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Online Control of SVC Using ANN Based Pole Placement Approach

***Abstract**. In this study, an online Artificial Neural Networks based Pole Placement algorithm is proposed to stabilize the 2-bus system with nonlinear SVC and variable power. It uses pole placement method. Proposed algorithm are examined in point of improving the bus voltages which change under different demanding powers and the temporary state performance are compared with PID control based results. Simulation results demonstrate a good performance and robustness.*

***Streszczenie.** W artykule zaprezentowano online algorytm Pole Placement z wykorzystaniem sieci neuronowych do stabilizacji dwu-szynowego systemu z nieliniowym, SVC (Static Var Compensator) i zmienną mocą. (**Sterowanie SVC przy wykorzystaniu algorytmu Poler Placement i sieci neuronowych**)*

Keywords: SVC, PID Control, Online ANN based Pole Placement, Linearization, Acermann Method.
Słowa kluczowe: SVC – static var compensator, sieci neuronowe.

Introduction

It is well known that shunt and series compensation can be used to improve the power system stability. With the improvement in current and voltage handling capabilities of power electronic devices that have allowed for the development of Flexible AC Transmission Systems (FACTS), the possibilty has been arise of using different types of controllers for efficient shunt and series compensation [1]. The most popular type of FACTS devices in terms of application is the SVC. These devices are well known to improve power system properties such as steady-state stability limits, voltage regulation and var compensation, dynamic over-voltage and under voltage control, and damp power system oscillations [2, 3].

Linearization is one of the most important issues for control of nonlinear systems. There are lots of study in the literature regarding linearization. For example, Taylor's series based expansion linearization method is applied to several examples, i.e. the asynchronous slip-ring motor and non-linear diode [4].In an another study, the design principles are examined using the direct feedback linearization technique to desing a nonlinear coordinated controller for the power systems [5, 6].

Today, the PID controllers, are widely used for automatic control mechanisms, and various methods have been developed for automatic parameter tuning of the PID [7, 8]. FACTS devices usually include PID controllers [9, 10]. On the other hand, in the modern control pole placement-based controller design techniques have been widely used. For example, Arvantis has presented some new approaches in adaptive pole placement problem for linear systems [11]. In another study, active vibration control applications have been tested for the applicability of the pole placement-based design techniques [12]. In Shakir's study is examined the performance of a state feedback controller method used in the pole placement method [13].

An artificial neural network (ANN) is a self-adapting method which has developed rapidly all over the world since the 1980s and is extensively used in many fields, such as image, speech and voice recognition, complex computations as well as trend prediction [14,15,16]. Moreover, It is being used successfully in many areas of power systems,such as power system control, prediction etc. [17, 18, 19]. For example, Girish has disscussed interesting applications of ANNs; load forecasting, dynamic safety evaluation and diagnostics [20].

In this study, a pole placement method is proposed for online control of SVC. A stable point is selected for pole placement. The system which is nonlinear is linearized around this point, and required feedback vector is obtained from ANN. Voltage stability of SVC is analyzed using proposed algorithm and compared to PID controller replies. Simulation results show that the output voltage is stable for reference voltage and various demand power. Furthermore PV curves show the system is stabilized in very short time.

System Model

Plant and SVC model

We consider a model for the generator and an SVC system that can be described by a two-bus system, shown in Fig. 1. This model can be viewed as a generalized case where the SVC is located at the end-point of a transmission line.

