Intelligent Multimodel Simulation in Decomposed Systems

Esko K. Juuso

Control Engineering, Faculty of Technology, University of Oulu, Finland, esko.juuso@oulu.fi

Abstract

Intelligent methodologies provide a good basis for multimodel simulation. Small, specialised systems have a large number of feasible solutions, but developing truly adaptive, and still understandable, systems for highly complex systems require domain expertise and more compact approaches at the basic level. The nonlinear scaling approach extends the application areas of linear methodologies to nonlinear modelling and reduces the need for decomposition with local models. Fuzzy set systems provide a good basis for understandable models for decomposed systems. Data-based methodologies are suitable for developing these adaptive applications via the following steps: variable analysis, linear models and intelligent extensions. Complex problems are solved level by level to keep the domain expertise as an essential part of the solution.

Keywords: nonlinear systems, intelligent methods, composite local modelling, linguistic equations, fuzzy logic

1 Introduction

Models are understood as relationships between variables and used to predict properties or behaviour of the system. Variable interactions and nonlinearities are important in extending the operation areas (Juuso, 2004a). Phenomenological models based on physics, chemistry and mathematics require domain expertise (Figure 1). Linear methodologies extended with principal components (Jolliffe, 2002; Gerlach et al., 1979) and semi-physical models (Ljung, 1999) provide a feasible solution for many applications. Nonlinearities have been handled commonly with interaction and quadratic terms (Box and Wilson, 1951). Linear parameter varying (LPV) extend these solutions to decomposed systems (Hjartarson et al., 2015; Theis et al., 2018).

Artificial neural networks (ANNs) starting from (Rummelhart et al., 1986) continue this by using more complex architectures with deep learning for complicated interactions within different sources of varying data (Schmidhuber, 2015). Big data analytics and deep learning are in high focus in data science (Najafabadi et al., 2015).

Knowledge-based information can be handled with fuzzy set systems introduced by Zadeh (1965): numerous methodologies have been developed, see (Takagi and Sugeno, 1985; Driankov et al., 1993; Dubois et al., 1999), and combined with neural networks (Fullér, 2000). Different fuzzy approaches can be efficiently combined (Juuso, 2014).

First order ordinary differential equations are solved by numerical integration and special solutions have been developed for identification (Ljung, 1999). These approaches, which are also used in fuzzy set systems (Babuška and Verbruggen, 2003) and low complexity neural networks (Sahoo et al., 2013), define structures for hybrid dynamic models (Figure 1). Local models need to be combined in complex systems (Sontag, 1981; Ljung, 2008; Jardine et al., 2006).

The linguistic equation (LE) approach originates from fuzzy set systems (Juuso and Leiviskä, 1992): rule sets are replaced with equations, and meanings of the variables are handled with scaling functions which have close connections to membership functions (Juuso, 1999a). The nonlinear scaling technique is needed in constructing nonlinear models with linear equations (Juuso, 2004a). Constraints handling (Juuso, 2009a) and data-based analysis (Juuso and Lahdelma, 2010), improve possibilities to update the scaling functions recursively (Juuso, 2011). The LE approach together with knowledge-based systems, neural networks and evolutionary computation form the computational intelligence part (Figure 1).

Three levels of smart adaptive systems (SAS) are identified in (Anguita, 2001): (1) adaptation to a changing environment, (2) adaptation to a similar setting without explicitly being ported to it, and (3) adaptation to a new or unknown application. The smart use of intelligence by integrating specific intelligent systems is essential in the development of complex adaptive applications. Implementation of smart adaptive systems on silicon has been proposed to to adapt perceptual and cognitive tasks autonomously to the changing environment (Valle, 2004).

Technically, an automatic black box modelling could be possible in various big data problems by using combinations of these methodologies. The domain expertise is an essential part in integrated solutions to understand and assess the applicability. This paper classifies modelling methodologies and focuses on the nonlinear scaling and integrates the LE approach into the modelling applications for complex systems. Various applications are shortly discussed.

This paper focuses on the LE modelling approach enhanced with statistical and knowledge-based methodologies within decomposed systems (Section 2). Different methodologies are combined in the multimodel LE simulation (Section 3). Various applications summarised in Section 4 are discussed in Section 5. Conclusions and future research presented in Section 6.

