ON THE SELECTION OF APPROPRIATE CONTROL SYSTEM DESIGN METHODOLOGIES

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Abstract: We will argue in this paper that the nature and magnitude of model uncertainty dictate the appropriateness of the control system design methodology. To obtain these arguments, we will pursue optimality of the control system design. Note *this is a philosophical paper,* in which we present our arguments *in qualitative terms*. We will identify the circumstances under which several control system design methodologies are appropriate. The design methodologies that will be considered are (1) optimal control and optimal feedback design, (2) model predictive control (receding horizon control), (3) active and passive adaptive control and (4) robust control. Robust control strategies are conservative and limit the possible improvements that can be obtained over say classical PID control. However, it will turn out that for certain types of control problems, improvements in performance are indeed limited. Roughly speaking, the area where we may expect (significant) improvement from advanced (optimal) control system design is very much limited by the uncertainty of the systems model. *Miracles* are not to be expected from advanced control. What can be expected is reflected in an active adaptive optimal control scheme introduced and discussed in this paper.

Keywords: controller selection, model uncertainty, active adaptive control, adaptive dual control, caution, probing, learning.

1. INTRODUCTION

Over the years our experience has taken us over the following control methodologies: PID, H-infinity, LQG, model predictive control, adaptive control, robust and optimal control. Our focus has been on optimal control and optimal feedback design, but several applications have also forced us towards model predictive control, adaptive control and sometimes even robust control (De Waard and De Koning, 1992; Tchamitchian and Van Willigenburg, 1993; Lees *et al* 1996; Chalabi and van Willigenburg, 1999; Timmerman et al, 2000; Van Straten *et. al*, 2002). We also witnessed significant developments and use of mathematics in control. Surprisingly however, little seems to have been published on the subject of this paper. This might be due to the fact that the subject of this paper is to a certain extent, mathematically intractable.

When faced with a control problem, a natural and important question to ask is: "Which existing control system design methodologies are appropriate and what performance could I expect?" This paper will argue that the nature and magnitude of the uncertainty associated with the model of the system dictates the answer. In addition, this paper argues the circumstances for which (1) optimal control incorporating optimal feedback design (Athans, 1971), (2) model predictive or receding horizon control (Allgöwer, 1999, Garcia *et. al*, 1989), (3) active and passive adaptive control (Filatov and Unbehauen, 2000; Bitmead *et al*, 1990) and (4) robust control (Mayne and Michalska, 1993) are appropriate control system design methodologies.

This paper is based strongly on the work of Bar-Shalom (1980). He classifies control problems as either *essentially deterministic*, *dominated by caution* or *dominated by probing*. This classification is based on a decomposition of the costs of a stochastic optimal control problem formulation. Although Bar Shalom (1980) starts from a solid mathematical basis, his classification is not strictly mathematical in nature. We believe however that the classification is very valuable from a philosophical point of view. Almost any control problem involving a non-linear systems model that is uncertain is not separable. Non separable control problems, in general, are mathematically intractable. Quoting Bar Shalom (1980): "The cost decomposition is believed to provide the only insight we now have towards the understanding of complex stochastic control problems for which the optimal solution is unknown". To the best of our knowledge, this statement is as valid today as it was more than twenty years ago.

If a control problem is not separable, the control has the so called *dual effect*, introduced and recognised for the first time by Feldbaum (1960, 1961, 1965). The control, apart from its direct effect on the system behaviour and performance, also influences the quality of the state and/or parameter estimation, which in turn influences the control performance. Because of this influence, the control may be selected to *enhance* the estimation. This is called *probing*. The state and parameter uncertainty degrades the control performance. Selecting the control to *limit* this degradation is called *caution*. If there is no uncertainty, caution and probing effects are not present and the control is obtained from solving a deterministic control problem.

We will modify the classification introduced by Bar Shalom (1980) in such a way that the classification depends only on the nature and magnitude of the uncertainty associated with a systems model, and is not dependent on the control criterion, as in the case of Bar Shalom (1980). Unlike Bar Shalom, our classification is not based on solid mathematical arguments. We will only provide philosophical arguments versed in *known control terminology*.

