INTELLIGENT DYNAMIC SIMULATION OF A SOLAR COLLECTOR FIELD

Esko K. Juuso
Control Engineering Laboratory
Department of Process and Environmental Engineering
FIN-90014 University of Oulu, Finland
Mail: esko.juuso@oulu.fi

KEYWORDS

Solar power plant, dynamic modelling, intelligent simulation environments, non-linear models, linguistic equations, fuzzy set systems

ABSTRACT

Linguistic Equation (LE) modelling approach has various applications in non-linear multivariable systems. Insight to the process dynamic operation is maintained, and automatic generation of systems, model–based techniques and adaptation techniques can be applied in developing and tuning systems for process modelling and control. The multimodel LE approach provides a compact modelling of more or less smooth input–output dependencies. The overlapping operating areas are obtained by fuzzy clustering. The Fuzzy–ROSA method (FRM) serves for a data–based rule generation to model a given input–output dependency and is efficient for modelling complicated local non-linear structures. These properties are combined in a hybrid data–based modelling concept applied to dynamic simulation of a solar collector field. The hybrid fuzzy LE simulator was tested in data–based modelling of dynamic behaviour of a solar collector field. The new adaptive controller tuned with this technique has reduced considerably temperature differences between collector loops. Efficient energy collection is achieved even in variable operating condition.

INTRODUCTION

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 techniques are necessary at least on the tuning phase. Adaptation to various non-linear 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 linguistic equation controllers, in which the basic PI type LE controller is extended with a working point controller and a module for asymmetry handling and braking. This new type of controller was first implemented on a solar collectors field in a solar power station at *Plataforma Solar de Almeria* [JBL97, JBV98]. Adaptive set point procedure and feed forward features have later been included for avoiding overheating. The present controller takes also care of the actual set points of the temperature [JV03].

The multilevel linguistic equation controller has been applied in the control of the burning end of the lime kiln [JJA01]. The multilevel LE controller has been in on–line use in an industrial lime kiln for more than four years, and the experiences are very similar to the simulation results [Juu98]. Smooth production rate changes are found to be preferable also in the real process. The robust dynamic simulator based on Linguistic Equations is an essential tool in fine–tuning of all these controllers.

SOLAR POWER PLANT

The aim of solar thermal power plants is to provide thermal energy for use in an industrial process such as seawater desalination or electricity generation. If such plants are to provide a viable, cost effective alternative to more polluting forms of power production, they must achieve this task despite fluctuations in their primary energy source, the sunlight. In addition to seasonal and daily cyclic variations, the intensity depends also on atmospheric conditions such as cloud cover, humidity, and air transparency. The purpose is not to maintain a constant supply of solar produced thermal energy in spite of the disturbances. Rather the aim of the control scheme should be to regulate the outlet temperature of the collector field in order to supply steam to the turbine in a range as constant as possible despite disturbances, changes of the solar radiation, ambient temperature, inlet oil temperature etc.

This is beneficial in a number of ways. Firstly, it collects any available thermal energy in a usable form, i.e. at the desired temperature, which improves the overall system efficiency and reduces the demands placed on auxiliary equipment as the storage tank. Secondly, the solar field is maintained in a state of readiness for the resumption of full-scale operation when the intensity of the

Proceedings 15th European Simulation Symposium
Alexander Verbraeck, Vlatka Hlupic (Eds.)

ISBN 3-936150-28-1 (book) / 3-936150-29-X (CD)

sunlight rises once again; the alternative is unnecessary shutdowns and start-ups of the collector field, which are both wasteful and time consuming. Finally if the control is fast and well damped, the plant can be operated close to the design limits thereby improving the productivity of the plant.

