Load Inertia Estimation Using White and Grey-Box Estimators for Power Systems with High Wind Penetration

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Abstract: The increasing penetration of wind farms in power systems has increased concerns over the frequency behaviour and control of synchronous power systems due to a low contribution from modern wind turbines to overall system inertia. With this trend of conventional generators being displaced by variable speed wind turbines, the contribution from load inertia becomes more significant. The need for greater consideration towards load inertia estimation, or even on-line tracking of load inertia, seems to be required. A white-box method for estimation of load inertia is examined using system frequency and generator output power signals from previous generator forced outages. A grey-box identification method is also applied to estimate the inertia of synchronous generators. The impact of sampling rates, time shifting and signal averaging on parameter estimation is also considered. The method is shown to be robust enough to be applied for load inertia estimation in control centres.

Keywords: Load Inertia, Wind Power, System Frequency, Generator Outage

1. INTRODUCTION

One of the main tasks of power system operators is to control system frequency excursions from nominal within safety margins to ensure reliable and secure operation and supply to customers (Kundur, 1994). The sudden loss of a generator will lead to excursions from nominal frequency. For such an event, the total system inertia determines the initial rate of change of frequency (ROCOF) (Chan, et al., 1971). Historically, the large rotating mass of thermal power units provided the greatest contribution to system inertia; however, other sources of inertia such as hydro units, fixed speed induction generator FSIG-based wind turbines and load inertia also play a role. FSIGs are essentially induction machines operating at a slip frequency higher than the system nominal frequency, with their response to frequency events naturally slower than synchronous generators. This results in a lower effective contribution to system inertia during the initial phase of a disturbance.

With a general trend towards lower carbon emissions in future, renewable energy sources are gaining more interest in electricity markets, with an accelerated growth in wind power, especially in Europe. Consequently, thermal power plants are being displaced by large numbers of variable speed wind turbines with no contribution to overall system stored energy. A greater contribution from DC interconnectors is also more likely, which don't naturally contribute to system overall inertia. As a result, the ROCOF in a system is likely to increase and frequency control strategies could face another limiting factor (Doherty, et al., 2010; Kennedy, et al., 2011). With variable speed wind turbines, the turbine-generator inertia is decoupled from the power system, thus further exacerbating the issue of reduced system inertia (Ruttledge and Flynn, 2011). Moreover, in small and/or isolated power systems, inertia plays a particularly significant role. From the system operational point of view, ensuring adequate system stored energy is becoming more important, implying a need for better strategies and methods regarding precise and fast estimation of generation and load inertia. Going forward with increasing wind power penetration levels, even real-time load inertia estimation may be required to ensure system security.

The time varying nature of the load inertia and spatial distribution of load throughout the system makes the load inertia estimation quite challenging. Due to such difficulties, as well as a low contribution from load inertia in large power systems, it has been customary to assume fixed values for load inertia or just to neglect the effect of load in ROCOF calculations (Concordia and Ihara, 1982). We will examine in this paper a white-box method for load inertia estimation through the use of time domain data of system frequency and generator output power, taking the power system of Ireland as a study case. As the method requires estimates of the overall contribution to system inertia from synchronous generators, a grey-box estimation of unit inertia is presented which can be invoked to verify the turbine-generator inertial constants. DC interconnector power as well as inertial contribution from FSIG-based wind turbines is taken into account. Since it can be difficult to obtain synchronized data for all units at sufficient resolution and accuracy, the effects of lower sampling rates, time shifting and averaging of data is examined and discussed using a simple test system.

The remainder of this paper is organized as follows. In Section 2 principles of system modelling and estimation, and applications to load modelling in power systems are reviewed. Section 3 presents a white-box estimation method for load inertia, while its application to the Irish power system is presented in Section 4. In Section 5 grey-box estimation of generating unit inertia based on time domain sampled data is presented. Section 6 considers the effects of sampling rate, time shifting and averaging estimation errors. Finally, Section 7 concludes this paper.

