Chapter 4

State-of-the-Art in Intelligent Controls

Deregulation requires that utilities exercise less conservative operation regimes and more precise power-flow control. This is possible only by monitoring and controlling the system in much more detail than is, or has been, the case in present and past practice.

The large quantity of information required can be provided in many cases through advances in telecommunications and computing techniques. There is still the need for evaluation techniques that extract the salient information from the large amount of raw data to use for higher-order processing. Up until now, the extraction of qualitative information is still done by the human expert, who can be overwhelmed in emergency situations when fast decisions are needed. The future operators also need to have the ability to specify the operating strategy in qualitative form, which is then translated into quantitative form in order to be processed by the computer control.

One of the main motivations for using intelligent systems is to provide this important interface between qualitative and quantitative information. Beside the control-center applications, intelligent control can be applied in a decentralized manner. For example consider closed-loop generator control. A consideration with existing control methods is that the control law is based mainly on a linearized model and the control parameters are tuned for certain operating conditions.* In case of a large disturbance, the system conditions will deviate significantly from the linearized condition, and the controller parameters may no longer be valid. In this case the controller may even add a destabilizing effect, such as negative damping.

Intelligent Systems can be categorized as:

- Expert Systems (ES) which process qualitative as well as quantitative knowledge with emphasis on the qualitative results.
- Fuzzy Systems (FS) which quantify qualitative knowledge including uncertainties.
- Artificial Neural Networks (ANN) which infer quantitative information through approximation techniques and classify quantitative data into higher-order qualitative categories.
- Decision Trees (DT) which classifies quantitative data into discrete sets of qualitative categories.

Expert System techniques are often associated with the software engineering concept of intelligent computing environments. Data and rules are formulated on a symbolic level in pseudo-natural language. In the ideal case, the “reasoning process,” i.e., the formulation of goals and the subsequent application of rules, are transparent to the user. Heuristic

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* Control is typically verified by nonlinear simulation for a limited number of operating conditions and disturbances.

reasoning (inspired by rules of thumb) are implemented in order to limit the number of branches of the decision tree to be exploited during the reasoning (i.e., deduction) process. Due to the nature of this approach, expert system techniques are often discussed in the context of an intelligent user-friendly human-machine interface, where not only real data and network topology maps but also abstract reasoning concepts like rules and decision trees are displayed graphically [4-1].

Expert system techniques are therefore usually implemented as off-line decision aids. Reference 4-2 discusses a voltage-control expert system for the off-line changes of on-load tap changer settings. It specifically draws attention to the fact that the heuristic nature of the off-line control rules limits their range of validity. Other examples of applications of expert systems for power system off-line monitoring and control can be found in reports published by several task forces of CIGRÉ WG 38.06 [4-3–7].

In the following we will concentrate on the applications of Fuzzy Systems, Artificial Neural Networks and Decision Trees to power system control.

4.1 Fuzzy Systems for Power System Control

Fuzzy sets and systems were first introduced by Zadeh [4-8]. Fuzzy systems come in two flavors:

- *Empirical* or *rule-based* fuzzy systems
- *Self-adaptive* fuzzy systems (self-organized or unsupervised fuzzy systems)

In the literature, fuzzy sets and fuzzy control are mostly discussed in terms of qualitative attributes like cold or warm and qualitative rules like “if temperature is cold with a likelihood of 0.7 then increase heating fast.” These empirical rules are often established from existing expertise in manual control and the corresponding fuzzy systems are referred to as empirical fuzzy systems.

However, in the area of power system control, as for example power system stabilizers, this expertise may not exist for unusual operating conditions. It’s therefore necessary to establish the fuzzy sets and rules in a more systematic, autonomous manner and the corresponding fuzzy systems are referred to as self-adaptive fuzzy systems.

Let us briefly illustrate these concepts by looking at the example of fuzzy temperature sets [4-9]. If the initial input set is the range of temperatures from 0^{o}F to 120^{o}F, the membership function describing the three fuzzy sets *cold*, *warm* and *hot* may be centered at $a_1 = 40^{o}$F, $a_2 = 70^{o}$F and $a_3 = 100^{o}$F, and have a triangular shape and a maximal width σ of 20^{o}F as shown in Figure 4-1.

Instead of defining center, shape and width of the membership function by empirical rules, one can choose a more systematic approach using data analysis. For example, in the case of load forecasting, sampling of the load data might indicate that the load exhibits three different behaviors correlated with the temperature. A clustering algorithm might have identified three typical temperatures a_1, a_2, and a_3, with the width of the cluster defining the width of the membership functions μ_1, μ_2 and μ_3.

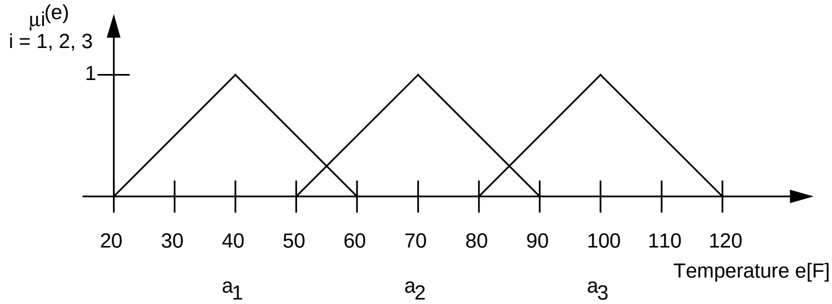

Fig. 4-1. Membership function for fuzzy temperature sets.

In addition, one can choose a *Gaussian function*, which is continuously differentiable, instead of the triangular (or the sometimes used trapezoidal shape) without altering the degree of membership of any given temperature significantly.

Whether one defines the membership function empirically or self-adaptively, there are always some degrees of freedom; for example, the number of fuzzy sets and membership functions.

As an analogy to crisp sets, one can define *union*, *intersection* and *complement* of two fuzzy sets A and B by defining the membership functions corresponding to union, intersection and complement. One can further define fuzzy rules either by establishing these rules empirically or in a self-adaptive manner.

Finally, a mapping from a crisp number to the fuzzy set can be defined consisting of this number only (singleton fuzzification). Also a mapping from a fuzzy set onto a number can be defined by choosing this number as the center of average of the integral defined by the fuzzy membership function (center of average defuzzification). Figure 4-2 shows the structure of *fuzzy system*.

For the purpose of power system control it is sufficient to note that the *fuzzy system* is a mapping

$$F: U^n \subseteq \Re^n \rightarrow \Re,\ F(\mathbf{e}) = u$$

This mapping F will be constructed as an approximation to the controller $\phi(e,t)$.

