Multiple Model Intelligent Simulation with Linguistic Equations and Fuzzy Logic

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ABSTRACT

A new dynamic simulation tool for intelligent control design has been developed on the basis of Linguistic Equation (LE) approach and fuzzy logic. The fuzzy LE approach combines various information sources including mechanistic models, data-driven learning algorithms and expert knowledge to dynamic approximators, state space models and semi-mechanistic models. Understanding of the underlying phenomena and structure of the model are dealed with interactions, and nonlinearities of the system are described by membership definitions tuned by input-output data. Interactions, membership definitions and effective time delays depend on working point conditions. Delays are handled as smoothly changing fuzzy numbers. In the multimodel approach, the smooth switching between various submodels provides a robust platform for testing controller alternatives. The robust dynamic simulator is continuously used in developing adaptive industrial controllers.

INTRODUCTION

Mathematical modelling of real systems is an important topic in many disciplines of engineering and science. Simulations can be used for analysis of the system behaviour, design of new processes and control systems. The main idea is to improve dealing with materials, energy and information through better understanding of the underlying mechanisms in the system. The trade-off between the necessary accuracy and resulting complexity becomes more and more important when the nonlinear and multivariable behaviour must be taken into account. Adaptation to various operating conditions would also be very useful for industrial practice (Juuso 1999).

Physical (mechanistic, first-principle, "white-box") modelling is based on a thorough understanding of the system's nature and behaviour which is represented by a suitable mathematical treatment. Real systems are usually too complex and poorly understood for a complete mechanistic modelling on an acceptable level of complexity. The obvious risk of unrealistic simulations is very dangerous in the subsequent steps of analysis, e.g. prediction and controller synthesis cannot be successful.

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 process data is available. The structure and parameters of these models do not necessarily have any physical or chemical significance, and therefore, these models cannot be adapted to different operating conditions.

Many nonlinear multivariable systems can be transformed into mechanistic models described by differential and algebraic equations. Also data-driven techniques are very useful in modelling, e.g. the linear regression is an efficient method in developing multivariable models. There are more difficulties with nonlinearities: interpreting, generalising and adapting of nonlinear regression models is not an easy task. In addition to this, there is usually a large amount of process knowledge in a qualitative form, which cannot be transformed to mechanistic models. This is the area where the *Computational Intelligence* can provide additional tools: fuzzy modelling is an excellent technique for handling qualitative information, and very complex nonlinear models can be constructed by neural networks.

Intelligent control provides many possibilities for the control of complex, nonlinear, partially unknown multivariable systems. Traditionally, these controllers have been developed from manual control. Simulation can provide many important tools for faster and more accurate tuning of the controllers, especially in slow processes where traditional trial-and-error based on-line tuning is not an efficient solution. However, the tuning of nonlinear multivariable controllers require same properties also in the dynamic models.

In this paper, the modelling and simulation is based on the Linguistic Equation (LE) approach. Also other techniques for nonlinear multivariable modelling and simulation are shortly described. Benefits of the approach are demonstrated through an applications on control design.

INTELLIGENT MODELLING

Humans can handle complex tasks including significant uncertainty on the basis of imprecise and qualitative knowledge. Intelligent methods are based on techniques motivated by biological systems and human intelligence, e.g. natural language, rules, semantic networks and qualitative models. These techniques were introduced by expert systems. There are various useful methods for knowledge acquisition, but handling of uncertainties is very difficult and time-consuming in conventional expert systems.

Fuzzy set systems

Fuzzy modelling and control provide extensions of the expert system techniques to uncertain and vague systems. Fuzzy set systems continue the traditions of physical modelling on the basis of understanding the system behaviour. Fuzzy rules and membership functions can represent gradually changing nonlinear mappings together with abrupt changes. Fuzzy models can help in extracting expert knowledge on an appropriate level (Juuso 1996). Fuzzy models can also be constructed from data, which alleviates the knowledge acquisition problem. Various techniques have been used to fit the data with the best possible accuracy, but in most cases the interpretation of results is not addressed sufficiently. Fuzzy models can also be considered as a class of local modelling approaches which attempts to solve a complex modelling problem by decomposing into number of simpler subproblems (Babuška et al. 1997).

