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MSAT-PPA: Multi-factor Sensitivity Analysis Tool for Renewable Energy Power Purchase Agreements from an End-User Perspective

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Abstract

Power Purchase Agreements (PPA) between end-users of electricity and renewable energy generators are of increasing significance in the Australian electricity sector. PPAs, depending on how they are structured, can allow end-users to achieve several objectives, including supporting renewable energy development, meeting corporate emissions reduction targets or mandated renewable energy requirements, accessing lower-cost electricity and managing cost uncertainty over the medium and long term. Previous work indicates that a wide variety of contract structures are being used to implement PPAs in Australia, while at the same time, many aspects of the future of the Australian electricity industry remain uncertain. This paper reports on a freely available MS Excel workbook that helps decision-makers assess a wide variety of potential PPA contract structures, their associated financial uncertainties and risks to future Australian electricity market developments. We have termed this, the Multi-factor Sensitivity Analysis Tool for PPAs (MSAT-PPA or MSAT for short). Contract for Difference PPAs are identified as of particular interest and the tool is demonstrated by exploring drivers of uncertainty for this type of PPA, using a hypothetical example, loosely modelled on the experience of the University of New South Wales (UNSW Sydney) with one such PPA. While contracting arrangements can vary considerably across jurisdictions, this analysis of Australian arrangements has wider relevance for other markets where PPAs are playing a role in driving new renewables deployment.

1. Introduction

Large energy users are increasingly encouraging new renewable energy entry through the use of Power Purchase Agreements (PPAs). In Australia, the energy consultancy Energetics (2019) reports that since 2016, PPAs have been signed with projects that have a combined capacity of 4 GW. Despite this large uptake, the wide variety of PPA structures observed in previous work by Mitchell and Mills (2017), suggests that end-users interested in signing a PPA may still face a complex decision-making process. Ongoing changes in the electricity industry, in part driven by the PPAs themselves, also add complexity. However, there are limited publicly available tools to assist in preliminary analysis by interested stakeholders. This analysis must be detailed and specific to have real value for decision making. Hence, this paper introduces an open source and publicly available PPA modelling tool to aid decision-makers, particularly end-users.

1.1. The use of financial derivatives in PPAs

Recent reports by Baker and Mckenzie, Energetics and Mitchell and Mills (2017; 2018; 2017) on PPAs in Australia's NEM reveal the common use of financial derivatives, particularly Contracts for Difference (CFDs), in the implementation of PPAs between large energy users and off-site renewable energy generation in the Australian National Electricity Market (NEM). This represents an expanding role for CFDs, which have traditionally been used in the NEM by generators and retailers to manage wholesale price risk, and have also aided forward price discovery, as discussed by Tham et al (2004). Increasingly, CFDs are addressing a broader set of concerns, for a wider range of potential users, some of which have less knowledge and experience in the electricity industry. Mitchell and Mills identified a broad set of drivers motivating energy user to procure off-site renewable energy, including environmental values, political/community values, end-user control, government policy vacuum, cost, cost hedging, branding, traceability/tangibility and flexibility for multi-site operation. The culmination of these factors represents a significant change in the context in which financial derivatives are being used.

1.2. Uncertainty

The deployment of new technologies, such as utility-scale wind, solar, battery energy storage and electric vehicles, as well as ongoing market reform and lack of long term policies, creates significant uncertainty around the future characteristics of the Australian electricity industry. Large energy users may seek to manage their exposure to risks generated by this uncertainty, particularly when considering energy procurement. However, the presence of epistemic uncertainty, caused by a fundamental lack of knowledge, in this case about the future, rather than just aleatory uncertainty, caused by randomness in observable populations, as discussed by Paté-Cornell (1996), creates a significant barrier to effective risk analysis. We consider sensitivity analysis to be an appropriate approach in this uncertainty context, because it helps decision-makers to assess the impact of uncertainty, without requiring the probability of future scenarios to be known. We also suggest that multi-factor sensitivity analysis may be beneficial because of potential interactions between PPA contract variables. We note similar methodologies, such as the use of Design of Experiments theory discussed by Groenendaal and Kleijinen (1997) and the random sampling of uniform distributions discussed by Marino et al. (2008), but the complexity and time required to understand and implement such approaches may outweigh the benefit for many potential users.

