Optimization of Measurement Systems using Soft Computing

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0. Abstract

This paper discusses softcomputing approaches to the design of learning fuzzy systems for measurement problems. It is shown, that the incorporation of genetic learning mechanism or neural learning mechanism into a fuzzy logic control system gives fuzzy systems enabling it to modify its parameters. The decided approaches to optimize the membership functions and rule base of fuzzy systems for measurement. By using this techniques it is possible to build measurement systems using non-measurable values to find optimal results.

1. Introduction

Fuzzy logic systems have been successfully applied to many areas as complex industrial processes and control systems. Till now there are only a few systems for special measurement problems available. The system, which is described here, have the opportunity to use non-measurable values. These values could be for example linguistic values or measurement values which are not able to measure in a direct way.

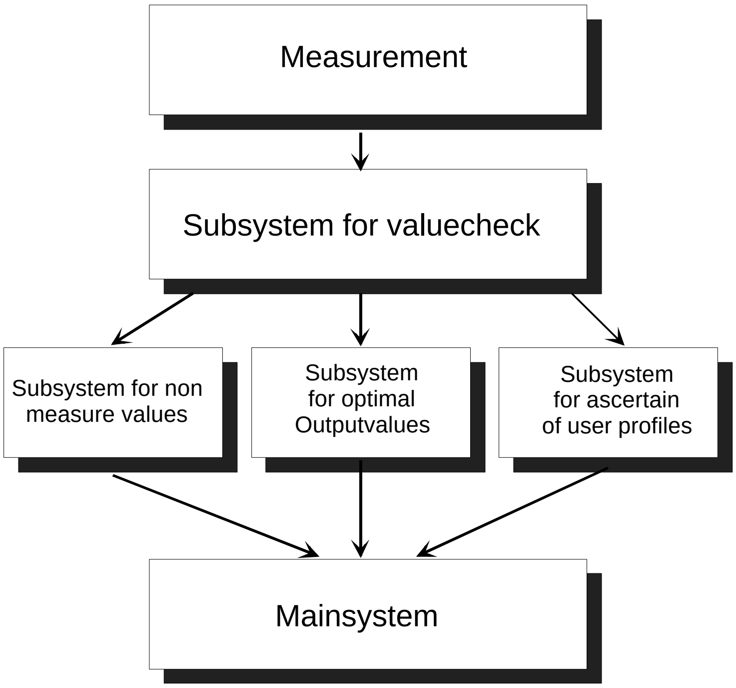
By using only fuzzy systems there is the limitation due to generic weakness of fuzzy logic, i.e. knowledge acquisition, learning and adaptation. The strength of a fuzzy system which lay in the rule base can be reduced by mistakes in its building, the knowledge acquisition or unknown situations which have not been found during implementation phase. In order to cope with previously unknown or changes in process dynamics it is necessary to modify the initial fuzzy rules and membership functions , decided input data in form of linguistic variables in the knowledge base of fuzzy systems for measurement problems. For solving complex measurement problems there have been proposed a self-organizing fuzzy logic measurement system. Till now some algorithm have been suggested. But systematic learning methods for fuzzy measurement systems are still largely unsolved. In this paper some learning schemas based on soft computing technology are discussed. These schemas will show ways to use soft computing in measurement problems.

2. *Problem formulation*

In a wide range of applications some necessary and useful system values are not able to measure or to get by using mathematical models. The reasons for these problems lies in the nature of problems

For example it is not possible to measure the value "quality" or the attrition of drills. Experts can often make a declaration about these values Also it is possible to get information about traffic jams and profiles of users. It is easy to see, that these information can be used for a better engine control to reduce petrol and emissions. A lot of such and other similar values can't be measured directly, but they can be described in a linguistic way. This is the access door for the fuzzy logic.

The general structure of such soft computing measurement system is shown in figure 1.



First of all measurement values will be taken from the process. After this all values will be checked for the right range or if there are any crosscombinations or the possibility for crosschecking this will be done. In the next step the whole system is splitting into several sub-systems to solve circumscribe problems. The reason for using subsystems are the necessary techniques of soft computing in use. In some of the subsystems only fuzzy logic is used without any other technique.

The problem is formulated as following: To create an application mechanism based on artificial genetic algorithm for tuning the parameters of the fuzzy logic measurement system to provide error convergence between the plant output and the refine model output to find non- measurable values.

3. *Realization*

3.1 Methods

In this paper the knowledge base of the used fuzzy logic system is described by following fuzzy conditional statements

IF e is A_1 AND e´ is B_1 THEN u is C_1
Also
IF e is A_2 AND e´ is B_2 THEN u is C_2 (1)
:
Also
:
IF e is A_n AND e´ is B_n THEN u is C_n
where e represents the control error e´ the change-in error and u the plant control input, A_i, B_i and C_i, i=1,..n are linguistic descriptions of e, e´, and u, respectively.

