Lenzen, Manfred; McBain, Bonnie; Trainer, Ted; Jütte, Silke; Rey-Lescure, Olivier; Huang, Jing Simulating low-carbon electricity supply for Australia". Published in Applied Energy Vol. 179, Issue 1 Oct., p. 553-564 (2016)

Available from: http://dx.doi.org/10.1016/j.apenergy.2016.06.151

Simulating low-carbon electricity supply for Australia

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Abstract

We offer a simulation of low-carbon electricity supply for Australia, based on currently and economically operating technologies and proven resources, contributing new knowledge by: featuring a GIS-based spatial optimisation process for identifying suitable generator locations; including expanded transmission networks; covering the entire continent; and investigating the significance of biofuels availability and carbon price. We find that nation-wide low-carbon electricity supply is possible at about 160 GW installed capacity, at indicative cost of around 20 ¢/kW h, involving wind, concentrating solar, and PV utilities, and less than 20 TW h of biofuelled generation. Dispatchable hydro and biofuel plants are required to plug gaps caused by occasional low-resource periods. Technology and cost breakthroughs for storage, geothermal and ocean technologies, as well as offshore wind deployment would substantially alter our assessment.

Keywords: Electricity generation simulation; Renewable energy; Transmission network extension; Low-carbon power

1 Introduction

1.1 Background

The recent G7 summit at Schloss Elmau in Germany culminated with leaders pledging to phase out the world's use of fossil fuels by the end of the 21st century. One of the technological centrepieces underpinning efforts towards this ambitious climate change abatement goal is the commissioning, and interconnection at a continental scale, of a renewable energy technology portfolio including photovoltaic utilities, wind turbines and concentrating solar power. As a result, researchers have been examining the question of whether available renewable energy sources provide for a sufficiently firm and economically viable supply[1]. Pertinent issues in this debate have been whether assumptions about potential future energy demand reduction, plant cost reduction, and technical potential of renewable energy technologies are realistic, and what the potential future role of biofuels can be, given land use competition [8,9]. One particular aspect in this research stream is the variability of the wind and solar resource, and the resultant challenges for supplying reliable power. In this respect, the idea of smoothing the variable supply of individual generators through large-scale geographical dispersion combined with technology diversification has been taken up in a number of studies (for a review see Sections 1.1 and 1.2 in Delucchi and Jacobson [1]). A critical issue in this context is that installed capacity in renewable grids can reach three to five times demand, resulting in significant capital cost, and some plant sitting idle for much of the time [10,11].

Modelling large-scale power systems with high penetration of dispersed and diverse renewable generators has traditionally been a topic of high relevance to both scope and readership of Applied Energy. Interesting contributions have appeared especially over the past two years, dealing with least-cost low-carbon configurations [12], the effects of generator interconnection [13] and storage [14], the impact of sub-hourly simulation [15], and with transitions towards a 100% renewable power supply for France [16].

Australia presents an interesting case in the debate surrounding decarbonisation of electricity grids. Being one of the most coal-reliant countries in the world (as recently pointed out by the executive secretary of the UN's Framework Convention on Climate Change[2]) it is aiming for a Renewable Energy Target (RET) of only 33,000 GW h by 2020, or 23% of projected 2020 generation.[3] On the other hand, Australian NGOs and industry bodies such as Beyond Zero Emissions, the Clean Energy Council, the Australian Conservation Foundation, and the Climate Council have called for more ambitious 100%-renewable targets. This debate forms the context to which our analysis aims to contribute new insight.

1.2 Prior work and knowledge gaps

There exist a handful of studies examining features of a low-emission[4] power grid for Australia. Elliston and co-workers[5] examine various scenarios for providing 100% renewable electricity for the NEM, and conclude that a mix of wind turbines, photovoltaic (PV) utilities and concentrating solar power (CSP) with a total capacity of about 110 GW is able to provide firm power meeting reliability standards. Similarly, the official electricity market operator's own study [22] arrived at total capacity estimates of around 100 GW for the same geographical area. Both studies share the necessity of recruiting typically 25–30 GW of dispatchable capacity in the form of either biofuelled gas turbines

(Elliston) or geothermal plants (AEMO). Huva et al. [23] assume gas-fired back-up in their study of Victoria.

The studies by Elliston et al., AEMO and Huva et al. point to a number of shortcomings in need of improvement or further investigation (see a summary in Trainer [24]): first, in the studies listed in the previous paragraph, spatial generator and transmission locations are pre-selected and fixed, and/or temporal resolution is limited. Second, previous work only examined parts of Australia. Third, some analysts consider biofuels in the short run as generating only about 10% of power [25], and current thinking focuses on replacing aviation and other transport fuels [26]. Fourth, limited track record, high cost (especially for drilling), and technical challenges mean that utility-scale geothermal power is not expected to be cost-competitive in 2020 and possibly beyond [27,28]. Fifth, natural gas for backup (as assumed by Huva et al.) does not meet the “100% renewables” criterion.

1.3 Aims and innovations of this study

The aim of this work is to demonstrate computational capability to search for spatial and temporal configurations of least-cost power supply where generators will meet demand for every hour of a whole year,[6] up to prescribed reliability standards. Least-cost configurations are found by simulating an hourly competitive selection process where demanders select generators based on resource availability and cost. Simulations are parametrised by a variable carbon price, leading to scenarios with different emission characteristics. For each scenario we are able to quantify overall capacity, generation, spillage, capacity, and energy carrier mix, as well as plant, operating and transmission cost.

We improve on previous work as follows: First, we do not restrict the geographical search space to pre-selected potential plant locations and pre-selected capacity when identifying least-cost solutions, but rather optimise over the entire Australian continent, by treating carrier- and location-specific capacity as an optimisation variable. For the first time, we include Western Australia and the Northern Territory into this kind of simulation. This is possible because our GIS-based wind speed and irradiation data sets cover the entire Australian continent [29]. We run our simulation at hourly temporal resolution, and are thus able to study limitations posed by stretches of low wind and solar resource (the “big gaps problem”, [30]). Using GIS-gridded hourly data means that this work can only be undertaken by using high-performance computing resources at the terabyte-RAM scale.

Second, we are able to compute GIS representations of new transmission networks for any spatial generator configuration, and thus improve on estimating transmission cost for future power supply systems.

Third, we examine a number of technological restrictions to low-emission power. We parametrise our simulations by varying the availability of biofuels. We also explore scenarios in which no new geothermal and ocean energy sources, no new fossil-fuelled generation, and no new hydropower[7] is added to existing capacity. We allow up to 15 h of storage attached to concentrating solar power plants, but we do not consider battery storage for PV systems because at the time of writing these were still considered uneconomical except in specialised applications such as grid stability and peaking [33–35].

Note that this study focuses its investigation purely on the technical capability of Australia to produce all its power from renewable sources. This specific focus considers neither the (political, economic, regulatory, financial and social) policy constraints that will affect the ability to achieve this goal, nor potential transition pathways. In addition, in order to limit the likelihood of over-optimistic results we took a deliberately conservative approach to simulation assumptions. For instance, we made no provision for demand to vary from present patterns even though demand reduction is a critical energy policy option for climate change abatement. We also made no allowance for future improvements in technology, future cost developments towards possible grid parity, taxation and subsidisation patterns, and future learning curves, but use capability that is achievable today, at current cost. Finally, we note that our aim is not to identify one "best" solution in terms of carbon and/or cost, but instead to present a range of options that ensue from varying sets of cost, and that might or might not be feasible from a policy point of view. In the following we will first explain our methods and data before presenting and discussing our results, and then offering our conclusions.

2 Methods

In the following we will sketch our simulation approach – a more formal exposition including a detailed description of all cost assumptions and data sources can be found in Appendices A1 and A2. In essence, we simulate an hourly competitive selection process in order to search for least-cost configurations (energy carrier mix and generator siting) that are able to supply Australia's power to a given reliability standard. In our work we distinguish the following energy carriers: black coal, brown coal, distillate, natural gas, biomass (from animal waste, bagasse, biogas, digester gas, landfill methane, municipal waste, sewage methane, and wood waste), hydro-potential, wind, solar PV (utility-scale and rooftop), concentrating solar, geothermal, and ocean (tidal and wave). We

– allow utility solar and wind technologies to grow to their resource potential,
- restrict fossil-fuelled, rooftop PV, geothermal, hydro and ocean power to existing capacity,
- test configurations with different availability of biofuels by fixing biofuelled power plant capacity at various multiples of existing capacity (1st simulation parameter),
- investigate the influence of a carbon price (in $/t, 2nd simulation parameter) on the overall energy carrier mix.

