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Techno-economic Analysis of Residential PV-battery Self-consumption

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Abstract

In recent decades, there has been a proliferation of behind-the-meter distributed energy resources (DER) and technologies in developed economies, and an increase in renewable energy resources (RER) generally. This rise is attributed to the quest for an increase in carbon-free energy by these countries and other environmental concerns. Furthermore, the traditional fossil fuel powered plants cannot continue serving in the long-run due to their dependence on dwindling reserves. More recently, there have been supportive policies to encourage the uptake of small- and large-scale RER, particularly the feed-in-tariffs and capital rebate schemes in the Australian context. These have resulted in increased DER uptake rates. However, the average retail electricity price in Australia is on the rise. In light of this, residential customers have resorted to increasing the self-consumption rates of their PV-battery systems, given the fall in the cost of solar PV and batteries. In order to assess the economic viability of customers' PV-battery systems, we utilise four energy management methods which aim to minimise customer electricity cost using a home energy management system (HEMS). Testing our methods on 52 customers from the *Solar Home Electricity Data*, our results show that utilising rule-based heuristic energy management strategies can result in near-optimal solutions, with lower computational requirements compared to principled optimisation techniques.

1. Introduction

In Australia, the US and other developed economies in the world, there are supportive policies for renewable energy resources (RER) to constitute a considerable part of the energy generation mix. Amongst RER, residential solar photovoltaic (PV) and battery storage systems (commonly known as distributed energy resources - DER) are prevalent due to their declining cost in recent years and the advancement in smart grid technologies. In addition, retail price hikes and the reduction in feed-in-tariffs (FiT) in Australia has motivated residential customers to increase the self-consumption rate of their PV systems using batteries since it is now an economically attractive option. With increased PV self-consumption, electricity cost savings are achieved and customers can recover their investment cost in the shortest possible time. This is typically accomplished using a home energy management system (HEMS). HEMS are automated decision-making devices that enable prosumers (consumers with PV and/or battery systems) to make the most of DER by providing optimised energy schedules that reduce electricity cost and maintain an acceptable home comfort level. Embedded in HEMS are the energy management algorithms needed to achieve its goals. These could comprise principled optimisation techniques or rule-based heuristics, which achieve the same purpose. In any case, computational feasibility and the ability of an energy management strategy to efficiently cater for the uncertainties of PV generation and load consumption are key. When compared to optimisation techniques, heuristic strategies have faster computation times but give sub-optimal solutions. Nonetheless, it has been shown in the relevant literature (Luthandar et al. and Merei et al. [1, 2]) that they provide reasonably good energy schedules and cost savings.

In this work, we consider three rule-based heuristic strategies, namely, *self-consumption maximisation* (SCM), *time-of-use arbitrage* (ToUA) and a combination of both (SCM+ToUA), and one principled optimisation technique, *mixed-integer linear programmming* (MILP) as energy management methods. In SCM, the generated PV output power is first used to meet the energy needs of the household, with any excess used to charge the battery (in case of battery ownership), or exported to the grid when the battery is full. However, SCM is plausible when there is a reasonably accurate forecast of PV generation and demand. Therefore, customers with historical demand or with a repeated consumption pattern can use persistence forecast methods to predict load consumption whilst relying on the weather forecasts to predict solar PV generation (Struth et. al [3]). ToUA is usually employed when a customer possesses a battery system and is on time-of-use (ToU) tariff. Here, the HEMS takes advantage of the price-differential of ToU tariffs during the day by pre-charging the battery when the price of electricity is low (off-peak periods) and discharges the battery when prices are high (shoulder and peak periods). This is particularly useful when there is a forecast of low PV generation during the day. The third strategy which is a hybrid of the aforementioned methods embodies the advantages of the two.

2. Literature review

As noted above, in order to maximise the benefits of PV-storage systems, residential energy users will use a HEMS to schedule their energy use.

We assume that PV-storage systems will be widely adopted for the following three reasons. First, when a customer's PV generation is higher than its electrical demand, the extra electrical energy will be either stored or/and fed back to the electrical grid. However, in Australia, feed-in tariffs are set to reflect the average cost of offset generation in the wholesale spot energy market, which means that selling power back to the electrical grid is uneconomical since retail tariffs for imports also account for network costs. Coupled with ever-dropping PV costs, there is a strong incentive for PV owners to self-consume as much locally generated power as possible. The conjecture is that in the near future this may happen in other parts of the world too. Second, time-varying pricing methods, such as time-of-use tariffs means that the users will want to operate the battery in such a way that its state of charge (SOC) is maximised at the beginning of time periods with peak price signals. A HEM system can aid in this time-of-use arbitrage operation. Third, an automated HEM system may also control the PV-battery system to achieve demand response [4–7] or direct load control [7, 8] for the financial benefit of customers but without human interaction. Given this, the underlying optimisation problem undertaken by the HEMS can be thought of as a *sequential decision-making process under uncertainty*. The problem contains two sets of stochastic variables, PV output and electrical demand, and solving this problem to optimality presents a number of technical and modeling challenges, including predicting demand behaviour and variations in PV output [9].

Several advanced optimisation-based methods have been proposed for solving the home energy management problem. They include stochastic *mixed-integer linear programming* (MILP) [10–12], *particle swarm optimisation* [13], *dynamic programming* (DP) [14], *approximate dynamic programming* (ADP) with temporal difference learning [15], and *policy function approximations* using machine learning [16, 17].

