Self-tuning Controller for Damping of Power System Oscillations with FACTS Devices

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***Abstract*— This paper describes an adaptive parameter tuning of a power oscillations damping (POD) controller for the Thyristor Controlled Series Compensator (TCSC). The adaptive control is based on pole shifting. In order to maintain good damping over a wide range of operating conditions, the parameters of the POD controller are adapted on-line, based on the measured system input and output. Simulation results are provided to demonstrate the effectiveness of the proposed controller.**

***Index Terms* - Power system oscillations, adaptive control, power oscillation damping (POD), Kalman Filtering techniques, pole shifting.**

I. INTRODUCTION

Satisfactory damping of power oscillations is an important issue addressed when dealing with the rotor angle stability of power systems. This phenomenon is well-known and observable especially when a fault occurs. To improve the damping of oscillations in power systems, supplementary control laws can be applied to existing devices. These supplementary actions are referred to as power oscillation damping control.

The controllers obtained from conventional approach are simple but work often only within a limited operating range. In case of contingencies, changed operating conditions can cause poorly damped or even unstable oscillations since the set of existing controller parameters yielding satisfactory damping for one operating condition may no longer be valid for another one. A more sophisticated controller which can maintain good damping over a wide range of operating conditions, is therefore needed. One solution of such controller is based on lately developed algorithm for on-line detection of electromechanical oscillations based on Kalman filter [1]. It gives the information about the actual dominant oscillatory modes with respect to the frequency and damping as well as about the amplitude of the oscillation obtained through on-line analysis of signals measured at appropriate places in the power system. This has further been used as a basis for a direct adaptive tuning of the FACTS POD parameters based on residue method [2].

In order to apply the latter proposed method, the system model has to be available in order to find optimal location for FACTS devices and consequently to calculate the values of residues for the controller design. For the self-tuning controller design technique proposed in this paper, no system model is required. An adaptive control based on pole-shifting is employed here. Allowing a self-tuning of the pole-shifting factor α, there is no need for manual tuning [3]. In general, the value of α depends on the actual operating conditions which are identified automatically using Kalman Filtering techniques. A similar approach has been applied to power system stabilizers [4]–[6].

II. ADAPTIVE MODEL IDENTIFICATION

In general, the power system dynamics is non-linear and varies with the operating point of the power system. The proposed approach to the adaptive control of FACTS is depicted in Figure 1. The considered model is linear, having single-input single-output (SISO) and time-varying parameters; also called AutoRegressive with an eXternal input (ARX-model). The theoretical assumption is that the power system is working around a certain operating point for a certain period of time, which enables the estimated coefficients of the time-varying linear model to converge to the actual values. The considered

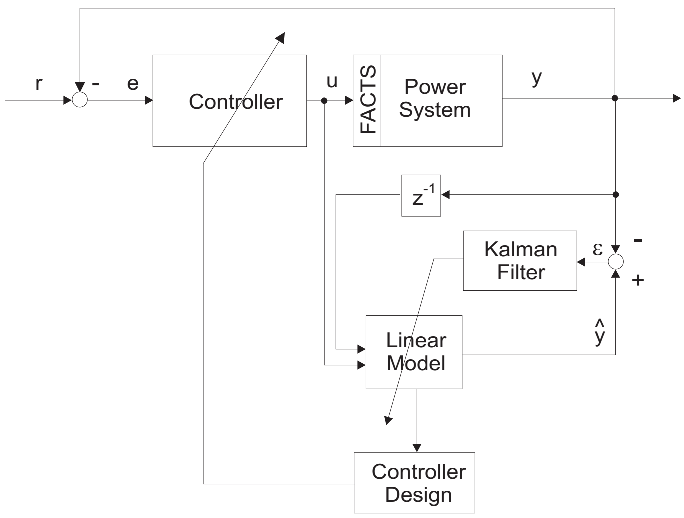

Fig. 1. Considered adaptive control scheme for FACTS.

