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PROCESS CONTROL IN DAIRY INDUSTRY

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Introduction

The most relevant requirements and challenges in the food industry are the development and competitive industrial production of products of a high and uniform quality. This opening statement, or better what it really means, should not be statically interpreted, rather it should be analysed in terms of developments observed in the key factors that influence and determine evolution, viz. - advances in science, progress in technology and changes in societal requirements and demands, in a word market changes.

Starting with market evolution, over the past twenty years significant changes have occurred in the international food market, which have led to significant demand of competitive production. The opening of frontiers in Europe, the global market, the wider availability and awareness of information and the increased purchasing power, with rapidly changing life style, have made customers more sophisticated and demanding of product quality. Also, the increasing concern and awareness about implementing sustainability directives led to the introduction of requirements and constraints for operation, substantiated in new quality management systems like ISO 9000 and other check systems based on EU and US directives. Last but not least, advances in digital technology have paved the way for bringing into the industrial practice new (computer-aided) methods for competitive process operations.

The food industry naturally had to adapt their whole chain of production processes to these market and technological changes, having in fact taken over recent years a large step towards better quality products and new, more efficient, process operation routines. Within these evolutionary mindset and practical reality a very important topic, which should be periodically re-visited, is precisely that of what kind of process operation

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policies should be implemented for increased productivity, safer production and greater efficiency with fewer losses.

This paper gives an overview of process control paradigms employed or potentially employable in the dairy industry, ranging from well established classical control approaches to more advanced techniques based on recent theoretical directions of knowledge processing.

Specificity of the dairy industry

The dairy industry as all other industrial areas has its own specificity.

Process plants are composed of large number of inter-linked process units, operating mostly in batch and fed-batch modes, designed for specific processing such as mixing of various ingredients, pasteurising, homogenising, ageing, flavouring, freezing and packaging. Each individual equipment has normally certain schedules for performing different tasks such as reacting, mixing, heating, holding and cooling. This whole structure requires both local control at unit level and optimal scheduling strategies at sector and plant levels.

The high variability of ingredients and the lack of a complete scientific understanding of the manufacturing processes additionally renders difficult the application of traditional process control structures.

The role of biological know-how in improving process operation was for many years the (almost only) dominant factor, and correctly so. Lactic fermentation serves well as illustration. This is the main biological process that occurs in dairy productions such as yoghurt, butter, cheese and several other milk-derived products. Lactic acid bacteria develop spontaneously in milk. Until pasteurisation was developed mid-way of the 19th Century it was hard to keep milk fresh. From a biological point of view, deeper basic insight into the metabolism and genetics of lactic acid bacteria enabled to modify the characteristics of these bacteria, thereby improving shelf- life as well as the taste and smell of existing milk derived products, while at the same time creating new ones.

Today, optimisation and control theories are generally accepted to have a role to play. Apart from the usual temperature and pressure control, an important challenge is still to perform optimally controlled lactic acid fermentation, under the requirement of guarantying the desired product specifications, like flavour and texture. It so happens that fermentation processes are intrinsically dynamical and highly non-linear and are normally difficult to control, often exhibiting oscillations on final product quality and quantity.

Today, the solution generally sought combines biology, engineering and systems theory for improved process operation.

Process control methodologies

Within the scope of the present paper, the question to address next is - what philosophies and methods of control engineering have we available for the dairy industry?

There are plenty of criteria to classify methods, viz. – (i) open-loop vs. closed-loop; (ii) feedback vs. feedforward; (iii) linear vs. non-linear; (iv) conventional vs. *advanced*; (v) mathematical vs. knowledge-based methods.

As it happens in other fields, and that will be emphasised below, methods may naturally be included in more than one of the cited categories.

Open-loop control

It is appropriate to start with a methodology that has dominated over the biochemical industries over the years. Essentially open-loop control consists of enforcing trajectories of the process manipulated variables that will expectedly lead to suitable profiles and final values of the relevant state variables. Such trajectories are defined off-line and *a priori*. There are of course several different forms of defining them, using experience-based considerations or model-based approaches. Strategies of trajectory re-evaluation and updating along process operation may be useful.

Optimal control

In *open-loop optimal control* optimal trajectories for manipulated and state variables are evaluated off-line according to some predefined economic profit function. In strict mathematical terms, *optimal* has implicit that the objective function is a *functional*. These optimal time profiles for the manipulated variables are *forced* on-line either actuating directly on the final control elements or through local closed loop algorithms, in both cases employing for instance programmable controllers. No automatic corrective action is taken if the optimal process path deviates from the nominal one. Hence, the key task in open-loop optimal control is to determine optimal trajectories for the most relevant process variables (relevant in respect to the process performance), using appropriate design procedures.

