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Technoeconomic parametric analysis of PV-battery systems

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A B S T R A C T

Application of integrated PV-battery systems for off-grid locations has a history exceeding four decades. With the observed fast reduction of PV and battery system prices in recent years, however, interest in the use of PV-battery systems has notably increased even at on-grid locations. The aim of this paper is to assess the impact of various technoeconomic parameters, such as geographic location, weather condition, electricity price, feed-in tariff, PV/battery system cost, and PV/battery specifications on the economic feasibility of grid-connected PV-battery systems. For this, we have used our inhouse decision support tool for investment decision making, optimal sizing, and operation scheduling of grid-connected PV/battery system with respect to these parameters. The results show that decision on the selection of the right PV-battery system is significantly sensitive to each and every one of these parameters. Within various price scenarios that we carried out, battery shows positive impact on NPV only at low installation costs (e.g. $\leq$750 \$/kWh). Neither the sales electricity tariff nor the feed-in tariff has alone a direct impact on the feasibility of installing a battery system. Rather, the magnitude of the difference between electricity price and feed-in tariff is the detrimental element in battery attractiveness. A case-study for Sydney, Australia, showed that at current sales/feed-in electricity tariffs, PV systems with prices of 2700 \$/kW, or less, not only reach parity with the grid electricity price but also reach parity with feed-in tariff. This implies the viability of installing large PV systems merely for selling the generated electricity to the grid.

1. Introduction

With the rapid reduction in PV system prices in recent years, interest in the use of grid-connected PV generation and/or battery systems has notably increased. Traditionally, PV systems have been used in two configurations, grid-connected without battery and off-grid (stand-alone) with battery (Fig. 1). Fig. 2 illustrates the key challenge of PV technology, even at infinitely high system sizes, to supply the full electricity demand of a typical household customer. PV systems cannot supply electricity demand outside daylight times. In off-grid applications, therefore, electricity storage becomes an inseparable part of PV generation (ignoring cost issues), to ensure higher power reliability.

According to the International Energy Agency, "as PV matures into mainstream technology, grid integration and management and energy storage become key issues" [1]. This necessity has triggered the term "community energy storage" [2,3], reflecting the need for electricity storage at the demand-side. This translates into the introduction of a third configuration, the grid-connected PV-battery system (see Fig. 3).

Initial efforts in the sizing of integrated PV-battery systems focused mainly on off-grid and rural areas, using approximate methods which resulted in over-sized or under-sized systems [4]. Later, iso-reliability curves were introduced by Egido and Lorenzo [5] which is based on developing numerous graphs of PV-storage sizes, each at a certain reliability value. A good review on the iso-reliability method and a rule-of-thumb approximation on that basis is given by Egido and Lorenzo [5]. As computers emerged, PV-battery sizing models also improved in rigor. For instance, instead of daily average solar irradiation or load data, real historical time series were used [6,7], or characteristic equations were used instead of simple efficiency values for PV panel, battery, inverters [8], etc.

With the global attention to the PV transformation within the last decade, there has been increasing interest in linking PV and/or battery systems with the electricity market and a need to develop an optimal operation schedule. Lu and Shahidehpour [9] developed a short-term scheduling model for battery use in a grid-connected

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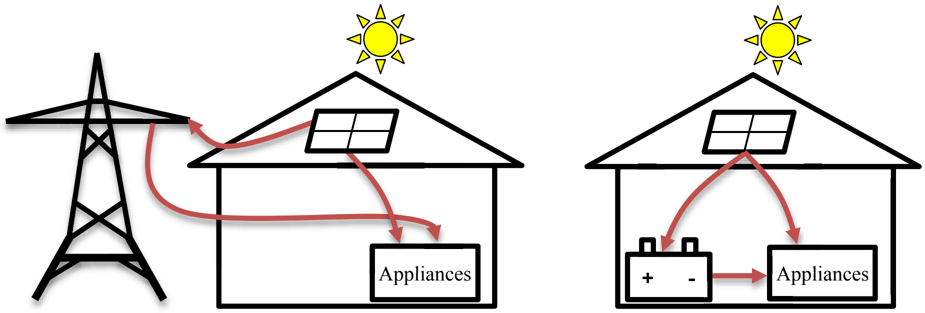

Fig. 1. Schematic of two DG configurations: grid-connected PV (left) and off-grid (stand-alone) PV with storage (right).

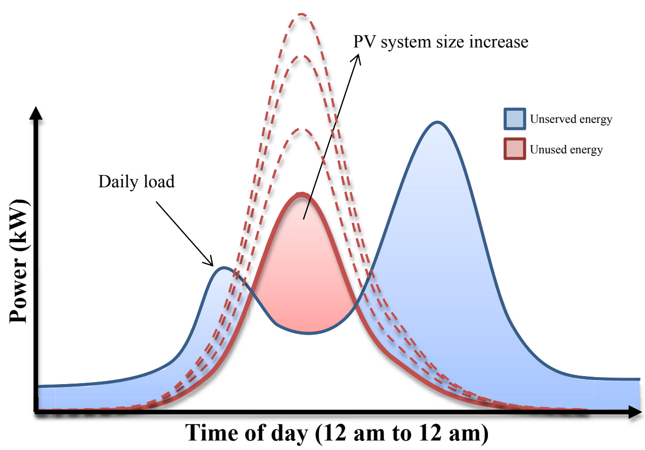

Fig. 2. The PV challenge: even a very large PV system cannot meet the full load of a typical household.

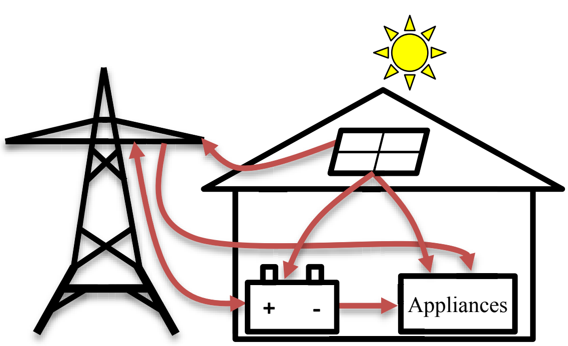

Fig. 3. Illustration of a grid-connected PV-battery system.

PV-battery system using a Lagrangian relaxation-based optimization algorithm to determine the hourly charge/discharge commitment of a battery in a utility grid. They used an eight-bus test system as a case study and investigated the impact of grid-connected PV-battery system on locational pricing. Kaushika et al. [10] developed a linear programming formulation for a stand-alone PV-battery system with an objective to find out the optimum combination of the number of batteries and PV modules to allow the operation of the system with zero loss of power supply probability (LPSP) or 100% reliability.

Some researchers have also used artificial intelligence techniques for sizing PV-battery systems [11]. Riffonneau et al. [12] presented a dynamic programming methodology for "day-ahead" predictive management of grid-connected PV systems with storage. The program, which also considered battery aging, successfully achieved its peak-shaving goal at minimum costs. Yu et al. [13] studied the problem of determining the size of battery storage for grid-connected PV systems. They proposed lower and upper bounds on storage size and introduced an optimization algorithm for finding the optimal battery size. They identified a unique critical value for battery size, below which the total electricity cost was high, whereas above that, increases in battery size had no impact on costs. Ratnam et al. [14] developed a framework based on quadratic programming which enabled the customer to justify expenditure on battery storage either through a least-cost option of capital investment or through choosing to utilize existing electric vehicle battery storage, if available.

Some researchers have focused on efficient operation of PV-battery systems. According to Halliday et al. [15], though PV systems account for a significant part of the initial investment in PV-battery systems, their share of lifetime capital cost (over 20 years) of the system is around one third. This is while batteries account for half of the total capital cost due to lowered expected battery lifetime as a result of inefficient battery operation (high temperatures, low SOC, etc.). As such, optimal control of battery charge/discharge (SOC) is a key component in improving the economics of the overall system. One of the earliest studies of efficient battery operation was by Appelbaum et al. [16], who developed geometrical regions on V-I characteristic graphs of solar systems for efficient charge/discharge of batteries and load control. More recently, Fragaki and Markvart [17] compared modeling and experimental data of PV-battery systems. Although their application of battery charging efficiency reduced the gap between experiment and model, they highlighted the necessity of development of a method to account for system memory effects imposed by the operation of the charge controller.

Pedram et al. [18] discussed that current homogeneous EES systems had limitations in simultaneously achieving desirable performance features such as high charge/discharge efficiency, high energy density, low cost per unit capacity, and long cycle life. As such they proposed the application of hybrid EES (HEES) systems with each EES element having strength in certain performance feature. Stadler et al. [19] developed a distributed energy resources customer adoption model (DER-CAM) based on a mixed integer optimization program. The model is capable of using various DG and storage types. Wang et al. [20] developed a dynamic programming model for integration of a residential-level HEES system for smart grid users equipped with PV power generation. The program objective was to reduce the total electricity cost over a billing period and to perform peak power shaving under arbitrary energy prices, also considering the characteristics of different types of EES elements, conversion efficiency variations of power converters, as well as the time-of-use- (ToU) dependent energy price function. They reported up to 73.9% profit improvement when using a combination of Li-ion and lead acid batteries compared with single-EES systems. The same group studied various aspects of HEES systems, namely networked architecture [21], balanced configuration [22], and charge allocation and replacement [23,24]. Khalilpour and Vassallo [25] developed an integrated decision support tool for concurrent optimal selection, sizing and operation scheduling of grid-connected DGS (e.g. PV-battery) systems.

