Estimation of Generator Inertia Available During a Disturbance

Peter Wall, Francisco Gonzalez-Longatt, *Senior Member, IEEE*, and Vladimir Terzija, *Senior Member, IEEE*

***Abstract*—The inertia of a power system is a key factor in determining the initial frequency decline after a disturbance. Low system inertia can allow large frequency declines to occur that could lead to violation of frequency security limits, particularly in smaller power systems, or play a key role in allowing cascading outages to occur. Future developments in power systems will mean that the system inertia will become highly variable and take values that would traditionally have been considered very low. Presented is a method for the robust estimation of the generator inertia available in the system during a disturbance. This method has been validated using simulations of the IEEE 39-bus system in DIgSILENT™ PowerFactory®. Inertia estimates for a variety of disturbance types and noise conditions have been made, and found to have a median error of 1.53% with inter-quartile range of 6.6%.**

***Index Terms*—: Generator Inertia, Inertia Estimation, Power system simulation, Power system dynamics, Smart grids.**

I. Introduction

THE developments anticipated in power systems will have far reaching consequences. The shift from a small number of technically similar thermal units to a far more diverse portfolio of generation technologies that differ radically from one another will mean that the generator inertia in the system will cease to be a relatively reliable system parameter. Instead, it will become highly variable and may frequently take values that traditionally would be seen as very low [1], [2]. This loss of inertia, and its negative effects, will be most evident in smaller power systems.

The system inertia plays a key role in determining the initial frequency behavior after a disturbance has occurred in the system [3]. Therefore, if the system inertia becomes highly variable then the frequency deviation that will occur after a specific disturbance, e.g. the reference incident of the system, will also become highly variable. This variation in the post-disturbance frequency decline could undermine the success of the existing control measures. Variations in the frequency behavior of a system is of particular concern as frequency declines can play a key role in allowing disturbances to propagate, potentially even allowing cascading outages [4].

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In the presence of significant variations in the generator inertia, a method for estimating the generator inertia online would offer a useful additional input to support any automatic control/protection in place. An example of this support would be using inertia estimates to support self-healing power systems [5] or adaptive load shedding [6].

Any method developed to produce online estimates of the generator inertia that is available during a disturbance must consider three criteria for its successful operation. The first criterion is *accuracy*. Any estimate made must be accurate so that the decisions made based on it will be the correct decisions. The second criterion is *reliability*. The estimates made must be reliable so that decision makers can depend upon them. The third criterion is *execution time*. This criterion exists because parameter estimation techniques require measurements of the system response, so the measured response can be compared to the estimated response. Therefore, generator inertia can only be estimated after a disturbance has occurred, as it is only then that the necessary measurements can be made. Furthermore, the variable nature of inertia, that is anticipated in the future, will mean that only the estimate made for the current disturbance can be relied upon to accurately reflect the generator inertia that is currently available. Therefore, the execution time of the inertia estimation method must be minimized, to ensure that the estimate of the generator inertia currently available can be used by other application/operators to deal with the potential consequences of the current disturbance.

Existing methods for estimating inertia can be separated into two broad groups. The methods in the first group use a *swing equation based method* to estimate the total system inertia based on post-mortem analysis of frequency measurements from a single location during a known disturbance to the system [7], [8].

The second group of methods is *based on precise models* of a specific generation technology and use parameter estimation techniques to find the value of inertia, and other parameters, for a specific generation unit. Examples of this can be found in [9], [10]. Whilst this work is successful in achieving its own goals, extending concepts similar to this for the application considered here would have issues satisfying the criterion of execution time.

A robust method for the estimation of the generator inertia available in a system during a disturbance is presented in this paper. This method uses a swing equation based approach, like those validated in [7], [8], with some alterations to allow

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the estimation of generator inertia online (e.g. data from multiple locations is used and power measurements are used instead of a known disturbance size). As the method presented is intended for eventual online use a data window concept was implemented to deal with the reliability issues seen in previous swing equation based methods.

This paper is structured as follows. Section II gives a definition and discussion of inertia. Section II introduces the basic swing equation that the robust inertia estimation is based on. Section III gives the motivation and considerations behind the robust estimation method and describes its execution. Section IV presents the results of some simulations of the IEEE 39-bus test system that were used to validate the proposed method and investigate its behavior.

II. Definition of Inertia

The inertia of a power system is a measure of the energy stored within the rotating masses connected to that system. Specifically, it defines the time for which the total energy stored within all of the rotating masses connected to the system could be used to supply their total rated power [3].

The energy stored within the rotating mass of an item of power system plant, e.g. a generator set, can be defined using the moment of inertia of the rotating mass, J (kg-m^2), and its present rotational speed, ω (p.u.). The inertia of this rotating mass can then be calculated by dividing the quantity of stored energy by the rated power of the plant, S_r (p.u.).