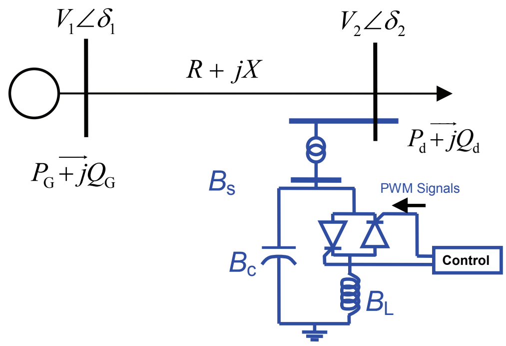

Fig. 1 The two-bus SVC system

Generator model

The system model for excitation control design and stability analysis is usually that of a single generator infinite-bus system. where $\delta(t)$, power angle of the generator; $\omega(t)$, rotor speed of the generator; Pm, mechanical input power; $P_e(t)$, active electrical power delivered by the generator; D_G, damping constant; M, inertia constant; X, reactance of the transmission line constant. The model can be written as follows,

$$\dot{\delta}(t) = \omega(t)$$
$$\dot{\omega}(t) = \frac{1}{M}\left(P_m - \frac{V_1 V_2 \sin\delta}{X} - D_G\omega\right) \qquad (1)$$
$$\dot{V}_2 = \frac{1}{\tau}\left(-v_2^2\left(\frac{1}{X} - B_S\right) + \frac{V_1 V_2 \cos\delta}{X} - kP_d\right)$$

where

$M = 1$, X=0.5, $V_1 = 1$, τ=8, k=0.25, D_G=0.1.

The steady state load demand is modeled through the parameter P_d, under the assumption that reactive power load demand is directly proportional to the active power demand, i.e, Q_d=k.P_d ; this parameter is used here to carry out the voltage collapse studies. SVC operated capacitive mode figures out compensation effect for power system stability. To simplify the stability analysis, resistance and line susseptance are neglected (R=0, B_L=0), P_m=P_d. The value belonging to limit point of system is $P_d^{max} = 0.78078$ pu [21]. The system acts non-linear at the value P_d > 0.78078 pu.

SVC model

The SVC systems are used with an electrical transmission line connecting various generators and loads at its sending and receiving end. It consists of a fixed capacitor in shunt with a thyristor-controlled inductor. The susceptance of the inductor is controllable through controlling the firing angle of the thyristor with PWM (pulse width modulation) control signals.

The SVC model equations is given as follows:

(2)
$$B_L = \frac{B_S(2\pi + \sin(2\alpha) - 2\alpha)}{\pi}$$
$$B_S = \frac{\pi B_L}{2\pi + \sin(2\alpha) - 2\alpha}$$

where $B_L(t)$ the susceptance of the inductor in SVC; α the firing angle; B_S(t) the full susceptance of the SVC.

Taylor Series Expansion Based Linearization

Taylor series expansion is widely used for linearization of the non-linear systems. This method can be applied to the power system shown in Fig. 1.

Let $f(x)$ be a one-variable function. Taylor series expansion of the $f(t)$ at point $\bar{x}$ can be written as

(3)
$$f(x) = f(\bar{x}) + \left.\frac{df}{dx}\right|_{x=\bar{x}} (x - \bar{x}) + \text{higher-deg. terms}$$

is obtained. A function is expressed in a great ratio by the first terms of the expansion. Therefore, higher degree terms can be ignored.

We consider following non-linear state sapace model:

(4.a)
$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x},\mathbf{u})$$

(4.b)
$$\mathbf{y}(t) = \mathbf{g}(\mathbf{x},\mathbf{u})$$

It's Taylor series based linearized state space model can be written as follows:

(5.a)
$$\dot{\mathbf{x}}(\mathbf{t}) = \mathbf{A}\mathbf{x}(\mathbf{t}) + \mathbf{B}\mathbf{u}(\mathbf{t})$$

(5.b)
$$\mathbf{y}(\mathbf{t}) = \mathbf{C}\mathbf{x}(\mathbf{t}) + \mathbf{D}\mathbf{u}(\mathbf{t})$$

