Self-tuning FACTS Controllers for Power Oscillation Damping: A Case Study in Real-Time

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Abstract

Design and real-time implementation of a self-tuning FACTS controller is illustrated for power oscillation damping. Although the system model is not required for self-tuning control design, it is shown to perform similar to a model based design. For parameter estimation, the classical recursive least square (RLS) is supplemented by a random walk (RW) with a switched structure and compared to standard variable forgetting factor (VFF) approach. It is shown that the random walk improves the accuracy and convergence of the estimated system parameters which is critical to self-tuning control following large disturbances. The performance is validated in real time using a commercial real time simulation platform. The control computation time is shown to be considerably less than the typical sampling time used for power oscillation damping applications demonstrating the feasibility of self-tuning FACTS controllers in practice.

1 Introduction

Securing permission for new transmission infrastructure is getting increasingly complicated. It is therefore critical to ensure that the existing transmission assets are fully utilised by loading them much closer to their capacity. One of the major concerns, then, is secure operation of the system due to presence of low frequency electro-mechanical oscillations [1] typically in the range of 0.1-1.0 Hz. A number of incidents of oscillatory instability have been reported, some of them eventually leading to widespread blackouts [2]. Such risks force the network operators to operate their system with significant stability margins. One way to get around this problem is to exert appropriate control to improve the dynamic behaviour of the system and thereby allowing system operation closer to the capacity, without compromising security.

The traditional approach to improve the dynamic behaviour of a power system has been through modulation of the excitation systems of the generators. More recently, control of flexible ac transmission systems (FACTS) devices have been attempted to achieve effective damping of inter-area oscillation.

Conventional control design is often based on a nominal operating condition and is tuned for certain off-nominal conditions of the power system. One of the concerns is the availability of accurate information for all the components required to model the entire power system. With increasing interconnection, ownership of different parts of the networks by many different utilities and participation of many independent power producers (IPPs), it is difficult to obtain accurate and up-to-date information about the overall system. These developments have prompted renewed research interest in control design approaches that rely solely on measurements and thereby, obviate the need for accurate information about all the system components.

Research in the application of adaptive self-tuning control in power systems began with a series of papers [3, 4, 5] on design of power system stabilisers (PSSs) primarily focused on damping local modes in a single machine infinite bus (SMIB) system. This was later extended to small prototype multi-machine systems [6] for damping multiple oscillatory modes in a decentralised fashion [7]. However, very little research attention has been focused on application of self-tuning control for damping inter-area modes using FACTS controllers until recent application of Kalman filter techniques with variable pole-shifting (PS) [8, 9]. The performance validation, however, was limited to computer simulation only.

A self-optimising PS algorithm [4, 10] could be computationally expensive for real-time implementation as it involves solution of an iterative optimisation in each step. Hence, the focus in this paper is on achieving accuracy and speed of convergence of estimated parameters such that a fixed pole-shifting factor is adequate to ensure satisfactory performance. In this context, the use of a random walk (RW) approach and a switched control technique is illustrated here. The advantages of these methods applied around the established RLS estimation and fixed PS control approach are demonstrated.

Utilities are usually reluctant to employ adaptive self-tuning controllers because of potential problems in real-time implementation. Due to obvious restrictions on using practical systems as test bench, a laboratory prototype of a power system is required to carry out performance validation in real time. Over the years, such prototypes of simple SMIB or even small multi-machine systems were set up in the laboratories [11, 12]. A simpler alternative is to use a hardware platform to simulate the behaviour of actual power systems

in real time. With such a test system in place, the controller can be tested in a real time configuration [13].

2 System Identification and Control

A schematic overview of the self-tuning controller is shown in Fig. 1.

At each sampling interval, the measured output $y(t)$ from the power system and the control input $u(t)$ to the FACTS device are used to estimate the oscillatory behaviour of the system. Based on the estimated parameters $\hat{\theta}(t)$, control signal $u(t)$ is computed as described in this section.