The use of the present rotational speed in the above calculation means that the inertia of a rotating mass will vary continuously. Therefore, it is common, to assume that the rotating masses within the system are always operating at their rated speed, ω_r [11]. This assumption allows the inertia to be redefined as the inertia constant, or H constant, that can be calculated as follows [3], [11].

$$H = \frac{\frac{1}{2} J \omega_r}{S_r} \tag{1}$$

This expression means that the inertia constant of an individual item of plant is normalized using the rated power of that item of plant. Therefore, when performing calculations that involve the inertia constant of several different items of plant it is necessary to recalculate the inertia constant of each item of plant using a common base power, defined here as S_B. When the inertia constant of each item of plant within the system is calculated using the same base power then the total inertia constant of the power system is the sum of these individual inertia constants [3].

III. The Swing Equation

The swing equation can be used to describe the response of a rotating mass, in terms of the rotational speed of that mass, to an imbalance between the active power being supplied to it and the active power being drawn from it.

The swing equation appears in many forms, the most common examples of which can be seen in [3], [11]. The form of the equation used in this paper is derived for a generator; all of the parameter values used are per unit values. It describes the initial change that will occur in the frequency, f, of the electrical output of a generator in response to an imbalance between the mechanical power supplied to the generator shaft, P_m, and the electrical load on the stator of the generator, P_e.

$$2H\Delta \frac{df(t)}{dt} = P_m(t) - P_e(t) \quad for \quad t = 0^+ \tag{2}$$

where, the Δ denotes that the change in the derivative of frequency at $t=0^+$ should be used and not the absolute value. The inertia constant, H, can be used to define this relationship because the energy stored in the rotating mass of the generator will immediately begin to change to compensate for the imbalance that has occurred [3].

The control actions that are available to maintain the power balance within a power system cannot act immediately. Therefore immediately after a large disturbance to the power balance, e.g. the short circuit of a bus bar or disconnection of a generator, the changes in the operating frequency of the power system can be described using the swing equation, (2). Therefore, this equation can be used to estimate the inertia constant of the power system during this disturbance if data is available that describes the frequency and active power of the system during the disturbance.

IV. Robust Estimation Method

The estimation method presented in this paper was developed to produce an estimate of the *generator inertia* available in the system. The generator inertia is defined as the sum of the inertia constants of each individual generator connected to the system.

The method is intended for use in the immediate aftermath of a disturbance being detected in the system. An estimate of the generator inertia available during this disturbance could serve as a useful input to adaptive protection and control applications.

The basic execution of the proposed method consists of estimating the inertia constant of each generator in the system, and then taking the sum of these estimates. The process for estimating the inertia of a single generator can be described in the following stages.

A. Necessary Input Data

The estimation process is based on the swing equation (2). Therefore, measurement data representing the response of the generator to a disturbance in the active power balance in the system is necessary to produce an estimate. Here this data consists of measurements of the active power flow and the rate of change of frequency at the point of connection of the generator, like those shown in Fig. 1. These measurements should be recorded at the generator point of connection during a disturbance in the system. Data of this nature will become increasingly available because of the growing deployment of synchronized measurement technology (SMT) in power systems [12].

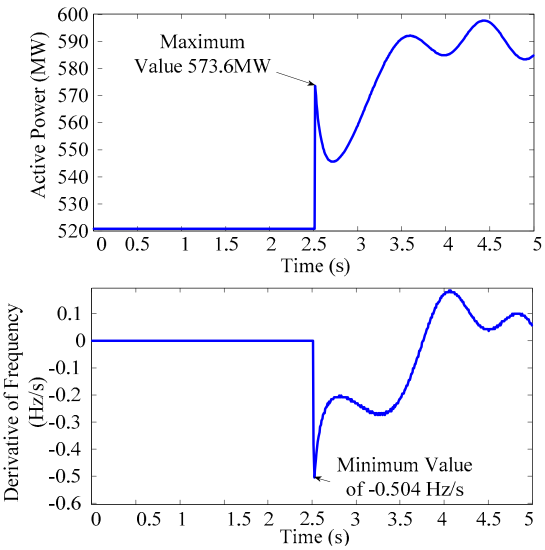

Fig. 1. Simulated examples of the measurements of active power and rate of change of frequency that are necessary to estimate the inertia of a generator. This data has a sampling frequency of 120Hz, i.e. 2 measurement are recorded every cycle, and there is a disturbance in the system at t=2.5s.

B. Removing Dependence on Mechanical Power from the Swing Equation

The mechanical power applied to the generator shaft is included as a term in the swing equation shown in (2). Measurements of mechanical power are very difficult too obtain in a practical power system and as such it is necessary to eliminate the mechanical power term from the swing equation to give the following equation.

$$2H\left(\frac{df(t^{+})}{dt}-\frac{df(t^{-})}{dt}\right)=P_e\left(t^{-}\right)-P_e\left(t^{+}\right) \tag{3}$$

where, t^+ is the time at which the first sample is taken after the disturbance and t^- is the time at which the last sample was taken before the disturbance. In effect, the mechanical power term in (2) has been approximated using a term that represents the electrical power flow before the disturbance occurred.

