right]\dot{e} \\ +\alpha \cdot e \end{matrix} \right\} \tag{19}$$

2.3. Stability

2.3.1. Stability in the Sense of Lyapunov

In the following, we shall denote a spherical region of radius *r* about an equilibrium state x_e as $\|x - x_e\| \le r$, where $\|x - x_e\|$ is called the *Euclidean Norm* and is defined as follows:

$$\|x - x_e\| = [(x_1 - x_{1e})^2 + (x_2 - x_{2e})^2 + \dots + (x_n - x_{ne})^2]^2$$

Let $S(\delta)$ consist of all points such that $\|x_0 - x_e\| \le \delta$ and let $S(\epsilon)$ consist of all points such that

$\|\emptyset(t; x_0, t_0) - x_e\| \le \epsilon \quad for\ all\ t \ \ge t_0.$

An equilibrium state x_e of the system equation is said to be *stable in the sense of Lyapunov* if, corresponding to each $S(\epsilon)$, there is an $S(\delta)$ such that trajectories starting in $S(\delta)$ do not leave $S(\epsilon)$ as t increases indefinitely. The real number δ depends on ϵ and, in general, also depends on t_0. If δ does not depend on t_0, the equilibrium state is said to be *uniformly stable.*

What we have stated here is that we first choose the region $S(\epsilon)$, and for each $S(\epsilon)$, there must be a region $S(\delta)$ such that trajectories starting within $S(\delta)$ do not leave $S(\epsilon)$ as t increases indefinitely [6].

2.3.2. Asymptotic Stability

An equilibrium state x_e of the system equation is said to be *asymptotically stable* if it is stable in the sense of Lyapunov and if every solution starting within $S(\delta)$ converges, without leaving $S(\epsilon)$, to x_e as t increases indefinitely.

In practice, asymptotic stability is more important than mere stability. Also, since asymptotic stability is a local concept, simply to establish asymptotic stability does not necessarily mean that the system will operate properly some knowledge of the size of the largest region of asymptotic stability is usually necessary. This region is called the *domain of attraction.* It is that part of the state space in which asymptotically stable trajectories originate. In other words, every trajectory originating in the domain of attraction is asymptotically stable [6].

2.3.3. Asymptotic Stability in the Large

If asymptotic stability holds for all states (all points in the state space) from which trajectories originate, the equilibrium state is said to be *asymptotically stable in the large.* That is, the equilibrium state x_e of the system is said to be asymptotically stable in the large if it is stable and if every solution converges to x_e as r increases indefinitely. Obviously, a necessary condition for asymptotic stability in the large is that there is only one equilibrium state in the whole state space.

In control engineering problems, asymptotic stability in the large is a desirable feature. If the equilibrium state is not asymptotically stable in the large, then the problem becomes one of determining the largest region of asymptotic stability. This is usually very difficult for all practical purposes; however, it is sufficient to determine a region of asymptotic stability large enough that no disturbance will exceed it [6].

2.3.4. Instability

An equilibrium state $x_e$is said to be unstable if for some real number $\epsilon > 0$ and any real number $\delta > 0$, no matter how small, there is always a state x_0 in $S(\delta)$ such that the trajectory starting at this state leaves $S(\epsilon)$.

2.3.5. Lyapunov Theorem on Stability

To prove stability (but not asymptotic stability) of the origin of the system, the following theorem may be applied. Suppose a system is described by $\dot{x} = f(x,t)$ where $f(0, 1) = 0$ for all t. If there exists a scalar function $V(x,t)$ having continuous first partial derivatives and satisfying the conditions

1. $V(x, t)$ is positive definite.
2. $\dot{V}(x, t)$ is negative semi definite

then the equilibrium state at the origin is uniformly stable.

It should be noted that the negative semi definiteness of $\dot{V}(x, t)$ [$\dot{V}(x, t) \leq 0$ along the trajectories] means that the origin is uniformly stable but not necessarily uniformly asymptotically stable. Hence, in this case the system may exhibit a limit cycle operation.