Having introduced our modified control problem classification, the main contribution of this paper is as follows. If the control problem is *essentially deterministic* the systems model is accurate and optimal control incorporating optimal feedback design is an appropriate control system design methodology. If the problem is *dominated by caution*, the systems model is highly uncertain and neither observations nor control can be employed to (significantly) reduce this uncertainty. In this case, robust control system design is an appropriate methodology. In addition if (almost) perfect state information is obtained, a (robust) model predictive control system design is more appropriate. If the problem is *dominated by probing* (we shall change this term into *dominated by learning* for reasons to be explained later in this paper) active or passive adaptive control system design is appropriate. In terms of possible improvements that can be obtained when the control problem is not separable, active adaptive control is the most general and promising.

Finally a new active adaptive controller scheme is presented. This scheme, we will argue, is valuable for two reasons: (1) it contains relatively well known and well understood control components, and is therefore very useful for active adaptive control system design and (2) other control system design methodologies considered in this paper may be viewed as special cases of active adaptive control.

The paper is organised as follows. Sections 2,3 and 4 describe in detail the three types of control problems recognised by Bar Shalom and modified by us. To each type a suitable control system design methodology is assigned. Section 5 focuses on active adaptive control and presents the new control scheme. Finally section 6 discusses the results put forward in this philosophical paper.

2. ESSENTIALLY DETERMINISTIC CONTROL PROBLEMS.

Consider a control problem, which is either continuous, digital or discrete-time. The systems model may be non-linear. The control problem is said to be *essentially deterministic* if the systems model is accurate, meaning that it produces accurate predictions of future states. If so, we would argue that *optimal* control incorporating *optimal* feedback design constitute an appropriate control system design methodology. This methodology forces the engineer to specify *explicitly* the control objectives through the control criterion which we consider highly important for two reasons: it forces the engineer to think carefully about, and formulate exactly, what they want and it enables computation of the best solution.

Application of optimal control, together with optimal feedback, results in the control system represented by Fig. 1. . The design of this control system takes place at two levels. At the highest level (“Level 1”), a deterministic optimal control problem is solved *off-line*. This optimal control problem is deterministic implying that a deterministic version of the systems model is used at this level of the control system design. Furthermore at this level of the design many difficulties, like system non-linearities and all types of constraints may be catered for and implemented easily. The off-line nature of the optimal control computation at Level 1 enables the design to deal with high dimensional systems models as well. These may be finite dimensional approximations of infinite dimensional systems.

At the second level (“Level 2”) of the design, an approximation of the model linearised about the optimal control, state and output trajectories (computed at Level 1) , is used to design the optimal feedback. The linearised model describes the dynamic behaviour of the perturbations accurately, as long as these remain small. LQG feedback design at Level 2 is highly appropriate as pointed out very clearly by Athans (1971). LQG design incorporates system and measurement uncertainty described by additive white noise processes. At Level 2 of the design (i.e. at the level of perturbation control), system and measurement uncertainty can be considered because the LQG problem is separable. In this way, the design at both levels is performed in an optimal manner, and the overall result is almost optimal, if the problem is essentially deterministic (Athans, 1971; Bar Shalom 1980).

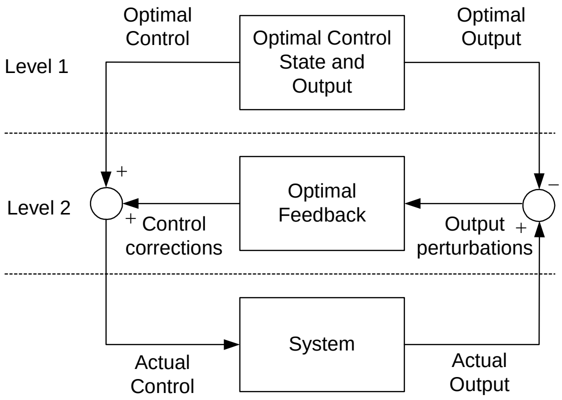

Fig. 1. Optimal control incorporating optimal feedback design

The computation of the LQG feedback controller', input and output gain matrices can also be performed off-line. These matrices must be stored in the controller "memory". *The on-line computations involve only a few matrix vector multiplications*. If the dimension of the systems model is very high, the storage of the LQG feedback controller matrices and the on-line computation time required by the matrix vector multiplications, may still pose a problem. In this case, optimal reduced-order LQG design is highly appropriate (Van Willigenburg and De Koning, 1999).

