Dynamic system parameters for the National Grid.

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Abstract

The paper describes the use of system identification techniques to estimate the parameters of a low-order dynamic model for the power system in England and Wales. The basic technique is to obtain an ARIMAX model by applying a prediction error method to data consisting of 1s samples of the system frequency and the power output of the Dinorwig fast-response pumped-storage station. From this model the natural frequency, damping factor and stiffness (or 'beta') of the power system are obtained. Both the daily and monthly variations of the parameters are analysed and the relationship between the total power system load and its stiffness is investigated.

1. Introduction

This paper considers the dynamic relationship between frequency variation and the real power input to the national grid. In England and Wales, National Grid Transco (NGT) monitors and controls the power system frequency by means of a mechanism known as Ancillary Services [1]. Contracts for short-term frequency control are agreed with generators to meet primary and secondary response times and maximising performance requires a good understanding of the interaction between the generating plant and the power system. An important tool in this respect is system simulation, which uses computer models to obtain insight into the behaviour of the system. Several authors have emphasised the need for estimating power system parameters directly from measurements in order to improve the accuracy of their computer simulations. For instance, Lin et al [2] view the improved precision with which stability limits can be calculated as critical to the planning and operation of power systems. Similarly, O'Sullivan & O'Malley [3] observe that the accurate prediction of system frequency following a disturbance, such as tripping of a large generator, can help to achieve an optimum trade-off between operating costs and system security. Inoue et al [4] have used estimates of power system parameters in a simulation to infer the available capacity of spinning-reserve support. In fact, the original motivation for the work presented here was to enhance a computer simulation of the Dinorwig pumped-storage power station used for investigating stability limits [5] and new control techniques [6]. Knowledge of power system parameters is also of interest in circumstances other than computer simulation – Chang-Chien et al [7], for instance, use an on-line estimate of a power system's stiffness (or 'β' characteristic) to set the frequency bias coefficient for tie-line control whereas Wu and Chen [8] use the sensitivity of the system frequency to load changes within an algorithm that determines reasonable spinning reserve requirements for an isolated power system.

In this work, the model is obtained as a 'black box' transfer function using the methods of linear system identification. Low-order power system models are discussed in the next section, concluding that a suitable model is a second-order transfer function, from which estimates of the power system's natural frequency (ω_n), damping factor (ζ) and 'stiffness' (β) can be obtained. This is followed by a brief survey of measurement and identification methods used by other researchers. The main features which distinguish this work from previous approaches are (a) the use of operational data instead of discrete 'events' involving large system disturbances and (b) use of an ARIMAX (**A**uto **R**egressive **M**oving **A**verage with **I**ntegrator in the noise model and e**X**ogeneous input) structure to model both the input-output relationship and disturbance due to the fluctuating load-generation imbalance. The mathematical background of the method itself, its validation for use in this application and the limitations imposed by signal to noise ratio (SNR) are described in [9]. A systematic examination of the time-variation of the parameters, over a contiguous period and on real data, is performed by applying the identification technique to records from 2001.

2. Power system models

For many studies, a power system can be approximated as an infinite busbar of constant voltage and frequency, capable of absorbing or delivering power without limit and at any rate. On the other hand, the real situation is extremely complex because the frequency changes on a sub-second timescale due to the synchronising oscillations between generators as they respond to load variation. The model assumed here lies in-between these extremes. A well-known simplifying concept in power systems representation is the 'uniform' or 'average' frequency, which filters out the relatively high-frequency synchronising oscillations so that the effect of all the interconnected machines on the Grid can be lumped together as an equivalent single machine. The simplest lumped representation is given by Kundur [10] as the first order transfer function:

$$\Delta f = \frac{1}{Ms + \beta}(\Delta P_e - \Delta P_L) \qquad (1)$$

where ΔP_e is the (known) power generated or absorbed locally; ΔP_L is the (unknown) change in load imbalance on the Grid (i.e. the difference between the total power fed into the Grid from many generation sources and the total power drawn by consumers such as motors, heaters, pumps, lamps and power electronic drives), Δf is the change in average Grid frequency and M is the inertia constant of the equivalent single machine. The power system stiffness, β, is the inverse of the steady-state sensitivity of frequency to changes in input power, assuming that the load imbalance is zero:

$$\beta = \frac{\Delta P_e}{\Delta f} \text{ MW / 0.1Hz} \qquad (2)$$

An alternative multivariable model, due to Welfender et al [11], is a 2 x 2 matrix of first-order transfer functions having a single zero in the numerators, which couples real and reactive power to both frequency and voltage. Lin et al [2] base their work on this model but show that a second or third order model captures the system's dynamic response more accurately. O'Sullivan and O'Malley [3] also use this model but omit both the cross-coupling voltage inputs, because the voltage swings are small (as is the case considered here) and the effect of the reactive power term on frequency is negligible [10]. Their approach also involved 'locking' the governors of the various generators on the system over the short duration of the test so that the frequency sensitivity of the load alone is measured. This is not possible here so a suitable model must include the effect of governor regulation, which tends to increase the measured value of stiffness, as discussed in [3]. The model selected is due to Anderson and Mirheydar [12], whose second order transfer function assumes that, over the time-scale of interest, the response is dominated by two time constants:

$$\Delta f = \frac{\omega_n^2 T_R}{\beta}\left(\frac{s + 1/T_R}{s^2 + 2\zeta\omega_n s + \omega_n^2}\right)(\Delta P_e - \Delta P_L) \qquad (3)$$

where: $\beta = \dfrac{DR_e + 1}{R_e} \qquad R_e = R(1 + d)$ (4)

and the natural frequency (ω_n) and damping factor (ζ) are:

$$\omega_n = \sqrt{\frac{DR_e + 1}{2HR_e T_R}} \qquad \zeta = \left(\frac{2HR_e + (DR_e + F_H)T_R}{2(DR_e + 1)}\right)\omega_n \qquad (5)$$

where :
T_R is the aggregate time constant of steam reheat plant
H is the aggregate inertia constant of all units connected to the Grid
R is the aggregate droop setting of all governors
R_e is the equivalent system droop
d is the relative deadband
F_H is the fraction of total power generated by non-reheat plant
D is the frequency dependence of the load

A rough estimate of ω_n, ζ and β may be obtained by supposing the parameters in the preceding list to be normally distributed, independent random variables (which strictly they are not) whose upper and lower limits are drawn from the literature [4], [10], [12], [13], [14]. These limits are equated to the 3σ values of the distributions, as summarised in Table 1.

Table 1 Assumed means and standard deviations for the parameters in (4) and (5)

Parameter	Mean	Range	3σ
T_R (s)	8	6 - 10	0.67
H (s)	4	3 - 5	0.33
R (pu)	0.04	0.03 - 0.05	0.004
d	2.4	-	0.33
F_H	0.3	-	0.05
D (pu)	1	1 – 1.5	0.1

Note that the governor droop (R) is modified for the effect of deadband, as described by Concordia et al [15], because the normal, operational load changes present in the identification data are mostly small relative to governor deadband settings and this increases the effective system regulation (R_e). A value of d = 2.4 is used, partly because it is quoted in [15] and partly because it yields a value for β within the range of 220 – 550 MW/0.1Hz quoted by Weedy [14] for the England and Wales Grid. Nonlinear transformation of the variables according to (4) and (5) gives the distributions of ω_n, ζ and β. This is analytically difficult but it is straightforward to generate their approximate Monte Carlo distributions, as shown in Figure 1, based on 10,000 random combinations. These predict mean values of β = 509 MW / 0.1Hz, ω_n = 0.36 r/s (0.058Hz) and ζ = 0.43.