2.3.6. Instability

If an equilibrium state $x = 0$ of a system is unstable, then there exists a scalar function $W(x, t)$ that determines the instability of the equilibrium state. We shall present a theorem on instability in the following. Suppose a system is described by $\dot{x}$= f(x, t) where f(0,t) = 0, for all $t \geq t_0$.

If there exists a scalar function $W(x, t)$ having continuous first partial derivatives and satisfying the conditions:

1. $W(x, t)$ is positive definite in some region about the origin.
2. W(x, t) is positive definite in the same region.

then the equilibrium state at the origin is unstable [4].

2.3.7. Stability in the crane model

All three conditions for a function to be considered a control-lyapunov function will be proven to be met by the controller and therefore its stability.

V is positive definite as proven in (20) since r is squared only its absolute value plays a role in V's final value therefore ensuring the condition if $\theta \neq 0$ and $\dot{\theta} \neq 0$.

$$V(\theta,u) = \frac{1}{2}r(\theta,u)^2 = \frac{1}{2}|r(\theta,u)|^2 > 0 \quad (20)$$

$\dot{V}$ is negative semi definite as shown in (21) for similar reasons as (20).

$$\dot{V}(\theta,u) = -\kappa V(\theta,u) = -\kappa\frac{1}{2}|r(\theta,u)|^2 < 0 \quad (21)$$

For every θ there's always a u which reduces V. Equation (12) is a linear first order differential equation with a solution of the form $V = V(0)e^{-\kappa t}$. We can therefore conclude that the error and error rate both decay exponentially to zero.

3. Controller optimization

Two methods of optimization will be carried out in this section: first by a simulation to predict an initial value of the parameters which will then be followed by experimental tests. The controller optimization was carried out first by simulation and afterwards experimentally. The simulation was done with Simulink while the experimental data was obtained at the lab [7]. The position PID controller of the system will also be tuned in this section.

3.1. Gradient based global Stochastic optimization of the simulated system

Optimization applications are common nowadays and certainly will be much more frequent in the future. Even in introductory courses global optimization techniques could be helpful: whenever we make curve or surface fitting, for example, an optimization process is in progress, taking into account that we are trying to minimize a specific measure of distance between a parametric model (curve or surface) and a set of points, normally obtained through a practical experiment - parameters defining the model are chosen so as to get exactly that.

In many scenarios, optimization problems involve variables that assume integer values only.

There are several ways to tackle a global optimization problem. Firstly it will be useful to classify the problem at hand and, depending on its type, we will have more or less methods and tools available.

There are many methods aimed at globally optimizing functions, but only a few have gained high popularity. In the deterministic and differentiable realm we have the gradient-based ones and its variations, that guide their search based on the negative of cost functions' gradient [6].

In optimization, gradient method is an algorithm to solve problems of the form $\min_{x\in\mathbb{R}^n} f(x)$ with the search directions defined by the gradient of the function at the current point. Examples of gradient method are the gradient descent and the conjugate gradient.

3.2. Simulation data

To optimize the controller initially an iterative process was carried out according to the Simulink blocks shown in Figure 2. A model of the system was used (implementing the mechanical equation previously obtained) and a pulse disturbance was fed into the system.

The simulation was run several times and the outputs analyzed so that the best response could be achieved. As shown in Figure 3. (last iteration) the optimal values were: $\alpha = 1.75 \& \kappa = 2$.