Although LQG feedback design is highly appropriate at Level 2 of the design, there are of course alternatives. A more robust design could be considered more appropriate. On the other hand, the optimal control problem is essentially deterministic suggesting that robustness is not a big issue. An interesting extension of LQG design, which enables robustness to be increased without obtaining conservative designs, is achieved by replacing some or all parameters of the linearised model, by white stochastic model parameters (R. Banning and W.L. De Koning, 1995).

Optimal control incorporating optimal feedback design is approximately optimal, whenever the systems model is accurate, i.e. when the control problem is essentially deterministic. The reason to apply a *different* control system design methodology than what is proposed earlier *must* be that the model is of insufficient quality. If this is the case, then we would argue that *the first step towards improved control performance is clearly to improve the model!*

3. CONTROL PROBLEMS DOMINATED BY CAUTION

This type of control problem is characterised by the fact that the systems model is poor and cannot be improved (significantly) by selecting appropriately the control and employing the associated observations. The first step towards improved control performance stated at the end of the previous section cannot therefore be met! In other words, performing identification experiments with the plant does not help in obtaining an accurate plant model. In general, a poor model demands a robust control system design to try to obtain an acceptable performance under a wide range of conditions. This implies a necessarily conservative control system design and so the improvement over simple, say PID control, is usually very limited. From the point of view of advanced control, which aims at performance optimisation, or at least performance improvement, this is the least favourable type of control problem.

Control system design employs the systems model for *both* control and state estimation. When however, (almost) complete state information is available (i.e. the complete state is measured accurately) then no state estimation is required. Then although the model is poor, the state information is almost perfect. Roughly speaking one could state that in this case one half of the problem relating to a poor model is circumvented. A major problem of the control scheme presented in Fig. 1. is that, when the model is poor, then after a while the optimal control, state and output trajectories, computed off-line at Level 1 of the design, no longer apply. This is so because the true state is completely different which in turn destroys the accuracy of the linearised model, used at Level 2 of the design. Therefore this control scheme 'falls apart'.

Having (almost) complete state information, the major problem with the control scheme in Fig. 1. can be resolved as follows. At each time instant, from the current (almost) perfectly measured state, compute a new optimal control using the poor model and apply this control until the next time instant. This control approach is known as *model predictive or receding horizon control*. Compared to the control scheme in Fig. 1. there is one major disadvantage. The number of on-line computations increases dramatically since now at each time an optimal control problem must be solved *on-line*. This problem may be relaxed by using the previously computed control as an initial guess for the current computation. Also observe that Level 2 of the design in Fig. 1. now becomes superfluous since feedback is implicit in this new control scheme: At each time instant, we start our computation from the current (almost) perfectly measured state. One may argue that, because the model is poor, the control computation should take into account some form of robustness. Usually however, the state feedback already guarantees some form of robustness. Taking into account robustness is (much) more difficult, requires even more on-line computations and finally introduces conservative performance (Mayne and Michalska, 1993).

In summary, if the control problem is caution dominated and if we have (almost) complete state information, model predictive control (receding horizon control) is appropriate. Otherwise robust control is appropriate.

4. CONTROL PROBLEMS DOMINATED BY LEARNING

This type of control problem is characterised by the fact that the systems model is poor initially but the model accuracy can be improved significantly by making suitable use of the observations, and possibly the control. Making suitable use of the observations only, is called *passive adaptive control*. When, in addition, the control is used to *further enhance* the accuracy of the model, this is called *active adaptive control*. The latter implies that the control has the dual effect. A topic closely related to active adaptive control is *optimal input design* which is concerned with the problem of finding the best control to identify the systems model (Goodwin and Payne, 1977, Stigter and Keesman, 2004). The reason that we have decided to change the term "dominated by probing" into "dominated by learning" is that we believe that *learning*, i.e. improving the model, is the essential feature of this type of problem. Because the types of control problems that we are considering are not separable, the dual effect is present, and the learning may be enhanced by probing. However, the enhancement due to probing may be *small* compared to the enhancement obtained from using the observations to improve the accuracy of the model. If this is the case, then passive adaptive control is appropriate (passive adaptive control does not probe).

