Modelling and Simulation in Adaptive Intelligent Control

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Abstract. The linguistic equation (LE) approach uses the same compact structures are used for models and control systems. Inverse, internal and predictive control can be combined with switching and fuzzy set systems. Measurement levels, interactions and composite local models are analysed in a gradually refined way in the data-based modelling. In the applications, specific models and indicators are selected and constructed from similar building blocks. Intelligent analysers produce informative indirect measurements and indices for the controller which operates like an agent-based solution where all the actions are available for activation when needed. All subsystems are presented as parametric systems which can be tuned for wide operating areas by using a balanced set of process situations. The control solution has been tested in three different applications which use the same blocks in a process specific way.

Introduction

Model-based control is widely applied in industry [1]. *Phenomenological models* provide a useful process insight and understanding of the interactions and time delays inherent in the process [2]. However, the control of an industrial kiln requires adequately accurate models which are not easy achieve [3]. *Feedforward control (FF)* can be based on models, e.g. most of the controllers tested in the solar collector field use model-based feedforward control based directly on the steady state energy balance relationships [4]. A FF controller has been combined with different feedback controllers, even PID controllers operate for this purpose [5], and FLCs could be improved considerably [6, 7].

Internal model control (IMC) uses inverse modes to remove the difference between the measured and predicted outputs. The feedback controllers should cope with modelling errors and disturbances. In principle any types of models can be used, e.g. fuzzy models [8], models based on partial differential equations [9], and nonlinear models based on local linear models [10]. The classical IMC can operate efficiently in varying time delay conditions [9]. The IMC approach is a good solution if the model is not too complicated. The 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 [8].

In *model predictive control (MPC)*, models are used for predicting the process output over a prediction horizon [11]. Intelligent methods can be used at the modelling level, in optimisation and in the specification of the control objectives [8]. Stages in the development of modelling algorithms and incorporating fuzzy models into controllers are described in [12]. Fuzzy internal models have been used in the MPC approach [13]. A MPC using fuzzy TS models is discussed in [14].

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, e.g. heuristic rules or predictions with models [15, 16, 17]. A combination of a switching algorithm and model predictive control (MPC) is presented in [18]. *Event based control*, also known as aperiodic or asynchronous control, uses sampling which is event-triggered rather than time-triggered [19, 20, 21]. It is close to a way a human behaves as a controller, and suits for distributed control systems.

Normal *feedback (FB)* and *feedforward (FF)* controllers can be extended to changing operating conditions with adaptation, model based approaches and high level knowledge based systems. Intelligent methods provide a good basis for handling nonlinear multivariable control systems, e.g. a large number of highly successful *fuzzy logic control (FLC)* applications are implemented in process industry. Fuzzy logic controllers can use normal state variables, $(x_1,\ldots,x_n)$, instead of error, change of error and sum of error. Then the controller is presented by rules. An example of a FF controller based on an inverted fuzzy model is presented in [22]. For wide operating areas, accurate models are more difficult to develop than introducing intelligent controllers to run in the whole are. Fuzzy logic controllers are good examples of this.

Fuzzy controllers can be converted to linguistic equation form by replacing the symmetric parts of the rules with linguistic equations where linguistic levels for the error, error derivative and change of control are represented by linguistic values [23].

This paper classifies combined linguistic equation models and control methodologies and discusses about their applicability in three applications. The solution includes data-based LE modelling, intelligent LE control and model-based tuning.

1 Data-based LE modelling

Directions of interactions can usually be understood on the basis of domain expertise but the nonlinear effects may become hidden by various nonlinear effects. In the LE approach, the nonlinearities of the process are handled by the nonlinear scaling of the variables, which reduces the complexity of the models drastically [23]. Composite local models provide useful extensions for the linear models [24].

1.1 Data analysis

The parameters of the scaling functions are obtained by data analysis based on generalised norms and moments. The generalised norm is defined by

$$||^{\tau}M_j^p||_p = (M_j^p)^{1/p} = [\frac{1}{N}\sum_{i=1}^{N}(x_j)_i^p]^{1/p}, \qquad (1)$$

where the order of the norm $p \in R$ is non-zero, and N is the number of data values obtained in each sample time τ. The norm (1) calculated for variables x_j, $j = 1,\ldots,n$, have the same dimensions as the corresponding variables. The norm $||^{\tau}M_j^p||_p$ can be used as a central tendency value if all values $x_j > 0$, i.e. $||^{\tau}M_j^p||_p \in R$. [25]. The norm can be extended to variables including negative values [26].