3. Approaches to power system parameter estimation.

The main obstacle to obtaining accurate estimates of the time-varying parameters in (3) is the fluctuation of the (unknown) load imbalance term, ΔP_L, which largely dominates the changes in system frequency. The approach taken here is to regard it as a random disturbance whose characteristics are identified from recorded data. Several researchers have considered how to estimate power system characteristics. The most common method is essentially spot-evaluation of power system parameters, relying on quite large and sudden disturbances caused by generator tripping or load shedding. Lin et al [2] measure the voltage, frequency and complex power during a rapid, large-amplitude transient caused by a ground fault and obtain a model by means of a least-squares fit of the data to an auto-regressive (AR) difference equation. Popovic and Mijailovic [13] derive a number of simple analytical expressions, based on a second order model similar to (3), which are used to estimate the model's parameters directly from the measured frequency transient and the known change in power which occurs on tripping a large generator. Similarly, the approach of Inoue *et al* [4] is to fit a polynomial approximation to frequency transients recorded at (unplanned) events on the Japanese power system. Values for the parameters M and β in (1) are derived from the polynomial coefficients. The results in this paper indicate that both the inertia and stiffness constants appear to have only a weak positive correlation to the current size (total load) of the power system, albeit on the basis of a limited number of measurements. Li and Malik [16] propose a multistage recursive least-squares method to identify the parameters of an equivalent two-machine model of an interconnected power system in emergency state. The focus of their work is detection and identification of the modified system parameters following the occurrence of a fault, rather than normal operation in the presence of load variation. The power and frequency data used by O'Sullivan and O'Malley [3] is measured during planned tripping of a small generator. A simplex search is then used to obtain the parameters of a first order transfer function which best fits a simulated response to the measured response, in a least-squares sense. In all the work cited above, the focus on relatively large, short-duration transients occurs because the SNR is briefly favourable and the measurement takes place at a well-defined time. An alternative approach is to use spectral analysis techniques, as proposed by Hayashi *et al* [17]. Their method considers only the identification of the stiffness constant and is best suited to a partial system, separated from the total system by a tie-line whose power flow can be measured. Provided the capacity of the partial system is small, compared to the total system, this allows the effect of the unknown load fluctuation of the partial system on frequency to be neglected. It is then possible to estimate a value for the stiffness constant from the cross-spectrum of frequency and measured power. The procedure proposed by Trudnowski and Donnelly [18] is similar in principle but with the added refinement of a low-level, random probing signal deliberately introduced to excite the oscillatory modes of interest. Chang-Chien's approach [7] estimates a moving-average of the β constant of a localised area of the system under automatic generation control (AGC). Their approach uses a recursive on-line least-squares algorithm and the estimates benefit from knowledge of the local area's power generation, load and tie-line flow. Even so, it is reported in [17] and [7] that averaging periods of 2-10 minutes are needed to obtain adequately low parameter variance when the measurements consist of normal operational values. Recently, Wies et al [19] have described a block processing technique for estimating electromechanical power system modes that is closely related to the method used here. They identify an ARMA model for a block of recorded power data, assuming a white-noise input (in effect a special case of the 'disturbance model' referred to in the next section) and hence obtain the system's estimated natural frequency and damping factor from the model's dominant pole locations. The system output is treated as a time series and does not take explicit account of an input. The ARIMAX model structure adopted here allows the parameters of the input-output and disturbance models to be estimated simultaneously. Because of the common denominator in (3), inclusion of the disturbance model aids identification of the input-output model. It also takes advantage of the exceptional features of the power that the Dinorwig pumped-storage station contributes to the Grid.

4. System identification method.

The Dinorwig pumped storage hydroelectric station is located in North Wales. It is equipped with six 317MW rated radial inflow Francis reversible pump-turbines driving synchronous generators, which can be brought from spinning reserve up to full power in 15s. The power output of each Unit and the Grid frequency are routinely sampled at 1s intervals and archived. A typical daily record (86400 points) is shown in Figure 2, where the total station power is the sum of the contributions by individual Units. The per-unit normalisation is:

$$Power(p.u.) = \frac{Power(MW)}{30GW} \quad \text{and} \quad frequency(p.u.) = \frac{frequency(Hz) - 50}{50} \qquad (6)$$

The intervals of negative power occur when the station is pumping, usually at night. Sharp changes in the power flow occur as Units are brought on- or off-line. The frequency is a random variable which remains mostly within a band of about ±0.1Hz of the nominal. The power spectral density function of the Grid frequency record is shown in Figure 3. Except for the small inflection in the range 0.3 – 0.4 r/s, it has a 20dB/decade roll-off with frequency, indicating that the frequency variation is substantially a 'random walk'.

The identification procedure is applied to data of the form shown in Figure 2. It makes extensive use of the powerful prediction-error method described by Ljung [20] and is implemented in the Matlab System Identification Toolbox [21]. The discrete time ARIMAX model is defined by (7)

$$
\begin{aligned}
&\Delta f(k) + a_1 \Delta f(k-1) + \ldots\ldots + a_{n_a} \Delta f(k-n_a) = \\
&\qquad b_0 \Delta P_e(k) + b_1 \Delta P_e(k-1) + b_2 \Delta P_e(k-2) + \ldots\ldots + b_{n_b-1} \Delta P_e(k-n_b+1) \\
&\qquad + w(k) + c_1 w(k-1) + c_2 w(k-2) + \ldots\ldots + c_{n_c} w(k-n_c)
\end{aligned} \tag{7}
$$

where $\underline{\theta} = [a_1 \ldots\ldots a_{n_a} \quad b_0 \ldots\ldots b_{n_b-1} \quad c_1 \ldots\ldots c_{n_c}]$ is the vector of parameters to be identified and w(k) is a Gaussian sequence of independent random variables with zero mean. Experiments with different model orders [9] showed that $n_a = 3$, $n_b = 2$ and $n_c = 3$ gave a good compromise between model accuracy and economy in the number of estimated parameters. The input-output part of (7) then has the 3rd order discrete transfer function:

$$
\frac{\Delta f(z)}{\Delta P_e(z)} = \frac{z^2(b_0 z + b_1)}{z^3 + a_1 z^2 + a_2 z + a_3} \tag{8}
$$

The 3rd order denominator is a consequence of allowing sufficient degrees of freedom in (7) for an adequate description of the disturbance (ΔP_L) component. The ARIMAX structure forces the same order of denominator on the input-output channel but it is generally the case that the identified transfer function possesses a near-cancelling pole/zero pair, which allows it to be reduced to 2nd order with little change in its transient or frequency response. However, rather than use formal model-reduction, the technique used here is to obtain the estimates of ζ and ω_n directly from the dominant pole locations of (8). The estimate of β is obtained from the steady-state value of (8).