This approximation is deemed reasonable based on the following properties of power systems. Control actions are taken continuously to ensure a good active power balance in the system. Therefore, in an undisturbed system the mechanical power and electrical power will be approximately equal [11]. The electrical power drawn from a generator can vary quickly but the mechanical power applied to their rotating shaft cannot. Therefore, the mechanical power before and after the disturbance will be approximately equal [11]. The limited effect of this approximation is shown in [13].

C. The Effects of Filtering

Unlike the measurements shown in Fig. 1, any measurements taken in the field will include noise and will consequently be filtered. The result of adding noise to the data presented in Fig.1 and then filtering it is shown in Fig. 2. The noise used is of the type described in Section IV. The filtering serves to extend the duration of the transient step in the system behavior from a single sample time to the width of the filter (W) and will attenuate the magnitude of this step.

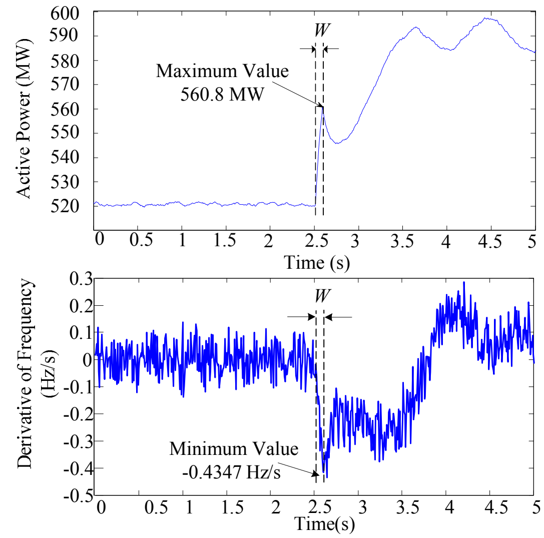

Fig. 2. This data has been filtered using a moving window filter with a width of ten samples. This filtering extends the duration of the transient step in the data from a single sample to the width of the filter (*W*). The peak value of the transient step is marked to show the attenuation in comparison to Fig. 1.

D. Using Data Windows to Improve Resilience Against Noise

If (3) were to be used directly to estimate H, then the estimate would be incredibly vulnerable to any noise in the four measurements used. Therefore, the robust estimation method presented here replaces these four individual values with the output of four data windows, like those in Fig. 3.

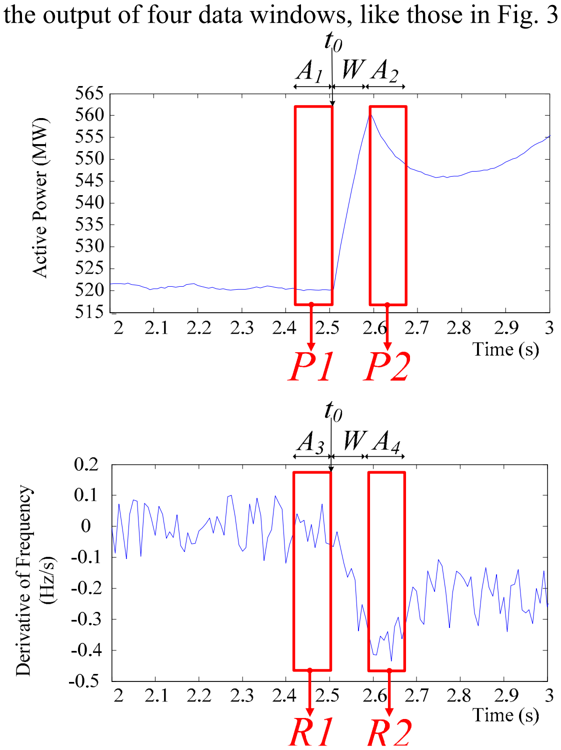

Fig. 3. Sampling windows can be used to produce reliable inertia estimates in the presence of noise. The separation between the windows, marked *W*, is to accommodate the filter extending the transient step from infinitely small to the width of the filter. A_1, A_2, A_3 and A_4 are the widths of the four data windows, t_0 is the time of the disturbance, and *R1*, *R2*, *P1* and *P2* denote the output of the data windows.

An important feature of Fig. 3 is that for both derivative of frequency and active power the two windows are separated by a period of W. This is necessary as this period represents the elongation of the transient step that is introduced by filtering the data. This section of data does not accurately reflect the system behavior and must be excluded from the calculation.