1.3. Approach

In the context of the discussions in above sections, it seems that there is adequate justification for further academic contribution to the set of resources available for end-users making decisions associated with PPAs. Furthermore, other tools developed thus far, such as the US National Renewable Energy Laboratory's System Advisor Model, focus on the project developer rather than the end-user (Blair et al., 2014). In order to address these issues, the tool needed to:

1. Cover a sufficiently broad range of PPA structures, that reflected the current options being chosen by energy users
2. Be accessible and transparent for the user
3. Adequately represent the more complex underlying mechanisms, such as CFDs and wholesale energy purchasing
4. Include options to aid users in assessing the uncertainties associated with various PPA options

The tool itself consists of a MS Excel workbook, which the authors have termed the Multi-factor Sensitivity Analysis Tool for PPAs (MSAT-PPA or MSAT for short), available online on the Centre for Energy and Environmental Markets webpage: http://www.ceem.unsw.edu.au/renewable-ppa-tool. An overview of the tool and how it meets the above goals are given in the methodology, section 2.1. A brief description of the model that provides details pertinent to the scenarios explored in this paper, is given in section 2.2. The sensitivity analysis used is described in section 2.3. The details of the examples are described in section 3 and the results are presented and discussed in section 4. Finally, a brief conclusion is given in section 5.

2. Method: General description of the MSAT

2.1. Tool overview

MSAT calculates cash flows resulting from PPA contracts and retail energy agreements. It allows the users to choose between five options of 1) No PPA, only charged retail tariff, 2) Off-site - Contract for Difference, the user signs a CFD with a renewable energy generator, 3) Off-site - Tariff Pass Through, the end-user is charged for renewable energy using a separate tariff, 4) Off-site - Physical Hedge, the end-user owns an offsite renewable energy generator, and 5) On-site RE Generator, energy is purchased from a generator located behind the end-user's meter. These allow the user to compare a broad set of contract structures. Calculations are done on a half-hourly basis to reflect the current NEM settlement process. All calculations done by MSAT are implemented as MS Excel formulas to achieve a high level of accessibility and transparency for the intended audience. A multi-factor sensitivity analysis feature was implemented in VBA to aid users in identifying drivers of uncertainty. Historical NEM wholesale price and renewable energy generation data is also made available in accompanying MS Excel workbooks, pre-formatted for use in MSAT, this data was originally sourced using NEMOSIS, an open-source data tool developed by Gorman et al. (2018).

2.2. PPA model case study

The general type of PPA being modelled for this paper, is one in which the end-user signs a CFD for a variable volume of renewable energy (RE), this may be termed a generation following PPA. The volume for the CFD is determined each half-hour by the actual production of the renewable energy generator. Within this general type, the end-user may also choose variable degrees of wholesale exposure for their load, by arranging for their retailer to pass through wholesale costs. Other options such as tariffs, production targets and LGC purchasing are also available. Other PPA types such as "firm-flat" or "shaped-firm" can also be modelled by manipulating the RE input profiles. The relevant mathematics for this PPA type is presented in sections 2.2.1 to 2.2.5.

2.2.1. Retail Time of Use energy charges

The cost of each Time of Use (TOU) charge is calculated on a half-hourly basis. For each half-hour, if the time is inside the charge's time of use window, then the cost is equal to

$$C_{TOU} = \sum_{i=0}^{n} V_{r,i} \times MLF \times DLF \times R$$

Where $V_{r,i}$ is the residual volume of load in a given half-hour, i.e. the volume of load being purchased through the user's standard retail contract and not at wholesale prices; n is the number of half-hours in the time-series; MLF and DLF are the marginal loss factor and the distribution loss factor for the end user's connection point; while R is the charge rate in \$/MWh. Marginal loss factors (MLF) represent the average losses associated with supplying load at particular points in the transmission network. They can change markedly as new generation and loads connect to the network, and currently there are no hedging arrangements that allow the risks of major changes in these factors to be managed.