If the control problem is dominated by learning, the common practice is to perform *separate identification experiments* with the plant, in order to improve the model quality, e.g. by means of optimal input design (Stigter and Keesman, 2004). Active and passive adaptive control aims at *keeping the plant in operation*. While keeping the plant in operation, initially, adaptive control focuses on the improvement of the model quality, possibly by means of adjusting the control (i.e. by means of probing; active adaptive control). As the systems model becomes more accurate, the control problem becomes essentially deterministic and the (active) adaptive control tends to the control approach described in section 2. This means that the highly attractive feature of (active) adaptive control is that it improves the model, while keeping the plant in operation, i.e. avoiding expensive identification experiments. Furthermore the adaptive control ends up in a situation where optimal control incorporating optimal feedback may take over.

5. ACTIVE ADAPTIVE CONTROL AND A GENERALIZED CONTROL SCHEME

The philosophy presented in the previous sections clearly indicates that the improvement that may be expected from advanced control, compared to say classical PID control, depends critically on the accuracy of the systems model. The most favourable situation is when this model is accurate from the start and the problem is essentially deterministic. Therefore most of our research concerning the development of control system design methodologies has focussed on optimal control and optimal feedback design. The next best favourable situation is when the model, while being inaccurate at the start, can become accurate by learning from the observations possibly through a suitable adaptation of the control. Since we believe that our research concerning (digital) optimal control together with (digital) optimal feedback has reached maturity, we intend to focus on active adaptive control methodologies.

A major difference between active adaptive control methodologies and optimal control incorporating optimal feedback design is that the associated control problems are now mathematically intractable. Therefore the philosophical content of this paper is important. Given this type of control problems, the best we can do is to take into account important properties of the control system design.

In a first attempt at this problem, we propose the active adaptive controller scheme represented in Fig. 2. . It uses two well established approaches in the control literature: the non-linear least squares estimator and the receding horizon optimal controller.

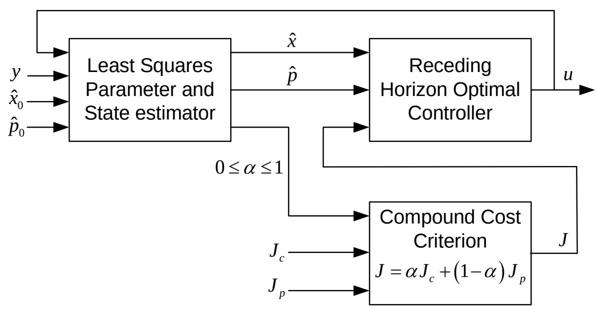

Fig. 2. Our active adaptive controller scheme

The active adaptive controller requires as inputs initial estimates of the state $\hat{x}_0$ and the uncertain parameters $\hat{p}_0$, the observations y, and the control objective represented by the control criterion J_c. The cost criterion J, which is used by the receding horizon optimal controller, is a compound cost criterion: it is obtained from the control criterion J_c and the criterion J_p, which is another input of the active adaptive controller. The criterion J_p reflects objectives to enhance the quality of the estimates $\hat{x}, \hat{p}$ of the states and the uncertain parameters respectively, to be met by adjusting the control. The use of J_p only makes sense if the control has a dual effect, which it has whenever uncertain system parameters are estimated. Finally $0 \le \alpha \le 1$ is a measure of the quality of the state and parameter estimates (i.e. $\alpha = 1$ corresponds to perfect state and parameter estimates). This measure may be obtained from the residuals of the state and parameter estimates.

The active adaptive controller, through J_p, takes into account as well as exploits the dual effect of control. This is a so called explicit active (or dual) adaptive controller. In the stochastic optimal control problem formulation of Bar Shalom (1980) the dual effect, i.e. the active adaptive nature of the controller, are implicit. The latter has the advantage of not having to be concerned with the selection of J_p and the use and selection of the measure α. We believe on the other hand that it uses rather poor and computationally very expensive approximations to compute the control. Implicit and explicit active adaptive (dual) controllers have been reviewed by Filatov and Unbehauen (2000).