The output of these four windows will be used to estimate H according to the following expression.

$$H = \frac{1}{2}\frac{P1 - P2}{R2 - R1} \tag{4}$$

where the output of the windows is calculated as follows, assuming that the active power and derivative of frequency measurements are in vectors labeled p and $dfdt$ respectively.

$$P1 = \frac{\sum_{i=t_0-M_1}^{t_0} p(i)}{M_1} \qquad P2 = \frac{\sum_{i=t_0+W}^{t_0+W+M_2} p(i)}{M_2}$$
$$R1 = \frac{\sum_{i=t_0-M_3}^{t_0} dfdt(i)}{M_3} \qquad R2 = \frac{\sum_{i=t_0+W}^{t_0+W+M_4} dfdt(i)}{M_4} \tag{5}$$

where, A_1, A_2, A_3 and A_4 are the widths of the four data windows, t_0 is the time of the disturbance, and W denotes the width of any filtering applied to the data.

The output of the data windows will not be a perfectly accurate reflection of the swing equation relationship, as measurements from times other than t=0$^+$ are used, and as such they will introduce some error into the calculation. This error will need to be balanced against the improved resilience against noise that these filter windows offer, when applying this method to a specific system.

The generator inertia available in the system during the disturbance can then be calculated by taking the sum of the individual estimates. This process could be used to estimate the generator inertia available in the entire system or just in selected parts of the system.

The windows proposed here essentially act like an averaging filter, like that discussed in Section IV-C. In section V a moving average filter is used to filter the input data before it is processed by the proposed window-based inertia estimation method. As the windows apply the same process as the filter, the input filtering could be eliminated from the process and similar results would be seen, provided that the window width was increased accordingly. However, the input filtering is included here to demonstrate that the proposed method can perform properly when applied to filtered data. This property of the method is of interest as the filtering of measurement data is a common practice in power systems engineering.

E. Summary of Method Execution

Having summarized the key steps in developing the method a brief set of steps for executing this method for an N generator system, where all window widths have a value of A and a filter with width W is used will be presented here.

1. A disturbance occurs in the system
2. Time of disturbance received from an external application

For all N Generators

3. Store the previous A measurements for f and P
4. Wait for an additional W+A measurements to be made for f and P
5. Filter the W+2A measurements for f and P
6. Calculate the derivative of frequency
7. Apply the data windows to the active power and derivative of frequency data
8. Calculate the inertia of the generator using (4)
9. Take the sum of the N estimates to calculate the generator inertia available during this disturbance.

A power network with sufficient SMT installed to monitor the connected generators will also most likely have the communication network and data processing facilities (e.g. Data Concentrators [12]) necessary to perform the summation of the individual inertia estimates. The issues of missing data and communication network latency are not addressed in this work. However, it must be noted that in the current method any inertia estimate that is missing from the summation, for any reason, will lead to an underestimation of the inertia. This issue must be addressed in future work on this topic.

V. Simulation Results

Simulations were performed for the IEEE 39-bus test system, shown in Fig. 4 and details of which can be found in [14], using DIgSILENT™ PowerFactory® [15]. The results presented here to validate the method were produced using a MATLAB® [16] script of the estimation method.

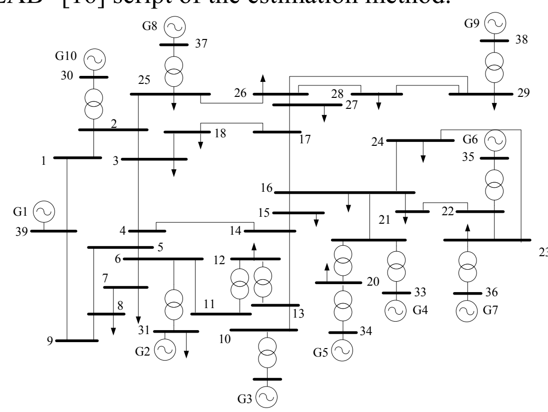

Fig. 4. Simulations of the IEEE 39 Bus Test System have been used to validate the inertia estimation method and investigate its behavior.

The simulated data presented in this section used a sampling frequency of 120Hz and the interpolation option in the simulation package was not used. The simulations were executed for five seconds and the disturbance occurs at 2.5s.

In all of the cases presented here, noise was added to the simulated signals for both frequency and power. The noise added to the frequency signal was ±0.0005% of signal and the noise added to the power signal was ±0.5% of signal. This noise level is higher than those seen for current PMUs [17], this higher level was selected to accommodate other sources of noise that may exist between the measurement point and where the method is executed. The filtering applied to this data consisted of a simple moving window filter with a width of 10 data points, i.e. 0.0833 seconds.

To ensure that the noise used in each set of tests was consistent, noise values were generated randomly in MATLAB® and stored as a data file. Each generator had one thousand, five-second noise signals, for both frequency and power, created for it, and stored in this way. For the purpose of this discussion a set of these noise signals, i.e. the five second frequency and power noise signals for each of the ten generators, is referred to as a noise profile. These one thousand noise profiles are used in all of the cases presented to allow a reasonable statistical analysis of the proposed methods behavior in the presence of noise.

For simplicity the width of the four data windows are all set as the same value and all data window widths, or *A* values, are given in terms of data points, not time. For the purposes of these initial simulations, the time of the disturbance is assumed to be accurately known. Accurate information regarding this can be difficult to obtain in real time for real data. However, it may be possible to obtain it by executing the P1 and P2 windows continuously and then detecting the time of the disturbance by checking for P1-P2 exceeding some predetermined threshold.

