Impact of Electric Vehicles and Solar PV on Future Generation Portfolio Investment

Peerapat Vithayasrichareon, *Member, IEEE*, Graham Mills, *Member, IEEE*, and Iain F. MacGill, *Member, IEEE*

***Abstract*—This study assesses the impact of electric vehicle (EV) uptake and large-scale photovoltaic (PV) investment on the economics of future electricity-generation portfolios. A Monte-Carlo-based portfolio modeling tool was used to assess the expected overall industry cost, associated cost uncertainty, and CO_2 emissions of future generation portfolios, where both EVs and PV generation have achieved major deployment. The Australian National Electricity Market (NEM) was used as a case study under uncertain future fuel and carbon prices, electricity demand, and plant capital costs. Two EV charging scenarios were considered: 1) unmanaged charging which commences immediately as the EVs arrive at suitable charging infrastructure and 2) managed charging where EV charging loads are managed so that they better align with PV output. Results show that there are potentially valuable synergies between PV generation and EV charging demand in minimizing future electricity industry costs, cost uncertainties, and emissions, particularly when EV charging loads can be managed. The value of PV generation and managed EV charging is greater for higher EV fleet size and moderate carbon prices.**

***Index Terms*—Electric vehicles (EVs), electricity generation portfolio, integration between EV and PV, solar PV.**

I. Introduction

PLUG-IN electric vehicles (EVs) and solar photovoltaics (PV) are highly promising new technologies and are widely expected to play a major role in the electricity industry in the coming decade. EVs are emerging as a potentially significant element of the future transport vehicle fleet with their uptake being driven by questions over future oil availability and pricing, as well as growing concerns over climate change. On the supply side, solar PV has been one of the fastest growing renewable technologies worldwide over the past decade due to its potential contribution toward addressing security of electricity supply and environmental challenges. With its falling costs, PV deployment seems certain to continue growing rapidly.

From the perspective of the electricity industry, EV uptake will result in increased demand along with an increase in absolute electricity industry CO_2 emissions [1], unless the electricity used to recharge EVs is sourced from renewable energy. At the same time, variable renewable 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 loads, and therefore, the large aggregated storage capacity associated with significant uptake. In this regard, there may be valuable synergies between PV and EVs in a future electricity system which has higher penetrations of both technologies.

While the interaction between PV and EVs might offer value, estimating and maximizing these benefits is a challenge for existing electricity industry planning and operational tools. Both technologies have rather different technical and economic characteristics from conventional generation technologies and end-user equipment. PV generation is cyclic over daily and seasonal time frames, somewhat uncertain, and hence, only partly dispatchable with its output not always coinciding well with demand patterns. EV charging is also cyclic, variable, and somewhat unpredictable, although EVs can offer significant energy-storage potential.

High penetrations of variable renewable generation such as PV can have long-term implications on capacity mix and conventional generating plant investments, as electricity industry planning has generally been based around dispatchable generation resources [2]. The charging of a large EV fleet, on the other hand, may significantly change the overall load profile, which can also have major implications on electricity industry operation and planning [3], [4]. Importantly, the potentially adverse economic and emission impacts of EV charging can be mitigated if there are effective measures for managing EV charging demand in ways that help defer or avoid investment in new generation capacity [5]. Given the potential for benefits yet also adverse impacts and interactions, there is a valuable role for tools that help us better understand the implications and opportunities of EV and PV integration. Such tools can guide decision-making on policy measures and electricity generation investments that will best facilitate high uptake of both technologies.

Generation investment and planning is increasingly moving beyond cost minimization toward more complex assessments incorporating risks and uncertainties and multiple criteria including greenhouse gas emissions [6]. This study explicitly incorporates these aspects when assessing future generation portfolio investment where large-scale PV is one of the main generation options, and EV represents a significant demand-side technology. Previous studies related to EV integration have primarily focused on the impact of EV uptake on power system operation and planning [7]–[9]. The implications of "managed" (or "smart") and "unmanaged" (or "dumb") charging of EVs

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The authors are with the Centre for Energy and Environmental Markets and School of Electrical Engineering and Telecommunications, UNSW Australia, Sydney 2052, Australia (e-mail: peerapat@.unsw.edu.au).

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using pricing and control mechanisms have also been analyzed [10], [11]. The synergies between EV charging and solar PV in reducing the net demand variability have also been assessed to some extent in previous literature, although they are in the context of small-scale systems such as urban, commercial, or industrial systems [12]–[14]. Cobenefits of EV and large-scale PV deployment have been assessed in [5], and it was suggested that mid-day charging can provide economic benefits to EV users by maximizing the PV output during the day. Despite these research efforts, the implications of high EV uptake and large-scale PV in the context of generation planning and investment have not been a focus of previous literature, particularly from the societal welfare perspective with respect to overall electricity industry costs and benefits.

The study described in this paper is intended to help address this current gap. In particular, it assesses the potential impacts and cobenefits of parallel EV and PV uptake within different possible future generation portfolios. These impacts are explored in the context of uncertain future fossil-fuel prices, carbon price, electricity demand, and plant capital costs. The impacts of different EV charging scenarios (managed and unmanaged), EV fleet sizes, PV penetrations, and carbon pricing are all investigated.

II. Modeling Methodology

The methodology employed for this study consists of two main components: Monte Carlo generation portfolio modeling and EV modeling. The EV modeling simulates temporal EV charging profiles based on actual travel patterns seen with conventional vehicles. In this study, two possible futures of EV charging infrastructure provision are considered: "residential" and "universal." Beyond unmanaged EV charging, measures to manage EV charging so that it aligns with PV generation output are also modeled. Hourly PV generation over the year and the simulated hourly EV charging profiles are inputs into a Monte-Carlo-based generation modeling tool described in detail in the next section.

A. Monte-Carlo-Based Generation Portfolio Modeling Tool

The modeling tool used in this paper 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 $\mathrm{CO_2}$ emissions for each possible generation portfolio comprising some mix of different generation options. These probability distributions can be represented as an expected annual cost and associated standard deviation (SD). While this paper refers to the SD 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 is 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) of expected (i.e., mean) costs and the associated cost uncertainty (i.e., SD) [15] for each of the different generation portfolios. EF techniques provide a basis for explicitly analyzing cost and risk tradeoffs among different generation 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 $\mathrm{CO_2}$ emissions.

