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Potential Value of Shiftable Domestic Hot Water Load in Facilitating Solar Photovoltaic Integration in the Australian National Electricity Market

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Abstract

Solar energy is expected to play a significant role in future low emission electricity systems. Due to the daily cycle of solar energy flux, future electricity generation scenarios with a high penetration of solar photovoltaic (PV) capacity typically identify challenges with integrating relatively short daily periods of high PV generation, and hence benefit from energy storage. While dedicated energy storage devices such as batteries show great promise, it is also important to consider other types of demand side management that may allow more cost effective and efficient integration of solar power. In the Australian National Electricity Market (NEM), a significant proportion of houses currently have storage hot water systems attached to controllable circuits, which are supplied only during off-peak hours, at present mostly overnight. These hot water loads constitute a substantial shiftable load resource with the technology for centralised dispatch already in place. In an electricity system with a high level of PV capacity, it is intuitive that dispatch of these loads during sunlight hours may assist in the integration of this solar generation. This study aims to quantify the system-level value of shiftable off-peak hot water in future NEM scenarios with high PV penetrations. The PLEXOS® Integrated Energy Model is used to optimise dispatch of the hot water load to minimise total system operating cost. This is compared against the existing ‘night shifted’ load profile as well as a simulated uncontrolled profile for water heating. Optimal dispatch of shiftable hot water load is found to reduce overall system generation costs on average by 5.8% per year, reduce generator ramping by 22% and reduce solar energy spill by around 37% relative to the uncontrolled simulation.

1. Introduction

Given strengthening international climate action goals, there is growing interest and attention towards increasing penetrations of renewable energy into existing fossil fuel-based power systems as a key means to reduce greenhouse gas emissions. Due to the enormous solar resource potential, continual improvements in performance and recent large cost reductions, solar photovoltaic (PV) technology offers considerable potential to be a leading source of renewable energy into the future. However, in addition to the uncertainty challenge common between PV and other variable renewable energy (VRE) sources such as wind, the significant predictable diurnal variability of solar output presents specific integration challenges at high PV penetrations.

A key solution is energy storage, to allow PV energy to be stored at the time of generation and then used when it is needed. While batteries are one potentially important form of energy storage, it is also important to consider loads that inherently incorporate energy storage. An important example in the Australian context is off peak hot water (OPHW), where a significant proportion of residential hot water storage systems are currently operated under a controlled load regime utilising ripple control systems, such that water is heated primarily during the night for use during the day. The potential for OPHW to be used to absorb high solar output during the day has been practically demonstrated to help manage voltage issues on a low voltage feeder with a high PV penetration in Australia (Swinson et al., 2015).

At a more aggregated level there is also the potential for a different OPHW shifting regime to assist with system integration of both wind and PV generation, by helping to maintain the overall balance between increasingly variable supply and partially flexible demand. The study presented in this paper examines the value impact of OPHW in a high renewables Australian National Electricity Market (NEM) future scenario with particularly high PV penetration. A profile for existing OPHW load in the NEM is developed based on half-hourly demand data from off peak circuits for over 1200 houses from the Australian Smart Grid Smart City trial. This load is modelled as a shiftable resource at a half hourly resolution over a five year period, using the PLEXOS® Integrated Energy Model. This approach helps fill several key gaps in the literature, bringing together detailed end use data with a system level supply-demand perspective across a substantial modelling time frame. Key results presented are the impact on overall system generation costs, effects on total generator cycling, and impacts on renewables spill as well as system emissions.

The rest of the paper is structured as follows The next Section provides context for the research. Section 3 describes the NEM scenarios used, analysis of the shiftable load data and its representation in PLEXOS, other PLEXOS model settings, and additional data inputs into the modelling. Section 4 presents results and discussion, and Section 5 gives conclusions from the work.