2.1 Australian electricity market background

The Australian National Electricity Market (NEM) interconnects five regional state networks of Queensland, New South Wales, Victoria and South Australia. Tasmania is connected to the NEM via an undersea DC link [36]. As of 2014, the NEM included 66 GW of installed generation (Fig. A1, [37]). Because of the large distances across Australia, the NEM is not connected to Western Australia and the Northern Territory, where a stand-alone network operates ([38,39], Fig. A2). In the NEM electricity is traded in a spot market managed by the Australian Energy Market Operator (AEMO). Generators submit offers to a spot pool, where AEMO matches supply and demand in real-time by determining and dispatching those generators that are able to meet demand in the most cost-effective way. Customers pay the spot market price to AEMO [40].

2.2 Optimisation problem

Finding least-cost configurations for a national power supply system is an optimisation problem. For example, Lohmann [41] determines a market equilibrium with welfare-maximising prices and quantities. We follow Elliston et al. [20], Short et al. [42], and AEMO [22] by determining the system configuration that satisfies hourly demand up to a particular reliability standard, for the lowest overall cost. In accordance with Elliston et al. [20] and AEMO [22], but unlike Short et al. [42], we do not deal with transmission constraints by explicitly modelling power flows through the transmission network, but rather assume a “copper plate” grid.[8] Finally, as in previous comparable work, we do not explicitly deal with cost arising from ancillary systems or effects of feed-in tariffs.

Cost minimisation of power supply involves potentially large decision variables (see Eqs. (A1.1)–(A1.4)). If assessed on a 100 × 100-raster grid, for 12 months or 8760 h, and for 12 energy carriers, a variable describing electricity generation alone would comprise more than 1 billion elements. Optimising the transmission network is an even more difficult nonlinear combinatorial problem that risks explosion of the number of alternatives in the search space [43]. Since such problems are clearly of prohibitive size for available solvers, researchers make certain simplifications and reduce the problem so it becomes solvable. Short et al. [42] simplify the year-long modelling period to 17 time slices, characterising each slice by typical resource potentials and probabilities describing resource variability. Similarly, Huva et al. [23] explain how large weather data and RAM requirements of their downward-gradient optimisation technique prevented both an hourly run over a whole year, as well as the utilisation of every geographical grid point available. They create a pseudo-year by splicing together seasonal snapshots in order to reduce runtime, and apply site pre-selection methods. Jägemann et al. [44] account for different demand structures by selecting three days for each of the four seasons, as well as 130 regions in their simulation of decarbonisation pathways for Europe. Elliston et al. [19] model hourly, but restrict their modelling runs by pre-specifying generator sites and capacity. Mason et al. [45] also model hourly, but treat New Zealand as one demand location and thus do not attempt spatial resolution. The AEMO [22] report describes hourly modelling, but a reduction of spatial resolution to 43 locational polygons in order to deal with the complexity. There is hence limited spatial optimisation present in the latter studies.

The philosophy pursued in this work is for as many parameters as possible to remain variable. We allow full generator site and energy carrier choice for the optimisation problem, and we do not prescribe any merit order. We follow prior work [22] by applying a time-sequential iterative approach for hourly supply-demand matching. We do not apply a probabilistic model based on synthetic time sets because we are particularly interested in examining the limitations posed by stretches of low wind and solar resource, and therefore need to investigate particular periods of low resource availability [30,46,47]. In addition, we allow carrying over unused stored energy, which is only possible in a time-sequential dispatch model ([22], p. 80).

2.3 Dispatch model

Our time-sequential iterative approach involves a multi-step hourly selection process narrowing down the generator location search space, by emulating an hourly competitive bidding process with bids set to equal variable plus fixed cost for a unit MW h of output plus transmission losses. The successful generator is therefore not necessarily one with the lowest operating cost, but also determined by the proximity to the demand point. In a first step, supply is matched optimally (ie lowest cost) to demand, iteratively and individually for each single hour of the simulation period. For 12 energy carriers on a 90 × 110-raster grid, hourly output counts about 120,000 elements, which is manageable on current HPCs.

Generator selection should ideally be based on a complete knowledge of all cost components. Variable and fuel cost are known for a unit MW h output, but not so the fixed capital, maintenance and transmission cost, which are only known for a unit kW of capacity (Table 1). Pre-run fixed cost per unit MW h cannot be determined because, at any hour during the simulation period, neither optimal generator locations, capacities and transmission lines connecting them, nor the total annual output of these generators are known, since this requires knowledge of the system over the entire time period (the “pre-run fixed cost” problem). In order to be able to consider full cost per unit MW h at every hourly bidding step, we base our generator selection on data[9] for variable cost plus estimates for fixed capital, maintenance, and transmission cost. At the end of each simulation run, we construct the expanded transmission network using tailored, accelerated link-distance functions (compare with [48]), and allocate transmission cost across generators based on network participation (see Appendix A.1.3). The generators previously selected in isolation for each hour are then compared and ranked based on their cost efficiency over the entire period, and uneconomic generators are being excluded. Runs are repeated, successively excluding generators, until an optimum is achieved over the spatial and energy carrier search space. This post-run successive exclusion is the algorithm feature that achieves generator sizing and location optimisation over the entire period. Section A2 in the Appendix describes our stepped, iterative procedure in further detail.

Table 1 Cost assumptions for various electricity-generating technologies (taken generally as the minimum of the columns labelled ‘AETA 2012’ and ‘Scenario 1 2030’ in [22] plus grid interconnection cost taken from [42] (Table 8), otherwise from [88]; see Appendix A.4 for more details and a literature review). Plant capacity factors listed here are only used for pre-run estimates of fixed and transmission cost (see Appendix A.2, steps 2.2.3 and 2.2.4).

Technology	Capital cost ($/kW)	Fixed O&Ma cost ($/kW/yr)	Variable cost ($/MW h)	Fuel cost ($/MW h)	Total cost ($/MW h)b	Plant capacity factor	Lifetime (y)f	CoVg Capital cost	CoV Fixed O&M cost	CoV Variable cost	CoV Fuel cost
Coal	3351	61	8.0	2.9c	28.7	0.85	50	30%	14%	37%	40%
Gas	1181	10	4.0	3.1d	12.1	0.85	45	50%	24%	23%	50%
Biomass	5350	109	7.0	1.5e	38.8	0.85	45	50%	26%	31%	100%
Hydropower	5114	48	6.7	0.0	26.2	0.85	55	42%	55%	41%	0%
Utility PV	1342	33	0.0	0.0	45.5	0.2	30	100%	113%	0%	0%
Wind	2693	35	10.5	0.0	52.5	0.4	25	50%	42%	137%	0%
CSP no storage	4756	53	13.1	0.0	95.8	0.3	30	30%	8%	200%	0%
CSP 5 h storage	5256	58	13.1	0.0	81.5	0.4	30	30%	8%	200%	0%
CSP 15 h storage	6256	68	13.1	0.0	67.2	0.6	30	30%	8%	200%	0%
Rooftop PVh	1075	22	0.0	0.0				100%	113%	0%	0%
Ocean	2738	166	15.0	0.0	46.4	0.95	30	70%	28%	0%	0%
Geothermal	5457	175	15.0	0.0	63.3	0.95	25	70%	28%	0%	0%

[a]Operation and Maintenance.
[b]Calculated as [capital cost ×(1+δι)/(8760 h/y × LT) + fixed O&M cost/8760 h/y]/capacity factor + variable cost + fuel cost, where *LT* is the plant lifetime, ι=8% is the assumed interest rate, and δ=50% is the debt fraction [42], Table 9).