2. SYSTEM IDENTIFICATION AND PARAMETER ESTIMATION: LOAD MODELLING IN POWER SYSTEMS

Load modelling methods in power systems generally involve the application of system identification and parameter estimation concepts, based on three high level approaches (Sjöberg, et al., 1995). A white-box approach starting from the basic physical equations governing the system under study, while potentially very complicated, has the ability to achieve precise and informative analysis. A grey-box identification procedure assumes a particular structure for the system potentially based on an understanding of underlying physical principles and adopts an input-output approach for parameter estimation. Based on knowledge of the system being analysed, a criterion, usually the mean square error, measures the 'goodness' of parameter estimation and/or model structure fitness. The grey-box approach does not consider the detailed internal physics of the system but can be straightforward to apply. The available data for the system being identified tends to drive selection of the estimation method. If detailed data is available for system components, or the modelling is intended to be a higher level estimation, a white box approach will be chosen. When the data available is partially structural and input-output measurements are available, a grey-box estimate may be more appropriate. The third approach, which is the black-box identification procedure, assumes a high level model structure, which is not essentially similar to the internal structure of the system and attempts to find a best fit from the input-output perspective (Ljung, 1999).

System identification and modelling of load parameters in power systems has been a challenging area for many years. The difficulties typically encountered are the composite and time varying nature of the load, as well as frequency and voltage variations across the system. Consequently it can be difficult to develop a simple model for overall behaviour with the complication and expense inherent in load parameter measurements. Due to the type of studies which are usually important in power systems, the load is normally represented by a combination of constant impedance, constant current, constant power and induction machine models (Welfonder, et al., 1989; IEEE Task Force, 1993). To estimate the load model parameters, it is required to analyse the load's active and reactive power sensitivity to voltage and frequency variation. In particular, the load power sensitivity to frequency, which links to load inertia, is important for system overall frequency response simulation. The white-box approach has been applied in different areas of power system modelling as well as load modelling (Bank Tavakoli, et al., 2009; Inoue, et al., 1997). The grey-box approach is widely used in power system load modelling as well (Welfonder, et al., 1989; O'Sullivan and O'Malley, 1996). Black-box studies for load modelling in power systems also exist; however, the complexities in translating the physical meaning of the estimated values mean that there are limited opportunities to employ pure black-box approaches (He and Shelli, 2009). Most load modelling approaches consider loads which are connected to a coupling point in the system and estimate the parameters using a grey-box approach. From a power system operator point of view, estimation of total system load inertia is considerably more informative. As load inertia estimation assumes a higher level single node presentation of the entire system, a white-box approach is applied for estimation.

3. WHITE-BOX LOAD INERTIA ESTIMATION

The overall behaviour of power systems, regarding sensitivity to frequency variations and power balance can be simply represented by a single rotating mass. The dynamic equations governing the system can be written as:

$$T_m - T_e - T_D = J \cdot \alpha \tag{1}$$

$$T_D = \left(D/2\pi\omega_0\right) \cdot \Delta\omega;\ T_m = P_m/\omega;\ T_e = P_e/\omega \tag{2}$$

$$J = 2H \cdot S_b / \omega_0^2 \tag{3}$$

where T_m and P_m are the mechanical torque and power, T_e and P_e are the electrical torque and power and T_D is the damping torque. J represents the combined moment of inertia of the system, ω is the system angular speed, f_0 is the pre-event frequency, $\omega_0=2\pi f_0$ is the pre-event angular speed, H and D are the equivalent inertial constant and mechanical damping coefficient of the combined system, S_b is the cumulative apparent power of all online generators, and α represents the system angular acceleration. Assuming that the system is operating close to nominal, equation (1) can be rewritten as:

$$\frac{2H \cdot S_b}{f_0}\frac{d\Delta f}{dt} + D \cdot \Delta f = \Delta P \tag{4}$$

where ΔP is the power mismatch. Under steady-state operation, the frequency deviation is zero. After a disturbance, say a generator outage, the power imbalance causes the system to move from the previous operating point and accelerate at a rate dependent on the power imbalance. The system overall inertial constant can be estimated from time domain frequency mismatches by:

$$E_{sys} = H \times S_b = \frac{f_0}{2} \times \frac{\Delta P}{\left.\frac{d\Delta f}{dt}\right|_{t=t_0}} \tag{5}$$

where E_{sys} is the overall system estimated stored energy at the time when the event occurred, i.e. $t=t_0$. E_{sys} simply indicates the overall system inertia available at the start of the event and thus includes those synchronous generators, fixed speed wind turbines, loads and any other rotating masses connected to the system. Using a precise method of system frequency tracking makes it possible to extract the load inertia at that particular time from the system overall stored energy by subtracting the contribution from online synchronous generators and FSIGs:

$$E_{load} = E_{sys} - E_{gen} - E_{wind} \tag{6}$$

where E_{load} is the load stored energy, E_{gen} is the total synchronous generator stored energy and E_{wind} is the FSIG wind turbine contributions to stored energy. Only fixed speed wind turbines are assumed to have an inertial contribution; however, this trend may change in future with new designs of variable speed wind turbines (Miller and Clark, 2010).

