Assessing the Potential Role of Large-Scale PV Generation and Electric Vehicles in Future Low-Carbon Electricity Industries

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Abstract—**This paper provides a quantitative assessment of the economic implications of large scale Photovoltaic (PV) investment and Electric Vehicles (EV) uptake for the Australian National Electricity Market (NEM). A probabilistic generation portfolio modelling tool is used to assess the potential impact of different combinations of PV and EV penetrations on the overall electricity industry costs, associated cost uncertainties, and greenhouse gas emissions of different future generation portfolios. The other generation options include conventional coal, combined cycle gas turbine (CCGT) and open cycle gas turbine (OCGT) plants. The impacts of EV uptake on hourly electricity demand was accounted for through the simulation of EV charging behaviour using actual Australian vehicle travel pattern survey data. Two EV charging infrastructure cases (residential only and universal charging) were included to account for the impact of possible infrastructure choices on the temporal characteristic of charging. Results highlight some potential synergies between PV generation and EV charging in reducing costs for future electricity industries, particularly in the context of significant carbon prices. However, results also emphasize the need for appropriate EV charging strategies to maximize the potential value of high PV and EV penetration levels within future electricity industries.**

Keywords-component; photovoltaics (PV), electric vehicles, Australian National Electricity Market (NEM), generation portfolio analysis

I. INTRODUCTION

Solar photovoltaic (PV) has been one of the fastest growing Renewable Energy (RE) technologies worldwide over the past decade. PV system costs in Australia have declined by around 30-35 per cent over the last few years [1] and the technology is becoming increasingly competitive with conventional generation options particularly if carbon emissions are priced [2, 3]. Beyond its falling costs, the potential role of PV in helping address the energy security and environmental challenges facing electricity industries worldwide is also expected to result in PV generation continuing to grow rapidly.

On the demand side, plug-in Electric Vehicles (EV) are emerging as a potentially significant element of the future transport vehicle fleet in both developed and developing markets with uptake driven by questions of future petroleum availability and pricing as well as concerns over climate change [4, 5].

From the perspective of the electricity industry, EV uptake will result in increased demand along with an increase in absolute CO_2 emissions [6] unless the electricity used to recharge EVs is sourced from zero emission sources such as RE. Variable and somewhat unpredictable RE generation such as PV could greatly benefit from the presence of EVs in the power system as a result of the flexibility of EV charging load and large aggregated storage capacity associated with significant uptake levels. In this regard, there may be synergies between the roles played by PV and EVs in future electricity systems which could facilitate higher penetrations of both EVs and PV than would otherwise be the case.

Accommodating high EV and PV penetration levels, however, poses significant challenges for the electricity industry [7]. While the interaction between PV and EVs within a future electricity system may result in benefits, both technologies have very different technical and economic characteristics to conventional generation technologies and end-user loads. As a result, significant deployment levels might prove quite challenging for electricity industry operation and planning. PV generation is cyclic, highly variable and somewhat unpredictable. EV charging is also cyclic, variable and somewhat unpredictable, although it also offers significant energy storage potential. Given the promise of both technologies and these challenges, there is value in better understanding their implications, separately and synergistically, on the economics of future electricity industries.

This paper aims to provide a quantitative assessment of the potential economic implications of large scale PV investment and EV uptake within the broader context of generation investment in the Australian National Electricity Market (NEM). The paper employs a novel probabilistic generation portfolio modelling tool [8] to assess the impact of different PV penetrations, and EV fleet sizes and associated charging infrastructure, on the overall electricity industry costs, associated cost risks, and CO_2 emissions of different possible future generation portfolios. The other

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generation options include conventional coal, combined cycle gas turbine (CCGT) and open cycle gas turbine (OCGT) plants. This simulation based modelling tool can assess these future generation portfolios against multiple objectives for a range of future uncertainties including coal and gas prices, carbon prices, plant capital costs and levels of electricity demand. The tool has been previously applied to a number of case studies including the economics of high wind and PV penetrations in the NEM [9, 10]. This paper however, represents the first application which incorporates both PV and EVs.

Section II describes the methodology used in this paper which is based on probabilistic generation portfolio analysis. Section III provides the description of the Australian NEM case study. The results and analysis are presented in Section IV followed by conclusions in Section V.

II. Methodology

A. Probabilistic Generation Portfolio Modelling

The modelling tool extends conventional Load Duration Curve (LDC) based optimal generation mix techniques by using Monte Carlo Simulation (MCS) to formally incorporate key uncertainties which directly impact overall generation costs into the assessment. The tool produces outputs which include the complete probability distribution of annual generation costs and CO_2 emissions for each possible generation portfolio comprising some mix of different generation options. For simplicity, these probability distributions can be represented as an expected annual cost and associated standard deviation. While this paper refers to the standard deviation as the 'cost uncertainty', it can be taken to have a similar meaning to 'cost risk' as used in the economic and financial context. The complete range of possible generation portfolios are considered by varying the share of each technology in the portfolios from 0% to 100 % of total installed system capacity.

