MODELLING AND SIMULATION IN ADVANCED CONTROL

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Abstract: Operating conditions are often changing so strongly that the changes in nonlinearities must be taken into account. Various approaches exist for handling nonlinearities in changing operating environment: nonlinear control is extended with adaptation approaches, model-based methodologies, intelligent analysers and expertise. Linguistic equation (LE) controllers combine various control strategies in a compact matrix-based environment. Importance of modelling and simulation is increasing with integration of the control approaches as the increasing number of adjustable parameters requires efficient comparisons of alternatives. Predefined adaptation models and mechanisms obtained by tuning with modelling and simulation facilitate fast operation in changing process conditions. The performance of these systems consisting of practical and interactive small scale intelligent systems has been demonstrated in several applications. This paper has been prepared for the Sim-Serv * roadmap of continuous and hybrid simulation.

* Sim-Serv The World's First Virtual Centre for Simulation, http://www.sim-serv.com

Keywords: adaptive control, nonlinear control, predictive control, intelligent control, model-based control, fuzzy set systems, multivariable systems.

1. INTRODUCTION

In industrial applications, operating conditions are often changing so strongly that the changes in nonlinearities must be taken into account. Pulp and paper industry has been in the pioneering role in the development of process automation already from the 1950s (Leiviskä, 2001). Modelling and simulation has been all the time an essential part of the process and control design. Various intelligent applications have been developed for fibre line, chemical recovery, bleaching, paper mill, and water treatment (Juuso, 2004*c*). Handling of nonlinearities is important in these applications, e.g. the calcination process, with its nonlinear reaction kinetics, long time delays and variable lime mud feed characteristics, make the lime kiln process inherently difficult to operate efficiently. Many interconnected variables must be considered and control actions must be designed to meet multiple and sometimes conflicting objectives, and changing operating conditions.

Sustainable energy plants should provide a viable, cost effective alternative to more polluting forms of power production and achieve this task despite fluctuations in their primary energy source. For solar thermal power plants, the energy source, the sunlight, has seasonal and daily cyclic variations, and the irradiance depends also on atmospheric conditions. As operating conditions cannot be reproduced and weather conditions have seasonal differences, dynamic simulators are needed in controller design and tuning. (Juuso, 1999*a*)

Efficient integration of subprocesses is important in pulp and paper industry. Lime kilns are used in the chemical recovery of the chemical pulping process. Internal water circulation is essential for an integrated pulp and paper mill as washing is done in many stages of the process. The water can be kept in the circulation if the treatment is capable to clean it. All disturbance of the purification result will later cause new disturbances in the pulping or paper making processes. (Juuso, 2004*c*)

In water treatment, methods of dosage control can be far from ideal, leading occasionally to inefficient plant operation, occurrence of unnecessary costs and in some cases decreasing water quality. However, the development of control strategies has been increased in recent years mainly due to tightened environmental requirements and decreasing water consumption in pulp and paper mills. (Joensuu *et al.*, 2004)

Waste handling has similar problems, e.g. measurements do not always give the correct information, which leads to wrong control actions, and eventually to switch-off of the automatic control strategy. The operator has lots of additional information for manual detection of the burn-out position. The control strategy should be designed for working with inputs from the operator (Oestergaard, 2004).

These application areas have similar requirements, e.g. a lime kilns can use bio fuels generated from biomass (Järvensivu *et al.*, 2001). Efficient use of chemicals, water and energy requires adaptation of the nonlinear multivariable processes into ever changing operating environment.

This paper summarises different modelling and simulation approaches aimed for adapting control systems to changing operating conditions. Adaptive linguistic equation controllers are taken as an example of integration of different control strategies in these application areas.

2. ADVANCED PROCESS CONTROL

Various approaches exist for coping with nonlinearities in changing operating environment:

- *Nonlinear* control extends the operating area of the control systems; especially intelligent methods provide new tools for this.
- *Adaptation*, first for linear controllers and later for nonlinear controllers, is primarily devoted to new operating conditions but recent progress in modelling have improved possibilities for predefined adaptation. Also new adaptation mechanisms have been introduced.
- *Model-based* control was already used in the very beginning of automatic process control. Model-based predictive control has recently become increasingly popular research topic. Various modelling approaches have been used in these applications.
- *Human* operators can control successfully processes which are very difficult for classical automatic control. The tradition of rule-based control has been extended by fuzzy control.
- *Multivariable* control should take into account a very large number of variables. This could be done technically but the complexity of these systems has introduced a need for software sensors or intelligent analysers.

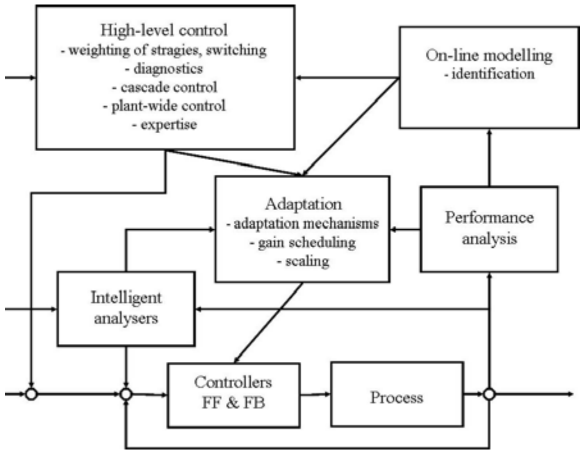

Fig. 1. Modules of advanced control (Juuso, 2004b).