The total retail energy cost for the end-user is then the sum of all the energy charges over the month or year. In this paper, we do not consider network or metering charges as they will not be impacted by the example PPA, but these can be modelled in MSAT. How environmental charges will be impacted by the PPA may depend on the bundling of LGCs, so they are similarly not considered in the scope of this article, but they can be modelled in MSAT.

2.2.2. Contracts for difference

The cash flow of the CFD is calculated on a half-hourly basis. The cost to the end-user is equal to:

$$C_{CFD} = \sum_{i=0}^{n} (P_{PPA} - P_{RRN,i}) \times V_{RE,i}$$

Where P_{PPA} is the PPA contracted price per unit of energy, $P_{RRN,i}$ is the wholesale energy trading price at the regional reference node, and $V_{RE,i}$ is the volume of renewable energy produced in a given half-hour. Note that no lower bound is placed on $P_{RRN,i}$, despite many PPAs increasingly implementing a zero price floor.

2.2.3. Wholesale energy

The cost of purchasing wholesale energy is calculated on a half-hourly basis. The cost to the end-user is equal to:

$$C_W = \sum_{i=0}^{n} P_{RRN,i} \times MLF \times DLF \times V_{W,i}$$

Where $P_{RRN,i}$ is the wholesale energy trading price at the regional reference node, MLF and DLF are the marginal loss factor and the distribution loss factor for the end user's connection point, and $V_{W,i}$ is the volume of energy the end-user is purchasing at wholesale prices for a given half-hour.

2.2.4. Production targets and penalties

The payment the end-user receives due to production shortfalls can be calculated on a yearly, quarterly or monthly basis. The payment for the given period is equal to

$$P_T = (V_t - V_g) \times R_P$$

Where V_t is the production target for the given period, V_g is the volume generated for the given period and R_P is the shortfall penalty rate. Payments cannot be negative if generation exceeds the target.

2.2.5. LGC costs

In examples used in the paper, we consider that LGCs are bundled in the PPA and thus do not come at an additional cost. However, in the model, the user can set a separate price and volume for LGCs.

2.3. Multi-factor sensitivity analysis

The multi-factor sensitivity analysis is an extension of the model that allows the user to specify a set of one to ten input variants for each model variable. A VBA script, modified from Katnaan (2015), then computes the combinations of all variables, each combination forming a scenario. Each scenario is then run, where VBA is used to insert the scenario variables into the model, and record its total retail and PPA cost outcomes. Additionally, the user can re-load a scenario to view its results in greater detail.

3. Method: Example PPA and sensitivity analysis

In this paper, we use a hypothetical CFD type PPA to explore the use of multi-factor sensitivity analysis. Calculations of cashflows were made for a single year of the PPA contract. The input scenarios are constructed around the University of New South Wales' (UNSW Sydney) load profile, the New South Wales (NSW) NEM region's wholesale trading price, and the generation profile of Broken Hill Solar Farm (note that the structure of the PPA and the chosen inputs do not reflect UNSW's actual PPA). However, the regional trading price is linearly scaled to a set of specific average prices to explore possible future scenarios and the solar generation output is scaled to 28% of its original volume, such that it does not exceed UNSW's consumption in any half-hour period. Figure 1 shows the set of inputs with scaled average wholesale prices of 80 \$/MWh, in 2018 the actual NSW average was 82 \$/MWh.