[C]Calculated as \$3.7/GJ/[3.6/ $\boldsymbol{\eta}$ MW h/GJ] [89], with $\boldsymbol{\eta}^{Coal}$= 0.35 being the thermal efficiency of coal-fired power plants.
[D]Calculated as \$4.5/GJ/[3.6/$\boldsymbol{\eta}$ MW h/GJ] [90], with $\boldsymbol{\eta}^{Gas}$ = 0.4 being the thermal efficiency of combined-cycle gas-fired power plants.
[E]Calculated as \$1.5/GJ/[3.6/ $\boldsymbol{\eta}$ MW h/GJ] [22], with $\boldsymbol{\eta}^{Wood}$= 0.27 being the thermal efficiency of combined-cycle gas-fired power plants.
[f]Compare Table 31 in Tidball et al. [88].
[g]CoV = Coefficient of Variation, taken from Tidball et al. [88].
[H]Rooftop PV not taking part in the bidding process.

3 Results

In the following we will present a number of simulation outcomes obtained under varying technological and cost assumptions. We stress that these outcomes do not represent a preferred technology configuration, but particular options that arise from underlying assumptions. We start with demonstrating the convergence behaviour of our algorithm, followed by some overarching findings in terms of capacity, cost, capacity factor, spilled energy and energy carrier mix, under variation of a number of simulation parameters. These are:

(a) The biofuelled power plant capacity β (in units of multiples of existing 1.7 GW biofuelled capacity) – we use this parameter because on one hand biofuels have been shown necessary to “plug gaps” in renewable power availability [19], and on the other hand availability is still limited by the viability of production, especially of second-generation biofuels that are not constrained to high-yielding agricultural areas important for food production ([49,50], see the Discussion section).

(b) The carbon price κ (in units of \$/t) – we use this parameter to examine the gradual exclusion of fossil fuels out of the grid.

(c) Cost multipliers φ, ψ, ϕ, and ω (describing departures of cost from our default values for PV (φ), CSP (ψ), biofuels (ϕ) and wind power (ω) respectively) – to examine the effect of cost increases and decreases on the simulation results. In this paper we mostly report results using cost multipliers $\varphi, \psi, \phi, \omega \in \{0.75,1.0,1.25\}$ (ie ±25% departure from default cost), and occasionally investigate $\varphi, \psi, \phi, \omega > 1.25$. Cost decreases are facilitated by technological learning and economies of scale [51–54]. Cost increases can occur for example because of supply tightness, price hikes of scarce raw materials, and interest rate rises [55–57]. Fig. 6 in Kaufman [58] shows that the ±25% range we assume is quite realistic.

We also compare our results with those obtained by [20].

3.1 Convergence of the optimisation algorithm

As a result of the successive exclusion of the most expensive generators, overall system cost continuously decline with successive iterations of the optimisation algorithm. Total capacity declines simultaneously, whilst the system’s capacity factor increases. Most simulation runs did not require more than eight iterations to invoke the termination criterion (Fig. 1). Whilst this is only an experimental demonstration of convergence, a more formal proof is the subject of future work.

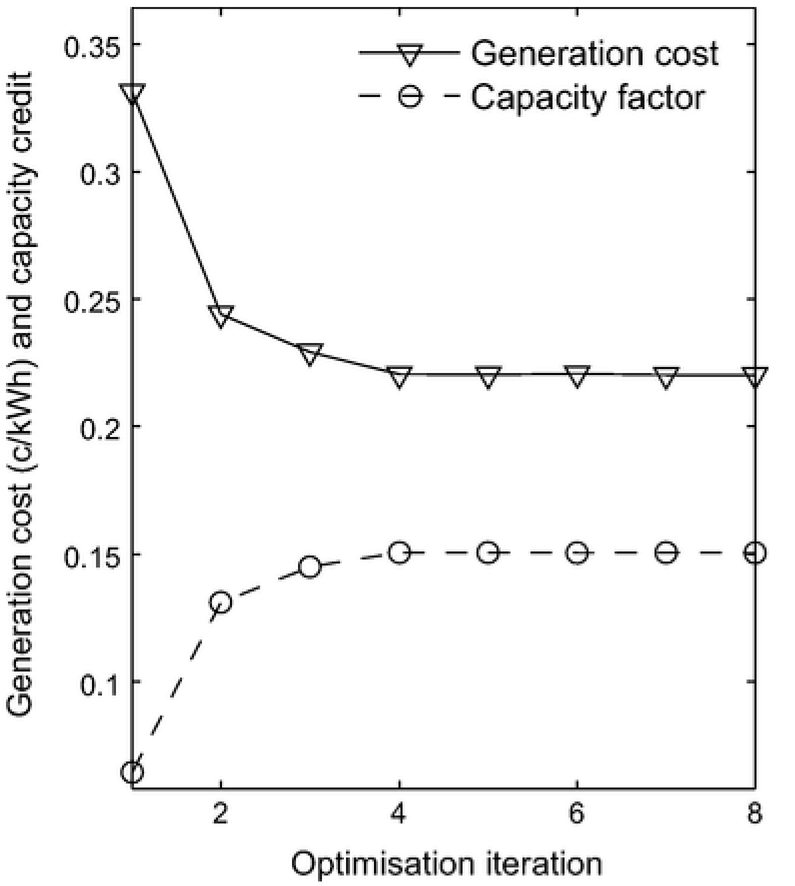

Fig. 1 Convergence in a run with β = 15, κ = 500 $/t, φ = 0.75, ψ = 1.25, ϕ = 2.5, ω = 0.75, and 5 h CSP storage. Overall system cost decline from 35 ¢/kW h to 23 ¢/kW h, whilst the system's capacity factor increases from 7% to 15%.

In order to test the optimisation behaviour of our algorithm, we ran additional scenarios in which we allowed only sites pre-selected on the basis of significant and well demand-correlated wind and solar resource. We did not find a statistically significant difference between the unrestricted and pre-selected model outcomes in terms of overall capacity and cost. In other words, pre-selecting sites achieved at least no improvement in the algorithm's convergence.

3.2 Influence of carbon price and biofuel availability on installed capacity, generation cost capacity factor and spilled energy

Fig. 2 presents the effects of various carbon price and biofuel availability combinations on several key performance indicators (installed capacity, generation cost, capacity factor, and spilled energy). These parameters have so far not been examined in similar power system models for Australia. On the whole, our simulations indicate the following:

- The current situation is represented by carbon price κ = 0 and biofuel capacity multiple β = 1, with about 50 GW required installed capacity, generation cost below 5 ¢/kW h, >60% system-wide capacity factor and negligible energy spillage.
- Installed capacity, generation cost and spilled energy increase with increasing carbon price κ, and decreasing biofuel capacity β. This is because at high κ fossil fuels have been pushed out of the market, and at low β only hydropower can supply significant amounts of firm power,

so that electricity is mainly supplied by renewable sources characterised by relatively low capacity factors.

- Adding significant dispatchable technology such as biofuelled plants to the capacity mix enables the generation of 100% renewable electricity at cost around 20 ¢/kW h (κ = 1000 and β = 15).
- If food production, biodiversity objectives or transport cost precluded the expansion of biofuelled power in Australia (β = 1), fossil fuels were abandoned (κ = 1000), and geothermal and significant storage were unavailable, demand could only be satisfied at current loss-of-load probabilities by installing around 300 GW10 of capacity operating at around 9% capacity factor and at a cost of around 25 ¢/kW h. The sharp increase in required capacity is a direct consequence of the "big-gap" problem described by Trainer [30].

We note that generation cost are measured at the demand side, including transmission cost and losses, but do not reflect electricity retail prices because we have not modelled any wholesale or retain margins.

3.3 Influence of carbon price and biofuel availability on the energy carrier mix

It is interesting to examine the energy carrier mix at different carbon prices and biofuel capacities (Fig. 3), because variations in technology mixes is what in the real world policy makers will need to choose between. At κ = 0 and β = 1 our simulation recovers the current capacity and generation mix (Figs. A1 and A8). At κ = 1000 and β = 15 we find biofuels being the dominant energy carrier, however we stress those amounts of biofuel are unlikely to be available given competing food and biodiversity objectives. We will return to this issue in the discussion section. It is interesting to see that our optimisation approach automatically excludes fossil fuels from the system when moving towards higher carbon prices, leaving only natural gas to supply about 50% of energy at 50 \$/t < κ < 100 \$/t,[11] and essentially simulating a renewables-only system beyond κ = 500 \$/t.