The orders, p, focus on different statistical properties of the dat distributions. The specific orders are chosen by using the generalised skewness,

$$(\gamma_k^p)_j = \frac{1}{N\sigma_j^k}\sum_{i=1}^{N}[(x_j)_i - ||^{\tau}M_j^p||_p]^k. \qquad (2)$$

The standard deviation σ_j is the norm (1) with the order $p = 2$. [27] The parameters can be recursively updated by using the norms with the spefied orders [26].

1.2 Nonlinear scaling

Scaling functions are monotonously increasing functions $x_j = f(X_j)$ where x_j is the variable and X_j the corresponding scaled variable. The function $f()$ consist of two second order polynomials, one for the negative values of X_j and one for the positive values, respectively. The corresponding inverse functions $x_j = f^{-1}(X_j)$ based on square root functions are used for scaling to the range [-2, 2], denoted linguistification. In LE models, the results are scaled to the real values by using the function $f()$.

The parameters of the functions are extracted from measurements by using generalised norms and moments. The support area is defined by the minimum and maximum values of the variable, i.e. the support area is $[\min(x_j), \max(x_j)]$ for each variable j, $j = 1,\ldots,m$. The central tendency value, c_j, divides the support area into two parts, and the core area is defined by the central tendency values of the lower and the upper part, $(c_l)_j$ and $(c_h)_j$, correspondingly. This means that the core area of the variable j defined by $[(c_l)_j, (c_h)_j]$ is within the support area.

1.3 Interactions

The basic form of the linguistic equation (LE) model is a static mapping in the same way as fuzzy set systems and neural networks, and therefore dynamic models will include several inputs and outputs originating from a single variable [23]. External dynamic models provide the dynamic behaviour, and LE models are developed for a defined sampling interval in the same way as in various identification approaches discussed in [28].

Dynamic LE models use the parametric model structures, ARX, ARMAX, NARX etc., but the nonlinear scaling reduces the number of input and output signals needed for the modelling of nonlinear systems. For the default LE model, all the degrees of the polynomials become very low:

$$Y(t) + a_1 Y(t-1) = b_1 U(t - n_k) + e(t) \tag{3}$$

for the scaled variables Y and U .

1.4 Composite local models

The *composite local model* approach constructs a global model as a weighted sum of local models, which usually are linear approximations of the nonlinear system in different neighbourhoods.*Linear parameter varying (LPV) models*, where the matrices of the state-space model depend on an exogeneous variable measured during the operation, are closely related to local linear models. The models can be state-space models or parametric models. The model switches between different modes as the state variable varies over the partition [24].

Fuzzy set systems can be used when the operating areas of the local models can be overlapping (Figure 1). Also additional special phenomena can be added with fuzzy set systems [29]. The LE approach can be combined with several fuzzy modelling methodologies: the fuzzy arithmetics and extension principle introduce uncertainty processing and fuzzy inequalities can be used in selecting local models [30].

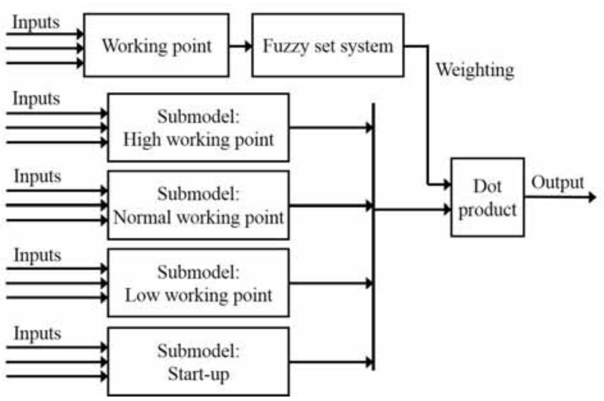

Figure 1: Composite local models of a solar collector field.

2 Intelligent LE control

The first direct LE controller was implemented in 1996 for a solar power plant [31, 32], and later the multilevel LE controller was installed in an industrial lime kiln [33]. The feedback LE control is enhanced with working point control and intelligent actions (Figure 2).

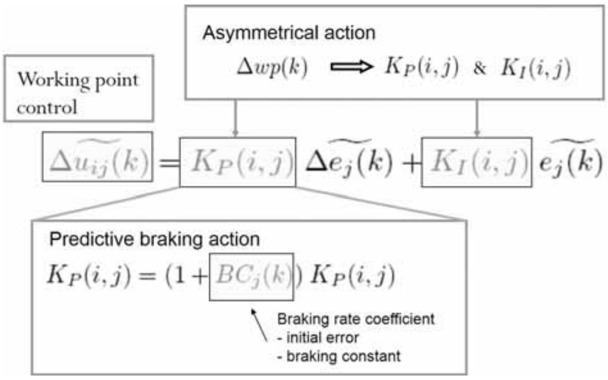

Figure 2: Adaptive LE controller.