These approaches extend the use of normal *feedback (FB)* and *feedforward (FF)* controllers to changing operating conditions. During the years, these approaches have been used mostly separated but practical industrial applications require combining these approaches in a hybrid control system. The resulting huge variety of features means that the tuning of the control system must be done with modelling and simulation. Both knowledge and data have been used to make control systems adaptive. The overall structure combines ideas from classical and advanced approaches (Fig. 1).

Intelligent methods provide a good basis for handling nonlinear multivariable systems. The first industrial *fuzzy logic controller (FLC)* was realised in 1978 for a Danish cement kiln by Holmblad and Oestergaard (1982). According to (Oestergaard, 1996), the first lime kiln control system based on FLC was installed in a Swedish pulp mill in the following year. Several industrial kiln control applications have since been reported, e.g. in (Järvensivu *et al.*, 2001). For the solar plant, a PI type conventional fuzzy logic controller presented in (Rubio *et al.*, 1995) was designed manually on the basis of the experience of the previous experiments. An automatic genetic design technique was later developed (Gordillo *et al.*, 1997) since the trial and error methodology make the improving task hard and difficult.

A large number of control structures have been proposed on the basis of *neural networks* in recent years(Liu, 2002). During the 90s, neural network (NN) based systems have been tested for the identification and control of the lime kiln process, as reported in (Ribeiro and Correia, 1993). NNs have also been tested for the quality prediction of the burnt lime, as described in (Järvensivu and Seaworth, 1998) and in (Ribeiro, 1998) and for the feedforward control of the kiln process in conjunction with high-level feedback controllers (Järvensivu *et al.*, 1994). A rule-based kiln control system, in which NNs are used to represent the rule set, has been reported in (Bo *et al.*, 1997).

Sliding mode control (SMC) (Utkin, 1977) is designed to converge to a sliding surface based on the plant dynamics, and model based switching controllers use a finite set of fixed controllers. The SMC controllers derived from variable structure theory can handle nonlinear and time-varying systems without a dramatic change in their behaviour. The SMC approach transforms the problem of stabilising an nth order system into the problem of stabilising a first order system (Arzen *et al.*, 1999). A combination of sliding mode control and fuzzy logic is presented in (Iglesias *et al.*, 2002). The conventional sliding surface is modified using a set of fuzzy rules, which are similar to that of a FLC.

Linguistic equation (LE) approach, which originates from fuzzy logic, has been applied in several applications (Juuso, 1999*a*). The LE approach provides a good basis for integration of several process units (Juuso, 2004*c*) and originally it was used in tuning of fuzzy controllers (Juuso *et al.*, 1996). The main idea in the LE control is based on nonlinear scaling and linear systems.

The basic feedback controller is a PI-type LE controller represented in the following form (Juuso, 1999*a*)

$$\Delta u = e + \Delta e, \tag{1}$$

which is a special case of the matrix equation $AX = 0$ with the interaction matrix $A = [\,1\ 1\ {-1}\,]$, and variables $X = [\,e\ \Delta e\ \Delta u\,]^T$. The first LE controller was implemented in a solar plant (Juuso *et al.*, 1997) and later it has been introduced to control a lime kiln (Järvensivu *et al.*, 2001) and a flotation unit (Joensuu *et al.*, 2004). One equation is needed for each control variable.

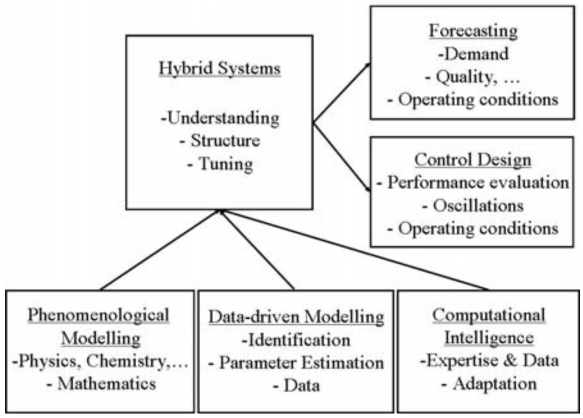

Fig. 2. Alternatives of modelling and simulation for advanced control applications (Juuso, 2004a).

The LE controller can combine various control strategies: all the modules presented in Figure 1 can be realised with the LE methodology. Nonlinear scaling provides an efficient basis for adaptation, and the compact matrix-based implementation extends these ideas to multilevel control systems. The adaptation models are based equations, and various special control strategies also use similar equations. All these are additional features which activated if the matrix calculation gives for them a non-zero value. The implementation is very compact since no special switching programs or rules are needed.

3. MODELLING IN CONTROL

Modelling has been an essential part of the process control already since the early 70s, e.g. models based on the dynamics of the solids phase, the fundamental principles of heat transfer mechanisms, and the kinetics of the drying, heating and calcining reactions are successful in simulation providing a useful insight into the kiln process and also increased our understanding of the interactions and time delays inherent in the process (see e.g. (Castro *et al.*, 2001)). However, the problem is that industrial control requires adequately accurate models which are not easy achieve (Barreto, 1997). Data-driven modelling and computational intelligence provide additional modelling alternatives also for control applications (Fig. 2).