The tool then applies financial portfolio methods to determine an Efficient Frontier (EF)[1] of expected (i.e. mean) costs and the associated cost uncertainty (i.e. standard deviation) for each of the different generation portfolios. EF techniques provide a basis for explicitly analysing cost and risk tradeoffs among different generation technology portfolios. In particular, the EF is made up of those generation portfolios which offer the lowest expected cost for some level of cost uncertainty.

Other EFs can also be constructed to represent other tradeoffs between objectives such as expected costs against CO_2 emissions. As such, the tool provides a flexible framework for undertaking multi-criteria assessments of future generation portfolios under multiple uncertainties.

B. Incorporating PV generation and EV load

PV generation and EV charging load are incorporated into the model by varying the time-series of electricity demand. As a result of PV's low operating costs compared to fossil-fuel generation, the analysis presented here assumes that PV is allowed priority dispatch. Using this assumption, simulated hourly PV generation is subtracted from hourly 'native' demand over the course of a 'representative' year. In contrast, hourly EV charging load is added to native demand in each period. In this manner, the temporal match of PV generation and EV charging with electricity demand is appropriately captured.

The resulting net demand in each period, after accounting of PV generation and EV charging load, is then rearranged in descending order of magnitude to obtain a residual (net) load duration curve (RLDC) to be served by conventional generation technologies in the portfolio.

Note that while the use of LDC and RLDC techniques have many advantages in investment planning, they do remove the underlying chronology (hour by hour change) associated with the underlying demand, solar generation and EV charging load. As such, the simulation tool is more suited to assessing long run societal investment costs and risks under high uncertainty, rather than problems requiring detailed operational modelling In particular, operational constraints associated with unit commitment such as start-up and shut down times, ramp rates, or network losses are not accounted for.

III. The Australian National Electricity Market (NEM) Case Study

The Australian National Electricity Market (NEM) is used as a case study with conventional coal, combined cycle gas turbine (CCGT), open cycle gas turbine (OCGT) and PV plant options. Like many electricity industries around the world, the NEM faces highly uncertain future fuel prices, carbon prices, electricity demand and plant capital costs. 2010 is used as the reference year with actual hourly electricity demand data, and PV generation simulated from satellite derived hourly solar estimates, across the same year.

Generator characteristics and cost parameters are based on the 2030 cost estimates provided by the Australian Energy Technology Assessment (AETA) report of the Bureau of Resources and Energy Economics (BREE) [1].[2] EV charging load profiles are simulated based on actual Australian vehicle travel pattern data obtained from the New South Wales Household Transport Survey (NSW HTS).

In order to capture the effects of different PV deployment and EV uptake levels, PV energy penetrations from 0% to 20% in 5% increments are simulated for all possible thermal generation portfolios. Three different EV fleet sizes were also considered: 0%, 20% and 50% of total residential vehicles.

A. Electric Vehicle Modelling

The temporal characteristic of EV charging load is a function of the transport behaviour of individual drivers and the locational availability of charging infrastructure. Therefore, in order to obtain a set of appropriate charging load profiles it is necessary to explicitly consider both passenger vehicle level transport behaviour and the location of recharging infrastructure available to satisfy EV charging energy requirements. Specifically, underlying vehicle use patterns were obtained from the NSW HTS which is a

[1] The efficient frontier concept is used in the Mean Variance Portfolio (MVP) theory for financial portfolio optimization [11].

[2] All monetary values in the paper are shown as Australian dollars which is about $US 0.9 at current exchange rate

logbook based household travel survey conducted in the Sydney Greater Metropolitan area [12]. This was combined with two infrastructure scenarios (*residential charging only* and *universal charging*) to account for the potential impacts of different infrastructure availability on the electric vehicle charging load profile.

The NSW HTS is a rolling survey of 5000 households a year which tracks the trips made by each vehicle over the course of one day during the working week and weekend. It includes details of trip distance, departure and arrival times, trip purpose, and parking location at the point of arrival for each vehicle. In order to improve the statistical validity of the transport sample, 10 years of pooled travel data was used between 2002 and 2012 in respect of 51,800 individual vehicles and 216,566 vehicle trips to obtain the EV charging load results presented here. While the NSW HTS contains trip data for a range of vehicle types, 4WDs, trucks, Motorcycles, Goods Vans, Utility Vehicles, and Family Vans, we have restricted our assessment to the passenger car category which represents a statistically weighted Sydney GMA passenger car fleet of 1,821,500 driven on the travel day surveyed.

In order to determine the charging behaviour of each electric vehicle in the NSW HTS fleet, a time based simulation method was used to establish the Battery State of Charge (SOC), charging load, and fuel consumption for each vehicle across the course of the simulated day (weekend or working weekday). The two charging infrastructure cases considered included residential charging in which a vehicle is able to recharge when parked at any residential location; and universal charging in which a vehicle is assumed to have access to recharging infrastructure at any location at which it is parked. In recognition that the willingness of a driver to recharge at a particular location will be a function of the time parked at that location, a minimum 10 minute dwell time constraint is applied such that a vehicle must be parked at a location for over 10 minutes in order to recharge. Recharging commences immediately upon arrival as long as this requirement is satisfied.