2.1 General System Model

The underlying model of the oscillations to be controlled can be represented as a general IIR filter where the control input $u(t)$ to the system and the measured output $y(t)$ are related through the difference equation:

$$\begin{aligned} y(t) = & -a_1 y(t-1) - \dots - a_{n_a} y(t-n_a) \\ & + b_1 u(t-k-1) + \dots + b_{n_b} u(t-k-n_b) \\ & + c_0 e(t) + c_1 e(t-1) + \dots + c_{n_c} e(t-n_c) \end{aligned} \quad (1)$$

In the z-domain, (1) simplifies to:

$$A(z)Y(z) = z^{-k}B(z)U(z) + C(z)E(z) \quad (2)$$

where

$$A(z) = 1 + a_1 z^{-1} + a_2 z^{-2} + \dots + a_{n_a} z^{-n_a} \quad (3)$$

$$B(z) = b_1 z^{-1} + b_2 z^{-2} + \dots + b_{n_b} z^{-n_b} \quad (4)$$

$$C(z) = c_0 + c_1 z^{-1} + c_2 z^{-2} + \dots + c_{n_c} z^{-n_c} \quad (5)$$

where k denotes the plant delay and $E(z)$ a sequence of independent identically distributed random error terms sampled from a normal distribution with zero mean and variance σ^2 , respectively [14].

2.2 Recursive Least Squares (RLS)

The objective of a system identifier, from the least squares concept, is to converge to the parameter vector:

$$\hat{\theta}(t) = [\hat{a}_1, \hat{a}_2, \dots, \hat{a}_{n_a}, \hat{b}_0, \hat{b}_1, \dots, \hat{b}_{n_b}]^T \quad (6)$$

which minimises the squared error between the measured $y(t)$ and the predicted $\hat{y}$ output:

$$\eta^2(t) = [y(t) - \hat{y}(t)]^2 \xrightarrow{\hat{\theta}} \min. \quad (7)$$

The predicted output can be expressed as:

$$\hat{y}(t) = \varphi(t)^T \cdot \hat{\theta}(t) \quad (8)$$

where $\varphi(t)$ denotes the data vector storing the last n_a samples of the system output and the last n_b samples of the system input, respectively:

$$\varphi(t) = [-y(t-1), \dots, -y(t-n_a), u(t-1), \dots, u(t-n_b)]^T \quad (9)$$

The above expression assumes no plant delay. In the presence of an integer plant delay, the RLS algorithm will drive the first k coefficients of $B(z)$ to zero.

The standard RLS update equations are given by [14]

$$K(t) = \frac{P(t-1) \varphi(t)}{1 + \varphi^T P(t-1) \varphi(t)} \quad (10)$$

$$P(t) = P(t-1) - K(t) \varphi^T P(t-1) \quad (11)$$

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(t) \eta(t) \quad (12)$$

where $K(t)$ is the gain vector at each sample instant and $P(t)$ the covariance matrix. It is initialized by a $(n_a + n_b)$ order identity matrix weighted with a scalar parameter δ :

$$P(0) = \delta \cdot I \quad (13)$$

If no reasonable assumption can be made for the estimated parameters, it is common to initialise the identifier to a single integrator with unity gain [14] as follows:

$$\hat{\theta}(0) = [-1, 0, \dots, 0, T_s, 0, \dots, 0]^T \quad (14)$$

where T_s denotes the sampling time and is the initial value of b_1 . At startup, the data vector $\varphi(0)$ is usually filled with zeros and the estimation process started after $(n_a + n_b)$ samples have been captured.

