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Unlocking market secrets: Revealing wholesale electricity market price dynamics with a novel application of spectrum analysis

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ABSTRACT

Understanding market participants' competitive behaviour is essential for optimising financial performance in liberalised electricity markets. However, this is challenging due to complex market structures, generation dependent on different primary energy sources and lack of transparency. This paper introduces a novel approach using power spectrum analysis applied to wholesale electricity markets to uncover hidden patterns. Applying this novel method to the Western Australian Wholesale Electricity Market (WEM) revealed periodic cycles in different fuel types and technologies that offered insights into competitor behaviour not immediately evident in the dataset. Surprisingly, the approach uncovered that in a power system with high penetration of renewable generation, there is a weak price response to demand changes, challenging assumptions about the direct link between demand and price formation. These insights could be applied gain a competitive edge in capital investment decisions and tactical bidding behaviour.

1. Introduction

Electricity market models tend to be constructed based on market design and data availability. There is not a single or general established pricing model for wholesale electricity markets, but instead, approaches and design principles that are applied based on research applications (Weron, 2014; Weron and Misiorek, 2008; Daganzo et al., 2012; Tonkes and Broadbridge, 2012; Kallabis et al., 2016; Savvidis et al., 2019; Liu, 2015). As a result, hundreds of different models, classifications, and approaches are supported by an extensive range of system and modelling tools (Chang 2021). It is a domain that remains an active area of research in wholesale electricity markets, as minor improvements can have wide-reaching impacts on significant investment decisions.

The periodic nature of renewable fuel resources (whereby they are abundant or scarce) does not necessarily match the same periodic cycles in the system demand curve. For example, as Fig. 1 shows, wind generation between 3:00 p.m. and 6:00 p.m. is low compared to system demand.[1]

These seasonal patterns, calendar effects and non-linearity drive volatility in wholesale electricity markets, which are an aspect of market dynamics that make accurate system demand and price forecasting challenging (Shah, 2016; Misiorek et al., 2006; Jan et al., 2022).

1.1. Implementation of periodic factors in wholesale electricity market models

As an active area of research, recent approaches in the literature concerning the inclusion of periodic components in electricity market models continue to improve the capturing of underlying patterns and changes in underlying datasets with a focus on consumption. The approaches decompose datasets into constituent components to effectively capture underlying patterns in the market data (Shah et al., 2020; Bu and Cho, 2020; Shah et al. 2021).

One established method of examining periodic aspects in system demand curves uses power spectrum analysis and spectrum decomposition based on Fourier analysis. Fourier analysis is widely used in many scientific fields to determine periodic patterns in datasets (Olson, 2017). The determination of multiple periodic cycles is an essential aspect in modelling electricity demand and spot prices, as it determines an estimation of a component to deal with trends and seasonality in the data (Janczura et al., 2013; Cruz et al., 2019; Bandara et al., 2021; Tashpulatov, 2013). Fast Fourier Transform (FFT) is used to identify

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[1] In addition, Fig. 1 shows that in a period of similar demand (i.e.,12:00 am to 7:30 am), the total generation provided by wind resources was significantly different.

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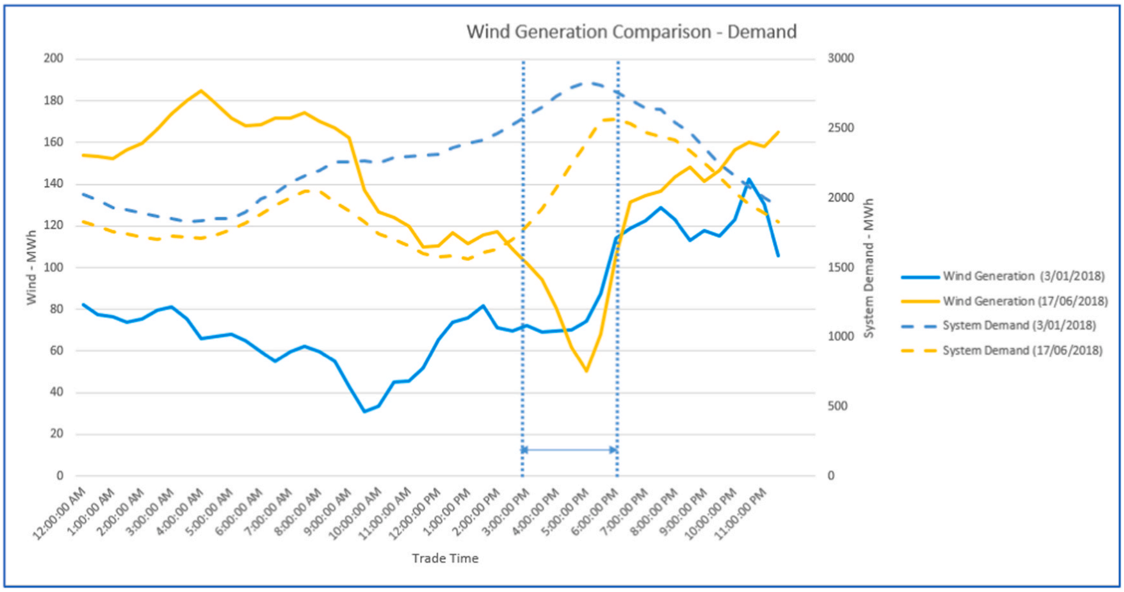

Fig. 1. Wind generation compared to system demand profiles on 3 January 2018 and 17 June 2018 (WEM).

deterministic cycles from the demand and spot-price data and has been shown to improve the modelling accuracy of weekly, seasonality, holiday and other effects (Erlwein et al., 2010; Seifert et al., 2007; Shah, 2016; Beiraghi and Ranjbar, 2011). The use of periodic cycles in modelling is accepted as good practice; however, the use of harmonics of the daily, weekly and seasonal variations and modulation by seasonal harmonics is still an active area of application for inclusion in market models (Yukseltan et al., 2020; Zhou et al., 2022; Sibtain et al., 2022). The authors agree with recent work that indicates that the effect of exogenous variables in functional model design should be further explored (Jan et al., 2022) and has high potential to be applied to other applications by examining different periodic coefficients (Cruz et al., 2019).

1.2. Application of periodic detection to system demand and price profiles

The application of power spectrum decomposition is focused on capturing seasonal variations in demand curves (Cheng et al., 2019; Müller and Seibert, 2019; Ghayekhloo et al., 2019; Gonzalez et al., 2017; Magnano and Boland, 2007; Moutter et al., 1986; Riddell and Manson, 1996; Shah, 2016). Social and weather factors in monthly periods are often assumed to be diluted in the cumulative nature of a monthly value. However, it has been established that these changes are highly influential in the determination of seasonal aspects of demand curves (González-Romera et al., 2008). Other periodic factors, such as bank holidays and linear trends,[2] have also been modelled using periodic elements (Jan et al., 2022; Conejo et al., 2005; Misiorek et al., 2006).

A limited amount of work has considered the seasonal aspect of non-firm[3] renewables in generation supply. Historically, research associated with renewable resources has primarily been limited to hydroelectric generation, which depends on precipitation and melting snow. This seasonality depends on the market location and can differ between markets (Kiesel et al., 2018; Cartea and Figueroa, 2005). Before the Energy Transition, it was established that seasonal fluctuations in system demand and supply translate into the seasonal behaviour of electricity spot prices (Bierbrauer et al., 2007). Consequently, the amount of research directly related to periodic effects and wholesale electricity prices is significantly smaller than that on system demand modelling. The relationship is changing, as found in the day-ahead market in Germany (Simoes et al., 2017; Hinderks and Wagner, 2020); photovoltaic (PV) and wind generation increasingly affect the price outcomes. The authors concluded that this area requires further research as the impact on price formation will become more pronounced as power systems transition to higher proportions of non-firm renewable generation.

1.3. Gaps and research questions

The literature review revealed significant and critical gaps in the application of spectrum analysis in wholesale electricity markets in relation to (1) the detection of periodic cycles in generation from diverse fuel types and facility technologies, (2) the identification of competitor behaviour, (3) the application in wholesale electricity markets with a high penetration of non-firm renewable generation; and (4) comparisons between system demand and price formation.

To address the gaps identified above, the authors examined the following question: '*How can the periodic examination of wholesale market price outcomes be extended to a power system with a high penetration of non-firm renewable generation*?' The novel contribution of this paper is the segmented power spectrum analysis on independent variables and subcomponents based on a generic supply-side wholesale electricity market model. This approach was tested using the WEM as a case study that found valuable insights that show the value of this innovative approach.

This paper is organised as follows: Section 1 provides the literature review on the use of periodic analysis in wholesale electricity markets and the research question; Section 2 provides details on the selection of the case study; Section 3 outlines the methodological approach adopted for this study; Section 4 applies and evaluates the methodology to the case study; Section 5 outlines the key findings; and Section 6, concludes the paper.

2. Case study

The selection of the case study was important, as the selected wholesale electricity market needed to be representative of other

[2] A linear trend is not periodic; however, the method used to model a linear trend can be treated the same as a sinisoldial.

[3] Non-firm is an industry term for generation that does not have a guarantee of continuous availability, typically, this is due to the primary fuel source that is from wind or solar.

Fig. 2. Location of the South West Interconnected System (SWIS) (which is displayed as the dark area) in southern Western Australia (image courtesy of (Western Power Corporation, 2022).

electricity markets with similar technologies, legal frameworks and market dynamics. In addition, the chosen market was required to have a power system in which non-firm renewable sources made high contributions to electricity production.

The WEM (see Fig. 2) was deemed a suitable market, as it is presently undergoing a rapid transition to renewable energy generation as the primary generation source and has the market attributes of an isolated grid. Furthermore, as a geographically isolated network, it had additional advantages, including that (1) interconnections from other power systems and markets did not need to be considered, and (2) the power system has to supply all services to keep the system in a secure operating state.[4]

As shown in Fig. 3, the WEM has rapidly progressed to supplying electricity from renewable generation sources. The total energy supplied by those sources has approached 50%, with the Australian Energy Market Operator (AEMO) having reported intervals when over 70% of the provided energy was from renewable sources (AEMO 2022b). To place this into comparison, the amount of energy provided from wind and solar resources in the United States, China, and the European Union regions is between 10% and 20% (IEA, 2021), with interconnected wholesale electricity markets such as California Independent System Operator (CAISO) regularly reporting intervals with over 75% of the energy provided by wind and solar resources (CAISO, 2023).

This trend over the last decade has placed the SWIS region at the forefront of the global Energy Transition. The WEM market dynamics were all suitable to explore and apply in the proposed examination using spectrum analysis.

3. Methodology

The methodology outlined in this section can be applied to any wholesale electricity market depending on the data available to complete the analysis. The critical outcome investigated was the application of a spectrum analysis to independent variable components and subcomponents to yield insights into market dynamics that were not apparent in the aggregate data set. The proposed methodology outlines the technical approach used to extract periodic cycles and describes how the market data was constructed for the analysis.

[4] Within the frequency boundaries and contingency management.

3.1. Innovative treatment

The technical approach is to apply spectrum decomposition using FFT to a time-series data set. The time-series data sets are used as the 'signal' to extract the periodic components. The traditional approach is to model the market, identify the periodic components from the System Demand, and use this in market price modelling. The modelled prices are then used to provide market insights, as conceptually illustrated in Fig. 4.

We examine underlying components in greater detail to provide insights into the market. A more detailed conceptual wholesale electricity model was developed in Fig. 5 as a suitable generic wholesale electricity market model to identify components that affect price outcomes. The model explicitly captures non-firm renewable generation and embedded PV to capture the effects of a dynamic supply curve (Appendix A). This enables the identification of datasets that can be treated as signals in the spectrum analysis. For the proposed model to be generic, a number of aspects that affect price formation had to be excluded, including network constraints, primary fuel costs, the macroeconomic environment and, most notably, power purchase agreements (PPAs).[5] These exclusions were intentional, as in many liberalised electricity markets, this data is confidential and unavailable. For the proposed research to be widely applicable, it must work in opaque market structures.

Once a suitable model was determined, application to the independent variables could be defined in the process as conceptually provided in Fig. 6.

In this research, we investigated supply-side aspects of the market, and the data was segmented into the following three groups for the investigation: (1) the independent supply-side variables determine price formation group; (2) the individual facility generation profile group; and (3) the aggregate market participant generation group.

These steps are defined as follows:

(a) Price Formation Components.

To determine the price formation using a supply-side model, as defined in Eq. 1 as follows:

$$P_t = f(\text{independent variables}) + \epsilon_t \quad (1)$$

f is defined as the function of price determination based on relevant wholesale market design. Independent variables refer to those components defined in the simplified model in Fig. 5, where P is the electricity spot price (units: \$/MWh), which is representative of the cost of providing electricity; UD is the underlying demand (units: MWh), which is the total demand for electricity met by all generation devices, including rooftop PV and other DERs; U is the unavailable grid-connected generation (units: MW); G is all the generation in the power system, including the DERs (units: MW); DER is the sum of all embedded generation used in the system. In the early stages of the battery adoption, this will typically be rooftop PV; *firm* is the firm generation set of the power system based on the primary fuel type (e.g., coal and gas); $non-firm$ is the non-firm generation set of the power system based on the fuel type (e.g., solar and wind); are the environmental variables. This set is defined as weather measurements (e.g., temperature, wind speed and rainfall), and $\epsilon$is a constant term used to capture white noise in the model.

