

Hybrid Intelligent Systems in Dynamic Simulation of a Solar Collector Field

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Abstract

Linguistic Equation (LE) modelling approach has various applications in nonlinear 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 nonlinear structures. These properties are combined in a hybrid data-based modelling concept which is applied to dynamic simulation of a solar power plant. The performance of the simulator is considerably enhanced with this concept, and the hybrid simulator can be used in control design. The hybrid approach was tested in data-based modelling of dynamic behavior of a solar plant.

Keywords: Solar power plant, dynamic modelling, intelligent simulation environments, nonlinear models, linguistic equations, fuzzy set systems

1 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 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 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 [1]. This new type of controller was first implemented on a solar collectors field in a solar power station at *Plataforma Solar de Almeria* [2, 3]. This approach has been applied to the control of the lime kiln. First the burning end was controlled with a multilevel linguistic equation controller [4], and later this approach has been extended to other control tasks.

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. The robust dynamic simulator based on Linguistic Equations is an essential tool in fine-tuning of all these controllers.

2 Solar Power Plant

The aim of solar thermal power plants is to provide thermal energy for use in an industrial process such as sea water 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 the disturbances and uncertainties, changes of the solar radiation, ambient temperature, inlet oil temperature etc.



Figure 1: Acurex Solar Collectors Field of the Plataforma Solar de Almeria.

This is beneficial in a number of ways. Firstly, it collects any available thermal energy in an 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 sunlight rises once again; the alternative is unnecessary shutdowns and startups 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 (Figure 1). 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 [2, 3]. 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 °C. When a dangerous condition is detected software automatically intervenes, warning the operator and defocusing the collector field.

2.1 Modelling Problem

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

2.2 Dynamic Simulators

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 nonlinear multivariable modelling on the basis of data with understanding of the process there are two alternatives: fuzzy set systems and linguistic equations.

Linguistic equation (LE) models provide a good overall behaviour in different operating conditions. 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 improvements also for load disturbances.

Flexible fuzzy models generated with the Fuzzy-ROSA method provided additional tools for these situations [5]. These fuzzy models are useful in handling special situations in limited operating range.

3 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.

3.1 Data preprocessing

Moving average or moving median are suitable methods for removing noise from the measurements. The direct measurement value is not always best one to be used in modelling. Sometimes moving variance, standard deviation or value range 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 [6]. The data set is updated only after accepting the operation. Several statistical operations can be applied also sequentially to the data, e.g. after trend removal the resulting data can be analysed with other statistical methods. Delay analysis can be done automatically to the data set. However, these approaches work only for small systems. For large systems, domain expertise is necessary in assessing these results.

3.2 Linguistic Equation Approach

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 [7]; a close connection to fuzzy systems was important already in the early applications [8]; data-driven modelling properties have brought the approach close to 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 [9, 2, 10, 3].

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 [11]. 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. 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.

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 [9], 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.

3.3 Dynamic LE modelling

Dynamic fuzzy models can be constructed on the basis of state-space models, input-output models or semi-mechanistic models [12]. 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:

$$y(k+1) = F(y(k), \dots, y(k-n+1), u(k), \dots, u(k-m+1)), \quad (1)$$

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 [13].

The basic form of the linguistic equation (LE) model is a static mapping in the same way as fuzzy 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.

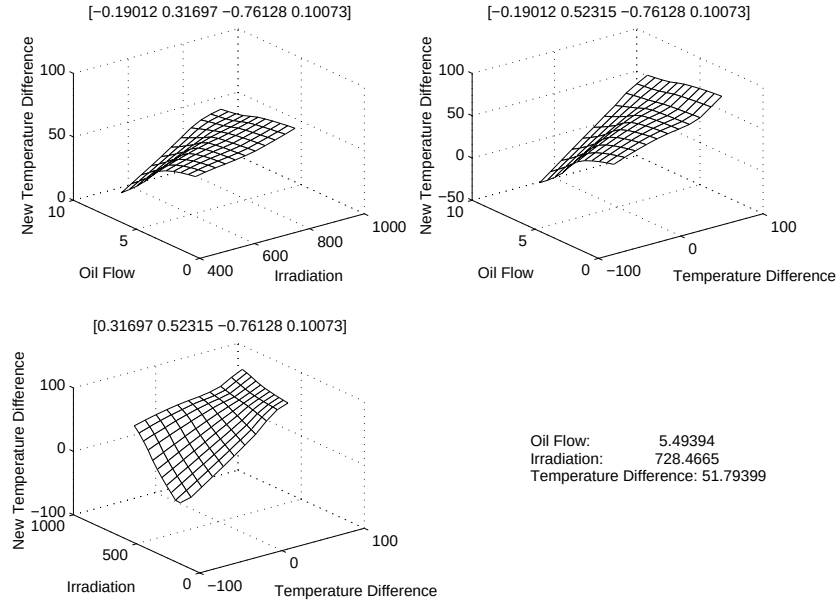


Figure 2: A dynamic LE model for temperature difference.