Bronski et al. [26] undertook an extensive model-based economic analysis of grid disconnection through finding grid-parity for PV-battery systems in each region. Their analysis was focused on five representative U.S. regions, New York, Kentucky, Texas, California, and Hawaii, with the objective of understanding how soon this grid defection could occur. The study revealed that grid parity already exists for a minority of electricity customers with high electricity prices, e.g. Honolulu in Hawaii, with the 2012 retail electricity price of 0.34–0.41 $/kWh. Grid parity will exist for Westchester in New York (~0.15–0.20 $(2012)/kWh) before 2030, and in the early 2030s for Los Angeles (~0.09–0.17 $(2012)/kWh).

In any decision-making task we deal with two sets of data, parameters and variables. Variables are those unknown values that the optimization program should find as the output of the study. Parameters are those "known" data that are provided to the program prior to the optimization study. These parameters are often not known with absolute certainty [27]. Examples relevant to PV-battery systems include electricity price, feed-in tariff (FiT), and PV/battery system cost. Also, some parameters such as weather condition vary with geography. In this paper we use the subcategory of the model by Khalilpour and Vassallo [25] considering only one generation technology, PV supply, and one storage technology, battery. We study various customer cases with initial given parameters. Then we assess the impact of various technoeconomic parameters, namely geographic location, weather condition, electricity price, FiT, PV/battery system cost, and PV/battery specifications, on the economic feasibility of grid-connected PV-battery systems.

2. Case study

A house in Sydney, Australia, has consumed within one year (July 1 to June 30) about 6.1 MWh of electricity, which is in the range of Sydney's average household electricity consumption. The consumer's half-hourly load profile during the base year is illustrated in Fig. 4 [28].

The current electricity price consists of three ToU tariffs: (off-peak, shoulder, and on-peak). Off-peak (13 c/kWh) includes 10:00 p.m. to 7:00 a.m. Shoulder (21 c/kWh) is during 7:00 a.m. to 2:00 p.m. and 8:00 p.m. to 10:00 p.m. on weekdays, and 7:00 a.m. to 10:00 p.m. during weekend/public holidays. The on-peak (52 c/kWh) period is during 2:00 p.m. to 8:00 p.m. on weekdays [29]. There is also a daily connection fee (supply charge) of $0.87. Under this electricity pricing scheme the house has spent $1974.35 for its electricity bill over one year. The consumer is interested to investigate the feasibility of installing a PV-battery system to curb the electricity bill. When feasible, it is of interest to find the best mix of PV/battery, with or without grid, which results in the minimum electricity cost.

The candidate PV panels have the standard efficiency of 0.17 and are available in various sizes within the house's area limitation for a maximum 10 kW PV system. The PV panels' efficiency is affected by ambient temperature. This is reflected in panel's periodical efficiency through multiplying the standard efficiency by a α factor ($\alpha = 1.09 - 036 \times$ *ambient temperature*)[30]. The PV output also decreases by 0.5% annually (due to aging). The annual ambient temperature and GHI profiles are illustrated in Fig. 5. The prices of PV systems are considered to be $2700 for a 1.0 kW system that follows a power-law economy of scale with power constant of 0.76 [31].

The house owner is interested to investigate the feasibility of six

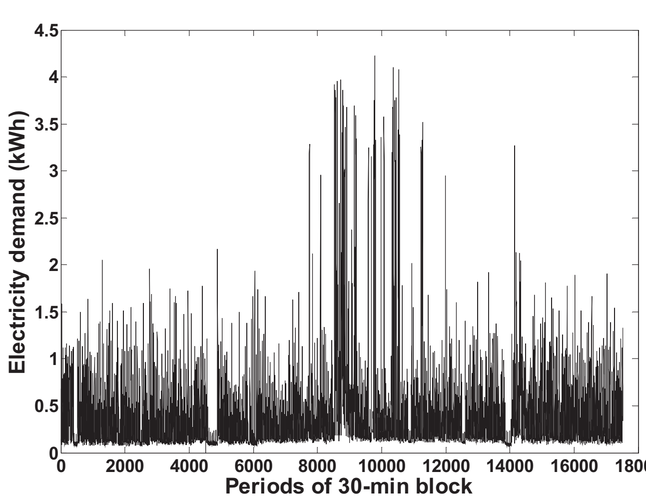

Fig. 4. The consumer's load profile during the base year.

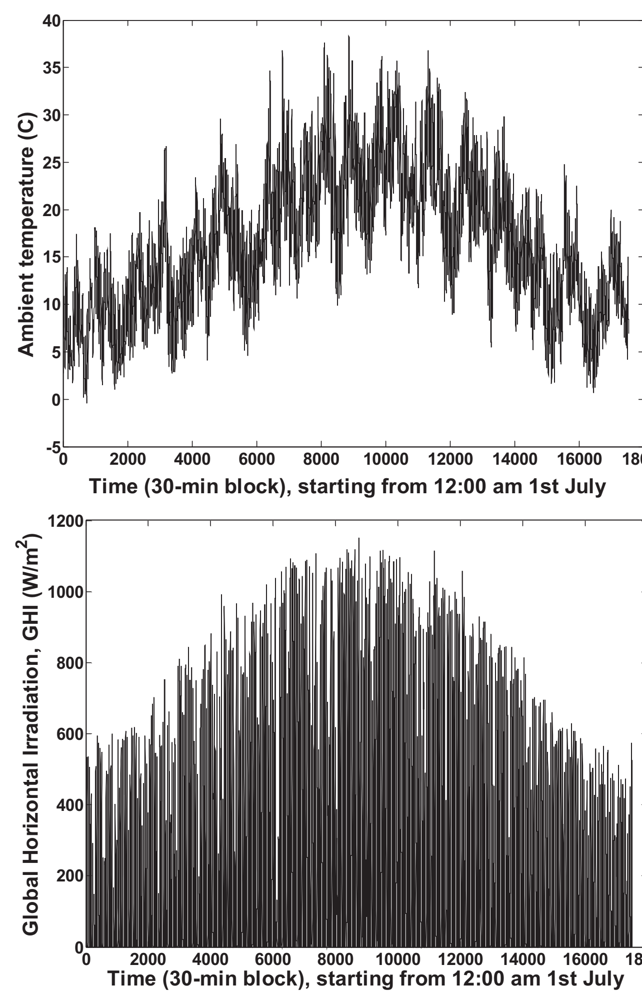

Fig. 5. Annual weather profile (July–June) at the shopping center's location; ambient temperature (top), and GHI (lower); Please note the seasonal differences of southern hemisphere.

battery types, each with different capacity and technoeconomic parameters. Table 1 lists the specification of the candidate batteries. The selected batteries will operate at a maximum DOD of 85%. The charge controllers and inverters have an assumed efficiency of 98%. The annual maintenance cost of the PV system is 0.5% of its capex, while it is 1.0% for batteries. The unit cost of batteries ($/kWh) during 2012 is given in Table 1. These prices have since fallen by 30% and also follow a power-law economy of scale similar to PV systems.

The solar FiT is 8.0 c/kWh during the base year [32]. The annual price escalation factor is 3% with a discount rate of 7% [33]. The consumer projects that the electricity consumption will increase by 0.5% annually over the next 10 years and wants to assess whether it is economical to install PV and/or battery systems. If yes, what are the specifications of the selected system(s) and how should the systems be operated? The objective function as stated elsewhere (refer to Eq. (20) in Ref. [25]) is the net present value (NPV) of cash flow over the planning horizon with P periods (p: 1, 2, …, P) with a given fixed length (minute, hour, etc.). It is given by,

$$NPV = \sum_{p=1}^{P}(L_p EP_p) - CX^{PV} - CX^{PV} - \sum_{p=1}^{P}\left(FOM_p^{PV} + FOM_p^{B}\right) - \sum_{p=1}^{P}\left(X_p^{GL} + X_{jp}^{GB}\right)EP_p + \sum_{p=1}^{P}\left(X_{jp}^{BG} + X_{ip}^{PG}\right)FIT_p$$

Where L_p is the baseload. CX^{PV} and CX^{B} are PV and battery systems' installation costs, respectively. FOM_p^{PV} and FOM_p^{B} are fixed operation and maintenance costs for PV and battery systems, respectively, during period p. EP_p and FiT_p are grid electricity price, and feed-in tariff, respectively. $X_p^{GL}, X_p^{GB}, X_p^{BG},$ and X_p^{PG} refer to the flow of electrical energy from the grid to local load, from the grid to battery(s), export from battery(s) to the grid, and export from PV to the grid, respectively. Therefore, the objective is to maximize the above-mentioned NPV equation so that it guarantees the maximum economic benefit of installing PV and/or battery system versus the condition that the user is fully reliant on grid electricity $\left(\sum_1^P L_P EP_P\right)$.

