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## Making the Power Grid More Intelligent

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## Making the Power Grid More Intelligent

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### Introduction

An electric power grid in general consists of components such as synchronous generators, transmission lines, transformers, loads, active/reactive compensators, switches and relays. The mathematical model of such a power network usually consists of thousands of states and multiple controllers with their own actuators and measurements. With the power industry in various stages of deregulation, the long distance power transfers between different regions –which can be hundreds of miles away from one another- are continuously increasing. Moreover, with the introduction of more industrial and residential loads, the system now operates closer to its security limits than before. Economical and sometimes environmental concerns often discourage the addition of new transmission facilities. This in turn might weaken the system against transient and/or dynamic disturbances.

Typically, the controllable components in the power grid, such as the synchronous generators and the FACTS devices are controlled using local (internal) controllers. All these local control schemes focus on controlling each component from an internal point of view, i.e., providing appropriate signals for the device in order to control some local quantity such as voltage, speed deviations or line power flow. However, with a number of these controlled devices close to one another in a power network, the issue of interaction between them arises. Moreover, each one attempts to be a good local controller, but has no information on the overall control objective of the entire system.

In addition to the above issues, modern power networks are affected by steadily increasing incidents of faults/disturbances that lead to inter-area rotor angle and power oscillations. As opposed to the local oscillation modes that are largely determined and influenced by the local area states, the inter-area modes are more difficult to study since they require a detailed study of the system as a whole and are influenced by the global states of larger areas of the power network [1].

To summarize, the traditional approach of controlling a power system using local control agents (decentralized control) suffers from the following disadvantages:

- Lack of information on the overall dynamics of the power system,
- Inadvertent and unwanted interactions between different local controllers,
- Sub-optimality of the local controllers over the wide range of operating conditions of the dynamically changing power network,
- Inability of the local controllers to effectively respond to most of the global modes of the power system.

Several researchers have proposed analytically based supervisory level control schemes in order to compensate for the above problems. Although these methods perform satisfactorily for small scale systems, their effectiveness degrades as the dimensions of the power system increase. Dependency of many of these schemes on a mathematical model of the power system that is valid over a wide range of system operating conditions, adds to their impracticality for real world applications. Therefore, in practice, most of the existing supervisory level schemes in power systems are nothing but human experts who observe the performance of the power system and take preventive or corrective actions when necessary. The knowledge base of these human experts is limited, not very detailed, not easily expandable and difficult to transfer or record.

This paper focuses on the applications of intelligent techniques for improving the performances of the power system controllers. Intelligent control techniques lay the foundation of the next generation of nonlinear controllers and have the advantage of further improving the controller's performance by incorporating heuristics and expert knowledge into its design. Most of these techniques are independent of any mathematical model of the power system, which proves to be a considerable advantage. They can also be trained over time that enables them to efficiently perform over a wide range of

operating conditions of the power system. However, in spite of these major advantages, intelligent controllers have not yet been widely used in power system applications.

The main reason lies in the fact that intelligent controllers often have a noticeably more complicated structure than that of a regular proportional-integral-derivative (PID) controller, and usually require a longer time to implement.

More importantly, for the average engineer, the conventional PID is still easier to understand and to analyze, and more of a “white box” compared to the intelligent controllers. Therefore, there has so far been a tendency in practical power system applications to continue employing conventional linear and rarely nonlinear controllers. The current trend indicates that intelligent controllers need more time to prove their reliability, efficiency and superiority over the traditional approaches.

The authors believe that the first step for incorporating intelligent techniques into power system applications need not necessarily be a comparison with a simple PID (which can be designed with little effort). Rather, the first step should be to apply these intelligent techniques to higher level (supervisory) control of the components in a large scale power network. This is the area where the traditional control theory often fails to function satisfactorily. This way, an intelligent controller can be applied to auto-tune the conventional local PID controllers, provide auxiliary inputs for them or optimally adjust their set-points.

Essentially, such an approach is similar to the nervous system in the human body where the higher level system (the brain) sends signals to control the set-points of simple nerve cells in the muscles, which are very similar to PID systems [2]. The brain acts as the central nervous system by performing the main decision making. The peripheral nervous system is constituted of local systems (muscles) that follow the command they receive from the brain.

In this paper, an intelligent control scheme based on the Adaptive Critic Designs (ACDs) theory is proposed for the supervisory level control of a benchmark 12-bus multimachine power system [17] with a FACTS device. The authors wish to emphasize the practicality of such a control scheme for large scale power systems and open the door for introducing more intelligent, model free, human expert independent approaches for controlling power systems. Such schemes could strengthen the existing power system infrastructure and reduce the

probability of large scale catastrophic failures leading to major blackouts.

## Supervisory Level Control in Power Systems

Figure 1 illustrates different types of control schemes that can be applied to a power system with  $n$  controllable components, such as generators and FACTS devices.