All the experiments were carried out in the *Acurex Solar Collectors Field of the Plataforma Solar de Almeria* located in the desert of Tabernas (Almeria), in the south of Spain. The *Acurex field* supply thermal energy (1 MW) in form of hot oil to an electricity generation system or a Multi–Effect Desalination Plant. The solar field consists of parabolic–trough collectors [JBL97, JBV98]. Control is achieved by means of varying the flow pumped through the pipes during the plant operation. In addition to this, the collector field status must be monitored to prevent potentially hazards situations, e.g. oil temperatures greater than 300 ^oC. When a dangerous condition is detected software automatically intervenes, warning the operator and defocusing the collector field.

Trial and error type controller tuning does not work since the operating conditions cannot be reproduced. The dynamic of the process depends on the general field operating conditions and characterised by the following aspects:

- Time varying transport delay depends on the manipulated variable (oil flow rate).
- The dynamics, in particular high frequency peaks in the frequency response of the plant, is difficult to model.
- The plant has a non-linear behaviour, and therefore linearised models depend on operating point.
- The solar radiation acts as a fast disturbance with respect to the dominant time constant of the process.

Test campaigns cannot be planned in detail because of changing weather conditions. Usually, test campaigns include step changes and load disturbances. Weather conditions take care of irradiation disturbances. As the process must be controlled all the time, modelling is based on process data from controlled process.

Operating conditions cannot be reproduced and weather conditions have seasonal differences. Therefore, dynamic simulators are needed in controller design and tuning. Conventional mechanistic models do not work: there are problems with oscillations and irradiation disturbances. For non-linear multivariable modelling on the basis of data with understanding of the process there are two alternatives: fuzzy set systems and linguistic equations.

DATA–BASED MODELLING

For the modelling of technical complex processes one is often restricted to only with data–based methods since a complete mathematical process description is not practicable with justifiable expenditure. 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.

Intelligent methods have extended the toolbox to 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. Linguistic equations have close links to both fuzzy set systems and neural networks.

Data Preprocessing

Direct measurement value is not always best one to be used in modelling. Sometimes moving variances, standard deviations or value ranges are more informative for the phenomena. Also moving skewness and kurtosis can be obtained. Selecting appropriate window for this moving statistics is also an important decision. Trend removal on the basis of the user defined window (moving average or median) can be included to the preprocessing if the variation around the trend is important for the modelling.

The FuzzEqu Toolbox developed in Matlab-Simulink environment provides tools for experimenting with different methods and windows [Juu00]. The data set is updated only after accepting the operation. Several statistical operations can applied also sequentially to the data, e.g. after trend removal the resulting data can be analysed other statistical methods. For small systems, delays can be taken into account by moving the values of input variables correspondingly.

Linguistic Equation Approach

Linguistic equation models consist of two parts: *interactions* are handled with linear equations, and nonlinearities are taken into account by *membership definitions* [Juu99]. The basic element is a compact equation

$$\sum_{j=1}^{m} A_{ij} X_j + B_i = 0, \qquad (1)$$

where X_j is a linguistic level for the variable j, $j = 1...m$. Linguistic values very low, low, normal, high, and very high correspond to integer numbers -2, -1, 0, 1 and 2. The direction of the interaction is represented by interaction coefficients A_{ij}. The bias term B_i was introduced for fault diagnosis systems. Linguistic equations can be used to any direction. The directions of interaction are usually quite clear in this kind of small systems: only the absolute values of the coefficients need to be defined.

The membership definition is a non-linear mapping of the variable values inside its range to a certain linguistic range, usually $[-2, 2]$. The mapping is represented with two monotonous, increasing functions, which must overlap in the center at the linguistic value 0. In the present system, these functions are second order polynomials. Coefficients are extracted from data or defined on the basis of expert knowledge.

