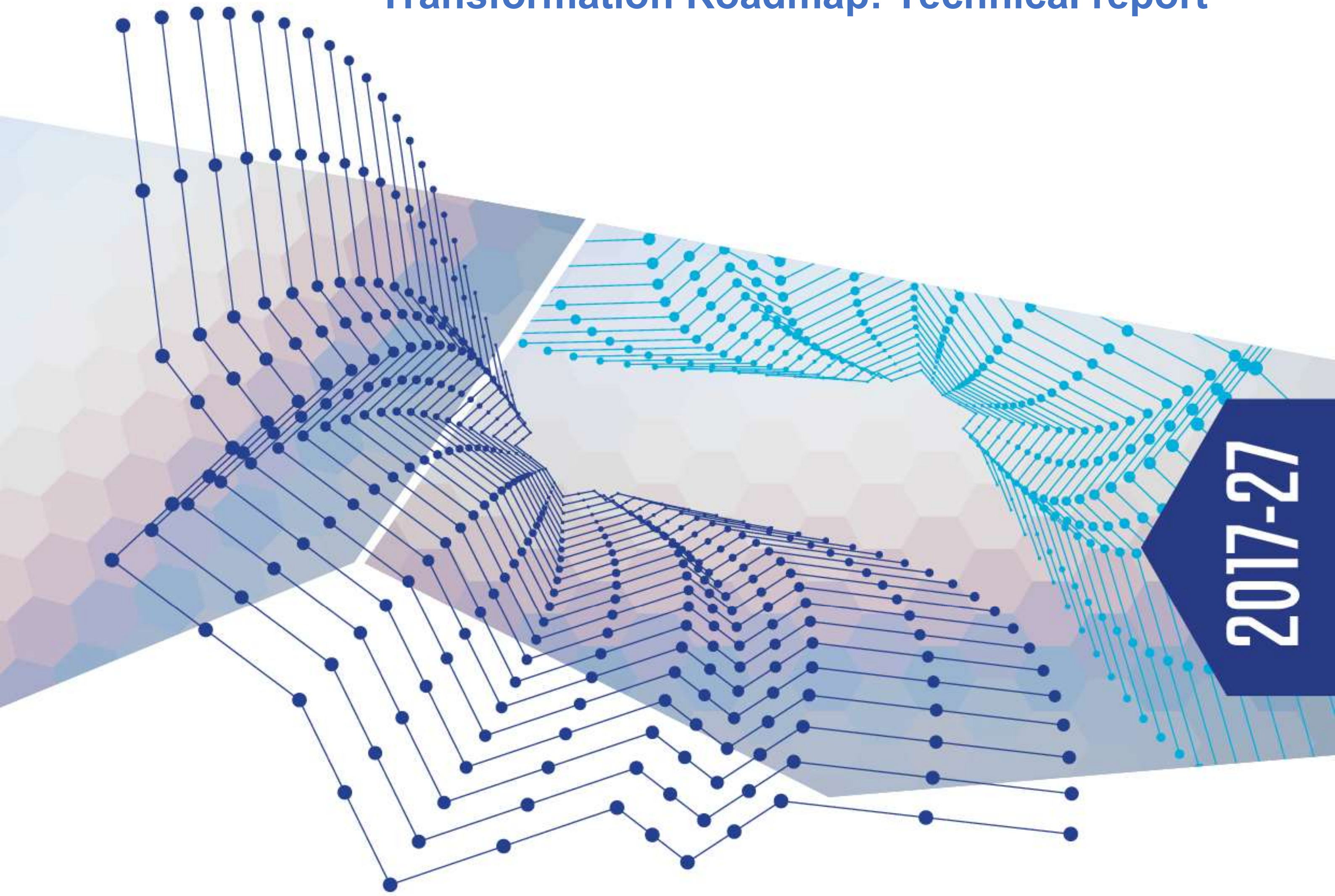
ELECTRICITY NETWORK TRANSFORMATION ROADMAP

Economic benefits of the Electricity Network Transformation Roadmap: Technical report



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Executive summary

The Electricity Network Transformation Roadmap has been developed to actively engage with a significant period of change in the global electricity sector in the coming decades. It provides an evidence based action plan for realising a balanced set of outcomes for customers: reliability, affordability, reduced greenhouse gas emissions, fairness and customer choice. Networks have a changing, but important, role in helping to enable balanced customer objectives through a connected energy future.

The *Roadmap* can only be delivered through collaboration and action from all stakeholders. It is therefore important to evaluate whether *the Roadmap* will generate sufficient value to justify the investment and focus required to deliver it. To this end, CSIRO has calculated the impact of *Roadmap* and *Counterfactual* scenarios to determine the value of the entire *Roadmap* (where quantification is possible). The *Counterfactual* scenario describes what happens if the status quo or extension of current trends prevails and the *Roadmap* is not implemented.

The *Roadmap* scenario includes combinations of elements from across the many ENTR investigations that support each other to deliver lower costs, decarbonisation, improved reliability, and fairer prices and rewards for energy services. These elements have been simplified into three broad key categories for the evaluation of the *Roadmap* scenario as follows: price and incentive reform to support optimised networks and markets, 20% adoption of electric vehicles by 2035 with managed charging, and electricity sector decarbonisation doing more than its proportional share of current national abatement targets, with strong power system security performance assisted by distributed energy resources orchestration. Decarbonisation achieves 40% below 2005 levels by 2030, with the trajectory accelerating to reach zero net emissions (100% abatement) in 2050.

Conversely, the *Counterfactual* scenario assumes that today's approach to pricing and incentive environment (relying on customer opt in to newer tariffs) prevails resulting in slow and incomplete adoption of incentives for demand management, no adoption of electric vehicles. It also assumes ongoing carbon policy uncertainty and lack of confidence in, and coordination of, resources for delivering lower emissions and high penetration of variable renewable energy (VRE) with high power system security performance. This leads to the electricity sector delivering abatement of only 35% by 2030 and 65% by 2050.

Both the *Counterfactual* and *Roadmap* scenarios show an increase in the cost of electricity in real terms from now to 2050, owing primarily to the increased wholesale cost of electricity generation, as renewable displaces fossil fuel generation as one of several possible strategies for reducing national greenhouse emissions. However, although the *Roadmap* scenario achieves much higher emissions abatement in 2050 than the *Counterfactual*, it is significantly lower cost overall, primarily owing to more efficient utilisation of distributed energy resources thereby reducing duplication and expenditure on network capacity. In the nearer term- in ten years, the *Roadmap* scenario provides only slightly more abatement of emissions and slightly lower costs than the *Counterfactual*. The improvement in cost and emissions performance in the *Roadmap* scenario is enabled by both more extensive tariff reform that provides incentives to customers to manage their impact on the grid, and an increase in total electricity consumption from higher electric vehicle use with managed charging.

Both the *Counterfactual* and *Roadmap* scenarios show a strong growth in rooftop solar PV, as battery storage prices decline, enhancing the ability of distributed generation resources to slow requirements for growth in network peak capacity. Where the *Counterfactual* scenario shows coal generation slowly being replaced by gas and small quantities of large scale solar PV, the *Roadmap* scenario shows fossil fuel generation vanishing by 2050, replaced by renewable energy generation, in the scenario explored here primarily wind generation and moderate quantities of large scale solar PV. Although the *Roadmap* scenario shows significantly less reliance on fossil fuels in the longer term, increases in electricity demand owing to electric vehicles results in a slower decline in fossil fuel use in the medium term to the 2030s. The *Roadmap* scenario relies significantly on battery storage to balance any mismatch between demand and renewable resource supply availability, due to the inherent intermittent variability of renewables, including large quantities of centralised renewables. This becomes increasingly important as emissions abatement levels approach 100%, and dispatchable fossil fuel generation becomes less available to compensate for extended periods of scarce renewable supply. The *Counterfactual* scenario also utilises battery storage, associated particularly with rooftop solar PV, which enables less pressure to be placed on grid network capacity.

In both scenarios wholesale electricity prices increase significantly in the 2030s, after rising slowly from their current levels of ~$40/MWh to ~$50/MWh in both scenarios. In the *Counterfactual* scenario wholesale prices rise steadily to ~$110/MWh in 2050, whereas in the *Roadmap* scenario, wholesale prices rise more fairly rapidly to the $110/MWh mark as early as the mid-2030s, remaining around that level to 2050. Because the *Roadmap* scenario has slightly higher wholesale prices for the later years in the projection period, the lower cumulative electricity system costs are achieved by improved utilisation of the electricity grid through more intelligent utilisation of distributed energy resources (enabled by appropriate incentives) resulting in savings in network costs per unit delivered energy.

Glossary

ABS	Australian Bureau of Statistics
ACT	Australian Capital Territory
AEMC	Australian Energy Market Commission
AEMO	Australian Energy Market Operator
AER	Australian Energy Regulator
APGT	Australian Power Generation Technology report
AREMI	Australian Renewable Energy Mapping Infrastructure
BREE	Bureau of Resources and Energy Economics
CBD	Central Business District
CCA	Climate Change Authority
CER	Clean Energy Regulator
CSIRO	Commonwealth Scientific and Industrial Research Organisation
CY2015	Calendar 2015
DNSP	Distribution Network Service Provider
EIA	Energy Information Administration
ENTR	Electricity Network Transformation Roadmap
EPRI	Electric Power Research Institute
EV	Electric Vehicle
FY1213	Financial Year 2012-2013
FY1314	Financial Year 2013-2014
FY1415	Financial Year 2014-2015
GIS	Geographic Information System
GALLM	Global and Local Learning Model
IEA	International Energy Agency
IMO	Independent Market Operator
LGA	Local Government Area
NEFR	National Energy Forecast Report
NEM	National Energy Market
NEXIS	National Exposure Information System
NSW	New South Wales

PCA	Principal Component Analysis
PV	Photovoltaic
Qld	Queensland
Roadmap, the	Electricity Network Transformation Roadmap
RAB	Regulated Asset Base
RIN	Regulatory Information Notices, provided to AER
SA	South Australia
SA2	Statistical Area Level 2
SAPs	Stand Alone Power systems
SGSC	Smart Grid Smart Cities
SOM	Self-Organising Map
STCs	Small scale Technology renewable energy Certificates
Tas.	Tasmania
TNSP	Transmission Network Service Provider
Vic.	Victoria
VRE	Variable Renewable Energy
WA	Western Australia

Acknowledgements

The authors acknowledge the work of Omid Motlagh, CSIRO, in developing Australian residential and commercial electricity customer profile clusters and for providing access to that existing data set and methodology.

The authors would like to thank the reviewers who provided input on previous drafts of this document. Any remaining errors or omissions remain the responsibility of the authors.

Introduction

This is the technical report underlying analysis presented in the *Electricity Network Transformation Roadmap* (ENTR). In addition, it provides details of data sourcing and preparation for not only evaluation of the roadmap as a whole, but also various pricing scenarios (see Energeia (2016)), and electric vehicle scenarios (Graham and Brinsmead 2016). The *Roadmap* scenario presented here consolidates the results of separate, more detailed analysis of the impact of pricing and incentive reform and electric vehicle adoption.

There is particular emphasis on assumptions that differ or are extended from the Future Grid Forum refresh report: Graham et al. (2015), which updated assumptions that were used in Future Grid Forum Participants (2013). While some of the assumptions and results of the analysis appear in Graham et al. (2015), Energeia (2016), and Graham and Brinsmead (2016), this technical report provides additional details on the preparation of data underlying the modelling not appearing elsewhere.

A significant difference in the modelling method between earlier work, Future Grid Forum Participants (2013) and the Future Grid Forum refresh (Graham et al. 2015) compared to subsequent ENTR analysis reported here, is the fineness of spatial resolution. Both the Future Grid Forum Participants (2013) and Graham et al. (2015) undertook maximum demand modelling at the state spatial scale. For the ENTR analysis, maximum demand projections in particular were derived from detailed modelling of each of approximately 2000 zone substations across 15 DNSPs across Australia. This included all states plus ACT in the National Electricity Market (Qld, NSW, ACT, Vic, Tas, SA), the South-West Interconnected System in WA, and the North-West of WA including the North-West Interconnected System, but excluding Power and Water, the DNSP in the Northern Territory, and excluding other off-grid systems. Note, the analysis was conducted before the merging of networks in Queensland.

The organisation of this technical report is primarily by domain area. Techno-physical and quantitative socio-economic assumptions, data sources and descriptions of data processing are organised by scale, from larger aggregate scale (that is, by state and distribution network) to smaller aggregate scale (that is, zone substation and customer).

Maximum demand projections played a significant role in the calculations, as these were assumed to determine network infrastructure capacity requirements and hence were calculated for several scenarios – initially as described in Energeia (2016), for pricing and incentive scenarios. This initial modelling of half-hourly demand was based on projected customer numbers, their choices of grid disconnection, tariff, solar and battery installation, and electric vehicle uptake.

Load at each zone substation was assumed to be composed of aggregates of residential, commercial and industrial customers based on up to forty-five representative residential customer annual half-hourly load profiles per DNSP and up to twenty representative commercial customer annual half-hourly load profiles across Australia. Various proportions of the residential and commercial customer populations across each DNSP were projected to take up alternative options: to leave the grid, to install energy technologies such as solar and/or battery storage, to change their electricity tariff, and the net impacts on the resulting load profile determined on a zone substation by zone substation basis.

These results were further modified for electric vehicle scenario comparisons (Graham and Brinsmead 2016). Maximum demand projections were also calculated for producing the *Roadmap* scenario. Annual projections of national electricity generation mix by state were also derived based on projected generation and storage technology costs.

Joint modelling framework

At the beginning of 2016, CSIRO and Energeia designed a joint modelling framework that would allow for a whole of electricity system analysis of the impacts of specific *Electricity Network Transformation Roadmap* (*the Roadmap*) milestones as well as describing the *Roadmap* as an integrated set of milestones and actions. A whole of system approach is required, firstly in order to be able to account for the inter-dependencies, often including feedback loops, along the electricity supply and end use chain. Secondly, the whole of system approach is necessary to combine impacts in different parts of the system to calculate total impacts on customers. This reflects the overriding principle that the *Roadmap* should deliver a balanced set of outcomes for customers including affordability, decarbonised electricity, reliability and security, fairness and more choice.

The design for the joint modelling framework is shown in Figure 1. It represents key concepts for how the modelling should be conducted. However, as discussed further below, Energeia and CSIRO each independently implemented this approach, in slightly different ways. As the modelling framework includes feedback, analysis can start from any point. For the purposes of explaining the approach, however, the modelling approach based on this framework can begin with a set of existing tariff offers from retailers which take into account the tariff structures of distributers and prices in the transmission and generation sector. Next, a customer adoption model is applied to project, under those tariff offerings, what combinations of tariff and technology adoption choices are made, inclusive of going off-grid in either standalone power systems (SAPs) or micro-grids. These technology adoption choices lead to modified customer load profiles which determine off-grid demand, as well as on-grid zone substation loads and aggregated network and state scale loads. The load projections, together with any policy assumptions, determine distribution, generation and transmission sector expenditure. The outcomes for expenditure determine the next round of tariff offerings completing the iterative framework.

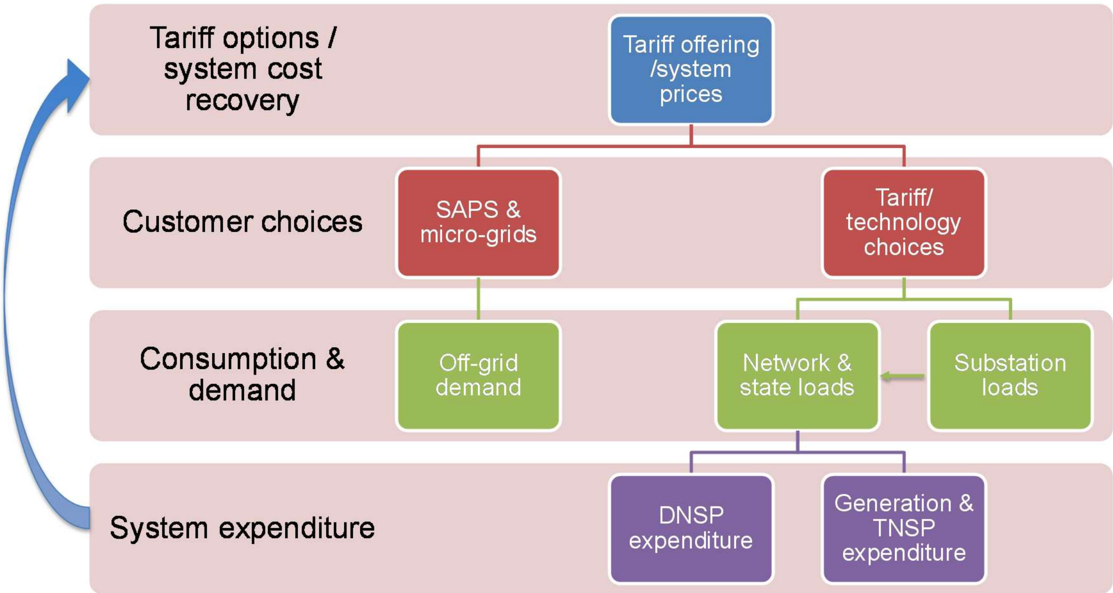


Figure 1: Joint modelling framework

Energeia's primary responsibility was to apply the joint modelling framework to milestones relating to changes in prices and incentives, including micro-grids (Energeia 2016). CSIRO examined efficient capacity utilisation through electrification of transport and buildings in Graham and Brinsmead (2016) and was responsible for aggregating the whole of the *Roadmap* impacts which are reported in the modelling results section of this report.

There are differences in how Energeia and CSIRO implemented the modelling framework. As outlined in Energeia (2017), Energeia implemented the modelling framework as a loop such that network prices, customer tariffs and distributed energy technology choices are updated each annual time step. The wholesale generation sector projections, due to its complexity, is modelled over longer time scales, and updated iteratively between model runs rather than within the annual loop. Additional details of the input data used in Energeia (2016) and Energeia (2017) are provided in this report. Table 1 shows where the details of data inputs that are identified in Energeia (2016 and 2017) appear in this report.

Table 1: Cross-reference from Energeia (2016) to this document

Location Mentioned	Description	Cross-reference to this document
2.2.1.1 Electricity Customers, p10	Customer numbers by substation and category	*Consumption and customer numbers by customer type,* p30
2.2.1.2 Agents, p11	Representative Residential Customers	*Residential Customer Load,* p37
2.2.1.3 Zone Substations, p11	AER Classification	*Zone characteristics, p29*
2.2.5.3 Calculate On-grid DER uptake probability	ROI-uptake curve	*Specific assumptions on cost driven behaviour change*, p47
2.2.5.5 Agent to Zone substation scaling	Representation scaling factor	*Individual Customer Load*, p37
2.4.1 Generators, p32	Plant build out and retirement profiles	*Electricity generation, p64*
Table 2, p35	Size of existing solar PV	*Photovoltaic installed capacity estimates,* p32
Table 2, p36	Solar PV Characteristics	*Customer scale sundry energy costs* p46
Table 2, p37	Batteries/ Inverters	*Customer scale sundry energy costs* p46

Table 2: Cross-reference from Energeia (2017) to this document

Location Mentioned	Description	Cross-reference to this document
Figure 11, p32	Tech Costs (PV, Storage)	*Customer scale sundry energy costs,* p46
Figure 11, p32	Underlying forecasts (peak/ energy growth)	*Past and projected state and network scale annual load,* p16
Figure 11, p32	Network model	*Past and projected network scale infrastructure costs,* p18 *Network characteristics,* p19
Figure 11, p32	RET	*State rooftop solar PV adoption*, p59
Figure 11, p32	Tech and fuel costs (large scale)	*Other national and state scale data,* p22
3.1.1 Customer Behaviour Model, p33	Customer Behaviour model	*Customer behaviour,* p46
3.1.2 Annual Load Profile and DER scaling, p33	Annual Load Profiling	*Zone Substation Load,* p24
3.1.3 Network Model, p33	Network Model	*Network characteristics,* p19

For consistency, CSIRO takes the projected customer tariff and distributed energy technology choices projected by Energeia as given, projecting outcomes for the full time period in each part of the supply chain, one part at a time, without updating customer choice projections. This means that, in principle, there is some potential for customer choices to become inconsistent with projected network and tariff price outcomes and this is scenario dependant. Fortunately, we found in practice that prices did not diverge significantly enough across the different roadmap studies for the scenarios explored for this to be of concern.

CSIRO and Energeia each maintain their own customer, demand, network and generation models. Both organisations expanded their models to incorporate the new data characterising zone substations and customer types. Three different types of generation models were deployed. Energeia maintains a spot market model of the national electricity market which solves the sequential dispatch algorithm. This model provides half-hourly spot prices which are needed to inform customer choices about likely returns from exports of their excess rooftop solar production and for average electricity generation prices. CSIRO maintains an intertemporal optimisation problem for determining which plant are built and retired in the electricity generation sector over the entire projection period at annual time resolution. This model was used to inform the type of plant that were available for dispatch in Energeia’s spot market model. CSIRO also recently constructed a model to optimise deployment of storage to meet energy balancing requirements under a high penetration of variable renewable generation. This model is a hybrid of the two previous models in that it optimises both deployment and operation (where dispatchable) of a given portfolio of generation technologies and chooses the optimal level of storage and peaking generation capacity to be deployed to balance energy supply and demand in each half hour of the year (solving each period simultaneously rather than the sequential approach of a spot market model).

Network and State Scale Data

This section describes sources of data and estimates at the scale of Distribution Network Service Providers (DNSPs) and Australian states (and the ACT) that were used in the modelling. These estimates include total existing electrical load, on an annual and half-hourly basis, future projected load, including both energy and maximum demand, network assets age profile and capital value, and customer numbers and consumption by type. It also includes annual fuel price projections, population growth projections and state by state electric vehicle load projections.

State and Network scale load and network costs

The scope of electricity system network analysis included fifteen (15) Distribution Network Service Providers comprising thirteen (13) in the National Electricity Market (NEM) and the remaining two (2) in Western Australia (see Table 3 for the list of DNSPs included, and their corresponding state or territory, as well as a slightly more detailed qualitative description of their geographical coverage). In Australia, the National Electricity Market includes the states Qld, NSW, SA, Tas., and Vic., as well as the ACT. Western Australian networks covered include the South-West Interconnected System, managed by Western Power, and networks in the North-West of WA including the North-West Interconnected System, managed by Horizon Power. Our analysis excluded Power and Water, the DNSP in the Northern Territory, and excluded other off-grid systems (see BREE 2013). The analysis was conducted before networks in Queensland were merged.

Past and projected state and network scale annual load

Projections of future annual energy consumption, winter maximum demand and summer demand were based on growth rate projections by state, using the 2016 National Electricity Forecast Report (AEMO 2016a) for NEM states and territories (ACT, Qld, NSW, SA ,Tas., Vic.) and projections by the Independent Market Operator (IMO 2015) for the DNSP, Western Power, which services the SWIS in WA. Regulatory Information Notice data (AER 2015) was collated for past annual energy and maximum demand for each of the thirteen (13) DNSPs in the NEM and two (2) DNSPs in WA.