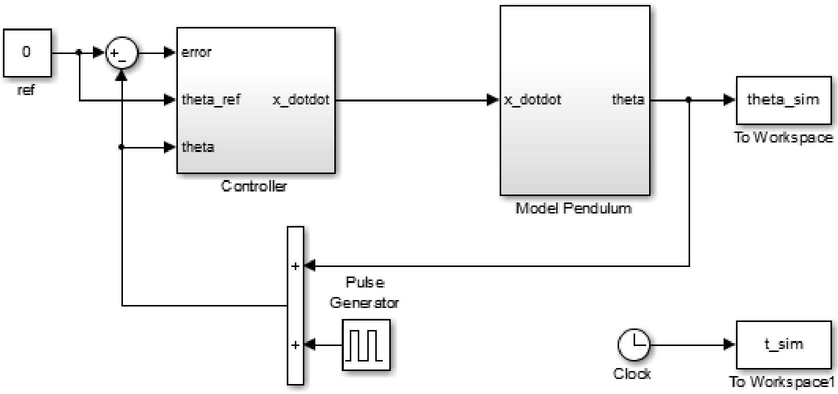

Fig.2. Simulink iteration: blocks layout used in the iterative tuning process.

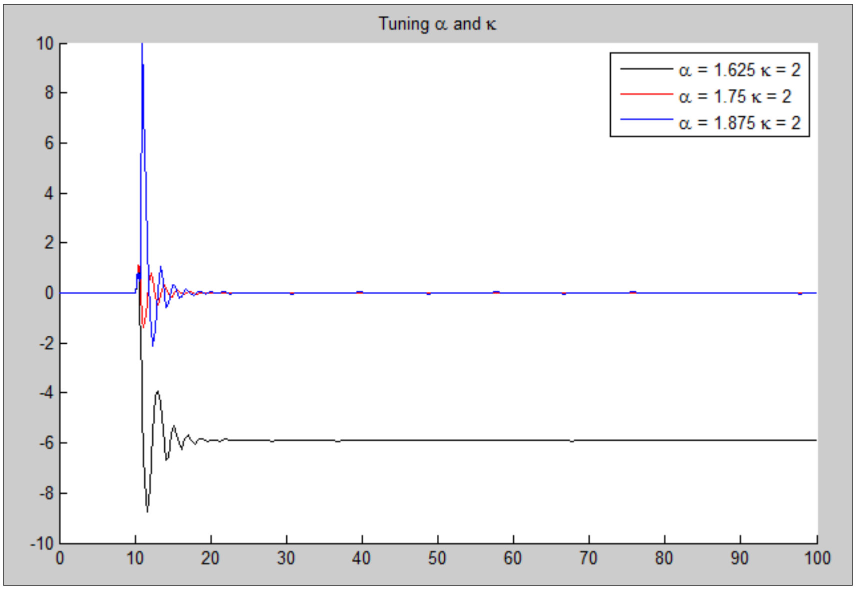

Fig. 3.Iteration outputs: system's outputs varying with $\alpha$and κ.

3.3. Experimental data

It was decided to tune the controller also considering the real system and for that a series of tests were carried out. Due to shortage of time and resources the experimental results obtained lack accuracy but can still illustrate and contrast with the model results. The results obtained from the simulation data were taking into account by trying similar or close values in this experiment.

In Figure 4 different values of α are shown for a fixed κ (the simulation optimal). From this figure it can be concluded that for that value of κ ($\kappa = 2$) $\alpha = 1.75$ reaches the best output. Something similar could be said about Figure 5 although due to lack of accuracy the results seem inconclusive. Contradicting the simulation results

$\kappa = 1.5$ $\alpha = 1.75$ seems to be the best value for the controller at least considering the amplitude of the first oscillation.

All the experimental results are summarized in Table 1. The table shows the values of θ_1 (Amplitude of the first oscillation) and t_s (settling time) for the different experiments conducted. The best amplitude is reached for $\kappa = 1.5$ $\alpha = 1.75$ while the best settling time is reaches by $\kappa = 2$ $\alpha = 1.75$.

Table 1.: Experimental Results.