Inputs into the modeling tool consist of economic and operating parameters of each generation options and probability of key uncertainties which are plant capital costs, fuel prices, carbon price, and electricity demand. Correlations between fuel and carbon prices are also accounted in the modeling since their prices have exhibited a considerable historical correlation in many markets such as the EU, UK, and US [16], [17]. For example, ambitious climate policies might involve high carbon prices that would increase the use, and hence, the price of gas in relation to coal [18]. The techniques for sampling these uncertain parameters are explained in Section III. A graphical description of the modeling tool is shown in Fig. 1. The details of this modeling including mathematical formulation are described in detail in [19].

For each Monte Carlo run, the total annual generation cost of each generation portfolio consists of total annual fixed costs and variable costs. The fixed cost is made up of annualized plant capital cost, fixed operation and maintenance (O&M), and annualized transmission costs associated with newly built solar PV plants for particular generation portfolios using (1)

$$\mathrm{FC}_n = (\mathrm{APC}_n + \mathrm{FOM}_n) \times I_n + \mathrm{ATC} \tag{1}$$

where APC_n is the annualized plant capital cost, FOM_n is the annual fixed O&M cost ($/MW), and I_n is the installed capacity (MW) of technology n in the portfolio, and ATC is the annualized transmission costs ($) (described in Section III).

The annual variable cost is calculated based on annual energy (MWh) generated by each technology in the portfolio for a given LDC. The variable cost comprises variable O&M, fuel costs, and carbon costs as shown in (2)–(4)

$$\mathrm{VC}_n = (\mathrm{VOM}_n + \mathrm{Fuel\,cost}_n + \mathrm{Carbon\,cost}_n) \times \sum_{t=1}^{T} P_{t,n} \tag{2}$$

$$\mathrm{Fuel\,cost}_n\,(\$/\mathrm{MWh}) = \mathrm{Fuel\,price}_n\,(\$/\mathrm{GJ}) \times \mathrm{HR}_n \tag{3}$$

$$\mathrm{Carbon\,cost}_n\,(\$/\mathrm{MWh}) = \mathrm{EF}_n \times \mathrm{Carbon\,price}\,(\$/\mathrm{tCO_2}) \tag{4}$$

where VOM_n is the variable O&M cost ($/MWh), HR_n is the average heat rate (GJ/MWh), and EF_n is the emission factor $(\mathrm{tCO_2/MWh})$ of generation technology n, and $P_{t,n}$ is the generation output of technology n in the portfolio in each hour t of the LDC as determined from the merit-order dispatch.

PV generation and EV charging loads are incorporated by varying the time series of electricity demand. As a result of PV's low-operating costs compared to fossil-fuel generation,

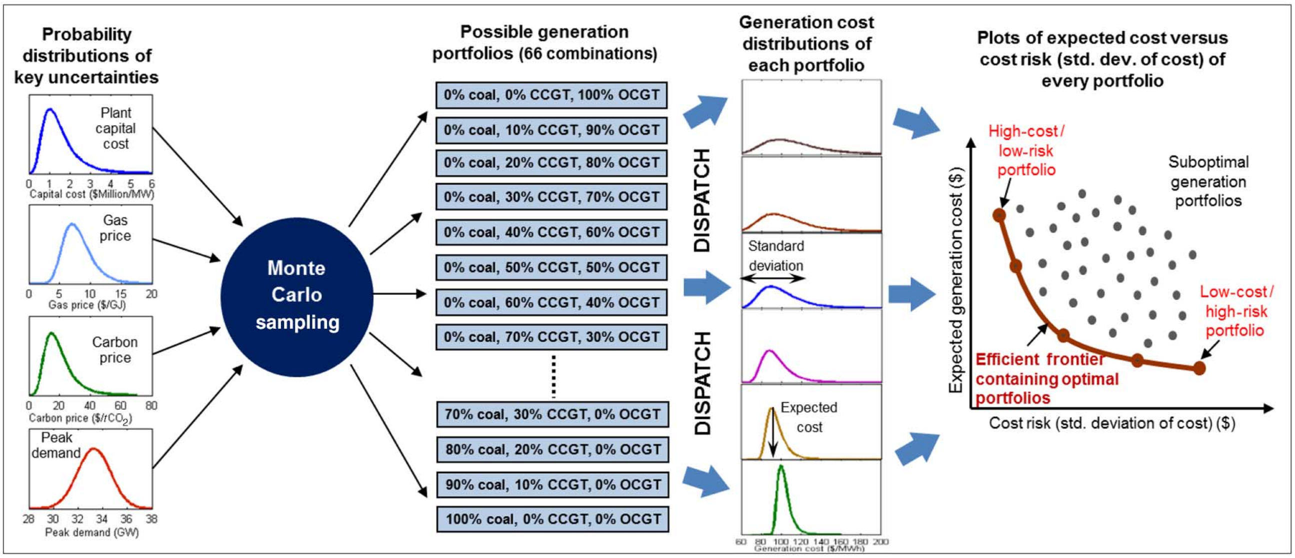


Fig. 1. Monte-Carlo-based generation portfolio modeling for each case combination of PV penetration and EV fleet size.

PV is allowed priority dispatch. Hence, simulated hourly PV generation is subtracted from hourly native demand over a representative year. In contrast, hourly EV charging load is added to native demand in each period. With this approach, the temporal match of PV generation and EV charging with electricity demand is 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). This curve is to be served by thermal generation technologies in the portfolio.

The modeling focuses on long-term generation planning and investment, and therefore, does not give detailed consideration to power system operational issues beyond economic dispatch.

B. Modeling EV Charging Profiles

1) Simulating EV Charging Patterns: In this study, EV demand profiles were obtained from simulation of charging in response to actual vehicle usage behavior obtained from the Household Transport Survey in the Australian State of New South Wales (NSW HTS).[1] The NSW HTS includes vehicle trip data between 2002 and 2012 with respect to 51 800 individual vehicles and 2 16 566 vehicle trips. This data was pooled and weighted to represent statistically valid vehicle travel in the Sydney Greater Metropolitan Area. Assuming each surveyed vehicle to be an EV, a time-based simulation method was applied 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) as a function of recharging infrastructure availability. A minimum 10-min dwell-time constraint is imposed such that a vehicle must be parked at a location with charging infrastructure for over 10 min in order to recharge. Recharging commences immediately upon arrival as long as this requirement is met. Full details of this simulation tool are provided in [20].