The simulation tool implements a medium sized passenger Plug in Hybrid Vehicle (PHEV) as the electric vehicle type investigated here with a series drivetrain and a petrol internal combustion engine for range extension (modelled using binary Charge Depletion/Charge Sustaining modes of operation). It is intended to be broadly representative of a General Motors Volt [13]. The model was implemented using the Simulink and Stateflow packages integrated into Matlab with state logic adapted from the framework for the operation of electric vehicles in a power system described in [14]. Battery electricity consumption when driven in Charge Depletion mode was established through the use of ADVISOR the vehicle drive train simulation software released by the National Renewable Energy Laboratory (NREL) [15]. ADVISOR was used with the US EPA Urban Dynamometer Driving Schedule (UDDS), which is representative of the velocity, acceleration, and breaking under urban driving conditions [16], to establish the average current draw, including the effects of regenerative braking. Gasoline consumption while in Charge Sustaining mode is taken to be 15.7 km/L corresponding to the premium gasoline fuel efficiency reported for the Volt [17].

The results obtained for each individual NSW HTS vehicle were then statistically weighted to the Sydney Greater Metropolitan Area fleet size using weightings supplied for that purpose from the NSW Bureau of Transport Statistics. Following weighting, Sydney GMA passenger car fleet results are then scaled to represent the passenger car fleet size for the Australian States making up the footprint of the NEM according to the penetration level desired.

B. Electricity Demand and PV Generation Modelling

Hourly electricity demand data is obtained by aggregating the actual 30-minute 2010 demand into hourly values. Note that actual wind generation, which accounted for about 5% of total generation in 2010, has also been incorporated into the RLDC.

System Advisor Model (SAM) [3] software was used to model hourly PV generation across different NEM locations including major cities and some regional areas. In this way the diversity value of PV across different locations was captured. The hourly PV output in each selected location was simulated based on a 1-MW fixed flat plate solar PV plant, with north-facing arrays and tilted at latitude angle, using satellite derived 2010 solar data and ground station weather data. For PV located in major cities, it is assumed that no additional network investment is required to accommodate this additional PV generation. However, additional transmission costs associated with centralized PV plants in regional locations are taken into consideration in the simulation as explained in detail in [9].

Installed PV generation capacity is assumed to be the same for each of the selected locations. For each penetration level the installed PV capacity is determined based on a constant PV capacity factor of 21% as estimated in [1]. The simulated hourly PV generation is then scaled up to the desired PV energy penetration level.

As previously explained in Section II, PV generation is given priority in the dispatch therefore being treated as negative load and subtracted from actual hourly demand. Simulated hourly EV charging load is then added to produce the net demand curve which is then rearranged to obtain a RLDC which is to be served by conventional generation technologies in the investigated portfolios.

Fig. 1 illustrates demand profiles with 5% PV penetration and EV charging load for a fleet size of 20% during a typical summer week for both EV charging infrastructure cases. EV charging load will ultimately increase overall peak demand for both charging infrastructure scenarios. However, the provision of universal EV charging infrastructure is observed to re-distribute to some extent EV charging load from the dominant evening charging peak, under the residential infrastructure case. Most significantly however, the universal recharging infrastructure case produces an EV charging load pattern which is better correlated with PV generation output. This suggests that the provision of EV charging infrastructure represents an important variable to consider when planning a future power system which will include high EV and PV (or other solar) penetrations.

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[3] SAM is a tool developed by the National Renewable Energy Laboratory (NREL) to model the performance and cost of grid-connected RE [18].

The RLDCs (to be met by conventional generation technologies) for each of the different PV and EV penetration levels are shown in Fig. 2 with an increasing difference in the RLDC observed between the two EV charging infrastructure cases for the 0% and 20% PV penetration levels. This difference is most notable at higher EV penetration levels and shows the effect of moving EV charging load from the evening peak, under the residential charging case, throughout the day thereby improving the correlation of EV charging with PV generation.

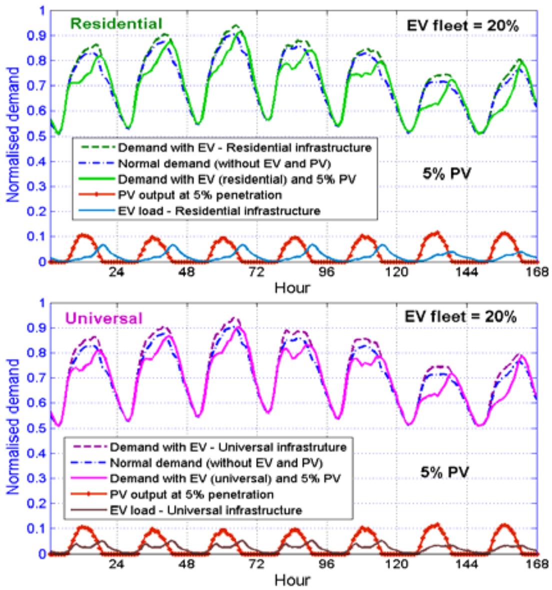

Figure. 1. Weekly demand, PV output and EV load during a typical summer week for residential and universal charging infrastructure cases.