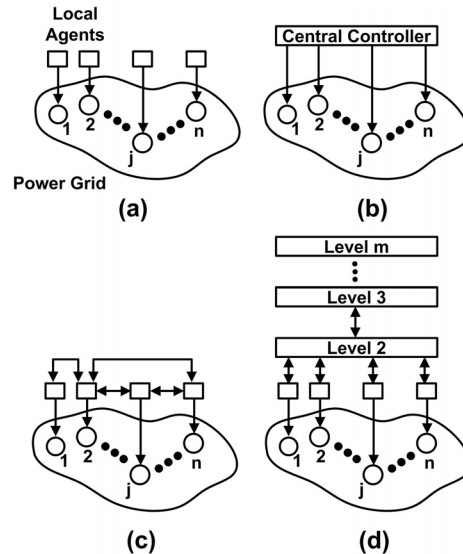


Fig. 1. Control schemes in power grid: (a). decentralized control structure, (b). centralized control structure, (c). multi-agent control structure, (d). hierarchical control structure.

The ideal solution to mitigate the problems associated with decentralized controllers would be a centralized control structure, in which a single supervisory level controller sends out all the required control signals to the various controllable components throughout the network. Clearly, the price of failure of the main controller for such a scheme is very high; therefore, it cannot be an appropriate solution for the power grid. Moreover, the longer processing time and the data transmission latency can increase the response time of the controller using global measurements. This might be a problem for some components with fast changing dynamics. The excessive computation time and unavailability of robust and redundant communication channels make this method unfeasible with today’s technology [3]. In addition, implementing such a controller is very difficult or even impractical as the dimensions of the power system to be controlled increase.

Centralized control schemes have already been successfully applied to the existing automatic generation control (AGC) and load frequency control systems for setting the active power set-points of the synchronous

generators [3]. However, this has been possible mainly due to the slower nature of this problem.

Another alternative solution, different from both centralized and decentralized control schemes, would be a multi-agent control structure in which all the semi-autonomous agents distributed in the network communicate and collaborate with one another to achieve a certain task [4]. Such a scheme requires communication and coordination not among all the agents but among those closely related agents with common interests [5]. Although the agents communicate with one another, each agent performs primarily based on its own interest; therefore care should be taken that no agent's actions should violate its own limits.

While multi-agent controllers are efficient for controlling complicated nonlinear systems, they become difficult to implement as the dimensions of the system increase. The efficiency of the multi-agent systems can be improved by incorporating the concept of hierarchical systems into the controller. The objective here is to define a set of sub-problems that can be considered independent at a certain level (subsystem level). Through the manipulation of the interplaying effect at a higher level (coordinator), the global solution is obtained [6]. The concept of multilevel control can be implemented by decomposing the hierarchical controller into a set of controllers at different levels.

Both multilevel and centralized controllers fall under the category of supervisory level control. In power system studies, the term "supervisory control" can cover a wide range of control structures. First and foremost, there is the question of how many components are being controlled by the controller. At its simplest case, this can be reduced to a component or device equipped with an external controller that provides some peripheral control objectives in addition to the main objective of the local (internal) controller of the device. Examples of this type of supervisory control are different shunt and series FACTS devices that are being controlled by an external supplementary controller (supervisor) in order to provide damping for low frequency power oscillations, transients and suchlike [7].

As the number of components/devices to be controlled by the supervisor increases, the term supervisory level controller is often replaced by *Wide Area Controller* (WAC). Generally, a WAC covers a large geographical area including many components. A hypothetical WAC is illustrated in Fig. 2 to emphasize that a WAC normally controls several components in the power system and it may include various supervisors/external controllers.

Different WAC schemes can be categorized based on their design philosophy and the nature of their generated control signals. A WAC may be designed to operate in the *normal (preventive)* control mode. In this case, it takes actions that try to adjust the operating conditions of the power system. The generated control signals can be either continuous or discrete (step-wise) and the nature of the controller response time is considerably slower than the local controllers. Examples of this type of control are setting the transformer tap changers, switching shunt capacitors and reactors on/off, changing the power reference of the synchronous generators and using the generator Var reserve. *Emergency (corrective)* mode WAC, on the other hand, takes actions in such a way that it saves the power system from a catastrophic situation such as rotor instability or voltage collapse. In most cases, the control signals are continuous and the WAC provides a faster time response compared to the normal control mode. Examples can be the sending of auxiliary control signals to the FACTS devices or boosting the exciter on a synchronous generator.

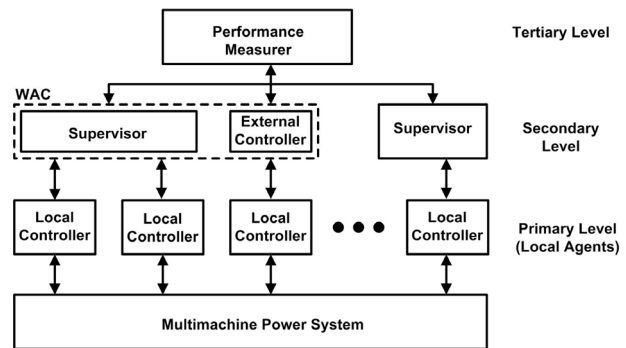


Fig. 2. Schematic diagram of the hierarchical 3-level control scheme for a power system.