Where,

(6)
$$\mathbf{A} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \frac{\partial f_1}{\partial x_3} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \frac{\partial f_2}{\partial x_3} \\ \frac{\partial f_3}{\partial x_1} & \frac{\partial f_3}{\partial x_2} & \frac{\partial f_3}{\partial x_3} \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} \frac{\partial f_1}{\partial u_1} & \frac{\partial f_1}{\partial u_2} \\ \frac{\partial f_2}{\partial u_1} & \frac{\partial f_2}{\partial u_2} \\ \frac{\partial f_3}{\partial u_1} & \frac{\partial f_3}{\partial u_2} \end{bmatrix},$$
$$\mathbf{C} = \begin{bmatrix} \frac{\partial g_1}{\partial X_1} & \frac{\partial g_1}{\partial X_2} & \frac{\partial g_1}{\partial X_3} \end{bmatrix}, \quad \mathbf{D} = \begin{bmatrix} \frac{\partial g_1}{\partial u_1} & \frac{\partial g_1}{\partial u_2} \end{bmatrix}$$

From Eqs. (1), the generator model is highly nonlinear. The systems of state variables $\delta(t)$, $\omega(t)$, v_2 ,and control variable B_S is described. In state space modeling **A**, **B**, **C** and **D** represent the case of Taylor series expansion around equilibrium point with the transient components.

(7)
$$x_1 = \delta,\ x_2 = \omega,\ \ x_3 = v_2,\ P_d = u_1,\ B_S = u_2$$
$$\dot{x}_1 = \omega = X_2 = f$$
$$\dot{x}_2 = -2x_3 \sin x_1 - 0.1x_2 + u_1 = f_2$$
$$\dot{x}_3 = 0.25x_3 \cos x_1 - 0.25x_3^2$$
$$+ 0.125x_3^2 u_2 - 0.03125u_1 = f_3$$
$$y(t) = v_2 = x_3 = g_1$$

The state variable values of operation point,

(8)
$$\delta = 0.36,\ v_2 = 0.8465,\ P_d = 0.6,\ \omega = 0,\ u_2 = 0$$

Operation poles;

(9)
$$p_1 = -0.066 + 1.255i;\ p_2 = -0.066 - 1.255i;$$
$$p_3 = -0.156$$

PID Controller Desing

The PID controller is probably the most used feedback control design. PID is an acronym for Proportional-Integral-Derivative, referring to the three terms operating on the error signal to produce a control signal. If $u(t)$ is the control signal sent to the system, $y(t)$ is the measured output and $y_r(t)$ is the desired output, and tracking error $e(t) = y_r(t) - y(t)$, a PID controller has the general form,

(10)
$$u = k_c(e + \frac{1}{T_i}\int e dt - T_d \frac{dy_f}{dt})$$
$$y_f = \frac{1}{1 + sT_d / N} y$$

PID controller parameters can be determined by closed-loop Ziegler – Nicholas tuning formula method [22, 23, 24]. Then, we calculate the PID controller parametres by using the constants k_u and t_u with the Zigler - Nicholes closed-loop oscillation method,

(11)
$$t_u = 5 \text{ and } k_u = 12$$
$$P = 7.2,\ I = 2.88,\ D = 43.2$$

Table 1. Ziegler-Nichols tuning Formula [24]

Controller	PID	PID
Proportional gain	k_c=0.6 k_u	k_c=0.6*12
Integral time	T_i=0.5 t_u	T_i=0.5*5
Derivative time	T_d=0.125 t_u	T_d =0.125*5

Pole Placement

Block diagram of pole placement is given in Fig. 2. If the linearized system considered is completely state controllable, then poles of the closed-loop system may be placed at any desired locations by means of state feedback through an appropriate state feedback gain matrix **K** [25].

By using Ackerman method State feedback gain matrix **K** can be obtained as follows (Kailath,1983):

(12)
$$\boldsymbol{\alpha}(\mathbf{A}) = \mathbf{A}^n + \alpha_1 \mathbf{A}^{n-1} + ... + \alpha_{n-1}\mathbf{A} + \alpha_n \mathrm{I}$$
$$\mathbf{q}_n^T = [0\ 0\ 0.....0\ \ 1]\mathbf{Q}_c^{-1}$$
$$\mathbf{Q}_c^{-1} = [\mathbf{B}\ \mathbf{AB}\ \mathbf{A}^2\mathbf{B}......\mathbf{A}^{n-1}\mathbf{B}]$$
$$\mathbf{K} = \mathbf{q}_n^T \alpha(\mathbf{A})$$