Two important points should be noticed. The first is that this requires a model that must be sufficiently detailed in order to describe the most important features of the process in relation to the economic profit function. The results of the optimisation procedure in industrial applications are invariably optimal feed rate profiles. The second is that, considering that no on-line corrective actions are taken, this control leads almost inevitably to sub-optimal process operation due to process disturbances and parametric uncertainty.

Traditionally, the open-loop control problem is solved by applying mathematical optimisation techniques based on Pontryagin's maximum principle. This technique is difficult to apply and is subject to some practical limitations. The most common constraint has to do with model complexity. In general terms simple models should be used to keep the mathematical analysis workload at bearable costs. The use of simple models precludes accurate results. Additionally, mathematical difficulties in dealing with practical constraints on the objective function and physical equipment and high development times even for experienced scientists further hinder the application of this method.

Some authors suggest the application of stochastic optimisation techniques. In relation to classical optimisation the advantages are clear: those methods are more robust, much simpler to apply and no restrictions on model complexity and objective function constrains are imposed. Recent contributions pointed out that random-search optimisation techniques such as chemotaxis algorithms, simulated annealing, evolutionary algorithms and genetic algorithms may provide results of the same quality as Pontryagin's technique with much less development cost. The only serious constraint is computation time. Considering that computing power is less and less a constraint, these represent attractive solutions for industrial applications of optimal open-loop control.

On-line optimising control

A brief comment on a topic that for sure will play a major role in the near future of process operation. Basically, on-line optimisation control consists of the optimisation of a cost function on-line and in real-time using successively measurements acquired on-line and/or off-line of the current process run, from where new corrective control laws are decided and implemented.

In fact, for the reasons stated above, the follow up of an open-loop control implementation is often the conclusion that the process is operated at sub-optimal conditions not coincident with the expected process performance computed by the off-line design procedure. The natural conclusion to be taken is that on-line optimising control should be implemented in order to improve robustness and high yield of the open-loop operation procedure.

Conventional closed-loop control

In general terms closed loop control aims at forcing the process state to follow some pre-determined path (reference). This path may be defined heuristically or mathematically and can be kept unchanged along the operation (regulator action) or subject to periodic adaptation (servo action).

Single loop feedback control

The feedback system operates by *feeding* the process output information *back* to the controller. Decisions based on such *fed back* information are then implemented on the process (Fig. 1a). This is for sure and by far the most employed process control strategy, so linked it is to Human intuition, a comment that equally will serve well to the discussion below on the PID (Proportional-Integral-Derivative) control decision algorithm.

Going back to the open-loop control discussion, an obvious application of closed-loop control is to enforce the optimal trajectories evaluated within the open-loop procedures. The off-line computed optimal command profiles are fed as set-points to local closed loop controllers operating on-line.

The viability of closed-loop control is constrained by the availability and robustness of on-line measurement devices for the controlled variables. Difficulties in measurements represent today's main bottleneck to process control. For many processes it happens that the required measurements either are inaccurate or are expensive or simply do not exist through direct means. In many situations the problem can be circumvented by implementation of estimation models that provide on-line and in real time estimates of the required variables. This general concept is also referred to as inferential measurement, state observer or software sensor implementation. Not surprisingly many control studies reported in the literature rely on linear or non-linear estimation/predictive (adaptive) models.

Several control strategies can be implemented ranging from classical PID (Proportional-Integral-Derivative) control to non-linear control.

<Figure 1 near here>

Classical feedback control strategies employing PID control algorithms are the most employed for process control. They have been used for more than seven decades. Nowadays conventional control approaches widely implemented in the process industry are housed in stand-alone controllers, in programmable logic controllers (PLC) or directly in control computers, with built-in digital versions of the original PID analog loop functions. The most common discrete control algorithms digitally realized in commercial controllers are summarised in Table 1.

<Table 1 near here>

PID controllers are simple to operate and to maintain but limited in their functions. Care must be taken in appropriate tuning of the controller parameters that is carried out under stability (safety) and accuracy considerations (this is the famous accuracy-stability dilemma – the more accurate, the less safe and vice-versa). Auto-tuning is a common feature of both stand-alone controllers and of control packages and periodic auto-tuning is today an easy task to perform. In digital PID filters should be employed to attenuate measurement noises or a conservative tuning should be adopted for the derivative action because, as it is well known, derivative action may amplify such noises significantly.

The main disadvantage of PID is that they perform well only for processes with low complexity and variability. Nevertheless, they are successfully implemented in fermentation tanks for controlling main variables, such as flow rate, temperature, pressure and pH.

