COORDINATED POWER FLOW CONTROL USING FACTS DEVICES

A. Oudalov P. Korba

ABB Switzerland Ltd., Corporate Research CH-5405 Baden-Dättwil, Switzerland {Alexandre.Oudalov, Petr.Korba}@ch.abb.com

Abstract: An application of fuzzy logic based control for power systems governing multiple Flexible Alternative Current Transmission System (FACTS) devices is proposed. Several relations have been derived to determine set points of FACTS devices using fuzzy reasoning in order to meet the requirements for power flows. The relations are based on so called coefficients of influence, which are online adapted employing a fuzzy gain scheduling method. The Swiss transmission network is used to demonstrate and to evaluate the effectiveness of the developed control algorithm. *Copyright* @2005 *IFAC*

Keywords: Power systems control, flexible AC transmission systems, power flow, gain scheduling, soft computing.

1. INTRODUCTION

The existing transmission networks often operate close to their limits. This stress can be reduced with a more effective utilization of existing transmission network capacity. The fundamental characteristic of alternating current (AC) electric power systems is the difficulty to control power flow from a generator to a distant load area along a specific "contract path". Uniform distribution of power flows between all transmission lines can be achieved using a flexible power flow control.

Thanks to a rapid development of power electronics and semiconductor technologies in the last two decades, a new family of devices with a common name of *flexible AC transmission systems* (FACTS) is becoming available. Coupled with advanced monitoring and control algorithms, FACTS can help utilities to nudge power flows in desired directions and allow practically complete utilization of the capacity of transmission elements up to their thermal limits (Korba *et al.*, 2003). Installations of multiple FACTS devices offer a great opportunity concerning the flexibility of system-wide power flow control. However, their control actions may cause mutual negative effects which affect the system security. The motivation for this research was the need to control multiple FACTS devices in order to manage system congestions in a continuously changing deregulated environment.

2. FLEXIBLE AC TRANSMISSION SYSTEMS

For any transmission line, three key parameters determine the power flow: terminal bus voltages, line impedance, and phase angle between the sending and receiving ends. V_1 and V_2 are magnitudes of the bus voltages at either ends of the line with the angle $\delta = \delta_1 - \delta_2$ between them. The line is assumed to have the impedance X_{12} . In this case, the expression for active power flow can be written as (1).

$$P_{12} = \frac{V_1 V_2}{X_{12}} sin(\delta_1 - \delta_2) \tag{1}$$



Fig. 1. Types of FACTS

This simple expression provides good insight into techniques available for the active power flow control. Voltage magnitudes cannot be varied significantly since they must be kept within regulated limits (normally \pm 5–10%) providing very limited scope for power flow control. The line reactance and the voltage angle difference are not circumscribed as heavily to such restrictions. They provide the only practical alternatives for power flow control.

The idea of FACTS for power flow control is depicted in Figure 1 and demonstrated here on a FACTS device called Thyristor Controlled Series Capacitor (TCSC) (Hingorani and Gyugyi, 2000).

The basic idea behind power flow control with the TCSC is to decrease or increase the overall line effective series transmission impedance adding a capacitive or inductive reactance, see (2),

$$\underline{z}_{sr} = j(x_{sr} - x_{TCSC}) = j((1-k)x_{sr})$$
(2)

where k is the so called degree of series compensation (3), which in our case varies in the range $-0.2 \le k \le 0.8$.

$$k = \frac{x_{TCSC}}{x_{sr}} \tag{3}$$

A variation of active power flow in a transmission line with TCSC due to a variation of TCSC's setpoint can be approximated by (4).

$$P_{AC} = a * X_{TCSC}^2 + b * X_{TCSC} + P_{AC}^0 \qquad (4)$$

3. COEFFICIENTS OF INFLUENCE

The influence of a FACTS device on the entire transmission network is closely related to the electrical distances: only a certain amount of neighboring lines, where the FACTS is sited, can be influenced by that FACTS. Starting from the center of the siting area, the influence decreases and becomes negligible on the remote circuits. In the case with multiple FACTS devices there are multiple influence areas, which correspond to different devices. If these devices are located relatively close to each other, there are intersections between their influence areas.

For any transmission line in a power system with a FACTS device, the direct control effect of this FACTS on the power flow through any other line can be expressed by (5), see also Figure 2a. Here, $Setpoint_{FACTS}$ stands for the direct control variable of a TCSC device (line reactance). This function has a non linear characteristic; for *i* lines and *j* FACTS devices, i^*j non linear functions to be considered in a direct power flow control.

$$P_{line} = f(Setpoint_{FACTS}) \tag{5}$$

However, (5) can be decomposed in two parts. The first part is the linear coefficient of influence K_{inf} and the second part is the non-linear regulation characteristic of the TCSC device (Figure 2b). The idea is to initialize the level of line overload as the controlled quantity and to find the required change of the indirect control variable of the TCSC (in this case, a power flow through the TCSC device) to remove that violation. Then, for a known level of power flow through the TCSC device one can find out the value of its direct control variable.