(b) Subcomponent Examination - Individual Facility Generation Profiles.

All generation(G) in a power system is the aggregate of multiple generation faculties. This information is used to analyse different facilities running profiles and was calculated using Eq. 2:

[5] PPAs are long-term electricity supply agreements that are effectively off-market financial arrangements. Such agreements result in bidding behaviour that is counter to pricing responses in a wholesale electricity market. For example, a fully contracted base load plant might want to offer low prices to ensure it is scheduled in the market.

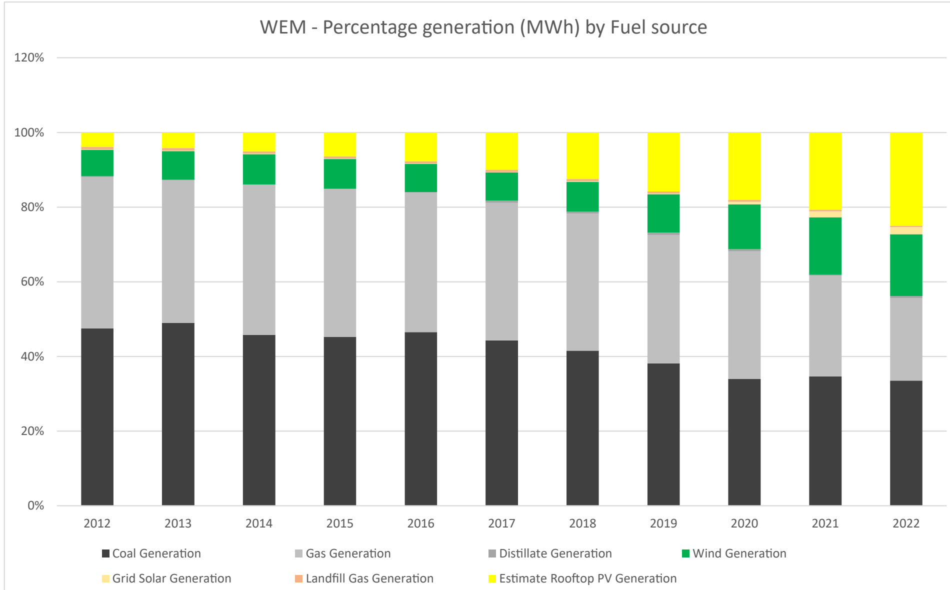

Fig. 3. WEM percentage generation by fuel source.

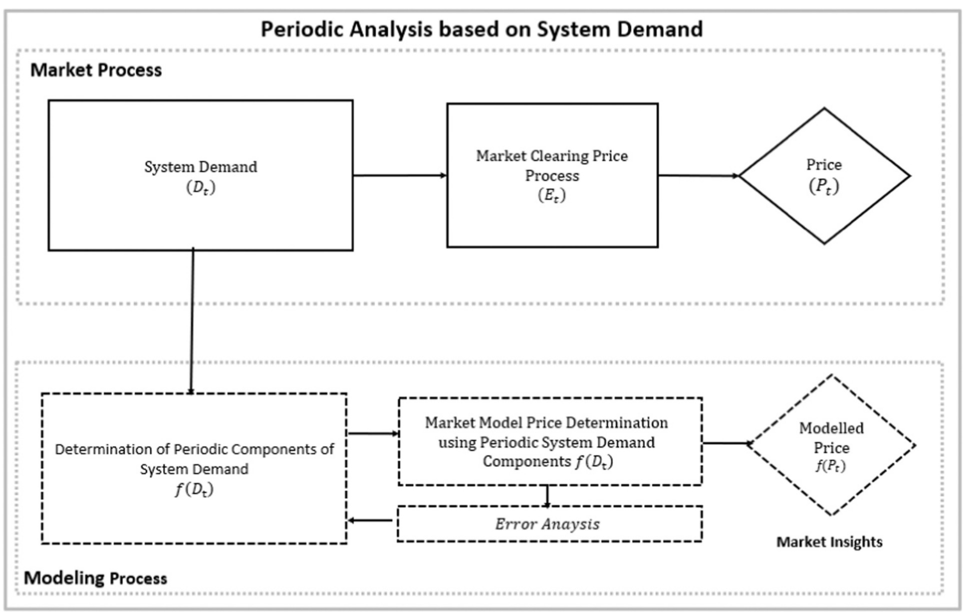

Fig. 4. Traditional application.

$$G = G_{Firm} + G_{Non-Firm} + G_{DER} \tag{2}$$

Where:

$$G_{DER} = \sum Behind \quad the \quad meter \quad net \quad generation$$

$$G_{Firm} = \sum Faciltiy(Firm \quad Generation)$$

$$G_{Non \quad Firm} = \sum Faciltiy(Non - Firm \quad Generation)$$

This is of particular interest when comparing generation technologies of the same type in a similar geographical location.

(c) Subcomponent Examination - Market Participant Generation Profiles.

The data set defined and examined was the net aggregate generation from ownership irrespective of technology type defined in Eq. 3 as:

$$G = \sum Faciltiy\text{Generation}(MP \quad Ownership) \tag{3}$$

3.2. Power spectrum implementation

The foundation technical approach (Olson, 2017) applied has been successfully applied in New Zealand (Moutter et al., 1986), the South Australian region in the National Energy Market (NEM) (Magnano and Boland, 2007), Spain (González-Romera, Jaramillo-Morán and Carmona-Fernández 2008), UK (Williams and Short, 2020) and to household consumption in Ireland (McLoughlin et al., 2013).

The method and definitions provided in the following steps can be applied to any wholesale electricity market:

Step 1: The required data set was sourced based on the market selected for the case study, and error checking and validation were conducted. The data set was combined and split into suitable subsets of

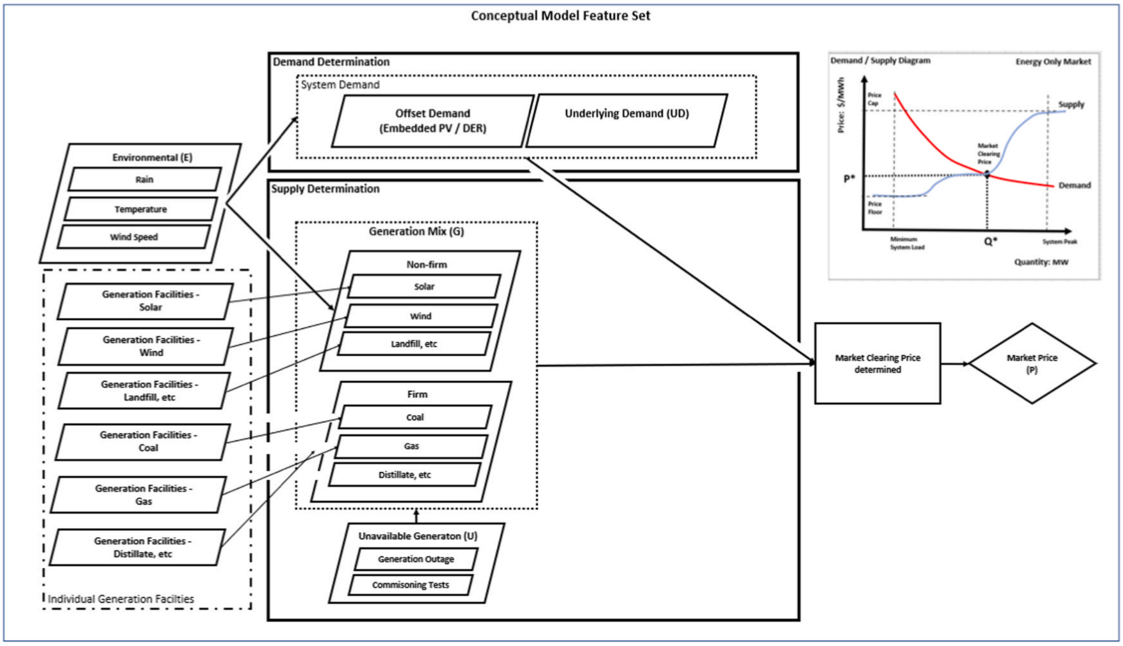

Fig. 5. Simplified supply-side pricing model.

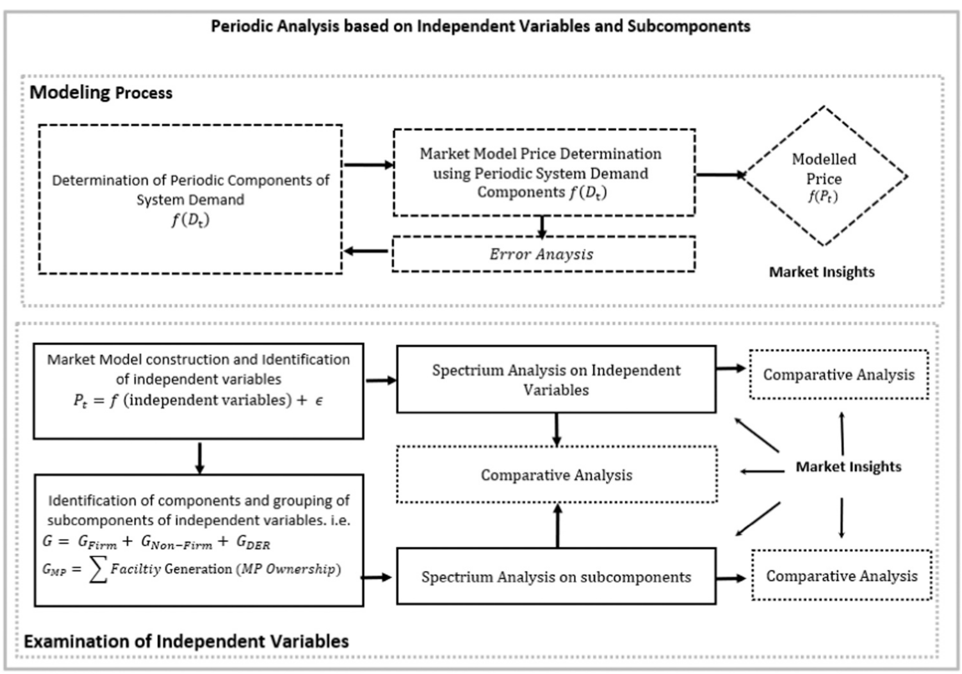

Fig. 6. Application to independent variables.

primary fuel type, facility and market participant, each with components for *generation, pricing* and *notional revenue.*[6] The nature of the DERs added complexity to how these data needed to be considered (see Section 3.1). All data was required to be represented as a time-series data set to be defined as a signal for analysis.

Step 2: The autocovariance of each data subset[7] was conducted, and the power spectrum was calculated by taking the FFT[8] of the autocorrelation results. It is important to note that in this application, each data set represents an abstract signal that was used as an equivalence with electrical signals. In the literature, it is referred to as the power spectrum, even when no physical power is involved. As such, the resulting values were relative.

[6] Notional revenue is determined from the generation and market spot price during each interval.

[7] The computational autocovariance library implemented in R (Venables et al., 2002).

[8] The computational FFT library implemented in R (Becker et al., 1988).

Step 3: The power spectral density (PSD)[9] and the modulus-squared discrete FFT were calculated on each data subset. The units were converted to dB/Hz to allow relative comparisons. In this work, the relationships were classified as *very strong, strong, weak or very weak* for ease of interpretation.

Step 4: Examine the periodic results.

3.3. Technical implementation

The data analysis and processing aspects of the research were completed using *Excel* and *R* on a Windows server platform. R studio and open-source R libraries were used to perform the computation. This process was effective and enabled the repeatability of analysis. The spectrum analysis was conducted in accordance with the steps outlined in the methodology section.

3.4. Treatment of DER

In most jurisdictions, DER does not form a formal part of defined wholesale electricity markets; market operators treat DERs as part of system demand. Post-1920, when electricity networks and systems moved into the large-scale provision of electricity, the distribution network had a negligible amount of distributed generation compared to the large capacity generation facilities built at the time (Stoft, 2002; Joskow, 1983). In addition, due to the cost and need to meter infrastructure, only large loads had interval meters, and residential consumption was measured by accumulation meters.

This approach is a practical simplification, as it is challenging to estimate the amount of generation offsetting the load behind the meter. The rapid growth of DERs, particularly rooftop PV, over the last decade has resulted in a significant electricity supply to a power system. Thus, DER generation needs to be treated as part of the overall electricity market[10] in any supply-side model, with Fig. 7 illustrating the treatment.

3.5. Data sources

The market data was collected from the local system operator from 1 July 2012 (when the balancing market commenced in the SWIS) to 28 February 2022. The data series comprised 169,327 observations. Each day comprised 48 observations, with each observation referring to a fixed 30-minute period of a trading day that commences at 8:00 a.m. The majority of data used was available from the AEMO public website (AEMO 2022a) and the Bureau of Meteorology (Bureau of Meteorology, 2022). Behind-the-meter PV data was constructed[11] from solar capacity factor traces sourced from Solar and Storage Modelling Pty Ltd (Solcast, 2022), with output determined from rooftop PV installation figures provided by The Clean Energy Regulator (The Clean Energy Regulator, 2022). The underlying demand estimates were calculated based on this estimate of output and system demand data.

