EVOLVING RULES-BASED CONTROL

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ABSTRACT An approach to control non-linear objects based on evolving Rule-based (**eR**) models is presented in the paper. Fuzzy rules, representing the structure of the controller are generated based on data collected during the process of control using newly introduced technique for *on-line* identification of Takagi-Sugeno type of fuzzy rule-based models. Initially, the process is supposed to be controlled for few time steps by any other conventional type of controller (P, PID or a fuzzy one with a fixed structure determined *off-line*). Then, in *on-line* mode the output of the plant under control (including its dynamic) and the respective control signal applied has been memorised and stored. These data has been used to train in a non-iterative way the **eR** model representing the fuzzy controller, which aim is to control the plant at a given set point. The indirect adaptive control approach has been used in combination with the newly introduced *on-line* identification technique based on unsupervised learning of antecedent and consequent parts separately. This approach exploits the quasi-linear nature of Takagi-Sugeno models and builds-up the control rule-base structure and adapts it in *on-line* mode. The method is illustrated with an example from air-conditioning systems, though it has wider potential applications.

KEYWORDS evolving fuzzy rule-based models, indirect adaptive control, on-line adaptation, air-conditioning systems

1. INTRODUCTION

Fuzzy rule-based controllers have found wide application during the last decade, including the area of air-conditioning (So et. al., 1994; Kuntze and Bernard, 1998). They have been responsible even for the thermal control of the Space Shuttle (Lea et. al., 1992). Soon after the pioneering paper of Mamdani and Assilian (1975) an important extension of the approach has been published (Mamdani and Procyk, 1979). It treats adaptation of the controller, self-organisation of its structure. In the initial works, however, the rule-base has been supposed to be provided by experts and only its tuning and adjustment has been seen as a leverage for adaptation.

Recently, so-called '*data-driven*' techniques (Cios et. al., 1998; Cooper and Vidal, 1996) are gaining impetus as more objective and easy to acquire, test and validate. They, however, are still mostly applied to classification and *off-line* modelling and control (Burkhardt and Bonissone, 1992; Carse et. al., 1996). The problems of *on-line* application of these control techniques are mostly related to the non-linear nature of the rule-base and computational expenses of the training technique (normally back-propagation or genetic algorithms). From the other hand, the non-linearity of the model/controller structure combined with the high level of transparency is their main advantage. It explains the good performance of these models and controllers with complex plants and control aims, but in the same time it makes difficult to design recursive, adaptive schemes.

Approaches for automatic generation of fuzzy rules (Furuhashi et. al., 1995; Angelov et. al., 2001) and for tuning of fuzzy logic controllers (Cooper and Vidal, 1996) has been developed based on evolutionary algorithms and on gradient-based techniques (Jang, 1993). Applying evolutionary techniques allows for tuning parameters of the fuzzy logic controllers with the aim to achieve the desired quality of control. It makes also possible to generate the whole structure of fuzzy rules of the controller *off-line*. Some practical applications of fuzzy logic and neural network-based controllers are called *self-learning* or *adaptive*, (Chiang et. al., 1996), but they are rather *self-adjusting* and *self-tuning*. They, normally, suppose **structure** of the controller **to be fixed** and apply adjustments to the parameters or make additive corrections only (Hepworth et. al., 1994).

On-line application in *real-time*, however, are hampered by the high computational costs of genetic algorithms and non-linearity of the models considered. Parameter adaptation, when possible, is time consuming because normally used learning schemes are iterative. The lack of a true adaptivity hampers application, including portability (the ability to use a system designed for one specific application to another quite similar one with as little modifications as possible), which is extremely important in industrial and software applications.

2. **ER** MODELS AND CONTROLLERS IN THE CONTEXT OF *SMART* ADAPTIVE SYSTEMS

There are currently pressing demands from different branches of industry and science to find effective approaches to build *adaptive*, *autonomous*, *self-developing* and *self-enriching* systems, which in the same time are *flexible* and *robust* (EUNITE, 2000). It is also necessary for their practical application that they are *computationally effective*, *compact* and *transparent*. They are needed to serve in autonomous *intelligent* sensors, self-diagnostic systems, evolving and re-usable decision support systems, *on-line* control and performance analysis, knowledge extraction, *intelligent agents* etc.