In accordance with the decomposition principle, the coefficients of influence K_{inf} (a ratio between controlled parameters and indirect control variables (Oudalov *et al.*, 1999)) are introduced in (6). Load flow computations with different values of direct control variables, which are uniformly distributed in the range between their maximal (0.8 p.u. X_{line}) and minimal (-0.2 p.u. X_{line}) limits, are carried out.

$$K_{inf_{ij}} = \frac{P_{line_i}^0 - P_{line_i}^{new}}{P_{FACTS_j}^0 - P_{FACTS_j}^{new}} \tag{6}$$



Fig. 2. The direct (a) and the decomposed (b) power flow control with TCSC

 $P_{line_i}^0$ is the value of active power flow in the controlled line i before changing the setpoint of FACTS j, $P_{line_i}^{new}$ is the value of active power flow in the same line after changing the setpoint of FACTS j, $P_{FACTS_i}^0$ is the value of active power flow in the line with FACTS j before changing its setpoint, and $P_{FACTS_{\,i}}^{new}$ is the value of active power flow in the line with FACTS j after changing its setpoint. The characteristic of K_{inf} is linear instead of quadratic when working with a direct FACTS control variable X_{TCSC} . Values of coefficients of influence must be calculated according to (6) for every line considering also the TCSC itself included subsequently in all lines; this results are grouped into a squared matrix of influence $[\mathbf{K}_{inf}]$. All diagonal elements of that matrix are equal to one and reflect a location of the TCSC. All other elements satisfy $|K_{inf}| \leq 1$. Small elements $(|K_{inf}| \leq \Phi)$ were eliminated from $[\mathbf{K}_{inf}]$ matrix in order to remove less effective control actions, to reduce a possible negative interactions between multiple devices and to facilitate a creation of a hierarchical control structure. Φ is a filtration index and its numerical value should be located between 0.1 and 0.2.

A regulation characteristic transforms the required amount of active power flow – as a modification of the actual power flow in the line – into a real set-point of the FACTS device; in case of TCSC line reactance (Oudalov *et al.*, 2003).

The magnitude of K_{inf} remains almost constant for a base transmission network topology under changes in generation-load profiles. However, a network topology changes continuously in the daily operation of the power system through the planned and emergency switching operations. Therefore, the elements of $[\mathbf{K}_{inf}]$ matrix must follow up to these modifications. The fast automatic



Fig. 3. The basic concept of the K_{inf} adaptation method: direct and indirect influence of the TCSC j on the line i

adaptation of $[\mathbf{K}_{inf}]$ matrix plays a principal role in the correct reaction of multiple FACTS devices on critical congestions so that a secure operation of power system can be guaranteed.

A method is required which can predict the values of all K_{inf} to remedy operational modes with convergence difficulties. The objective was to determine mainly a direction of changing of the magnitude of K_{inf} while a new magnitude itself may have a small error.

A fuzzy gain scheduling technique can be used to obtain the elements of $[K_{inf}]$ matrix without direct load flow recalculations after an outage of any single transmission line.

The applied method is based on the hypothesis that the influence of the TCSC j on the line iafter the outage of the line k $(K_{inf_{ij}\ new})$ consists of a direct influence, i.e. the actual $K_{inf_{ij}}$ and an indirect influence via the outage line k, i.e. a composition of $K_{inf_{kj}}$ and OUT_{ik} (Figure 3) according to (7):

$$((K_{inf_{kj}}); (OUT_{ik})) \to \Delta K_{inf_{ij}}$$
$$= (K_{inf_{ij new}} - K_{inf_{ij}}) \quad (7)$$

Where $K_{inf_{kj}}$ is an influence of the TCSC j on power flow in the line k in the base topology (line k is switched on), OUT_{ik} is an influence of the outage of line k on power flow in the line i, and $\Delta K_{inf_{ij}}$ is a variation of the coefficient of influence due to the outage of transmission line k. OUT_{ik} is taken from the matrix [**OUT**] which consists the coefficients of influence of all possible single line outages on the variation of active power flows in transmission network. This matrix is calculated during an off-line preparation step.