In general, a power system can have three levels of control as illustrated in Fig. 2 [3]. The primary level comprises the local controllers that are designed to provide control signals for individual components. The loop of these local controllers' reference commands are closed at the secondary level by means of a supervisory level controller, also referred to here as the supervisor, which determines their set-points. The second level may consist of a single supervisor or multiple supervising controllers that span the power network into subsystems. The third and highest level of control comprises a performance measurer (PM), also referred to as system optimizer (SO), that uses global information throughout the network and tries to optimize certain characteristics of the power system by sending appropriate signals to the supervisor(s). The existence of the PM is not necessary for all the hierarchical control schemes; however, when

present, it can modify the actions, update the parameters and/or overrule the decisions taken by the secondary level supervisor.

It is normally assumed that the secondary level controller coordinates the actions of the various agents throughout the network by using the supervisory control and data acquisition (SCADA) system, phasor measurement units (PMU) or other wide area dynamic information systems.

## Why Intelligent Control?

Many researchers have focused on applying traditional analytically based linear or nonlinear methods for designing multi-level controllers in power systems. Much of the work in the past has focused on designing Power System Stabilizers (PSS) with global measurements [4], [8]-[10], or designing external supplementary controllers for various FACTS devices in order to improve the transient/dynamic stability of the power system [5], [8], [9], [11].

However, the complexity of a large power network often makes it difficult for an analytically based control technique to perform a supervisory level control of the system. Analytical methods often fail to provide optimal control solutions for a real life multi-agent system. Moreover, the operating condition of the power system is continuously subject to change as loads and transmission lines are switched on and off. All these can affect the effectiveness of the linear supervisory level designs and degrade their performance. Nonlinear robust/adaptive schemes are efficient alternatives; however, they have more sophisticated structures and are more difficult to implement. One major drawback of most traditional nonlinear approaches is the fact that they rely on a mathematical model of the power system, which in most cases is difficult to obtain. Even if the mathematical model of the system were to be fully or partially available, it is often based on a linearized approximation of the actual nonlinear power system model.

Computational intelligence techniques on the other hand, have the capability of dealing with such a nonlinear, non-stationary system in the presence of noise and uncertainties. Neural networks and fuzzy logic based controllers can be effectively designed with no need for any mathematical model of the plant to be controlled. Application of heuristics and reinforcement based learning enables these techniques to deal with situations where deriving detailed analytical information about the dynamics of the plant would otherwise be tedious or even impossible to achieve. Some of the advantages of intelligent wide area controllers over traditional schemes are briefly listed below:

- These intelligent schemes are mostly independent of a mathematical model of the power system.
- Intelligent controllers can be trained offline using sufficient information on the dynamic performance of the system, or online while the system is under normal operation.
- With the proper selection of inputs and outputs, the intelligent controller is able to respond to virtually any kind of application.

## Adaptive Critic Designs

Adaptive Critic Designs (ACDs) theory can be applied to neural network and/or fuzzy logic based controllers in order to provide optimal control over the finite or infinite horizon time of the problem in the presence of noise and uncertainties [12]. The parameters of the controllers designed using the ACD theory are adjusted based on reinforcement learning, hence, making the controller largely insensitive to the size of the control problem. This proves to be specifically useful for power system applications where the process to be controlled is a nonlinear non-stationary multi-input multi-output process, whose operating conditions change continuously with time.

ACD controllers are capable of optimizing some measure of utility or goal satisfaction, over multiple time periods into the future [13], [14]. In other words, they perform maximization or minimization of a predefined utility function over time. A utility function  $U(t)$  along with an appropriate choice of a discount factor should be defined for the ACD controller. At each time step  $t$ , the plant output (a vector of measured variables)  $X(t)$  are fed into the controller, which in turn generates a policy (control signal)  $A(t)$  in such a way that it optimizes the expected value function over the horizon time of the problem which is known as the cost-to-go function  $J$  given by Bellman's equation of dynamic programming [15] as:

$$J(t) = \sum_{k=0}^{\infty} \gamma^k \times U(t+k) \quad (1)$$

where  $U(\cdot)$  is the utility function and  $\gamma$  is a discount factor for finite horizon problems ( $0 < \gamma < 1$ ). A discount factor of zero uses the present value of the utility function as the optimization objective (similar to the minimization of one step ahead error), while a discount factor of unity considers all the future values of the utility function equally important and is more suitable for the infinite horizon problems.

Figure 3 shows the schematic diagram of a model free ACD controller, referred to as Action Dependent Adaptive Critic Designs (ADACD) controller [13]. It consists of:

- An Action network, which can be a neural network or a fuzzy controller and functions as the controller, and is trained to send the optimum control signals to the plant, resulting in minimization or maximization of the cost-to-go function  $J$  over the time horizon of the problem,
- A Critic network, which is a neural network trained to accomplish the task of dynamic programming by approximating the true cost-to-go function  $J$  with no prior knowledge of the system.