2. Context

2.1. Wind and solar PV in Australia

Variable renewable generation in Australia consists primarily of utility scale wind and behind the meter rooftop solar, estimated for 2015 at around a 5% energy contribution from wind (AEMO data accessed through NemSight®), and around 2.8% from solar (Johnston & Egan, 2016). However, with the continuing fall in the costs of solar PV and recent construction of multiple utility scale plants in the NEM, there is the potential for the solar contribution to rise considerably into the future. Current federal level renewable energy targets in Australia aim to achieve at least 20% of electricity from renewables by 2020, and a number of Australian States have independently adopted more ambitious targets. This work thus aims to gain a better understanding of future energy scenarios where both the potential for much higher levels of VRE, and a relatively higher proportion of solar PV are realised.

2.2. The renewables integration challenge and demand side management

The potential to shift loads to better match generator output broadly falls under the definition of demand side management (DSM), which includes demand response (DR) to a signal as well as energy efficiency and conservation, distributed generation and distributed storage. The potential of various types of DSM, and particularly DR, for renewables integration has attracted strong research interest over the last decade (Hungerford et al., 2015).

Key areas of research include DR for provision of reserves (Parvania & Fotuhi-Firuzabad, 2010) and balancing and ancillary services (Ma et al., 2013). Several studies particularly focus on the ability of DR to mitigate the uncertainty due to wind forecasting error (Kowli & Meyn, 2011; Paterakis et al., 2015), using two-stage unit commitment models. While this area is an important potential value of DSM, the turnover of the ancillary services and reserve markets in Australia are very low compared with the wholesale energy market at present, and this aspect has not been considered in this work.

Peak load reduction using DSM in high renewables systems has also attracted considerable research interest. For example, in (Papavasiliou & Oren, 2010) a coupling algorithm is developed to enable renewables to capture 'capacity credit' for a shiftable load. In (De Jonghe et al., 2014), DR based on price elastic load is used to reduce peak load, emissions and also renewables curtailment. A short time frame study also based on price elasticity (Ikeda et al., 2012) also uses DR to reduce the number of operating units during the peak time. The price elasticity approach is common, and relies on very high level assumptions about demand reduction.

2.3. Use of the PLEXOS® Integrated Energy Model

A key aim of our study is to bring together detailed end use data with a large systems model. PLEXOS is well suited to this task as a highly flexible tool with inbuilt DSM features which has been used extensively for academic research on the NEM (Molyneaux et al., 2013; Wagner et al., 2014; Wilkie et al., 2015) as well as other electricity markets (Brouwer et al., 2016; Lew et al., 2013), and particularly the Irish All Island SEM (Foley et al., 2013; O'Dwyer & Flynn, 2015). Despite its inbuilt DSM features, we are only aware of a few instances of shiftable loads being represented in PLEXOS. In (Foley et al., 2013) the 'purchaser' class of PLEXOS is used to represent flexible electric vehicle (EV) loads, and the authors found centralised optimisation of the charging regime reduced system emissions, cost of charging, and the need for peaking generation. A recent study also uses PLEXOS to examine a range of types of DSM including both curtailment and shiftable loads (Brouwer et al., 2016). This paper investigates flexible industrial, commercial and residential loads in Western Europe. The cost and benefit of demand response is compared with alternatives of increased transmission and battery storage for integration of high levels of renewable energy, and DR is found to be the most beneficial to total system costs.

3. Methodology

3.1. Modelling the Australian National Electricity Market (NEM)

The Australian National Electricity Market (NEM) consists of five interconnected regional markets for the states of Queensland, New South Wales, Victoria, South Australia and Tasmania. The NEM is a gross pool energy only spot market with 5-minute dispatch intervals, which are averaged within half hour trading periods to give half-hourly dispatch prices. The wholesale spot market is complemented by a set of frequency control ancillary services (FCAS) markets in addition to financial derivatives markets traded over the counter and through the Sydney Futures Exchange, which provide financial hedges for market players. Generator bidding behaviour in the NEM is strongly influenced by their derivative positions.

Market power is also recognised to be a significant factor controlling market prices in the NEM, and is routinely monitored by the Australian Energy Regulator (AER) (AER, 2015).

Due to the complexity of NEM operation, it is very challenging to accurately model generator bidding behaviour. As the focus of this research is to gain an indication of the potential underlying value of shiftable load in a high renewables scenario, the modelling simply uses least cost dispatch optimisation, without taking into account generator strategic behaviour or the impact of financial derivatives. In addition, to retain modelling simplicity, the NEM is treated as a single 'copper plate' area, although inclusion of transmission constraints represents a potential area for future work.