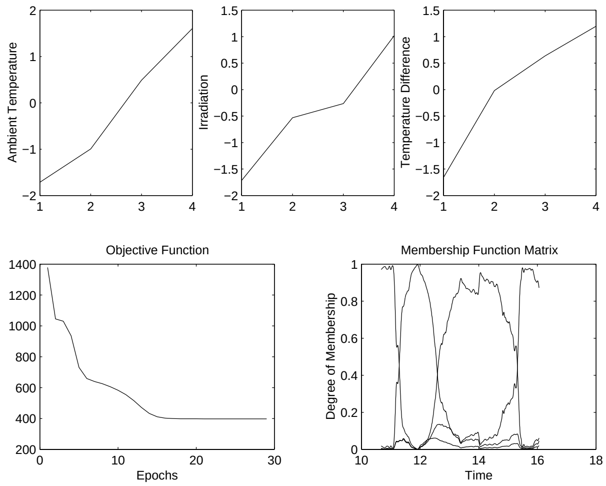

Figure 1: Four operating areas obtained by Fuzzy C-Means Clustering.

Modelling with linguistic equations has following stages:

- Membership definitions are generated by using preprocessed data.
- Linguistic relations are obtained by non-linear scaling.
- Linguistic equations are generated from the scaled data denoted as linguistic relations.
- Selecting equations from alternatives is based either on the overall fit or on the prediction performance.
- Tuning modifies membership definitions, linguistic equations or both to improve fitting to the training data.

Real-valued approach is now the main method in applications because of efficient tuning techniques. A neural network based tuning can be done for selected variables. A recently generated genetic tuning method can handle several variables at a time by varying parameters of membership definitions.

The modelling technique can be extended to several equations as well, e.g. by using Takagi-Sugeno (TS) type fuzzy models together with ANFIS method for development of local linear models for different operating areas. As *LE* models are non-linear, also these local models are non-linear.

For model development, the training data consist of several data sets. Some overlap of the working point areas is automatically introduced when process data is used. Fuzzy C-Means Clustering is used for finding these overlapping operating areas (Figure 1). Alternatively the operating areas can be obtained by Self-organizing Maps as well (Figure 2). The delays are taken into account in tuning. The interaction matrix is normally 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.

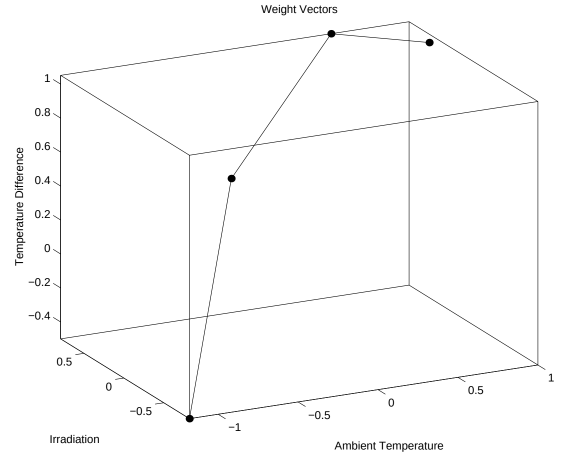

Figure 2: Four operating areas obtained by a Self-organizing Map.

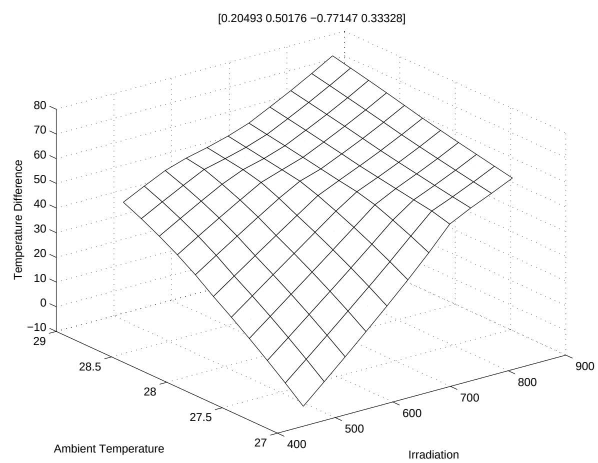

Figure 3: LE model for working point variables.

The working point variables already define the overall normal behaviour of the solar collector field. The model shown in Figure 3 has a quite high correlation to the real process data (Figure 4). The differences have a clear relation to operating conditions, e.g. oscillatory behaviour is a problem when the temperature difference is higher than the normal. Separate dynamic models (Figure 5) are needed to capture the dynamic behaviour in different operating conditions (Figure 1).