Ideally, such a system has to respond to the **external influence** (possible changes in the environment) or the **internal stimuli** (change in the object of modelling or control itself possibly due to wearing, ageing, degradation or fault development). It should incorporate or mimic human-specific activities like *perception*, *reasoning*, and action to achieve multiple (possibly conflicting) goals while functioning autonomously in non-stationary environments. A desirable ***smart*** adaptive system by differ from a 'simply' *adaptive* (normally linear) systems have to be:

- ✓ able to change, *evolve its structure* simultaneously with the parameters;
- ✓ *autonomous* (to act and evolve on their own);
- ✓ to *accumulate experience* (to build-up their structure during the routine operation);
- ✓ *intelligent* (to take decisions);
- ✓ able to *react to a surprise*, to unexpected input, to *distinguish outlays*;
- ✓ adaptation mechanism itself could change (evolve) with time;

One promising alternative is so-called **e**volving fuzzy **R**ule-based (**eR**) models (Angelov, 2000), which could be used as a tool for building such *smart* adaptive systems. They combine the flexibility of the non-linear, in general, rule-based models with the adaptive, recursive schemes, normally used in linear control theory by an effective mechanism of rules *innovation* and parameters up-date (Angelov and Buswell, 2001). They make possible to generate the structure and parameters of the rule-base *on-line* and to adapt them later in respect to the change in the environmental or internal changes. In this context such fuzzy controllers could be characterised as *self-learning, evolving* control schemes.

A *smart* adaptive controller is proposed in the paper, which is based on **eR** models in combination with the indirect adaptive learning scheme. It has been tested and illustrated with the example of controlling the outlet air temperature of a cooling coil of a real air-conditioning system.

3. ADAPTIVE CONTROLLER USING EVOLVING FUZZY RULES

The adaptive control scheme presented here uses the indirect learning (IL) mechanism introduced initially by Psaltis et. al. (1988). Effectively, it is based on the approximation of the inverse dynamics of the plant. As it is well known, the neural networks and fuzzy rule-based models are both proven to be universal approximators (Hornk, 1991; Wang, 1992).

In the original works on IL-based control (Psaltis et. al., 1988; Andersen et. al., 1994) neural networks has been used for learning purposes. As it is known, however, the learning techniques for NN are iterative and, therefore, Andersen et. al. (1994) have trained the neuro-controller *off-line*. Additional important disadvantage of neural networks in comparison to the fuzzy rule-based models is their lack of interpretability and transparency. We use fuzzy rule-based models to represent the controller and we employ recently introduced technique for unsupervised *on-line* learning of such models called **eR** models (Angelov, 2002).

It should be mention that there exist various schemes for adaptive control (Astrom and Wittenmark, 1984). The IL-based adaptive control scheme is preferred, because it is convenient for recursive, *on-line* implementation. It supposes model-free concept and instead of feeding back the error between the plant output and the set-point it feeds back the integrated (or memorised one-step back) output signal (Fig.1):

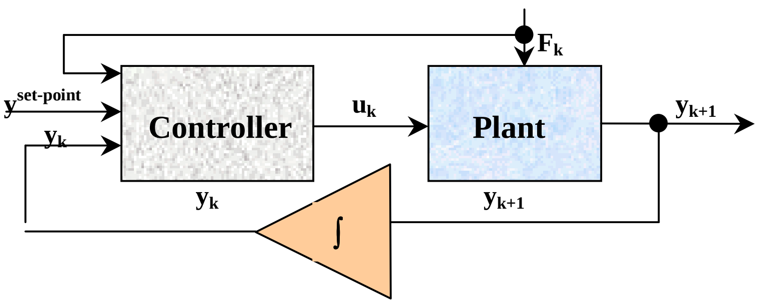

Fig.1 IL-based adaptive control (control phase)

Fig. 1 represents the IL-based controller in use (in the so called 'control phase'), when it is supposed that its structure and parameters are known. The learning process itself is performed at each time-step in the so-called 'learning phase' (Fig.2).

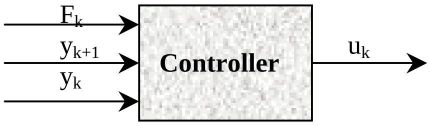

Fig. 2 IL-based adaptive control (learning phase)

As it is seen, in the learning phase the actual output signal (y^{k+1}) achieved at the time-step (k+1) is supplied instead of the set-point signal ($y^{set\text{-}point}$). This output has been a result of application of the control action u_k having an output signal (y^k) at the time step (k), e.g. before the control signal is applied. The data set (y_k, y_{k+1}, F_k, u_k) necessary to train and adapt the controller could easily be collected by memorising or integrating the real output from the plant (y_{k+1}) and recording the disturbance (F_k) and the control signal applied (u_k).