Table 3: Australian Distribution Network Service Providers

DNSP	State	Geographical Range
ActewAGL	ACT	Australian Capital Territory
Ausgrid	NSW	Inner Sydney, Central Coast and Newcastle, Hunter Valley
Ausnet Services	Vic	Outer northern and eastern suburbs of Melbourne and Eastern Victoria
Citipower	Vic	Melbourne city and inner suburbs
Endeavour Energy	NSW	Sydney's Greater West and Southern Highlands and Illawarra
Energex	Qld	Southern South-East Qld, Brisbane and surrounds, Ipswich, Sunshine Coast, Gold Coast
Ergon Energy	Qld	Qld, excluding Brisbane and remote west
Essential Energy	NSW	NSW, excluding Greater Sydney region, Central Coast and Hunter Valley
Horizon Power	WA	South-West and Northern WA, Western Australia
Jemena	Vic	Northern and South western suburbs of Melbourne
Powercor	Vic	Western suburbs of Melbourne and Western Victoria
SA Power Networks	SA	South Australia
TasNetworks	Tas	Tasmania
United Energy	Vic	South suburbs of Melbourne and Mornington Peninsula
Western Power	WA	Perth and surrounds

Source: Distribution Network Service Providers. Note: the analysis was conducted before networks in Queensland were merged.

Past and projected network scale infrastructure costs

RIN data (AER 2015) provides existing written down asset value, that is, the Regulated Asset Base (RAB) for NEM DNSPs, with corresponding data for Horizon Power and Western Power derived from their annual reports (Horizon Power 2015 and Western Power 2015). Estimates of the asset age structure are reported in Graham et al (2013), p44ff. A summary of these data appears in Table 4, including an indicative average residual life. Note that while the interpretation of the RIN information is somewhat comparable across DNSPs because the calculation method is specified in AER regulations, the data for the Western Australian DNSPs may have a slightly different interpretation depending on the particular proxy value selected and how it was calculated.

Table 4: DNSP Infrastructure: key technical and economic data (FY1415 and CY15)

	Annual Supply	Non*-coincident Max. Demand	Network Infrastructure RAB	Residual life
DNSP	(MWh)	(MW)	($ million)	(yrs)
ActewAGL	2 830	615	945	14.4
Ausgrid	25 523	4 977	15 028	33.9
Ausnet Services	7 448	1 880	3 199	19.5
Citipower	5 919	1 507	1 719	22.7
Endeavour Energy	15 637	3 815	5 900	39.8
Energex	20 838	5 038	11 743	37.9
Ergon Energy	13 716	3 196	10 254	25.6
Essential Energy	12 030	2 327	7 259	21.8
Horizon Power	991	*NA*	259	*NA*
Jemena	4 136	1 029	1 114	19.2
Powercor	10 333	2 484	3 143	26.9
SA Power Networks	10 603	3 066	3 837	17.7

TasNetworks	4 112	242	1 625	13.6
United Energy	7 696	2 198	1 950	24.0
Western Power	19 114	*4 032	4 030	*NA*
Total	160 926	36 406	72 003	

Source: AER 2015, Horizon 2015 p18, Western Power Annual Report 2015,
*Maximum demand for Western Power from annual report is coincident.

Network characteristics

Network scale customer data and asset age distribution

RIN data provides customer numbers for each DNSP by four customer categories (corresponding to tariff options available to each customer) for those DNSPs in the NEM. Western Australian data is derived from annual reports. Again, the customer categories reported for the WA DNSPs in their annual reports may have a different interpretation from those reported in the RIN for NEM DNSPs.

Table 5: Customer numbers 2014-15 by category by DNSP

DNSP	Residential	Commercial tariff	Low voltage demand tariff	High voltage demand tariff	Annual Supply (GWh)
ActewAGL	163 664	14 028	1 867	25	2 830
Ausgrid	1 482 986	148 981	36 989	351	25 523
Ausnet Services	611 407	69 039	2 054	100	7 448
Citipower	271 323	51 605	1 738	85	5 919
Endeavour Energy	843 867	79 296	4 353	352	15 637
Energex	1 270 554	112 037	11 243	577	20 838
Ergon Energy	615 781	103 312	8 580	79	13 716
Essential Energy	725 879	93 310	4 055	193	12 030

Horizon Power	38 786	8 832	190	26	991
Jemena	285 834	24 922	1 977	79	4 136
Powercor	658 281	97 788	2 553	181	10 333
SA Power Networks	750 596	95 733	5 340	236	10 603
TasNetworks	237 366	41 203	884	121	4 112
United Energy	591 489	53 366	4 082	90	7 696
Western Power	927 511	94 043	28 818	265	19 114
Total	9 311 660	1 073 467	112 856	2735	160 926

Source: AER 2015, Horizon 2015 p18, Western Power 2015

Residential consumption data and customer number data are also available from the RIN. See Table 6 for average load per residential customer by DNSP. Note that this is slightly inconsistent with the RIN data in Table 5, as they come from different sources in the RIN and in some cases correspond to slightly different years (some data are reported by financial year and others by calendar years, and this also varies by DNSP).

Table 6: Residential consumption in FY1415 and CY15 by DNSP

DNSP	Annual Supply (GWh)	Average Residential consumption (MWh pa)	Average Residential consumption (kWh/day)	Residential Customer Count
ActewAGL	1 155	7.30	20.0	163 664
Ausgrid	8 521	5.43	14.9	1 482 986
Ausnet Services	3 125	5.36	14.7	611 407
Citipower	1 201	4.65	12.7	271 323
Endeavour Energy	5 509	5.83	16.0	843 867

Energex	7 559	5.92	16.2	1 270 554
Ergon Energy	3 911	7.31	20.0	615 781
Essential Energy	4 457	6.85	18.8	725 879
Horizon Power	*NA*	12.91	35.4	38 786
Jemena	1 211	5.48	15.0	285 834
Powercor	3 298	4.82	13.2	658 281
SA Power Networks	3 758	5.84	16.0	750 596
TasNetworks	1 883	8.14	22.3	237 366
United Energy	2 679	5.04	13.8	591 489
Western Power	*NA*	4.48	12.3	927 511
Total	160 926	5.74	15.7	9 204 017

Source: AER 2015 and Energeia (2016)

Rooftop solar PV generation profiles

Rooftop hourly solar profiles by state were generated from AEMO (2013). First, state (capital city) profiles were interpolated to half-hourly profiles by averaging. See Figure 2, which shows daily half-hourly profiles, by season, and state, both for a representative day in each season, and averaged over each season. Not including rooftop solar PV profiles, renewable resources time series from AEMO 2013 were available at a spatial resolution of forty-three (43) regions covering NEM customers, each region referred to as a renewable resource polygon. In order to recover some spatial diversity for rooftop solar profiles, also at the scale of renewable resource polygons, the capital city rooftop profiles were rescaled, by half-hourly time period, by the ratio of the large scale (single axis tracking) solar PV output from each polygon to that of the polygon corresponding to each state's capital city. For NEM states, each zone substation was assigned the rooftop solar profile corresponding to that of the closest polygon. For Western Australia, all of Horizon Power's zone substations were assigned the rooftop solar profile of polygon number five (5), a mid-latitude Queensland polygon similar to the latitudes of Onslow and Exmouth. All of Western

Power's zone substations were assigned the rooftop solar profile of polygon number (twenty-six) 26, a polygon in South Australia covering southern latitudes similar to those of Perth and Albany. Greater spatial diversity across each of these two DNSPs in Western Australia could have been achieved by imposing a closer dependence on the estimated location of each zone substation, in particular, improved matching of latitudes.

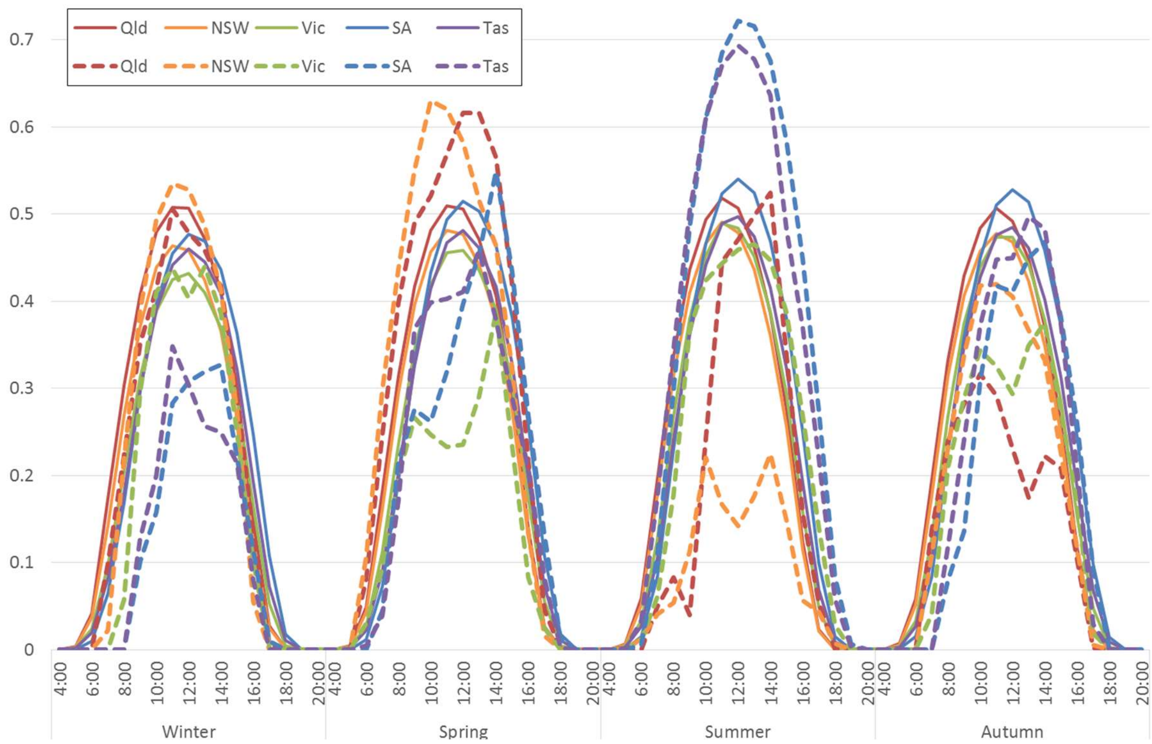


Figure 2: Rated output normalised PV output by state, seasonal average (solid) and selected daily (dotted), seasonal daily load profiles by hour

Other national and state scale data

Fuel price projections

For fuel and carbon emissions price assumptions, as referred to in Energeia (2016), Table 2, see Graham et al. 2015, p. 46. Oil price projections are derived from the EIA (2016), high, medium, and low scenario cases. The five-yearly projections to 2040 are interpolated to derive annual projections, and from 2040 to 2050 the projections are extrapolated using the average annual growth rate between 2020 and 2040.

Gas price projections are derived from the oil price projections described above, using the ratio between oil and gas prices from the IEA (2015) in their Current Policies scenario at ten-yearly intervals to 2040. The ten-yearly projections to 2040 are interpolated to derive annual projections, and from 2040 to 2050 the projections are extrapolated using half the average annual growth rate between 2030 and 2040.

Population, generation technology cost and electric vehicle uptake projections

Population growth projections by state are sourced from ABS (2012), series B, the mid-range projections. These are used to project growth in customer numbers for each electricity supply region. For existing capacity and cost projections for centralised generation technology, see Graham et al (2015). This also provides sources for cost projections for solar PV and battery storage. Electric Vehicle uptake projections are from Graham et al. (2015) and Graham and Brinsmead (2016), see also the Electric Vehicle Scenario Analysis section following

Substation scale data

This section describes sources of data and estimates that were used in the modelling that vary by zone substation. These data and estimates include half-hourly load profiles, including future projections, zone substation “head room” – the ratio of maximum demand to substation installed capacity, local population density and zone substation reliability requirements, customer numbers and existing consumption by customer type, installed solar PV capacity by customer type and half-hourly electric vehicle load projections.

Zone Substation Load

While total annual energy consumption and maximum demand by DNSP is useful, for the purposes of modelling the impact of tariff and technology choices on future energy costs, it was desired to undertake analysis at a finer spatial resolution than by DNSP and at a finer temporal resolution than annually. RIN network infrastructure data is provided at the scale of zone substation, ranging between 300 kW and 150 MW (Median 33.4 MW, interquartile range 13.8-59 MW, see Figure 3). Furthermore half-hourly time resolution data is recorded at each zone substation.

Most of the zone substation load data was initially obtained via request from each DNSP under AEMC rule 2014-1, resulting in up to ten (10) years of zone substation load data at frequency of at least half-hourly. As the Western Australian DNSPs are not subject to AEMC rules, these networks instead provided data via a different route, as did Endeavour Energy. We were unable to obtain load data by zone substation from Essential Energy. Table 7 shows, for each DNSP, the state (territory) and number of zone substations for which load data was analysed (or synthesised, in the case of Endeavour Energy and Essential Energy, see below).

Table 7: Zone substation count by state/ territory and DNSP

DNSP	State / Territory	Represented Zone count	State zone count
Ausgrid	NSW	211	
Endeavour Energy	NSW	161	**739**
Essential Energy	NSW	353	(incl. ACT)
ActewAGL	ACT	14	
Energex	Qld	243	**679**
Ergon Energy	Qld	436	
Powercor	Vic	60	
Jemena	Vic	25	
Citipower	Vic	36	**218**
United Energy	Vic	46	
Ausnet Services	Vic	51	
SA Power Networks	SA	215	**215**
TasNetworks	Tas	43	**43**
Western Power	WA	153	**196**
Horizon Power	WA	43	
Total	**Australia**	**1879**	

Source: DNSPs and CSIRO

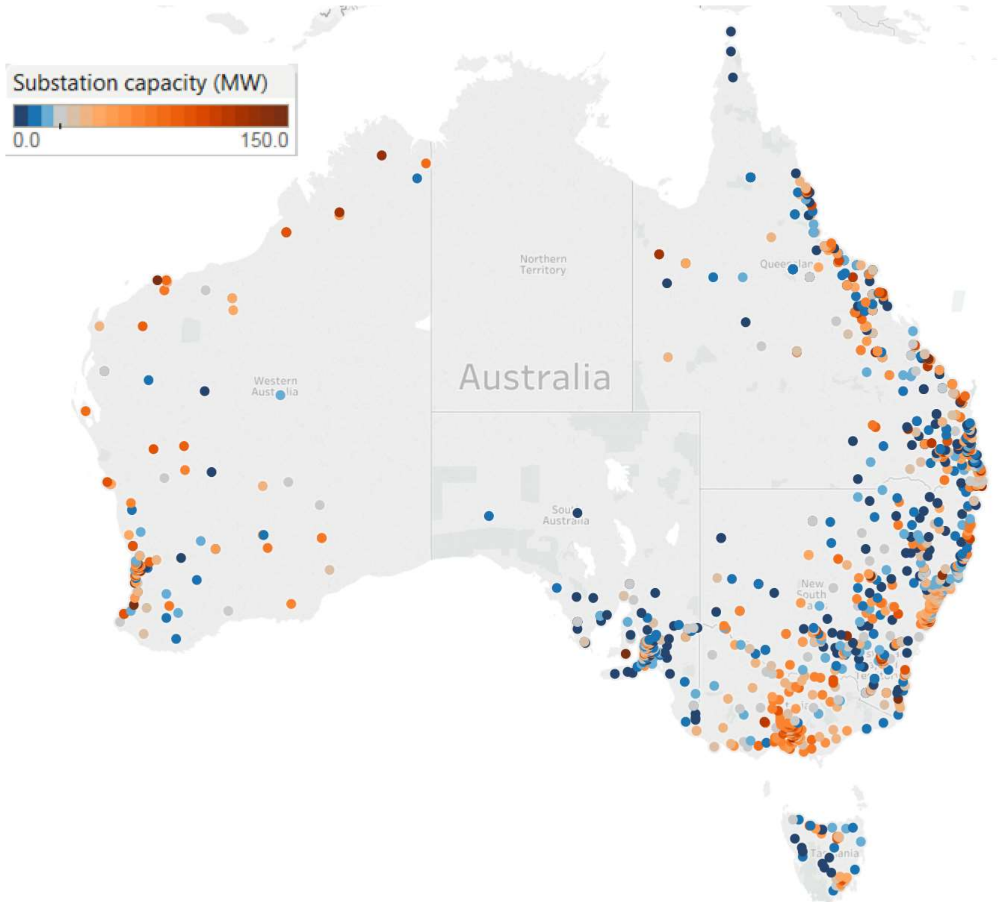


Figure 3: Substation capacity by location

Zone substation load data from fourteen (14) DNSPs (that is, excluding Essential Energy) was converted to a common format, corresponding to half-hourly time steps. Real power was used where provided, otherwise apparent power only was recorded.

Data quality was checked, though not systematically. For some load data it was inferred that some original data had been unintentionally described in incorrect units, for all or part of a time series, and so was rescaled by three orders of magnitude. Sometime stamp data were inferred to be erroneous as a consequence of incorrect specification of date formats, and adjusted accordingly. Suspicious outlier data (such as zero load or significant periods of constant load) were eliminated via a non-systematic process.

Subsequently, missing or removed time series data was replaced with interpolated values. A simple interpolation scheme was used – an average of previous and subsequent half-hourly time periods was used, if the data was available, otherwise an average of the loads at the same hour on previous and subsequent days was used, again only where the data was available. Failing that, the average of the same hour and day of previous and subsequent weeks or the average of loads corresponding to previous and subsequent years. This resulted in reasonably good coverage for the interpolated data in the years of interest.

Representative year FY1213 was used for all DNSPs except for Endeavour Energy, where FY1314 data was more complete. We also used FY1415 for Citipower for those zone substations where data only post 2015 is available.

Synthetic Zone substation half-hourly load: Endeavour Energy and Essential Energy

Since Endeavour Energy had a significant number of zone substations for which data was missing, and measured data for Essential Energy was unavailable, it was necessary to synthesise annual half-hourly load profiles for these two DNSPs from NSW. In order to do so, we based the load profile shapes on known metered zone substation data (in particular from other Endeavour Energy zones, and from Ergon Energy zones respectively), and based the scale on known capacity of each zone substation, which is available from the Regulatory Information Network notices (AER 2015), and an assumed ratio for the substation capacity to maximum demand ("head room") for each zone substation based on known distributions of head room ratios.

For Endeavour Energy, where there were a few zone substations missing some time series – we interpolated across zones by directly copying time series for the load profile shape and scaling by zone substation capacity. We first calculated the capacity to peak ratio of known zones, then, sampling at random from this distribution, assigned identical capacity to peak ratios of the unknown zones to determine peak estimates. In order to assign load profile shapes of known zones to unknown zones, we matched unknown zones to known zones based on population density ranking (see *Zone substation location and population density estimates*), such that no more than two unknown zones were assigned a shape based on the load profile shape of any given known substation. While matching known profiles to unknown substations approximately by population density gives the load profile shape, these profiles were then rescaled by a constant factor across time for each zone in order to match the peak based on the assumed head room ratio.

A similar process was undertaken for Essential Energy synthetic load data, where the zone substation load profile shapes used were based on known zone substation data from another primarily rural DNSP, Ergon Energy, slightly reshaped by normalised (over one year) ratios of demand by state (that is NSW to Queensland) by half-hourly time period. (The reshaping data were based on 2010 NEM load data available from AEMO). We again matched zone substations approximately by estimated population density, ensuring that no more than one Essential Energy zone substation load profile shape was based on any given Ergon Energy zone substation. For Essential Energy, we imposed a random distribution on the head room ratio, that is, the ratio of maximum demand to zone substation capacity. The distribution chosen was the normal distribution with a mean of 0.5 and a standard deviation of 0.2, this approximates the head room ratio distributions observed for other DNSPs. These head room ratios were initially distributed at random across the zone substations, but later correlated with zone substation capacity so that the total estimated maximum demand more closely matched that reported in the RIN.

Zone substation half-hourly load: Projections

For the purposes of modelling, the representative years of half-hourly load profiles were extrapolated to future years from 2016 to 2050 based on projections of annual energy consumption, winter maximum demand, summer maximum demand, and minimum demand projections. For the year 2016, the representative load profiles for each of the zones was rescaled by a factor that was constant across zones within each DNSP and across time, such that the total annual energy was consistent with the RIN. Projections of future annual energy consumption, winter maximum demand and summer demand were based on growth rate projections by state (see *Past and projected state and network scale annual load*.)

Half-hourly demand in each zone substation was extrapolated by being subject to nonlinear (quadratic) rescaling using a least-squares optimisation criterion to minimise the weighted sum of squared errors in the annual maximum summer demand, maximum winter demand, annual energy, and minimum demand, relative to future projections provided by AEMO's 2016 National Electricity Forecasting Report and the IMO in Western Australia and assumptions of no growth in minimum demand. In the absence of growth projections for Horizon Power, those for Western Power, the other DNSP in WA, were applied. See Graham et al. 2015 for a brief description of the extrapolation method as applied there to half-hourly demand by state. In particular, for each time period *t*, we apply to the demand d_t in a representative base year, the extrapolation

$$D_t = p(d_t)^2 + qd_t + r,$$

where D_t is demand by period in the alternative year and p, q, r are scaling parameters to be found (subject to $\partial D_t / \partial d_t > 0$ for all time periods). The scaling parameters are chosen to minimise a weighted cost function:

$$\alpha\left(A - \sum D_t\right)^2 + \beta(S_M - \max_{St}\{D_t\})^2 + \gamma(W_M - \max_{Wt}\{D_t\})^2 + \delta(N - \min_t D_t)^2$$

where A, S_M, W_M, N are annual targets for respectively total energy demand, maximum summer demand over the summer periods S_t, maximum winter demand over the winter periods W_t and minimum annual demand over all time periods, and $\alpha, \beta, \gamma, \delta$ are cost function weights. In this case we used $\beta = \gamma = \delta = 17520\alpha$ where 17520 is the number of half-hourly periods in a year.

Zone characteristics

Zone substation location and population density estimates

The location of some (approximately 1000) zone substations was available from the Australian Renewable Energy Mapping Infrastructure (AREMI) data set (ARENA and CSIRO 2016) with GIS data. For the remaining zone substations, we estimated a location based on the zone substation name. We looked for components of the zone substation name first in a suburb name database, then looked in a LGA name database, then looked at individual names manually trying to find a match on a street name, major industrial plant or other geographic feature in attempt to locate the most likely suburb. We estimated the zone substation location as the centroid of the corresponding suburb.

Knowledge of a zone substation location estimate permitted an estimate of local population density. These were based on the simple average of the population density of the nearest identified LGA and Australian Statistical Geography Standard SA2 area, based on ABS (2011) data.

