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Rapid Detection Of Modal Deterioration In Large Interconnected Power Systems: A Systematic Review Of Advanced Monitoring Techniques

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***Abstract*—The occurrence of system disturbance is a major problem in a large interconnected power system with the consequence of creating an intra-area oscillating modes. These modes which are basically decaying sinusoids are also termed as the transient responses of the power system network to excitation. Proper and immediate identification of any dangerous oscillating mode occasioned by disturbances such as equipment failure would ensure both security and stability of interconnected power system. Consequently, the power utility must then deploy the correct damping control methods. Both rapid detection of critical and significant changes due to the breakdown of equipment and the estimation of modal parameters for an interconnected power system networks, which is observed to be in a stable and normal operation are basically the two major areas of focus as far as power system monitoring is concerned. This article presents a comprehensive review of advanced monitoring methods for quickly detecting modal deterioration, with a focus on short-time frame detection. We discuss various techniques, including energy-based detectors (EBD), Kalman innovation detectors (KID) and optimal individual mode detectors (OIMD), and highlight their strengths and limitations. The review aims to provide a valuable resource for researchers and engineers working on power system monitoring and control. The practical applications of this research include; improved system reliability, reduced risk of catastrophic failures and enhancement of overall grid resilience.**

Keywords: Interconnected Power Systems; Optimal Detection Strategy; Rapid detection of modal deterioration, Power System Monitoring; Power System Stability.

1. INTRODUCTION

Large interconnected power distribution networks, occasioned by global evolution of the economy of the electrical utility industry, has resulted in particular emphasis being laid on reliable and secure operations [1]. To facilitate security and reliability of operations, wide-area observation and control are needed in large interconnected power systems. Several wide-area monitoring strategies have been established in order to meet up with these requirements [2],[3]. Within the distribution network, the power system can be monitored at various locations. This is one of the key strategies including employing Global Positioning System (GPS) which can be used to synchronize the acquired information [4].

Modal analysis being a mathematical tool is deployed in power system to carefully study small signal stability and inter-area oscillations. It highlights a clear technical solution used to attenuate inter-area oscillations and how such solution can be applied to a specific scenario. It equally determines the critical and precise network parameters that should to be known in order to adequately diagnose any eventual inter-area oscillation [5]. Monitoring the situation and condition of power system stability is very critical for power distribution network with particular emphasis on inter-area oscillations whereby this stability, to a large extent depends on all inter-area oscillations being positively damped. These are oscillations that correspond to transient power flows among plants within a specific area in the large interconnected power system [6]. Monitoring and control of these oscillations is very critical and has particularly proven to be challenging compared with monitoring and control of oscillations associated with a single generator [6].

Inter-area oscillation appears when generators on one side of the connection line starts to oscillate against generators on the other side resulting in periodic electric power transfer along the line. They are observed in large power systems connected by weak tie lines though can affect smaller systems too [5]. In the transient ability of the system to stabilize post disturbance, it is the “ring-down” time of the damping factor that is of consequence. Therefore, to minimize power flows between the generation clusters and reduce the associated stresses within the generation and transmission infrastructure, it is important that the transient time is stable and quick. As a consequence, there has been much work done regarding estimation of damping factor in large distributed power systems. Existing research works have deployed Eigen analysis [7] as well as Prony’s analysis [8]. For proper and accurate estimation of damping factor, a large amount of relevant data is needed [8]. Therefore, conventional damping factor estimation techniques are not suitable for rapidly detecting sudden changes in modal damping. This work addresses these drawbacks by explaining a number of new monitoring methods which can provide signs of detrimental modal parameter change with very short data records in minutes.

2. EXISTING MODAL ESTIMATION METHODS

Traditional modal estimation strategies are techniques which focus on accurately estimating modal parameters (frequency damping and mode shape) under steady state conditions. Power systems have become large and interconnected with some complexities thereby affecting the efficiency of the system in terms of vulnerability to system instability. This challenge has made it a necessity to perform reliable detection of system disturbances from modal oscillation data records, whether it is those from single isolated disturbance or continuous random disturbances.

2.1 Eigen analysis of Disturbance Modes

Eigen Analysis is a technique of decomposing a system into its fundamental modes of oscillation. It provides information on mode shapes, frequency, system dynamics and it is used to analyze overall system behavior [9]. In carrying out Eigen analysis of a power system, a system matrix is formed and the QR algorithm is deployed to compute the eigenvalues of the matrix [9],[10]. Thereafter, relevant parameters of the modal oscillation can be determined from the eigenvalues. This strategy has proven to be very reliable and has been adopted globally by different power utilities. Sadly, this method is not best fitted for large interconnected power systems, which is the reason for its various modifications by researchers. Uchida and Nagao made modification in eigen analysis by proposing the use of the “S matrix method”[7]. In this method, it is assumed that the dynamics of power systems can be linearly approximated with a set of differential equations of the form, x = Ax, where x is the vector state of the system and A is the system matrix. Byerly *et al*. equally developed the best-known algorithm called; Analysis of Essentially Spontaneous Oscillations in Power Systems (AESOPS). The advantage of the algorithm is that it does not require the explicit formation of the system state matrix [11]. The challenge of the AESOPS effort is the deficiency it has in analyzing very large interconnected systems.

2.2 Prony’s Method of Spectral Analysis

Exponentially damped sinusoids in a signal can have its parameters estimated by deploying Prony’s method. Also, it can be used to analyze power system oscillations such as those caused by faults and disturbances [10][12]. Though, it was delayed until the advent of digital computer, this method originated in an earlier century with the capacity to be practically implemented.

Researches on the use of this technique for oscillation modal parameter estimation have been conducted [13], with many providing deep insights into the concept. Ideally, the effectiveness of Prony’s technique is only guaranteed whenever the noise power is negligible. Gomez Martin and Carrion Perez introduced some extensions in working with noisy data with the application of Prony’s method. This was done by using a moving window in both forward and backward directions [14]. This position was further collaborated by Kannan and Kundu [15].

2.3 The Sliding Window derivation

Basically, the method used the rate of deterioration of the Fourier transform as a rectangular window slides to determine the damping factor of the mode [16]. The result showed good correlation compared to conventional techniques. However, the limitation was the restrictions on the length of the window that could be used. Such restriction was necessary to avoid errors occasioned by the interference from the superposition of the positive and negative frequency components [16],[17]. This interference was formulated by the large side lobes of the spectral *sinc* function introduced by the rectangular windowing. In line with the research, the window lengths only had certain discrete values, at which the interference turned out to be zero. The challenge was that the window length was dependent upon the modal frequency. Therefore, this frequency had to be correctly and initially estimated before implementation of windowing.