ARX-model has in the time domain the form (1).

$$y(k) = \sum_{i=1}^{n_a} a_i(k)y(k-i) + \sum_{j=0}^{n_b} b_j(k)u(k-j) \quad (1)$$

$$\varepsilon(k) = \hat{y}(k) - y(k) \quad (2)$$

For the estimation error given by (2), equation (1) can be written as (3).

$$\hat{y}(k) = \sum_{i=1}^{n_a} a_i(k) y(k-i) + \sum_{j=0}^{n_b} b_j(k) u(k-j) + \varepsilon(k) \tag{3}$$

The goal of the parameter estimation is to identify (n_a+n_b+1) coefficients $a_i(k)$ and $b_i(k)$ of the model (1) so that the sum of the squared prediction errors (4) is minimized.

$$J = \min \varepsilon^2(k) = \min_{a_i, b_i} \left[\hat{y}(k) - y(k)\right]^2 \tag{4}$$

Hence, for the model to be optimal for $\forall k$, its parameters must be updated recursively once per sampling period T_s for each new measurements $u(k)$ and $y(k)$. The method employed here to track in real-time the values of the model parameters is based on techniques applied in [1] to monitor the dominant oscillatory modes. Unlike in [1], the input signal $u(k)$ is measured here together with the output $y(k)$ and fed into the estimated model here. From a theoretical point of view, the employed Kalman Filtering technique (KF) provides a unifying framework for the complete family of recursive least-squares filters. The solution is computed recursively, applying without modification to time-varying or time-invariant environments. From a practical point of view, KF has shown an acceptable prediction error and short estimation time (the number of iterations necessary for the parameters to converge) in the presence of measurement noise (first results with simulated and real measured data published in [1]). Moreover, KF enables to use both the measurement and process noise directly as tuning parameters. The set of the standard KF equations in a recursive form to be solved once per sampling period T_s) is given by (5)-(8). The variables are described in Table I. The theory of KF is well reviewed e.g. in [14].

$$g(k) = K(k-1)\varphi(k)\left[\varphi^T(k)K(k-1)\varphi(k) + Q_m\right]^{-1} \tag{5}$$

$$\hat{y}(k) = \varphi^T(k)p(k-1) \tag{6}$$

$$p(k) = p(k-1) + \left[\hat{y}(k) - y(k)\right] g(k) \tag{7}$$

$$K(k) = K(k-1) - g(k)\varphi^T(k)K(k-1) + Q_p \tag{8}$$

To ensure good numerical robustness, the set of the standard equations (5)-(8) has been enhanced by (9) and (10). The covariance matrix $K(k)$ is enforced by (9) to remain symmetrical. For a better parameter tracking, a regularized constant trace algorithm (10) has been employed with experimentally obtained $c_1/c_2 \cong 10^4$ and I being the unity matrix of the same dimension as $K(k)$ [13]. The tuning procedure of the estimation with KF has been described e.g. in [1].

$$K(k) = \frac{K(k) + K^T(k)}{2} \tag{9}$$

$$K(k) = \frac{c_1 K(k)}{tr(K(k))} + c_2 I \tag{10}$$

As a result of the described adaptive model identification technique, the power system model (11) required for the controller design becomes available at any time k.

TABLE I

VARIABLES OF THE ALGORITHM FOR PARAMETER ESTIMATION

Variable	Description
$y(k)$	output measurement (desired response of model at time k)
$u(k)$	input measurement (controller output at time k)
$\hat{y}(k)$	model output (response of model at time k)
$\varphi(k)$	buffered measurements $\varphi(k) \in \mathcal{R}^{(n_a+n_b+1)\times 1}$
	$\varphi(k) = [y(k-1), \ldots, y(k-n_a), u(k), \ldots, u(k-n_b)]$
$\varepsilon(k)$	estimation error at time k
$p(k)$	vector of estimated parameters $p(k) \in \mathcal{R}^{(n_a+n_b+1)\times 1}$
	$A(k) = [1, -p_1(k), \ldots, -p_{n_a}(k)] \in \mathcal{R}^{(n_a+1)\times 1}$
	$B(k) = \left[p_{(n_a+1)}(k), \ldots, p_{(n_a+n_b+2)}(k)\right] \in \mathcal{R}^{(n_b+1)\times 1}$
$g(k)$	Kalman-gain, $g(k) \in \mathcal{R}^{n \times 1}$
$K(k)$	correlation of estimation error, $K(k) \in \mathcal{R}^{n \times n}$
Q_m	correlation of measurement noise, $Q_m \in \mathcal{R}^{1 \times 1}$
Q_p	correlation of process noise, $Q_p \in \mathcal{R}^{n \times n}$

III. POLE SHIFTING CONTROL

Pole shifting method is based on pole assignment (placement) method [5]. A controller based on the pole assignment of a closed control loop is designed to achieve the pre-defined poles of the characteristic polynomial [10]. Like pole assignment method, pole shifting method deals with closed loop poles. The poles of the open loop system are first obtained from characteristic polynomial and then shifted toward the origin of the unit z circle by a pole shifting factor α.