Developing kiln control systems based on empirical models, as described e.g. in (Uronen and Aurasmaa, 1979; Bailey and Willison, 1986) was the second step. The first commercial supervisory-level system for the lime kiln was developed on the basis of these studies and its first industrial applications appeared already at the end of the 1970s in a Finnish pulp mill (Elsilä *et al.*, 1979). The structure and parameters of empirical models

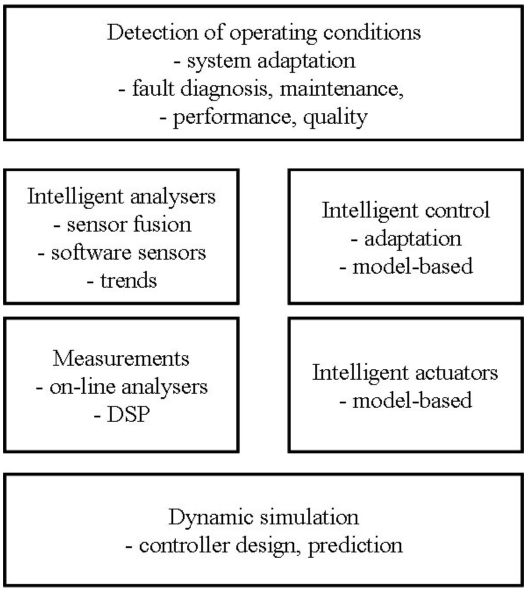

Fig. 3. Functions and features of a smart adaptive control system (Juuso, 2004e).

do not necessarily have any physical significance, and therefore, these models cannot be directly adapted to different operating conditions.

Data-driven modelling approaches are based on general function approximators (black-box structures), which should capture correctly the dynamics and nonlinearity of the system. The identification procedure, which consists of estimating the parameters of the model, is quite straightforward and easy if appropriate data is available. Essentially, system identification means adjusting parameters within a given model until its output coincides as well as possible with the measured output. Validation is needed to gain confidence on the model. More details of the algorithms and theories are presented in (Ljung, 1999).

Intelligent methods are based on techniques motivated by biological systems and human intelligence, e.g. natural language, rules, semantic networks and qualitative models. Most of these techniques were already introduced by conventional expert systems. Computational intelligence can provide additional tools since humans can handle complex tasks including significant uncertainty on the basis of imprecise and qualitative knowledge (Juuso, 1996; Juuso, 2004*e*).

Models are used in adaptive control, and there are various methods for direct model-based control. Adaptation can be also integrated to the model-based control. Modelling is used also in on other levels of advanced control: high-level control is in many cases based on modelling operator actions, and intelligent analysers and software sensors are developed by modelling. Smart adaptive control systems integrate all these approaches (Fig. 3).

4. MODELS IN ADAPTIVE CONTROL

Adaptive controllers generally contain two extra components compared to the standard controller (Driankov *et al.*, 1993). The first is a *process monitor*, which detects changes in the process characteristics either by *performance measure* or by *parameter estimator*. The second is the *adaptation mechanism*, which updates the controller parameters. In normal operation, efficient reuse of controllers developed for different operating conditions is a good operating practice as the adaptation requires always time.

An adaptive controller is a controller with adjustable parameters. Traditionally, the on-line adaptation has been considered as main feature of the adaptive controllers. However, controllers should be also adapted to changing operating conditions in processes where the changes too fast or too complicated for on-line adaptation. Therefore, the area of adaptation must be expanded, i.e. the adaptation mechanism can be either *on-line* or *predefined.*

High-level control summarised in section 6 can supervise the whole adaptation by introducing plant wide requirements and expert knowledge. The adaptation can be raised to higher levels by introducing intelligent analysers, which provide more informative measurements for the controller as described in section 7. The extended adaptation procedure contains various alternatives (Fig. 1).

4.1 On-line adaptation

On-line adaptation includes *self-tuning, auto-tuning, self-organisation.* For on-line adaptation, changes in process characteristics can be detected through on-line identification of the process model, or by assessment of the control response (performance analysis). The choice of *performance* measures depends on the type of response the control system designer wishes to achieve. Alternative measures include overshoot, rise time, settling time, delay ratio, frequency of oscillations, gain and phase margins and various error signals (Driankov *et al.*, 1993).

The *identification* block typically contains some kind of recursive estimation algorithm which aims at determining the best model of the process at the current instant (Fig. 4). The model can be a transfer function, a discrete time linear model, a fuzzy model or a linguistic equation model. Adaptation mechanisms rely on parameter estimates of the process model, e.g. gain, dead time and time constant.

Classical adaptive schemes do not cope easily with strong and fast changes unless the adaptation rate

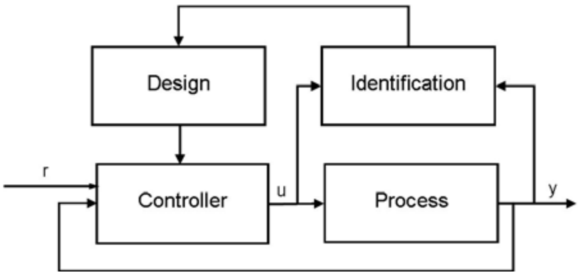

Fig. 4. On-line adaptation with model identification.

is made very high. This is not always possible: some a priori knowledge about the plant dynamic behaviour should be used. One alternative for these cases is a switching control scheme which selects a controller from a finite set of predefined fixed controllers. The multiple model adaptive control is here classified into model-based control (section 5.3).

Intelligent methods provide additional techniques for on-line adaptation with traditional techniques. Jantzen and Poulsen (2003) studied the update mechanism of a fuzzy self-organizing controller, SOC. A self-tuning fuzzy control of a rotary dryer is presented in (Pirrello *et al.*, 2002). In a meta-rule approach, parameters of a low-level controller are changed by a meta-rule supervisory system whose decisions are based on the performance of the low-level controller. Meta-rule modules consist typically a fuzzy rule base that describes the actions needed to improve the low-level FLC (Maeda and Murakami, 1992; Daugherity *et al.*, 1991; Isomursu and Rauma, 1994).

