A comprehensive approach for the design of intelligent mechanisms with model based control methods

Nandish R Calchand*, **Stijn de Bruyne***, **Marco Gubitosa***, **Stijn Donders***

*Siemens Industry Software NV.
Interleuvenlaan 68
B-3001 Leuven (Belgium)
nandish.calchand@siemens.com

Abstract

Mechatronics design now requires a more holistic approach than ever. This is due to the fact that components are becoming more intelligent and provide much more functionality. The usual approach in engineering is to design the mechanical components, electrical components and software seperately and then assembled them together to create a mechatronics system. For the design of complex industrial products nowadays, this sequential approach causes problems, given the need to optimize the system-level product performance and the difficulties to do so in a process that is focused on the design of individual components and functions. This can be resolved by adopting a systems design approach, in which all components and their controllers are represented within a system model that can be optimized.

In this paper, we concentrate on the design of controllers. Though many ways exist to design controllers, MPC control[1] has been found to be very versatile. It has the advantages of being able to systematically include constraints and/or limits on the system.

In MPC-based controller development and validation, models are used not only as plant models, but also inside the controllers to define the control strategy. A prototype implementation has been made that links an MPC process block into LMS Imagine.Lab AMESim. With MPC in the AMEsim workflow, controls engineers can follow a systematic streamlined procedure to implement a model-based control strategy for multi-variable, constrained mechatronic systems, dealing with high complexity on an industrial application size. The value of this approach has been demonstrated for linear time invariant systems [3]. Towards more realistic representation of the engineering design practice, a next step worked out in this paper to address the compensation of unknown external disturbances that act on the system. This is a known pain in the controls engineering design practice. For example on a vehicle, irregular road profile and wind gusts impact the trajectory to a certain extent, and the controller must operate well while not being affected by such disturbances.

MPC control is basically an optimization algorithm which at every time step calculates the input value that will steer the states of the system to the desired value by minimizing some cost function.

A linear system can be described in state space form as:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) \end{aligned} \tag{1}$$

where $x(k)$ are the states, A is the state transition matrix, B is the input matrix, $u(k)$ is the input, y are the measurement and C is the measurement matrix. Then an MPC controller solves a finite time optimal control to find a set of inputs $U = [u(1), u(2) \ldots u(N)]$ to drive the system optimally to the desired states by minimizing a cost function usually given by

$$J(x(0), u) = \sum_{k=0}^{N-1} x'(k)Qx(k) + u'(k)Ru(k) + x'(N)Px(N) \tag{2}$$

where Q, P and R are weights matrices which assigns relative importance to the states and inputs. At each time step, the controller calculates U and then only the first input $u(1)$ is applied to the system.

Usually for any system, we cannot measure all its states (x). Only a subset of these states (y) can be measured due to various reasons. Either the states might be inaccessible or the cost incurred to measure them might be prohibitive. In such cases, an observer is useful. Its role is to estimate the unavailable states using the measured values. In our methodology we therefore also include an observer. As for

controllers, many types of observers exist. Two of the most common ones are the Luenberger observer and the Kalman Filter[4]. Figure 1 shows the block diagram of a system together with a Kalman Filter and an MPC controller.

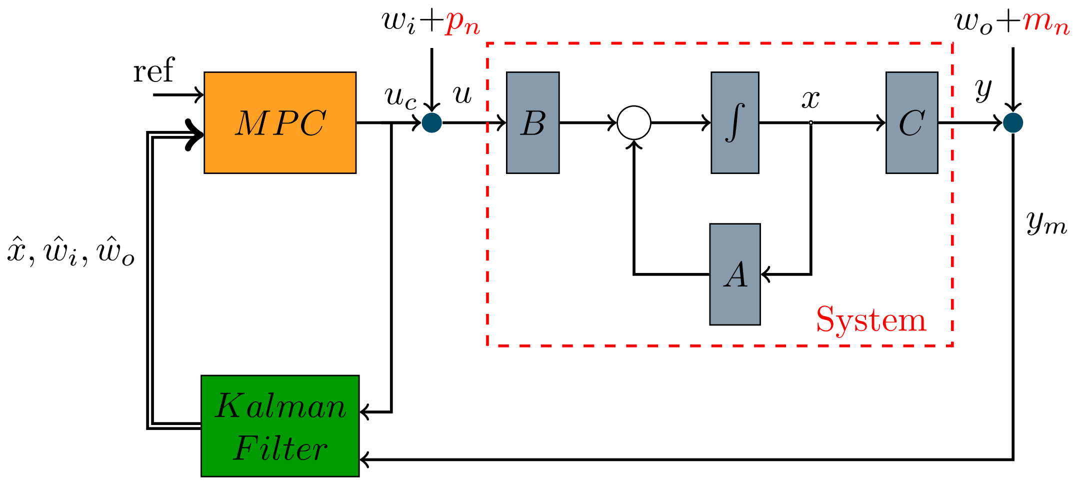

Figure 1: *System (enclosed within dashed rectangle) with Kalman Filter (observer) and MPC controller.* The measurements (y_m) are fed to the Kalman Filter which estimates the states/distubances ($\hat{x}, \hat{w_o}, \hat{w_i}$) which is fed to the MPC controller.

In addition to estimating the states, observers can also be used to estimate the disturbance entering the system. Typically, in MPC control to achieve offset free tracking, the ability to estimate the disturbances[2] is crucial. One of the main problems of disturbance estimation in MPC control is the need for a good disturbance model. Usually, given only the model of a system, it is not obvious where and how disturbances affect the system especially if the system contains integrators. This can be partially solved in AMESim which uses component-level modeling (resistors, inductors, masses, springs etc...) to extract the disturbance model.
In this paper we explain the process adopted to integrate the model based control design approach sketched above in the general purpose multi-physics modeling environment of AMESim. This methodology is further enlightened by the realization of two demonstration applications. The first one involves a single rotating inertia attached to DC motor and where we control the angular position subjected to an unknown disturbance. The second realization aims at showcase the applicability of modern control techniques in automotive domain by employing them for the design of an active suspension system. The plant reproduces the kinematic and compliance behavior of a single automotive suspension undergoing the vertical (semi-)random excitation of a rough road profile. A simplified representation, capturing the gross dynamic characteristics of the plant, is hence adopted for the definition of the control and state estimation scheme depicted above.
Conclusions are finally drawn in the last paragraph of the paper, highlighting the benefits of an integrated design tool, which grants the possibility to tackle the nowadays pressing needs of mechatronic systems design.

References

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