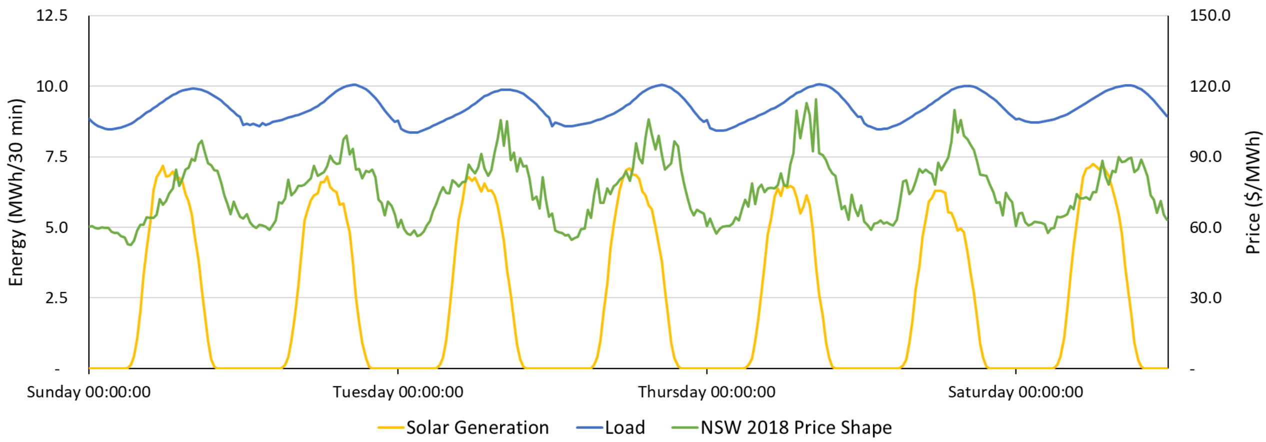

Figure 1 Average weekly summer input profiles, with a scaled version of Broken Hill Solar Farm, the NSW 2018 trading price scaled to an average value of 80 $/MWh and UNSW's load profile.

The complete set of input variations used is detailed in Table 1, the combinations of these inputs result in 3645 scenarios. On the authors' machine running this set of scenarios took approximately 2 h, or 2 s per scenario (running at 3.5 GHz with 8 logical processors). Section 3.1 provides further details on the input variations used and section 3.2 provides details on inputs that are held constant across all scenarios. Importantly, the retail energy charges are not varied in these scenarios, thus the results represent the short-term sensitivity in cash flows, i.e. the changes possible in cash flows during the retail agreement period (while energy charges are agreed in advance). In other words, longer-term sensitivity would be best explored while also varying the retail energy charges.

3.1. Input variations

Descriptions of the input variations are provided in sections 3.1.1 to 3.1.4, these are summarised in Table 1. The variations used do not necessarily attempt to produce likely scenarios, but rather aim to test the contract's sensitivity to changes. Where time-series inputs are drawn from different years, values are matched on month, day and time.

Table 1 Input variants

Variables	**Input variants**					**Scenarios**
	1	2	3	4	5	
Wholesale Price ID	NSW 2018	Simple Noon Trough	Simple Noon Peak			3
Average Wholesale Price ($/MWh)	20	80	140			3
Wholesale Exposure Volume	No Exposure	All RE	All Load			3
Load ID	Input Load	Load 1.1	Load 0.9	Load offset 6h	Load offset 12h	5
Generator ID	RE Generator	Gen Out Feb	Curtailed			3
Target Period	Monthly	Quarterly	Yearly			3
Load MLF	0.9	1	1.1			3
Total number of scenarios						**3645**

3.1.1. Wholesale price profiles

Three different profiles are used to determine how the wholesale price varies throughout the year; the average weekly summer profiles are shown in Figure 2. The 'NSW 2018' profile uses the actual historical 30 minute price for the NSW Region in 2018. The 'Simple Noon Trough' profile uses a Sine wave of the form:

$$P_{RRN} = \frac{Sine\left(2t\pi + \frac{\pi}{2}\right)}{2} + 1$$

Where P_{RRN} is the price, and t is the fraction of time passed in the current day. The 'Simple Noon Peak' profile uses a Sine wave of the form:

$$P_{RRN} = \frac{Sine\left(2t\pi - \frac{\pi}{2}\right)}{2} + 1$$

These produce daily cycles in wholesale prices that remain constant throughout the year. In this case they test the PPAs' sensitivity to changes in daily pricing patterns, but the user may wish to use alternative profiles to test other sources of sensitivity. These profiles provide the wholesale shape only and are scaled linearly to achieve the specified average wholesale price.