Regulatory information notice data (AER 2015) provides, for each DNSP, the number of zone substations categorised into ratings indicating required reliability, namely: CBD, Urban, Short Rural and Long Rural. These classifications determine the regulated minimum service reliability requirements for each corresponding region. Population density thresholds, dependent on DNSP, were selected for classification to give approximately correct total zone substations within each reliability category (see Table 8).

Table 8: Population density thresholds for estimated substation reliability ratings

DNSP	Population density thresholds (persons/km^2) Long Rural	Short Rural	Urban	CBD
ActewAGL	< 1	1 - 10	10 - 6 000	> 6 000
Ausgrid	< 1	1 - 50	50 – 10 000	>10 000
Ausnet Services	< 4	4 -180	180 - 6 000	> 6 000
Citipower	< 0.2	0.2 - 2	2 - 4 800	> 4 800
Endeavour Energy	< 1	1 - 20	20 - 6 000	> 6 000
Energex	< 1	1 - 150	150 - 6 000	> 6 000
Ergon Energy	< 0.3	0.3 - 10	10 – 10 000	>10 000
Essential Energy	< 0.7	0.7 - 30	30 – 10 000	>10 000
Jemena	< 2	2 - 500	500 - 6 000	> 6 000
Powercor	< 10	10 - 150	150 – 10 000	>10 000
SA Power Networks	< 1.5	1.5 - 7	7 - 2 700	> 2 700
TasNetworks	< 1.1	1.1 - 2	2 - 800	> 800
United Energy	< 1	1 - 450	450 – 8 000	> 8 000
Western Power	< 1.7	1.7- 10	10 – 1 800	> 1 800

Consumption and customer numbers by customer type

A disaggregation of each substation’s annual load into components by customer type (residential, commercial and industrial) was undertaken based on relative estimated floor area for each zone substation’s nearby LGAs (see Do, Thomas-Agnan and Venhams 2014, using floor area by customer type as the auxiliary disaggregation data). Data obtained from the National Exposure Information System (NEXIS, Geoscience Australia, 2016) was used to estimate the residential, commercial and industrial floor area in each LGA. Using location estimates of each zone substation (see *Zone substation location and population density estimates* above) the four closest zone substations to each LGA was identified, and the distance d in km between the zone substation location and LGA estimated. A weighting score $w = \left(4\sqrt{d^2+1}\right)^{-1}$ which decreases with distance d, in km, was applied to each of the four closest zone substations, and the LGA total floor area associated with each end user customer type was disaggregated and assigned to each of the four nearest zone substations proportionally to the distance weighting.

Then, total electricity consumption by customer type for each DNSP was obtained from RIN data (AER 2015, taking low voltage customers on demand tariffs as well as those on commercial tariffs as commercial customers, and only those high voltage customers on demand tariffs as industrial customers). This electricity consumption by DNSP and customer type was then further disaggregated and assigned to each zone substation in proportion to the floor area for the DNSP corresponding to that customer type, as estimated above. This estimation of energy consumption by customer type and zone substation was then finally used to estimate, for each zone substation, the proportion of consumption by each customer type. Customer numbers by type and zone were then estimated given average load by DNSP by customer type, and consumption by customer type and zone. Where it was desired to further disaggregate residential customers further into small, medium and large customers this was achieved via the choice of representative residential customer loads on the basis of the scale distribution of the source population (see *Individual Customer Load*).Results of this estimation process, indicating the proportion of estimated consumption corresponding to residential customers, by zone substation location, appears in Figure 4.

Future projections of customer number for both residential and commercial customers are obtained by assuming growth rates in numbers corresponding to population growth rates by state.

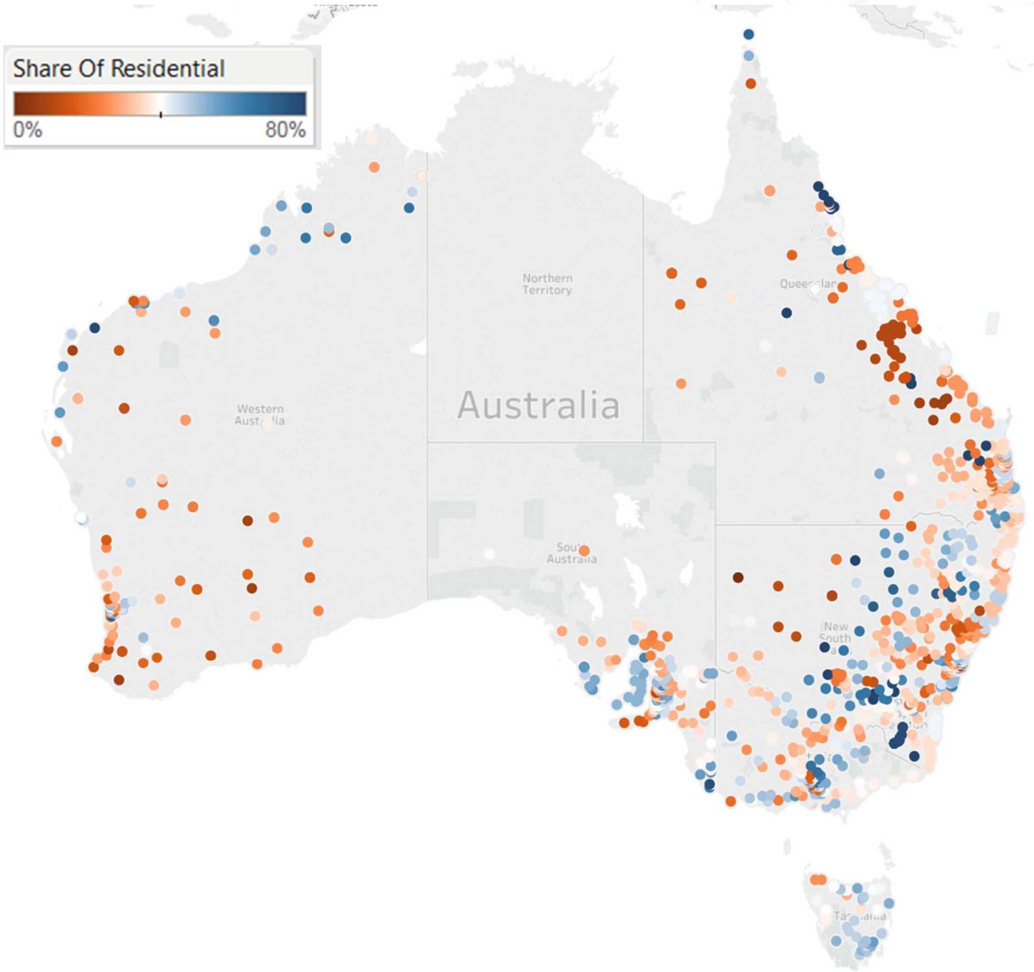


Figure 4: Estimated residential share of load by location

Photovoltaic installed capacity estimates

The existing capacity of installed solar PV by customer type (residential or commercial) by postcode is available from the Clean Energy Regulator (CER 2016). This data was used to estimate the existing capacity of installed solar PV by customer type by zone substation, using population data by SA2 and ABS (2011) information relating SA2 regions to postcodes to derive an estimate of the intensive variable, installed capacity by customer type per head of population by SA2. This was assumed to be proportional to kW installed capacity per zone substation annual energy load (ignoring customer type – an alternative to which is to consider only annual load for residential and commercial customers), each of which can be assigned to an SA2 via its location estimate. (This approach avoids a requirement to directly estimate a contribution of each zone substation's load, an extensive variable, to each postcode). Similarly to the above, using location estimates of each zone substation, the four closest substations to each SA2 region were identified, then each zone substation assigned the weighted average solar PV capacity by customer type per head of the SA2 regions for which the substation is one of the four closest, with weights $w = \left(4\sqrt{d^2+1}\right)^{-1}$, which decreases with the estimated distance d in km between the zone substation and postcode. Relative population by zone substation and DNSP is given by estimated residential customer load from the above, which can be multiplied by the assigned average solar capacity per head by customer type, and normalised to match total installed solar PV capacity by state. Additional nonlinear scaling of f an initially estimated fraction of the load supplied by PV

$$F = \frac{(1-f_0)Lf}{(L-f_0)+(1-L)f}$$

was applied where necessary. In the above, F is the new rescaled fraction, and the parameters L and f_0 are respectively the maximum rescaled fraction and the fraction amount that remains unchanged by rescaling. Using $L = 0.5$ ensures that less than 50% of the load by substation is supplied by PV after rescaling, and $f_0 = 0.25$ gives $F = f/2(1+2f)$. Results of this estimation process, indicating the penetration of solar PV in 2016 relative to the assumed maximum of 50% capacity, by zone substation location, appears as Figure 5.

Projected future solar PV uptake is estimated on an essentially individual customer by customer basis, as determined by individual customer load profiles, tariffs available, projected cost of PV installation and propensity of the customer to take up new technologies as a function of payback period (see *Customer behaviour change* and Energeia 2016).

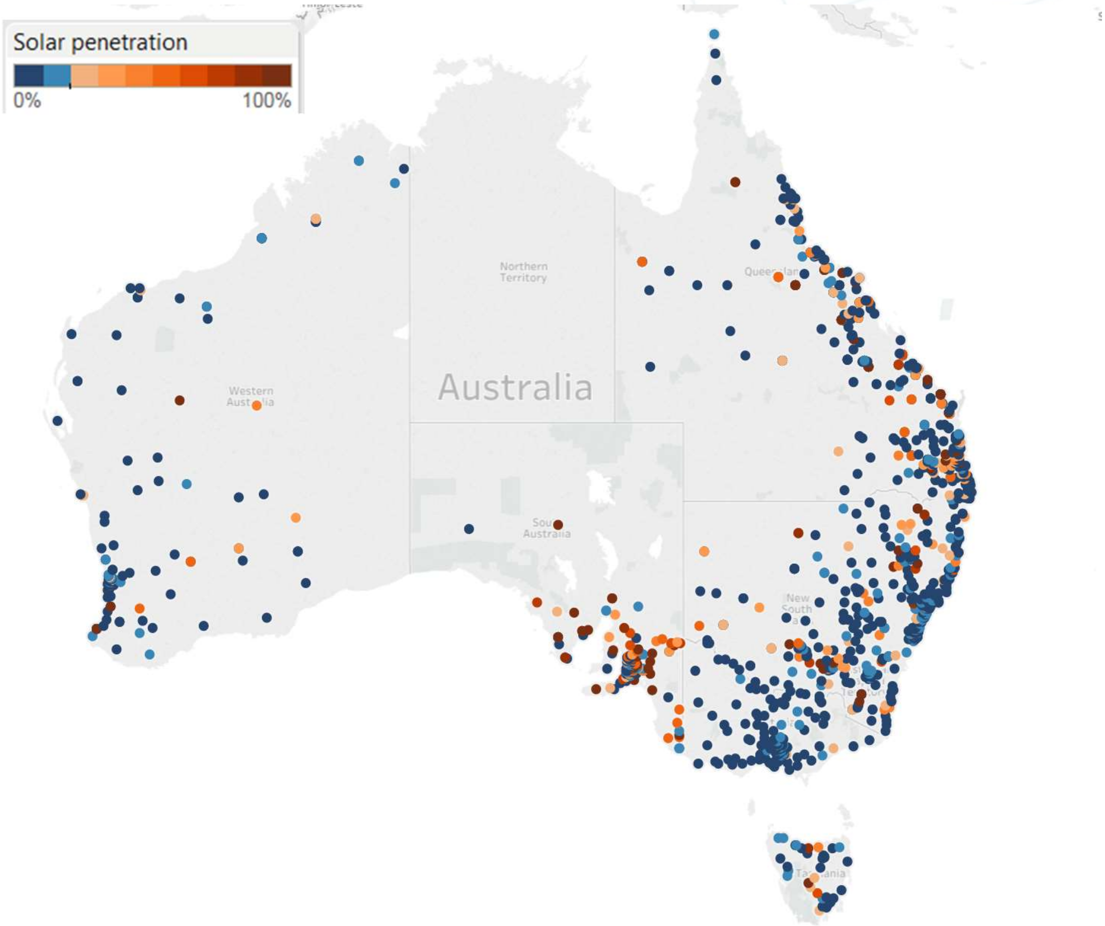


Figure 5: Estimated solar penetration by location, 2016

Electric Vehicle projections and load profiles

Annual electricity consumption by electric vehicles by state is calculated a medium electric vehicle adoption scenario that was selected in (Graham and Brinsmead 2016) from a wide variety of Australian projections. This consumption is disaggregated by zone substation within each state as customer adoption by substation is allocated using a formula described in Graham and Brinsmead (2016) which takes into account a number of demographic properties of each substation. Electric vehicle number projections correspond to *Electric Vehicle Energy Demand* projections described above based on 4080 kWh per vehicle per year. In some circumstances this may result in the implied number of vehicles for some zone substations being non-integer.

One of two options for EV daily load profiles (averaged over customers) is used. One for convenience charging, another less aggressive with capped demand and allowing for further managed charging (see Figure 6). We assume no difference between weekday and weekend charging. These profiles are as reported in Graham and Brinsmead (2016) and were developed based on a convenience charging profile reported in EA technologies (2016) that was adapted for two different charger sizes.

The “convenience” charging profile shows a customer average peak demand at zone substation scale at approximately 8pm of about 2.5 kW, and limited load on the network in the early morning hours. This average is based on an assumption of individual customer charger sizes of 7kW, and takes into account a diversity of travel and home arrival times. This represents a situation where the majority of EV owners recharge their vehicles at their maximum rate essentially as soon as they return home in the evening. It can be observed that this demand profile does not impose much load during the early morning off-peak hours, is quite similar in shape to a typical residential profile of a working household, and does not make particularly efficient use of grid capacity. This convenience charging profile was applied in Graham and Brinsmead (2016) to explore the impact on demand and electricity system costs of providing no incentive for off-peak charging of electric vehicles. However, under the *Roadmap* scenario, such incentives are in place and electric vehicle charging is shifted to off-peak times. Note that under the *Roadmap*, the less aggressive “capped demand” charging profile based on a 3.5kW charger, as shown in Figure 6, is the starting point for customers before further managed charging adjustments involving the shifting of charging times to off-peak hours.

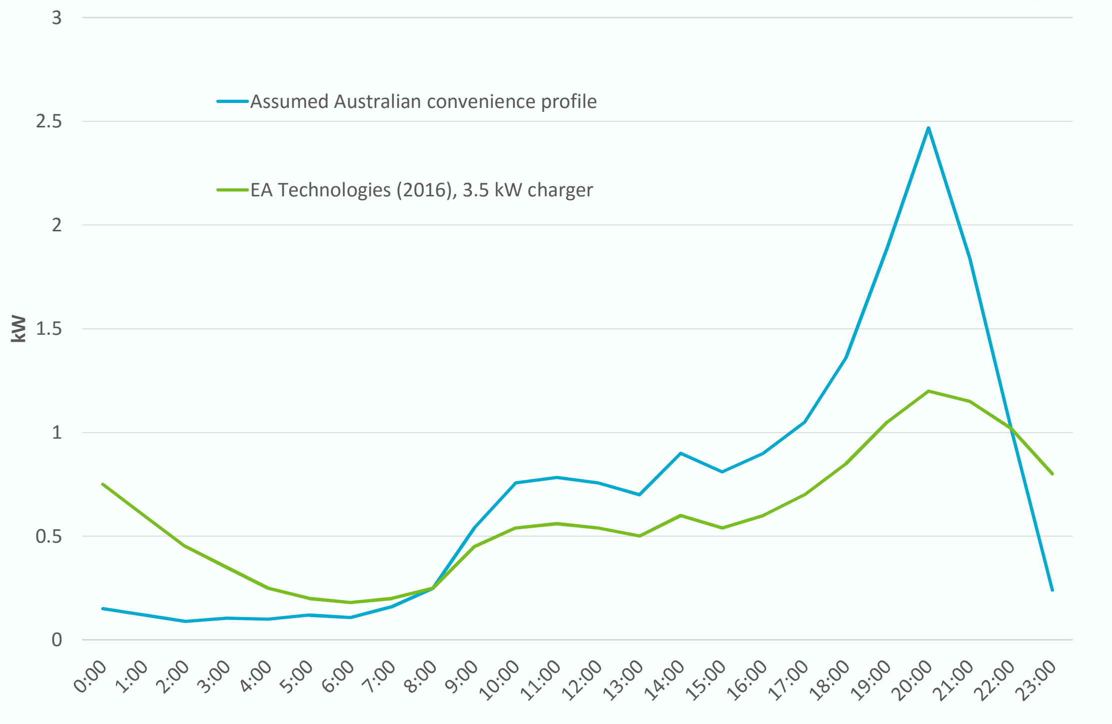


Figure 6: Electric Vehicle convenience charging profiles – EA Technology United Kingdom trial using 3.5 kW charger and assumed future Australia profile with 7kW charger as the standard size.

Substation age and capacity head room

The frequency distribution of network infrastructure assets by age for each DNSP, as estimated above (see *Network characteristics*) was downscaled to individual substations by random assignment. Existing capacity of individual zone substations is available from Regulatory Information Notices (AER 2015), and together with maximum annual demand projections, the capacity "headroom" can be calculated. Zone substation capacity is obtained from Regulatory Information Notices and maximum demand from zone substation load profiles (see *Zone substation half-hourly load: Projections*). Zone substation age is used to determine whether and when the asset should be replaced. Capacity and head room information is used to determine whether and when the asset capacity should be expanded. For the modelling in Energeia (2016), zone substation capacity was upgraded the first year that capacity head-room is reduced to 20%, upgrading so that the resulting head-room is 40%.

Customer scale data

This section describes sources of data and estimates in the modelling that vary by individual customer. These estimates are half-hourly load profiles, for both residential and commercial customers, half-hourly solar PV generation profiles, electricity tariffs and distributed energy resources technology (e.g. solar PV and battery storage) costs. They also include behavioural parameters, such as propensity to adopt new technologies or switch tariffs.

Individual Customer Load

The process for developing annual load profiles at half-hourly resolution for individual customers, as mentioned in Section 2.2.1.2 and Table 2 of Energeia (2016), involved deriving residential customer load profiles from Smart Grids Smart Cities (SGSC) data collected by Energy Australia (Department of Industry 2015) and commercial (and industrial) load profiles from aggregated zone substation data (see *Zone Substation Load*).

Residential Customer Load

Smart Grid Smart Cities data included almost eighty thousand (80 000) load profiles of de-identified residential customers in the Sydney and Hunter Valley region of NSW. A selection of representative residential customers from the SGSC data was extracted via clustering analysis and their corresponding annual half-hourly loads were modified slightly by DNSP to provide 45 representative residential customer loads for each DNSP, each representative standing in for an equal proportion of the residential customer population.

The process for deriving representative customer load profiles for each DNSP followed the following three steps. First, clustering analysis identified forty-five (45) representative customer load profiles from the SGSC data set. Clustering analysis also identified typical zone substation load profiles for each DNSP. Next, the shape of the individual customer load profiles was modified by the shapes identified for typical load profiles corresponding to zone substation clusters. Finally, the scale of individual customer load profiles was adapted by DNSP, by customer, so that the distribution of annual demand for the 45 representative customers met a specified target distribution for each DNSP.

Cluster Analysis

Some of the eighty thousand (80 000) customer load profiles from the SGSC data were supplemented with other information about the corresponding households. In order to select representative customer loads, a subset of some seven thousand

(7000) of these residential load profiles, where the other information about the customer households was mostly available, was first extracted, and the corresponding load profiles disaggregated into four (4) clusters, plus one cluster of outlier profiles.

Each of the four clusters was further disaggregated into three (3) sub-clusters. An individual representative central load profile was selected from each cluster and sub-cluster, in the sense that the central load profile is close to all other cluster or sub-cluster elements. From each sub-cluster, three (3) individual load profiles that were close to a sub-cluster central representative, and from each cluster, the representative central load profile was selected. This gave ten (10) representative load profiles from each cluster. Five (5) additional load profiles from the cluster of outlier profiles was also selected to give a total of forty-five (45) individual load profiles selected from 7000. Some, but not all, of these customers were associated with controlled load profiles as well as “general supply” loads. These 45 individual load profiles were deemed to represent the shape (but not necessarily the scale) of 45 representative customers from Ausgrid, the DNSP for the residential customers represented by the initial SGSC data. See Figure 7 for an average daily profile at half-hourly resolution for three (3) of the 45 representative residential customers, selected to include each of a small, medium and large average demand.