Table I gives an example of the output of each of the windows that form part of this method for the example case of the disconnection of generator G1. The resulting inertia estimate for the generators is also shown. Noise, of the type described previously in this section, was added and an *A* value of 30 was used. The power and inertia values in Table I are given on a base of 6141MW (the installed capacity prior to the disturbance) whilst the frequency values are given in pu/s.

TABLE I
OUTPUT OF METHOD STAGES FOR THE OUTAGE OF GENERATOR 1

	R1	*R2*	*P1*	*P2*	*H*
	(pu/s) $*10^{-3}$	*(pu/s)*	*(pu)*	*(pu)*	*(s)*
G1	–	–	–	–	–
G2	0.2248	-0.0045	0.0848	0.0895	0.4947
G3	-0.0515	-0.0047	0.1059	0.1115	0.5988
G4	0.0813	-0.0029	0.1030	0.1057	0.4536
G5	-0.0049	-0.0009	0.0826	0.0834	0.4797
G6	0.0330	-0.0023	0.1058	0.1084	0.5598
G7	0.1037	-0.0025	0.0912	0.0933	0.4139
G8	0.083	-0.005	0.0879	0.0925	0.4466
G9	-0.0338	-0.0039	0.1352	0.1406	0.7039
G10	0.0548	-0.0048	0.0407	0.0482	0.7770

The sum of the individual generator inertia estimates is 4.928s, when in fact the inertia was 4.716s, this is an estimation error of -4.491%. Error values calculated in this way are used in the following sections to analyze the performance of the inertia estimation method.

A. Resilience against Noise

The purpose of the first set of simulations was to demonstrate that the proposed method could reliably produce accurate estimates of inertia in the presence of noise. To investigate the effect of the window width, widths of 1, 2, 3, 4 … and 54, in terms of samples, were considered.

1) Generator Outage

The data presented in this section was produced as follows. The disconnection of each of the ten generators in the IEEE 39-bus system was simulated and the frequency and active power measured at the connection point of the generators still connected to the system was then stored for each of the ten disturbances. Then for each of these ten disturbances the estimation method was applied, for the range of window widths considered and for each of the one thousand noise profiles discussed in the introduction to this section. For each case, this produced a set of data values, like those shown in Table I, which were used to estimate the generator inertia in the system. This estimate was then compared to the known value of the generator inertia in the system and the error in the estimate was calculated. The result of this process is a data set for each of the window widths considered that contains the error in each of the ten thousand estimates of the generator inertia.

These *error data sets* for each window width were used to analyze the reliability of the estimation method in the presence of noise. This analysis was performed using statistical measures of the distribution of the estimate errors in the data set. These measures were the *median*, *inter-quartile range* (IQR) and *absolute range* of the errors in the data set for each window width. The median and IQR of the error data set for each window width are shown in Fig. 5.

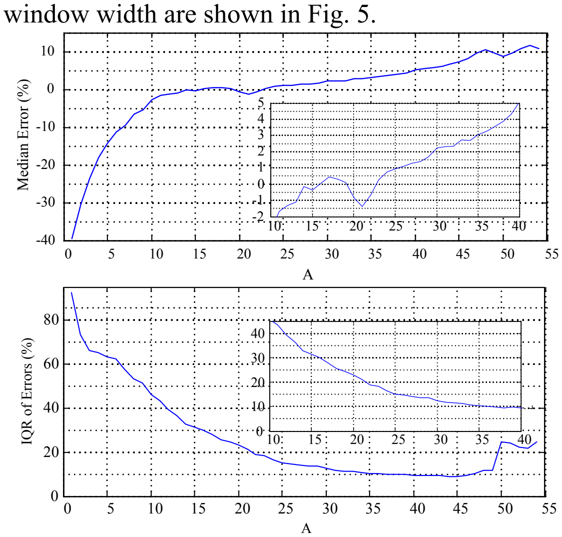

Fig. 5. Median and IQR of the errors in the estimate of the generator inertia in the system for ten thousand different cases and for a range of window widths, the insets show a focused view for the results for window widths between 10 and 40 points.

The results presented in Fig. 5 show that the robust estimation method performs very well for window widths of between approximately 15 and 45 points. The median and inter quartile range of the errors for this set of points are shown in detail in the inset of Fig. 5. Selecting the 'best' window width from this range is a challenge of balancing the superior median error seen for the lower values in the range against the superior inter quartile range seen for the higher values in the range. A window width of 30 points appears to offer the best balance with a median error of 1.68% and an IQR of 13.5%.

For window widths of below 15 points, the noise rejection offered by the data windows is insufficient and this leads to very large errors. Conversely, for window widths above 45 the swing equation relationship begins to decay rapidly and a consequently the median and inter quartile range of the errors increases rapidly.