Feedback cascade control

Often processes occur in series, with specific loads affecting intermediate variables (Fig. 1b). In those cases where the inner process is faster than the outer one and where the intermediate variable is measurable cascade control is an useful and efficient strategy for fast attenuation of inner loads and/or of inner process non-linearities. As the figure illustrates, cascade control consists of a set of two (master-slave) controllers, where the outer one (master) receives the main process control variable and the inner one (the slave) receives the master output as set-point and the measurement of the inner process variable.

Controller tuning is easily performed in much the same way as in the single loop controller: first, the slave controller is tuned with the master controller off; then the master is tuned, with the slave on. It is clear that with digital control packages the cost of implementing cascade control is almost limited to the cost of the second measurement device.

Feedforward control

The basic idea behind feedforward control is to measure important process disturbances (loads) and take action on the manipulated variables in such a way that no effect is felt on the controlled variable (Fig. 1c). The controller action is based on information that is being *fed forward*.

The main features of the feedforward configuration have to do with the choice of the disturbances to be measured, that are linked to the ability of measuring them, and with the question of the controllers eventually designed being physically realisable.

This philosophy provides very interesting improvements when the effect of major load components have to be compensated, but it has several limitations that basically lead to never being advisable to implement the method on its own, viz. - (i) the load disturbances would have to be all known and measured on-line, a requirement that is not achievable in practice; (ii) the controller has no information about the actual process output, thus it is not possible to determine the accuracy of the disturbance compensation; (iii) often ideal feedforward controllers that are theoretically capable of achieving perfect control are not physically realizable.

In practical applications, and for all reasons, digital feedforward control is usually used in combination with digital feedback control (Fig. 2). Within this combined approach the accuracy of the feedforward controller is not the most relevant question and independently of further considerations the lead-lag function algorithm for feedforward action is generally employed (Table 1). With today's digital technology such feedback-feedforward combination is very easily implemented, leading to very effective control solutions.

<Figure 2 near here>

As for controller tuning of this configuration the feedback controller should be tuned just following the tuning considerations for such controllers. For the feedforward controller the tuning parameters are decided from inspection of the dominant terms of the theoretical controller function.

Advanced model-based control

What does it mean *advanced?* The result of recent developments? Probably. Not yet largely employed in industrial practice? For sure.

Strategies of the recent days make use of the information available through *process models* in order to more efficiently develop control algorithms suitable and adapted to specific process features. This applies to both local and plant control and from here stems the concept of *model-based control*.

The traditional way of process modelling for many years has been the development of mathematical equations identified from *physical knowledge*. Model-based control can be classified as linear or non-linear depending on the type of model they are based on.

Additionally the control system may be adaptive if on-line measurements are used to tune controller parameters, either directly or through the process models. They may also be predictive if the control action is based on the prediction of its own influence in the process dynamic behaviour for a given time horizon. Many applications of all these control strategies were reported in the literature in recent years.

Model-based adaptive predictive control

This approach computes at each time k the control action sequence u_{k+j} that minimize a cost function of the difference between the desired (*ref*) and the predicted output values of the process $\hat{y}_{k+i/k}$ for p time steps on the prediction horizon (Fig. 3). These predicted (future) values are estimated on the basis of a process model that is periodically updated using the past outputs y_{k-j}. For each control sequence computed at the current time k, only the control action u_k is implemented and the other values are discarded. The whole procedure is repeated at the next sampling moment.

Model-based predictive control (MBPC) and the related version embedding adaptive concepts became indeed the first commercial alternative to conventional control systems (based on PID algorithms). This commercial success was mainly due to its ability to cope efficiently with the special properties of processes such as time delays between actions and responses, non-linearities and severe process constraints, to the ability to naturally include feedforward compensation in the controller design and finally to the possibility of presenting reasonably simple-to-use packages to the end-user.

<Figure 3 near here>

Adaptive linearising control

This is a very useful non-linear procedure to design non-linear feedback controllers, which ensures linear behaviour of the closed loop system (Fig. 4). The linearising control problem consists of deducing and implementing a non-linear law such that the convergence error between the reference and the actual measured output (ref-y_m) be governed by a pre-specified stable linear differential equation, known as reference model. The controller design procedure may include on-line estimation of the non-measured process states and varying parameters.

<Figure 4 near here>

This is a particularly important approach for fermentation processes, namely where sufficient amount of information is available concerning the kinetic law structure.