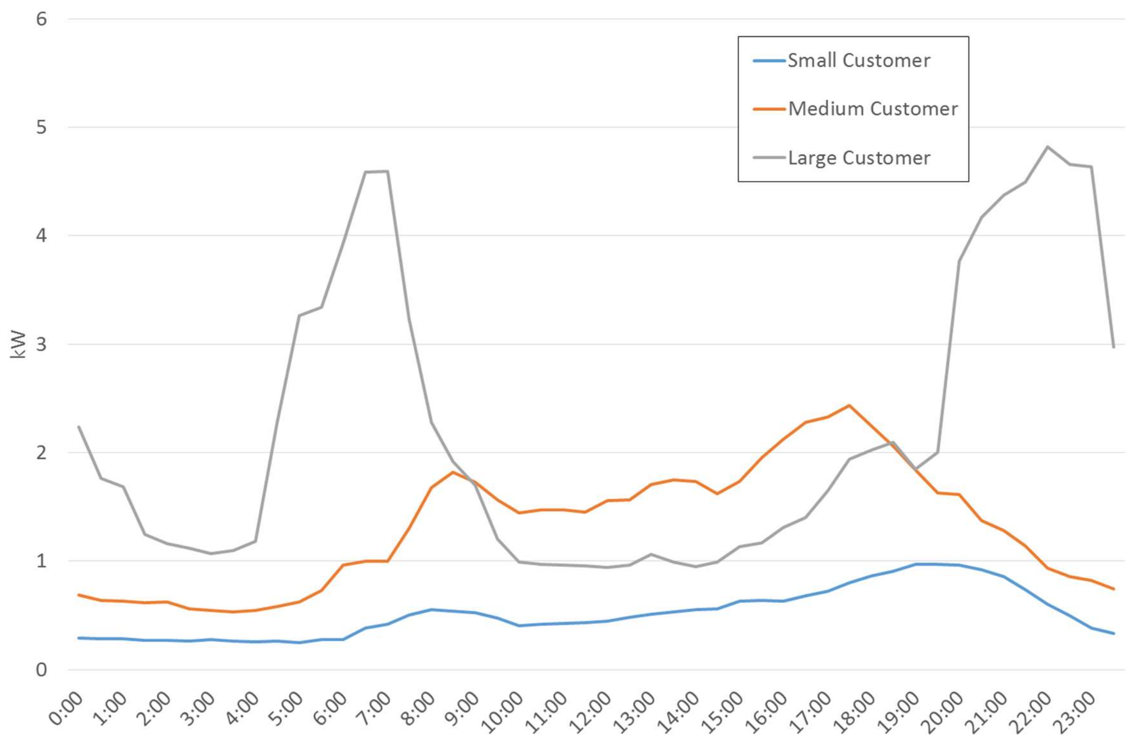


Figure 7: Daily average half-hourly load profiles for three representative residential loads

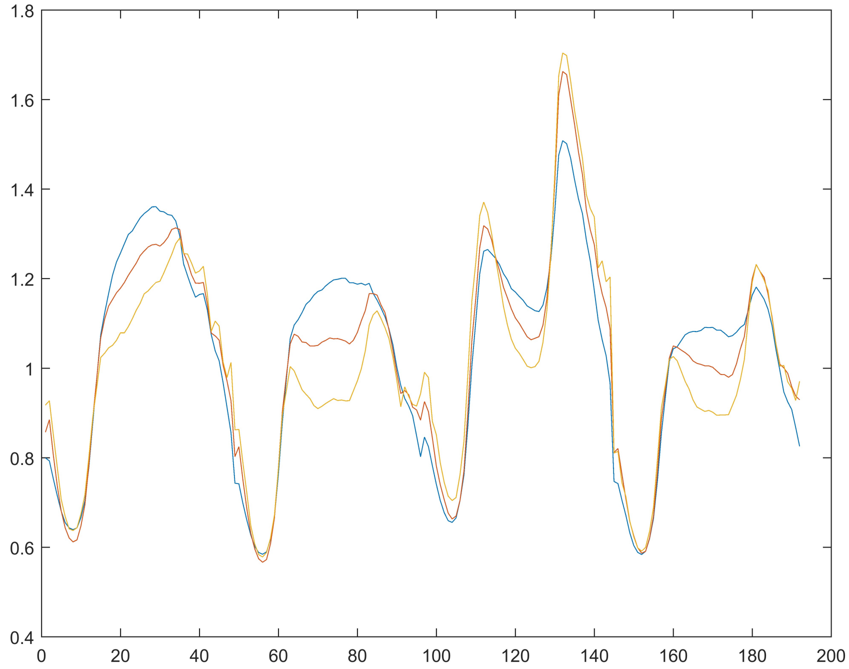
The clustering method is as applied in Berry et al. (2015). The aim is to reduce spatial and temporal complexity of the subset of 7000 profiles. The clustering algorithm bundles households with similar demand profiles. It consists of two stages, compression of profiles, followed by clustering of profiles. Initially consider the dataset of $H \times D$ diurnal load profiles, where H is the number of households (that is, over 7000 SGSC homes) with diurnal profiles available for D days (e.g., 365 days for an entire year).

Compression: The first step involves data compression to eliminate redundancies and unnecessary details from the daily load profiles. This step is analogous to a low pass filter that eliminates (high frequency) noise while retaining essential (low frequency) features of the data. However, rather than using a decomposition using a pre-specified basis – a Fourier series -with a cut-off frequency, we use a (more general) principal component analysis (PCA) where the elbow on the information content of the forty-eight (48) half-hours is used as the cut-off point. The profiles are then transformed into compressed orthogonal space. Experimentally, residential electricity profiles shows a sharp elbow often on the fifth (5^{th}) or sixth (6^{th}) component, while the first three (3) components often contain around 70% of correlation information.

Clustering: The second step is to bundle houses based on a similarity metric. We use cosine similarity of profiles score vectors in orthogonal (principal component) space. This reflects day by day similarity across households. A coefficient of variation of these similarities along D days period is the similarity metric. A self-organising map (SOM) without supervision is used to bundle households that have high similarity scores for their respective daily profiles.

Load profile reshaping by DNSP

Recognising that the general shape of customer profiles might vary across distribution networks, further processing on these 45 representative customers was undertaken. Each DNSP provided load data aggregated to the zone substation scale (see *Zone Substation Load*). Using similar clustering analysis methods for fourteen (14) other DNSPs (excluding Essential Energy, for which no zone substation data was available), the approximately two thousand (1879) zone substation profiles (ranging in number from fifteen (15) for ActewAGL to some four hundred or so (436) for Ergon Energy) for each DNSP were split into clusters. Zone substation profiles were normalised prior to clustering in order to make profiles shape features more prominent rather than the less relevant magnitude aspects (which merely reflect zone substation size). A cluster average profile shape was calculated as the mean normalised load at each time step.



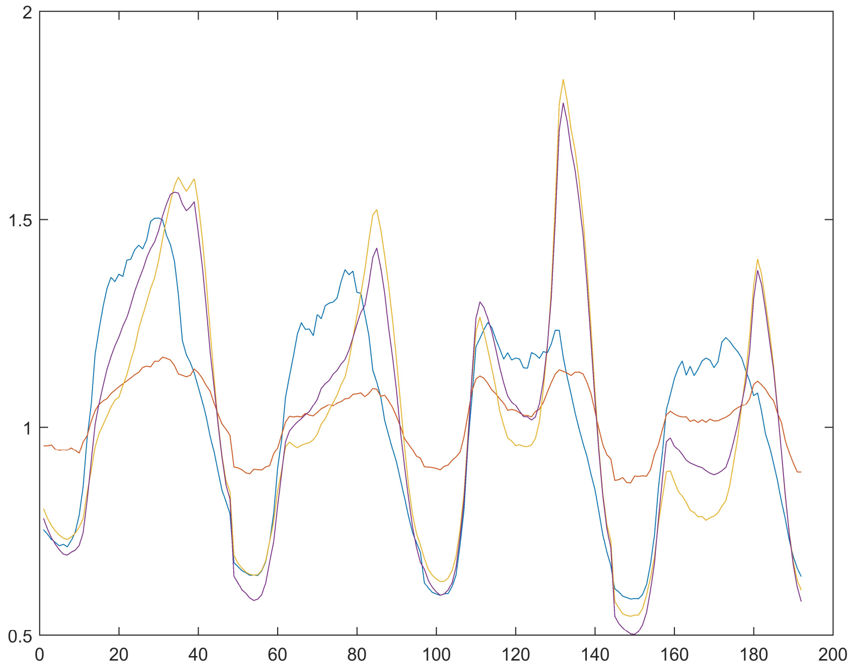


Figure 8: Normalised, seasonal average, seasonal daily load profiles by half-hour for zone substation cluster average loads across three clusters in Ausgrid (above) and four in Western Power (below).

Each of the 45 representative customer load profile shapes for the Ausgrid network, as derived from individual Smart Grid Smart Cities load profiles, was matched to one of three normalised cluster average zone substation profiles for the Ausgrid network. For each of the other DNSPs, each normalised cluster average zone profile was matched to one of three normalised average zone substation profiles for Ausgrid. Representative customer load profile shapes for each DNSP were then derived by rescaling those derived for Ausgrid. The rescaling factor was derived as the half-hourly stepwise ratio of the normalised cluster average zone substation profile for each DNSP to the corresponding cluster average zone substation profile for Ausgrid, which also corresponds to the zone substation cluster for the representative Ausgrid individual profile (see Figure 10 for an indicative comparison DNSP clusters, in particular, of three (3) Ausgrid clusters and four (4) Western Power clusters).

Load profile rescaling by DNSP

Finally, in order to recover the distribution, across each DNSP by residential customer, of total annual loads, a scaling factor that is constant across time, was applied for each representative residential customer profile shape (excluding the controlled load), such that the distribution across each DNSP of total annual loads followed a log-normal distribution with population mean consistent with that reported by each DNSP as part of the Regulatory Information Notices (see *Past and projected state and network scale annual load*.) Table 9 records the parameters of the target distributions.

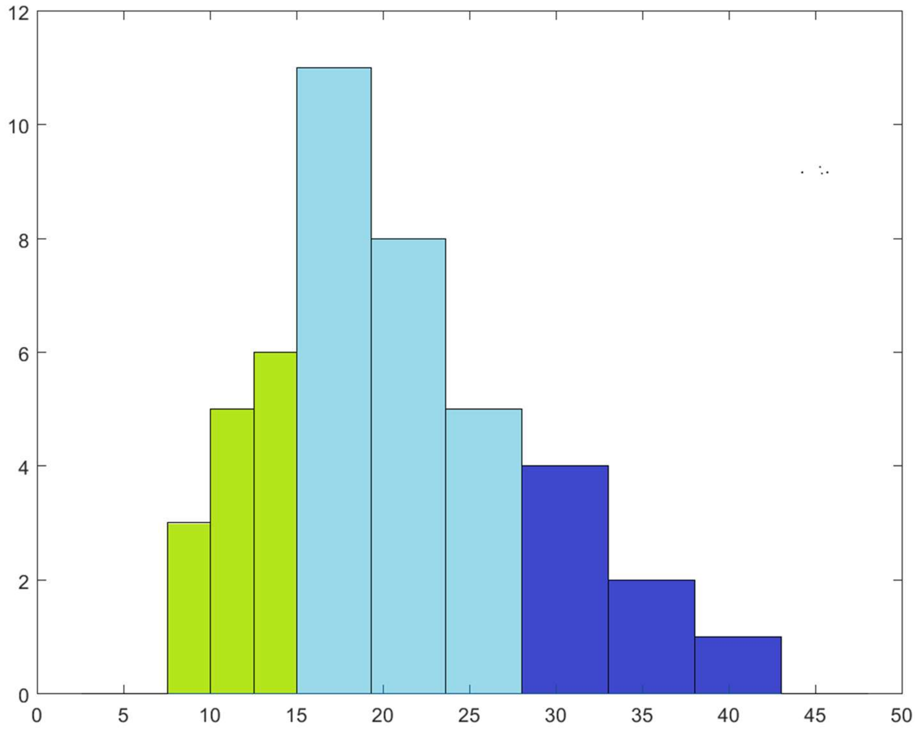


Figure 9: Frequency histogram of average daily demand (kWh) for rescaled representatives: Ausgrid

It is then possible to classify each of the 45 representative customers as either large, medium or small. Thresholds were chosen for this classification such that, assuming equal weighting for each of the 45 representative residential customers, the energy supplied to each magnitude customer category is approximately one third of the total residential load. Small customers are those with less than 15kWh/day consumption and large are those with more than 28kWh/day. The representative residential customer loads selected for Ausgrid include fourteen (14) small customers, twenty four (24) medium sized customers, and seven (7) large customers (see Figure 9).

Table 9: Residential customer scale distribution by DNSP

Residential Load (kWh pa)	(Arith) Mean	St Dev	Geometric Mean	Geometric Mean × St Dev Log	Mean log	St Dev Factor	St Dev Log
DNSP	μ(.)	σ(.)	exp(μ [ln(.)])	exp(μ [ln(.)]) × σ [ln(.)]	μ [ln(.)]	exp(σ [ln(.)])	σ [ln(.)]
ActewAGL	7 214	3 168	6 656	2 874	8.803	1.54	0.432
Ausgrid	5 439	2 388	4 968	2 145	8.511	1.54	0.432
Ausnet Services	5 035	2 211	4 585	1 980	8.431	1.54	0.432
Citipower	4 254	1 868	3 835	1 656	8.252	1.54	0.432
Endeavour Energy	6 006	2 637	5 489	2 370	8.611	1.54	0.432
Energex	6 433	2 825	5 901	2 548	8.683	1.54	0.432
Ergon Energy	8 211	3 606	7 552	3 260	8.930	1.54	0.432
Essential Energy	7 042	3 092	6 468	2 792	8.775	1.54	0.432
Horizon Power	11 603	5 095	10 599	4 575	9.268	1.54	0.432
Jemena	4 924	2 162	4 477	1 933	8.407	1.54	0.432
Powercor	3 716	1 632	3 339	1 441	8.113	1.54	0.432
SA Power Networks	5 885	2 584	5 381	2 323	8.591	1.54	0.432
TasNetworks	7 519	3 302	6 942	2 997	8.845	1.54	0.432
United Energy	4 743	2 083	4 317	1 864	8.370	1.54	0.432
Western Power	6 089	2 674	5 570	2 404	8.625	1.54	0.432

Source: DNSPs, Energeia and CSIRO

Commercial Customer Load Profiles

Representative commercial customer load profiles were constructed from the annual half-hourly load profiles of selected zone substations (see Table 10). These substations were selected manually, based on inspection of the daily average half-hourly load profiles (and weekly average daily loads), where they matched the typically expected daily pattern and weekly pattern of a commercial customer. The expected daily pattern is an overnight approximately constant base load, with higher consumption during working hours with a single peak tending towards mid-afternoon. The expected typical weekly pattern is for higher consumption during work days than on weekends. The annual half-hourly load profiles for each selected zone substation were normalised by average load to provide twenty representative per unit commercial load profiles. The twenty representative commercial customer loads were applied to all DNSPs, with no attempt to modify them to take into account climate or other spatial differences. See Figure 10 for an average daily profile at half-hourly resolution for three (3) of the twenty (20) representative commercial customers.

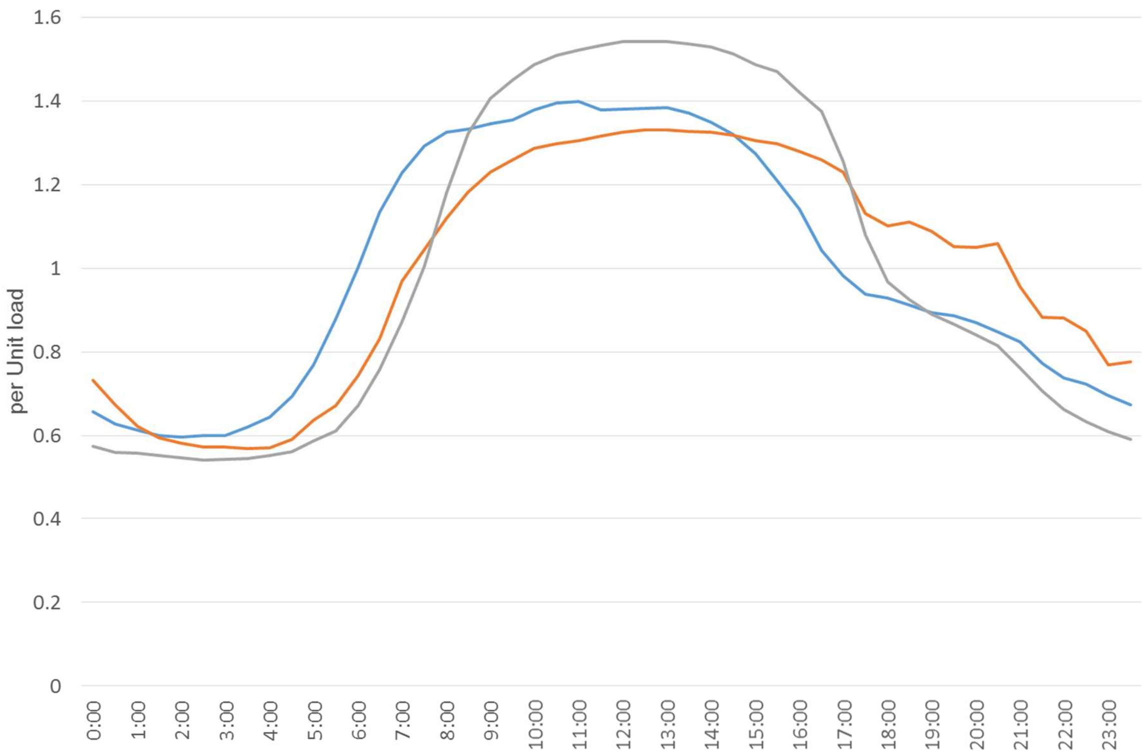


Figure 10: Normalised daily average half-hourly load profiles for three representative commercial loads

Table 10: Selected zone substations representing commercial load profiles

DNSP	Zone Code	Substation Name
ActewAGL	-	Raymond Terrace 33_11kV
Ergon Energy	-	Alpha Generator - Transformer
	BERS	Berserker - 66/11kV Substation Total
	CACI	Cairns City - Connection Point load with losses applied
	CETO	Central Toowoomba - 33/11kV Substation Total
	OAKE	Oakey - Substation Total
	RAGL	Raglan - 66/22kV Substation Total
Energex	AST	Ann St
	ATC	Astor Terrace
	CPC	Carole Park Central
	CST	Charlotte St
	CPL	Coopers Plains
	DRA	Darra
	LYTB	Lytton B
	MST	Makerston St
	OXL	Oxley
SA Power Networks	-	Cudmore Park 66/11kV
	-	Kilburn 66/11kV
Western Power	HAY	Hay Street
	MIL	Milligan Street

Source: Distribution Network Service Providers

Other Customer Scale Data

Customer scale sundry energy costs

The sources of cost estimates for customer scale technologies such as smart meters, solar PV and batteries, as mentioned in Energeia (2016), Table 2 are described below.

Metering costs for smart meters are as reported in Graham et al. (2015), p. 20. The projected costs for solar PV installation are consistent with those reported in EPRI (2015), based on reductions in costs due to technological learning modelled using the Global and Local Learning Model (GALLM) reported in Hayward and Graham (2013). Projected costs of batteries are consistent with Brinsmead et al. (2015). The solar PV cost projections include inverter costs, based on lowest identified international costs. It is assumed that an inverter that is suitable for both a PV and battery system is a more expensive model – the premium per $kW installed PV capacity for an inverter suitable for both PV and battery relative to a PV system alone is calculated as being equal to the difference between an average of identified inverter costs for small residential systems and the lowest identified cost. Battery costs per kW of installed PV are calculated on the basis of 2kWh of battery per kW of PV, that is, the equivalent of 2 hours storage. Price projections for Small scale Technology renewable energy Certificates (STCs) are taken from ACIL Allen (2015), Table 5, as described in Graham et al. (2015), pp31ff.

Customer behaviour

Traditional economic models have known shortfalls in regard to representing customer behaviour. The following points summarise our approach to modifying traditional economic approaches to accommodate more realistic consumer behaviour as it relates to the electricity sector.

- **Irrational economic behaviour**: To take into account that customers will not react in an optimal rational economic way to price signals, customer responses to alternative tariff and technology choices were modelled using a consumer adoption curve approach, partially calibrated to empirical evidence from past adoption of rooftop solar. A consumer adoption curve approach (also known as a logistic or S-curve) incorporates irrational behaviour from an economic point of view. At one extreme it assumes that a portion of customers will adopt new tariff/technology choices before it is economically rational to do so. At the top end of the curve it assumes that after a product choice becomes mainstream and overwhelmingly beneficial, there will be a portion of customers who will withhold adoption. While an adoption curve is a crude mathematical construct, it captures the concept of non-economic drivers which may accelerate or prevent customers from adopting new tariff/technology choices as they become available.

- **Capturing outcomes for active and passive customers**: Given we expect some customers will be active and others will remain passive in regard to new tariff/technology choices (regardless of the economic benefit), the economic modelling tracks the outcomes for customers throughout the projection period to determine whether proposed tariff reform pathways are beneficial to both types of customers. In other words, the economic modelling does not assume a scenario is beneficial unless it benefits a range of customer types, not just the '"average"' customer.
- **On tariff opt-in**: The economic modelling broadly accepts that there will be a low adoption of new tariffs if customers are required to be pro-active (e.g., where they are simply given the choice to opt-in). Accordingly, the economic modelling explores, through scenarios, different arrangements for tariff assignment including both opt-in and opt-out approaches (this is broadly covered in Energeia, 2016).
- **Relationship between network and retail tariffs**: Whilst examining the benefits of more cost reflective network tariffs, the economic modelling does not specifically assume that these tariffs need to be presented to customers directly in retail tariffs to achieve their intended outcomes. New network tariffs create a price signal that customers could directly access; however, retailers and other market actors could choose to internalise these signals and offer simpler price incentive/technology packages to customers and ensure that technology is operated in a way that makes the most of the network tariff structures or incentives.
- **Price elasticity**: The economic modelling broadly accepts the view that electricity consumption and load profiles are inelastic to price signals. Price responses are assumed to be modest and include rebound effects. On the whole, consumer load profiles are assumed to remain similar to present with technologies such as storage deployed to address price incentives.

Specific assumptions on cost driven behaviour change

A diversity in customer attitudes to taking up new technologies such as solar PV and batteries, or a willingness to take up new tariffs was represented as individual customers having differing thresholds, as expressed in return on investment (equivalently, payback period) required before motivating a behaviour change.

The long run population proportion *S(r)* that is expected to take up the option is assumed to be a function of return on investment *r*, modelled as an approximation to a cumulative normal distribution curve with two parameters, μ and σ, where the mean threshold μ is the return on investment at which 50% of the population is expected to adopt the option and σ determines the spread of the distribution, representing one standard deviation of the normal distribution curve.

Rather than using the cumulative normal distribution $(r) = \Phi(z) = \Phi(\frac{r-\mu}{\sigma})$, where $z = \frac{r-\mu}{\sigma}$, we use the approximation $\Phi(z) \approx (1/2)^{\exp\{-z/1.1\}}$ which departs from low values (representing early uptake) more quickly than the cumulative normal distribution and approaches unity (saturation) more slowly. This becomes an S-curve as a function of investment return

$$S(r) = (1/2)^{\exp\{(\mu-r)/1.1\sigma\}}$$

The parameters μ and σ of the total population distribution are developed assuming that the total population comprises five (5) groups as denoted in Table 11, each group with a normal distribution of investment returns required, with a 5% standard deviation. The total population distribution of required returns is then also approximately normal, with a mean and variance given by the weighted averages of the contribution from each group.

Table 11: Population density thresholds for estimated substation reliability ratings

Group	Weight (% of total)	Description of required rate of return	Mean return required	Std Dev
Autonomous	2.5%	Zero Nominal	-2.0%	5%
Technology Aware	5.0%	Zero Real	0.0%	5%
Active Consumers	30.0%	Savings Account	5.0%	5%
Passive Consumers	47.50%	Investment	10.0%	5%
Service Dependent	15.0%	Higher Risk Investment	15.0%	5%
Total	100.0%		8.45%	6.52%

The resulting range of effective payback period required covers:

- more technologically optimistic early adopters, or customers enthusiastic about the prospect of independence, who might be willing to accept a break-even return in nominal terms, through
- proactive consumers who might be willing to accept a return corresponding to interest in a savings account, mortgage, or financial investment product, through

- late adopters with a shorter term horizon commensurate with consumer goods or private motor vehicle financing, to
- vulnerable or risk-averse customers who might have a rate of return requirement similar to credit card interest rates.