Plant results with adaptive schemes, e.g. a self-tuning PI controller based on a pole-placement approach (Camacho *et al.*, 1992) and a prescheduled adaptive control by resonance cancellation (Meaburn and Hughes, 1994), have clearly demonstrated the importance of adaptive tuning in the solar plant application.

4.2 Predefined adaptation

Predefined adaptation is becoming more important as the use of modelling and simulation provides flexible methods. Gain scheduling provides a gradual adaptation technique for a fixed control structure. Dotoli and Turchiano (2003) proposed a fuzzy gain scheduling (FGS) technique for on-line adjustment and improved performance of an MIMO PID controller. Linguistic equation based gain scheduling (LEGS) is based on adaptation models.

The scaling of nonlinearity was introduced to the first linguistic equation controllers developed to maintain the outlet oil temperature of a $1MW_t$ solar power plant (Juuso *et al.*, 1997). Operation of the controller is modified by variables describing operating conditions (Eq. 3). The working point adaptation makes the control surface steeper or flatter. The same adaptation method was applied in the lime kiln control (Järvensivu *et al.*, 2001): the working point depends on loading state of the process, power of the control variable, and the cumulative rate of the control actions. In the water treatment case, the water quality indicator (Ainali *et al.*, 2002) is essential in avoiding on the other hand oscillations and on the other hand too slow operation (Joensuu *et al.*, 2004).

The adaptation is very fast as the predefined actions remove the need for on-line identification, or for classical mechanism based on performance analysis. For these cases, the controller could be called as a linguistic equation based gain scheduling (LEGS). However, the adaptation also includes possibility to change membership definitions: this is done in the braking and asymmetrical actions. The adaptation model is generated from the local tuning results but the directions of interactions are usually consistent with process knowledge.

The predefined adaptation approach allows using very detailed models, e.g. distributed parameter models can be used in tuning of the adaptation models of the solar plant (Juuso, 2004*d*). The resulting adaptation models or mechanisms should be able to handle in real-time operation all these special situations without using directly the detailed simulation models.

5. MODEL-BASED CONTROL

Model-based control is widely applied to industrial applications (Camacho and Bordons, 1995). Various modelling approaches try to combine the advantages of the physical and data-driven modelling techniques, e.g. parameters for mechanistic models are approximated by black-box techniques. Since the identification is on a practical level only for linear systems, a lot of work with local linear models is needed. The models should be designed for forecasting (Fig. 2).

5.1 Feedforward control

Feedforward control (FF) can be based on models, e.g. most of controllers tested in the solar collector field at PSA use model-based feedforward control based directly on the steady state energy balance relationships can be based on measurements of solar radiation and inlet temperature (Camacho *et al.*, 1992). A feedforward controller has been combined with different feedback controllers, even PID controllers operate for this purpose (Valenzuela and Balsa, 1998).

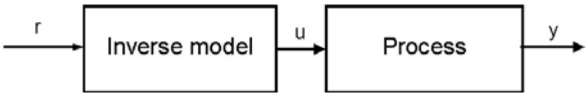

Fig. 5. Inverse model control.

A nonlinear controller can be designed by inverting a fuzzy model of the process (Fig. 5). In most cases an approximate inverse is used. Babuška (1998) introduced an exact fuzzy inverse scheme for fuzzy singleton models.

Linguistic equation models can be inverted exactly as they are based linear equations. The lime kiln control system presented in (Järvensivu *et al.*, 2001) uses several FF controllers: rotational speed, feed of different fuels and draught fan speed. The fuel feeds need also a feedback controller. The original neural models were replaced by linguistic equation models. In the water treatment application, one chemical is controlled by a model-based FF controller (Joensuu *et al.*, 2004).

Feedforward controllers need some additional feedback compensation since disturbances and model errors cause problems for pure open-loop schemes. Model-based feedforward control provides also a good comparison value for the control action proposed by feedback controllers.

5.2 Internal model control

Internal model control (IMC) compares the process output to the predicted output and uses the inverse model to remove the difference (Fig. 6). The model works in parallel with the process to subtract the effect of the control action from the process output. If the predicted and measured outputs are equal, the error is zero and the controller operates as a feedforward controller.

In principle any types of models can be used. Babuška (1998) used fuzzy models. The models of (Farkas and Vajk, 2002) are based on partial differential equations. (Fink *et al.*, 2002) use nonlinear based on local linear models.

The classical IMC can operate efficiently in varying time delay conditions (Farkas and Vajk, 2002). Internal model control does not suffer from the disadvantages of the feedforward controllers as modelling errors and disturbances are taken into account. The IMC approach is a good solution if the model is not too complicated.

The IMC scheme can also contain on-line adaptation, e.g. a fuzzy model can be adapted and the consequent parameters are transferred to the inverse model (Babuška, 1998).

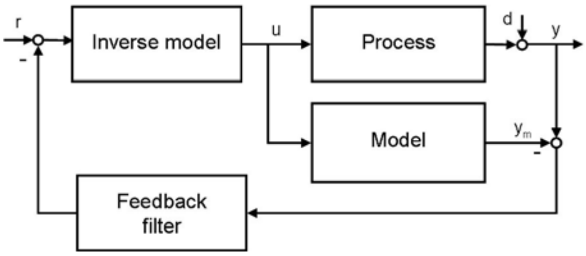

Fig. 6. Internal model control.

5.3 Multiple model adaptive control

Multiple model adaptive control (MMAC) allows different control structures, i.e. each mode corresponds to one model and one controller. Switching control strategies are based on selecting a controller from a finite set of fixed controllers. In the MUSMAR algorithm (Mosca *et al.*, 1984), a supervisor controller selects the controller to be active by choosing the one, which best fits the plant model. In the solar plant application, the MUSMAR algorithm has shown to have robust characteristics with respect to unmodelled dynamics (Coito *et al.*, 1997). Each controller has been tuned in order to match a region in the plant operating conditions (Rato *et al.*, 1997).