Robust control

The robust control concept is based on the idea of using a simple process model, which is augmented with a norm bounded uncertainty description to capture the discrepancy between the simplified model and the real process. It is a particularly powerful method when variations in process parameters are to be considered and the bound of the parameter changes are known. In this case instead of assuming the parameters as time varying functions they are considered as having nominal values and known intervals of variation. The design objective is to find the best controller structure under input constrains that decide optimally between conflicting objectives (tracking and robustness), assuming the worst case of disturbance action. The performance specifications are defined in the frequency domain by proper weighting functions. The H-inf theory provides a reliable procedure for synthesizing a robust controller to optimise the process performance and stability for the worst-case effect of uncertainty, disturbance and noise influencing the process. Although the H-inf robust control approach was successfully applied in aircraft and chemical industries it is still at a research level for generalised application to (bio)processes.

New trends - knowledge-based control

Most of process control methods discussed above are based on first-principles and/or simple input-output models. It is a known fact that where highly complex systems are at stake, as particularly in (bio)chemical engineering, it is often difficult to formulate accurate models by just taking into account mechanistic considerations or single input-output correlation methods.

The existence of different sources of process knowledge is something recognised for many years. What in more recent days is being put forward is a set of theories and methods for capturing and integrating the information available from such different sources. This is known as hybrid modelling and is naturally expected to lead to more efficient (model-based) control procedures.

Heuristic knowledge is usually available in large quantities in the industrial environment. It is often stated in terms of rules of thumb. Fuzzy theory provides methods for quantifying this qualitative knowledge in the form of fuzzy inference systems and expert systems. *Knowledge hidden in the process data* acquired during process operation is another valuable source that can be captured through multivariate correlation methods such as artificial neural networks (ANN). The combination of these different sources of knowledge (mechanistic, heuristic and data-driven) seems thus to be a promising strategy for covering the existing gap between the theory and the practice of process operation. Some of the most innovative knowledge-based control approaches are briefly reviewed in this section.

<u>Fuzzy control</u>

Fuzzy control does not make use of mathematical models, rather it treats qualitative information using linguistic rules. For this reason the approach is considered to be suitable for fermentation processes where such qualitative information is usually a main source of knowledge.

Expert systems represent the frames employed for implementing the concepts. The method consists of using fuzzy defined intervals for the process variables to simulate human reasoning with all its uncertainty. This is achieved by providing control actions such as ‘open a little’ or ‘cool stepwise’ or ‘add a small amount of’, etc..

The main purpose of the expert system is to assist the operator in running and improving the process performance. They are particularly valuable for processes with imprecise, uncertain and incomplete knowledge. The first step in developing an expert system is to store in a knowledge-base the data extracted from previous process runs and the know-how of experienced operators. Then the knowledge-base is converted in a formalised way, i.e. organised in the form of symbolic production rules within certain intervals: if *antecedents* then *consequent*. The expert system, once build up, can be used for on-line optimising process control and supervision, for experimental simulation of the effects of fundamental decision parameters like temperature, production rate, growth rates, for fault detection and sensor break downs.

From the preceding, it should be clear that the quality of fuzzy control performance relies on the knowledge obtained by the experts in the area and on the reliability of the fuzzy rules. It is a delicate and sensitive step to decide and define linguistic rules (*if-then* type) and membership functions. Recent published applications include a number of fermentations controlled by fuzzy knowledge-based controllers.

Neuro control

Neuro controllers employ ANNs that receive as inputs information desired set-points and process state and produce as outputs commands for actuating final control elements.

ANNs are highly interconnected networks of non-linear processing units whose parameters (termed weights) are adjustable by 'learning'. Several algorithms for performing the 'learning' procedure are described in the literature. One of the most well known and well documented is the error back propagation algorithm (BPA). The method is based on the gradient descent search on the error surface. Alternatives to BPA are the chemotaxis algorithm and the conjugate gradient method. It should be stressed that all training methods and their modifications are faced with the same problem of local minima when minimising the cost function.

Over the past decade ANNs have been receiving significant attention for their (apparent) ability of knowledge acquisition focusing on estimation and prediction of process variables and process control. As pros and cons of the method, the following should be emphasized - (i) reliable performance of both neuro estimators and neuro controllers require consistent historical data and some expert knowledge about the behaviour of the process; (ii) it is known that within the training regions neuro controllers possess robustness properties against noisy measurements and serve as filters for rejecting high-frequency noises; (iii) the application of ANNs on their own raises in general a problem of confidence on the behaviour when operating outside training regions, this being related to the lack of transparency of the mathematical structure and of physical meaning of the network parameters.

In all, the indication, supported by the literature, is that this is a very useful method even if only to be applied within hybrid structures.

Neuro-fuzzy control

The neuro-fuzzy control strategy was first proposed as a somehow obvious solution to retain qualities and overcome limitations of individual approaches, viz. - lack of confidence of ANNs vs. lack of learning ability of fuzzy structures.