For a simplification of the processing of huge numerical sets of coefficients of influence $(K_{inf}$ and OUT) obtained by simulations. The numerical expressions in (7) can be replaced by linguistic expressions such as:

IF $K_{inf_{kj}}$ is negative small (NS) **AND** OUT_{ik} is positive large (PL)

THEN $\Delta K_{inf_{ij}}$ is negative close to medium (NCM)

The knowledge required to generate the fuzzy rules is based on the understanding of the behavior of power system under coordinated control, known e.g. from simulations or derived from an experienced operator, see Table 1.

Table 1. The rule base with 49 rules for an acquisition of $\Delta K_{inf_{ii}}$

	OUT_{ik}						
$K_{inf_{kj}}$	NL	NM	NS	Z	$_{\rm PS}$	PM	PL
NL	PL	PCL	PCM	Z	NCM	NCL	NL
NM	PCL	PM	PS	Z	NS	NM	NCL
NS	PCM	PS	PVS	Z	NVS	NS	NCM
Z	Z	Z	Z	Z	Z	Z	Z
PS	NCM	NS	NVS	Z	PVS	PS	PCM
PM	NCL	NM	NC	Z	PS	PM	PCL
PL	NL	NCL	NCM	Z	PCM	PCL	PL

The whole process of adaptation of K_{inf} is executed by a fuzzy logic controller.

Two different types of fuzzy logic controllers have been considered in this work. First controller is the central fuzzy logic controller, which has two loops. One loop is for the centralized $[\mathbf{K}_{inf}]$ adaptation and another loop for the coordinated control of FACTS devices in the places where their control areas have intersections. Second controller is the individual fuzzy logic controller for each FACTS device. These local fuzzy logic controllers use the parts of the common updated $[\mathbf{K}_{inf}]$, which are distributed by the central fuzzy logic controller to the local knowledge bases.

Experiments showed that the prediction of the direction of change of K_{inf} values works always

correct, however, some of the values have a substantial error. This error was caused by the simple uniform distribution of membership functions. Thus, the neuro-adaptive learning technique have been employed to adjust all membership functions automatically. It assumes to have a collection of input/output data. They can be obtained from simulations or from power flow measurements. A network-type structure similar to that of a neural network maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs. The parameters associated with the membership functions change through the learning process (back propagation was applied to adjust the parameters to reduce the sum of the squared difference between actual and desired outputs) (Mori, 2000), (Song, 1998). The neuro-adaptive learning was applied for a selection of the best amount and form of membership functions for two inputs. The search for the appropriate type and number of membership functions for input variables is shown in Figure 4 (7 membership functions is a reasonable compromise between computation time and accuracy).

4. COORDINATED CONTROL OF MULTIPLE FACTS DEVICES

A two level hierarchical control structure was developed for the operation and coordination of multiple FACTS: a device level and an area level. The process of construction of two different levels of hierarchical coordinated control system is based on the analysis of filtered $[K_{inf}]$ matrix which has dimension $l \times k$, where l is a number of transmission lines and k is a number of TCSC devices. Lines with one non-zero K_{inf} element were subscribed to the corresponding local controllers. These controllers does not have any intersections and form a device level of control hierarchy. Remaining lines have at least two nonzero K_{inf} elements: they are sensitive to control actions of at least two TCSC devices. These lines were subscribed to a controller at higher level of hierarchy – area level.

The objective function F has been formulated as a minimization of system overloads. The active power P_l in the line l should not exceed a specific maximal thermal limit for a steady state operation $P_{l\mbox{max}}$ (8), where the absolute value of P_l takes into account different directions of the power flow in the transmission line l.

$$|P_l| \le P_{l max} \tag{8}$$

Assume there are new measurements of active power flow P_{l0} . If the expression (8) is false then calculate the power flow violation (overload) as in (9).



Fig. 4. The results of neuro adaptive learning procedure: optimal forms (a) and number (b) of membership functions and related computation time

$$\Delta P_l = \frac{|P_{l0}| - P_{l max}}{P_{l max}} \times 100\%$$
 (9)

Finally, the objective function will have the following form (10), where w_l is weighting factor, which allow to provide a higher level of importance to overloads at critical lines.

$$F = \sum_{l=1}^{i} w_l \Delta P_l \Rightarrow min \tag{10}$$

5. RESULTS

The following example of multiple FACTS coordination in a meshed transmission network is based on a reduced model of the Swiss electric power system (OFEN, 2001) shown in Figure 5. An application of multiple FACTS devices in the Swiss transmission network has been considered in order to increase a safety transit of electricity from Germany to Italy without line thermal limit violations in normal and emergency network topologies. This task became a very important especially after the blackout on September 23, 2003 in Italy which demonstrated a weakness of the Swiss–Italian interface.

