Network capacity charge for sustainability and energy equity: A model-based analysis

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Abstract:

It is long known that the afternoon peak demand accounts for over-investment in the electricity network assets. This results in a high price of delivered electricity which does not fairly differentiate between peak and non-peak users. Energy tariff is proven to be one of the best demand-side management (DSM) tools for shaping consumers' behaviour. While electricity pricing models, such as inclining block and time-of-use tariffs, have received decent attention as successful mechanisms, there are little discussions about another efficient tariff known as a rollover network capacity charge. It is a penalty for the highest recorded power usage over the previous reading cycle (or year) which is introduced to commercial users in some jurisdictions.

With recent price reduction in distributed generation and storage (DGS) systems, the interest has increased in devising policies for directing the household and commercial consumers' behaviour towards using DGS systems in line with DSM objectives. In this paper, we have integrated the rollover network capacity charge into DGS systems investment analysis. The results from a few case studies show the positive impact of capacity charge in directing the peak-consumers' investment decisions towards DSM tools (e.g., energy storage) to curb their peak demands. This not only improves the resilience of the network but also promises as an effective mechanism in energy-justice nexus by avoiding the transfer of the associated costs of peak demand to all users.

Keywords: Energy-justice nexus; energy equity; demand-side management (DSM); distributed generation and storage (DGS); energy storage; rollover network capacity charge; demand charge.

1. Introduction

1.1 The issue of critical peak demand

In the electricity market, along with the daily demand peaks, there is another form of a peak known as "critical peak demand (CPD)" that occurs for a limited number of hours during a year. Generally, a CPD is a coincident demand that happens due to air-conditioning use in extreme weather conditions (e.g., very hot summer days) by all consumer types. The electricity supply chain infrastructure (generation, transmission, and distribution) should be designed to satisfy such maximum load incidences. This translates to the development of an oversized infrastructure.

Figure 1 shows the demand profile of New South Wales (NSW), Australia, in 2013. During that year, except for two days, the load was always below 12 GW. However, January 8th, a summer day, witnessed the fifth hottest day on record, with the ambient temperature reaching 42.3 ˚C. The consequent air-conditioning usage made a sharp increase in the state-wide demand, reaching almost 13 GW during the afternoon. This was not the only shock to the network that year, as ten days later the temperature reached 45.8 ˚C. During this hottest day since 1939, the demand peaked at 13.8 GW. Therefore, the critical peak load during two hot afternoons in 2013 necessitated bringing 1.8 GW of extra generation capacity online.

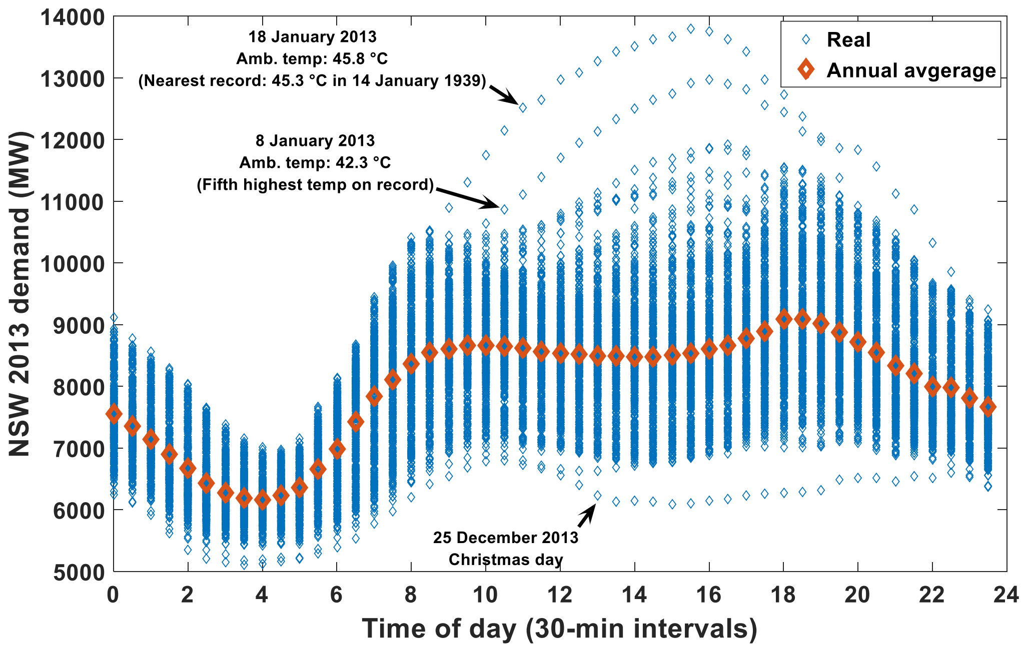


Figure 1: Time of day electricity demand profile of New South Wales, Australia, during 2013

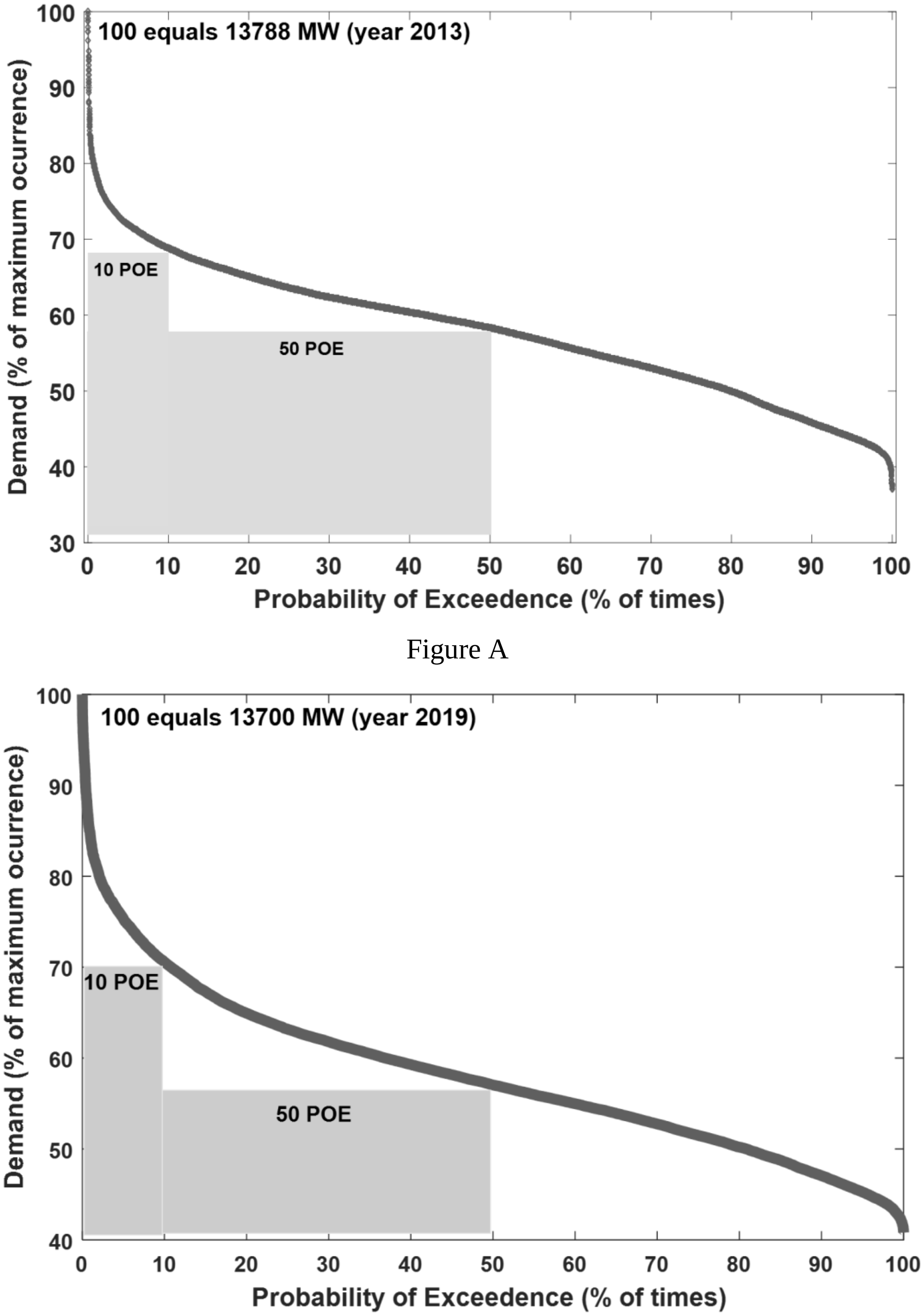


Figure A

Figure B

Figure 2: Cumulative distribution function (CDF) profile of electricity demand in New South Wales, Australia, during 2013 (A) and 2019 (B)

The cumulative distribution functions (CDFs) of the same load of Figure 1 is illustrated in Figure 2A. The probability of exceedance (POE) value of 100 in the Y-axis is identical to the maximum demand occurrence during that year (i.e., 13.8 GW). The 50 POE line shows that the demand was less than 58.4% of the maximum occurred load (i.e., 8 GW) over half of the times. According to the 10 POE line, over 90% of the times, the demand was less than 68.8% of maximum load. More interestingly, 99% of the times the demand was satisfied with less than 78.7% of the maximum load. In other words, 21.3% of the generation capacity was used only during 1% of the times. Figure 2B shows more updated data, for 2019. For this year, the 50 POE and 90 POE lines cross, the curve at 57.0%, and 70.6 %, respectively. In 2019, 15.7% of the generation capacity was used only during 1% of times.

A simple definition of reliability is the extent of the demand that a supply chain is capable of delivering within a certain timeframe, which can be for instance quantified with the loss of load probability (LOLP) [1]. This example clearly shows the detrimental role of CPD in the network asset investment and supply reliability. Therefore, the consequent question is how to address demand volatilities, in general, and CPD particularly, in a reliable energy supply chain planning. There are two demand management approaches: A) passive, and B) active illustrated in Figure 3 and described next.