For more information and step-by-step guide regarding designing a ACD controller, the reader is referred to [16].

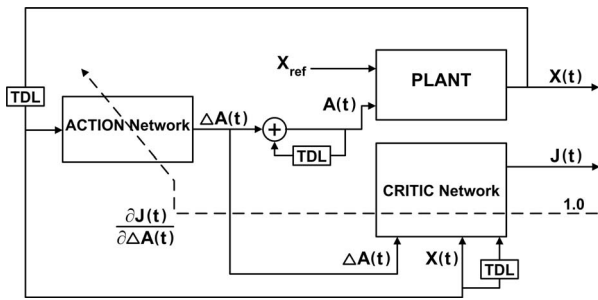


Fig. 3. Schematic diagram of a ACD based controller.

## Multimachine Power System

A 12-bus 3-generator FACTS benchmark power system (Fig. 4) [17] is considered in this paper together with a shunt connected Static Compensator (STATCOM). The STATCOM is connected to bus 4 to provide extra voltage support during the steady state for the load area (buses 4 and 5).

The power system is modeled in the PSCAD/EMTDC<sup>®</sup> environment, with the dynamics of the generators' AVR, exciter and governor taken into account. The STATCOM is controlled using two PI controllers, and its main control objective is to maintain a desirable voltage profile at the point of common coupling (PCC). For more details regarding the STATCOM internal control structure the reader is referred to [18].

## Intelligent Supervisory Level Control

The objective of this paper is to present two intelligent supervisory level controllers for the multimachine power system in Fig. 4: a neuro-fuzzy external controller for the STATCOM that provides additional dynamic damping; and an optimal wide area controller that

controls/supervises the performances of the three generators and the STATCOM.

### STATCOM Neuro-fuzzy External Controller

Figure 5 shows the schematic diagram of the proposed STATCOM neuro-fuzzy external controller. The objective here is to use the STATCOM to provide damping for both generators 3 and 4 during dynamic and transient disturbances. In order to achieve this, the external controller receives the speed deviations of generators 3 and 4, and in turn generates a control signal  $\Delta V_{ref}$  that is applied to the line voltage reference of the STATCOM.

The structure of the proposed neuro-fuzzy controller is illustrated in Fig. 6. The plant in Fig. 6 consists of the multimachine power system and the STATCOM internal controller. The input to the plant is the modulation index  $m_a$  generated by the  $PI_V$  controller (which is used to control the line voltage) and its output  $X(t)$  is the vector of the speed deviations of generators 3 and 4. The proposed external controller consists of two main components: the neuro-fuzzy controller, and a Critic neural network which is trained to approximate the cost-to-go function  $J$  and provides the appropriate training signals for updating the parameters of the neuro-fuzzy controller.

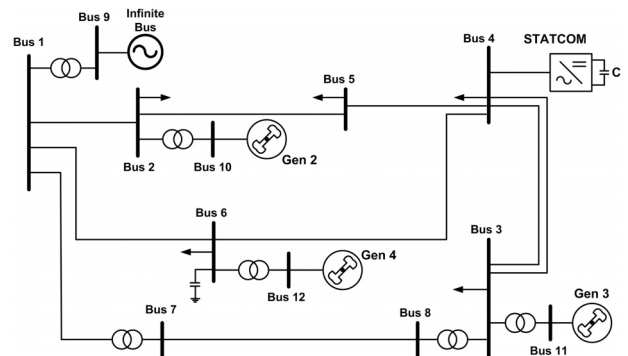


Fig. 4. Schematic diagram of the 12-bus FACTS benchmark power system with a STATCOM.

*Neuro-Fuzzy Controller:* A first order Takagi-Sugeno fuzzy model is used for implementing the controller, which is a special case of the Mamdani model [19]. The input to the fuzzy controller is the vector of the selected states of the power system as in (2):

$$X(t) = [\Delta\omega_3(t), \Delta\omega_4(t)]^T. \quad (2)$$

The neuro-fuzzy controller in return generates a control signal  $\Delta V_{ref}$ , which is added to the line voltage reference

of the local  $PI_V$  controller (Fig. 5). The details of the fuzzy inference engine, the input/output membership functions and the rule base are provided in the authors' previous work in [20].

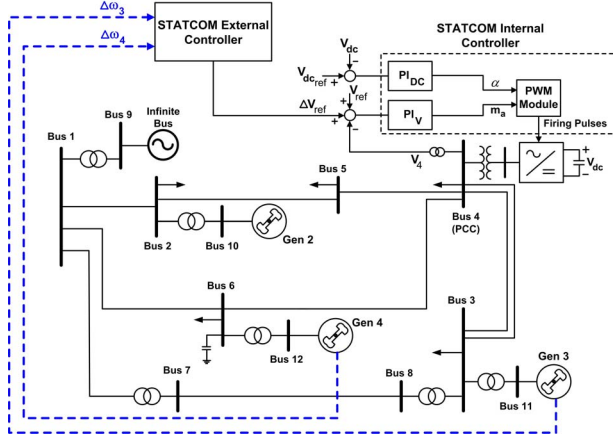


Fig. 5. Schematic diagram of the STATCOM external controller.