Neuro-fuzzy control combine the learning and structural properties of an ANN with the rule based explanations associated with fuzzy systems. Knowledge of the process extracted from experienced process operators and engineers is formulated as a set of language-based fuzzy rules. This knowledge is complemented by algorithmic systems, such as statistical analysis, mathematical modelling and ANNs for state estimation or control. A possible configuration is depicted on Fig. 5, where the membership functions of fuzzy control are adjusted in accordance with the changing patterns of the process measured outputs, recognised on-line by a neural network. Several other architectures of neuro-fuzzy control approaches can be found in the literature.

<Figure 5 near here>

Hybrid knowledge-based control

The basis for the hybrid approach is the design of a (*hybrid*) process model that rationally takes advantage of all available information concerning the process. The process is seen as partitioned in modules according to the different type of knowledge available for the process. The different modules will have a role either complementing themselves or competing among each other, this leading to two types of hybrid modular structures - modular complementary and modular competitive structures. In the former, different kinds of information for different sub-systems complement themselves; the case depicted in Figure 6a) proposes the combination of an ANN kinetic model (black-box model) with the mechanistic mass balance equation (white-box model) for process description. As for the latter, modular competitive (Figure 6b), different forms of information about the same sub-system are available for possible utilization; in the example, a mechanistic/empirical - Monod type- kinetic model (white-box module), a fuzzy kinetic model (grey-box module) and an ANN kinetic model (black-box module) are available to describe the kinetics term. A mechanism for dynamical weighting of each single model is necessary (Figure 6b). This mechanism should obey the criterion that for the current set of inputs the best model should have the greatest weight for the final output while the worst model should have the lowest weight.

The hybrid modular process model serves as a relevant tool for computing optimal operation profiles (when open loop control is applied), as state observer or as a reliable model for model-based control. Applications have been reported where the combination of hybrid modelling for state estimation with linearising control laws were employed at pilot fermentation plants [Fig. 6c].

Conclusions

This paper has been written to provide an overview of classical and advanced process control concepts that are either routinely applied or should appropriately find application in the process industries, including the dairy industries.

It is a fact today that competitive process production and process operation under ever more stringent requirements of quality, safety and sustainability are goals only achievable through adopting appropriate theoretical and technological (computer-aided) process operation methodologies and tools. Control system design can take several forms, to a large extent depending on specific process operation conditions, namely on the type of process information available.

The classical control structures reviewed are nowadays a common practice in several dairy productions. Much is to be expected from the utilisation of conventional digital approaches, namely from the combined use of feedback-feedforward control.

Model-based (adaptive) predictive control is already available in industrial control equipment for straightforward utilisation. It should lead to significant improvement in process operation in a number of difficult control problems and also, once again, when accounting in its model structure for feedforward action to compensate for disturbances in known process loads.

Knowledge-based control concepts like neuro, fuzzy or particularly hybrid knowledge-based control represent the certain future. The main concept is *knowledge integration*. Though not yet with the status of well established available tools for process operation these novel control approaches reveal clear advantages in all areas where process knowledge, traditionally known and designated as *physical* knowledge is scarce.

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Notation

d, d1,d2, - process disturbances

e, e1, e2 – errors (ref-y_m)

ref, ref1, ref2 – reference process signals

u – control input

y, y1, y2 – process outputs

$\hat{y}$ - predicted process output

<u>Subscript</u>

fb - feedback

ff – *f*eedforward

j, k – time instant indices

m – measured signal

<u>Superscript</u>

* - Sampled value

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Figure 1 - Classical control structures: a) Feedback control; b) Cascade control; c) Feedforward control