It is shown [4-9] that there is a class of self-adaptive fuzzy systems F with Gaussian membership functions ϕ_j that can be written in a closed form as:

$$\boxed{u = F(\mathbf{e}) = \sum_{j=1}^{m} b_j\, \phi_j(\mathbf{e})}$$

Self-adaptive fuzzy systems given in closed form have the advantage that stability analysis can be performed and tasks like optimal control can be addressed.

Self-organizing fuzzy controllers therefore fall into the class of adaptive controllers and the related stability issues can be explored with adaptive control techniques. Stability of power system controllers is discussed in more detail in reference 4-10.

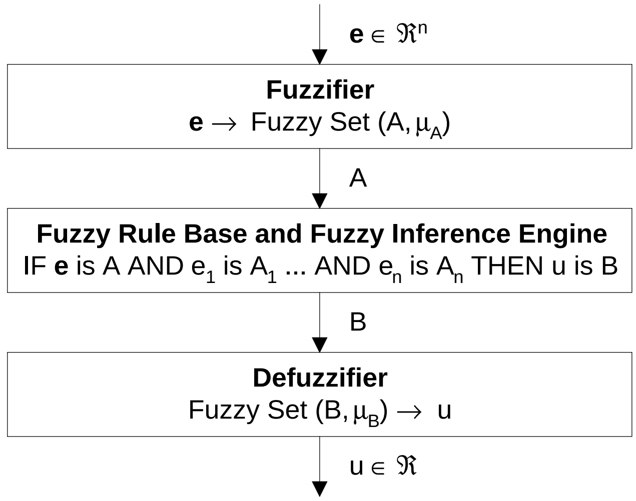

Fig. 4-2. Structure of a fuzzy system.

Neither approach to fuzzy systems necessarily needs a detailed state-space model of the controller. The advantage of the empirical approach is that heuristics and human knowledge can be incorporated. However, the demonstration of stability for this type of controller is very tedious if not impossible.

4.1.1 State-of-the-art of fuzzy control for power systems

We now give an overview of studies of fuzzy systems in the area of power system or generation control [4-11].

The majority of fuzzy controllers can be found in the area of excitation control, especially power system stabilizers (PSS). An upcoming important area is control of power electronic devices. Although the majority of investigations perform feasibility studies using computer simulation only, several authors study the implementation of the fuzzy controller on a PC or DSP in order to control actual small generators or motors in a laboratory environment. In most cases, the membership functions are established based on data samples.

The comparison of fuzzy controllers and conventional controllers stresses advantages of fuzzy controllers as being “generic” parametric models instead of circuit-based state space models. The self-adaptive controllers can be easily tuned to different operating conditions, and all projects report better tracking capabilities of the fuzzy controllers compared to conventional controllers.

However, the sensitivity issues concerning the range of validity of the tuning and the detection of changes of operating conditions still needs to be investigated for conventional as well as for fuzzy controllers. This is especially important for power system control where topology, load, and generation can change stochastically and discontinuously.

A lot of progress has been made concerning the application of fuzzy systems to power system control problems. For feasibility studies, most authors experiment with empirical rules and data. A few projects, using self-organizing techniques, however, have been installed on a microprocessor and tested in a research lab environment either in academia or a utility. The next section describes an operational application of fuzzy control in a real power system.

Hassan, Malik and Hope applied the fuzzy logic control (FLC) to PSS design [4-12]. In this method, the output stabilizing signal was calculated based on the representation of the alternator state in the phase plane. Hiyama, Kugimiya, and Satoh proposed PID type fuzzy logic PSS [4-13]. They took into account the PID information of the generator speed. Additional parameters were also tuned off-line to minimize the performance index. Recently, the self-organizing Fuzzy Auto-Regressive Moving Average (FARMA) controller was studied to enhance the low frequency damping of a synchronous machine [4-15]. In contrast with a conventional FLC, where the rule base and membership functions are supplied by an expert or tuned off-line through experiment, the FARMA FLC needs no expert in making control rules. Instead, rules are generated using the history of input-output pairs. The generated rules are stored in the fuzzy rule space and updated on-line by a self-organizing procedure.

4.1.2 Implementation of fuzzy logic PSS

In joint research, Kumamoto University and the Kyushu Electric Power Company proposed a microcomputer-based fuzzy logic power system stabilizer (FLPSS) to enhance power system stability through control of thyristor exciters. Through simulation studies, experiments on a 5 kVA laboratory system, and implementation on an actual 5 MVA hydro unit, the effectiveness of the FLPSS was demonstrated [4-13]. In addition, a two-year evaluation of the FLPSS was finished in March 1996 on 30.2 and 23.4 MVA hydro units in the Kyushu Electric Power System [4-14]. Damping of oscillations were significantly increased. The FLPSS has been in service since June 19, 1997 on a hydro unit with the rating of 90 MVA at the Hitotsuse Hydro Power Station in the Kyushu Electric Power System.

The proposed fuzzy logic power system stabilizer (FLPSS) is set up by using a microcomputer with AD and DA conversion interfaces. All the signal conditioning and the generation of stabilizing signals are performed by the on-line microcomputer. See Figure 4-3.

4.1.3 The future of fuzzy logic power system stability controls

There is continued debate on the fuzzy versus conventional control (reference 4-59 is entertaining and instructive). Although the fuzzy logic power system stabilizers are field tested as described above, there is limited experience, even in the simulation world, of fuzzy logic power system stability controls in large power systems with multiple, interacting oscillation modes. Experience with the more sophisticated types of fuzzy logic control is even more limited.

Although most of the literature on power system fuzzy logic control is on replacement of conventional control, many actual industrial applications (in other industries) are for higher level or supervisory control [4-60,4-61]. In power systems, fuzzy logic controls may be attractive for higher level, nonlinear, and discrete controls, rather than as replacement of essentially linear continuous controls.

4.2 ANN for Power System Control

Artificial neural networks have been applied in technical areas since the early 1960s, when Widrow and Hoff developed an adaptive least square estimator called ADALINE. ANNs come in two major categories:

- supervised ANNS,
- unsupervised ANNs.

Supervised neural networks perform approximation tasks using a special combination of non-linear basis functions called sigmoid functions. They therefore solve problems similar to problems solved by regression and parameter estimation techniques.

