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# An application of economic model predictive control to inventory management in hospitals[☆]

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ABSTRACT

In this paper, we present experimental results from the application of model predictive control (MPC) to inventory management in a real hospital. In particular, the stock levels of ten different drugs that belong to the same laboratory have been controlled by using an MPC policy. The results obtained after four months show that the adopted approach outperforms the method employed by the hospital and reduces both the average stock levels and the work burden of the pharmacy department. This paper also paper presents some practical insights regarding the application of advanced control methods in this context.



## 1. Introduction

The satisfaction of the clinical needs of a hospital requires the existence of stocked drugs and other materials. Inpatients have a need for medication; doctors use gloves, masks, and tools whenever surgery is carried out; likewise, hospitals also provide specific medicines for external patients, such as those used to treat diseases like AIDS and cancer, which are not supplied in retail pharmacies. These are just a few examples of the hundreds of activities performed in a hospital. To a certain extent, some of these activities are foreseeable. For example, many surgeries are programmed weeks in advance. Others, however, are as unpredictable as accidents and heart attacks. Given the critical nature of the activities performed in a hospital, a certain amount of stocked drugs and materials is necessary to avoid shortages that may have fatal consequences. Hence, inventory management is one of the most important activities carried out in the pharmacy department of a hospital. However, due to the high prices of some of these medicines, whose cost can scale up to hundreds or thousands of euros per unit, this activity also has a substantial impact on the hospital's budget: approximately one-third of the hospital's expenses in goods and services are originated at the pharmacy department (Alvarez & Callejon, 1999).

In this context, operation management is essential to achieve efficiency because it involves planning, organising and supervising the provision of the pharmacy services. An analysis of different quantitative model-based research in operation management is presented in Bertrand and Fransoo (2002). System dynamics is an appropriate approach to study operations management. For example, Größler, Thun, and Milling (2008) shows how system dynamics theory can be very useful to deal with operations management problems. In Mingers and White (2010), the main systems theories and their applications have been considered, including the systems approach, system dynamics, operation research, and so on. Within the operation management area, inventory management is a common need in many businesses and organisations; for example, in supply chains (Cachon, 2001; Çetinkaya & Lee, 2000; Dong, Zhang, & Nagurney, 2004; Kouvelis, Chambers, & Wang, 2006). An optimal management should reduce the average stock levels as far as possible while minimising stockouts. It is necessary to establish a policy that determines when new orders have to be placed while taking into account different types of limitations; for example, uncertainties in demand and delivery times, economic and storage constraints, and the availability of human resources to place orders, receive deliveries, and store goods properly, to name a few. It is needless to say that most stock policies ignore some of these issues for the sake of simplicity. Many of the tasks related to inventory management are still performed manually by staff with only a basic knowledge regarding this matter. For example, the reorder point is one classical approach to this problem, which consists of making an order to have a fixed amount of stocked items whenever the stock is below a certain threshold. This policy is closely related to fixing the amount of items to be ordered,

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whenever the stock is below the threshold. In general, these methods optimise their parameters based on assumptions such as constant delay times and Gaussian distributions for demand. See (Brewer, Button, & Hensher, 2001; Tayur, Ganeshan, & Magazine, 1999) for similar policies.

Given the cross-cutting nature of the problem, in the last few decades many solutions have been proposed to deal with this issue from different areas of research. For example, in Parlar (1988), game theory is applied to an inventory system where two products with random demands are considered. In Axsäter (1993), an inventory system with one warehouse and $N$ retailers is considered. The strategy at the warehouse is similar to an echelon stock, with a periodic review *order-up-to-S* policy. Optimal production control and stock-rationing policies are applied in Ha (1997), where the problem is formulated as a queueing control model. In addition, in the area of control theory, some research related to inventory problems – for example, (Ortega & Lin, 2004)– where the objective is to reduce inventory variation, reduce demand amplification and optimise ordering rules. In this area, the basic approaches can be classified within stochastic control theory and deterministic control theory. Several applications of stochastic control theory to operations research are described in (Neck, 1984). A sliding-mode inventory policy is proposed in Ignaciuk and Bartoszewicz (2010), which also uses stochastic approaches. An implementation of deterministic control theory applied to production–inventory control using frequency domain, was presented by Wikner (1994).

In this article, we work with model predictive control (MPC), which is a successful control method with multiple applications in the industry. MPC uses a mathematical model of the system being controlled to predict its evolution as a function of the sequence of actions implemented during a certain horizon (Camacho & Bordons, 2004). In this way, it is possible to calculate the inputs that optimise a given cost function that penalises any deviation of the expected evolution of the system with respect to the target behavior. From the sequence of actions calculated, only that corresponding to the current time step is actually applied to the system; the rest is discarded and the optimisation is repeated at the next time instant in a receding horizon fashion. As a computer based control approach, it is possible to include issues such as constraints, delays in the problem variables, and disturbances explicitly in the formulation of the optimisation problem. In other words, MPC provides us with a continuous replanning policy that recalculates control actions at each time instant according to the most recent information available that is relevant to the problem being solved, such as unexpected consumption peaks, variation in prices, demand forecast, strikes on the delivery companies, and so on.