2.3 Pole-shifting (PS) Control

Consider the feedback control setup shown in Fig. 2. The system to be controlled is described by the identified coefficients of $A(z)$ and $B(z)$, respectively. The general transfer function for the controller is given by:

$$U(z) F(z) = -Y(z) G(z) \quad (15)$$

where

$$G(z) = g_0 + g_1 z^{-1} + g_2 z^{-2} + \dots + g_{n_g} z^{-n_g} \quad (16)$$

$$F(z) = 1 + f_1 z^{-1} + f_2 z^{-2} + \dots + f_{n_f} z^{-n_f} \quad (17)$$

It can be shown that the optimal orders of the control polynomials are related to the order of the identified system as follows [3]:

$$n_g = n_b - 1 \quad (18)$$

$$n_f = n_a - 1 \quad (19)$$

The closed loop transfer function from Fig. 2 is given by:

$$T(z) = \frac{C(z) F(z)}{A(z) F(z) + B(z) G(z)} \quad (20)$$

Shifting the closed loop poles towards the origin of the unit circle by a factor α , where $0 \leq \alpha \leq 1$, with respect to the open loop pole location is equivalent to satisfy the following equation:

$$A(z) F(z) + B(z) G(z) = A(\alpha z) \quad (21)$$

Comparing the coefficients on both sides of (21), the coefficients of the controller are obtained using:

$$Z = M^{-1} \cdot L \quad (22)$$

where

$$M = \begin{bmatrix} 1 & 0 & \cdot & 0 & b_1 & 0 & \cdot & 0 \\ a_1 & 1 & \cdot & 0 & b_2 & b_1 & \cdot & 0 \\ \cdot & a_1 & \cdot & \cdot & \cdot & b_2 & \cdot & \cdot \\ a_{n_a} & \cdot & \cdot & \cdot & b_{n_b} & \cdot & \cdot & b_1 \\ 0 & a_{n_a} & \cdot & 1 & 0 & b_{n_b} & \cdot & b_2 \\ \cdot & 0 & \cdot & a_1 & \cdot & 0 & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \cdot & a_{n_a} & 0 & 0 & \cdot & b_{n_b} \end{bmatrix} \quad L = \begin{bmatrix} a_1(\alpha - 1) \\ a_2(\alpha^2 - 1) \\ \cdot \\ a_{n_a}(\alpha^{n_a} - 1) \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix} \quad Z = \begin{bmatrix} f_1 \\ f_2 \\ \cdot \\ f_{n_f} \\ g_0 \\ \cdot \\ \cdot \\ g_{n_g} \end{bmatrix} \quad (23)$$

The control input can then be calculated by evaluating:

$$u(t) = \xi^T(t) \cdot Z \quad (24)$$

where $\xi(t)$ is the data vector similar to $\varphi(t)$ and is given by:

$$\xi(t) = [-u(t-1), \dots, -u(t-n_f), -y(t), \dots, -y(t-n_g)]^T \quad (25)$$

3 Test System

To illustrate the application of self-tuning control for damping power system oscillations, a simple test system with four generators and two areas [1], shown in Fig. 3, is considered for the case study. The generators are represented by a sub-transient model with DC excitation. During steady state, approximately 400 MW flows from area 1 to area 2 over a 220 km transmission line. To control and facilitate this tie-line power flow, a thyristor controlled series capacitor (TCSC) [15] is installed to provide 10% compensation in steady state and it has a dynamic range of variation from 1 to 50%. The details of the system can be found in [16].

There are two possible line outage scenarios for this system while maintaining the system integrity. These are outage of one of the lines connecting buses 7 and 8 or an outage of the one of the lines between buses 8 and 9 which excite poorly damped inter-area oscillations.

To improve the damping of the resulting oscillations, a supplementary damping control is to be designed for the TCSC using the measured flow in line 10-9 for the reasons mentioned in [17]. Besides the nominal 400 MW export from area 1 to area 2 other tie-line power transfer conditions e.g. reverse power flow from area 2 to area 1 could be considered for validation of controller performance.

4 Control Design

4.1 Motivation

One problem with the standard RLS algorithm, described in Section 2.2, is slow adaption of parameters, in general, following large disturbances. Power systems are highly non-linear and time varying and the operating condition can change quite drastically. Hence, it is critical to ensure that such changes are reflected in the estimated coefficients as quickly and accurately as possible.

