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Study of Closed-Loop Model Reference Adaptive Control of Smart MicroGrid with QNU and Recurrent Learning

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Abstract: An adaptive quadratic polynomial neural unit (QNU) controller for optimization of a conventional Smart Microgrid control loop is studied and proposed. The parameters associated with the studied grid plants are considered to be known in this study, with the fact that the load is unknown and time-variant. A sample-by-sample real-time recurrent learning algorithm of an additional QNU controller is derived, with its performance tested and discussed as a result of this paper.

Keywords: *Smart Grids, Microgrids, Diesel Engine Generators (DEG), Photovoltaic panels (PV), Wind Turbine Generators (WTG), Flywheel Energy Storage System (FESS), Battery Energy Storage System (BESS), QNU Controller, Linear and Non-linear Controllers.*

1. Introduction

Smart Grids (SGs) can be deemed as rather complex, large systems, in which smart control is one of the necessary conditions for SG realization (Neuman, 2011, 2012, 2014). In late 1990's, the main issues related to Distributed Grids (DG), nowadays referred to as MicroGrids, were widely considered by the working groups of the International Council on Large Electric Systems (CIGRE) and the International Conference and Exhibition on Electricity Distribution (CIRED) in their review reports (Chowdhury et al., 2009).

Smart control methods and other tasks in SGs often involve computational intelligence tools such as artificial neural networks (Mori and Awata, 2006) or fuzzy logic (Bevrani et al., 2012). MicroGrids (MGs) are subsystems of complex Smart Grids. Till now, Phasor Measurement Unit (PMU) technology is often categorized as a significant tool to implement Smart Grids (Mitani et al., 2014). With regards to their control techniques, adaptive reference model approaches have proven their relevance as such in the works (Gibson et al., 2013; Narendra and Valavani, 1979). A key contribution of this paper is the introduction of a novel closed-loop model reference adaptive control scheme. For efficient real-time learning algorithms as such that of the gradient descent algorithm (GD) and the Levenberg-Marquardt (L-M) batch training algorithm, higher order neural units (HONUs), have proven to be computationally efficient in achieving adequate convergence in square error whilst achieving desirable control performance for both non-linear unknown systems as well as linear systems of SISO structure. The conception of quadratic neural units (i.e.

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a second order HONU) along with their application to both linear as well as non-linear engineering processes have been studied throughout the works (Bukovsky et al., 2010; Gupta et al., 2003 & 2013). A more recent application of HONUs for real-time adaptive control may be found in the work (Bukovsky et al., 2015) where HONUs were applied in extension to the previously employed conventional control loops for successful optimisation on various SISO engineering processes.

To demonstrate this novel approach for application to SG design, we derive the recurrent adaptation of a closed loop for control of a sub-component of a microgrid model (adopted from (Bevrani et al., 2012)). In this case study, two serial plants representing DEG, MG, FESS, and BESS subsystems are classically shown in a general PID closed loop in Fig. 1, where the individual grid components are generalized as known linear plant transfer functions, with respective parameters detailed in Table 1.

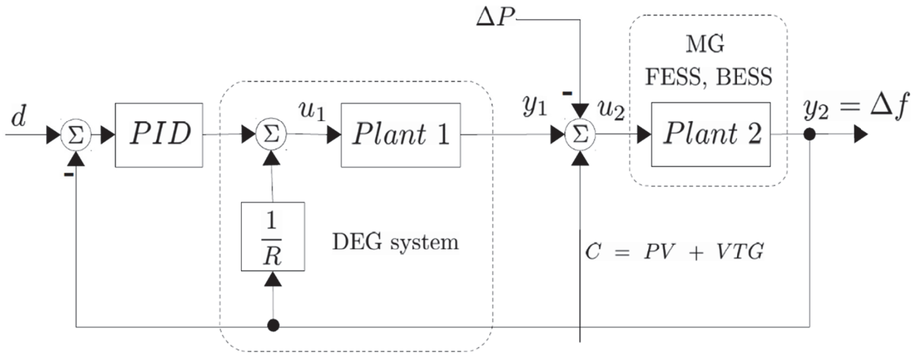

Fig. 1: *Closed loop of Smart Micro Grid part as given in Fig.1 with details in Tab. 1 (adopted from (Bevrani et al., 2012)).*