Presented in Fig. 6 is a comparison of the absolute (100%) range of the errors in the data set with the 99% and 90% range of the errors in the data set. (Note that here the 90% range refers to the difference between the 5th percentile and the 95th percentile.) This comparison shows that the absolute range of the errors is highly variable with only a small period of consistent behavior between approximately 30 and 40. In contrast the behavior of the 99% range is similar to that of the inter quartile range.

This extreme variation exists because a few extreme outliers dominate the size of the 100% range. This can be seen in the relationship between the three ranges presented in Fig. 6. The difference between the 99% range and the 100% range is at least an order of magnitude greater than the difference between the 99% and 90 % range. This indicates that outer 1% of data causes a vastly larger increase in the range than the next 9%.

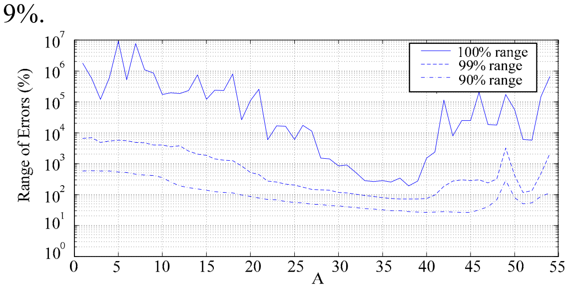

Fig. 6. The 100%, 99% and 90% range of the errors for the range of window widths. This data is plotted with a logarithmic scale on the y-axis due to the extreme differences between their respective values.

Noticeable in Fig. 6 is the increase in the range of the errors as the window size increases beyond approximately 40. This behavior, similar to that seen in Fig. 5, is an indication of the rapid decay of the degree to which the measurements being used actually reflect the swing equation relationship.

The extreme outliers that cause this behavior could be dealt with by using an improved function for the data window, e.g. some form of recursive mean calculation that eliminates points based on their deviation from the mean.

2) Comparison of Results for the Outage of Generator G9 and G10

This section of the paper offers a comparison of the estimation results for the outage of generator G9 and the outage of generator G10. This particular comparison was chosen because the outage of G9 was one of the largest generator outages, whilst the outage of G10 was the smallest.

A comparison of the median of the error data sets for the outage of G9 and G10 is presented in Fig. 7. This comparison shows that the estimation of the inertia has a smaller median error for the key window sizes between 15 and 40 for the outage of G9. This improvement occurs because the estimation method appears to be more accurate for larger disturbances. This is likely because for a larger disturbance the deviations in frequency and power that occur are larger, and therefore less vulnerable to noise. A comparison of the inter quartile and 90% range of the error data sets is presented in Fig. 8. This comparison shows that the estimates are also far more reliable for the larger disturbance. An interesting feature in Fig. 8 is the pronounced peaks, centered at window sizes of approximately 5 and 45, in the inter quartile range of the error data set for the outage of G10. These peaks exist because the outage of G10 initiates dynamic behavior in the system that occurs around these points.

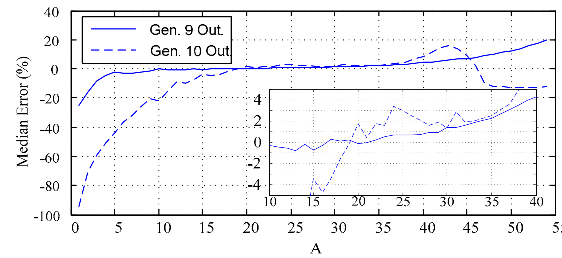

Fig. 7. This comparison of the median of the data set of inertia estimate errors for the outage of G9 and G10 shows that the estimation method offers superior results for larger disturbances. The inset shows a view of the errors between *A* values of 10 and 40.

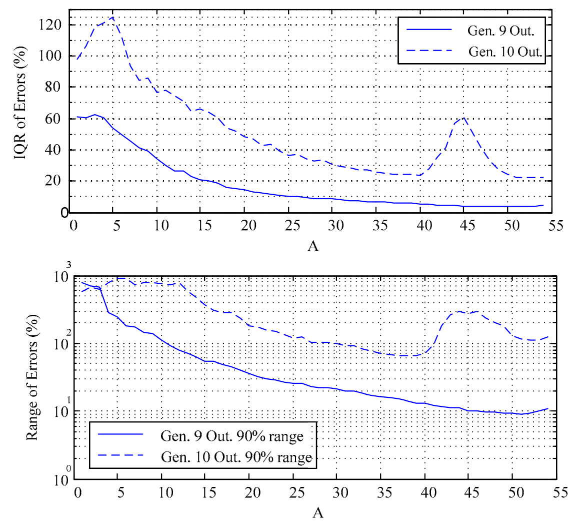

Fig. 8. A comparison of the inter quartile range and 90% range of the data set of errors for the outage of generator's G9 and G10.

