Linguistic Equation Based Data Analysis for Fault Diagnosis and Forecasting

Esko K. Juuso
Control Engineering Laboratory, Infotech Oulu and Department of Process Engineering
University of Oulu, P.O.Box 4300, FIN-90410 Oulu, Finland
Phone: +358-8-5532463, Fax: +358-8-5532466
email: esko.juuso@oulu.fi

ABSTRACT: Linguistic equations are useful for taking into account non-linearity especially in multivariable application systems. The main benefit **{**XE "fuzzy logic"**}{**XE "linguistic relations"**}** is better and more accurate decision-making due to the model-based approach and systematic knowledge management**{**XE "material purchasing"**}**. Insight to the process dynamic operation is the most important issue. Automatic generation of systems, model-based techniques and adaptation techniques are very valuable in developing and tuning systems for fault diagnosis and forecasting. The linguistic equation approach increases the performance by combining various specialised models in a case-based approach. The LE approach is very efficient as a modelling technique: models can be generated from data, various types of fuzzy rule-based models can be represented by LE models, and any LE model can be transformed to fuzzy rule-based models. The LE approach is successfully extended to dynamic modelling.

KEYWORDS: data analysis, linguistic equations, fuzzy modelling, case-based reasoning, decision making, dynamic simulation, adaptive systems, nonlinear systems, multivariable systems

INTRODUCTION

The process industries face considerable control challenges, especially in the consistent production of high quality products, more efficient use of energy and raw materials, and stable operation on different conditions. The processes are nonlinear, complex, multivariable and highly interactive. Usually, the important quality variables can be estimated only from other measured variables. Constraints, e.g. physical limitations of actuators must be taken into account. Significant interactions between process variables cause interactions between the controllers. Various time-delays depend strongly on operating conditions and can dramatically limit the performance and even destabilise the closed loop system. Uncertainty is an unavoidable part of the process control in real world applications.

For the overall production processes, the control systems take care of several subprocesses. For example the overall performance of paper machines can be rated to the operating efficiency, which is the percent of time the sheet is on the reel divided by the time machine is ready to make paper. Operating efficiency varies depending on breaks and the duration of the operations caused by the web break. The web breaks account for 2 –7 percent of the total production lost. The reason for breaks can be classified to process related, mechanics related and automation related breaks. Most of the indistinct breaks are due to dynamical changes in the chemical process conditions. The process related breaks are especially important in the wet end of the paper machine. These parts of the process are continuous, nonlinear and there are many and long time varying delays. There are also process feedbacks at several levels, closed control loops, factors that exist and cannot be measured and interactions between physical and chemical factors.

Different things are emphasised in the process industry and in the electronic manufacturing industry, but the process control needs to be more and more adaptive in both industrial areas. The production control should utilise the degrees of freedom in the process control to be able to reschedule the production on an appropriate way in changing operating conditions. All the time various possibilities are open to those who can utilise them. Fuzzy set systems can improve these systems in many ways. Linguistic equations provide a new novel technique for combining expertise and data to make the overall production control easier. The technique has been developed in process control and modelling, where it extends the possibilities of fuzzy set systems. Because of very compact implementation, these systems can be extended to both case-based and dynamic applications.

Linguistic equation approach combines various intelligent modelling techniques on a unified framework: it was originally developed for handling large knowledge bases in process design [Juuso 1999]; a close connection to fuzzy set systems was important already in the early applications; 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. The LE approach is already used in control [Juuso et al. 1997, Juuso et al. 1998b], in intelligent analysers [Murtovaara et al. 1998], in fault diagnosis [Juuso et al. 1998a], and in model based control design [Juuso 1998].

Fault diagnosis and intelligent analysers are combined in *model-based diagnostical process analysis (MDPA*) [Juuso 1997]: the resulting systems can be used in various ways suitable for software sensors, risk analysis and detection of sensor failures. Sophisticated trend information can be utilised by temporal reasoning on the recent process history. The MDPA methodology has been tested with simulations, expert knowledge and real data.

In changing operating conditions, the forecasting problem consists of following subproblems:

- *Classification:* Fault diagnosis is based on classification. Operating conditions should also be detected before forecasting since they will define the process dynamics.
- *Dynamic modelling:* Dynamic models are developed for each case on the basis of an appropriate data cluster. Fuzzy set systems combine these models into a smoothly operating overall model.