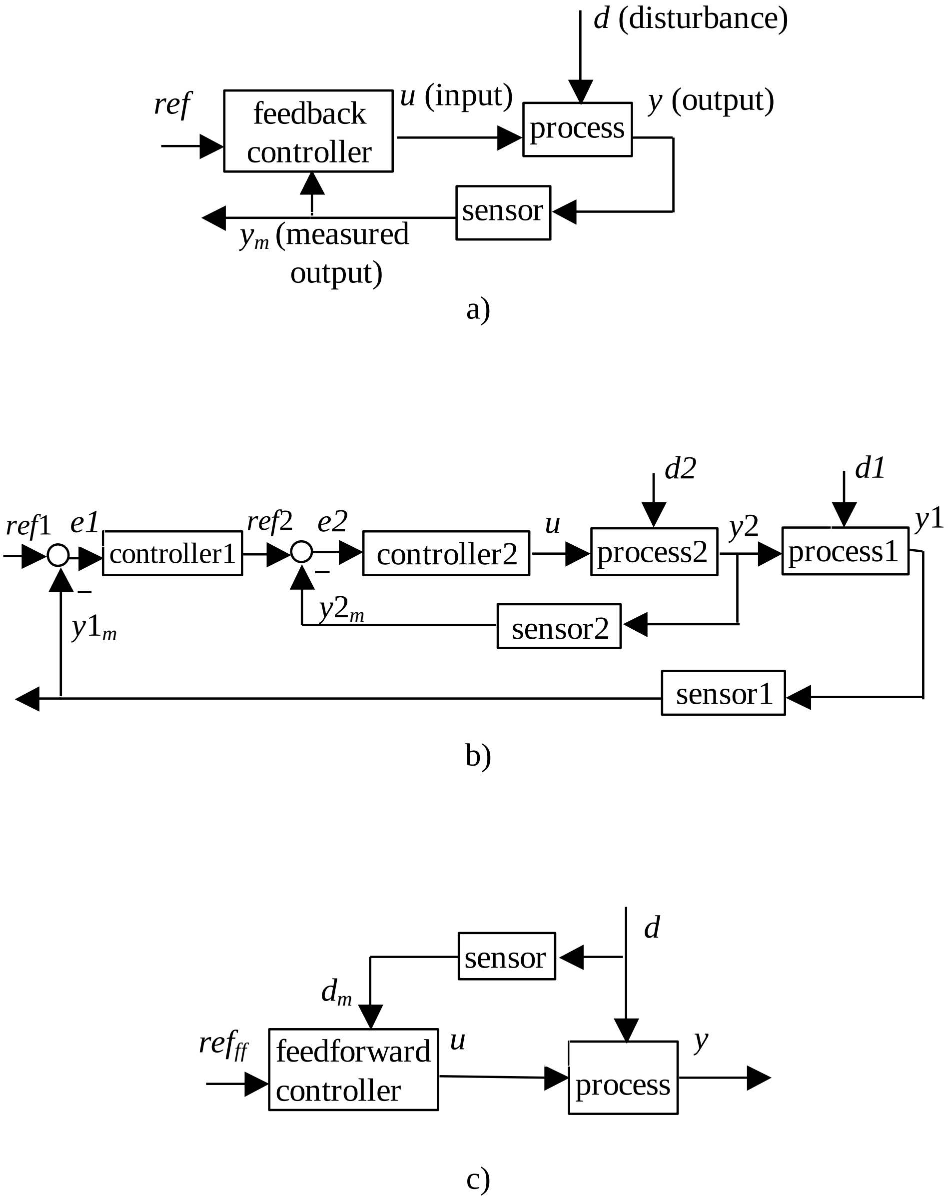


Figure 2 - Digital feedback-feedforward control

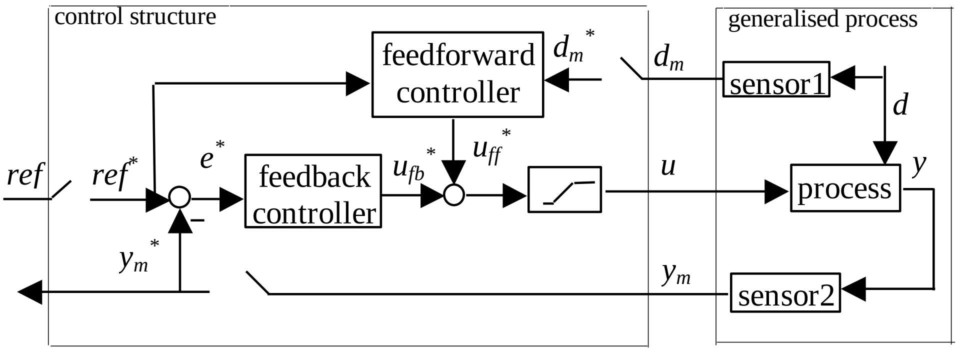
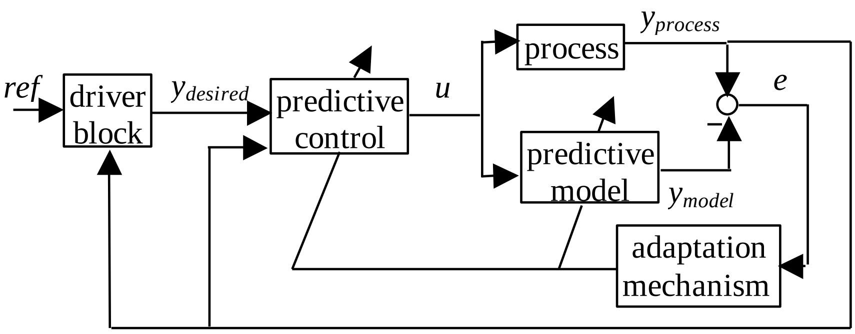