2.4 Auto-correlation Techniques

Since the auto-correlation function of a system triggered by white noise reveals the impulse response of that system, then obviously the auto-correlation function of the differentiated power system disturbance output should be the impulse response of the power system. This means that it will take the form of a sum of complex exponentials, then the modal parameters can be determined using Prony analysis [18].

Auto-correlation techniques were further examined by [10] through modeling disturbances using noise to depict customer’s load variations and an impulse to connote a disturbance thereby determining resonant frequencies and mode shape. The simulation results though provided concrete relationships to a known system’s eigenvalue, mode shape and resonant frequencies, it did not make any reference to the several drawbacks of mode spacing [10].

2.5 Kalman Filter Innovation Techniques

This strategy is a very critical and optimal linear estimator; which has been used severally in different areas such as; state and parameter estimation, stochastic models etc. There are many variations of Kalman filter for non-linear systems including unscented and extended Kalman filters. In this review, emphasis is on the Kalman filter innovation which is defined as the difference between the measured output and the estimated output. Provided the assumed model parameters are valid, it is well known that the innovation from a Kalman filter is spectrally white. But under fault conditions, the innovation sequence should demonstrate large systematic trends since the model will no longer connote the physical system [10]. A number of Kalman filter innovation methods designed for the detection of system fault, diagnosis of dynamic systems and estimation of least square are discussed in [19],[20]. This review describes how the Kalman filter model can be used to estimate the system output. Sudden adverse changes in the model parameters can be detected by monitoring the whiteness of the innovation else the innovation sequence is equivalent to the initial excitation under normal plant conditions [10].

2.6 Polynomial Phase Estimation Strategies

To have an insight into the frequency and phase trajectory of a component or mode that conforms to a polynomial model, it is quite important that the polynomial phase coefficients be determined. Through the direct Maximum Likelihood method, a solution to the problem can be achieved by obtaining estimates of these parameters. But, as discussed in [10], the implementation of this strategy is very cumbersome and difficult since it requires a P-dimensional search. As a way of overcoming this challenge, various authors have designed other methods of solving this problem [10], [21]. These strategies deploy multi-linear transforms with the capacity to reduce the search requirements from a P-dimensional search to a more computationally efficient P-one-dimensional search.

2.7 Conclusion on Existing Modal Estimation Methods

Even with the progress made so far regarding modal parameter estimation techniques, the reality which many authors have established is that there is no individual technique that can capture all the unique scenarios that arise in practice. Each strategy has its own merits and applications, and provides a different situation and view into dynamic system behaviour. With recent and rapid advancement in technology regarding power systems, the need to consistently improve algorithms of oscillation modal estimation is very critical. Reliable detection of sudden changes in modal oscillations is also quite important so much so that damaging failures can be totally prevented. To date, research on optimal procedures for such detection has been modest. In addition to these traditional strategies, recent research has focused on rapid detection techniques as discussed in subsequent sections.

3. RAPID DETECTION OF MODAL DAMPING DETERIORATION

This modern strategy focuses on quickly detecting changes in modal damping due to structural degradation and uses machine learning or signal processing techniques to analyze real-time data with emphasis on speed and adaptability [5][10]. A long data record of an hour or more of data is required to produce accurate estimates when adopting standard modal parameter estimation methods. If there is a sudden and seriously problematic change of damping, this is obviously a long time to wait. Unlike accurate estimation of the modes which requires long time scales, detection of sudden deterioration from a familiar quiescent point can be carried out in much shorter time scales, for instance, a minute. It is important to note that sudden changes in system modes can be easily detected through energy changes. However, to be able to make an important decision on the possibility of any change occurring, a statistical characterization of the quiescent system energy must be well established. Immediately the statistical characterization has been formulated, the benchmark or thresholds for rapid detection of modal deterioration may be set in a manner as to provide an alarm bench mark with an established confidence level.

Rapid detection of deteriorating modal damping carefully examines the energy of the systems signs in its entirety. It provides a simple method to identify rapid modal deterioration within a system. In single mode system, any subsequently detected deterioration naturally represents the mode deterioration. This is opposed to a multi-mode system, where information that there had been a damping deterioration would be provided though, without mode identification [10].

3.1 The Power System Model in the Quiescent State

In formulating energy characterization of the power system, there is dare need to fully understand system behavior. In [18],[22], the power systems are assumed to be in normal operation and therefore excited by multiple quasi-continuous random disturbances. Such disturbances are triggered by load changes. Once excited, each of the disturbances is then damped according to the modal resonances of the power system. This kind of situation can be modelled with a single continuous random background noise exciting a filter whose resonances are characteristic of the power system [18].

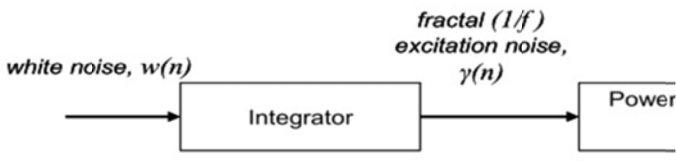


Fig. 1. Model for quasi-continuous modal disturbances in a power system

The model in Fig 1 can assist in the formulation of an equivalent model as shown in Fig 2. Now, if the output of the power system is differentiated as indicated in figure Fig 2, the resulting signal, *y(n)*, can be considered to have been obtained from a white noise based excitation of the power system filter, *h(n).* It is important that the measured output, *x(n),* be taken as the angle of the generator cluster at the measurement point, with respect to the steady state (i.e.*50Hz/60Hz*) angle. The measurement point to extract the angle of the generator cluster is obtained according to the procedure in [4]. With the power system model properly established, a statistical characterization of the system energy will be formulated in the following section.

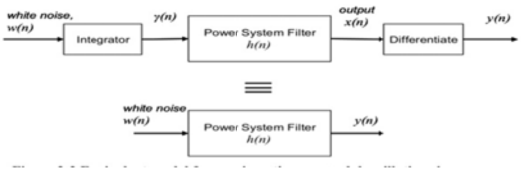


Fig. 2. Equivalent model for quasi-continuous modal oscillations in power system

3.2 Statistical Characterization of the System Energy

The knowledge of the power system model established in [18] is used to generate a statistical system characterization. A formula is derived for a probability density function (PDF) of the energy y(n) under quasi-stationary operating conditions. The statistical characterization of the energy y(n) enables an accurate threshold to be set so alarms can be raised if the energy deviates significantly from these quasi-stationary operating conditions. The types of techniques described in [18], help to determine these operating conditions. Since the detection condition is for large detrimental change, then the False Alarm Rate (FAR) for detection is usually set fairly low, for instance 1% or lower. Such a low false alarm rate helps to facilitate the minimization of unwanted false alarms. Continuous and consistent monitoring of the system energy is necessary once an alarm has been triggered. Also, sequential data windows can be collected and a statistical analysis with respect to the PDF undertaken. It must be noted that corrective action by the power system utility would be induced due to repeated alarms occasioned by consistently high energy readings.