4. LOAD INERTIA ESTIMATION OF IRISH POWER SYSTEM

The combined power system of Ireland and Northern Ireland currently has a peak demand of approximately 6950 MW, and incorporates conventional generation, comprising predominantly steam, OCGT and combined cycle gas turbine (CCGT) generators, a HVDC interconnector with Great Britain and approximately 1800 MW of wind generation. The largest generator on the system is 480 MW against a minimum demand of approximately 2500 MW (EirGrid, 2011). Static sources of reserve include pumped storage, HVDC interconnection, interruptible load and load shedding. To estimate the system and load stored energy, six generator outage events were selected for the all-island power system, as summarised in Table 1. The system frequency measurement is determined at the system control centre where time stamped synchronous data of the output power of generators is also available. The ROCOF following a contingency event, which is required for system inertia estimation in (5), can be extracted from the original frequency signal using a polynomial curve fitting procedure. A polynomial order of 6-12 tends to provide the best fit. Using the curve fitting approach and proper selection of the polynomial function order, unwanted inter-area frequency oscillations can be effectively filtered (Inoue, et. al., 1997). The system pre-event stored energy is balanced to the system nominal frequency, i.e.

$$E_{sys(f_n)} = E_{sys(f_0)} \times f_n^2 / f_0^2 \tag{7}$$

where f_n is the nominal system frequency. 15-min resolution data of actual power from each wind farm is used to identify the online wind farms for a particular event and estimate the number of online FSIGs. An assumed inertial constant of 3 MWs/MVA is applied for FSIGs, which have essentially a slower response to frequency decline compared with synchronous generators (Kennedy, et al., 2011). The per unit base for the overall system inertial constant is the sum of the apparent power of all online generators for each event, while the load inertial constant is based on the all-island system demand. The results of the proposed white-box load inertia estimation are depicted in Figs. 1-3.

Table 1. Six events for load inertia estimation

	Day (Time)	Wind Generation (MW)
A	Fri. (10:37)	216
B	Fri. (10:59)	344
C	Thu. (12:41)	171
D	Sun. (21:34)	149
E	Mon. (11:41)	387
F	Sun. (12:25)	1087

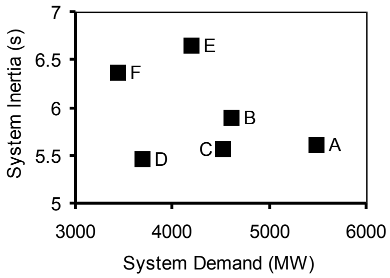

Fig. 1. System inertia with respect to system demand

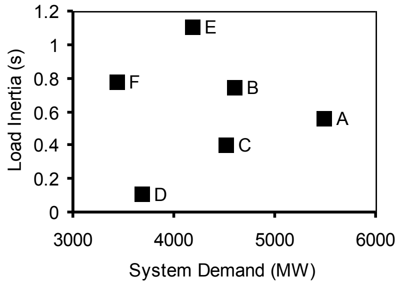

Fig. 2. Load inertia with respect to system demand

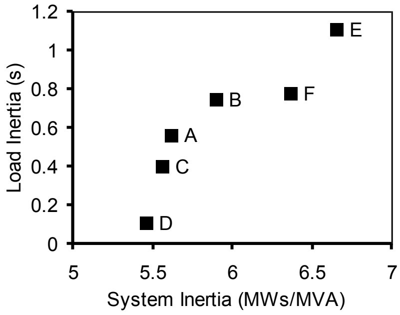

Fig. 3. Load inertia with respect to system inertia

For a system with low wind penetration, increasing demand usually implies more synchronous generators online and higher system inertia; however, in a system with high wind penetration, the demand may be supplied by significant wind power with a low inertia contribution, if any. From Fig. 1 it is obvious that the usual interpretation that higher demand implies higher system stored energy is not directly applicable (Inoue, et al., 1997). Moreover, the operational policy of the system ensures a minimum system stored energy of ~25000 MWs from synchronous generators which limits the minimum system inertial constant in Fig. 1 (EirGrid, 2011). Consequently, at low loads, additional units may be kept on-line to provide inertial support and reactive power control.