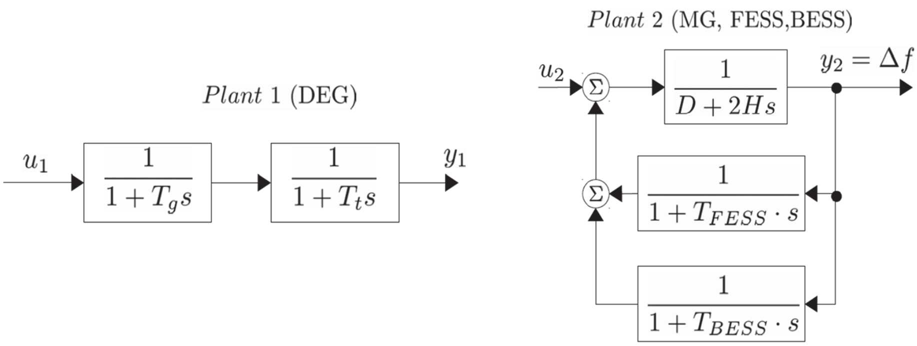

Fig. 2: *Models of Smart Grid part as given in Fig.1 with details in Tab. 1 (adopted from (Bevrani et al., 2012)).*

Tab. 1: *Sub-part of microgrid model configuration as adopted from (Bevrani et al., 2012).*

Plant 1 DEG system [s]	Plant 2 MG system	FESS[s]	BESS [s]
$T_t = 0.4$ $T_g = 0.08$ $R = 3\,[\mathrm{Hz/pu}]$	$D = 0.015\,[\mathrm{pu/Hz}]$ $2H = 0.1667\,[\mathrm{pus}]$	$T_{FESS} = 0.1$	$T_{BESS} = 0.1$

2. Discrete Time Control Loop with QNU Controller

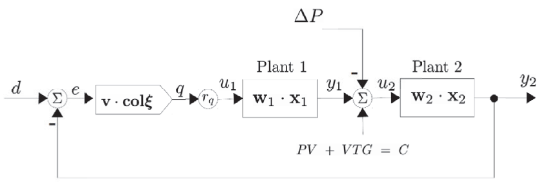

Fig. 3: *Control loop with adaptive QNU controller in a discrete-time form, where d=const. and ΔP is the immeasurable load.*

The discrete time model of the control loop for the purpose of discrete-time controller learning may be designed as follows. The grid frequency offset $\Delta f = y_2$ is the output of a serial block of two linear plants as in Fig. 3, which may be given via the following relation.

$$\Delta f(k) = y_2(k) = \mathbf{w}_2 \cdot \mathbf{x}_2(k) \tag{1}$$

where the input vector is

$$\mathbf{x}_2(k) = \begin{bmatrix} y_2(k-1) \\ y_2(k-2) \\ \vdots \\ y_2(k-n_{y2}) \\ u_2(k-1) \\ u_2(k-2) \\ \vdots \\ u_2(k-n_{u2}) \end{bmatrix} = \begin{bmatrix} y_2(k-n_{y2}:k-1) \\ u_2(k-n_{u2}:k-1) \end{bmatrix} = \begin{bmatrix} \mathbf{y}_2 \\ \mathbf{u}_2 \end{bmatrix} \tag{2}$$

and where $\mathbf{w}_2$ is a long row vector of $n_{y2} + n_{u2} = n_2$ adaptive parameters (neural weights) based on a priori approximate of the discrete time plant parameters. Further, the control input u_2 may be calculated via the following summation.

$$u_2(k) = y_1(k) + C(k) + \Delta P(k) \tag{3}$$

where ΔP is the immeasurable grid load and C stands for other external grid input components (that are beyond the scope and hence, not considered in depth within this paper).

Similarly, the output of the serial two-plant block before the load input is calculated may be given as follows

$$y_1(k) = \mathbf{w}_1 \cdot \mathbf{x}_1(k), \tag{4}$$

where the input vector is

$$\mathbf{x}_1(k) = \begin{bmatrix} y_1(k-n_{y1}:k-1) \\ u_1(k-n_{u1}:k-1) \end{bmatrix} = \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{u}_1 \end{bmatrix}, \tag{5}$$

and where $\mathbf{w}_2$ is a long vector of $n_{y2} + n_{u2} = n_2$, based on the a priori approximate plant parameters. Furthermore, the control error e, may be defined as follows

$$e = d - y_2, \tag{6}$$

where the set point $d=d(t)$, is a constant.

