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A variable-structure adaptive fuzzy-logic stabilizer for single and multi-machine power systems

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Abstract

This paper proposes a new power system stabilizer based on adaptive fuzzy systems. The new controller is a fuzzy-logic-based stabilizer that has the capability to adaptively tune its rule-base on line. The change in the fuzzy rule base is done using a variable-structure direct adaptive control algorithm to achieve the pre-defined control objectives. This algorithm has two merits. First, it has a good performance in the training phase as it makes use of the initial rule base defined for the fuzzy logic stabilizer. Second, it has a robust estimator since it depends on a variable structure technique. The adaptive nature of the new controller significantly reduces the rule base size and improves its performance. This statement is confirmed by simulation results of a single-machine infinite-bus system under different operating points and exposed to both small and large disturbances. Extension to the multi-machine case is also included to illustrate the effectiveness of the proposed stabilizer in damping oscillations that follow a three-phase to ground short circuit.

Keywords: Power system stabilization; Fuzzy-logic control; Adaptive control

1. Introduction

Power generators are conventionally equipped with automatic voltage regulators (AVRs) to improve their dynamic limits and control their terminal voltages. Unfortunately, AVRs introduce negative damping torques, which adversely affect stability (DeMello & Concordia, 1969). Exposed to disturbances, such as short circuits and operating point variations, power systems may exhibit unacceptable oscillations or loose synchronism. Power system stabilizers are normally incorporated to suppress and damp these oscillations (Yu, 1983). Conventional power system stabilizers (CPSS) are based on linearized machine model and thus tuned at a certain operating point. If the system drifts from the original operating point, the performance of a CPSS degrades significantly and an expert control engineer has to retune the CPSS.

Alternative control techniques including self-tuning regulators, pole placement, robust control, and pole shifting have been investigated for the design of power system stabilizers (Ghosh, Ledwich, Malik, & Hoper, 1984; Chen, Malik, Hope, Qin, & Xu, 1993; Soliman, Elshafei, Shaltout, & Morsi, 2000; Wang, Hill, Middleton, & Gao, 1994). Adaptive control techniques are introduced to automate the tuning of power system stabilizers in Ghosh et al. (1984). The implementation of an adaptive power system stabilizer faces some technical difficulties. For example, the estimator, which is the heart of any adaptive controller, will not produce reliable estimates unless the measurements are persistently exciting. Furthermore, the performance of adaptive controllers during the learning phase is usually unacceptable (Sastry & Bodson, 1989).

Recently, fuzzy-logic control has emerged as a promising design technique of power system stabilizers (El-Metwally & Malik, 1996; Malik & El-Metwally, 1998; Elshafei & El-Metwally, 1997). Fuzzy logic provides a convenient method for constructing nonlinear controllers via the use of expert knowledge (Drainkov, Hellendoorn, & Reinfrank, 1993). This knowledge is usually provided by a control engineer who has performed extensive mathematical modeling,

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analysis, and development of control algorithms for power systems. Since, power system stabilizers are lead compensators, it turns out that a generic rule-base is available in the literature to help in constructing such a controller (Drainkov et al., 1993). Still, the design of a fuzzy-logic power system stabilizer (FLPSS) requires the selection of the size of the rule-base, the shape and parameters of the membership functions, and the rule inference mechanism. Increasing the number of rules to improve the performance of the FLPSS corresponds to a substantial increase in memory requirements. That is known in the fuzzy literature as the rule explosion phenomenon (Kosko, 1997). Implementing a fuzzy system with a small rulebase is the concern of many researchers (e.g. Wang, 1999; Guven & Passino, 2001; Trillas & Alsina, 2002). It is also noted that the FLPSS lacks the ability of self-tuning.

This paper proposes a new adaptive fuzzy-logic power system stabilizer (AFPSS) that grasps the merits of adaptive and fuzzy-logic techniques and overcomes their drawbacks. The proposed stabilizer is initialized using the rule-base of a standard FLPSS to ensure an acceptable performance during the learning stage. The rule-base is then tuned on-line so that the stabilizer can adapt to different operating conditions. The adaptive feature of the proposed stabilizer results in a satisfactory performance using a significantly small rule base as compared to the FLPSS. This is advantageous, since the proposed AFPSS is typically implemented using a micro-controller technology. To relax the excitation requirements, a variable structure algorithm estimates the controller parameters.