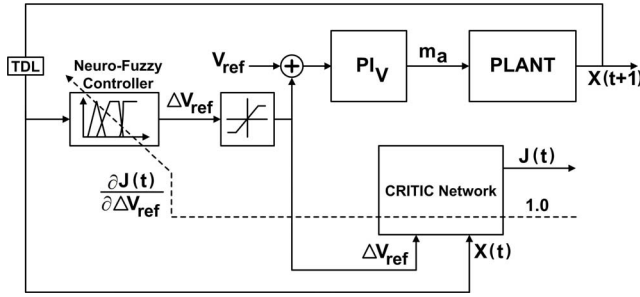


Fig. 6. Schematic diagram of the STATCOM ACD based neuro-fuzzy external controller.

**Critic Neural Network:** An ACD based approach is applied in order to provide appropriate training signals for the parameters of the neuro-fuzzy controller. A Critic network is trained in order to learn the cost-to-go function associated with the power system. The utility function for the Critic network is comprised of two terms (decomposed utility function):

$$U^e(t) = U_1^e(t) + U_2^e(t), \quad (3)$$

where:

$$U_1^e(t) = |\Delta\omega_3(t) + \Delta\omega_3(t-1) + \Delta\omega_3(t-2)|, \quad (4)$$

$$U_2^e(t) = |\Delta\omega_4(t) + \Delta\omega_4(t-1) + \Delta\omega_4(t-2)|. \quad (5)$$

The two terms are necessary because the rotors of generators 3 and 4 have different swings and therefore, the STATCOM should try to improve the performance of both generators at the same time. The cost-to-go function estimated by the Critic network is:

$$J(t) = \sum_{i=0}^{\infty} \gamma^i U^e(t+i), \quad (6)$$

Two sub-Critic networks are therefore used, where each one learns one part of the cost-to-go function. Utility function decomposition speeds up the process of Critic network learning, since each sub-Critic is estimating a simpler function [16]. Figure 7 shows the schematic diagram of the Critic network. It consists of two separate multilayer perceptron (MLP) neural networks [21], with 10 neurons in the hidden layer of each one and the same input from the Action network, i.e., the neuro-fuzzy controller. The hyperbolic tangent is used as the activation function of the hidden neurons. For details on the step by step training procedure of the Critic network and the neuron-fuzzy controller, the reader is referred to [20].

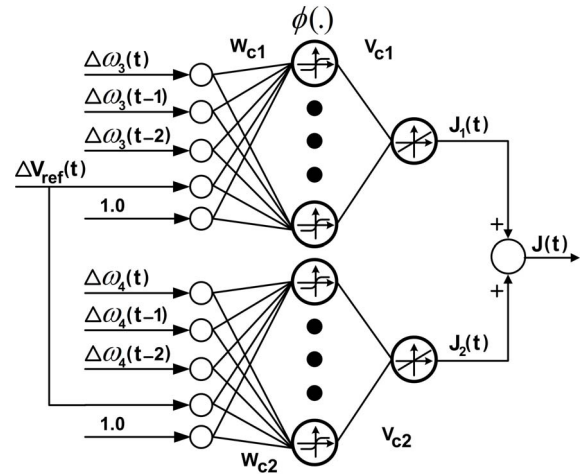


Fig. 7. Schematic diagram of the STATCOM Critic network.

### Intelligent Wide Area Controller (WAC)

Figure 8 shows the schematic diagram of the WAC. The objective of the WAC in this study is to provide auxiliary control signals for the three generators and the STATCOM in Fig. 4 in order to improve the dynamic stability of the power system. The auxiliary control signals are in the form of additional reference signals that are added to the steady state set-points.

The controller consists of a Critic and an Action neural network. The Critic is trained to estimate the cost-to-go function  $J(t)$  in the Bellman's equation [15]. Once its weights have converged, the Critic network is used to train a second network, an Action neural network that provides the auxiliary reference signals  $A(t)$  for the three generators' AVRs and the STATCOM voltage reference (Fig. 8).

**Utility Function:** The vector of the states of the power system is considered to be comprised of the speed

deviations of the three generators (Gen 2, Gen 3 and Gen 4 in Fig. 4) in (1):

$$X(t) = [\Delta\omega_2(t), \Delta\omega_3(t), \Delta\omega_4(t)]^T. \quad (7)$$

Similar to the previous section, a utility function decomposition approach is adopted that helps speed up the training process of the Critic network. Three separate utility function components  $U_2$ ,  $U_3$  and  $U_4$  are defined for the WAC:

$$U^w(t) = U_2(t) + U_3(t) + U_4(t), \quad (8)$$

where each function  $U_j$  corresponds to the speed deviations of one of the synchronous generators, i.e.,  $\Delta\omega_j$ :

$$U_j(t) = |\Delta\omega_j(t) + \Delta\omega_j(t-1) + \Delta\omega_j(t-2)|. \quad (9)$$

**Critic Network:** Three sub-Critic networks are used in this paper, one for each of the three utility functions  $U_2$ ,  $U_3$  and  $U_4$  respectively, where each one learns one part of the cost-to-go function. For more information, the reader is referred to the authors' previous work in [22].