3.6. Data preparation

The data was combined into a single data set. Data cleaning was completed using a process of manual inspection, and the data sources underwent a statistical analysis and verification. Overall, the data had minimal duplicate data and no missing values. The data was reorganised into the following groups for investigation: fuel types, registered facilities and registered market participants.

Wholesale electricity spot prices are known to be highly volatile and produce data points with extreme values. These extreme values have the potential to cause distortion in the modelling of market behaviour. In spectrum analysis, such events may cause amplitude distortion and frequency leakage. A threshold value replacement approach (Shah et al., 2021) was applied to the extreme value identified using a 3rd standard deviation filter with the results compared with the unfiltered results. It was found that the highest ten frequencies had an average amplitude increase of 2% with no change of relative ranking. These changes were non-material, and as such, the analysis detailed in this paper is based on unfiltered values to ensure a consistent approach was applied across the results.

4. Assessment and discussion

4.1. Visual inspection—comparison of demand and price results

Visual inspections of the SWIS system demand, final balancing prices and notional revenue were undertaken. The data (for summary graphs, see Appendix B and for the full power spectrum results, see Appendix C) show a degree of similarity between the three data sets, and aspects such as the relationship between the daily cycles were consistent between the three; that is, the morning and evening peaks were consistent across all the profiles. Monthly and seasonal trends were evident in the data. The effect of DER and the resulting 'duck curve' effects were observed in the results. The visual trends for the solar and wind patterns revealed a daily cycle. These seasonal observations were consistent with the literature review, were used to identify frequency harmonics in the resulting data and were removed from the results (see Sections 4.1, 4.3, 4.4 and 4.5). This step was consistent with other work on removing multiple harmonics (Giovanni and Stefania, 2015).

When examining the power spectrum results in Fig. 8, the same periodic cycles were evident in both the system demand and in the balancing price. The strength of the frequency response for the balancing price was less pronounced than the system demand response. This indicates that the periodic factors that drive the balancing prices are not as strong as those that drive system demand.

4.2. Summary power spectrum results

The period aspects of the high-level features of the case study are shown in Fig. 9. The variables shown are consistent with the model defined (Fig. 5), with additional analysis undertaken on PPAs, the Short Term Energy Market (STEM), and independent power producers (IPPs) production.

A number of findings were consistent with the literature reviewed. Notably, in relation to system demand, high and sharp peaks appeared in the frequencies corresponding to the periods[12] of daily (71), twice-daily (66), weekly (50) and seasonal patterns[13] (58).

Directly comparing these results with prior studies was not possible due to the different markets and time periods, but the method was shown to be effective as it did capture all periods as found in

[9] The PSD of the signal describes the power present in the signal as a function of frequency per unit frequency. The PSD is commonly expressed in watts per hertz (dB/Hz).

[10] This is based on the broad definition of a market, that is; a place where buyers and sellers can meet to facilitate the exchange or transaction of goods and services.

[11] The data set provided from AEMO was the same data set that was used for the publication of the 2022 Western Australian Electricity Statement of Opportunities (AEMO 2022c)

[12] A period was defined as the number of cycles that occur across one year. Thus, a frequency of 365 corresponds to an increase in the signal that occurs once a day (i.e., a single peak load period each day), a frequency of 730 corresponds to a twice-daily event (i.e., a morning and evening peak), and a yearly peak would have a frequency of one, and this might respond to a peak load period that occurs once a year due to extended hot or cold weather cycles.

[13] The demand cycle in the case study had a peak summer load profile with autumn/spring periods considered shoulder periods with a relatively low heating load in winter.

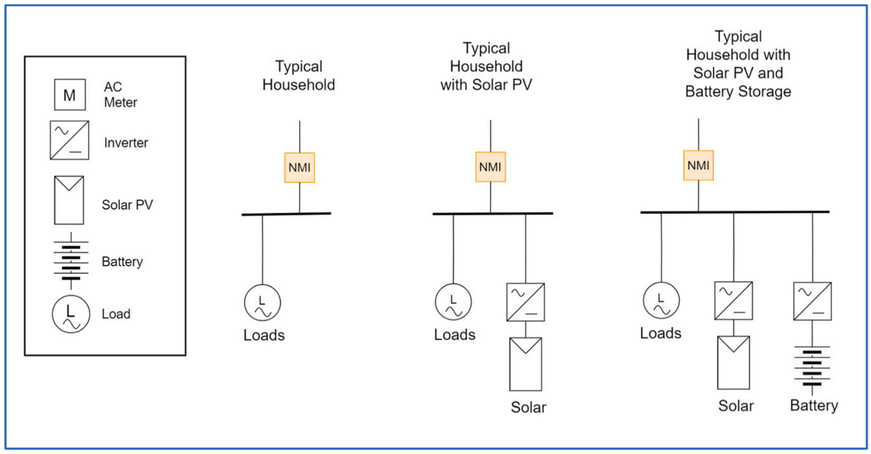

Fig. 7. Wire diagram of different DER configurations.

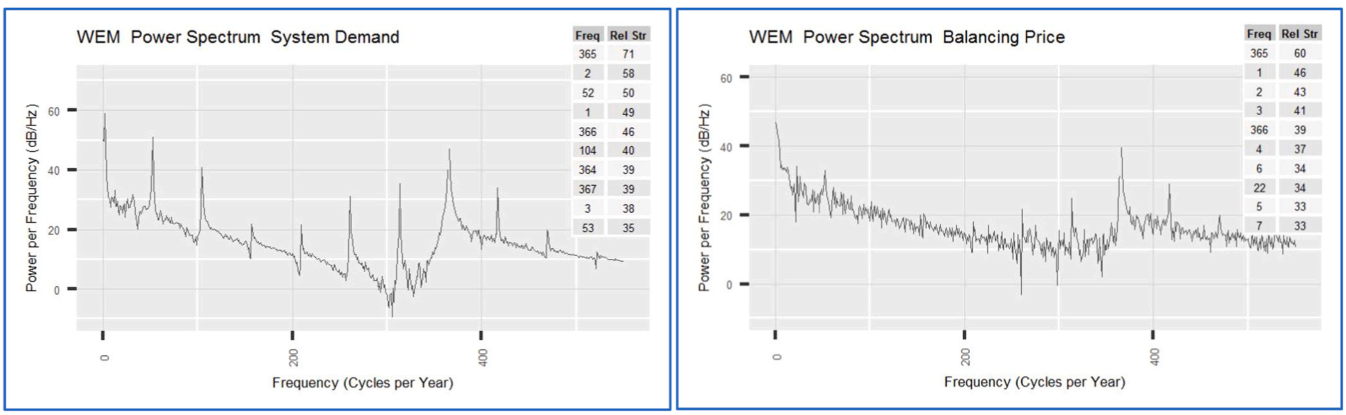

Fig. 8. WEM power spectrum graph—System demand and balancing price.

		Case Study key feature Set														Environment		
Freq	**Description**	System Demand	Underlying System Demand	Balancing Price	Notional Value	PPA Energy Volume	STEM Vol	Rooftop PV	Rooftop Notional Value	Synergy Generation	Synergy Notional Value	IPP Generation	IPP Notional Value	Generation Outage	Commissoning Test	Air Temp	Wind Speed	Rainfall
365	Daily	71	75	60	64	71	52	76	67	66	63	70	64			70	60	
730	Twice Daily	66	57	60	62	65	38		49	60	60	66	62					
1	Yealy	49	49	46	43	49	57	52	47	53	44	49	43	45	58	74	60	36
52	Weekly	50	50		38	51			29	47	39	49	38		41		28	20
12	Monthly	33	32	33	33		37			36	34		33	40	40	30	28	15
2	Summer/Winter & Autumn/Spring	58	58	43	48	53	49	39	36	52	48	59	48	43	48	42	33	23
3	Winter / Summer & Autumn/Spring	38	38	41	40	42	46	36	33	46	43	37	39	47	48	39	28	
4	4 Seasons	34	34	37	36	37	45	33	29	41	38	36	36		46	37	28	15

Key
- Very Strong Response
- Strong Response
- Weak Response
- Very Weak Response

Note: Blank items refer to results that have weak or no response to that frequency. Harmonics have been removed (identified by examination of raw data). Slight frequency variations due to leap years have been removed.

Fig. 9. Periodic factors for high-level features of the WEM (dB/Hz).

comparative studies, that is the daily and weekly cycles in New Zealand (Moutter et al., 1986), the three patterns (weekday, weekly and monthly) identified in South Australian and Spain (Magnano and Boland, 2007; González-Romera et al., 2008), the intraday, day, and weekly cycles observed the UK (Williams and Short, 2020) and finally the daily period the time series for household consumption found in Ireland (McLoughlin et al., 2013).

No comparative work has been conducted on wholesale price outcomes, and it was found that in relation to the balancing price, sharp and high peaks occurred once (60) and twice daily (60). The generation response of the rooftop PV (offset demand) did not match the twice-daily price (60) and notional rooftop PV revenue cycle (67, 49). This was an expected pattern due to the 'duck curve' (Maticka, 2019; Wilkinson et al., 2021) eroding commercial operation during the day, leaving revenue peaks in the morning and evening periods (twice daily). This was further supported when comparing the underlying demand and the system demand responses, which was DERs offset consumption on the operation demand value, resulting in a weaker daily response (71 vs 75).

A number of findings in the data provided several additional insights. Notably, the relationship between system demand (71) and balancing price (60) was weak, with the weekly periodic[14] relationship near the white noise. Historical studies that assume a direct periodic relationship between system demand (in that all three results would exhibit the same response) need to be revisited. Both these factors indicated a weaker price response to changes in system demand than expected.

Thus, the periodic factors that drive the market spot price are not as strong as those that drive system demand. In addition, the spot price does not have a comparison response to the weekly demand period over the weekend. This further shows a weak price response to changes in system demand. As a collective, IPPs have a monthly notional value response higher than the government-owned generator,[15] which may indicate an ability to respond to price signals more effectively.

4.3. Fuel generation response

A direct application of the methodology was to determine if the innovative approach could capture hidden relationships that were not immediately apparent or unexpected based on primary fuel consumption.

The analysis described in this section is based on the primary fuel in the case study and is summarised in Fig. 10. Consistent with reports in the literature, landfill gas generation (yearly response: 61) did not respond to changes in system demand, and the generation output only responded to yearly variations due to seasonal patterns (air temperature: 74). Other generation profiles of non-firm renewables (solar: 68 and wind: 50) generation matched the associated primary fuel sources. This is consistent with a near-zero Short Run Marginal Cost (SRMC) cost generator operating to maximise electricity production based on fuel availability.

Unexpectedly, the data showed that wind-based generation achieved a twice-daily revenue response (right-hand side table value: 56, 53) compared to the daily generation response (left-hand table value: 60), which corresponded to the pricing response shown in Fig. 9. This response is different from solar generation, for which there was no twice-daily response. Thus, in the case study, wind generation had not displaced[16] other wind generation facilities, but solar had. This suggests that comparison investment in wind generation over solar generation is worth considering in greater detail.

4.4. Market participant response

The results of the methodology, when applied to the market participants' generation and notional revenue, are provided in Fig. 11 and. The results revealed different responses from the market participants. This was partly due to different generation technologies and varying customer loads, but this still enabled a participant-level comparison to gather additional insights into competitor behaviour. In addition, the comparison of mismatches between notional revenue and generation periods provided greater insights into how market participants operate.

WPGENER refers to the state-owned gentailer, Synergy, that accounts for over 40% of generator capacity and approximately 50% of retail consumption. This market dominance is shown in the data, as Synergy responds to all changes in operation demand and period effects in revenue. Several market participants operating as price takers, such as Landfill Gas and Griffin (coal), generate at a constant level, as evidenced by the lack of daily or weekly periodic cycles, and the periodic frequencies associated with revenue were correlated with market price changes.

The market participants that solely operate wind farms (i.e., Collgar, Emu Downs Wind Farm, Mumbida, Blairfox and Mt Baker) displayed different operating behaviours due in part to the varying wind patterns of the geographically separate locations. The large wind farms (i.e., Collgar and EDWFMAN) had twice-daily periodic cycles compared to Mumbida, Blairfox and Mt Baker, which had single daily periodic cycles. Thus, this study showed that Alcoa responds to changing price outcomes (a twice-daily response) that are not aligned to the single periodic response from generation (once daily).

4.5. Facility response

Over 50 operating facilities were included in the case study, and our key observations have been extracted and provided in Fig. 12. The comparison selected is based on a subset of (1) coal generation, (2) wind generation, (3) gas generating facilities (of the same technology) and (4) grid-scale PV facilities. The complete set of results is provided in Appendix D.