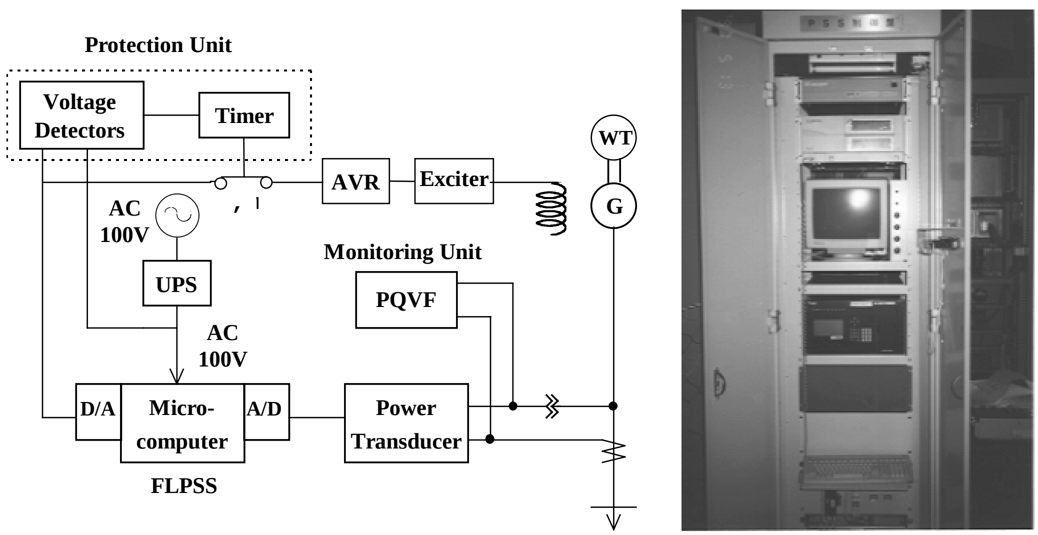

Fig. 4-3. Basic configuration of PSS prototype and its overview.

In this framework, classification tasks can be formulated as the task of finding a regression model for the function which maps an input vector **x** onto its class label, for example *TRUE* or *FALSE* coded with binary numbers.

The *multi-layer perceptron* (MLP) is probably the most heavily investigated supervised ANN model. It can be used in nearly every area of power systems where a task can be formulated as an approximation problem. As a classifier (approximation of the Boolean function secure/insecure or trip/no-trip signal) it is applied in power system security assessment [4-16] and on-line security control to initiate load shedding at a bus [4-17].

The MLP is often used in combination with *Fuzzy Systems* where qualitative attributes like hot or cold temperatures are first translated into numbers. The MLP is then used as a regression tool in order to estimate additional parameters [4-18].

Unsupervised networks reduce the complexity of the data sets by either reducing the dimensionality of the input data or by grouping input data into categories of "typical" data and by constructing a typical presentation (code vector) for each class. Unsupervised neural nets fall into the same class of tools as statistical non-parametric data analysis, clustering algorithms, and encoding or decoding techniques.

Unsupervised ANNs which quantize data into categories provide a choice of free parameters. The *ART* networks fixes the radius of the class but allows a variable number of classes, whereas *Kohonen's self-organizing feature map* fixes the number of categories but allows varying class sizes.

In the area of power system security assessment the ART network [4-19] and the Kohonen map [4-20] are used to reduce the space of all feasible operating points into a finite set of typical operating points.

Unsupervised ANNs are often used in combination with supervised approaches or conventional tools. The unsupervised net serves as pre-processing tool for data reduction and the supervised net estimates associated parameters like security classes [4-21,4-22].

4.2.1 ANN applications

In the 1970s simple ANN-based machine-learning techniques were explored for transient stability [4-23]. With the emergence of more powerful computers, ANN gained renewed interest from 1988 on, when Sobajic *et al.* [4-24], and Aggoune *et al.*, [4-25] assessed their potential for transient stability and static security assessment. These projects have led to a sudden upsurge in applying neural net approaches to many power system problems. A bibliographical survey covering 1988–1993 world-wide is presented in the paper by the CIGRÉ Task Force 38.06.06 on Artificial Neural Net Applications in Power Systems [4-4]. This survey was updated by Niebur and Dillon [4-26] based on a review of more than 400 publications regrouped into 200 different projects published before April 1995.

Time-series prediction in the area of load forecasting has been one of the most examined areas for ANN applications. It was mainly motivated by the lack of automated tools in the utilities and by the expected economic gain. Research in other major application areas like security assessment attempts to exploit the data reduction, classification, and regression capabilities of ANN in combination with conventional simulation techniques. The potential of ANNs for non-linear adaptive filtering and control stimulated research in the area of control of highly non-linear power system behavior.

For power system control, the control tool, whether conventional or ANN has to be operated on-line. Available reaction time is extremely limited and control errors can easily lead to a breakdown in a substantial portion of the interconnected system. Therefore power system control is still done in the most conservative manner. In critical situations, it's the practice of some experienced operators to even remove conventional controllers like power system stabilizers. New control tools need to be extensively tested before they can be integrated into the existing complex power system. Field tests for control, however, have been reported for isolated components like photovoltaic storage [4-27].

Similar remarks apply to the area of security assessment. Further, in both areas, data covering significant periods of operation are not readily available and have to be collected for the specific ANN applications.

In the area of control, field tests are reported by Kumamoto University and Sanyo Electric, Japan [4-27]. For fast dynamic security monitoring in a medium scale network with diesel and wind power production, a pilot installation is running successfully in the island of Lemnos, Greece [4-28].

4.2.2 ANN application in security assessment

Security assessment can be divided into two levels: classification and boundary determination. Classification involves determining whether the system is secure or insecure under pre-specified contingencies. Classification does not in itself indicate distance from the operating condition to the insecure conditions. Boundary determination, on the other hand, involves quantifying this distance. A boundary is represented by constraints imposed on parameters characterizing pre-contingency conditions. These pre-contingency parameters are called critical parameters. Once the boundary is identified, security assessment for any operating point can be given as the "distance" between the current operating point and the boundary. Assessment in terms of pre-contingency operating parameters instead of the post-contingency performance measure is more meaningful to the operator as it directly identifies the parameters to control, as well as how to adjust them, in order to maneuver the system with respect to security boundaries.

In many North American utilities, the traditional boundary characterization is a two-dimensional graph called a nomogram [4-29–31]. To develop a nomogram, two critical parameters are chosen and all other critical parameters are set to selected values within a typical operating range. The non-critical parameters are set to constant values. Points on the nomogram curve are determined by repeating computer simulations, varying one critical parameter while keeping the other constant. The main disadvantages of this approach include intensive labor requirement, inaccurate boundary representation, and little flexibility in integrating with the energy management system (EMS). The inaccuracy of the nomogram results mainly from linear interpolation between boundary points and insufficient information contained in critical parameters. An ANN technique has been used in a security boundary visualization method to overcome these disadvantages [4-32,4-33].

The procedure for boundary visualization consists of the following major steps:

1. *Security problem identification*: Identify the specific set of security problems to be characterized and operating parameter candidates that may have influence on them.

2. *Base case construction*: Construct a base case power flow solution that appropriately models the system conditions.