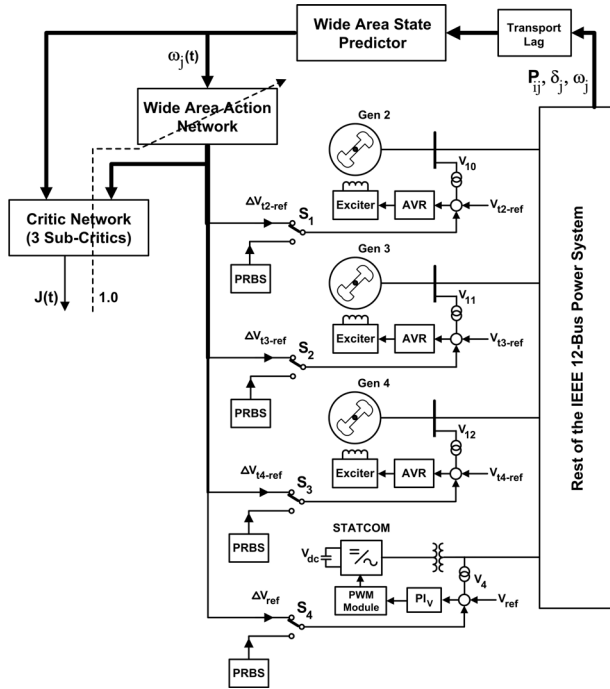


Fig. 8. Schematic diagram of the WAC.

**Action Network:** A Functional Link (FLN) neural network is used as the Action network. This neural network structure avoids unwanted interactions between the various control signals generated by the WAC. A detailed discussion appears in [22].

## Simulation Results

### STATCOM Neuro-fuzzy External Controller

In this section, the STATCOM is considered to be equipped with an external controller as shown in Fig. 5 that improves its damping capabilities during disturbances. The performance of the STATCOM external controller is evaluated with the neuro-fuzzy controller (Fig. 6) and a typical linear controller (Fig. 9). The parameters of the linear external controller are derived by trial and error, at a specific operating condition [20]. Dynamic damping provided by the STATCOM for the generator rotor speeds, as well as the control effort provided, are considered as the main basis of comparison between these hierarchical controllers.

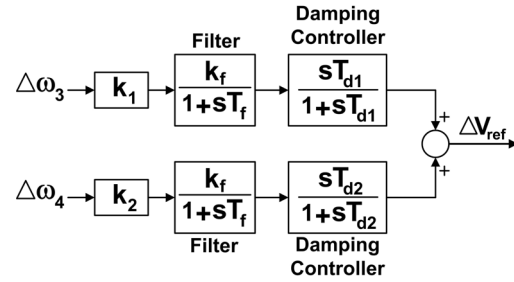


Fig. 9. Schematic diagram of the STATCOM linear external controller.

**Case Study 1: Short Circuit midway along the Transmission Line 7-8:** A 100 ms three phase short circuit is now applied to the transmission line connecting buses 7 and 8. This section of the power system is relatively weak and sensitive to disturbances. Figure 10 illustrates the effectiveness of the neuro-fuzzy external controller in restoring the system back to the steady state condition. Figure 11 emphasizes the fact that the STATCOM, externally controlled by the neuro-fuzzy controller, injects less initial reactive power into the network when responding to the fault. This leads to having solid state switches with smaller current ratings which are less expensive. Simulation results indicate that the STATCOM controlled by the neuro-fuzzy controller reduces the peak reactive power injection by almost 14 MVar, from 376 MVar to 362 MVar. Based on a typical conservative price of 50\$/kVar, this reduction results in approximate savings of \$700,000.

**Case Study 2: Short Circuit along the Transmission Line 3-4:** In the next test, a 100 ms three phase short circuit is applied to the middle of one of the parallel transmission lines connecting the STATCOM to generator 3. Figures 12 and 13 show the effectiveness of the proposed neuro-fuzzy controller in damping out the rotor speed oscillations and indicate that the proposed neuro-fuzzy controller manages to improve the dynamic damping of



both generators, even though the rotors of the two machines have different, and at times, opposing excursions.