3.4 Comparison with Elliston et al. [20]

The scenarios described by Elliston et al. [20] are represented by κ = 1000 and β = 15, where there are no fossil energy carriers left in the system, but where biofuelled capacity is around 15 times higher than today at about 25 GW. Despite the different simulation approaches, our results are in reasonable agreement with those obtained by Elliston et al. [20]. Our values for installed capacity are higher at around 160 GW (Elliston et al.: 110 GW), however our generation cost (around 20 ¢/kW h vs 10–15 ¢/kW h), capacity factor (both around 20%) and spilled energy[12] (20% vs 10%) agree reasonably well. The differences in installed capacity between the two studies are due to a combination of factors:

a) we include Western Australia and the Northern Territory (about a +15% increase, see Fig. A8);
b) we add an operating reserve (p. 33 and Table 11 in Short et al. [42], and p. 101 in AEMO [22]; +15%) to account for short-term balancing of stochastic variability, frequency regulation, outages, and forecasting errors;
c) we impose an operation threshold of 2 kW h m−2d−1 ≈ 200 Wm−2 on CSP plants [64], see Fig. A3b; +5–10%); and
d) we exclude pumped-hydro plants (<+5%).

In unison, these effects cause an increase in installed capacity compared to Elliston et al. [20] of about a factor of 1.4, or from 110 GW to 160 GW, as found in our results (Fig. 2, top left panel, $\kappa = 1000$ and $\beta = 15$).

For the scenarios described by Elliston et al. [20] ($\kappa = 1000$ and $\beta = 15$) we find wind to be the dominant energy carrier in the capacity mix, which agrees well with Elliston et al.'s findings (Fig. 3, left panel). However, the majority of our scenarios feature wind providing 25% or less of total generation. This result is probably more realistic than Elliston et al.'s 50%+ wind share, given that a number of studies demonstrate severe integration problems or excess spillage at wind penetration rates above 20%.[13]

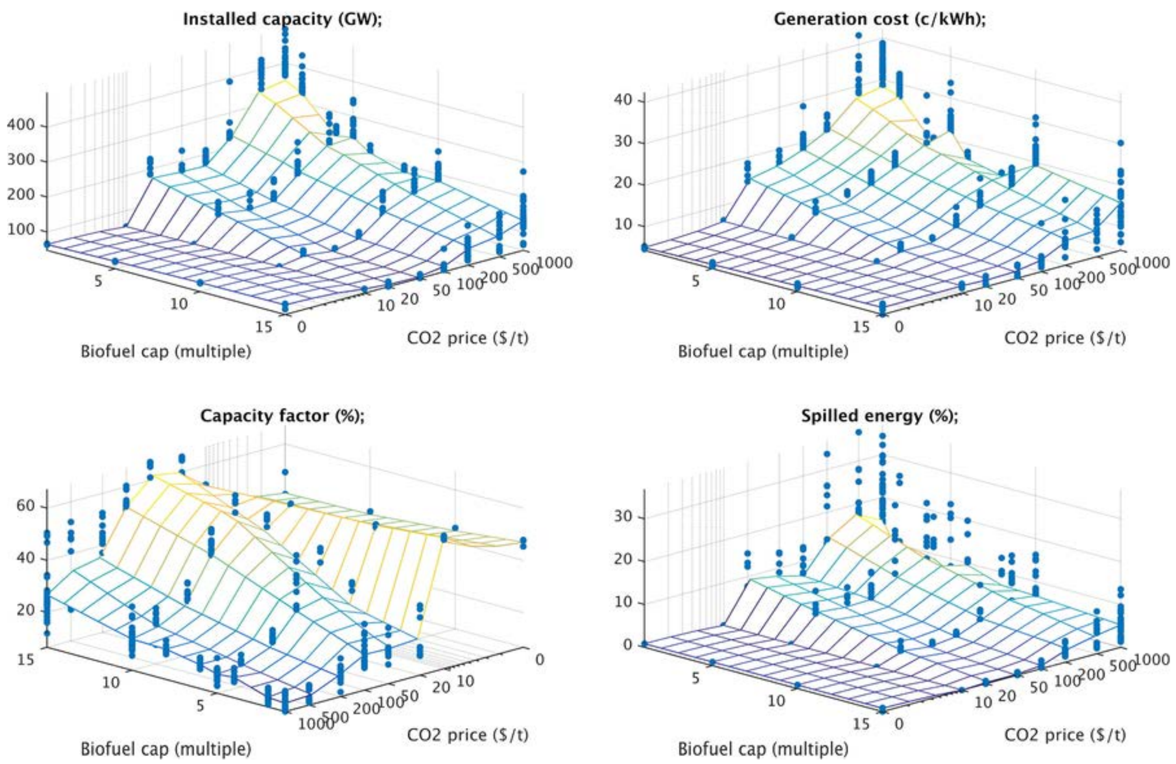

Fig. 2 System-wide installed capacity, cost, capacity factor and spilled energy for runs parameterised by $1 \leqslant \beta \leqslant 15$ and $0 \leqslant \kappa \leqslant 1000$. The surface interpolates average values obtained from runs with varying cost multipliers $0.75 \leqslant \varphi, \psi, \phi, \omega \leqslant 1.25$ (blue dots). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

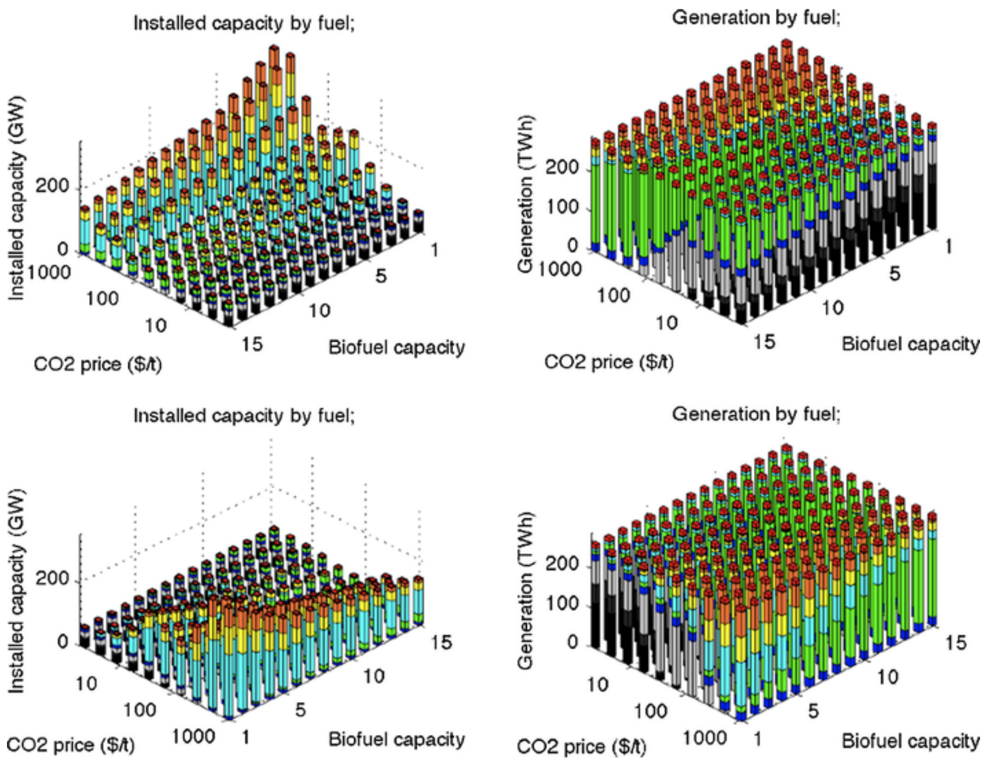

Fig. 3 System-wide installed capacity (left panels; front view top, rear view bottom) and generation (right panels) for runs parameterised by $1 \leqslant \beta \leqslant 15$ and $0 \leqslant \kappa \leqslant 1000$. Colours from column top to bottom: Red = rooftop PV, orange = CSP, yellow = utility PV, light blue = wind, green = biomass, dark blue = hydro,

grey = natural gas, black = coal and oil. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