3. *Data generation*: Automatically generate a database with each record consisting of pre-contingency operating parameters and the corresponding post-contingency measure.
4. *Feature selection*: Select the best subset of pre-contingency operating parameters for use in predicting the post-contingency performance measure.
5. *Neural network training*: Train a neural network using the selected parameters and the database to map the relationship from the pre-contingency operating parameters to the post-contingency performance measure.
6. *Visualization*: Provide an easily understood automatic visualization of the security boundary in the space of operating parameters that can be monitored and controlled by the system operator.

Data generation is a very important step [4-34]. The ultimate boundary captured by the whole procedure will characterize the data that is provided to the neural network. If this data does not reflect what actually occurs in system operations, the boundary will be incorrect. A systematic method, call ASAS [4-35] has been developed to generate the data for neural network training. This data consists of a large number of samples, with each sample corresponding to a simulation of the same contingency but for different operating conditions, and consisting of values for pre-contingency operating parameters together with the post-contingency performance measure. This data is used to train a neural network to compute the post-contingency performance measure R as output given the pre-contingency operating parameters $\underline{x}$ as input, resulting in the relation $R = f(\underline{x})$, where f represents the neural network mapping function. Standard MLP networks have been used for this application.

Once the neural network is trained, the relationship between the post-contingency performance and the pre-contingency operating parameters can be inverted, subject to the power flow equations, in identifying the boundary. That is, the problem of boundary identification is solved by finding $\underline{x}$ that simultaneously satisfies:

$$f(\underline{x}) - Rb = 0 \qquad (1)$$

$$\underline{h}(\underline{u}) = \underline{0} \qquad (2)$$

where (1) represents the neural network mapping function, (2) represents the power flow equations, $\underline{x}$ is the critical parameter vector, Rb is the threshold value of R, and $\underline{u}$ is the input parameter vector to the power flow program. The vector $\underline{x}$ may include both independent critical parameters (e.g., real power injections) and dependent critical parameters (e.g., flows), and is therefore a function of $\underline{u}$. Because the presented parameters (those corresponding to the two coordinate axes) must be varied in drawing the boundary, the influence of these variations on dependent critical parameters should be considered accordingly.

For visualization of an individual boundary, i.e., the boundary for a single security problem under a given contingency, the computation used in solving equations (1) and (2) is based on a derived form of the neural network mapping function, expressed as

$$f\,(\underline{z},\ g_y\,(\underline{y}0,\ \Delta z1,\ \Delta z2)) - Rb = 0 \qquad (3)$$

where $\underline{x}=[\underline{z},\underline{y}]$, $\underline{z}$ is the independent critical parameter vector, $\underline{y}$ is the dependent critical parameter vector, $\underline{y}0$ is the dependent critical parameter vector corresponding to a specific operating condition, and g_y models the influence of the z1 and z2 changes on the dependent critical parameters $\underline{y}$, where z1 and z2 represent the two presented parameters. The visualization algorithm starts from the minimum value of z1 and solves equation (3) for z2. Then it increases z1 by a fixed step, updates $\underline{y}$, solves for z2, and repeats until it reaches the maximum of z2.

In visualizing a boundary comprised of two or more constraints, we proceed as follows. As shown in Fig. 4-4, for each interval $\Delta z1$, we first identify the two individual boundary functions that are binding for the composite boundary. To do this, we rank the functions in descending order of z2. For each pair of neighboring functions in this rank, we check an arbitrarily selected point (marked with crosses) between them to see if it is secure for all security constraints. If so, this point is inside the secure region, and the corresponding neighboring individual boundary functions must be the binding functions for the composite boundary for this interval. The composite boundary is therefore identified as this pair of individual boundaries. In the next interval, if there are no other individual boundary functions between the two binding functions identified in the previous interval, then these functions are also binding for the new interval. In this case, it is not necessary to perform the check for this interval. Once it is no longer possible to find any secure point, then the algorithm stops.

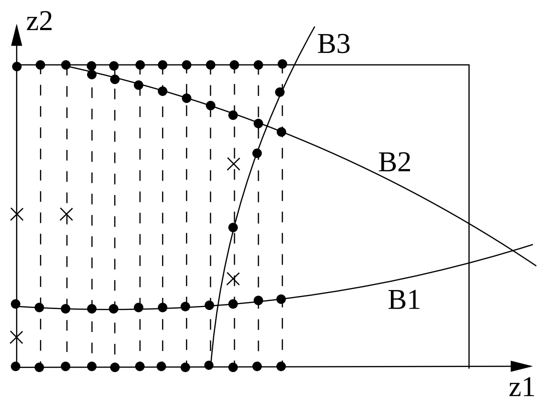

Fig. 4-4. Algorithm illustration for composite boundary visualization.

4.2.3 ANN application in power system stabilization

Control of large-scale systems such as power systems has been recognized as a foremost challenges in control engineering due to its nonlinearity and complexity. The use of an artificial neural network is very attractive because of its nonlinear mapping ability. For complexity coming from high dimension or from the spatial distribution of a large-scale system, decentralized control is a practical approach. Neural networks have attractive capacity in handling sensory information, and performing collective learning from the data sets given for a subsystem in the decentralized control approach. The approximation property of neural networks can make it possible to organize subsystem dynamics to a certain degree by training the input/output relationships obtained in the full system operation. From this point of view, a neural network based power system stabilizer can be designed for a large-scale power system when only local input/output information data for a subsystem, i.e., power plant data, is available.

A practical power system stabilizer to enhance the damping of the low-frequency oscillations must be robust over a wide range of operating conditions. However, conventional PSS design approaches based on linearization around the normal operating point have deficiencies and difficulties coming from nonlinearities in the system. Recently, neural networks have been investigated for power system stabilizing control. Most cases are limited to speed deviation control with supplementary excitation signal for a single generator–infinite bus system.

Difficulties in a power system stabilizer design come from the handling of nonlinearities and interactions among generators. During the low-frequency oscillation, rotor oscillates due to the unbalance between mechanical and electrical powers. Electrical power has nonlinear properties, and this is a key variable affecting the rotor dynamics. Thus, handling the nonlinear power flow properly is the key to the PSS design for a multi-machine power system. The use of neural networks' learning ability avoids complex mathematical analysis in solving control problems when plant dynamics are complex and highly nonlinear.

Neural networks in control has mainly used Model Reference Adaptive Control (MRAC) [4-36–40]. However, the MRAC approach has difficulty in selecting an appropriate reference model. Recently, a general purpose controller, an Optimal Tracking Neuro-Controller, was developed to minimize a general quadratic cost function of tracking errors and control efforts [4-41]. This results in a hybrid of *feedback* and *feedforward* neuro-controllers in parallel. The feedforward neuro-controller (FFNC) generates the steady-state control input to keep the plant output to a given reference value, and the feedback neuro-controller (FBNC) generates the transient control input to stabilize error dynamics along the optimal path while minimizing the cost function. A novel inverse mapping concept is developed to design the FFNC using a neuro-identifier. The use of general quadratic cost function provides "optimal" performance with respect to trade-off between the tracking error and control effort. Since the cost function is defined over a finite time interval, a Generalized Backpropagation-Through-Time (GBTT) algorithm was developed to train the feedback controller.