Neural computing

Artificial neural networks (ANN) introduced new learning and adaptation capabilities by imitating biological neural systems on a simplified level. An ANN can be considered as a fairly complex nonlinear black- box approximator, which has similar benefits and drawbacks as conventional identification techniques: easy to use but difficult to explain and relate to physical system properties. The number of effective parameters should on an appropriate level in order to get a model that can also generalise the results. Large and complex problems are divided into a set of subproblems by modular hierarchical systems (Lampinen 1997).

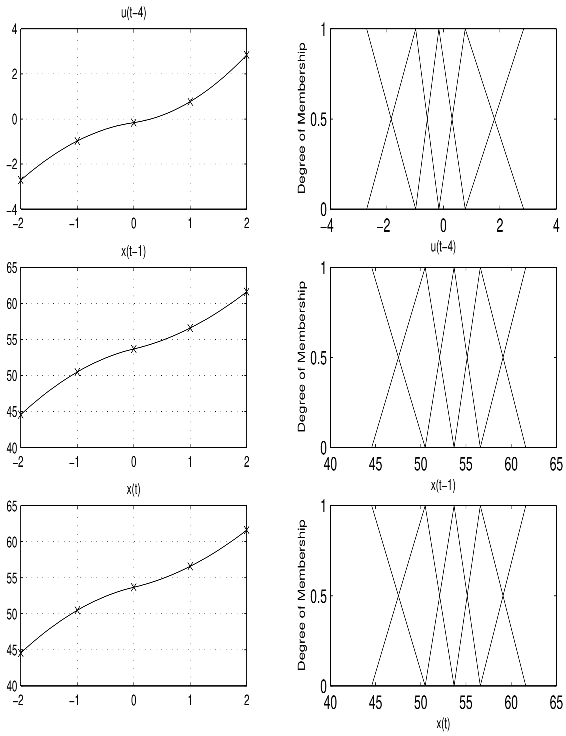

Figure 1: Membership definitions and membership functions.

Linguistic equations

Linguistic Equations (LE) approach combines various intelligent modelling techniques on a unified framework: it was originally developed for handling large knowledge bases in process design (Juuso and Leiviskä 1992); a close connection to fuzzy set systems was important already in the early applications (Juuso 1994); data-driven modelling properties have brought the approach close ANN techniques. Fuzzy modelling and control was the main application area. Properties of the LE approach are continuously improved and extended on the basis of industrial experience with various application areas, and recently, emphasis is moving from development to direct applications (Juuso et al. 1996, 1997, 1998a, 1998b).

Each equation represents a multivariable interaction: the directions and strengths of interactions are defined by coefficients of the interaction matrix. Only the variables with nonzero coefficient belong to the interaction (Juuso 1996). Nonlinearities are taken into account by membership definitions consisting of two polynomial functions, one for positive and one for negative side labels. With these definitions the values of input variables are mapped to the range $-2...2$ which correspond to the labels *very low .... very high* (or *negative big ... positive big*); *normal* (or *zero*) is always zero (Figure 1. After the matrix calculations, the outputs are mapped from linguistic level to the real scale. Since only five parameters is needed for each variable, the LE systems can be adapted to various working conditions.

Hybrid methods in modelling

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 intelligent methods have extended the toolbox of these hybrid, semi-mechanistic or grey-box modelling. Fuzzy clustering is an extension of fuzzy knowledge based systems to data-driven techniques. Neuro-fuzzy modelling and identification techniques include fuzzy-logic-based methods to neural computing.

The FuzzEqu toolbox includes routines for building a single LE system from large fuzzy systems including various ruleblocks implemented in FuzzyCon or Matlab FLT. Fuzzy models on any fuzzy partition can be generated from LE models: rules or relations are developed either sequentially or simultaneously (Juuso et al. 1996), and membership functions are generated from the membership definitions on any location in the range $-2...2$. In each equation, the locations of membership functions of one selected variable can be defined by the model.