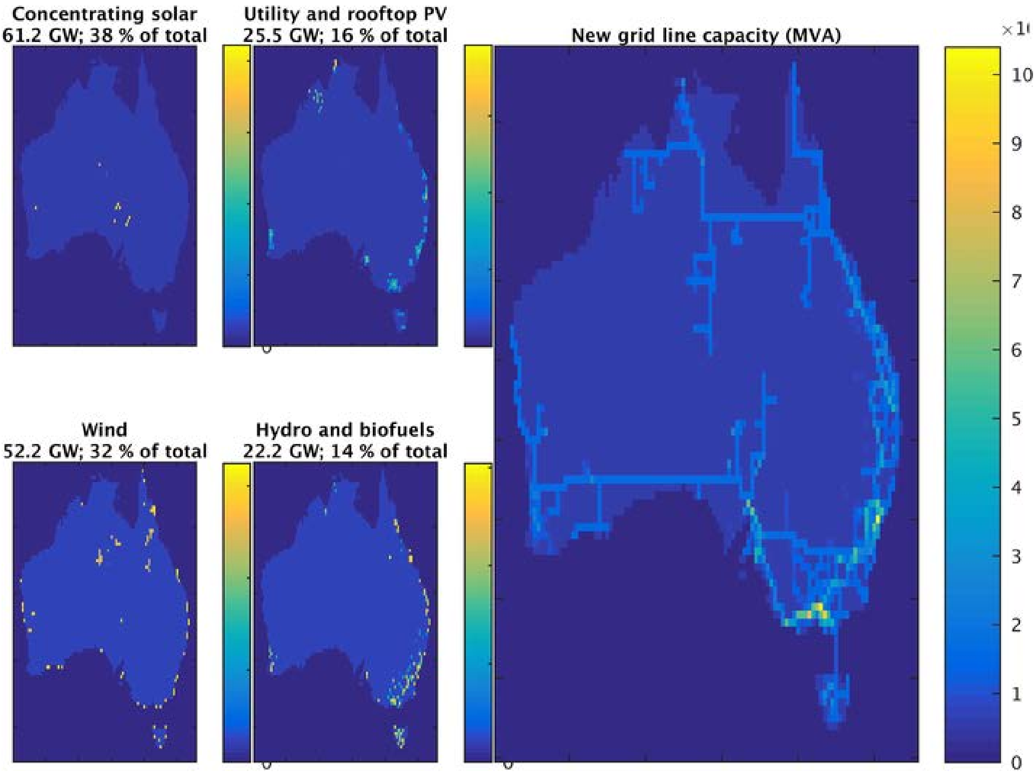

Fig. 4 Spatial distribution of capacity, and expanded transmission network for a run with β = 15, κ = 1000 $/t, φ = 1.00, ψ = 0.85, ϕ = 4.10, ω = 1.10, and 15 h CSP storage.

3.5 Influence of generation cost on installed capacity, generation cost, capacity factor, spilled energy, and energy carrier mix

We have varied the cost of PV (φ), CSP (ψ), biofuels (ϕ) and wind power (ω), upwards and downwards, by 25%. We find that installed capacity, generation cost and spilled energy are low, and capacity factors are high, at low biofuel and CSP cost (ψ = 0.75 and ϕ = 0.75) and high wind and PV cost (φ = 1.25 and ω = 1.25; right centre panels in Figs. A11–A14). In this situation, capacity and generation are generally dominated by relatively few biofuelled and CSP plants operating at relatively high capacity factors (Figs. A15–A18). The opposite holds for high biofuel and CSP cost (ψ = 1.25 and ϕ = 1.25) and low wind and PV cost (φ = 0.75 and ω = 0.75; left centre panels in Figs. A11–A14), where capacity and generation are generally dominated by relatively many wind and PV plants operating at relatively low capacity factors (Figs. A15–A18). These trends come about because both biofuelled and CSP plants with 15 h of storage are less afflicted by variability than PV and wind power, and hence require less capacity to supply a given amount of electricity. Intermediate cost combinations yield results in between the extremes described above.

These results can be readily understood by examining the default total cost data in Table 1, applying cost multipliers φ, ψ, ϕ, ω, and then establishing rank orders of the energy carriers based on multiplied total cost (Table A4). Clearly, biofuelled power is always the most competitive (ranked 1 – lowest cost), only constrained by availability (β). Comparing Fig. A18 with Table A4, we see that wind is consistently the second-choice carrier in the north/north-west panels, CSP in the south-east panels, and utility PV in the south-west panel. The relationships emerging from our simulations (Fig. A18) can thus be supported by the underlying cost assumptions listed in Table 1.

3.6 Generator siting, transmission expansion, cost and generation profile for a selected renewables-only case study

Out of the multitude of scenarios described in Figs. 1 and 2, we select one scenario that (a) requires less than 20 TW h of biofuelled generation, (b) features less than 30% wind penetration (given integration issues[13]), (c) has a total installed capacity of around 160 GW, and (d) spills no more than 20% of total generation. This scenario might come close to what would be implemented in the real world. In order to achieve a sufficiently low biofuels participation, we needed to increase the bidding price by ϕ = 4.10[14] and allow for a multiple of β = 15 of current capacity. Here we present results for a run with β = 15, κ = 1000 \$/t, φ = 1.00, ψ = 0.85, ϕ = 4.10, ω = 1.10, and 15 h CSP storage.

This case study matches the set targets in that it (a) utilises only 16.3 TW h of biofuelled generation, (b) features 29% wind penetration, (c) has a total installed capacity of 162 GW, and (d) spills about 20% of total generation (Table 2, compare Fig. A21). Concentrating solar provides the bulk of generation, followed by wind and PV. Hydro generation is lower than currently, allowing for potential future drought and climate change.[15] The overall system's capacity factor is 25% (compare Fig. 5, right panel). Generating cost are around 18 ¢/kW h, which is mostly due to fixed cost of CSP, biofuel and wind generators.

Table 2
Energy and cost balance, capacity size and utilisation for a run with β = 15, κ = 1000 \$/t, φ = 1.00, ψ = 0.85, ϕ = 4.10, ω = 1.10, and 15 h CSP storage. Variable cost in ¢/kW h coincide with values in Table 1 once cost multipliers are considered. 'System' denotes the entire continental power network, showing sums of TW h and GW, and weighted averages of% capacity factors and ¢/kW h cost.

	Hydro	Biofuels	Wind	Utility PV	CSP	Rooftop PV	System
Used (TW h)	7.4	16.3	80.8	29.2	138.0	8.4	281.0
+ Transmission loss (TW h)	0.1	0.2	1.7	0.7	2.4	0.1	5.4
= Generated (TW h)	7.5	16.5	82.5	29.9	140.0	8.5	286.0
Spilled (TW h)	0.0	0.0	5.1	9.2	47.0	0.0	61.2
Capacity (GW)	2.6	19.6	52.2	23.1	61.2	4.1	162
Capacity factor (%)	32	10	19	19	35	28	25
Fixed cost (¢/kW h)	5.2	115.0	10.4	6.3	10.7	1.7	15.7
+ Variable cost (¢/kW h)	0.7	3.5	1.2	0.0	1.5	0.0	1.3
+ Transmission cost (¢/kW h)	3.4	5.1	5.0	3.4	0.8	0.2	2.7
= Total cost (¢/kW h)	9.3	123.0	16.7	9.8	13.0	1.9	19.7

