Fuzzy controller development from information granules for a heat exchanger

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Received 21 May 1999; accepted 5 May 2000

This paper discusses the experimental results of on-line fuzzy control of a heat exchanger unit. Fuzzy controllers are a class of model independent controllers, which use common sense logic, expressible in linguistic form and is more amenable to human way of decision-making. A collection of information granules, regarding the process under study, is documented first. Using the same, the steps of formation and justification of the fuzzy look-up table is demonstrated. An efficient fuzzy control is established using multiple look-up tables. These tables are further adapted to accommodate conflicting control demands of 'low overshoot' and 'small rise time'. An algorithm for on-line table switching is also proposed.

Conventional PID controllers are model-dependent and give reasonably good response for linear processes. These controllers do not yield satisfactory response for nonlinear processes. Astrom and Wittenmark have suggested various adaptive techniques by which the initial PID parameters or any other controller parameter can be adjusted depending upon controller performance over a range of operation. It is, however, observed that experienced human operators can efficiently control highly nonlinear processes like distillation column etc. using their intuitive judgment and knowledge. Two knowledge based model independent control schemes are presently gaining popularity, namely Fuzzy Controller (FC) and Artificial Neural Network Controller (ANN). FCs try to derive control rules by capturing artisan knowledge and/or intuitive judgment about the system and ANNs try to encode the system dynamics from a set of input-output data.

Numerous works have been published in the areas of nonlinear process control using FC. Most of these works, however, are centered around theoretical or simulation based study of highly nonlinear conceptual problems, for example: balancing inverted pendulum, truck backer upper system, ball on a beam problem, etc. Another group of researchers have carried out simulation based study of real industrial process, for example, activated sludge wastewater plant, anti-skid braking system, magnetic heating system, etc. Examples of on-line control of real process using FC are relatively fewer; examples are available in cement kiln control, heating system control and water bath temperature control by Khalid et al.

In general, design of a fuzzy controller involves the following steps: construction of a fuzzy model, construction of a fuzzy rule base, selection of fuzzy inference mechanism and selection of de-fuzzification mechanism. If fuzzy model is built by capturing expert experience, it is generally in the form of if-then-else rules and directly forms a fuzzy rule base. In absence of an expert operator, the authors' application, a collection of information granules about the system under study is made, generally touching upon the salient features, boundary conditions and other operating constraints. Fuzzy rules are derived from this fuzzy model by deductive reasoning. A subjective element is, however, always associated with a FC design. Tanig and Sugeno provide a critical discussion on the different methods of FC design.

The initial fuzzy rules generated by interviewing an expert or by inferring from a fuzzy model are to be adapted and justified to obtain a set of optimum rules. Baski and Mamdani proposed a prescriptive method in which the best rules are determined by carefully analyzing the control rules within a prescribed fuzzy band. Our aim, however, is to obtain optimum performance throughout the whole range of operation. A method of rule justification applicable over the whole operating range using the closed loop response and the phase plane trajectory was proposed earlier. It was observed that, the phase plane trajectory, when superimposed on the fuzzy look-up
The same set of optimized rules, however, are not applicable for different regime of operation. A need for multiple rule bases is, therefore, felt. An alternative is to use a variable scaling parameter or gain along with a single table as used to control a thermal process. It is an established technique in FC to switch over to a second finer look-up table when the error and derivative of error have sufficiently narrowed down to a preset limit. Li and Gatland advocated the use of two different sets of scaling gains to obtain the effect of coarse and fine control, thus reducing time and effort of multiple table tuning. However, the subjective elements put into the design of coarse and fine control rule base cannot be expected in variable gain method. In the present work, the coarse and fine tuning tables are not only different in terms of magnitude of control action, but also in strategy. A single fine-tuning controller is chosen, which is incremental type, making it suitable around any value of setpoint within the range.
Moreover, the effort of tuning the variable gain is comparable to that of tuning a fuzzy database if number of tables is limited. The authors, therefore, prescribe multiple rule base of coarse control of the so-called "bang-bang" type. These rules are tailor-made for different control regimes based on the characteristics of the final control element. It is found that designing the rule bases are easier and less arbitrary when a hybrid model of the process is available in terms of information granules. It is demonstrated that multiple rule bases can be tuned to obtain small rise time starting from any initial point within the operating range. The bang-bang type rules ensure that the rise time is comparable to the limiting rise time governed by the system hardware. The incremental type fine-tuning rules along with an online table switching algorithm gave satisfactory response with small rise time and low overshoot.

**Theory**

Fuzzy logic has been viewed earlier as a super set of conventional bivalent logic and comes with immense potential to describe or model complex observations or concepts, which cannot be expressed through crisp data. Zadeh, who introduced the fuzzy terminology to technical literature has later expanded the horizon of fuzzy logic to a more broad based "Computation with Words". A fuzzy set $F$ in a
Fig. 1—Defuzzification steps. (a) Calculation of \( e \) and \( \Delta e \). (b) Rule fired for \( e \). (c) Rule fired for \( \Delta e \). (d) Defuzzification.