This procedure has been validated by means of simulation [9]. First, a selection of models of the form (7) were identified from different sections of the data record. These were then simulated with input sequences (ΔP_e) drawn from other periods of the day and the identification procedure applied to the simulated data. There was good agreement between the models identified from the simulated data and the original model thus indicating that they are not sensitive to the input sequence, i.e. the identified model is not an artefact of the input. Similarly, several models of the form (7) were simulated with a common input sequence $\Delta P_e(k)$ but different noise sequences w(k). Again, models identified from the simulation output agreed well with the original, indicating that the identification procedure is not sensitive to the particular sample of noise. These tests provided good evidence that the method extracts useful information about the dynamic input-output relationship, irrespective of the particular input or disturbance sequences present. The final stage of validation examined whether the identification procedure discerns changes in a model's parameter values. This was done by simulating a slow, sinusoidal perturbation of a model's parameters about their means and comparing the identified values with the known values. It was clear that the method is capable of tracking the parameter variation but is adversely affected by poor SNR, especially during periods when no substantial changes of power are made by Dinorwig. Overall, it was concluded [9] that the values of ω_n, ζ and β identified by this method are valid measures of the power system's dynamic characteristics but that their precision is limited by the SNR of the data.

5. Results

A typical set of results for the 8 parameters in $\underline{\theta}$ is given in Figure 4(a), where the 24-hour record is divided into twelve 2-hour periods and the bars indicate the 1σ standard deviations of the estimates. They are computed from the covariance matrix of the estimated parameters [20] and indicate by how much the parameters could vary if the identification were to be repeated using the same model structure but a different data set. They are therefore a measure of how much uncertainty in the parameter estimates is caused by the disturbance ΔP_L. Figure

4 shows that the values of a_1, a_2 and a_3, which determine the pole locations of (8) and hence ω_n and ζ, remain fairly constant over the day. There is, however, a substantial change in b_0 and b_1, which contribute to the d.c. value of (8) and hence determine the stiffness β. It is noticeable from Figure 4(b) and (c) that the variance of the parameter estimates increases as the averaging period diminishes, which places limits on the detection of short-term changes. Further analysis was conducted with a 90-minute period, as a trade-off between resolution and accuracy. The identification procedure was run in batch mode for the 480 90-minute periods of the March 2001 record. The results are shown in Figure 5 and Table 2. Comparison with Table 1 shows that there is good agreement with the expected range of values.

Table 2 Mean and standard deviations of the parameters for March 2001

	mean	std dev
ω_n rs^{-1}	0.327	0.078
ζ	0.59	0.16
β MW/ 0.1Hz	573	178

Figure 5 shows that ω_n does not exhibit any discernible trend over the month although a slight downward trend in ζ and an upward one in β are evident. This indicates that the power system's average properties remain constant for a lengthy period. The importance of using the correct parameter values is illustrated in Figure 6 where the response of a single Unit at Dinorwig to a small step increase in load has been simulated [5]. The nominal values are taken as the means in Table 2 and the 'low' and 'high' values as the mean ± (twice the standard deviation). Both the steady-state and dynamic characteristics of the electrical power output during frequency-control are affected by the condition of the Grid.

Despite the 90-minute data segments used for identification, there remains substantial scatter on the parameter values which obscures short-term variation. It is possible, however, to obtain useful information by regarding them as stochastic variables with added measurement noise arising from the identification procedure. The spectral characteristics of the three parameter records in Figure 5 are shown in Figure 7. The spectral density for ω_n does not exhibit a pronounced cyclic variation and drops away at about 8dB/decade over the frequency range 0.02 to 0.2 rs^{-1} (approximately 48h – 4.8hr period), which suggests that it is less susceptible to short-term variation than the other two parameters. In contrast, the spectral density for ζ is almost flat, suggesting that it is more or less random. The spectral density for β displays 3 pronounced peaks at periods of 24, 12 and 8.3 hours, so this parameter has a cyclic behaviour.

It is interesting to compare the variation of β with the total load on the system over the month. This is shown in Figure 8 and its spectrum in Figure 9, where the cyclic characteristic is evidently similar to the spectrum of β. When the records of β and total power are cross-correlated, a clear cyclic component is revealed whose maximum value occurs at a delay of 7 periods (i.e. about 10 hours). This is illustrated in Figure 10. Here the β record has been normalised to its mean value and then smoothed by a 5th order Butterworth zero-phase, low-pass filter with break frequency at 0.067 cycles/hour, to leave only the 24 hour cyclic component. When this is superimposed on the (normalised) total system load, the shift between the two graphs is clear. In Figure 11a, the period-averages of the total load and the stiffness have been calculated and plotted on polar co-ordinates to represent a 24-hour cycle. The minimum of the total power occurs at period 3 (4.30 – 6.00am) whereas the minimum stiffness occurs at period 9 (1.30 – 3.00pm). When the graph of β period-averages is shifted by 7 periods, as in Figure 11b, the fit between the two variables is much better. Therefore, the Grid stiffness does not appear to be directly correlated to the total load which corroborates the results in [4]. There are, however, two peaks of stiffness which occur at periods 4 and 14 when the total power is, respectively, rising and falling rapidly and it is possible that the stiffness may be related to the rate of change of power.

In order to investigate longer-term trends, the daily-averages of ω_n, ζ and β were obtained for 4 months in 2001. The results are shown in Figure 12 and indicate that the average value of natural frequency remains substantially constant throughout the year. The damping factor and stiffness, however, exhibit small but opposing seasonal trends with a tendency to become stiffer but less well damped during the autumn.

6. Conclusions

This paper has described the results of applying a prediction-error identification method to obtain low order ARIMAX models for the power system in England and Wales. Values of the natural frequency, damping factor and stiffness for the power system are derived from the models, for daily and monthly variation of the model parameters. The main contribution of this work is the general picture that it gives of the Grid's dynamic behaviour. It is shown that ω_n remains mostly in a band between 0.3 – 0.4 rs^{-1}, ζ in a band between 0.4 – 0.7 and β in a band between 500 – 700MW / 0.1Hz, and this information is valuable for computer simulation studies. Note, however, that the work is not intended directly for control system purposes - in this respect a related but different technique [22] for predictive frequency control is appropriate. It is also clear that there is significant variation in the parameter values during the day, which is not surprising given that the low order linear transfer function is attempting to represent a real system which is complex, nonlinear and time-variant. The parameter estimates can themselves be regarded as random variables and it is shown that the stiffness appears to have a strong cyclic component which is correlated with, but shifted with respect to, the total system load. The results also indicate that the long-term Grid properties are stable although a seasonal change in the stiffness and damping parameters is discernible. Firmer conclusions could be drawn by extending the analysis to cover all recent records but this would require a substantial data-processing exercise.

The main obstacle encountered in this work was the low SNR of the data, which results in substantial uncertainties in the identified parameter values. It may be the case that large changes in power system characteristics occur over short periods of time, as major plant are brought on- or off-line, and that these are obscured by the averaging inherent in the method. In terms of future work, it is possible that other system identification methods could be used to draw out the power system characteristics more effectively. For instance, hybrid estimation techniques - treating the system as a jump-Markov process whose parameters change abruptly - may be applicable. It would be interesting to investigate whether the SNR could be improved by means of a probing signal. Injecting a small amplitude, random signal with carefully designed spectral properties continuously onto the power system would not impair the quality of the frequency regulation, nor be large enough to change its 'small-signal' properties. Finally, the identification procedure would be helped by better physical insight into the mechanisms which change the power system's properties. A multi-machine computer model could then be used to simulate the power system at an appropriate time-scale and hence validate the identification method.