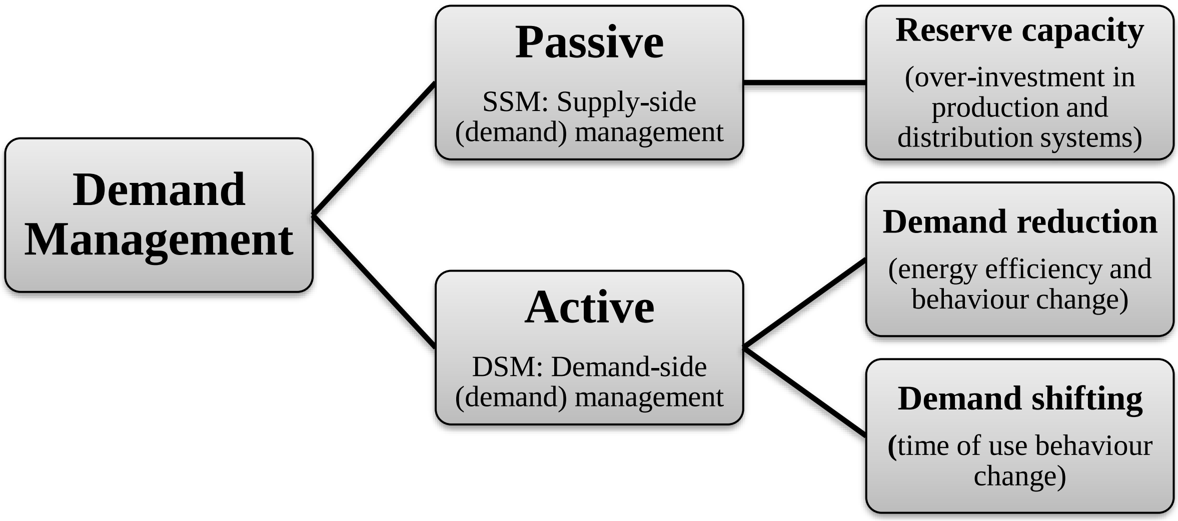


Figure 3: Approaches for demand management

A) Passive demand management: Supply-side management

Passive demand management takes the historical and forecast demand as a base, and attempts to supply it with the specified reliability standards. For this, a supply chain operator develops its planning based on the occurrence of the maximum projected demand during the planning horizon. This includes considerations of some reserve capacity for the security of supply in case of any component failure or critical demand (See Figure 4A). This capacity margin depends on the POE basis of the investment. The lower the POE value, the higher would be the installed capacity and the lower would be the reserve capacity (See Figure 2).

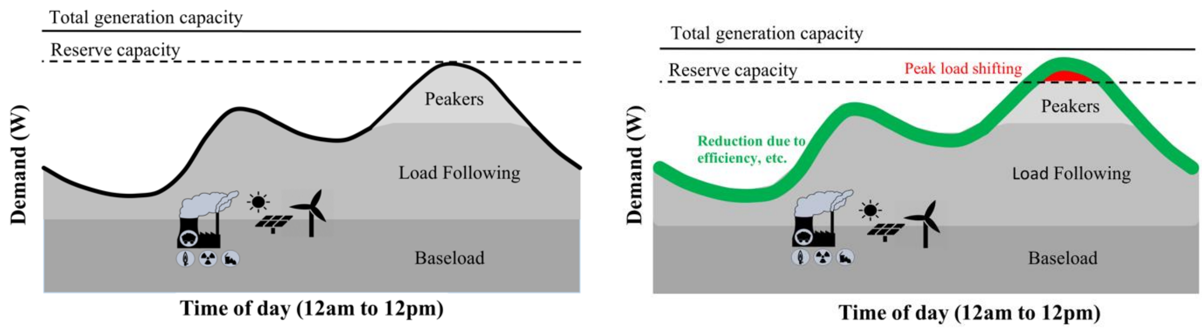


Figure A Figure B

Figure 4: Schematic of demand management in the electricity supply chain: A) Passive, with supplying the demand, B) Active, with energy efficiency measures and load shifting

Generally, reserve capacity can be as high as 20% [2]. A high reserve generation capacity is not the only burden of volatile demand. The transmission and distribution network also needs to be designed based on the peak load conditions. Today, therefore, we have (at least across industrialized countries), overly-invested electricity grids with a significant part of the fleet being utilized for a limited number of hours per year. This is to satisfy social welfare in terms of 24/7 continuous access to electricity, even in extreme weather conditions. Of course, this welfare comes with elevated delivered energy costs. For example, productivity analysis in some jurisdictions shows that 25% of household electricity bills account for generators that operate for fewer than 40 hours per year (during critical peak demand periods) [3]. On the other hand, in most developing countries, when a high reserve capacity is not an accessible option, the partial blackout is the general consequence of critical demand or component failure. Such pieces of evidence highlight the weakness of passive demand management and the necessity of alternative options. Energy storage at the generation side is another form of passive demand management which attempts to improve supply security and also reduce emissions footprint with the highest renewable energy utilization.

B) Active demand management: Demand-side management

Active demand management is, in fact, reverse demand management in which network operators attempt to reshape customers' demand profile rather than over-investing in reserve capacity (See Figure 4 right). This is known today as demand-side management (DSM). It was in the early 1970s that the shock in energy prices drew attention towards energy efficiency and productivity, and when DSM became a field of research and development in the academic

forum [4]. DSM can be categorized into two groups: (1) load reduction through energy efficiency and conservation, and (2) load shifting through demand response (See Figure 4 right). A detailed review of these approaches is provided elsewhere [5].
The significance of energy efficiency is evident. Demand response, however, comprises endless innovative techniques with the goal of flattening the load curve by shifting the demand from the peak to non-peak periods. Time shifting of demand has proven to be one of the most effective approaches for improving reliability and reducing the supply chain delivery costs of commodities.

1.2 Smart and fair tariffs for active demand management

According to McKinsey, active DSM has six levers: tariff rates, incentives, information, control, education, and customer insight and verification [6]. Although a fraction of customers, given education and insight, might take voluntary actions to participate in demand response, for most people active incentives (e.g., low tariffs for off-peak) or passive incentives (bill rebate after participation) would be detrimental to participation.

Energy storage technologies are great DSM options. However, there are two concerns, one being the cost and efficiency of storage technologies [7]. The other and the most critical concern is that they cannot support the network alone, and they will be effective when combined with smart tariffs [4]. Smart tariffs have proven to be the most influential tool in demand-side management [8]. Allcott et al. [9] showed that real-time pricing is more efficient than a flat fee structure. A study by the Energy Networks Association (ENA) demonstrated that both time-based and market price-based tariffs have a positive effect on peak-demand reduction compared to a flat-tariff [10]. Sterioitis et al. [11] showed that tariffs could be tailored down to individual customers based on their consumption behaviour.
Not only could the design of smart tariffs reduce the peak load, but it can also be a useful tool in the hands of policy-makers for designing fair pricing mechanisms to improve social equality in the energy-justice nexus. For instance, the Productivity Commission of Australia has given an interesting example: "Currently, a low-income household without an air conditioner is effectively writing cheques to high-income users who run air conditioners during "peaky" periods. For example, a household running a two kilowatt (electrical input) reverse cycle air conditioner, and using it during peak times, receives an implicit subsidy equivalent of around $350 per year from other consumers who do not do this" [3]. More examples of tariff discrimination are discussed by Simshauser [12]. Therefore, a smart tariff would incentivize customers who consume less energy during peak times and increase the charges of peak users.

In brief, when households and businesses are not exposed to time-based, cost-reflective network pricing, they lack encouragement to shift their consumption away from the peak demand periods. This leads to an over-investment in peak-specific systems and grid reinforcement as well as higher fuel costs through increased ramp rates, thus, reducing the social benefits for the consumers [13]. Consequently, these costs are shared equally, but unfairly, between peak and non-peak consumers.

Time of use and inclining block tariffs

There are currently two main tariff structures in effect internationally: inclining block and time-of-use (ToU). Figure 5 shows the schematics of the inclining block and ToU tariffs, respectively. The inclining block might be a good tariff for network-based commodities such as water and gas. Its effectiveness for electricity peak management is however questionable. In this tariff, the electricity price increases with the accumulative energy consumption over a certain period (e.g., month or season). Therefore, this method contributes to the DSM by encouraging customers to reduce their overall consumption, but it lacks any mechanism to address peak consumption. Furthermore, it is arguable that the inclining block is not a fair mechanism as it does not differentiate between the inhabitant numbers per connection point. For instance, a household of five would end up paying more per unit of electricity consumed than a household of two, even with lower energy consumption per capita. On the other hand, the ToU mechanism tackles peak demand by offering a relatively high tariff during peak periods. This can be socially fairer and technically more effective, though it does not address overall consumption reduction.

Currently, a critical philosophical question around consumption behaviour is almost emerging. The widespread uptake of clean, renewable technologies, such as photovoltaic (PV) cells, can bring us sustainable and affordable energy at near-zero-emissions. We have been educated to consume less following social, ethical, and sometimes religious norms. But, will renewable energies affect this norm? Why not have over-shiny houses at night when the energy is supplied by the wind? The findings in Fikru et al. [14] suggest that households with own energy resources consume more energy than those without.

It can also be anticipated that utilities will shift away from providing energy commodities to providing energy services [15]. The fierce competition among retailers further encourages innovative energy services to reflect the changing consumer expectations [16]. Inching block tariffs are set based on a socialist assumption which does not encourage overconsumption. It is expected that at least in countries without subsidized energy costs, block tariffs might be retired over time and different types of time-based tariffs are introduced to reflect the variability of renewable resources. Fairness is also critical for renewable energy feed-in tariffs [17], and for the same reasons discussed here for energy purchase, ToU tariff may prevail flat tariff for energy export, from both fairness and DSM aspects.

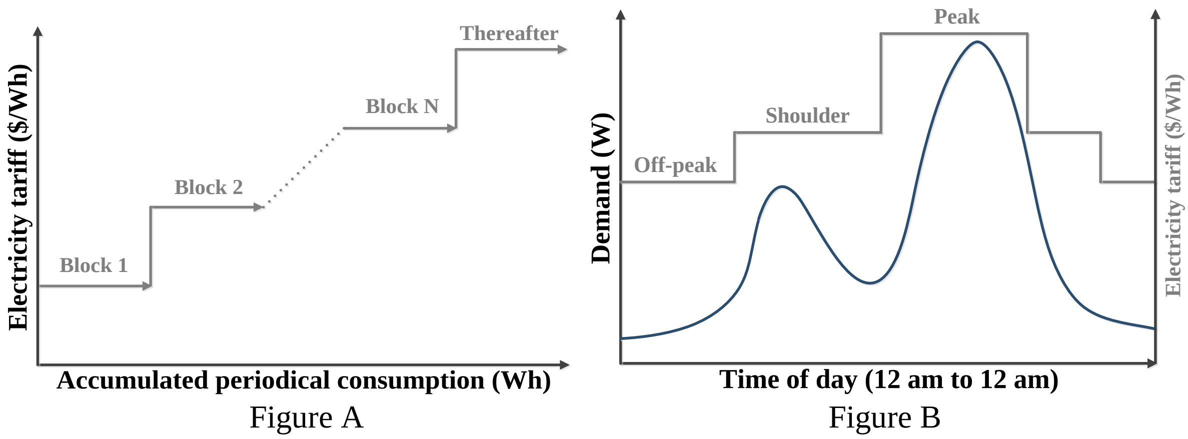


Figure 5: Schematic of A) inclining block energy tariff, and B) time of use energy tariff

Rollover network capacity charge

So far, two major tariffs for targeting overall energy consumption and peak period demand are discussed. However, there is evidence that none of these can address the critical peak demand efficiently (See Figure 1 and Figure 2 as an example). One approach to address this problem, especially on a community scale, is dynamic pricing [18]. Alternatively, some supply chain companies introduce a rollover network capacity charge, also known as network charge, capacity charge, or demand charge. It is composed of a fixed number ($/power/time) multiplied by the highest demand occurrence during the previous billing period at a given measured interval of the smart meter (e.g., kW), multiplied by time. For instance, assume the capacity charge is based on the highest occurrence in the previous year. For a given company, the occurred highest demand was 1000 kW with a capacity charge of 130 $/kW/year. This translates to $130,000 added to the bill. Now, imagine that the company's load was almost always below 700 kW, and it exceeded this number only a few times in a hot summer. This implies that the company is paying (1000-700)×130=$39000 extra over this year because of those few critical demand incidences rolled over from last year. Obviously, any user will source for options to avoid its critical peak demand. At a macro level, this demand-side behaviour is expected to reduce the critical peak demand at the generation and transmission side, and thus reduce the need for large reserve capacity (See Figure 2).

