

Topic Title: Signal Processing for Smart Grid – Frequency Tracking for Single Power System

Student Name: Muyao He

Student ID: z3456417

A. Problem statement

In the smart grid under the ideal situation, there exists a stable status, which the total generation equals to the total consumption plus losses. In this state, the system frequency is maintained to the nominal value. However, in reality all signals are corrupted by noise during practical usage. Therefore, the tracking strategy need to be robustness to noise. In order to achieve fast tracking, the tracking method must have a low computation cost.

B. Objective

Review and study on the existing tracking strategies
Implement and evaluate some existing methods
Propose and implement a novel method for frequency tracking

C. My solution

Implement the algorithms by using Matlab programming
Simulate the methods with constant frequency
Simulate the methods with step change frequency
Propose a novel algorithm by combining the EKF with theA&M algorithm

D. Contributions (at most one per line, most important first)

New algorithm has low computational cost
New algorithm has no overshoot
New algorithm is suitable for fasting tracking in real time applications

E. Suggestions for future work

Improve the accuracy of the proposed method
Implement the proposed method in the presence of noise and harmonics

While I may have benefited from discussion with other people, I certify that this report is entirely my own work, except where appropriately documented acknowledgements are included.

Signature: 何报臣

Date: 27 / 10 / 2016

Pointers

List relevant page numbers in the column on the left. Be precise and selective: Don't list all pages of your report!

8	Problem Statement
11	Objective

Theory (up to 5 most relevant ideas)

9,10	Signal Model
15 - 17	The Extended Kalman Filter
20	The interpolation algorithm
21, 22	Window function
38	Computational complexity

Method of solution (up to 5 most relevant points)

28, 31, 36	Simulate the methods with constant frequency
29, 34, 37	Simulate the methods with step change frequency
24	Propose a novel algorithm by combining the EKF with the A&M algorithm

Contributions (most important first)

38	New algorithm has low computational cost
36 - 37	New algorithm has no overshoot
36 - 37	New algorithm is suitable for fast tracking in real time applications

My work

16, 25, 26	System block diagrams/algorithms/equations solved
N/A	Description of assessment criteria used
16, 23, 24	Description of procedure (e.g. for experiments)

Results

27 - 38	Succinct presentation of results
27 - 38	Analysis
36 - 38	Significance of results

Conclusion

40	Statement of whether the outcomes met the objectives
41	Suggestions for future research

Literature: (up to 5 most important references)

20	[10]
15	[8]
6	[2]
13	[6]
8	[4]

THE UNIVERSITY OF NEW SOUTH WALES



SCHOOL OF ELECTRICAL ENGINEERING
AND TELECOMMUNICATION

Signal Processing for Smart Grid - Frequency Tracking for Single Power System

by

Muyao He

Thesis submitted as a requirement for the degree
Bachelor of Engineering (Electrical Engineering)

Submitted: October 27, 2016
Supervisor: Elias Aboutanios

Student ID: z3456417
Topic ID: EAB23

Abstract

The measurement of frequency is a fundamental and significant topic for the power system. In this report, a novel method for single power system is proposed to track the frequency of a real single-phase sinusoid with white Gaussian noise. This technique combines the Extended Kalman Filter with an interpolation algorithm created by Aboutanios and Mulgrew (the A&M algorithm). Two existing techniques are simulated in the report. The proposed method is simulated to emphasise the advantages comparing with the existing methods. All algorithms are carried out with both constant frequency and step change frequency.

Acknowledgement

I would like to thank my supervisor, Dr Elias Aboutanios, for the teaching and guiding in the past months. His expert idea and advice made me to have a new vision on digital signal processing and gave me great help on completing the thesis work.

I want to thank Mr. Jiadong Sun and Mr. Shanglin Ye for their support and patience. They helped me with understanding my tasks and some digital signal processing knowledge and algorithms.

I am also thankful to my assessor Dr Vidhyasaharan Sethu. His questions and suggestions during the poster open day made me think and improve the thesis work.

Abbreviations

AC Alternating Current

EKF Extended Kalman Filter

NEM National Electricity Market

SNR Signal-to-Noise Ratio

the A&M the Aboutanios and Mulgrew Algorithm for Real Sinusoid

Contents

1	Introduction	6
1.1	Context	6
1.2	Problem Statement	8
1.3	Report Outline	8
2	Background	9
2.1	Signal Model	9
2.2	Objective	11
3	Literature Review - Existing Techniques	12
3.1	Modified Zero-Crossing	12
3.2	Modified Extended Kalman Filter	15
3.2.1	Signal Model	15
3.2.2	Operation Principle	16
3.3	The Combination of Window Function and the A&M Algorithm	20
3.3.1	The A&M Algorithm	20
3.3.2	Window Function	21
3.3.3	Operation Principle	23
4	Proposed Algorithm	24
5	Implementation and Evaluation	27
5.1	Extended Kalman Filter	28
5.1.1	Steady State	28

5.1.2	Step Change on Frequency	29
5.1.3	Summary	30
5.2	Combination of Window Function and the A&M	31
5.2.1	Steady State	31
5.2.2	Step Change on Frequency	34
5.2.3	Summary	35
5.3	Proposed Method	36
5.3.1	Steady State	36
5.3.2	Step Change on Frequency	37
5.3.3	Summary	37
5.4	Analysis of Computational Cost	38
5.5	Summary	39
6	Conclusion	40
6.1	Conclusion	40
6.2	Future Work	41
	Bibliography	42

List of Figures

- 1.1 Frequency Deviation Following a Contingency Event 7

- 2.1 System Signal with Noise 10

- 3.1 Block Diagram of the Modified EKF 16
- 3.2 Rectangular Window 21
- 3.3 Hamming Window 22
- 3.4 Diagram of Window Shifting 23

- 4.1 Block Diagram of the Proposed Method 25

- 5.1 Modified EKF Tracking 50 Hz 28
- 5.2 Tracking Step Change 50 to 51 Hz 29
- 5.3 Simulation Result of the Combination of Rectangular Window and the A&M 31
- 5.4 Simulation Result of the Combination of Hamming Window and the A&M 32
- 5.5 Bandpass Filter 33
- 5.6 Simulation Results 34
- 5.7 Step Change 50 Hz to 51 Hz 35
- 5.8 Simulation Result of Proposed Algorithm 36
- 5.9 Step Change 50 Hz to 51 Hz 37

List of Tables

3.1	The A&M Algorithm	20
4.1	The Proposed Algorithm	26
5.1	Parameters of the Bandpass Filter	33
5.2	Comparison of Computational Complexity	38

Chapter 1

Introduction

1.1 Context

As the development of power system, signal processing has become a significant evaluation tool to allow engineers to design and operate the smart grid. Signal processing is applied in a lot of applications and has become an essential class of tools for analysis of the power system [1]. In the power system, the trend of the frequency indicates the dynamic balance between the power generation and load. Therefore, frequency is an important quantity in the power system. When the frequency of the grid varies, the speed of the motors which connected to that grid will change as well. Either a higher or lower frequency may result in damage to the machine. So it is necessary to maintain the power system frequency stable.

To protect and control the power system, many applications are applied. Frequency is used directly or indirectly in some of those applications. For example [2], the frequency is used in power system stabilizers (PSS) as the control target to reduce the system oscillations. The frequency relays are designed to be used for protecting the generators and turbines against the under or over frequency. The remedial action schemes (RAS) are relying on the system frequency to detect abnormal system conditions, and automatically make corrective actions to prevent large area black out. Obviously, frequency is one of the most significant parameters in power system and in order to ensure the power system

working in a safe and stable condition, the frequency variation needs to be strictly limited. Thus, it is important for the electric power company to monitor how frequency changes dynamically over time. For this purpose, the strategy of frequency tracking is involved.