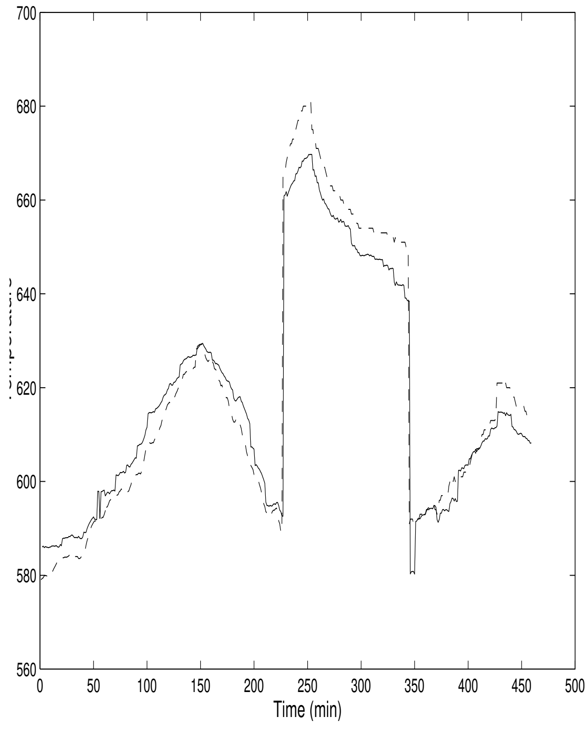

Figure 2: One-step-ahead simulation with training data.

DYNAMIC SIMULATION

Dynamic fuzzy models can be constructed on the basis of state-space models, input-output models or semi- mechanistic models (Babuška et al. 1997). In the state-space models, fuzzy antecedent propositions are combined with a deterministic mathematical presentation of the consequent. The most common structure for the input-output models is the NARX /Nonlinear AutoRegressive with eXogenous input) model which establishes a relation between the collection of past input-output data and the predicted output:

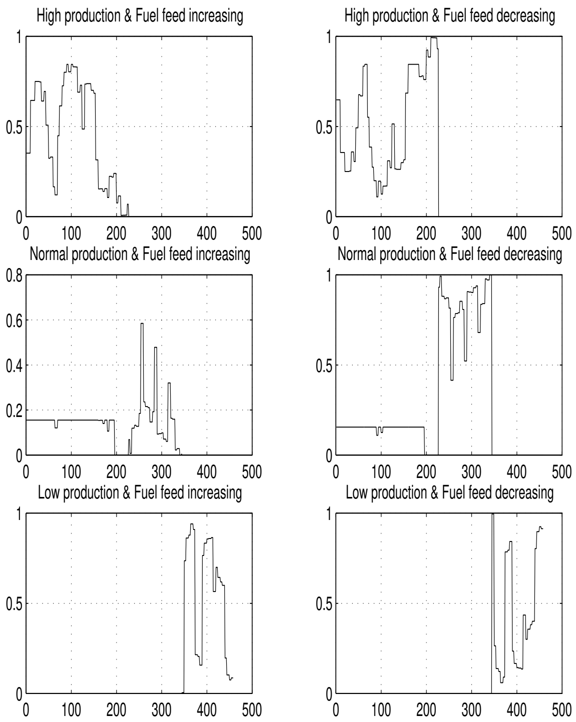

Figure 3: Degrees of membership for different working areas during the simulation test.

$$y(k+1) = F(y(k), ..., y(k-n+1), u(k), ..., u(k-m+1)), \tag{1}$$

where k denotes discrete time samples, n and m are integers related to the systems' order. MIMO systems can be built as a set of coupled MISO models. Delays can be taken into account by moving the values of input variables correspondingly. In the semi-mechanistic models, the modelling task is divided into two subtasks: the well-understood mechanisms, e.g. mass and energy balances, are modelled with mechanistic methods, and the approximations of partially known relationships and parameters with fuzzy methods. Dynamic neural networks and linguistic equations can be based on similar structures as the dynamic fuzzy models (Juuso 1998).