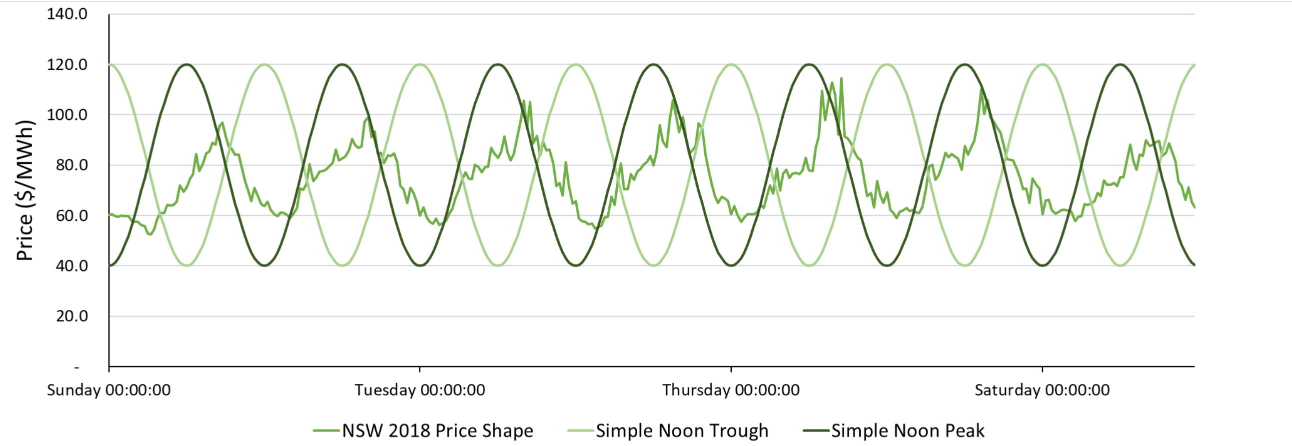

Figure 2 Example of average weekly summer price profiles, scaled linearly to achieve an average price of 80 $/MWh.

3.1.2. Wholesale exposure

This is the method that determines the end user's exposure to wholesale pricing on a half-hourly basis. This would likely be fixed when the contract is initially negotiated but is of interest because it may affect the contract's sensitivity to other factors, such as wholesale prices. Additionally, an end-user may be forced to re-negotiate this volume if their retail agreement is signed on a shorter term than their PPA. The values used are 'No Exposure' where the end-user has no wholesale exposure, 'All RE' where the wholesale exposure is equal to the RE generators volume, and 'All Load' where the whole load is exposed to wholesale prices.

3.1.3. Load profiles

Five variations of the end-user load profile are used: UNSW's actual load profile for the period between 01-03-2016 and 28-02-2018, profile increased by 10 %, profile decreased by 10 %, profile shifted forward by 6 h, and profile shifted forward by 12 h. The average weekly summer profiles are shown in Figure 3.

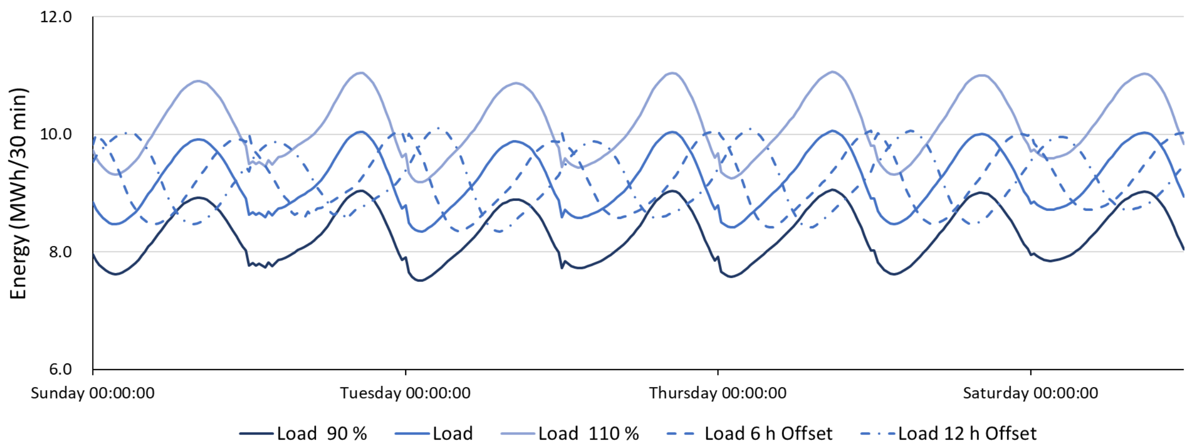

Figure 3 **Average weekly summer load profiles**

3.1.4. Generator profiles

Three variations of the RE generator's profile are used. (1) Broken Hill Solar Farm's profile downscaled to 28%, changing its effective capacity from 53 MW to 15 MW, (2) the downscaled profile with no generation in February, representing a month-long outage, and (3) the downscaled profile curtailed at 12 MW consistently.

