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Expertise and uncertainty processing with fuzzy systems for automation

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1. Background and aims

Domain expertise and uncertainty processing need to be integrated in automation solutions which rely on data analytics and artificial intelligence. In many cases, the result might look very good but is precisely wrong if the solution is based on overfitting or important facts or data are not taken into account. The systems should have a level for assessing what is approximately correct.

Statistical models are in various ways used in data-driven modelling and rule-based systems form the basis for handling expertise. Case-based systems, neural computing and machine learning expand the solutions to large-scale problems. Complexity of the systems can be reduced by using nonlinear scaling for variables.

The solutions are aimed to bring the expertise and uncertainty processing to integral parts of the Cyber Physical Systems (CPS) [1].

This paper analyses alternatives of fuzzy extensions of parametric systems where the meanings of variables, different types of fuzzy and parametric systems are used as building blocks. Fuzzy systems provide tools for uncertainty processing and integrating domain expertise.

2. Materials and methods

Parametric statistical models based on multivariable linear regression are the basic solution for the interactions. Response surface methods include more complex interactions. Linear solutions can be extended to case-based systems by using linear parameter varying (LPV) models. Neural networks can further extend the complexity of nonlinear interactions considerably through machine learning.

Fuzzy systems are based on rules, relations and local models, which include fuzzy numbers and labels represented by membership functions (MFs). The uncertain facts are processed by calculations with the degrees of membership.

Nonlinear scaling improves the numerical calculations in these systems. The nonlinear effects are as much as possible taken into account with the nonlinear scaling [2, 3].

3. Solution

The solution is based on three stages: (1) Meanings of the variables, (2) Uncertainty of the variables and model coefficients are represented by fuzzy numbers, and (3) Both lines of system development, statistical and fuzzy, are efficiently extended to nonlinear applications by modifying the meanings of the variable levels. The linear models and rulebases focus here on the directions of interactions.

Uncertainties of the inputs are taken into account by using fuzzy numbers as the inputs of different fuzzy systems which are combined embedded parametric systems. These solutions are extended by nonlinear scaling functions (NSFs) which also make them easier to combine and tune.

When fuzzy rule-based systems are represented with scaled fuzzy inputs, membership functions (MFs) can be developed from NSFs and existing MFs can be used in developing NSFs. Fuzzy set systems and linguistic equation systems are consistent within the limits of detail. In recursive analysis, both meanings and interactions on all levels can be tuned together with genetic algorithms.

4. Applications

In applications, the modular overall system consists of similar subsystems, which are normally used. Uncertainty is included with extensions to with the fuzzy extensions.

- **Case-based models** can utilize fuzzy working point models or LPV model solutions where the LE submodels can have fuzzy inputs and or fuzzy coefficients [4, 5].

- **Intelligent control solutions** use combined fuzzy and LE models in intelligent analyzers which provide informative indices for the control and decision making. In the solar thermal power plant, the focus is in the working control where all the actions are integrated [6].
- **Diagnostic solutions** are fuzzy systems where condition monitoring and process data are combined with performance indices in intelligent analyzers. Symptoms are versatile facts, including labels, inequalities and trends. [7] Natural language interface is important in diagnostics [8].

The compact fuzzy modules can be developed for specific tasks which are combined within Cyber Physical Systems (CPS) [1]. The fuzzy extensions provide a feasible way for the sensitivity analysis of the solution.

5. Conclusions

Expertise and uncertainty processing can be efficiently integrated by compact nonlinear scaling which simplifies statistical, fuzzy and neural solutions. In large-scale parametric systems, fuzzy systems are used for balancing contradictory information, non-numeric expertise and operating areas.

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