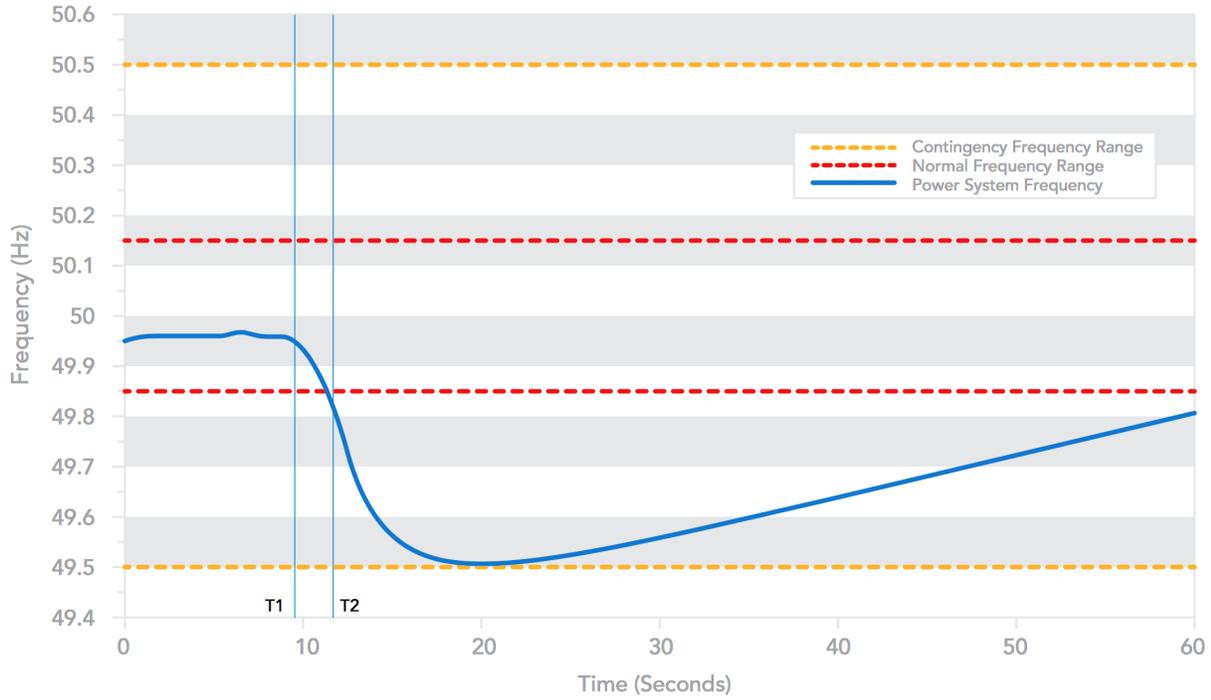


Figure 1.1: Frequency Deviation Following a Contingency Event

Since the waveform of each phase of the signal in the smart grid is presented as a single-phase sinusoid, to develop a method for frequency tracking is an important and classical research issue in digital signal processing. The National Electricity Market (NEM) is the largest electricity wholesale market in Australia, it supplies around 80% electricity consumption of Australia [3]. Figure 1.1 shows an example of control of frequency in NEM. In this figure, there is a contingency event of a sharp drop at time T1 and the power system frequency falls out of the normal range at time T2. In this case, an adjustment and control should be involved to stop the falling and restore the frequency into the normal range.

The above series of actions is based on the tracking of the system frequency. Because of the significance of frequency for power system, the frequency is expected to be tracked in an

accurate manner. In [4], it stated three conditions of a frequency tracking strategy should achieve: 1) fast speed of convergence; 2) robustness to noise; 3) accuracy of frequency estimation. And in order to support the fast frequency tracking, the complexity of the computation of the tracking technique should be reduced to minimum [5].

1.2 Problem Statement

In the smart grid under the ideal situation, there exists a stable status, which the total generation equals to the total consumption plus losses. In this state, the system frequency is maintained to the nominal value. However, in reality all signals are corrupted by noise during practical usage. Therefore the tracking strategy need to be robustness to noise. In order to achieve fast tracking, the tracking method must have a low computation cost.

1.3 Report Outline

The report includes six chapters. In Chapter 1, it gives a brief introduction on the background and the importance of frequency. Chapter 2 shows the signal model and objectives of this thesis work. In Chapter 3, it reviews other researchers' work. Then, Chapter 4 explains the proposed algorithm in details. Chapter 5 demonstrates all the simulation results and analysis. At last, Chapter 6 concludes the whole report and presents some future plans.

Chapter 2

Background

2.1 Signal Model

In the single power system, the electric power is distributed and delivered in the form of alternating current (AC). In Australia, the single-phase voltage is often described as a 230 volt AC with frequency of 50 Hz sinusoidal waveform. And usually, there is additive noise accompanying the signal. Therefore, the single-phase signal model can be represented as:

$$x(t) = A\cos(2\pi ft) + v(t) \quad (2.1)$$

where $y(t)$ is the signal, A is the amplitude, f is the true frequency and $v(t)$ is the noise.

The signal will be sampled to be discrete-time signal with the sampling frequency f_s . The sampled discrete-time signal can be shown as:

$$x[n] = A\cos(2\pi \frac{f}{f_s}n) + v[n] \quad (2.2)$$

In equation (2.2), we assume the sampling frequency is large, which also means the sampling period is very short and the frequency does not change during a sampling period. The noise term $v[n]$ is white Gaussian noise with zero mean and variance σ^2 . The variance is determined by the signal-to-noise ratio (SNR). SNR in dB is obtained by:

$$SNR_{dB} = 10\log_{10}(SNR) \quad (2.3)$$

Apply the definition of SNR

$$SNR_{dB} = 10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) \quad (2.4)$$

$$SNR_{dB} = 10\log_{10}\left(\frac{A^2}{\sigma^2}\right)$$

According to equation (2.4), the variance of noise can be determined by:

$$\sigma^2 = A^2 10^{-\frac{SNR_{dB}}{10}} \quad (2.5)$$

Figure 2.1 presents a single-phase power system signal with white Gaussian noise.

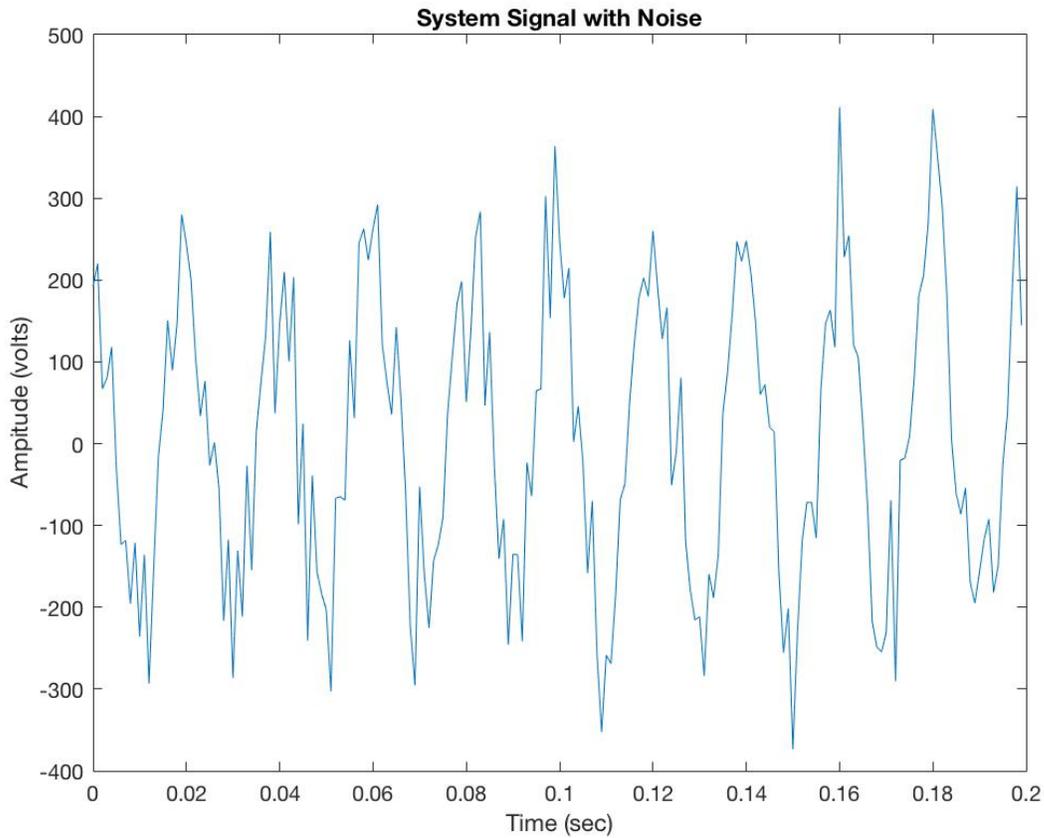


Figure 2.1: System Signal with Noise

2.2 Objective

The ultimate aim of the thesis is to develop a novel method of frequency tracking for single-phase system signal. First, a review on the existing tracking strategies will be presented. Then, the thesis will implement, evaluate and compare some existing methods. Finally, propose and implement a new method for frequency tracking. Also, a comparison of all methods will be shown at last.

Chapter 3

Literature Review - Existing Techniques

The frequency tracking techniques have been developed and studied for a very long time. Many frequency estimation methods have been proposed by researchers. In this chapter, three techniques for frequency tracking will be introduced and explained. The three techniques are modified zero-crossing method, modified EKF method and the combination method of window function and the A&M algorithm.

3.1 Modified Zero-Crossing

Zero-crossing method is the most common and popular strategy to measure the frequency. [2] specified the principle of zero-crossing technique: zero-crossing points of the signal waveform will be detected, and the number of samples between each two zero-crossing points will be counted, therefore, the period of the waveform can be calculated from the number of samples and sampling frequency. Zero-crossing is a simple and widely used method and easy to implement, it also has the advantage of insensitivity to the variation of the amplitude. However, the traditional zero-crossing method suffered from the inaccuracy of detecting zero-crossing points due to the sensitivity to noise, presence of harmonics and DC component.

In [6], a modified zero-crossing method combined zero-crossing with data smoothing technique by using least squares technique is introduced. For this method, environmental noise are considered in the signal model, so that the modified zero-crossing technique can be used in the power system in the presence of noise. The steps of the algorithm are presented below.

The signal model used for this method is like shown in equation (2.1). And the sampled signal is presented in equation (2.2).