Historically, users with capacity charge tariffs, especially commercial buildings, have managed their critical demands through efficiency and flexibility measures [19]. In recent years, energy storage has been attracting interests from peak-users to provide them with flexibility in their demand management. The principle of equity requires that any tariff design fully reflects the supply costs and provides investment signals. However, with high installation costs of energy storage systems, this option is not yet a widespread feasible choice if only inclining block or ToU is considered. The capacity charge can help to achieve more cost-reflective electricity network tariff. However, its effectiveness depends on whether the customer’s coincident demand occurs at the time when network peaks are likely to occur [20]. Though the capacity charge is often introduced for commercial and large-scale consumers, some studies show the efficiency of this tariff even for residential customer [21]. Young et al. [22] simulated various tariff designs for the operation of household PV and energy storage and found that incorporating capacity charge in the tariff design yielded the highest peak demand reduction. This becomes particularly noticeable in the networks where the dominant cost driver is the required reserve to meet the highest electricity consumption. The need for the capacity charge to facilitate the uptake of energy storage is further supported by Stelt et al. [23] who found that under the current storage investment costs and energy tariffs energy storage is economically infeasible for households.

The capacity charge has another benefit of managing the negative load (export from renewable generators) or shifting coincident peaks from one period to another. However, Eid et al. [24] emphasized that capacity charge can be considered effective only if the peak load is clipped or distributed over a longer time period instead of shifting it to another time period. The capacity charge can be enabled only if an advanced metering infrastructure (AMI) is deployed in the network. Hakyoort et al. [25] highlighted that the problem of split-incentives related to the AMI would discourage a distribution system operator (DSO), retailer or a customer to be the sole entity that makes the investment. Khalilpour and Vassallo [4] have discussed the concern over the emergence of new peak demands in times other than the current afternoons. They have also discussed the potential problems with sharp changes in load profiles during the periods at which ToU tariffs are shifting from one threshold to another. In a typical energy storage operation program, there are constraints to control the storage charge rate and also prevent the storage SOC from being above/below a maximum/minimum. Other constraints limit the battery charge/discharge rates at design charge/discharge caps. While these are valid constraints, there can still be a problem. The issue is that the off-peak period is typically close to 10 hours (from late night to early morning) while a battery with C-rate of 0.5 requires only two hours for a full charge. This two-hour period could occur at any time within the 10-hours of off-peak period. A severe grid management problem could occur when all batteries are programmed to charge (or discharge) at a similar time. This has been demonstrated in the literature for causing a new peak in a common off-peak period [4]. Similar to our morning peaks (e.g., for hot water use) the future houses with stationary battery and electric vehicles (EVs) may cause sharper morning peaks. Imagine when people wake up in the morning, one or two hours before the shift of electricity tariff from off-peak to shoulder/peak. The immediate thing they might think of would be to plug in their storage systems. With the rapid uptake of stationary batteries and EVs, such problems could easily occur unless smart storage control systems, along with smart electricity tariffs, are introduced.

To avoid this, one approach is to add a further random constraint, so-called "operational charge limit (OCL)," for off-peak periods in order to distribute the battery charge over the entire off-peak period [4]. This prevents charging to be delayed until the last one or two hours before tariff change. While this constraint proved to work efficiently, it is not a binding constraint for customers to use and in practice, unwanted new demand peaks are possible in future. Capacity charge, however, is not time-relevant and can be used as an enforcing tool by policymakers for encouraging customers to reduce their peak at any time during a day. With a capacity charge, there might be less or no requirement for OCL constraints.

Currently, in most energy storage investment analyses, the benefit of capacity charge is not considered, while this can notably improve the value proposition of energy storage options. There could be various reasons for ignoring capacity charge ranging from the inexistence of such tariff mechanisms in some jurisdictions to the complexity of bringing it to the optimization problem formulation. The key objective of this study is to bring rollover network capacity charge constraints into distributed generation and storage systems' sizing and scheduling, and assess how it can affect the decisions.

2. Literature on sizing and operation modelling of distributed generation and storage

Today, renewable energy technologies are no more topics of merely academic interest. Fortunately, renewable energy is finding its way into our fossil-fuel-based energy industry and even to our rooftops. Distributed energy resources have several advantages, including abundance and relatively scattered geographic distribution. As such, exploring the utilization of local (renewable) energy sources has been a matter of economic benefit and security for energy-importing societies. Furthermore, the possibility of generating energy on the demand-side has many advantages in terms of energy efficiency, as it can reduce the required reserve generation capacity, lessen the network footprint, and minimize the power losses in the transmission system network. All these features have stimulated the idea of moving from traditional, often low-efficiency, and centralized macrogrids to a decentralized form with numerous small but smart grids fueled by local resources.

Various combinations of energy generation and storage technologies have been studied. For obvious reasons, solar systems have been of the highest interest for small-scale demand-side applications. The earliest simple configurations were PV-grid, PV-diesel [26], and PV-battery. The configurations have diversified over time with the inclusion of various hybrid DGS systems such as PV-hydrogen, PV-diesel-battery [27], PV-wind-battery [28], PV-wind-diesel [29], PV-wind-diesel-battery [30], and PV-wind-diesel-hydrogen-battery [31]. The list of configurations could be much longer if other generation types (e.g., bioenergy, hydro, gas turbine) and storage (e.g., hydro, compressed air, flywheel, capacitance, chemical conversions) are included [32]. For energy network planners and operators, DGS provides a great degree of freedom for DSM through load shifting, if efficient rules and regulations for the operation of the DGS systems are implemented.

Table 1 lists some key literature on the optimal sizing and operation of DGS systems. The first and most crucial step in DGS decision-making is the selection of the right technology, right mix, and right sizes. Then comes the reliable operation of the selected technologies. Initial efforts in the sizing of DGS systems were related to the integrated PV-battery systems. The studies focused mainly on off-grid and rural areas, using approximate methods which resulted in over-sized or under-sized systems [33]. Later, iso-reliability curves were introduced by Egido and Lorenzo [34] which are based on developing numerous graphs of PV-storage sizes, each at a certain reliability value. A good review of the iso-reliability method and a rule-of-thumb approximation on that basis is given by Egido and Lorenzo [34]. As computers emerged, PV-battery sizing models also improved in rigorousness. For instance, instead of daily average solar irradiation or load data, real historical time series were used [35, 36], or characteristic equations were used instead of simple efficiency values for PV panel, battery, inverters [37], etc.

With the global attention to the PV transformation within the last decade, there has been an 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 [38] developed a short-term scheduling model for battery use in a grid-connected 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 the grid-connected PV-battery system on locational pricing. Kaushika et al. [39] 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 or 100% reliability. Pham et al. [40] examined five energy storage technologies and found that Li-Ion battery has the highest suitability index to support a stand-alone PV system. A study to find the optimum ESS size considering different battery chemistries was carried out by Hesse et al. [41]. The results showed that lithium-nickel-manganese-cobalt battery is more economically effective for residential application with annual demand bellow 20,000 kWh, while lithium-iron-phosphate batteries are better for households with large demand.

Some researchers have also used artificial intelligence techniques [42] or heuristic optimization techniques, such as particle swarm optimisation (PSO) [43] and metaheuristics with MINLP [44] for sizing PV-battery systems. Riffonneau et al. [45] 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. [46] 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. [47] 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 the efficient operation of PV-battery systems. According to Halliday et al. [48], 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 a lower expected 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 [49, 50]. One of the earliest studies of efficient battery operation was by Appelbaum et al. [51], 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 [52] compared modelling 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. [53] discussed that current homogeneous electric energy storage (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 the strength in certain performance feature. Stadler et al. [54] developed a distributed energy resources customer adoption model (DER-CAM) based on a mixed-integer optimization program. DER-CAM can also model various DG and storage types. Mashayekh et al. [55] improved the DER-CAM model by formulating multi-node design to account for the cable losses.

Wang et al. [56] developed a dynamic programming model for the 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 a 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 [57], balanced configuration [58], and charge allocation and replacement [59, 60]. Manshadi and Khodayar [61] identified the vulnerable components and studied the potential causes of disruptions in multiple energy carrier microgrids.

Abdulla et al. [62] found that accounting for battery degradation and including even simple load and generation forecast models can significantly increase the value and performance of energy storage systems. Khalilpour and Vassallo [4, 63] developed a few integrated decision support tools for concurrent optimal selection, sizing and operation scheduling of grid-connected DGS systems (including but not limited to PV-battery). The importance of the optimal location for ESS was also emphasized in Novoa et al. [64] and Alsaidan et al. [65].

Atia and Yamada [66] built an energy system operation model based on Newton-Raphson Linear Programming (NRLP) algorithm. This model iteratively schedules resources to maximize profits while compensating for the complicated nonlinear nature of the problem. An optimal combination of DGS system candidate units was found using a genetic algorithm (GA). The initial combination of units was randomly generated and separately evaluated using the NRLP algorithm. Xiang et al. [67] argue that the real peak demand can occur between discrete time steps and proposes a continuous approximation for the state of energy function using Fourier-Gegendere series to address this problem.

EINozahy et al. [68] used a probabilistic sizing of battery storage. The uncertainties associated with the local power supply and demand were addressed through multiple PV and load profiles; generated using principal component analysis (PCA). The supply and demand profiles from the PCA were then employed in a Monte Carlo (MC) simulation to obtain random load profiles. Their model resulted in lower voltage fluctuations and network losses. Bai et al. [69] reduced electricity costs and network losses in the distribution network using a virtual portioning model. It takes the minimum annual cost as the upper-level objective to determine the investment in PV systems and the minimum sum of equivalent load variance as the lower level objective through the virtual partition to determine the energy storage configuration.

Umeozor and Trifkovic [70] proposed a microgrid management strategy where the variability and uncertainty of renewables are solved with the parametric optimization approach (p-MILP), thus removing the dependency of the solution on weather and load forecast data. Zhou et al. [71] introduced a multi-objective sizing and optimization of DGS systems including demand response. Assuming a linear relationship close to the market equilibrium point, Zhou et al. established an electricity price elasticity matrix based on historical data and compared models with and without demand response. An improved non-dominated sorting genetic algorithm (NTGA II) was used to find the optimal DGS capacity. They found that adding demand response in the optimization model reduces the required PV and battery storage capacity. Demand response constraints also have a positive effect on maximizing profits for microgrids with combined heat and power (CHP) plants as found by Alipour et al. [72]. Storage sizing based on stochastic network calculus (SNC) with a tie line penalty constraint ensured balanced microgrid operation during import/export transition periods in Xie et al. [73]. Pandžić's model [74] is a deterministic battery sizing with consideration of ToU tariff. However, the model is integrated with various load scenario sets to accommodate the uncertainty in the future demand profile.