Instead of a conventional PID controller, we propose an adaptively tuned quadratic neural unit (QNU), i.e., second-order non-linear polynomial controller of the following structure

$$q(k) = \mathbf{v} \cdot \mathbf{col}\xi(k) \tag{7}$$

where the long-column vector $\mathbf{col\xi}$ of polynomial input terms in the sense of a QNU may be defined as vector

$$\mathbf{col}\xi = \left[\{\xi_i \cdot \xi_j\}\right]; i = 0 \ldots n_{y2}+1, j = i \ldots n_{y2}+1 \tag{8}$$

and where the ξ_i, ξ_j are elements of the controller input vector $\boldsymbol{\xi}$ that is defined as follows

$$\xi = \begin{bmatrix} \xi_0 \\ \xi_1 \\ \xi_2 \\ \vdots \\ \xi_{n_{y2}+1} \end{bmatrix} = \begin{bmatrix} 1 \\ q(k-1) \\ y_2(k) \\ y_2(k-1) \\ \vdots \\ y_2(k-n_{y2}+1) \end{bmatrix}, \tag{9}$$

and $\mathbf{v}$ in equation (7) is the long-row vector of adaptable parameters with respect to the adaptive controller defined as follows

$$\mathbf{v} = \left[\{v_{i,j}\}\right]; i = 0 \ldots n_\xi, j = i \ldots n_\xi, \tag{10}$$

Where $n_\xi = 2 + n_{y2}$. Finally, the output of the QNU controller (7), according to Fig. 3 multiplied with inclusion of an additional gain, may be given as follows

$$u_1(k) = r_q \cdot q(k), \tag{11}$$

where r_q is an additional (optional) static gain that may be incorporated for example, in cases where a QNU may result in large output magnitudes corresponding to low static gains of the controlled system.

3. Reference Model Design for The Closed Loop Scheme

For the adaptive closed loop scheme in Fig. 3, we propose the discrete time reference model via Z-transfer function as follows

$$Y_{ref}(z) = \frac{r_o \cdot \left(z^2 - z\right)}{(r_o \cdot T_d - 1) \cdot z + 1} \Delta P(z), \tag{12}$$

where its parameters T_d and r_o define the decay rate and gain respectively. To demonstrate the effectiveness in terms of suppression to an introduced disturbance. Fig. 4 illustrates the step responses of the designed reference model to an introduced disturbance under various configurations of decay rate and gain.

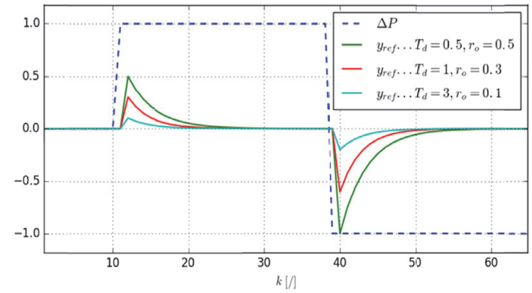

Fig. 4: *Step responses of the closed loop reference model (12) to a disturbance ΔP under various configurations.*

4. Controller Learning Rule

The parameters of the QNU controller are proposed to be adapted by the gradient descent learning rule as

$$\mathbf{v}(k+1)=\mathbf{v}(k)+\Delta\mathbf{v}, \tag{13}$$

where we adaptively enforce the control loop (Fig. 3) to adopt the behavior of the reference model (12) as follows

$$\Delta\mathbf{v}=-\frac{\mu}{2}\frac{\partial e_{ref}^2(k)}{\partial\mathbf{v}}=\mu\cdot e_{ref}(k)\frac{\partial y_2(k)}{\partial\mathbf{v}}, \tag{14}$$

where the reference error is defined as $e_{ref}=y_{ref}-y_2$, and where

$$\frac{\partial y_2(k)}{\partial\mathbf{v}}=\mathbf{w}_2\cdot\frac{\partial\mathbf{x}_2(k)}{\partial\mathbf{v}}, \tag{15}$$

where the partial derivatives of control input $\mathbf{u}_2$ in $\mathbf{x}_2$ are according to (3) and Fig. 3 as follows

$$\frac{\partial u_2}{\partial\mathbf{v}}=\frac{\partial(y_1+C+\Delta P)}{\partial\mathbf{v}}=\frac{\partial y_1}{\partial\mathbf{v}} \tag{16}$$

because neither C nor ΔP depends on the QNU controller weights $\mathbf{v}$. In (16) we can see that the unknown load, when assumed as the additive perturbation (3), does not affect the learning rule of the QNU controller.