First, a measurement window, $X[n]$, is defined. It presents a set of M consecutive samples:

$$X[n] = \begin{bmatrix} x[n+1] & x[n+2] & \dots & x[n+M] \end{bmatrix}^T \quad (3.1)$$

The measurement will be restarted whenever the counter counts that there are half of the samples are positive (or negative). We assume M is an even integer. In order to smooth data, the set of sampled signal need to be fitted into an l -th degree polynomial $p_l : R \rightarrow R$:

$$p_l(t) = a_0 + a_1t + a_2t^2 + \dots + a_l t^l = \sum_{j=0}^l a_j t^j \quad (3.2)$$

The coefficients can be calculated by using the least square technique:

$$K \cdot a = X[n] \quad (3.3)$$

$$a = (K^T K)^{-1} K^T X[n] \quad (3.4)$$

The equation (3.3) is quite possible to use in real-time because it does not involve the inversion of $K^T K$. The performance will be better if the degree of the polynomial is small, such as second or third order. The less the degree of the polynomial, the more stable of the system. Next, we need to calculate the roots of $p_l(t)$:

$$p_l(\hat{t}_j) = a_0 + a_1 \hat{t}_j + \dots + a_l \hat{t}_j^l = 0 \quad (3.5)$$

As the measurement window moving along the waveform, the values of \hat{t}_j will correspond to the approximate zero-crossing points of the signal. And the difference between every two odd or even subscripted solutions will represent periods of the signal. The frequency can be obtained by finding the inverse of the period.

$$\hat{f}_j = \frac{1}{\hat{t}_j - \hat{t}_{j-2}} \quad (3.6)$$

The noise in the signal can be suppressed effectively. The speed of the algorithm is reasonably fast since it is possible to calculate the frequency every half cycle. The author also applied simulation for this method. The simulation results show that the modified zero-crossing method has good performance under steady state. And under the transient condition, it can track frequency with satisfied results. However, there is a potential problem of the method, it is sensitive to the switching transients in the waveform. This problem can cause corruption to its performance for about 30 cycles after the transient.

3.2 Modified Extended Kalman Filter

Kalman filter is basically an optimal recursive data processing algorithm [7]. The Kalman filter technique can provide quality measurement results for the frequency estimation. It has the property of scalability which can be applied in various situations. In [8], a novel modified method in the design of the Extended Kalman Filter (EKF) with noise distortion is introduced.

This modified EKF is proposed due to decreasing the convergence time and increasing the accuracy of the tracker. The modification is made according to the noise variance technique [9]. The noise variance can be adjusted based on the tracking performance of the EKF. When the EKF performs in a satisfactory manner, the noise variance will be set to zero. Otherwise, it will be set to a larger number. This modification has the ability to adapt the tracking system based on the its performance. This method can provide a better frequency estimation than the normal EKF. And the modified EKF is more suitable to be applied to real-time applications.

3.2.1 Signal Model

As mentioned in Chapter 2, the signal model is set as equation (2.1). In the EKF, this signal can also be described with state space model. An measurement signal z_t at time t can be indicated as a sum of x_t and white Gaussian noise v_t :

$$z_t = x_t + v_t \quad (3.7)$$

where $x_t = A\cos(2\pi ft)$ and $v_t = v(t)$. The measurement noise v_t is the white Gaussian noise with variance σ_v^2 .

Figure 3.1 illustrates the block diagram of the modified EKF, where $Q(t)$ is the process noise covariance.

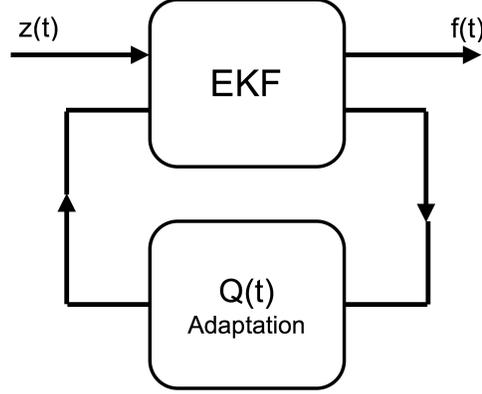


Figure 3.1: Block Diagram of the Modified EKF

3.2.2 Operation Principle

In the EKF, the measurement and state changing models can be presented as differential equations. The disadvantage of EKF is it requires a lot of computation cost. EKF can be applied for estimating a unknown parameter of a system with corrupted measurements and known stochastic model. Also, it can determine the state vector and stochastic model of the future measurement of the system. Equation (3.8) describes the state model in the system model of EKF and equation (3.9) describes the measurement model.

$$x_t = Ax_{t-1} + Bu_t + w_{t-1} \quad (3.8)$$

$$z_t = Hx_t + v_t \quad (3.9)$$

In the system model, x_t is the state vector updating at time t which symbolized the signal to be estimated in the EKF. For this method, the control value u_t is assumed to be zero in the system. The w_{t-1} and v_t are the process noise and measurement noise respectively. Noise vectors are in Gaussian distribution and statistically independent. To obtain the process noise covariance Q and measurement noise covariance R , we can substitute the process and measurement noise in to the following equations (equation (3.10) and equation (3.11)):

$$Q_t = E\{w_t w_t^T\} \quad (3.10)$$

$$R_t = E\{v_t v_t^T\} \quad (3.11)$$

In the EKF, there are prediction and correction equations which are presented as:

$$\hat{x}_t = K_t Z_t + (1 - K_t) \hat{x}_{t-1} \quad (3.12)$$

Equation (3.12) demonstrates the relationship between the estimated value updating at time t and the estimated value at the previous step. In the equation, K_t is the Kalman gain and Z_t is the measurement value. Equation (3.12) is aim to compute the estimation value of each step time by applying time updated Kalman gain (K_t). In order to achieve that purpose, there are two different types of equations have developed in EKF. The first type is illustrated in equation (3.13) and equation (3.14), which are the prediction (estimation) equations:

$$\hat{x}_t^- = A \hat{x}_{t-1} \quad (3.13)$$

$$P_t^- = A P_{t-1} A^T + Q \quad (3.14)$$

The second type is shown in equation (3.15) to equation (3.17), which are called correction (observation) equations:

$$K_t = P_t^- H^T (H P_t^- H^T + R)^{-1} \quad (3.15)$$

$$\hat{x}_t = \hat{x}_t^- + K_t (z_t - H \hat{x}_t^-) \quad (3.16)$$

$$P_t = (1 - K_t H) P_t^- \quad (3.17)$$

In the equation, the P_t means the error covariance matrix. The estimation values are the priori estimations (\hat{x}_t^- and P_t^-) before the correction, which are determined by applying the prediction equations. The updated posterior estimation values, which are calculated by substituting priori estimation values in correction equations are \hat{x}_t and P_t . Then, the priori estimations are recalculated by applying the updated posterior estimation values that are produced in the earlier step. This update procedure carries on in an iterative way.

As mentioned before, in the modified EKF, the process noise covariance (Q) can be adjusted by the tracking performance. For this method, Q can be presented in the form showing below:

$$Q_t = \begin{bmatrix} \sigma_{w1}^2 & 0 \\ 0 & \sigma_{w2}^2 \end{bmatrix} \quad (3.18)$$

where σ_{w1}^2 and σ_{w2}^2 are Gaussian random variables with zero mean. The system signal magnitude and frequency are chosen as state variables. Equation (3.19) presents the statevariable of the system:

$$\hat{x}_t = \begin{bmatrix} a_t \\ f_t \end{bmatrix} \quad (3.19)$$

where a and f are amplitude and frequency respectively.

To adjust the process covariance matrix Q_t adaptively according the tracking performance, an algorithm called lock detection is introduced in [9]. If the tracking performance is satisfactory, σ_{w1}^2 and σ_{w2}^2 will be set to zero. If the tracking performance is unsatisfactory, the values of σ_{w1}^2 and σ_{w2}^2 will be determined by the modification algorithm. For this method, the error equation at time t can show the tracking performance of the EKF. Equation (3.20) displays the error function:

$$e_t = (z_t - H\hat{x}_t^-) \quad (3.20)$$

The tracking performance entirely relies on the error equation. In this method, the average of recent errors are used for comparison. If the average value is smaller than γ times $\sqrt{R_t}$, where R_t is the measurement noise covariance, it is satisfactory for the tracking performance. γ is a constant value with a pre-defined threshold value range ($1.0 \leq \gamma \leq 3.0$). On the contrary, if the performance is unsatisfactory, the covariance matrix will be set by modification system as shown in equation(3.21):

$$\sigma_{w1}^2 = \sigma_{w2}^2 = \frac{f_t^2}{12} \quad (3.21)$$

The Kalman gain will increase as the increasing of σ_{w1}^2 and σ_{w2}^2 . The lock detection algorithm is modifying the EKF by locking and unlocking Kalman gain. The lock detection technique is outlined below:

$$\begin{aligned} \sigma_{w1}^2 = \sigma_{w2}^2 = 0 & \quad \text{as } \frac{1}{M} \sum_{m=1}^M e_m \geq \gamma \sqrt{R_t} \\ \sigma_{w1}^2 = \sigma_{w2}^2 = \frac{f_k^2}{12} & \quad \text{as } \frac{1}{M} \sum_{m=1}^M e_m < \gamma \sqrt{R_t} \end{aligned} \tag{3.22}$$

The convergence time is decreased and the accuracy is increased by applying the lock detection algorithm. Therefore, the tracking performance of the EKF is improved.

3.3 The Combination of Window Function and the A&M Algorithm

3.3.1 The A&M Algorithm

The Aboutanios and Mulgrew algorithm (the A&M) is a real single sinusoid frequency estimator, which is based on the interpolation on Fourier coefficients [10]. The A&M algorithm can give estimated frequency, amplitude and phase of a group of data of sine wave. A summary of the A&M algorithm is presented in Table 3.1 [10].

