10.1 Introduction

Subspace identification is a technique that can be used for identification of state-space models from input-output data. This technique has drawn considerable interest in the last two decades [1, 2], especially for linear time-invariant systems. A reason for this is the efficient way in which models are identified for systems of high order and with multiple inputs and outputs. Subspace identification can be used to form a subspace predictor for prediction of future outputs from past input-output data and a future input-sequence. This subspace predictor can be computed without realization of the actual state-space models, which significantly reduces computational requirements. In [3] the subspace predictor has been combined with model predictive control [4], resulting in a control algorithm that has been given the name subspace predictive control (SPC). In SPC, the output predicted by the subspace predictor is part of the cost function of the predictive controller. As a result of the subspace predictor being generated completely from input-output data, the SPC algorithm is a data-driven one.

In this chapter, which is partly based on [5], extensions are made to the SPC algorithm that include the derivation of the subspace predictor in a stochastic closed-loop setting and the recursive update of this predictor. In previous papers in which SPC has been used [3, 6, 7], the subspace predictor has been derived using open-loop subspace identification techniques. However, when the SPC algorithm is active, the data gathered to update the predictor inherently is closed-loop data. It has been proven that using closed-loop data from a stochastic system for subspace identification...
results in a biased predictor [8]. Therefore, a number of different methods have appeared in literature to deal with this issue [8, 9, 10]. Most of these methods require explicit knowledge of the controller or are based on (overly) stringent assumptions that limit their applicability. Recently, a practically applicable closed-loop subspace identification method that does not require explicit knowledge of the controller has been developed in [11]. Based on this method a subspace predictor under closed-loop conditions can be derived [12], which is also used in this chapter.

Another novel feature of the SPC algorithm presented in this chapter is the way in which the subspace predictor is updated in a recursive manner. This updating scheme differs from others that are based on the “receding horizon” principle, such as, for example, the scheme proposed in [6]. In the “receding horizon” updating scheme the predictor is based on input-output data from a fixed time window lagging behind the current time sample. In the recursive updating scheme new data is appended to the old data, which is discounted with an exponential forgetting factor. This scheme has the advantage that it can be implemented in a computationally efficient manner by using Givens rotations [13].

The implementation of SPC as an adaptive controller makes it very suitable for fault-tolerant control (FTC) of aircraft. Most FTC systems deal with faults by using pre-designed or parameter dependent controllers depending on the type of fault that has occurred [14]. These systems require that the faults either be known in advance or be modelled by a variation of specific parameters [15, 16, 17]. In this way control designs can be made for each anticipated fault. Besides the fact that this approach can be very involved, unanticipated faults or faults that cannot be modelled by parameter changes such as severe structural damage can occur. An advantage of SPC is that it can adapt on-line to this type of fault. This property is the result of the subspace predictor that is continuously updated using new input-output data. The main contribution of this chapter is to display the usefulness of SPC for realistic FTC problems. The developed SPC-based FTC system is applied to the benchmark model. Simulations are performed with this model, in which the objective is to fly a pre-defined flight trajectory even after the occurrence of a number of critical faults. The considered fault conditions are stuck control surfaces and the fault condition of the aircraft during the disaster with EL AL flight 1862, that crashed into an apartment building in Amsterdam in 1992. This disaster is also referred to as the “Bijlmerramp”.

Most aircraft flying today have control laws that are designed using classical single-loop control methods. These methods are preferable over multivariable control methods from a clearance point of view [18]. However, single-loop control methods are likely to display a degraded performance in case of faults that cause cross-couplings between flight modes. These cross-couplings are the result of loss of symmetry of the aircraft after faults. Multivariable control methods can cope better with these cross-couplings because they simultaneously achieve several control objectives. Multivariable control methods are therefore to be preferred over single-loop control methods from an FTC point of view [19, 20]. This is one of the reasons that research into multivariable flight control recently has attracted considerable