3.2. Scenarios

The modelling scenarios consist of a single generation portfolio combined with three different demand scenarios.

3.2.1. Generation portfolio

Solar PV and wind capacity are set such that each technology provides 20% of total NEM electricity served across a 5 year modelling period, disregarding spill, for a 40% total VRE contribution. Cogeneration, distillate and hydro capacity are based on existing NEM capacities. To base the remaining fossil fuel technologies on the existing NEM, the generation capacity for each technology is set so that energy served by technology remains in approximately the same proportion within these technologies as historical levels for the study period. Total generation capacity is kept the same for all modelling years, and adjusted so that the highest level of unserved energy seen across the entire period is approximately equal to the NEM reliability standard of 0.002% for the historical demand profile.

3.2.2. Demand scenarios

Three different demand scenarios are used: an historical, an optimised and an uncontrolled OPHW scenario. The historical load scenario directly uses the historical load from 2006-2010 for the NEM, obtained from AEMO data using NemSight® from Creative Analytics. This period was chosen due to coincidence of available generation profiles for the renewable technologies. The optimised scenario involves subtraction of a developed hot water demand profile based on Smart Grid, Smart City (SGSC) trial (Ausgrid, 2014) data from the first profile, enabling the load to be added back as a shiftable object (described in Section 3.3.1). The uncontrolled scenario simulates an uncontrolled hot water usage profile (described in Section 3.3.2), which is scaled to be of equal size to the subtracted OPHW profile and added back to the demand curve to give a demand profile simulating overall demand if existing OPHW systems were supplied on-demand rather than using the remotely controlled 'ripple' circuit.

3.3. Smart Grid Smart City trial data analysis

Most of the data analysis for this section was performed using the software R (R Core Team, 2015), complemented by Microsoft Excel®.

3.3.1. Development of the off peak hot water demand profile

This study takes advantage of publicly available data from Australian's first commercial smart grid project, the Smart Grid, Smart City trial. This dataset includes half hourly general supply and controlled load data for over 3000 households, matched with detailed household survey data. The controlled load circuits are supplied either only during the night, or during all hours except for a set period during the evening peak, and it is expected that the greater majority of the load they supply is either off peak hot water or pool pump load. As pool pump ownership is included in the survey data, households with pool pumps could be excluded from the analysis to eliminate pool pump demand from the controlled load data. Houses with gas hot water systems were also excluded as well as all households with blank or zero entries for 'number of occupants', as these indicated either unoccupied residences or incomplete surveys. After these exclusions, around 1200 households remained, and the data for these was averaged for each time point to give a per-household profile. The monthly peak demand obtained in the analysis ranged from 1.9 to 2.4 kW per household, which corresponds well with expected hot water system demand, e.g. (Koon & Negnevitsky, 2013). Average daily demand ranges between 4.6 kWh per household in summer to 8.3 kWh in winter.

Average profiles were created for different times of year, and the main difference observed across one year of data was a significant increase in the total energy consumption in winter months. Thus it was decided to adopt a single average usage shape for the year, with a scaling factor applied by month to capture seasonal variability. In addition, while the SGSC profile shows one very distinct late night peak, this reflects the specific area of the network (Ausgrid) where the SGSC trial was conducted. Based on two evident late-night shoulders in the NEM load data as well as other information on more staggered triggering patterns (e.g. as seen in (Swinson et al., 2015)), approximately one third of the peak occurring at 11:30 pm in the SGSC data was shifted 1.5 hours later. This profile was then scaled to the size of the NEM using the most recently available Australian Bureau of Statistics data for off peak hot water ownership data by state from 2008.