An important difference to the gain scheduling scheme is that each controller can have a completely different structure. Each individual controller can have own specific advanced features, i.e. switching control can be used for higher level decisions. The switching strategy can be based on heuristic rules or predictions with models.

5.4 Model predictive control

Model predictive control (MPC) is a general methodology for solving control problems in the time domain. Models are used for predicting the process output over a prediction horizon. Control actions are calculated over a control horizon in such a way that the predicted process output is as close as possible to a desired reference signal, and the first control action in sequence is applied in each step (Fig. 7).

Intelligent methods can be used at the modelling level, in optimisation and in the specification of the control objectives. Building of fuzzy model-based process control has been studied for long (Babuška, 1998). Stages in the development of modelling algorithms and development of methods of incorporating fuzzy models into controllers are described in (Postlethwaite, 2002).

Internal models can be used model predictive control (Fig. 8). The IMC scheme is employed to compensate the disturbances and modelling errors as described in section 5.2. Fuzzy internal

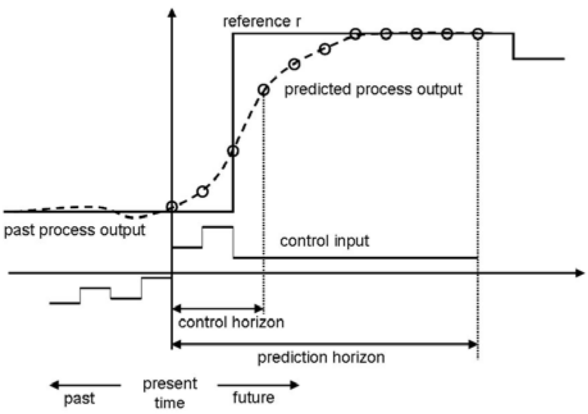

Fig. 7. The basic principle of model-based predictive control.

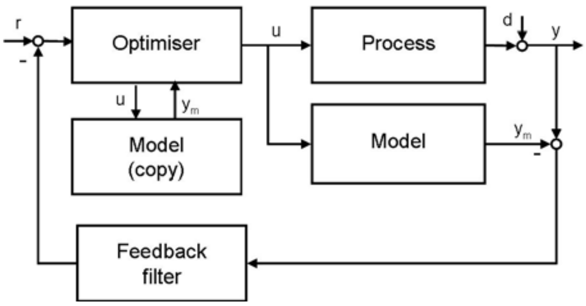

Fig. 8. Internal model predictive control.

models have been used in this approach (Arzen *et al.*, 1999).

Rotary kiln applications based on the MPC approach have been reported in the literature (Smith and Aggarwal, 1997; Valiquette *et al.*, 1999; Carter and Rozek, 2000). Prediction of the future plant behaviour is used to compute the appropriate control actions and, therefore, the controller requires a dynamic model of the process. Obtaining models that are applicable over the whole operational range of the process may, however, necessitate a considerable amount of identification work, see e.g. (Morari and Lee, 1999). Nevertheless, the MPC approach is also widely used in other fields of the industry, and it is inevitable that interest in MPC will continue and even intensify.

For solar plant applications, a generalized predictive control (GPC) based on a gain scheduling algorithm was able to handle different operating conditions and sudden perturbations caused by clouds (Camacho and Berenguel, 1994). An adaptive GPC approach provided fast response with high overshoots and some oscillations (Camacho *et al.*, 1994). A nonlinear neural model predictive control was presented in (Arahal *et al.*, 1997): the models are not accurate enough for eliminating the offset, but under extreme solar radiation conditions the controller worked fairly well since the neural network models introduced a kind of feedforward effect. A combination of switching with the MUSMAR algorithm and model predictive control (MPC) is presented in (Lemos *et al.*, 2002)

Normal model predictive control has difficulties in coping with quickly changing operating conditions. Therefore, a braking action based on analysing the speed of the change was developed in the solar application (Juuso *et al.*, 1997). Following a good trajectory is built in and the membership definitions are adapted to the changing operating conditions. The braking action is implemented by a correction factor that increases the importance of the change of error when the temperature goes towards the set point. This implementation is very compact if compared to the model predictive controllers. In the original version, the braking action became stronger when the controlled variable approached the target value (Juuso, 1999*a*). A smooth version for coping with the long measurement delays of the lime kiln control was presented in (Järvensivu *et al.*, 2001).

Additional predictive actions were later introduced for avoiding oscillatory conditions in the solar application (Juuso and Valenzuela, 2003). These additional smart control features prevent too high temperatures usually resulting in following cases:

- fast increase of the inlet temperature from the level known to the feedback controller,
- too fast temperature increase, and
- too high temperature difference between the inlet and the outlet compared to acceptable level corresponding to the recent average of the corrected irradiation.

Additional change of control is introduced if at least one of these cases is active. The first and second ones of these actions are predictive, and the third one is corrective. If the first and the second operate properly the third action will never activate.

The braking and asymmetrical actions and the smart control features described above could be implemented with the MPC approach but the dynamic fuzzy LE model is fairly complex. In addition to this the prediction is not very useful if the irradiation is fluctuating. Therefore, a predefined adaptation approach (section 4.2) was chosen. The predictive actions described above can be considered also as sophisticated feedforward controllers.