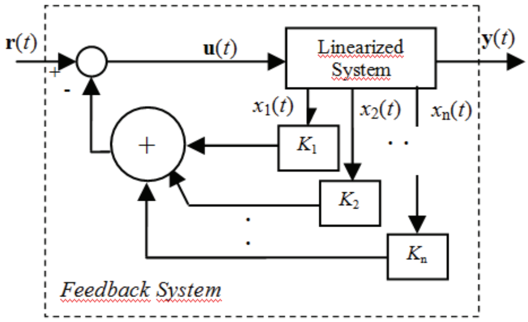

Fig. 2 Block diagram of pole placement

Then from Fig. 2, for feedback linearized system we can write,

(13) $$\mathbf{u}(t) = -\mathbf{Kx}(t)$$

modifies the system equation to,

(14) $$\dot{\mathbf{x}}(t) = (\mathbf{A} - \mathbf{BK})\mathbf{x}(t) + \mathbf{B}r(t)$$

the desired closed-loop poles are to be at,

(15) $$s = \mu_1, \mu_2 \ldots, \mu_n, \qquad |\mathbf{sI} - \mathbf{A} + \mathbf{BK}| = (s-\mu_1)(s-\mu_2)\ldots\ldots\ldots.(s\text{-}\mu_n)$$

Online pole placement method is developed using Taylor series expansion. Each point is linearized and then feedback matrix **K** is caculated. However this takes a long time and causes delay in the control. To speedup the process, online pole placement using ANN is developed.

Online ANN Based Pole Placement

ANN based pole placement approach is created to speed up the pole placement online data calculations. The feedback gain matrix K can be calculated in a short period of time by ANN. The ANN based pole placement controller structure is obtained by using the matrix table K which is obtained for the different values of *P*d (0.48 - 1.0pu) in online pole placement system. 20 training values and 5 testing values are used from the table.

To construct an adaptive controller such that the closed loop poles remain at a fixed position, the system as well as controller parameters are updated at each instant of time.

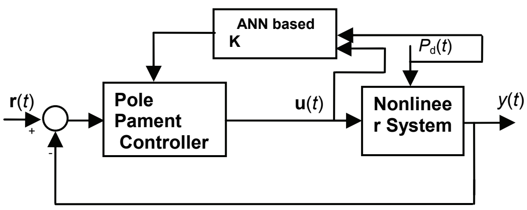

Fig. 3 Proposed Online ANN based Pole Placement

Fig. 3 represents the adaptive feedback Online ANN based Pole Placement control architecture. The plant output *y(t)* is a response of control input *u*(*t*) and disturbances P_d (*t*).

The components of the input pattern consisted of the control variables of the machining operation (power), whereas the output pattern components represented the measured factors (pole placement matrix **K**). The nodes in the hidden layer were necessary to implement the nonlinear mapping between the input and output patterns. In the present work, 1-input, 10-hidden layers, 3 output layer feedback propagation neural network has been used.

The Neural Network Toolbox under MATLAB used had been here. The structure of the proposed neural Networks used for feedforward back propagation (FBP) is shown in Fig. 4. We trained the neural networks until the error function was less than $1x10^{-4}$. Other neural networks parameters are gradient $3.08x10^{-6}$, mu $1x10^{-6}$, learning rate 0.6, momentum 0.8 .

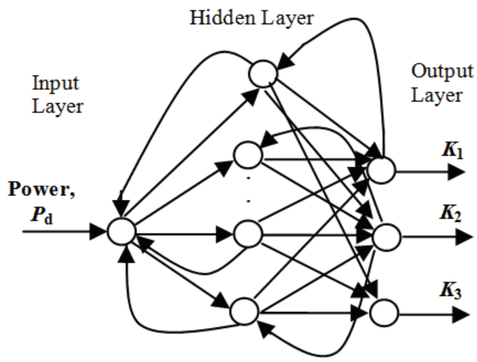

Fig. 4 The structure of FBP

In the present study, a hyperbolic tangent sigmoid and pure linear functions given in below is employed as an activation function in the training of the network.