However, deploying optimisation-based methods to HEM problems requires adding a real-time control strategy to the battery energy management operations, to compensate for unforeseen variations of the energy flows in the home. This strategy filters the optimisation solution to ensure that no violations to the battery's state of charge limitations and dis/charge rates are made (e.g. see [17]). Despite the need for this form of control, this step is often omitted in studies of optmisation-based HEM algorithms. However, without it, it can be difficult to directly compare heuristic and optimisation-based energy management strategies

On the other hand, despite the attention devoted to optimisation-based HEM operation methods, most batteries are operated in practice using relatively simple heuristics. These include the SCM and ToUA strategies considered in this paper. Given this, the purpose of this paper is to clearly demonstrate the benefits of using an optimisation-based procedure over that of some commonly employed heuristics.

3. Simulation Methodology

In this paper, we utilise the above-mentioned heuristic energy management strategies to examine the techno-economic feasibility of PV and PV-battery systems of 52 residential customers in the Sydney region of Australia, considering both the perfect and persistence forecast of solar PV generation and demand. We adopt the framework in Figure 1 to assess techno-economically, various energy management strategies. More specifically, we carry out financial analysis and battery degradation study on the different energy scheduling methods. The economic viability indicators include the net present value (NPV), the internal rate of return (IRR) and the simple payback period (SPP) of investment, while the battery degradation indicators include the battery state of health (SOH), annual full

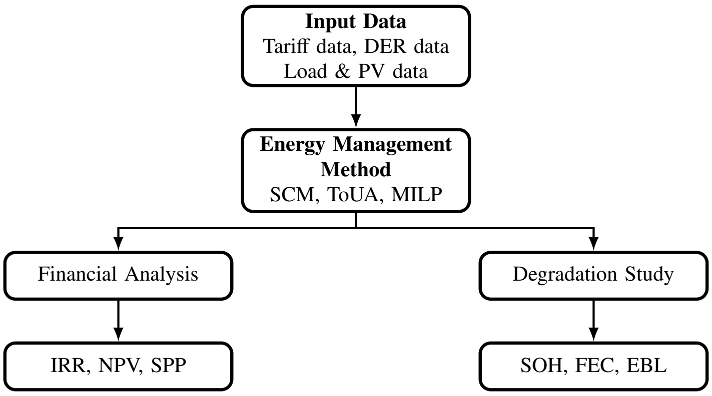


Figure 1: Framework

Table 1: Retail Charges

Tariff Type	Fixed Charge ($/day)	All Usage (c/kWh)	Off peak Usage (c/kWh)	Shoulder Usage (c/kWh)	Peak Usage (c/kWh)	Feed-in Tariff (c/kWh)
Flat	1.551	31.317	-	-	-	9.0
ToU	1.551	-	21.340	37.147	38.588	9.0

equivalent cycles (FEC), and expected lifetime (EBL). Demand, PV, DER and tariff data are fed as input to the energy management scheduling algorithm. The output of this algorithm which includes the power exchange results, battery charge/discharge power, and the battery SOC is then used to carry out financial analysis and battery degradation study.

3.1. Electricity tariffs

The retail charges utilised in this study are obtained from Origin Energy [18], one of the big three electricity retailers in New South Wales, Australia. Table 1 shows the residential electricity prices of Origin Energy for customers in the Essential Energy distribution zone. These prices include the actual cost of electricity, retailer's risk management and service fees, and the network (Essential Energy) charge.

3.2. Load and DER data

The demand and solar PV generation data was obtained from the Ausgrid (another network company in NSW) *Solar Home Electricity Data* [19]. This dataset comprise three years of 30-minute resolution electricity data for the period between July 2010 to June 2013, for 300 residential customers in the Sydney region of Australia. Although the dataset contains anomalous or incomplete demand and PV profiles for some customers due to reasons like inverter failure, Ratnam et al. [20] extracted 52 clean customer demand and PV profiles which are utilised in this paper. The size of the solar PV ranges from 3 to 10 kWp (in steps of 1kW), with an average value of about 5 kW (which corresponds to the average PV size in Australia). Statistically, 9.60%, 28.85%, 38.5%, 7.69%, and 15.38% of the 52 customers have installed PV capacities of 3.0, 4.0, 5.0, 6.0, and 7.0-10 kWp, respectively.

These customers did not have batteries connected to their premises. As such, we allocated batteries to each customer, where the battery size of the customer depends on the size of the solar PV installed. The PV-battery size combinations are shown in Table 2 [21] while the battery specifications are given in Table 3.

The battery round-trip efficiencies, given by the manufacturers (in Table 3) do not include the battery inverter efficiency, and also they have not considered losses due to the energy drawn from the battery management system. SMA technologies have completed a comprehensive study in [22] on the average efficiency of lithium-ion batteries. This study shows that the round-trip efficiency of a typical lithium-ion battery including losses is around 84%. We have used this value for our optimisation and analyses.

Table 2: PV and Battery Size Combinations

Solar PV Size (kWp)	Battery Size (kWh)	Battery Type
3 - 4	6.5 (LG Chem RESU 6.5)	Lithium-ion
5 - 6	9.8 (LG Chem RESU 10)	Lithium-ion
7 - 10	14 (Tesla Power Wall 2)	Lithium-ion

Table 3: Battery Specifications

Battery Type	Nominal Capacity (kWh)	Usable Capacity (kWh)	Max. Power (kW)	Round-trip Efficiency (%)
LG Chem RESU 6.5	6.5	5.9	4.2	95
LG Chem RESU 10	9.8	8.8	5.0	95
Tesla Power Wall 2	14.0	13.5	5.0	90

3.3. Home energy management strategies

In this section, we describe the different energy management strategies considered in this work. We consider three rule-based heuristic approaches and one principled optimisation technique:

- Heuristic approaches
  - Self-consumption maximisation
  - Time-of-use arbitrage
  - Self-consumption maximisation with time-of-use arbitrage
- Optimisation approach
  - Mixed-integer linear programming

Self-consumption maximisation (SCM)

Here, the inverter is set such that the energy from the PV serves demand, with surplus energy used first to charge the battery, and second, fed back to the grid. This method works well for most consumers, and it is the default strategy employed by retailers and battery suppliers.