In the literature, MPC has been considered on many occasions as a suitable strategy for this type of problem. For example, in Wang, Rivera, Kempft, and Smith (2004) and Wang, Rivera, and Kempf (2005) an MPC policy deals with supply chain management in semiconductor manufacturing. Likewise, in Maestre, Muñoz de la Peña, and Camacho (2011), distributed MPC is applied in simulation to the MIT Beer Game. In Stoica, Arahal, Rivera, and Rodríguez-Ayerbe (2009), robust MPC is used to control a production–inventory system. In Perea-López, Ydstie, and Grossmann (2003), a model predictive control strategy is used to maximise profit in supply chains with multiproduct, multiechelon distribution networks with multiproduct batch plants. In Schwartz, Wang, and Rivera (2006), a simulation-based optimisation is presented to decide, optimally, the internal parameters of internal model control and the model's predictive control policies for inventory management in supply chains under uncertainties are supply and demand. An approach for applying control strategies to inventory management problem in a production–inventory system is presented in Schwartz and Rivera (2010), which uses an internal model control and model predictive control to calculate decision policies for inventory management. In Subramanian, Rawlings, Maravelias, Flores-Cerrillo, and Megan (2013), a distributed model predictive control is proposed to optimise supply chains, particularly cooperative model predictive control. Finally, a variation of MPC is used for the management of inventories and supply chains in Rasku, Rantala, and Koivisto (2004).

In this work, we deal specifically with a recently proposed type of MPC approach; that is, of economic MPC. Under this paradigm, the controller takes the economic objective of the process being controlled as the objective function of the control system (Rawlings, Angeli, & Bates, 2012). Hence, the proposed controller tries to minimise the expenses associated with inventory operations management in the pharmacy department. In particular, we present for the first time real results from a pilot implementation of MPC in a hospital, which was located in *San Juan de Dios* hospital in the Spanish city of Córdoba. In contrast to our previously published works (Jurado, Maestre, Velarde, Ocampo-Martinez, Fernández, Tejera, & del Prado, 2016; Maestre Torreblanca, Velarde, Jurado, Ocampo-Martinez, Fernandez, Isla Tejera, & del Prado Llergo, 2014; Velarde, Maestre Torreblanca, Jurado, Fernandez, Isla Tejera, & del Prado Llergo, 2014), where we carried out simulations to assess several stochastic MPC methods to control inventory levels of individual medicines in a simpler problem setup (e.g., neither storage costs nor storage limits were considered), here we work with all of the drugs belonging to a given laboratory, which is more practical in a real world scenario. Also, to gently introduce this methodology to the pharmacy staff, we designed an MPC strategy that was inspired by the approach followed by the pharmacists to work as a decision support system for them. The controller recommends either placing an order for the drugs or not doing anything. In this very first implementation, we also decided to use the mean consumption of drugs during the last year as the future demand forecast and we aimed to avoid stockouts by means of a safety stock. In this way, the transition towards the implementation of more sophisticated configurations of the MPC will be smoother.

The rest of this paper is structured as follows. In Section 2, the problem setting of inventory management in hospitals is presented. Section 3 describes the formulation of the MPC controller that we implemented. Section 4 presents the results of the application of this controller during four consecutive months and compares these results with historical data from the hospital's database. Finally, Section 5 ends the paper with some concluding remarks and guidance for future work.

## 2. Problem formulation

This section presents the mathematical model used to build the MPC optimisation problem.

### 2.1. Pharmacy inventory system

To define a general system, it will be assumed that there are $N_i$ different drugs in the pharmacy inventory. Depending on the demand and the orders, the stock level of each will vary. The stock level evolution for each drug is represented by a discrete linear model, which for the particular case of drug $i$ is

$$s_i(t+1) = s_i(t) + o_i(t-\tau_i) - d_i(t), \tag{1}$$

where $s_i(t) \in \mathbb{Z}$ is the stock of drug $i$, $o_i(t) \in \mathbb{Z}$ is the number of ordered items of the drug $i$ at time $t$, considering only one provider, $\tau_i$ is its corresponding transport delay, therefore, $o_i(t-\tau_i)$ is the number of ordered items of the drug $i$ at time $t-\tau_i$ and delivered at $t$, and $d_i(t)$ represents the aggregate demand of drug $i$.

To differentiate the drugs that need to be ordered from those that do not, a new variable is introduced, $\delta_i(t)$, which is a Boolean variable. If $\delta_i(t) = 1$, then an order for drug $i$ is placed during time $t$, otherwise $\delta_i(t) = 0$. That way, the number of ordered items can also be represented as $\delta_i(t-\tau_i)o_i(t-\tau_i)$, and $o_i(t) \in \mathbb{Z}$ represents the number of ordered items of drug $i$, only in those cases where $\delta_i(t) = 1$. This is one of the complicating issues of this type of application because it leads to mixed-integer optimisation problems.