3.2. Inputs held constant

3.2.1. PPA contracted price

A hypothetical PPA fixed contract price of 50 $/MWh is used in all presented scenarios. This is reasonably conservative given achieved PPA prices in the present market.

3.2.2. Retail energy charges

The following energy charges apply to all scenarios.

- Peak – AM, 85 $/MWh, between 7 and 10 am on weekdays
- Peak – PM, 85 $/MWh, between 5 and 10 pm on weekdays
- Shoulder, 70 $/MWh, between 10 am and 4 pm on weekdays
- Off-peak, 65 $/MWh, between 10 pm and 7 am on weekdays
- Off-peak, 65 $/MWh, all hours on weekends.

Note public holidays are not considered to affect charges.

3.2.3. Generation targets and penalty charges

The following parameters are used to calculate penalty payments in all scenarios. The yearly production target, which calculated shortfall volumes are based on, is 33,000 MWh, approximately 90% of the volume of the un-modified solar generation profile used. The penalty rate is 15 $/MWh, the difference between the PPA contract price and the off-peak energy charge.

4. Results and discussion

The results in this paper are presented primarily as a demonstration of MSAT. The authors also consider them useful in exploring uncertainty in PPA costs. However, they and the results of MSAT in general, reflect reality only to the extent that underlying assumptions represent a given PPA contract. Additionally, some sources of uncertainty may not be represented at all in the model, such as counterparty credit risk and other qualitative risks.

The results focus on four variables, wholesale exposure volume, MLF, total load volume, and average wholesale price. While additional variables were also tested in the sensitivity analysis, these were not explicitly analysed, but do provide a background level of variation that contextualises trends highlighted in sections 4.1 to 4.3. All results have been normalised to the end user's energy bill, calculated assuming no PPA, paying the same retail energy charges, an MLF equal to 1.0 and the unadjusted load profile.

4.1. Trends by wholesale exposure volume

Figure 4 presents the trends in total energy bills with average wholesale prices, aggregated by wholesale exposure volume. For scenarios where there is no wholesale exposure, the end-user is 'over hedged' and higher average wholesale prices result in lower bills. This change is caused by the CFD, the end-user gets larger payments through the CFD, but all other costs remain the same, so their net bills go down. For scenarios with all load is exposed to wholesale prices, the end-user is 'under hedged' and higher average wholesale prices result in higher bills. The payments from CFD are not enough to compensate for the increased price of wholesale energy. Additionally, for these scenarios the spread of total bills increases with average wholesale price, this is explored in section 4.3. For scenarios where the wholesale exposure volume is equal to the PPA volume relatively little variation is observed, the exact matching of the PPA and exposure volumes means the changes in the CFD payments are almost fully cancelled out by changes in wholesale energy costs, the 'almost' is explored in section 4.2.