C. Generator Data

The amount of installed conventional generation capacity is determined using a probabilistic approach to ensure that there is sufficient generation capacity to meet the expected demand for at least 99.998% of the time during the year. Table I shows the installed PV capacity, peak demand and installed fossil fuel generation capacity for each of the different PV and EV penetration levels.

TABLE I. INSTALLED PV AND CONVENTIONAL CAPACITY FOR DIFFERENT PV PENETRATIONS, EV FLEET SIZES AND CHARGING INFRASTRUCTURE OPTIONS

EV fleet size (%)	PV (%)	Installed PV capacity (GW)	Residential charging		Universal charging	
			Residual peak demand (GW)	*Installed fossil-fuel capacity (GW)*	*Residual peak demand (GW)*	*Installed fossil-fuel capacity (MW)*
20	0	0 34.	4	38.5	34.3	38.4
	5	5.7 34		38	33.4	37.5
	10	11.3 34		38	33.4	37.4
	15	17 34		38	33.4	37.4
	20	22.6 34		38	33.4	37.4
50	0	0 37.	5	42	36.4	40.8
	5	5.7 37.	5	42	36.2	40.5
	10	11.3 37	5	42	36.2	40.5
	15	17 37.	5	42	36.2	40.5
	20	22.6 37	5	42	36.2	40.5

New entrant generation data for each conventional generation technology were based on the 2030 cost estimates obtained from the 2012 AETA report and are shown in Table II. Annualized capital costs are determined using a 5% discount rate.

TABLE II. GENERATOR DATA

Parameters	Technology			
	Coal CC	*GT*	*OCGT*	*Solar PV*
Plant life (years)	50	40	30	30
Capital cost ($/MW)	2,950,000 1,	110,000	750,000 1,	570,000
Fixed O&M ($/MW/yr)	50,500	10,000	4,000	25,000
Variable O&M ($/MWh)	7	4	10	0[a]
Thermal Efficiency (%)	41.9	49.5	35	N/A
Heat Rate (GJ/MWh)	8.591	7.272	10.285	N/A
CO_2 emission factor (tCO_2/MWh)	0.773 0.	368	0.515	0
Fuel price ($/GJ)	1.65	8	8	0

a. Already included in fixed O&M

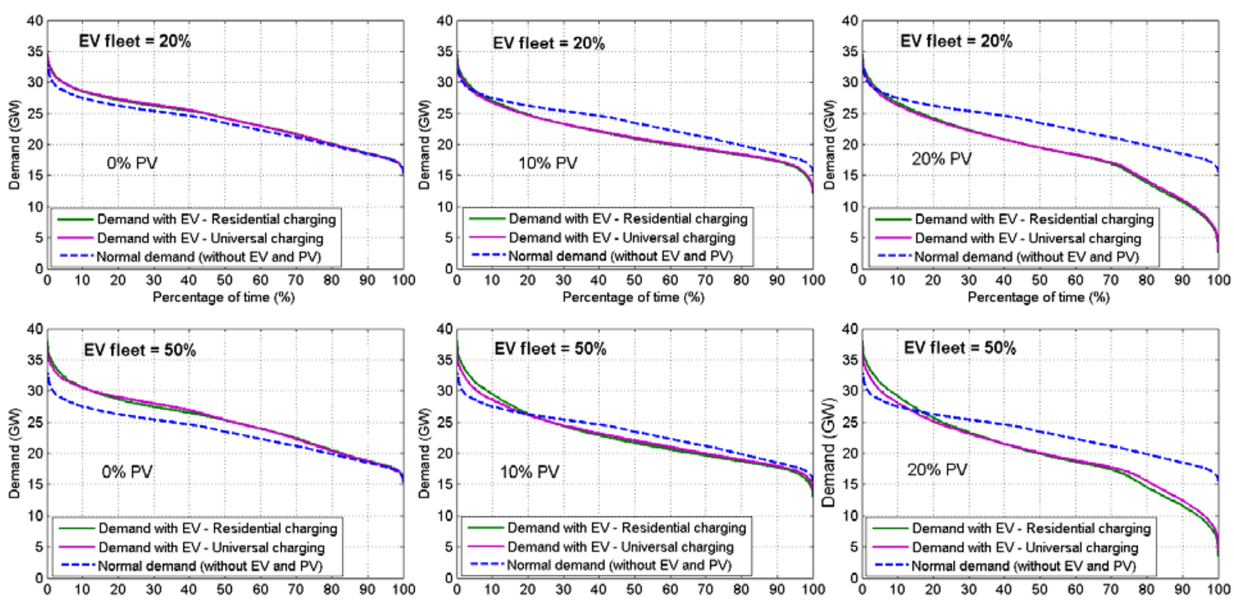

Figure. 2. LDCs and RLDCs for different EV fleet sizes and PV penetrations for different charging infrastructure scenarios.