Time-of-use arbitrage (ToUA)

This strategy is similar to SCM but involves pre-charging the battery to a certain pre-determined state-of-charge (SOC) using cheap off-grid or off-peak power, to be used later during the day when electricity prices are higher. Intuitively, this method is only beneficial with ToU tariffs and for certain customers whose load profile is well suited (i.e. those with large loads during peak price periods).

Self-consumption maximisation with time-of-use arbitrage (SCM+ToUA)

This is a hybrid of the SCM and ToUA strategies. The baseline strategy here is SCM, but ToUA is applied only where there is a perfect forecast of low PV generation

Mixed-integer linear programming (MILP)

This method, unlike the first two, explicitly takes the actual electricity cost and FiT into account in an optimisation framework. The objective of this HEMS approach is to minimise electricity cost, given known fixed tariff prices and load and PV generation forecasts over a decision horizon. The full details of this optimisation problem can be found in [23], but the objective is given by:

$$\underset{\substack{p^{\mathrm{g+}}_{d,h}, p^{\mathrm{g-}}_{d,h}, p^{\mathrm{b+}}_{d,h}, p^{\mathrm{b-}}_{d,h}, \\ d^{\mathrm{g}}_{d,h}, s^{\mathrm{b}}_{d,h}, e^{\mathrm{b}}_{d,h},}}{\text{minimise}} \sum_{d \in \mathcal{D}} \left[\sum_{h \in \mathcal{H}} T^{\mathrm{flat/ToU}} p^{\mathrm{g+}}_{d,h} - T^{\mathrm{fit}} p^{\mathrm{g-}}_{d,h} \right] \tag{1}$$

subject to:

1. Power balance constraint
2. Battery SOC constraint
3. Maximum grid connection limits
4. Upper and lower limit on continuous variables

Algorithm 1 MILP Rolling Horizon Algorithm

$\mathcal{C}$: set of customers
$\mathcal{D}$: set of days in a year
$\mathcal{H}$: set of half hours in a day

```
for each customer c ∈ C do
    Read yearly load and PV profile
    Set e^soc_{1,1} = 0.5ē^soc
    for each day d ∈ D, h ∈ H do
        Solve (1) for day d to d + 1                ▷ 2 day rolling horizon
        Return p^{g+}_{d,h}, p^{g−}_{d,h} e^soc_{d,h} for day d
        Set e^soc_{d+1,1} = e^soc_{d,|H|}
    end for
end for
```

3.4. PV and Demand Persistence Forecasting

We implemented a simple persistence forecasting algorithm similar to that in [3] in the following way for demand and PV prediction ($\tilde{P}_d$ and $\tilde{P}_{pv}$ respectively).

Demand $\tilde{P}_{\mathrm{d}}$ prediction
The weekday demand profile of customers are predicted based on their load profile a week before, to reflect the seasonality in their consumption pattern. Therefore the forecasted demand for the h^{th} time-step ahead is considered to be same as the demand a week before at the same time step implying $\tilde{P}_d(h + i) = P_d(h + i - 7days)$.

PV $\tilde{P}_{\mathrm{pv}}$ prediction
Here, we have considered the forecasted PV generation to be the same as the day before, but with a random variable ξ to account for the prediction error. The random variable is assumed to follow a uniform distribution. Therefore, the PV generation for the h^{th} time-step ahead is given as $\tilde{P}_{pv}(h + i) = P_{pv}(h + i) + \xi$.

4. Financial Analysis

To assess the economic viability of the PV-battery system using the different energy management strategies, we employ four financial indicators namely, Annual cost savings, Net present value (NPV), Internal rate of return (IRR) and Simple payback period (SPP).

4.1. Cost Parameters

The cost parameters used in the financial analysis are shown in Table 4. The initial investment cost of PV-battery systems are given as the total cost of the PV and battery systems as shown in Table 5 [21]. We have neglected the inverter cost in this study since we are comparing across different energy management methods. Also we have assumed an annual electricity price increase of 3% for the next 20 years [24]. If this inflation is not catered for, there will be relatively lower NPV and IRR values.

Table 4: Cost Parameters

Cost Parameter	Value
Annual electricity price inflation, e	3%
Discount rate, d	5%
System lifespan, $\mathcal{N}$	20 years

Table 5: PV-battery Market Prices

Price	PV-battery Sizes (kW/kWh)							
(× $1000)	3/6.5	4/6.5	5/9.8	6/9.8	7/14	8/14	9/14	10/14
PV	4.4	5.3	6.1	7.5	8.9	10.3	11.7	13.1
Battery	6.6	6.6	8.8	8.8	9.4	9.4	9.4	9.4
Total, C_0	11.0	11.9	14.9	16.3	18.3	19.7	21.1	22.5

4.2. Financial Indicators

In our economic analysis, we use the following indicators as a basis of comparison for all the methods:

- Cost savings: To calculate the annual cost savings, we employ the formula:
  Annual electricity cost savings = Annual electricity cost without PV-battery − Annual electricity cost with PV-battery
  Total annual cost savings (cash inflow) = Annual electricity cost savings + revenue from FiT