The problem is solved for 10 years of operation (fixed period length of one) using CPLEX 12.4.0.1 on a desktop PC with 16 GB RAM. The optimization program suggests that it is more economical to invest in a PV-battery system than to buy electricity completely from the grid. The optimum decision is identified as a 2.0 kW PV system with a high energy Li-ion battery of 5.5 kWh size.

Fig. 6 illustrates the annual-average daily profile of the house's electricity supply obtained from the program results. It is evident that this integrated PV-battery system has reduced the house's direct dependence on the grid to 45.7% during the first year of operation. Under this condition, the house receives 2801.2 kWh of electricity directly from the grid within the first year. The remaining demand is satisfied by the PV system (1554.2 kWh, i.e. 25.4%) and battery (1773.55 kWh, 28.9%).

The PV output is mainly allocated for local use, providing for the local load (46.8%) and battery charge (38.3%). The small surplus PV generation (504.6 kWh, i.e. 14.9%) is dispatched to the grid. The battery does not dispatch electricity to the grid during any period. Within the first year, the battery receives 598.8 kWh (31.5%) of electricity from the grid, mainly during off-peak periods, and its remaining charge (1300.1 kWh, 68.5%) is supplied by the PV system. The selected 5.5 kWh battery never operates below 15% SOC, i.e. 0.83 kWh charge, and its average annual SOC is 2.79 kWh.

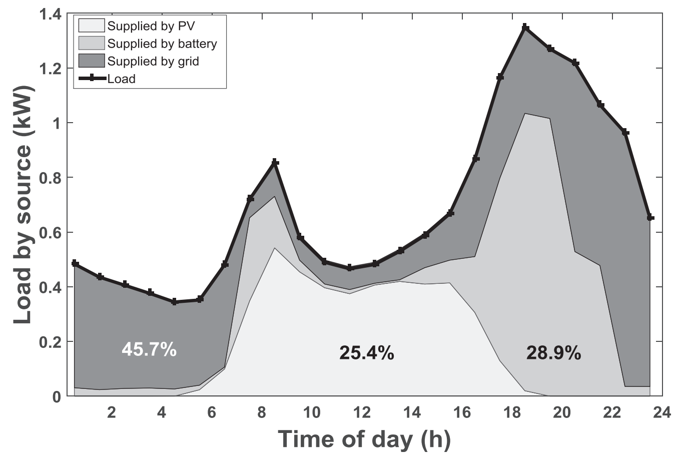

Fig. 6. Annual average daily profile of the house's load by supply sources.

In summary, without the PV-battery installation, the average annual electricity demand is 0.70 kW. With installation of the PV-battery system, the average demand from the grid decreases to 0.39 kW (0.32 kW for load and 0.07 kW for battery charge). Under the given conditions, this investment can save $949.50 (NPV of cash flow) in the electricity bill over the next 10 years.

3. Parametric analysis

3.1. Impact of technology size

Here we investigate the impact of PV/battery sizes on the economics of installation. The PV systems are in the size range of 0–20 kW and the batteries are high energy li-ion with size ranges of 0–15 kWh. The given parameters are similar to the previous example.

The optimization program suggests that the highest NPV is achievable in two regions. When smaller PV ranges are allowed (say less than 10 kW), the program selects a 1.5 kW PV-only system with the highest NPV of $447.00. However, when larger PV systems are allowed (e.g. 0–20 kW in this study), the model prefers the largest possible size (here 20 kW). The maximum NPV is found in this study to be $1650.00 with a 20 kW system. Fig. 7 illustrates the impact of PV system and battery size on the NPV. The trend of the profile shows that the NPV could increase with even larger PV systems. This prospect is debatable, due to the impact of economy of scale which brings the installation cost of a 20 kW system down to $1315.6/kW $[(2700 \times (20)^{0.76})/20]$. For small PV systems, the

Table 1
Technoeconomic specifications of candidate batteries for the house (parameters mainly from Ref. [35]).

Battery type	Manufacturing round-trip efficiency	Annual efficiency loss factor due to aging	Dis/charge duration (hours)	Base capex ($2012/kWh)
Advanced lead acid A	0.800	0.960	2	1100
Advanced lead-acid B	0.900	0.960	5	870
Valve-regulated lead acid A	0.680	0.955	2	800
Valve-regulated lead acid B	0.780	0.955	4	625
Li-ion high energy	0.920	0.970	2	875
Li-ion high power	0.910	0.970	1	1200

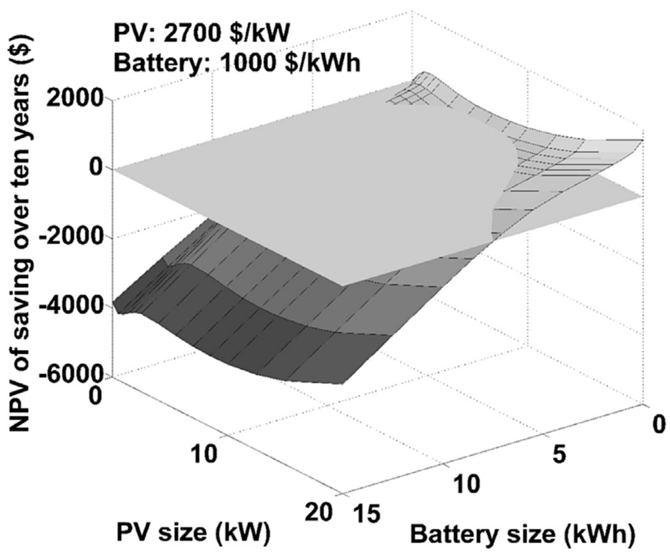

Fig. 7. Impact of PV and battery sizes on NPV of saving for a house with load profile as per Fig. 1 (PV: $2700/kW, Battery: $1000/kWh, economy of scale factor: 0.76, electricity price (c/kWh): 13 (off-peak), 21 (shoulder), and 52 (peak)).

price is relatively high per unit size. As such, we notice in Fig. 7 that at small PV ranges, the model does not prefer large systems. It just finds the best size to supply the local load. However, as the size increases, the installation cost per unit size decreases to the extent that the PV system reaches (and exceeds) parity with the grid feed-in tariff (8 c/kWh). This moves the household into a new paradigm in which it becomes an energy generator and exporter to the grid at feed-in tariff of 8 c/kWh. This export is an arbitrary option that the house selects to install a larger system and to make a profit. It is also evident that, with the given battery price, it does not have positive impact on NPV.

The impact of PV and battery sizes on the house's independence from the grid is illustrated in Fig. 8. It is evident that, with the increase in PV and battery sizes, the level of independence increases sharply up to a certain range, after which its rate of increase slows. The negative independence in the figure refers to the condition that the house has a battery-only system. In such a condition, part of the house's load comes directly from the grid, while another part is first

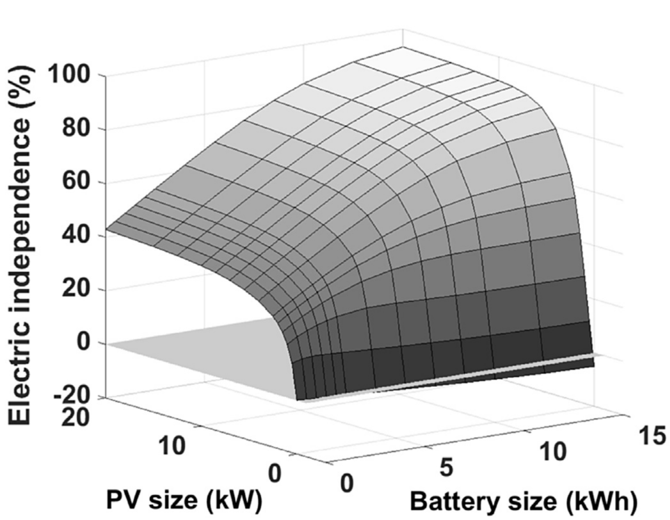

Fig. 8. Impact of PV and battery sizes on the house's independence from the grid.

stored in the battery (during low tariff periods) and later sent to local appliances (during high tariff periods). Given that battery system efficiency is less than 100%, the energy purchase from the grid (and thus dependence) increases for the same load consumed. However, the battery allows shifting of the load from expensive ToU periods to less-expensive periods and minimizes the electricity bill.

3.2. Impact of technology price

Here we investigate the impact of a probable decline in technology installation costs on the feasibility of installing PV-battery systems. In the previous example, a feasible NPV region was found for systems with PV and battery prices of $2700/kW and $1000/kWh, respectively (both with economy of scale factors). Here, we study the impacts of PV base prices in the range $1000–3000 and battery base prices in the range $250–1000 on the economic feasibility (note that the economy of scale factor of 0.76 still applies).