In this paper the tuning of the parameters of fuzzy controller is to change the center and shapes of membership functions. It is used following procedure.

a) Coding of points characterized center and shape of each membership functions
b) Determination of evaluation function. The evaluation function that we use, by which the genetic algorithm rates each solution, is given by:

$$F= 0,5 \sum_{k=1}^{m} [y_i(k) - y_i^m(k)]^2 \qquad (2)$$

c) Adjusting of membership functions. We use the genetic algorithm to find the optimal values of parameters of trapezoid membership functions to minimize (2). The genetic algorithm generates the optimal fuzzy membership function (in accordance with (2)) on following procedure:

- generate an initial population (IP) (referred as set of encoding points of membership functions;
- evaluate IP in accordance with (2);
- if maximum generation number (in this paper 150) is reached the acting of the genetic algorithm will be stoped, in otherwise generate new population (NP);
- evaluate NP in accordance with (2) and return to previous step;
-end

3.2 Subsystem for non-measure values

In this part fuzzy logic, neuro-fuzzy and genetic algorithm are used to calculate and to determine the values which are not measurable.

First the measured values will be checked and analyzed. Noise and known errors will be eliminated by special fuzzy rules. The initial rules of the knowledge base are based on physical knowledge, tests, observance or by other methods of knowledge acquisition. The calculate values are for example the traffic, drill attrition, deeper engine temperatures etc.

This system has to calculate his values at first, because this values will be used in all other subsystems.

Following a part of a possible rule base for traffic.

IF Driver is normal AND Alteration of the Gas pedal is fast AND Gas is low THEN Traffic jam is near

:

IF Driver is in_hurry AND Alteration of the gas pedal is fast AND Gas low THEN Traffic is jam

:

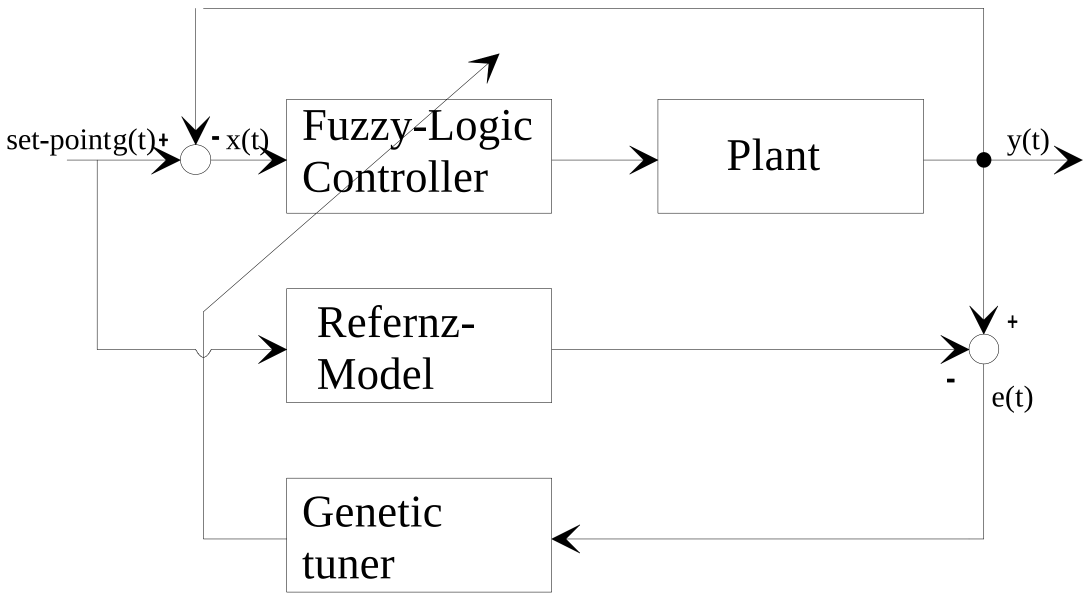
IF Driver is normal AND Alteration of the gas pedal is normal AND Gas high THEN Traffic is free

:

IF Driver is slowly AND Alteration of the gas pedal is fast AND Gas low THEN Traffic jam is near

3.2 Subsystem for ascertain of user profiles

This subsystem detect and learn the profiles of users. These profiles can have high dynamic parts as also non-steady parts. It is easy to see that one user haven't the same reaction as an other user in the same situation. Figure 2 shows the principle structure of such subsystem.



In the beginning the system can use three initial profiles of users. These profiles are founded during the implementation. The system will use one of these profiles which is the nearest to the new profile. After this the system learned the new profile based on the first used. This reduce the time for learning a new profile up to 20 %.

4 Conclusion

By using soft-computing techniques it is possible to get values of a process which are not to measure. Simulation has shown that fuzzy genetic and neuro-fuzzy-genetic approaches gives better results than conventional adaptive fuzzy systems.

Simulations in a real project shows that by using this methods for a car control the used petrol is reduced by 8 % and the emission up to 10 %.

5. References

[1] Bonfig, K.W., u.a. „Fuzzy-Logik in der industriellen Automatisierung„, Expert Verlag, 1992

[2] Aliev R., Bonfig, K.W., Aliew, F. „Messen, Steuern, Regeln mit Fuzzy-Logik„ Franzis Verlag, 1994

[3] Kosko, B. „Neural Networks and Fuzzy Systems„, Prentice Hall, 1992

[4] Yager R.R., u.a. „ Fuzzy Sets, Neural Networks and Soft Computing, Von Nostrad Reinhold, New York, 1994

[5] Wieland, F. „Adaptive Control Systems with Neuro-Fuzzy-Genetic-Approach„ Proccedings of ICAFS´96, Siegen, 1996

[6] Seifert,B, u.a. „ Description of a Fuzzy Expert System for very large rail bound mining devices in surface work minig areas„, Proccedings of ICAFS´96, Siegen, 1996

[7] Bonfig, K.W. „Neuro-Fuzzy„, Expert Verlag, 1995