In principle any kind of model could be used in the MPC approach but the limitations are obvious as a significant computing power would be needed if the models are too sophisticated. Then the predefined adaptation is much better than the MPC approach, e.g. distributed dynamic LE models (Juuso, 2004*d*) can be used model-based tuning but not in real-time implementations. In these cases, the MPC approach is used together with simulation in the tuning phase.

6. HIGH-LEVEL CONTROL

The first rule-based expert system for kiln control was developed in 1982 and, since then, the system has been further developed, as described in (Dekkiche, 1991). Other rule-based systems for controlling rotary kilns have also been developed and reported, e.g. by Hall (1993) and Hagemoen (1993). The rule-based approach, although it is widely used in various types of expert system, may lead to serious testing and maintenance problems in large-scale applications where the rule-base becomes extremely large.

Traditional fuzzy logic control extends the ideas of rule-based expert systems. The first fuzzy controllers were inspired by instructions found in a textbook for kiln operators, which contained control rules for manual operation. FLC provides a unified framework for modelling operators actions and for taking incomplete information into account. However, acquiring the required knowledge, e.g. on the basis of operator interviews, may be a tedious and time-consuming task.

High-level control is a natural area for intelligent control (Oestergaard, 1996; Juuso, 1999*a*). Weighting of several control strategies should be based on operating conditions. In this way even several control loops can operate consistently in changing operating conditions (Juuso, 2004*e*). On this level, automatic control is interacting with operator actions (Oestergaard, 2003).

In the solar application, these features are sufficient if irradiation conditions are changing smoothly and if the start-up is kept on moderate temperatures. The new version of the adaptive controller (Juuso and Valenzuela, 2003) combines smoothly various control strategies in a single controller: adaptive set point procedure and feedforward (FF) features are essential for avoiding overheating and oscillations, limitations of the actuators are taken into account. The set point is automatically lowered if the heating effect is too low for the required temperatures.

7. INTELLIGENT ANALYSERS

Multivariable control has a serious problem in combining the controllers in such a way that individual controllers do not disturb each other. Intelligent methodologies provide solutions for combining technically a huge number of variables but in the same time the process insight disappears.

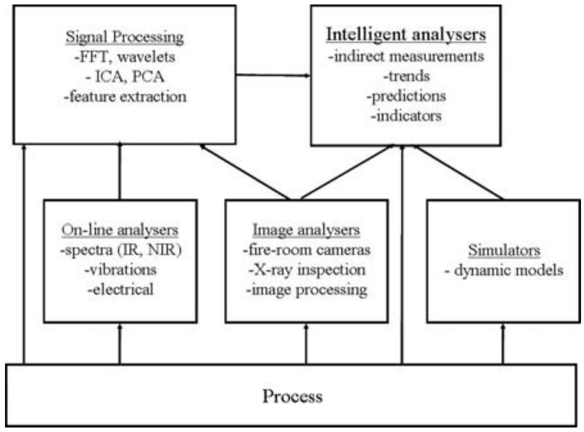

Fig. 9. Intelligent analysers for advanced control applications.

The control performance can be enhanced by linking it with soft sensors and fault diagnosis (Juuso, 2004*e*). Resulting smart adaptive systems consist of functions and features classified in Fig. 3. Intelligent analysers or software sensors produce new measurements for control, and adaptive control uses these measurements to improve performance of the operation. Modelling is essential in software sensors, diagnostics, and model predictive control.

In this classification, modelling includes dynamic modelling and simulation. Intelligent analysers may also use different on-line analysers, image analysers and signal processing (Fig. 9).

7.1 Software sensors

Software sensors are used in making the existing measurements more efficient or in replacing the nonexisting measurements with software systems that form the measurements signals e.g. from other, existing measurements, laboratory analyses and a priori expert knowledge. Adaptation needs come from the necessity to correctly react to changing raw material quality, to different product specifications, or even to different processing alternatives. As intelligent methodologies can handle nonlinear multivariable systems in a flexible way, they provide remarkable improvement potential for on-line measurement and analysis systems. Detection of operating conditions provides a smooth alternative for switching strategies.

Benefits of model-based software sensors have been clearly demonstrated in water treatment applications (Ainali *et al.*, 2002). The software sensor of the fuel quality is also the corner stone of the rotary kiln controller presented in (Järvensivu *et al.*, 2001). Both these applications use model-based performance analysis of the control actions, i.e. chemical dosage and fuel feed, respectively.

In solar application, effective solar irradiation, temperature difference between inlet and outlet temperatures and ambient temperature were used to define the working point by an additional linguistic equation (Juuso and Valenzuela, 2003).

7.2 Detection of operating conditions

Detection of operating conditions is essential in an indicator developed for the prediction of paper machine runnability (Ahola *et al.*, 2004). This indicator was developed as a Case-based reasoning (CBR) type application with linguistic equation (LE) approach and fuzzy logic. The foundation of this application is a case base containing models of various operating situations with different amount of breaks. The indicator compares on-line measurements to the examples in case base and uses the information of the best fitting case to identify the current situation.

This approach can be used as a switching strategy or as a basis for an intelligent analyser. Actually, the software sensors developed for the fuel quality (Juuso *et al.*, 2001) and for the water quality (Ainali *et al.*, 2002) are based on the same idea.

Intelligent analysers are in these systems the main source of detecting the need of adaptation. The quality indicators include also performance analysis. New model case is needed if a low membership is obtained for all the current model cases.

7.3 Quality prediction

Batch processes have additional requirements for forecasting the quality in a quite long horizon. Dynamic LE-modelling and simulation have been used for forecasting the final granule size in a fluidised bed granulator (Mäki *et al.*, 2004). Dynamic LE-models have also been developed for forecasting the SuperBatch cooking result: residual alkali, lignin and dissolved solids. The simulator is adapted to the changing operating conditions with configurable parameters (Juuso, 2003*b*). For a fed-batch fermentation, a dynamic simulator is used on-line for predicting the process operation in a time window (Saarela *et al.*, 2003).