The *FuzzEqu* toolbox contains tools for all the development and tuning stages described above [Juu00]. It also contains routines for modifying membership definitions interactively to adapt the models to changing operating conditions and routines for building *LE* systems from large fuzzy systems including various ruleblocks implemented in FuzzyCon or *Matlab*(r) FuzzyLogic Toolbox. Other fuzzy modelling approaches can be used as channels for combining different sources of information. Fuzzy systems as *Dora for Windows* bocks can be included in *Simulink* environment.

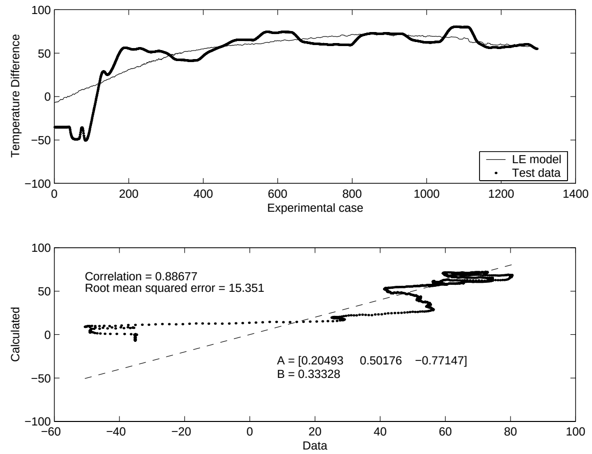

Figure 4: LE model for working point variables.

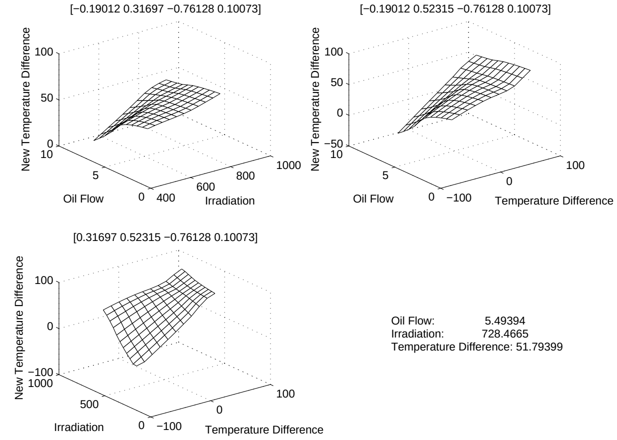

Figure 5: A dynamic LE model for temperature difference.

Dynamic LE modelling

Dynamic fuzzy models can be constructed on the basis of state–space models, input–output models or semi–mechanistic models [Juu99]. 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 /Non-linear AutoRegressive with eXogenous input) model which establishes a relation between the collection of past input–output data and the predicted output:

$$y(k+1) = F(y(k), ..., y(k-n+1), u(k), ..., u(k-m+1)), \tag{2}$$

where k denotes discrete time samples, n and m are integers related to the systems' order. Multiple input, multiple output (MIMO) systems can be built as a set of coupled multiple input, single output MISO models.

Effective delays depend on the working conditions (process case); e.g. the delays are closely related to the production rate in many industrial processes. Initial estimates of the delays can be developed by correlation analysis, but similarities detected by the correlation analysis can be accidental in some cases. The delays should be assessed against process knowledge, especially if normal on-line process data is used [Juu99]. An appropriate handling of delays extends the operating area of the model considerably.

The basic form of the *LE* model is a static mapping, and therefore dynamic *LE* models could include several inputs and outputs originating from a single variable [Juu99]. However, 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. Comparisons with different parametric models, e.g. autoregressive moving average (*ARMAX*), autoregressive with exogeneous inputs (*ARX*), *Box-Jenkins* and Output-Error (*OE*), show that the performance improvement with additional values is negligible.