2.1 Feedback control

Feedback linguistic equation (LE) controllers use error $e_j(k)$ and derivative of the error $\Delta e_j(k)$. These real values are mapped to the linguistic range $[-2, 2]$ by nonlinear scaling with variable specific scaling functions in the same way as in LE models. The linguistic values of the inputs, $\widetilde{e_j(k)}$ and $\widetilde{\Delta e_j(k)}$, are limited to the operating range: outside the scaled values are -2 and 2 for low and high values, respectively.

A *PI-type LE controller* is represented by

$$\widetilde{\Delta u_{ij}(k)} = K_P(i,j)\ \widetilde{\Delta e_j(k)} + K_I(i,j)\ \widetilde{e_j(k)}, \tag{4}$$

which contains coefficients $K_P(i,j)$ and $K_I(i,j)$. The strengths of effects of $\widetilde{e_j(k)}$ and $\widetilde{\Delta e_j(k)}$ can be tuned by membership definitions $(f_e)_j$ and $(f_{\Delta e})_j$, respectively. However, the direction of the control action is fixed in (4). Different directions and strengths can be handled with this controller.

The output i of a single input single output (SISO) controller is calculated by adding the effect of the controlled variable j to the manipulated variable i:

$$u_i(k) = u_i(k-1) + \Delta u_{ij}(k). \tag{5}$$

2.2 Intelligent analysers

The LE control included predictive braking and asymmetry actions (Figure 2) already in the first implementations. The efficient handling of cloudy conditions intro-

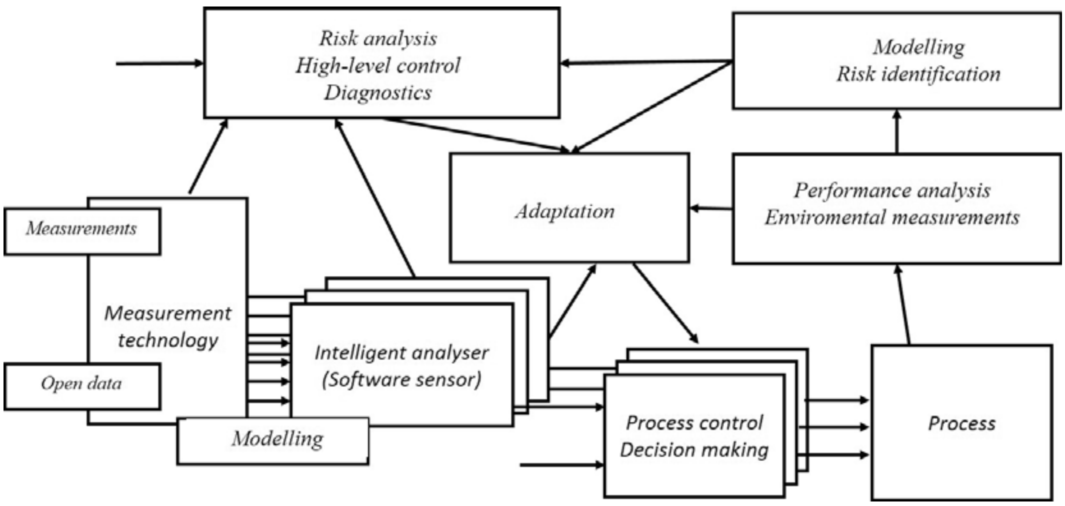

Figure 3: Intelligent analysers and control.

duced a fluctuation indicator [34]. Braking and asymmetry actions are not activated when fluctuations are high. There are additional safety actions for both drastic and accumulating effects. The intelligent analysers produce informative calculated variables for the controller (Figure 3). The indices can be interpreted in natural language.

Predictive braking indication. Braking is activated when a very large error is detected. The calculated braking coefficient, $bc_j(k)$ is used to emphasise the influence of the derivative of the error by means of the following equation:

$$K_P(i,j) = (1 + bc_j(k))\, K_P(i,j) \qquad (6)$$

A new solution has been introduced to detecting the large error.

The realisation of the braking action is process specific. In the solar plant, the control actions are large at the beginning of the correction and the braking is used in stopping the fast change. In the lime kiln, the braking is used in the beginning to start the correction with care.

Asymmetry detection. The action is activated only close to the set point if there are no strong fluctuations of the controlled variable evaluated by $e_j{}^-$ and $e_j{}^+$. The earlier calculation based on the solar noon operated well on clear days but they do not take into account actual irradiation changes in the solar application.

