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MIMO feedback linearization control for power systems

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ABSTRACT

Effectiveness of a multi-input, multi-output (MIMO) feedback linearization controller (FBLC) for power oscillation damping is illustrated in this paper. Oscillatory behavior of the system is estimated online from the measured quantities using a special form of neural network compatible with the feedback linearization framework. Levenberg–Marquardt (LM) algorithm is adapted to operate in a sliding window batch mode for estimation of the neural network parameters. The coefficient vector in the FBLC formulation is updated adaptively using the projection algorithm to suit changing operation scenarios. A case study is presented on a reasonably large-scale power system having three critical oscillatory modes. Two power electronic actuators located on separate transmission lines are used to control these modes resulting in a MIMO controller. Proposed FBLC is shown to yield acceptable closed-loop dynamic response with very little information about the plant model. Performance of the FBLC is benchmarked against a conventional model based controller.

1. Introduction

Power systems behavior is highly nonlinear in nature. Under stressed operating conditions the nonlinear effects are more prominent. However, linear controllers are usually designed to provide satisfactory performance around a single operating condition. The performance radius of such linear controller can be widened using robust control techniques [1–4]. However, following severe contingencies, the post-contingency system can be significantly different from its nominal operating states and even beyond the performance radius of designed robust controllers. In addition, the robust control designs require a system model for certain operating condition and the performance radius is extended around that operating point.

Conventional model based techniques [4–7] are used for control design which rely on the availability of accurate parameters and knowledge of the operating condition of the system. This depends on the accurate information of network topology and power flow scenario [8]. These are often difficult to obtain in real-time environment. To ensure very little reliance on accurate system model, different adaptive techniques have been proposed such that the controller is 'self-tuned' at each operating condition [4]. These techniques have been widely used for different nonlinear systems such as robotics and aircraft systems. Similar techniques have also been adopted for power system applications. Self-tuning control, relying solely on measured signals, has been proposed for power system stabilizers (PSSs) [9] and flexible ac transmission systems (FACTSs) devices [10] to overcome some of the problems of model based designs [7], which are difficult to obtain in the real-time environment.

Oscillatory behavior of the system is usually estimated in auto regressive moving average (ARMA) form or standard neural network structures using least square technique. For linear control, pole-shifting controller has been mostly proposed based on the estimated model [11]. But presence of nonlinearity in the measured signal can affect the performance of the linear controller [12]. While neural network type of nonlinear approximator and controller have been proposed by many researchers [13], a classical nonlinear control framework is hard to find [14–16].

NN offers a tool to model nonlinear data which is applied in modelling of complex relationships between inputs and outputs. It is an extremely powerful and growing rapidly in the many applications, for example, where tasks involving information processing, learning and adaptation are required. In most of the industrial applications, NN is an adaptive system that changes its structural parameters based on the external or internal information that flows through the network. The useful and important characteristics of NN are:

- large number of neurons, highly parallel neuron units,
- strongly connected neurons, robustness against the failure of neuron unit, and
- learning from data.

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Nomenclature

ARMA	auto regressive moving average	w_s	number of samples in a window
SISO	single-input, single-output	$\bar{e}$	error vector over a window
MIMO	multi-input, multi-output	χ	learning rate-estimation
NN	neural network	$\mathbf{W}$	input weights of NN
MLP	multi-layered perceptron	$\mathbf{V}$	output weights of NN
RBF	radial basis function	$\bar{x}$	measurement vector
RNN	recurrent neural network	$\bar{u}$	control vector
SRN	simultaneous recurrent neural network	$\mathbf{J}$	Jacobian
GN	generalized neuron	$\bar{p}$	estimated parameters (weights) of NN
FLNN	feedback linearizable neural network	$\Psi(\cdot)$	nonlinear function of hidden layer neurons
LM	Levenberg Marquardt algorithm	n	number of previous measurements
CCL	conventional control	m	number of previous control inputs
FBLC	feedback linearization control	n_p	number of outputs
PSS	power system stabilizers	m_p	number of inputs
TCSC	thyristor controlled series capacitor	N	number of neurons in hidden layer
FACTS	llexible AC transmission systems	$\mathbf{x_d}$	desired trajectories over a window
BP	back propagation	$\mathbf{y_s}$	system outputs over a window
BPTT	back propagation through time	$\mathbf{r}$	filter error
$y(\cdot)$	actual output	Λ	initial coefficient vector in FBLC
$\hat{y}(\cdot)$	estimated output	K_v	gain of the error feedback loop
$\hat{y}_d(\cdot)$	desired output or desired trajectory	γ	learning rate-FBLC
$u(\cdot)$	control signal	α	arbitrary constant