The most common approach to improve recursive estimation of parameters following large disturbances is the introduction of a forgetting factor λ , which divides each entry of the covariance matrix such that old data gets discarded exponentially [18]. Variable forgetting factors (VFF) are often used forcing them to assume values lower than 1 during a disturbance and then tending to 1 with decreasing estimation error [14]. For the VFF technique, the variation of the estimated parameters is usually very high during adaption ($\lambda < 1$) compared to the case where $\lambda \approx 1$. Control synthesis on the basis of the highly varying estimated coefficients leads to a noisy control output. Hence, closed loop response with the self-tuning control takes a while to settle down.

For a damping control application it is important to converge as fast as possible with small parameter variations. This paper therefore, focuses primarily on a fast and smooth convergence of estimated parameters. This allows similar closed loop damping ratios to be achieved using a smaller pole-shifting factor than with VFF-RLS. Moreover, the need for adaptive self-searching [3, 10] algorithms, which involves iterative computation, is avoided.

A random walk (RW) technique, described in Section 4.3, is applied here to overcome the drawbacks of a varying forgetting factor while retaining the adaptability of the control.

The RW serves a similar purpose as a forgetting factor by putting more emphasis on new data and thus improving parameter estimation [14]. The advantage is that it leads to faster and smoother convergence than VFF as evident from the comparison in Fig. 4. For RW, a disturbance detection logic (DDL) is employed to exactly specify the time frame τ_{id} of parameter adaption during which RW is enabled before returning to standard RLS with even lower variance. Additionally, the DDL enables PS control to switch on only after a certain time delay τ_c to ensure that the control output is based on reasonable estimates of the oscillatory behaviour and not the high frequencies excited immediately after a large disturbance. The control action is disabled by a steady-state detector (SSD) as soon as the oscillation in the feedback signal settles down and a steady state is attained. The parameters are reset so that the controller is prepared for the next event.

The overall control structure is shown in Fig. 5. The following subsections describes the random walk (RW), disturbance detection logic (DDL) and steady-state detector (SSD) and their integration within the standard framework of RLS and PS.

4.2 Disturbance Detection

An oscillation in a measured signal can be detected using several algorithms. For most systems, it is sufficient to simply check against a certain threshold, i.e.

$$|y(t)| \leq P_{th} \quad (26)$$

If the DC level is filtered out by a high pass washout block, the comparison with a predefined constant indicates whether or not a fluctuation above the background noise level is present requiring the control to be enabled. Proper allowance has to be given for the background noise level to prevent spurious turn on. The elapsed time since the last disturbance, detected at time t_0 , is given by:

$$\tilde{t} = t - t_0 \quad (27)$$

4.3 Parameter Estimation via Random Walk (RW)

Random walk extends the covariance matrix update equation (11) by an suitably chosen semi-positive definite random walk matrix $R(t)$ as follows:

$$P(t) = P(t-1) - K(t) \varphi^T P(t-1) + R(t) \quad (28)$$

Most importantly, by defining a whole matrix instead of a scalar λ , each covariance matrix entry can be altered independently of the others. This allows smoother and faster parameter convergence with respect to VFF approach. The particular choice of $R(t)$ is given by:

$$R(t) = \begin{cases} \frac{\varphi^T(t)P(t-1)K(t)}{n_a+n_b} \cdot I & \text{if } t - t_0 < \tau_{id} \\ 0 & \text{otherwise} \end{cases} \quad (29)$$

This holds the covariance matrix trace at a constant level up to τ_{id} seconds after a disturbance has been detected. During this time range, the system is adapted faster than with standard RLS and smoother than with VFF-RLS.

An attractive feature of the random walk matrix is that it does not introduce additional parameters that need to be tuned. Moreover, the covariance matrix $P(t)$ is prevented from diminishing and becoming numerically ill-conditioned during steady state, as would be the case with VFF-RLS approach.

4.4 Controller Dead Zone

To allow some time for the estimated parameters to settle, it is helpful to introduce a controller dead zone where no control output is fed back into the system, although the identifier has already started estimation. At each sampling interval the control output (24) is multiplied with the following:

$$q(t) = \begin{cases} 0 & \text{if } t - t_0 < \tau_c \\ 1 & \text{otherwise} \end{cases} \quad (30)$$

This ensures that the system runs in open loop up to τ_c after the disturbance, allowing enough time for the fast transients in the measured signal to settle down and for the parameter estimates to converge such that the control action is based on sensible values.