3.3.2. Development of an uncontrolled hot water usage profile

As the existing usage pattern for OPHW demand is the result of controlled load dispatch, in order to compare with an uncontrolled baseline it is desirable to investigate the shape of uncontrolled hot water demand. For this purpose, appliance level data from the SGSC trial specifically monitoring load from hot water systems was analysed. This dataset consists of non-synchronised cumulative meter readings by customer for approximately 90 different customers across just under one year, with intermittent periods of missing data for each customer. In order to enable analysis, each customer's readings were organised into chronological order and each time stamp rounded to the nearest half hour using R software. Sequential cumulative readings were then subtracted so that each reading consists of the kWh of energy usage since the previous reading. In order to avoid high misleading readings where there were long periods between readings, all data points where the time interval from the previous reading was greater than 2 hours were then discarded. Furthermore, all negative readings were eliminated to exclude occasional large negative readings due to apparent meter resets, and all readings above a 5 kWh threshold were eliminated to remove a few remaining outlier readings most likely caused by meter error.

In order to gain a sense of the average behaviour of each customer, individual customers' usage profiles were aggregated across a 1-year time frame to obtain a single average daily usage profile for each customer. While many of the customers displayed a similar demand pattern to that of the OPHW load determined in section 3.2, 11 customers were able to be identified with an apparent uncontrolled profile, with hot water usage distributed throughout the day and generally displaying two peaks in the morning and evening. The data from these 11 customers was then used to create aggregated average usage profiles for the year, including summer and winter weekday and weekend profiles. As these profiles did not show clear seasonal or day of week differences, a single annual average profile was derived, and used in the modelling to simulate the shape of uncontrolled hot water demand. This profile was then scaled based on the values used to simulate OPHW from Section 3.3, to create an overall profile with the same total energy consumption as the OPHW profile described in the previous section.

3.4. PLEXOS® model

3.4.1. Shiftable load representation

Shiftable load is represented in PLEXOS® using its 'purchaser' class. Maximum load is set based on the maxima from the average usage shape developed in section 3.3.1 and the scaling factors applied using a 'variable' object. This approach was also used to define a maximum and minimum daily energy sum of equal value to ensure the desired amount of shiftable load is dispatched each day, split into two 12-hour blocks per day based on the energy distribution displayed in the uncontrolled usage profile described in section 3.3.2, as the flexibility around when the water is heated should be based on when it is used rather than the current dispatch pattern.

3.4.2. PLEXOS model settings

MOSEK is used as the mathematic solver, and similarly to (Baringa, 2016; Foley et al., 2013), rounded relaxation is also used, as this was found to deliver similar or better optimisation results to the full mixed integer solution with much shorter modelling times. A single rounding threshold of 0.5 was used, since tuning was found to extend modelling times with minimal effect on results. A scheduling interval of 30 minutes was combined with a step size of one day with an additional 1 day of look-ahead at an 8-hour resolution, across the 5-year modelling time period.

3.4.3. Additional data inputs

As cogeneration plant operation is seen to be largely dictated by heating requirements, historical cogeneration profiles were used, obtained through NemSight®. Generation profiles for new build wind and solar were obtained from ROAM hourly profiles provided as part of the AEMO 100% renewables study (AEMO, 2013), interpolated to give half hourly values. These profiles are based on the eastern part of Australia divided into 42 different polygons, with a per-MW profile given for each polygon based on hourly satellite data for PV, and weather forecasting system outputs for wind. For the present modelling a single NEM-wide profile was created by distributing generation capacity evenly between a selected subset of polygons, ensuring that even at very high VRE penetration the generation potential would not be exceeded in any of the polygons, to allow scalability.

Operational characteristics for thermal plant including minimum operating levels, ramp rate restrictions, heat rates, fuel costs, variable operations and maintenance costs (VOM), fixed operations and maintenance costs (FOM), startup and shutdown costs, capital costs and emissions rates were obtained from ACIL Allen data used in the NTNDP 2015 (AEMO, 2015). Averages by technology were used for most data inputs where there is variation between particular plant. This approach was also used to obtain average plant sizes. Cycling characteristics including ramping costs and start-up and shutdown times were obtained from (Lew et al., 2013).

3.4.4. Analysis of PLEXOS® results

In addition to the PLEXOS® results interface, the R package 'rplexos' (Barrows et al., 2016) was found to be extremely efficient for retrieving results to .csv files which were then analysed using Matlab® and Microsoft Excel®.