Optimal tracking neuro-controller. We consider a system in the form of the general nonlinear auto-regressive moving average (NARMA) model:

$$y(k+1) = f\left(y(k), y(k-1), \cdots, y(k-n+1), u(k), u(k-1), \cdots, u(k-m+1)\right), \qquad (4)$$

where y and u, respectively, represent output and input variables, k represents time index, and n and m represent the respective output and input delay orders.

The above control objectives can be achieved by minimizing the following well-known quadratic cost function:

$$J = \frac{1}{2}\sum_{k=1}^{N}(Q(yref - y(k+1))^2 + R(uref - u(k))^2), \qquad (5)$$

where y_{ref} is a reference output, u_{ref} is the steady-state input corresponding to y_{ref}, and Q and R are positive weighting factors. This quadratic cost function or performance index not only forces the plant output to follow the reference, but also forces the plant input to be close to the steady-state value in maintaining the plant output to its reference value.

An optimal tracking neuro-controller (OTNC) is designed with two neuro-controllers in order to control a nonlinear plant that has a non-zero set point in steady-state [4-41]. A *feedforward* neuro-controller (FFNC) is constructed to generate feedforward control input corresponding to the set point, and trained by the well-known error Backpropagation algorithm. A *feedback* neuro-controller (FBNC) is constructed to generate feedback control input, and trained by a Generalized BTT (GBTT) algorithm to minimize the quadratic performance index. An independent neural network named neuro-identifier is used when the above two neuro-controllers are in training mode. This network is trained to emulate a plant dynamics and to backpropagate an *equivalent error* or *generalized delta* [4-36] to the controllers under training. Fig. 4-5 shows an architecture for the optimal tracking neuro-controller for a nonlinear plant. In the figure, the *tapped delay operator* Δ is defined as a delay mapping from a sequence of scalar input, $\{x_{(i)}\}$ to a vector output with an appropriate dimension defined as $\vec{x}_{(i-1)} = (x_{(i-1)}, x_{(i-2)}, \ldots, x_{(x-p)})$, where $p = n$ for the output variable *y*, and $p = m$-1 for the input variable *u*.

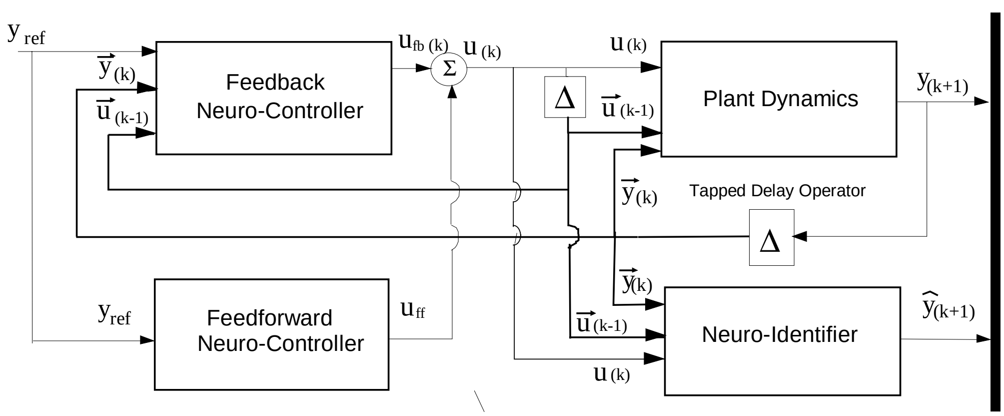

Fig. 4-5 Block diagram for the optimal tracking neuro-controller.

The study power system. The neuro-controller is applied to a 5-bus power system [4-42] to stabilize low-frequency oscillations (Figure 4-6). The power system consists of three power plants: two are thermal units and one is a hydro unit. The power system has sustained low-frequency oscillations due to disturbances. The control objective is to improve system damping by using a supplementary excitation control applied to the second generator.

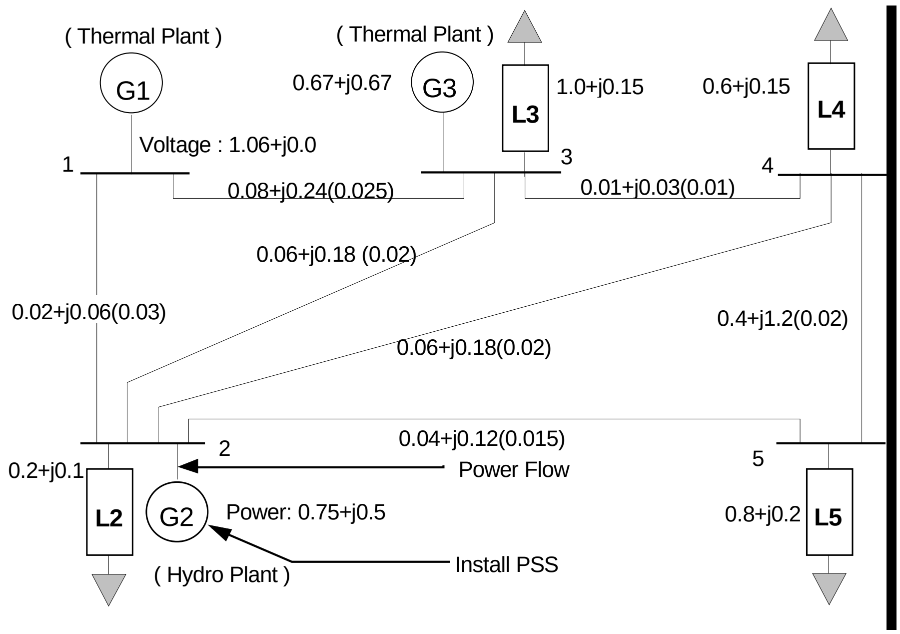

Fig.4-6. The power system with 3 generators and 5 buses.

Typical IEEE governor and turbine models are used: TGOV1 (2nd order) for the thermal plant and IEEEG2 (3rd order) for the hydro unit [4-43]. The IEEE exciter and voltage regulator model EXST1 (4th order) is used for this study on which supplementary excitation control input is to be injected. As a result, a 9th order model for thermal plants and a 10th model for the hydro plant are used to represent the nonlinear characteristics and the low-frequency oscillations in simulations.