Two boundary infrastructure cases *(residential and universal)* are considered in order to capture the potential variation in EV charging demand due to different levels of infrastructure availability. Residential charging involves a vehicle charging when parked at any location denoted as being residential in the NSW HTS. Universal charging, however, allows a vehicle also to recharge at other parking locations, such as work, shopping, and education facilities.

The simulation model implements a medium-sized passenger plug-in hybrid EV with a series drivetrain and a petrol internal combustion engine for range extension (modeled using binary charge depletion/charge sustaining modes of operation) intended to broadly represent a GM Volt. The model was implemented using the Simulink and Stateflow packages integrated into MATLAB with state logic adapted from the framework for the operation of EVs in a power system described in [21]. Charge-depletion mode electricity consumption for the modeled PHEV was then established through the use of ADVISOR, the vehicle drivetrain simulation software released by the National Renewable Energy Laboratory (NREL) [22]. 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 [23].

Results obtained for each vehicle within the simulated passenger vehicle fleet were then statistically weighted, aggregated, and scaled to represent the passenger car fleet size making up the footprint of the Australian National Electricity Market (NEM) of 11 193 000 [24].

2) "Managed" EV Charging: This study has implemented an approach to control EV charging in such a way that it better aligns with PV output, referred to here as "*managed*" charging. This approach requires the scheduling of EV charging across the simulated EV fleet. Each vehicle is subject to a charging control signal which prevents recharging outside a specified 3-h window. Specifically, the first vehicle commences its 3-h

[1] The NSW HTS is a rolling survey of 5000 households a year which tracks the trips made by each vehicle in a day during the working week and weekend. It includes details of trip distance, trip departure and arrival times, trip purpose, and parking location at the point of arrival for each vehicle.

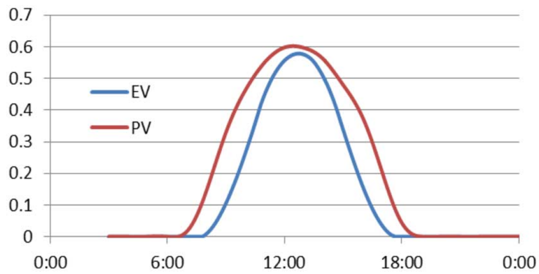


Fig. 2. Average normalized hourly PV outputs based on 1-MW fixed flat plate across different locations (PV), the proportion of the simulated EV fleet which commences charging at each point of the day.

charging window at 8 A.M. with groups of subsequent vehicles commencing at 1-min increments afterward. The percentage of fleet vehicles in a charging group is determined from the PV energy production in that time increment, as a percentage of the total energy produced over the course of the day. Fig. 2 compares the proportion of the EV fleet allowed to recharge across the day with the normalized hourly PV output showing the extent of the match between charging opportunity and PV output.[2]

In order to ensure that the charging management scheme does not increase liquid fuel usage (hence reducing electricity industry costs but requiring greater liquid fuel purchases), a transport energy requirement (TER) constraint is applied which reserves sufficient energy within the vehicle battery to meet upcoming transport requirements. The TER constraint represents the minimum EV battery SOC profile which satisfies transport needs (without any surplus), and for which charging commences at the latest possible time prior to departure. The TER constraint is specific to the travel patterns and recharging opportunities available to each individual vehicle and is established through a method presented in [25]. The EV charging characteristics presented here were obtained by applying the TER to the simulation of each individual vehicle so as to impose a minimum battery SOC across the day. If the vehicle battery SOC falls to this minimum level, charging is commenced immediately irrespective of the charging control signal.

Note that the ability to better align EV charging with solar PV outputs relies on EVs having access to charging infrastructure during hours in which the sun is shining. Such a requirement is contrary to the commonly held notion that EV recharging will occur primarily at residential locations since "*residential charging*" results in a limited ability to shape load throughout the day to match PV output without increasing vehicle fuel consumption. Therefore, this study will focus on the "*universal charging*" infrastructure when considering the management of EV charging to better align with PV output.

III. Test Case Descriptions

The case study of EV and PV in this paper is based on the Australian National Electricity Market (NEM) in 2030 under highly uncertain future fuel prices, carbon prices, electricity demand, and plant capital costs. Four new generation options were assumed: coal, combined cycle gas turbine (CCGT), open cycle gas turbine (OCGT), and PV generating plants.

Three EV charging scenarios are considered: "residential charging (RESI) unmanaged," "universal charging (UNIV) unmanaged," and "universal charging (UNIV) managed." The implications for future generation portfolios in terms of costs, cost uncertainty, and CO_2 emissions are then explored for these different scenarios. In order to capture the impacts of different PV deployment and EV uptake levels, this study also considers a range of PV penetration and EV fleet sizes for each of the EV charging scenarios. Five PV penetrations range from 0% to 20% and two different EV fleet sizes of 20% and 50% of total residential vehicles are examined.

A. Electricity Demand, PV Outputs, and EV Charging Profiles

Hourly electricity demand was obtained based on the actual demand in the NEM in 2010. Note that actual wind generation (5% of total generation) was also incorporated. Simulated hourly PV generation was also based on 2010 weather data.

Hourly PV outputs were simulated across different locations in major cities and regional areas using System Advisor Model (SAM) software released by NREL [26]. This enables the value of geographic diversity of PV to be captured. The hourly PV output was simulated based on 1-MW fixed flat-plated solar PV plant, with north-facing array, using hourly satellite solar data and ground station weather data over 2010. Additional transmission costs for new centralized PV plants in regional areas were also taken into consideration. These additional costs were determined based on their maximum PV capacities and distances to the nearest load centers or major transmission hubs using transmission cost estimates provided by the Australian Energy Market Operator (AEMO) [27]. The indicative transmission cost estimates for high-voltage ac lines is \$700/MW/km. Total transmission costs for each regional location were determined for each of the PV penetration levels considered in this study.

Fig. 3 illustrates hourly PV output and EV charging profiles for a typical week for different EV fleet sizes and PV penetrations under each of the three EV charging scenarios. For the unmanaged charging case, EV charging load is at its highest under both of the charging infrastructure provision cases during evening peak periods. Although the universal infrastructure (unmanaged) case sees some load shifted from the dominant evening peak, there is still significant potential to further redistribute the EV charging to better align with PV output. Under the managed charging scenario, therefore, EV charging can be made much better correlated with the PV output. The resulting residual (net) demand (after deducting PV output and adding EV load) for each PV penetration and EV scenario is rearranged into the RLDC shown in Fig. 4.