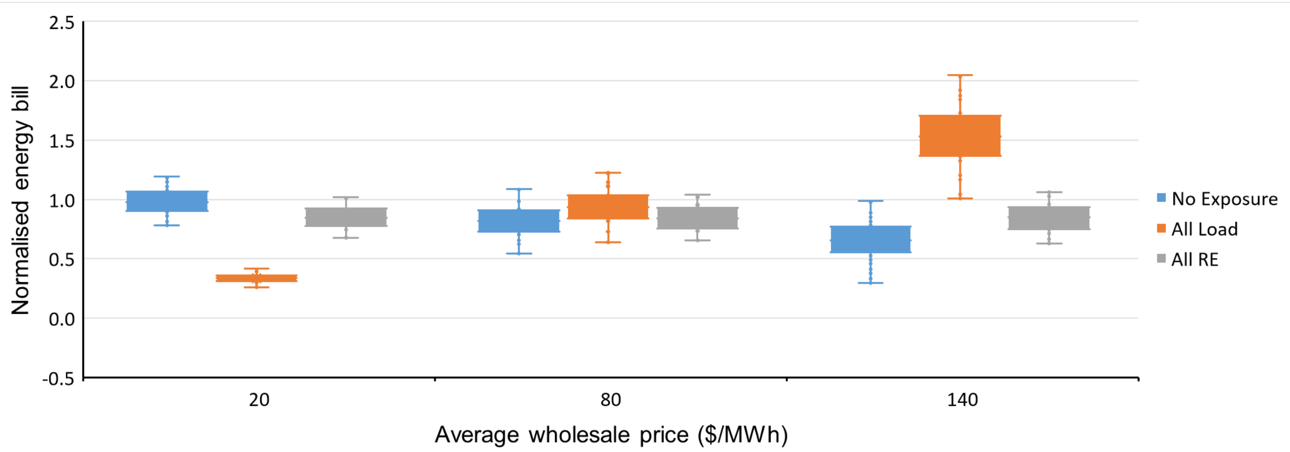

Figure 4 All scenarios: trends in normalised energy bills with average wholesale prices, aggregated by wholesale exposure volume. Bills were normalised by the total bill under a no PPA scenario, with an MLF equal to 1.0 and an unmodified load profile.

These results demonstrate the strong interactions between average wholesale prices and over or under hedging, an effect that is perhaps well understood by generators and retailers, but maybe less well understood by businesses who historically have less experience in this area. End-users entering PPAs may see wholesale exposure as a variable under their control, but this may not be true depending on their contract structure, how it interacts with their retail agreement and any future renegotiation of their retail agreement.

4.2. Trends by MLF

Figure 5 presents the results for scenarios with a wholesale exposure equal to the RE generator volume and shows the average wholesale price trends' impacts aggregated by MLF. For scenarios with an MLF of 1.1, higher average wholesale prices result in higher bills, because in this hypothetical contract, the PPA contracted price refers to the regional reference price, whilst the end-user pays the regional reference price multiplied by the MLF for the purchase of wholesale energy. For scenarios with an MLF of 0.9, the effect is the opposite, hence higher average wholesale prices result in lower bills. For scenarios with an MLF of 1.0, the average wholesale price has no effect on bills. These results demonstrate interactions between average wholesale prices and MLFs and their effect on bills.

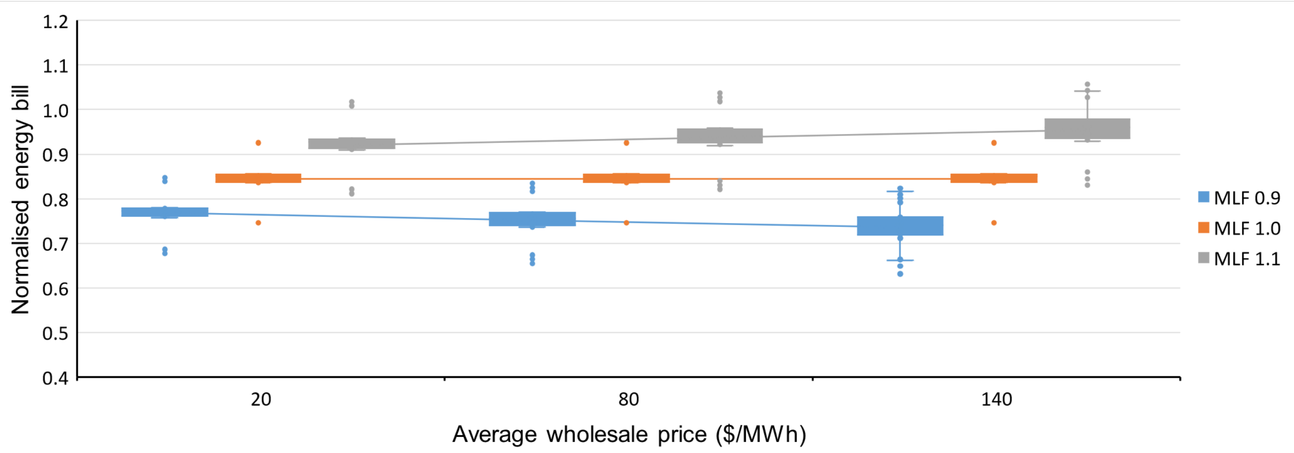

Figure 5 All RE exposure: trends in normalised energy bills with average wholesale prices, aggregated by MLF. Bills were normalised by the total bill under a no PPA scenario, with an MLF equal to 1.0 and an unmodified load profile.

