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Grid Frequency Estimation Using Multiple Model with Harmonic Regressor: Robustness Enhancement with Stepwise Splitting Method

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Abstract: Reduction of inertia in electricity networks due to high penetration level of renewable energy sources will require wind turbines to participate in frequency regulation via Active Power Control. The performance of frequency regulation and protection system depends strongly on the performance of network frequency estimation. Fast frequency variations and uncertainties associated with unknown harmonics and measurement noise in the network signals are the main obstacles to performance improvement of frequency estimation with classical zero crossing method, which is widely used in industry. The same uncertainties introduce challenges in model based frequency estimation. These challenges are addressed in this paper within the framework of multiple model with harmonic regressor.
Additional challenges associated with computational complexity of matrix inversion algorithms and accuracy of inversion of ill-conditioned matrices in the multiple model are also discussed in the paper. New high order algorithms with reduced computational complexity are presented. Instability mechanism is discovered in Newton-Schulz and Neumann matrix inversion techniques in finite precision implementation environment. A new stepwise splitting method is proposed for elimination of instability and for performance improvement of matrix inversion algorithms in the multiple model. All the results are confirmed by simulations.

Keywords: Accurate Frequency Tracking in Electricity Networks, Harmonic Regressor, Multiple Model, High Order Algorithms, Stepwise Splitting, Roundoff Errors, Numerical Instability, Newton-Schulz Algorithm, Neumann Series

1. INTRODUCTION

High penetration level of (1) renewable energy sources, (2) power electronics, (3) advanced transmission systems, and (4) higher nonlinear loads and new types of loads in future electricity networks will (a) essentially reduce grid inertia and (b) introduce significant distortions in voltage and current signals.
These distortions will result in fast deviations from fundamental frequency, appearance of additional harmonics and hence in reduction of efficiency of equipment, power losses, heating, increased noise levels and others.
Frequency regulation, enabled via active power control of wind turbines, load-side control and others will play an important role in future electricity networks for performance improvement. Notice that *reliable frequency measurement is necessary for high performance network control as well as for system protection.* Errors in frequency measurements will result in erroneous control action and even in frequency oscillations. This paper addresses a very important issue of accuracy improvement of frequency estimation algorithms in the presence of harmonics and noise (electrical noise, measurement noise and others) in future electricity networks. A brief overview of existing frequency estimation methods is given below.

1.1 Existing Frequency Estimation Methods and Further Developments

Zero crossing detection and calculation of the number of cycles that occur in a predetermined time interval is a direct, simple and widely used methodology for frequency detection, see Friedman (1994). However, the disturbances associated with harmonics and noise, which will appear around zero crossing points of the signals in future electricity networks deteriorate accuracy of the grid frequency estimation via classical zero crossing method. Modifications of zero crossing method (described for example in Stotsky (2016), see also references therein) aiming for improvement of estimation accuracy are all based on more accurate detection of zero crossing points. These methods require additional signal processing techniques, which introduce delays. The delays are significant for noise contaminated signals with a large number of harmonics and introduce significant limitations in the performance of modified zero crossing methods in the case of fast frequency tracking. Future frequency estimation algorithms should be model based, that allows complete reconstruction of the frequency contents of the signals for high performance frequency estimation.
A number of interesting surveys on model based frequency

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estimation is available in the literature, see for example Quinn et al. (2013) and references therein. Promising multi-harmonic frequency estimators are based on optimization techniques, which maximize periodogram as a function of frequency, see Walker (1971) or minimize the error sum of squares with respect to unknown quantities, such as frequencies, phase shifts and coefficients. The best model matching provides the most accurate estimates. However, a number of extremum seeking algorithms, which are often realized as iterative search procedures can be ineffective due to local extrema and restricted region of attraction, which in turn are present due to a highly nonlinear nature of the problem. Computational complexity is an additional problem associated with the search procedures.

These difficulties can be avoided by applying multiple model approach (see for example Sakakura et al. (2016) for recent developments in general multiple model method), where the set of models is defined and each model is associated with different fundamental frequency. Residual error, which is associated with this set can be presented as a function of frequency and the frequency, which corresponds to the minimal value of residual error is the true frequency. Moreover, minimal residual error is also associated with the variance of the measurement noise.

All the residual errors can be calculated simultaneously, using parallel calculations, which essentially reduce execution time of the algorithm.

A simple and computationally efficient minimum seeking algorithm, realized as the interval reduction method is developed in Section 2 for fast and accurate calculation of the minimal value of the residual error and high performance estimation of the frequency and the variance of the measurement noise.