This modular approach can aid in understanding the problem. Structures used for multilevel linguistic equation controllers [Juuso et al. 1997, Juuso et al. 1998b] are applicable to dynamic modelling and forecasting as well. Data analysis discussed in this paper is normally linked with assessment based on expert knowledge, especially in large case-based systems [Juuso et al. 1998a].

INTELLIGENT KNOWLEDGE BASED CONTROL

Most industrial applications of fuzzy control are based on using expert knowledge. Fuzzy modelling can increase the performance of controllers extensively. The adaptive fuzzy control is also mainly related with model-based techniques. The linguistic equation approach extends the performance of the fuzzy control in many ways. The number of the fuzzy control applications has increased very fast, especially during the 90's. Traditionally, the rule base is constructed from expert knowledge by trial-and-error, and most applications are still based on this approach. Various methodologies have been developed for automatic generation of fuzzy systems and inverting fuzzy models; i.e. fuzzy systems can be regarded as flexible mathematical approximation tools. However, the fuzzy controllers should be kept transparent to interpretation and analysis on the basis of understanding the process behaviour since this insight is more important than close correlation to experimental data.

Many fuzzy controllers are implemented as two dimensional fuzzy logic decision tables where control actions and input conditions are expressed in terms of membership functions. The rule base is essentially linear, and the nonlinearity can be introduced by adjusting membership functions or by modifying rules. Modified rule bases are used in multivariable controllers, especially for feedforward purposes. Some experiments with automatic control based on deterministic decision tables were carried out already before fuzzy control. For a cement plant, these decision tables were inspired by instructions found in a textbook for kiln operators, which contained the control rules for manual operation. First experiments with real cement plants were done since 1972 in Denmark [Juuso 1999].

Linguistic equations have been used in replacing and developing control rules for FLCs. This approach can easily be combined with other approaches for FLC design, e.g. to a conventional way of acquiring knowledge from experts by interviews. The traditional fuzzy systems described by if-then rules are represented by matrix equations if nonlinearities are handled by membership functions. The original approach has been extended to fuzzy and real valued linguistic equations with variable specific partition levels [Juuso 1999]. For a symmetrical fuzzy PI type controller, all the rules can be obtained from a single linguistic equation

$$\Delta u = e + \Delta e \,,$$

which is a special case of the matrix equation

$$A \cdot X + B = 0 \,,$$

where the interaction *matrix A = [1 1 –1]*, the bias term *B = 0*, and variables $X = \begin{bmatrix} e & \Delta e & \Delta u \end{bmatrix}^T$. In the rule base, the linguistic values {NB, NS, ZO, PS, PB} are replaced by integer numbers -2, -1, 0, 1 and 2. The control surface of the fuzzy PI controller can be obtained by using the integer valued linguistic equation together with trapezoidal membership functions. Alternatively, fuzzy rule bases are represented by real valued relations [Juuso 1999].

The LE controller produces on any fuzzy partition a rule set, which is complete, consistent, and continuous. If a non-complete set is satisfactory, a part of the rules can be deleted already before tuning. The best similarity with the LE controller is achieved if the positions of all the fuzzy sets are coordinated with the real valued linguistic equations. The real valued LE controller provides a very smoothly changing control surface (Figure 1). Feedforward controllers based on steady state models can have interactions with different strengths. Linguistic equation controllers implemented on the basis of real valued equations need only the *membership definitions*. Nonlinearity is introduced to the system by membership definitions, which correspond to membership functions used in fuzzy logic controllers.