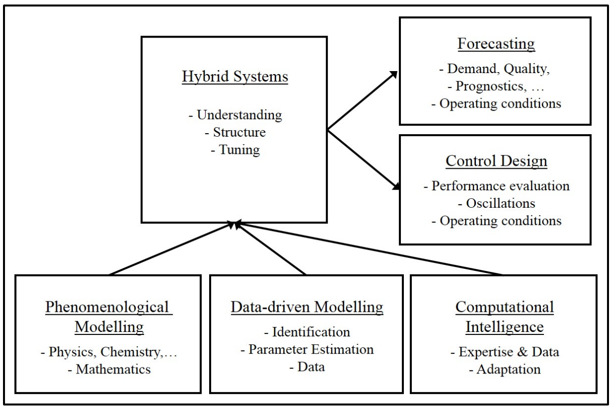

Figure 1. Methodologies and application types of modelling and simulation, modified from (Juuso, 2004b)

2 Modelling methodologies

The modelling methodologies include statistical analysis, knowledge-based methodologies and decomposition solutions.

2.1 Statistical analysis

Nonlinear scaling and steady-state statistical modelling with linear methodologies are the basis of the LE modelling. Dynamic modelling introduces additional model structures.

2.1.1 Nonlinear scaling

The nonlinearities of the process are handled by the nonlinear scaling of the variables. The scaling functions are monotonously increasing functions $x_j = f(X_j)$ where x_j is the variable and X_j the corresponding scaled variable. The function $f()$ consist of two second order polynomials, one for the negative values of X_j and one for the positive values, respectively. The corresponding inverse functions $x_j = f^{-1}(X_j)$ based on square root functions are used for scaling to the range [-2, 2], denoted linguistification. In LE models, the results are scaled to the real values by using the function $f()$. (Juuso, 2004a)

The support area is defined by the minimum and maximum values of the variable, i.e. the support area is $[\min(x_j), \max(x_j)]$ for each variable $j, j = 1, \ldots, m$. The central tendency value, c_j, divides the support area into two parts, and the core area is defined by the central tendency values of the lower and the upper part, $(c_l)_j$ and $(c_h)_j$, correspondingly. This means that the core area of the variable j defined by $[(c_l)_j, (c_h)_j]$ is within the support area. The parameters of the functions are extracted from measurements by using generalised norms and moments (Juuso and Lahdelma, 2010).

2.1.2 Steady-state modelling

The steady-state simulation models are linear *multiple input, multiple output (MIMO)* models $\vec{y} = F(\vec{x})$, where the output vector $\vec{y} = (y_1, y_2, \ldots, y_n)$ is calculated by a linear function F from the input vector $\vec{x} = (x_1, x_2, \ldots, x_m)$. Statistical modelling in its basic form uses linear regression for solving coefficients for a linear function. Linear methodologies are suitable for large multivariable systems. Quadratic and interactive terms are not used here. Principal components compress the data by reducing the number of dimensions with a minor loss of information (Jolliffe, 2002). Partial least squares regression (PLS) is an extension of these ideas (Gerlach et al., 1979). Known semi-physical models of inputs are important in linear modelling, see (Ljung, 1999).

2.1.3 Dynamic modelling

Data-driven modelling with parametric models, also known as identification (Ljung, 1999), is the key methodology in the dynamic modelling (Figure 1). Nonlinear scaling reduces the number of input and output signals needed for the modelling of nonlinear systems. For the default LE model, all the degrees of the polynomials become very low:

$$Y(t) + a_1 Y(t-1) = b_1 U(t - n_k) + e(t) \quad (1)$$

for the scaled variables Y and U. Phenomenological models can be integrated with these solutions.

2.2 Knowledge-based methodologies

Knowledge-based information can be introduced by *fuzzy logic* which emerged from approximate reasoning: the connection of fuzzy rule-based systems and *artificial intelligence (AI)* is clear, e.g. the vocabulary of AI is kept in fuzzy logic (Dubois et al., 1999). *Fuzzy set theory* first presented by Zadeh (1965) form a conceptual framework for linguistically represented knowledge.

Domain expertise can be combined with statistical models with following fuzzy methodologies:

- *Linguistic fuzzy models* (Driankov et al., 1993), where both, the antecedent and consequent are fuzzy propositions, suit well for natural language, heuristics and common sense knowledge.

