A Stochastic MPC approach to controlling biological variable processes

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Abstract: The main challenge when controlling agricultural machinery is the biological variability of the incoming crop. This variability renders any process model time-variable and uncertain. Most robust control techniques start with a computationally intensive initialisation method which has to be repeated each time the model changes. Moreover, these techniques mostly focus on process stability, and not process performance. In this paper a different approach is taken with focus on process performance and attention for the computational complexity. The Stochastic MPC framework is used to design a controller that responds as swiftly as possible at all times. Two models are defined, one for the process variables and one for the model error on each of the process variables. The actual configuration parameters of the Model-based Predictive Controller are then calculated in each time step based on the operator settings and the estimated model error. The model error is also used to convert the deterministic process constraints into stochastic constraints which are respected with a given accuracy. Finally this approach is implemented and validated on a capacity control system for a combine harvester.

Keywords: Agriculture, Machinery, Model-based Control, Predictive control, Recursive Least Squares, Robustness, Stochastic variables

1. INTRODUCTION

Over the last decades, the capacity of farming machinery has steadily increased. Till recently, increasing capacity was synonym for enlarging the machine. Due to limitations on the machine dimensions to allow transport over the road, enlarging the machines is no longer possible (Kutzbach 2000). Machine manufacturers are thus looking to automation for alternatives to boost the efficiency and to reduce labour cost.

Rather than the theoretical capacity of the machine, i.e. the capacity obtained by the perfect operator, we are interested in the effective capacity, which is reached by the average operator. The gap between the average operator and a perfect operator can be decreased through the introduction of automation (Coen et al. 2008a,b,c, Coen 2009). An automation system does not get tired, and does not get distracted. Thus, operating the machine closer to its limits, can increase the effective capacity of a machine. This actually comes down to replacing the operator partially by an electronic control system. Alleviating the operator task with control systems is only possible if those control systems have the same information as the operator has. In recent years much research has been done into the design of sensors that measure for instance the actual crop load on a machine. Modern control systems can use these sensors to regulate the system towards a given throughput set point.

The capacity gain obtained by adding such automatic control systems is very difficult to measure. The only way to quantify the performance of the control system is to compare it to an operator. Since the performance of such a reference operator depends amongst others on the skill, circumstances and the fatigue of the person, a large number of experiments is required to make a reliable comparison. Next to the performance improvement, these systems also increase the operators comfort, and allow less skilled operators to drive the combine close to its throughput limit.

This paper focuses on the control system. First a brief description of the working principle of a combine harvester is given. Secondly, the model which will be used by the Model-based Predictive Controller (MPC) is presented. Since the model uncertainty, as well as the plant itself, varies with time, stochastic MPC (SMPC) is preferred to more common robust control techniques. Finally the SMPC controller is validated in practice on a combine harvester (courtesy of CNH Belgium N.V.).

2. SYSTEM DESCRIPTION

2.1 Combine harvester

A combine harvester (Figure 1) mows the grain (barley, wheat, canola, corn,...), threshes the crop, and separates the chaff from the grain. The clean grain is stored in the grain tank, whereas the straw and the chaff are thrown on the field, chopped or otherwise. The process

Fig. 1. Combine harvester in corn (Courtesy of New Holland)

dynamics of the machine contain significant delays, and the behaviour is strongly non-linear and time-variable (Maertens 2004). The time-variable behaviour is caused by the dependency of the process on crop properties and environmental conditions.

The power source on a combine harvester is a diesel engine. Several process components such as the cleaning mechanism are mechanically connected to the diesel engine (Coen et al. 2006). This implies that, in the field, the diesel engine always needs to run at the same (maximum) engine speed to allow the process to function correctly. The diesel engine also delivers the power for the propulsion system. The engine drives a variable-gain hydrostatic pump, the gain of which is controlled by the operator. This pump drives a fixed-gain hydrostatic engine, which is connected to the front axle. Since the speed is determined by the pump setting, the pump setting will be the control output of the control system, and is actually the only controllable signal for this study. On the road the operator may vary the diesel engine speed as well, which gives an extra degree of freedom to the control system (Coen et al. 2008b). The fuel injection of the diesel engine is controlled by the engine control unit (ECU) in order to keep the engine speed at the desired set point. The fuel injection (expressed in percentage of the maximum fuel injection) is also called the engine load.

The experimental results discussed in this paper are all obtained during the corn season. In corn the header pulls the crop down through the header to remove the cups. The cups are then transported to the straw elevator by means of chains and an auger. The stem is chopped by the rotating knifes positioned underneath the corn header. The torque needed to power the auger (in the header), the chopper (underneath the header) and the straw elevator is measured jointly, and is called the feed rate (Strubbe and Missotten 1999). The feed rate is proportional to the amount of biomass that enters the machine. This is one of the process variables that is used in the control system. Alternative measurements for the biomass flow are the torque on the threshing drum (Littke and Kis 2001, Fechner et al. 2005) and the layer thickness in the straw elevator (Diekhans 1998). The feed rate measured as the torque on the auger, the chopper and the straw elevator, has the best characteristics. It exhibits only a very small delay (relative to input changes) and has a good signal to noise ratio. Therefore, this sensor is used in this research.

Once the crop has been fed into the machine, it is threshed by an axial or conventional threshing drum. The combine harvester used in this study (a New Holland CR, by CNH) contains an axial threshing system. The threshed grain is thrown onto the preparation section, and transported further onto the cleaning section by a shaking movement. The heavier parts migrate to the bottom of the layer, and the lighter parts to the top. This simplifies the task of the cleaning section, which separates the grain kernels from the chaff and the straw by means of a combination of wind and shaking sieves. The grain kernels that are still contained in the straw flow at the point that the straw leaves the machine are called the separation loss. Up till now there is no sensor available to measure these losses online.

The cleaning section itself consists of two sieves, placed on top of each other, with separately adjustable sieve openings (Craessaerts et al. 2007). A fan blows through both sieves to blow the chaff away. If the fan blows too hard, grain kernels may be blown out of the machine as well. The material that stays on the upper sieve, exits the machine at the end of the upper sieve. The kernels present in this flow are called the sieve loss. These losses are measured by a sensor at the end of the upper sieve (Diekhans and Behnke 1990). The material that falls through the upper sieve and through the bottom sieve is transported to the grain tank by the grain elevator. At the top of the grain elevator a sensor is placed to measure the grain mass flow with an accuracy of 1% (Missotten and Busschaert 2003). This process variable will also be used by the control system.

2.2 Process model

The process model is shown in Figure 2. It consists of a number of dynamic submodels connected with delay lines. Each delay line also contains a time-variable process gain, which is estimated online using Recursive Least Squares (RLS). The uncertainty of the different process states (such as engine load and feed rate) can then be quantified based on the uncertainty of the online estimated gains (Coen et al. 2010a,c).

3. MODEL-BASED PREDICTIVE CONTROL (MPC)

3.1 Classical MPC

MPC controllers are designed based on a dynamical model of the system that has to be controlled (i.e. the plant) and use mathematical optimisation techniques in order to obtain the optimal inputs to be applied to the plant (Camacho and Bordons 2004). In MPC an objective function is optimised over all possible input sequences, subject to equality and inequality constraints. The objective is expressed as a function of the states, outputs and inputs of the system. The states and outputs are predicted over a given prediction horizon, as a function of the inputs, which can be varied over the control horizon. In each