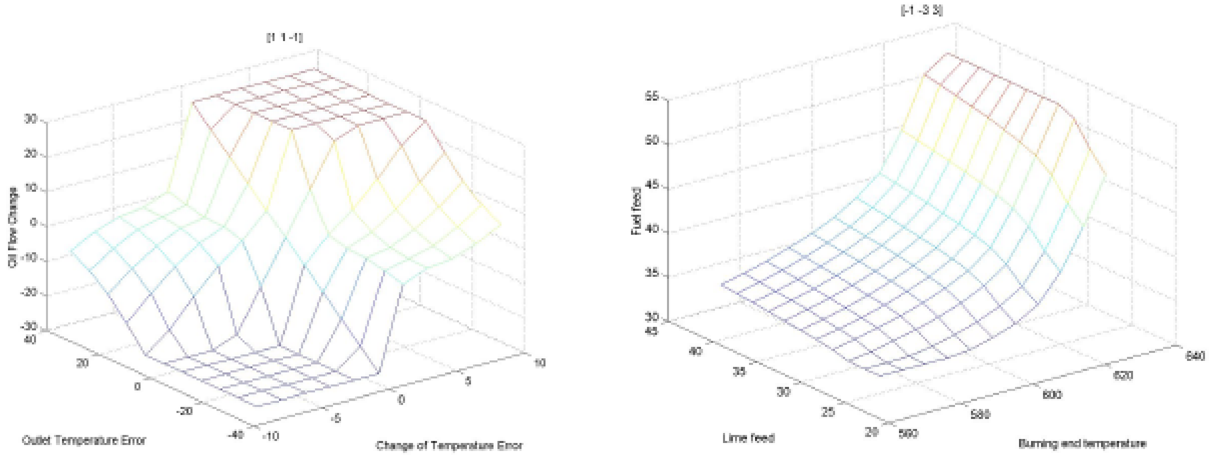

Figure 1: Examples of linguistic equation controllers

For large disturbances, this controller implementation can lead to a large overshoot, which is problematic if small control actions are required, e.g. in oscillation situations. This problem is removed by taking the original error into account. The *braking action* is implemented by a correction, which increases the importance of the change of error Δe when the controlled variable goes towards the setpoint, i.e. the LE controller tries to slower the speed of error compensation already before the error goes to zero. The braking action is automatically activated when the error becomes large enough, and the system returns to the normal operation when the fast trend is removed. In changing operating conditions, some trends may push the controlled variable causing a slight offset, which is removed very slowly if the control surface is symmetric. Since different asymmetry is needed in different working conditions, the *asymmetrical correction* is defined by the trend variable. If several trends effect to the offset, an asymmetry equation can be introduced. This action is not used simultaneously with the braking action [Juuso 1999].

This implementation is very compact if compared with model-based predictive controllers, which are an alternative solution for these situations. The overall operation corresponds to a three-level cascaded controller:

- Basic PI type LE controller handles the normal operation with symmetrical membership definitions;
- Operation condition controller changes the control surface of the basic LE controller by modifying the membership definitions for the change of control variable;
- Predictive LE controller changes the membership definitions for the derivative of the error. This level contains both the braking and asymmetrical actions.

MODELLING WITH LINGUISTIC EQUATIONS

Fuzzy modelling is an extension 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 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 [Babuska et al. 1997]. All these models can approximate both static and dynamic nonlinear systems. Data-driven fuzzy modelling can be based on various methodologies, e.g. fuzzy clustering, self-organizing maps, neurofuzzy methods and linguistic equations. Different approaches can be combined in the tuning phase: the linguistic equation approach is designed for combining different sources of information.

Each linguistic 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. Nonlinearities are taken into account by membership definitions that consist of two polynomial functions, one for positive and one for negative side labels. The control surfaces shown in Figure 1 are both based on a single linear equation and three membership definitions. Additional examples of membership definitions are shown in Figure 2. 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 b*ig); *normal* (or *zero*) is always zero. After the matrix calculations, the outputs are mapped from linguistic level to the real scale. Since only five parameters are needed for each variable, the LE systems can be adapted to various working conditions.

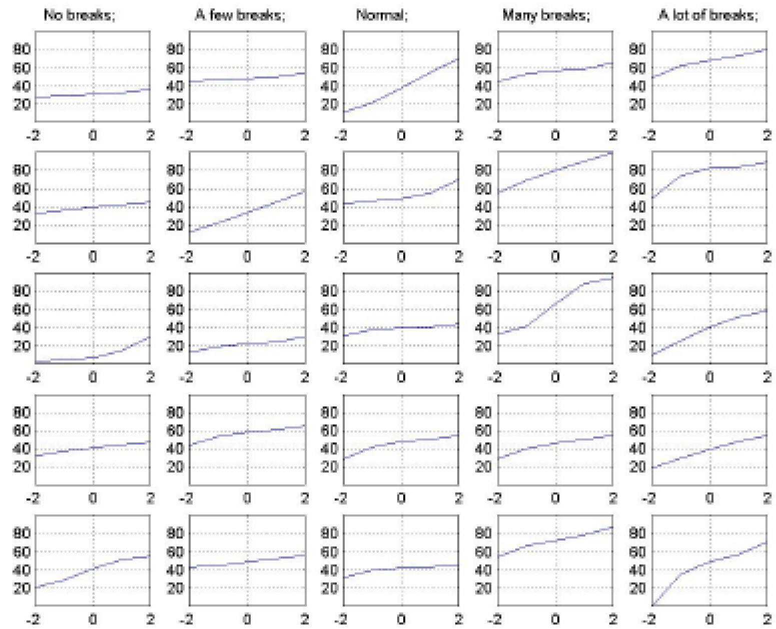

Figure 2: Examples of membership definitions for several cases.