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 2. 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 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.

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 3). Alternatively the operating areas can be obtained by Self-organizing Maps as well (Figure 4). 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.

The working point variables already define the overall normal behaviour of the solar collector field. The model shown in Figure 5 has a quite high correlation to the real process data (Figure 6). 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 2) are needed to capture the dynamic behaviour in different operating conditions (Figure 3).

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 generalisability 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.

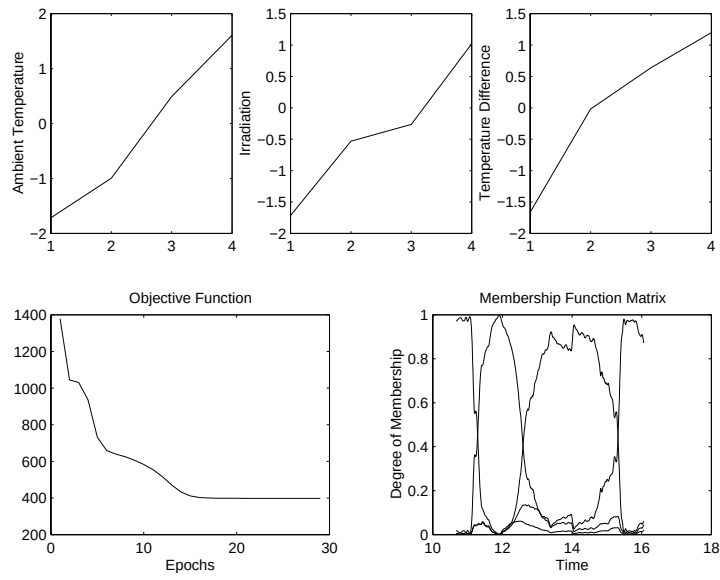


Figure 3: Four operating areas obtained by Fuzzy C-Means Clustering.

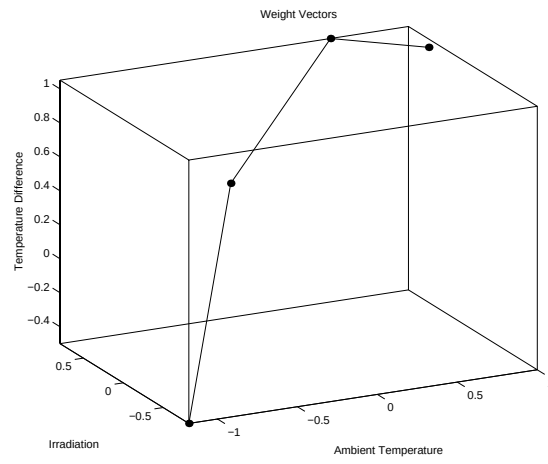


Figure 4: Four operating areas obtained by a Self-organizing Map.

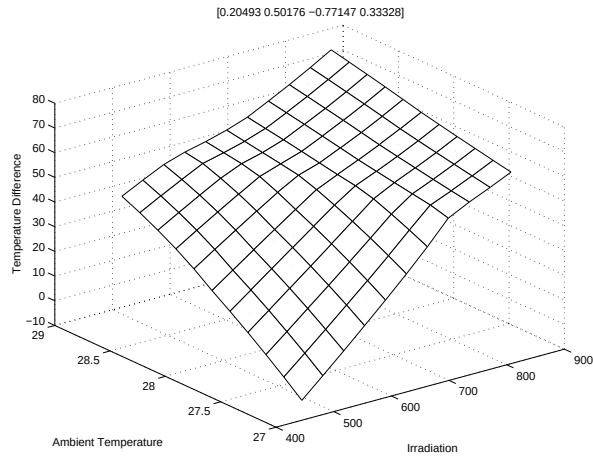


Figure 5: LE model for working point variables.