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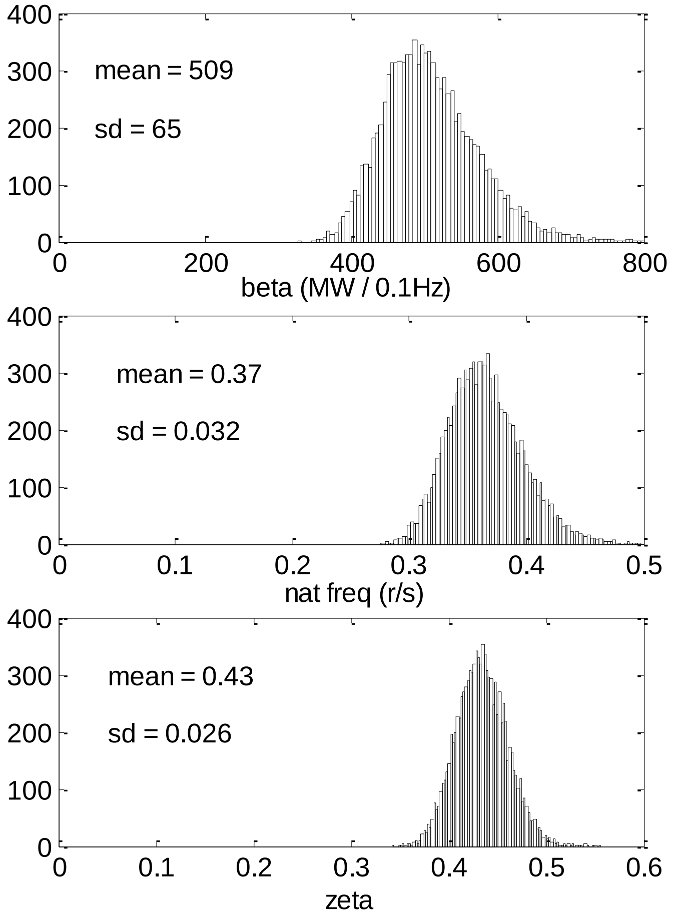


Figure 1 Approximate Monte Carlo distributions of ω_n, ζ and β for typical power system parameter values.

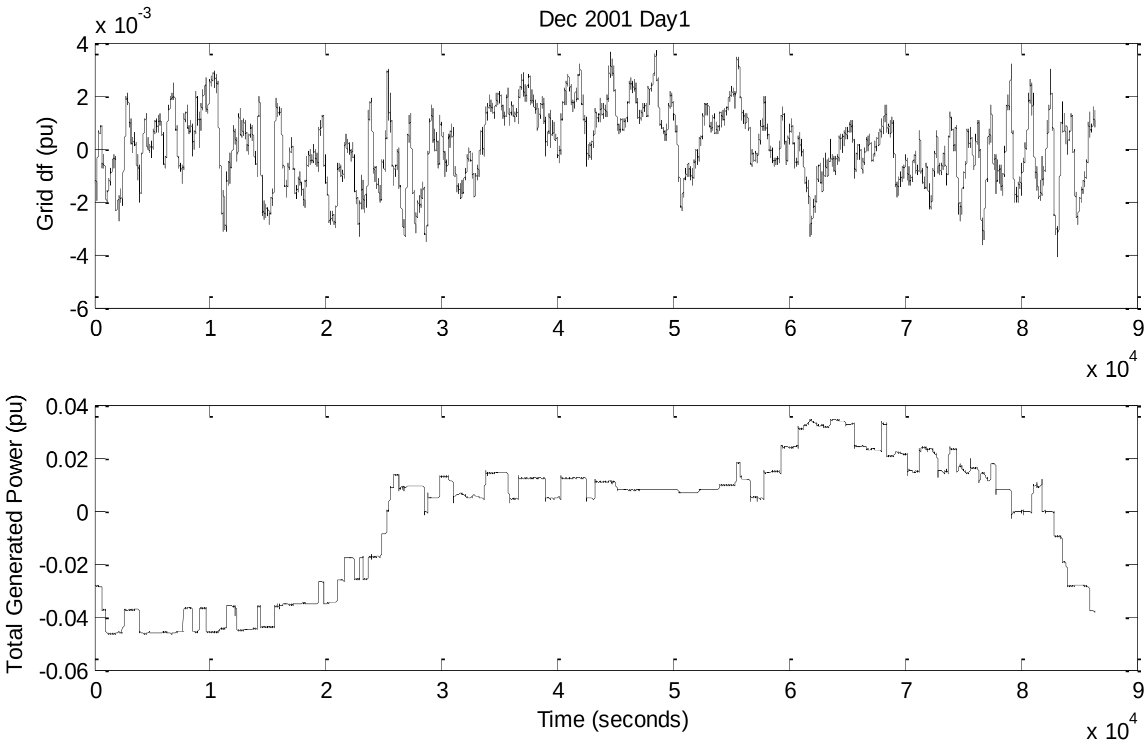


Figure 2 Normalised power-frequency record at Dinorwig.

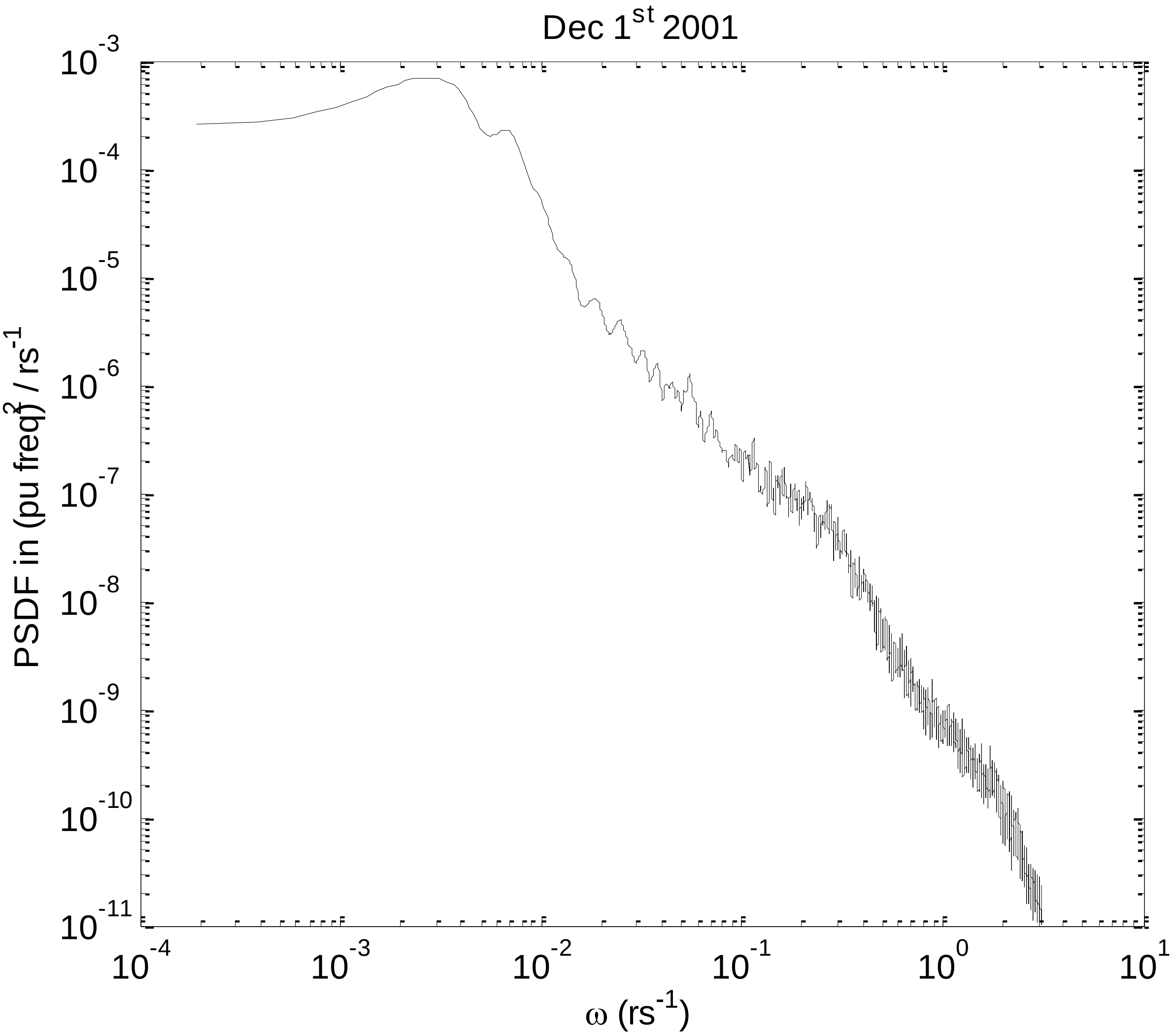


Figure 3 Spectrum of the Grid frequency variation for Dec 1st 2001.