(16) $$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$ and $$f(x) = x$$

where x in denotes weighted sum of the inputs. The maximum number of epochs is arbitrarily kept at 1000.

Resulting of training regression and the Matlab/ SIMULINK ANN based online pole placement structure is shown in Fig. 5 and Fig. 6, respectively.

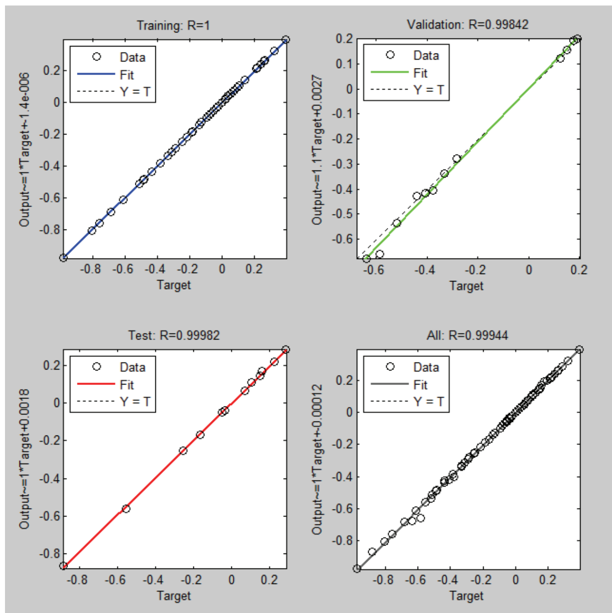

Fig. 5 Training regression

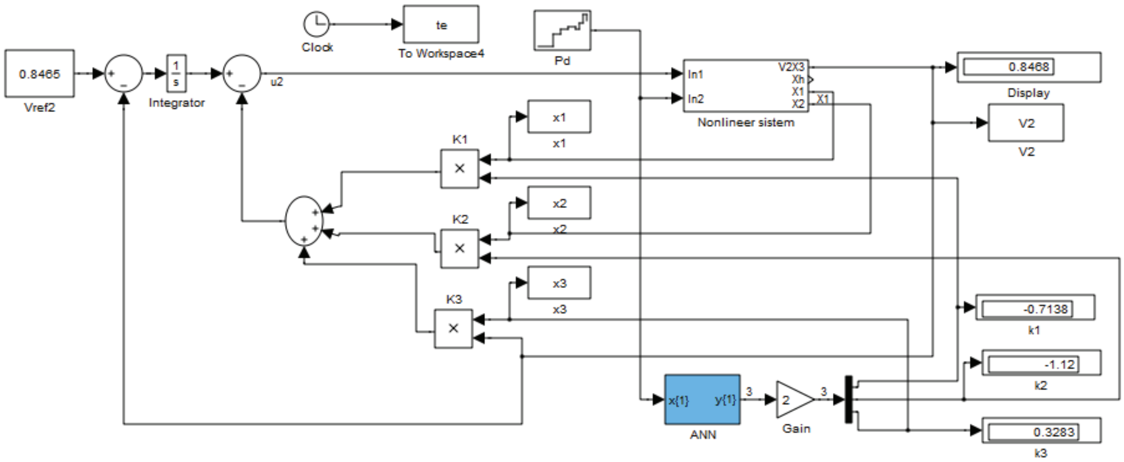

Fig. 6 Matlab/SIMULINK model using online ANN based pole placement approach

Simulation Results

Simulation studies are carried out according to the constant variation of the demand power in Table 2.

Table 2. Simulation parameter

Time (second)	Demand power P_d (pu)
0	0.6
40	0.7
60	0.73
80	0.75
100	0.73
110	0.78
120	0.85
130	0.8

At each operating point, the generator terminal voltage is maintained at 0.8465 pu.