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. Any equation can be rejected or modified on the basis of expert knowledge before or during the tuning phase.

The dynamic model of the solar collector field is based on a compact LE model for the temperature difference is shown in Figure 5. The new temperature difference between the inlet and outlet depends on the irradiation, oil flow and previous temperature difference. This model provides the driving force for the simulator, and the speed of the change depends on the operating conditions.

A multimodel 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 non-linearities. 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.

Various modelling methodologies have been compared for both dynamic and working point models in the FuzzEqu Toolbox. Feedforward neural networks, radial basis networks and ANFIS method provide better fitting to the training data but generalisation is worse in these systems as they include parts which are not consistent with process operation. Each LE submodel could include several alternative equations combined with fuzzy logic but these models have same overfitting problems. According to the tests with real process data, the fuzzy LE system with four operating areas is clearly the best overall model.

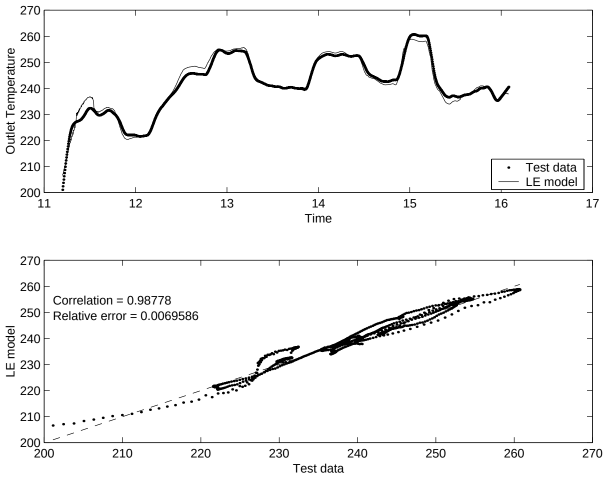

Figure 6: Simulation results of the LE model.

Fuzzy–ROSA Method (FRM)

The Fuzzy–ROSA[1] method (FRM) serves for a data–based generation of fuzzy rules which model a given input–output dependency. The basic idea of the FRM is to apply a relevance test to single fuzzy rules to assess their ability to describe a relevant aspect of the system under consideration. This reduces the problem of finding a good rule base to the problem of finding single relevant rules. On the other hand, since each rule with high relevance is supposed to express an important aspect of the system, such rules are meaningful by themselves, which leads to more transparent and comprehensible rule bases.

The FRM uses generalising (incomplete) rules, which consist of a varying number of linguistic statements (combination depth) in the premise. If there are fewer statements than input variables, one rule covers several linguistic input situations. The rule generation process is divided into four main steps [JSSK00]. There are alternative strategies available for each step, so that FRM can be adapted to different application requirements (e.g., for modelling, classification, approximation or prediction) and problem sizes (e.g., numbers of variables, linguistic values and data sets).

Combined Approach

Linguistic equation (LE) models provide a good overall behaviour in different operating conditions (Figure 6). Oscillations are well represented, and the temperature is on an appropriate range in the case of irradiation disturbances. However, some problems have been detected in extensive comparisons with process data: there is a shift in temperature level for some operating conditions. In some conditions the shift is positive and in some conditions negative. The present model needs

[1] **R**ule**O**rientated **S**tatistical **A**nalysis

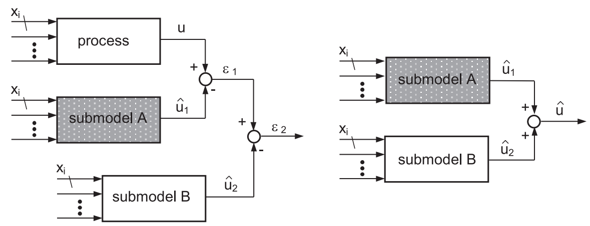

Figure 7: Cascaded modelling (left) and resulting model (right)

improvements also for load disturbances.