Fluctuation indicators. Detecting cloudiness and other varying situations is important in avoiding oscillations. The fluctuations are detected by calculating the difference of the high and the low values of the corrected irradiation as a difference of two moving generalised norms:

$$\Delta x_j^F(k) = ||^{K_s\tau} M_j^{p_h}||_{p_h} - ||^{K_s\tau} M_j^{p_l}||_{p_l}, \qquad (7)$$

where the orders $p_h \in \Re$ and $p_l \in \Re$ are large positive and negative, respectively. The moments are calculated from the latest $K_s + 1$ values, and an average of several latest values of $\Delta x_j^F(k)$ is used as an indicator of fluctuations. [34]

2.3 Adaptive control

Adaptive LE control takes into account process situation, manipulating variables and previous control actions in a predefined procedure. The correction factor is a weighted sum of the following scaling coefficients:

- working point wp_i is the deviation from the normal operating conditions;
- control power is calculated by a specific LE model for each manipulating variable;
- cumulative rate of control actions is used for avoiding the accumulation of a very large control action in slow processes.

Invidual scaling coefficients and the correction factor are are within the range $[-2,2]$. The correction factor modifies the final scaling of the change of control. Each manipulating variable needs to be constrained into the acceptable ranges defined by the physical constraints.

The adaptation uses indirect measurements provided by the intelligent analysers and weight factors and constraints defined by the high level control (Figure 3).

2.4 Model-based control

The LE model types summarised in Section 1 have linear interactions and can thus be used in the control as inverse process models. Feedforward controllers can also be based on heuristic LE systems and manually constructed scaling functions. The linear interactions make the highly flexible solution includes both switching between inverse models and using the weighted sums of inverse models.

The compact LE controllers can be used in the model-based predictive control if the operation is fairly smoothly. Strong fluctuations are harmful also for this kind of model-based control. Mainly the modelling part is embedded in the development of the intelligent analyses from measurements and open data (Figure 3). Online LE modelling could also be implemented, but it is not feasible in applications which have a lot of strong disturbances and fluctuations. The online modelling is restricted in performance and risk analysis.

3 Applications

Three applications of different kind are discussed in this section. Fast adaptation to changing operation conditions are needed in the solar plant. Several controlled and manipulating variables are needed in the lime kiln control where the FF actions are important. Two differently operating chemicals are essential in the control of water treatment which combines FF and FB actions.

3.1 Solar thermal power plant

Solar power plants should be designed to collect all the available thermal energy in a usable form within a desired temperature range. In cloudy conditions, the collector field is maintained in a standby mode ready for full-scale operation when the intensity of the sunlight rises again. Control is achieved by means of varying the flow of oil pumped through the pipes during the plant operation. For the solar collector field, the goal is to reach the nominal operating temperature 180 - 295 ^oC and keep it in changing operating conditions. The main challenge is to extend the operation to less favourable operating conditions.

Feedforward control. The *energy balance* of the collector field can be represented by expression [5]:

$$I_{eff}A_{eff} = (1-\eta_p)F\rho c T_{diff}, \tag{8}$$

where I_{eff} is effective irradiation (Wm^{-2}), A_{eff} effective collector area (m^2), η_p a general loss factor, F flow rate of the oil (m^3s^{-1}), ρ oil density kgm^{-3}, c specific heat of oil $(Jkg^{-1}K^{-1})$ and T_{diff} temperature difference between the inlet and the outlet (^oC). The effective irradiation is the direct irradiation modified by taking into account the solar time, declination and azimuth. The volumetric heat capacity increases very fast in the start-up stage but later remains almost constant because the normal operating temperature range is fairly narrow.

Feedback control. The feedback controller is a PI-type LE controller (4) with one manipulating variable, oil flow F, and one controlled variable, the maximum of the outlet temperatures of the loops, or shortly denoted as the outlet temperature T_{out}. The original controller was defined by the coefficients $K_P(i,j) = K_I(i,j) = 1$ [31, 32] and extended to real-valued coefficients in [35]. The basic LE controller is defined for the normal working point $wp_i = 0$.

Adaptive control. The LE controller is adapted to different operating conditions by using a working point LE model

$$wp = \tilde{I}_{eff} - \tilde{T}_{diff}, \tag{9}$$

where $\tilde{I}_{eff}$ and $\tilde{T}_{diff}$ are obtained by the nonlinear scaling of variables: efficient irradiation I_{eff} and temperature difference between the inlet and outlet, $T_{diff} = T_{out} - T_{in}$. The working point, wp, represents a fluctuation from the normal operation.