4. Results and Discussion

4.1. Generation cost impact

Annual total generation costs (TGC) for each of the existing control scenario and the PLEXOS optimised control scenario are compared with the uncontrolled hot water simulation for each year. The existing control scenario shows very poor performance for this generation portfolio, with higher costs in some years shown by the negative savings value seen in Figure 1, and an average annual increase of $1.7 million. The optimised control regime provides a significant benefit in all modelling years and an average annual reduction of $152 million.

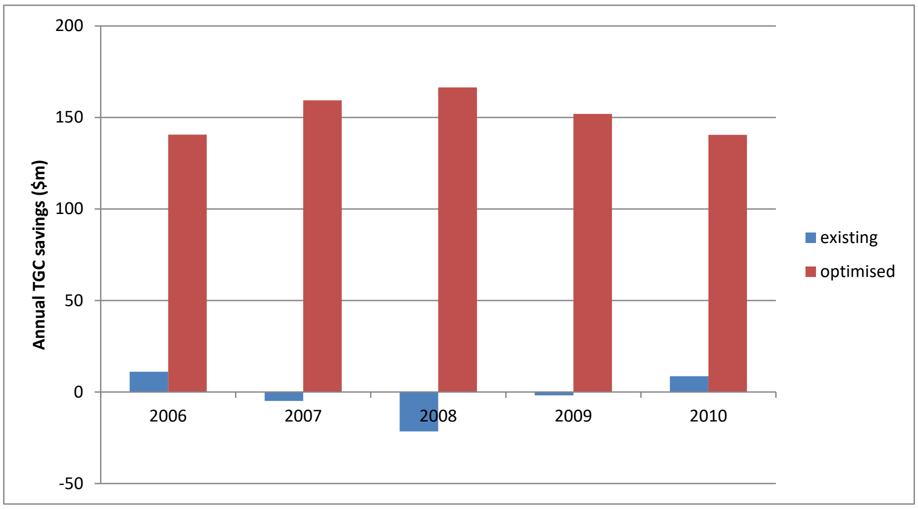

Figure 1. Annual TGC savings relative to the uncontrolled hot water demand scenario for the existing and optimised OPHW control regimes.

These findings demonstrate the unsuitability of late night OPHW dispatch in a high VRE, high solar system. In the optimised regime, OPHW is generally activated during the day. The significant cost savings for the optimised pattern occur due to a slight decrease in wind spill and a shift from OCGT generation towards cheaper coal generation.

4.2. Generator ramping

A key predicted outcome of increasing VRE penetration is increased cycling requirements for conventional thermal plant. As the modelling includes ramping costs, the optimisation engine will minimise ramping behaviour where this is possible without increasing other generation costs. As seen in Figure 2, in all modelling years the existing control regime reduces total ramping of dispatchable plant relative to the uncontrolled simulation, and the optimised regime reduces this even further. On average ramping is reduced by 8% in the existing regime and 23% in the optimised regime.

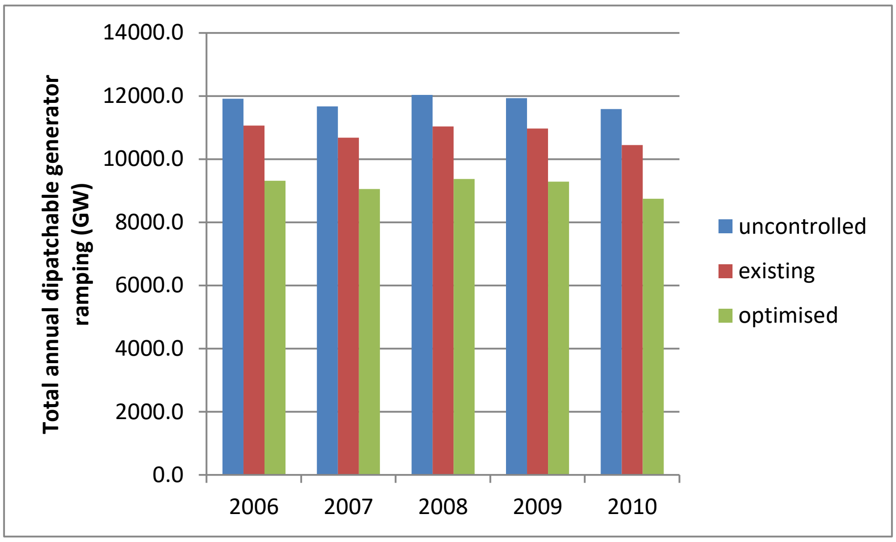

Figure 2. Total annual dispatchable generator ramping by year for the different control regimes.