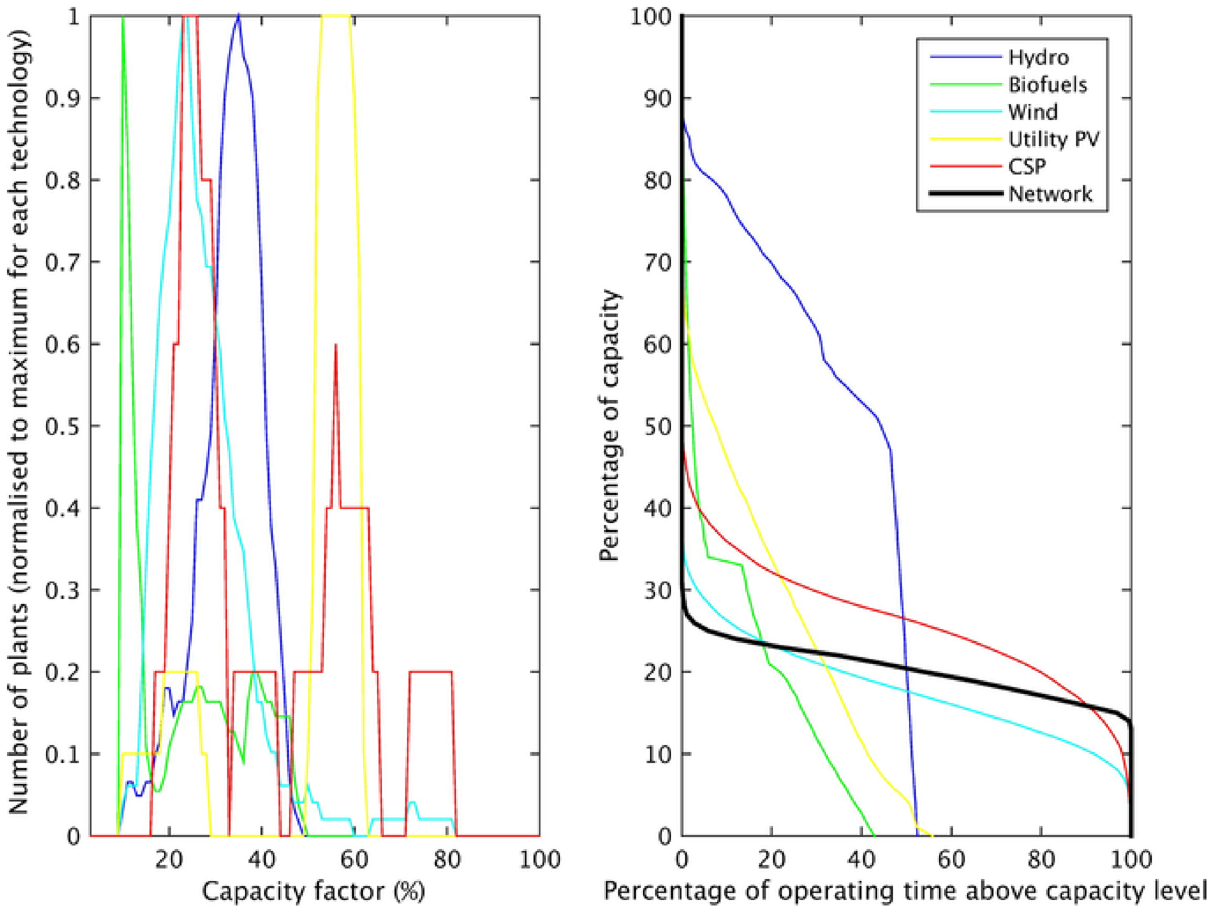

Fig. 5 Size distribution of capacity factors by technology (left panel, normalised separately for each technology to show a maximum of 1) and load duration curves by technology (right panel). The size distributions for CSP and PV show discontinuities simply because their number of plants is not as high as for other technologies. This is because a typical CSP and utility PV installation in one mesh point is larger than a wind installation, because the capacity densities are quite different, with $\lambda^{CSP} = 62$ MW km^{-2} $> \lambda^{PV} = 48$ MW km^{-2} $>> \lambda^{wind} = 5$ MW km^{-2}

The load duration curve shows the percentage of time (x-axis) that plants are above a certain capacity utilisation level (y-axis). The area under the load duration curve represents the 25% capacity factor (compare with Table 2).

Whilst hydro, biofuelled and rooftop PV generators are concentrated in the more densely populated southeast of the continent, wind, CSP and utility PV generators are distributed across the continent, with most of the wind plants situated around the coastline, and the CSP and PV plants mainly situated in the arid regions (see Fig. 4 in units of GW capacity; see Fig. A19 for maps in terms of TW h generation). We find some degree of spatial clustering which is brought about automatically in our algorithm, because isolated generators would be excluded as uneconomical because of the high transmission cost per unit kW h of generated electricity. Given that (a) transmission cost are lower than fixed cost on a per-kW h basis, (b) transmission losses are relatively low at 1% per 100 miles ([42], p. 30), and (c) generation is spatially dispersed in a renewables-only grid, we find that cross-continental links of the currently stand-alone WA, NT and NEM networks becomes beneficial in terms of keeping overall capacity down. In this case study, cumulative line capacity increases 2.5-fold.[16]

Operating characteristics of generators obviously depend on their technology, but also on their location, the latter determining solar and wind resource and the plants' proximity and therefore contribution to urban demand. We find a broad distribution of capacity factors across plants, even within the same technology (Fig. 5, left panel). As expected, CSP shows the largest capacity factors, due to the assumption of 15 h storage. Whilst hydropower essentially shows the current capacity utilisation at around 1/3, biofuelled plants are severely under-utilised, showing that their high cost multiplier of ϕ = 4.10 leads to them being recruited only during times of wind and solar resource shortage. Another way of looking at technology utilisation are load duration curves (Fig. 5, right panel). Only CSP and wind plants (in unison) are not affected by periods of zero output.

It is interesting to examine two particularly different sub-periods of time within the year examined. Here, we show generation profiles for the "best" and "worst" 5-day stretches for renewables, in the sense that low resource availability meant that significant support from biofuels and hydropower was necessary (Fig. 6). In 2010, the best and worst 5-day stretches happened around 6 April (2313 h) and 26 December (8639 h), respectively. Interestingly, on 8 April 2010, 19.6 GW of biofuelled capacity (compare Table 2) is needed to plug the gap in wind and solar resources. The two generation profiles illustrate the ability of the hydro and biofuel resource to be "spared for tough times", but also how this ability comes at the price of large unutilised capacity.