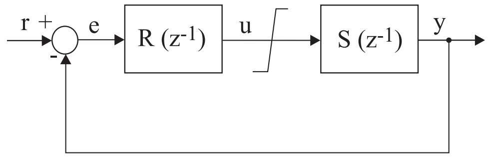

Fig. 2. Considered closed loop control system for adaption frozen in time.

The uncontrolled system is identified by a discrete model of the form:

$$S(z^{-1}) = \frac{Y(z^{-1})}{U(z^{-1})} = \frac{B(z^{-1})}{A(z^{-1})} \tag{11}$$

with polynomials

$$A(z^{-1}) = 1 + a_1(k)z^{-1} + a_2(k)z^{-2} + \ldots + a_{n_a}(k)z^{-n_a} \tag{12}$$

$$B(z^{-1}) = b_1(k)z^{-1} + b_2(k)z^{-2} + \ldots + b_{n_b}(k)z^{-n_b} \tag{13}$$

where the system parameters a_i and b_i are known from a real-time parameter identification method for any time k. The poles of the open-loop system are first obtained by solving the open-loop characteristic equation from (12) frozen for the actual time k:

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} + \ldots + a_{n_a} z^{-n_a} = 0 \tag{14}$$

The discrete transfer function of the considered controller, with zero reference value r is given by

$$R(z^{-1}) = \frac{U(z^{-1})}{E(z^{-1})} = \frac{G(z^{-1})}{F(z^{-1})} \tag{15}$$

where

$$F(z^{-1}) = 1 + f_1 z^{-1} + ... + f_i z^{-i} + ... + f_{n_f} z^{-n_f} \quad (16)$$

$$G(z^{-1}) = g_0 + g_1 z^{-1} + ... + g_i z^{-i} + ... + g_{n_g} z^{-nf} \quad (17)$$

and $n_f = n_b - 1$, $n_g = n_a - 1$, [6].
The transfer function of the closed loop system, illustrated in the block diagram in Fig. 2, than takes the form

$$\frac{Y(z^{-1})}{E(z^{-1})} = \frac{B(z^{-1})G(z^{-1})}{A(z^{-1})F(z^{-1}) + B(z^{-1})G(z^{-1})} \quad (18)$$

The transfer function of the closed loop system has to be suitably adjusted by choosing a controller transfer function to guarantee the overall stability of the closed loop system. According to pole assignment method, by choosing the characteristic polynomial

$$P(z^{-1}) = 1 + \sum_{i=1}^{n_p} p_i z^{-i} \quad (19)$$

in the polynomial equation

$$P(z^{-1}) = A(z^{-1})F(z^{-1}) + B(z^{-1})G(z^{-1}) \quad (20)$$

where $n_p = max(n_a + n_f, n_b + n_g)$, one should achieve the pre-set poles. The characteristic polynomial (20) can by defined by various algorithm [9]. In pole shifting algorithm, $P(z^{-1})$ takes the form of a polynomial $A(z^{-1})$ multiplied with an array of α,

$$P(z^{-1}) = 1 + \sum_{i=1}^{n_p} p_i z^{-i} = 1 + \sum_{i=1}^{n_a} \alpha^i a_i z^{-i} \quad (21)$$

where $0 \leq \alpha \leq 1$ and the prescribed coefficients $p_i = 0$ for $i > n_a$. This implies that the resulting close-loop poles will be the roots of the characteristic equation given by

$$P(z^{-1}) = 0 \quad (22)$$

Substituting (12), (13), (16), (17) and (21) into (20) and comparing the coefficients at the same power of z^{-1} on the both sides, gives:

$$M \cdot R = L \quad (23)$$

where

$$M = \begin{bmatrix} 1 & 0 & . & 0 & b_1 & 0 & . & 0 \\ a_1 & 1 & . & 0 & b_2 & b_1 & . & 0 \\ . & a_1 & . & . & . & b_2 & . & . \\ a_{n_a} & . & . & 1 & b_{n_b} & . & . & b_1 \\ 0 & a_{n_a} & . & a_1 & 0 & b_{n_b} & . & b_2 \\ . & 0 & . & . & . & 0 & . & . \\ . & . & . & . & . & . & . & . \\ 0 & 0 & . & a_{n_a} & 0 & 0 & . & b_{n_b} \end{bmatrix}$$

$$R = \begin{bmatrix} f_1 \\ . \\ . \\ f_{n_f} \\ g_0 \\ . \\ . \\ g_{n_g} \end{bmatrix}; \qquad L = \begin{bmatrix} a_1(\alpha - 1) \\ a_2(\alpha^2 - 1) \\ . \\ . \\ a_{n_a}(\alpha^{n_a} - 1) \\ 0 \\ . \\ 0 \end{bmatrix}$$