In developing the PDF for the energy in *y(n),* the model in fig. 2 must be taken in account, hence,

$$= \frac{N}{\sigma^2}\begin{bmatrix} \frac{1}{2}|H(0)|^{-2}e^{-xN\frac{1}{2}}|H(0)|^{-2}\sigma^{-2} \\ * \ |H(1)|^{-2}e^{-xN}|H(1)|^{-2}\sigma^{-2} \\ *.* \ |H(N/2)|^{-2}e^{-xN}|H(N/2)|^{-2}\sigma^{-2} \end{bmatrix} \quad (1)$$

Where * signifies convolution.

Establishing the 1% false alarm rate is obtained through the cumulative summation of the PDF area until the 99% point is determined. The result of the PDF can then be deployed for detection of change.

3.3 Method of Implementation

To be able to apply real data to the energy detection strategy, a long term estimator is required to provide an estimation of the quiescent modal values. First, the long term estimator establishes estimates for the system transfer function, so that an estimated impulse response can be determined. With this knowledge, an approximation of the variance of the excitation signal, w(n) in fig.1, can be estimated. Once the system transfer function, h(n), and the excitation variance □, have been estimated then the expected energy PDF can be formulated. This formulated PDF then enables a threshold to be set considering a suitable false alarm rate. This threshold can be adjusted based on the periodically updated long term estimate.

Differentiation of the power system output signal considering the model in fig. 2, is the foremost step in the process for simultaneously performing long term estimation, generating the energy estimate, setting threshold and alarming. The long term modal estimator used in this review is based on [10],[23] and applies a greater than one hour data window to the differentiated output signal, y(n), and generates a system transfer function in the Laplace domain. Both individual modes and an estimated impulse response can be determined through the application of the traditional inverse Laplace transform method of partial fraction expansion. Once an estimate of the transfer function is determined, an estimate of the excitation spectrum may be found according to:

$$\widehat{w}(k) = \frac{y(k)}{\hat{H}(k)} \quad (2)$$

Where y(k) and $\hat{H}(k)$ denote the DFTs of *y(n)* and *h(n)* respectively, evaluated at bin, k. Then the estimate of the excitation variance ie noise power is estimated as:

$$\sigma_w^2 = \frac{1}{N}\sum_{k=0}^{N-1}|w(k)|^2 \quad (3)$$

The two system characteristics, □□and *H* □k□ are then established and can be deployed to generate the required system PDF. A suitable threshold for alarm can be set with respect to a desired FAR once the system PDF is established.

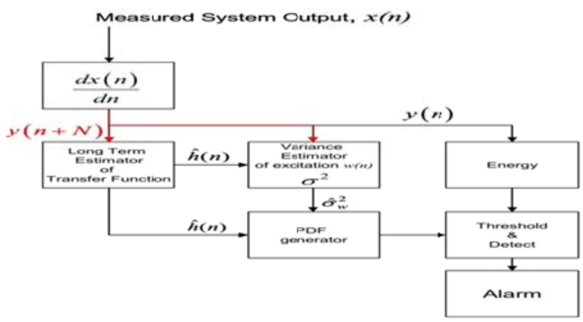


Fig. 3. Short Term Energy Detection

Data in red denotes past data used to formulate long term estimates

4. RAPID DETECTION OF CHANGES IN INDIVIDUAL MODES IN MULTI-MODAL POWER SYSTEMS

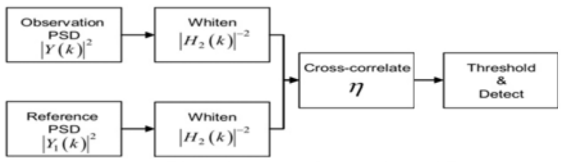
Rapid detection of changes in individual modes carefully monitors all modes to determine where critical adverse change is taking place in the power system. Whenever and wherever sudden deteriorating damping is experienced, rapid detection of deteriorating modal damping examines the energy of the system's signal in its entirety providing sufficient information in a single mode power system. However, in multi-modal power systems, it would be very necessary to highlight specifically which particular mode(s) may be experiencing detrimental damping conditions. This would help the power utilities to administer early corrective action in the correct manner. Because of the need to have more specific modal identification, this section introduces a new strategy for rapidly detecting individual modal deterioration in large interconnected multi-modal power systems. Any sudden detrimental change of an individual mode is detected using strategies derived from optimal detection theory. A statistical characterization of a mode's test statistic is used to establish reliable thresholds for detection of individual mode changes. To enable individual monitoring of modal damping conditions, the power system is again assumed to be excited by on-going random disturbances, corresponding to such things as load changes [18].

4.1 Stochastic Power System Model

From fig.1, once y(n) is obtained through differentiation of the measured output then the filter impulse response, h(n), can be estimated using long term estimators [18]. From the system impulse response, estimate of the power of the white noise excitation, w(n), may also be determined. A long term parametric estimator such as Prony's method [12], may be used to determine the filter impulse response, h (n) and its transfer function H (z), once it is assumed that the power system has been in a quasi-stationary operating environment for a long period of time (This assumption is necessary for the purpose this section). Subsequently, the individual modal contributions that combine to formulate H (z) may be determined using partial fraction analysis. Therefore, for any given mode i, the transfer function Hi (z) as well as the impulse response hi (n) can be determined.

4.2 Application of the Optimal Detection Strategy

To enable the detection of negative changes to individual modes, the theory of optimal detection of random signals is deployed. The implementation of the optimal detector is as follows: let the system impulse response, h (n), be considered to be the sum of h_1 (n) and h_2 (n), with h_1 (n) representing the mode of interest, and h_2(n) representing the sum of all the other modal components of h(n) . Then the output, y(n) is considered to have two components, y_1 (n) and y_2 (n) , with y_1 (n) being the output of the mode of interest and y_2(n) being the output due to the remaining modes. Defining the observed signal as y(n), and the reference signal as y_1(n), the procedure for the generation of the optimal detection statistic is depicted in Fig. 4 [10]. It involves the whitening of both the power spectral density (PSD) of the reference signal $|H_1\ (k)|^2$ and the PSD of the observed signal $|H_1\ (k)|^2$, followed by cross-correlating. The whitening filter transfer function is the inverse of the discrete Fourier transform of h_2 (n). N samples are assumed in the observation.



. Fig. 4. Generation of the optimal detection statistics

Setting the threshold for appropriate detection is quite important. First is to determine the Probability Density Function (PDF) of the cross correlated output. The availability of the PDF enables accurate thresholds to be set so that one can create alarms if the modal response deviates significantly from the normal operating conditions. Since the main focus of this section is the rapid detection of large detrimental modal change as opposed to monitoring minute changes, thresholds are typically set to yield False Alarm Rates (FARs) of 1% or less. In practical application, the monitoring process would ideally involve the application of the detection algorithm to all the modes individually and simultaneously. In other words, an n-mode power system would require n parallel detectors to monitor each mode. The computational overhead does not provide any serious barrier to monitoring all of the individual modes. This is because the detection algorithm can be implemented fairly rapidly. Once an alarm has been raised, it is important to consistently monitor the modes. A series of sequential data windows are collected and statistical comparisons are made with the stationary condition PDFs. Corrective action will be triggered regarding the deteriorating mode once readings are consistently high.