  If inflation of electricity price is catered for, the annual cash inflow escalates over the system lifespan. Therefore, we find the levelised total annual cost savings by applying the *levelising factor* (LF), given in (2). The equivalent discount rate d', considering annual electricity price inflation e is given by (3) [25]:

$$LF = \left[\frac{(1+d')^n - 1}{d'(1+d')^n}\right] . \left[\frac{d(1+d)^n}{(1+d)^n - 1}\right] \tag{2}$$

$$d' = \frac{d-e}{1+e} \tag{3}$$

  Hence, levelised total annual cost savings = LF.Total annual cost savings
- Net present value (NPV): To find the net present value of investment, we discount over the time period, $\mathcal{N}$, all future cash inflows to the present using discount rate d', using (4). A positive NPV indicates a profitable investment.

$$\text{NPV} = -C_0 + \sum_{n \in \mathcal{N} \setminus 0} \frac{C_n}{(1+d')^n} = -C_0 + \sum_{n \in \mathcal{N} \setminus 0} \frac{LF.C_n}{(1+d)^n} \tag{4}$$

  where C_n = Cash inflow, C_0 = Initial investment cost
- Internal rate of return (IRR): The internal rate of return r is the discount rate at which NPV is zero. In other words, IRR measures how quick we break even or recover our initial investment cost. It is calculated by solving for r in (5). However, the IRR for the investment with electricity price inflation r' is given by (6):

$$\text{NPV} = -C_0 + \sum_{n \in \mathcal{N} \setminus 0} \frac{C_n}{(1+r)^n} = 0 \tag{5}$$

$$r' = r(1+e) + e \tag{6}$$

  where r = Internal rate of return (IRR) without inflation
- Simple payback period (SPP): The simple payback period measures the recovery time of the initial investment cost without considering the time value of money. It is calculated using (7) if electricity price inflation is catered for.

$$\text{SPP} = \frac{C_0}{\sum_{n \in \mathcal{N} \setminus 0} LF.C_n} \tag{7}$$

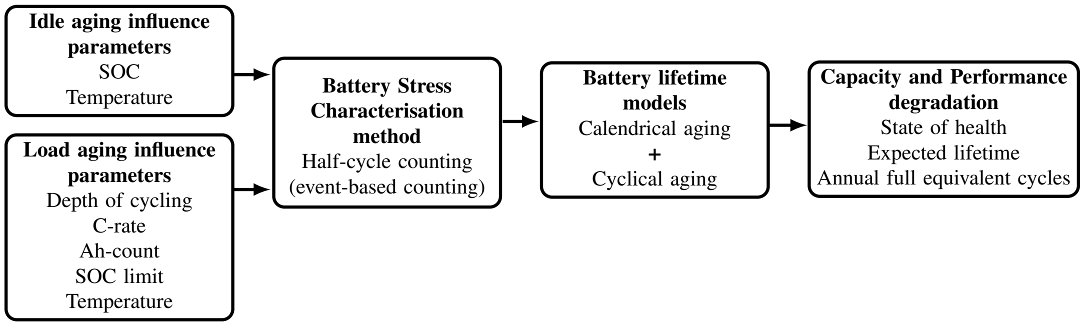


Figure 2: SimSES battery degradation model [26]

5. Battery Degradation Study

To assess the degradation of the battery over the system lifetime, we utilise the SimSES (software for techno-economic simulation of stationary energy storage systems) open-source software described in [26]. It enables a detailed simulation and evaluation of stationary energy storage systems, particularly lithium-ion batteries. The SimSES battery degradation model is depicted in Figure 2. The model receives the battery *Idle* and *Load* aging input parameters and implements the half-cycle counting battery stress characterisation method to estimate calendrical and cyclical aging. Thereafter, the combined effects of the calendar (idle stress) and cyclic (load stress) aging are used to estimate the battery capacity degradation and expected lifetime (12). The yearly battery charge/discharge power and SOC which are outputs of the energy management simulation, along with other aging parameters given in [26] are the inputs to the model. The aging influence parameters include the battery depth of cycling (DOC), C-rate, Ah-count, SOC limit, and temperature while the output of the model includes the battery state of health (SOH) after 20 years, the average annual full equivalent cycles and the expected lifetime (at 80% SOH). We estimate the SOH, calendric and cyclic capacity degradation using (8) to (10) respectively [27, 28]. The battery aging model is given in (11) and (12) [29].

$$\mathrm{SOH} = \frac{C_{\mathrm{max}}}{C_{\mathrm{rated}}} * 100\% \tag{8}$$

where C_{max} = maximum releasable battery capacity (which declines with time), C_{rated} = battery rated capacity

$$\Delta\mathrm{C}_{\mathrm{cal}} = \frac{0.2.C_{\mathrm{rated}}}{t_{\mathrm{cal}}} \tag{9}$$

where ΔC_{cal} = capacity degradation due to calendric aging,
t_{cal} = calendric time period until battery degrades by 20% of its rated capacity

$$\Delta\mathrm{C}_{\mathrm{cyc}} = \frac{0.2.C_{\mathrm{rated}}}{k_{\mathrm{cyc}}(DOC).DOC} \tag{10}$$

where ΔC_{cyc} = capacity degradation due to cyclic aging
k_{cyc} = amount of equivalent full cycles until battery degrades by 20% of its rated capacity.

$$a(t) = a_0 + \sum_{t \in \mathcal{T}} da(t) = a_0 + \sum_{t \in \mathcal{T}} (da_{\mathrm{cal}}(t) + da^{+}_{\mathrm{cyc}}(t) + da^{-}_{\mathrm{cyc}}(t)) \tag{11}$$

$$v(t) = 1 - (1 - v_{\mathrm{e}})a(t) \tag{12}$$

where $a(t)$ = battery age, a_0 = scaling constant, $da_{\mathrm{cal}}(t)$ = battery calendric aging, $da^{+/-}_{\mathrm{cyc}}(t)$ = battery cyclic (charge/discharge) aging, $v(t)$ = normalised battery capacity, v_{e} = normalised battery capacity at end of life, $\mathcal{T}$ = Total simulation time.