4.3. Trends by total load volume

Figure 6 presents the results for scenarios where all the load is exposed to wholesale prices with an MLF equal to 1.0, and shows the average wholesale price trends' impacts aggregated by total load volume. As expected, lower volumes lead to reduced energy bills, however, they also reduce the rate with which energy bills increase as price increases, as demonstrated by the differing slopes in the mean trendlines. While this result may be obvious, considering the proportionality of bills to wholesale prices, presenting it in this context reframes total energy consumption as a key driver of PPA uncertainty alongside other factors that may otherwise receive more attention. Further to this, it allows energy efficiency to be viewed not just as a cost reduction measure, but also a risk mitigation measure.

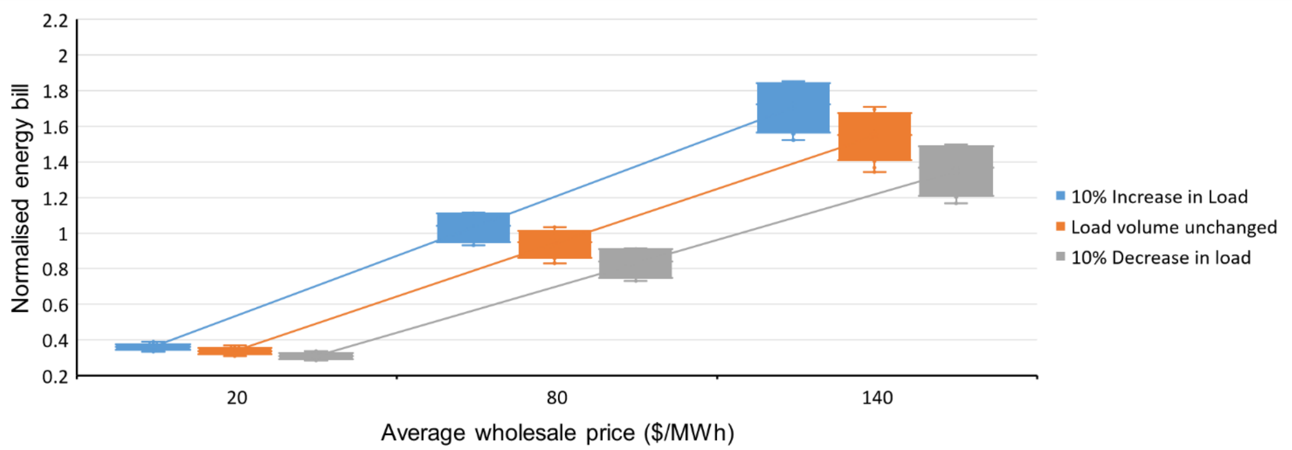

Figure 6 All Load exposure with MLF equal to 1.0: trends in normalised energy bills with average wholesale prices, aggregated by load volume. Bills were normalised by the total bill under a no PPA scenario, with an MLF equal to 1.0 and an unmodified load profile.

5. Conclusion

This study was motivated by the growing and changing role of PPAs in the Australian electricity industry. The wide and growing range of future electricity market uncertainties and risks facing energy consumers entering such PPAs highlights the potential value of multi-factor sensitivity analysis as an appropriate framework for financial analysis. The MSAT workbook and an example use case were presented. Over hedging was shown to result in an interaction whereby higher average wholesale prices can lower end-user bills, but conversely lower price will lead to increases. While under hedging was shown to produce the opposite effect in either instance. In contracts where wholesale exposure and CFD volumes are exactly matched, it was shown that end-user MLFs with a value other than exactly 1.0 prevent the user from decoupling their total bills from average wholesale prices. These results, while potentially specific to the examples presented, demonstrate the potential for strong interactions between key PPA contract variables and hence the value of MSAT-PPA and more generally the appropriateness of multi-factor sensitivity analysis in this context.

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