The increasing penetration of wind power suggests that the natural inertial value will essentially decrease in future reaching the limiting level of system stored energy required for secure operation applied by the system operator. Load inertia estimation is required to obtain the correct representation of system stored energy, as part of further decisions regarding wind curtailment or rescheduling of generating units. Moreover, representing the load inertial contribution should result in any system-related inertial constraint becoming binding less often.

The estimated load inertia with respect to the system demand for the selected events is shown in Fig 2. The load inertia is generally less than 1 second, but experiences significant variation with regard to system demand, indicating the time varying nature of system load behaviour. The load inertia is also a function of the connected load and demand requirements, time of day, weekday/weekend and time of year. From Fig. 2, weekdays seem to present higher value of load inertia, with similar days and times showing relatively similar values of load inertia while load inertia is lower at weekends. Another interesting case is the load inertia at night when system inertia reduces further due to low industrial/commercial activities. System load inertia, however, tends to increase with respect to the overall system inertial constant, as illustrated in Fig. 3. The base load units of the system are predominantly coal-fired power plants with the next power plants scheduled to come into operation being CCGTs with higher inertial constants and this leads to higher system inertia as depicted in Fig. 3.

The time varying nature of the load inertia requires as many events as possible to draw an overall picture of system load inertia. The selected events illustrate only 6 sample load inertia points for the white-box estimation procedure. Keeping in mind that new electrical loads connecting to the system may have different behaviour regarding their inertial contribution, it is recommended to establish an event database and update system inertia estimates for each event to cover load inertia variation across the year. It is also required to revisit load inertia estimation over time to track changes in load types and behaviour.

5. GREY-BOX TURBINE-GENERATOR INERTIA ESTIMATION

The load inertia estimation procedure in Section 3 requires that the inertia of all generating units be known in advance. Usually, a single figure is given for a multi-mass system and the sum of the inertia of all rotating masses is assumed to contribute to system stored energy. However, there are many units in practice whose data are not available or may be unreliable. It is possible to analyse the output power signal of power plants after a generator outage to estimate the online inertial constant based on a grey-box approach. The output power signal after a frequency decline comprises the natural response of the rotating mass to the fall of frequency, which is essentially a function of the inertial constant, and the governor action to increase mechanical input power (Fox, et al., 2007). Utilizing a standard dynamic model for the governor and including the inertial response of the unit, it is possible to "simulate" the output power of the unit utilizing the actual frequency trace fed into the model. It is now a question of optimization to determine which parameter set best fits the measured output (grey-box estimation). Moreover, steam, hydro, CCGT, OCGT and pumped storage power plants essentially comprise different governor dynamic models. It is therefore required to implement a suitable model for each operating unit. The primary parameters to be tuned are the inertial constant, governor droop and forward loop time constants e.g. servomotor time constant, reheater or turbine discharge delay. Nevertheless, the estimation procedure requires caution due to two potential sources of error during the optimization procedure. Due to variations in load and frequency in the system and the action of load and frequency control loops in the power plant, the power output signal of the generator may not be smooth. Quantisation and sampling make the situation worse, such that deviations in input data may cause the algorithm to track non-necessarily good fits. Moreover, to estimate the unit inertia, the governor's natural response should be recognised, otherwise the obtained value will be overestimated. To overcome the above mentioned problems, a weighted mean square error is proposed as the optimization goal function:

$$MSE = \frac{1}{TW}\int_{0}^{TW}\left\{\left[E_{sim}(t) - E_{meas}(t)\right]\cdot e^{-t/T}\right\}^{2}\cdot dt \qquad (8)$$

where $E_{sim}(t)$ is the simulated output energy of the generating unit, i.e. the integral of the output power versus time, $E_{meas}(t)$ is the output energy of the unit computed from the measured output power signal, T is the time constant set to compensate the governor response and TW is the overall processing window. Using the energy output as the goal function minimizes the effect of noise and disturbances on the optimization process. However, if high quality, high resolution data is available, mismatch errors of the power signal can be used as well. Implementing the above mentioned procedure for a coal-fired steam unit is shown in Fig. 4. The estimated generator inertia agrees well with manufacturer data in test simulations. It is worth mentioning that applying the goal function of (8) ensures that the first few seconds of the measured data have the dominant effect on the optimization procedure, i.e. the inertial constant changes are weighted by the optimization cost. Thus the curves in Fig. 4 acceptably diverge for later simulation times. This procedure can also be extended to confirm governor response and so obtain agreement with grid code and/or other generator performance requirements.