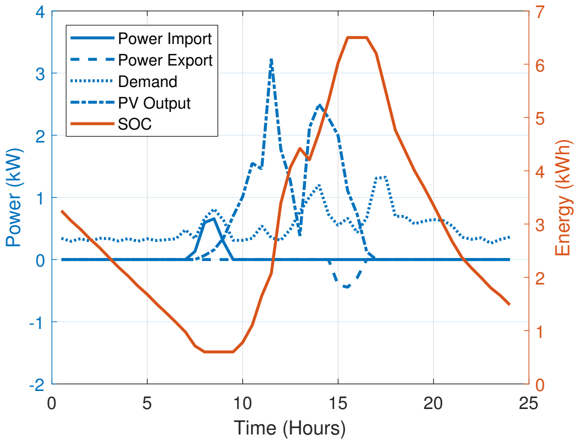
6. Results and Discussion

In the following sections, we present the energy scheduling results, the financial analysis of PV and PV-battery systems, and the battery degradation results of the different energy management strategies.

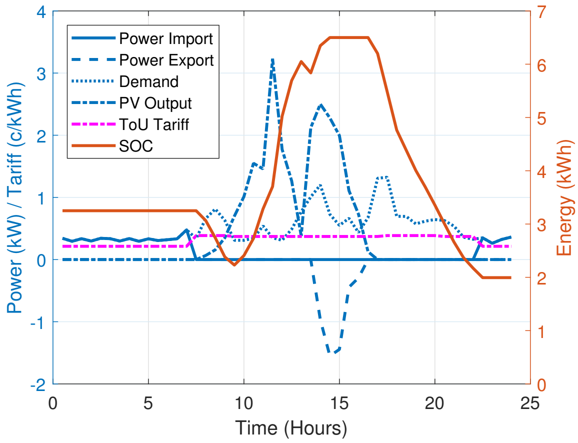
6.1. *Scheduling Results*

The results in this section show the battery schedule and power exchange with the grid using different energy management strategies. In Figure 3, we show the scheduling results of a randomly selected customer (Customer 47) on the first day of the year. The battery scheduling in SCM (Figure 3a) and MILP (Figure 3c) are similar, since MILP also maximises self-consumption because of the low FiT rate relative to the electricity retail price.

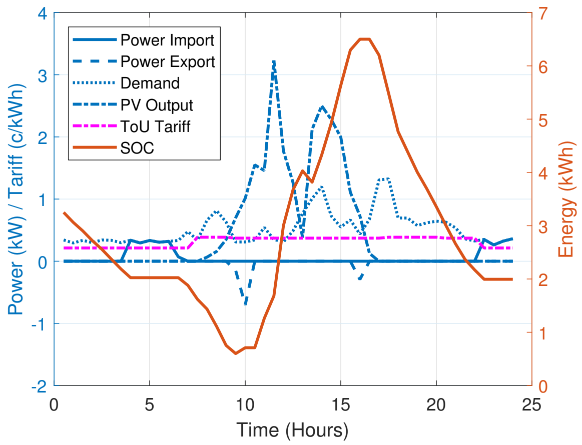
However, there is a slight difference. In SCM, with battery power available, the algorithm imports power mostly when PV starts generating, unlike in MILP when the decision to import power is done relative to cost minimisation. In ToUA (Figure 3b), the algorithm ensures a certain battery power (in this case, 30% of the maximum battery SOC) is left at the end of the day, by charging the battery with cheap off-peak grid power. And at the beginning of the day, the battery will be idle if discharging will cause its SOC to fall below the 30% SOC threshold, until the start of the high price (off-peak and shoulder) electricity periods. This is a form of energy security, which is useful when there is a day-ahead forecast of low PV generation. Figure 3d shows how the household demand is met from different power sources (PV, battery or grid), and how the PV power is utilised, using the MILP (with ToU tariff) energy management strategy.



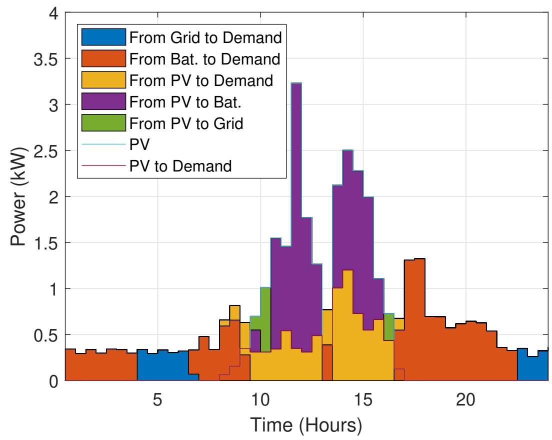
(a) SCM



(b) ToUA



(c) MILP with ToU tariff



(d) MILP with ToU tariff (Household demand)