As shown in Fig. 7, a PV-only system is always feasible (NPV > 0) with PV base prices below $2700. Therefore, here the analysis is more focused on the impact of PV-battery price combinations. Fig. 9 illustrates the NPV results for six different combinations of PV and battery price bases. For the price combination of PV $3000 and battery $1000 there is a very narrow range for positive NPV. At this price, PV-only systems with size below 1.5 kW are feasible, with the maximum NPV of $102.10 for a 1.0 kW PV system. With the reduction of technology costs to (PV $2500, battery $1000), and (PV $2000, battery $1000), the feasibility region (positive NPV) further increases. But in none of these scenarios does the battery have a positive impact on NPV. With the base price of $750, however, the battery begins to have some positive impact on NPV over certain ranges. With the battery price of $500 the battery feasibility region further increases. At base price of $250, the battery has a positive impact on NPV over the entire range studied. For instance, at the price of $500, this house with a battery-only system has a maximum NPV of $1043.50 with an 8.5 kWh battery system and at $250 base price, the highest NPV of a PV-only system is found with a 15 kWh system (upper bound of the range) with value of $1963.00.

3.3. Impact of electricity tariff type

The electricity tariff structure is a critical factor in decision-making regarding PV-battery installation. Here we investigate the impact of two tariffs, ToU and flat. The values of ToU tariff were given earlier. The flat tariff is $0.28/kWh. Fig. 10 illustrates the feasible region (positive NPV) across PV-battery sizes for flat (left) and ToU (right) tariffs. It is evident that the feasibility region for the flat tariff is smaller. This is due to the fact that with a flat tariff there is no need for the battery to shift load. The only use of the battery is thus for storing surplus PV output to use at a later time.

3.4. Impact of electricity price

While the global market prices of PV and battery technologies at any given period of time might lie in a relatively narrow range, the price of electricity (EP) varies significantly across different jurisdictions. It might be less than 10 c/kWh in Washington and above 30 c/kWh in Denmark [34]. Fig. 11 illustrates the NPV profile for three EP scenarios, $0.1/kWh (left), $0.3/kWh (center), and $0.5/kWh (right). At the EP of $0.1/kWh there is no positive NPV over the 0–20 kW PV and 0–15 kWh battery ranges. At the EP of $0.3/kWh, however, there are some positive regions. It is evident from this figure that for large PV systems (reduced installation cost per unit size), it becomes economical to generate and sell electricity to the

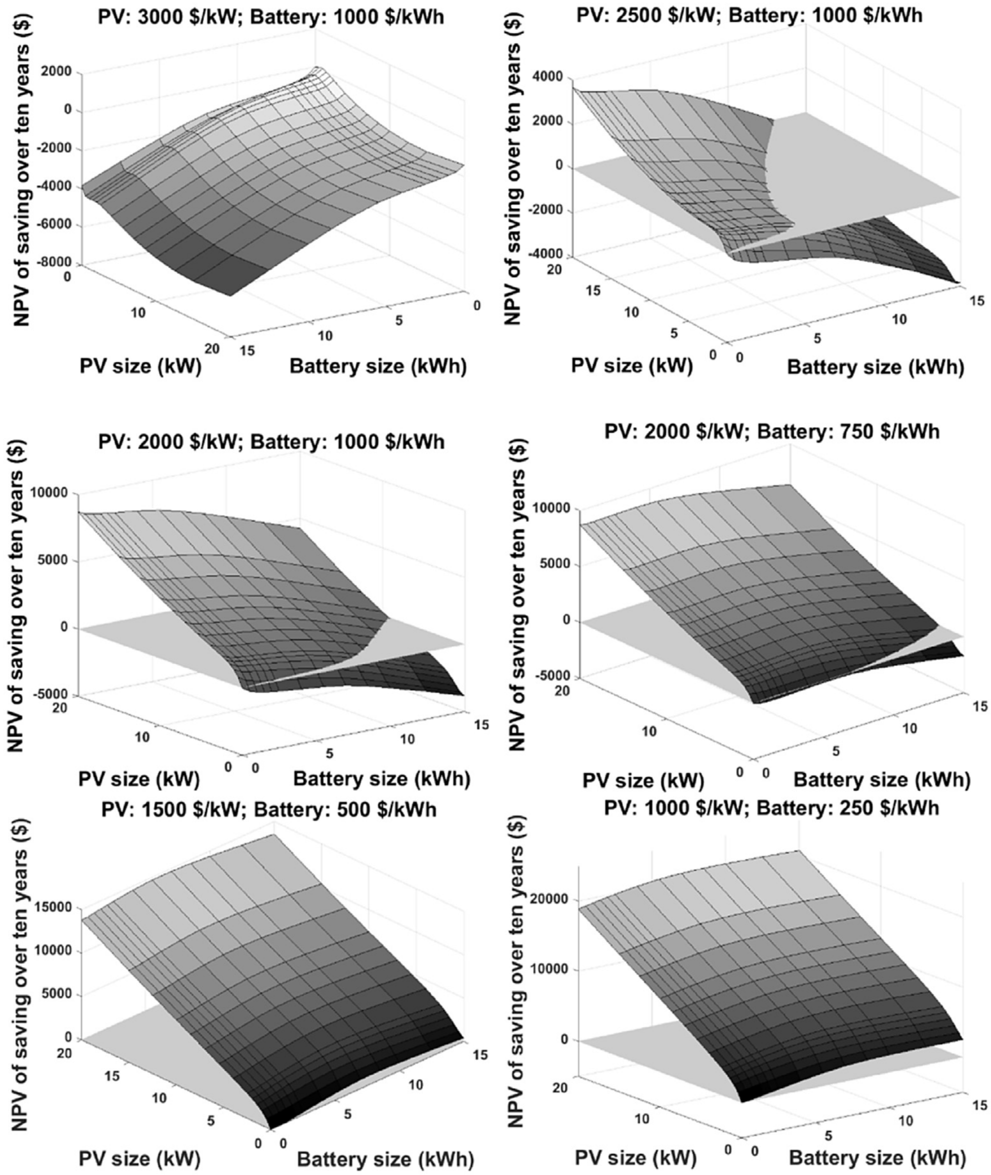

Fig. 9. Impact of PV and battery base installation costs on economic feasibility (economy of scale factor: 0.76, electricity price (c/kWh): 13 (off-peak), 21 (shoulder), and 52 (peak)).

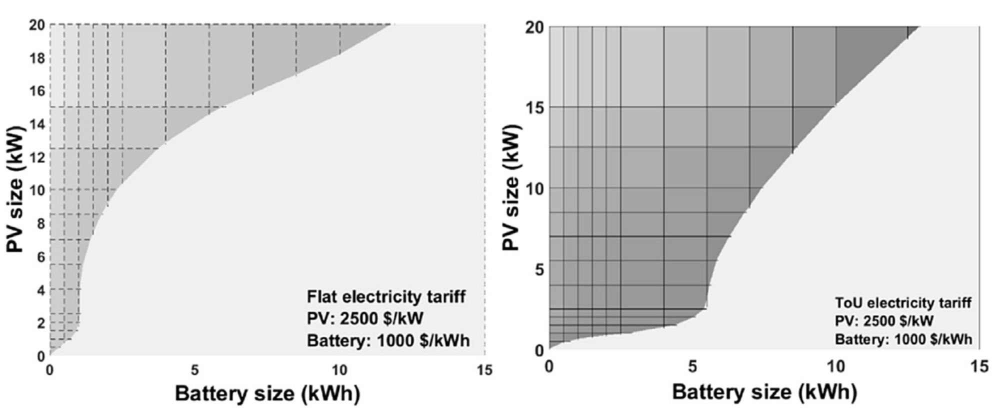

Fig. 10. Impact of electricity tariff type (ToU and flat) on the feasibility of PV-battery systems (ToU electricity price (c/kWh): 13 (off-peak), 21 (shoulder), and 52 (peak), flat price: 28, FiT: 8.0).