$\boldsymbol{\kappa}$	1		1.5		2	
$\boldsymbol{\alpha}$	$\theta_1(°)$	t_s(s)	$\theta_1(°)$	t_s(s)	$\theta_1(°)$	t_s(s)
1	NA	NA	-15.59	2.21	-22.28	2.69
1.75	-15.59	2.19	-12.13	1.48	-12.91	1.36
2	-19.58	2.71	-17.28	1.88	-17.3	1.98

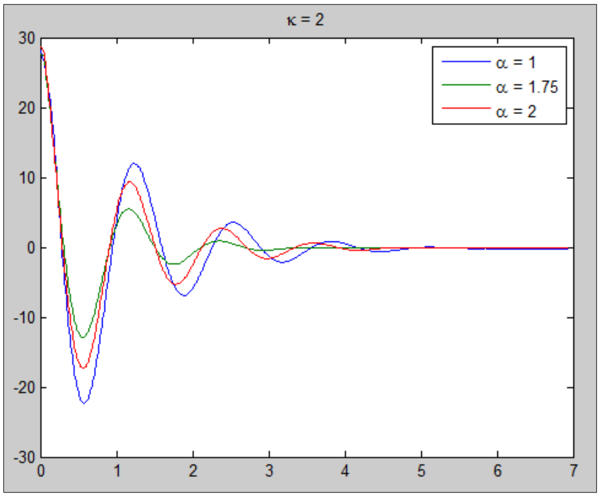

Fig.4. Experimental outputs 1: system’s output with fixed optimal kappa.

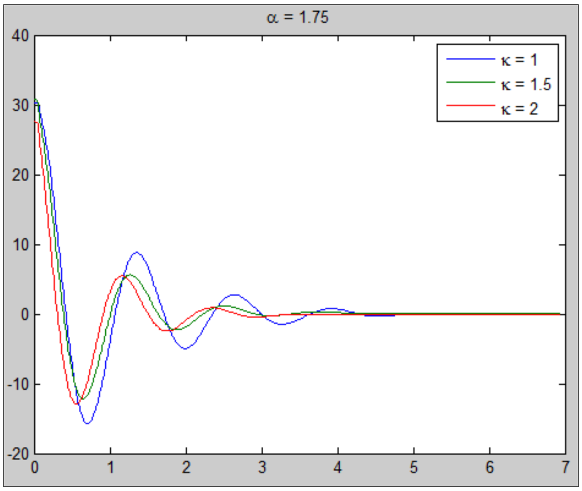

Fig. 5.Experimental outputs 2: system's output with fixed optimal alpha.

3.4. Tuning PID controller

The PID controller parameters were tuned online for a pulse reference input. For this step the Lyapunov controller was ignored while only the position controller (PID) was being used. The procedure consisted of increasing the proportional gain until the first signs of overshoot appeared, then the integral and derivative gains were used to compensate it. Figure 6 shows the best achievable output for the system's input using the values in table 2.

In the interface used in ControlDesk during the online PID tuning the PID gains could be changed with the different numerical inputs and position and position reference were shown in a plotter. Angle and angle reference are also being plotted although not used.

Table 2.PID parameter values.

	K_P	K_I	K_D
Pulse	11	1.5	0.7

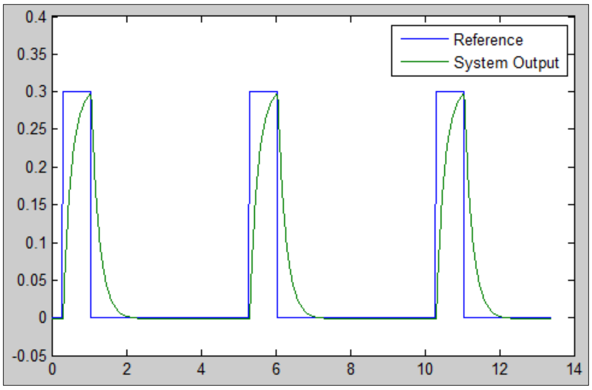

Fig.6.PID output: system's output with pulse reference.