The analysis revealed behaviour that was not immediately apparent in the raw data set. The periodic evaluation of the Pinjar Gas generation units (Pinjar 1–11) showed that the facilities (that have similar technical configurations) follow varying schedules. The Pinjar units showed similar operating profiles for units [1,2], [3, 7, 9], [4,5] and [10,11]. All the units were of similar capacity and had access to the same fuel cost (same owner and location); however, there was an underlying pattern in the different operation of these units.

Similar results were found in relation to the coal generation facilities (Bluewaters and Collie). These facilities are in the same coal mining region (the Collie sub-basin[17]). Fuel is the single largest cost for thermal generation; however, these facilities are managed differently. The periodic cycles with generation were similar, but Collie achieved a sharper revenue response. This may be due to a combination of contractual obligations and facility age. Further investigations and analyses need to be conducted to understand the reasons for the disparities in the management of these facilities that may not have been initially identified.

5. Key findings

The case study made a number of key findings, as summarised below:

i) The detection of periodic cycles in diverse fuel types and facility technologies

   The decomposition of the data proposed in the methodology and applied to the data set provided a number of insights into the case study. We confirmed the expected running profiles for a number of generation technologies but also observed cases in which the price response indicates potential for further investment for some generation technologies (Sections 4.2 and 4.3).

ii) The identification of competitor behaviours

   Periodic analysis can be applied to gain insights into

[14] The analysis investigated the effect of public holidays. Apart from the yearly occurrence of public holidays periods (Easter and Christmas), public holidays in Western Australia do not follow any regular yearly frequency; thus, the periodic response to public holidays was very weak.

[15] Synergy, the government-owned gentalior in Western Australia, non-contestable energy consumption is captured under the 'notional meter' that accounts for the majority of the organisation's consumption.

[16] In this context, the generation displacement occurs because as the penetration of a non-firm renewable generation increases in similar locations they are subject to the same primary fuel availability (wind and/or solar patterns in this discussion) and this colocation and generation put downward pressure on market prices due to low SRMC. This erodes revenue streams in energy-only based wholesale electricity market designs.

[17] The Collie sub-basin is the location of significant coal reserves mined primary for electricity generation in the southwest region of Australia.

WEM - Generation Power Spectrum Strength (by primary fuel type and environmental variables)										
Frequency	Description	Coal	Gas	Distillate	Landfill Gas	Solar	Wind	Air Temp	Wind Speed	Rainfall
365	Daily	66	69	59		68	50	70	60	
730	Twice Daily	56	58	57						
1	Yearly	57	48	47	61	59	56	74	60	36
52	Weekly	49	42	35					28	20
12	Monthly	41						30	28	15
2	Summer/Winter & Autumn/Spring	56	49	40	56	51	49	42	33	23
3	Winter & Summer & Autum/Spring	48	46	44	53	48	45	39	28	
4	4 Seasons	43	43	41	50	45	43	37	28	15

Note: Blank items refer to results that have weak or no response related to that frequency. Harmonics have been removed (identified by examination of raw data). Slight frequency variations due to leap years have been removed.

WEM - Notional Revenue Power Spectrum Strength (by fuel type)										
Frequency	Description	Coal	Gas	Distillate	Landfill Gas	Solar	Wind	Air Temp	Wind Speed	Rainfall
365	Daily	71	65	58	61	61	56	N/A		
730	Twice Daily	57	57	55	56		53			
1	Yearly	46	44	46	50	53	50			
52	Weekly	39	35							
12	Monthly	35			35					
2	Summer/Winter & Autumn/Spring	49	46	39	43	46	49			
3	Winter& Summer & Autum/Spring	40	41	42	43	43	42			
4	4 Seasons	37	38	39	39	39	40			

Key
Very Strong Response
Strong Response
Weak Response
Very Weak Response

Fig. 10. WEM power spectrum strength by fuel generation and notional revenue (compared to the environmental response) (dB/Hz).

WEM Market Particpant MW/h Quantity Spectrum Strength by Registered Particpant (Jun 2012- Feb 2022)

Freq	Description	ALCOA	ALINTA	COLLGAR	EDWFMAN	GLDFLDPW	GRIFFIN2	GRIFFINP	LNDFLLGP	MBARKER	MHPS	NEWGEN	NGENEERP	PERTHNRGY	STHRNCRS	TIWEST	TSLA_MGT	VINALCO	WENERGY	WGRES	WPGENER	GRNOUGH	MERREDIN	TSLA_GER	TSLA_NOR	TSLA_KEM	DCWL	MUMBIDA	BLAIRFOX	CTE	GRENOUGH	MPOWER	ALBGRAS	NSFPTNRS	MERSOLAR	WARADGE
365	Daily	52	58	58	42	55			39			63	64		37	50	18		58		66	72	31		17	18		49	45	47	69	72		72	70	51
730	Twice Daily		45	31	33	51						51	54		37	51			57		55				13							58		55		35
1	Yealy	59	52	47	52	51	65	60	59	49	57	60	46	61	61	51	17	68	48	59	51	42	31			18	49	48	44	63	58	55	34	56	59	56
52	Weekly		38						38	35											46								38	42			36			
12	Monthly	47	35		33		48	47	41		52	40	37	42	37	38		49		42	37			28		18		36	34	40						
2	Summer/Winter & Autumn/Spring	60	50	40	43	43	60	49	54	44	57	57	48	57	53	49	18	61	42	56	52		31	29	11	17	42	45	49	54	47	36	43	37	46	52
3	Winter& Summer & Autum/Spring	53	47			38	57	59	51		57	54	46	53	50	46	18	61	43	54	45		30	26			33	37	39	50	43				44	43
4	4 Seasons	50	46		34	42	56	57	48		56	52	45	52	47	44	21	57	44	51	42		25			17			35	48	40		34		41	35

Key
Very Strong Response
Strong Response
Weak Response
Very Weak Response

WEM Market Particpant Revenue Power Spectrum Strength by Particpant Registered (Jun 2012- Feb 2022)

Freq	Description	ALCOA	ALINTA	COLLGAR	EDWFMAN	GLDFLDPW	GRIFFIN2	GRIFFINP	LNDFLLGP	MBARKER	MHPS	NEWGEN	NGENEERP	PERTHNRGY	STHRNCRS	TIWEST	TSLA_MGT	VINALCO	WENERGY	WGRES	WPGENER	GRNOUGH	MERREDIN	TSLA_GER	TSLA_NOR	TSLA_KEM	DCWL	MUMBIDA	BLAIRFOX	CTE	GRENOUGH	MPOWER	ALBGRAS	NSFPTNRS	MERSOLAR	WARADGE
365	Daily	56	63	52	51	57	58	59	60	51		63	62	59	53	59	20	53	57	59	63	70	30		16	18	53	51	54	56	62	65	51	64	60	57
730	Twice Daily	47	56	49	45	53	53	54	54	48		56	54	53	53	57			55	52	54				13		46	51	45	53		46	47	43		52
1	Yealy	51	43	41	45	46	57	44	48	46	53	51	42	52	58	45	20	63	47	47	44	43	31			19	49	43	42	57	51	51	34	52	53	48
52	Weekly		36						35	32											38								29							
12	Monthly	41		31			39	39	35		48	36	35	36	35	35		45	34	37	35			28		19				36						
2	Summer/Winter & Autumn/Spring	56	48	41	46	39	54	42	45	46	53	49	45	46	50	45	20	59	41	45	48		30	28		20	44	45	46	49	46	36	43	39	41	50
3	Winter& Summer & Autum/Spring	46	43	37	35	33	46	45	43	36	53	44	42	45	48	42	22	56	42	44	42		30	26		18	36	36	36	45	38	33		34	40	40
4	4 Seasons	47	41	33	35	34	46	48	39	34	52	39	41	43	44	36	24	54	41	41	39		24				35	31	33	40	34		32		36	34

Note: Blank items refer to results that have weak or no response to that frequency. Harmonics have been removed (identified by examination of raw data). Slight frequency variations due to leap years have been removed.

Fig. 11. Upper panel - Market participant cyclical periods for generation (dB/Hz) Lower panel - Market participant cyclical periods notional revenue (dB/Hz).

competitor behaviour. The periodic examination enabled us to determine when the market participants managed generation portfolios in systematically different ways, including in relation to identical primary fuels and/or generation technology cases (Sections 4.4 and 4.5).

iii) Application in a wholesale electricity market with a high penetration of non-firm renewable generation

The case study validated the use of the approach in a power system with a high penetration of renewable generation. It provided an efficient method to identify the different periodic cycles and responses. Notably, it showed how DERs have eroded revenue due to displacement, and that facility market revenue is now only generated in the morning/evening period. The analysis identified a disconnect between wholesale market pricing responses and generation due to the different primary fuel sources and the operating characteristics of different technologies. This was particularly apparent when examining wind, solar and DER responses that showed a divergence between generation and revenue.

iv) Comparisons between system demand and price formation

The direct comparison of the price formation and system demand was extended to the components that make up system demand. This step effectively compared pricing outcomes to these components. With a

WEM MW Revenue Power Spectrum Strength by Facility type (Jun 2012- Feb 2022)

Freq	Description	BW1_BLUEWATERS_G2	BW2_BLUEWATERS_G1	COLLIE_G1	EDWFMAN_WF1	GRASMERE_WF1	INVESTEC_COLLGAR_WF1	PINJAR_GT1	PINJAR_GT10	PINJAR_GT11	PINJAR_GT2	PINJAR_GT3	PINJAR_GT4	PINJAR_GT5	PINJAR_GT7	PINJAR_GT9	GREENOUGH_RIVER_PV1	AMBRISOLAR_PV1	NORTHAM_SF_PV1
365	Daily	59	58	60	51	52	52	38	56	58	39	45	44	42	43	57	63	65	64
730	Twice Daily	54	53	50				33	49	51	34	36	36	31	34	49			
1	Yearly	44	57	47	45	40	41	36	51	51		35	33	35	33	46	51	51	52
52	Weekly			40		33		27					30		27				
12	Monthly	39	39	37			31	28	33	37	28	31	29	29		38			
2	Summer/Winter & Autumn/Spring	42	54	51	46	43	41	40	48	48	34	32	35	30	34	39	46	36	39
3	Winter& Summer & Autum/Spring	45	46	47	35	36	37	35	45	47	28	36	35	33	27	48	37	33	34
4	4 Seasons	48	46	42	35	34	33	34	47	40	27		32	30	30	45	34		

Key

- Very Strong Response
- Strong Response
- Weak Response
- Very Weak Response

WEM MW Quantity Power Spectrum Strength by Facility type (Jun 2012- Feb 2022)

Freq	Description	BW1_BLUEWATERS_G2	BW2_BLUEWATERS_G1	COLLIE_G1	EDWFMAN_WF1	GRASMERE_WF1	INVESTEC_COLLGAR_WF1	PINJAR_GT1	PINJAR_GT10	PINJAR_GT11	PINJAR_GT2	PINJAR_GT3	PINJAR_GT4	PINJAR_GT5	PINJAR_GT7	PINJAR_GT9	GREENOUGH_RIVER_PV1	AMBRISOLAR_PV1	NORTHAM_SF_PV1
365	Daily			55	42		58	35	52	54	36	44	43	41	43	52	70	72	72
730	Twice Daily			45	33		31		42	42		33			29	42	56	58	55
1	Yearly	60	65	52	52	40	47	39	56	57		41	40	40	38	54	58	55	56
52	Weekly			44		36									30				
12	Monthly	47	48	42	33		30	34	38	42	32	36		35		43			
2	Summer/Winter & Autumn/Spring	49	60	56	43	39	40	45	56	55	39	38	39	39	38	47	46	36	37
3	Winter& Summer & Autum/Spring	59	57	51				40	51	52	33	42	40	41	34	54	42		
4	4 Seasons	57	56	47	34			40	54	46			37	37	34	52	39		

Note: Blank items refer to results that have weak or no response to that frequency.
Harmonics have been removed (identified by examination of raw data). Slight frequency variations due to leap years have been removed.

Fig. 12. Subset of facility cyclical periods for generation (upper table) and notional revenue (lower table) (dB/Hz).

daily system demand response of 71 dB/Hz compared to the market spot price of 60 dB/Hz with a weekly periodic demand response of 50 dB/Hz with a price response near to the white noise.

This is a notable outcome of the research, as it challenges the assumption in the literature related to the strength of the relationship between demand and pricing outcomes. Wholesale market pricing responds to the same cycles as changes in system demand; however, the response is dampened and not directly linked to all primary fuel generation technologies. This was particularly apparent when examining wind, solar and DER responses that showed a divergence in this relationship in the case study. In a rapidly transforming power system, these are important findings.

6. Conclusion

The novel approach provided insights into competitors' behaviours in terms of how different market participants respond to system demand changes, and from a broader market level, it found it could measure different periodic responses to system demand and price formation. The case study showed that this difference could be captured and found that the wholesale market price response was dampened compared to the system demand response. With a daily system demand response of 71 dB/Hz compared to the market spot price of 60 dB/Hz with a weekly periodic demand response of 50 dB/Hz with a price response near to the white noise. This challenges assumptions in many studies that assume that there is an equal periodic relationship between system demand and price formation.