DYNAMIC LE MODELLING

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. External dynamic models as state-space

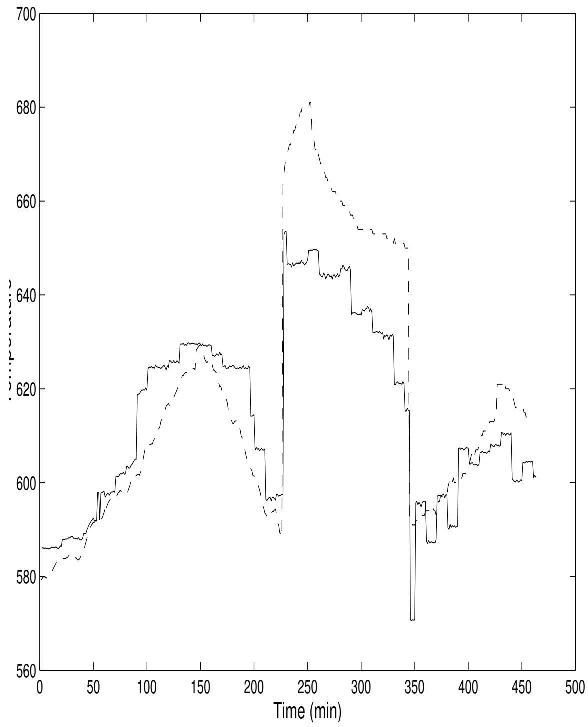

Figure 4: Simulation test with training material.

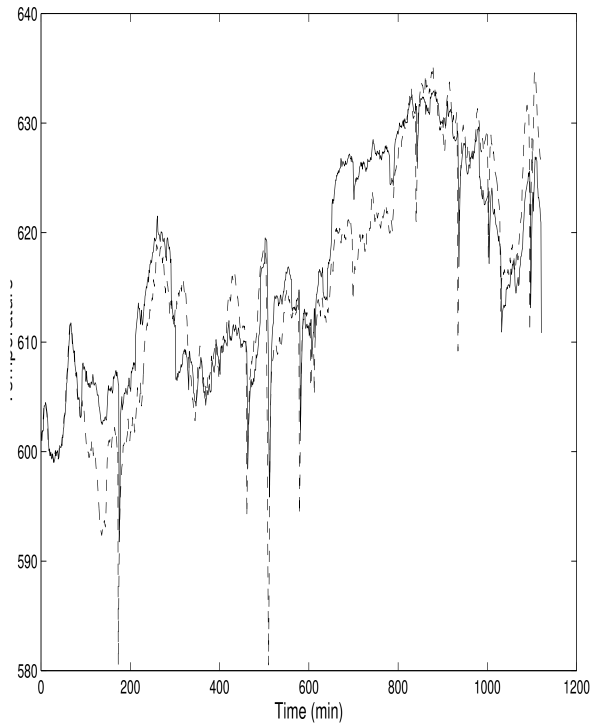

Figure 5: One-step-ahead simulation test with testing material.

models, input-output models or semi-mechanistic models provide the dynamic behaviour. Rather simple input-output models, e.g. the old value of the simulated variable and the current value of the control variable as inputs and the new value of the simulated variable as an output, can be used since nonlinearities are taken into account by membership definitions.

For state-space modelling, each rule corresponds to a different working point, and the deterministic equations on the consequent part are transformed into a linguistic equation model. Since the LE model can handle nonlinearities, at least some of the rules can be combined. Local linear models can be combined with this technique which is closely related to Takagi-Sugeno -type fuzzy models.

In semi-mechanistic models, approximation rules are combined into linguistic equations. The approximation rules can be based on qualitative knowledge, and the mechanistic models take care of the basic level dynamic simulation.

Effective delays usually depend on the working conditions (process case), e.g. the delays are closely related to the production rate in many industrial process. Therefore, an appropriate handling of delays will extend the operating area of the model considerably.

Single model approach

In the single model approach, also variables affecting to the working point of the model are included to the model. In small models, all the interactions are in a single equation. For larger models, the equation system is a set of equations where each equation describes an interaction between two to four variables. The development work starts with an automatic generation of membership definitions, which are then used in generation of interaction alternatives. The equations with best fit to the data are selected to the interaction matrix: each new equation introduces at least one variable to the model. Any equation can be rejected or modified on the basis of expert knowledge before or during the tuning phase.