3) Short Circuit

The data used for the assessment of the methods performance for a simulated short circuit was performed using the same process described in Sub-section V-A-1. Therefore, the error data sets produced contain the errors for thirty-nine disturbances, i.e. one per bus. A comparison of the distribution of the error data sets for the short circuit simulations and the generator outage simulations is presented in Fig. 9. It shows that the method has similar behavior for both disturbance types.

The median and inter quartile range of the error data sets is smaller for the short circuit cases than they are for the generator outages. These differences appear to be consistent with those seen for the comparison of the two generator outages, shown in Fig. 7 and Fig. 8. The superior performance of the method for a short circuit is likely due to the power imbalance that occurs for a short circuit being larger than that seen for a generator outage. This larger disturbance causes larger changes in the measured signals and therefore the process is less vulnerable to noise. A comparison of the 90% range of the error data sets for the two disturbance types also demonstrates the same improved reliability that was seen in Fig. 8. Finally, the data presented in Fig. 11 shows that the estimates made based on the short circuit disturbances are vulnerable to the same extreme outliers that are seen in the generator outage case, shown in Fig. 6.

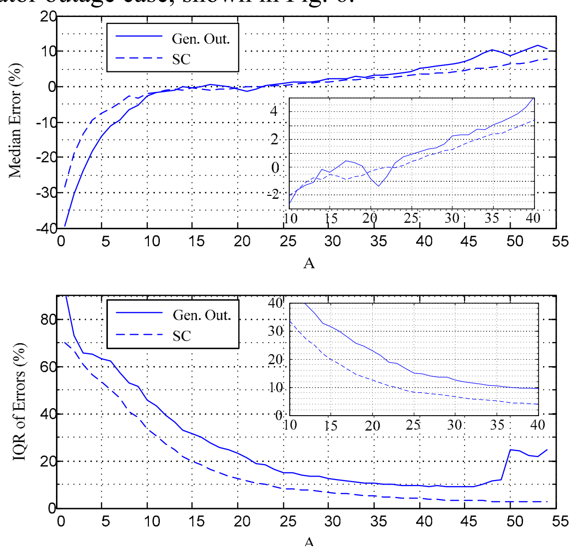

Fig. 9. Comparison of the Median and inter quartile range of the error data sets for estimates made for a Generator Outage and Short Circuit.

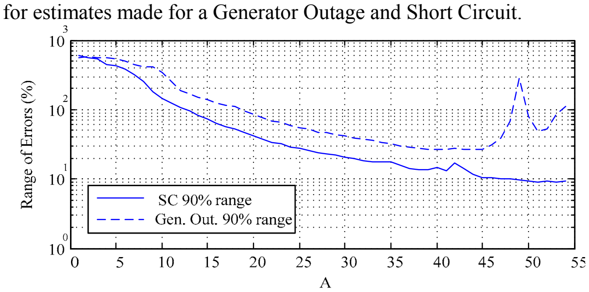

Fig. 10. Comparison of the 90% range of the errors for estimates made during Generator Outage and Short Circuit Disturbances.

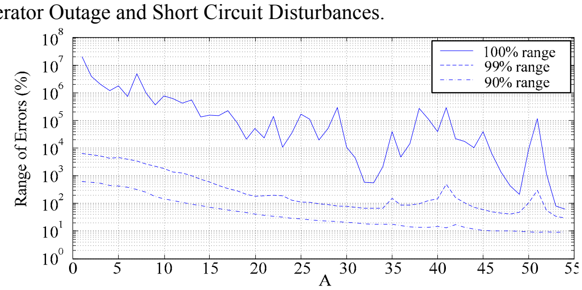

Fig. 11. 100%, 99% and 90% range data for estimates made during short circuit disturbances. This data is plotted with a logarithmic scale on the y-axis due to the extreme differences between their respective values.

B. Impact of Incorrect Disturbance Time (t_d)

The dependence of this inertia estimation method upon a known disturbance time will limit its potential for online implementation. This is because, despite the existence of methods that allow on-line disturbance detection, it is unreasonable to expect access to perfect data regarding the time of the disturbance. To address this potential weakness, the simulations performed in Sections V-A-1 are repeated here using window widths of 30 and 40. However, instead of using the true disturbance time, which is 2.5s, the error data sets that are discussed in the following sub-sections were created by applying the estimation method for each of the generator outage cases with the disturbance time used by the method ranging from 2.2s to 2.833s.

The median and inter quartile range of the error data sets produced in this way are shown in Fig. 12. They demonstrate that when the disturbance time used is less than the true disturbance time (2.5s) the method can still produce useful results. In fact, the results for the window width of 40 are almost equivalent to those seen when the true disturbance time is used for assumed disturbance times of 2.4s.