4.3 Statistical Details of Individual Mode Detection

In specifying the optimal detector for an individual mode, the following quantities are defined using discrete Fourier transformation, ζ:

$y(n) \Longrightarrow Y\ (k) = W(k)H\ (k)$ (4)

$h_1(n) \Rightarrow H_1(k)$ (5)

$h_2(n) \Rightarrow H_2(k)$ (6)

$y_1(n) \Rightarrow Y_1(k) = W\ (k)H_1\ (k)$ (7)

$y_2(n) \Rightarrow Y_2(k) = W\ (k)H_2\ (k)$ (8)

To detect a change in the mode of interest; choosing Y_1 (k) as the frequency domain reference signal, the remainder of the frequency domain observation, Y_2 (k), will becomes the interference signal. Therefore, in line with a standard optimal detection theory, a whitening filter is created to whiten the interference:

$$Hwh\ (k) = H_{2^{-1}}\ (k)\ (9)$$

Again, consistent with standard optimal detection theory, the whitening filter is applied to both the reference and observation signals. The corresponding PSDs are then determined as follows:

$$PSD_{obs}\ (k) = |\ X\ (k)|2|H_{wh}(k)|^2 = |W\ (k)|^2|H_{obs}(k)|2|H_{wh}(k)|^2\ (10)$$

$$PSD_{ref}\ (k) = \ |\ H_1(k)\ |^2|H_{wh}(k)|^2E\ \{|W\ (k)|^2\}\ (11)$$

Where E { } denotes the expected value.

Now cross-correlate (10) and (11) to obtain the detection statistic n shown in Figure 4:

$$n = \sum_{k=-N/2}^{N/2} PSD_{ref}\ (k)PSD_{obs}\ (k).\ (12)$$

To practically apply the detection statistic in the detection process, a threshold level must be determined. A probability density function (PDF) of the detection statistic is required to be able to accurately set the threshold based on the PDF at a desired level of confidence.

4.4 Statistical Characterization of the Detection Statistic η

The formulation of Mode 1 detection statistic PDF, being the mode of interest, is as follows: To derive the detection statistic PDF, (12) can be expanded using (10) and (11) to give:

$$n = \sum_{k=-N/2}^{N/2} E\{|W\ (k)|^2\}\ |H_1\ (k)|^2|H\ (k)|^2|H_{wh}(k)|^2|W\ (k)|^2\ (13)$$

Re-written as;

$$n = \sum_{k=-N/2}^{N/2} |Z(k)|^2|\ W\ (k)|^2\ (14)$$

Where Z (k) is defined as:

$$Z\ (k) = \ |H_1(k)||H\ (k)||H_{wh}\ (k)|^2\ \sqrt{E\{|W\ (k)|^2\}}.\ (15)$$

It must be noted clearly that the expression in (14) contains W(k) which is a complex Random Variable (RV) with real and imaginary parts. Furthermore, the squared magnitude of $|W (k)|^2$ is:

$$|W(k)|^2 = \ Real\ \{W\ (k)\}^2 + \ Imag\ \{W\ (k)\}^2\ (16)$$

Where Real { } and Imag{ } denote the real and imaginary parts respectively. It is assumed that the variance of w(n) is σ^2. Then W(k) is a complex Gaussian RV with variance, $\frac{\sigma 2}{N}$ [10]. Then the left hand side of (16) is a chi-squared RV with two degrees of freedom and variance, $\frac{\sigma 2}{N}$ [10]. That is, the PDF of any discrete "bin" in the W(k) power spectrum is:

$$f\{x\} = \frac{N}{\sigma 2}\ e^{\frac{-xN}{\sigma 2}}\ ,\ (17)$$

where x, is the random variable power.

Using (14) and (17), the PDF of $|Z\ (k)|^2\ |W\ (k)|^2$ at discrete ensemble frequency k can be deduced:

$$JZW_k(x) = \left|\frac{1}{|Z\ (k)|^2}\right|\ f.\langle\frac{x}{|Z\ (k)|}\rangle = \frac{N}{|Z\ (k)|^2\ \sigma^{2^e}}\frac{-xN}{|Z(k)|^2\sigma^2}\ (18)$$

From (14), it is apparent that the detection statistic is obtained by summing N random variables (RVs). Only half of these random variables are independent, because the negative frequency half, of the spectrum contains the same information as the positive frequency half. Since one side of the spectrum contains all the information necessary, then the PDF of the detection statistic is formulated from only one half of the spectrum. Now, the detection statistic in (12) is reformulated and redefined as (19):

$$n\ \sum_{k=1}^{\frac{N}{2}} PSD_{ref}\ (k)PSD_{obs}(k) + \frac{1}{2}\ PSD_{ref}\ (0)PSD_{obs}\ (0).\ (19)$$

Because (19) indicates that the threshold is the sum of N/2 +1 independent random variables, its PDF can be computed by convolving the PDFs, the N /2 +1 individual random variables. Consequently and the PDF of the detection statistic for the mode of interest is given by:

$$fn\ (zw) = fzw_{N/2}\left(zw_{\frac{N}{2}}\right) * \ fzw_{\frac{N}{2}-1}\left(zw_{\frac{N}{2}-1}\right) * \frac{1}{2}\ fzw_0\ (zw0).\ (20)$$

Expanding the above gives the PDF of the test statistic for the mode of interest - Mode 1 as:

$$f_n(zw) = \frac{N}{\sigma^2}\begin{bmatrix} \frac{1}{2}|Z(0)|^{-2}e^{-x\frac{N}{2}z(0)^{-2}\sigma^{-2}} \\ * \ |Z(1)|^{-2}e^{-x\frac{N}{2}z(1)^{-2}\sigma^{-2}} \\ * \ |Z(2)|^{-2}e^{-x\frac{N}{2}z(2)^{-2}\sigma^{-2}} \\ * \ |Z(N/2)|^{-2}e^{-x\frac{N}{2}z(N/2)^{-2}\sigma^{-2}} \end{bmatrix} (21)$$

Where * denotes convolution. From the PDF in (21), the threshold for detection of change can be formulated. To establish the 1% false alarm rate, the cumulative summation of the PDF area is taken until the 99% point is determined.