It is further assumed that there is also a diversity of time lags which individual customers require before a behaviour change takes place, even if their individual payback period threshold is met. The uptake S-curves $S(r)$ show a relationship between the return on investment of a discrete option and the long run proportion of the population that is expected to take up that option. To take account of the time delay, the equation controlling the rate of adoption of a discrete option (or equivalently, the likelihood that any individual in the unchanged population will take up the new option) is defined by

$$ {}^{d}\!/_{dt}\left[\frac{p}{S(r)}\right] = \frac{1}{T(r)} \cdot \frac{4}{\left[1+\frac{1}{4}\beta\right]^2}\left\{1-\frac{p}{S(r)}\right\}\left\{\frac{p}{S(r)}+\frac{1}{4}\beta\right\} $$

where *p* is the proportion of the population that has taken up the option. This is a typical logistic differential equation closely related to the Bass diffusion model in Denholm, Drury and Margolis (2009) and R. W. Beck, Inc. et al. (2009). The time rate of change parameter, the turnover time, *T(r)* controls the rate at which the long run proportion of the adopting population is approached. The formulation of population growth above is quadratic in $\frac{p}{S(r)}$, reaching a maximum of $\frac{1}{T(r)}$ when the population proportion satisfies $\frac{p}{S(r)} = \frac{1}{2}\left(1-\frac{1}{4}\beta\right)$. However, it is also strictly positive even at an existing population proportion of zero, representing the autonomous, “advertising effectiveness” component of technology diffusion, in contrast to the “word-of-mouth” component that is proportional to the existing takeup. This autonomous component has a value approximately $\frac{\beta}{T(r)}$ for small positive fractions $0 < \frac{1}{4}\beta \ll 1$. We choose $\beta = \frac{1}{4}$. It is assumed that the turnover time is equal to the simple payback period $T(r) = \frac{1}{r}$, up to a maximum of *T(r)*=25 years for r<4%. This gives an autonomous component of ${}^{d}\!/_{dt}\left[\frac{p}{S(r)}\right] \sim \frac{1}{100}$ for payback periods greater than 25 years.

Pricing Scenario Analysis

The following sections describe results of modelling and analysis that is based on the data sources described in this report. Only brief summaries of results from, incentives and pricing analysis, and the electric vehicle component, transport and building electrification analysis, are given here, because the results are presented in more detail in other reports. The results of the modelling of *Roadmap* benefits, however, are presented here in greater detail, see *Evaluation of Roadmap benefits*.

The Pricing Scenario analysis, provided an analysis of various alternative network tariffs, incentive and cost assignment structures is likely to affect various key indicators of the performance of Australian electricity networks. These include:

- overall economic cost and greenhouse gas emissions performance
- customer decisions whether to remain grid connected, whether to invest in distributed energy resource technologies, and if so, how much and how to operate, which electricity tariff of available alternatives to select, and what behavioural changes in the patterns of demand might result.
- expenditure on network infrastructure, including smart meter infrastructure
- network prices and consumer bills.

The results are reported in Energeia (2017), with the modelling details presented in Energeia (2016): see also Table 1 herein for a cross-reference between the data assumptions and the location in this report where the sourcing is described in more detail.

Pricing Scenarios

Various scenarios were investigated, split into two sets. “First wave” pricing reform scenarios, involve comparatively modest tariff reform with advanced metering permitting time-of-use and maximum demand based tariffs. More sophisticated “Second wave” pricing reform scenarios, involve additional tariff options including a “critical peak” pricing tariff. This is where electricity prices available to consumers and their timing may change at short notice, subject to limitations, to allow networks to encourage the use of distributed energy resources during the specific, short duration, time periods of otherwise high demand.

There were three “First wave” pricing reform scenarios, plus a supplementary sensitivity scenario. These were

- Scenario 1 – A base case approach to network tariff and incentives, retaining current tariff structures, time-of-use pricing and peak demand pricing, over the projection period. Customers may change their tariff from their current ones, but only on an opt-in basis.
- Scenario 2 – While current tariff structures are retained, all new and replacement customers, as well as customers who adopt or upgrade

distributed energy resource technologies (PV and/or batteries) are assigned advanced meters and maximum demand tariffs on an opt-out basis.

- Scenario 3 – As for scenario 2, with the modification that from 2021 all other customers, in addition to new, replacement customers and those that adopt or modify their distributed energy technologies, are also assigned advanced meters and tariffs by default.
- Scenario 3 (Adjusted) – When the universal change to an opt-out maximum demand tariff is implemented in 2021, the relative assignment of costs to maximum demand and energy delivery is permitted by the regulator to allow greater weighting to be placed on the capacity component.

There were three additional "second wave" pricing reform scenarios. These pricing scenarios are distinguished by tariffs that are dynamic (that is specific prices and timing may be determined after the beginning of the contract period) and may also be locational (that is specific to substation zone). The second wave pricing scenarios are:

- Scenario 4 – As in Scenario 3, with the addition of an opt-in, non-locationally specific, Critical Peak Price tariff alternative in 2021.
- Scenario 5 –As in Scenario 3, but where consumers are not offered a Critical Peak Price tariff alternative, but instead a tariff that permits the network operator to operate their batteries, which is exploited (locationally) to manage peak demand at each zone substation.
- Scenario 6 – As in Scenario 5, but also allows short-term contracting (up to 3 years) of additional distributed energy resources in any substation zone in order to defer network augmentation.

Pricing Scenarios Results Summary

The results of the analysis of "First wave" tariff reform demonstrate economic benefits from moving to more cost-reflective pricing, but also suggest that an opt-out tariff change framework is a key strategy for ensuring more cost-reflective tariffs are adopted.

The analysis also finds that there are additional benefits to managing the network in a way that is specific to both the timing and location of peak capacity demands on the grid. This could be achieved via additional tariff offerings investigated as part of the "second wave" pricing reform scenarios to ensure that there are incentives that are aligned with both the timing and location of costs and/or savings of the operational adjustments that could be implemented.

Electric Vehicle Scenario Analysis

Analysis of transport and building services electrification is reported in Graham and Brinsmead (2016). It provides an analysis of the potential for electricity to substitute for other energy sources (primarily gas) in buildings, as well as potential costs and benefits of electrification of the national transport fleet. The data described in this report was used extensively in the transport electrification analysis, but less so for the building electrification analysis. Therefore, in this section we provide a brief summary of the vehicle electrification results.

The analysis builds on results from Energeia (2016), considering the impact of electric vehicle uptake on network infrastructure requirements under two alternative pricing scenarios (see also *Pricing Scenarios*). These include Pricing Scenario 1, essentially the base case, with relatively unsophisticated electric vehicle and network control, and Pricing Scenario 5, one of the "second wave" pricing reform scenarios allowing time and location based distributed energy resource management, which corresponds to an electric vehicle charging regime that is also time and location managed to optimise benefits to the network.

The key indicator of the performance of these alternatives is the extent to which network maximum demand is affected by the inclusion of electric vehicles as part of the total electricity demand.

Electric Vehicles Scenarios

In order to investigate the potential impact of electric vehicles on network maximum demand we considered the following scenarios.

- Pricing Scenario 1 – no EVs

    Starting with projected demand by zone substation (see *Zone substation half-hourly load: Projections*), demand was amended by the addition of solar profiles according to the percentage provision of load from PV, by year and zone substation, as provided by Energeia representing Pricing Scenario 1 of Energeia (2016). This enabled the calculation of demand by zone substation, both gross and net of solar generation.

- Pricing Scenario 1 – with EVs, all convenience charging

    As for the scenario above, but with EV charging profiles added as well. In this scenario, the EV profiles considered are "convenience charging" profiles rather than "capacity constrained" profiles (see Figure 6). The EV charging profiles are not specifically managed to limit demand on the network.

- Pricing Scenario 5 – no EVs

  Starting with projected demand by zone substation (see *Zone substation half-hourly load: Projections*), demand was amended by the addition of solar profiles according PV uptake results provided by Energeia representing Pricing Scenario 5 of Energeia (2016).

- Pricing Scenario 5 – with EVs, significant deployment of PV, battery load balancing, capacity constrained and overnight managed charging of EVs

  As for the scenario above, but with EV profiles added. In this scenario, the EV profiles initially considered are "capacity constrained" charging profiles rather than "convenience" profiles. The capacity constrained charging profile has been specifically designed to limit maximum demand. In addition, it is assumed that a proportion of EVs are further managed to limit maximum demand on the local zone substation network. As a consequence, an additional proportion of electricity demand due to EVs is spread out during the day. The proportion of managed EVs corresponds to the percentage of residential customers who are not on a flat tariff, these figures provided by Energeia as part of the results of Pricing Scenarios. Detailed analysis of the impact of electric vehicle charging regimes indicates that, for most zones, the electric-vehicle charging peak coincides strongly with the peak of the balance of demand. Managed charging, however, enables a significant proportion of the peak due to electric-vehicles to be shifted elsewhere.

Electric Vehicle Scenarios Results Summary

The modelling finds that electric vehicles could play a very significant role in improving network capacity utilisation. However the benefits are largely in the period between 2030 and 2050 rather than immediate. This is because the medium case scenario examined does not lead to significant electric vehicle adoption in the road passenger vehicle fleet until after the late 2020s.

The modelling also finds that the benefits of electric vehicle adoption are maximised if deployed into a pricing and incentive environment that encourages almost all customers to undertake off-peak charging. However, the since the additional consumption of electricity is proportionally greater than the impact on peak demand in the worst case scenario, electric vehicles remain beneficial even if price reform proceeds at a slower pace.

Evaluation of *Roadmap* benefits

Networks have a changing, but important, role in helping to enable balanced customer objectives through a connected energy future. *The Electricity Network Transformation Roadmap*, has been developed to analyse a significant period of change in the national electricity sector. It provides an evidence based action plan, for realising a balanced set of outcomes for customers: reliability, affordability, reduced greenhouse gas emissions, fairness and customer choice*.* Many elements of the *Roadmap* scenario are based on some of the results of analysis of pricing and incentives and efficient capacity utilisation (including electric vehicles).

CSIRO has calculated the impact of the *Roadmap* and *Counterfactual* scenarios to determine the value of the entire *Roadmap* (where quantification is possible). The *Counterfactual* scenario describes what happens if the *Roadmap* is not implemented and the status quo or extension of current trends prevails.

Electricity Network Transformation *Roadmap* Scenarios

Roadmap scenario

The *Roadmap* scenario includes combinations of activities from across the many *Roadmap* domains and milestones that support each other to deliver lower costs, decarbonisation, fairer prices and rewards for energy services and improved reliability. These have been simplified into three broad key elements for the evaluation of *the Roadmap* scenario as follows:

- **Price and incentive reform plus optimised networks and markets** means distributed energy resources adoption is enabled and delivering network capacity reduction tuned to each zone substation (See Scenario 5 in Energeia 2016, 2017 and *Pricing Scenario Analysis* herein.)
- **Efficient capacity utilisation** is achieved through 20% adoption of electric vehicles by 2035 with managed charging (See Graham and Brinsmead 2016 and *Electric Vehicle Scenario Analysis* herein.)
- **Electricity sector decarbonisation** does more than its proportional share of current national abatement targets (i.e. achieving 40% below 2005 levels by 2030) and accelerates that trajectory by 2050 to reach zero net emissions (100% abatement) due to strong power system security performance assisted by distributed energy resources orchestration

Counterfactual scenario

Conversely, the *Counterfactual* scenario includes the following three broad key elements:

- Today's approach to pricing and incentive environment prevails (relying on customer opt in to fair and efficient tariffs) resulting in **slow and incomplete**

adoption of incentives for demand management (See Scenario 1 in Energeia 2016, 2017 and *Pricing Scenario Analysis* herein.)

- **No adoption of electric vehicles,** consistent with current national electricity system planning assumptions
- Electricity sector delivers abatement of 35% by 2030 and 65% by 2050 reflecting **ongoing carbon policy uncertainty and lack of confidence in and coordination of resources** for delivering lower emissions and high variable renewable energy (VRE) penetration with high power system security performance

Scenario modelling assumptions

The main modelling assumptions with respect to technology costs, fuel prices and other model inputs have been discussed in previous sections. However, the following provides more specific information on the key scenario assumptions.

Emissions pathways

Although the *Counterfactual* represents an extension of current trends it would not be plausible to assume that Australia does not reduce electricity sector emissions given our current intended national emission target of 26-28 percent below 2005 levels by 2030. In fact all extant, economy wide, analyses of decarbonisation show that it is most efficient for the electricity sector to do more than its proportional share of abatement, given the lack of comprehensive solutions to emissions reduction in other sectors (Treasury, 2011). The longer term commitment to stabilising the additional average global temperature increase to 1.5-2 degrees Celsius also implies that the electricity sector will need to accelerate abatement either before 2030 or in the period 2030 to 2050 towards zero emissions (CCA, 2016).

In the *Counterfactual* scenario the electricity sector delivers only moderately more than its proportional share in 2030 and does not accelerate abatement but rather continues the same rate of abatement per annum (Figure 11). The *Roadmap* scenario is a more ideal emission reduction pathway in the sense that it meets expectations of what will be required for the electricity sector to support national emissions reduction goals in 2030 and in the longer term.

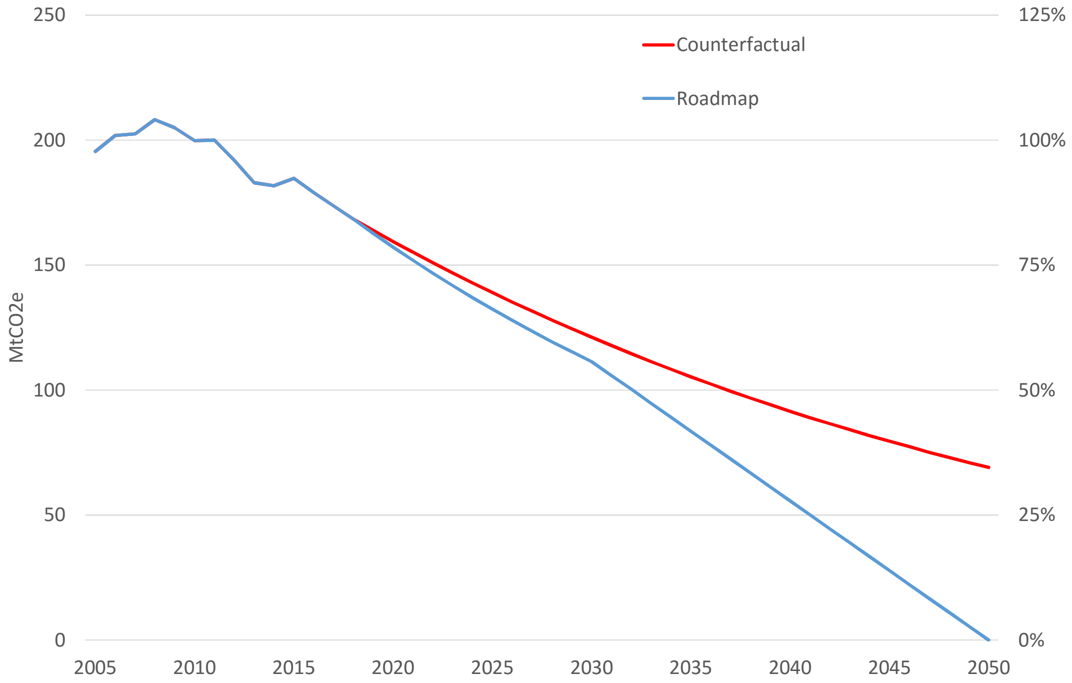


Figure 11: Greenhouse gas emissions reduction pathways under the Roadmap *and Counterfactual scenarios*

These emission targets are applied as a constraint in the modelling framework, representing any scheme whereby there is a limited amount of allowable emissions and new plant is subsidised by the system to come in and lower the emissions rate as older existing plant are forced out. An emission intensity or baseline and credit scheme would be the most analogous market based policy framework to achieve this outcome. Additional research commissioned for the *Roadmap* completed by Jacobs (2016) found an emission intensity scheme would have the lowest impact on electricity bills. This is a finding also supported by CCA (2016).

Pricing and incentives

The specific assumptions with regard to pricing and incentives are adopted from the analysis by Energeia (2016) who examined six alternative tariff pathways for Australia (see *Pricing Scenario Analysis*). The “Pricing Scenario 1” presented in Energeia (2016) is the closest to an extension of current trends representing slow changes in electricity pricing and incentives and is adopted as the *Counterfactual* case in this report. “Pricing Scenario 5” in Energeia (2016) is the closest to the ideal outcome for pricing and incentive reform and is adopted as the pricing and incentive assumption for the *Roadmap* scenario. The pricing and incentive environment is important because it determines the uptake of distributed energy resources such as rooftop solar PV, battery storage and electric vehicles and can support more efficient use of those resources to support not only customer needs but also the needs of the electricity system. Changes to prices and incentives also more fairly assign costs to customers according to their use of the electricity system. Figure 12 shows how the percentage of customers who have taken up fairer and more efficient tariffs differs between the *Roadmap* and *Counterfactual* scenarios.

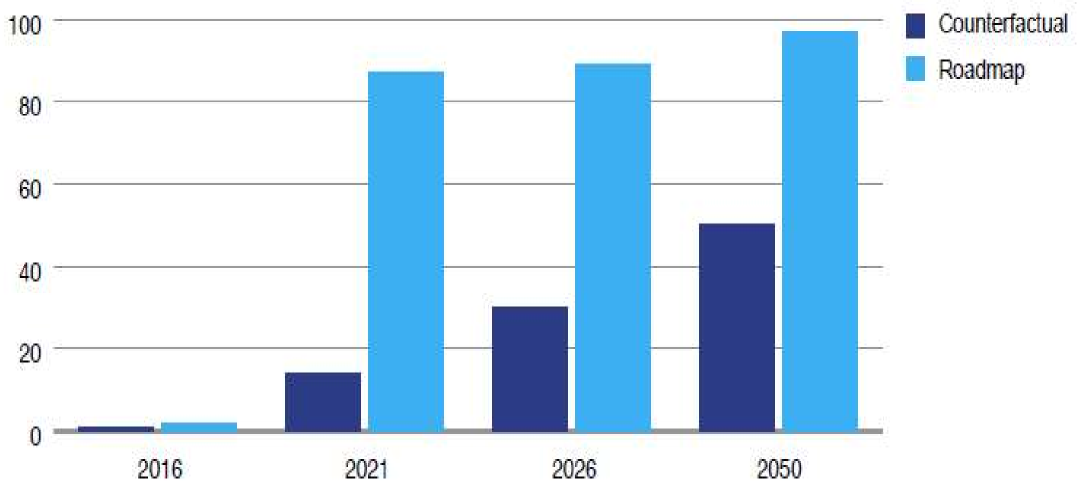


Figure 12: Percentage of customers who have taken up fairer and more efficient tariffs under the Roadmap *and Counterfactual scenarios*

Electric vehicle adoption

The origin of the *Roadmap* scenario electric vehicle adoption assumptions is explained in Graham and Brinsmead (2016). It explores a mid-range electric vehicle adoption scenario under the Energeia (2016) faster reform of pricing and incentives scenario ("Pricing Scenario 5"). As such the electric vehicle charging is well managed in response to incentives so that peak demand does not increase significantly. However, electric vehicle adoption adds a significant amount of additional consumption which is shown in Figure 13.

Consistent with current AEMO electricity forecasting, the *Counterfactual* assumes no electric vehicle uptake during the projection period (other than the negligible number of vehicles already in the fleet).

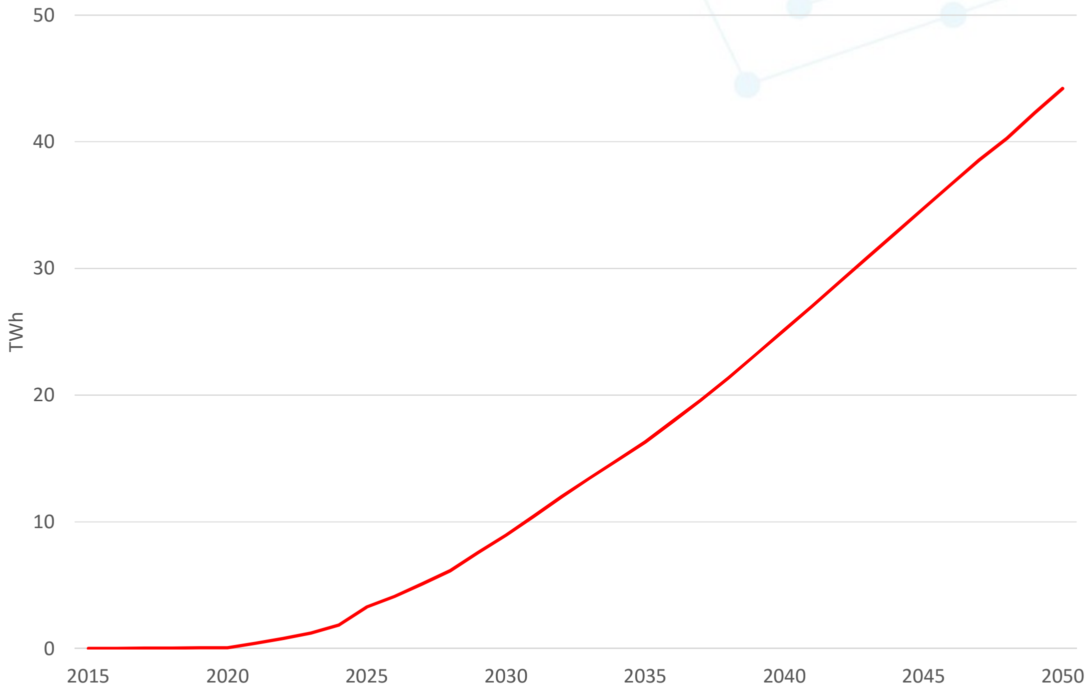


Figure 13: Additional electricity consumption from electric vehicle adoption under the Roadmap *scenario*

Demand and rooftop solar adoption

State electricity consumption is assumed to be equal to that in AEMO (2016a) but with two changes:

- AEMO's projected adoption of rooftop solar PV and batteries is replaced with that which Energeia (2016) projected for the *Counterfactual* and *Roadmap*
- As discussed above, the *Roadmap* scenario adds consumption from electric vehicle adoption.

The projected adoption of rooftop solar PV and batteries for the *Roadmap* and *Counterfactual* scenarios is shown in Figure 14. It reflects both increased share of customers as well as large solar/storage system sizes. The *Roadmap* scenario has slightly lower projected adoption of rooftop solar PV and batteries by 2050, but the differences are not large. The slight difference is because electricity bills are lower in the *Roadmap* scenario due to the impact of more efficient and fairer changes to electricity bills, reducing the relative attractiveness of distributed energy resources. However, distributed energy resources remain highly attractive in both scenarios because, due to the impact of decarbonising the electricity sector, retail electricity prices are increasing and the cost of these technologies are falling.