Empirical analysis showed how the new application can discover insights into competitor behaviour to identify market actors that do not respond in expected ways, such as changes in system demand or running facilities of the same technology (and primary fuel) differently but in a predictable manner, not immediately transparent in the market. Finally, the innovative approach showed how it is possible to examine how non-firm renewable generation (such as wind, solar and DER) responses diverge between generation and revenue due to increased penetration eroding revenue or fuel availability not corresponding to system demand.

This paper outlines how to obtain market insights and increase the transparency of competitor behaviour not immediately apparent in contemporary models or market data. Due to the generic technical approach proposed, this work can be applied to any wholesale electricity market where there is a need to gain a competitive edge.

As the case study only considers the WEM, empirical work on other wholesale and retail electricity markets and integration into established and emerging models is recommended. Further investigation of the findings related to the divergent response of price formation and system demand is essential to understanding power systems in the Energy Transition. This could be explored using a combination of functional-based models combined with Bayesian analysis to understand the stochastic component interaction.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors acknowledge the AEMO who provided access to the public classified data as defined in the Market Rules provided for the case study.

Appendix A. – Dynamic supply curve

Price Formation—A dynamic supply curve

Wholesale electricity market supply curves are defined by a series of price-quantity pairs at which market participants are prepared to offer generation for each market interval. A power system's electricity consumption represents the demand curve, and the intersection with the supply curve allows spot-price formation[18] in accordance with the relevant market design and associated market rules. The system operator dispatches all the generators that have offered energy below the determined spot price. A conceptual view of the price determination is provided (Fig. 5), in which each interval is termed a trading interval. This process occurs continuously, 24 h a day.

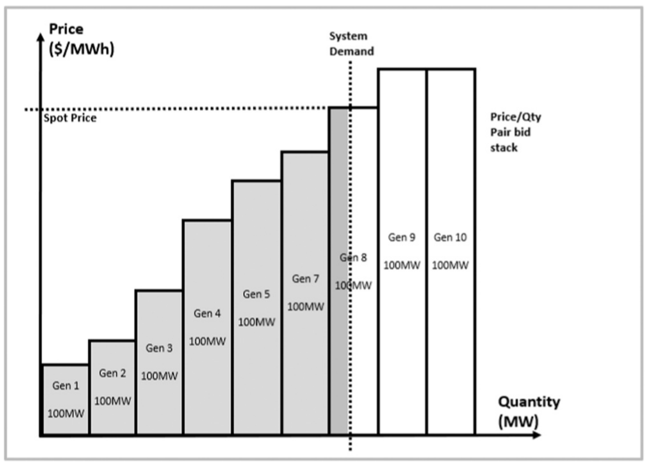

Fig. 13. Conceptual representation of a price formation.

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The system demand price is inelastic in the short term (Burke and Abayasekara, 2018) and only becomes elastic when prices become relatively high (Fan and Hyndman, 2011). The effect of this inelasticity in a wholesale electricity market is that the demand curve remains relatively vertical, and price formation is predominately dependent on changes in generation supply. As a result, wholesale electricity markets with a material amount of non-firm renewable generation can cause significant variations in price outcomes at the same system demand point. This is illustrated conceptually in Fig. 14, Fig. 15 and Fig. 16. These figures provide a conceptual example of the effect of a reduction of non-firm renewable generation due to a lack of primary fuel (i.e., reducing wind speed or cloud formation), which results in a higher price with no shift in the system demand. As the volume of low-cost electricity drops, the system operator dispatches higher-cost generation to meet the system demand. This effect is reversed when the primary energy becomes more abundant. Such a variation can occur within one trading interval (e.g., rolling cloud cover over a photovoltaics [PV] generation or gusty wind conditions affecting wind farms) or due to intraday weather patterns (e.g., tidal movements, morning/evening wind patterns) or seasonal changes (e.g., rainfall, solar profiles, summer/winter temperature variations).

[18] This term is referred to as the 'balancing price' in a number of wholesale electricity markets

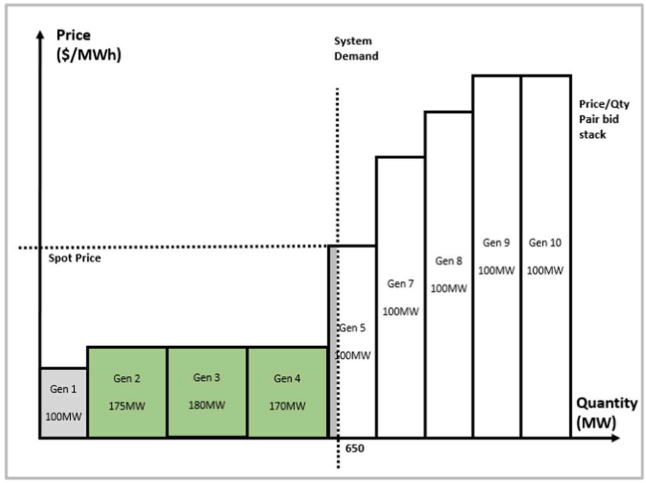

Fig. 14. Non-firm renewable—High output.

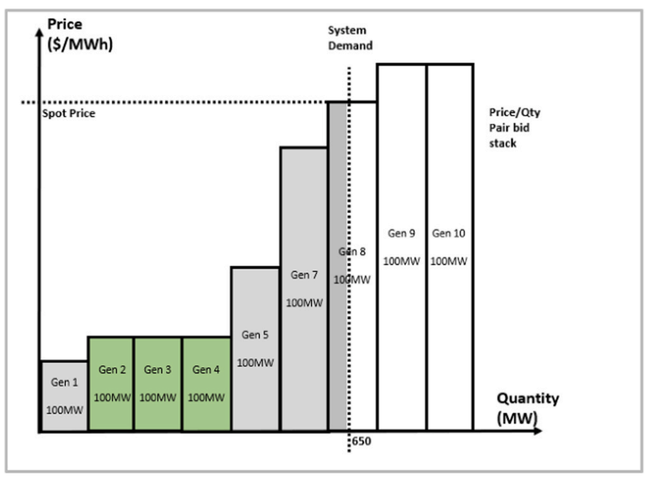

Fig. 15. Non-firm renewable—Mid-level output.

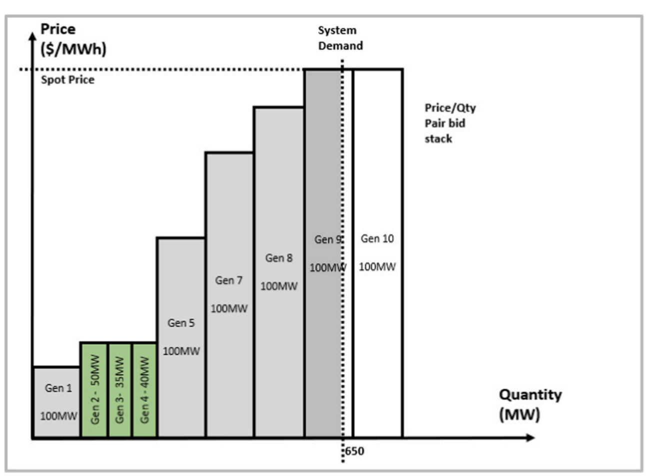

Fig. 16. Non-firm renewable—Low output.

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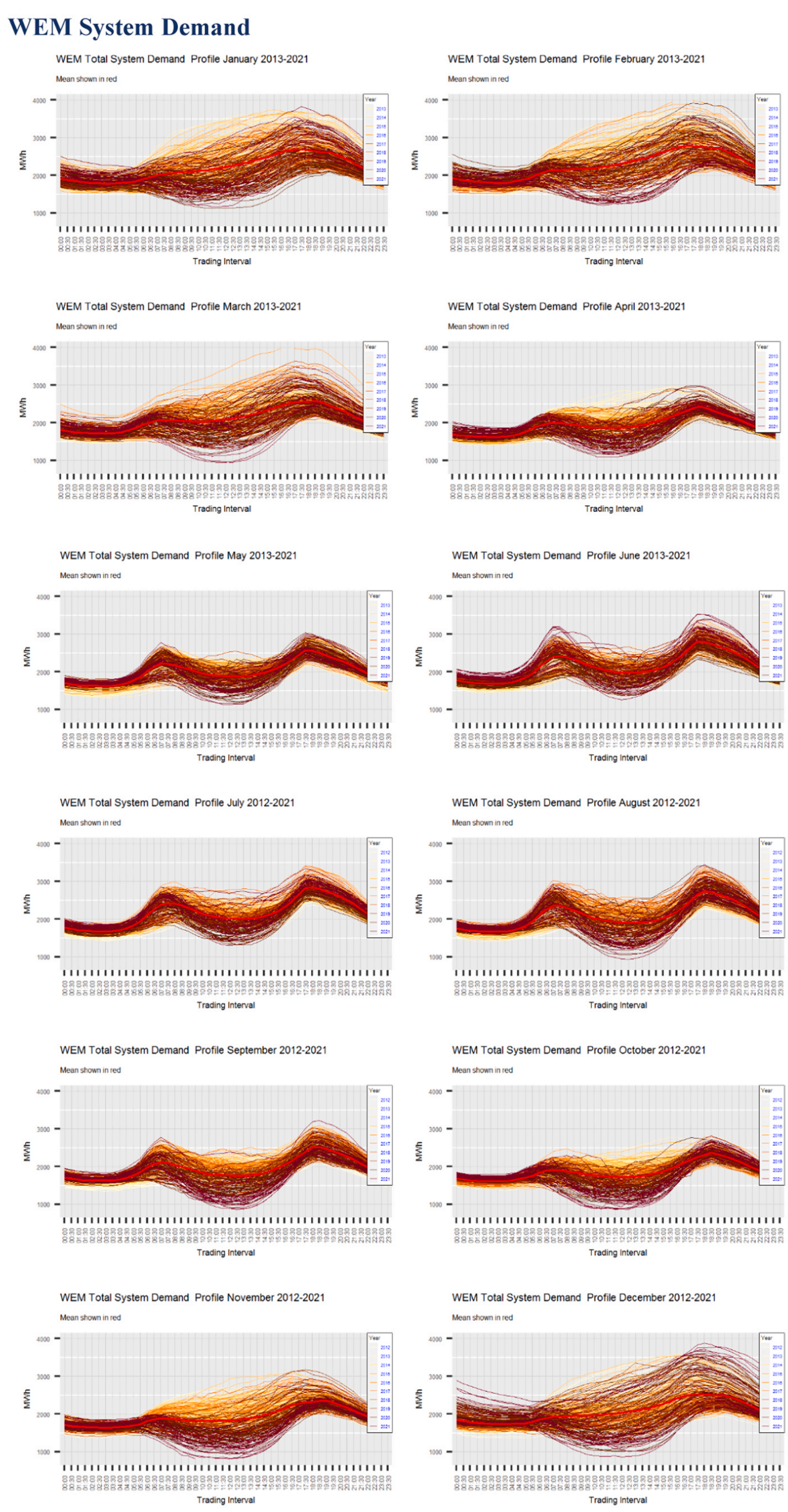
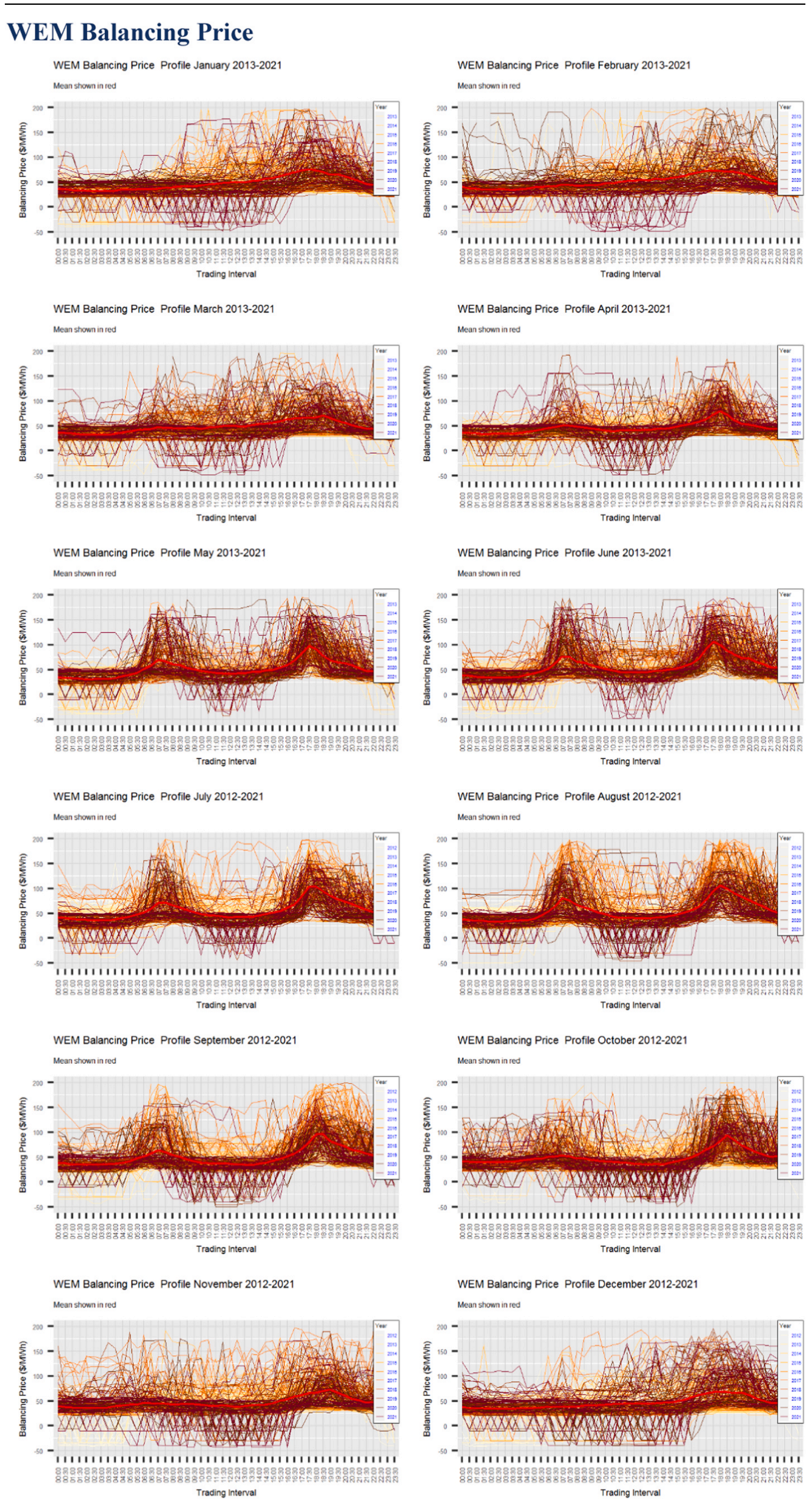
Appendix B. —WEM profile graphs