4. Implementation

In order to introduce the previously designed controller into the real system MATLAB's Simulink was used. The final block diagram is simplified on behalf of easier understanding in Fig.7. A position reference is given by the joystick which is then treated by a PID controller and finally fed into the system. When the final destination is reached a trigger should be pushed in the joystick which would enable the lyapunov controller (inner loop in Fig. 7) using the switch block.

Values used while implementing the system in the block diagram are presented and described in table 3.

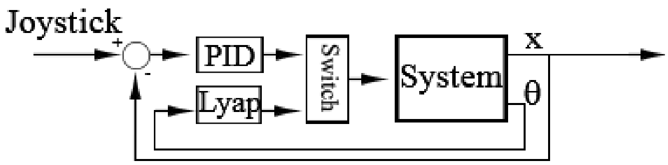

Fig.7. Closed-loop: system's own block layout.

Table 3. Variable values.

Variable	Value	Unit	
R	0.46	m	Length of the pendulum rod
g	9.8	$m \cdot s^{-2}$	Gravity acceleration
m	0.939	kg	Mass hanging from the pendulum
μ	0.1	$kg \cdot m^2 \cdot s^{-1}$	Angular friction coefficient
κ	2	s^{-2}	Tuning parameter
α	1.75	s^{-2}	Tuning parameter

5. Experimental results

After a series of tests aimed at different properties of the system some data was gathered and presented here. To transfer data from ControlDesk to MATLAB the following procedure was followed: stopped measuring, right click in the plotter and select *Save Displayed Data as New Measurement*. Then opened the *Project* window and in *Measurement data directory* selected the new file, double clicked it, then right click and *Export* selecting .mat file [8].

5.1. Effect of mass

This set of tests were aimed at the effect of the mass hanging from the pendulum on the system's output depending on the initial angle. The pendulum was set to 15°, 30° and 45° for each mass and the output recorded. As shown in Figure 8 the initial angle was set manually using an analog scale that was implanted in the pendulum.

The masses were changed by using the metal parts shown in Figure9. The first mass was made by using only the lighter piece on the left, the second was the left and middle ones together and the last experiment with heavier mass was conducted with all three masses together.

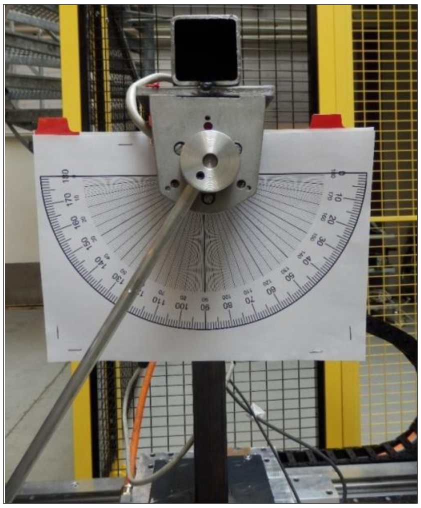

Fig. 8. Analog scale: scaling system used to conduct the mass experiments.

Fig. 9. Experimental masses: different masses available at the laboratory used for the mass experiments.

The next three graphs show each the system's output angle with a fixed mass and different initial angles. Figure 10 shows the first experiment with a mass of roughly$m_1 = 0.036$ kg, a similar graph is shown in Figure 11 with a mass of $m_2 = 0.939$ kg and figure 12 $m_3 = 1.842$ kg.