Usually, fuzziness is taken into account by membership definitions - linguistic equations approach does not necessarily need any uncertainty or fuzziness. However, also the linguistic equations can be used in fuzzy form [Juuso 1999], i.e. all the variables are not included to the model. The fact that experts do not always agree with interactions can also be taken into account by using several interaction matrices with different coefficient values. On the other hand, the directions of interactions can depend on the working area in nonlinear systems. In these cases, different interaction matrices have different degrees of membership. Different combined effects can be taken into account as well.

Real valued linguistic equations (RLE) provide a basis for sophisticated nonlinear systems where fuzzy set systems are used as diagnostical tools. Fuzzification and defuzzification are integrated to the flexible scaling generated for membership definitions [Juuso 1999]. These systems can be tuned by neural networks, e.g. self-organizing maps and linear networks have been tested. Linguistic equations provide a method for generalising results of neural networks. A real valued linguistic equation system can be even considered as a new neural network type. Extension to real numbers was introduced because of difficulties to handle variables with dissimilar fuzzy partitions. The RLEs are also used in a tuning algorithm for reducing the error between model and training data.

The modelling can be done with *FuzzEqu* toolbox created in *Matlab®* environment. Automatic data analysis is started with generating the membership definitions from the data (Figure 3). Linguistic equations are developed from real valued relations obtained from the data by nonlinear scaling based on the membership definitions. In small systems, the directions are usually quite clear: only the absolute values of the coefficients need to be defined. For more complex systems, a set of alternative equations is developed first, and the final set of equations is selected on the basis of error measures and process knowledge. Membership definitions can be tuned for selected variables: the variable alternatives are restricted by the equation set. The tuning is implemented as a linear neural network. Some equations can be removed from the equation set during the tuning phase if there are problems in tuning for certain variables. This will affect to the whole set because each equation should bring at least one variable that is not included to other equations.

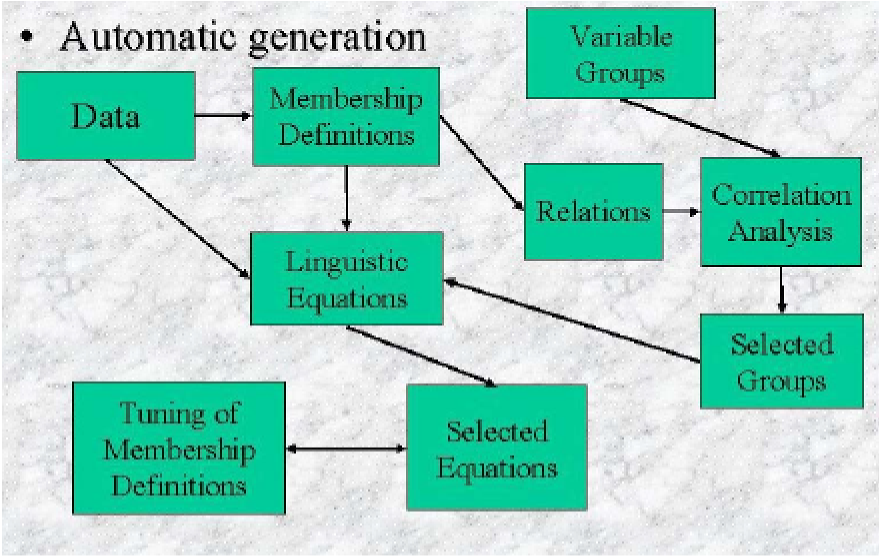

Figure 3: Automatic data analysis in the *FuzzEqu* Toolbox.

For large systems, the number of possible variable combinations becomes very large, e.g. the case models of the web break indicator system includes 24 variables, which means that there are 2024 alternative three variable interactions. Most of these alternatives are useless, and therefore, correlation analysis is used for selecting alternative groups for processing (Figure 3). In this application, the number of selected groups reduces to 100…300. For the models, only from 7 to 22 equations are needed (Figure 4), i.e. usually much less than 1 % of the original alternatives. The last column is the bias vector, which is essential in fault diagnosis. The final set of selected groups can be built in a modular way: some groups may include also four or five variables, and different subgroups can be developed for different subsets of variables. Redundant measurements are included to the same groups only for the fault diagnosis of measurement devices.