If the variable α in matrix L is fixed, one has a special case of the pole assignment control algorithm where the coefficients of the controller transfer function, $f_i(i = 1, ...n_f)$ and $g_i(i = 1, ...n_g)$, can be calculated at every sample from (23) by

$$R = M^{-1}L \quad (24)$$

and the control u can be calculated, as shown in Fig. 2, by

$$\frac{U(z^{-1})}{E(z^{-1})} = \frac{G(z^{-1})}{F(z^{-1})} = R(z^{-1}) \quad (25)$$

rewritten in the time domain as

$$u(k) = \varphi^T(k)R(k) \quad (26)$$

with $\varphi(k)$ derived in Table I.
Proper value of the pole shifting factor depends on the operating conditions. From that reason it is desirable to adapt the parameter α on line. From (26) it is obvious that the control at time k, $u(k)$, is a function of pole shifting factor at that time. Sensitivity function can be calculated from (26) as

$$\frac{\delta u}{\delta \alpha} = \varphi^T \cdot \frac{\delta R}{\delta \alpha} \quad (27)$$

Substituting (24) into (27) gives

$$\frac{\delta u}{\delta \alpha} = \varphi^T \cdot M^{-1} \cdot \frac{\delta L}{\delta \alpha} \quad (28)$$

$$\frac{\delta u}{\delta \alpha} = \varphi^T \cdot M^{-1} \cdot [a_1, 2a_2\alpha, ..., n_a a_{n_a} \alpha^{n_a - 1}] \quad (29)$$

The modification factor α is given by

$$\Delta\alpha = K \cdot \mid \frac{\delta u}{\delta \alpha} \mid^{-1} \cdot \Delta u \quad (30)$$

where Δu is the control margin defined as

$$\Delta u = \begin{cases} u_{max} - u & u \geq 0 \\ u - u_{min} & u \leq 0 \end{cases} \quad (31)$$

The variable pole shifting factor, $\alpha(t)$, can be calculated by

$$\alpha(k) = \alpha(k_0) + \Delta\alpha \quad (32)$$

where $\alpha(t_0)$ is any value between 0 and 1.

IV. Case studies

Using the described tuning algorithm, TCSC POD controller was implemented in two different power systems described in this section. Nonlinear simulations presented in this section were obtained using MATLAB/Simulink.

A. Two Area System

Two area system, introduced in [11] as a benchmark system for inter-area oscillations studies, consists of two generators on each area, connected via a 220 km tie line. All generators are equipped with DC exciter models and modeled with transient models. The on-line diagram of the test system is given in Fig. 3. TCSC used in the simulations are modeled using the current injection model, [2]. The first question has to be answered is, which signal to choose as a feedback signal. The proposed method is applied so far just for PSS, [3]–[8]. Unlike to PSS, for TCSC application, there are a few appropriate signals to be used as the feedback. Since the FACTS devices are located in transmission systems, local input signals like power deviation ΔP, bus voltages or bus currents, are always preferable. In this paper, ΔP is used as feedback signal. As in a case of choosing the feedback signal, the optimal sitting of the FACTS device is also very important. Here, the TCSC is located in line 8-9 as shown in Fig. 3, [12].

In order to check controller ability to stabilize the system,

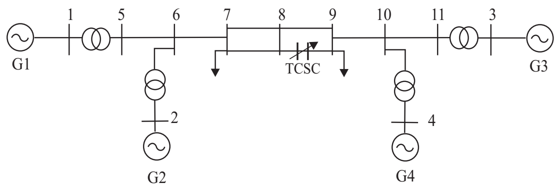

Fig. 3. Two-area system single line diagram.