4.5 Method of Implementation

Initial estimates of the quasi-stationary system parameters are required to assist modal characterization. That is, a long term estimator (LTE) is applied to a relatively long record, for instance one hour of quasi-stationary data. Under normal operating conditions, while the modal deterioration algorithm is applied continuously, the estimates are updated once every half an hour. The long term estimator technique under review is outlined in [10], and provides estimates of the measurement site transfer functions and modal parameters. From this, the individual modal response estimates at any selected site can be extracted. In this application, since the variance of the noise feed is unknown, the detector PDFs are initially formulated with the noise variance in (21) set to unity. To correctly de-normalize the PDF, a rescaling factor is necessary. The rescaling factor can be obtained by simply taking K short-term, N length test statistic measurements over the M length long-term analysis window and finding the mean value (where K = M/N). Once re-scaling is performed and the threshold is established, the detection process begins on all concurrent short term measurements until another threshold update corresponding to an update set of quasi-stationary conditions is instigated at a later time.

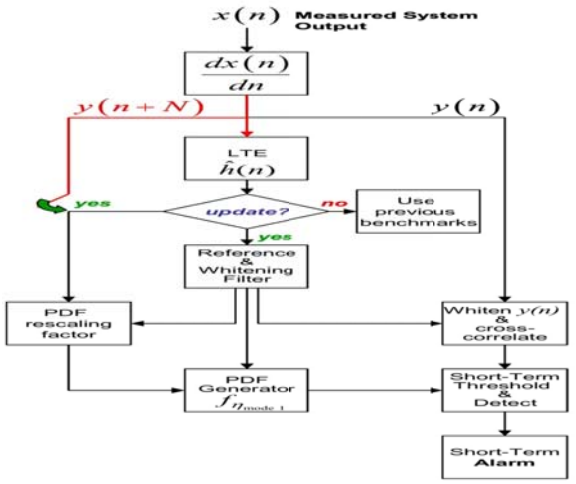


Fig. 5. Short Term Modal Detection Applied to Real Data.

Finally, the method analyzed in this section, can provide short term alarming of individual modal deterioration in large interconnected power systems. The alarming can be set to a desired level of confidence whereby false alarms occur within expected theoretical rates when the system is under quasi-stationary conditions. In specific terms, this technique aimed at alarming large negative changes in modal damping rather than monitoring small drifts in damping values. The ability of the optimal detector is however limited by the relative strength of the modes but this limitation needs to be put into perspective. First, the stronger modes are what dominate the system response, and so the inability of the optimal detector to work well with very weak modes is not of paramount concern. To ratify alarms for weaker modes, longer time windows can be used in parallel with shorter time windows and a dynamic alarm response strategy can be designed.

5. RAPIDLY DETECTING MODAL CHANGES USING KALMAN FILTERING APPROACH

Again, conventional damping factor estimation techniques are limited by the requirements of long data records. Even though these estimation techniques provide accurate and reliable means to monitor power systems under normal operating conditions, they do not accommodate the need for rapidly detecting sudden modal damping changes that may be harmful to power system reliability and stability. To address this shortcoming, this section seeks to present another method which is able to provide indications of modal parameter change based on short data records. Consequently, a Kalman filter is then set up to estimate the output arising from the disturbances. The innovation is then determined as the difference between the measured output and the estimated output. Provided the assumed model parameters are valid, it is very clear that the innovation from a Kalman filter is spectrally white [10]. One can then detect if there are changes in these parameters through continuous monitoring of the whiteness of the innovation [10].

5.1 Stochastic Power System Model

Using [18] as the initial point of reference for the power system model, the power system itself is modelled as an IIR filter so that the power system response to disturbances can be modelled as the output of an IIR filter driven by integrated white noise. The measured power system output such as power and angle at site i is differentiated to provide the signal $y_i(n)$. As illustrated in Fig. 6, this is the signal that would have been obtained if the white noise, w(n), had excited the power system. Therefore, the power system model deployed in this section is the single measurement site, single excitation model.

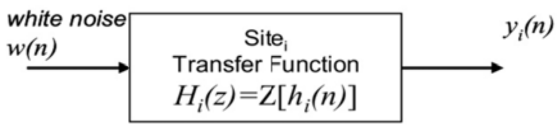


Fig. 6. Equivalent model for the individual response of a power system to load changes

It is important to consider that the IIR power system filter is the plant. Based on standard Kalman estimator, the general Kalman estimator for a plant driven by a control signal, u(n), perturbed with white noise, w(n), with multi-dimensional output measurements, y(n), corrupted by measurement noise, v(n), is depicted in Fig.7 [10].

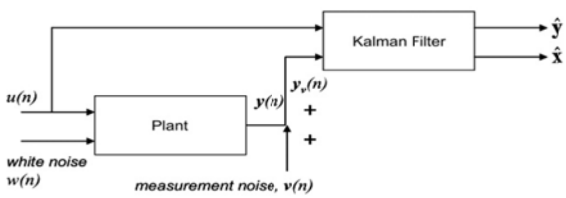


Fig. 7. General Kalman filter estimator

From the application, the control signal, u(n), is zero and the plant is only excited by the white noise, w(n). Generally, the output of the Kalman filter provides estimates of the plant output, y(n) and of the states, x(n). The plant represents a large interconnected power system and the current measured from plant output, y(n), corresponds to a vector of measurements from multiple recording sites. In real life scenario, the measurements are voltage angle measurements rather than power measurements because the potential for modal information extraction is greater for voltage signals than for power signals [18]. The optimal placement of these measurement sites within a large distributed power system is discussed in [4]. The vector v(n) represents noise measurements from each selected site. In a practical application, the plant output measurement vector, y(n) can be recorded at a GPS synchronized wide area monitoring centre [4].

If there is a sudden change in the power system response, the spectrum of the innovation will highlight this change with a peak around the modal frequency in question. Conversely, in a power system operating under stationary conditions, the innovation will be white and will have a flat Power Spectral Density (PSD). Therefore, with a suitable threshold set, large undesirable damping changes can be readily detected. A suitable threshold is one which is set to give a False Alarm Rate (FAR). For instance, if the FAR is set to 1% then when an alarm occurs, one knows that it is a genuine alarm with 99% confidence. The purpose of this method is to detect sudden large detrimental changes and not to detect small changes in system parameters [10]. Consequently, while still providing the required rapid alarming of sudden system deterioration, thresholds should be set to minimize false alarm. The innovation is said to detect a frequency shift instead of a damping change whenever the innovation's PSD display a peak around the new modal frequency and a trough around the original modal frequency.