Fig. 2—Motorized valve characteristics.
universe of discourse $U$ can be represented as a set of ordered pair of a point element $x$ and its membership function $\mu_F(x)$ as

$$F = \{x, \mu_F(x)\}, \quad x \in U$$

By suitably modifying the extent of the point $x$ and the definition of equality various shapes of extension hull of a point can be obtained. One of the simplest, from the viewpoint of on-line computational load, is a triangle and is adopted here. Thus a fuzzy variable "Large Positive" within the Universe of Discourse (UD) of "Error" is defined by a triangular spread, with values of error just below the apex having maximum fuzzy membership function to large positive, and membership function linearly decreases to zero on either side.

Construction of fuzzy model—A fuzzy model of a system is a collection of qualitative and quantitative information granules. Those information are collected, which aid in identifying the requisite UD and the extent of the fuzzy variables within the respective UD as shown in Table 1. The fuzzy model also helps to formulate linguistic control rules in the form of "if-then-else" statements connecting fuzzy variables across the UDs. A typical control rule may be "if error is large positive and change in error is large negative, then change in controller output is small positive".

Construction of fuzzy rule base—A collection of all such fuzzy rules, conveniently expressed in the form of a matrix is called a fuzzy rule base (Table 2). It may also contain special rules for exceptional handling as well as for startup and shutdown. A fuzzy rule base is somewhat general and is portable across similar plants.

Construction of fuzzy database—Fuzzy variables like "large positive", etc. and hedges like "very", etc. are expressed quantitatively and tabulated in the form of a look-up table (Table 3). In absence of input from an experienced operator, fuzzy look-up table may be built taking help of the fuzzy model, intuitive judgment and technical common sense.

Selection of fuzzy inference mechanism—Fuzzy inference mechanism is a method of deriving conclusion from a set of fuzzy rules as proposed earlier. Depending upon the semantics of logical connectivity of fuzzy sets, a linguistic fuzzy rule "if $x$ is $A$ then $y$ is $B$" can be essentially of two types:

(i) A coupled with B. (e.g. "if temperature is high, then cooler-on time is long").
(ii) A entails B. (e.g. "if temperature is high, then discomfort is high").

The first implementation essentially represents a fuzzy AND operation which can again have two prominent ways to interpret:
Therefore, linguistic statement that indicates chosen the other is simply left out. This, on the one hand, tolerates imprecision in measurement of the two fuzzy sets as long as one is smaller than the other; on the other hand, the result does not reflect the characteristics of the two fuzzy sets being ANDed. Therefore, linguistic statement that indicates interaction of two objectives where both are to be satisfied, sup-product operator is a better choice. For control application, the fuzzy "if-then-else" statements relate error and change in error of measured variable with manipulated variable and does not indicate any interaction. Therefore, sup-min is more appropriate.

Selection of defuzzification mechanism—The final control element demands a crisp output, therefore, a suitable defuzzification mechanism is to be established. Literature survey reveals that different researchers preached different mechanism, whose merits are often compared based on the result of the application. Braae and Rutherford30 gave an interesting discussion. The defuzzification mechanism selected for the present work is the much-used centroid of area method and is explained with an example of firing of bang-bang type fuzzy rules in Fig. 1.

Experimental Procedure
A laboratory standard plate type non-mixing heat exchanger unit, supplied by Feedback Instruments Ltd. (UK), is chosen for experimentation. The process fluid temperature at the outlet of the heat exchanger is measured with a thermo-couple, equipped with compensating cables. The manipulated variable is heating fluid flow rate and the final control element is a stepper motor operated valve. The unit is described elsewhere31. Experiments are conducted at a sampling rate of 0.1 s, while each sampled data point represents statistical average of 500 consecutive readings.

Results and Discussion
PID control—As a starting value, approximate settings are determined from experimental process reaction curve, and the same is later modified based on response study to obtain the following optimized parameters.

(i) "Sup-minimum" operator,32.
(ii) "Sup-product" operator.

The choice of operator should be made after careful observation of the context to which they are applied. The first operator basically indicates "no interaction" because as soon as the minimum is chosen the other is simply left out. This, on the one hand, tolerates imprecision in measurement of the two fuzzy sets as long as one is smaller than the other; on the other hand, the result does not reflect the characteristics of the two fuzzy sets being ANDed. Therefore, linguistic statement that indicates interaction of two objectives where both are to be satisfied, sup-product operator is a better choice. For control application, the fuzzy "if-then-else" statements relate error and change in error of measured variable with manipulated variable and does not indicate any interaction. Therefore, sup-min is more appropriate.

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For setpoint other than 45°C, the response is found unsatisfactory with the same 7x7 look-up table described above. It is observed that the response is oscillatory at lower setpoint and at higher setpoint it is sluggish. The observation is ascribed to three reasons.