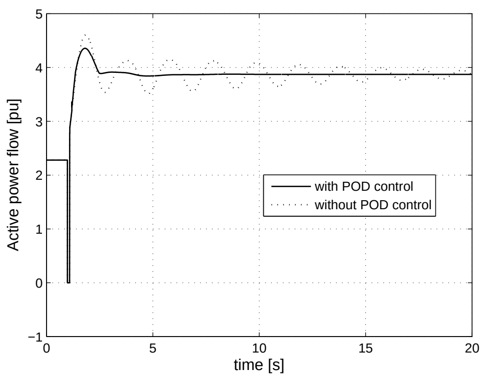

Fig. 4. Active power flow in the controlled line 8-9 with and without damping control after three phase fault is applied in parallel line.

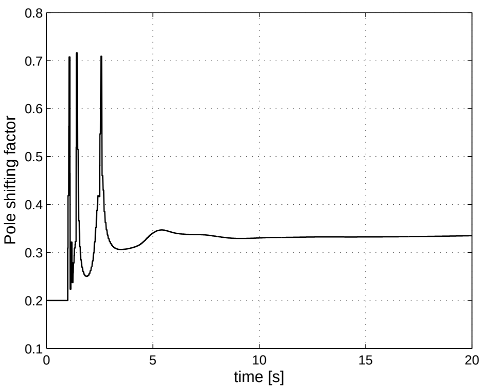

Fig. 5. Variation of the pole shifting factor, α.

a fault is applied in the parallel line 8-9. The fault is cleared after 100 ms by opening the faulted line.

Fig. 4 shows direct comparison between the active power flow response of the system to the fault with adaptive tuned parameters of POD controller and without POD controller. Fig. 5 shows the time variations of the pole shifting variable α. On startup, α can have any value between 0 and 1, but it will achieve its appropriate value after some period of time.

B. New England System

In order to check ability of the proposed POD controller on bigger system, the New England test system is investigated. A one-line diagram of the New England test system is given in the Fig. 6. The power flow data for this system can be found in [10]. For this test system, the optimal sitting is investigated based on the residue method, with ΔP as the feedback signal. Here, the most effective location means the best location of the POD controller, while the compromise has to be found for the location of both, the power flow control and POD controller. To find the best siting for the TCSC different location in the test system are tested. Residues associated with critical mode are calculated using the transfer function between the TCSC active power deviation ΔP and the TCSC input, that is control variable, characterized by the compensation degree Δk_c, i.e. the compensation in p.u. of the line reactance. According to [2], the line 34-37 has the largest residue and therefore the most effective location to apply the feedback control.

Fig. 7 and Fig. 9 show direct comparison between the active

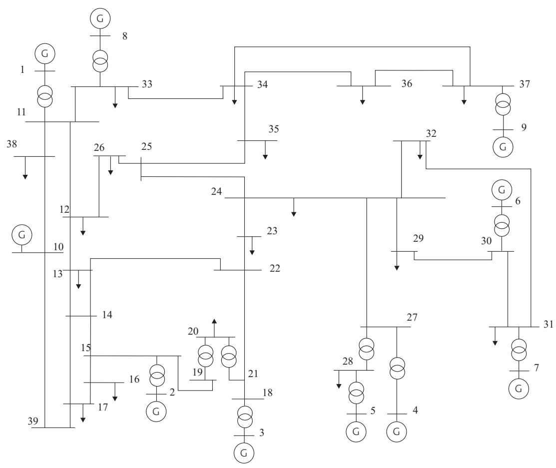

Fig. 6. System configuration for the case study.

power flow response of the system to the fault with fixed POD parameters and adaptive tuned parameters of the POD controller, for two different cases. The fixed POD parameters are tuned using the residue method. The results given in this figures show that the oscillations of the system are damped out efficiency and demonstrates the ability of the system to adapt to a new operating conditions. Fig. 8 and Fig. 10 show the pole shifting variable α.

One more result of the adaptive model identification is shown on Fig. 11 and Fig. 12. Fig. 11 shows the poles of the closed loop system with the POD parameters tuned using the residue method, in the case with the fault applied in the line 25-35 and line 33-34 out of service, frozen for actual time k. Fig. 12 shows the poles of the characteristic polynomial equation of

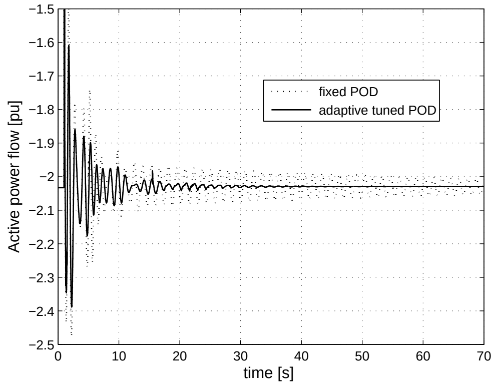

Fig. 7. Active power flow in controlled line 34-37 after fault applied to line 12-26 with line 29-30 out of service.