Further derivations from (16) follow as

$$\frac{\partial y_1}{\partial\mathbf{v}}=\mathbf{w}_1\cdot\frac{\partial u_1}{\partial\mathbf{v}}=\mathbf{w}_1\cdot r_q\cdot\frac{\partial q}{\partial\mathbf{v}}, \tag{17}$$

where according to (7)

$$\frac{\partial q}{\mathbf{v}}=\mathbf{col}\xi^T+\mathbf{v}\cdot\frac{\partial\mathbf{col}\xi}{\partial\mathbf{v}}, \tag{18}$$

where the quadratic term derivatives may be calculated as follows

$$\frac{\partial\mathbf{col}\xi}{\partial\mathbf{v}}=\frac{\partial\xi_i}{\partial\mathbf{v}}\cdot\xi_j+\xi_i\cdot\frac{\partial\xi_j}{\partial\mathbf{v}}, \tag{19}$$

Finally the partial derivatives of vector $\boldsymbol{\xi}$ may then be given as follows

$$\frac{\partial\xi(k-\iota)}{\partial\mathbf{v}}=\begin{bmatrix}\mathbf{0}\\ \dfrac{\partial\mathbf{q}(k-\iota-1)}{\partial\mathbf{v}}\\ \dfrac{\partial\mathbf{y}_2(k-\iota)}{\partial\mathbf{v}}\\ \partial\mathbf{y}_2(k-\iota-1)\\ \vdots\\ \dfrac{\partial\mathbf{y}_2(k-\iota-n_{y2}+1)}{\partial\mathbf{v}}\end{bmatrix} \tag{20}$$

that recurrently develop from zero initial conditions via (15) - (20).

5. Closed-Loop Performance of the Proposed Adaptive Control

This section illustrates the resulting adaptive controller tuning in a closed loop and compares the controller performance of a linear adaptive controller in Fig. 5 and of quadratic non-linear controller (QNU) in Fig. 6. From the two figures, it can be concluded that the algorithm results in an adequate convergence of both architectures towards the desired reference model set point values. With the quadratic neural unit architecture in particular, exhibiting smoother adhesion to the desired reference model under introduced perturbations in comparison to the LNU controller output.

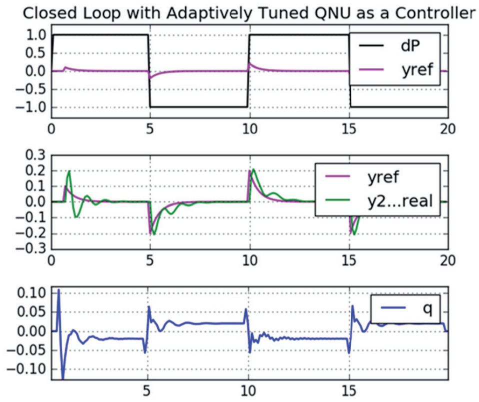

Fig. 5: *Step response of a closed control loop to disturbance steps ΔP during last adaptation epoch of (non-linear) QNU controller.*

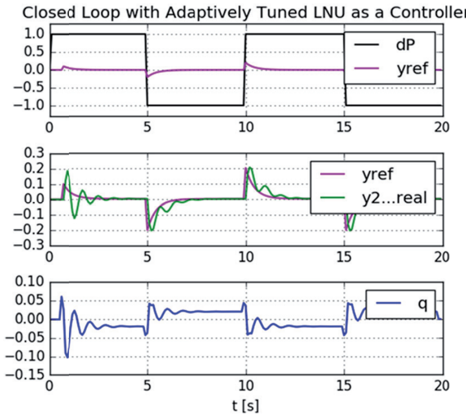

Fig. 6: *Step response of a closed control loop to disturbance steps ΔP during last adaptation epoch of LNU controller.*

6. Conclusions

Throughout this paper, a novel approach of model reference adaptive control via a quadratic polynomial neural unit (QNU) controller for control of Power Systems in a closed loop, with immeasurable load and constant set point was presented. The potentials of which is of utmost importance and relevance towards Smart Microgrid control applications. The presented simulation results have shown that learning (adaptation) extends in a closed loop and also converged for a non-linear controller architecture. These results demonstrate the correctness of the chosen development direction and authorizes the necessity for further research within this field. The resulting sampling of the whole discrete closed control loop of the 50Hz phasor model is 0.1 sec, which correlates to the speed of whole system response, further justifying the applicability of the method. An aim for further research, is directed towards a comparison of linear versus non-linear controllers from the viewpoint of control quality for different controlled systems and operating conditions.

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