The capacity charge is not a new tariff. However, there is a gap in the literature on bringing this tariff into optimization framework in the context of DGS systems. In this paper, we integrate capacity charge constraints with energy storage sizing and scheduling algorithm. For the sake of paper continuity and in favour of readers with broader interests we have provided the full formulation in Appendix 1. Unlike the current application of capacity charge for the import from the grid, we anticipate that in the future, there might also be a requirement for such a capacity charge for energy export to the grid. As such we consider two capacity charges; one for export, and one for import. We assess the impact of capacity charge consideration in DGS systems selection, sizing, and operation. We also investigate the inherent performance of such a tariff in active demand-side management. The most relevant paper for the sizing and operation of ESS are summarized in Table 1.

Table 1. Key literature on the optimal sizing and operation of DGS. The following abbreviations are used: WT – wind turbine, CHP – combined heat power, FC – fuel cell, GT – gas turbine, G – genset.

Study Model			Network Considerations			Tariff Considerations					
	Operational Criteria	**Operational Model**	**Application**	**Additional Components**	**Network topology**	**Fixed Price**	**ToU**	**Capacity Charge**	**Spot Price**	**FIT**	**Reference**
-	Cash Flow	Mathematical (DP)	DER	PV		✓				✓	[45]
-	Energy Costs	Mathematical (QP)	DER	PV		✓				✓	[47]
-	Energy Costs	Analytical (geometrical)	DER	PV		✓	✓			✓	[49]
-	Energy Costs	Analytical	DER	PV		✓	✓				[14]
-	Energy Costs	Mathematical (p-MILP)	DER	PV, WT			✓		✓	✓	[70]
-	Revenue	Mathematical (MILP)	Microgrid	WT, CHP, FC					✓		[72]
Non-cost-based sizing											
ENS	-	Mathematical (LP)	Stand-alone	PV							[39]
ENS	-	Analytical (rule-based)	Stand-alone	PV							[52]
ENS	Battery Capacity	Analytical (rule-based)	Stand-alone	PV							[40]
Network Congestion	Transformer Overloading	Probabilistic (MC)	DER	PV	✓						[68]
Zero Net Energy	-	Mathematical (MILP)	Microgrid	PV	✓		✓		✓	✓	[64]
Cost-based sizing											
NPV	Energy Costs	Analytical (technometric)	DER	PV		✓	✓			✓	[50]
Annualized Costs	Energy Costs	Mathematical (MILP)	DER	PV		✓	✓			✓	[46]
Annualized Costs	Energy Costs	Mathematical (DP)	DER	PV		✓	✓				[56]
NPV	-	Mathematical (LP)	Microgrid	PV, G		✓		✓			[27]
Annualized Costs	Energy & Operation Costs	Mathematical (MILP)	DER	PV	✓✓	✓		✓		✓	[55]
NPV	Energy Costs	Mathematical (MINLP)	DER	PV			✓			✓	[63]
LCOE	Energy Costs	Mathematical (MILP)	DER	PV	✓				✓		[23]
Annualized Costs	Energy Costs	Mathematical (GA+LP)	DER	PV, WT	✓				✓		[71]
Annualized Costs	Energy Costs	Mathematical (MILP)	DER	-			✓	✓			[74]
Annualized Costs	Energy & Operation Costs	Mathematical (MILP)	Microgrid	-							[65]
Annualized Costs	Energy Costs	Mathematical (MINLP)	DER	PV			✓				[44]
Investment Costs	Energy & Operation Costs	Mathematical (MILP)	Microgrid	PV			✓	✓			[75]
Annualized Costs	Energy Costs	Mathematical (LP)	DER	PV		✓				✓	[41]
Annualized Costs	-	Mathematical (MILP)	Microgrid	PV, WT, GT	✓				✓		[65]
Investment Costs	Energy Costs	Mathematical (SNC)	Microgrid	PV, WT		✓				✓	[73]
Annualized Costs	-	Analytical	DER	PV	✓						[67]
Investment Costs	Energy Costs	Heuristics (PSO)	DER	PV		✓				✓	[43]

3. Case studies

3.1. With a supply charge

A supply chain company (here on called "the company") has an inventory in Melbourne, Australia, with an annual electrical load profile given in Figure 6. The inventory has consumed 6,633.7 MWh of electricity over the base year with the load varying between 212.0 kWh and 1344.8 kWh (occurred 6 pm, 23 Feb, a summer day). Almost all of the top 20 peak demand incidences have occurred over Dec-Mar (evident in Figure 6), which are summer months in Melbourne. This implies the use of air-conditioning as a major contributor to peak demand. Table 2 provides an explicit list of electricity tariffs the company has paid with an additional 10% goods and service tax (GST). The cost is composed of retail charges for the peak and off-peak usage, environmental schemes, network, market operator, and metering. In Table 2, the capacity charge is one of the tariffs under "network charges" category. The company has paid $908,158.7 over the year for its electricity bill. Given the capacity charge of 134.7 $/kW/y and the incurred highest demand of 1344.8 kW, the company has to pay $181,175.4 as a capacity charge in the following billing year.

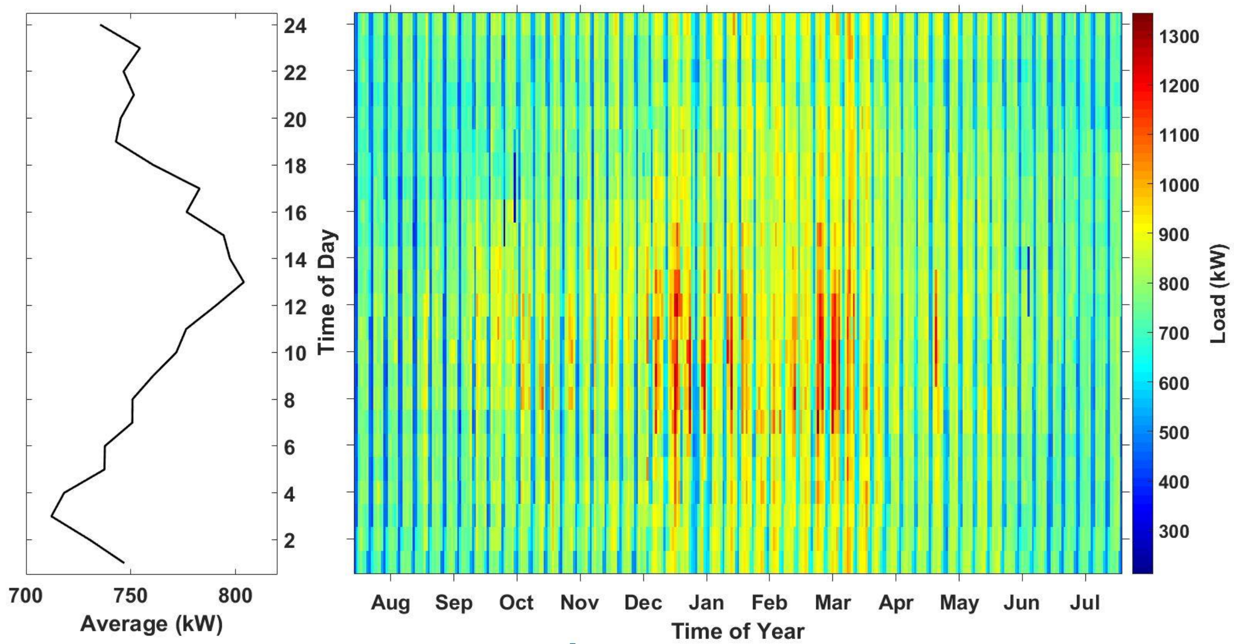


Figure 6: The Company's carpet-plot of electricity load during the base year (July-July); the high demands during Dec-March imply the use of air-conditioning over the summer (for the southern hemisphere).

Given that the declining PV prices, the company is interested to assess the feasibility of investing in PV as well as in battery storage systems. The preferred payback period for the company is less than ten years.

The candidate PV panels have a standard efficiency of 0.17. They are available in various sizes, and the company puts no upper limit on the potential system size. The PV output decreases by 0.5% annually (due to aging). The annual ambient temperature and GHI profiles are illustrated in Figure 7. The recent PV system prices show almost linear functionality with size (though with different multipliers for small-, medium-, and large-scale systems). For this study, the customer considers a linear function for the PV installation cost with a multiplier of 1500 $/kW.

Table 2: The tariff breakdown of the company's electricity bill with GST of 10%

Charges	Charge type	Applied to (unit)	Unit Price (c/kWh, unless mentioned)	Loss factor	Total Unit Price (excl. GST)
Retail Charges	Peak	Peak consumption (kWh)	5.0192	1.09479	5.4950
	Off Peak	Off-peak consumption (kWh)	2.9611	1.09479	3.2418
Environmental Schemes	Large-scale renewable energy Certificates (LRECs)	Total consumption (kWh)	0.9426	1.09130	1.0287
	Victorian energy efficiency certificates (VEECs)	Total consumption (kWh)	0.4691	1.09130	0.5119
	Small-scale renewable energy Certificates (SRECs)	Total consumption (kWh)	0.3857	1.09130	0.4209
Network Charges (for large low voltage demand)	Peak	Peak consumption (kWh)	4.7905	-	4.7905
	Off Peak	Off-peak consumption (kWh)	2.8514	-	2.8514
	Capacity	**Highest demand occurred (kW)**	**134.7229 ($/kW/y)**	**-**	**134.7229**
Market Operator Charges	AEMO Ancillary Fee	Total consumption (kWh)	0.0178	1.09130	0.0194
	AEMO Market Fee	Total consumption (kWh)	0.0315	1.09130	0.0344
Metering Charges	Meter Charge	Number of meters (mtr)	1120 ($/mtr/y)	-	1120

- Peak: 7am-9pm weekdays; Off-peak: other weekday times and weekend/holidays.
- GST: 10%