- *Takagi-Sugeno (TS) fuzzy models* (Takagi and Sugeno, 1985), where each consequent y_i, $i = 1, \ldots, n$, is a crisp function of the antecedent variables $\vec{x}$, can integrate local linear models. A smoothing technique is needed for drastically different local models (Babuška, 1998).

- *Singleton models* can be regarded as special cases of both the linguistic fuzzy models and the TS fuzzy models.

The *extension principle* is the basic generalisation of the arithmetic operations if the *inductive mapping* $F(x_j)$ is a monotonously increasing function of the input. The interval arithmetic presented by Moore (1966) is used together with the extension principle on several membership

α-cuts of the fuzzy number x_j for evaluating fuzzy expressions (Buckley and Qu, 1990; Buckley and Hayashi, 1999; Buckley and Feuring, 2000). The fuzzy sets can be modified by intensifying or weakening modifiers (De Cock and Kerre, 2004; Le and Tran, 2018)

Type-2 fuzzy models introduced by Zadeh (1975) take into account uncertainty about the membership function (Mendel, 2007; Sadeghian et al., 2013).

Dynamic fuzzy models use the same parametric structures as the statistical models (Babuška and Verbruggen, 2003; Sahoo et al., 2013).

2.3 Decomposition

Decomposition is needed to extend the solutions to different subprocesses, process phases, phenomena and multiple operating conditions.

2.3.1 Subsystems

Modelling problems are divided into smaller parts for developing separate models for subprocesses or different stages in the process operation interconnected with process streams. In addition to spatial or logical blocks, the decomposed modelling can be based on different frequency ranges. Cluster analysis provides hundreds of algorithms for the data-driven analysis (Xu and Tian, 2015). The mixed systems may also include models based on the first principles. Clustering is used in the data analytics to find feasible areas for local models.

2.3.2 Composite local models

The composite local model approach constructs a global model from local models, which usually are linear approximations of the nonlinear system in different neighbourhoods. If the partitioning is based on a measured regime variable, the partitioning can be used in weighting the local models. In linear parameter varying (LPV) models, the matrices of the state-space models depend on an exogenous variable measured during the operation (Hjartarson et al., 2015; Theis et al., 2018). Piecewise affine (PWA) systems extend the local linear models to a polyhedral partition where the models can be state-space or parametric models (Christophersen, 2007). The model switches between different modes as the state variable varies over the partition. However, a high number of local models brings an overfitting risk.

2.3.3 Intelligent systems

Composite local models enhanced with fuzzy set systems form feasible solutions to handle partially overlapping models. Fuzzy models combine local modelling approaches and facilitate gradual changes. The smoothing problem around the submodel borders of Takagi-Sugeno (TS) fuzzy models needs special techniques, e.g. smoothing maximum, or by making the area overlap very strong. The ANFIS method (Jang, 1993) is widely used in the tuning of TS fuzzy systems, but it increases the overlap of clusters and destroys the meanings of the individual linear models, e.g. the role of some submodels may transform into a part of a smoothing algorithm. A Kalman-based learning algorithm has been proposed for online TS identification (Vafamand et al., 2018).

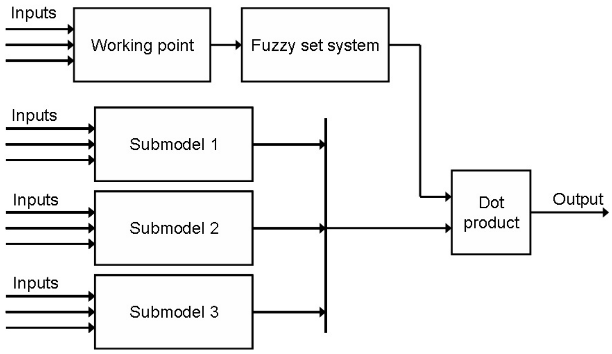

Figure 2. Multimodel LE system with a fuzzy decision module (Juuso, 2009b).

In multiple neural network systems, the task decomposition and an ensemble of redundant networks improve generalisation. Ensemble averaging is the process of creating multiple models and combining them to produce a desired output. Multimodel ensamble methods are important in deep neural networks (Xiao et al., 2018).