Figure 3 - Model based adaptive predictive control: a) General structure; b) Input and output time trajectories



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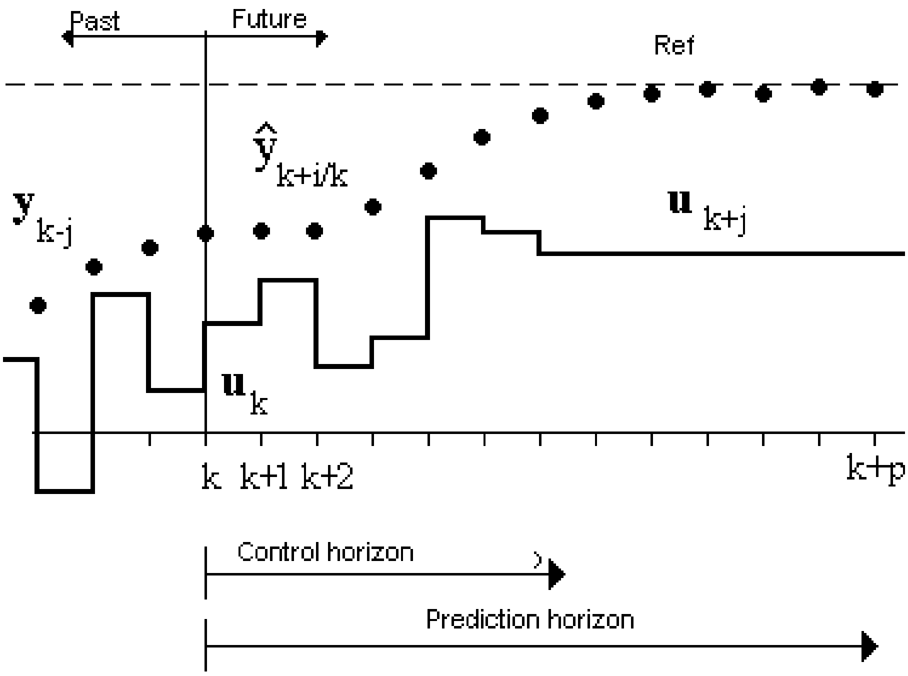
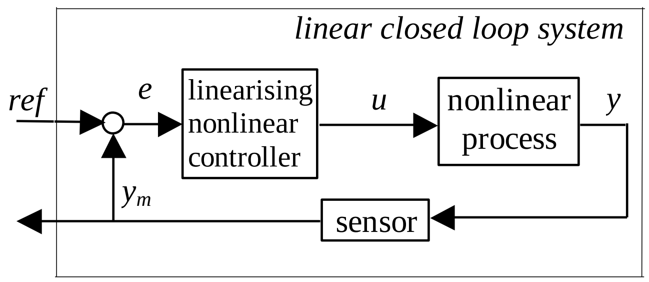


b)

Figure 4 - Linearising feedback control: a) General structure; b) Error reference model trajectory



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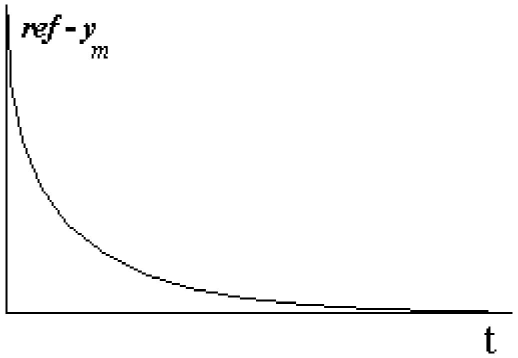


b)

Figure 5 - Neuro-fuzzy control structure

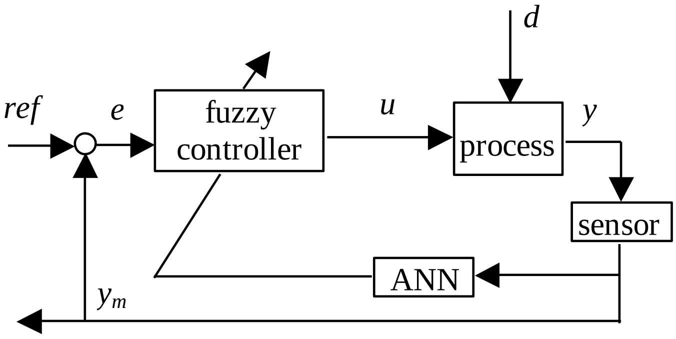
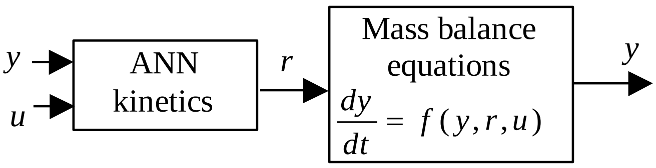