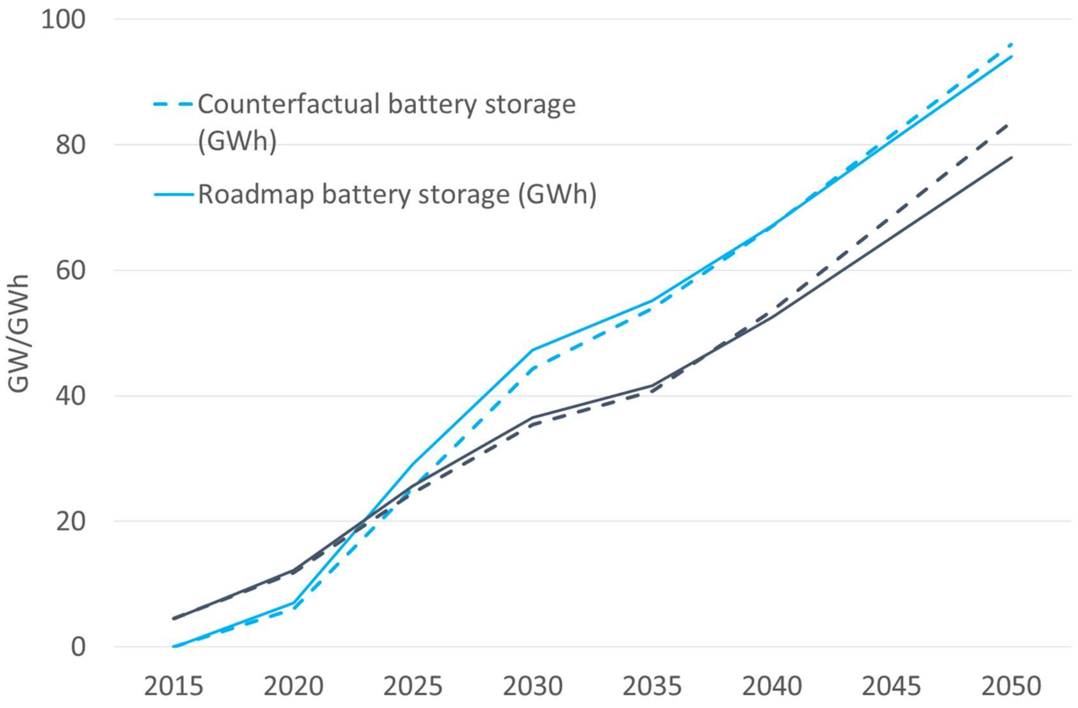


Figure 14: Projected adoption of rooftop solar and battery storage under the Roadmap *(left) and Counterfactual (right) scenarios*

State rooftop solar and battery adoption assumptions under the *Roadmap* scenario

In this section we provide state detail on rooftop solar PV and on-site battery adoption which are assumed to occur under the *Roadmap* scenario from which the original source is Energeia (2016). Given the similarity in outcomes we do not disaggregate the state results for the *Counterfactual* scenario but the state trends remain broadly relevant for that scenario as well.

State rooftop solar PV adoption

Rooftop solar PV reached just over 5.5 GW in 2016 with the state differences largely reflecting historical state subsidies, the relative solar irradiance and population sizes. Subsidies provided in South Australia and Western Australia have allowed those states to achieve high rooftop solar PV installation rates relative to their population sizes. These were generally in the form of a guaranteed price for rooftop solar PV exports to the grid that was well above the wholesale price of electricity. *The Roadmap* assumes that there will not be a further round of specific state subsidies (and that the national subsidies available from the Small-scale Renewable Energy Target will also decline to zero). Consequently, future rooftop solar PV adoption will be increasingly driven by customers evaluating the merits of ownership on a non-subsidised basis, rather than any state specific policy interventions.

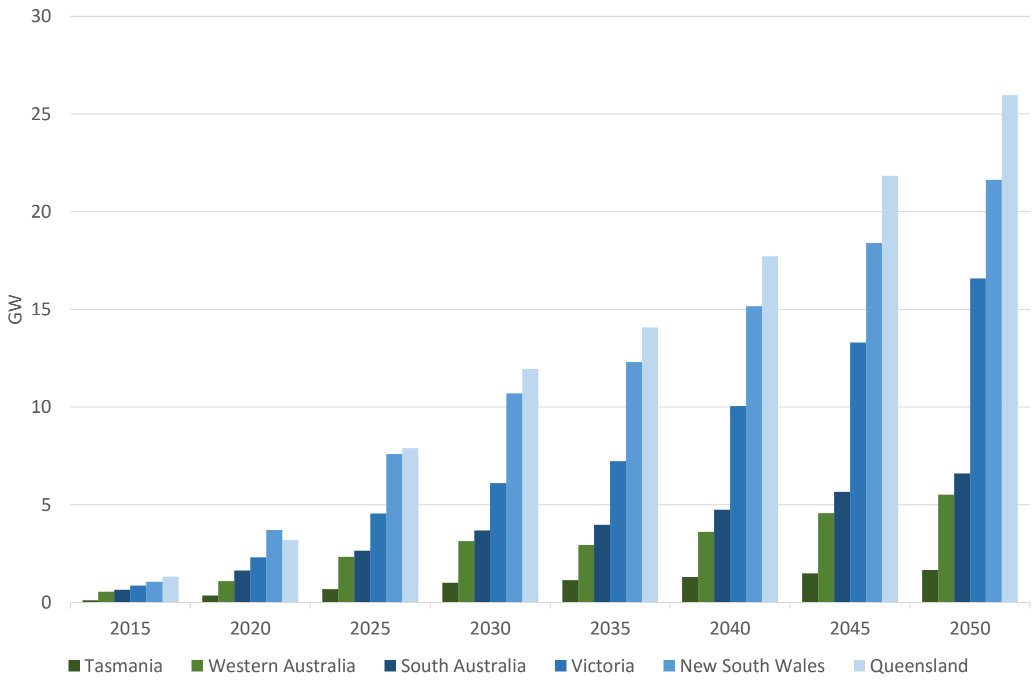


Figure 15: Projected installations of rooftop solar by state

With grid supplied electricity prices expected to increase due to the cost of decarbonising the large scale electricity generation sector, an increasing share of both residential and commercial customers are expected to install rooftop solar PV (Figure 15). Rooftop solar PV will be most attractive for customers in northern or western states where solar irradiance is higher. However, after this factor is taken into account, the relative differences in state installations reflect the population distribution. The higher absolute level of solar capacity reflects both increasing customer adoption and larger average systems sizes – average new system sizes have historically increased from around 2kW in 2010 to 5.5kW in 2016 and this trend is expected to continue.

State onsite battery storage

While negligible to date, installations of battery storage for home or business onsite energy balancing have commenced in Australia such that they now can be purchased as a standardised product with and without rooftop solar panels. To understand the state results we first need to review the drivers for battery adoption overall.

The collection of installation data is in its infancy, however, it is widely reported that existing rooftop solar PV owners, seeking to derive greater value from their existing investment, are the primary early adopter group. Battery storage also represents an opportunity for customers to further reduce their dependence on the grid, which can be an important non-financial driver.

Future drivers of battery adoption are expected to be become more complex over time. In the first period to the early 2020s, battery storage installation is expected to be primarily driven by the advantages to rooftop solar PV owners of allowing them to reduce the amount of solar output that has to be exported when demand on site is too low when the energy is available. As discussed above, state government subsidised export prices for rooftop solar have largely come to an end. The prices received for exports without those subsidies are now around 6c/kWh which is well below the value of that electricity if the owner were able to use it on site (which we could value at prevailing retail prices for grid supplied electricity of around 22-27 c/KWh).

From a purely financial point of view, battery storage capacity is viable if it can be installed at a cost that is lower than the value of exploiting this ‘gap’ in solar export and grid import prices. Although that case is marginal at present, there is a strong expectation that the ‘gap’ will widen over time and battery storage costs will fall.

In the period of the mid-2020s to 2050, the motivation for battery storage installation under the *Roadmap* are expected to change as prices and incentives change. With a much larger cohort of customers receiving a service that includes a demand based tariff, batteries will be doing more than shifting rooftop solar output. In addition, they will be used to manage network critical peak days (5 days per year) and daily peak pricing periods. As the electricity market evolves further it is anticipated that battery owners may delegate control of their battery to other agents who can fine tune and aggregate battery operation to maximise the rewards for assisting with energy balancing, for both the local network zone substation and the state generation node.

This wide ranging and very important role envisaged for battery storage means that the factors that will play into state level adoption include existing and future solar installations, the specific critical peak and daily peak prices offered in each state, the state opportunities for avoided network augmentation and the relative need for wholesale market energy balancing or variable renewable penetration. Of these, rooftop solar PV adoption is the strongest factor, as the similarity to Figure 15 of the projected installations in Figure 16 suggests. Nevertheless, others factors will increase in importance over time.

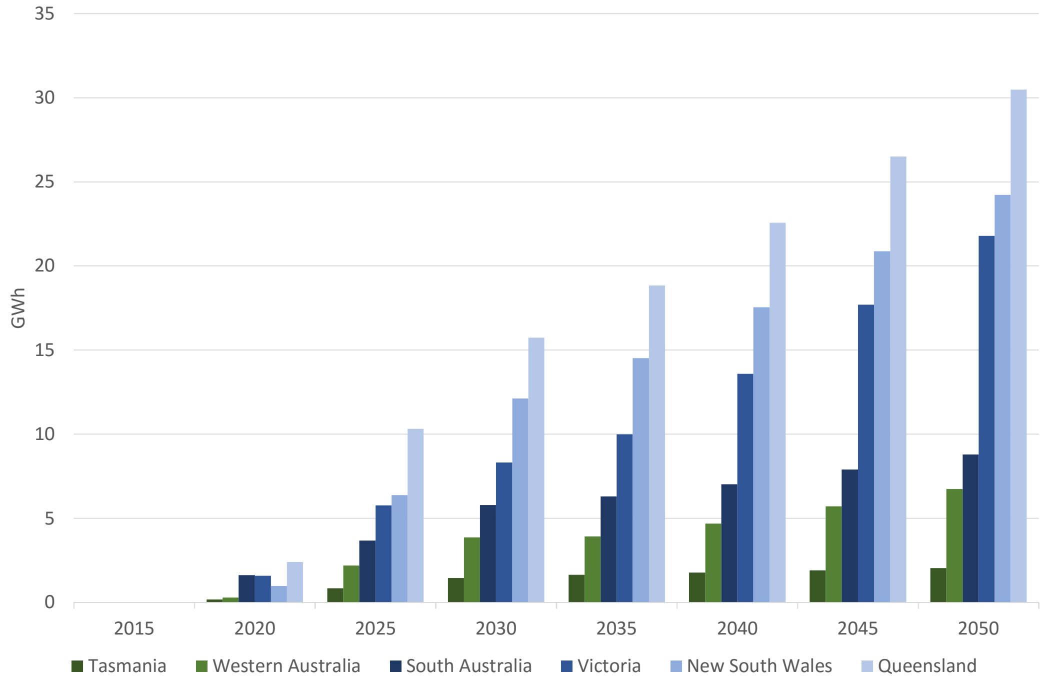


Figure 16: Projected installations of onsite battery storage by state

Maximum demand

The projection for maximum demand was established by using the AEMO (2016a) forecast as a starting point from which Energeia (2016) applied their tariff and technology adoption model to establish a new maximum demand projection. The new maximum demand projection is based on customer responses to tariff options and subsequent operation of their distributed energy resources to minimise their electricity bills. The type of tariff adoption is different in the *Roadmap* and *Counterfactual* scenarios, with the *Roadmap* scenario having much lower growth in peak demand due to more efficient use of distributed energy resources which reduces demand peaks at the substation level. The projections for non-coincident aggregate zone substation peak demands under the *Roadmap* and *Counterfactual* scenarios are shown in Figure 17.

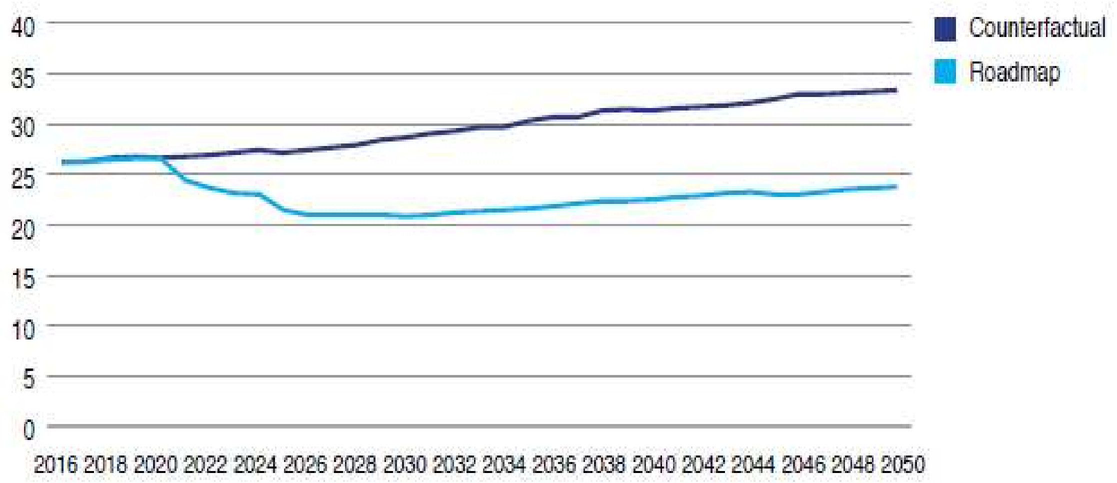


Figure 17: Non-coincident zone substation peak demand under the Roadmap *and Counterfactual scenarios (in GW)*

CSIRO makes a slight modification to the *Roadmap* projection by adding electric vehicles which were not part of the Energeia (2016) analysis. Electric vehicle adoption is fairly negligible before 2030 and in the period between 2030 and 2050 is well managed due to high adoption of prices and incentives that encourage off-peak charging of electric vehicles. Consequently, the inclusion of electric vehicles adds just less than 1GW by 2050.

Additional capital requirements in a low synchronous generation system

The *Roadmap* scenario achieves a 100 percent reduction in greenhouse gas emissions through deployment of largely non-synchronous renewable generation technologies such as solar photovoltaics and wind. As we will see in the modelling results section we manage the half hourly supply and demand matching challenges of such a high variable renewable generation system through a combination of battery storage, dispatchable biogas peaking plant and the natural diversity in renewables supply. Conservatively, we do not rely on state interconnections to support supply and demand balancing but provide some indicators that it would also be a useful strategy.

However, the ability to match demand and supply does not guarantee the stability of a high variable renewable system. Electricity systems also require frequency control services which are a bi-product of existing synchronous generation technologies but are not supplied by non-synchronous variable renewables. There are expectations that batteries will be able to supply these services. However, to be conservative, the modelling has assumed an additional capital cost of $200/kW in proportion to battery capacity installed (in watts) to cover the cost of additional frequency control equipment. This could, for example, take the form of synchronous condensers.

Roadmap modelling results

In this section we outline the modelling results of the *Counterfactual* and *Roadmap* scenarios for the generation and network sectors and conclude with impacts on customers.

Electricity generation

Counterfactual generation mix

Under the *Counterfactual* scenario, total electricity consumption is increasing, consistent with AEMO forecasts, however generation supplied by large scale, transmission connected, generation technologies falls due to greater generation from rooftop solar panels (Figure 18). To meet the emission pathway constraint, in addition to greater rooftop solar PV generation there is an initial reduction in brown coal generation, reflecting the planned Hazelwood closure and an expansion in wind and large scale solar. Expansion of wind and large scale solar is initially in support of the Renewable Energy Target. However we assume that the Victorian target of 40 percent of renewables by 2025 is also met.

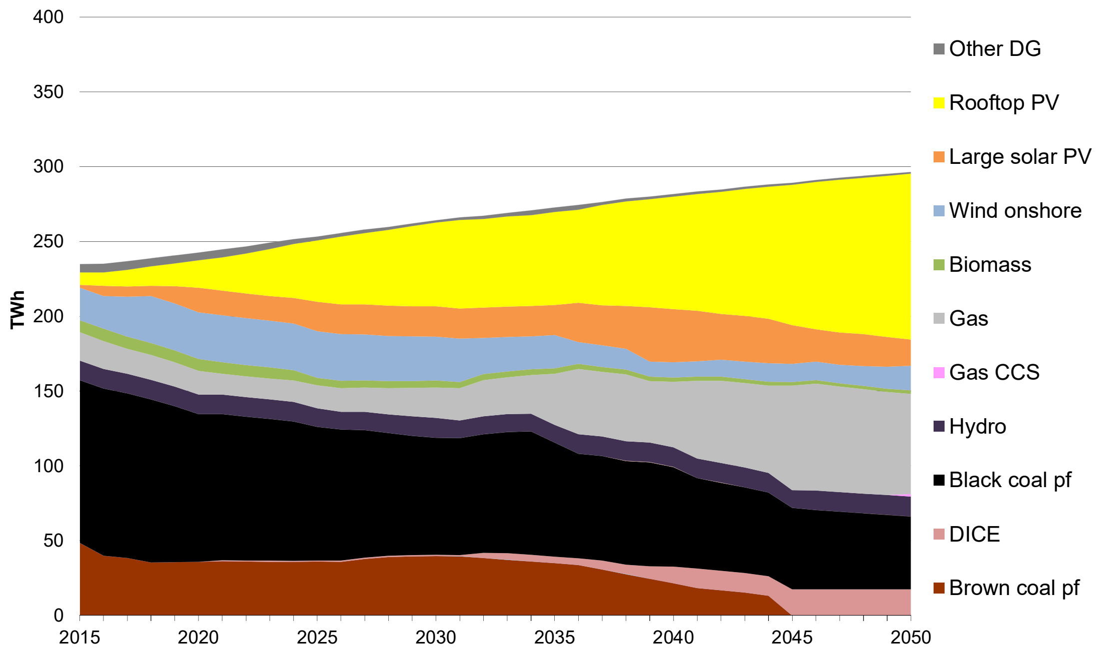


Figure 18: Projected large scale and onsite electricity generation by technology type under the Counterfactual scenario

Gas-fired generation is projected to increase from the late 2020s. This expansion accelerates in the 2030s with the increasing rate of retirement of existing black and brown coal plant. Large scale solar and direct injection carbon engines (which are a type of diesel engine using a coal based liquid fuel) are also deployed during this period. In the last year of the projection period there is a small deployment of gas with carbon capture and storage. However, overall, the projection suggests that carbon capture and storage technologies are not generally required to meet the emission limit – a combination of existing coal retirements, deployment of new mid-range emission fossil fuel technologies plus solar and wind reduce emissions below the assumed target for this scenario.

Roadmap generation mix

The projection for large scale and onsite generation for the *Roadmap* scenario is shown in Figure 19. Total electricity consumption is higher than the *Counterfactual* scenario owing to the demand from electric vehicles. To meet additional demand in the period to 2030, the *Roadmap* scenario includes fewer black coal retirements and higher natural gas-fired generation.

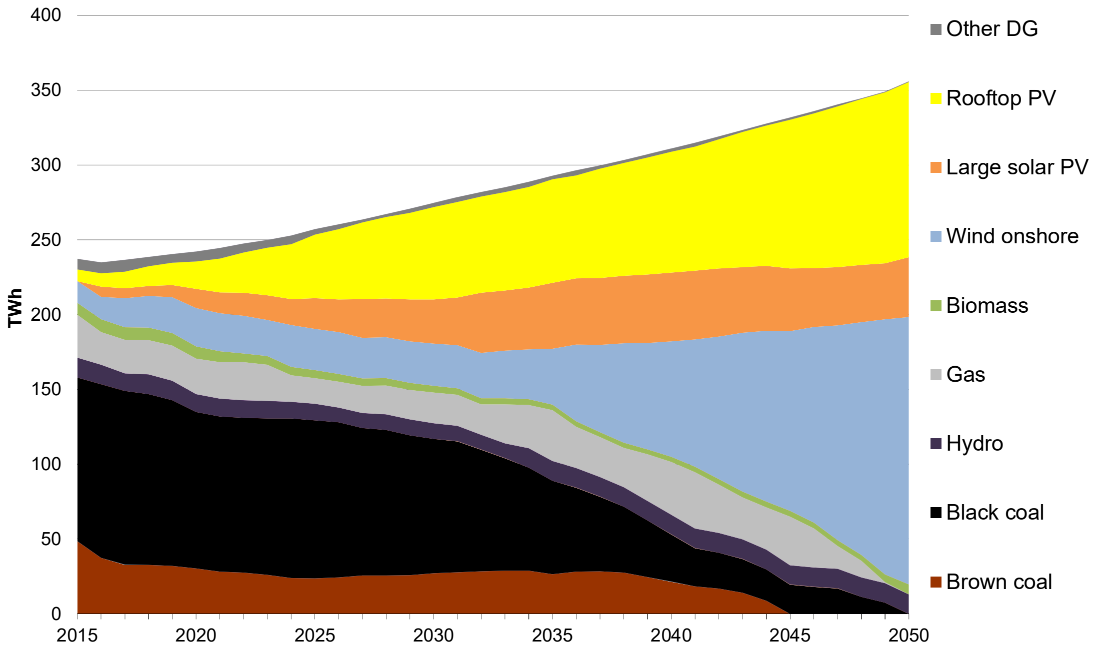


Figure 19: Projected large scale and onsite electricity generation by technology type under the Roadmap *scenario*

In the period 2030 to 2050, the generation mix converges towards decreasing coal and gas, replacing them with the currently most commercial renewables – large scale solar photovoltaics and wind – supported by battery storage. This does not represent a least cost zero emission electricity mix. To optimise such a system for least cost would have taken an enormous amount of study of alternative options including expanded transmission, pumped hydro, power to gas, solar thermal with storage, nuclear, enhanced geothermal and carbon capture and storage (perhaps including biomass) and hydrogen fuel cells. Instead our goal was to find one plausible, reasonable cost way of meeting the target of zero emissions by 2050 using technologies that were reasonable well understood. Wind, solar and batteries have a high degree of commercial maturity, however, it is recognised they have not been deployed at the scale envisaged here. We also recognised that a large volume of batteries were likely to be deployed through customer choices regardless of the policy settings for large scale generation. Therefore, this represents a potential resource that can be utilised by the generation sector with appropriate pricing and incentive arrangements.

The modelling generally finds that renewable diversity is valuable in balancing a high variable renewable generation sector and hence the *Roadmap* scenario leads to a more even share of solar and wind generation by 2050 than the *Counterfactual* scenario. The following section provides more detail on how the system was balanced under high variable renewable generation share.

***Roadmap* battery storage modelling**

A key task in modelling this *Roadmap* generation mix was to determine how many batteries would be required to balance the system. A specific modelling tool was developed to determine the optimal amount of battery storage required in each state. Given the computational intensity of the analyses, the storage optimisation model was only applied at each decade interval. However, this was sufficient to conclude some broad trends and relationships and ensure that costs of storage could be incorporated into the *Roadmap* system costs. A more detailed description of the nature of the analysis and results for an example year in South Australia can be found in the Appendix.

Figure 20 shows the required ratio of battery capacity to variable renewable generation capacity to achieve energy balancing for a given renewable energy share, by state. It indicates that battery storage is generally not required until high levels of renewable energy share but may form part of an optimised system in Victoria and Queensland when renewable share reaches 30-40 per cent. The data also indicates more than one possible storage level within each state and renewable share. This is because in some implementations of the storage optimisation tool we allowed the state to “overbuild” renewable capacity (at a loss to their average capacity factor) and at high renewable share this is more cost effective than building additional storage.