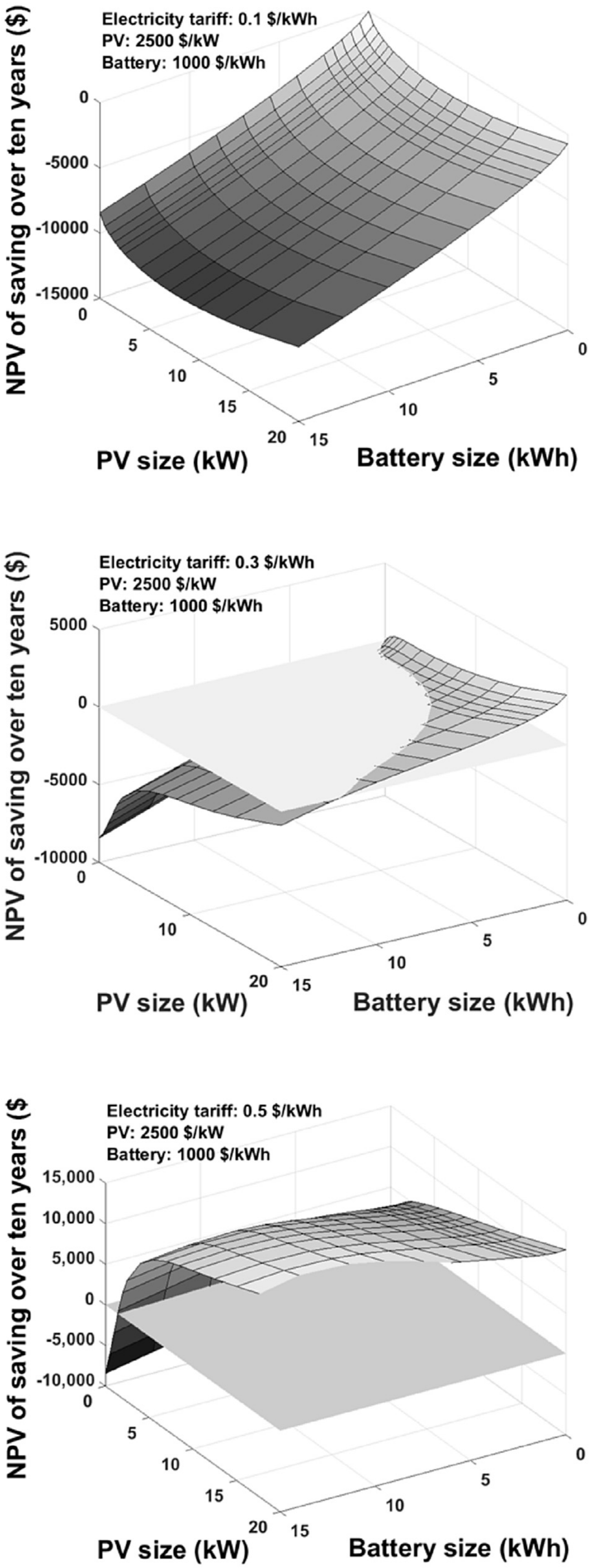

Fig. 11. Impact of electricity price on the feasibility of PV-battery systems (flat tariff (c/kWh): 10, 30, and 50; FiT: 8).

grid. Nonetheless, neither at the EP of $0.1/kWh nor at $0.3/kWh does the battery have a positive impact on the NPV. However, at the EP of $0.5/kWh, not only does the positive NPV region expand to include almost all PV-battery size ranges (except small PVs with large batteries), batteries also begin to have a positive impact on NPV. As an example, the house with a 4.0 kW PV-only system will have the NPV of $5980.30 (EP $0.5/kWh). At this PV size, the highest NPV of $9023.10 is achievable with a 10.0 kWh battery, 50.9% higher than the PV-only system. This can be easily explained by the difference between EP and FiT (0.5−0.08 = 0.42 $/kWh) in the amount that the storage of PV surplus electricity could save (ignoring the battery system losses).

3.5. Impact of feed-in tariff

Feed-in tariff is a price structure for the exported renewable energy from small-scale generators. The right tariff can motivate higher uptake of renewable technologies and vice versa. Here we take the same house with ToU tariff and study the impact of FiT in three scenarios of 0.04, 0.08, and $0.12/kWh (note that off-peak tariff is $0.13/kWh). Fig. 12 illustrates the NPV profile for these three FiTs. As evident, at FiT of $0.04/kWh there is a very narrow range of positive NPV at small PV-battery sizes. At FiT of $0.08/kWh, the PV system (without battery) becomes advantageous across the entire size range 0–20 kW. This FiT, at the given technology price, makes it feasible to install large PV systems and sell the extra to the grid. Obviously the economic feasibility of the system further improves at FiT = $0.12/kWh. Interestingly, the battery has no positive impact on the NPV over these scenarios. In fact, with an increase in FiT the attractiveness of the battery reduces as the gap between EP and FiT (which is detrimental to the feasibility of battery) reduces. This makes it more attractive for the house to sell its redundant electricity directly to the grid.

3.6. Impact of daily consumption pattern

Customers have various electricity consumption styles. One customer might have a morning peak followed by a larger afternoon peak. Another customer might have only an afternoon peak, and so on. Here, our objective is to investigate the impact of electricity consumption patterns on the feasibility of PV-battery systems. Fig. 13 illustrates the annual average daily profile of six houses with various consumption patterns. Houses #1 and #2 have midnight to early morning peaks; house #3 has a small peak in the morning and a large peak in the afternoon; house #4 has the opposite pattern to #3, with the large peak in the morning and smaller peak in the afternoon; house #5 has almost constant consumption during the day, with a peak in the afternoon; the consumption of #6 declines from midnight till around noon, after which it increases again until midnight. All these load data are real (provided by Ausgrid [28]) and we have only adjusted their magnitude so that the total annual consumption of each house is 7.0 MWh. The selected houses also have similar seasonality patterns (all winter-peak). This allows us to assess only the impact of daily consumption pattern on the economics of the PV-battery system. All technoeconomic parameters are similar to those of the first example.

The optimization results for these six cases are shown in Fig. 14. It is evident that the worst scenarios for PV-battery occur for the houses with midnight peaks (e.g. #2). This is firstly because at midnight PV output is unavailable and secondly because the grid electricity price is lower, making a battery less attractive (off-peak). In the other cases (#3–#6), the best result is found for #3 which has a small morning peak and a large afternoon peak. This house has a maximum NPV of $1692.80 with a 4.0 kW PV-only system, under the given conditions. Compared with #3, battery becomes less attractive for #4 which has a larger peak in the morning and a

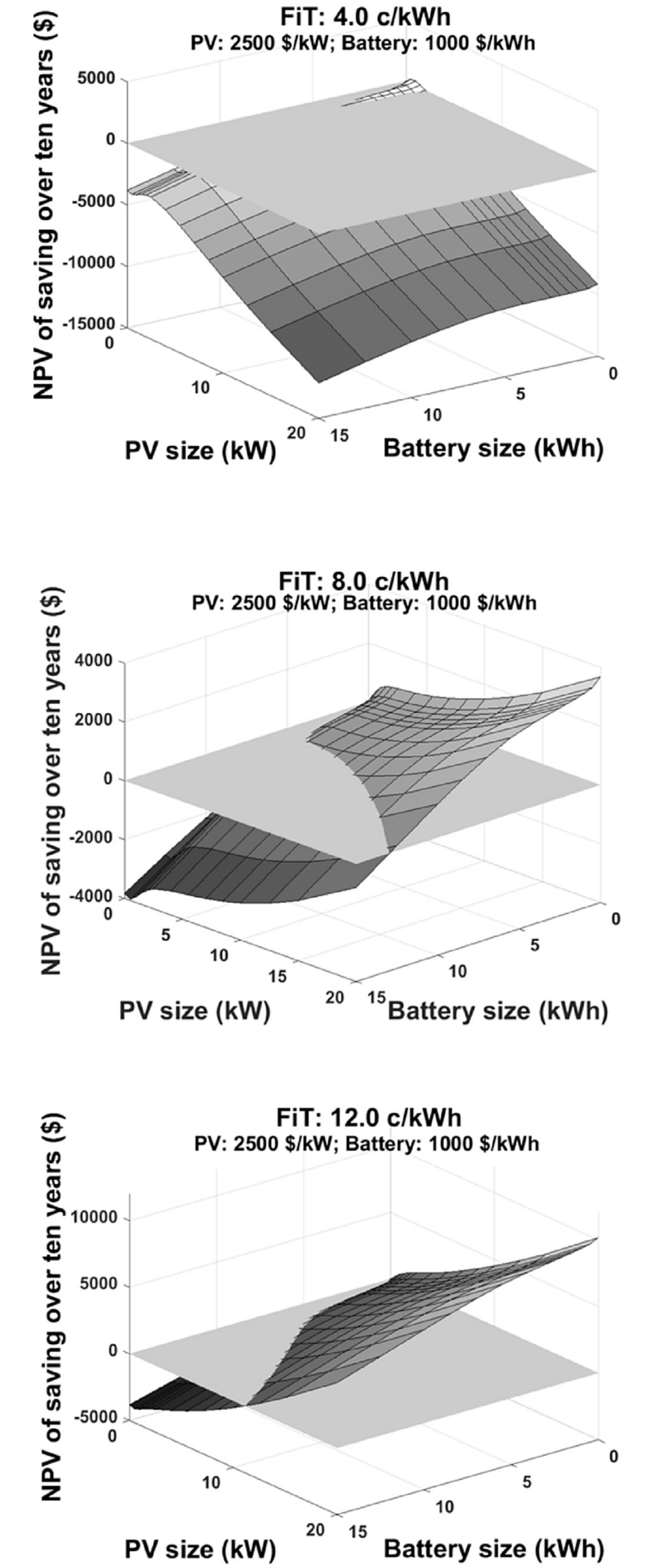

Fig. 12. Impact of feed-in tariff on the feasibility of PV-battery systems (ToU electricity price (c/kWh): 13 (off-peak), 21 (shoulder), and 52 (peak), FiT: 4.0, 8.0, and 12.0).

smaller one in the afternoon. Houses #5 and k6 are seen to be less attractive for battery power than with #3 or #4 because their high-