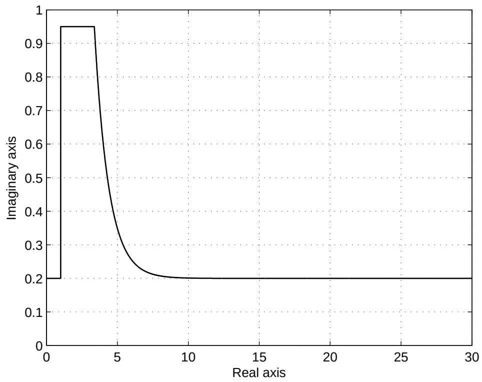

Fig. 8. Variation of the pole shifting factor, α, for case in Fig 7.

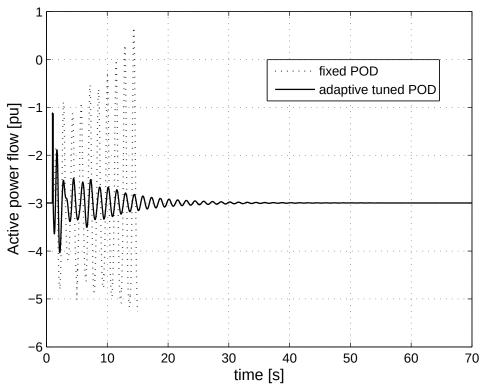

Fig. 9. Active power flow in controlled line 34-37 after fault applied to line 25-35 with line 33-34 out of service.

the system closed with an adaptive tuned POD controller (22), frozen as well for actual time k.

V. Conclusion

This paper presented a adaptive tuning method based on pole shifting approach, applied to TCSC. Using the proposed indirect adaptive control scheme, there is no need to know

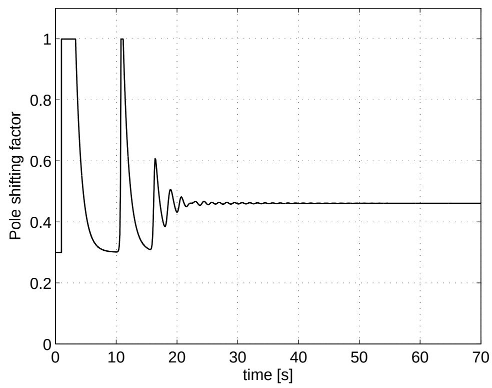

Fig. 10. Variation of the pole shifting factor, α, for case in Fig 9.

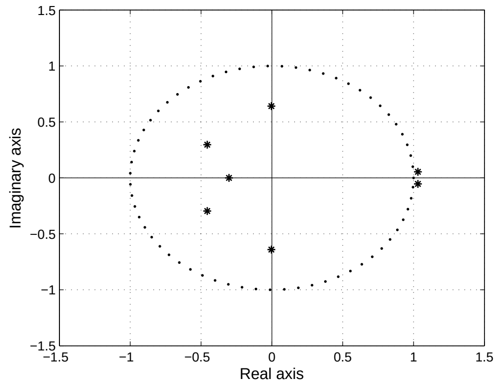

Fig. 11. Poles of the closed loop system with fixed tuned POD controller for case in Fig 9.

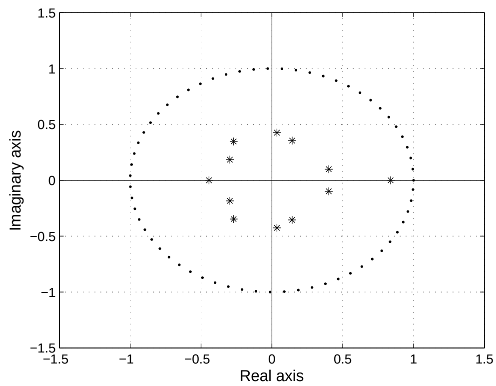

Fig. 12. Poles of the closed loop system with adaptive tuned POD controller for case in Fig 9.

a priori the actual parameters of the power system model in order to design the controller. This is a practical advantage of the presented method. Simulations showed that the proposed method led automatically to an improvement of the damping characteristic under different operating conditions.

VI. ACKNOWLEDGEMENTS

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