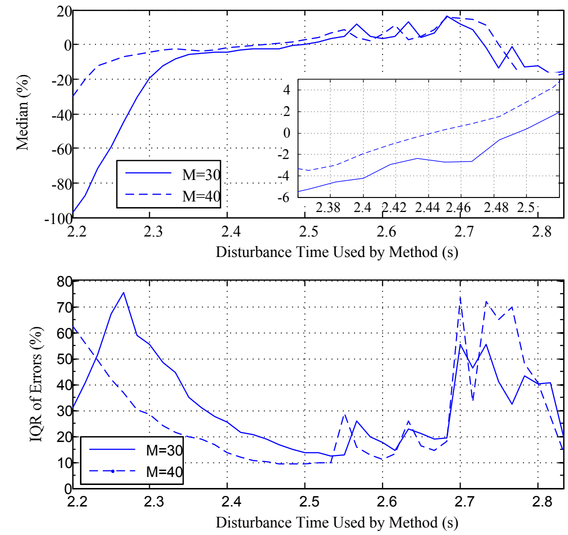

Fig. 12. The median and inter quartile range of the error data sets for two window widths (30 and 40) when the time of the disturbance used by the method is inaccurate (true time is 2.5s).

However, when the disturbance time used is greater than the true disturbance time (2.5s) the method cannot reliably produce accurate estimates. This is because, in this case, the value calculated for the pre-disturbance rate of change of frequency and power includes values for the post disturbance behavior, thus compromising the performance of the estimation method. This issue cannot be completely overcome; however, it could be alleviated somewhat by using recursive mean calculations, like those proposed to deal with extreme outliers in subsection V-A-1. Furthermore, in light of the sustained good performance of the method for an assumed disturbance time of 0.1s seconds below the true disturbance time, some form of guard time could be implemented to limit the risk of using a disturbance time that is greater than the true disturbance time.

Finally, the low value of the inter quartile range for the window width of 30 points, which occurs for an assumed disturbance time of 2.2s, is misleading, and occurs for the same reason as the median error of approximately -100% seen for this disturbance time. This occurs because the disturbance time used is so far from the true disturbance time that post-disturbance data windows do not actually 'see' the disturbed system. Therefore, the inertia estimate returned is purely based on the noise in the system, and is thus approximately zero.

VI. Conclusions and Further Work

This paper presented a robust method for the estimation of the generator inertia available in the system during a disturbance. With proper selection of the width of the data windows, this method is capable of offering a very good level of accuracy. With a window width of 30 the 10,000 estimates performed using varying noise profiles and simulated data of generator outage disturbances in the IEEE 39-bus test system produced estimates with a median error of 1.68% and an inter quartile range of 13.5%. Similarly, the 39,000 estimates performed for short circuit disturbances in the system produced estimates with a median error of 1.53% and an inter quartile range of 6.6%. The method is capable of producing results that are approximately equivalent to these even if the disturbance time used by the method is not accurate. Accurate and reliable generator inertia estimates of this nature could prove a valuable input for adaptive protection and control schemes, and help limit large frequency excursions in future power systems that are left vulnerable by low and variable inertia.

The measurement intensive nature of this application means that more development is necessary before simulation results could be realistically compared to measured results, or the method applied to a real power system. A key first step in this development is reducing the number of measurement locations. This could be achieved by selecting a number of locations that are considered to represent the equivalent frequency response of the system, and then performing the estimate based on measurements from these locations. Such a change would unfortunately introduce errors in to the process. Another key issue that must be overcome is that in a real power system, a single event will constitute a much smaller percentage of the total system than in the system considered here. This will mean that the output of the windows will be smaller, and hence more sensitive to noise, as seen in the results in section V-A-2.

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VIII. Biographies

Peter Wall graduated from the University of Manchester with a Bachelors degree in Electrical and Electronic Engineering (2008) and with a Masters degree in Power Systems (2009). His main area of interest is power system dynamics and frequency stability. He is currently a PhD student at The University of Manchester.

Francisco M. González-Longatt (S'01, M'03, SM'2009) was born in Cagua-Venezuela, on July 30th, 1972. He graduated on Electrical Engineering of Instituto Universitario Politécnico de la Fuerza Armada Nacional, Venezuela (1994), and Master of Business Administration of Universidad Bicentenaria de Aragua, Venezuela (1999) and PhD of Universidad Central de Venezuela (2008). His main area of interest is renewable energy resources and power system dynamic on Smart Grids. He is former associate professor on Electrical Engineering Department of Universidad Nacional Politécnico de la Fuerza Armada Nacional, Venezuela. He is currently a Post Doctoral Associate Research in the School of Electrical and Electronic Engineering, The University of Manchester.

Vladimir Terzija (M'95, SM'2000) is the EPSRC Chair Professor in Power System Engineering in the School of Electrical and Electronic Engineering, The University of Manchester, where he has been since 2006. From 1997 to 1999, he was an Assistant Professor at the University of Belgrade. In 1999, he was awarded a prestigious Humboldt Research Fellowship. From 2000 to 2006, he was with ABB AG, Germany, working as an expert for switchgear and distribution automation. His main research interests are application of intelligent methods to power system monitoring, control, and protection, switchgear and fast transient processes, as well as DSP applications in power.