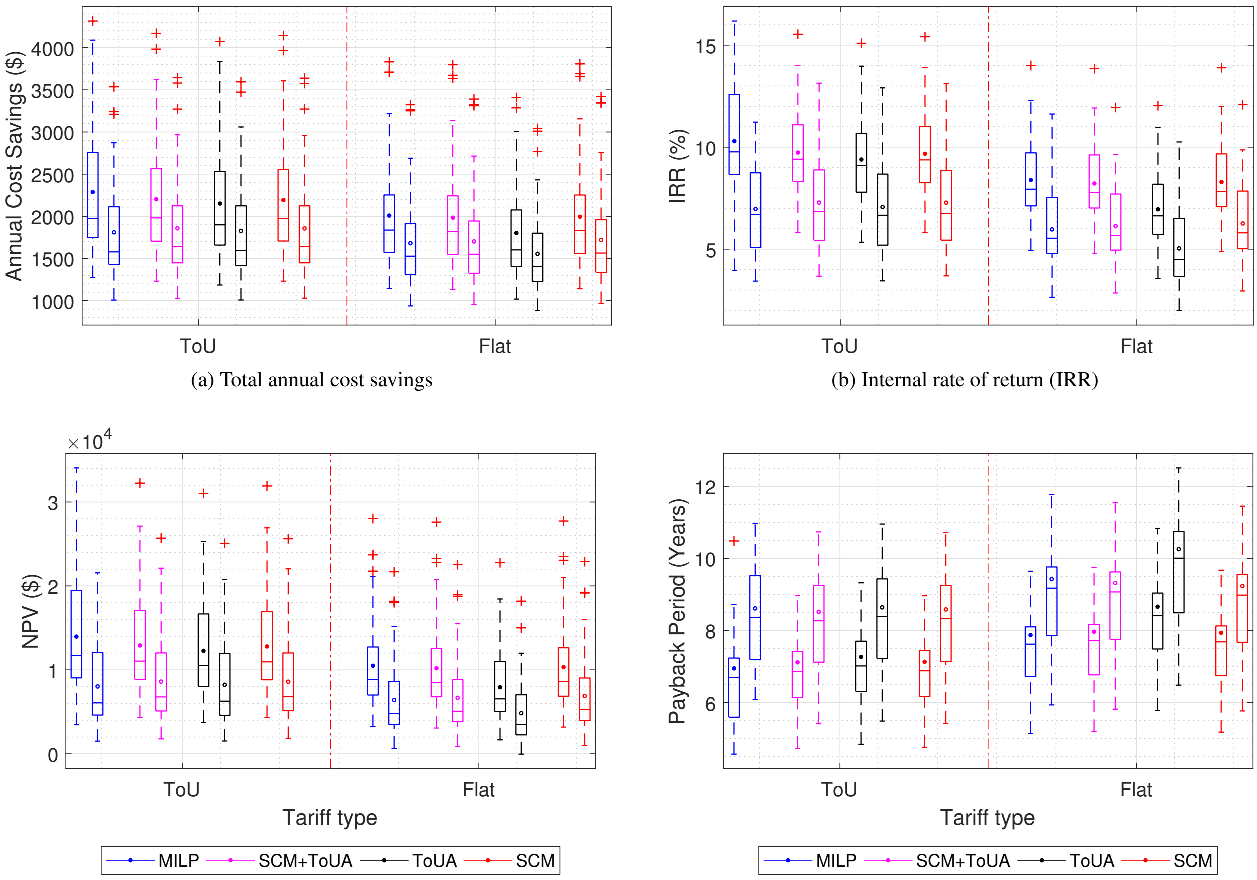
Figure 3: Daily Scheduling for Customer 47 (4 kWp PV, 6.5 kWh Battery), Day 1

6.2. Economic viability

Using the financial indicators described in Section 4.2, we now compare the economic viability of the PV-battery system using the different energy management methods in this section. The plots in Figure 4 show the statistical results of the financial indicators for all 52 customers while Table 6 compares the annual revenue (considering perfect forecast of PV and demand) and yearly computation times of a randomly selected customer across the four energy management strategies.

In Figure 4a, the total annual cost savings (median value) assuming perfect forecast of PV and demand is highest with MILP, followed by SCM+ToUA and SCM, both of which are relatively close. ToUA has the least cost savings and this is more apparent with flat tariffs than with ToU tariff. The is expected, because performing arbitrage on a daily basis is not economically worthwhile if the stored battery power is not effectively utilised due to available PV generation during the day. A similar pattern follows for IRR, NPV and SPP.

However, with imperfect forecast, MILP and ToUA had the least values across all economic indicators. MILP performs better than ToUA with flat tariffs while ToUA is better with ToU tariff. Generally, because MILP is a principled optimisation method that minimises cost, it's performance will be more adversely affected with imperfect forecast when compared with the heuristic strategies, especially with imperfect price response using ToU tariffs. SCM and SCM+ToUA both perform similarly and better than MILP and ToUA. This shows that with imperfect forecast (and no additional controllers on the battery operation under MILP), the best strategy tends to be to maximise PV self-consumption.



(a) Total annual cost savings

(b) Internal rate of return (IRR)

(c) Net present value (NPV)

(d) Simple payback period (SPP)

Figure 4: Financial indicators for all 52 customers with PV-battery systems, considering perfect (•) and imperfect forecast (∘). '+' indicates box plot outliers.