B. Generator Data

New entrant generator data and cost parameters for each technology were based upon the 2030 cost estimates obtained from the 2012 Australian Energy Technology Assessment

[2]Note that this approach is at the fleet level and does not account for the situation of a particular vehicle with respect to their ability to charge. As such, the results obtained are suboptimal and should be interpreted as a first-order approximation of possible outcomes.

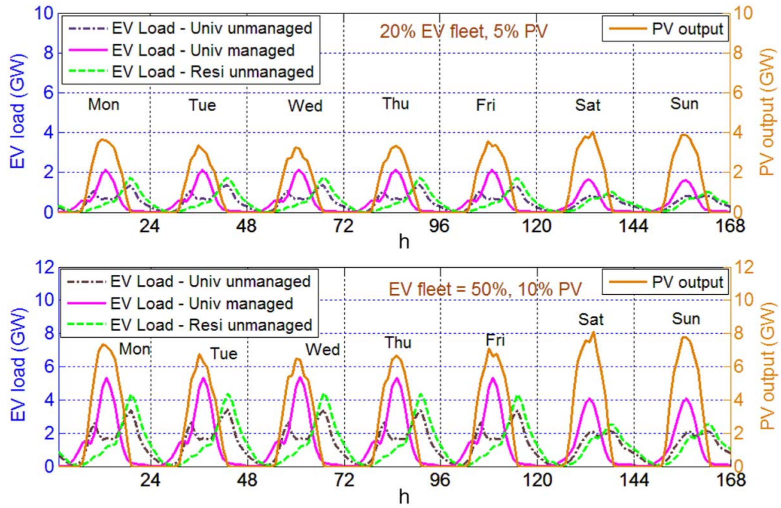


Fig. 3. Typical hourly PV outputs and EV charging load for managed and unmanaged charging (for 20% and 50% EV fleet size and 5% and 10% PV).

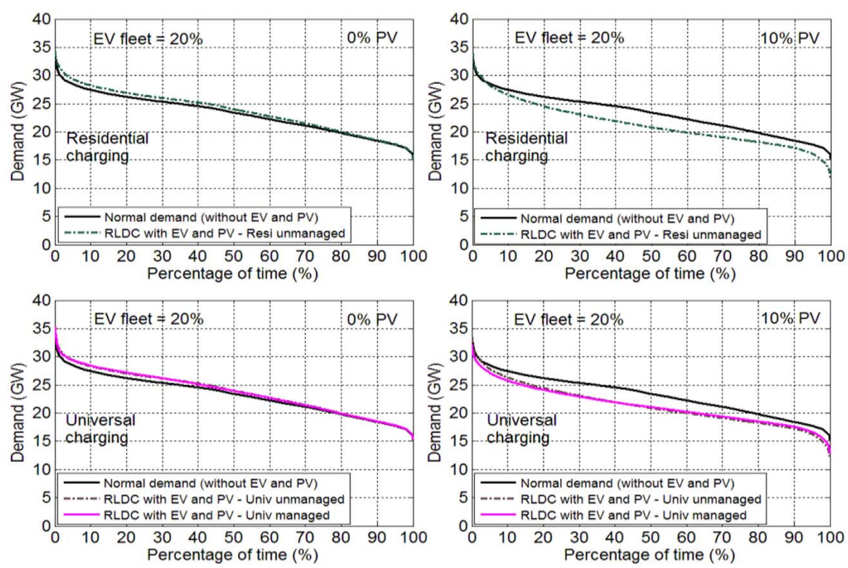


Fig. 4. Examples of RLDCs for different PV penetrations and EV charging scenarios.

TABLE I
GENERATOR DATA

Parameters	Coal	CCGT	OCGT	Solar PV
Plant life (years)	50	40	30	30
Capital cost ($million/MW)	2.95	1.1	0.8	1.6
Fixed O&M ($/MW/yr)	50 500	10 000	4 000	25 000
Variable O&M ($/MWh)	7	4	10	0
Thermal efficiency (%)	42	50	35	N/A
CO_2 emission (tCO_2/MWh)	0.77	0.37	0.52	0
Fuel price ($/GJ)	1.7	8	8	0
Capacity factor (%)	N/A	N/A	N/A	21

(AETA) [28], and are shown in Table I. All monetary values are in Australian dollars.

C. Modeling Key Uncertainties

Key parameters for which uncertainty is explicitly modeled in this study include future fuel prices, carbon prices, electricity demand, and plant capital costs. Lognormal distributions were applied to estimated fuel and carbon prices, and capital costs in 2030 to reflect the asymmetric downside risks associated with their future values. Demand uncertainty was modeled by assuming a normal distribution of residual peak demand for each EV scenario and PV penetration.

Both lognormal and normal distributions are characterized by their mean and SD. The central projections (mean) and SDs of the uncertain parameters were obtained based upon the estimates by AEMO and the Australian Government [28], [29]. Correlated samples of fuel and carbon prices were generated from their marginal distributions using multivariate MCS techniques, which reproduce random variables while preserving their marginal distribution properties and correlation structure.[3] Probability distributions of 10 000 simulated gas price, plant capital costs, and demand are illustrated in Fig. 5. Demand

[3]The correlation between gas and coal prices was estimated based upon historical gas and coal prices in OCED countries. The correlations between fuel and carbon prices were approximated from historical data in EU and U.K. markets as well as a number of previous studies [18], [30], [31].

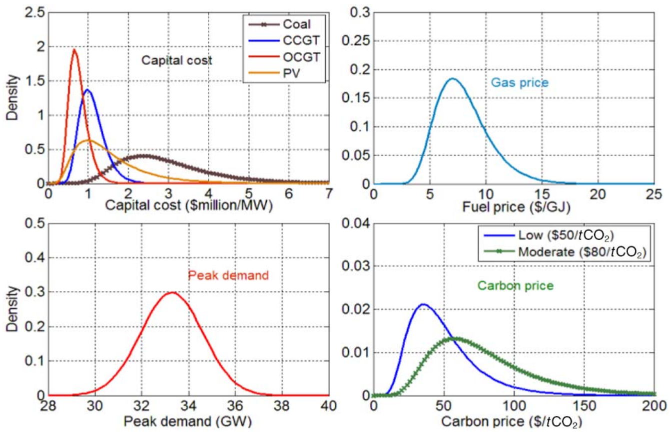


Fig. 5. Probability distributions of plant capital costs, gas price, demand, and different carbon prices over 10 000 Monte Carlo simulations.