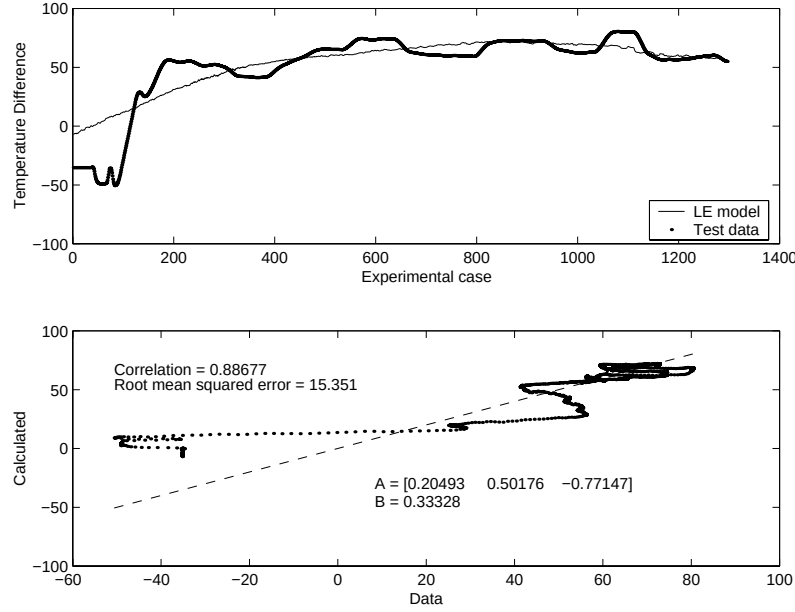


Figure 6: LE model for working point variables.

3.4 Fuzzy–ROSA Method (FRM)

The Fuzzy–ROSA¹ 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 [14, 15]. 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 [5]. 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).

3.5 Combined Approach

In many real-world applications the functional relationship between the output variable and the input variable may be partly smooth and partly complicated nonlinear [5]. 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 this problem, a cascaded rule generation (Figure 7 left) has been proposed in [16]: 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). The applicability of this approach has been demonstrated in [17, 18] for the load prediction.

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 [5].

¹RuleOrientated Statistical Analysis

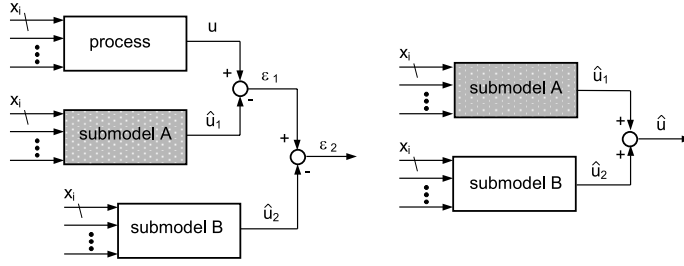


Figure 7: Cascaded modelling (left) and resulting model (right)

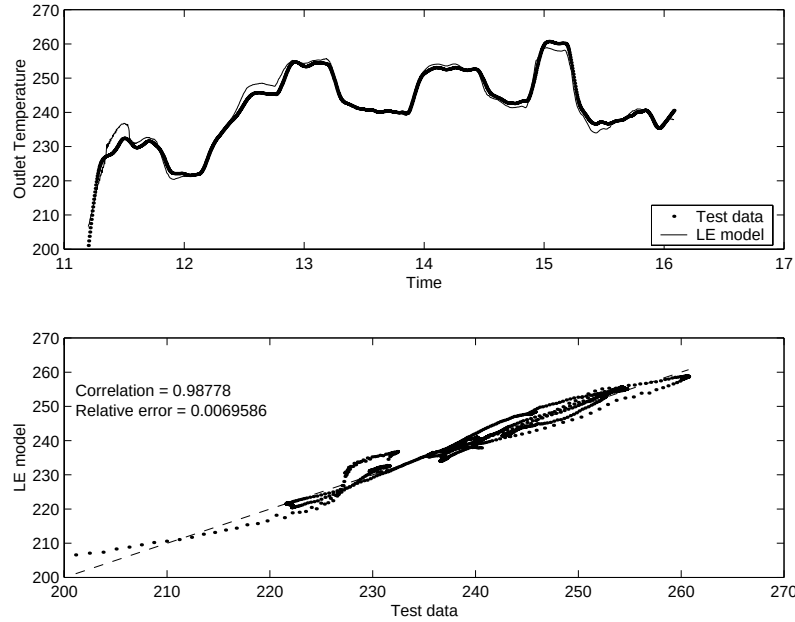


Figure 8: Simulation results of the LE model (July 23, 1998).