From Table 6, we can conclude that although the MILP algorithm performs best with regards to cost savings,

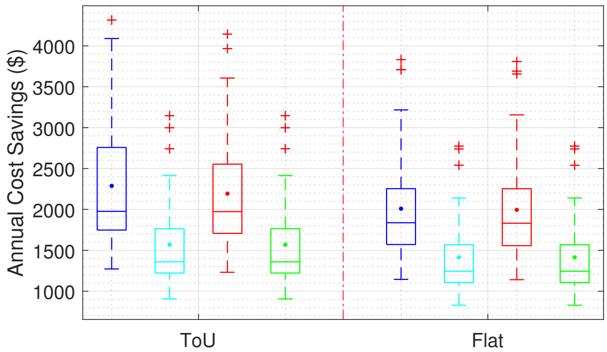
Table 6: Annual Revenue for Customer 27 (5 kWp PV, 9.8 kWh Battery)

Management strategy	Annual savings with flat tariff ($)	Annual savings with ToU tariff ($)	Yearly computation time (s)
SCM	1463.3	1569.3	0.257663
ToUA	1283.3	1502.8	0.605875
SCM + ToUA	1452.3	1574.7	0.363017
MILP	1468.1	1610.9	22.257553

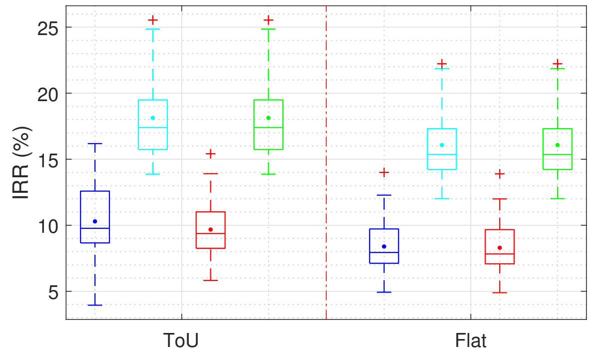
the heuristic strategies will be preferred to the MILP algorithm in terms of computational performance. The SCM algorithm can execute a yearly energy management problem in less than 0.3 seconds while the MILP takes over 22 seconds to execute same task. Actually, this is not a barrier to implementing MILP since other principled optimisation techniques like the DP and ADP take even longer [30]. However, the advantage of SCM over MILP becomes apparent when the energy scheduling of multiple households need to be evaluated over longer time periods. Furthermore, on a customer basis, SCM+ToUA with ToU tariffs can result in higher cost savings than using either SCM or ToUA alone.

6.3. Battery Storage Profitability

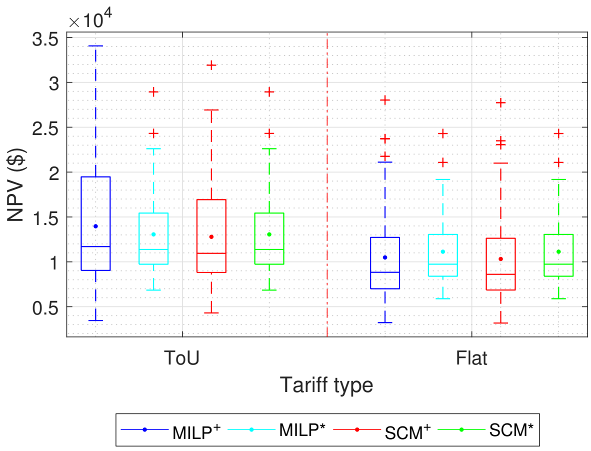
In this section, we examine the profitability of adding battery storage to a customers' PV system, considering perfect PV and demand prediction. In light of this, we have not considered ToUA and SCM+ToUA, since these algorithms involve the use of the battery to arbitrage electricity price differential during the day.



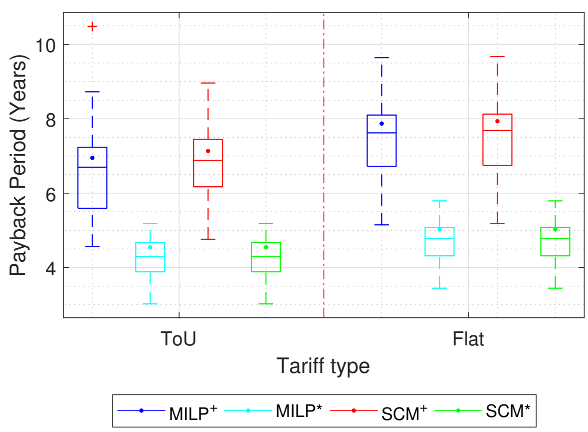
(a) Total annual cost savings



(b) Internal rate of return (IRR)



(c) Net present value (NPV)



(d) Simple payback period (SPP)

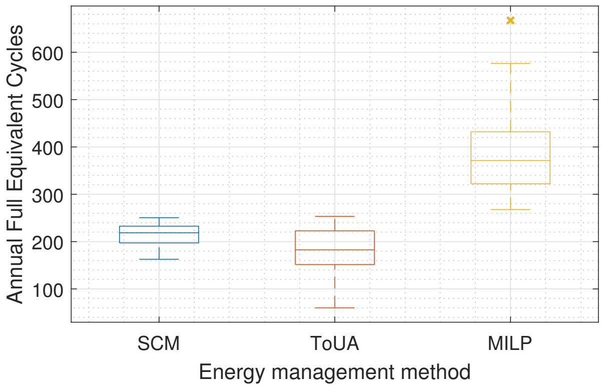
Figure 5: Financial indicators for all 52 customers with PV (∗) and with PV-battery (+) systems, considering perfect (•) forecast only. '+' indicates box plot outliers.