All the tasks shown in Figure 3 can be performed automatically, but more important is that any intermediate result can be modified on the basis of expertise. The *FuzzEqu* toolbox contains routines for modifying membership definitions interactively: definitions can be extended or contracted independently on positive or negative or on both sides; definitions can be moved as well. All proposed changes are checked in the *FuzzEqu* Toolbox. With these tools the system can be adapted to changing operating conditions.

Fuzzy models can be changed into linguistic equation models by replacing linguistic labels with real numbers. The *FuzzEqu* toolbox [Juuso 1999] includes routines for building a single LE system from large fuzzy systems including various ruleblocks implemented in *FuzzyCon* or *Matlabâ FuzzyLogic Toolbox*. Other fuzzy modelling approaches can be used as channels for combining different sources of information. Fuzzy models on any fuzzy partition can be generated from LE models: rules or relations are developed either sequentially or simultaneously [Juuso 1999], and membership functions are generated from the membership definitions on any location. Every equation can define the location of each membership function for one selected variable.

CASE-BASED MODELLING WITH LINGUISTIC EQUATIONS

In the case-based modelling, non-linear multivariable models are constructed for each case in three parts: directions of interaction are handled with linear equations, and nonlinearities are taken into account by membership definitions, and time delays depend on operating conditions (process cases). Membership definitions are generated directly from process data on the basis of areas of operation and variation for each process case. An example of membership definitions for one variable is presented in Figure 2. In this Figure web break sensitivity increases from left to right and there are five examples in each category. Similar set of membership definitions is developed for 32 variables. Totally the prototype includes 25 sets of equations, one for each process case. The set of equations includes typically from 7 to 22 equations. Although the web break indicator consisting of two subsystems corresponds to a fuzzy system with 30,000 rules, it runs real time in a normal PC.

Knowledge based information can be handled almost in the same way in the LE based data analysis. In these applications, various fuzzy rule bases are generated by personnel interviews and data collected from databases, e.g. in the functional testing project, the steps of various measurements are variables and they are grouped as a group of measurements. Different groups consist of 1 - 4 variables and 3 - 50 rules and the total number of rules is more than 300. Each variable has 3 or 5 membership functions. The fuzzy rule base has been tested with real test data by using *FuzzyCon*, which is a Windows application developed in Control Engineering Laboratory [Juuso 1999]. The reliability of the rules has been verified and membership functions have been tuned during the testing [Komulainen et al. 1997]. The *FuzzEqu*-toolbox has been used to form linguistic equations from rules and data.

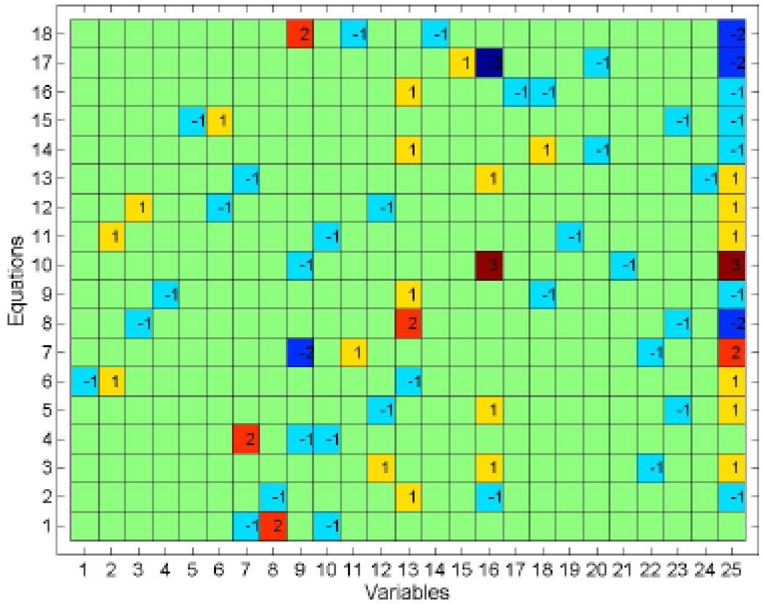

Figure 4: An example of the interaction matrix *A* for a single case.

DYNAMIC MODELLING WITH LINGUISTIC EQUATIONS

Dynamic fuzzy models can be constructed on the basis of state-space models, input-output models or semi-mechanistic models [Babuska 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. 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. Dynamic neural networks and linguistic equations can be based on similar structures as the dynamic fuzzy models [Juuso 1998].