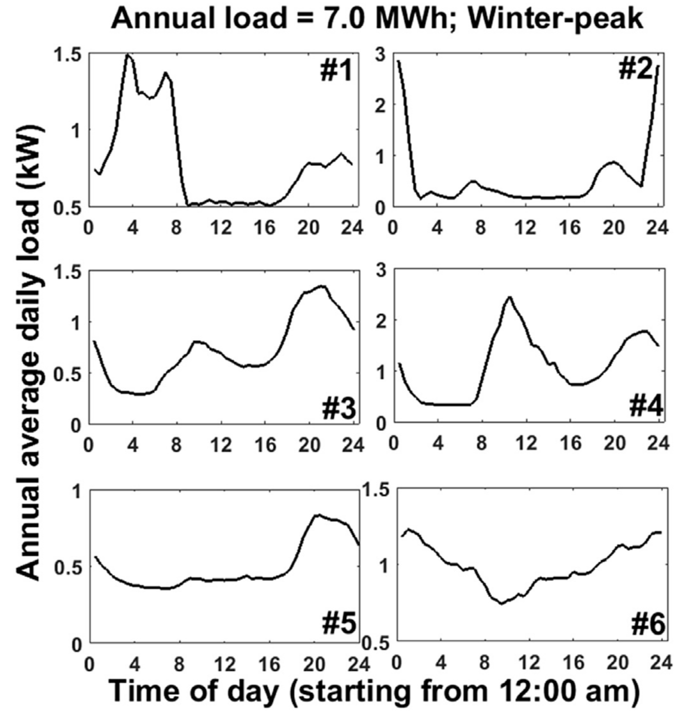

Fig. 13. Annual average daily consumption pattern of six residential electricity consumers with total annual load of 7.0 MWh

consumption times occur mainly (but not entirely) during off-peak periods.

3.7. Impact of location and load seasonality

The feasibility of renewable technologies is critically dependent on the location's richness in terms of energy resources (e.g. GHI for PV system and wind speed for wind turbine).

Fig. 15 shows graphically the distribution of global horizontal irradiation (GHI) over the world (top) and in Australia (lower). It shows how significantly the annual GHI varies around the world, from below 0.7 MWh/m^2.y to above 2.7 MWh/m^2.y. Also evident is that Australia is one of the few countries whose GHI spans from very low in the south (Tasmania, latitude −42.8) to extreme high values in the center and northwest. This feature enables us comfortably to select cities from within Australia for parametric analysis of the impact of location on DG performance.

We select three locations with low to high GHI. The first is Hobart (latitude −42.8 and average annual GHI 1.40 MWh/m^2), the second is Sydney (latitude −33.9 and average annual GHI 1.67 MWh/m^2), and the third, with the highest irradiation, is Alice Springs (latitude −23.8 and average annual GHI 2.25 MWh/m^2). The GHI profiles are illustrated in Fig. 16.

The feasibility of renewable technologies also depends on the load profile. Here, we investigate these two factors. We select two houses, house A with winter peak and house B with summer peak. The annual load profiles for the two houses are given in Fig. 17. House A has consumed 6.92 MWh of electricity during the base year and the consumption of house B is similar, at 7.06 MWh.

The NPV profiles of these scenarios are illustrated in Fig. 18. The impact of location is obvious from the figures. For house A (with a winter peak), in Hobart, with relatively poor GHI, the feasible PV range is very narrow ($\leq$2 kW), with a negligible positive NPV. In Sydney, the feasibility range increases, though the NPV is still in the range of a few hundred dollars. In Alice Springs, however, with a

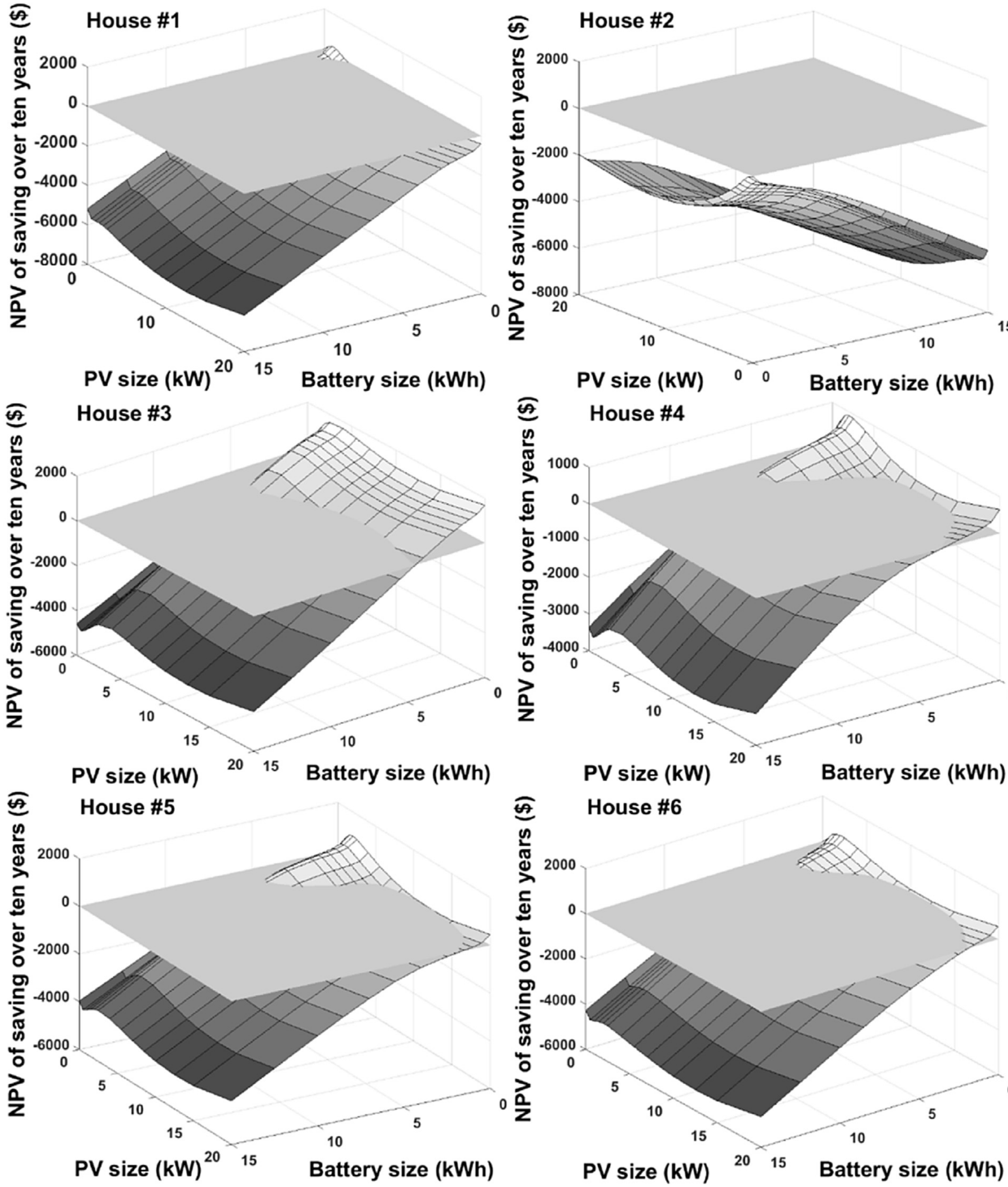

Fig. 14. Impact of electricity consumption pattern on the feasibility of PV-battery systems (PV: $2500/kW, battery: $1000/kWh, economy of scale factor: 0.76; ToU electricity price (c/kWh): 13 (off-peak), 21 (shoulder), and 52 (peak), FiT: 8.0).

high GHI, the feasibility region spans a very wide range with NPVs reaching the order of a few thousand dollars. For instance, if the house is located in Alice Springs and has enough space to install a 20 kW PV-only system, its NPV becomes $7764.20 over the first 10 years of installation (at PV base cost of 2500 $/kW and battery base cost of $1000/kWh).