Flexible fuzzy models generated with the Fuzzy-ROSA method provided additional tools for these situations [JSSK00]. These fuzzy models are useful in handling special situations in limited operating range. However, functional relationship between the output variable and the input variable are partly smooth and partly complicated non-linear [JSSK00]. A *straightforward* application of the FRM may result in a high number of rules or an undesired competition between locally and globally acting rules.

To overcome these problems, a cascaded rule generation (Figure 7 left) has been proposed in [Kie99]: A first pass generates a submodel A for the more or less smooth global structure, a second pass generates a submodel B for the remaining usually locally complicated error ε_1 between submodel A and the real process. The final model is the superposition of the submodels A and B (Figure 7 right).

Since smooth dependencies can be described easily by simple equations, we take the Linguistic Equations (LE) as a promising approach for the generation of a compact submodel A. Since complicated local structures are efficiently detected by the FRM, we apply the FRM for the generation of submodel B. Thus the cascaded modelling with the LE and FRM combines the advantages of both methods, which can result in a considerable improvement of the quality of the resulting final model. Feasibility of the combined LE–FRM approach was demonstrated by applying it to a solar power plant [JSSK00].

Dynamic LE Simulator

The dynamic model for temperature difference between inlet and outlet temperatures of the collector field has been developed for the solar collector field. The simulator includes models for different operating conditions. Smooth transitions between the models are based on fuzzy logic. Working point model is defined by the irradiation and the difference between the inlet and outlet temperatures.

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

(Figure 6). In steady weather conditions, the present simulator operates within 2 degrees centigrade. Oscillatory conditions are also handled correctly. The simulator is based on the multimodel LE approach with four specialised LE models developed for different operating conditions. The simulator moves smoothly from start-up mode via low mode to normal mode. Later the field visits shortly in high mode and low mode before returning to low mode in the afternoon.

Correlation between the calculated and measured temperatures is very high for all time period: 0.992 for the whole day, 0.988 for the normal operating area and 0.961 for the start-up period. The relative errors are 2.9 percent for the whole day, 0.7 percent for the normal operating area and 16.8 percent for the start-up period [JSSK00].

For start-up the dynamic LE simulator requires improvement since the process changes considerably during the first hour [JSSK00]. The simulator underestimates the temperature growth because of unevenness of the oil flow. For radiation disturbances, the LE simulator operates quite well: the temperature is on the appropriate range all the time and the timing of the changes is very good. The simulator can also handle correctly oscillations although the dynamics depends on the operating point. A considerable temperature shift can be seen some periods. The LE model should be improved in these areas. Another alternative is to combine LE modelling and fuzzy modelling.

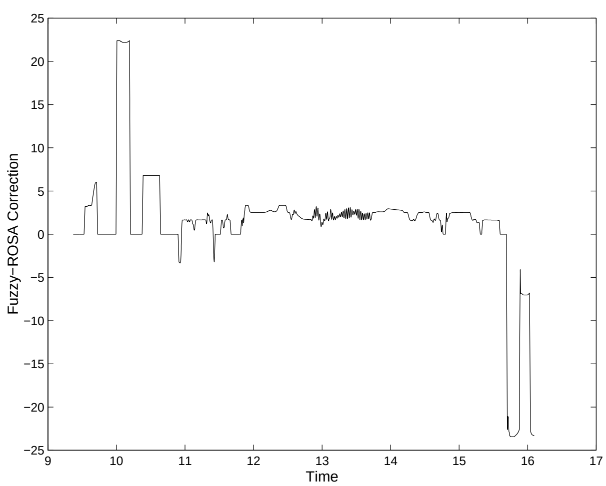

Figure 8: Model obtained with the FRM.

Fuzzy–ROSA Modelling

As described in Section we apply the FRM to model the remaining error of the LE-model. The learning data consist of simulation results of four selected days. In a preliminary feature selection process, we found the following seven input variables to be strongly correlated to the output variable: *daytime*, *oil flow*, *corrected radiation (moving average)*, *ambient temperature*, *delayed inlet temperature*, *delay* and *working point*.