D. Modelling Uncertainties

The inherent uncertainty associated with the future values of key cost parameters and electricity demand is explicitly accounted for in the modelling approach applied in this study. Key parameters for which uncertainty is modelled include fuel prices, carbon price and plant capital costs, which are modelled by lognormal distributions. A normal distribution is assumed for electricity demand uncertainty. Both Lognormal and Normal distributions can be characterised by their mean (expected value) and standard deviations (SD).

The expected values and SDs of fuel prices and capital costs are determined from the 2030 estimates and the percentage uncertainties provided in the 2012 AETA report [1]. The SDs of coal and natural gas price distributions are estimated to be 6% and 30% of their expected values respectively. Different expected (mean) carbon prices are considered in this study with their SDs assumed to be 50% of their expected values given present uncertainties regarding future climate policy efforts. Correlations between fuel and carbon prices are accounted for and are estimated based on historical trends in OECD countries [8]. Table III and IV show the expected values and SDs of fuel prices and plant capital costs for each technology option.

TABLE III. MEAN AND SD OF FUEL PRICES

$/GJ	Coal price	Gas price
Mean 1.	65	8
SD	0.1 2.	4

TABLE IV. MEAN AND SD OF PLANT CAPITAL COSTS

$/MW C	oal	CCGT	OCGT	PV
Mean 2,	950,000	1,100,000	800,000	1,600,000
SD	1,200,000 3	20, 000	230,000	940,000

A Multivariate Monte Carlo simulation technique[4] is used to generation correlated samples for coal, gas and carbon prices from their respective marginal lognormal distributions.

Electricity demand uncertainty is modelled using the variations in the RLDC according for each PV penetration, EV fleet size and charging infrastructure case. Each sample RLDC is derived based on each sample of net peak demand for each PV penetration, EV fleet size case and charging infrastructure scenario. The SD of net peak demand is estimated based on the likelihood that the maximum demand will exceed projections for any given year using 90%, 50% and 10% 'probability of exceedance' (POE) provided by AEMO [19]. The SD of peak demand is approximated as 4% of the central projection, which corresponds to the 50% POE case. The difference between a sample and reference peak demand is then used to adjust the demand in every period of the reference RLDC. There are some instances in which the simulated residual peak demands exceeds the installed conventional generation capacity resulting in energy not being served. The value of energy not served used in this study is $12,900/MWh, which is the current NEM market ceiling price. The cost of energy not served is included in the overall generation cost during each Monte Carlo run.

[4] Multivariate simulation techniques are used for reproducing random samples of uncertain parameters while preserving their respective marginal distribution properties and correlation structure.

IV. SIMULATION RESULTS AND ANALYSIS

For each PV penetration level, EV fleet size and charging infrastructure scenario, the calculation of overall industry costs and emissions for each conventional generation portfolio is repeated for 10,000 simulations of uncertain future fuel prices, carbon price, demand and plant capital costs. In total, 66 possible combinations of conventional plant were considered with the proportions of coal, CCGT and OCGT being varied from 0% to 100% in 10% intervals.

The sensitivity of the results to carbon prices can be assessed by running the model with different carbon price inputs. The carbon prices used in this study focus on moderate to high prices given that many of the modelled estimates for what future global carbon prices will be required to effectively address climate change are in the range of $100/tCO$_2$ over the next twenty years [20, 21].

Fig. 3 shows the distribution of 10,000 simulated coal, gas and carbon prices (at $20/tCO$_2$) as well as the scatter plots which highlight their correlations.

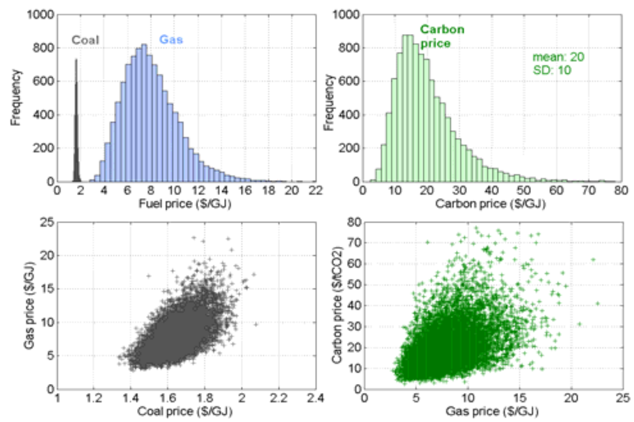

Figure. 3. Distributions of 10,000 sample of correlated fuel and carbon prices and their scatter plots showing their correlations.

The capital cost distributions resulting from the 10,000 simulations for each generation option are shown in Fig. 4.

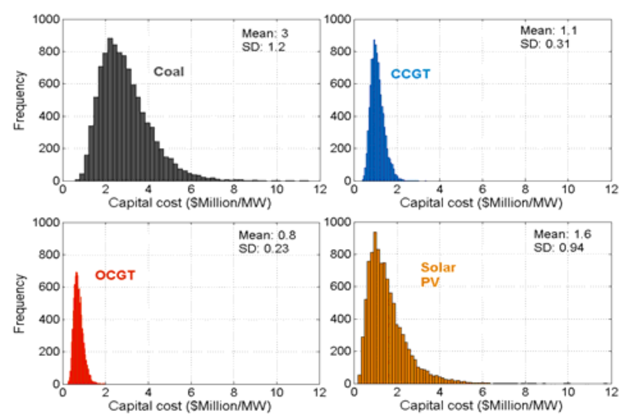

Figure. 4. Distribution of capital costs for each generation technology.