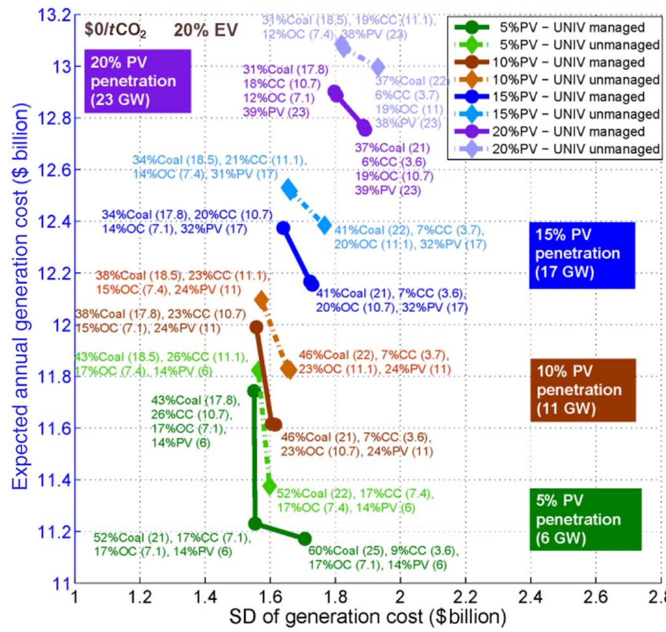


Fig. 6. Efficient frontiers (EF) containing optimal generation portfolios for different PV penetrations and 20% EV fleet size for the universal charging (UNIV) infrastructure scenarios. The capacity is presented (GW, in brackets) as well as the percentage share. The dotted lines represent the unmanaged charging while the solid lines represent the managed charging scenario.

uncertainty is modeled as the uncertainties in the RLDC for each EV charging scenario and PV penetration level.

The baseline results are simulated without a carbon price (hence no carbon price uncertainty). However, a sensitivity analysis with different expected carbon prices was also conducted. These include low ($\$50/\mathrm{tCO_2}$) and moderate carbon prices ($\$80/\mathrm{tCO_2}$), with their probability distributions shown in the lower right graph of Fig. 5. These carbon prices are in line with the low and medium projections of carbon prices in 2030 modeled by the Australian Treasury [29].

IV. Simulation Results

For each of the three EV charging scenarios considered (RESI unmanaged, UNIV unmanaged, and UNIV managed), the costs and CO_2 emissions of each possible generation portfolio mix for each EV fleet size and PV penetration were calculated for 10 000 simulated coal and gas prices, electricity demand, and plant capital costs (according to the distributions shown in Fig. 5). Two EV fleet sizes (corresponding to 20% and 50% of current NEM state passenger vehicle fleet penetration levels) and six PV penetration levels (0%, 5%, 10%, 15%, 20%, and 25%) were considered. For each PV penetration level and EV charging scenario, the proportions of coal, CCGT, and OCGT were then altered from 0% to 100% in 10% increments of total installed fossil-fuel capacity.

A. Impacts of PV Generation and EV Charging Measure

Fig. 6 shows the modelling outcomes for a selection of generation portfolios for the universal charging (UNIV) infrastructure (managed and unmanaged) scenario for a 20% EV fleet size. Only generation portfolios that lie on the cost versus cost uncertainty (SD of cost) "efficient frontier" (EF) for each PV penetration are included on the graph. Any portfolio that is not on the EF is considered suboptimal, and therefore excluded. Fig. 6 shows that there are tradeoffs between portfolios on the EF (i.e., cost uncertainty can be reduced but only by increasing expected costs).

With the EV fleet size constant at 20% and in the absence of a carbon price, it is not surprising that higher PV penetration

TABLE II
Installed Capacity of the Least Cost Portfolio With 20% EV Fleet Size for Different PV Penetrations

EV charging scenario	Installed capacity (GW)								
	5% PV (6 GW)			10% PV (11 GW)			20% PV (23 GW)		
	Coal	CC	OC	Coal	CC	OC	Coal	CC	OC
RESI unmanaged	22.4	7.5	7.5	22.4	3.7	11.2	22.4	3.7	11.2
UNIV unmanaged	22.1	7.4	7.4	22.2	3.7	11.1	22.2	3.7	11.1
UNIV managed	25	3.6	7.1	21.3	3.6	10.7	21.3	3.6	10.7

increases overall costs. Cost uncertainty, however, remains largely the same between EV charging scenarios. The increase in cost arising from the additional capacity is required as a result of PV's low capacity factor (i.e., higher capacity is required to maintain system adequacy). Of most relevance to this study, Fig. 6 also shows that overall portfolio costs on the EF under the managed charging case are below to that of unmanaged charging for all PV penetration levels. The saving is generally of the order of \$200 m/year or around 2% of overall portfolio costs. Also, cost uncertainty is not greatly impacted by managed EV charging.

For each PV penetration level, required installed capacity (GW) is lower with managed charging compared to the unmanaged case, although the percentage shares of generation technologies in the optimal portfolios remain similar under both scenarios. For example, with 10% PV penetration, the technology share in the least cost portfolio for both EV charging scenarios is the same (46% coal, 7% CCGT, 23% OCGT, and 24% PV) except that the unmanaged charging scenario requires 1 GW more of total installed capacity. Table II compares the capacity (GW) of the least cost portfolios for each EV charging scenario under different PV penetrations. The additional capacity required under the unmanaged charging scenario is as