Input	A real sine wave $x(n)$, $n = 0, 1, \dots, N - 1$
Calculate	$X(k) = FFT(x)$ and $Y(k) = X(k) ^2$
Calculate	$\hat{m} = \underset{k}{\operatorname{argmax}} Y(k)$, if $\hat{m} \geq \frac{N}{2}$, $\hat{m} = N - \hat{m}$
Set	$\hat{\delta} = 0$ and $\hat{A} = 0$
Loop	For i from 1 to Q do
	(1) $\tilde{X}_{\pm} = \sum_{n=0}^{N-1} x(n)e^{-j\frac{2\pi}{N}(\hat{m}+\hat{\delta}\pm 0.5)n}$
	(2) $\hat{S}_{\pm} = \hat{A}^* \frac{1+e^{-j4\pi\hat{\delta}}}{1-e^{-j\frac{2\pi}{N}(2\hat{m}+2\hat{\delta}\pm 0.5)n}}$, and $\hat{S} = \tilde{X}_{\pm} - \hat{S}$
	(3) $\hat{\delta} = \hat{\delta} + \frac{1}{2}\Re\left\{\frac{\hat{S}_+ + \hat{S}_-}{\hat{S}_+ - \hat{S}_-}\right\}$
	(4) $\hat{A} = \frac{1}{N} \left(\sum_{n=0}^{N-1} x(n)e^{-j\frac{2\pi}{N}(\hat{m}+\hat{\delta})n} - \hat{A}^* \frac{1+e^{-j4\pi\hat{\delta}}}{1-e^{-j\frac{4\pi}{N}(\hat{m}+\hat{\delta})n}} \right)$
Calculate	$\hat{f} = \frac{\hat{m}+\hat{\delta}}{N}$, $\hat{a} = 2 \hat{A} $ and $\hat{\phi} = \angle\hat{A}$

Table 3.1: The A&M Algorithm

3.3.2 Window Function

In digital signal processing, the window function is a closed mathematical interval with the outside of the interval remains to zero. In normal implementations, the window functions are represented as smooth, symmetric, non-negative and bell curved [11]. The window can also be rectangular or triangle.

Rectangular Window

The rectangular window is a simple window that sets the outside values to zero and inside N values not changing. It makes the waveform appear as suddenly turns on and off:

$$w(n) = 1 \tag{3.23}$$

Figure 3.2 shows the time domain and frequency domain of the rectangular window.

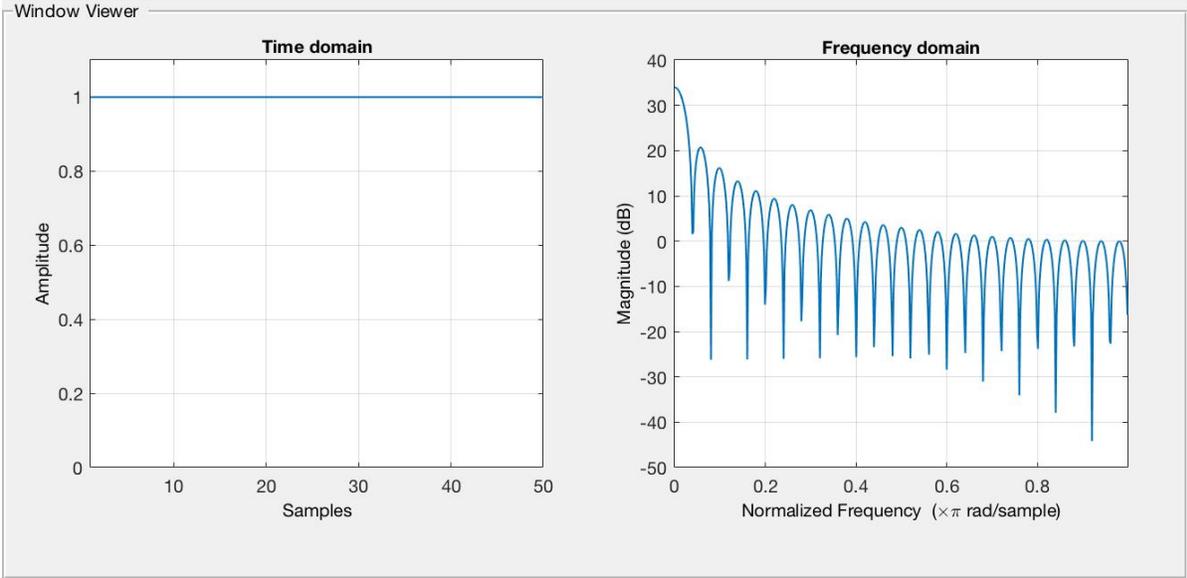


Figure 3.2: Rectangular Window

Hamming Window

The Hamming window function has a bell-curve shape. The window appears as a wide peak and low side lobes as shown in Figure 3.3. The Hamming window approaches zero but does not reach zero at the ends. Therefore, there still has a little discontinuity remaining in the signal. Due to that characteristic, the Hamming window is suitable for minimising the nearest side lobe and it will result a higher accuracy for the frequency of the original signal. The form of Hamming window is demonstrated in equation (3.24)

$$w(n) = \alpha - \beta \cos\left(\frac{2\pi n}{N-1}\right), \quad \text{where } \alpha = 0.54, \beta = 1 - \alpha = 0.46 \quad (3.24)$$

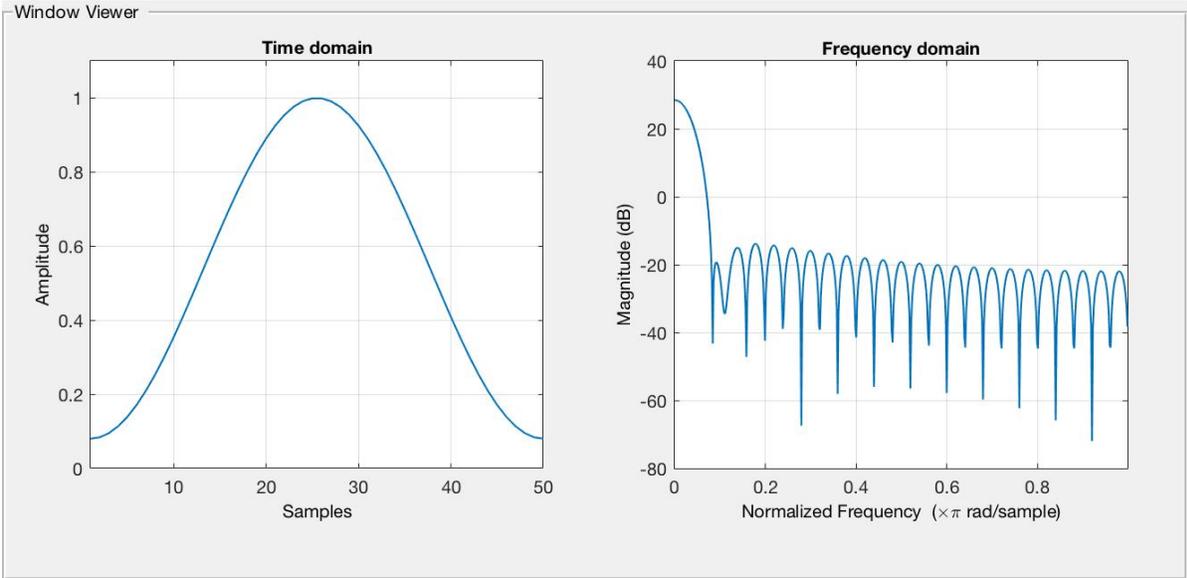


Figure 3.3: Hamming Window

3.3.3 Operation Principle

This technique is an expansion from the A&M algorithm, it combines the window function with the A&M algorithm. Figure 3.4 illustrates how the window function is applied on the signal data.

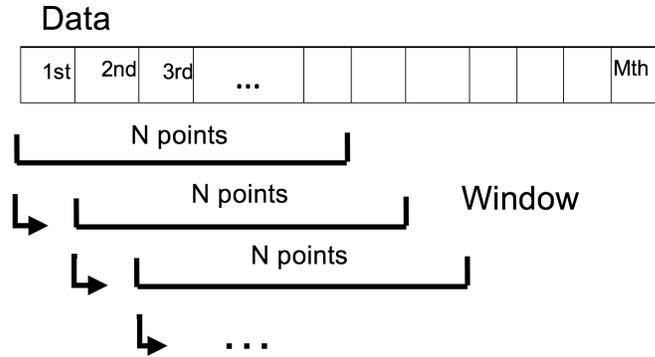


Figure 3.4: Diagram of Window Shifting

A window of size N is created to contain the data, where N is an integer number of samples. Suppose the size of the input data signal is M , where M is also an integer. Then let the window of size N times the input signal, the window now contains the first N samples (from the 1st sample to N th sample) of the input data. The window with N samples of the input data can be put into the A&M algorithm. The estimator will output the estimated frequency, amplitude and phase of the input data. For this thesis, we only focus on the frequency of the system, so we only need the estimated frequency from the estimator of the A&M. After applying the A&M algorithm to that window, the window will shift to right by one sample on the input signal. Then the window will contain from the 2nd sample to $(N + 1)$ th sample of the signal. After that, the A&M will be applied to the window. This process will continue until the window reaches the end of the input signal data.

The last N points of the input data are from the $(M - N + 1)$ th sample to the M th sample. Therefore, for an input signal data of size M samples, there will be $(M - N + 1)$ estimated frequency values.

Chapter 4

Proposed Algorithm

From the literature review, the EKF method and the combination method of window function and the A&M algorithm are known. The EKF is known as a high accuracy technique for frequency tracking. However, the EKF method applies the filter on a sample per sample basis. If the signal is sampled at a frequency much larger than the original frequency $f_s \gg f$, say 5000 Hz, then this will have quite a lot computation cost. In order to keep the accuracy of the EKF while at the same time to reduce the computation load, one way is to combine the A&M algorithm with the EKF.