The proposed scheme is represented in the Fig.3. Initially, during the first few (N) time steps it is possible to apply any conventional control algorithm, like P, PID or a fuzzy logic controller trained *off-line*. There is a constraint, which apply to N: N>n; where n denotes the number of inputs to the controller, here n=3; N denotes the number of initial time-steps (Angelov, 2002). Practically, as the experiments indicate N could be as low as 5÷10 and the structure of the controller could practically be developed by *'learning trough experience'*.

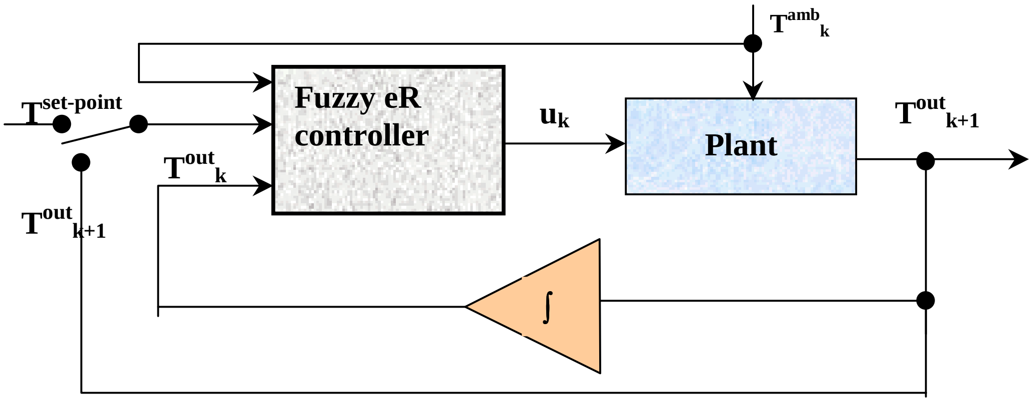

Fig. 3 **eR** control scheme based on indirect learning principle

4. COOLING COIL CONTROL

The cooling coil cools the warm air that flows on to the coil. The cool air is used to maintain comfortable conditions in an occupied space. One of the principle loads on the coil is generated due to the supply of ambient air; required to maintain a minimum standard of indoor air quality. The test system is shown in the Fig. 4.

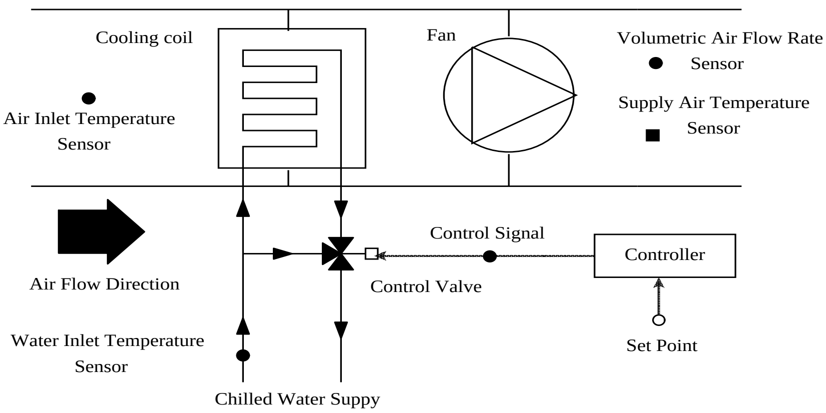

Fig. 4: The Test Rig

Supply air temperature, which is outlet from the coil is controlled to some predetermined set point by regulating the mass flow rate of chilled water through the coil. This is achieved via a control signal (**u**) that commands an electrically driven actuator, which operates the control valve diverting the water flow from one port to the other. The measurements of air inlet (in fact, the ambient temperature, T^{amb}) and outlet temperatures (T^{out}) are used as inputs to the **eR** controller. Volumetric flow rate of air (m_a=1.0,kg/s), moisture content (g=0.008,kg/kg), and the temperature of the water (T_w=10,^{o}C) are supposed to be constant. The sample interval is 1 minute.

Results of application of the eR controller are depicted in the Figs.5a and 5b.