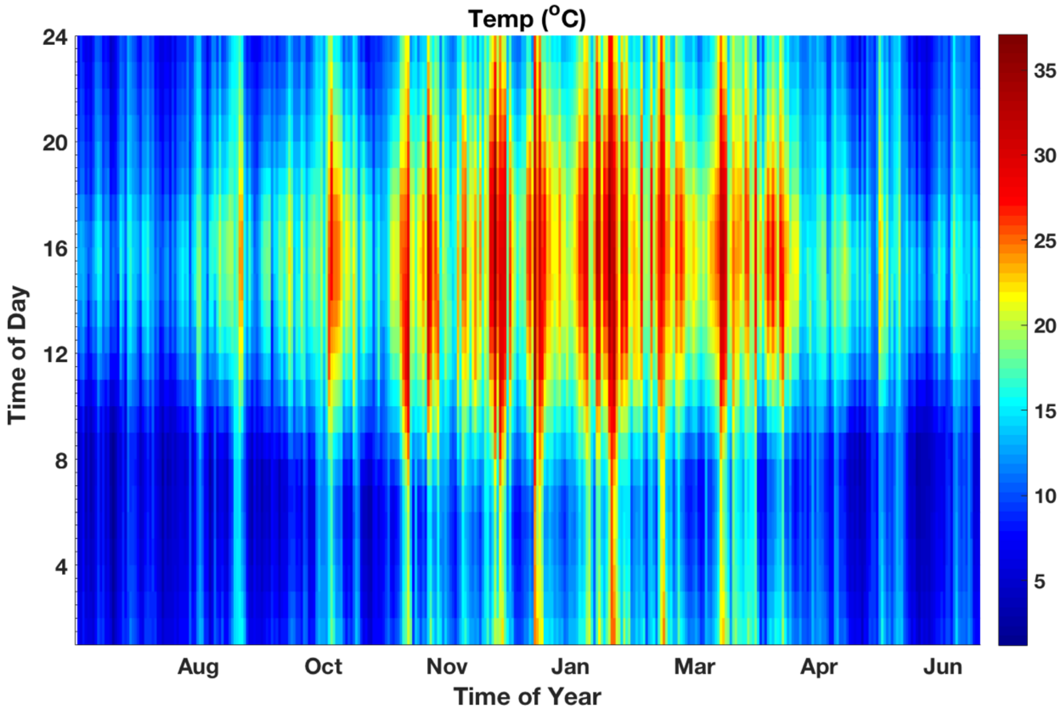


Figure A

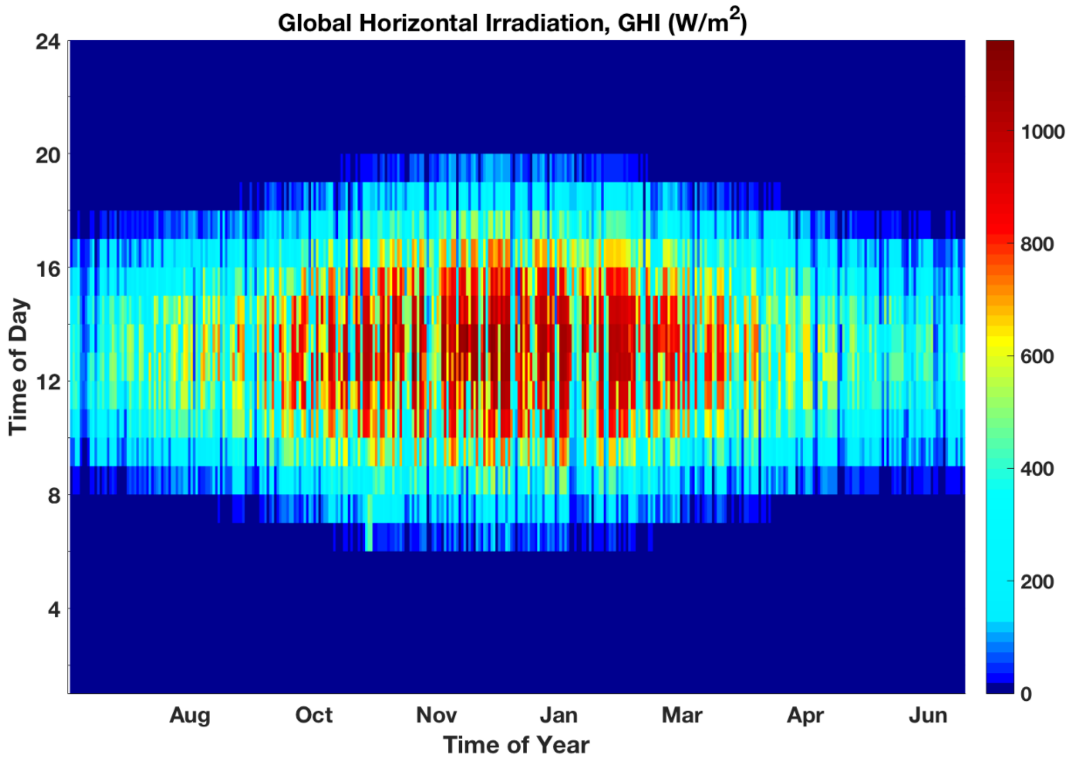


Figure B

Figure 7: Heat map of annual ambient temperature (A) and GHI (B) for Melbourne city (July-June). Please note the seasonal differences of the southern hemisphere.

The company is interested to investigate the feasibility of eight battery types, each with different capacity and techno-economic parameters. Table 3 lists the specifications of the candidate batteries. The installation prices are from [76] with the assumption of a 20%

reduction since the year 2012. 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 capital expenditure (CAPEX), while it is 1.0% for batteries [4].

Table 3: Techno-economic specifications of the candidate batteries for the hospital (the parameters are mainly from [76])

Candidate battery No.	Battery type	Manufacturing round-trip efficiency	Annual efficiency loss factor due to aging	Dis/charge duration (hours)	Life (years)	Base CAPEX ($/kWh)
J1	Li-ion high power	0.910	0.960	1	8	950
J2	Li-ion high energy	0.920	0.960	2	8	700
J3	Advanced lead acid	0.800	0.960	2	8	900
J4	Advanced lead-acid	0.900	0.960	5	8	700
J5	Valve-regulated lead acid	0.680	0.955	2	6	650
J6	Valve-regulated lead acid	0.780	0.955	4	6	500
J7	Sodium Nickel Chloride	0.870	0.965	4	10	600
J8	Sodium Sulfur	0.730	0.980	7	16	350

Given the policy sensitivity of feed-in tariff, the company desires to make the investment analysis without consideration of any revenue stream from it (FIT=0 c/kWh). The government is supporting the investment in renewable energy technologies such as PV by offering renewable energy certificates (RECs) as per $/MWh generated. The value of RECs is defined by market dynamics, and the company has decided to assume it at 40 $/MWh. The annual price escalation factor is 3% with a discount rate of 7% [77]. The company does not project any change in electricity consumption. With these given factors, the company wants to assess whether it is economically feasible to install PV and/or battery systems. When feasible, the proceeding questions are the specifications of the selected system(s) and the operation mechanism of the system.

We formulated the problem using the model presented in Appendix 1. The problem, consisting of 4,642,931 equations and 5,431,348 variables, was solved for 10 years of operation using CPLEX 12.4.0.1 on a desktop PC with a dual-core 3.2 GHz Intel Xeon processor and 115 GB RAM. The execution time was 339.204 CPU s. 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 1323.8 kW PV system with a high-power Li-ion battery of size j1=127.6 kWh. This NPV of savings is $626,760.2 over ten years with a payback time of 7.2 years.

According to the optimization results, this integrated PV-battery system will reduce the company's direct dependence on the grid to 70.7% during the first year of operation. Under this condition, the company receives 4,687,931 kWh of electricity directly from the grid within the first year. The remaining demand is satisfied by the PV system (1,883,605 kWh, i.e., 28.4%) and battery (62,164.5 kWh, 0.9%).

The PV output over the first year is 2,075,900 kWh. It is mainly used for the local load (92.6%). The remainder goes to the battery (3.4%) or dispatched to the grid (4.0 %). Within the first year, the battery receives 70,698.1 kWh (83.1%) of electricity from the PV system, and its remaining charge (14,388.5 kWh, 16.9%) is supplied by the grid, mainly during off-peak periods. The selected 5.5 kWh battery never operates below 15% SOC and its average annual SOC is 35.9% (i.e., 45.8 kWh), over the first year.

In summary, the selected PV-battery system not only reduces the company's energy costs and thus dependence on the grid with a reasonable payback time of 7.2 years, but it also supports the sustainability of the electricity supply chain by reducing the critical peak demand. Figure 8 (A and C) illustrates the company's energy exchange profiles with the grid under the base scenario, without investment in DGS systems (A), and with a PV-battery system (C). It is evident from the comparison of Figure 8A with Figure 8C that with a PV-battery system the values of peak demand incidences have reduced (to below 1100 kW) and also negative loads (export or curtail) have appeared. Figure 8 (B and D) illustrates the same annual profiles on a daily basis. The comparison of Figure 8B with Figure 8D clearly shows the impact of the DGS system on demand reduction not only during mid-day but also during the afternoon peak. The average hourly energy import value from the grid (shown with a solid line in the figures) has reduced from 757.3 kWh to 535.1 kWh, over the first year. This value is even lower (526.3 kWh) if the energy exchange average (which also considers export) is considered.

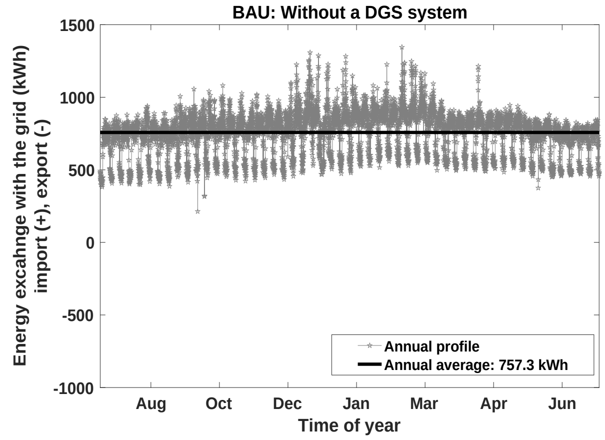


Figure A

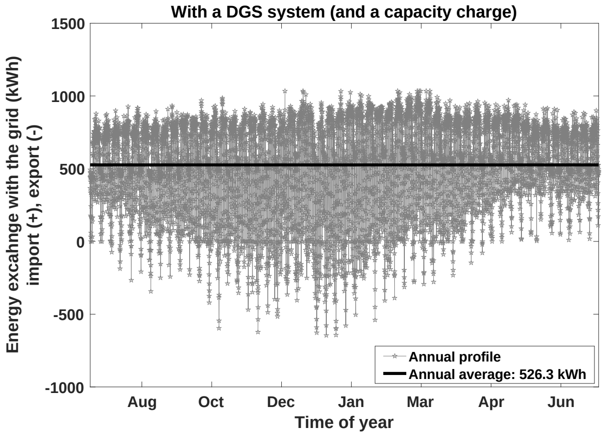


Figure C

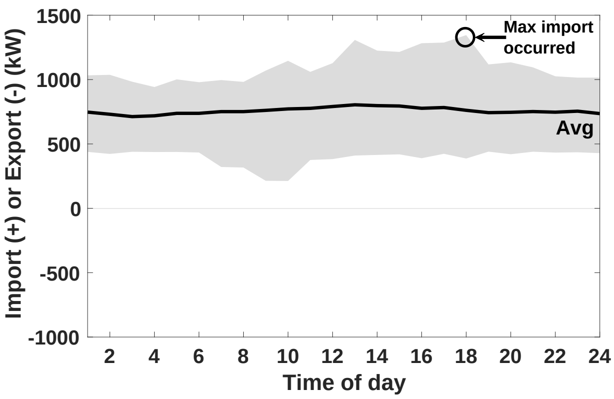


Figure B

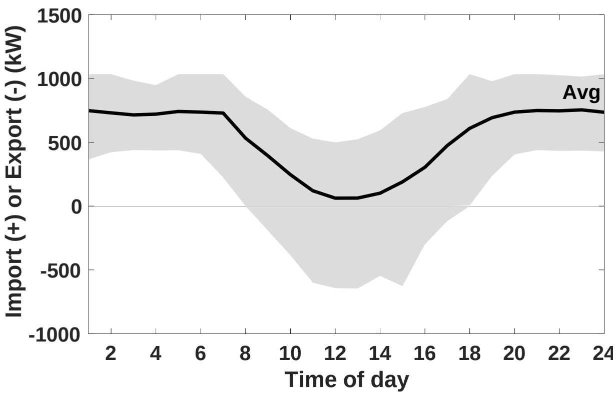


Figure D

Figure 8: The Company's energy exchange profiles at base case (A and B), and with a PV-battery system (C and D); C vs. A and D vs. B show the reduction of peak demand incidences, and also the appearance of negative loads (export or curtail).