5.2 Kalman Application in Power System Analysis

5.2.1 Kalman formulation in Power System

In the power system model under review, the state and output equations are as follows:

X(n+1) = A*x(n)* + G*w (n) (22)*

$Y_v(n)$ = C*x(n)* +D*w(n)* +*v(n)* (23)

Where, A, G, C and D denote the usual state and output equation matrices [10]. The noise processes, w(n) and v(n), are zero mean Gaussian white noise sequences with co-variances given by the following equations:

$E\{w(n)w(n)^T\} = Q$ *(24)*

$E\{v(n)v(n)^T\} = R$ *(25)*

$E\{w(n)v(n)^T\} = N$ (26)

Where E(.) denotes expected value. Two assumptions are important, first; will be that w(n) and v(n) are uncorrelated and that the plant is excited by a common white noise source, w(n). However, the plant response to such excitation is measured at various geographic locations. The measurement noise, v(n), is a vector that is congruent to the wide-area monitoring of inter-area oscillations. The load variations become close to Gaussian when there are large number of independent customer loads [18],[24]. In normal stationary operation, the optimal Kalman state estimator is given by the following set of discrete equations [20]:

$\hat{x}(n+1/n)$ = A$\hat{x}$ (n/n) + G*w(n)* (27)

$\hat{x}(n/n)$ = $\hat{x}(n/n-1) + My(k)$ (28)

$\hat{y}(n) = C\hat{x}(n/n-1)$ (29)

Y(n) = y_v (n) - $\hat{y}$(n) (30)

Where y(n) is the white zero mean Gaussian "innovation" sequence with units rad/sec. The gain matrix, M, is calculated from the following equations:

P (n+$1/n) = AP\ (n/n)A + Q$ (31)

V = CP $(n/n-1)C'$+R (32)

M = P $(n/n-1)C^TV^{-1}$ (33)

P (n/n) = P $(n/n-1) - MCP\ (n/n-1)$ (34)

Where P (i/j) is the estimation error co-variance of the state estimates vector, $\hat{x}$(i/j), and v is the co-variance of the innovation vector, y(n). The gain matrix, M, is derived by solving the discrete time Ricatti equation [10],[25],[26].

5.2.2 State space representation of the power system model

To effectively generate the matrices A, G, C and D for the power system model in Fig. 6, the transfer function of h(n) is first identified. This enables proper formulation of the state space matrices into controllable canonical form. To illustrate the process, a power system example comprising a two mode system with single site measurement and disturbance is considered. The impulse response at the site is assumed to be:

h(t) = $h_1(t)$ +$h_2(t)$ (35)

Where

$h_i(t)$ =$A_ie^{-\sigma_it}$ sin(ω_it) i = 1, 2. (36)

σ_i is the modal damping, , ω_i is the modal frequency and A_i is the magnitude respectively of the i^{th} mode. Taking the Laplace transform of (35) yields the continuous time power system transfer function.

H(s) = $\frac{A_1\omega_1}{(s+\sigma_1)^2+\omega_1^2} + \frac{A_2\omega_2}{(s+\sigma_2)^2+\omega_2^2}$ (37)

If the sampling period is T, then the discrete time transfer function for the site is; H(z) = $\frac{A_1ze^{-\sigma_1t}\sin(\omega_1T)z^{-1}}{1-2e^{-\sigma_1t}\cos(\omega_1T)z^{-1}+e^{-2\sigma_iT}Z^{-2}}$ + $\frac{A_2ze^{-\sigma_2t}\sin(\omega_2T)z^{-1}}{1-2e^{-\sigma_2t}\cos(\omega_2T)z^{-1}+e^{-2\sigma_2T}Z^{-2}}$

$= \frac{b_1 z^{-1} + b_2 z^{-2} + b_3 z^{-3}}{1 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3} + a_4 z^{-4}}$ (38)

Where the coefficients, $\{b_1, b_2, b_3, a_1, a_2, a_3, a_4\}$ are given by:

$b_1 = A_1 z e^{-\sigma_1 t} \sin(\omega_1 T) + A_2 z e^{-\sigma_1 t} \sin(\omega_1 T)$ (39)

$b_2 = -2e^{-T(\sigma_1+\sigma_2)}(A_1 \sin(\omega_1 T) \cos(\omega_2 T) + A_2 \sin(\omega_2 T)\, cos\omega_1 T))$ (40)

$b_3 = (A_1 e^{-T(\sigma_1+\sigma_2)} \sin(\omega_1 T)\, A_2 e^{-T(\sigma_1+\sigma_2)} \sin(\omega_2 T))$ (41)

$a_1 = -2(e^{-\sigma_1 T} \operatorname{Cos}(\omega_1 T) + e^{-\sigma_2 T} \operatorname{Cos}(\omega_2 T))$ (42)

$a_2 = e^{-2\sigma_2 T} + 4e^{-T(\sigma_1+\sigma_2)} \operatorname{Cos}(\omega_1 T) \operatorname{Cos}(\omega_2 T) + e^{-2\sigma_1 T}$ (43)

a_3 = -2$(e^{-T(\sigma_1+2\sigma_2)} \operatorname{Cos}(\omega_1 T) e^{-T(2\sigma_1+2\sigma_2)} \operatorname{Cos}(\omega_2 T))$ (44)

$a_4 = e^{-2T(\sigma_1+\sigma_2)}$ (45)

The state space matrices in controllable canonical form can be determined from the transfer function [27]:

$$A = \begin{bmatrix} -a_1 & -a_2 & -a_3 & -a_4 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad (46)$$

$$G = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (47)$$

C = $[b_1 \quad b_2 \quad b_3 \quad 0]$ (48)

D = [0] (49)

5.2.3 Kalman Solution

With the discrete state space plant defined in (46)-(49), the Kalman solution depicted in Fig. 7, can be realized. Accordingly, the Kalman estimator equations, (27) - (30) are evaluated and then the normalized innovation is defined:

$Y_n(n) = K\, \gamma(n)$, (50)

The gain K which normalizes the innovation to unity variance is known as normalization again. The normalization gain can be defined as the square root of the inverse power of the innovation window. If the normalized innovation sequence results from a significantly different system than the one considered, then the concentration of spectral energy around the mode of significant change will still demonstrate a strong threshold crossing. Kalman analysis operates, if the the power system model and noise data satisfy the drawbacks outlined in [10],[28],[29]. This means that the plant and noise data must satisfy conditions and relationships such as; detection of plant transfer function state space matrices, (51), measurement noise variance must be zero (52), left hand side of (53) must be non-zero and matrix defined by the left hand side of (54) must have no uncontrollable modes on the unit circle [10].

(C, A), (51)

$\bar{R} > 0$, (52)

$\bar{Q} - \bar{N}\overline{R^{-1}} - 1\bar{N}T \geq 0$, (53)

$(A - \bar{N}\overline{R^{-1}}C, Q - \bar{N}\overline{R^{-1}}\, N^T)$ (54)

where [21];

$\bar{Q} = GQG^T$ (55)

$\bar{R} = R + DN + N^T D^T + DQD^T$,(56)

$\bar{N} = G(QD^T + N)$ (57)

5.2.4 Detection using the Innovation

Under stationary operating conditions, the normalized innovation defined in (50) is white and Gaussian [10], with zero mean and unity variance thereby causing the power spectral density of the innovation to be flat. It is important to assume that the observation window has N samples and that the sampled PSD is found by taking the squared magnitude of the Discrete Fourier Transform (DFT) of, $\gamma_n(n)$, i.e.