For each model, initial estimates of the delays are developed by correlation analysis. The method is suitable for handling data from process experiments where the changes are defined by the experimental programme. For normal process data, levels of changes are not so clear, and therefore, similarities detected by correlation analysis can be accidental in some cases. For the lime kiln, the resulting delays were too large for some variables. The delays should be assessed against process knowledge, especially if normal on-line process data is used (Juuso 1998). The delays can also be tuned with linguistic equation models.

In the present system, delays are handled as triangular fuzzy numbers already on each single model. The

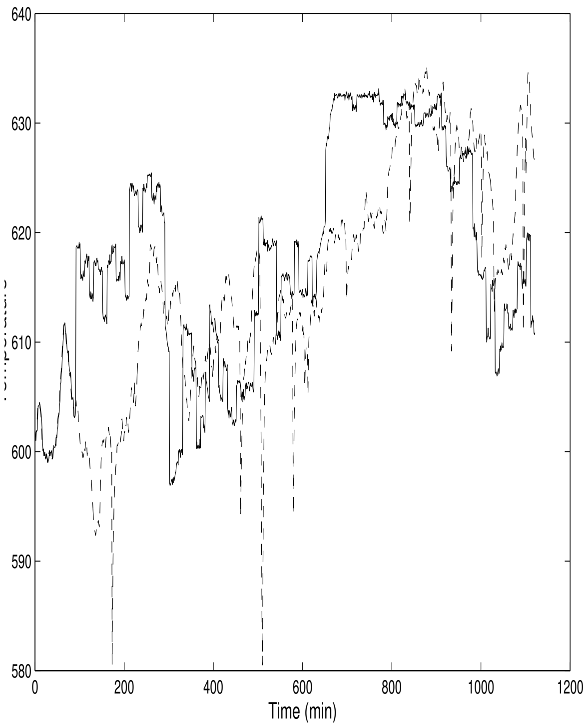

Figure 6: Simulation test with testing material.

location and the width of the membership function depends on the production rate. The estimates of the effective delays can be improved by applying the correlation analysis to the linguistic relations, which are obtained from the original data by nonlinear scaling with membership definitions.

For model development, the training data consist of 6 data sets (Figure 2) corresponding six working point areas defined by production and fuel trend. Some overlap of the working point areas is automatically introduced since the fuel rate is not continuously increasing or decreasing as can be seen from simulation results shown in Figure 3. The delays were removed before tuning. The interaction vector is the same for all working areas, which is quite reasonable since the directions of interactions do not change considerably between different working points. The differences between the models are handled with membership definitions.

Multiple model approach

A multiple model approach based on fuzzy LE models has been developed for combining specialised submodels. The approach is aimed for systems that cannot be sufficiently described with a single set of membership definitions because of very strong nonlinearities. Additional properties can be achieved since also equations and delays can be different in different submodels. In the multiple model approach, the working area defined by a separate working point model.

In the FuzzEqu toolbox, the model can include n x m submodels if there are n working areas and m subareas. Each submodel is a single model whose output is a vector of singleton values. Singleton values of each output variable are aggregated by the weighted average method. The weight of each submodel is equal to its degree of membership defined by the working point model. The calculation of the degree of membership can be a simple fuzzification procedure or a very complex LE system, e.g. in the web break indicator, the working point model consists of 25 cases, each modelled with about 20 equations (Juuso et al. 1998a). The working point model is usually a steady state model based on direct measurements and some trends. For some variables, changes in signal level or variances and peak values could be useful.

Each submodel has its own delay vector for the variables. In this way the delay is changing with time as the multimodel system switches gradually from one submodel to another. For slow processes, also trends are analysed for some variables: the fuel trend is used both in the simulation model and in the LE controller of the lime kiln. The results are used as additional working point variables. Usually several process cases have a non-zero degree of membership, and these degrees are changing in time, i.e. the delays can be considered as smoothly changing fuzzy numbers. The smooth changes are important for the reliable operation.