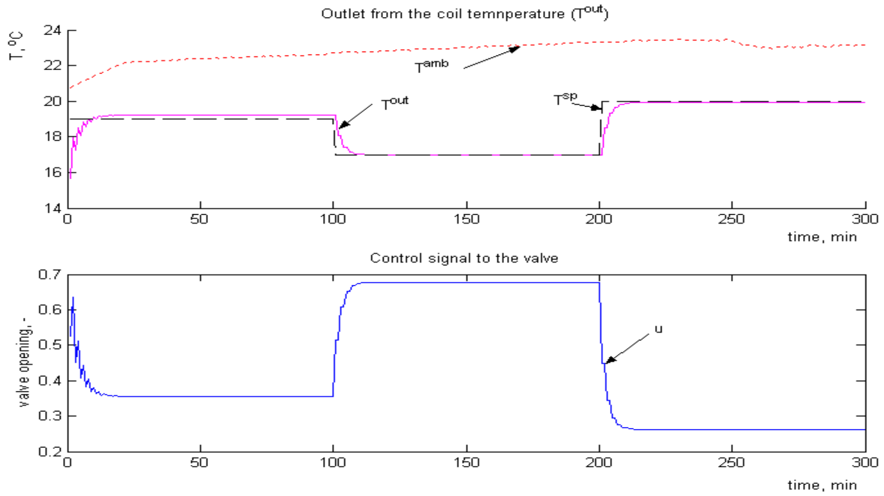

Fig.5a **eR** control of outlet temperature of a cooling coil - case 1

Data from a real system, located in Iowa, USA, generated from the ASHRAE funded research project RP1020 (courtesy of ASHRAE) has been used. The ambient temperature on 22 August 1998 (dotted line on Fig 5a) has been considered as the disturbance to the HVAC plant and input to **eR** controller respectively (Figs.1 and 3). The set points ($T^{set\text{-}point}$) for the outlet from the coil air temperature (T^{out};solid line), which is supplied to the occupied zone has been fixed on 19^{o}C for the first 100 minutes, 17^{o}C for the next 100 minutes and on the 20^{o}C for the rest 100 minutes (Fig.5a).

Initially, a fuzzy controller is applied, which has three fuzzy rules generated *off-line* based on the data (100 data points) from the same system. The rules of this *off-line* trained controller are:

R_1: **IF** (T_k^{amb} is *Low*) **AND** (T_{k+1}^{out} is *High*) **AND** (T_k^{out} is *High*) **THEN** (u_k is *Low*) (1)

R_2: **IF** (T_k^{amb} is *High*) **AND** (T_{k+1}^{out} is *Medium*) **AND** (T_k^{out} is *Medium*) **THEN** (u_k is *High*)

R_3: **IF** (T_k^{amb} is *Very Low*) **AND** (T_{k+1}^{out} is *High*) **AND** (T_k^{out} is *High*) **THEN** (u_k is *Very Low*)

Where the linguistic labels are assigned to membership functions representing respective fuzzy rule. They are depicted in the Fig.6 for the variable T^{amb} and they are similar for the other variables. For the output (control signal, u) singletons are used, with the following values: Very Low is 0.0698, -; Low is 0.3178, -; Medium is 0.4751, -; Rather High is 0.5065, -; High is 0.7519, -.

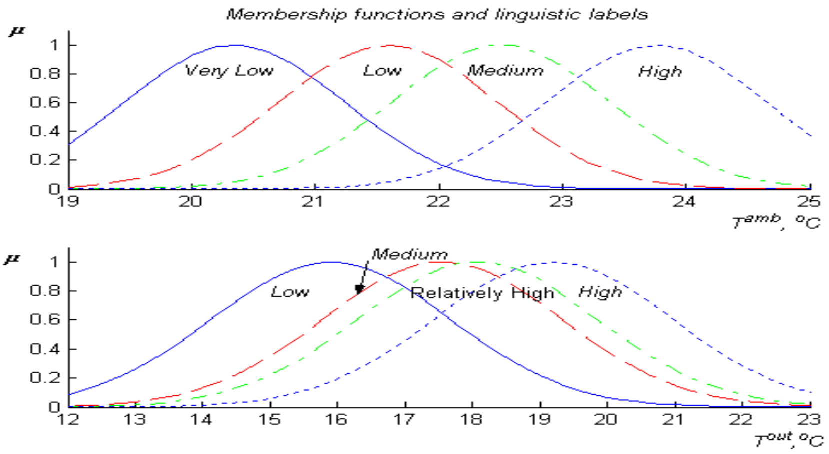

Fig.6 Membership functions and linguistic labels of the fuzzy variables T^{amb} and T^{out}

Then starts the on-line phase. In *real time* the new triplet of data has been recorded ($T_k^{out}, T_k^{amb}, u_k$). They are memorised and at the next time step they will effectively be ($T_{k-1}^{out}, T_{k-1}^{amb}, u_{k-1}$). Adding to this triplet the current data for T_k^{out} a new set of data for training **eR** controller is collected. It is added to the already existing set of data based on the *off-line* training and a recursive up-date of the controller structure and parameters starts. This process is repeated for every time instant (from 1 to 300 in this example) and calculations take several seconds making possible real-time application.