Training of the neural networks. The Optimal Tracking Neuro-Controller is applied to Generator 2 to provide supplementary excitation signal as a power system stabilizer. Since the output variables, frequency, angle, and the power flow, are all deviations from the respective references, the feedforward controller was not used. The training patterns of the Neuro-Identifier are generated by the power system simulations starting from the steady-state initial value in a wide range of operating conditions and randomly generated control inputs history within the conventional PSS operation region. During the low-frequency oscillation in the range of 1~2 Hz, it’s assumed that the exciter can be approximated as a second-order model. Therefore, the Neuro-Identifier is constructed to emulate the power flow dynamics as a third-order model that includes the dynamics of exciter and the excitation field voltage. The discrete-time training patterns are obtained with the time step of 0.04 sec in simulation. This allows at least twenty sampling points in a cycle of the low-frequency oscillation under 1.25 Hz.

The Neuro-Identifier consists of one hidden layer with 40 nodes, an input layer with 7 input nodes and an output layer with one node. Three of the seven input nodes are for its output history, $\Delta Pe_{(k)}, \Delta Pe_{(k-1)}, \Delta Pe_{(k-2)}$; two are for control input history, $u_{(k)}, u_{(k-1)}$; and two for $\Delta\omega_{(k)}, \Delta\delta_{(k)}$. The Neuro-Controller has one hidden layer with 40 nodes, an input layer with 6 input nodes and an output layer with one node. Three of the six input nodes are for output history, $\Delta Pe_{(k)}, \Delta Pe_{(k-1)}, \Delta Pe_{(k-2)}$; one is for previous control input $u_{(k-1)}$ and two are $\Delta\omega_{(k)}, \Delta\delta_{(\mathrm{k})}$. The cost function for the N-step ahead controller is set with the weightings Q = 1.0 and R = 0.02.

To avoid oscillation during training stage, weight parameters in the Neuro-Identifier are corrected with the average of corrections calculated for ten patterns. Training of the Neuro-Controller is done in two phases. First, training is done with a small N (= 3) since in the beginning it has little knowledge of control. A small number of steps prevents the system from diverging. Training is carried on with a gradually increasing N until it reaches 8 so that the system can be controlled for a longer duration of time. Then, training is carried on with N fixed at 8. It takes about 30 minutes on an IBM-PC 486 computer to train two neural networks: the Neuro-Identifier and the Neuro-Controller.

Comparison of the control results. Figure 4-7 shows the speed deviation of Generator 2 for a three-phase ground fault at midpoint of a half the line 4–5, which cleared after 0.2 sec. The figure compares the cases without a control and with supplementary excitation controls by the conventional PSS, STAB4 [4-43], and the Neuro-PSS.

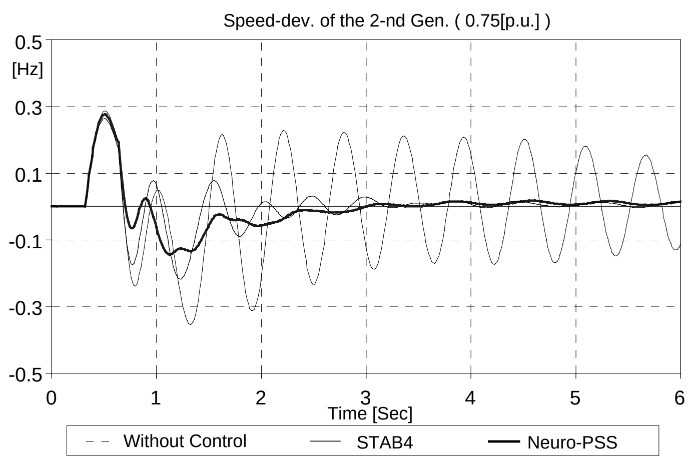

Fig. 4-7. The speed deviation of generator 2 for the line fault disturbance in a normal load condition.

Figure 4-8 shows the speed deviation for the same disturbance when the power system is in a light loading condition (0.5 p.u. generating power) and Figure 4-9 shows speed deviation for a heavy loading condition (1.0 p.u.). The figures show that both controllers work very well judging from small swings with large damping. The performance of the controllers are compared in Table 1with the integral-time-error (ITE) computed with the cost function (5). Observations from the table show that the Neuro-PSS works very well judging from the ITE performance in both the heavy or the light load compared to the normal load condition. The ITE performance of the conventional PSS shows larger variation to loading conditions because the parameters in the STAB4 were optimized in the normal loading condition.

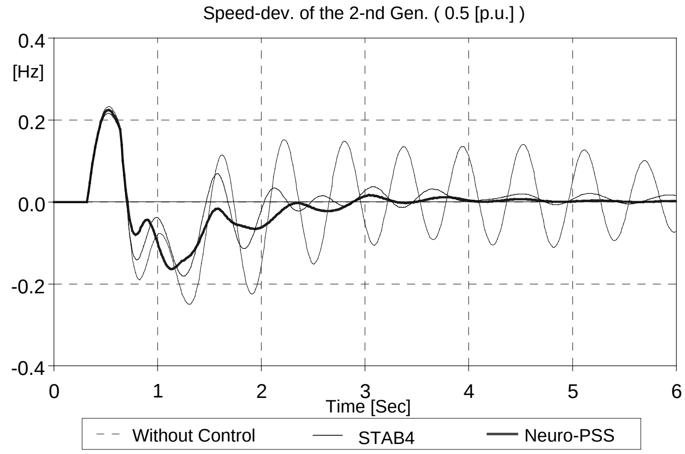

Fig. 4-8. The speed deviation of generator 2 for the line fault disturbance in a light load condition.

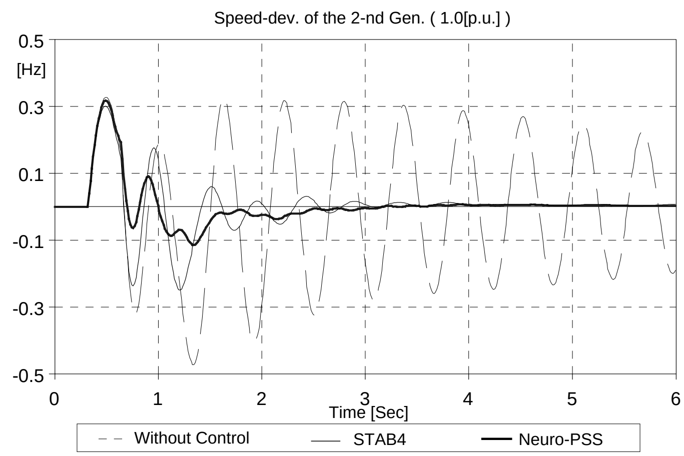

Fig. 4-9. The speed deviation of generator 2 for the line fault disturbance in a heavy load condition.

