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# Model predictive control of systems with deadzone and saturation

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ABSTRACT

Actuator nonlinearities such as saturation and deadzone may be responsible for bad control performance, if their presence is not correctly addressed in the design of the control system. This paper focuses on a plant showing a non-symmetric deadzone and saturation of the control action. The authors implement and test two different control strategies based on Model Predictive Control (MPC): the former relies on Hybrid MPC, the latter is based on deadzone inversion and on standard MPC. The performances and the robustness of the two schemes are evaluated with simulations and with experiments on a laboratory scale overhead travelling crane.

## 1. Introduction

The control of plants with actuators showing a nonlinear behaviour (saturation, deadzone, hysteresis, backlash...) is one of the most common issues in the industrial framework. Mechanical actuators in fact may not only show intrinsic nonlinear behaviour, but are also subject to an unavoidable ageing process which alters their dynamic. This results in a nonlinear and uncertain behaviour and consequently in poor control performances. This work focuses on a plant with DC motors whose dynamic is characterised by the presence of a non-symmetric deadzone and a saturation of the control signal. According to the literature, the problem can be faced in different ways, also relying on approaches which were developed for different types of nonlinearities. Among these techniques adaptive control (Recker, Kokotovic, Rhode, & Winkelman, 1991; Tian, Tao, & Ling, 1996), Nonlinearity Inversion (Liñán & Heath, 2012a; Su et al., 2009; Tian et al., 1996) and Hybrid MPC (Herceg, Kvasnica, & Fikar, 2009; Zabiri & Samyudia, 2006) are worth mentioning. Our aim is to implement and investigate two different control schemes based on Model Predictive Control (MPC) which are able to cope with the nonlinearity of the actuators.

### 1.1. Model predictive control

The choice of MPC as the fundamental layer for control strategies is motivated by its flexibility: MPC allows to directly use process models, for example empirically derived from experiments, to explicitly consider state and input constraints in the control formulation. Defining a complete MPC controller requires then:

- a process model;
- input, output and state constraints;
- a cost function $J$ defined over a finite horizon $N$ ("prediction horizon");
- an optimisation algorithm;
- the application of the so-called "Receding Horizon (RH) Principle".

At any time instant $k$, based on the available process information, RH requires to solve the optimisation problem (optimise $J$) with respect to the future control sequence $\mathbf{u}_{[k,\dots,k+N-1]} = [u(k),\dots,u(k+N-1)]$ and then to apply its first element only. Then, at time instant $k+1$, basing on the new process information, a new optimisation problem is solved over the temporal window $[k+1, k+N]$ and the procedure is repeated (Magni & Scattolini, 2014). Standard MPC algorithms can be easily used to introduce a saturation of the control input, but cannot be used to directly address the problem of the deadzone. More sophisticated MPC algorithms are needed to manage its presence. In particular our first choice is Hybrid MPC, which allows to consider the deadzone directly in the dynamics of the plant. This requires to introduce in the optimisation problem logic constraints and variables that can be first translated into mathematical constraints with integer variables and then solved by means of Mixed-Integer solvers (Borrelli, Bemporad, & Morari, 2017). Examples of Hybrid MPC developed for nonlinear actuators handling can be found in Zabiri and Samyudia (2006), Zabiri and Samyudia (2004) and Herceg et al. (2009). The second approach instead relies on constrained MPC and on the introduction of an inverse deadzone model, as described in Liñán and Heath (2017). In the

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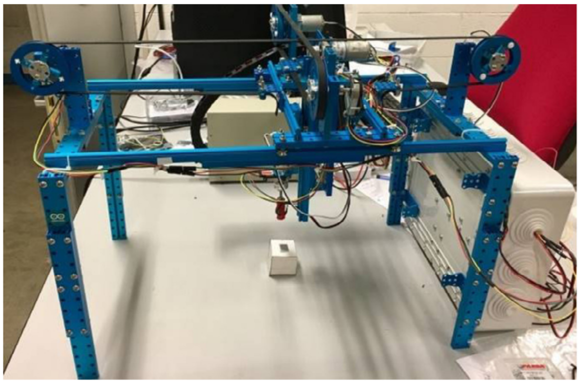

**Fig. 1.** The laboratory scale overhead travelling crane used for experiments.

following this will be referred as *Equivalent Saturation (ES) MPC*. This approach is investigated in Liñán and Heath (2012a) and Liñán and Heath (2012b). There the authors claim that further research is needed to assess the algorithm performance in presence of model uncertainties. In addition, no extensive experimental ES validation has been performed in conjunction with an MPC controller.