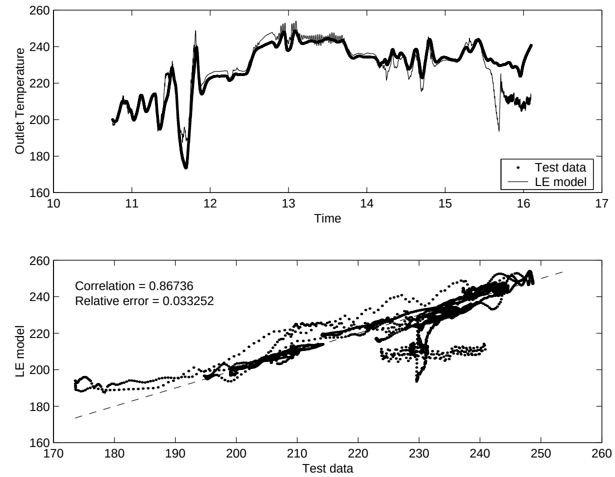

Figure 9: Simulation results of the the combined LE–FRM model.

In order to reduce the computational effort we use only these input variables for the fuzzy–modelling. The membership functions of the input and output variables are extracted knowledge based by considering their distributions. This leads to seven linguistic expressions for the input variables and nine for the output variable. For rule generation we apply a complete search considering all rules which refer to not more than four input variables (maximum combination depth of four). As the data are disturbed strongly by stochastic influences, we choose the Mean Value Based Index as test- and rating strategy.

This approach leads to a fuzzy rule base of 173 relevant rules, which model the remaining error of the LE–model. In a second step we apply the optimising conflict reduction. The final rule base consists of 77 rules and the modelling error on learning data is reduced to 2.7 degrees centigrade in the combined approach.

DYNAMIC SOLAR PLANT SIMULATOR

The fuzzy model was combined with the LE–model and used in a close–loop operation in the dynamic simulation [JSSK00]. This serves for validation as the dynamic simulation generates situations (data sets) which differ from the learning data sets.

Fuzzy error model is included to the estimation of the new temperature difference goal. The fuzzy system developed with Fuzzy–ROSA method[2] was included as a *Dora for Windows 6.2* block to the *Simulink* simulator. The fuzzy system produces additional temperature difference (Figure 8) in the dynamic model. For the clear day, there is hardly any correction, which means that the model is not much improved. Important is that the Fuzzy–ROSA method does not develop any rules for the conditions where it cannot improve performance. Correlation between the calculated and

[2]Obtained with the WINROSA 2.0 software tool: http://esr.e-technik.uni-dortmund.de/winrosa/winrosa.htm .

measured temperatures was about the same as for the LE model: 0.991 for the whole day, 0.981 for the normal operating area and 0.960 for the start-up period. The relative errors are 3.0 percent for the whole day, 0.8 percent for the normal operating area and 17.0 percent for the start-up period.

For the period after radiation disturbances (Figure 9), the combined model improves the result considerably from the results of the LE model. Correlation between the calculated and measured temperatures depends now on the operating conditions: 0.964 for the whole day, 0.967 for the normal operating area, 0.969 for the start-up period and 0.176 for the load disturbance in the end of the day. The relative errors are 6.6 percent for the whole day, 1.8 percent for the normal operating area, 18.9 percent for the start-up period and 8.9 percent for the load disturbance.

The dynamic LE simulator is a practical tool in the controller design. The LE controller tuned with this simulator combines smoothly various control strategies into a compact single controller. Control strategies ranging from smooth to fast are chosen by setting the working point of the controller. The controller takes care of the actual set points of the temperature. The operation is very robust in difficult conditions: startup and set point tracking are fast and accurate in variable radiation conditions; the controller can handle efficiently even multiple disturbances. Adaptive set point procedure and feed forward features are essential for avoiding overheating. The new adaptive technique has reduced considerably temperature differences between collector loops. Efficient energy collection was achieved even in variable operating condition [JV03].