Section 2 describes briefly the basis of the FLPSS. Section 3 discusses the theoretical and implementation issues related to the proposed AFPSS. Section 4 illustrates the performance of the AFPSS as it is applied to single machine and multi-machine models. It also compares the AFPSS to the FLPSS. The conclusions are given in Section 5.

2. Fuzzy-logic power system stabilizer (FLPSS)

The basic configuration of a fuzzy-logic controller is composed of four parts: the fuzzifier, the knowledge base, the inference engine and the defuzzifier; see Fig. 1. The fuzzifier maps the input values into fuzzy variables using normalized membership functions and input gains. The fuzzy-logic inference engine deduces the proper control action based on the available rule base. The fuzzy-control action is translated to the proper crisp value through the defuzzifier using normalized membership functions and output gains (Drainkov et al., 1993).

In El-Metwally and Malik (1996), the speed deviation, $\Delta\omega$, and the deviation in accelerating power (electrical power—mechanical power), ΔP, of the synchronous machine are chosen as the inputs. The use of accelerating power as an input to the power system stabilizer has recently received considerable attention due to its inherent low level of torsional interactions (Larsen & Swann, 1981). Practical difficulties of eliminating the effect of mechanical changes appear to have been overcome by utilizing a heavily filtered speed signal which approximately corrects for mechanical power variations (Larsen & Swann, 1981).

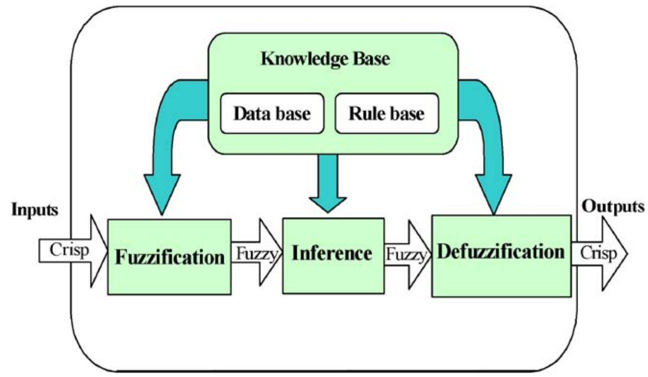

Fig. 1. The basic structure of the fuzzy controller.

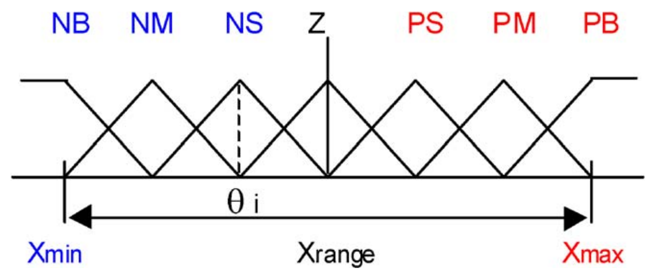

Fig. 2. Fuzzy variable, Xi, seven membership functions.

The output control signal from the FLPSS, U_{PSS}, is injected to the summing point of the AVR; see Appendix A.2. Let the letters N, Z, and P stand for the linguistic values negative, zero, and positive, respectively. Also, let the letters B, M, and S stand for big, medium, and small, respectively. Each of the FLPSS input and output fuzzy variables is assigned seven linguistic values varying from, Negative Big (NB) to Positive Big (PB). Each linguistic value is associated with a membership function to form a set of seven normalized and symmetrical membership functions for each fuzzy variable as shown in Fig. 2.

The values X_{max} and X_{min} represent maximum and the minimum variation of the input and output signals. These values are selected based on simulation information. Let $X_{max} = -X_{min}$. The range of each fuzzy variable is normalized between -1 and $+1$ by introducing a scaling factor to represent the actual signal so that: $k_\omega = 1/\Delta\omega_{max}$, $k_p = 1/\Delta P_{max}$, $k_u = 1/U_{PSS_{max}}$. The values of maximum variation of the input and output signals ($\Delta\omega_{max}$, ΔP_{max}, $U_{PSS_{max}}$) can be easily found form