The proposed method is to combine the estimator of the A&M algorithm with the modified EKF. The signal model is same as previous, which is shown in equations (2.1) and (2.2). The block diagram of the proposed method is presented in Figure (4.1)

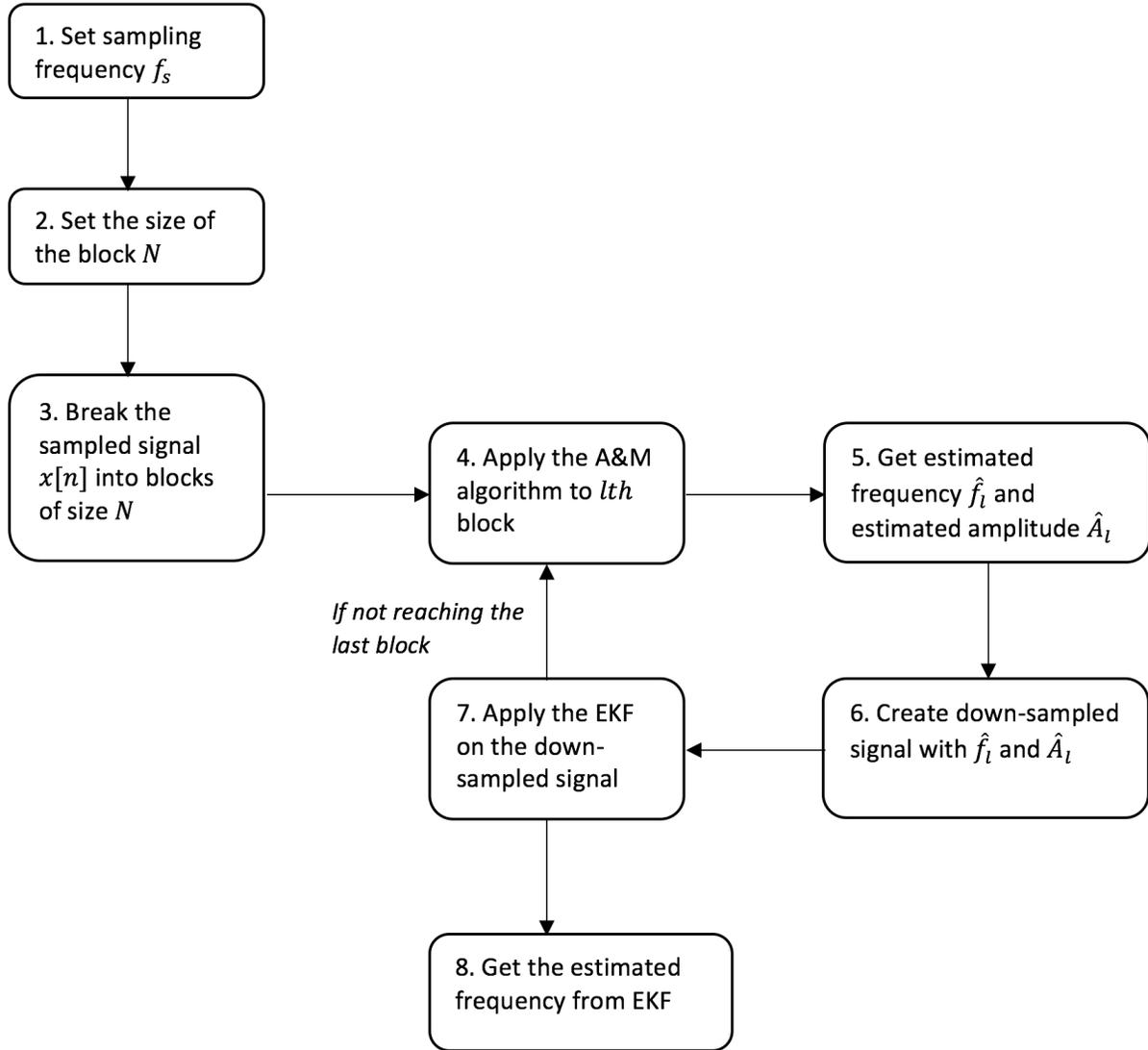


Figure 4.1: Block Diagram of the Proposed Method

Imaging the frequency changes at a much slower rate than the sampling time $T_s = \frac{1}{f_s}$. More specifically, let the sampling frequency of the EKF at a rate much slower than the original sampling frequency f_s . And f_s has a common factor of N , where N is an integer of number of samples. Next, we can break the signal into blocks of size N which is the 3rd step in the block diagram. And the l th block can be written as:

$$y[l] = [x[lN] \quad x[lN + 1] \quad \dots \quad x[(l + 1)N - 1]]^T \quad (4.1)$$

For each block, the A&M algorithm is applied to estimate the frequency \hat{f}_l and amplitude \hat{A}_l of block l (The 4th and 5th steps in Figure (4.1)). Then, we can write a down-sampled version of the original signal at a new sampling rate $\frac{f_s}{N}$ with the estimated frequency and amplitude (The 6th step in Figure (4.1)). The down-sampled version signal is shown in equation (4.2):

$$\hat{x}_1[l] = \hat{A}_l \cos(2\pi l N \frac{f_l}{f_s}) \quad (4.2)$$

Finally, the modified EKF can be applied to the down sampled signal at a lower rate of $\frac{f_s}{N}$, which is the 7th step in Figure (4.1). The whole process will be repeated until the last block of the signal. The summary of the proposed method is shown in Table 4.1.

Input	A real single-phase sinusoid $x(t)$
Set	Sampling frequency f_s
Get	Sampled signal $x[n], n = 0, 1, \dots, M - 1$
Set	The size of the block N
Do	Break $x[n]$ into $\frac{M}{N}$ blocks of size N
Get	l_{th} block: $y[l] = [x[lN] \quad x[lN + 1] \quad \dots \quad x[(l + 1)N - 1]]^T$
Loop	For l from 1 to $\frac{M}{N}$ do
	$[\hat{f}_l \quad \hat{A}_l] = \text{the A\&M}(y[l])$
	$\hat{x}[l] = \hat{A}_l \cos(2\pi l N \frac{f_l}{f_s})$
	$\hat{f} = EKF(\hat{x}[l])$
Finally	Estimated frequency = \hat{f}

Table 4.1: The Proposed Algorithm

Chapter 5

Implementation and Evaluation

In this chapter, the simulation results of the modified EKF, the combination of window function and the A&M algorithm and the proposed method will be presented. The tracking performance of those results will also be analysed and compared. Each method is simulated under two conditions: **1. Steady state of 50 Hz** and **2. Step change 50Hz to 51 Hz**.

The modified zero-crossing method is a classical method used for frequency tracking, the advantage of the method is simple. However, the accuracy of the zero-crossing method is questionable, especially under the noise conditions. Therefore, the modified zero-crossing method is not implemented.

5.1 Extended Kalman Filter

The simulations are carried out for single-phase power system signal with white Gaussian noise. The simulations are conducted by using Matlab programming. The sampling frequency (f_s) used in the modified EKF is 1 kHz. The white noise in the system signal is with SNR 57 dB, which means the variance of the white Gaussian noise is about 0.1 which is a large variance. Then, we can see the performance of the modified EKF under the condition with bad noise distortion.

5.1.1 Steady State

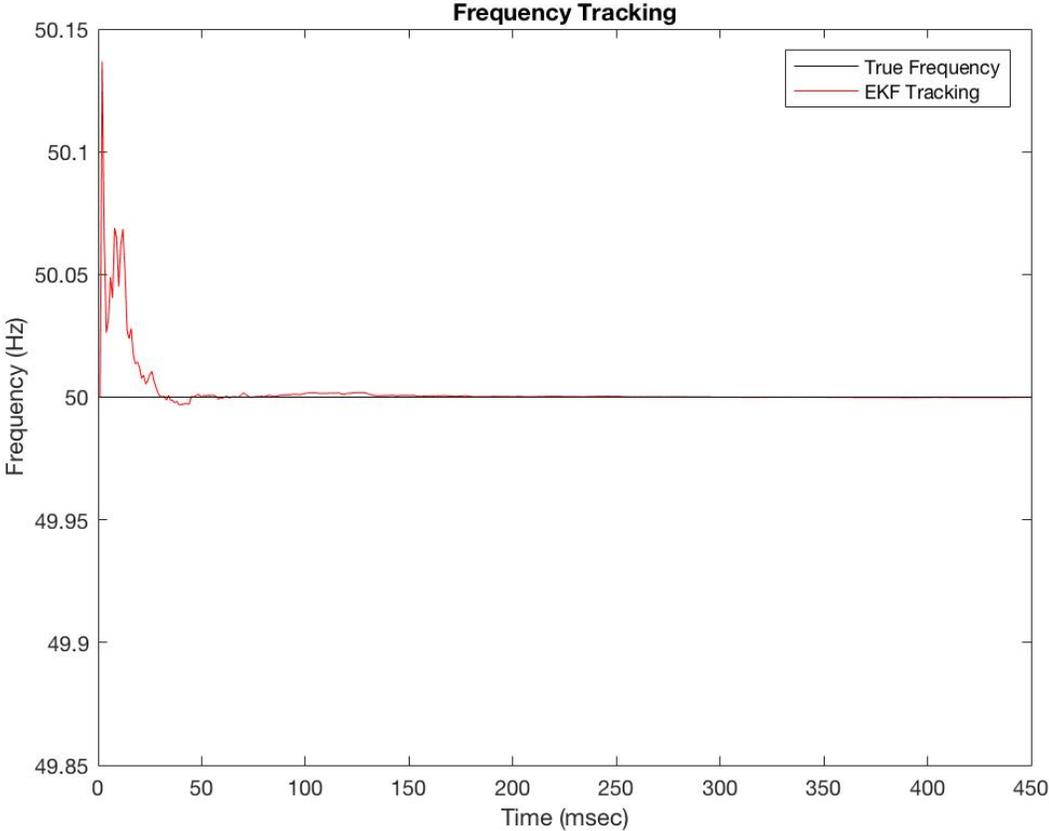


Figure 5.1: Modified EKF Tracking 50 Hz

Figure 5.2 shows the tracking result of the modified EKF with step change on frequency. In this case, the frequency is suddenly increased from 50 Hz to 51 Hz. There are large overshoots when the frequency is increased. The convergence time is still about 50 ms. After the tracking is converged, it keeps tracking in an accurate manner.