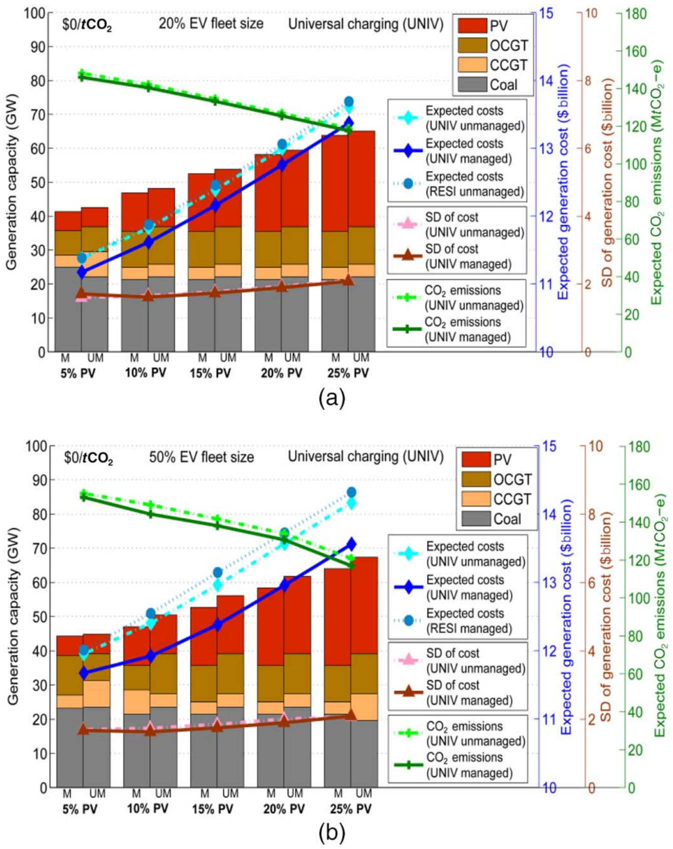


Fig. 7. Installed capacity, expected costs, SD of costs (cost uncertainty), and CO_2 emissions of the least cost portfolio for each PV penetration in the case with no carbon price. (a) 20% EV fleet. (b) 50% EV fleet size.

a result of higher system peak demand due to the charging of EVs coinciding with evening peak loads, which contributes to higher expected industry costs.

The installed capacity, expected cost, cost uncertainty, and CO_2 emissions of the least cost portfolio are shown in Fig. 7 for each PV penetration level for a 20% EV [Fig. 7(a)] and 50% EV fleet size [Fig. 7(b)]. The figure shows that the RESI scenario (unmanaged) has the highest expected industry cost.[4]

From Fig. 7(a), it can be seen that with a 20% EV fleet size, the charging management results in expected annual industry costs being reduced by 2% relative to the unmanaged charging scenario for PV penetrations of 5% or more. This saving does not increase once PV penetrations rise beyond 10%. This reduction is in addition to slightly lower cost uncertainty and lower CO_2 emissions. These cost benefits appear to increase with higher PV penetrations, suggesting that the alignment of EV charging with PV output increases the economic benefits associated with additional PV capacity. Although additional PV capacity increases overall costs, it should be noted that no carbon price is being imposed which fails to value the significant CO_2 reductions of 7 $\mathrm{MtCO_2}$ for every 5% increase in PV.

[4]Without a charging measure, our previous work [32] showed that the expected cost, cost uncertainty, and CO_2 emissions in the UNIV are only slightly lower than the RESI infrastructure for any EV fleet sizes and PV penetration levels. Therefore, the results will focus on the UNIV scenarios.

B. Implications of Different EV Fleet Sizes

The benefits of managing EV charging to align with PV output increase with EV fleet size, as evident from Fig. 7(b) for a 50% EV fleet size. Although a larger EV fleet size results in an increase in overall industry cost and emissions, the differences between the managed and unmanaged charging become more apparent compared to those with a 20% EV fleet size. With a 50% EV fleet size, charging management can potentially provide cost savings of up to \$600 million annually or around 5% (compared to \$200 million in the 20% EV fleet size case shown previously). This cost reduction increases as PV penetrations rise up to 15%–20%. These results highlight that as EV uptake increases, the management of EV charging so as to align with PV output can play an important role in reducing overall industry costs, cost uncertainty, and CO_2 emissions.

Fig. 7 also shows that as the EV fleet size increases from 20% to 50%, the additional generation capacity required to match the increase in EV charging demand is much smaller under managed charging relative to the unmanaged charging scenario. For example, with a 20% PV penetration, an increase in the EV fleet size from 20% to 50% only requires an additional 0.2 GW of capacity with managed EV charging, compared to 1.4 GW when EV charging is unmanaged. Through charging management, increased EV charging demand (from a larger EV fleet size) occurs during the day when there is sufficient reserve capacity which results in generating plants operating at higher capacity factors. By contrast, increased EV demand without management increases evening peaks resulting in greater additional generation capacity being required.

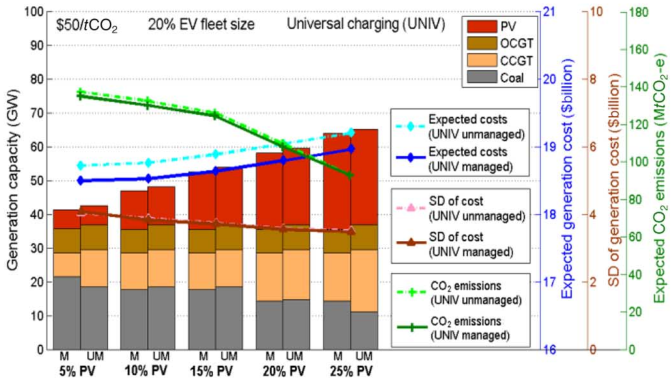
Considering the capacity mix, Fig. 7 shows a considerable proportion of coal-fired capacity in the least cost portfolio while the share of CCGT is very moderate under both EV charging scenarios. In the absence of a carbon price, installing new coal plants appears less costly and less exposed to uncertainties relative to CCGT, despite producing significantly higher emissions. The proportion of peaking OCGT in the least cost portfolio is also quite prominent, indicating the important role of OCGT in providing low-cost peaking generation, particularly at higher PV penetrations. As PV penetration increases, total generation capacity also increases considerably due to the amount of additional PV capacity required given its relatively low capacity factor.