As the renewable energy share approaches 100 per cent the amount of battery storage increases non-linearly and approaches a ratio of the order of 1 to 1 with installed capacity of variable renewables. However, there is significant variance around this average ratio by state which reflects the character of renewable resources available. Tasmania generally requires a much lower ratio due to its large existing hydro power capacity and there are circumstances where New South Wales and South Australia may be able to deploy a lower ratio of batteries. Queensland and Victoria require higher ratio possibly reflecting poorer wind resources in the former and solar resources in the latter. However, given the modelling only explored one weather year, further study would be required to draw strong conclusions.

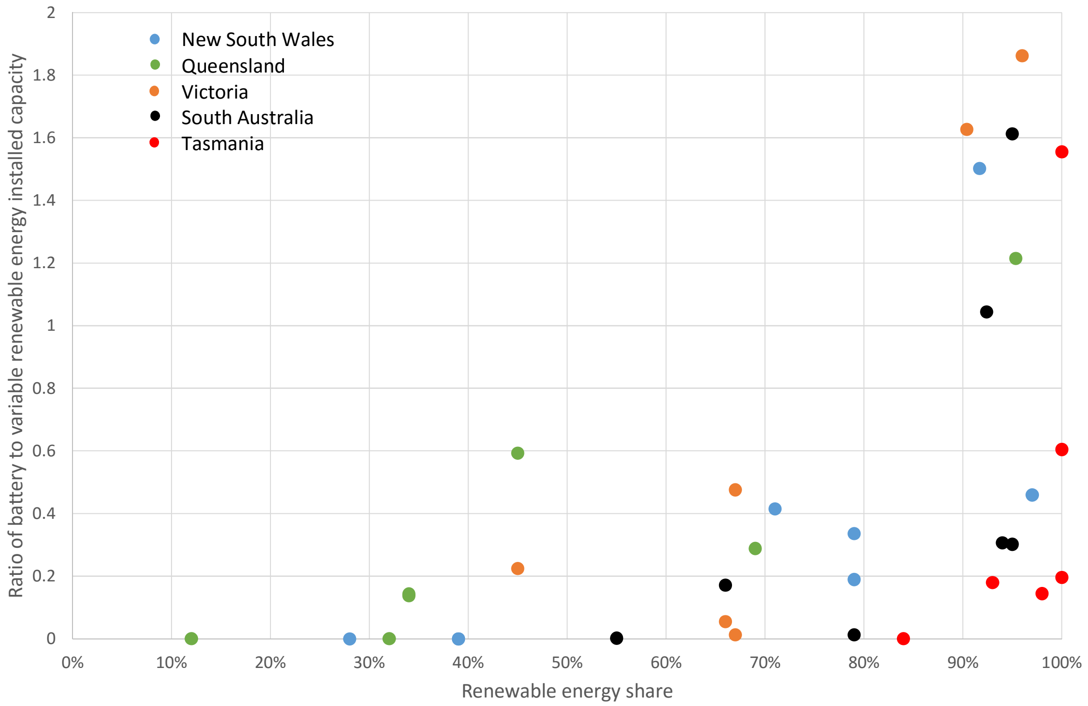


Figure 20: Projected ratio of battery capacity to variable renewable generation capacity to achieve energy balancing for a given renewable energy share, by state

To provide more insight into the analysis we also plot the hours of battery capacity at average state load against the renewable share in Figure 21. The analysis indicates that up until 80 per cent renewable share, less than five hours of battery storage at average state load are required to support energy balancing. See the Appendix for a case study example of a typical profile of storage and generation for high percentage of intermittent renewables. However, approaching 100 per cent renewable share, with the exception of Tasmania, battery storage hours required increases non-linearly. We found in some cases the battery requirement becomes very large relative to the load, at greater than 20 hours. In these cases it was concluded that additional gas peaking capacity would be more effective (and biogas is used when the emission constraint does not allow for natural gas). The total capacity of gas peaking plant required was not equal to peak demand. Rather since the peak demand day always has good sun in summer peaking states the required peaking capacity was around 60% peak demand. In Tasmania, which is winter peaking the requirement is less due to existing hydro capacity.

Compared to Figure 20 there is a greater alignment of estimated battery requirements under when viewed from the perspective of average load rather than the ratio of battery capacity to installed variable renewable generation capacity. This indicates that while variable renewable generation creates a need for additional battery storage it may not necessarily be installed via a formula relating to installed capacity. Rather the total battery requirement more strongly relates to being able to meet average state load for an increasing number of hours. Again, beyond the range of 5-10 hours state load, we found that peaking plant was more cost effective at energy balancing otherwise the requirements for battery capacity becomes non-linear.

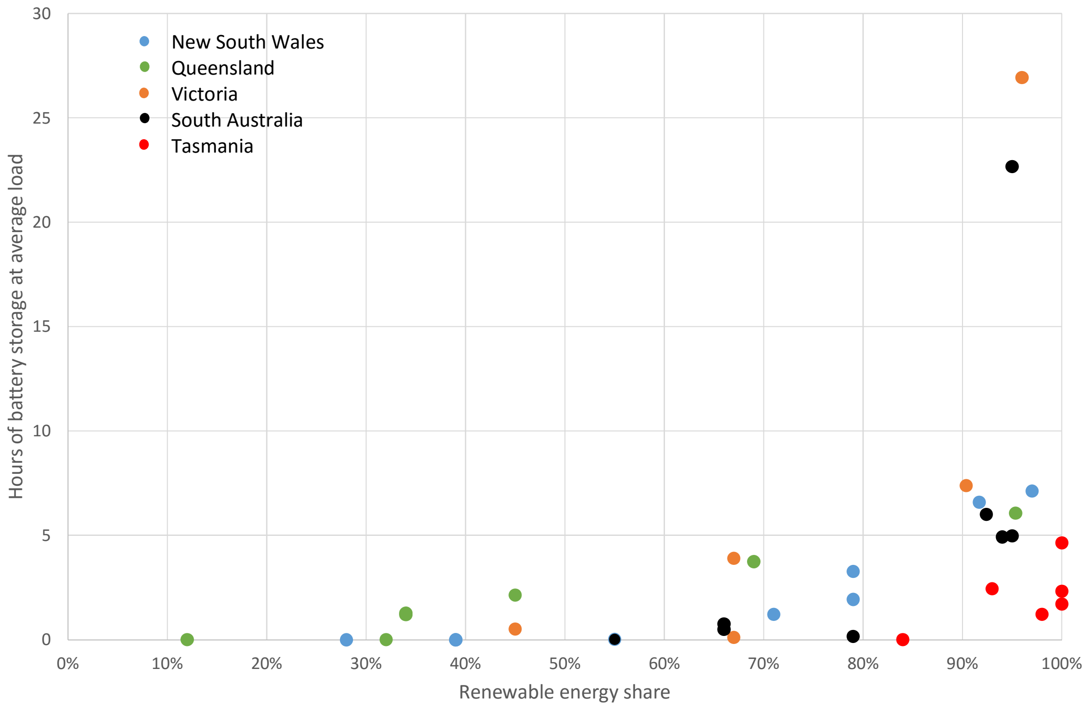


Figure 21: Projected hours of battery storage to achieve energy balancing for a given renewable energy share, by state

The role of state interconnectors

While, to be conservative, the modelling did not include growth in state interconnectors to meet energy balancing needs, an analysis of the diversity of state renewables can provide some guidance as to where stronger interconnection is likely to be useful. To analysis diversity we needed to understand what diversity was important. The system modelling found that a combination of both wind and solar photovoltaic generation was efficient for system balancing in each state. Solar provides a relatively economic and predictable daytime supply in all states. However, a significant contribution from wind power is crucial to fill in the supply gaps at night together with storage and dispatchable gas capacity. Consequently we focussed on the diversity of wind power across states.

Figure 22 shows the average coincident capacity factor of wind generation on the summer and winter maximum demand days in selected demand regions. It shows that on their respective summer peak days, Queensland and Victoria would benefit from stronger interconnection with New South Wales and South Australia to access evening and night wind generation. In winter, the roles are somewhat reversed. On the New South Wales winter maximum demand day it would be beneficial for system balancing purposes to have stronger interconnection to South Australia and Victoria.

On South Australia's winter maximum demand day, Queensland and Victoria wind power could supply the strongest support to that state's system balancing. Overall, it appears likely, based on the diversity of wind generation that a case could be explored for strengthening a number of connections across the Eastern States as the share of variable renewables increases. Strengthening links to Tasmania would be more likely to be motivated by access to renewable hydro generation and storage capacity. Further research could perform this analysis over additional weather years to see whether these observations are consistent over time, as would be necessary to support an interconnection investment.

Figure 22: Historical (2009-10) coincident wind generation capacity factors on winter and summer maximum demand days in selected states

Roadmap state renewable shares

Projected renewable generation as a share of state generation is shown in Figure 23 under the *Roadmap* scenario. An important assumption in regard to this projection is that only the Victorian renewable target was included in the modelling as a hard constraint and so should other states legislate their renewable targets then results may differ considerably (e.g. the proposed Queensland target of 50 per cent of consumption would encourage more renewable generation sooner in that state). The differences between the states also narrow if renewable generation included net imports, however we chose here to focus on the states own generation.

There are two major implications which can be drawn from the projected state large scale renewable shares. The first is that, relative to other states, South Australia and Victoria will likely need to bring forward actions relating to managing power system security as they are expected to reach high renewable shares earlier (Tasmania's existing and projected high renewable share consists primarily of hydro power). The second is that as other states with currently low renewable shares accelerate renewable adoption, there are 5 year periods where they will need to sustain a renewable build rate of an average 1 gigawatt per annum. This high build rate occurs particularly in Victoria, New South Wales and Queensland and relates to periods where there are significant existing multi-gigawatt coal-fired power capacity retirements. Large solar or wind project tend to be around 0.2 gigawatts in size so this amounts to five projects per year. This intense level of project development, shifting between states at different times to coordinate with capacity retirements in those states will require strong market investment signals.

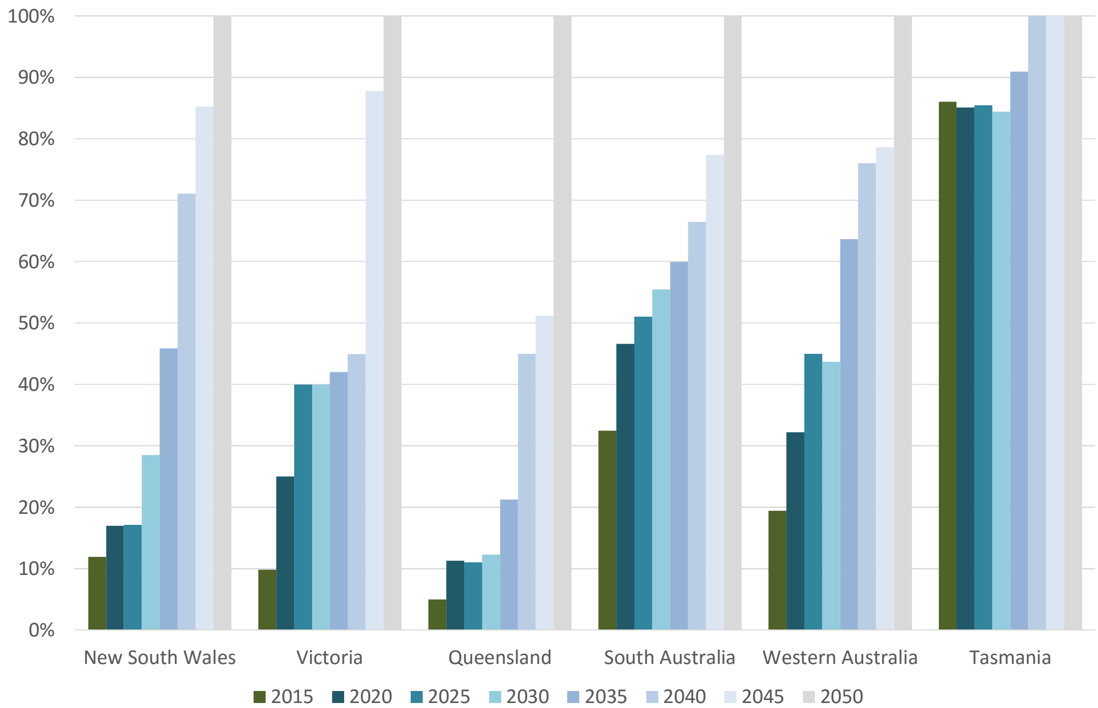


Figure 23: Projected renewable generation as a share of state generation under the Roadmap *scenario*

Generation sector prices

Modelling of both the *Roadmap* and *Counterfactual* scenarios project that generation sector electricity prices will remain low during the late 2010s and through the 2020s (Figure 24). Recent higher generation prices have reflected reasonably one-off events such as outages of the Basslink and Heywood interconnectors and plant retirements. Whilst there may be more unexpected constraints which increase prices for short periods, the dominating theme for the generation sector is increased renewable generation capacity in the form of rooftop solar and large scale PV and wind, driven by customer decisions and national and state renewable targets respectively, regardless of the market signalling that it is in excess supply. This means the modelling still expects to see an extended period of low prices which are below the long run marginal cost of new plant. One thing that could resolve this excess supply in increase prices is faster retirement or mothballing of existing gas and coal plant. However, prices are sufficient for those generators (more so coal) to run at short run marginal cost so economic retirements are not necessary and become increasingly unattractive if the expectation is that prices will eventually rise.

In the period from the late 2020s the sector is beginning to come under pressure to deploy new plant and so electricity prices are forced to increase rapidly up to a level that would give confidence to investors that they would be able to recover long run marginal costs. The *Roadmap* scenario experiences the sharpest increase in wholesale prices reflecting a faster replacement of existing capacity using mainly higher cost renewables. In the *Counterfactual*, the more gradual increase includes both renewable and conventional generation such as gas and coal-fired power which is not as high cost.

By 2050 the major task of extending and/or replacing existing generation capacity is complete and prices are stabilising at around $110/MWh in both scenarios. In the *Roadmap* scenario this represents the cost of large scale solar PV and wind power at about $60 to $70/MWh plus a $40 to $50/MWh premium to support their variability with battery storage. In the *Counterfactual* scenario the 2050 price reflects the increasing cost of gas over time which is expected to be in demand by many countries given its usefulness is supporting energy balancing and lower emission intensity than coal (see Graham et al 2015). However, the price also reflects the need to begin investing more heavily in lower emission technologies such as gas with carbon capture and storage which begins in 2050 (noting that we run the model to 2065 to ensure investment decisions taken during the projection period remain cognisant of need to remain under the emission cap as demand continues to increase beyond 2050). In the APGT 2015 data set we are applying, gas with carbon capture and storage has a long run marginal cost of around $110/MWh (CO2CRC, 2015).

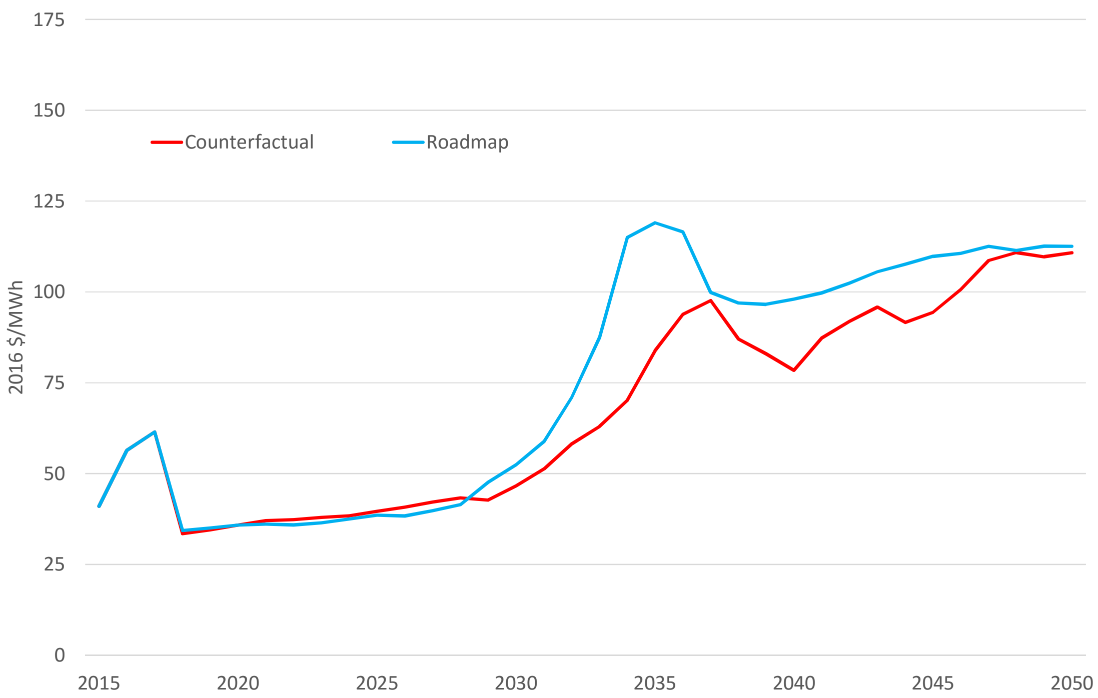


Figure 24: Projected average generation sector prices under the Roadmap *and* Counterfactual *scenarios*

Distribution and transmission costs

The modelling assumptions established the projected outcomes for consumption and maximum demand growth and these are the main drivers of distribution and transmission costs. In particular maximum demand growth is the main driver of distribution and transmission expenditure, whilst consumption growth determines how those network costs will be shared across customers. Given the low growth in consumption and our assumption that states would achieve their energy balancing without additional state interconnectors, we do not need to include additional state transmission links in the network costs. However, it is important to note that this is not necessarily an optimised outcome. Recent analysis by AEMO (2016b) suggests that there would be a positive economic outcome from additional state interconnectors. However, they also provide the caveat that their calculations are not at the standard that would be required for a full regulatory investment test for transmission.

The projected change in distribution network capacity utilisation for the *Roadmap* and *Counterfactual* scenarios is shown in Figure 25. The capacity utilisation is calculated as the amount of energy delivered divided by the implied amount of energy that could have been delivered if the distribution capacity were fully utilised. It indicates that capacity utilisation is around 60 per cent, on average, and will fall to 50 per cent in the

Counterfactual scenario. The *Roadmap* scenario capacity utilisation falls at first but improves from the late 2020s as electric vehicle adoption accelerates and more efficient tariffs lead to improved customer management of peak demand. As adoption of more efficient tariffs saturates, utilisation falls slightly to 60 per cent by 2050, similar to the present.

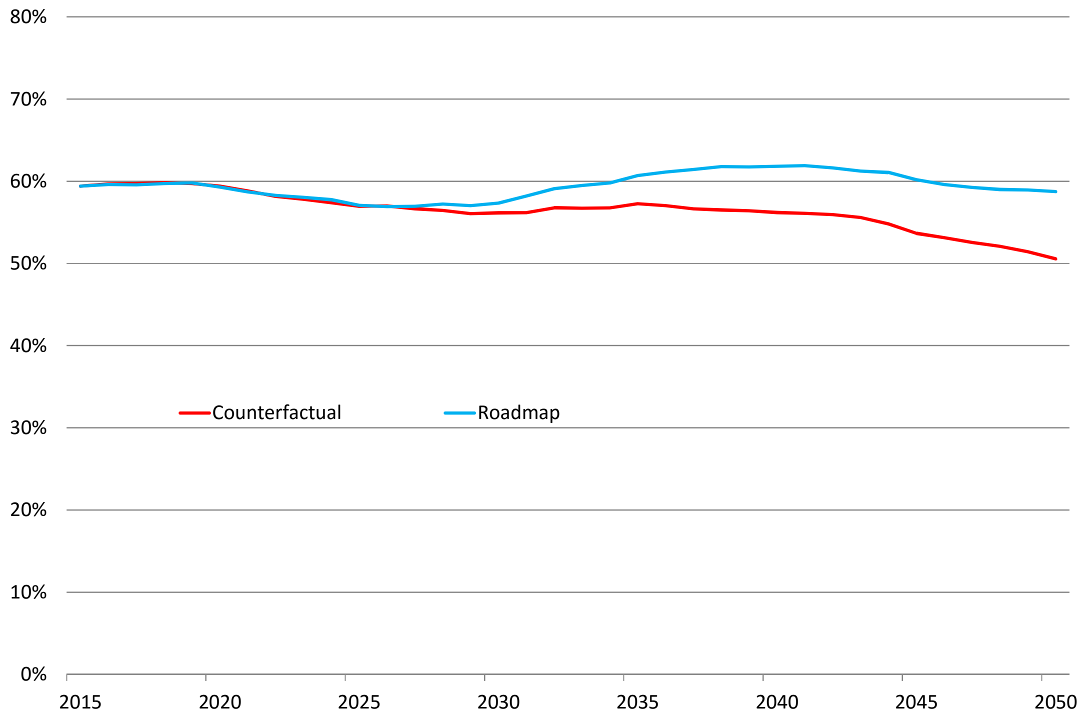


Figure 25: Projected distribution sector capacity utilisation under the Roadmap *and* Counterfactual *scenarios*

Although the scenarios include changes in distribution tariff structures, for purposes of illustrating the prices trend, Figure 26 shows the average residential distribution and transmission unit prices in cents per kilowatt hour. The trend in distribution prices reflects the changes in capacity utilisation. After a period of stability, distribution prices increase with falling utilisation in the 2020s. For the *Counterfactual* scenario this trend continues through to 2050 resulting in a 47 per cent increase overall compared to 2016. In the *Roadmap* scenario network prices fall again in the 2030s owing to improving capacity utilisation. By 2050, the distribution price is projected to be only 6 per cent higher than in 2016. For the transmission sector, the differences between prices in the *Roadmap* and *Counterfactual* scenarios are of a similar proportion but the overall levels are lower.