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 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.

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. A multimodel approach based on fuzzy LE models has been developed for combining specialised submodels [Juuso 1998]. 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 multimodel approach, the working area defined by a separate working point model. The submodels are developed by the case-based modelling approach.

APPLICATIONS

Fault diagnosis applications require various specialised knowledge and large amounts of data. Although the system development can be started either from knowledge or from data, an appropriate performance is achieved only by combining both data and knowledge. The forecasting problem is closely related to the dynamic simulation.

The *web break indicator* is aimed to give process operators a continuous indication of web break sensitivity in an easily understandable way. The effect of different process variables on the sensitivity to web breaks has been analysed using actual measurements from a paper machine. The data contains 43 different measurements on the time period of three years. In addition to the actual measurements, the data also contains information of the break occurrence. The development work is concentrated on the consistency of the machine pulp and other variables effecting the operation of the mixing chest. Altogether 32 variables have been included in the analysis for two parallel versions of the indicator. The web break indicators have been implemented as Case-Based-reasoning –type applications with Linguistic Equation approach. The indicators compare online data to example cases in the database and give a numerical estimation of the risk level of web breaks as an output. Both versions have been tested with off-line data and also some online experiments have been carried out at a paper mill. According to these results, both versions of the web break indicator seem to operate as planned.

Functional testing is the main method to prevent defective products to be delivered to customers. Test personnel has a lot of knowledge on reasons of different kind of failures. An adaptive and intelligent system has been developed using process failure information in the functional testing of plug-in units [Komulainen et al. 1997]. Only few human experts with long experience can handle the complicated relations to the production process. Most common failures are easy to find based on failure information, but additional measurements are often needed. One of the problems in functional testing is the inexactness of failure information. A failed or damaged component is identified using information, which points the place of the failure. A fuzzy rule base has been generated by personnel interviews and data collected from databases. The steps of various measurements are variables and they are grouped as a group of measurements. The system consists of three levels of hierarchy: channel level, group level and step level. When there is a lot of failed test results, conclusions are made using rules, which indicate the right group. Rules have partly been represented by linguistic equations.

Forecasting is based on the same approaches as dynamic simulation and intelligent analysers. Dynamic LE models have been tested in control design for a solar power plant at Plataforma Solar de Almería and for a lime kiln at UPM Kymmene Pietarsaari mills. 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. In these applications, the temperatures can be forecasted for very long periods of time. This multimodel approach based on fuzzy LE models can applied to different forecasting problems. Some properties of the fuzzy multilevel approach can be transformed into new structures similar to those used in the multilevel LE control.

Forecasting problems can be handled with intelligent analysers. Linguistic equation models have been developed to forecast Kappa number in continuous cooking. By measuring the liquor concentrations from different circulations of the digester the Kappa number can be estimated in different stages of the cooking process. The control actions can be done before the pulp will reach the blow line of the digester. Measurements of the ABB's Cooking Liquor Analyzer (CLA 2000), temperature and the on-line Kappa measurement have been used in the modelling. According to the tests in different plants, the linguistic equation models work better than the neural network and regression models. The LE model is very suitable for the prediction because it is not so sensitive for changes in process conditions. Linguistic equations offer also tools for adaptive modelling the system in several operating conditions [Murtovaara et al. 1999].

CONCLUSIONS

Linguistic equations are useful for taking into account non-linearity especially in multivariable application systems. The main benefit **{**XE "fuzzy logic"**}{**XE "linguistic relations"**}** is better and more accurate decision-making due to the model-based approach and systematic knowledge management**{**XE "material purchasing"**}**. Insight to the process dynamic operation is the most important issue. Automatic generation of systems, model-based techniques and adaptation techniques are very valuable in developing and tuning the controllers. The linguistic equation approach increases the performance by combining various specialised models in a case-based approach. The LE approach is very efficient as a modelling technique: models can be generated from data, various types of fuzzy rule-based models can be represented by LE models, and any LE model can be transformed to fuzzy rule-based models.

The linguistic equation approach is successfully extended to case-based modelling and dynamic modelling. Case-based approaches have used in fault diagnosis. For functional testing, large fuzzy expert systems were systematically constructed from expert knowledge. For most cases, the rule base was transformed into a compact set of linguistic equations. These applications provide a good basis for wider use of intelligent systems together with other techniques in improving fault diagnosis and forecasting.

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