All these models are well suited for the model predictive control (section 5.4) or to the predefined adaptation (section 4.2). Differences between the measurements and the predicted values could be used also for detection of operating conditions. These models are also useful in predicting process trends in slow processes where also the control actions need a lot of time to be seen.

8. HYBRID CONTROL SYSTEMS

Fast adaptation to various operating conditions is very useful for industrial practice (Juuso, 1999*a*). Modern process operation and production methods are characterised by an increasing demand of flexibility, a stronger nonlinear behaviour, more loops and interactions, and integrated information systems with sophisticated human interfaces (Verbruggen and Bruijn, 1999). This section presents hybrid control systems based on the linguistic equation approach.

8.1 Model-based tuning in hybrid systems

Different approaches for coping with nonlinearities in changing operating conditions are getting closer to each other: models are essential in adaptive control, and model-based control includes more adaptive features. Intelligent analysers can used in various ways to enhance the efficiency of the control systems. Expertise is introduced to these systems via knowledge-based approaches, especially fuzzy set systems. Combining all these features is possible but requires a compact implementation.

On-line adaptation based on identification or on adaptation mechanism is sometimes too slow. Also reliable switching between models is not always robust enough. The trade-off between the necessary accuracy and resulting complexity becomes increasingly important when the nonlinear and multivariable behaviour must be taken into account. Modelling is used for predicting in a long horizon, especially in batch processes, and for control design to cope with fast changes in operating conditions (Fig. 2).

The applications of LE controllers (Juuso, 2004*e*) are based on predefined adaptation, i.e. the adaptation model is developed on the basis simulation experiments. Different performance monitoring and adaptation mechanisms are used during the simulations. Evolutionary computation can used for sophisticated control systems having a large variety of features. This means that the dynamic modelling and simulation is an essential part of the control design.

Lime kiln control has been based on almost all the methodologies presented above: starting from phenomenological and data-driven modelling integrated with linear control approaches to intelligent modelling integrated with expert control. Different adaptation mechanisms and model-based control have been used. The latest technique is based predefined adaptation with LE models.

The history of solar plant applications is quite similar starting from feedforward control, adaptive and model-based methodologies. In this application the model-based predefined adaptation can be partly developed from physical principles. As operating conditions cannot be reproduced and weather conditions have seasonal differences, dynamic simulators are needed in controller design and tuning.

Self-organising controllers have problems in water treatment control but a combination of an intelligent analyser and an adaptation model provide good results. Predefined adaptation is needed for practical applications where the operating conditions have fast changes.

Simulation is a very fast method to achieve control parameters, but it requires a reliable dynamic process model. Dynamic LE models have been used for control design in three processes: solar power plant (Juuso, 2003*a*), lime kiln (Juuso, 1999*b*) and water treatment (Ainali *et al.*, 2002). The dynamic models were tested with independent on-line data. According to testing results, the models predict the output very well: the collector field model the outlet temperature, the lime kiln model the hot end temperature, and the flotation model the outlet turbidity, respectively.

For the control design, a realistic dynamic behaviour, including oscillations, is necessary, and this was achieved in all these models. In the water treatment application, the model is a part of the water quality indicator. Benefits of predefined operation increase with complexity of the control system. Also distributed parameter models can be used for tuning special situations in the solar application (Juuso, 2004*d*).

8.2 Applications

The multilevel LE controller has already very many actions extending the basic PI type LE controller, which is designed for the normal operation. Operation condition controller changes the control surface of the basic LE controller. Predictive LE controller adapts the operation with the braking and asymmetrical actions. All these are used in the solar application. The lime kiln control does not include the asymmetrical action. The water treatment is based on the first two levels: a basic LE controller and an adaptation model. All these properties are implemented into a very compact control program. Modularity is beneficial for the tuning of the controller to various operating conditions, and most important is that the same controller can operate on the whole working area.

Combining several feedforward (FF) controllers to the system has a clear benefit in the lime kiln control as the FF components do not need to wait for the influence of the load disturbances (Järvensivu *et al.*, 2001). Improved control performance and smooth overall operation guarantee practical optimisation (Fig. 10).

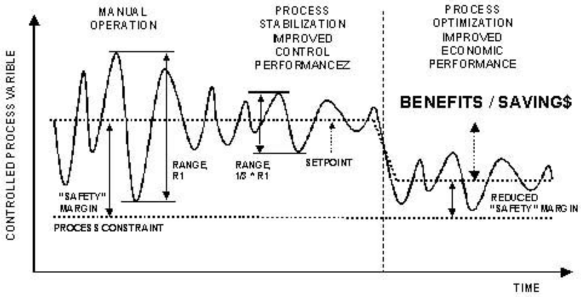

Fig. 10. Optimisation of the lime kiln temperatures (Juuso, 2004e).

The adaptive linguistic equation control approach has been tested in three applications, which need fast adaptation in a wide operating area. Almost all the modules presented in Figure 1 have been used online in these cases. On-line modelling approach has not been used because all these processes are characterised by strong and fast disturbances.

The aim of *solar thermal power plants* is to provide thermal energy for use in an industrial process such as seawater desalination or electricity generation. The controller combines smoothly various control strategies into a compact single controller. Control strategies ranging from smooth to fast are chosen by setting the working point of the controller. The controller takes care of the actual set points of the temperature. The operation is very robust in difficult conditions: start-up and set point tracking are fast and accurate in variable radiation conditions; the controller can handle efficiently even multiple disturbances. Adaptive set point procedure and feed forward features are essential for avoiding overheating. The new adaptive technique has reduced considerably temperature differences between collector loops. Efficient energy collection was achieved even in variable operating conditions (Juuso and Valenzuela, 2003).