Another representation of energy exchange profiles is illustrated in Figure 9 based on the probability of exceedance (POE). This figure clearly shows how the DGS system has successfully reduced the critical peaks occurred at POE < ~3%. Figure 9 also shows that the import from the grid has notably reduced at large POE values (the off-peak or low-demand periods). This implies that at a lower storage price there could be more potential for the installation of a larger storage system.

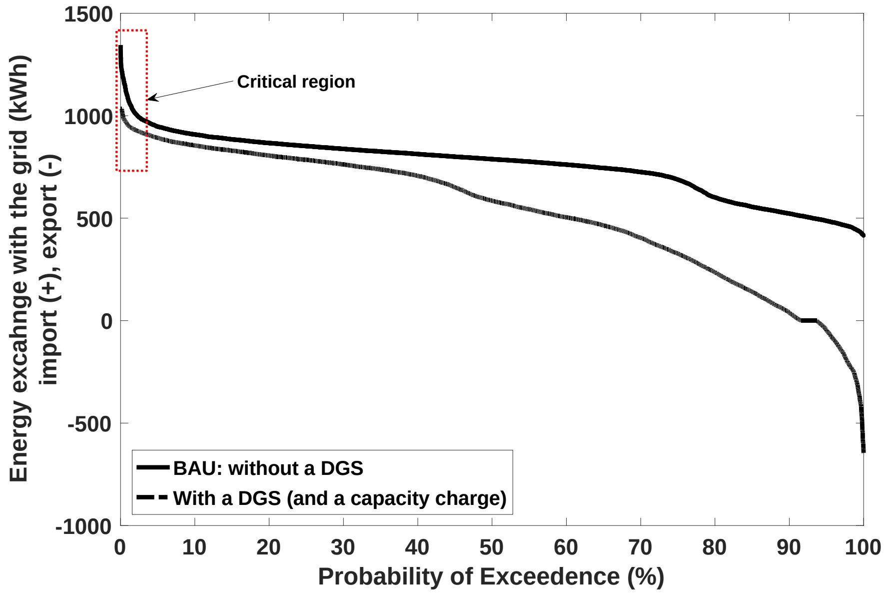


Figure 9: The case-study company's energy exchange profiles based on the probability of exceedance (POE)

In another note, the highest export value (negative in the figure) is -645.6 kW. This value is still less than the highest import incidence (i.e. 1034.0 kW). However, with reduced PV installation costs and future installations of larger PV systems, there could be conditions that the critical load on the grid reverses from import to export (highest export incidence exceeds that of the highest import). This was the main reason that we introduced a capacity charge for energy export.

The average annual average SOC of the installed battery over the first year is illustrated in Figure 10. It is evident from the figure that the battery makes on average two cycles a day. It charges at night and discharges in the morning before the PV system peaks. During noon and early afternoon, it charges again to support the late afternoon peak demand.

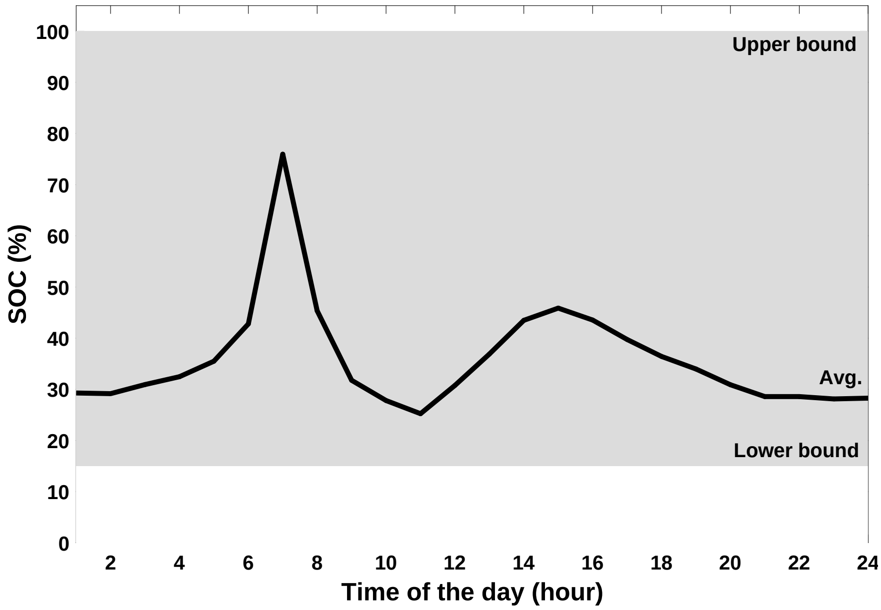


Figure 10: The annual-average daily profile of the company's battery system' SOC during the first year of operation

3.2. Without a supply charge

This scenario is similar to the previous example. However, here we would like to assess the impact of the capacity charge on decision-making. For this, we assume that the company receives a new electricity tariff structure as shown in Table 2, but without any capacity charge. The other tariff terms are however multiplied by a factor (in this case 1.237) so that the total annual bill for the base year is unchanged. This means that the off-peak and on-peak tariffs will be 23.7% higher than the previous scenario, but the capacity charge will be zero. With this modification, the optimization problem, with a similar size of Scenario 1, was executed with a CPU time of 412.5 s.

Under the new condition, the best investment decision is found in installing 1489.0 kW PV system (larger than 1323.8 kW for the previous scenario). The program does not suggest investing in an energy storage system. With this arrangement, the company's NPV of saving is $858,365.5 over the first ten years of the PV system operation with the payback time of 6.7 years.

The PV output over the first year is 2,334,935.9 kWh. It is mainly used for the local load (2,122,715.6 kWh, 90.9%) and the remainder is exported to the grid (9.1%) or curtailed. Overall, this integrated PV system supplies 31.4% of the load and reduces the company's direct dependence on the grid to 68.6% during the first year of operation. This value is even better than the scenario with capacity charge (70.7%), but it comes at the cost of a lesser reduction in the critical peak load as evident from Figure 11.

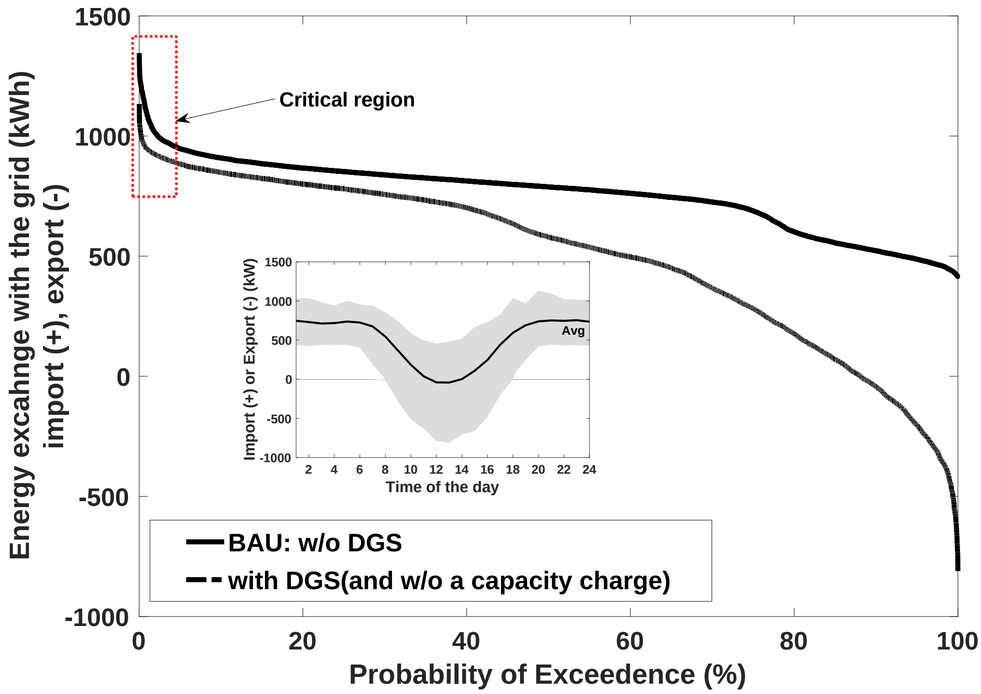
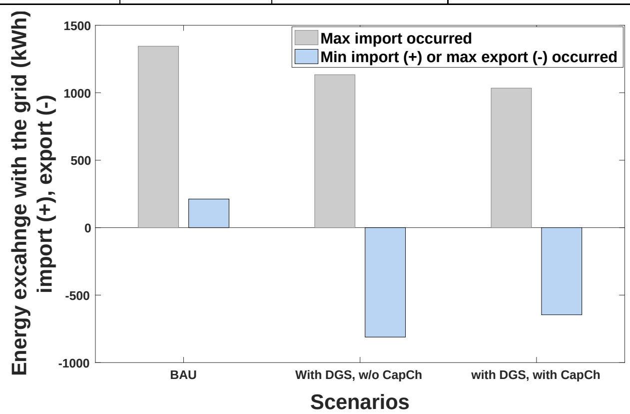


Figure 11: The Company's energy exchange profiles without a capacity charge tariff

The performance comparison of the business as usual (BAU) scenario with the two case-studies, with and without a capacity charge, is provided in Table 4. The business as usual scenarios refer to a company in Melbourne which has paid $908,158.7 for its electricity consumption either with a capacity charge and energy tariffs as per Table 2 or without a capacity charge but with 23.7% extra cost per unit of energy consumed. For each of the given scenarios, the DGS investment model gives the optimal design and provides the optimal operation decisions and scheduling summarized in the last two columns of Table 4.

In summary, the lack of a capacity charge tariff with higher energy rates promotes investment on larger generation systems to curb energy costs. The investment has a relatively better payback-time (6.7 y) with grid dependence reduced to 68.6%. With a capacity charge, these numbers are lower (smaller PV system size and higher grid dependence). Also, the energy cost of the company is higher with the capacity charge. However, the capacity charge promotes the installation of storage systems and thus reduces the peak import and export from the grid better than the scenario without a capacity charge. From a network perspective, with the BAU scenario, the company's critical demand incidence is 1344.8 kW, with high energy tariff, without capacity charge this value becomes 1133.4 kW, while with capacity charge, it further declines to 1034.0, contributing to the improvement in network efficiency. Therefore, one conclusion could be that in a society with energy security issues, avoiding capacity charge can promote investment in larger generation capacity by consumers, however, for societies with peak demand challenges, the capacity charge is seen as an efficient tool to direct the behaviour of consumers towards peak-demand management.