A. Without a Carbon Price

In order to illustrate the concept of, and outputs produced by the modelling tool, Fig. 5 shows the expected annual generation cost, associated cost uncertainty, and CO_2 emissions of different thermal generation portfolios in the absence of PV generation, EV load, or a carbon price. Note that not every generation portfolio is presented to aid clarity.

The cost-risk Efficient Frontier (EF) which contains three optimal generation portfolios, as denoted (A), (B) and (C), is presented on the graph as shown by a solid line. The lowest cost portfolio is (A) which contains 70% coal, 10% CCGT and 20% OCGT while the lowest risk portfolio is (C) which contains 50% coal, 30% CCGT and 20% OCGT. The tradeoff in terms of expected cost, risk and emissions among portfolios can be seen on the EF. For example portfolio (A) has the lowest expected cost but also has relatively higher risk compared to portfolios (B) and (C).

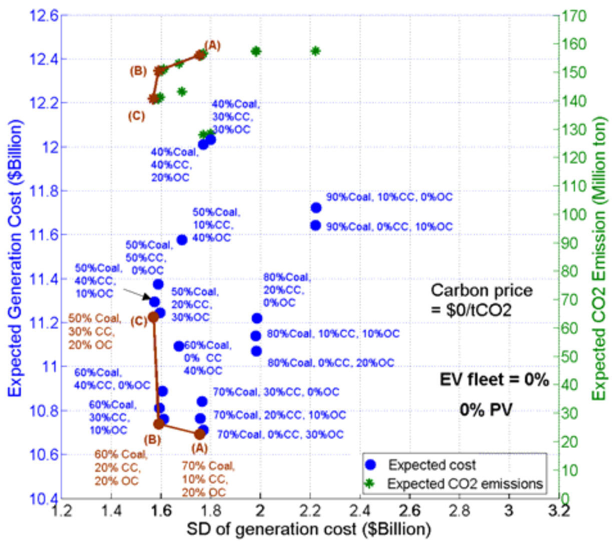

Figure. 5. Expected annual system costs, cost uncertainty and CO_2 emissions of generation portfolios for the case without EV, PV or a carbon price. The expected costs are represented by the circles and the CO_2 emissions of the corresponding portfolios are represented the asterisks in the same vertical line.

Fig. 6 shows the impact of different EV penetration levels on the cost-risk EFs for the case without a carbon price or any PV generation. Given that EV charging involves a net increase in electricity system load, we see that higher EV penetration levels increase electricity generation costs in the case without PV as indicated by the upward movement of the EF as EV fleet size increases for both charging infrastructure cases.

The impact of PV generation on expected annual generation cost and associated cost uncertainty is shown in Fig. 7 for the case with 20% EV fleet size and without a carbon price. By holding the EV penetration level constant at 20% and increasing the PV penetration, we see that higher PV penetration increases overall system generation costs as well as cost uncertainty. This increase is due to the additional capital costs associated with PV plants due to their low capacity factor relative to conventional technologies (i.e. a higher amount of capacity is required to meet the same amount of demand). In addition, we observe that there is a difference in cost between the two EV charging infrastructure scenarios with the overall system cost being somewhat lower under the universal charging case when compared to the residential charging case. These cost differences become more apparent at higher PV penetration levels due to the EV load profile under the universal infrastructure case having a higher correlation with the PV generation profile. As a result, the provision of non-residential charging infrastructure in a power system with high EV and PV penetration levels is observed to provide an economic benefit in electricity system operations through a reduction in expected operating cost.

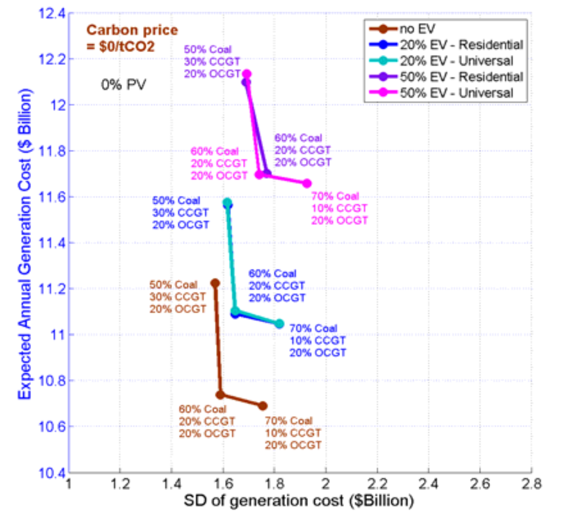

Figure. 6. Cost-risk efficient frontiers for different EV fleet sizes in the case without a carbon price and PV generation.