Supervisory control of the *lime kiln* process is in many respects a demanding task. Lime kilns are therefore frequently one of the last areas in a pulp mill to be automated and most of the kilns have been and are still operated without a supervisory control system. The linguistic equation (LE) based control system (Järvensivu *et al.*, 2001) integrates almost all the approaches described above. In addition to the easily quantifiable energy savings and increase in production rate, improvements in lime quality have also been obtained by the significant reduction in the variability of the hot-end temperature (the quartile

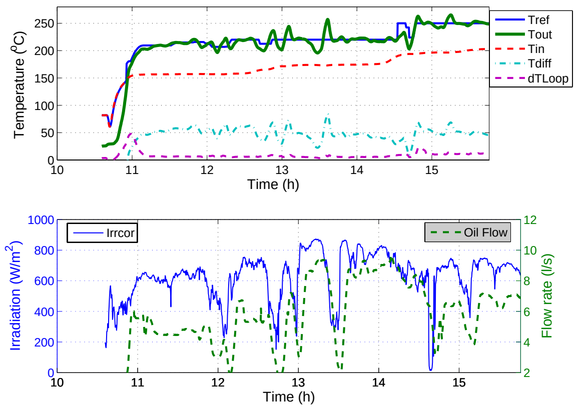

Fig. 11. Testing results of the multilevel LE controller on a solar collector field (June 12, 2002): temperatures, oil flow and irradiation (Juuso and Valenzuela, 2003).

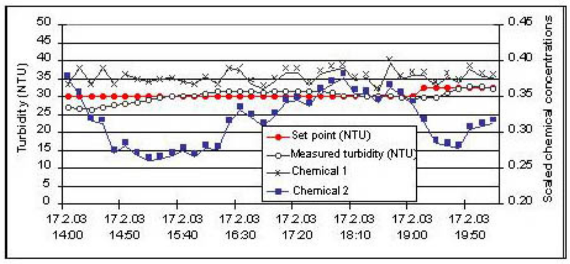

Fig. 12. Dosing control in water treatment (Juuso, 2004c).

range and the standard deviation of the hot-end temperature have declined nearly 50

The key to efficient chemical dosage control in *water treatment* processes is the addition of proper amount of chemical to the process. If too much chemical is added, treatment targets will be reached but costs will increase and extra sludge waste is produced. If chemical is added too small amount, it will lead to poor treatment result and problems in subsequent processes such as filtration, flotation and sedimentation. The appropriate chemical dose depends on the quality of the raw water and the purification target.

Water treatment processes are often complex and highly nonlinear. In addition, the amount and quality of process water can change greatly. Operational principle of the adaptive feedback LE-controller is different compared to the self-tuning PID-controller. Modification of the control parameters is based on the information obtained from the properties of water in a predefined way. Pre-tuning facilitates fast operation in changing process conditions (Joensuu *et al.*, 2004). The controller does not need time for finding correct parameters (Fig. 12).

9. FUTURE POTENTIAL

Modelling has been an integral part of control design and various methodologies have been developed for handling changing operating conditions. Control systems combining various intelligent control and prediction techniques that are capable of adapting to changes in the operating conditions will be the future trend. As the on-line adaptation of classical controllers is far from sufficient, various modelling and simulation approaches are coming more and more important.

Benefits of the hybrid approach have been seen in applications. Solar collector field is an extensively studied comparison case. Cloudy conditions and load disturbances can be handled efficiently. Lime kiln control needs to take into account very complicated interactions. Lime kiln is an important process for efficient chemical recovery in pulp plants. Additional challenges arising from the bio fuel required special software sensors for obtaining the fuel quality. Water treatment is neglected but important for the water circulation. Water quality indicator is maybe the most important part of the control system.

All these controllers can be tuned manually but the predefined adaptation based on dynamic modelling and simulation improves the operation. These systems continue from principles of gain scheduling but various features of adaptive control have been included. Intelligent analysers, which are strongly model-based, provide more appropriate information for the controllers, and the integration of the intelligent analysers and the controllers is the main approach for extending the operating area of the advanced control.

Many control strategies are available for activation, and the activation does not need any special rules or switching strategies. The classical control theory can be fully utilised in the LE approach since the operating mode of the controllers is linear after the nonlinear scaling, i.e. several methods for autotuning and self-organisation could be used as well.

Importance of modelling and simulation is increasing with integration of the control approaches as the increasing number of adjustable parameters requires efficient comparisons of alternatives. The main approach is based on predefined adaptation since these systems are devoted for strongly changing operating conditions. Intelligent analysers bring the multivariable control systems into practical use.

The integration of different modelling and control possibilities are essential in applications on sustainable energy and environment. Intelligent methodologies combined with predictive control are useful in slow biotechnical processes. Dynamic simulation models needed for detection of fluctuations and predicting the process trends to give more time for the control actions.

10. CONCLUSIONS

Advanced control systems can be built for integrating variety of control strategies and different types of models. Adaptation mechanisms can be either on-line or predefined, and modelling and simulation is an essential part of the control design. Predefined adaptation models and mechanisms obtained by pretuning with modelling and simulation facilitate fast operation in changing process conditions. The performance of these systems consisting of practical and interactive small scale intelligent systems has been demonstrated in three applications. These systems are aimed not only to adaptive or intelligent control but to smart adaptive control.

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