Interestingly, although houses *A* and *B* have similar annual energy consumption (7.0 ± 0.1 MWh), their load pattern has a significant impact on PV-battery feasibility, especially in regions with low-medium GHI. We know that PV output depends on the sun's location; it increases in summer and reduces in winter. We would expect, therefore, that a PV system would be more economical for a house with a summer peak. But from Fig. 18 we find that the NPV profile is not notably different between houses A and B in Alice Springs except that, as expected, it increases slightly for house B (summer peak). However, the NPV profiles are notably different for these two houses in Sydney and Hobart. This is arguably due to the fact that the seasonal changes are much sharper as latitude

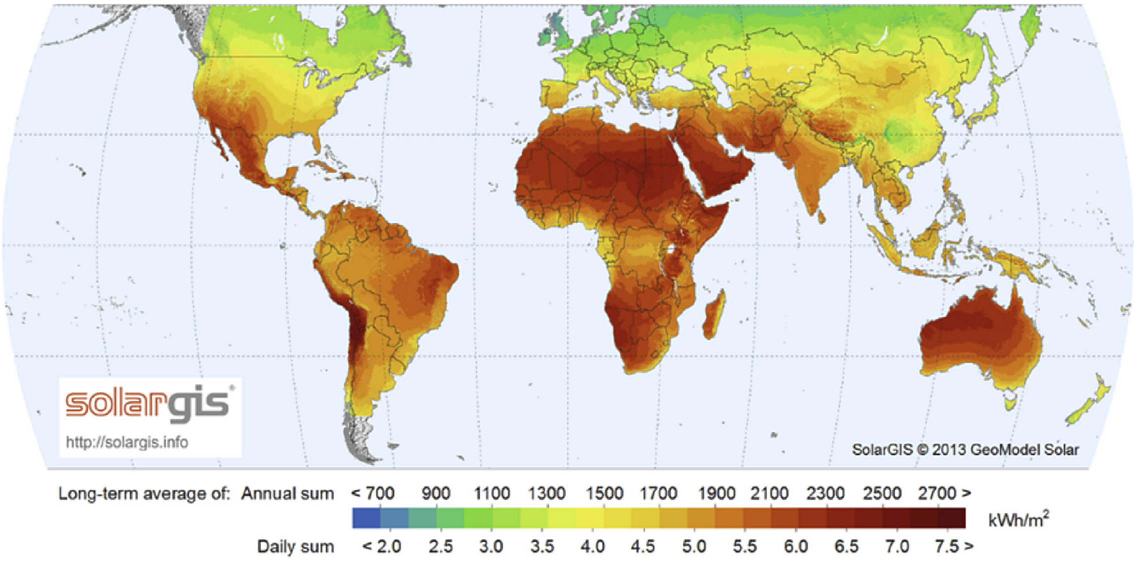

Fig. 15. Graphical distribution of global horizontal irradiation (GHI) around the world (top) and in Australia (lower).

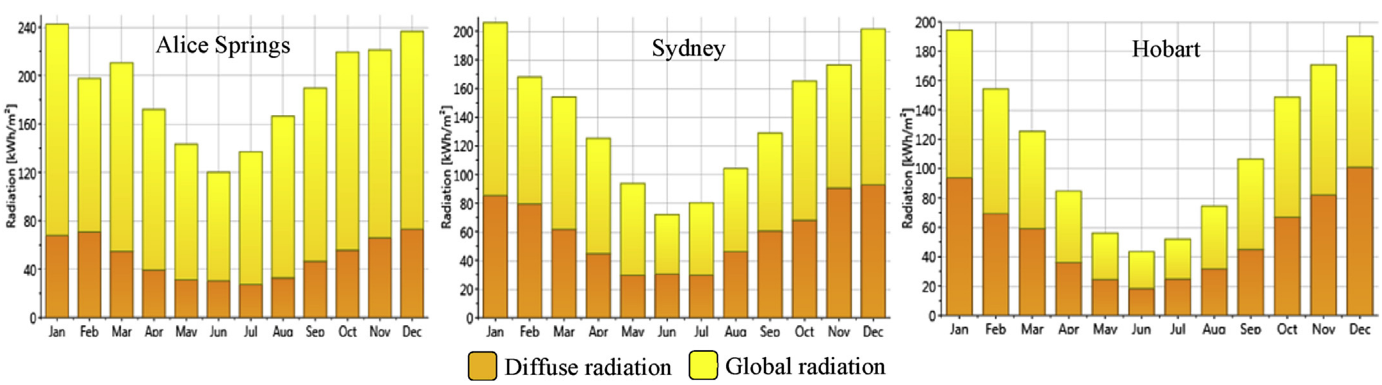

Fig. 16. Monthly average GHI of Alice Springs (1986–2005), Sydney (1990–2007), and Hobart (1991–2010).

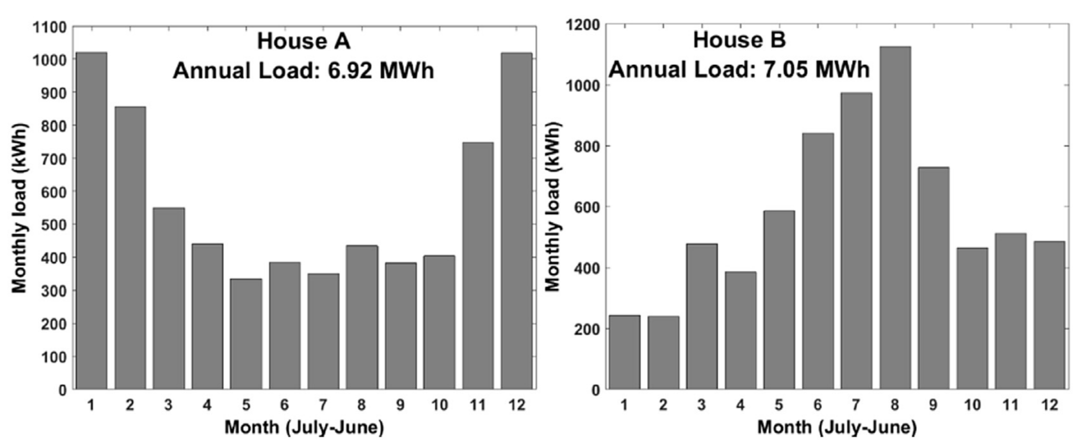

Fig. 17. Monthly load profile for a winter-peak (left) and a summer-peak (right) house.

increases.

Fig. 16 shows the GHI differences of the three locations from January to December. Comparison of the GHI values for January and July for these three locations highlights the significant difference between Hobart and Alice Springs. The GHI of Hobart in July is 26.8% of that in January. The magnitude of this difference is 39.0% for Sydney and 56.4% for Alice Springs. Therefore, it can be concluded that Alice Springs not only benefits from higher GHI but also it has less sensitivity to the seasonality of irradiation. As a result, its sensitivity to the seasonality of load also reduces. Given

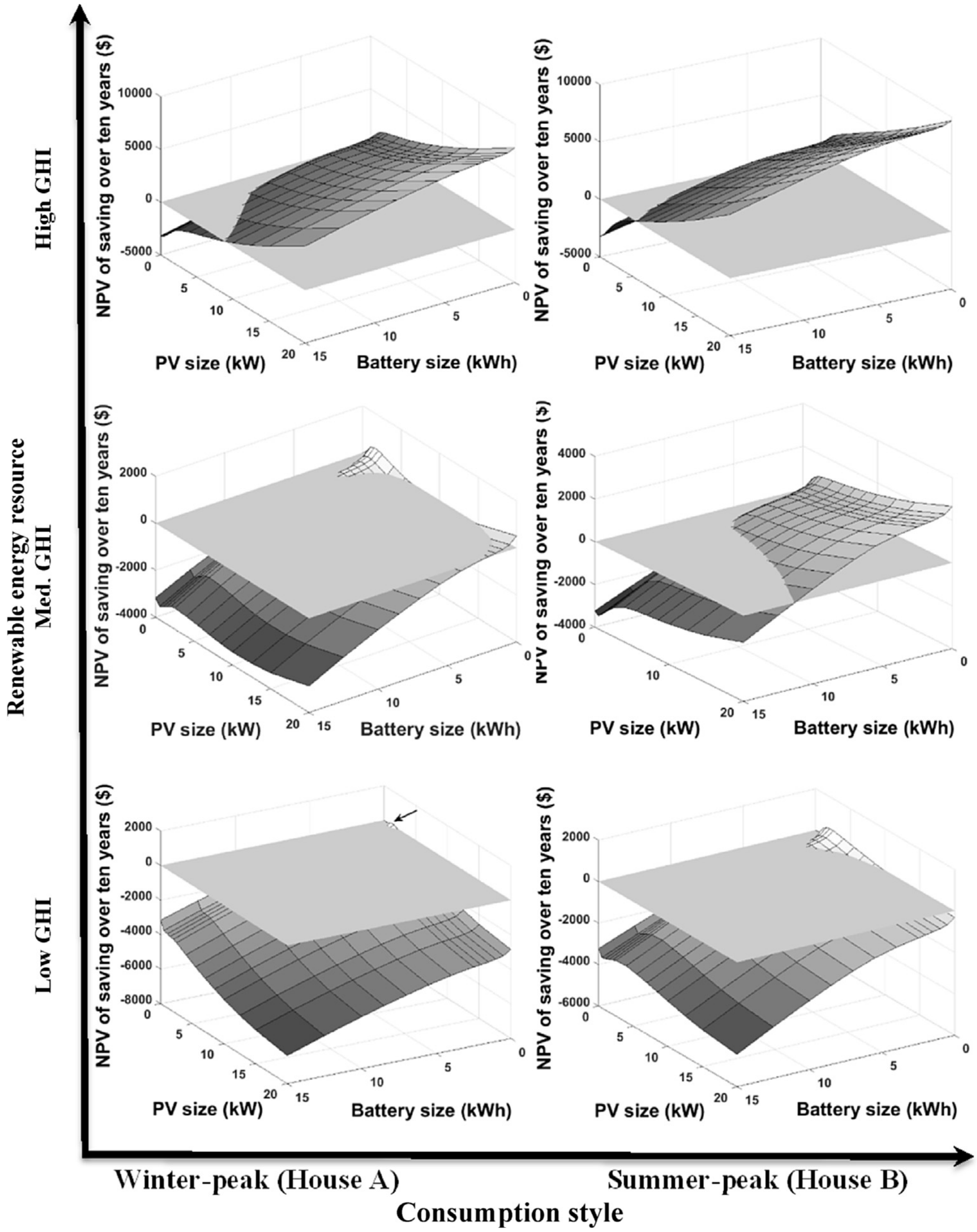

Fig. 18. Impact of location and load profile on the feasibility of PV-battery systems (PV: $2500/kW, battery: $1000/kWh, economy of scale factor: 0.76; ToU electricity price (c/kWh): 13 (off-peak), 21 (shoulder), and 52 (peak), FiT: 8.0).

that the other two cities have relatively low GHI in winter, a winter-peak consumption style only favors PV-battery across a narrow range of PV-battery sizes.

