

Making Predictions About the Power Transformer's Technical State with Fuzzy Logic and the Dissolved Gas Analysis Method

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Abstract

Fuzzy logic has been introduced in many researches as in to force the PV to work around MPP. FLC has the advantages of working with imprecise inputs, not needing an accurate mathematical model, and handling nonlinearity. FLC generally consists of three stages: fuzzification, aggregation, and defuzzification. During fuzzification, numerical input variables are converted into a membership function. The output of the systems has linguistic relations with the inputs of the system. These relations are called rules and the output of each rule is a fuzzy set. More than one rule is used to increase conversion efficiency. Aggregation is the process whereby the output fuzzy sets of each rule are combined to make one output fuzzy set. Afterward, the fuzzy set is defuzzified to a crisp output in the defuzzification process.

Introduction

Most of the real-world processes that require automatic control are nonlinear in nature, i.e., their parameter values alter as the operating point changes over time. As the conventional control schemes (P, PI, and PID) are linear, the controller can only be tuned to give good performance at a particular operating point or for a limited period of time. The controller thus needs to be retuned periodically if the process changes with time. This necessity to retune has driven the need for adaptive controllers that can automatically retune themselves to match the current process characteristics.

The fuzzy controllers are nonlinear, and so they can be designed to cope with a certain amount of process nonlinearity. However, such a design is difficult, especially if the controller must cope with nonlinearity over a significant portion of the operating range of the process. Also, the rules of a fuzzy logic controller (FLC) do not have the capability to cope with process changes over time. Hence, there is a need for an adaptive fuzzy logic controller.

Fuzzy logic controllers

Fuzzy logic controllers are based on fuzzy logic, which are derived from fuzzy sets, a mathematical system that analyzes analogue input values in terms of logical variables that take on continuous values between 0 and 1. No models are required, and for a thorough description of fuzzy set theory, please refer to Zadeh (1965). Variables such as pH and temperature values can be classified as “very low,” “low,” “medium,” “high,” “very high” (fuzzy values) as against just “low” and “high.” A fuzzy controller converts the input variable(s) values into fuzzy values via a process called fuzzification, and then an inference is made by applying fuzzy approximate reasoning with IF-OR-AND-THEN rules based on the fuzzy values. Finally, the results of all the rules are combined to give a crisp output in a process termed defuzzification that

informs the actuators. Fuzzy logic controllers have the advantage of cheaper performance cost in comparison to model-based controllers and are more robust than PID controllers as they can cover a broader range of operating conditions.

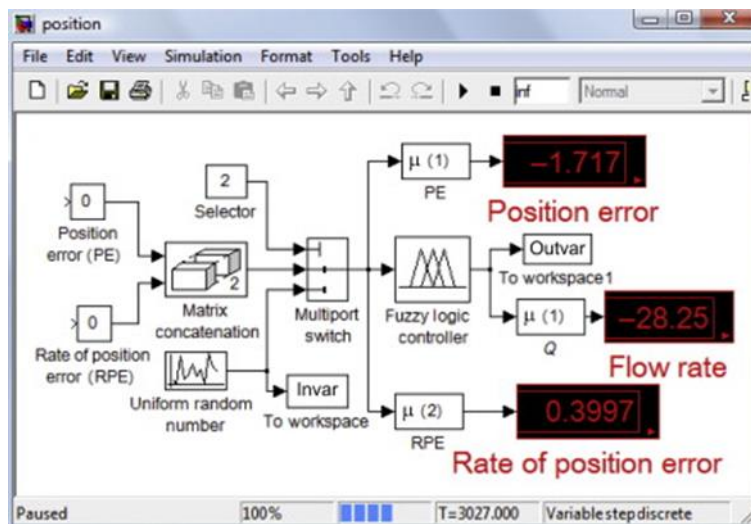
HDNFLC controllers generally contain two extra components on top of the standard controller; they are: A “process monitor” that detects changes in the process characteristics. This takes usually two forms:

- A performance measure that assesses how well the controller is controlling,
- A parameter estimator that constantly updates a model of the process.