C. Sensitivity Analysis With Different Expected Carbon Prices

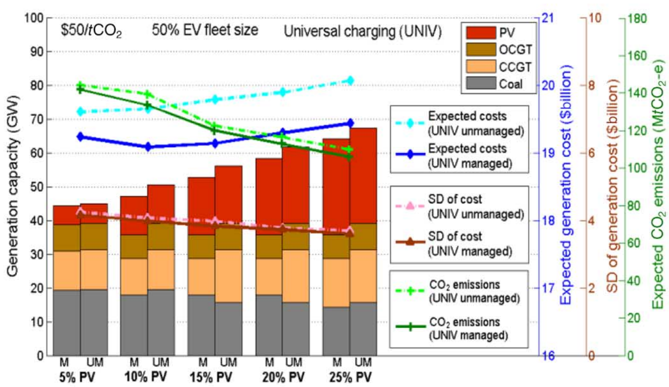
With growing international efforts to address present electricity market failures associated with climate change, consideration of carbon price effects is necessary in order to assess the value of different possible future generation portfolios. Therefore, a sensitivity analysis was conducted, which considers two probability distributions of expected carbon prices centered at \$50 and $\$80/\mathrm{tCO_2}$ (shown in Fig. 5).[5]

Fig. 8 provides the least cost portfolio for each PV penetration for $\$50/\mathrm{tCO_2}$ carbon price sensitivity and 20% EV fleet size. Consistent with previous results, expected costs under

[5]A very low carbon price sensitivity of $\$20/t\mathrm{CO_2}$ was also simulated and the results were similar to the base case, and therefore, are not presented here.



(a)



(b)

Fig. 8. Installed capacity, expected costs, SD of costs (cost uncertainty), and CO_2 emissions of the least cost portfolio for each PV penetration level for a $\$50/tCO_2$ of carbon price. (a) 20% EV. (b) 50% EV fleet size.

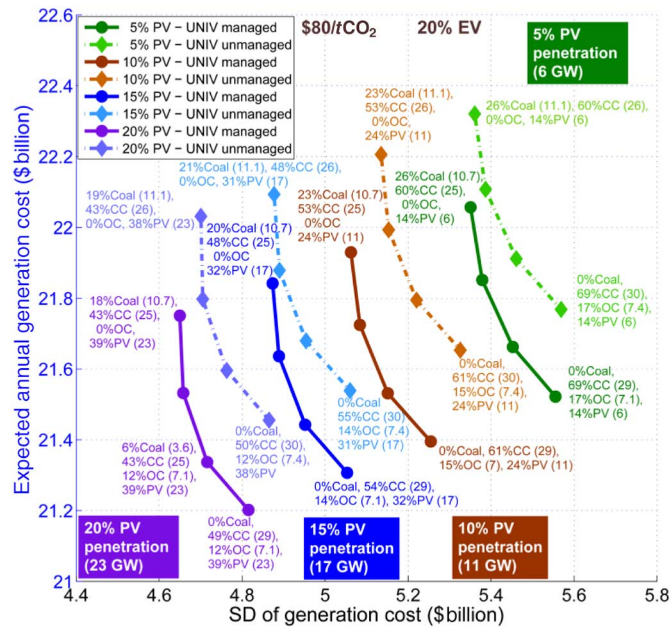


Fig. 9. Efficient frontiers (EF) containing optimal portfolios for an expected carbon price of $\$80/tCO_2$ and 20% EV fleet. The dotted lines represent the unmanaged charging and the solid lines represent the managed charging case.

managed charging are lower than the unmanaged charging scenario. However, there are economic benefits observed from having additional PV at this carbon price (recall that without a carbon price, additional PV would result in an increase in overall cost for any EV charging scenarios). For the 20% EV fleet size shown in Fig. 8(a), a reduction in cost is observed as PV increases from 0% to 5%. This cost reduction is more pronounced in the managed charging scenario ($100 million or 1% compared with $40 million or 0.2% in the unmanaged charging case). This cost reduction occurs as a result of variable generation costs offset by PV decreasing more than the increase in fixed costs associated with additional PV. For a carbon price of $\$50/tCO_2$ and a 20% EV fleet, these results suggest that an economic optimum level of PV penetration is at around 5%, although penetrations up to 15% still have lower expected costs than the case without PV.

With a larger EV fleet size of 50%, shown in Fig. 8(b), industry costs are further minimized at a 10% PV penetration level for all of the EV charging scenarios. This suggests that the economic benefits of PV generation under managed EV charging increase with larger EV fleet sizes in the same manner as for the case without a carbon price. For a carbon price of $\$50/tCO_2$, increasing PV penetration is also seen to considerably reduce the generation cost uncertainty (SD of costs) for any of the EV charging scenarios. These results suggest that cost uncertainty is reduced by around 5% with every 5% increase in PV penetration.

For the $\$80/tCO_2$ carbon price sensitivity (with 20% EV fleet size), there are four optimal generation portfolios on the EF for each PV penetration level as shown in Fig. 9. The downward movement in the EFs for each charging scenario indicates reductions in both the expected cost and cost uncertainty as PV penetration increases (in contrast to the case without a carbon price shown in Fig. 6). For this carbon price sensitivity, the cost uncertainty of generation portfolio is relatively large as a result of high carbon price uncertainty. The spread of generation cost (i.e., SD) of the corresponding optimal generation portfolios is illustrated by Box-Whisker plots in Fig. 10.

Details of the least cost generation portfolio for each PV penetration are shown in Fig. 11. At this carbon price, the cost of coal generation, due to its high emissions, is significantly higher than both CCGT and OCGT. Hence, no coal is observed in the least cost generation portfolio for any PV penetration level. Fig. 11 also suggests that increasing PV generation would further reduce the overall cost, which is minimized at 25% PV penetration (highest penetration considered) compared to 5% PV in the $\$50/tCO_2$ carbon price sensitivity. As with the lower carbon price sensitivities, EV charging management is seen to reduce both the cost and emission impacts from the EV charging. The benefits of PV and the EV charging management also increase with higher EV fleet sizes.

Results from the sensitivity analysis suggest that carbon pricing provides economic benefits for PV, and subsequently, enhances the value of the EV charging management. With a moderate carbon price, additional PV can lead to reductions in overall costs in addition to cost uncertainty and emissions.