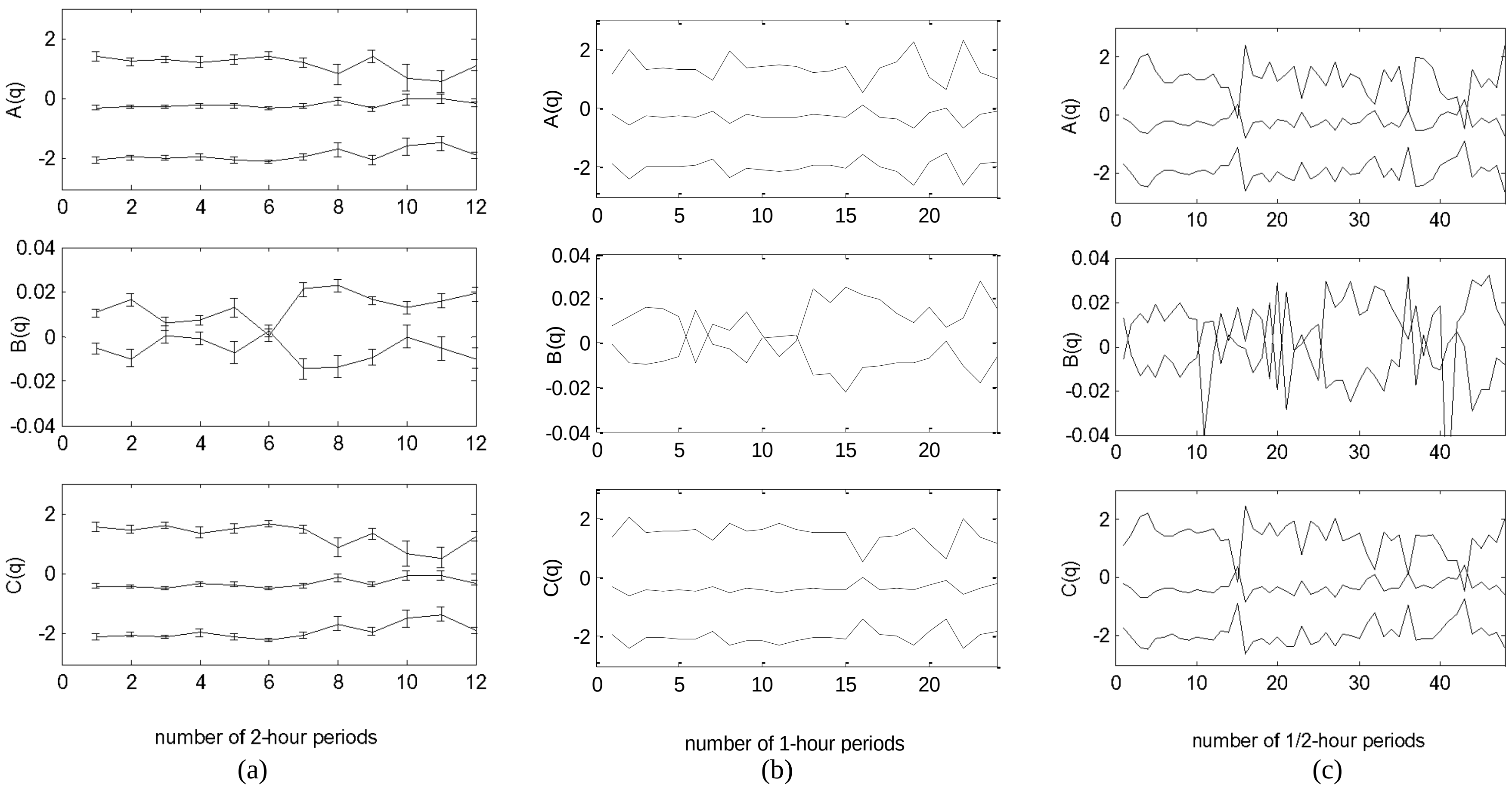


Figure 4 Variation of the ARIMAX model parameters, March 3rd 2001, averaging over 3 different period lengths.