4. Conclusion

We used a rigorous decision support program to investigate the impact of various parameters, namely PV/battery installation costs, electricity tariff, feed-in tariff, geographic location, and load profile, on the feasibility of grid-connected PV-battery systems. We found that the decision as to selection of the right PV-battery is significantly sensitive to all the parameters. Within the various price scenarios that we investigated, a battery had a positive impact on NPV only at low installation cost (e.g. < $750/kWh base). The difference between electricity price and feed-in tariff was the detrimental element in battery attractiveness.

The study on the impact of location showed that regions with higher absolute latitudes not only have less average GHI, but also suffer from high seasonal variation of GHI, compared with locations with lower absolute latitudes. As such, the former locations are more sensitive to load seasonality and PV technology is less attractive for such locations when a customer has a winter-peaking load. This might imply that for winter-peaking users at locations with higher absolute latitudes, when electric heating is the main reason for high demand, hybridization of PV-battery system with less-costly heating sources might be more advantageous.

References

[1] IEA, Technology Roadmap-solar Photovoltaic Energy, International Energy Agency, Paris, 2010.

[2] A. Nourai, R. Sastry, T. Walker, A vision & strategy for deployment of energy storage in electric utilities, in: Power and Energy Society General Meeting,

2010, IEEE, 2010, pp. 1–4.

[3] B.P. Roberts, C. Sandberg, The role of energy storage in development of smart grids, Proc. IEEE 99 (2011) 1139–1144.

[4] J.M. Gordon, Optimal sizing of stand-alone photovoltaic solar power-systems, Sol. Cells 20 (1987) 295–313.

[5] M. Egido, E. Lorenzo, The sizing of stand alone pv-systems - a review and a proposed new method, Sol. Energy Mater. Sol. Cells 26 (1992) 51–69.

[6] E. Lorenzo, L. Narvarte, On the usefulness of stand-alone PV sizing methods, Prog. Photovoltaics 8 (2000) 391–409.

[7] A. Fragaki, T. Markvart, Stand-alone PV system design: results using a new sizing approach, Renew. Energ 33 (2008) 162–167.

[8] K. Peippo, P.D. Lund, Optimal sizing of grid-connected pv-systems for different climates and array orientations—a simulation study, Sol. Energy Mater. Sol. Cells 35 (1994) 445–451.

[9] B. Lu, M. Shahidehpour, Short-term scheduling of battery in a grid-connected PV/battery system, Power Syst. IEEE Trans. 20 (2005) 1053–1061.

[10] N.D. Kaushika, N.K. Gautam, K. Kaushik, Simulation model for sizing of stand-alone solar PV system with interconnected array, Sol. Energy Mater. Sol. Cells 85 (2005) 499–519.

[11] A. Mellit, S.A. Kalogirou, L. Hontoria, S. Shaari, Artificial intelligence techniques for sizing photovoltaic systems: a review, Renew. Sust. Energ Rev. 13 (2009) 406–419.

[12] Y. Riffonneau, S. Bacha, F. Barruel, S. Ploix, Optimal power flow management for grid connected PV systems with batteries, IEEE T Sustain Energ 2 (2011) 309–320.

[13] R. Yu, J. Kleissl, S. Martinez, Storage size determination for grid-connected photovoltaic systems, Sustain. Energy, IEEE Trans. 4 (2013) 68–81.

[14] E.L. Ratnam, S.R. Weller, C.M. Kellett, An optimization-based approach for assessing the benefits of residential battery storage in conjunction with solar PV, in: Bulk Power System Dynamics and Control - IX Optimization, Security and Control of the Emerging Power Grid (IREP), 2013 IREP Symposium, 2013, pp. 1–8.

[15] J. Halliday, T. Markvart, J.N. Ross, Battery management for PV systems, Power Eng. 17 (2003), 46–46.

[16] J. Appelbaum, A. Braunstein, J. Bani, Performance analysis of a solar-electrical system with a load and storage batteries, Energy Convers. 16 (1977) 105–110.

[17] A. Fragaki, T. Markvart, System memory effects in the sizing of stand-alone PV systems, Prog. Photovoltaics 21 (2013) 724–735.

[18] M. Pedram, N. Chang, Y. Kim, Y. Wang, Hybrid electrical energy storage systems, in: Proceedings of the 16th ACM/IEEE International Symposium on Low Power Electronics and Design, ACM, Austin, Texas, USA, 2010, pp. 363–368.

[19] M. Stadler, M. Groissböck, G. Cardoso, C. Marnay, Optimizing distributed energy resources and building retrofits with the strategic DER-CAModel, Appl. Energ 132 (2014) 557–567.

[20] Y. Wang, X. Lin, M. Pedram, S. Park, N. Chang, Optimal control of a grid-connected hybrid electrical energy storage system for homes, in: Design, Automation & Test in Europe Conference & Exhibition (DATE), 2013, 2013, pp. 881–886.

[21] Y. Kim, S. Park, N. Chang, Q. Xie, Y.Z. Wang, M. Pedram, Networked architecture for hybrid electrical energy storage systems, in: 2012 49th ACM/EDAC/IEEE Design Automation Conference (DAC), 2012, pp. 522–528.

[22] Y. Kim, S. Park, Y.Z. Wang, Q. Xie, N.Y. Chang, M. Poncino, M. Pedram, Balanced reconfiguration of storage banks in a hybrid electrical energy storage system, in: 2011 IEEE/ACM International Conference on Computer-aided Design (ICCAD), 2011, pp. 624–631.

[23] Q. Xie, Y.Z. Wang, Y. Kim, M. Pedram, N. Chang, Charge allocation in hybrid electrical energy storage systems, IEEE Trans. Computer-Aided Des. Integr. Circuits Syst. 32 (2013) 1003–1016.

[24] Q. Xie, Y.Z. Wang, M. Pedram, Y. Kim, D. Shin, N. Chang, Charge replacement in hybrid electrical energy storage systems, in: 2012 17th Asia and South Pacific Design Automation Conference (ASP-dAc), 2012, pp. 627–632.

[25] R. Khalilpour, A. Vassallo, Planning and operation scheduling of PV-battery systems: a novel methodology, Renew. Sustain. Energy Rev. 53 (2016) 194–208.

[26] P. Bronski, J. Creyts, L. Guccione, M. Madrazo, J. Mandel, B. Rader, D. Seif, P. Lilienthal, J. Glassmire, J. Abromowitz, M. Crowdis, J. Richardson, E. Schmitt, H. Tocco, in: J. Creyts, L. Guccione (Eds.), The economics of grid defection: when and where distributed solar generation plus storage competes with traditional utility service, Rocky Mountain Institute, Boulder, Colorado, 2014.

[27] R. Khalilpour, I.A. Karimi, Parametric optimization with uncertainty on the left hand side of linear programs, Comput. Chem. Eng. 60 (2014) 31–40.

[28] Ausgrid, Solar homes electricity data, in: Ausgrid, Australia, Sydney, 2011.

[29] AGL, AGL NSW Electricity Standing Offer Prices, 2013.

[30] V.J. Fesharaki, M. Dehghani, J.J. Fesharaki, H. Tavasoli, The effect of temperature on photovoltaic cell efficiency, in: 1st International Conference on Emerging Trends in Energy Conservation, Tehran, 2011.

[31] Solar-choice, Solar PV Price Index-June 2013, 2013.

[32] IPART, Solar feed-in tariffs-The subsidy-free value of electricity from small-scale solar PV units from 1 July 2013, in: Independent Pricing and Regulatory Tribunal of New South Wales, Sydney, 2013.

[33] V.M. Summers, J.G. Wimer, QGESS: Cost Estimation Methodology for NETL Assessments of Power Plant Performance, National Energy Technology Laboratory, USDOE, 2011.

[34] B. Mountain, Electricity Prices in Australia: an International Comparison, Energy Users Association of Australia, Melbourne, 2012.

[35] KEMA-Sandia, in: A. Nourai (Ed.), ES-Select™ Documentation and User's Manual-version 2.0, Sandia National Laboratories, 2012.