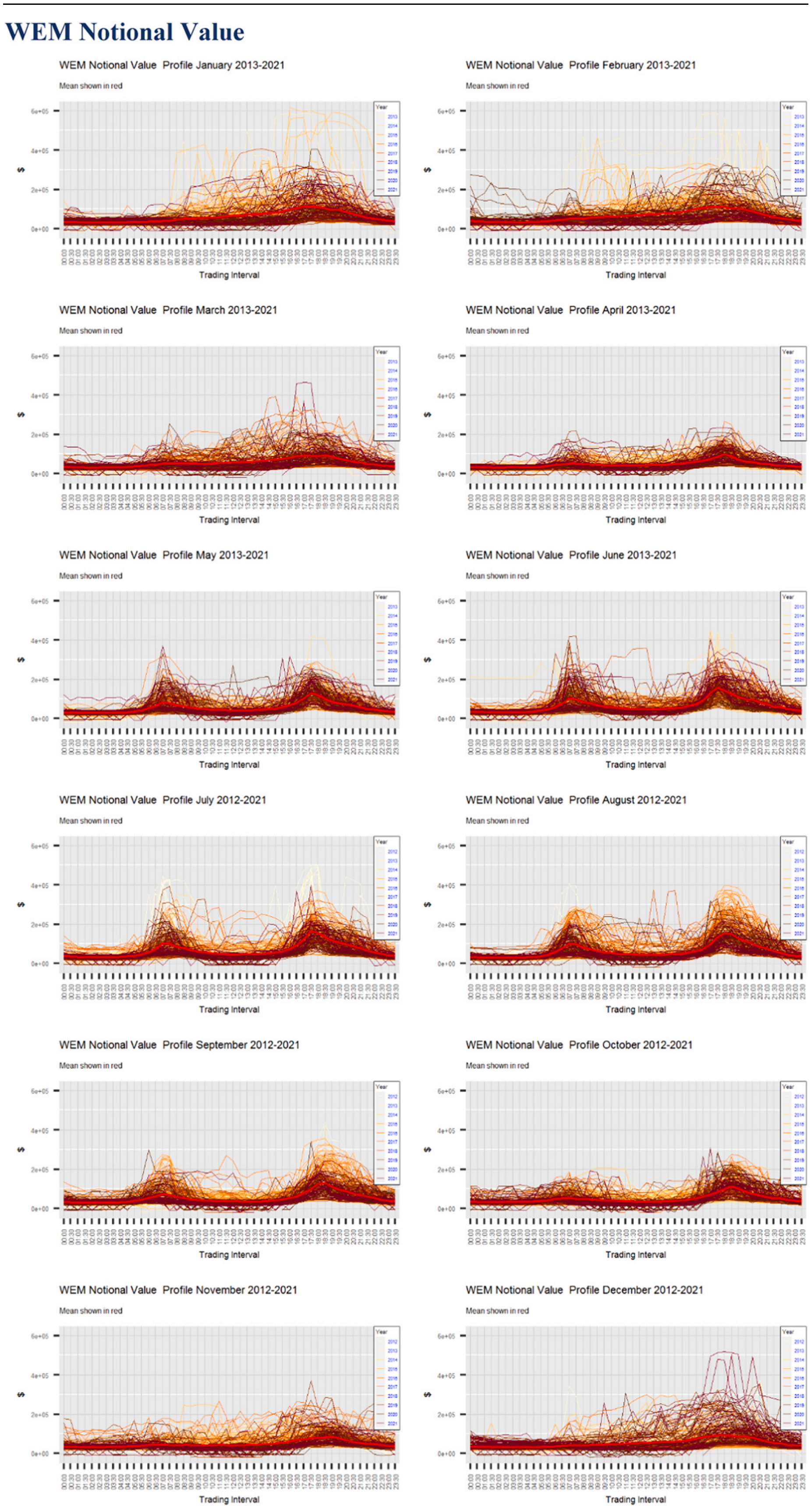
WEM System Demand.



WEM Balancing Price.

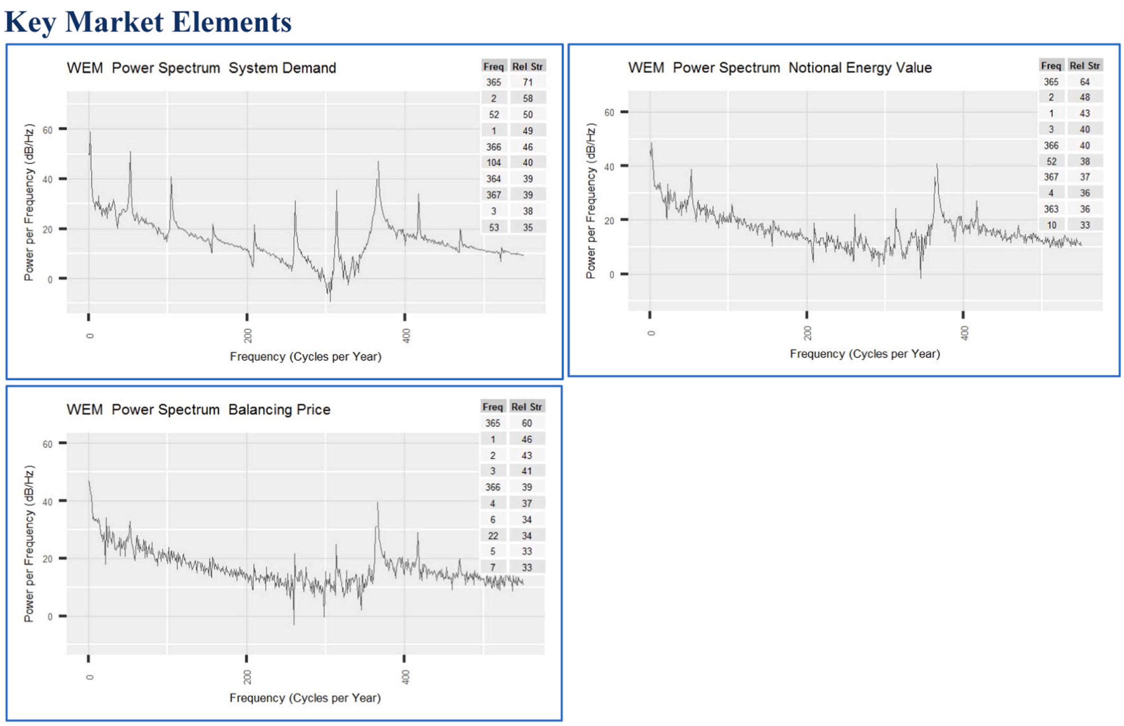


WEM Notional Value.

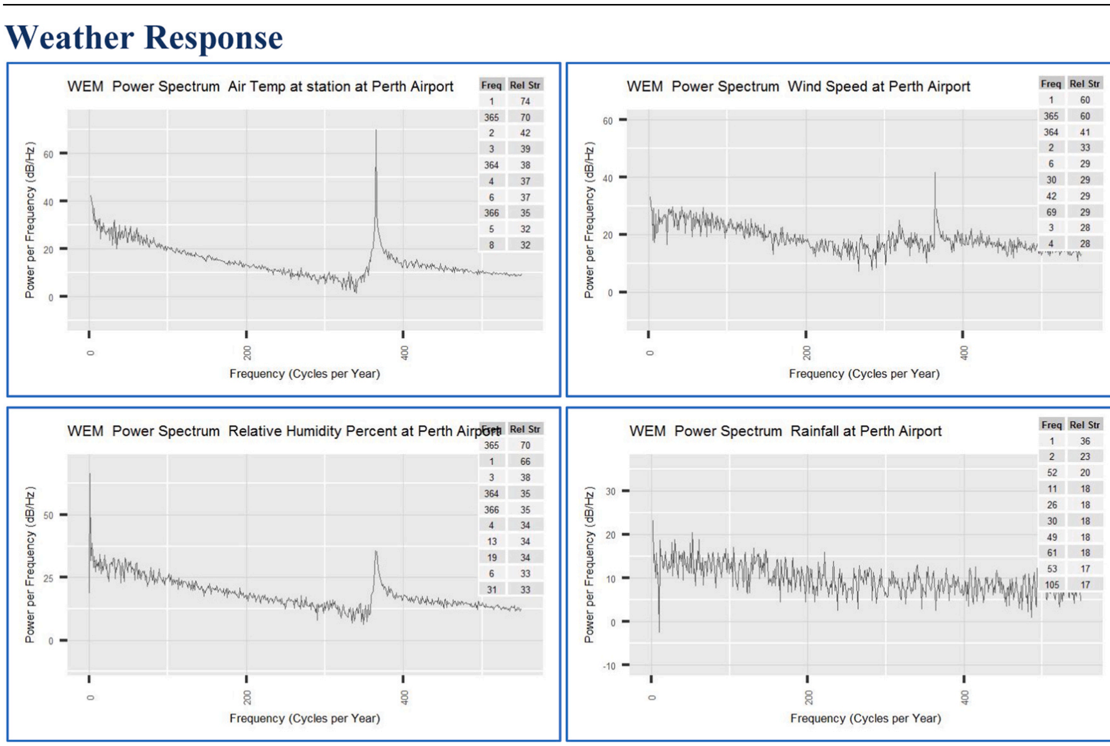


Appendix C. —Power spectrum graphs

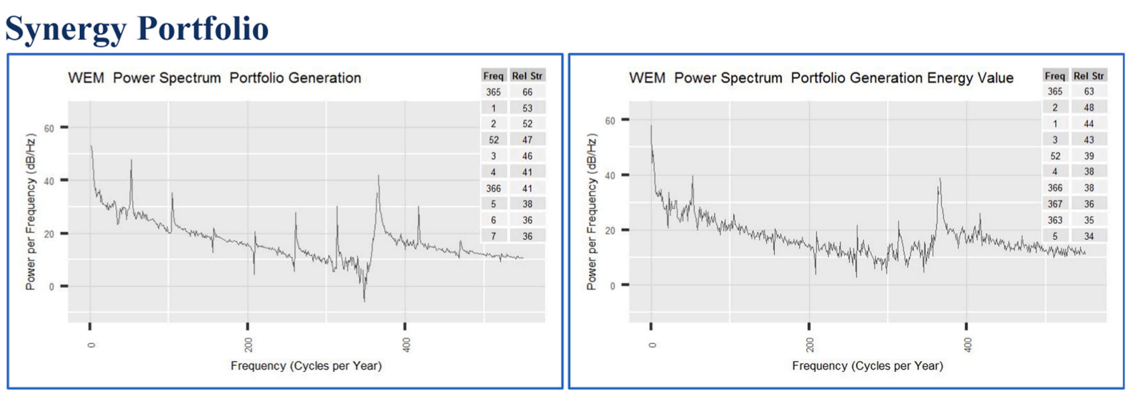
Key Market Elements.