Figure 4-10 shows the speed deviation for other disturbances coming from stepwise loading conditions: 0.15 p.u. increase at 0.24 sec, decrease at 0.96 sec. and cleared at 1.44 sec when the power system is in the heavy loading condition. The figure shows that the Neuro-PSS works very well judging from small swings.

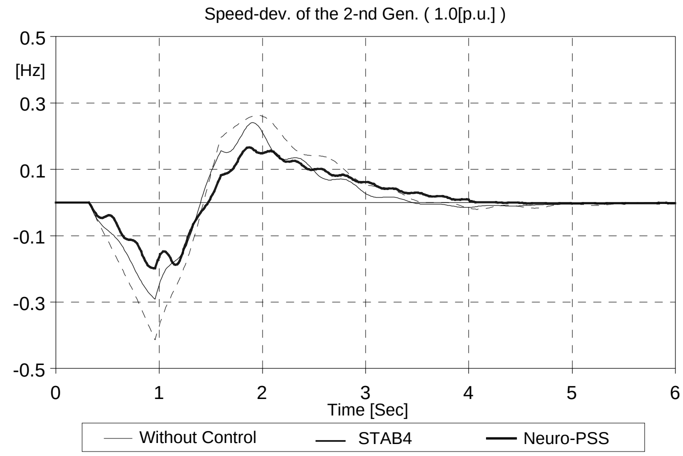

Fig. 4-10. The speed deviation of generator 2 for the load change disturbance in a heavy load condition.

Table 1. ITE performance evaluation for the line fault disturbance

Loading	0.5 p.u.		0.75 p.u.		1.0 p.u.	
Without Control	6.04	100(%)	12.03	100(%)	22.24	100(%)
STAB4	1.81	30.0(%)	2.19	8.2(%)	2.83	12.7(%)
Neuro-PSS	1.67	27.6(%)	1.89	15.7(5)	1.92	8.6(%)

4.3 Decision Trees for Power System Control

Decision trees (DTs) are learn-by-example classifiers which are particularly well suited for discrete event control [4-44,4-45]. Artificial neural networks (ANNs) can also be used for discrete event controls, and they are more general than decision trees. Neural networks can associate their input vectors with a continuous range of output values, whereas decision trees are only suited for classification problems having a small number of output categories such as stable/unstable. But when a problem can be reduced to a small number of choices, then decision trees have important advantages. The decision trees reported in [4-46–50] require only a few minutes to train whereas neural networks usually require much more computation for the training. When a particular case is classified by a DT, we can see which threshold criteria were met, i.e., why the case was classified and how the outcome would have changed if certain input variables had been different. Another advantage of decision trees is that when you have training data with maybe 250 variables in each input vector, the DT training algorithm usually selects a much smaller subset, perhaps 25 variables, to be used for classification.

4.3.1 Relation of angle stability decision trees to on-line dynamic security assessment

Decision trees have been developed for on-line preventive control and also for real-time remedial action control. The first research and industrial use of DTs for angle stability control was in the area of on-line preventive control [4-51–53]. These DTs are designed to perform on-line dynamic security assessment (DSA). Training sets are extracted from off-line simulations of critical contingencies applied to a large number of pre-fault equilibrium conditions. The input vector contains various static parameters from the pre-fault equilibrium point such as key generation and transfer levels. The desired output reflects whether any of the contingencies caused instability for that equilibrium. The DTs are then used on-line to predict the vulnerability of the power system in its present equilibrium state to those contingencies.

The DTs for real-time remedial action control [4-46–50] could be trained either from off-line simulations or from on-line simulation tools that are being developed to perform on-line DSA. Power system protection and large-scale stability controls have traditionally relied upon off-line simulations that are transformed into decision rules by engineers. Classifier training algorithms can perform the same tasks using large numbers of simulations and predictor variables. An emerging possibility is to train the classifiers using on-line DSA [4-54,4-55]. These on-line simulations can already be used to program discrete event controls such as generator tripping (see Chapter 5). The resulting controls are custom tailored to the current operating conditions. The same simulation capabilities could generate the training sets for DTs that perform real-time, remedial action control.

4.3.2 Decision trees for real-time transient stability prediction

The earliest research on DTs for real-time control investigated prediction of angle instability using synchronized phase angle measurements from all 10 generators in the New England 39 bus test system [4-46,4-47]. In that work, it was proposed to train DTs off-line to handle a specific range of operating conditions. Training sets were created by simulating three-phase faults of various duration on all the buses and transmission lines. Simulated generator angle measurements were taken over an eight cycle window immediately after fault clearing. Three successive measurements of the generator angles were used, and then two velocities and one acceleration were computed from the angle measurements of each generator. From this snapshot immediately after fault clearing, the decision trees correctly predicted whether loss of synchronism would occur in the next four seconds with over 97% accuracy. Robustness to variations in the operating point was investigated using a test set of 40,800 transient stability simulations for 50 randomly generated operating points. Accuracy in excess of 95% was obtained for the 40,800 contingencies.

One way to use DTs for real-time control is to train a DT to predict whether loss of synchronism will occur without control and train another DT to predict whether loss of synchronism will occur with some particular control. In simulations of a 176 bus model of the western U.S., a combination of generator tripping at Palo Verde and load shedding at Tesla and Vaca-Dixon was found to stabilize long duration three-phase faults for five transmission lines in the Arizona area [4-48]. A test set of 500 random duration, three-phase faults on these lines without control contained 232 stable cases and 268 unstable cases. If control is applied when the DTs predict stable with control and unstable without, then 215 of the 232 stable cases have no unnecessary control intervention. The remaining 17 stable cases had control intervention without adverse effect. The controller operated in all 268 of the unstable cases, and stabilized 263 of them. The remaining 5 cases had very long fault durations and hence were too serious to control.

4.3.3 Decision trees for response-based control

Prior to 1996, the research on DTs for real-time control had assumed there would be some way to detect that an event had just occurred so that the immediate post-event measurements could be fed into the decision tree. More recently, decision trees have been adapted to continuously follow the measurements and select control action as soon as the need becomes apparent [4-50,4-58]. This response-based operation effectively turns the classifier approach into a natural generalization of the way engineers determine relay settings and discrete-event control laws. For example, in the development of the R-Rdot out-of-step relay [4-56,4-57], apparent resistance R and its rate of change Rdot were plotted for both stable and unstable transient events. The apparent resistance was measured at Malin substation near the electrical center of the Pacific AC Intertie (PACI) in order to detect loss of synchronism across the PACI. Using large-scale simulations, the designers learned to differentiate between stable and unstable swings based on their trajectories in the R-Rdot phase plane. Decision boundaries were then drawn to classify new swings as either stable or unstable and to order circuit breaker operation as appropriate.