The multiple model approach is necessary for the modelling of the lime kiln, especially because of varying delays, but there are also considerable differences in membership definitions. Since the lime kiln process is fairly slow, and the working point is continuously changing (Figure 3), the individual single models should not be to different from each other in order to achieve a smoothly changing operation.

Tuning

Tuning is based on real valued linguistic equations and membership definitions. Final membership definitions become consistent with the interactions. Each equation model can be tuned and used to any direction, i.e. any variable can be calculated if sufficient number of other variables is known. For more complex systems, the limitations for solving a matrix equation are taken into account in the development environment. Usually, one variable at a time is tuned by using the equations on an appropriate sequence.

In the tuning of membership definitions, a polynomial function is fitted for the data points and the corresponding linguistic levels obtained by the current membership definitions and interactions. A practical solution is a neural network including four linear neurons and a bias. This technique is identical to the recursive linear regression.

The basic form of the LE model is static mapping, and therefore dynamic models will include several inputs and outputs originating from a single variable. The meaning of levels is not changing very fast, i.e. the membership definitions for the input and output temperatures are the same. This technique allows also adaptive tuning in the same way as it is done in adaptive linear neurons. In the multimodel approach, submodels are tuned separately.

Testing

The multimodel simulator was tested with the training data. The one-step-ahead simulation is very accurate (Figure 2) although the multimodel system does not always use the same model which was used in the tuning as can be seen from Figure 3. A more demanding test is to use the calculated temperature as an input temperature on the following simulation step, the operating areas used during this modelling are identical to the previous case since the fuel feed was not changed. For some cases, the error is now considerably larger since the changes are too fast because the delays are not properly handled (Figure 4).

Testing with independent data is essential in order to use the dynamic models in control design. One-step-ahead testing produces again very accurate results (Figure 5): a considerable difference can be found only on two periods of time. This is quite natural since the changes are fairly small on each simulation step. For controller tuning, more tests are needed since the accuracy requirement is very high.

A more demanding test is again to use the calculated values always as inputs on the following simulation step. The results are very good (Figure 6): the only considerable differences are on the same time periods as in the previous test. According to analysis with additional simulation tests, these differences can be caused by fairly short disturbances in fuel quality. Another reason for this kind of behaviour could be an oscillation of kiln temperature caused by earlier control actions.

LE CONTROLLER DESIGN

In intelligent control design, hybrid techniques combining different modelling methods in a smooth and consistent way are essential for successful comparison of alternative control methods. Switching between different submodels in multiple model approaches should be as smooth as possible. For slow processes, predictive model-based technique is necessary at least on the tuning phase. Adaptation to various nonlinear multivariable phenomena requires a highly robust technique for the modelling and simulation.

Dynamic simulators based on linguistic equations are continuously used in development of multilayer

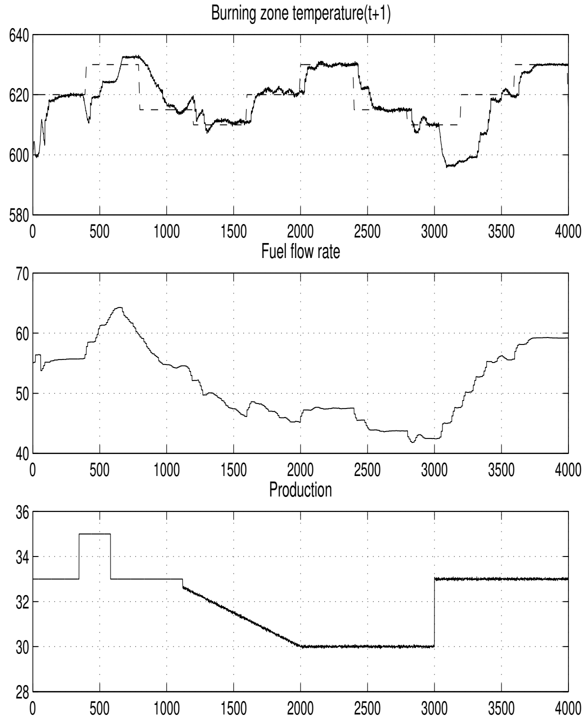

Figure 7: Controller testing with the LE simulation model.

linguistic equation controllers, in which the basic PI type LE controller is extended by a working point controller and a module for asymmetry handling and braking. This approach has been applied to the control of the burning end of the lime kiln. The burning end controller is a multilevel linguistic equation controller (Järvensivu and Juuso, 1998). This new type of controller was first implemented on a solar collectors field in a solar power station at Plataforma Solar de Almeria (Juuso et al. 1997, 1998b).