Table 4: Comparison of the business as usual scenario with two DGS investment analyses scenarios: 1) with a capacity charge tariff; 2) Without a capacity charge tariff, but with a higher energy cost

Key features	Business as usual (BAU)		Investment in DGS systems	
	w/o CapCh	with CapCh	w/o CapCh	with CapCh
Size of selected PVs (kW)	-	-	1489.0	1323.8
Size of selected batteries (kWh)	-	-	0	127.6
NPV of saving over 10y ($)	0	0	$858365.5	626760.2
Payback time (y)	-	-	6.7	7.2
Electricity import over the one year (MWh)	6,633.7	6,633.7	4,553.4	4,702.3
Energy tariff	123.7% of Table 2	As Table 2	123.7% of Table 2	As Table 2
Electricity cost over the one year ($)	908,158.7	908,158.7	619,378.5	664,499.7
Grid dependence on direct import	100	100	68.6	70.7
Critical peaks:				
Maximum import from grid (kW)	1344.8	1344.8	1133.4	1034.0
Min import from the grid or max export (kW)	212.0	212.0	-811.2	-645.6

3.3. Impact of techno-economic parameters

In the previous two examples, we assessed the impact of capacity charge on the DGS investment decisions. The results clearly showed that capacity charge motivates investment in energy storage. Here, we take the same example with capacity charge (Section 3.1) and investigate the impact of some key techno-economic factors on the investment decisions. We have selected four factors including FIT, RECs, PV price, and battery price. We have considered a few price scenarios for each of the factors, FIT ($/kWh): 0 and 0.05; REC ($/MWh): 0, 20, 40, and 60; PV CAPEX ($/kW): 1000, 1500, and 2000; Battery CAPEX ($/kWh): 300, 500, 750, and 1000. It is noteworthy that for this analysis we used only one type of battery (j2 in Table 3) with varied CAPEX values. All other parameters are the same as the first case-study (Section 3.1). Combination of two price scenarios for FIT, four scenarios for REC, three scenarios for PV CAPEX, and four scenarios for battery CAPEX gives a total of 96 different problem scenarios. All these optimization problems are executed and their optimal PV size, battery size, and operation schedules, as well as the objective values (NPV of saving over ten years), are obtained. The results are illustrated in Figure 12.

Scenarios					Optimisation results		
Scenario No	FIT ($/kWh)	PV capex ($/kW)	Bat. capex ($/kWh)	REC ($/MWh)	NPV over ten years ($000)	PV size (kW)	Battery size (kWh)
1	0	1000	300		840	1423.9	212.0
2	0	1000	300	20	1217	1649.9	230.0
3	0	1000	300	40	1658	1984.1	248.4
4	0	1000	300	60	2225	2723.7	614.7
5	0	1000	500	0	800	1417.0	169.9
6	0	1000	500	20	1176	1640.3	172.8
7	0	1000	500	40	1614	1970.0	179.9
8	0	1000	500	60	2171	2633.5	183.7
9	0	1000	750	0	760	1411.3	132.9
10	0	1000	750	20	1134	1633.4	138.4
11	0	1000	750	40	1571	1965.0	144.0
12	0	1000	750	60	2127	2631.2	149.8
13	0	1000	1000	0	751	1384.3	0.0
14	0	1000	1000	20	1118	1614.4	0.0
15	0	1000	1000	40	1551	1948.4	0.0
16	0	1000	1000	60	2101	2600.7	0.0
17	0	1500	300	0	234	796.8	279.7
18	0	1500	300	20	486	1166.7	187.7
19	0	1500	300	40	803	1394.3	203.6
20	0	1500	300	60	1174	1627.2	222.8
21	0	1500	500	0	187	980.7	180.2
22	0	1500	500	20	449	1162.1	163.2
23	0	1500	500	40	763	1390.2	169.9
24	0	1500	500	60	1133	1616.1	172.8
25	0	1500	750	0	148	1036.5	20.9
26	0	1500	750	20	410	1155.1	127.7
27	0	1500	750	40	723	1384.8	133.0
28	0	1500	750	60	1091	1608.5	138.4
29	0	1500	1000	0	148	1032.0	0.0
30	0	1500	1000	20	409	1126.5	0.0
31	0	1500	1000	40	715	1362.3	0.0
32	0	1500	1000	60	1075	1584.2	0.0
33	0	2000	300	0	100	0.0	264.3
34	0	2000	300	20	118	165.2	355.1
35	0	2000	300	40	214	732.7	307.4
36	0	2000	300	60	456	1139.4	187.7
37	0	2000	500	0	48	0.0	224.4
38	0	2000	500	20	49	75.8	264.6
39	0	2000	500	40	161	958.8	191.0
40	0	2000	500	60	418	1133.4	163.2
41	0	2000	750	0	0	0.0	0.0
42	0	2000	750	20	0	0.0	0.0
43	0	2000	750	40	120	1031.3	16.8
44	0	2000	750	60	380	1127.3	127.7
45	0	2000	1000	0	0	0.0	0.0
46	0	2000	1000	20	0	0.0	0.0
47	0	2000	1000	40	120	1030.7	0.0
48	0	2000	1000	60	379	1097.2	0.0
49	0.05	1000	300	0	921	1737.6	203.4
50	0.05	1000	300	20	1429	2431.7	211.6
51	0.05	1000	300	40	2102	3081.1	220.1
52	0.05	1000	300	60	2982	4269.7	202.3
53	0.05	1000	500	0	882	1732.7	165.8
54	0.05	1000	500	20	1389	2428.5	169.4
55	0.05	1000	500	40	2062	3088.4	165.4
56	0.05	1000	500	60	2948	4316.4	126.6
57	0.05	1000	750	0	843	1727.8	132.8
58	0.05	1000	750	20	1349	2431.7	132.6
59	0.05	1000	750	40	2030	3188.1	0.0
60	0.05	1000	750	60	2946	4457.7	0.0
61	0.05	1000	1000	0	836	1715.9	0.0
62	0.05	1000	1000	20	1341	2455.3	0.0
63	0.05	1000	1000	40	2030	3188.1	0.0
64	0.05	1000	1000	60	2946	4457.7	0.0
65	0.05	1500	300	0	234	843.6	266.0
66	0.05	1500	300	20	508	1311.4	187.6
67	0.05	1500	300	40	876	1689.4	203.4
68	0.05	1500	300	60	1365	2358.0	211.6
69	0.05	1500	500	0	192	1021.2	166.1
70	0.05	1500	500	20	470	1308.0	163.1
71	0.05	1500	500	40	837	1684.8	165.9
72	0.05	1500	500	60	1326	2357.8	169.4
73	0.05	1500	750	0	157	1046.9	0.0
74	0.05	1500	750	20	432	1303.1	127.7
75	0.05	1500	750	40	798	1681.0	127.5
76	0.05	1500	750	60	1285	2360.9	132.6
77	0.05	1500	1000	0	157	1046.9	0.0
78	0.05	1500	1000	20	431	1275.6	0.0
79	0.05	1500	1000	40	791	1666.1	0.0
80	0.05	1500	1000	60	1277	2375.2	0.0
81	0.05	2000	300	0	100	0.0	264.3
82	0.05	2000	300	20	118	165.2	355.1
83	0.05	2000	300	40	214	732.7	307.4
84	0.05	2000	300	60	474	1274.3	187.6
85	0.05	2000	500	0	48	0.0	224.4
86	0.05	2000	500	20	49	75.8	264.6
87	0.05	2000	500	40	165	993.7	173.0
88	0.05	2000	500	60	436	1268.1	163.1
89	0.05	2000	750	0	0	0.0	0.0
90	0.05	2000	750	20	0	0.0	0.0
91	0.05	2000	750	40	129	1041.7	0.0
92	0.05	2000	750	60	398	1258.4	127.7
93	0.05	2000	1000	0	0	0.0	0.0
94	0.05	2000	1000	20	0	0.0	0.0
95	0.05	2000	1000	40	129	1041.7	0.0
96	0.05	2000	1000	60	398	1235.0	0.0

Figure 12: Optimization result summary for 96 scenarios based on four techno-economic factors: FIT (c/kWh): 0 and 5; REC ($/MWh): 0, 20, 40, and 60; PV CAPEX ($/kW): 1000, 1500, and 2000; Battery CAPEX ($/kWh): 300, 500, 750, and 1000.

According to the results, FIT improves the attractiveness of investment in DGS systems and the optimal size of PV increases across all scenarios. However, the introduction of FIT motivates the direct export of surplus energy and reduces the urgency of battery storage installation. For instance, while on average the 48 scenarios with FIT=0 require 139.1 kWh battery, this value reduces to 119.1 kWh with a FIT=0.05 $/kWh.

The price of PV shows a strong impact on the optimal size of PV and the NPV. The average size of PV across 32 scenarios with PV CAPEX of 1000 $/kW is 2417 kW. At 1500 $/kW, this value is 1430 kW (>40% drop). For the remaining 32 scenarios with PV CAPEX of 2000 $/kW, this value becomes notably low, 549 kW, which is almost one-fifth of the scenarios with PV CAPEX of 1000 $/kW. The NPV of savings also drops with the reduction in the PV size. However, the PV price does not show an evident impact on battery size. Likewise, battery CAPEX does not reveal any correlation with the optimal PV size. The battery CAPEX is the most influential factor in its optimal size. With battery CAPEX of 1000 $/kWh, none of the 24 scenarios selects any battery. With the CAPEX of 750$/kWh, the average battery size becomes 79.6 kWh. With the CAPEX of 500 $/kWh, this value increases with more than two-fold (181.4 kWh). At battery CAPEX of 300 $/kWh, the average battery size reaches 255.6 kWh.

The results clearly show that that FIT and REC are effective policies for motivating the investment in DGS systems. However, as both REC and FIT are renewable energy generation incentives, they motivate investment in generation (here PV) quantity and cannot tackle the prosumers' peak-management. As such, we observe in Figure 12 their significant impact on optimal PV size and a negligible impact on battery size. The FIT even reduces the attractiveness of battery storage. Therefore, from DSM policy-making perspective, a tailored combination of REC, FIT, and the capacity charge is needed for encouraging both investments in renewable energy and load shifting technologies.

4. Conclusions

Tariff design is one of the most critical tools for demand-side management (DSM) and for shaping consumer behaviour. With recent price reduction in distributed generation and storage (DGS) systems, interest has increased in devising policies for directing the consumers' behaviour towards using DGS systems in line with DSM objectives. This has further increased the complexity of tariff modelling. On the one hand, a smart tariff structure is required to reflect the economic value of a DGS system for its owner and thus promote widespread DGS uptake. On the other hand, it should satisfy the key DSM goals such as peak load reduction. The current tariff mechanisms such as time-of-use and inclining blocks, though effective tools, cannot guarantee peak load reduction. As we discussed in Section 3.3, renewable energy subsidies in the form of REC or FIT, though efficient for investment in generation technology, cannot lead to peak load reduction.

While ToU and inclining block tariffs, as well as renewable energy subsidies, have received decent attention as successful policies, there is another less-discussed efficient tariff known as rollover network capacity charge. It is a penalty for the highest recorded power usage over the previous reading cycle (or year). We anticipated that the consideration of capacity charge might improve the economic feasibility of energy storage and thus motivate its demand-side uptake. To investigate this, we integrated rollover network capacity charge into DGS system sizing and scheduling.