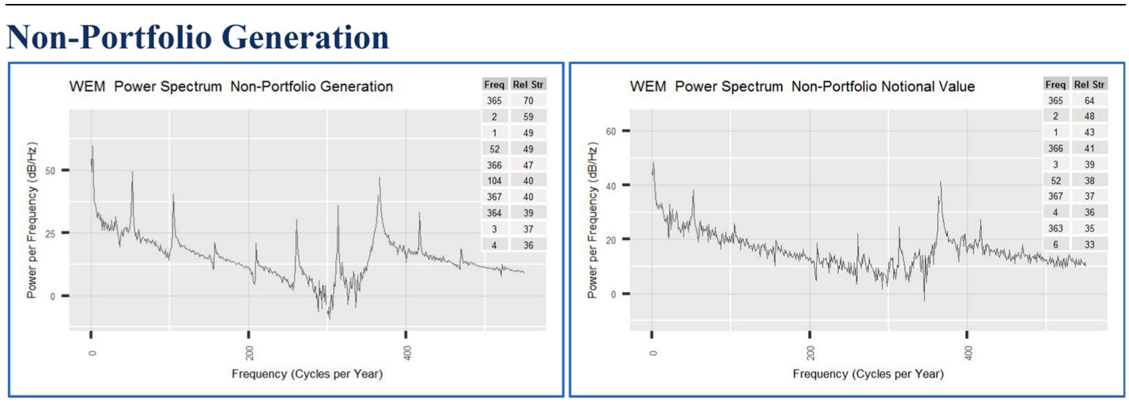
Weather Response.



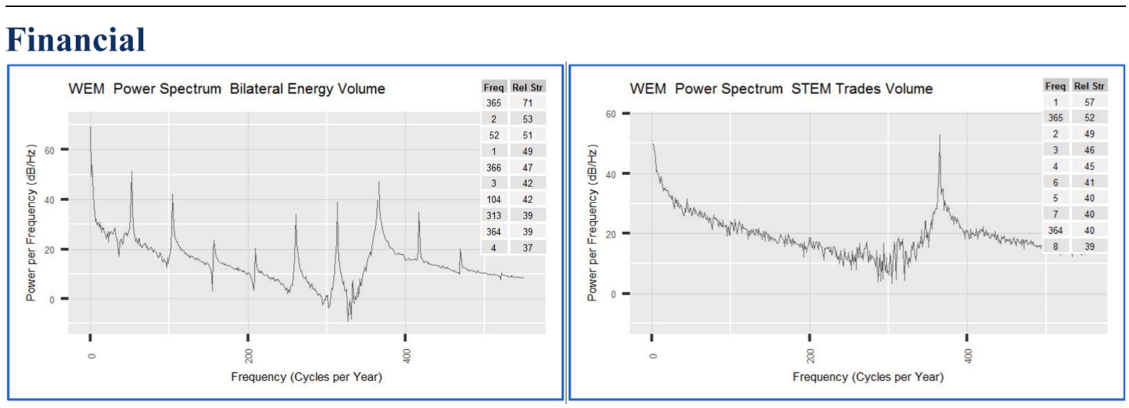
Synergy Portfolio.



Non-Portfolio Generation.

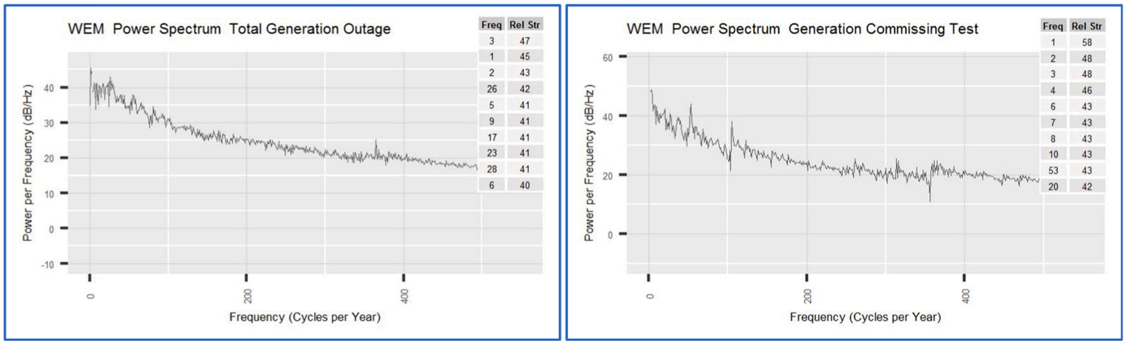


Financial.



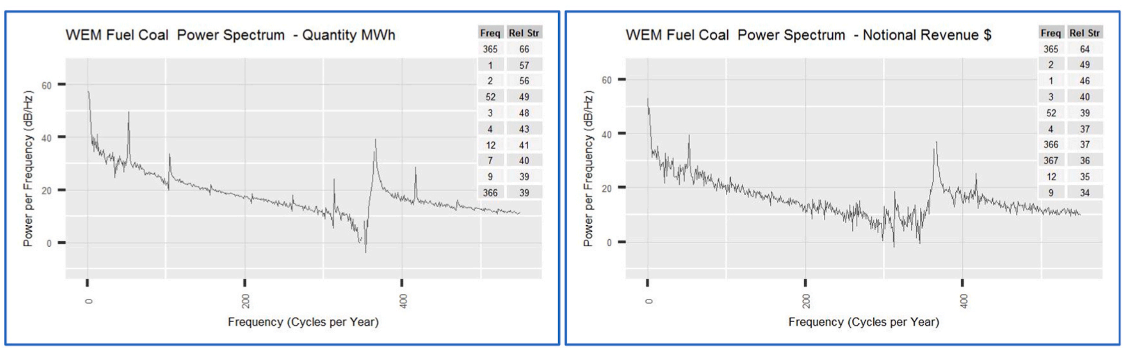
Outages and Commission Test.

Outages and Commission Test



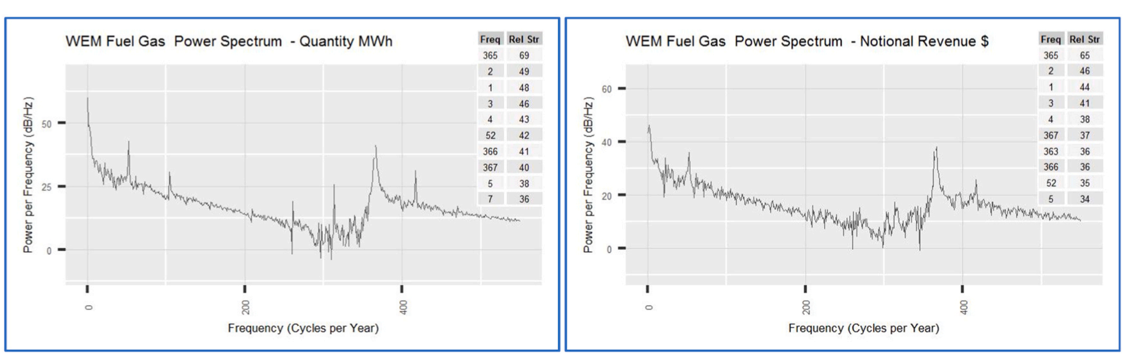
Generation based on Primary Fuel Source Coal.

Generation based on Primary Fuel Source Coal



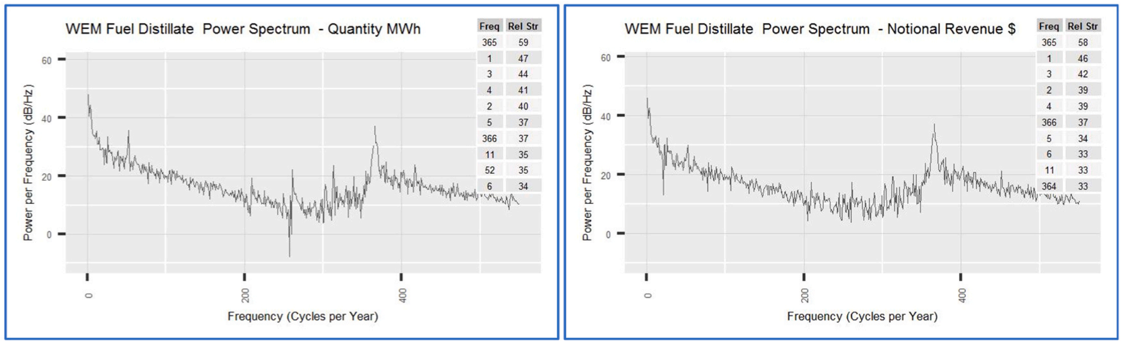
Gas.

Gas



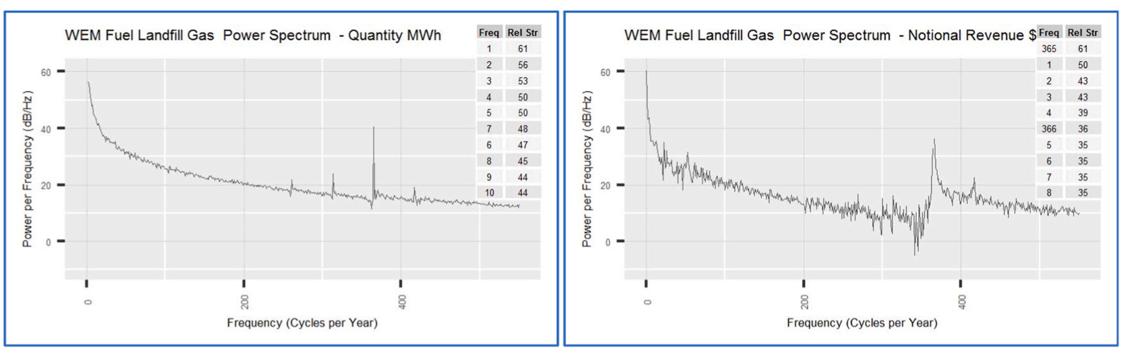
Distillate.

Distillate



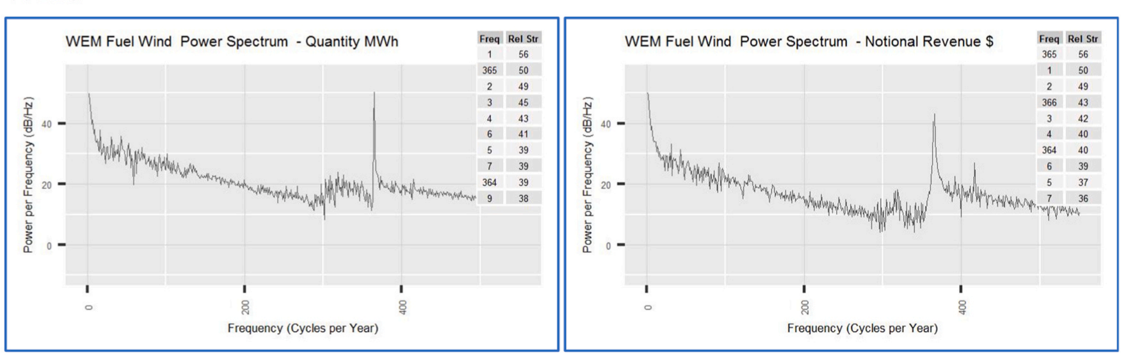
Landfill.

Landfill



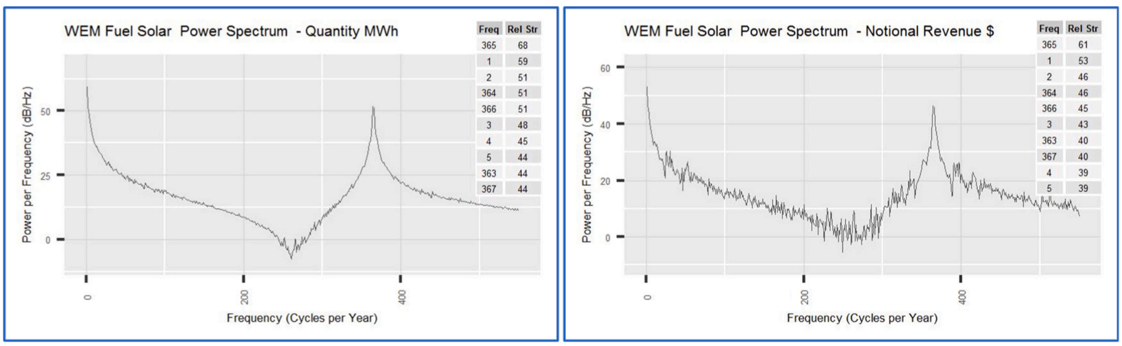
Wind.

Wind



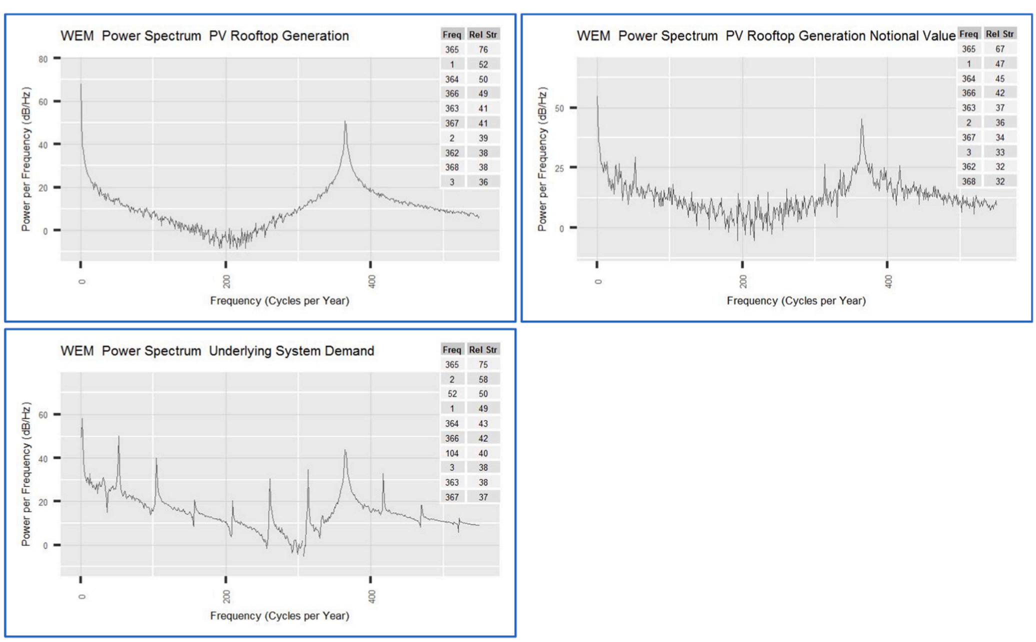
Solar.