$\Lambda(k) = |\zeta_d\{\gamma_n(n)\}|^2$ k=0, 1,.N-1, (58)

Where $\zeta_d\ \{\gamma_n(n)\}$ is the Discrete Fourier Transform (DFT).

The samples of DFT of white noise are chi-squared with two degrees of freedom. It is equally known as exponential distribution [30],[31],[32] i.e.

$f\{\Lambda(k)\}$ = N$e^{-\Lambda(k)N}$, (59)

Where, $f\{x\}$ denotes the probability density function, x [10]

At a theoretically determined confidence level found through the cumulative sum of the area under the probability density function (PDF) (59), a suitable threshold can be set within the PSD. A 99% confidence interval could be found by solving (60):

0.99 = $\int_0^{CI} F_\Lambda\{\Lambda\} d\Lambda$ (60)

For stationary system, the normalized innovation PSD is expected to remain white. It resides and within the threshold set at a given level of confidence. As the system experiences a large detrimental deviation from the stationary system model as defined in (22)-(23), a spike may appear above the threshold in the innovation PSD. In practical application, if the damping is deteriorating, there would not be an automatic protection relay to trip a line. The response would be to ramp back generator settings or to trip an offending aspect of the plant provided it can be identified

5.2.5 General Guide in tuning the Kalman Filter

In practical scenario, Kalman filter requires adequate tuning to achieve the desired optimal estimation when dealing with real data applications. Usually, Q and R, values are known and can be easily tuned. Such prior knowledge of the error covariance matrices may not be available in real life scenario. Knowledge of the measurement transducer performance or measurement noise however, could be obtained through testing. Even so, a technique of tuning is still necessary to allow for changes over time. In addressing this issue, the selection of the error co-variance Q is particularly important, such that Q >> R [10][33][34]. This would ensure the adaptive capability of the Kalman filter. It is recognized that the measurement error covariance would be negligible; hence the determination of appropriate values in this analysis can be obtained empirically, by first setting Q to unity, and then adjusting R so that the pseudo-stationary innovation result was close to white. Further techniques such as machine learning techniques for tuning the filter can be derived from [35][36][37].

5.2.6 Conclusion on Kalman Filtering Approach

The Kalman estimator is an optimal linear estimator which has proven to be effective for rapidly detecting modal changes in both simulated and real world power system scenarios. This detection strategy has demonstrated the capacity to identify the mode which has changed at a particular time and also rapidly detect large changes to power system modes. Multi-site measurements can be used to provide greater confidence in the detection alarming. This has significant implications for power utility intervention strategies. Clearly, this method is effective in terms of computing power and can effortlessly be implemented in real-time.

6. SIGNIFICANCE AND LIMITATIONS OF EBD, OMID AND KID IN LARGE INTERCONNECTED POWER SYSTEMS

When applied to real systems, the EBD is reliable and simple and can be easily tuned in the power system. While it provides a rapid indication of sudden detrimental change, it cannot tell precisely which mode the change is associated with. Therefore, it provides detection, but not identification. Though it is still attractive to multi-modal systems to provide short-term monitoring, it is well suited for single mode power systems. The OIMD strategy which is suitable for use under certain conditions can equally be exploited for application in dominant mode, multi-modal systems. It can provide detection, but may be ambiguous in identification under undesirable conditions. But for the difficulty in tuning the Kalman filter adequately, the KID method has proven to be able to provide both detection and mode identification. Therefore, in practical scenario, this may not be an easy task which makes the more informative detector the most complicated to implement [10][38].

7. CONCLUSIONS AND FURTHER STUDIES

This work has reviewed extensively, strategies deployed to assist power utilities to consistently and quickly monitor and confirm the modal condition within a large interconnected power system. Three modern methods of rapidly detecting deteriorating modal damping have been presented; the energy based method (EBD), optimal individual mode detector (OIMD) and Kalman innovation method (KID). EBD is excellent for monitoring the system output as a whole and would be particularly suitable for single mode systems. But OIMD and KID are designed to provide both alarming of sudden negative damping and the identification of the offending mode. These strategies deploy analytical means to characterize the expected system measurement and determine the desired threshold. This work provides a comprehensive review of existing modal estimation methods and proposes a new framework for rapid detection of deteriorating modal damping.

Future studies should aim to demonstrate the adequacy of the methods by way of simulations, verification and real data analysis from the Nigerian interconnected power system. Such studies should also provide close to expected false alarms under adequately damped quasi-stationary conditions of the power system. Also, exploring the application of machine learning techniques for modal estimation or investigating the impact of renewable energy sources on power system stability are critical areas for future research.

Disclaimer (Artificial intelligence)

Author(s) hereby declare that NO generative AI technologies such as; Large Language Models (ChatGPT, COPILOT, metaAI and so on etc.) and text-to-image generators have been used during writing or editing of the manuscript.

REFERENCES

1. Vittal V. Consequence And Impact of Electric Utility Industry Restructuring On Transient Stability And Small-Signal Stability Analysis, *Proceedings of the IEEE*, 2000;88:196-207.

2. Begovic M, Novosel D, Karlsson D, Henville C. and Michel G. Wide-Area Protection And Emergency Control, *Proceedings of the IEEE*, 2005;3:876-891.

3. Bertsch J, Carnal C, Karlson D, McDaniel J, and Vu K. Wide Area Protection and Power System Utilization, *Proceedings of the IEEE*, 2005;93,997-1003.

4. Palmer EW and Ledwich G. Optimal Placement of Angle Transducers in Power Systems, *Power Systems, IEEE Transactions on*, 1996;11:788-793.

5. Dussaud F. An application of modal analysis in electric power systems to study inter-area oscillations, Electric Power Systems Lab, Royal Institute of Technology, *Stockholm*, *Sweden , 2015, 87p*

6. Klein M, Rogers GJ and Kundur P. A Fundamental Study of Inter-Area Oscillations in Power Systems, *Power Systems, IEEE Transactions on*, 1991; 6:914-921.

7. Uchida N and Nagao T. A New Eigen-Analysis Method of Steady-State Stability Studies for Large Power Systems: S Matrix Method, *Power Systems, IEEE Transactions on*, 1988;3:706 - 714.

8. Trudnowski DJ, Johnson JM. and Hauer JF. Making Prony Analysis More Accurate Using Multiple Signals, *Power Systems, IEEE Transactions on*, 1999;14:226-231.

9. Kundur P. and Dandeno PL. Practical Applications of Eigenvalue Techniques in the Analysis of Power Systems Dynamic Stability Problems, *presented at 5th Power System Computation Conference*, Cambridge, England, September, 1975.