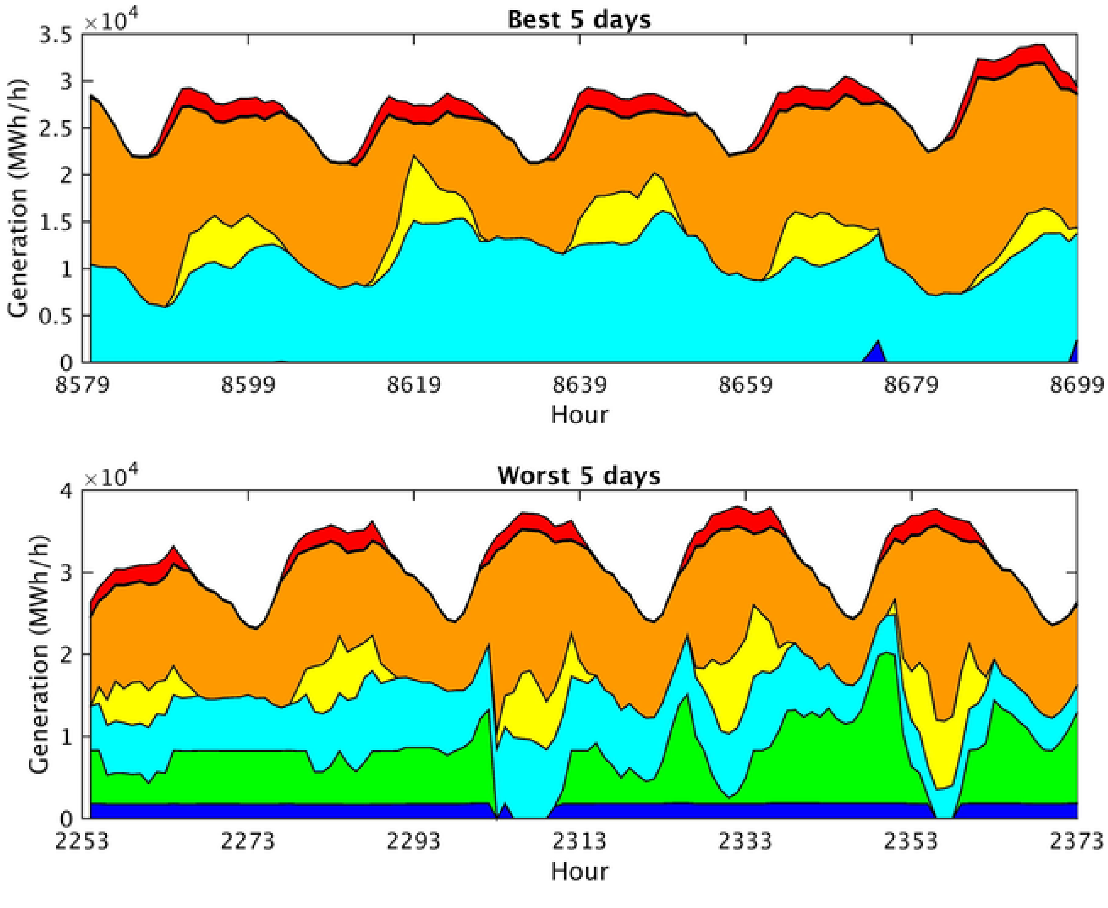

Fig. 6 5-day generation profiles for one period with minimum combined hydro and biofuelled generation ("best 5 days" in 2010 for renewables, 26 December or 8639 h, top panel), and one period with the maximum combined hydro and biofuelled generation ("worst 5 days", 6 April or 2313 h, bottom panel). Dark blue: hydro,

green: biofuels, light blue: wind, yellow: utility PV, orange: CSP, red: rooftop PV. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4 Discussion and conclusion

It is important to qualify the results presented in the previous section. In particular, our study does not touch upon issues of (a) technical integration of renewables at high penetration rates, (b) availability of biofuels, and (c) likely future cost developments. In addition, there are limitations presented by the temporal and spatial resolution of the weather data. Here we briefly discuss how these factors can potentially change our results.

4.1 Qualification I: Challenges to integration of variable sources at high penetration rates

Some of our scenario results in Fig. 3 feature wind energy covering more than 25% of generation. There exists a number of studies that mention either severe integration problems (for example frequency control issues and grid instability, [47]), excess spillage [66], or low capacity credits [65] at wind penetration rates above 20%. These grid integration problems are however being solved progressively, through measures such as improved forecasting, governor controls to adjust wind output and, more recently, efforts to provide synthetic inertia to the system.[17]

Holttinen [68] provides an overview of experiences with large-scale wind integration, describing increased short- and long-term term reserve requirements in from of spinning and quick-start additional capacity for balancing below-hourly variability and above-hourly prediction errors respectively, as well as impacts of wind variability on the efficiency of other generators in the grid, and on the power flow in the transmission network. Holttinen [68] shows that operating reserve requirements increase with increasing penetration of wind in the grid. In general, reserve capacity will be larger for systems with high penetrations of non-dispatchable technologies with relatively low capacity credits, ie with limited abilities “to start up or shut down within a given time horizon, […] to ramp up or down quickly once online, [and] maintaining such capabilities when tasked to perform them repeatedly over a multi-annual timeframe” [22]. In our study, in order to account for reserve requirements for a wide range of technology mixes, we have adopted a constant value of 15% (half of which constitutes contingency and frequency regulation, and the remaining half forecast errors) from Short et al. [42].[18]

Operating reserve requirements can be reduced by adding more flexible generation technologies such as hydro, geothermal and biofuels into the technology mix. Mason et al. [45] for example have little problem demonstrating 100% renewable supply for New Zealand because of abundant dispatchable hydro and geothermal resources. Similarly, the AEMO [22] study arrives at relatively low values of installed capacity and reserve because of the large contribution of geothermal power. In our study, biofuels take on this role. The strategy of emphasising flexible generation technologies may run up against limitations. We already mentioned limited water availability restricting hydro expansion in Australia [31,32], as well as limited track record, high cost (especially for drilling), and technical challenges restricting geothermal power [27,28]. However, given that biofuels are already technically feasible and available in Australia we will offer some pertinent discussion in the following subsection.

4.2 Qualification II: Capacity factor of wind farms

In the simulation we selected for Table 2, wind farms reach an overall capacity factor of 20% (instead of 30% in Elliston et al. [20]). Such low capacity factors are consistent with results from studies on closely-spaced, large wind farms experiencing shading effects (see Fig. 1 in Miller et al. [72][19]; +10%). However, currently operating wind farms in Australia feature much larger capacity factors of around or more than 30% (see Fig. A25). Similarly, because of the absence of constraints in land availability, future wind farms in Australia could be spaced to avoid the shading effects. In addition, due to technological improvements enhancing the performance of turbines at low wind speeds, an overall capacity factor for wind farms of 30% would be more realistic.[20] We have however selected the case study in Table 2 to show, as explained in the introduction, that renewables-only power supply for Australia is possible even under very conservative and restrictive assumptions.

4.3 Qualification III: Biofuel availability

Some of our scenario results in Fig. 3 feature biofuelled power covering more than 25% of generation. There has been some debate about whether biofuels will be able contribute significantly to power generation. The main, currently viable contributors to bioenergy are agriculture, forestry and urban waste. Agricultural sources include stubble (the volume of which is highly rainfall-dependent) and pasture grasses (the volume of which is highly dependent on the year-to-year extent of pasture land use; [49]). Bioenergy production from stubble is variable, but in principle well-suited to complement solar energy given that years with low solar downwelling may be years with increased rainfall and greater agricultural crop productivity. Sources of biomass from forestry (plantations and native forests) and urban waste are less variable over time. The actual contributions of biofuels to the overall energy mix are highly uncertain. Large contributions of biofuels may be technically feasible. For instance, Crawford et al. [49] arrive at 85 TW h/yr for 2010 (ranging between 60 and 190 TW h/yr, excluding the Northern Territory and Western Australia), and Farine et al. [74] state 55 TW h/year. Estimates depend on which feedstocks are considered and which data are used. Rather than technical feasibility, the greatest uncertainties around actual constraints are social, logistical and political and will depend on the ability of policy to support such large transformation of land use and infrastructure in a way that is equitable (e.g. accounting for impacts on regional communities, minimising land degradation), just (e.g. ensuring ongoing food security and biodiversity protection), accounts for local markets (e.g. availability of capital, competing land use such as forests for carbon sequestration), accounts for global market settings (e.g. competing forest and food products) and the impacts of climate change [75]. Analysing such uncertainties were beyond the scope this study.

4.4 Qualification IV: Future cost developments

Most of our cost estimates are derived from sources compiled at a time when Australia was undergoing a minerals boom, and when the Australian $ was nearly equal to the US$. At the time of writing it was close to 70 US¢. Given that a large part of renewable technology components are imported into Australia, the actual cost to build renewable plants at the time of writing, and possibly in the foreseeable future, could be considerably higher than has been assumed in cost estimates made during the past decade.

4.5 Qualification V: Influence of weather data resolution on generator siting and technology selection

The weather data used in this study [29] were initially available as half-hourly values on a 390 × 479 raster grid (8.9 km grid boxes), but for the analysis was aggregated to hourly values on a 90 × 110-

raster grid (38.6 km grid boxes), in order to reduce runtime and RAM requirements on our HPCs. These aggregations have consequences for the generator siting and technology selection outcomes. The hourly temporal resolution of irradiance data creates discrete “fronts” delineating areas with and without sunshine (see Fig. A22). As these fronts traverse the continent in hourly steps, some areas (within a front) receive up to two hours more sunshine than areas directly adjacent (outside the front). This circumstance leads to a streaked pattern in generator selection for utility PV plants.

The wind speed data (see Fig. A5 bottom panel) shows a marked increase at the continental coastline, with wind speeds being significantly higher off-shore. We conducted a numerical simulation where we increased the area permissible for generator locations by one grid cell around the entire continent, thus including an off-shore area of roughly 39 km distance. We observed (a) an increased concentration of selected generator sites around the coastline at the cost of inland sites (Fig. A23), (b) a decreased need for biofuels, concentrating solar, and hydropower to plug supply gaps created by the variability of wind energy (Fig. A24), (c) an increase of wind’s capacity factor from 18% to 31%, as evident from load duration curves (Fig. A25), (d) a concurrent increase of biofuel and concentrating solar capacity factors to 39% and 44% respectively, and (e) a decrease of overall installed capacity to 110 GW, mainly due to a decrease of biofuelled capacity to about 4 GW. Given these changes in simulation outcomes, it is important to adequately discern coastal areas in terms of wind speed information and its alignment with other GIS data, possible by simulating at higher resolution with increased RAM endowment, and potential multithreading of simulation code. These issues are the topic of future work.