A multilevel linguistic equation controller has been tested with the simulation model of the lime kiln (Figure 7). For constant production rate, set point tracking is fast with very smooth fuel feed changes. The controller operates very well for smooth production rate changes as well. Compensation of disturbances caused by fast production rate changes take more time since the lime kiln process is slow. For safety reasons, the maximum cumulative change of control on predefined time intervals is limited, and this saturation can be seen in the cases of fast production rate changes. Model-based predictive control could be a useful method in tuning these limits for different operating areas.

The multilevel LE controller is now on on-line use in an industrial lime kiln, and the experiences are very similar to the simulation results. Smooth production rate changes are found to be preferable also in the real process. Tuning of the LE controller with the robust dynamic simulator is needed because the process is slow, e.g. the simulation shown in Figure 7 corresponds to almost three days operation. Also testing with the solar power station is continuing, and the same technique will tested in the rotary dryer as well (Juuso 1999). The robust dynamic simulator based on linguistic equations is an essential tool in fine- tuning of all these controllers.

APPLICATIONS

Lime kilns are used in paper industry to convert lime mud to lime in the recovery cycle. Because of the large quantities of lime mud handled, it is desirable to employ an effective control scheme for the economical production of good quality lime. The control of the lime kiln is multivariable by nature. The reaction time in a rotary kiln system is long and varying and there is a large quantity of lime mud and lime in process within the system at any given time. Classical model based supervisory control of process is nearly impossible, and the experience of veteran operator is often the best solution. Control changes should be made in small increments, allowing sufficient time to observe the effect after each change has been made. Overreaction leads to overcompensation, which generally causes oscillations and upsets which may take hours to bring back to normal operation.

Control Engineering Laboratory, University of Oulu has been active in lime kiln modelling and control (Juuso et al. 1996): the very early modelling studies in 70's led to a commercial computerised control system for the lime kiln; lime kiln models were also included in a steady-state flowsheet simulation package; later sensor based applications and an expert system application for lime kiln control were studied; good results were also gained using fuzzy control in an actual rotary lime kiln in the beginning of 90's. Construction of the rule-base and tuning of the controller was done in co-operation with personnel.

A new fuzzy modelling technique based on Linguistic Equation (LE) approach was introduced in (Juuso et al. 1996). In the modelling, data from an industrial scale lime kiln at Wisaforest Pietarsaari mills and from the fuzzy control system developed for it. The LE approach was used in replacing and developing the control rules of fuzzy controller for the lime kiln flue gas fan. Rule-based deduction was replaced by matrix operations by using integers instead of linguistic levels. Fuzzy logic control has been successfully implemented in the control of an industrial scale lime kiln. This experience is now transferred to a wider control system. The LE approach proved to be a flexible and compact method for developing and testing complex systems.

Another simulator has been developed for a solar power station in Spain. According to the test results at the Plataforma Solar de Almeria, the dynamic simulator of the solar collector field represents very accurately the field operation. In steady weather conditions, the present simulator operates within maximum 2 K error. Oscillatory conditions are also handled correctly. The simulator is based on the multiple model approach and linguistic equations. Dynamic LE models have been used in tuning of LE controllers for a solar power plant and for a lime kiln.

CONCLUSIONS

A hybrid of various adaptive and intelligent methods is a feasible solution for modelling of lime kilns, and the LE approach is a flexible platform for combining expert knowledge, experimental data and simulation results. Adaptive multilevel linguistic equation controllers can be developed by the same methodology. For the lime kiln, the implementation of the LE controller was originally based on these tests with the LE simulators. At present the developed LE controller is used in on-line control at the UPM Kymmene Pietarsaari mills. Similar dynamic LE simulators are now continuously used in the controller design.

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