5.1.3 Summary

The advantages of the modified EKF are highly accurate and having short convergence time. However, the computation is complicated and the computation cost is high.

5.2 Combination of Window Function and the A&M

As mentioned before, the simulations are carried out for single-phase power system signal with white Gaussian noise (equation(2.1)) by using Matlab programming. In order to maintain consistency and to compare the simulation results with simulation results of other methods, the parameters used in the simulation are same as the one used in the modified EKF. The sampling frequency (f_s) used for this method is 1 kHz and the white noise in the signal is with SNR 57 dB. The size of the window N is 50.

5.2.1 Steady State

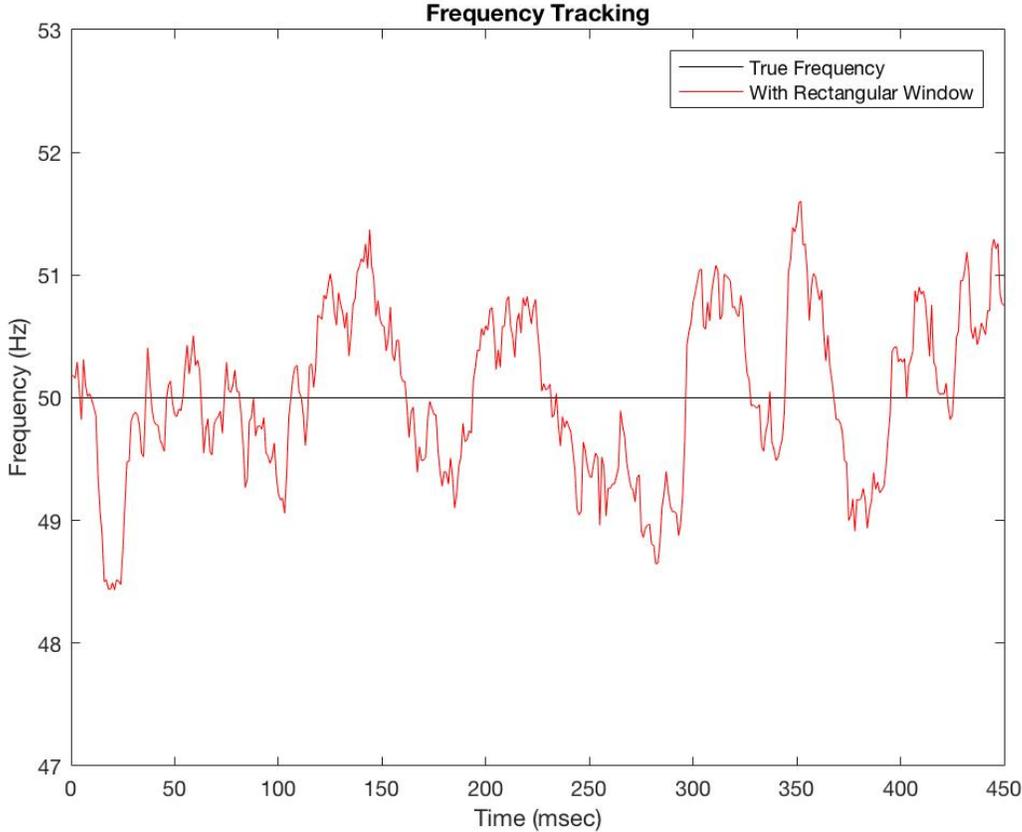


Figure 5.3: Simulation Result of the Combination of Rectangular Window and the A&M

The simulations are conducted with the frequency of 50 Hz in the signal Model. Figure 5.3 shows the simulation result of the combination of the rectangular window and the A&M algorithm. From the result, we can see that the tracking trace oscillates strongly around 50 Hz. The maximum deviation from 50 Hz is about 1.5 Hz.

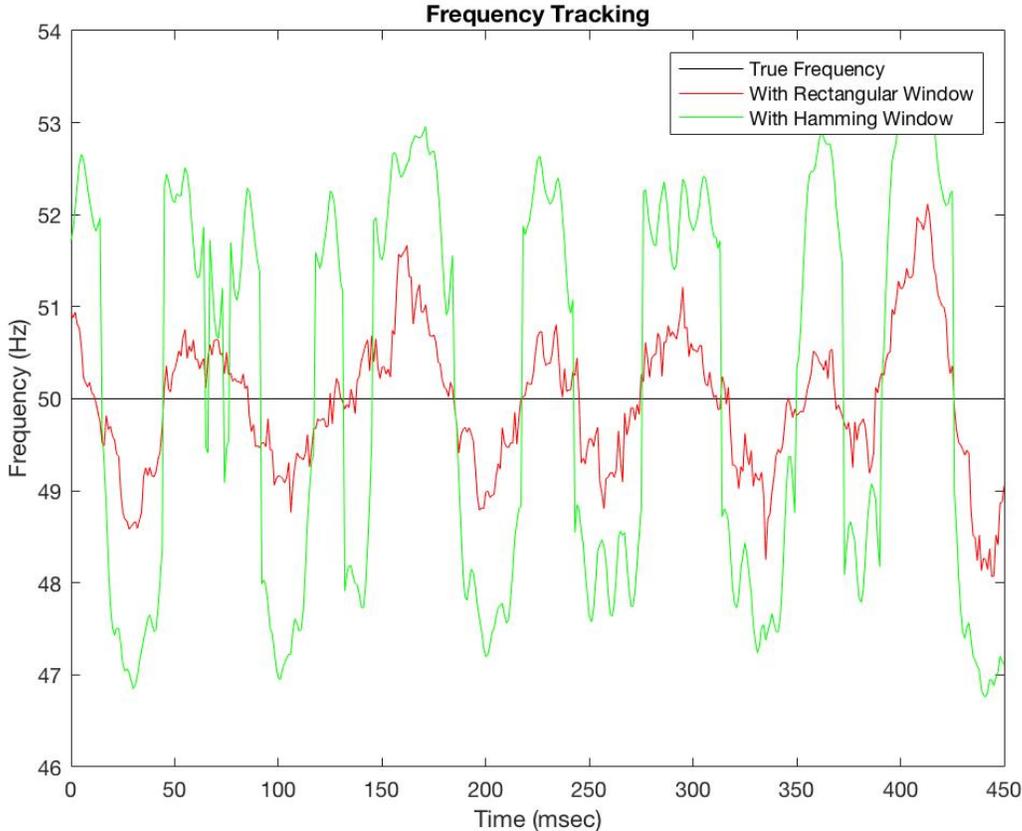


Figure 5.4: Simulation Result of the Combination of Hamming Window and the A&M

In Figure 5.4, the green line illustrates the simulation results of the combination of Hamming window and the A&M. The maximum deviation from 50 Hz is around 3 Hz, which is a very large error. From Figure 5.4, comparing the tracking performance of Hamming window with the one with rectangular window, the one with Hamming window is much worse than the one with rectangular window.

Bandpass Filter

In order to improve the tracking performance of this technique, a narrow bandpass filter is developed. A bandpass filter is filter that allows the signal between two frequency values to pass. The narrow bandpass filter is used after the input data getting into the window, before the A&M algorithm applies to the window of data. The spectral plot of the narrow bandpass filter is shown in Figure 5.5. The parameters of the narrow bandpass filter is provided in Table 5.1.

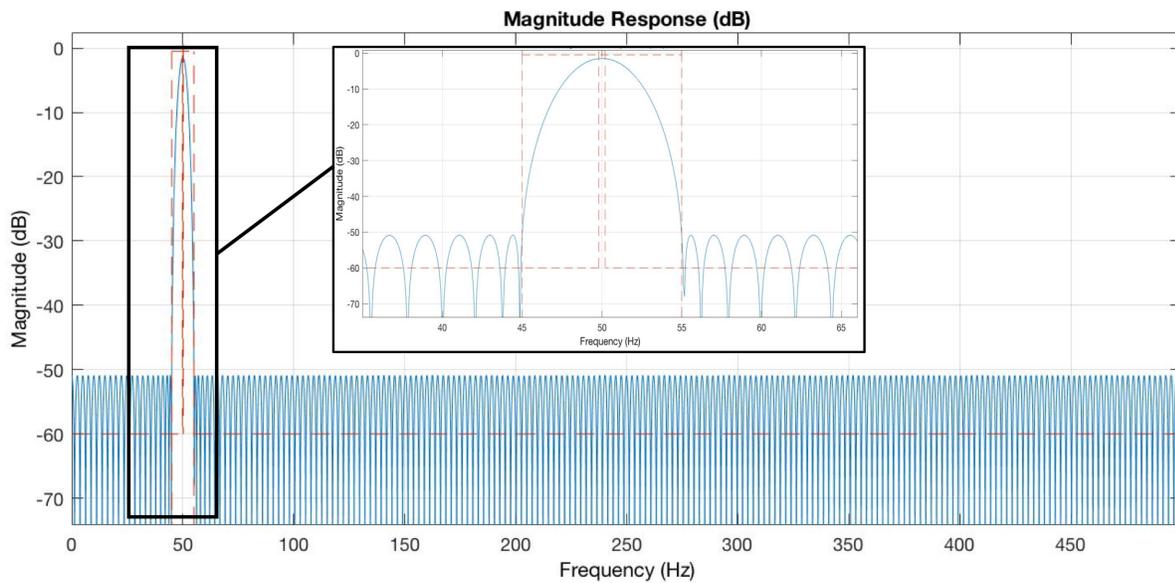


Figure 5.5: Bandpass Filter

Name of Variable	Value
Centre Frequency	50 Hz
Cutoff Frequency 1	49.8 Hz
Cutoff Frequency 2	50.2 Hz
Bandwidth	0.4 Hz
Quality Factor	125

Table 5.1: Parameters of the Bandpass Filter

The simulation result with adding the bandpass filter is demonstrated in Figure 5.6. The red line illustrates the tracking trace of the combination method of rectangular window and the A&M algorithm. The blue line denotes the tracking performance by applying a narrow bandpass filter to the original algorithm. From Figure 5.6, we can see that there are some improvements with the bandpass filter, although they are inconspicuous.