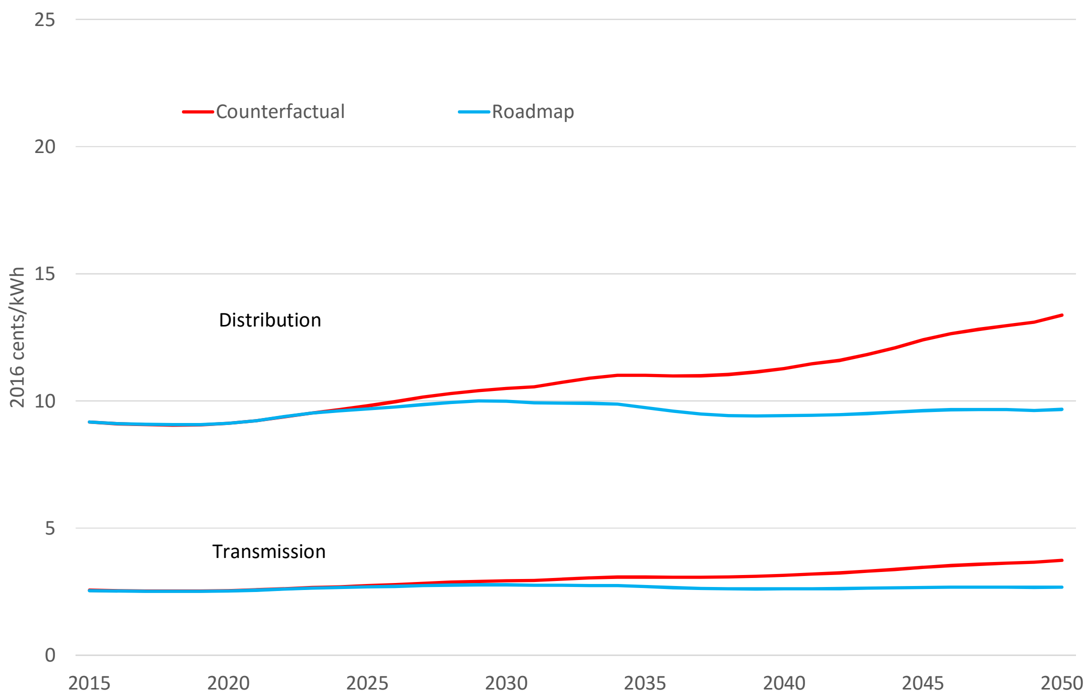


Figure 26: Projected average residential distribution and transmission unit prices

Customer impacts

In this section we focus on the impact of the *Roadmap* scenario residential bills. Energeia (2016) provide more detail on commercial bills.

Average residential bills

An average residential bill is calculated by summing the total expenditure by all customers on grid supplied electricity and on-site distributed energy resources such as rooftop solar panels and battery storage and dividing through by the number of customers. Grid-supplied electricity costs are calculated via the preceding analysis which has defined the components of the residential retail price such as generation, distribution and transmission costs, plus a proportional value for retailer's margin.

The current average residential electricity bill is approximately $1500. Going forward there are two key sources of savings in residential electricity bills under the *Roadmap* scenario. The first is that reformed prices and incentives for network optimisation of distributed energy resources deliver a reduced need for expenditure on network capacity replacement and augmentation. The second source of lower bills is a more efficient utilisation of capacity, because the cost of each unit of capacity is recovered from a larger customer base. Effectively, new uses of the energy network contribute to meeting system costs, with electric vehicle adoption (with managed charging), being the main driver of this outcome.

While electricity bills will increase due to higher costs associated with decarbonisation, Figure 27 shows that average residential electricity bills are lower under the *Roadmap* scenario in both 2027 and 2050 due to reduced network capacity expenditure and more efficient utilisation of the network. In 2050, the absolute reduction in average residential electricity bills relative to the *Counterfactual* is $414 per annum (in real terms) down from approximately $2200 to $1800. The difference in average bills is only $34 in 2027. However, this does not reflect the potential for significantly different outcomes for some customer segments who are unable to take up distributed energy resources. For instance, Energeia (2016) calculate a mid-size family which was 'passive' and did not install distributed energy resources is approximately $350 per annum better off in 2027 under the *Roadmap* scenario due to fairer tariffs.

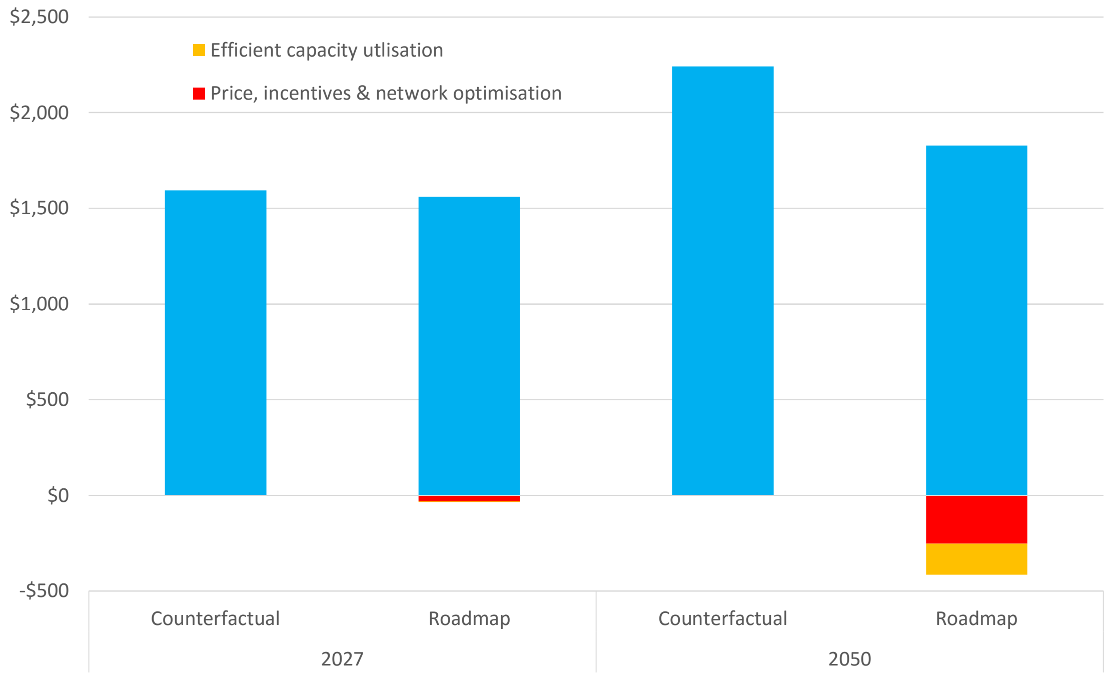


Figure 27: Projected average residential electricity bill under the Roadmap *and* Counterfactual *scenarios in 2027 and 2050*

Diverse residential bills

Average customer outcomes can mask quite different outcomes for individual household types. While customer bills will differ due to different household energy needs, it is important to minimise inequitable outcomes or unintended cost transfers that might arise due to less cost reflective pricing structures, distorted incentives, or customer vulnerability. Customer vulnerability is a term we use here to describe the situation where customers are not able for various reasons to take up opportunities that would enable them to save on electricity bills.

To capture the diversity in customer bill outcomes, CSIRO selected a set of sample customer profiles representing four household types. Adopting the approach applied in Energeia (2016) electricity bills were calculated under two different assumptions. Firstly, it is assumed the customer was active in seeking distributed energy resources, including solar PV and batteries, to reduce energy bills. Secondly, it assumed the customer was passive and did not, or could not, seek to invest in distributed energy resources to reduce energy bills.

Table 12 shows that under the *Counterfactual* scenario there is a significant difference between active and passive customer outcomes. Under the *Roadmap* scenario, which includes more cost-reflective pricing and incentives as well as other cost saving measures, there are two clear benefits. The first is all customers are better off, whether they are active or passive. Secondly, the 'gap' between active and passive customers has narrowed across the households by between 30 to 66 per cent.

	Counterfactual			*The Roadmap*		
	Active $	Passive $	The Gap $	Active $	Passive $	The Gap $
Working Couple	$1,346	$1,811	**$465**	$1,123	$1,422	**$299**
Medium Family	$1,816	$2,601	**$785**	$1,428	$1,988	**$560**
Large Family	$2,794	$3,950	**$1,156**	$2,346	$2,734	**$288**
Single, Retired	$1,058	$1,730	**$672**	$883	$1,355	**$472**

Table 12: Residential bill outcomes for selected Australian household types in 2050 under the Counterfactual *and* Roadmap *scenarios*

Identifying zone substations potentially under stress or stranding risk

One of the key challenges the *Roadmap* seeks to meet is to maintain system security and reliability whilst achieving other goals. The *Roadmap* did not undertake any detailed power quality modelling which could pin-point specific power quality issues as this requires specialised high temporal and spatial resolution modelling. However, to provide some indication of when different regions may need to address power quality issues at the distribution level, we reviewed the projected load at each of the approximately 2000 zone substations in Australia (excluding the Northern Territory).

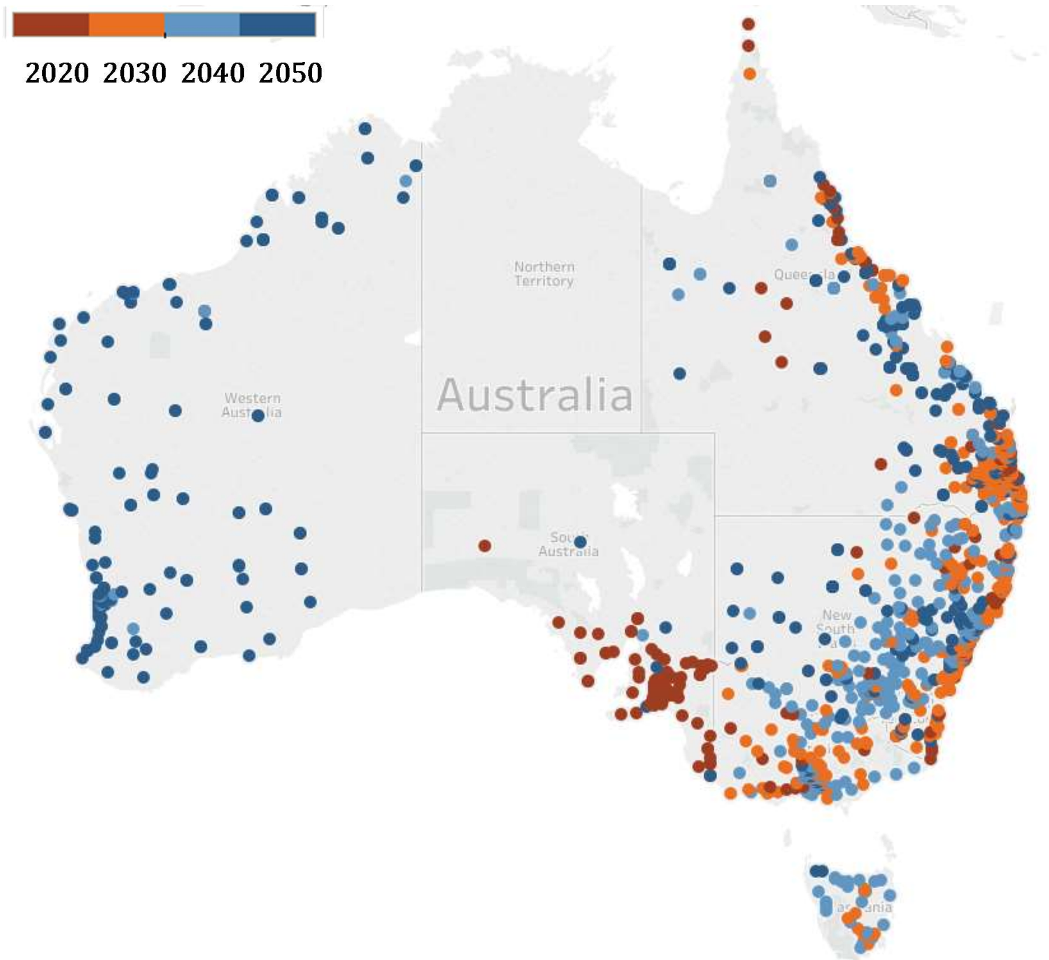


Figure 28: Projected decade in which each zone substation will reach a threshold indicative of reverse power flow due to rooftop solar PV adoption

The load at each zone substation was calculated based on background growth derived from applying AEMO's demand forecasts and the *Roadmap's* projections of the adoption of distributed energy resources such as rooftop solar PV and onsite battery storage. If there are no other changes, high shares of rooftop solar PV will hollow-out the load during the middle of the day, leading to rising voltages on the local distribution system and could eventually lead to reverse power flows between regions. However, the *Roadmap* projects significant deployment of battery storage as customers seek to capture greater value from their solar systems and respond to incentives provided by networks and other system actors. The addition of storage allows a zone substation to potentially absorb a higher penetration of solar without running into issues but requires coordinated action to provide incentives or rewards for storage to be utilised in a way that addresses zone substation level needs.

CSIRO reviewed the relationship between rooftop solar share of total annual load at the zone substation and reverse power flows as a general indicator of other power quality issues. It was found that reverse power flows occurred at 30 per cent rooftop solar load but were common from around 40 per cent of load. We then examined when each substation, during the period to 2050, to determine when they reach this 40 per cent threshold. The results are shown in Figure 28.

The zone substation analysis indicates that zone substations in South Australia have already met the threshold or will do so around 2020. The remainder of the Eastern states will have a significant share of substations over the threshold by around 2030, more so in the populated areas of the coast, but not exclusively so. Western Australian substations tend to meet the threshold from the 2040s, reflecting a period of stable electricity bills in the 2030s relative to other states owing to slower growth in renewable share in power generation at that time.

If significant reductions in peak demand were to occur on the distribution networks, this may lead to some existing distribution network assets being under-utilised or “stranded.” If assets became under-utilised for persistent periods, regulatory pressure to consider asset impairment could arise. Zone substation transformers are particularly susceptible to stranding risk, but this risk could be managed in an uncertain environment by taking advantage of increased optionality when making asset replacement decisions.

Further analysis is required in order to better understand the impacts of increasing quantities of intermittent generation as well as decentralised generation, storage and demand management on electricity supply at time scales shorter than the financial settlement period of thirty minutes. This includes the requirement for rapid response technologies such as high ramp-rate generators and real or synthetic inertia to maintain frequency stability by the provision of frequency control ancillary services, the maintenance of voltage via the management of reactive power flows, the impact on protection infrastructure including the detection of faults and capability for device fault ride-through, as well as the impact on power quality of the development of harmonic power flows.

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Appendix: Example high renewable generation profiles

Half-hourly storage modelling was undertaken in order to verify the ability of variable generation with storage to supply the required demand in each NEM state, and to inform the generation technology deployment model (see *Roadmap* generation mix and following sections) of the required amount of storage costs to take into account in its projections. Load and supply by technology were modelled at half-hourly time intervals for selected sample years, and the optimisation of battery deployment and operation over the entire year calculated using a linear program.

Battery storage was chosen as the representative storage technology, as cost and performance data was the most mature and readily accessible. Only a single time series representing the availability of each variable generation source (non-tracking solar for domestic rooftop PV, tracking solar for large scale PV, and wind) in each of the NEM states was permitted. Furthermore, there was no allowance for electricity trade among states. Both these assumptions are restrictive, making the results of the analysis conservative.

This formulation has several degrees of freedom enabling demand to be met at low cost.

- Firstly, battery storage allows generation in excess of demand to be stored for later use.
- Secondly, at high percentage contributions of variable renewables, the least cost solution includes “excess” renewable generation capacity, in the sense that some generation is “spilled” when battery storage levels are at their maximum, and renewable resource availability exceeds demand, resulting in capacity factors that are lower than the maximum possible for each renewable resource.
- Thirdly, the installation of low capital cost dispatchable generation plant such as open cycle gas turbines permits demand to be met at times where battery storage levels are at their minimum and intermittent generation resources are not available. This occurs relatively infrequently, resulting a capacity factor for such peaking plant that is lower than that currently, at lower levels of penetration of variable renewable energy.
- Finally, it is conservatively assumed that it is necessary to back up variable renewable generation capacity with the equivalent capacity of synchronous generation to provide electrical system inertia.

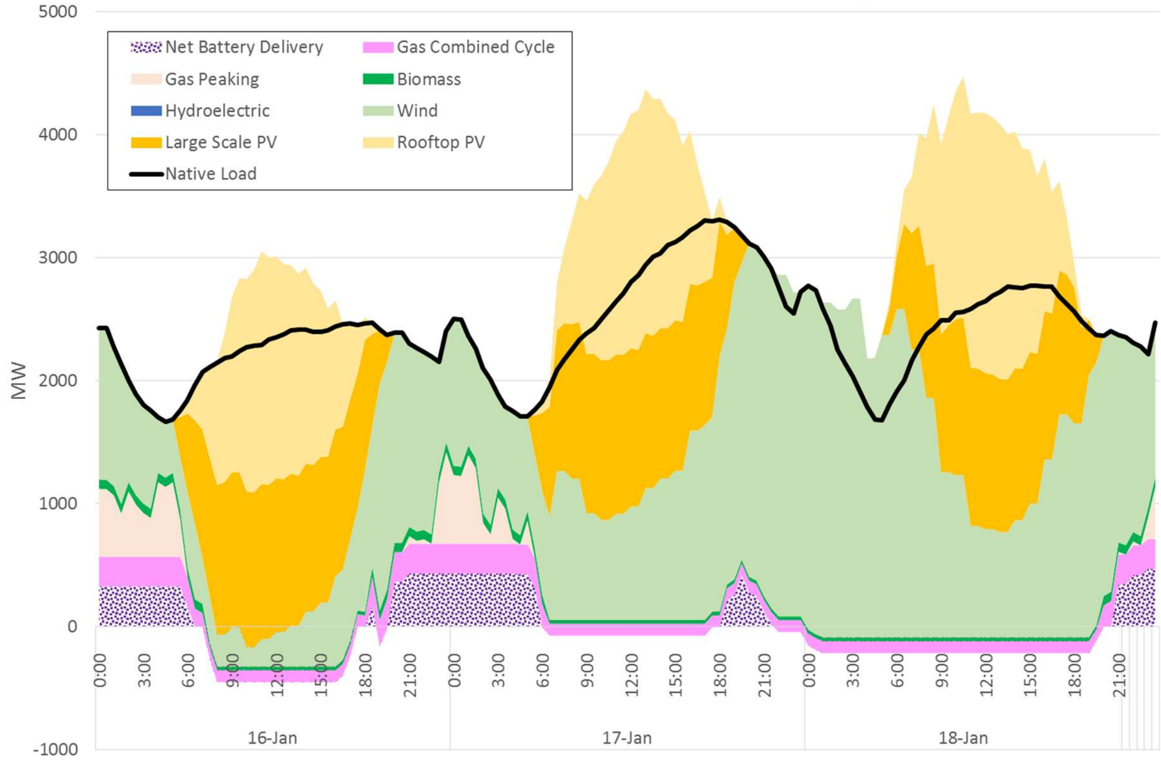

Figure 29: Half-hourly generation and storage, South Australia, three example Summer days

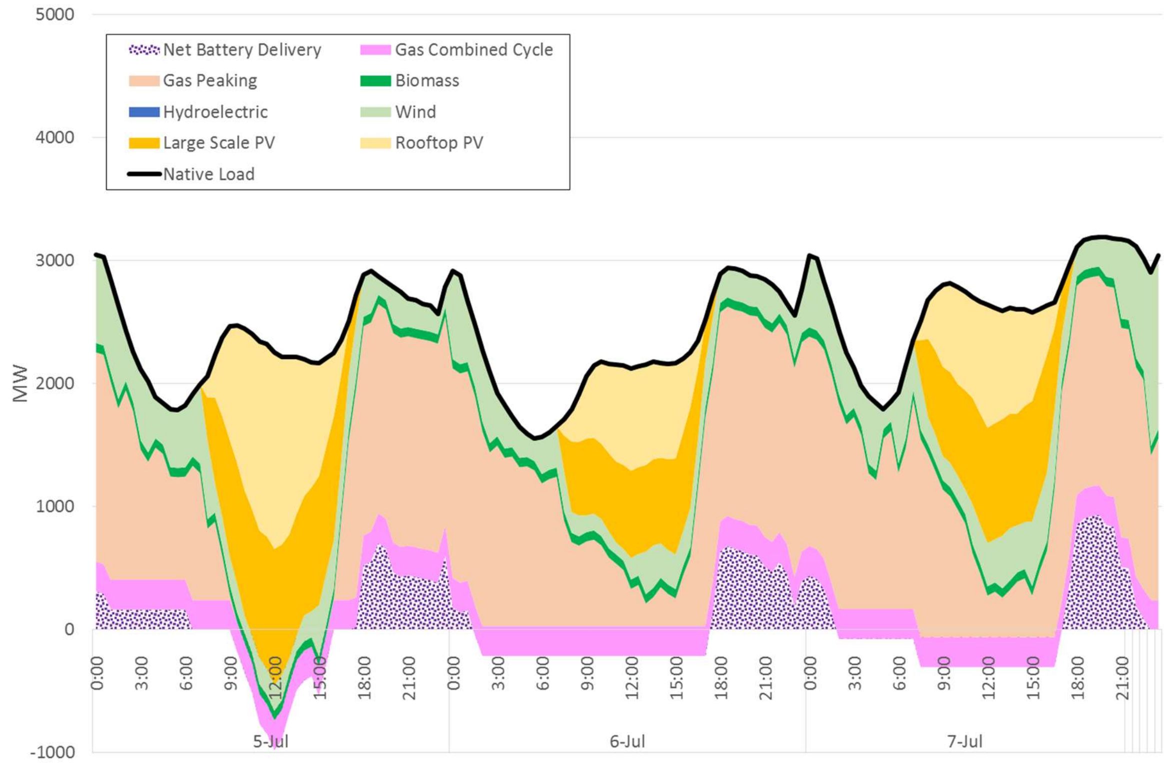

Figure 30: Half-hourly generation and storage, South Australia, three example Winter days

While several sample years to 2050 across all NEM states were investigated, and we ran a great number of scenarios with alternative renewables shares, we provide results for the following case study of supply and demand balancing in South Australia, exploring the role of storage and peaking gas in supporting a very high renewable electricity generation share electricity system. In this particular example, we explore a generation mix to meet 80% renewables by 2036 using optimisation methods to determine the amount of back-up storage peaking gas capacity required to balance demand and meet the required renewable energy share.

The following projected analysis of the South Australian system at 80% renewables in 2036 shows how some of the energy balancing solutions could work together over a twelve month period. These charts show three days for both the summer (Figure 29) and winter (Figure 30) seasons.

In the example shown for summer (Figure 29), excess energy will be produced in the middle of the day, some of which is transferred to battery storage. Overnight demand is met from battery storage, in combination with some baseload, peaking gas and a small amount of dispatchable biomass. Figure 29 also indicates that on the third day it remained sufficiently windy overnight (green), which allowed for renewable diversity to meet the energy balance on that day without the need for other capacity.

In Figure 30, winter renewable output in 2036 can be observed as being lower than during summer, and as such the system producing less energy for battery storage during the day. This results in the system needing to utilise gas peaking plant much more during this period. It should be noted that this example could be modified to include other solutions such the deployment of further demand management or state interconnectors.

These results show the feasibility of meeting half-hourly demand at about 80% intermittent renewable share for wholesale costs in the \$90-\$110/MWh range. This is broadly consistent with results of Blakers, Lu and Stocks (2017), who consider pumped hydro rather than battery energy storage, biogas and biomass feedstocks for dispatchable plant, and also explicitly consider costs of required additional transmission capacity connecting the pumped hydro storage facilities to the remainder of the network.

This example ultimately demonstrates that individual NEM region balancing is unlikely to rely on one single strategy or solution but will need to consider combinations of solutions to provide a secure and reliable power system at low cost.