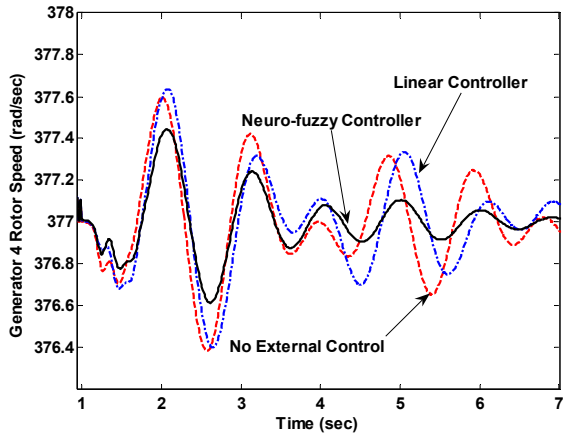


Fig. 10. Rotor speed deviations of generator 4 (Fig. 4) during case study 1.

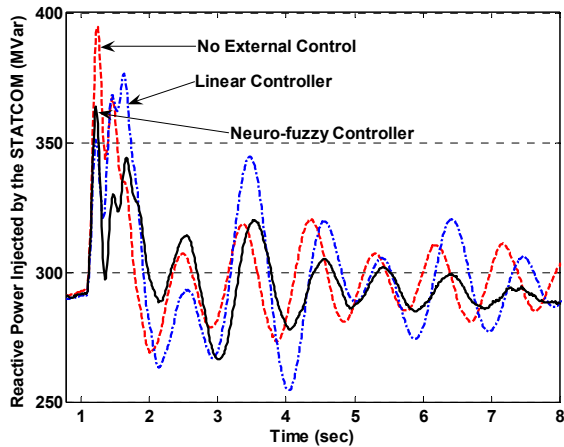


Fig. 11. Reactive power injected by the STATCOM during case study 1.

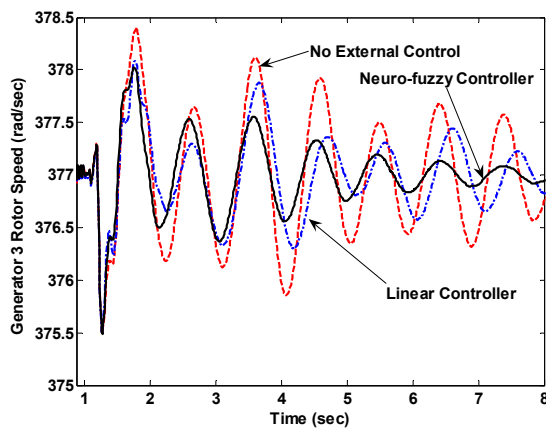


Fig. 12. Rotor speed deviations of generator 3 during case study 2. Intelligent Wide Area Controller

Several tests are now carried out in order to evaluate the effectiveness of the proposed WAC in Fig. 8. The performance of the power system equipped with the WAC is compared with an uncompensated system, as well as the system with locally tuned PSSs for each generator. These PSSs are fine tuned at a single operating condition in order to provide positive damping over a range of system frequencies. The parameters and the structure of the power system stabilizers appear in [22].

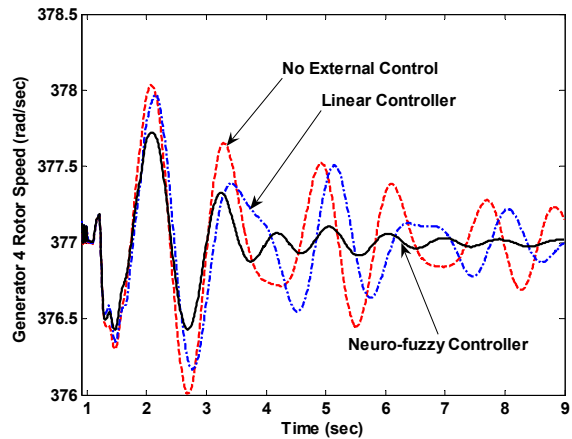


Fig. 13. Rotor speed deviations of generator 4 (Fig. 4) during case study 2.

*Case Study 3: Three Phase Short Circuit at Bus 5:* In the first of these tests, a three phase short circuit occurs at bus 5. The fault is cleared after 100 ms and therefore, it does not permanently change the power system topology. Figure 14 illustrates some typical results and shows that the WAC is only slightly more effective than the local PSS in damping out the speed oscillations.

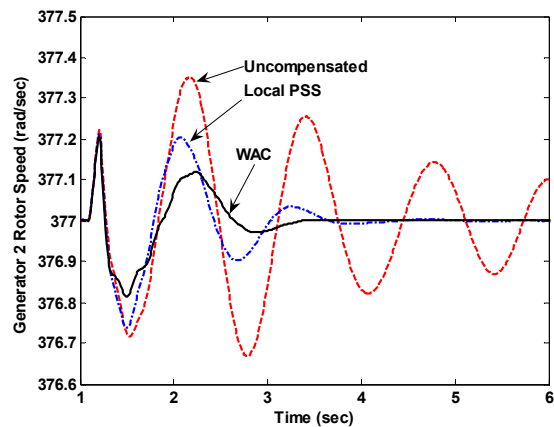


Fig. 14. Rotor speed deviations of generator 2 during case study 3.