The success of our active adaptive control scheme depends on whether or not the state and parameter estimates converge, in which case α tends to one. Note that this convergence in general implies that the model structure must have been selected appropriately. Once the system parameter estimates are accurate and α is close to one, the control problem has become essentially deterministic, and the control scheme may be replaced by the one in section 2, which is computationally much cheaper. In this respect the control scheme represented in section 2 is a special case of our active adaptive controller scheme.

When the control problem is dominated by caution, the systems model is of poor quality and no significant improvement of the systems model can be obtained from the observations, whatever the control. The parameter estimation in Fig. 2. becomes ineffective and with it the probing associated with J_p. Given the caution dominated nature of the control problem, the state estimator and receding horizon controller that remain, should preferably be designed in a robust manner. When the problem is caution dominated and we have perfect state information, the state estimation part in Fig. 2. is also ineffective and we are left with the robust receding horizon (model predictive) controller.

Note finally that if $\alpha = 0$, the criterion $J = J_p$ and the controller scheme represents optimal input design, because the control objective J_c is completely ignored. Effectively then we are performing a separate identification experiment. If from this experiment we obtain an accurate model, then following previous reasoning the problem becomes essentially deterministic and we may switch over from $\alpha = 0$ to $\alpha = 1$ and obtain the control scheme presented in section 2. This is the well known procedure where we build the model from separate identification experiments and then design an optimal controller. The interesting feature of the active adaptive controller scheme in Fig. 2. is that it keeps the plant in operation and *gradually* shifts the focus from probing towards the control objective, while the model improves.

6. CONCLUSIONS AND DISCUSSION

What issues have triggered the development of this paper? There were several issues which initiated this work. Having been concerned with the development of algorithms for digital optimal control and digital optimal reduced-order LQG feedback design, we noted that their application in industrial practice is often hampered by the fact that the systems model is of insufficient quality. This paper makes a clear statement: the accuracy of the systems model is crucial for the success of advanced control and that one should not underestimate the importance of improving the model. We believe that, apart from the use of observations and control, which we promote in this paper, employing first principles of modelling based on the physics of the plant is the key to obtaining an accurate model. Although this might be cumbersome, the exercise has to be performed only once, and provides *insight*, which from our experience is also considered very valuable in industry (De Waard and De Koning, 1992; Chalabi and van Willigenburg, 1999).

Some of us have been concerned with control problems relating to agriculture, such as climate control in greenhouses and storage buildings (Tchamitchian and Van Willigenburg, 1993; Lees *et al* 1996; Timmerman et al, 2000; Van Straten *et. al*, 2002). In these cases the weather variables act as external inputs to the systems, and in the case of greenhouse climate control, the solar radiation should be *exploited* for plant growth. Since accurate models of the weather cannot be obtained while accurate state information on weather variables is available, receding horizon (model predictive) control has been applied (Van Straten *et al*., 2002). Passive adaptive control is currently under investigation, where plant observations, apart from feedback, are also employed to improve the estimation of plant model parameters.

A next step would be to apply active adaptive control, because it is known that the estimation of plant model parameters can be enhanced by a suitable choice of the control. Another application area in agriculture is concerned with the control of vehicles and equipment performing several operations in the field. In this case a major source of systems model uncertainty is caused by the shaking of vehicles. This shaking can be prevented by moving vehicles over rails, or other flat parts. The control philosophy presented in this paper strongly promotes to do this, or in more general terms, to change the design of the system to reduce or eliminate uncertainty.

Control problems in general do not necessarily belong to one of the three classes of control problems identified in this paper. We believe however that the recognition of these classes of control problems would help in the selection of appropriate control system design methodologies. We have been able to show that active adaptive (dual) control is the most general methodology because other control approaches considered in this paper may be viewed as its special cases. The active adaptive controller scheme that we have presented is built out of components that are well understood in the control literature. We believe that the proposed controller scheme is very valuable for the design of active adaptive controllers, and we would direct our future research in this area.

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