Moreover, neural network architectures are easy to reshape into a desired form depending upon the application type, as in this work NN is reshaped into novel structure called FLNN. Whilst selecting a network type for function approximation, a compromise between several desired features must be made. The NN is chosen in this work because of its suitability for recurrent use and online specific features (suitability for online identification, etc.).

Use of multi-layer perceptron (MLP), radial basis function (RBF), recurrent and simultaneous recurrent neural network (RNN and SRN) has been reported for online estimation of input–output mapping of systems [16–18]. These methods typically use back-propagation (BP) or back-propagation through time (BPTT) to update the neural network parameters online. Each of these have their own limitations related to convergence time and accuracy [16–18]. In classical nonlinear control framework, controlling nonlinear systems through feedback linearization is focused around geometric techniques. However, applicability of these approaches has been quite limited, because they rely on exact knowledge of nonlinearities. To relax some of the exact model-matching restrictions, several adaptive schemes have recently been introduced that tolerate some linear and nonlinear parametric uncertainties [19].

In order to exploit the capabilities of neural networks (NNs) for estimation of nonlinear dynamics while keeping a classical nonlinear control framework, an online LM [20] algorithm is adopted in this paper in conjunction with the feedback linearization controller [21–24]. In [25], the FBLC has been used to damp single modal oscillation using a single-input, single-output (SISO) controller. This paper is an extension in the MIMO framework. The MIMO system provides more limitation for the choice of controller design over SISO system. A special form of nonlinear neural network called feedback linearizable neural network (FLNN) compatible with the FBLC, is used to represent the nonlinear low frequency dynamics of the system. This paper shows that the FBLC and FLNN can be utilized to generate different control laws for multiple actuating devices under various operating scenarios without the need of manual re-tuning. The use of online LM algorithm for estimation of the system model provide faster convergence and better accuracy which can be used to damp low frequency oscillations in the power systems. For the current online application, the classical LM is modified to work in sliding window batch mode.

The efforts were made for an improved control of PSS/FACTS devices by using the FBLC controllers [4–6]. In order for the PSS/FACTS devices to provide an appropriate damping over a wide range of operating points, its parameters needs to be fine-tuned in response to the oscillations. Power systems are highly nonlinear with time varying parameters, and a fixed control design based on the linearized model may not guarantee satisfactory performance over various operating conditions [26]. Also to restrict the controller in the linear domain might not be workable especially under sever loading conditions. Thus, in this paper FBLC controller takes account of the nonlinearities in system and adapts to the changes in operating conditions could potentially yield better results. This is achieved by introducing the adaptive coefficient vector in FBLC at each time step, to suite different operating scenarios. The controller structure and weight update is devised to avoid divide-by-zero problem for the implementation of the FBLC.

Although the broad topics areas are the same in this paper and [25], however, this one paper differs from the [25] as follows:

1. This paper presents the online identification control of MIMO system and feedback linearization structure of neural network (FLNN) is used for the modelling of nonlinear dynamic behavior of the power system. While [25] describes the SISO identification and control of power systems with simple neural network structure.
2. The test system in this paper is 16-machines, 5-area power system and is multi-modal with highly nonlinear characteristics. While in the paper [25], 4-machines, 2-area power systems has a single mode and is easy to damp the oscillations as compared to 16-machine, 5-area power system.
3. The parameters update equations in this paper are done in a more effective way as compared to [25].
4. Here in this paper, Section 2.4 is introduced which is not present in [25]. It was observed that the process of choosing the lambda in (14) is not easy. Moreover, FBLC