4.5 Control Reset

Once the oscillations in the feedback signals settle down, the self-tuning control parameters are reset to their initial values. Resetting the controller is crucial since the covariance matrix will not build up on its own due to absence of any forgetting factor. This would lead to unsatisfactory estimation following the next disturbance. The steady state detector generates a reset signal if the system is considered to have attained the steady state, resetting the identifier parameters back to their initial values.

The simplest way to test for steady state is to observe the system output $y(t)$ for T_{obs} seconds, storing the measurements in a vector:

$$Y_{obs}(t) = \left[y(t), y(t-1), \dots, y\left(t - \frac{T_{obs}}{T_s}\right) \right] \quad (31)$$

The range of the signal can then be compared to a predefined threshold, i.e.

$$\max \{Y_{obs}(t)\} - \min \{Y_{obs}(t)\} \leq \varepsilon \quad (32)$$

where ε denotes the steady state band within which the signal has to stay for at least T_{obs} seconds before the controller can be reset.

4.6 Choice of Parameters

Table 1 summaries the self-tuning control parameters chosen for the test system, described in Section 3. Except for the control limits u_{min} and u_{max} and the pole-shifting factor α , which are dependent on the particular FACTS device to be controlled, the parameter values are generally applicable and little tailoring to the specific test system was required.

One of the important parameters to choose is the order of the estimated system. For the test system considered, there are two areas and hence only one inter-area mode. Such uni-modal oscillatory behaviour can, in principle, be modelled by a third order equation [3].

However, following a large disturbance other frequencies are excited and this is particularly important immediately after the disturbance where the dominant mode is not necessarily the only one observed in the measured signal. Therefore, a higher model order of 10 was found to be more suitable because it allows additional degrees of freedom for parameter estimation.

The order of the estimated system describing the oscillatory behaviour would not necessarily increase in proportion to the size of the system. The order is only dependent on the number of dominant inter-area modes which is reasonably small even for large practical power systems. The time required for control computation is primarily dependent on the order of the estimated system. Hence, this algorithm has the potential to be computed in real time for large systems.

A sampling time $T_s = 10$ ms (i.e. sampling frequency of 100 Hz) offers an adequate resolution for damping low frequency (0.1-0.8 Hz) oscillations. In the authors' experience, it is sufficient to choose τ_{id} and τ_c in the range of 0.1 to 1 s as 100 samples (assuming 100 Hz sampling) contain enough information to obtain reasonably accurate parameter estimates. Since there is no excitation signal except external noise, it is advisable to choose:

$$0 \leq \tau_{id} - \tau_c \leq (n_a + n_b) \cdot T_s \quad (33)$$

in order to generate some input to the system before releasing the covariance matrix trace and returning to standard RLS.

The choice of the initial value of the covariance matrix δ remains a trade-off between fast ($10^3 \leq \delta \leq 10^6$) and smooth ($\delta < 100$) convergence, with the latter being more important for the present application. Even if the identified parameters lack accuracy to an extent, smooth convergence of the identified system parameters and hence, the control coefficients is favoured for self-tuning systems.

The parameters introduced by the fault detection (P_{th}) and control reset (T_{obs} and ε) algorithms are comparably easy to choose and verify since they are concerned with the measured signal itself rather than the inherent parameters of the control algorithm. This makes the proposed scheme more applicable for a practical realization.

5 Simulation Results

The proposed self-tuning controller, described in Section 4, was implemented in MATLAB/Simulink. To validate the performance, closed loop simulations were carried out with the test system described in Section 3. The measured power flow and the control signal to the TCSC formed the inputs to the self-tuning control block and the computed control action was applied to the TCSC, see Fig. 3.