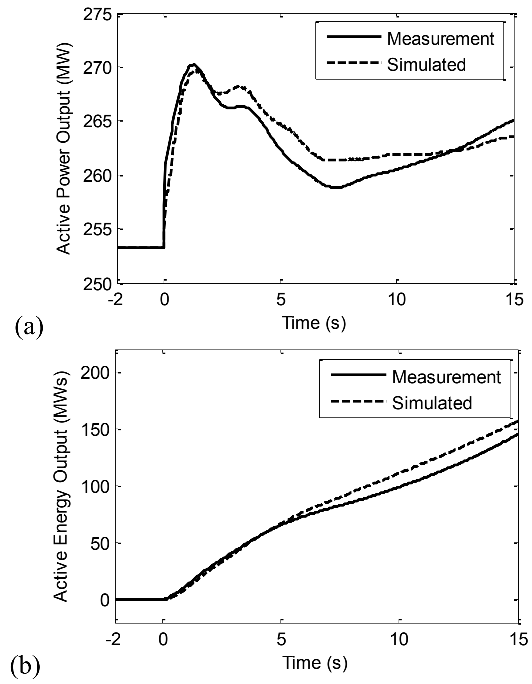

Fig. 4. Simulated and measured signals, (a) power, and (b) energy

6. SAMPLING RATE, TIME SHIFTING AND AVERAGING EFFECTS

Load inertia estimation in Section 3 and generator inertia estimation in Section 5 both require time sampled data from actual events. While high resolution, i.e. high sampling frequency, is desirable to increase precision, it increases the data volume as well. The available resolution for data samples may be in the range 1 to 10 Hz, although it is possible to achieve higher sampling rates in the range of some kHz using digital fault recorders. However, recording equipment, communication requirements and storage limitations usually limit the availability of high resolution data. Any data recorder implements a processing window with a predefined width. When the device is triggered to record data, samples within the window will be recorded and made available. Depending on the exact time that an event occurs and the triggering moment, different samples of the original signal may be available in the processing window, the time shifting effect. Moreover, moving average based filters may be employed to smooth or down-sample the recorded data. To investigate the above mentioned effects with regard to inertia estimation, an event is considered to generate noise-free frequency and power signals with a high sampling rate, i.e. 100 Hz. The frequency signal is then fed into the white-box and grey-box estimators to generate the ideal values for load inertia and generating unit inertia. Next, the original frequency signal is intentionally down sampled, time shifted and filtered by averaging and is again fed to the white-box and grey-box estimators. Comparison is made between the results using the original frequency and power signals and those using down-sampled, shifted and averaged signals.

Fig. 5 shows the effects of sampling rate, time shifting and averaging on the original frequency signal. The processing window is 3 seconds in (a) and (b) while in (c) the processing window is variable in the range of 0.5-1 s. In the first two cases, the time shifting and sampling effect were investigated which are essentially independent from the processing window. Case (c) just shows the effect of averaging on processing window when the processing window length is changed with the longer window length being less precise. The error between the estimate using the original and manipulated frequency signals for load inertia estimation (white-box estimator) and unit inertia estimation (grey-box estimator) are depicted in Fig. 6 and Fig. 7. As can be seen, the moving average approach introduces the largest error; however, averaging is usually avoided after signal sampling. Time shifting does not cause significant errors at high sampling rates. Nevertheless, at lower sampling rates time shifting may be noticeable. Fig. 6 and Fig. 7 show the effect of time shifting for a sampling period of 0.5 s (i.e. 2 Hz sampling rate). Thus, if the sampling rate is low, the actual sampling window length is important. The best solution is to keep the sampling rate rather high, i.e. 8 Hz and more. A higher sampling rate is, of course, desirable, but the error obtained is acceptable for lower sampling rates, even up to 1 Hz, if averaging doesn't occur, as illustrated in Fig. 6. In contrast to grey-box estimation, the error in white-box load inertia estimation is not acceptable for lower sampling rates relative to the actual values obtained, see Fig. 7. Utilizing data with a time resolution of 0.1 second or more is usually available in power system communication facilities and thus the errors in white and grey-box estimation procedures should be low.