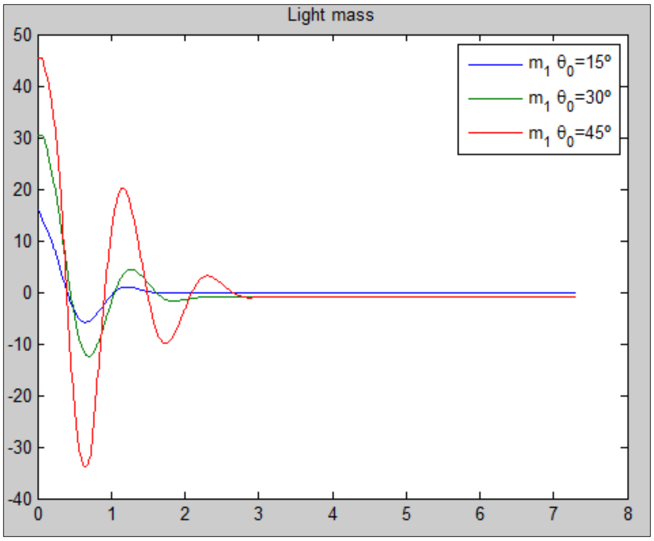

Fig. 10. System's output for the lighter mass: outputs recorded for the lighter mass for different initial angles.

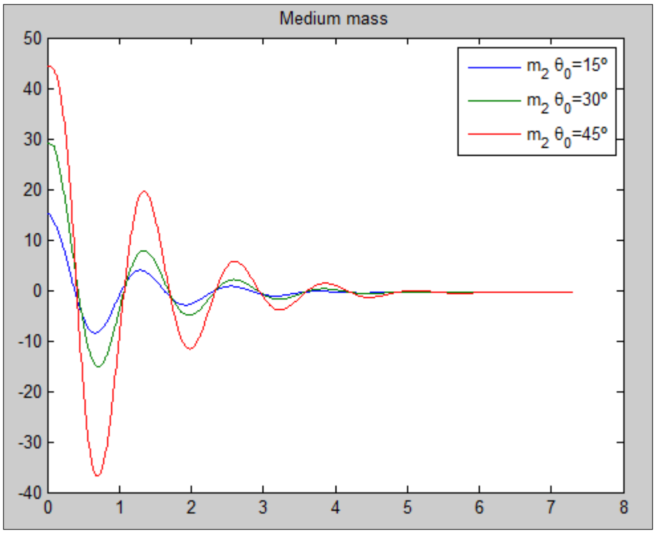

Fig. 11. System's output for the medium mass: outputs recorded for the medium mass for different initial angles.

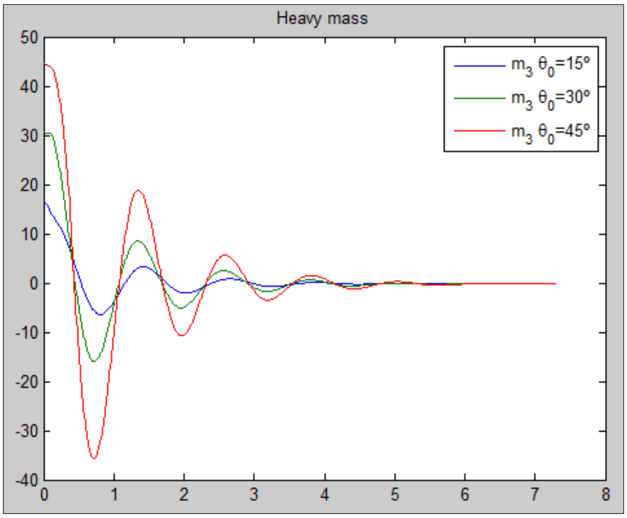

Fig.12. System's output for the heavier mass: outputs recorded for the heavier mass for different initial angles.

Some conclusions can be drawn from Figure 3 and Table 4since as logic would suggest a heavier mass comes with a higher oscillating amplitude (θ_1 amplitude of the first oscillation) and settling time (t_s). A heavier mass would make the assumptions when creating a mechanical model more precise since we assumed the pendulum bar had no mass and the center of mass was located at the lower end.

Each of the experiments seems to result in a 10° reduction during the first cycle and a settling time between 2 and 5 seconds depending on the mass and initial angle. The option of repeating the experiment with the third mass should be considered since the results don't seem to match the tendency of the previous ones.