3 Multimodel LE simulation

A multimodel approach has been developed for combining specialised linguistic equation (LE) submodels where the nonlinear scaling need to be done by a set of functions due to very strong nonlinearities. Additional properties are achieved because equations and delays are allowed to vary between different submodels. In this multimodel approach, the working area is defined by a separate working point model. The submodels are developed using the case-based modelling approach.

3.1 Fuzzy LE models

The multimodel system contains several submodels and a fuzzy decision system for selecting and weighting suitable models for each situation using several working point variables. If several inputs are combined into a single working point index, the fuzzy set system is reduced to a fuzzification block.

Linguistic Takagi-Sugeno fuzzy models (LTS) belong to this class of models with one limitation: the fuzzy partition is defined with the same variables as the models. As LE models are nonlinear, the local models are also nonlinear. LTS models can be developed and tuned with the same methods as the normal TS models with one difference: the variable values are scaled with the nonlinear scaling functions. Correspondingly, the LTS models extend the normal LE model by handling the equation part with a fuzzy set system. (Juuso, 2009b)

Table 1. Steady-state LE model applications.

Case	*Application area*	*Modelling*
Electric furnace	DSS for process design	Nonlinear models transformed to LE models
		Interactions
Lime kiln	Feedforward control	Fuel feed in changing capacity conditions
Solar collector field	Control adaptation	Steady-state working point model:
		Irradiation, temperature difference,
		special cases with fuzzy set systems
Continuous cooking	Quality control	Quality forecasting
Fatigue	Stress contributions	LE based stress-cycle curve
		2nd order and logarithmic scaling
Water treatment	Feedforward control	Turbidity for control
		Forecasting residual aluminium
Wastewater treatment	Diagnostics	Operating conditions

Table 2. Dynamic LE model applications.

Case	*Application area*	*Modelling*
Gas furnace	Modelling	Tuning: training, validation, testing
Solar collector field	Controller tuning	Time varying transport delay
		Cloudy periods
Fatigue	Forecasting fatigue risk	Cumulative sum of stress contributions
		Rolling mill, LHD machines
Water treatment	Controller tuning	Water quality indicator
		Water circulation, Drinking water
Condition monitoring	Prognostics	Recursive tuning

3.2 Nonlinear parameter (NPV) models

The LE models are defined by the parameters of the scaling functions and the coefficients of the interaction models. The idea of the exogenous variables can be used for these parameters, which opens a set of new modelling approaches for the nonlinear parameter (NPV) varying models. There are three levels of complexity: (1) individual scaling functions are compressed or expanded, (2) the shape of the functions is modified, and (3) also the coefficients of the equations are modified.

Clustering methodologies are used for finding areas for the submodels. The clustering variables define the operating conditions are not necessarily included in the submodels.

3.3 Genetic tuning

Evolutionary computing is widely used to tune intelligent systems which incorporate expert knowledge with data. Genetic algorithms are well suited for LE models based on nonlinear scaling and linear interactions. The scaling functions handle efficiently the parameter constraints of the monotonously increasing second order polynomials and the whole system is configured with a set of parameters. (Juuso, 2009a)

4 Applications

Nonlinear scaling forms the basis for the LE modelling: an important benefit of the linear approach is that the models can be inverted, technically to any direction. The compact basic solution makes extensions to dynamic and case-based systems possible. Complex models for steady-state and dynamic systems can be built with the cascade and interactive structures.

4.1 Steady-state LE models

Steady-state LE models are mainly used in adaptation and feedforward control (Table 1). In most cases, the models include only a single linear equation. The first LE model developed for designing submerged arc furnaces was an exception which used well known relations represented by five equations (Juuso and Leiviskä, 1992). A steady-state LE model was developed in an early control application from the process measurements of a lime kiln (Juuso et al., 1997). For continuous cooking, a LE model has been developed for predicting the Kappa number, which is widely used quality variable (Leiviskä et al., 2001).

The working point model presented in (Juuso et al., 1998) is still an essential part of the model-based LE control of a solar power plant (Juuso and Yebra, 2013). Stress-cycle (S-N) curves, also known as Wöhler curves, are rep-

Table 3. Decomposed LE model applications.