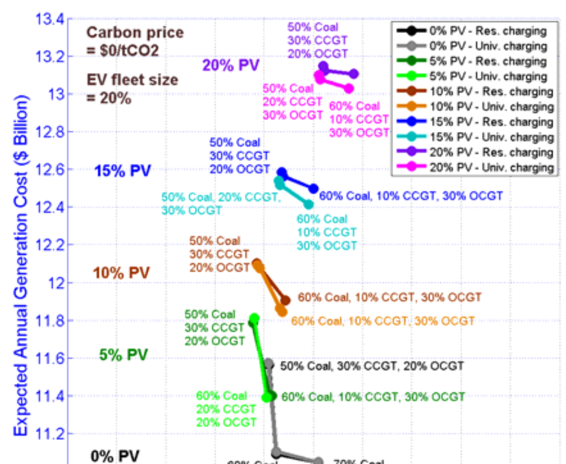

Figure. 7. Cost-risk efficient frontiers for different PV penetrations

We can see from Fig. 6 and Fig. 7, that in the absence of a carbon price (or with a very low price), the optimal generation portfolios consist mainly of coal supplemented by differing amounts of CCGT and OCGT. However, given international concerns over climate change and the movement of a growing number of countries to address the market failures associated with the negative external costs of climate change there is a need to consider the effects of meaningful carbon pricing on optimal generation mixes.

B. With a Carbon Price

This section presents results obtained when a carbon price is included thereby allowing impacts in the optimal generation portfolios on the EFs given the different PV and EV cases to be identified.

1) A Carbon Price of \$50/tCO_2

Fig. 8 shows the cost-risk EF for an expected carbon price of \$50/tCO_2. At this carbon price, the increase in the expected system generation cost arising from higher PV penetration is, as expected, less than in the case without a carbon price. Indeed, as the PV penetration level increases from 0% to 5% a reduction in overall generation cost is observed under both EV charging infrastructure scenarios. As an example, the expected generation costs of portfolios A – C in the case of 5% PV are actually lower than the 0% PV case when a carbon price of \$50/tCO_2 is applied.

The results presented in Fig. 8 show that the lowest cost generation portfolio for every PV penetration is portfolio A (50% coal, 30% CCGT, 20% COGT) except for 20% PV which is portfolio G (40% coal, 30% CCGT, 30% OCGT)[5] which represents a significant reduction in the amount of coal generation from the case without carbon pricing.

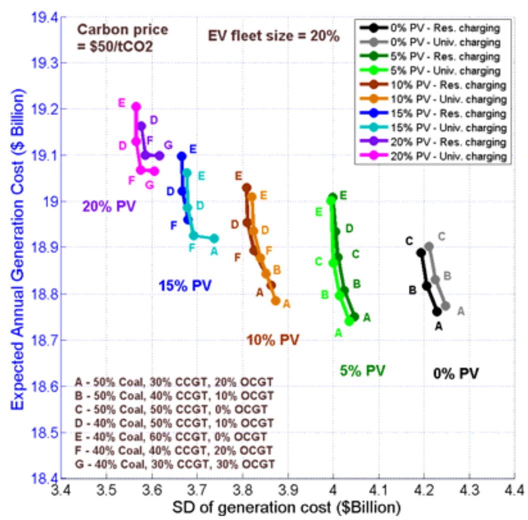

Figure. 8. Cost-risk EF showing optimal generation portfolios for different PV penetrations in the case of \$50/tCO_2 and 50% EV.

In order to see how the optimal generation mixes change as PV penetration levels increase, Fig. 9 presents the generation mix making up the lowest cost generation portfolio for each PV penetration level under the residential EV charging case. From this, the total generation capacity is seen to increase quite considerably, from about 40 GW in the case without PV to 65 GW in the case of 25% PV penetration. The extent of this increase can be explained by the additional PV capacity which is required to compensate for its relatively low capacity factor.

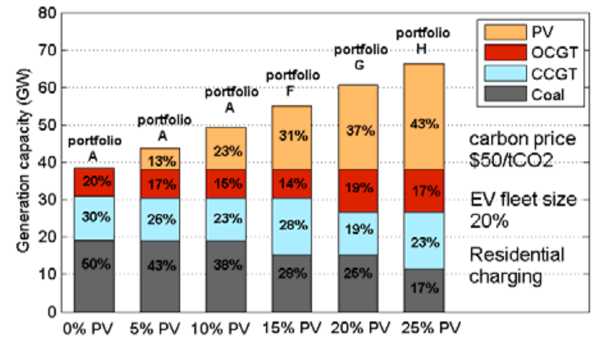

Figure. 9. Installed capacity of each technology of the lowest cost portfolios for different PV penetrations in the case of \$50/tCO_2 and 20% EV.