(a) The heating fluid temperature is always near 80°C, therefore, at lower setpoint the rate of heat transfer is more due to large difference between the cold and hot fluid streams, thereby making the response more sensitive.

(b) A reverse situation is observed at higher setpoint.

(c) It was found that there are three distinct regions in the characteristics of the final control element as shown in Fig. 2.

It is planned to implement multiple fuzzy tables to improve the performance over the entire operating range. To reduce rise time, three fuzzy tables with bang-bang type rules are selected for operating ranges of "low temperature", "near 45°C" and "high temperature". These three tables roughly take care of the steady state operating regime for the three distinct characteristics of the final control element. An incremental type tuning table is also selected for control near setpoint. An algorithm is also made for on-line table selection.

The values in these tables directly give controller output in 0-1V scale. Note that controller output for zero error is undefined in a bang-bang situation. In a real fuzzy rule base for bang-bang control, the values of controller output are first assigned within the range from 0.05V (minimum) to 0.05V (maximum) with equal intervals. Extreme values are avoided as a safety measure against jamming (Table 1). The resulting
look-up table is then used for setpoint tracking experiments with setpoint value of 35°C, which falls in the first regime AB of valve characteristics (Fig. 2). Since, for bang-bang type of rules, the controller output corresponding to zero error is undefined, another fine tuning table of incremental type is used when error approaches zero. For the incremental table, one unit of increment (or decrement) is taken as \( \frac{1}{12} V \) so that a very fine control is obtained. Necessary corrections in the fuzzy look-up table are then made, studying the closed loop response and utilizing the proposed guideline. Experience gained in adaptation of earlier incremental type table made it possible to tune this table with lesser trial and error. The modified values are shown in Table 7. Similar effort is repeated for setpoints 45°C and 55°C, which are representative of the other two regimes BC and CD of valve characteristics. The modified values are shown in Tables 5 and 6 respectively. Comparing the Tables 4, 5 and 6 it is seen that the controller outputs are drastic and same for extreme values of errors namely LN and LP. However for other grades of fuzziness in error, the controller output is larger for higher setpoint. For very high range of setpoint, 55°C since the output temperature of cold water normally does not overshoot setpoint, controller output value for negative errors are kept same as that of lower setpoint (45°C). Whereas for positive error, the controller output values are kept higher to decrease the rise time. To establish an efficient and automatic on-line controller for the full operating range, a selection flow chart is also formulated as given in Fig. 3. The fine-tuning table (Table 7) is used when there is no error and change in error has converged to a small value and approaching setpoint from either side. However, in order to avoid overshoot, Table will not be used when the response is moving away from the setpoint in positive error side because incremental type action will take more number of sampling instances to change the trend from diverging to converging. This table switching algorithm is valid when the process fluid is heated to a higher setpoint. For cooling applications, suitable modification is necessary. A comparative study of closed loop
response using PID, single table fuzzy and multiple table fuzzy control is shown in Fig. 4. It is evident that the best control, in terms of overshoot and rise time, is achieved using multiple tables. The oscillations are also eliminated when the proposed controller is used.

The closed loop response for the three different temperature regions using the proposed controller is shown as curve B of Fig. 5. This figure shows that the rise time has been reduced for all the three regions when combinations of coarse and fine tables are used. The second advantage of using multiple table is that overshoot is virtually eliminated for all regions. The proposed fuzzy controller is also tested for deliberately introduced disturbances. Fig. 6 shows the effect of step change of ±50 cc/min in cold water flow rate from the original 240 cc/min. It is observed that the controller is able to track the setpoint temperature within about 100 s, after the initial overshoot due to disturbance. It is, therefore, concluded that the proposed multiple table fuzzy controller is robust.

Conclusion

Observations made during the course of experimentation show that fuzzy look-up tables can be modified through trial and error to accommodate the conflicting demands of controller objectives. This can be attributed to the localized nature of the fuzzy controller.

It is also observed that fuzzy look-up table tuned around a certain setpoint to obtain good control may not be equally effective when applied to some other setpoint. Hence there is a need of multiple tables. A practical and effective tradeoff is to have as many tables as distinctive regions of the characteristics of the final control element. However even if the final control element does not have distinctive regions within its working range, it doesn’t imply that a single fuzzy table will be equally effective throughout the range. This conclusion can be logically drawn from the fact that for a setpoint near the lower range of operation (35°C), the rate of rise in temperature is very rapid when the valve is fully open, while near the upper limit (55°C) it is considerably slower. These factors should be suitably represented in the fuzzy database in order to satisfy the control requirements.

For the experimental setup chosen, it is found that a combination of a single incremental type fine-tuning table and multiple bang-bang type coarse tables along with an intelligent table switching algorithm gives a satisfactory closed loop response over the entire range of operation. It is expected that this combination will be effective for similar process control problems.

References