10. Wiltshire RA. *Analysis of Disturbances in Large Interconnected Power Systems,* PhD Thesis, Queensland University of Technology Brisbane, Australia, 2007.

11. Byerly RT, Bennon RJ. and Sherman DE. Eigenvalue Analysis of Synchronising Power from Oscillations in Large Power Systems, *IEEE Transactions, 1982;* PAS-101:235-243.

12.Kumaresan R and Tufts DW. Singular Value Decomposition and Improved Frequency Estimation Using Linear Prediction, *IEEE Transactions on Acoustics, Speech and Signal Processing*, 1982; vol. ASSP-30:671-675.

13.Donnelly MK, Trudnowski DJ and Hauer JF. Advances in the Identification of Transfer Functions Models Using Prony Analysis, presented at *Proceedings of the American Control Conference*, San Francisco, CA, 21st -23rd June, 1993;2:1561-1562.

14.Gomez Martin R and Carrion Perez MC. Extended Prony Method Applied to Noisy Data,1986; *Electronics Letters*, 22:613-614.

15. Kannan N and Kundu D. Estimating Parameters in the Damped Exponential Model, *Signal Processing*, 2001; 81:2343-2351.

16. Poon K.P and Lee, KC. Analysis of Transient Stability Swings in large Interconnected Power Systems by Fourier Transformation, *Power Systems, IEEE Transactions on*, 1988;3:1573-1581.

17. Deele LB, Ozuomba S. and Okpura NI. Design and Parametric Analysis of a Stand-Alone Solar-Hydro Power Plant with Pumped Power Storage Technology. International Journal of Engineering and Technology (IJET), 2019; 4(1): 9 – 23

18. Ledwich G. and Palmer E. Modal estimates from normal operation of power systems, *Power Engineering Society Winter Meeting, IEEE*, 2000;2:1527-1531

19. Martin V and Stubberud A. An additional requirement for innovations testing in system identification," *Automatic Control, IEE Transactions on*,19:583-584, 1974.

20. Willsky AS. A survey of design methods for failure detection in dynamic systems," *Automatica*, 1976; 12:601-611.

21. Boashash V and O'Shea, P. Polynomial Wigner-Ville Distributions and their Relationship to Time-varying Higher Order Spectra, *Signal Processing, IEEE Transactions on [see also Acoustics, Speech, and Signal Processing, IEEE Transactions on]*, 1994; 42:216-220.

22. Nta EE, Udofia KM and Okpura NI. Development of an Energy Theft Detection and Location System for Low Voltage Power Distribution Networks, *Journal of Multidisciplinary Engineering Science and Technology (JMEST),* 2022;15240 – 15249

23.Okpura NI, Okafor ENC and Udofia-Kufre M. Identification and Classification of High Impedance Faults on 33kV Power Distribution Line using ANFIS Model. *European Journal of Engineering and Technology,* 2020; 7(6): 68 – 74

24.Okpura NI, Okafor ENC. and Udofia, Kufre. M. Comparative Analysis of Fuzzy Inference System (FIS) and Adaptive Neuro-Fuzzy Inference System (ANFIS) Methods in the Classification and Location of High Impedance Faults on Distribution System. *European Journal of Engineering Research and Science,* 2020; 5(8):966-969.

25.Etuk D, Udofia K and Okpura N. Modelling and Optimization of Cost Function for Hybrid Power Generarion System using Genetic Algorithm. *International Journal of Power Systems*, 2020; 5

26.Owoeye KS, Okpura NI and Udofia KM. Sensitivity Analysis of an Optimal Hybrid Renewable Energy System for Sustainable Power Supply to a Remote Rural Community. *International Journal of Advances in Engineering and Management (IJAEM), 2022;* 4(4): 1100 – 1194.

27. Ogata K. *Discrete-time control systems*, 2nd ed. Englewood Cliffs, N.J: Prentice Hall, 1995.

28.Owoeye KS, Udofia KM and Okpura NI. Design and Optimization of Hybrid Renewable Energy System for Rural Electrification of an Off-Grid Community. *European Journal of Engineering and Technology*, 2022; 10(1):28 – 42.

29.Okpura NI, Ukut UI and Kalu C. Load Flow Solution for Power Distribution System Using Gauss-Seidel Model. International Multilingual Journal of Science and Technology (IMJST), 2022; 7(6):6066 – 6073.

30.Urkowitz H. Energy Detection of Unknown Deterministic Signals, *Proceedings of the IEEE*, 1967; 55:523-531.

31. Okpura N, Isaiah UI and Nsikak EU. Simulated Life Cycle Cost and Carbon Balance Analysis of Grid-Connected Solar Photovoltaic Power System for A Hospital in Abuja, Nigeria. *Journal of Multidisciplinary*

Engineering Science and Technology (JMEST), 2022; 9(12):15987 – 15998

32. Okpura NI, Ogunrombi TS and Itoro EU. Sizing and Performance Analysis of Off-Grid Solar Photovoltaic Power System for Remote Smart City Application-Ready Bus Shelter. *International Multilingual Journal of Science and Technology (IMJST)*, 2022; 7(10): 6120 – 6131.

33.Ogoamaka C, Udofia KM and Okpura NI. Open Circuit Fault Detection for 11kV Distribution Network using ANFIS. *International Journal of Power Systems* 2020; 5:23 – 30

34. Ayegba OG, Obot AB and Okpura NI. Reduction of Current Harmonics in 11 KV Distribution System using Active Power Filter and Discrete Wavelet Transform. *Multidisciplinary Engineering Science and Technology (JMEST),* 2021; 7(12): 4140 - 4143

35. Ukut UI, Obot AB and Okpura N. Comparison of the Power Flow Analysis Using a Deterministic Approach and Artificial Neural Network. *Journal of Multidisciplinary Engineering Science and Technology (JMEST)*, 2022; 9(9):15918 – 1593

36. Agorodi D, Okpura N and Udofia K. M. Prediction of Power Demand in Nigeria Using Particle Swamp/Trust-Region Optimization and Fuzzy Inference System. *Journal of Multidisciplinary Engineering Science and Technology (JMEST)*, 2022; 9(1):15963 – 15968

37. Zhang Y., Li J, Chen X, Hou Y and Xu Z. Deep Learning-based Models for Predicting Poorly Damped Low-Frequency Oscillations in Power Systems. *IEEE Transactions on Power Systems*, 2020;35 (4): 2720 - 2729

38.Owoeye KS, Udofia KM, Okpura NI and Abiola AE. Load Profile Validation for Design of Sustainable Optimal Hybrid Renewable Energy Systems. *International Journal of Latest Technology in Engineering management and Applied Science (IJLTEMAS), 2022;* 11(4): 20 -26.