Fig. 10 compares the expected cost, cost uncertainty and CO_2 emissions of the lowest cost portfolios for each PV penetration level for a \$50/tCO_2 of carbon price and 20% EV fleet size. While a reduction in system generating cost is observed as PV penetration is increased from 0% to 5%, (which occurs as a result of variable generation costs offset by PV decreasing greater than the increase in fixed capital costs associated with additional PV installation) as PV penetration levels increase above 5%, costs begin to increase which suggests an economic optimum PV penetration level of around 5%. In contrast to the increase in expected cost, increasing PV penetration levels are observed to result in a significant reduction in generation cost uncertainty and CO_2 emissions.

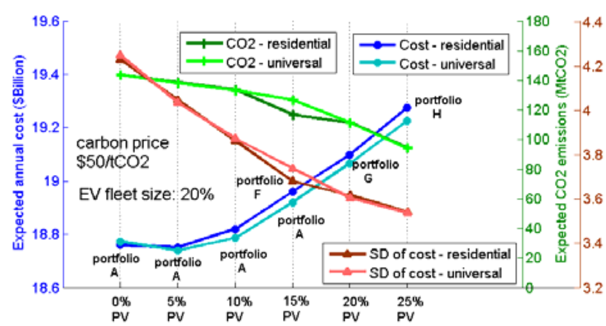

Fig. 10. Expected costs, SDs and CO_2 emissions of the lowest cost generation portfolios for different PV penetrations in the case of \$50/tCO_2 and 20% EV.

2) A Carbon Price of \$80/tCO_2

In order to assess the sensitivity of the results to a higher carbon price Fig. 11 shows the expected cost, cost uncertainty and CO_2 emissions of the least cost generation portfolios for a carbon price of \$80/tCO_2. At this carbon price, overall industry expected costs decline significantly as PV penetration levels increase. At a carbon price of \$80/tCO_2 the cost difference between the 25% PV and 0% PV cases is approximately \$0.6 billion per year. Consistent with previous results, the costs associated with universal EV charging infrastructure are observed to be lower than under the residential charging infrastructure case.

[5] Note that the percentage shares of the portfolios shown in this paper are the (residual) thermal technology portfolios after accounting for the share of PV. For example the actual technology share of portfolio G (40% coal, 30% CCGT, 30% OCGT) for 20% PV is actually 25% coal, 19% CCGT, 19% OCGT, 37% PV.

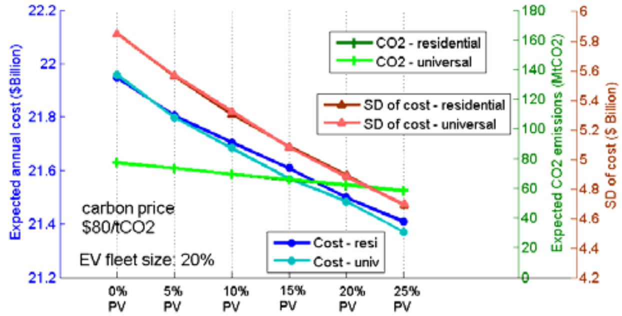

Figure. 11. Expected costs, SDs and CO_2 emissions of the lowest cost generation portfolios for different PV penetrations in the case of \$80/tCO_2 and 20% EV. Note that the CO_2 and SD of cost curves are largely overlapping for both infrastructure cases.

V. CONCLUSIONS

This paper has provided a high level analysis of the potential economic implications of large scale future PV and EV penetrations within the broader context of generation investment in the Australian National Electricity Market (NEM). A probabilistic generation portfolio modelling tool was employed to assess the expected costs, cost uncertainties and CO_2 emissions of possible future generation portfolios given different PV penetrations, carbon prices, and EV fleet sizes. In addition to the two EV charging infrastructure cases considered (residential and universal) the analysis considered four generation investment options: coal, CCGT, OCGT and PV. Uncertainty with respect to future coal, gas, and carbon prices in addition to electricity demand and plant capital costs were included in the model via the use of Monte Carlo methods.

Simulation results highlight the value of PV generation in satisfying a proportion of the additional demand for EV charging depending on future carbon price levels. Low carbon prices result in additional PV increasing overall system costs and EV penetration increasing cost uncertainty. However, for moderate carbon prices (i.e. starting from \$50/tCO_2), additional PV generation capacity begins to reduce overall costs due to variable costs declining faster (as a result of avoided fuel and carbon costs) than the increase in capital costs due to the lower PV capacity factor. Regardless of the carbon price, PV generation reduces reduce CO_2 emissions resulting from EV charging load.

While results show that additional EV charging load increases electricity demand and subsequently the overall industry costs, the impact of EV charging infrastructure availability on the temporal characteristic of EV charging load has an impact on overall industry costs, with the universal charging option having slightly lower costs than residential only charging. Such cost differences become more apparent with increasing PV and EV penetrations due to is due to its EV load profile being better correlated with the PV generation.

Results suggest that there are potential synergies between PV and EVs in reducing overall system costs, cost uncertainties, and CO_2 emissions particularly in the case of moderate to high future carbon price. However, in order for future electricity industries to achieve maximum value from high PV and EV penetrations there is a need for better charging management measures to be implemented. In addition to future carbon pricing and EV charging infrastructure provision, active management strategies will be required to manage the EV charging load patterns to take full advantage of PV generation. This aspect will be explored in future work.

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