The results in Figure 5 show the economic indicators for MILP and SCM with and without batteries. Generally, we can deduce that having a PV-battery system is less profitable than having PV alone, given the high cost of batteries. Although the annual cost savings for a PV-battery system is higher than that without battery storage, other economic indicators show that a PV system alone is more viable. However, we expect this to change in the coming years with the recent predictions which show a high annual decline rate of battery cost [31, 32].

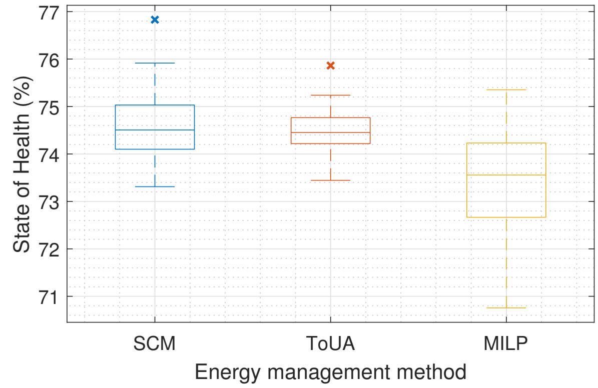
More so, without battery storage, the MILP has a close performance with SCM across all economic indicators. This is because without battery scheduling taking into account in the MILP cost minimisation, the MILP algorithm maximises self-consumption similar to the SCM algorithm.

6.4. Battery Degradation Results

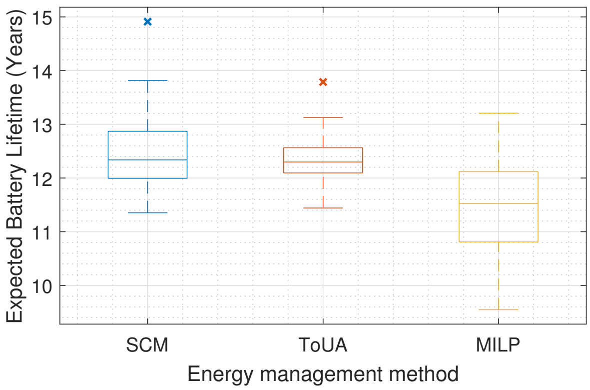
The results from the battery degradation study are given in Figure 6. These include (a) the average annual full equivalent cycles (b) the battery state of health after 20 years (c) the expected lifetime (at 80% SOH) and (d) the average cycle depth. More so, for the MILP energy management strategy, we have evaluated battery degradation with flat tariff only.



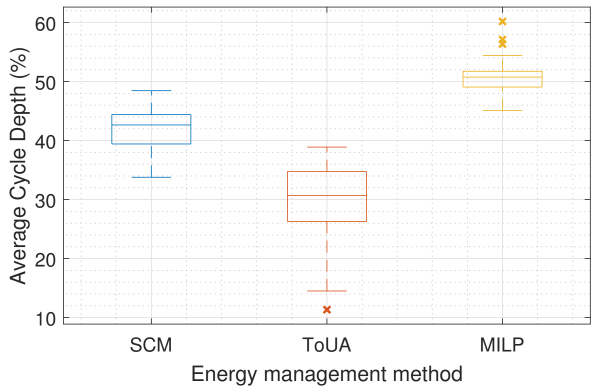
(a) Annual full equivalent cycles (FEC)



(b) State of health after 20 years (SOH)



(c) Expected battery lifetime in years (EBL)



(d) Average cycle depth (DOC)

Figure 6: Battery degradation results

As shown in Figure 6a, the battery is subjected to over 1.5 times the amount of (full equivalent) cycles compared to the heuristic strategies, due to the more frequent charging/discharging in response to cost minimisation. Following this, the MILP strategy impacts the battery state of health the most. Results show a median SOH of 73.6% with MILP after 20 years while SCM and ToUA have values of 74.5% and 74.4% respectively (see Figure 6b). Therefore, the expected median battery lifetime (Figure 6c) is least with MILP at 11.5 years. Lastly, Figure 6d shows the annual average cycle depth (DOC) for the three energy management strategies. Again, MILP has the highest average cycle depth (of 51%) as expected while the ToUA has the least. With ToUA, the battery is left idle during the off-peak periods, if discharging it will cause the SOC to fall below the pre-defined limit. As such, there are relatively lower loading periods with ToUA compared to the other methods.

7. Conclusions and Further Work

In this work, we carried out a techno-economic comparative study of four energy management methods, including one optimisation method and three rule-based heuristic strategies. Our results show that well-tuned heuristic strategies can give near-optimal solutions when compared to a principled optimisation technique. We can conclude that self-consumption maximisation (SCM), which is the baseline heuristic strategy, performs close to the MILP in terms of cost savings. And this can be slightly improved when combined with time-of-use arbitrage (SCM+ToUA) with a storage system. Furthermore, given the current battery prices, our results show that investing in PV alone is more profitable than investing in a PV-battery system.

More so, if computational speed is of more relevance to the end-user, the rule-based heuristics can provide faster near-optimal battery schedules, compared to MILP. With regards to battery degradation, the rule-based heuristics also show better battery aging performance compared to MILP. This is because of the more frequent use (charge/discharge cycles) of the battery with MILP, in order to respond to cost minimisation.

For future work, we will employ different machine learning energy management methods to provide fast online battery schedules. To accomplish this, it is necessary to train an artificial neural network (ANN) using customers' historic PV and demand data. The training can be done offline with a bit more computational overhead compared to the online phase. The advantage of this approach is that the trained neural network can be utilised for a long period of time without needing re-training. The energy management neural networks will be trained using generic customer load profiles as well as customer-specific profiles for the purpose of comparison.

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