4 Solar Plant modelling

4.1 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 is 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 8). 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 startup 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 are very high for all time period: 0.992 for the whole day, 0.988 for the normal operating area and 0.961 for the startup 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 startup period [5].

For startup the dynamic LE simulator requires improvement since the process changes considerably during the first hour [5]. 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.

4.2 Modelling with the Fuzzy–ROSA Method

As described in Section 3.5 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*.

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 [19] 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 [15].

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.

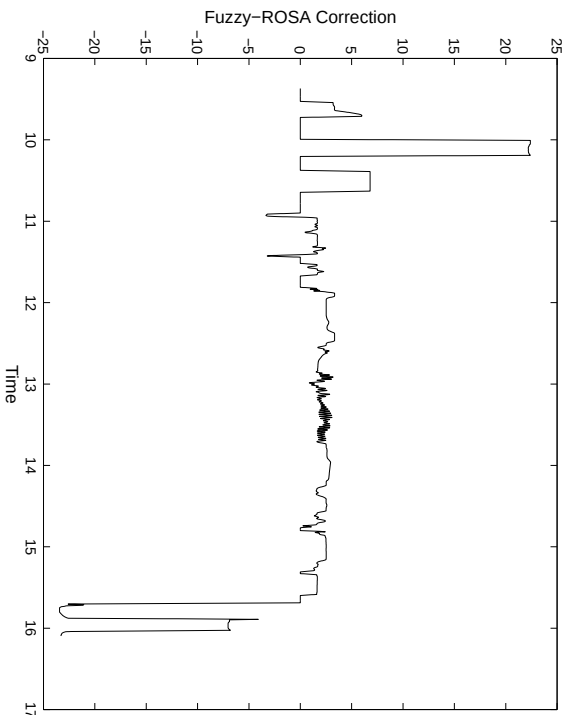


Figure 9: Model obtained with the FRM (June 17, 1997).

5 Dynamic Simulation of Solar plant

The fuzzy model was combined with the LE–model and used in a close–loop operation in the dynamic simulation [5]. 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 method² was included as a *Dora for Windows 6.2* [20] block to the *Simulink* simulator. The fuzzy system produces additional temperature difference (Figure 9) 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 measured temperatures were 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 startup 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 startup period.

For the period after radiation disturbances (Figure 10), 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 startup 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 startup period and 8.9 percent for the load disturbance.

²Obtained with the WINROSA 2.0 software tool [20]:

<http://esr-e-technik.uni-dortmund.de/winrosa/winrosa.htm>.

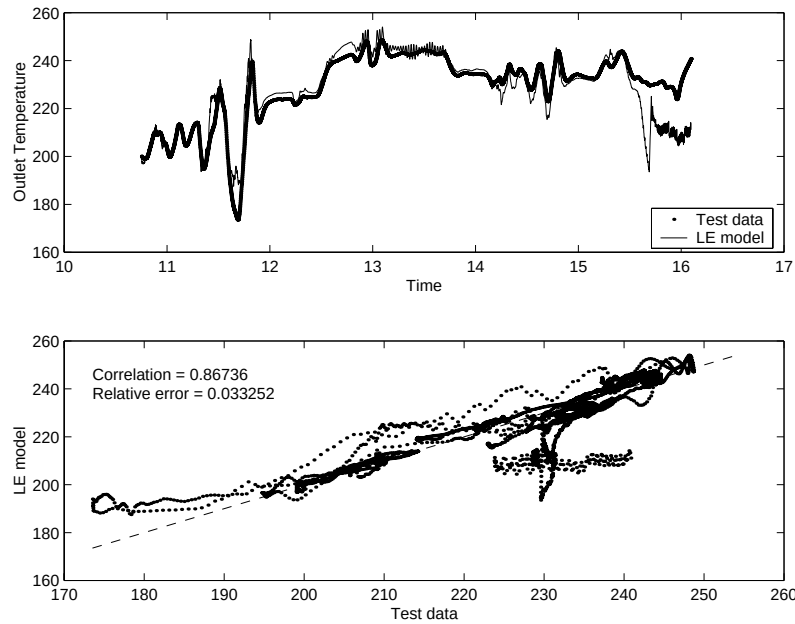


Figure 10: Simulation results of the the combined LE-FRM model (June 17, 1997).

6 Conclusions and Outlook

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.

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