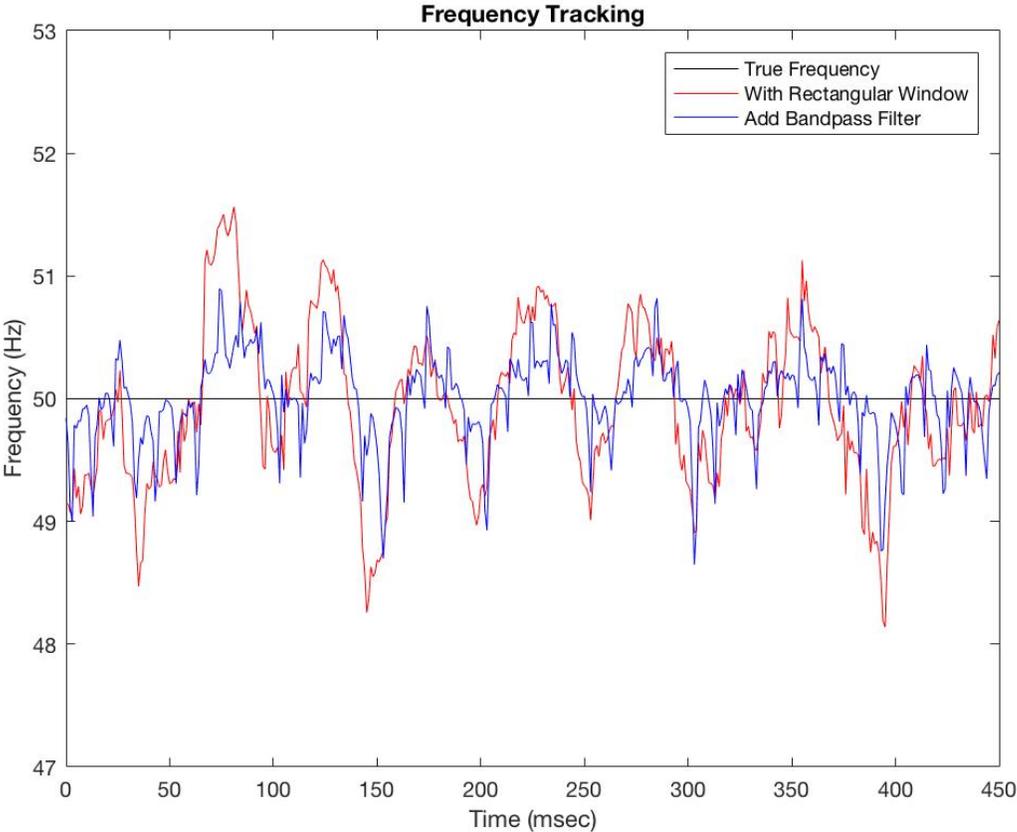


Figure 5.6: Simulation Results

5.2.2 Step Change on Frequency

The frequency in the signal is suddenly changed from 50 Hz to 51 Hz. Figure 5.7 illustrates the tracking performance of the method with the rectangular window and the bandpass filter. From the plot, there are very large overshoot when frequency changes. For the red line, the overshoot is about 15 Hz, for the blue line is around 10 Hz. The representation

of red and blue lines are indicated in the figure. From the tracking results, we can see that there is some improvement with adding the bandpass filter.

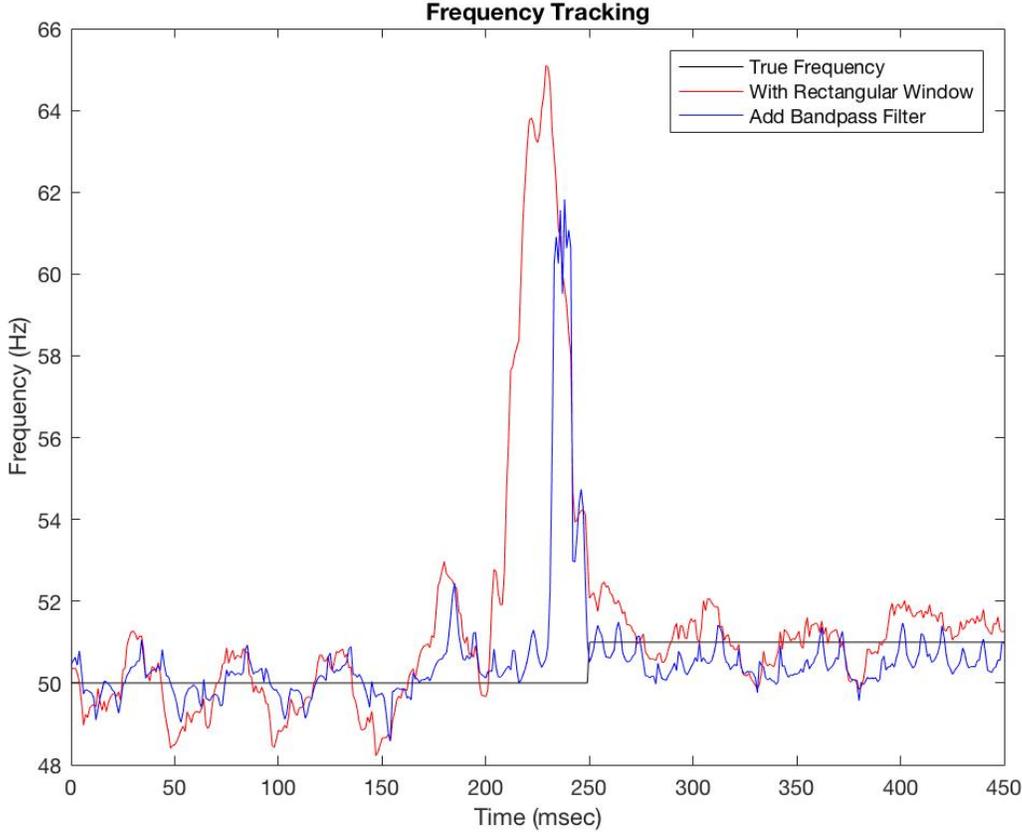


Figure 5.7: Step Change 50 Hz to 51 Hz

5.2.3 Summary

It is an exploration of applying the estimator of the A&M algorithm on frequency tracking. From the simulation results, we can see that this method does not have satisfactory tracking ability. The accuracy is not high.

5.3 Proposed Method

Similarly, the simulations are carried out for single-phase power system signal with white Gaussian noise (equation(2.1)) by using Matlab programming. In order to keep consistency, the sampling frequency (f_s) used for this method is 1 kHz and the white noise in the signal is with SNR 57 dB. The size of the block N is 50.

5.3.1 Steady State

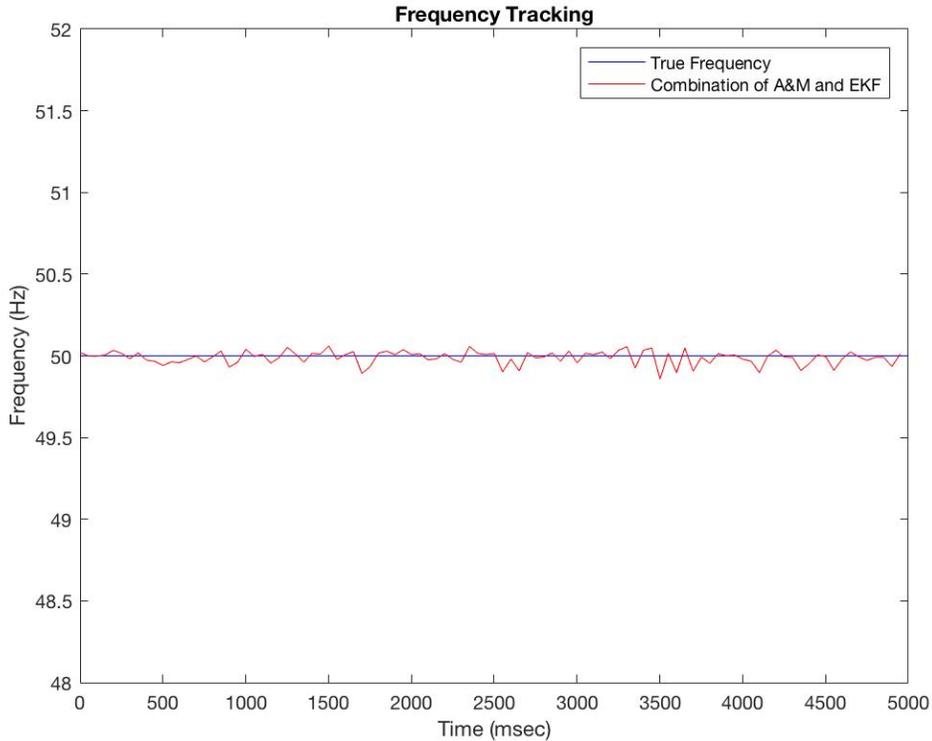


Figure 5.8: Simulation Result of Proposed Algorithm

The simulations are conducted with the constant frequency of 50 Hz in the signal Model. Figure 5.8 illustrates the tracking performance of the proposed method. The tracking trace oscillates around 50 Hz and the maximum deviation from 50 Hz is about 0.2 Hz . The accuracy is improved a lot compare to the combination method of window function and the A&M, but still worse than the EKF. However, the computation cost is highly decreased compare to the EKF. This is a trade off between the accuracy and the computation cost.