5.1 Performance of the Estimator

With the test system under closed loop condition, initial tests were designed to assess the speed and accuracy of convergence of the estimator by comparing the estimated frequency with that obtained from linear analysis. The frequency obtained from linear analysis is not manifested immediately after a large disturbance as the effect of non-linearities persist for a while. Hence, following detection of disturbance at $t_0 = 5$ s, the self-tuning controller is activated with a dead-zone $\tau_c = 5$ s. It is worth pointing out that $\tau_c = 5$ s is used for this illustration only. For validation of system performance (simulations shown in the next subsection), $\tau_c = 0.1$ s is used as mentioned in Table 1. No other control parameters have been modified for this test.

Fig. 4 shows the variation of the estimated parameters, identified frequency and trace of the covariance matrix for the RW method against the VFF under the aforementioned test conditions. This clearly illustrates the less oscillatory convergence with RW approach as compared to VFF through comparison with the frequency obtained from linear analysis (gray lines in the bottommost subplots). Since the forgetting factor is directly related to the estimation error, it has a dominant influence on the covariance matrix trace, which varies over a much wider range than with RW. Therefore, the parameter estimates, in the VFF case, do not converge quickly. On the other hand, the switched RLS with RW provides much smoother convergence. At $t = 28.49$ s, the control is reset since the feedback signal met the specified steady state criterion.

For the reasons outlined in Section 4 along with the simulation results shown in Fig. 4, a switched control with RW was found to be more appropriate compared to the variable

forgetting factor (VFF) approach.

5.2 System Performance with Self-tuning Control

Simulations were carried out for two line outages to demonstrate the performance and robustness of the designed self-tuning controller. Three-phase solid faults were simulated at bus 8 for 80 ms followed by an outage of one of the adjacent lines, either 8-9 or 7-8. Line outages were considered due to their severity in terms of exciting inter-area oscillations. The dynamic behaviour of the system following outages of tie-lines 8 – 9 and 7 – 8 are shown in Figs 6 and 7, respectively.

The two subplots on the top show the angular separation between generators G1, G3 and G4, G2; the one on the bottom-left exhibits power flow in line 10-9 and the bottom-right one shows the variation in percentage compensation of the TCSC about its steady state setting of 10%. A comparison of the gray (without control) and black (with self-tuning control) lines, in Fig. 6, shows that the designed controller is able to damp the oscillations within 6-7 s. The variation of the percentage compensation of the TCSC is within the specified limits of 1 and 50% around a steady state setting of 10%. After 28.49 s, the control reset block detects steady state and resets the control forcing the percentage compensation of the TCSC to come back to the pre-fault value of 10%. This is hardly noticeable in the figures, though.

Figure 7 shows a comparison between the performance of the proposed self-tuning control and a multiple model adaptive control (MMAC) from [19]. The design of the latter requires linearized system models around different operating conditions. It can be seen that the self-tuning control is able to produce almost similar performance without any prior knowledge about the system model. It is to be noted that with the MMAC scheme, there is a very low frequency mode in closed loop which, in spite of adequate damping, takes a while (almost 100-150 s) to settle. If the simulation results are seen for such an extended period, percentage compensation of TCSC in Fig. 7 comes back to its steady state value of 10%.

To demonstrate the performance of the proposed controller under a completely different operating condition, the power flow from area 1 to 2 has been changed to from 400 MW to -300 MW (i.e. from export to import). Figure 8 shows the damping performance after the

outage of tie-line 8 – 9 at the new operating point. The self-tuning controller damps the oscillation within 15 s which shows the ability of the control algorithm to adapt to different operating conditions.

5.3 Stability Considerations

The self-tuning controller discussed in this paper has a fixed structure. However, the coefficients vary according to the coefficients of the identified transfer function so as to ensure a particular damping in closed loop. Hence, the coefficients and consequently the pole-zero locations of the controller are different depending on the operating condition encountered. The closed loop stability can be ensured by including the following constraint on the pole shifting factor [9]:

$$|\alpha \cdot \lambda_{max}| \leq 1 \quad (34)$$

where λ_{max} is the pole of the estimated discrete-time model with the highest absolute value. This guarantees design of stabilizing controllers. In order to ensure stable controllers at each sampling time, the controller parameters are not updated if a pole of the polynomial F lies outside the unit circle, i.e. (22) becomes (35).

$$Z(t) = \begin{cases} M(t)^{-1} L(t) & \text{if } |\text{roots}(F(t))| < 1 \\ Z(t-1) & \text{otherwise} \end{cases} \quad (35)$$

This approach has been found to work well yielding stable controllers at each step with typical pole-zero locations as shown in Fig. 9.