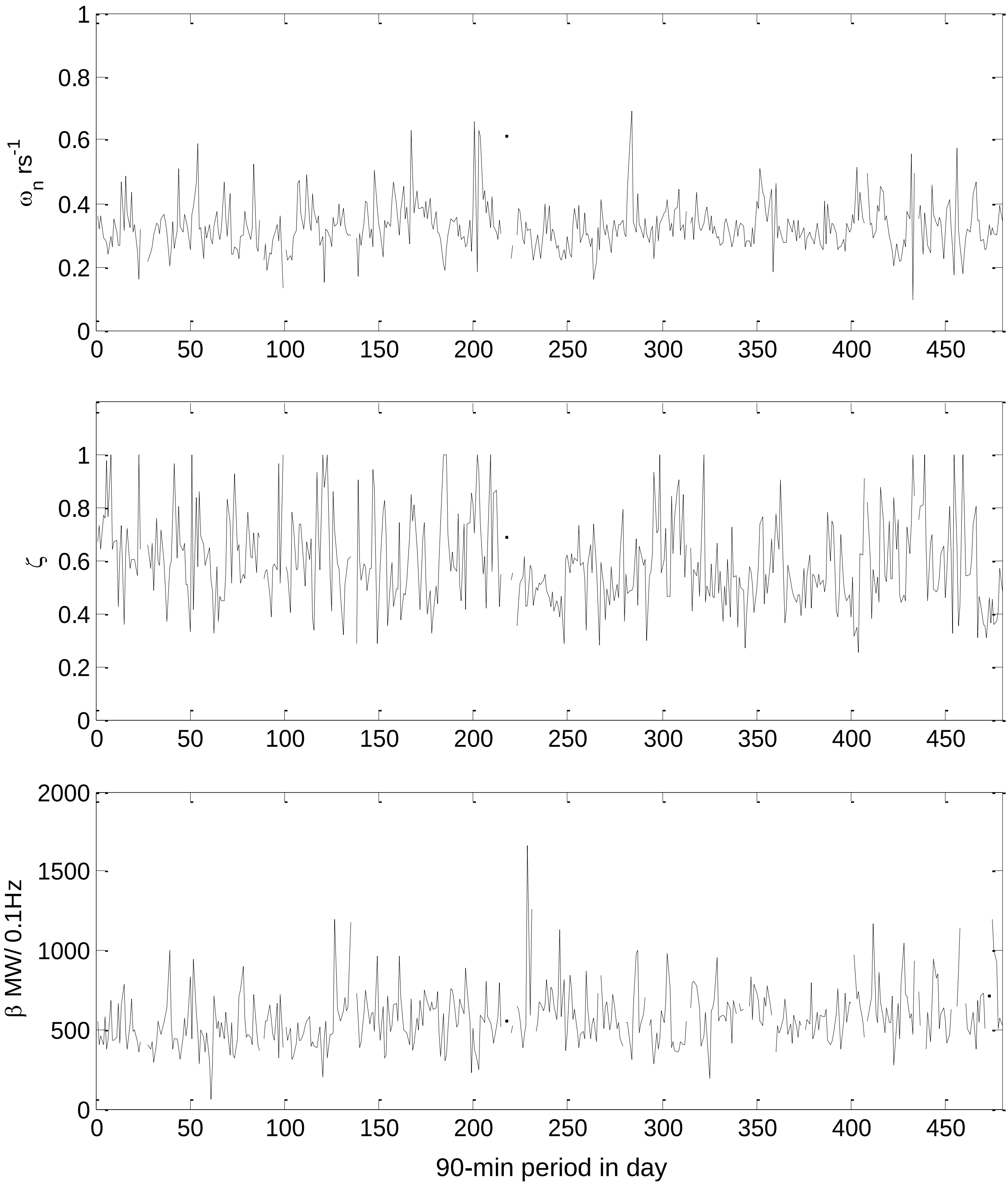


Figure 5 Power system parameter values from the identified models for 480 periods throughout March 2001.

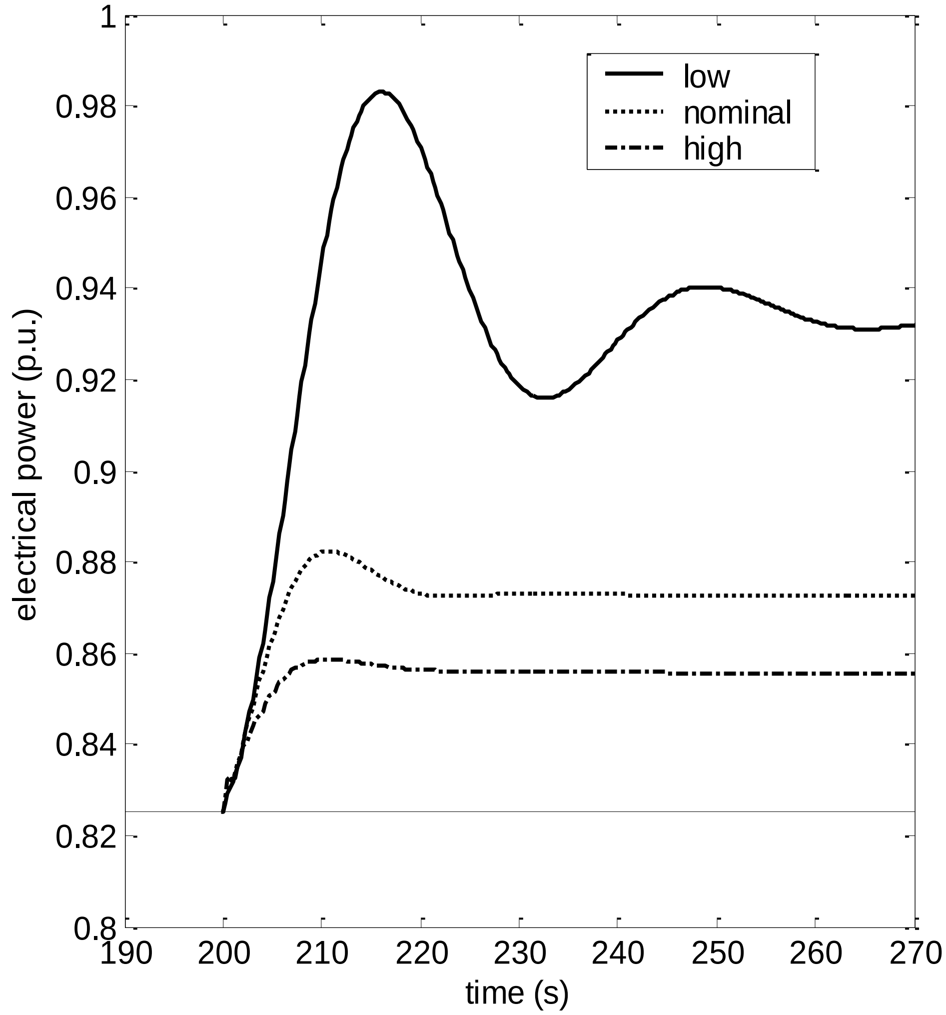


Figure 6 The power produced by a single unit at Dinorwig in response to a step increase in load on the Grid, (low) ω_n = 0.17r/s, ζ = 0.27 and β = 3.62p.u., (nominal) ω_n = 0.327r/s, ζ = 0.59 and β = 9.55p.u., (high) ω_n = 0.48r/s, ζ = 0.91 and β = 15.5p.u.

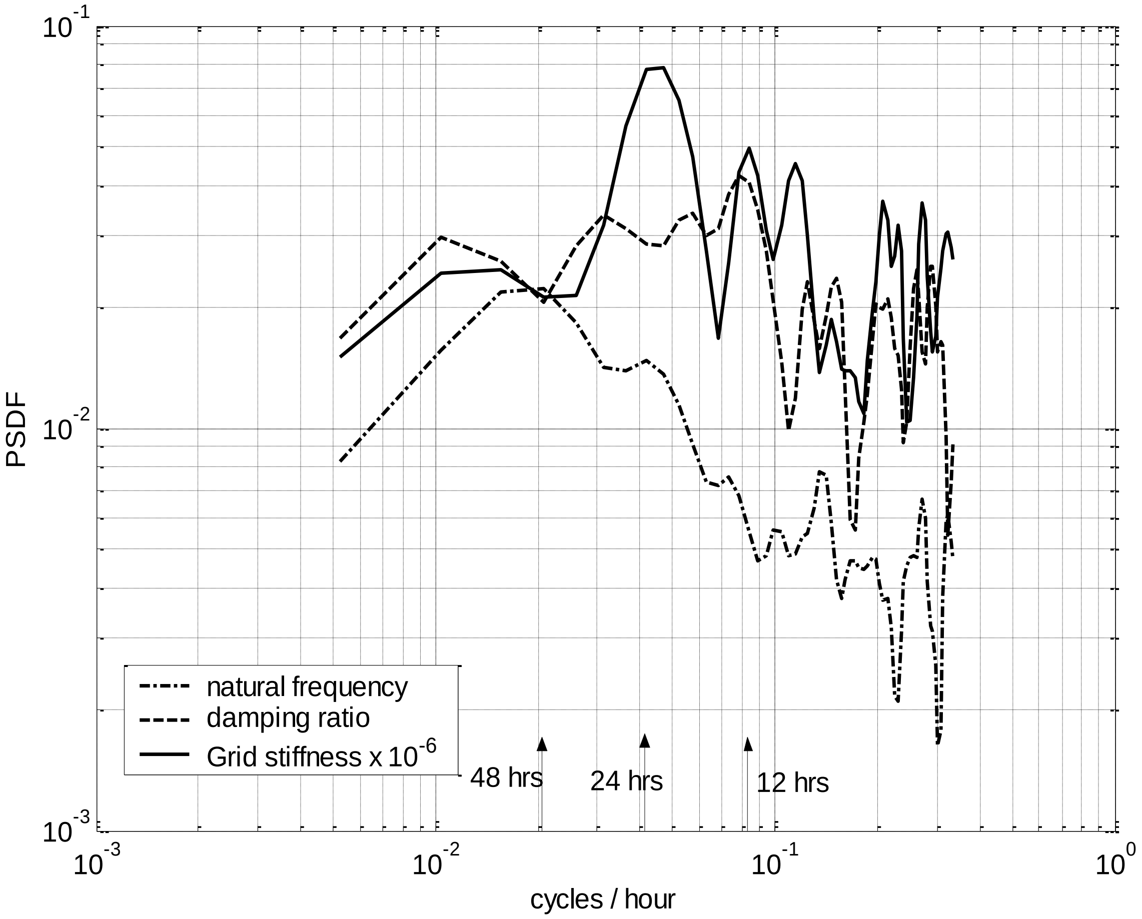


Figure 7 Spectral characteristics of the parameter values obtained for March 2001.