5.3.2 Step Change on Frequency

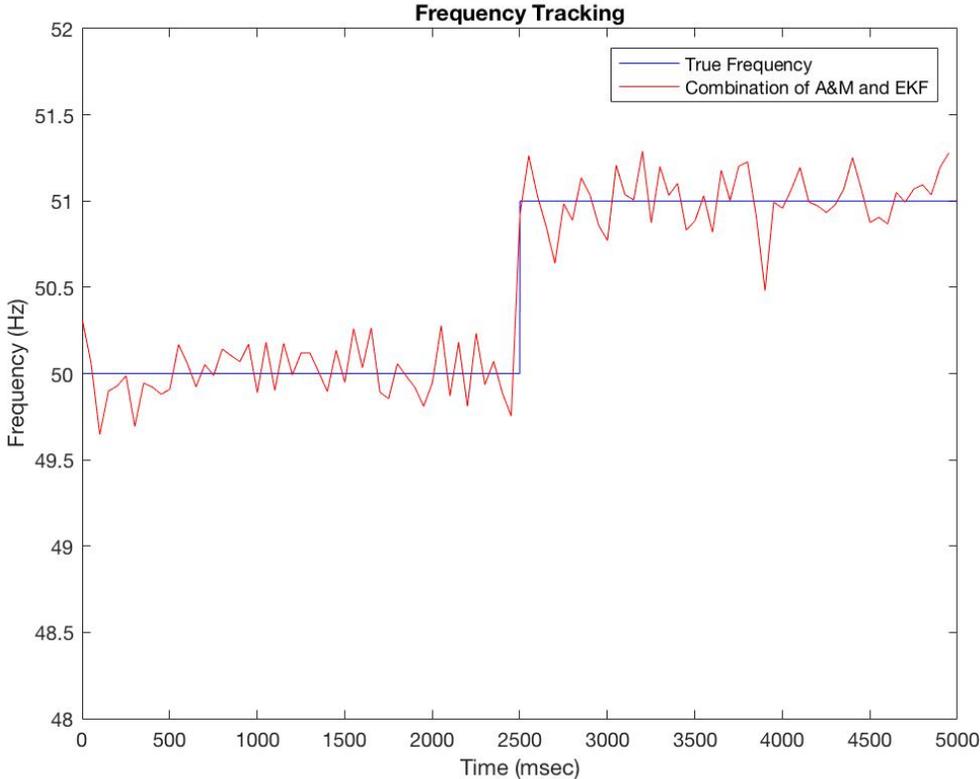


Figure 5.9: Step Change 50 Hz to 51 Hz

Figure 5.9 presents the tracking performance of the proposed method with step change on frequency. From the graph, there is no overshoot when the frequency is suddenly increased. This is good since the overshoot is usually not desirable in tracking process. It also performs satisfied accuracy during tracking, the maximum deviation from the original frequency is about 0.5 Hz.

5.3.3 Summary

The proposed method has satisfactory accuracy and no overshoots. It also requires low computation cost. The proposed method has good tracking ability.

5.4 Analysis of Computational Cost

An analysis of the computation cost of the modified EKF and the proposed method will be presented here. In order to compare the computation costs of the two techniques, parameters used in the algorithms must be set equally. The total sample time interval is chose as 1 second, and the sampling frequency is set as 1 kHz.

For the EKF, with 1 kHz sampling frequency, it runs 1000 times in 1 second. In the EKF, it consumes a large amount of computational resources, which is $O(k^{2.4} + n^2)$ [12].

For the proposed method, the EKF is applied on a down-sampled rate of $\frac{f_s}{N}$, where N is the size of each block. So, with $f_s = 1$ kHz and $N = 50$, the EKF is sampled at a rate of 20 Hz. Therefore the EKF runs 20 times in 1 second. There are iterations for the A&M algorithm for each block in the signal. The numbers of iteration was set to 4 during the simulation. There are 20 blocks with $f_s = 1$ kHz and $N = 50$, so the A&M algorithm runs $4 \times 20 = 80$ times in 1 second. Since the A&M algorithm is based on FFT, the computational complexity of the A&M is $O(N \log_2 N)$ [10].

A comparison of the computational complexity of two methods is demonstrated in Table 5.2. Since the proposed method has much less numbers of runs and the A&M algorithm ($O(N \log_2 N)$) is less complex than the EKF ($O(k^{2.4} + n^2)$), the proposed method requires much less computational cost than the EKF.

Method	Computational Complexity
The Modified EKF	1000 runs of EKF
The Proposed Method	20 runs of EKF and 80 runs of the A&M

Table 5.2: Comparison of Computational Complexity

5.5 Summary

The simulation results and the analysis of computational cost of the three tracking methods are presented. It is known that the modified EKF technique has short convergence time and excellent accuracy, however it consumes a lot of computational resources during running. The combination method of the window function and the A&M has worst accuracy among the three algorithms. It is not suitable for tracking. At last, the proposed method has very low computational cost comparing to the modified EKF technique. Although the accuracy is a little worse than the modified EKF, it requires much less computations. It is a trade off between the accuracy and computational cost. Another advantage of the proposed method is there is no overshoot during tracking.

Chapter 6

Conclusion

6.1 Conclusion

This report describes the importance of frequency in the power system and provides the necessity of frequency tracking in the smart grid. The author implements and evaluates two existing frequency tracking methods. And based on the implementations and literature review, a new technique of a combination of the modified EKF and the interpolation algorithm created by Aboutanios and Mulgrew (the A&M) is proposed. The proposed method can be applied on a real single-phase sinusoid with white Gaussian noise, which is suitable for fast tracking in power system. The existing technique of the modified EKF has outstanding accuracy during tracking, however, the high computational cost of this algorithm will reduce the efficiency of the filter. The combination method of the window function and the A&M demonstrates a poor tracking performance. But it provides great help and foundation for the proposed method. The proposed algorithm has low computational cost and satisfactory accuracy. Also, there is no overshoot during tracking. Therefore, the proposed method is a good tracker and is suitable for real-time application.

6.2 Future Work

1. Because of the lack of time, it is unfortunate that the Root-Mean-Square Error analysis has not been finished. Thus, the first future plan is to finish the RMSE calculations for the algorithms.
2. Although the accuracy of the proposed method is satisfactory, there is still space for improvement. So the second plan is to improve the accuracy of the proposed technique.
3. In the power system, the distortion is not only noises, there are also harmonic distortions. The ability of a tracking technique working in the presence of harmonics is also important. Third plan is to implement the proposed algorithm under noise and harmonics environment.

Bibliography

- [1] Paulo Márcio Ribeiro Augusto Santiago Cerqueira Paulo Fernando Ribeiro, Carlos Augusto Duque. *Power Systems Signal Processing for Smart Grids*. John Wiley and SonsLtd, 2014.
- [2] Spark Y Xue and Simon X Yang. Accurate and fast frequency tracking for power system signals. In *2007 IEEE International Conference on Systems, Man and Cybernetics*, pages 2754–2759. IEEE, 2007.
- [3] AEMO. Fact sheet: Frequency control. online, <https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Security-and-reliability/-/media/80004354B88B4FEF96EAB673DDC99820.ashx>.
- [4] M Akke. Frequency estimation by demodulation of no complex signals. *IEEE Power Engineering Review*, 17(1):43–43, 1997.
- [5] Qipeng Liu. Refined algorithm for frequency estimation of a real sinusoid in smart grid. Thesis B Report.
- [6] Miroslav M Begovic, Petar M Djuric, Sean Dunlap, and Arun G Phadke. Frequency tracking in power networks in the presence of harmonics. *IEEE Transactions on Power Delivery*, 8(2):480–486, 1993.
- [7] Hamid Moradkhani, Soroosh Sorooshian, Hoshin V Gupta, and Paul R Houser. Dual state–parameter estimation of hydrological models using ensemble kalman filter. *Advances in Water Resources*, 28(2):135–147, 2005.

- [8] Cengiz Polat Uzunoglu, Serap Cekli, and Mukden Ugur. Adaptive frequency estimation of distorted power system signals using modified extended kalman filter. *Gazi University Journal of Science*, 24(1):85–89, 2011.
- [9] Peter F Driessen. Dpll bit synchronizer with rapid acquisition using adaptive kalman filtering techniques. *IEEE Transactions on Communications*, 42(9):2673–2675, 1994.
- [10] Shanglin Ye, Donna L Kocherry, and Elias Aboutanios. A novel algorithm for the estimation of the parameters of a real sinusoid in noise. In *Signal Processing Conference (EUSIPCO), 2015 23rd European*, pages 2271–2275. IEEE, 2015.
- [11] Curtis Roads. *Microsound*. Number ISBN 0-262-18215-7. MIT Press, 2002.
- [12] Cyrill Stachniss. Summary on the kalman filter and friends: Kf, ekf, ukf, eif, seif. online, <http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam08-kf-wrapup.pdf>.