Figure 5, illustrates a scheme of the Swiss–Italian interface. It incorporates two 380 kV transmission lines: 206-606 Lavorgo–Musignano and 195-602 Soazza–Bulciago (blue lines) and five 220 kV transmission lines (red lines). For a winter low load period we simulated two new electrical transactions by increasing a power production in Germany and load in Italy by 900 MW. Simultaneously we considered an outage of the 380 kV transmission line 190-195 Sils–Soazza (Figure 5, black crosses). This mode brought the line 213-605 Serra–Pallanze to an overloaded condition by 16%. All lines of the interface except the overloaded line 213-605 have enough available transmission capacity for an accommodation of sup-



Fig. 5. A study of the Swiss–Italian interface with 8 TCSC devices and an overload in the line 213-605 Serra–Pallanze

plementary power flows. Thus, there is some potential to shift the excessive power flow from the overloaded line 213-605 to less loaded lines. In this example, only one overload in the line 213-605 has been considered. Due to the transmission line 190-195 outage, K_{inf} of all TCSC devices have to be adapted to the new condition. The coefficient OUT of the outage line 190-195 on the overloaded line 213-605 (OUT=0.032 i.e. it increases a little bit a value of the overload in the line 213-605) and the K_{inf} of the TCSC 208-210 on the outage line 190-195 in the normal configuration $(K_{inf}=0,031)$ were used. Thus, the adaptation value ΔK_{inf} is equal to 0,002 and in accordance with (7) $K_{inf}^{new} =$ $K_{inf}^{base} + \Delta K_{inf} = -0.516 + 0.002 = -0.514$. The influence was slightly decreased. This is due to the fact that the outage line 190-195 is electrically remote from the TCSC devices and the overloaded line 213-605. However, it confirms that the fuzzy logic adaptation has an acceptable accuracy. The overloaded transmission line is sensitive to control actions of six TCSC devices. Therefore, control action is taken at the central level. A required compensation in the overloaded line 213-605 is 44 MW. This value is shared between available



Fig. 6. Diagrams of the iterative coordinated control for multiple TCSC devices: variation of objective function (a) and of TCSC setpoints (b)

TCSC devices proportionally to their participation weights. A control process consisted on several iterations until the magnitude of objective function F was minimized (Figure 6a). Variation of setpoints of selected TCSC devices during an iterative process as well as final setpoints for the local controllers are shown in Figure 6b.

6. CONCLUSIONS

A fuzzy gain scheduling based approach to a hierarchical power flow control employing TCSC has been shown. The application of the presented control technique can be extended for any other FACTS device suitable for power flow control. If one FACTS device has a small influence area, it becomes necessary to install multiple devices to control power flow throughout the power network. However, without an appropriate coordination, this often leads to a mutual negative effect which degrades the overall performance of the single power flow controllers. An original algorithm based on fuzzy logic and sensitivity analysis has been proposed here to overcome this problem in a simple way. The disadvantage of the fuzzy logic approach is the absence of guidelines for fine tuning of the fuzzy membership functions. Therefore, an adaptive neuro-fuzzy learning technique was applied to solve this problem. The advantage of this simple control approach is the possibility to provide a fast response for different working conditions with a minimum a priori information (initial power flows through overloaded lines and FACTS devices).

REFERENCES

- Hingorani, N. and L. Gyugyi (2000). Understanding FACTS. IEEE Press, New York, USA.
- Korba, P., M. Larsson and C. Rehtanz (2003). Detection of Oscillations in Electric Power Systems using Kalman Filtering Techniques. In: *Proceedings of the IEEE Conference on Con*trol Applications. Vol. 1. Istanbul, Turkey. pp. 183–188.
- Mori, H. (2000). Fuzzy Neural Network Applications to Power Systems. Proceedings of Power Engineering Society Winter Meeting pp. 1284–1288.
- OFEN (2001). Statistique Suisse de l'Électricité 2000. Office Fédéral de l'Énergie, Worbentalstrasse 32, 3003 Berne, Switzerland. http://www.admin.ch/bfe.
- Oudalov, A., R. Cherkaoui, A.J. Germond and M. Emery (2003). Coordinated Power Flow Control by Multiple FACTS Devices. Proceedings of IEEE Power Tech Conference, Bologna, Italy.
- Oudalov, A., R. Cherkaoui and A.J. Germond (1999). Coordinated Control of Multiple Series FACTS Devices. Proceedings of 11th Power System Automation and Control Conference, Bled, Slovenia pp. 71–77.
- Song, Yong-Hua (1998). Application of Fuzzy Logic in Power Systems. II. Comparison and Integration with Expert Systems, Neural Networks and Genetic Algorithms. *Power Engineering Journal* 12(4), 185–190.