We executed some scenarios with and without a capacity charge. The results showed that high energy rates promote investment in larger PV generation systems to curb energy costs. The investment has a relatively better payback-time and less grid dependence. With lower energy rates but with the introduction of the capacity charge, these numbers are slightly lower (smaller PV system size and higher grid dependence). Also, the energy cost of the peak-user is higher with the capacity charge. However, it promotes the installation of storage systems and thus reduces the peak import and export from the grid more efficient than the scenario without a capacity charge. The results lead us to the following key conclusions.

- **Effective energy-justice mechanism**

Capacity charge transfers the network over-investment costs to the critical-peak users by enforcing them to pay extra for their critical peak consumption. This gives an incentive to invest in DSM systems, such as energy storage, to shift or reduce their peak import from the grid. However, reducing the consumption or changing the consumption pattern is not always possible and making new investments in DGS systems is preferred. With falling PV and battery costs, DGS systems are becoming more attractive to energy users. However, a strong DSM policy with the capacity charge induces customers to make investments in demand-side management earlier. This is particularly important for electricity networks that are facing peak demand challenges already today. Therefore, this is a fair mechanism which enforces those who contribute more to critical peak loads to take more responsibility in addressing the problem.

- **Addressing the challenges of new peaks**

One of the big concerns in the power systems is a possibility of new peak demands in the future [3]. The capacity charge not only can curb the current afternoon peak loads but can also avoid any unconventional new peaks in the future. It can even address the possible challenges of sharp changes in load profiles during the moments when the ToU tariff shifts from one price threshold to another. There are at least two new peaks anticipated for the future. One such new peak pertains to mid-day solar power export. As the probability of exceedance (POE) curves (e.g., Figure 9) show, the significant ratio of PV generation occurs in low demand periods (high POEs), e.g., sunny mid-day. With widespread PV uptake, there is a risk of voltage and frequency failure due to over-export to the network. Consideration of capacity charge can also curb export (As the example in Section 3.2 showed) and motivate shifting the export time by energy storage or any other mechanism. The other new peak is related to energy import at times known traditionally as off-peak periods. The continuous decline in battery prices and the consequent widespread uptake of stationary or EV batteries may encourage consumers to arrange the charging time of their appliances at currently known off-peak periods (with lower electricity tariff) which may lead to new peak demands. The capacity charge appears as an effective mechanism to curb any form of new peaks including the mentioned ones. In conclusion, from the DSM policy-making perspective, a tailored combination of renewable energy certificates, energy tariffs, and a capacity charge is needed for encouraging both investments in renewable energy and load management.

Appendix 1

Table 5: The formulation of a decision support program for DGS system screening, selection, sizing, and scheduling with inclusion of capacity charge tariff

Formula	Formula description	Note
$\sum_{i=1}^{I} y_i \leq N^{DG}$	Limit on the number of selected DG systems	$y_i = \begin{cases} 1, & \text{if DG system } i \text{ is selected} \\ 0, & \text{otherwise} \end{cases}$
$\sum_{j=1}^{J} y'_j \leq N^{S}$	Limit on the number of selected storage systems	$y'_j = \begin{cases} 1, & \text{if storage system } j \text{ is selected} \\ 0, & \text{otherwise} \end{cases}$
$\sum_{i=1}^{I} y_i A_i + \sum_{j=1}^{J} y'_j A_j \leq A^m$	Limit on the total area occupied by the DGS system	Total area limit: A^m
$\sum_{i=1}^{I} y_i V_i + \sum_{j=1}^{J} y'_j V_j \leq V^m$	Limit on the total volume occupied by the DGS system	Total volume limit: V^m
$FC_{ip} = X_{ip}^{DG} F_{ip} / \eta_{ip}^{DG}$	Feed supply cost of DG unit *i* at period *p*	F_{ip}: Feed price per unit supply for DG unit *i* at period *p* X_{ip}^{DG}: Total generation of DG unit *i* at period *p* η_{ip}^{DG}: Efficiency of DG unit *i* at period *p*
$E_{ip} = X_{ip}^{DG} CI_{ip} / \eta_{ip}^{DG}$	CO_2-equivalent GHG emission from DG *i* at period *p*	CI_{ip} : Carbon intensity of DG unit *i* per unit of feed energy at period *p*
$GHC_{ip} = E_{ip} CP_p$	Incurred GHG cost for DG *i* at period *p*	CP_p: CO_2-equivalent GHG emission penalty at period *p*
$X_{ip}^{DG} = X_{ip}^{DG.G} + X_{ip}^{DG.L} + \sum_{j=1}^{J} X_{ijp}^{DG.S} \leq y_i C_{ip}^{DG}$	Limit on the total energy production from DG *i* at period *p*	C_{ip}^{DG}: The maximum "generatable" capacity of a DG unit *i* at period *p* $X_{nip}^{DG.N}$: Export from DG *i* to network *n* at period *p* $X_{kip}^{DG.K}$: Supply from DG *i* to load *k* at period *p* $X_{ijp}^{DG.S}$: Supply from DG *i* to storage *j* at period *p*
$X_p^{G.L} + \sum_{i=1}^{I} \eta_{ip}^{DGin} X_{ip}^{DG.L} + \sum_{j=1}^{J} X_{jp}^{S.L} \leq L_p$	Local load limit in any period *p*	$X_p^{G.L}$: Supply from grid to load at period *p* L_p: demand during period *p* $X_{ip}^{DG.L}$: Supply from DG *i* to load at period *p* $X_{jp}^{S.L}$: Supply from storage *j* to load at period *p*

$B_{jp} = (1-\beta_{jp})(\eta_j^{CC}\eta_{jp}^{C}X_{ijp}^{DG.S} + \eta_{jp}^{Sin}\eta_j^{CC}\eta_{jp}^{C}X_{jp}^{G.S} - X_{jp}^{S.G}/(\eta_{jp}^{Sin}\eta_j^{CC}\eta_{jp}^{D}) - X_{jp}^{S.L}/(\eta_{jp}^{Sin}\eta_j^{CC}\eta_{jp}^{D}))$	Input-output balance of storage system *j* in period *p*	β_{jp}: Self-discharges of storage system *j* during period $X_{jp}^{G.S}$: Supply from grid to storage *j* at period *p* $X_{jp}^{S.G}$: Supply from storage *j* to grid at period *p* η_{jp}^{C} and η_{jp}^{D}: charge and discharge efficiency of storage *j* at period *p* η_{ip}^{DGin} and η_{jp}^{Sin}: inverter efficiency of DG system *i* and storage system *j* at period *p* η_j^{CC}: efficiency of charge controller for storage *j*
$SOC_{jp} = \sum_{p'=1}^{p} B_{jp'}$	SOC of storage system *j* at period *p*	
$y_j' SOC_j^L \leq SOC_{jp} \leq y_j' SOC_j^U$	Lower and upper limit on SOC of storage system *j*	SOC_j^L: Lower bound on SOC SOC_j^U: Upper bound on SOC
$GC_h = \sum_{p=(h-1)P'+1}^{hP'} \left(X_p^{G.L} + \sum_{i=1}^{I} (X_{ip}^{DG.G}) + \sum_{j=1}^{J} (X_{jp}^{S.G} + X_{jp}^{G.S}) \right)$	Magnitude of grid connectivity during horizon *h*	$X_p^{G.L}$: Supply from grid to load at period *p*
$GC_h \leq M.y_h''$	If connected to grid during horizon *h*	$y_h'' = \begin{cases} 1, & \text{if } GC_h > 0 \\ 0, & \text{if } GC_h = 0 \end{cases}$ *M*: constant number (big-M method [78])
$L_{h-1}^{*} = \max\ [L_p]$	Rollover capacity, without DGS, for horizon *h*	
$GI_{h-1}^{*} \geq X_p^{G.L} + \sum_{j=1}^{J} (X_{jp}^{G.S})$	Rollover import capacity, with DGS, for horizon *h*	GI_{h-1}^{*}: Import capacity during horizon *h*
$GE_{h-1}^{*} \geq \sum_{j=1}^{J} (X_{jp}^{S.G}) + \sum_{i=1}^{I} (\eta_{ip}^{DGin} X_{ip}^{DG.G})$	Rollover network capacity charge for export, with DGS, for horizon *h*	GE_{h-1}^{*}: Export capacity during horizon *h*

$NPV_c = \sum_{i=1}^{I} CX_i^{DG} + \sum_{j=1}^{J} CX_j^{S} + \sum_{h=1}^{H} \left[\sum_{p=(h-1)P'+1}^{hP'} \left(\sum_{i=1}^{I} y_i FOM_{ip}^{DG} + \sum_{i=1}^{I} y'_j FOM_{jp}^{S} \right) \right] \Big/ (1+r)^h + \sum_{h=1}^{H} \left[\sum_{p=(h-1)P'+1}^{hP'} \left(X_p^{G.L} EP_p + y''_h CF_p + GI_{h-1}^{*} RCI_p + GE_{h-1}^{*} RCE_p + \sum_{j=1}^{J} \left(X_{jp}^{G.S} EP_p - X_{jp}^{S.G} FIT_p \right) - \sum_{i=1}^{I} \left(\eta_{ip}^{DGin} X_{ip}^{DG.G} FIT_p \right) + \sum_{i=1}^{I} \left(FC_{ip} + GHG_{ip} \right) \right) \right] \Big/ (1+$	Objective function for the net present value of costs	r: Discount rate over h FOM_{ip}^{DG} and FOM_{jp}^{S}: FOM of DG system i and storage system j at period p CX_i^{DG} and CX_j^{S}: Installation cost of DG system i and storage system j EP_p: electricity price at period p CF_p: Connection fee (or supply charge) at period p RCI_p: Rollover network capacity charge for import at period p. RCE_p: Rollover network capacity charge for export at period p. FiT_p: Feed-in-tariff during period p
$NPV_S = \sum_{h=1}^{H} \left[\sum_{p=(h-1)P'+1}^{hP'} \left(L_p EP_p + CF_p + L_{h-1}^{*} RC_p \right) \right] \Big/ (1+r)^h - NPV_c$	Objective function for the net present value of savings	
Planning horizon: H segments (weeks, months, years) with P' multiple periods of a given fixed length (minute, hour, etc.)		

List of Abbreviations

CAPEX	capital expenditure
CPD	critical peak demand
CDF	cumulative distribution functions
CHP	combined heat and power
DER	distributed [renewable] energy resources
DG	distributed generation
DGS	distributed generation and storage (Here DGS means: “distributed generation, or storage, or both”)
DOD	depth of discharge
DSM	demand-side management
EES	Electrical energy storage
EV	electric vehicle
FIT	feed in tariff
FOM	fixed operation and maintenance cost
GHG	greenhouse gas
GST	goods and service tax
GW	gigawatt
GHI	global horizontal irradiation
LPSP	loss of power supply probability
MILP	mixed-integer linear program
MINLP	mixed-integer nonlinear program
NPV	net present value
NRLP	Newton-Raphson linear programming
NTGA	non-dominated sorting genetic algorithm
NSW	New South Wales
OCL	operational charge limit
OPEX	operational expenditure
PCA	principal component analysis
POE	probability of exceedance
PR	performance ratio

PV	photovoltaic
REC	renewable energy certificate
SOC	state of charge
ToU	time-of-use
LLP	loss of load probability
UN	United Nations

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