### 1.2. Aim of the paper

The contribution of this work is twofold:

- the robustness analysis of both Hybrid and ES MPC;
- the experimental validation of the two algorithms on a laboratory scale overhead travelling crane exhibiting severe nonlinearities.

The analysis highlights that the two approaches can produce comparable results applied under nominal conditions. On the other side Hybrid MPC seems to behave more robustly when in presence of unmodelled nonlinearities.

## 2. Plant description and model identification

A laboratory scale version of an overhead travelling crane (see Fig. 1) is used for the experimental trials in this work. The crane allows to pick up and release a small load by means of a small electromagnet. Motion is allowed in all the three dimensions $(x, y, z)$, with the same hardware configuration on the three motion axis (results for the $x - axis$ only will be reported, since the other two share a similar behaviour and do not provide any extra information to the discussion). The process was entirely built in the Process Control laboratory of University of Pavia, and features the following hardware:

- the crane structure, which is realised using Makeblock components (Mak).
- a 9 V DC motor equipped with a belt, used as actuator (Makeblock components);
- a quadrature encoder (CUI AMT-102V), used to sense the position and the direction of motion.

The system is driven by means of Arduino Mega circuit board and interfaced with Matlab Real Time Toolbox for control purposes. The input to the process is the voltage over the DC motor. This will be used as control variable. The load position represents instead the output of the process.

The main goal of the control system is then to place the load as precisely as possible in the desired position, while avoiding any oscillations during motion. Note that the encoder shows a granularity that results in a linear position measurement error bounded by $[-0.1; +0.1]$ cm. The actuation instead shows a non-symmetric deadzone behaviour that is evident when supplying a purely sinusoidal input voltage to the DC motor and collecting the corresponding position (see Fig. 2 as example). Note that the position drifts in the negative direction: a wider extension of the deadzone for positive voltages can then be expected. In addition, due to physical limitations, control voltages are constrained in a limited range, introducing a saturation effect on the control action. In the following of this section a mathematical description of nonlinearities affecting the actuation is introduced and the overall model identification phase is discussed.

### 2.1. Deadzone

The first step required for system modelling is the definition of the limits of the deadzone. It can be expressed as follows:

$$u_{dz}(t) = \begin{cases} u(t) - high & \text{if } u(t) \geq high \\ 0 & \text{if } low < u(t) < high \\ u(t) - low & \text{if } u(t) \leq low \end{cases} \quad (1)$$

and is depicted as in Fig. 3a. Recall that the plant shows a non-symmetric deadzone. Deadzone identification is carried out experimentally, by applying a weak slew rate voltage ramp (with a positive slope first, then with a negative one) to the DC motor and verifying the input voltage value corresponding to the instant in which the system starts moving. Measures are repeated with the load placed in different positions and a "conservative" model is defined by choosing the maximum $high$ and the minimum $low$ measured values:

$$low = -2.4 \text{ V} \quad high = 2.6 \text{ V}$$

### 2.2. Saturation

Fig. 3b depicts a general signal saturation, which can be defined as:

$$u_{sat}(t) = \begin{cases} u_{max} & \text{if } u(t) \geq u_{max} \\ u(t) & \text{if } u_{min} < u(t) < u_{max} \\ u_{min} & \text{if } u(t) \leq u_{min} \end{cases} \quad (2)$$

The voltage control input of the considered plant shows a saturation whose limits are given by:

$$u_{max} = 9 \text{ V} \quad u_{min} = -9 \text{ V}$$

### 2.3. DC motor

As previously stated, a 9 V DC motor is used as the main actuator for each axis in the plant. Angular motion is turned into linear motion by means of a belt pulley. The typical DC motor Input–Output models (with the control voltage as input and the linear speed as output) are two poles transfer functions, where the "slow" pole is related to the mechanical time constant of the motor, while the "fast" pole is related to its electrical time constant (Leonhard, 2012). Preliminary tests show that the electrical pole can be neglected in our case. An integrator is then introduced to move from speed to position. To sum up, the model for the linear part of the actuator can be written as follows:

$$G(s) = \frac{P(s)}{U_{dz}(s)} = \frac{\mu}{s(1 + sT_m)} \quad (3)$$

where $\mu$ is the static gain and $T_m$ is the motor mechanical time constant. The scheme of the whole actuator is presented in Fig. 4, with a complete definition of signals.

Under the hypothesis of having the nonlinearity confined to deadzone and saturation, and that the model of the deadzone is sufficiently reliable, a grey-box identification can be setup (see Fig. 5). The dataset can be obtained in three steps:

- inject a series of sinusoidal inputs $u(t) = sin(\omega t)$ at different frequencies $\omega$ into the motor (avoiding saturation) and collect the position $p(t)$ as output;