K matrix components vary as seen in Fig. 7 in online ANN based pole placement system.

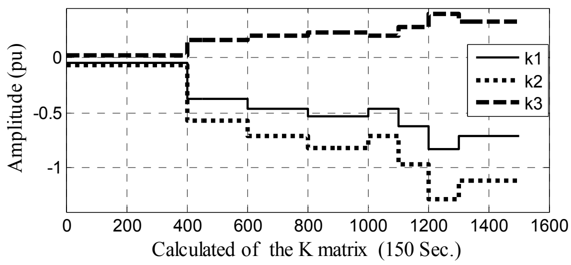

Fig. 7 **K**-matrix components change with online ANN based pole placement

The **K** matrix components are calculated them constantly during the 150-second simulation. ANN of the system are calculated with the help of the feedback matrix **K** against the changing demand powers. 1501 variable **K** components are calculated during the 150-second simulation.

Control variable susceptance variation, variation of output voltages, variation of PV curves, performance analysis of temporary state and variation are given in Fig. 8, Fig. 9, Fig. 10, Table 2 and Table 3, respectively.

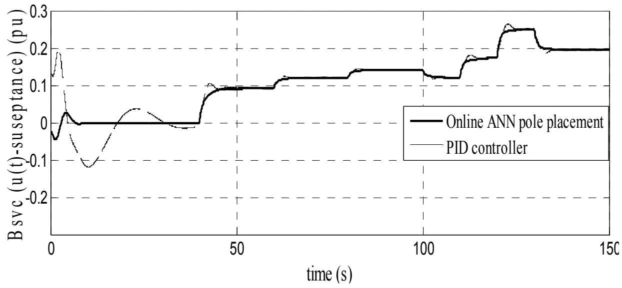

Fig. 8 SVC susceptance values

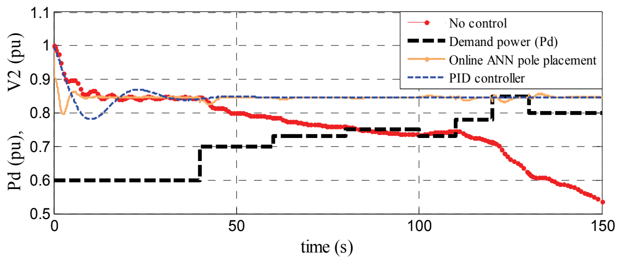

Fig. 9 Output voltage

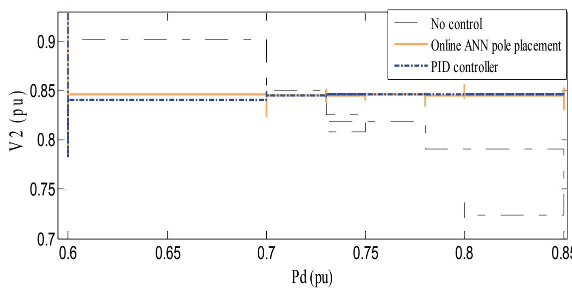

Fig. 10 PV curves of no control, proposed algorithm and PID control

The settle time with ANN based pole placement control is very short while requested power (P_d) is constant and the settle time with PID took a long time as it can be seen in Fig 9. at the output voltages in 40 seconds.

Table 3. The amount of overflow for the best conroller values maximum overshoot, rise and setting time and steady state error

Controller	*M*p	r_s	s_t	t=40s for P_d=0.7 pu, s_t	*e*
PID	0.0226	18.4	39.07	2.01	0.030
Online ANN based pole placement	0.0171	4.6	7	4.8	0.005

Conclusion

Online ANN based pole placement method is proposed in this study. The control of SVC by PID and proposed method is studied for voltage stability enhancement. The online pole placement controller developed for SVC is designed with Taylor series expansion and Acermann method. Output voltage and PV curve simulations show that PID and proposed control algorithm delay the collapse. The online ANN based pole placement shows the best performance in point of the performance criteria (maximum overshoot, best rise and setting time and steady state error) shown in Table 3.

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