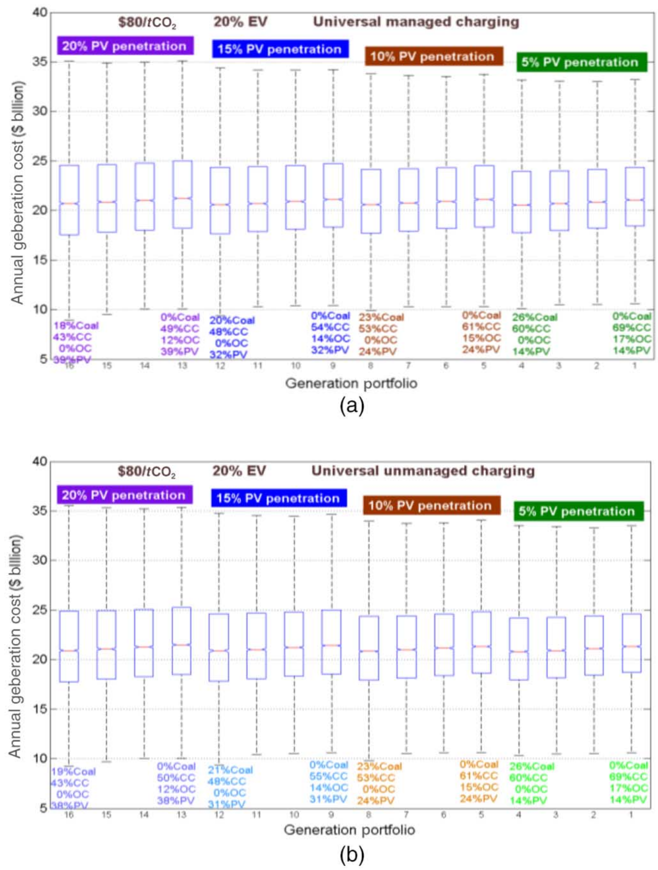


Fig. 10. Whisker plots showing the spread of generation costs of optimal portfolios for an expected carbon price of $\$80/\mathrm{tCO_2}$ and 20% EV fleet size. (a) Managed charging. (b) Unmanaged charging.

V. Conclusion

This study has examined the potential impacts of EVs and PV deployment on the future overall industry costs, associated cost uncertainties, and CO_2 emissions of different generation portfolios. In particular, potential synergies between PV generation and managed EV charging have been assessed.

Results show that EV charging management to better align EV charging demand with PV output is valuable as a means to maximize benefits and minimize costs associated with high EV and PV penetrations in future electricity industries. Although EV charging is found to increase overall costs and emissions for the electricity industry, such increases can be reduced through PV generation, particularly when EV charging is managed to align with PV output. With such EV charging management, the system can accommodate higher EV uptake without significant additional conventional generation capacity, as EV charging demand can be satisfied by day-time PV output. In addition, the capacity factors of conventional generators that were operating at part load can be improved as a result of day-time EV charging. By contrast, unmanaged EV charging demand is highest during evening peak-demand periods, resulting in higher system peak demand. This leads to higher industry costs and emissions due to the considerable amount of additional capacity required and increased output from conventional generating plants. The value of PV in the presence of managed day-time EV charging becomes more apparent as EV fleet size increases.

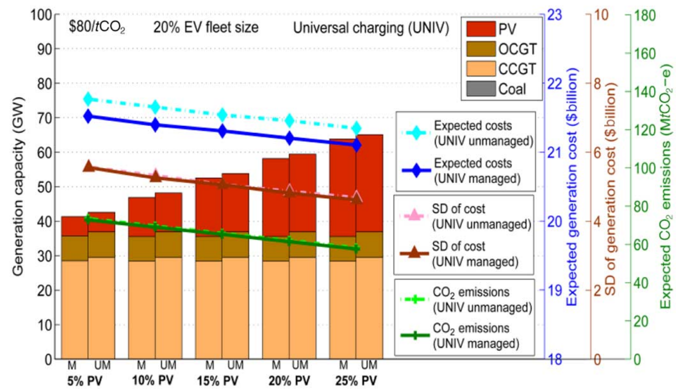


Fig. 11. Installed capacity, expected costs, SD of costs (cost uncertainty), and CO_2 emissions of the least cost portfolio for each PV penetration level for a $\$80/\mathrm{tCO_2}$ of carbon price.

These results also highlight the important role of carbon pricing in improving the economic merit of PV, and subsequently, the value of EV uptake in the presence of managed daytime charging. Without a carbon price, adding more PV is likely to increase overall industry costs due to its high capital cost, despite significantly reducing CO_2 emissions and cost uncertainty. With moderate carbon prices starting from around $\$50/\mathrm{tCO_2}$, however, increasing PV penetration results in cost reductions, particularly for larger EV fleet sizes. As the carbon price increases, the share of coal in the optimal portfolios is also reduced as a result of its high carbon costs.

While the EV modeling indicates that sufficient load flexibility exists to significantly align EV charging with PV output, examining the issues associated with such an arrangement (including direct control and tariff measures) represents an area of future work. Note that while the use of LDC techniques has many advantages in generation planning, the chronology of demand, solar generation, and EV charging load is only partially captured. As such, the simulation tool used in this study is best suited to assess long-run societal investment costs and risks under high uncertainty, rather than problems requiring detailed operational modeling. Addressing these limitations represents another possible area for future work.

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Peerapat Vithayasrichareon (S'09–M'11) received the B.Eng. (Elec.) degree with Honours from the University of Melbourne, Australia, the M.E. degree in energy economics and planning from the Asian Institute of Technology, Thailand, and the Ph.D. degree in electrical engineering from the University of New South Wales, Sydney, Australia.

He is a Research Fellow with the School of Electrical Engineering and Telecommunications and Centre for Energy and Environmental Markets at the University of New South Wales, Sydney, Australia. His research interests include generation planning and investment under uncertainty and multiple objectives, risk analysis, and renewable energy integration.

Graham Mills (S'11–M'14) received the B.Eng. (first class, Hons.) degree from the Australian National University, Canberra, Australia, in 2006. He is currently pursuing the Ph.D. degree at the School of Electrical Engineering and Telecommunications, University of New South Wales, Sydney, Australia.

His research interests include electric vehicles, photovoltaics, energy economics, and environmental/regulatory markets.

Iain F. MacGill (M'91) received the B.Eng. (Elec.) degree with Honours and the M.Eng.Sci. (Biomed.) degree from the University of Melbourne, Australia, in 1987 and 1990, respectively, and the Ph.D. degree in electrical engineering from the University of New South Wales, Australia, in 1999. He is an Associate Professor with the School of Electrical Engineering and Telecommunications, University of New South Wales, Sydney, Australia, and Joint Director for the university's interdisciplinary Centre for Energy and Environmental Markets. His teaching and research interests include electricity industry restructuring and sustainable energy technologies, with a particular focus on distributed resources and energy policy.