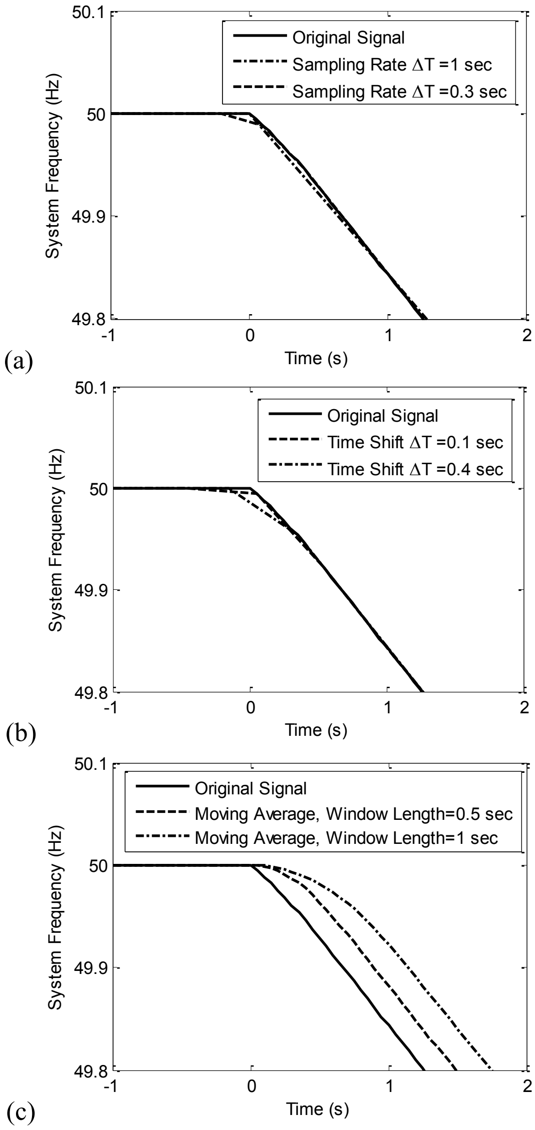

Fig. 5. (a) Sampling rate effect, (b) time shifting effect, and (c) averaging effect on original frequency signal

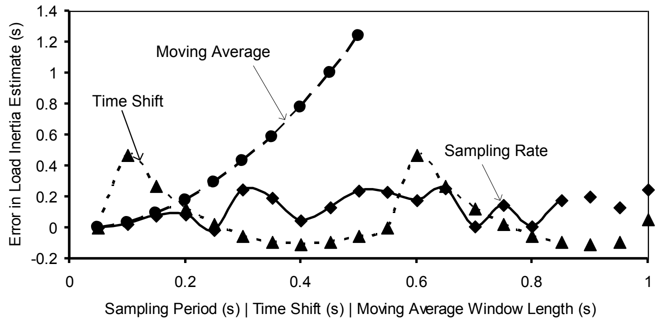

Fig. 6. Sampling rate, time shifting (at sampling rate 0.5 s) and averaging effects on load inertia estimation

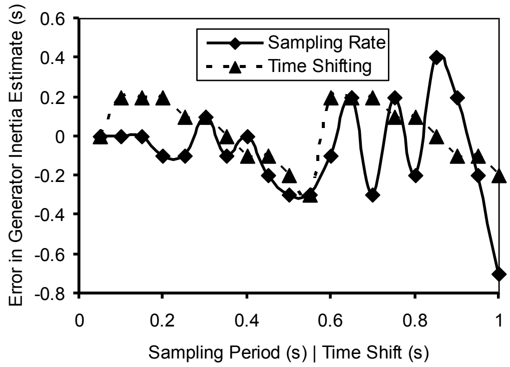

Fig. 7. Sampling rate and time shifting (at sampling rate 0.5 s) effect on generator inertia estimation

7. CONCLUSION

By increasing wind power penetration and displacing conventional thermal power plant, the system overall inertia will decrease. It is now more probable that system inertia will be a limiting factor for system operation. Consequently, it is more desirable to obtain a proper estimation of load inertia as a contributor to the system overall frequency response. A white-box estimation approach was presented for load estimation utilizing post-event data sampled and concentrated in a processing centre. A grey-box estimation method was also introduced for generating unit inertia estimation to estimate the stored energy of generating units. The sensitivity of the results to sampling rate, time shifting and averaging was also investigated. The general outcome of the procedures indicates that the methods yield promising results for load inertia estimation. A load inertia database can be developed to estimate the time varying load contribution to stored energy of the overall system and will help to define the minimum stored energy required for secure system operation. Creating a comprehensive load inertia database is a long term plan and requires data from all available events to be analysed and validated. Updating this database should lead to a detailed picture of load inertia for different operating conditions which could be used ultimately in drawing a more realistic picture of real system operating states.

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