The adaptation mechanism uses a deep learning algorithm like CNN, which uses the information passed to it by a “process monitor” to update the controller parameters and so adapts the controller to the changing process characteristics. Depending on the “process monitor” method used, the HDNFLC controllers can be classified as performance-adaptive or parameter-adaptive controllers.

Usually, in an HDNFLC, the following sets of parameters are altered to modify the controller performance: The scaling factors for each variable.

The fuzzy set representing the meaning of linguistic variables (membership function of variables).The if-then rules.



As shown in Fig. 5, an HDNFLC system performs a conventional fuzzy inference, attempting to develop a value for the solution variable from the rules in its knowledge base. The characteristics of the fuzzy region created for the solution variable are stored in a time- or process-phased buffer, where they can be assessed. To produce a feedback signal in a fuzzy model, a performance metric that measures the change between sensor measurements interrogates the current and the stored array of past solutions. This signal is fed back into the DNN model, which decides what changes to make in the underlying fuzzy model. The adaptation machine, based on the signal it receives, modifies the scaling factors, membership function of variables, and rules to adapt to the changing environment.

Altering scale factors

Whenever there is a change in the environment, the oscillations may increase. These oscillations can be reduced by varying the gain of the controller, which is usually achieved by varying the scaling factor. The variation in the scaling factor is achieved by making use of rules that will modify the scaling factor based on the performance measure. As the performance measure is provided as input to the adaptation machine, the rules corresponding to a situation will get fired resulting in change of the scaling factor.

Based on the simplified model of the system, simulations are carried out for examining the designed control system. In the control system, the desired position is set up as a constant that feeds a signal to a summer. Since this is a reference signal, the signal input is designated as positive. This signal is summed with the output of the cushion system that is designated as a negative input to the summer. The resulting error signal serves two purposes: it gives a clear indication of whether the system output is above or below the desired value, and it allows computation of the derivative of the error signal to determine if the error is increasing or decreasing in time. Both the error signal and its derivative are fed to a multiplexer (Mux) that provides input to the fuzzy controller. The output signal of the fuzzy controller is then fed to an air-cushioned system. All signals that are desired as outputs can be monitored using a variety of output devices.

Comparison study between the performances before and after the genetic optimization

An evaluation of the FLC performances, before and after the genetic optimization, is made. Thus, by evaluating the number of correctly classified examples (TP and TN) and those badly classified (FP and FN), ACC, Se and Sp performances are deduced from the obtained confusion matrix. Tables 7 and 8 summarize the FLC performances achieved before and after the genetic optimization, respectively. In each table, bold values indicate the highest and lowest class performances, as well as the average ACC.

Fuzzy logic control

In nature, most systems and concepts are naturally unpredictable and fuzzy, hence the importance of fuzzy set theory in real problems and especially in human physiology. In fact, fuzzy logic control is adequate for medicine because it is tolerant of peculiar imprecision. The fuzzy concept is based on fuzzy rules of the form IF ... THEN. A fuzzy logic controller is equivalent linguistically to a PI controller (Mahfouf et al., 2001).

In the literature, fuzzy logic controllers are the most incorporated control algorithms in medicine applications. Some of them are described in the paragraphs that follow.

Fuzzy logic control problem in anesthesia

Fuzzy logic controllers are widely adapted and used in anesthesia (Derrick et al., 1998). Generally, anesthetists fix the rules of this type of controller since they have extensive experience with patients. One example of these rules is IF “blood pressure is decreased” THEN “reduce drug infusion.” More sophisticated rules are also composed.

Conclusion

Fuzzy logic controller is also used to regulate blood glucose in type 1 diabetic patients. This type of controller is based on zero order Takagi-Sugeno fuzzy logic architecture (Nath et al., 2018). This controller is characterized by two inputs and one output. The inputs are the error and the derivative in subcutaneous glucose concentration. The output of the fuzzy controller is the exogenous insulin infusion rate.

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