Table 4. Experimental data.

	m_1		m_2		m_3	
θ_0	θ_1(°)	t_s(s)	θ_1(°)	t_s(s)	θ_1(°)	t_s(s)
15°	-5.778	1.51	-8.352	2.21	-6.318	2.68
30°	-12.33	2.23	-15.1	3.46	-15.77	3.38
45°	-33.93	2.66	-36.76	4.66	-35.62	4.59

5.2. Disturbances

This experimental part consists of a series of tests aimed at the effect of disturbances into the system. At first the motor was moved with the joystick from one side to the other and then the Lyapunov controller was enabled. In the second tests the Lyapunov controller was enabled from the very beginning and some manual disturbances were fed into the system.

5.2.1. Joystick disturbance

As previously mentioned the system was moved by joystick control therefore the working controller was the PID controller. Then at a given time (around 22 seconds in Figure 14) the swinging compensation was enabled and the control signal corresponds to the designed Lyapunov controller. As can be seen in Figure 14 the control signal (upper right picture) changes from a semi digital reference given by the joystick to a continuous signal for the swinging compensation.

Even though in that same figure we can observe that the Lyapunov function (lower right picture) has a value different than zero the trigger was not being pushed so therefore that value was not being used.

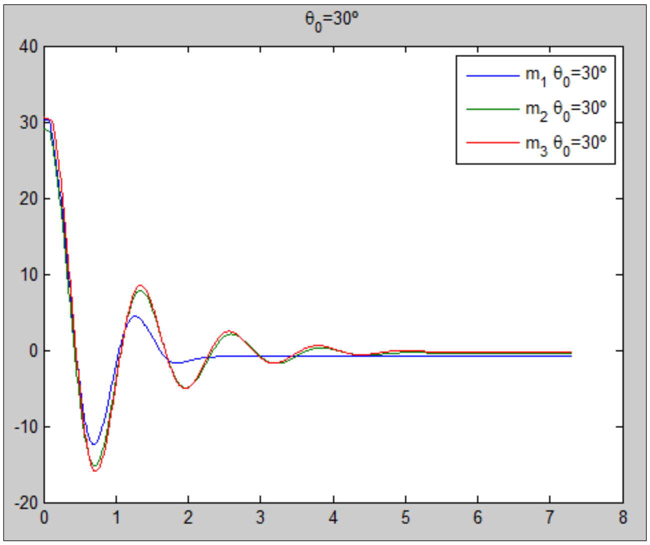

Fig.13. System's output for 30° initial angle: summary of the experiment with a 30° degree angle.

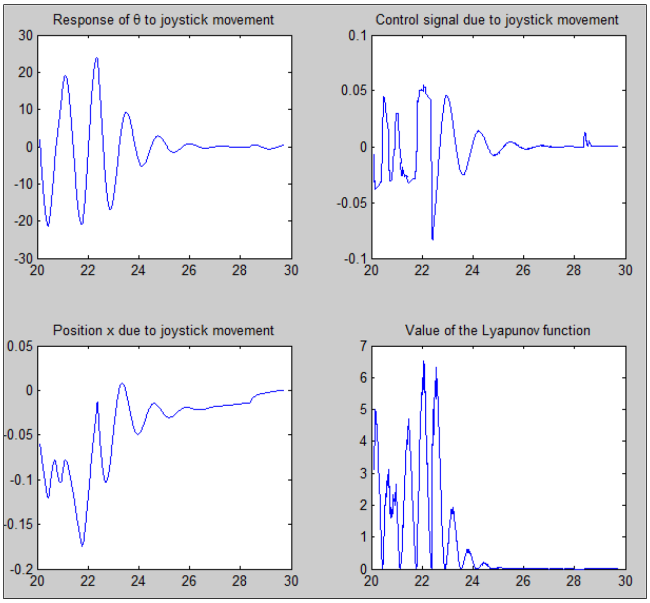

Fig.14. Joystick disturbance: response of the angle, control signal, position and Lyapunov function value.