On the other hand, application of the multiple model (which consists of a large number of models) requires significant computational efforts, especially for a large number of harmonics. This introduces numerical challenges in finite precision implementation environment associated with inversion of information matrices of a large size and condition number (for fast varying frequency).

In other words the development of new matrix inversion algorithms with reduced computational complexity and improved robustness is required. These algorithms are presented in Section 3 and Section 5.

2. MULTIPLE MODEL ESTIMATION

2.1 Description of the Minimal Residual Method

Suppose that a measured signal y_k can be presented in the following form

$$y_k = \varphi_k^T \theta_* + \xi_k \tag{1}$$

where θ_* is the vector of unknown constant parameters and φ_k is unknown harmonic regressor presented in the following form:

$$\begin{aligned}\varphi_k^T = [&cos(q_0 k)\ sin(q_0 k)\ cos(2q_0 k)\\ &sin(2q_0 k)\ ...\ cos(hq_0 k)\ sin(hq_0 k)]\end{aligned} \tag{2}$$

where q_0 is unknown fundamental frequency of network (for example $q_0 = 50$ Hertz), h is unknown number of harmonics, and ξ_k is a zero mean white Gaussian noise, $k = 1, 2, ...$ is the step number. The system has four unknown quantities : 1) the fundamental frequency of network q_0, 2) the number of harmonics h, 3) the vector of parameters θ_*, and 4) the variance of the measurement noise. It is assumed that the upper bound $\overline{h}$ of the number of harmonics is known and $h \leq \overline{h}$. The algorithm for frequency and parameter estimation can be presented in the following steps, which are executed in each step k.

Step 1: Estimation for the Initial Set of Frequencies. Define the frequency interval as the following vector of size r:

$$f_1 = [\ \hat{q}_{11}\ \hat{q}_{12}\ \hat{q}_{13}\ ...\ \hat{q}_{1(r-1)}\ \hat{q}_{1r}] \tag{3}$$

where the frequencies $\hat{q}_{1i}$, $i = 1, ..., r$, $r \geq 3$ are presented in increasing order. The frequency interval should cover unknown fundamental frequency of the system q_0.

Substep 1: Estimation of the Variance. The regressor vector $\hat{\varphi}_i$ is introduced for each frequency $\hat{q}_{1i}$ as follows:

$$\begin{aligned}\hat{\varphi}_i^T = [&cos(\hat{q}_{1i} k)\ sin(\hat{q}_{1i} k)\ cos(2\hat{q}_{1i} k)\\ &sin(2\hat{q}_{1i} k)\ ...\ cos(\overline{h}\hat{q}_{1i} k)\ sin(\overline{h}\hat{q}_{1i} k)]\end{aligned} \tag{4}$$

forming a multiple model of the regressor with the frequencies corresponding to the components of the vector (3). Notice that the size of the model of each regressor (4) is larger than or equal to the size of unknown regressor (2) since $h \leq \overline{h}$.

Multiple model of the signal (1) with adjustable parameters θ_i is presented in the following form:

$$\hat{y}_i = \hat{\varphi}_i^T \theta_i \tag{5}$$

The signal y_k is approximated by the multiple model $\hat{y}_i$ for each frequency corresponding to the components of the vector (3) in the least squares sense in each step k of a moving window of a size w.

The frequency estimation algorithm is based on minimization of the following error E_i with respect to argument i, which corresponds to the certain frequency in the multiple model (5):

$$E_i = \sum_{p=k-(w-1)}^{p=k} (\hat{y}_{pi} - y_p)^2 \tag{6}$$

for a fixed step k, where $k \geq w$.

The least squares solution for estimation of the parameter vector θ_i can be written as follows:

$$A_i \theta_i = b_i \tag{7}$$

$$A_i = \sum_{p=k-(w-1)}^{p=k} \hat{\varphi}_{pi}\ \hat{\varphi}_{pi}^T \tag{8}$$

$$b_i = \sum_{p=k-(w-1)}^{p=k} \hat{\varphi}_{pi}\ y_p \tag{9}$$

where the matrix A_i is an information matrix (see Stotsky (2010),(2015) where the properties of this matrix are discussed for systems with harmonic regressor), and the parameter vector θ_i satisfies (7). The parameter vector can be calculated with high accuracy in the finite precision implementation environment using high order algorithms, described in Section 3 and Section 5.