The working point variables already define the overall normal behaviour of the solar collector field, $wp = 0$, where the irradiation $\tilde{I}_{eff}$ and the temperature difference, $\tilde{T}_{diff}$, are on the same level. A high working point $(wp > 0)$ means low $\tilde{T}_{diff}$ compared with the irradiation level $\tilde{I}_{eff}$. Correspondingly, a low working point $(wp < 0)$ means high $\tilde{T}_{diff}$ compared to the irradiation level $\tilde{I}_{eff}$. The normal limit $(wp_{min} = 0)$ reduces oscillations by using slightly lower setpoints during heavy cloudy periods. Higher limits, e.g. $(wp_{min} = 1)$, shorten the oscillation periods after clouds more efficiently.

Intelligent analysers. The working point (9) is an important intelligent analyser which is used all the time. Predictive braking indication (6) is activated when a very large error is detected, e.g. after a drastic setpoint change. The asymmetry detection is activated only close to the setpoint. Cloudy conditions detected with the indicator (7) are taken into account in selecting a suitable working point $wp_i = 0$ when needed. This overrides the manual settings of the working point to avoid oscillations. Since this set of indicators operate very well, the indicators for fast changes of temperatures (inlet, outlet and difference) or too high temperatures activate in the current system very seldom [36].

Intelligent analysers are essential in transforming the complex control system into an agent-based solution where all the actions are available for activation when needed.

3.2 Lime kiln

Feedforward LE controllers are important in the lime kiln control in keeping good operating conditions when process input changes: draught fan speed, kiln rotational speed and fuel feeds are controlled by an inverse model. The fuel feeds are adjusted with the feedback LE controllers. The FB control, which is required in order to maintain the hot-end temperature within the most favourable range for the lime quality, is used for the fuels: sawdust and oil. The controllers are PI-type LE controllers based on two controlled variables: the hot end temperature and the cold end temperature with weights 0.7 and 0.3, respectively. The error is calculated as difference of two moving average [33].

Adaptive scaling, braking action and the fuel quality analyser are the key parts in the FB control. The fuel quality indicator is the most important for the biofuel. Another important requirement is the need to cope with the long time delays. The cumulative rate of control actions is essential in avoiding excess control actions to one direction. The working point is defined by the production rate and the draught fan speed.

The more efficient control solutions reduce the fluctuations of the product quality and minimise the environmental impact through smooth operation close to the process operation constraints. This brings the process optimisation into real practise.

3.3 Water treatment

The adaptive FB controller of the faster effecting chemical reacts efficiently to the change of the water quality and to the halving of incoming flow: the setpoint is kept, and there is no offset. The FF controller of the slowly affecting chemical (Chem1) is needed for the fast changes of flow and water quality (Figure 4). LE controllers have been successfully implemented at a mill [37]. Pre-tuning facilitates a fast operation in changing process conditions: the controller does not need time for finding correct parameters, since the changes are detected by the water quality indicator.

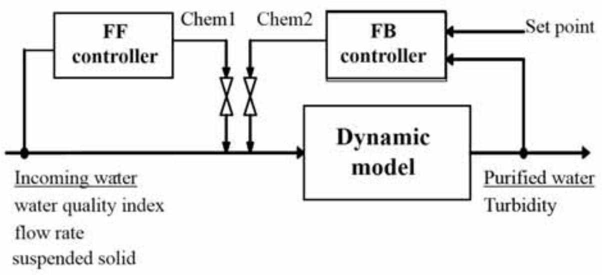

Figure 4: Dosing control in water treatment.

4 Model-based tuning

Dynamic LE models have been used for developing, testing and tuning the controllers in changing process conditions without disturbing the process.

A balanced set of different operating conditions is needed since the multilevel LE control system should operate in a wide operating area. The optimisation based on genetic algorithm can be used simultaneously for a large number of parameters, including

- parameters of the scaling functions for variables, errors and changes,
- model coefficients (working point, quality indices, cumulative rate, FF),
- correction factors, and
- weight factors.

In the applications, the number of parameters is from 40 to 100. Model-based predictive control is suitable for the tuning of the braking action.

In the water treatment, the dynamic simulator contains a dynamic LE model for the flotation basin, controllers for two chemicals and a soft sensor for the detection of incoming water quality. Simulation made the implementation faster without any re-tuning of control parameters was needed. [38]

5 Conclusions

The linguistic equation (LE) approach is an efficient solution for model-based intelligent control. Measurement levels, interactions and composite local models are analysed in a gradually refined way and the models and indicators are constructed from similar building blocks. The controller operates like an agent-based solution where all the actions are available for activation when needed. The parametric systems can be tuned for wide operating areas.

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