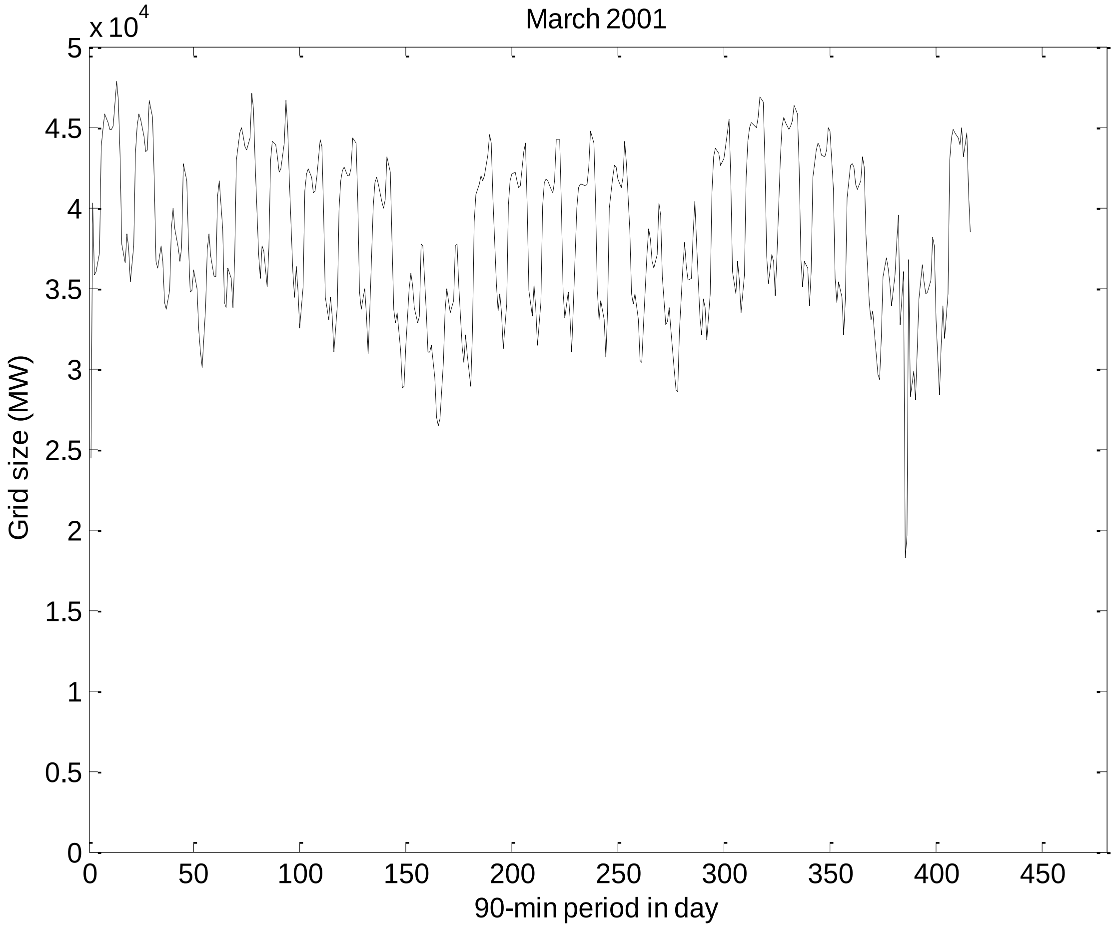


Figure 8 Plot of total system load for March 2001.

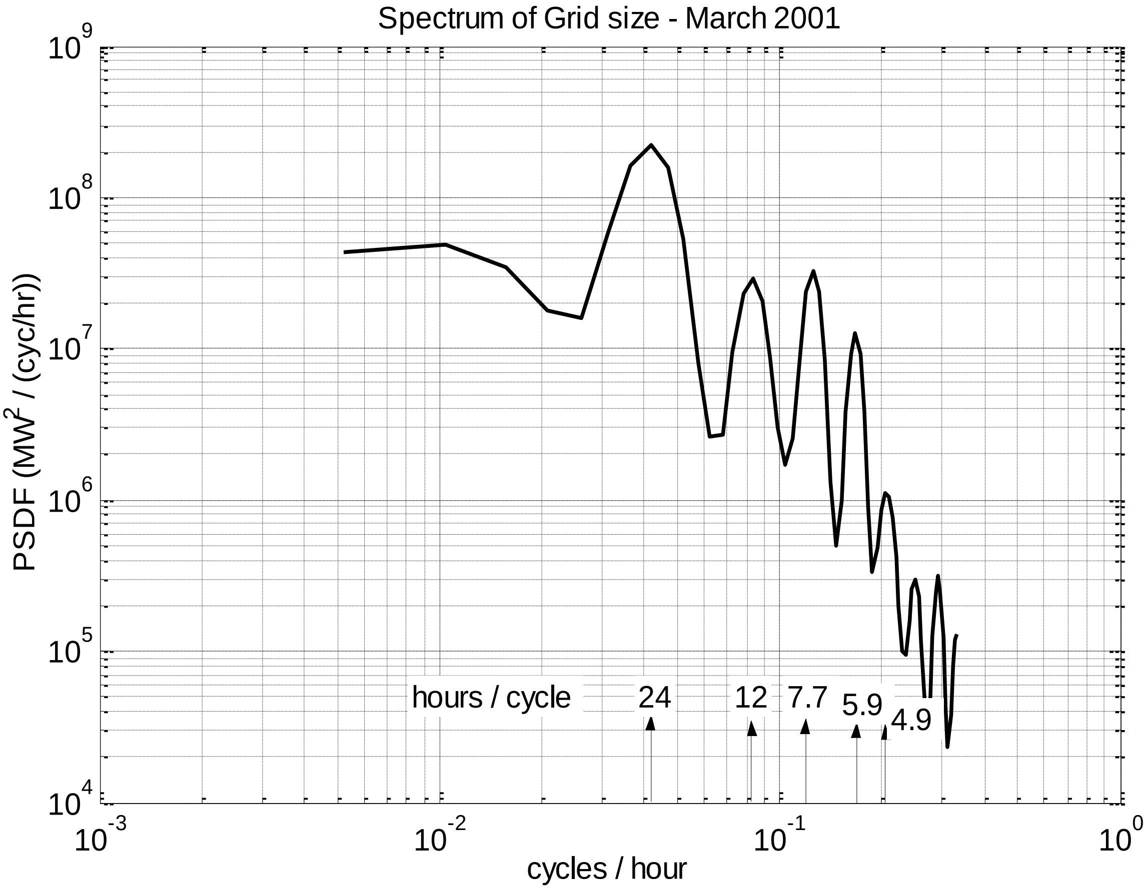


Figure 9 Spectral characteristics of the power system load data.