Solar



Distributed Generation and Estimate System Demand—Power Spectrum Graphs.

Distributed Generation and Estimate System Demand—Power Spectrum Graphs



Appendix D. —Facility response

WEM MW Revenue Power Spectrum Strength by Facility type (Jun 2012- Feb 2022)

Freq	Description	ALBANY_WF1	ALCOA_WGP	ALINTA_PNJ_U1	ALINTA_PNJ_U2	ALINTA_WGP_GT	ALINTA_WGP_U2	ALINTA_WWF	ATLAS	BW1_BLUEWATERS_G2	BW2_BLUEWATERS_G1	CANNING_MELVILLE	COCKBURN_CCG1	COLLIE_G1	EDWFMAN_WF1	GERALDTON_GT1	GRASMERE_WF1	HENDERSON_RENEWABLE_IG	INVESTEC_COLLGAR_WF1	KALAMUNDA_SG	KEMERTON_GT11	KEMERTON_GT12
365	Daily	53	56	59	59	55	55	56	53	59	58	66	54	60	51	22	52	59	52	14	52	52
730	Twice Daily	43	47	54	53	39	44	50	37	54	53	42	38	50	45		44	52	49		49	47
1	Yearly	38	51	48	47	36	52	49	57	44	57	44	47	47	45		40	47	41		30	29
52	Weekly	33				33	35					52	42	40			33			15	28	
12	Monthly	31	41	37		37	35	32	38	39	39		39	37				37	31			
2	Summer/Winter & Autumn/Spring	44	56	45	49	38	44	43	52	42	54	47	50	51	46	22	43	45	41		35	33
3	Winter& Summer & Autum/Spring	39	46	49	43	43	45	34	48	45	46	38	45	47	35		36	44	37		28	35
4	4 Seasons	36	47	43	47	38	41	32	46	48	46	37	47	42	35	20	34	41	33		30	30

Freq	Description	KWINANA_G5	KWINANA_G6	KWINANA_GT1	KWINANA_GT2	KWINANA_GT3	MHPS	MUJA_G3	MUJA_G4	MUJA_G5	MUJA_G6	MUJA_G7	MUJA_G8	MUNGARRA_GT1	MUNGARRA_GT2	MUNGARRA_GT3	NEWGEN_KWINANA_CCG1	NEWGEN_NEERABUP_GT1	PERTHENERGY_KWINANA_GT	PINJAR_GT1	PINJAR_GT10	PINJAR_GT11
365	Daily	53	49		57	57		48	49	57	57	59	60	48	55	54	63	62	57	38	56	58
730	Twice Daily				51	51				49	51	51	52		35		56	54	55	33	49	51
1	Yearly	48	48		41	45	53	63	58	58	53	55	51	56	38	57	51	42	47	36	51	51
52	Weekly	41													35					27		
12	Monthly	41	43		38	36	48	46	44	45	44	40	38	38	39	39	36	35	34	28	33	37
2	Summer/Winter & Autumn/Spring	53	59		53	48	53	58	56	53	52	50	53	54	49	54	49	45	41	40	48	48
3	Winter& Summer & Autum/Spring	48	48		47	42	53	54	55	50	53	50	46	49	45	51	44	42	42	35	45	47
4	4 Seasons	47	46	15	46	45	52	54	47	45	49	47	42	49	43	46	39	41	41	34	47	40

Freq	Description	PINJAR_GT2	PINJAR_GT3	PINJAR_GT4	PINJAR_GT5	PINJAR_GT7	PINJAR_GT9	PPP_KCP_EG1	PRK_AG	RED_HILL	ROCKINGHAM	SKYFRM_MTBARKER_WF1	SOUTH_CARDUP	STHRNCRS_EG	SWCJV_WORSLEY_COGEN_CO	TAMALA_PARK	TESLA_PICTON_G1	TIWEST_COG1	WEST_KALGOORLIE_GT2	WEST_KALGOORLIE_GT3	GREENOUGH_RIVER_PV1	NAMKKN_MERR_SG1
365	Daily	39	45	44	42	43	57	60	57	59	56	51	59	53	59	60	20	59			63	30
730	Twice Daily	34	36	36	31	34	49	54	53	53	51	48	54	53	47	54		57			48	
1	Yearly		35	33	35	33	46	56	46	52	54	46	49	58	52	47	20	45			51	31
52	Weekly			30		27				35		32				35				32		
12	Monthly	28	31	29	29		38	36		36	40		34	35	39	35		35				
2	Summer/Winter & Autumn/Spring	34	32	35	30	34	39	51	39	47	47	46	46	50	52	44	20	45	36	35	46	30
3	Winter& Summer & Autum/Spring	28	36	35	33	27	48	47	33	45	49	36	43	48	44	42	22	42	37	36	37	30
4	4 Seasons	27		32	30	30	45	45	34	42	48	34	39	44	50	39	24	36			34	24

Freq	Description	TESLA_GERALDTON_G1	KALBARRI_WF1	TESLA_NORTHAM_G1	TESLA_KEMERTON_G1	BREMER_BAY_WF1	MUJA_G1	MUJA_G2	DCWL_DENMARK_WF1	MWF_MUMBIDA_WF1	BLAIRFOX_KARAKIN_WF1	BLAIRFOX_WESTHILLS_WF3	BIOGAS01	AMBRISOLAR_PV1	NORTHAM_SF_PV1	BADGINGARRA_WF1	BLAIRFOX_BEROSRD_WF1	MERSOLAR_PV1	YANDIN_WF1	WARRADARGE_WF1	Comment
365	Daily		54	16	18	54	42	42	53	51	58	48	56	65	64	51	51	60	56	57	Blank items refer to results have weak or no response to that frequency. Harmonics have been removed (identified by exmination of raw data). Slight frequency variations due to leap years has been removed.
730	Twice Daily		42	13		43			46	51	42	37	53	46	43	50	46	38	53	52	
1	Yearly		51		19	44	57	54	49	43	45	30	57	51	52	46		53	48	48	
52	Weekly											39									
12	Monthly	28	35		19	35	46	47			29		36								
2	Summer/Winter & Autumn/Spring	28	50		20	48	61	59	44	45	45	40	49	36	39	48	48	41	46	50	
3	Winter& Summer & Autum/Spring	26	47		18	43	55	61	36	36	36		45	33	34	37	33	40	45	40	
4	4 Seasons		45			40	59	54	35	31	32		40			39		36	40	34	

WEM MW Quantity Power Spectrum Strength by Facility type (Jun 2012- Feb 2022)

Freq	Description	ALBANY_WF1	ALCOA_WGP	ALINTA_PNJ_U1	ALINTA_PNJ_U2	ALINTA_WGP_GT	ALINTA_WGP_U2	ALINTA_WWF	ATLAS	BW1_BLUEWATERS_G2	BW2_BLUEWATERS_G1	CANNING_MELVILLE	COCKBURN_CCG1	COLLIE_G1	EDWFMAN_WF1	GERALDTON_GT1	GRASMERE_WF1	HENDERSON_RENEWABLE_IG1	INVESTEC_COLLGAR_WF1	KALAMUNDA_SG	KEMERTON_GT11	KEMERTON_GT12
365	Daily	33	52	51	50	56	56	47				66	52	55	42	22			58	14	54	54
730	Twice Daily			40			37	33				39		45	33				31	13	51	48
1	Yearly	38	59	56	54	42	57	57	60	60	65	47	52	52	52		40	59	47		35	32
52	Weekly	36				38	38					54	46	44			36			15		
12	Monthly		47	44	41	40	37	36	39	47	48	30	40	42	33			42	30	7	24	24
2	Summer/Winter & Autumn/Spring	40	60	49	54	41	48	41	54	49	60	42	51	56	43	22	39	56	40	13	33	29
3	Winter& Summer & Autum/Spring	34	53	54	53	48	49	35	51	59	57	39	47	51				54			30	38
4	4 Seasons	33	50	53	53	41	44		48	57	56		50	47	34	21		51			32	35

Freq	Description	KWINANA_G5	KWINANA_G6	KWINANA_GT1	KWINANA_GT2	KWINANA_GT3	MHPS	MUJA_G3	MUJA_G4	MUJA_G5	MUJA_G6	MUJA_G7	MUJA_G8	MUNGARRA_GT1	MUNGARRA_GT2	MUNGARRA_GT3	NEWGEN_KWINANA_CCG1	NEWGEN_NEERABUP_GT1	PERTHENERGY_KWINANA_GT1	PINJAR_GT1	PINJAR_GT10	PINJAR_GT11
365	Daily	49	44		46	47		34	31	51	49	53	53	47	55	51	63	64	58	35	52	54
730	Twice Daily					39						43	44		37		51	54	57		42	42
1	Yearly	52	55		51	54	57	66	62	64	61	60	59	61	46	60	60	46	48	39	56	57
52	Weekly	42	34	17																		
12	Monthly	45		12	44	44	52	49	48	50	48	46	46	42	41	42	40	37		34	38	42
2	Summer/Winter & Autumn/Spring	53	61		59	53	57	59	60	58	58	54	59	58	51	57	57	48	42	45	56	55
3	Winter& Summer & Autum/Spring	51	50		54	51	57	55	59	55	59	56	53	53	49	54	54	46	43	40	51	52
4	4 Seasons	47	50		54	54	56	56	52	50	56	54	48	53	46	51	52	45	44	40	54	46

Freq	Description	PINJAR_GT2	PINJAR_GT3	PINJAR_GT4	PINJAR_GT5	PINJAR_GT7	PINJAR_GT9	PPP_KCP_EG1	PRK_AG	RED_HILL	ROCKINGHAM	SKYFRM_MTBARKER_WF1	SOUTH_CARDUP	STHRNCRS_EG	SWCJV_WORSLEY_COGEN_COG1	TAMALA_PARK	TESLA_PICTON_G1	TIWEST_COG1	WEST_KALGOORLIE_GT2	WEST_KALGOORLIE_GT3	GREENOUGH_RIVER_PV1	NAMKKN_MERR_SG1
365	Daily	36	44	43	41	43	52	48	55					37		37	18	50			70	31
730	Twice Daily		33			29	42		51					37				51			56	20
1	Yearly		41	40	40	38	54	67	51	59	56	49	63	61	60	60	17	51			58	31
52	Weekly					30						35										
12	Monthly	32	36		35		43	48		40	44		42	37	47	41		38				
2	Summer/Winter & Autumn/Spring	39	38	39	39	38	47	62	43	54	55	44	58	53	60	52	18	49	39	39	46	31
3	Winter& Summer & Autum/Spring	33	42	40	41	34	54	59	38	53	54		54	50	59	50	18	46	40	39	42	30
4	4 Seasons			37	37	34	52	56	42	50	54		52	47	56	47	21	44			39	25

Freq	Description	TESLA_GERALDTON_G1	KALBARRI_WF1	TESLA_NORTHAM_G1	TESLA_KEMERTON_G1	BREMER_BAY_WF1	MUJA_G1	MUJA_G2	DCWL_DENMARK_WF1	MWF_MUMBIDA_WF1	BLAIRFOX_KARAKIN_WF1	BLAIRFOX_WESTHILLS_WF3	BIOGAS01	AMBRISOLAR_PV1	NORTHAM_SF_PV1	BADGINGARRA_WF1	BLAIRFOX_BEROSRD_WF1	MERSOLAR_PV1	YANDIN_WF1	WARRADARGE_WF1	Comment
365	Daily		37	17	18	42				49	54	42	47	72	72	42	40	70	48	51	Blank items refer to results have weak or no response to that frequency. Harmonics have been removed. Slight frequency variations due to leap years, year/month/weekly miss alignments has been removed.
730	Twice Daily			13							37	33		58	55			51	36	35	
1	Yearly		57		18	43	62	57	49	48	49	33	63	55	56	46		59	53	56	
52	Weekly					35						45	42				36		36		
12	Monthly	28	40		18		50	50		36	33	32	40			35	36				
2	Summer/Winter & Autumn/Spring	29	54	11	17	46	64	61	42	45	46	42	54	36	37	46	51	46	47	52	
3	Winter& Summer & Autum/Spring	26	49			39	59	63	33	37	33		50				39	44	51	43	
4	4 Seasons		47		17	38	63	57					48			36		41	44	35	

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