6 Real-time Simulation

To validate the performance in real time, a simulation platform developed at Imperial College with processors supplied by Opal-RT was used. A schematic overview of the real-time simulation setup is shown in Fig. 10 [13]. The self-tuning control algorithm was implemented on the rapid prototyping controller (RPC) and the test system on the real time station (RTS) with only an analog interface between them via ADC/DACs. Such

a configuration with analogue interface ensures that the controller (RPC) is unable to recognise whether the signals going into it is interfaced with an actual power system or an emulated version of it. Reference [13] describes this setup in details.

The system response, available as analog signals out of the RTS, was captured in an oscilloscope and is shown in Fig. 11. The plots show the variation in generator angle difference G1-G3 without and with control over two consecutive disturbance cycles following line outage 8-9. The simulation result from the MATLAB/Simulink environment is placed below the oscilloscope screenshots for comparison. Almost identical nature of the simulation results in MATLAB and in real time simulator confirms successful implementation of self-tuning control in real time. The reason for such similarity between the plots in Figs 12 and 11 is clear from Fig. 13 which shows the control computation times for each 10.0 ms sampling time over an interval of 10.0 minutes. It can be seen that the maximum computation time is 181 μs , which is well below 10.0 ms and therefore, there is no instances of overrun where control computation could not be completed.

Although the present exercise is on a simple test system, the findings are encouraging even from a large scale system point of view. The driving factor regarding computational complexity is the model order used to estimate the oscillatory behaviour and then to synthesize the controller parameters. It determines the size of the matrices P and M , which are subject to matrix multiplication (P) and inversion (M) at every sampling instant. Computational complexity of these operations grows in cubic proportion $\mathcal{O}(n^3)$. However, the model order does not grow proportionately with the actual size of the power system, since there is only a limited number of critical inter-area modes to be damped. Depending on the number of inter-area modes the model order required for actual estimation could be in the range of 15 – 20 even for large scale power systems. A model order of 20 would lead to a maximum control computation time of about 2 – 5ms which is well below the typical sampling time (tens of milliseconds) used for inter-area oscillation damping problem. This indicates that real-time implementation of such self-tuning control is feasible.

7 Conclusion

A self-tuning FACTS controller for power oscillation damping has been designed and tested in real time on a simple two area system. The design of a self-tuning controller does not require the system model and yet it has been shown to perform similar to model based adaptive control. The controller is capable of adapting to new system conditions due to online identification. Use of a random walk technique with switched control improves the accuracy and speed of convergence of the estimated parameters compared to the conventional variable forgetting factor approach. This obviates the need for adaptive self-searching PS control which can be computationally more demanding for real-time implementation. Fast and accurate convergence of estimated parameters ensures desired performance even with fixed pole-shifting factor as is illustrated through real time simulation. The control computation time was shown to be well below the typical sampling time for the presented case study on a simple system. For large scale systems, the computational effort required would be greater as more inter-area modes would have to be identified. However, the number of inter-area modes is limited even for very large power systems and therefore the computational effort does not grow proportionately with the actual size of the system. Thus self-tuning FACTS controllers are feasible as far as implementation in real time is concerned. Adaptive pole shifting is computationally intensive but promises better performance and is going to be tested in real-time in future.

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Table 1: Self-tuning Control Parameters

General		Coordination		Identification		Control	
n_a	10	P_{th}	0.05 pu	τ_{id}	0.3 s	u_{min}	-0.09 pu
n_b	10	T_{obs}	7 s	τ_c	0.1 s	u_{max}	0.4 pu
T_s	10 ms	ε	0.01 pu	δ	50	α	0.968

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