4.3. Renewables spill and emissions

Renewables spill shows a consistent trend with the existing control regime actually increasing spill relative to the uncontrolled simulation by an average of 18%, and the optimised regime reducing spill on average by 37%, as shown in Figure 3. This again demonstrates the unsuitability of the existing OPHW control regime for a high renewables, high solar case.

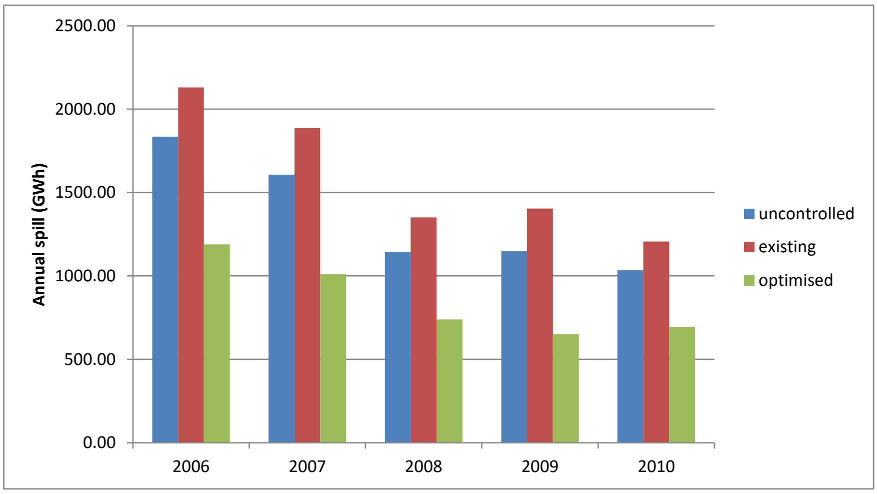

Figure 3. Annual renewables spill based on the three different control regimes.

Both control regimes have a minimal impact on emissions, with the largest magnitude of change in any one year less than 0.1%. The existing control regime on average very slightly reduces emissions relative to the uncontrolled simulation (-0.01%) and the optimised control very slightly increases emissions (+0.01%). This is determined by shifts in the relative proportions of energy provided by the different generating technologies. In the existing control regime, the increase in renewables spill increases emissions, but this is counterbalanced by a small overall shift away from black coal towards less polluting CCGT generation. In the optimised regime, while renewables spill is significantly reduced, the overall flattening of the residual load profile also results in a significant shift from OCGT generation to more polluting black coal, resulting in an on-average increase in emissions.

5. Conclusions

Overall the findings of this study demonstrate significant system economic benefits of an optimised control regime for hot water load in a 40% VRE scenario with half of variable renewable energy provided by solar PV. Interestingly, the existing regime actually results in higher system operating costs in some years, and consistently increased renewables spill. While optimised control actually slightly increases overall emissions, it does offer significant system cost benefits, as well as a substantial reduction in renewables spill. Both control regimes consistently reduce dispatchable generator ramping requirements, and this effect is strongest in the optimised control case. By shifting load away from the peak times, both control regimes also offer similar benefits to generation capacity requirements.

Key areas for future work include incorporating transmission constraints, considering other DSM resources, examining a wider range of renewables scenarios and also investigating the impact of changes in the fossil fuel plant mix. It is important to also note that this modelling takes a 'perfect foresight' approach, and thus it would be interesting to see the effect of modelling using imperfect forecasting followed by real-time recourse decisions. In addition, while the employment of an economic dispatch model here is useful for assessing underlying potential value, it is important to consider that the real world impact on electricity market outcomes is more difficult to predict as dispatch decisions are made based on generator bidding patterns, which are very challenging to model.

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