As mentioned earlier the Lyapunov controller was enabled from the beginning and the pendulum was moved manually so that the system would try to compensate it.

As can be seen in Figure 15 the Lyapunov function (lower right picture) has different values depending on the amplitude of the given disturbance and the control signal (upper right) has an almost inverse proportional relation with the actual angle.

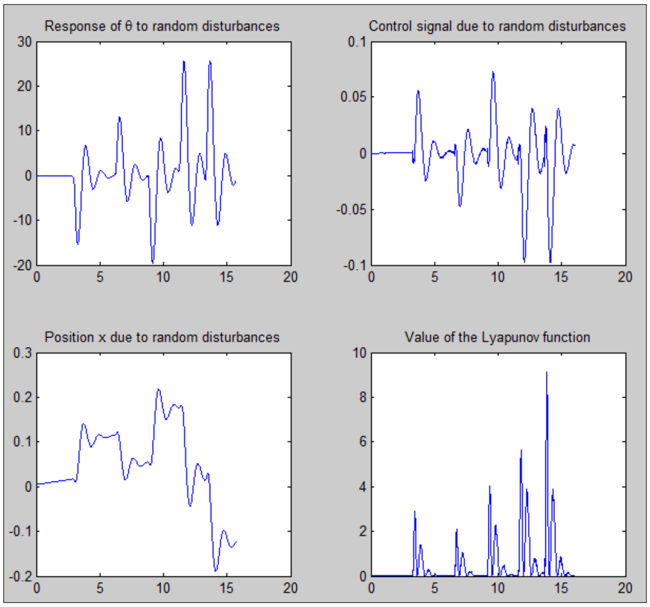

Fig.15. Manual disturbance: response of the angle, control signal, position and Lyapunov function value signals.

6. Conclusion

This chapter will discuss the procedures conducted and the results obtained. The first assumption was creating a mathematical model for the complete real system which was later used for designing, implementing and tuning the Lyapunov controller.

The efficiency and robustness shown by the system after implementing the designed controller regardless of the value chosen for its parameters proves Lyapunov's stability since the system always converges to zero. Figure 16 shows the convergence of one of the tests ($m_1$and$\theta_0 = 30°$) in an angle-position curve.

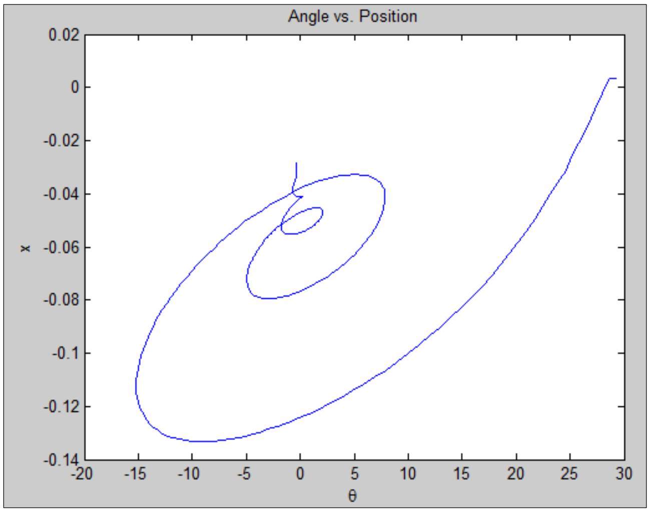

Fig. 16. Angle vs position: angle-position relation during one of the tests conducted at the laboratory.

Everything was done to simulate the overhead crane load swinging problem for which an original approach was taken reducing the driver's role in the compensation of swinging problem allowing 100% manual control until the destination is reached and then the designed controller is enabled compensating the swinging automatically. The results were satisfactory concluding that implementing this system in real systems (real overhead cranes) could greatly improve productivity especially in lack of a skillful crane operator.

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