Case	*Application area*	*Modelling*
Lime kiln	Fuel quality Adaptive control	Controller tuning by using multiple models
Solar collector field	Controller tuning for oil flow	Models for different operating conditions Distributed parameter models
Batch cooking	On-line forecasting	Three interactive models: alkali, lignin and dissolved solids
Fluidised bed granulation	Forecasting	Three interactive models: temperature, humidity and granular size
Fed-batch fermentation	On-line forecasting	Submodels of three growth phases, each including three interactive models, totally nine interactive models
Wastewater treatment	Detection of operating conditions	Three submodels: load, treatment and settling Trend analysis

resented by a linguistic equation (Juuso and Ruusunen, 2013).

In drinking water applications, models have been developed for forecasting and control (Tomperi et al., 2013). Operating conditions are detected in diagnosing the wastewater treatment process (Juuso and Laakso, 2013).

4.2 Dynamic LE models

The basic dynamic LE model is represented by the parametric model (1) with an appropriate number of variables. The approach was first tested in a gas furnace data provided by (Box and Jenkins, 1970). The dynamic models of the solar plant are based on test campaigns, which cannot be planned in detail because of changing weather conditions (Juuso, 2003a). The basic dynamic flotation model is the core of the quality indicator in water treatment (Ainali et al., 2002; Joensuu et al., 2005). A dynamic LE model has been used for the fatigue prediction in (Juuso and Ruusunen, 2013). In all these models, only one equation is needed. The applications are indirect measurements and controller tuning (Table 2). Drinking water applications focus on model-based control and forecasting (Tomperi et al., 2016). Trend analysis is important in the wastewater treatment (Tomperi et al., 2017).

4.3 Decomposition in LE models

The multimodel LE system can include several submodels and complex interactions (Table 3). All basic models are represented by the model (1) with an appropriate number of variables.

The model with a fuzzy decision module was first used for a lime kiln (Juuso, 1999b) and then for a solar thermal power plant (Juuso, 2003a). The lime kiln model had six operating areas defined by the production level and the trend of the fuel feed (increasing, decreasing). The model of the collector field includes four operating areas: start-up, low, normal and high operation. For handling special situations in the solar plant, additional fuzzy models have been developed by using the Fuzzy-ROSA method (Juuso et al., 2000). Interactive dynamic models were needed in several cases: batch cooking (Juuso, 2003b), fluidised bed granulator (Mäki et al., 2004), industrial fed-batch fermenter (Saarela et al., 2003) and wastewater treatment (Juuso et al., 2009). Linguistic equations, neural networks and fuzzy modelling with several variants have been compared by using the process data obtained from the fed-batch fermenter.

4.4 Distributed parameter LE models

In the distributed parameter models, the solar collector field is divided into modules, where the dynamic LE models are applied in a distributed way (Juuso, 2004b). The same single equation model (1) with an appropriate number of variables is used in all modules. Element locations for partial differential equations (PDEs) are defined by the flow rate. In cloudy conditions, the heating effect can be strongly uneven.

5 Discussion

The nonlinear scaling methodology is the key in the extensions of the linear methodologies. Steady-state models form the basis and extended to dynamic applications with additional structures. Several steady-state and dynamic models are combined with fuzzy set systems. The ensemble averaging could be used in the neural computing with linear networks. Distributed parameter systems can use the same algorithms. All the applications discussed in Section 4 use the scaling functions explained in Section 2.1.1 have been developed before the current data-based analysis. Clustering is used in finding the areas of the submodels.

All parameters of the multimodel LE systems can be tuned with genetic algorithms. Constraints are taken into account in the coding which means that penalties are not needed in the optimisation.

The variable specific recursive analysis of the parameters of the scaling functions is feasible for the machine learning phase. The multimodel structure facilitates deep learning extensions.

6 Conclusions

The nonlinear scaling approach extends the application areas of linear methodologies to nonlinear modelling: the meanings of variables and interactions are analysed sequentially. Local nonlinear models reduce the need for decomposition with local models. The close connection to the fuzzy set systems provides a good basis for understandable models. Data-based methodologies are suitable for developing models for decomposed systems. Big data problems are solved level by level to keep the domain expertise as an essential part of the solution. The basic models are compact and additional properties, including dynamics, uncertainty and decomposition are included if needed.

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