Decision tree training algorithms can draw decision boundaries in phase planes as well as in higher dimensional spaces. The R-Rdot relay provides a good demonstration of DTs for response-based control. Instead of using only the immediate post-event electrical measurements, response-based DT control is achieved by using every time sample in the simulation for an input-output pair. Using 28,728 data points extracted from 168 transient simulations on the 176 bus model, a DT was trained to associate each pair of R and Rdot measurements with whether the angle across the PACI exceeded 90 degrees when the measurements were taken. The 168 contingencies in the training set contained 6 different fault scenarios for each of 28 transmission lines: one-cycle fault, three cycle fault, four cycle fault, six cycle fault, one cycle fault followed by loss of the Pacific DC Intertie (PDCI), and one cycle fault followed by loss of the Intermountain Power Project (IPP) DC line. All faults were three-phase short circuit to ground with the faulted line removed at clearing time. Each simulation in the training set was three seconds long. The test set contained data extracted from 784 simulations which were five seconds long; 756 of the test set events were double contingency outages, each involving two of the 28 study lines. The resulting DT tripped correctly on 70 events, tripped incorrectly on 10 events, correctly refrained from tripping on 704 events, and never failed to trip on an unstable event. In addition to achieving response based control, these DTs also respond appropriately to single-phase faults. The training sets can be generated using industry standard power system models.

Specifying misclassification costs during the training has been particularly helpful for building DTs to perform response-based control. A circuit breaker controlled by this DT will be programmed to trip and stay open once the DT outputs "trip." Hence there is no remedy for a false trip; once the breaker opens it must stay open. If, however, the DT fails to trip on a case where the intertie angle has in fact exceeded 90 degrees, then it still has the option of tripping later. There will always be an area of uncertainty between when the DT should trip versus not trip. For a truly unstable event, the need to trip should become more obvious over time and it would be desirable to train the DT to wait until the need to trip is nearly certain. This behavior can be obtained by assigning a high misclassification cost to false trips. The resulting DT will only trip if the trajectory enters a region where stable trajectories almost never enter. For training the DT shown in Figure 4-11, the misclassification cost of false trips was set 50 times higher than the misclassification cost of failures to trip.

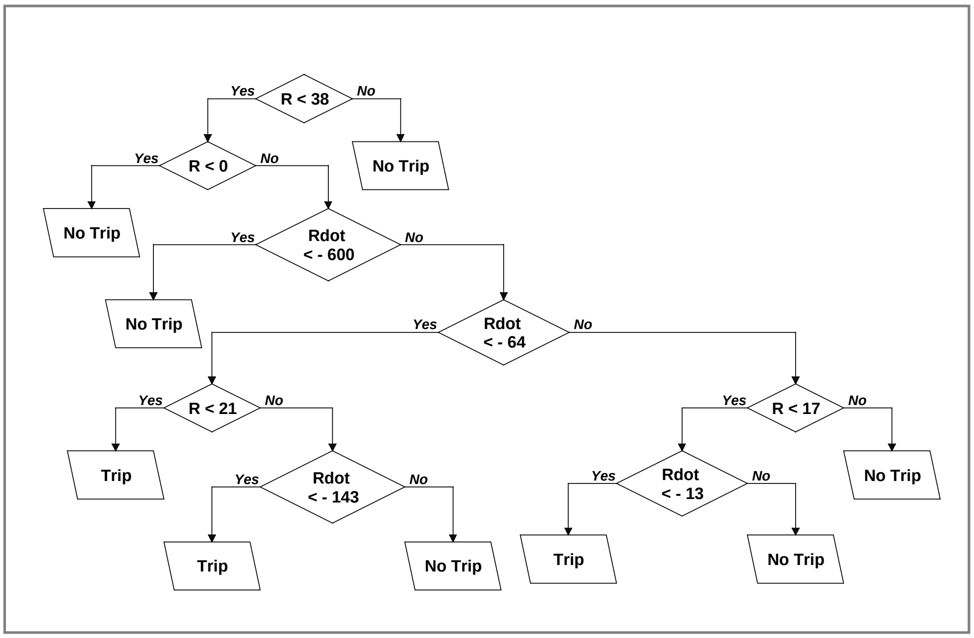

Fig. 4-11. Decision tree for an R-Rdot out-of-step relay.

4.3.4 Decision trees for improving dynamic performance

Decision trees can perform response-based discrete-event control to improve the dynamic performance of stable transient events [4-49,4-50]. In order to automatically train a classifier to associate the incoming measurements with an appropriate discrete-event control, it's necessary for a computer algorithm to determine which control to assign each case in the training set. If a control makes the difference between stability and instability, then the choice is clear. When instability is not an issue and the goal is to improve the dynamic performance, an objective measure of the post-event behavior must be used. The following objective function is used to calculate the severity of simulated transient events with and without control.

$$J = \int_0^T \sum_i M_i (\delta_i - \delta_{\text{coa}})^2 \, dt$$

This performance index is like the weighted sum squared “error” comparing the simulated swing curves to a hypothetical “ideal” trajectory where all the generator angles are constant with no angle differences. The sum does not have to contain all the generators in the model. A sampling on the order of 10–100 of the larger generators distributed throughout the power system is sufficient to have J be a fairly good numerical measure of the amount of interarea oscillation following a disturbance. Between two simulations, everything is held fixed except for some control action that needs to be evaluated. Controls that reduce J tend to have the strongest smoothing and stabilizing effects on the post-event oscillations. In addition to improving dynamic performance, the performance index can also be used to determine powerful combinations of discrete event controls for stabilizing strongly unstable events [4-48].

Decision trees were trained to improve dynamic performance using data extracted from 93 transient simulations on the 176 bus model. Each contingency was simulated with and without a 500 MW fast power increase on the IPP DC line immediately after fault clearing, and a DT was trained to predict from real-time phasor measurements whether the numerical improvement in dynamic performance would exceed a threshold [4-50]. The decision tree was tested on three cycle, three-phase faults and five cycle single line to ground faults applied to the same 31 transmission lines used in the training set. The DT ordered a 500 MW fast power increase at some point in 44 of the 62 simulations and had a positive effect in 42 of the 44 simulations it tried to control. Fifty-one of the 62 simulations were stable for the first two seconds, and 39 of the 44 DT operations occurred during stable events. The average performance index improvement for the 39 stable contingencies was 2.4 and the maximum improvement was 4.7. Most of the stable events had performance index scores between 40 and 80. Using 60 as a rough estimate of the average score for stable cases, the improvement from the DT controller is roughly 2.4/60 = 4.0%. For comparison, a 500 MW IPP DC ramp in response to the initial events would have prevented the cascading outage that occurred on December 14, 1994 by reducing overloads which caused some of the transmission lines to trip [4-49,4-50]. Performance index calculations applied to the large-scale simulations of the initial December 14 events showed an improvement of 4.1% resulting from the DC fast power change.

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