In most of the cases no changes are required as the informative potential of the new data sets is not high enough to replace, modify or add a new rule and correct the parameters, but in two cases there was new data sets with high enough potential. In such a way, at time instant *k=3* (3 minutes after the *on-line* control starts) a new data point is informative enough to generate a new fuzzy rule:

R_5: **IF** (T_k^{amb} is *Medium*) **AND** (T_{k+1}^{out} is *Low*) **AND** (T_k^{out} is *Low*) **THEN** (u_k is *Medium*) (4)

Additionally, there was one data set, which has informative potential, not high enough to add a new rule, but high enough to modify the rule-set, and the centre of this new rule is not very close to existing rules as well as linguistic labels are not close to existing ones. Based on this, the fuzzy rule R_3 has been replaced by the more informative rule R_5 in a way described in more details in (Angelov, 2002):

R_5: **IF** (T_k^{amb} is *Medium*) **AND** (T_{k+1}^{out} is *Relatively High*) **AND** (T_k^{out} is *Medium*) **THEN** (u_k is *Medium*) (4)

In a similar way, the second test has been performed (Fig 5b). This time the set point $T^{set\text{-}point}$; solid line) has been fixed on 17°C. The controller has generated its four fuzzy rules *on-line* during the control of the T^{out} starting from the T^{out}=22°C (dotted line, Fig.5b).

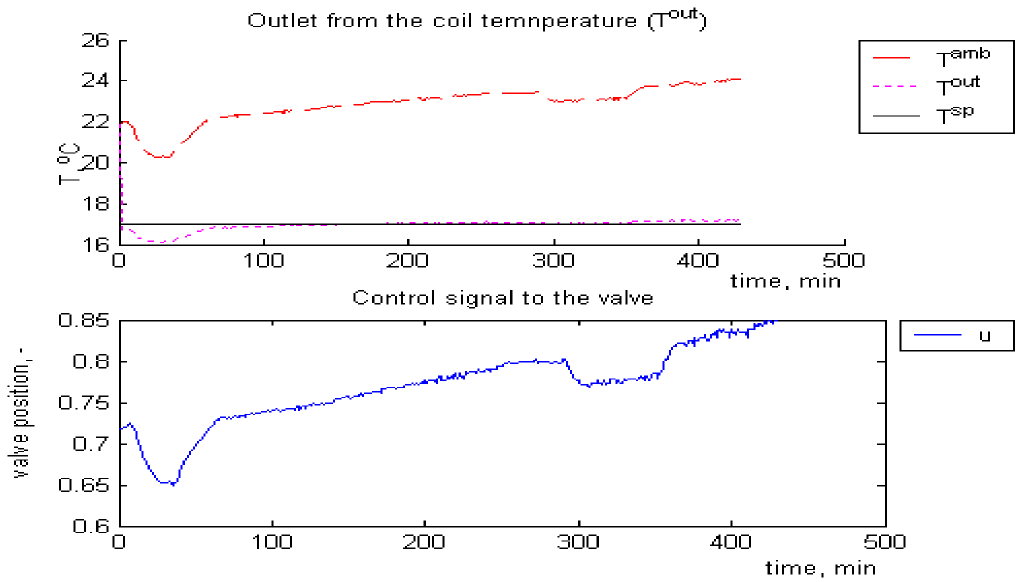

Fig.5b eR control of outlet temperature of a cooling coil - case 2

5. CONCLUSIONS

A new approach for adaptive control based on evolving Rule-based (**eR**) models is presented in the paper. Fuzzy rules, representing the structure of the controller are generated based on data collected during the process of control using newly introduced technique for *on-line* identification of Takagi-Sugeno type of fuzzy rule-based models. Initially, the process is supposed to be controlled for few time steps by any other conventional type of controller (P, PID or a fuzzy one with a fixed structure determined *off-line*). Then in *on-line* mode the output of the plant under control (including its dynamic) and the respective control signal applied has been memorised and stored. These data has been used to train in *real time* **eR** model representing the fuzzy controller, which aim is to control the plant at a given set point. The indirect learning-based adaptive control approach has been used in combination with a newly introduced *on-line* identification technique. The proposed approach exploits the quasi-linear nature of the Takagi-Sugeno models and builds-up an adaptive *on-line* modelling and control rule-base structure. The method is illustrated with an example from air-conditioning systems (control of a cooling process of the air through water mass flow rate), though it has much wider potential applications.

6. ACKNOWLEDGEMENTS

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