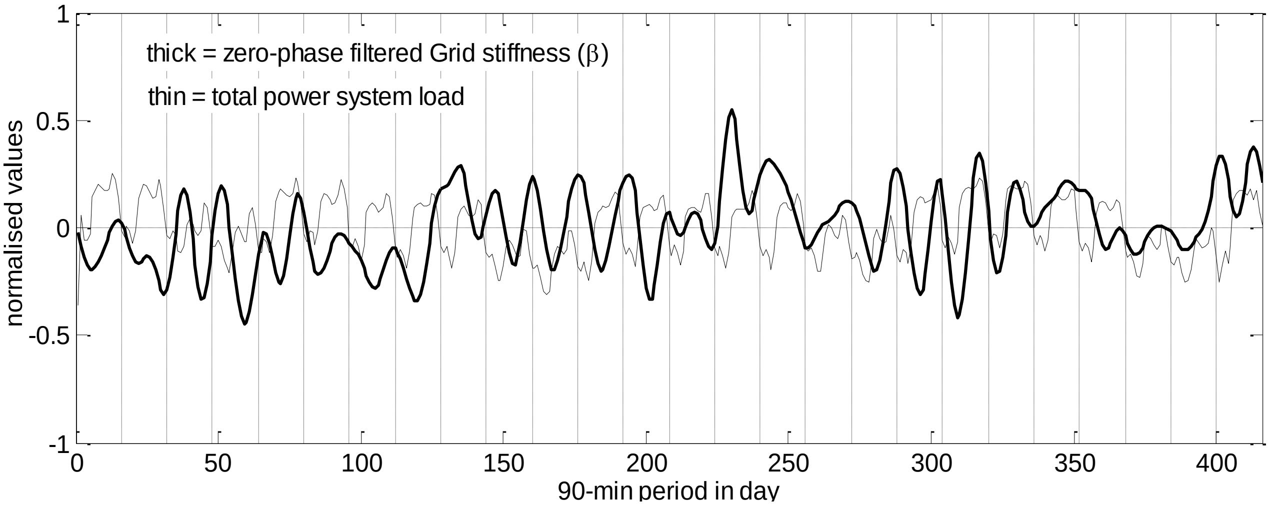
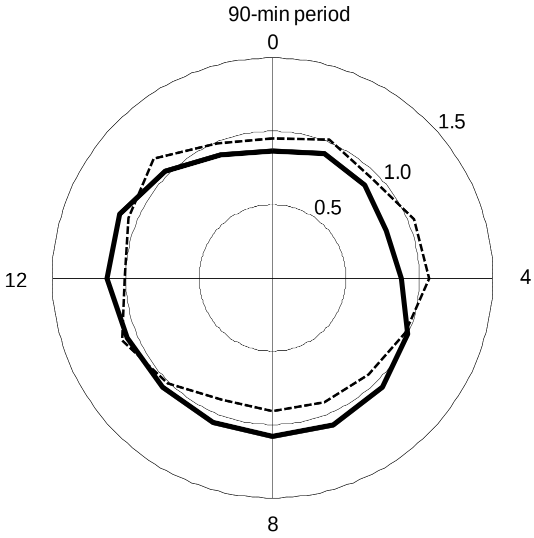
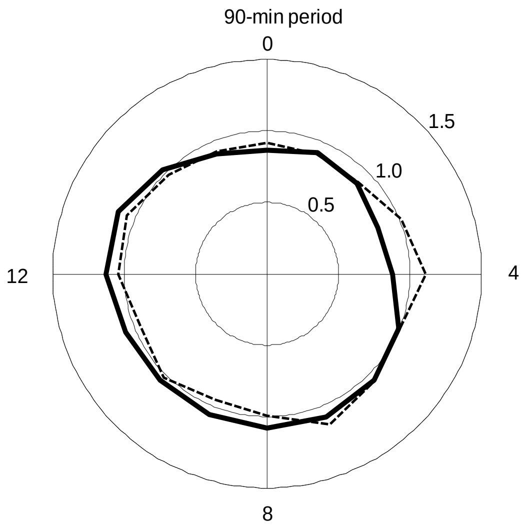


Figure 10 Comparison of fundamental cyclic component of β parameter variation with total load power.



(a)



(b)

Figure 11 Normalised power (full line) and stiffness (broken line) for each 90-min period, averaged over the month, (a) both plotted at their corresponding period, (b) the stiffness shifted by 7 periods.

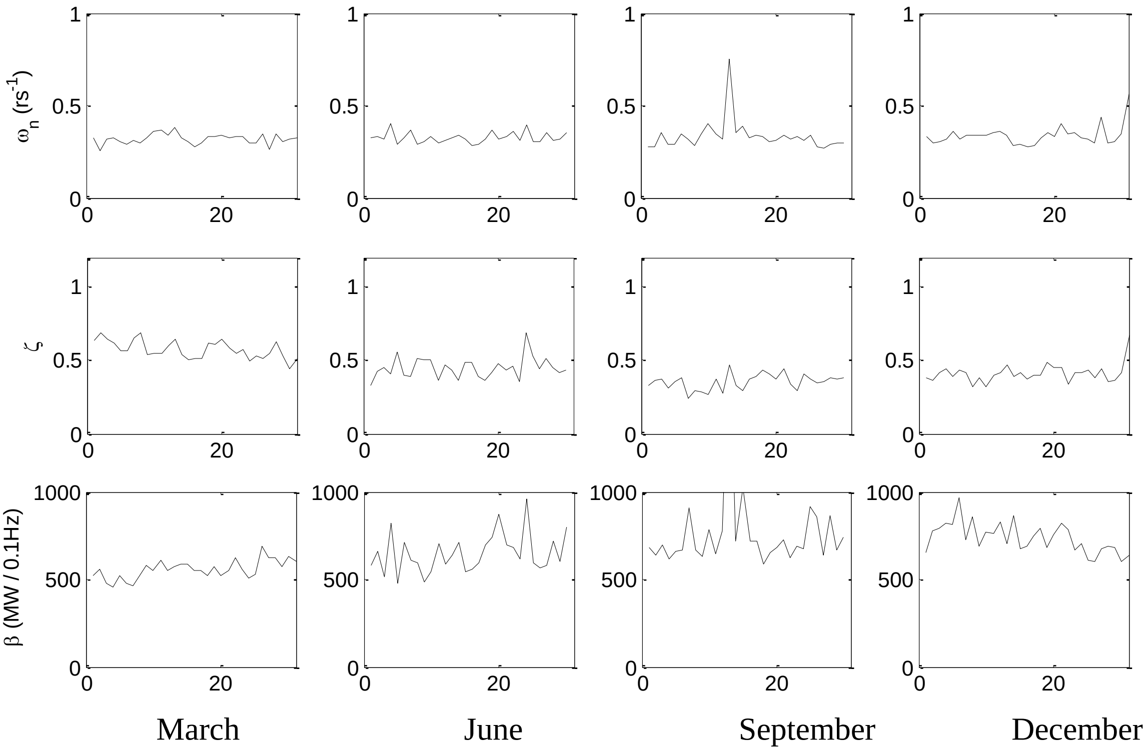


Figure 12 Variation of ω_n, ζ and β for 4 months in 2001.