4.6 Summary and outlook

Subject to the qualifications made in the previous subsections, we have shown that Australian electricity demand can be met at indicative cost around 20 ¢/kW h, including demonstrated low-carbon hydro, wind, concentrating solar, rooftop and utility PV technologies, without using fossil fuels, and at current stringent loss-of-load and reserve requirements, provided a contribution is made by a flexible renewable technology featuring high capacity credit, such as biofuels. At less than 30% of wind penetration (avoiding integration problems) and less than 20 TW h energy contribution by biofuels (allowing for competing uses), overall installed capacity would be in the order of 160 GW. A competitive selection process based on current generation cost but otherwise very conservative assumptions indicates that such a 100%-renewable generation mix would emerge at carbon prices above 500 $/t, which is in line with results from European studies with high shares of renewables.[21] In its essence, this result supports previous conclusions by Elliston et al. [20], however we additionally show that (a) this conclusion holds even when allowing for reduced wind capacity factors and penetration rates, a significant operation threshold for CSP, an overall 15% reserve margin, and including the whole of Australia; that (b) pre-selected windy or sunny sites must not necessarily be optimal sites in a systemic sense, because in addition to being endowed with a significant resource for the entire year, wind and sun must also come at the right time, that is when demand is high and when other generators are down, and be located close to demand points and other generators in order to minimise transmission cost and losses; and that (c) the additional transmission capacity required comes at a cost of less than the capital cost for the plant.

This work is directly relevant to efforts to realise Australia’s Renewable Energy Target (RET) of 33,000 GW h by 2020, and in particular to the renewable energy promotion mandates of the government’s Australian Renewable Energy Agency and Clean Energy Finance Corporation, of industry bodies such as the Clean Energy Council, local councils such as the City of Sydney with its ambitious renewable energy master plan, and of NGOs such as Beyond Zero Emissions, the Climate Council and the Australian Conservation Foundation. For example, in order to direct investment towards the RET, the most cost-effective generator sites in Australia need to be assessed and identified on the basis of long-term and whole-of-country information. Further, our analysis can assist NGO advocacy in confirming – on the basis of an improved methodology – viewpoints about the feasibility of a 100%-renewable power system for Australia even under conservative and restrictive technology assumptions.

Obviously, the widespread availability of cheap energy storage and technically viable and economical geothermal and wave generators, as well as new control options to smooth wind turbine output [77] would significantly change such an assessment. Future work could focus on (a) varying further parameters such as the solar multiple of CSP plants, rooftop PV penetration, or ramping rates, and running the simulation at increased (for example 400 × 400 mesh points) resolution, (b) integrating load shifting, interruptible loads and flexible demand into the simulation, (c) introducing more storage capacity for example in the form of electric vehicles,[22] (d) optimising for minimum economy-wide emissions [10] or other environmental impacts [21], (e) relaxing the constant reserve margin assumption and linking statistical effective load carrying capability calculations into the simulation, and (f) including embodied emissions.[23] Finally, whilst in our study the ability to investigate the performance of low-carbon grids over more than one year has been limited by computational resources, long-term simulation runs are important, given significant inter-annual variations of wind and solar resource availability[24].

Acknowledgments

We thank Sebastian Juraszek from the School of Physics for managing our 2tb-RAM server. This work was financially supported by University of Sydney Equipment Grant #G176690. The authors thank Barney Foran, Ben Elliston, Mark Diesendorf, Iain MacGill and Jenny Riesz for valuable comments on a draft of this paper.

Appendix A

Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2016.06.151

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Footnotes

[1]See Delucchi and Jacobson [1], Jacobson and Delucchi [2], and the ensuing debate in Fthenakis et al. [3], Delucchi and Jacobson [4], Trainer [5], Jacobson and Delucchi [6], Trainer [7].
[2]http://www.smh.com.au/federal-politics/political-news/australia-will-have-to-move-away-from-coal-un-climate-head-says-20150506-ggvfvz.html.
[3]https://www.environment.gov.au/climate-change/renewable-energy-target-scheme.
[4]We prefer the term "low-emission" to "zero-emission" because even 100% renewable energy requires so-called embodied emissions for the production of plant components [17,18].
[5]Elliston et al. [19,20], Turner et al. [21].
[6]We choose 2010 as the year of our analysis in order to be able to compare our results with those obtained by Elliston et al. [20].
[7]Due to limited water availability, hydro-potential has reached its limit in Australia [31,32].
[8]By "copper plate" we mean the assumption that the grid is viewed free of power flow restrictions such as congestion. We do consider transmission losses.
[9]See Table 1 and Appendix A.4 for data used in our simulations. Rather than estimating future cost developments we conduct sensitivity analyses by varying cost data using cost multipliers.
[10]This amounts to about five times installed capacity at the time of writing. Large capacity overheads in zero-carbon grids – factors three to five – have been reported previously, see [10,11]. Results of a large-scale European study [59] simulating a 2.5-fold capacity expansion still included 20% fossil-fuelled capacity. A recent study for the UK ([60], p. 21) reports a quarter of demand still supply by natural gas despite a quadrupling of wind and solar capacities (scenario Re.80). Capacity overheads could be limited to twofold only by supplying 40% of demand through "zero-carbon firm (ZCF)" technologies such as biomass, carbon capture and storage, and new nuclear (scenario Mix.80).
[11]Compare with Nelson et al. [61] and Kunz and Kirrmann [62].
[12]Spilled energy, especially from wind turbines, appears in the order of 30% in Figs. 8 and 9 in Huva et al. [23] (compare with [63]), and in the order of 10% in a UK study including a quarter of demand supplied by natural gas ([60], p. 21, scenario Re.80).
[13]Voorspools and D'haeseleer [65], Hoogwijk et al. [66], Meibom et al. [67], Holttinen [68], Resch et al. [69].
[14]We could have lowered cost of wind, CSP and hydro relative to biofuels, however this would have meant a more significant departure from cost values documented in the literature.
[15]Annual generation by Australian hydropower plants between 2000 and 2013 varied between 11 and 18 TW h [70].
[16]See Fig. A20, and compare with similar results reported for Europe by Fürsch et al. [59].
[17]Thanks to Ben Elliston for pointing this out during a review of an earlier draft.

[18]Riesz et al. [71] comment that the concept of a reserve margin may not be meaningfully applied to a 100% renewable power system, given that the most severe constraints on capacity occur most likely overnight, ie off-peak, and that therefore adding a reserve margin to peak demand may not make sense.
[19]Based on Short et al. [42] (p. 11) we assumed a wind capacity density limit of $\boldsymbol{\lambda}^{wind}$ -5 MW km^{-2}. Miller et al. [72] show that for this installed capacity density, delivered energy density will not exceed 1 MW km−2 (their Fig. 2, see also Adams and Keith [73]), and hence capacity factors will be limited to 20% (their Fig. 1, blue bar).
[20]Thanks to Mark Diesendorf, Ben Elliston and Iain MacGill for pointing this out during a review of an earlier draft.
[21]Compare with (a) Kunz and Kirrmann [62] p. 52, who arrive at a carbon price of "at least 80–100 €/t" for "ambitious renewables targets", with (b) Jägemann et al. [44], who determine carbon cap compliance cost of 197 €/t in their 2-IV-H scenario still featuring 10% natural gas generation, and with (c) Nagl et al. [76], who show 20–30% of capacity being fossil-fuelled at CO2 prices of up to 75 €/t.
[22]See Kempton and Tomić [78,79], Tomić and Kempton [80], Lund and Kempton [81].
[23]Lenzen [82], Lenzen and Munksgaard [83], Crawford et al. [84], Fthenakis and Kim [85], Lenzen [86].
[24]See for example the "wind drought" analysis by Katzenstein [87].