CONCLUSIONS

The combined modelling approach improves performance of the dynamic simulator. The smooth and fairly accurate overall behaviour is achieved with Linguistic Equations. The result is further improved by fuzzy systems generated for special situations with Fuzzy–ROSA method. The combined dynamic model is feasible for controller tuning but more special cases need to be analysed to expand the operating area of the dynamic simulator. Fuzzy clustering methods provide feasible techniques for selecting new cases for modelling from the extensive experimental data. The new adaptive control technique has reduced considerably temperature differences between collector loops. Efficient energy collection was achieved even in variable operating condition.

References

[JBL97] E. K. Juuso, P. Balsa, and K. Leiviska. Linguistic Equation Controller Applied to a Solar Collectors Field. In *Proceedings of the European Control Conference -ECC'97, Brussels, July 1 - 4, 1997*, volume Volume 5, TH-E I4, paper 267 (CD-ROM), 6 pp., 1997.

[JBV98] E. K. Juuso, P. Balsa, and L. Valenzuela. Multilevel linguistic equation controller applied to a 1 mw solar power plant. In *Proceedings of the ACC'98, Philadelphia, PA, June 24–26, 1998*, volume 6, pp. 3891–3895. ACC, 1998.

[JJA01] M. Järvensivu, E. Juuso, and O. Ahava. Intelligent control of a rotary kiln fired with producer gas generated from biomass. *Engineerin Applications of Artificial Intelligence*, 14(5):629–653, 2001.

[JSSK00] E. K. Juuso, D. Schauten, T. Slawinski, and H. Kiendl. Combination of linguistic equations and the fuzzy-rosa method in dynamic simulation of a solar collector field. In *Proceedings of TOOLMET 2000 Symposium - Tool Environments and Development Methods for Intelligent Systems, Oulu, April 13-14, 2000*, pp. 63–77, Oulu, 2000. Oulun yliopistopaino.

[Juu98] E. K. Juuso. Intelligent dynamic simulation of a lime kiln with linguistic equations. In *ESM'99: Modelling and Simulation: A tool for the Next Millenium, 13th European Simulation Multiconference, Warsaw, Poland, June 1–4, 1999*, pp. 395–400, Delft, The Netherlands, 1998. SCS.

[Juu99] E. K. Juuso. Fuzzy control in process industry: The linguistic equation approach. In H. B. Verbruggen, H.-J. Zimmermann, and R. Babuska, editors, *Fuzzy Algorithms for Control, International Series in Intelligent Technologies*, pp. 243–300. Kluwer, Boston, 1999.

[Juu00] E. K. Juuso. Linguistic equations for data analysis: FuzzEqu toolbox. In *Proceedings of TOOLMET 2000 Symposium*, pp. 212–226, Oulu, 2000. Oulun yliopistopaino.

[JV03] E. K. Juuso and L. Valenzuela. Adaptive intelligent control of a solar collector field. In *Proceedings of Eunite 2003 - European Symposium on Intelligent Technologies, Hybrid Systems and their implementation on Smart Adaptive Systems, July 10-11, 2003, Oulu, Finland*, pp. 26–35. Wissenschaftsverlag Mainz, Aachen, 2003.

[Kie99] H. Kiendl. Design of advanced fuzzy systems. In *Proceedings of TOOLMET'99 Symposium-Tool Enviroments for Intelligent Systems*, pp. 57–76, Oulu, Finland, 1999.

ACKNOWLEDGEMENTS

All the experiments described in this paper were carried out within the projects "Innovative Training Horizons in Ap-plied Solar Thermal and Chemical Technologies" (C.N: ERBFMGECT950023) and "Improving Human Potential Programme-Access to Research Infrastructures Activity" (C.N: HPRI-CT-1999-00013) supported by the DG XII. The combined modelling research was sponsored by the Deutsche Forschungsgemeinschaft (DFG), as part of the Collaborative Research Center Computational Intelligence (531) of the University of Dortmund.