*Case Study 4: Short Circuit at the Middle of the Transmission Line 3-4:* In the next test, a 100 ms three phase short circuit is applied at the middle of one of the

parallel transmission lines connecting buses 3 and 4. The line is disconnected after the fault is cleared. Figure 15 compares the performances of the WAC and the local PSSs with an uncompensated system and shows that the WAC is more effective than the case of the power system compensated with local PSSs.

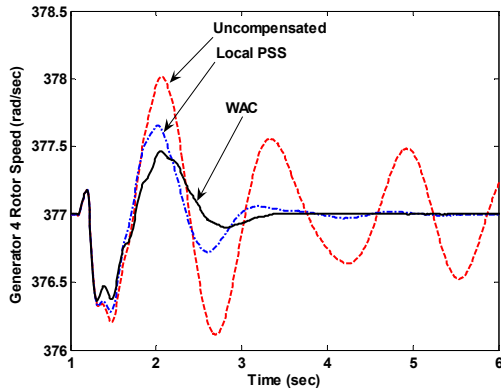


Fig. 15. Rotor speed deviations of generator 4 during case study 4.

*Case Study 5: Transmission Line 4-6 Disconnected:* The next test investigates the effect of a major change to the topology of the power system by switching off a transmission line which connects buses 4 and 6. This changes the operating condition of the power system and therefore reduces the efficiency of the locally tuned stabilizers that are normally tuned to provide effective damping in a certain frequency range. Figures 16-17 contain some typical results. Figure 17 shows that for generator 4 the local PSS is still performing effectively; however, the WAC is considerably more effective for rotor speed deviations in generator 3 (Fig.16). This can be due to the fact that the dynamics of generator 3 are affected more by the topology change in the power system.

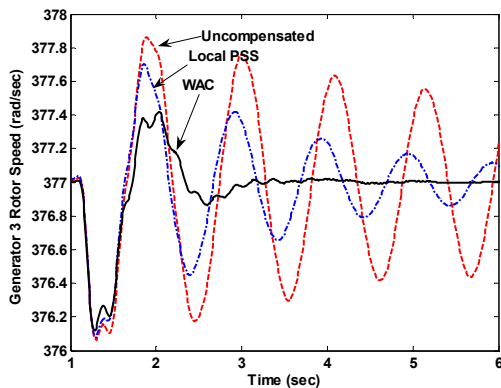


Fig. 16. Rotor speed deviations of generator 3 during case study 5.

## Summary

The traditional approach of controlling a power system using local control agents suffers from several disadvantages namely, the lack of information on the overall dynamics of the power system, inadvertent and unwanted interactions between different local controllers, sub-optimality of the local controllers over the wide range of operating conditions of the power network and the inability of the local controllers to respond to most of the global modes of the power system.

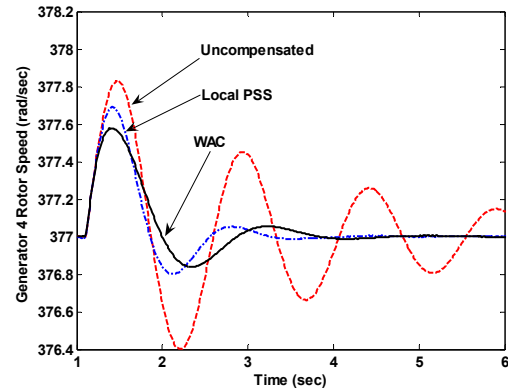


Fig. 17. Rotor speed deviations of generator 4 during case study 5.

These problems can be solved by using a supervisory level control scheme that has information on the overall performance of the power system and its local controllers. Such controllers can provide continuous or discrete auxiliary control signals to the controllable devices such as synchronous generators and/or converter based FACTS devices.

However, the traditional control methods often fail to provide a very effective solution due to the complexities and the nonlinearities of the multi-input multi-output non-stationary power system. Moreover, these techniques are mostly dependent on a mathematical model of the system to be controlled, which for a multimachine power system in most cases is not feasible to obtain.

The aim of this paper is to introduce the concept of intelligent supervisory level control for a multimachine power system. Adaptive critic designs are used that can provide optimal control over a wide range of operating conditions. The fact that this scheme is independent of a mathematical model of the power system makes it an appropriate option for a nonlinear system such as the power network. In addition, the ACD based controller is trained based on reinforcement learning. Therefore, it is highly insensitive to the size of the power system under study. All the required information for training such controllers can be obtained using input/output data sampling during the performance of the power system.

These intelligent supervisory level controllers can be designed on a semi-local (external control) or a global basis.

Two intelligent controllers have been introduced in this paper for external control of a STATCOM, and for wide area control of a multimachine power system. The methods introduced in this paper are applicable to any power system and/or any controllable component.

Even though intelligent controllers such as the ones proposed in this paper can be equally effective for internal control of generators and/or FACTS devices, the authors believe that implementing such supervisory level control schemes can be the first step towards the introduction and acceptance of these schemes by the power utilities and design engineers. With more intelligent controllers, many of the large scale failures in the power grid can be avoided.

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