Figure 6 - Hybrid modular structures: a) Modular complementary structure: combination of an ANN kinetic model with mechanistic mass balance equations; b) Modular competitive structure: competition between a mechanistic/empirical -Monod type- kinetic model, a fuzzy kinetic model and an ANN kinetic model; c) Hybrid knowledge-based control



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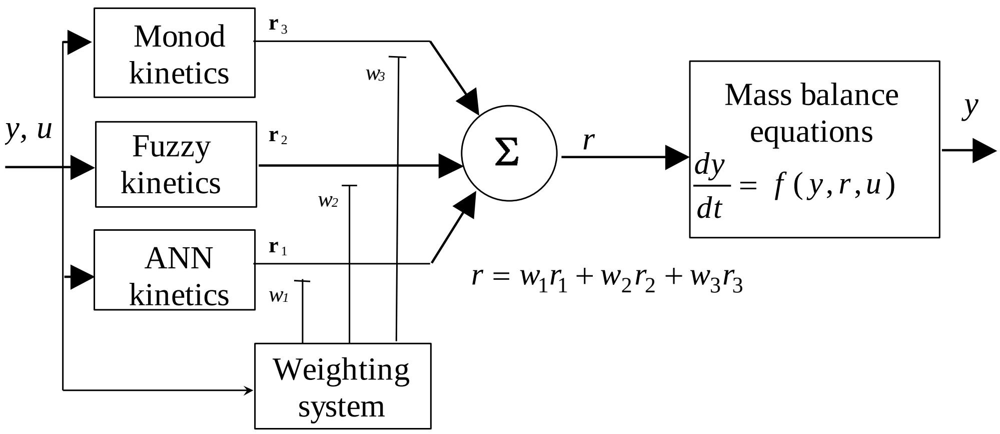

b)

Table 1 Classical digital control algorithms

<table>
<tr><td>Generalized 4th-order discrete control alg.</td><td>$u_k = \sum_{j=1}^{4} a_j u_{k-j} + \sum_{j=0}^{3} b_j e_{k-j}$</td><td rowspan="9">Specific notation:

a_j, b_j - coefficients of the linear combination
u_{ss} - steady state control action
K_C, K_{ff} - controller gains
τ_i - integral time constant
τ_d - derivative time constant
T – sampling period
τ_{ff1}, τ_{ff2} - lead-lag time constants</td></tr>
<tr><td colspan="2">Feedback control</td></tr>
<tr><td>PID position algorithm</td><td>$u_k = u_{ss} + K_c\left(e_k + \frac{T}{\tau_i}\sum_{j=1}^{k} e_j + \frac{\tau_d}{T}(e_k - e_{k-1})\right)$</td></tr>
<tr><td>PID modified position algorithm</td><td>$u_k = u_{ss} + K_c\left(e_k + \frac{T}{\tau_i}\sum_{j=1}^{k} e_j + \frac{\tau_d}{T}(y_{m_{k-1}} - y_{m_k})\right)$</td></tr>
<tr><td>PID velocity algorithm</td><td>$u_k = u_{k-1} + K_c\left((e_k - e_{k-1}) + \frac{T}{\tau_i} e_k + \frac{\tau_d}{T}(e_k - 2e_{k-1} + e_{k-2})\right)$</td></tr>
<tr><td>PID modified velocity algorithm</td><td>$u_k = u_{k-1} +$
$K_c\left((y_{m_{k-1}} - y_{m_k}) + \frac{T}{\tau_i} e_k + \frac{\tau_d}{T}(-y_{m_k} + 2y_{m_{k-1}} + y_{m_{k-2}})\right)$</td></tr>
<tr><td colspan="2">Feedforward control</td></tr>
<tr><td>Exact discrete lead-lag algorithm</td><td>$u_{ff_k} = \frac{\tau_{ff1}}{\tau_{ff2}} K_{ff} e_{ff_k} + (1 - \frac{\tau_{ff1}}{\tau_{ff2}}) f_k$,
$f_k = K_{ff}\left(1 - \exp(-T/\tau_{ff2})\right) e_{ff_k} + \exp(-T/\tau_{ff2}) f_{k-1}$</td></tr>
<tr><td>PD algorithm (proportional derivative)</td><td>$u_{ff_k} = u_{ff_{k-1}} + K_c\left((e_{ff_k} - e_{ff_{k-1}}) + \frac{\tau_d}{T}(e_{ff_k} - 2e_{ff_{k-1}} + e_{ff_{k-2}})\right)$</td></tr>
</table>