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Consumer preferences for household-level battery energy storage

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ABSTRACT

This paper examines the role of the consumer in the emerging household-level battery market. We use stated preference data and choice modelling to measure household preferences for battery attributes and functionality. Our survey sample has been sourced from the State of Queensland, Australia, which has some of the highest per capita PV installation rates in the world and has many characteristics of an early-adopter market for battery storage. While cost will be a key determinant for mass market uptake, our study found that drivers encouraging self-sufficiency and grid independence will have a strong influence on battery system preferences. A majority of the 268 respondents to our survey would prefer to buy medium or large battery systems despite higher costs and longer payback periods. Nearly 70% of respondents hope to eventually disconnect from the existing centralized electricity supply network. Should these findings translate more broadly, and battery prices decline as forecast, changing energy market dynamics could result in a range of negative outcomes. Declining infrastructure utilization, asset impairment, rising electricity costs and negative social outcomes could eventuate as consumers attempt to reduce their reliance on existing electricity supply systems. To proactively manage these risks, our study demonstrates the clear need to better understand and address consumer motivations in the impending energy market transition.

1. Introduction

Centralized electricity supply systems contribute nearly 40% of global energy-related greenhouse gas emissions [1]. Despite recent progress in reducing the emissions intensity of the sector, additional measures are urgently required to avoid the worst impacts of climate change [2]. With some governments and industries struggling to deliver on this challenge, it is the rise of a large and engaged consumer base which may provide the impetus for transformational change in the electricity sector.

Rapid growth in residential rooftop solar photovoltaic systems (PV) in recent years has shown the collective and disruptive power of the consumer. Global PV deployment increased from approximately 1.3 gigawatts (GW) in 2000 to 177 GW by the end of 2014 [3,4]. This growth is expected to continue with some forecasts suggesting solar power could generate up to 16% of the world's electricity by 2050 [5].

In Australia, PV capacity increased from 17 MW (MW) in 2008 to more than 4.5 GW in 2015 [6,7]. Approximately 18% of homes in Australia, or more than 1.5 million households, now have PV installed which means Australia has some of the highest PV penetration rates in the world [8]. Queensland with nearly 1.5 GW of installed PV has the highest capacity in Australia with more than 29% of homes having solar installed [9].

The rapid uptake in residential PV demonstrates the power of consumer-led deployment. It is particularly impressive considering it has largely occurred in the past five years. With grid parity achieved for most of Australia, solar growth of more than 20% per annum is forecast, with a total of more than 20 GW of solar likely to be installed in Australia by 2035 [10].

Household-level battery storage is now emerging as the next generation of energy technology on the cusp of mass-market penetration. Access to viable and affordable electricity battery storage will give consumers greater autonomy and control over their electricity use while reducing exposure to increasing electricity prices.

Depending on the functionality that consumers are seeking, they could:

- install small batteries to shift the time electricity is drawn from the network, particularly during peak demand periods so as to lower total electricity bills
- install medium sized batteries to maximize the use of solar electricity from home panels, using the grid only for backup
- disconnect entirely from the grid with all household energy needs met from a large solar and battery home energy system.

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Despite the many applications of battery storage, its high cost continues to impede uptake and it is used only in niche markets or where consumers are driven by non-economic factors [11,12]. Recent developments have however triggered substantial investments in technology development and manufacturing capacity, resulting in dramatic price declines.

Electric vehicle company Tesla is building a $5 billion factory in the United States that will manufacture 500,000 batteries by 2020, resulting in an estimated reduction in battery costs of 30% by 2017 [13]. Other global battery manufacturers have also significantly increased production while a number of governments have implemented subsidy arrangements to encourage storage uptake [14,15].

In the past two years, industry and academia have made strong forecasts about price declines for storage with some suggesting that battery prices could halve by 2020 [15–19]. Should this occur, grid parity for solar PV and storage would be achieved for Australia in less than a decade, along with other key international markets such as Germany and California [16,20,21].

These bullish forecasts were considered with scepticism by many in the broader electricity industry. However in early 2015, Tesla announced pricing for two new home battery storage solutions which undercut all previous price expectations and resulted in recalibration of battery forecasts [22]. The 10kWh Tesla battery pack priced at $350 kWh was approximately 7 years ahead of many projections [23].

With battery storage prices dropping to a point where payback periods are becoming achievable for mainstream markets in the short to medium term, industry and governments must actively prepare for uptake of battery storage. Failure to do so could see inefficiencies and negative consequences along the electricity supply chain as consumers use batteries to change their electricity consumption behavior and reduce their reliance on the existing electricity network.

Despite the significance of these developments, there is little published research that examines the role of the consumer in the growing household-level battery market. Past research has analysed the consumer's relationship with energy markets and the motivations that may encourage uptake of a range of distributed energy technologies. However, a gap exists for primary research that specifically looks at consumer motivations and how they relate to battery attributes and functionality.

To help address the gap, this paper examines the role of the consumer in the emerging household-level battery market. We use stated preference data and choice modelling to demonstrate the specific financial and non-financial factors that will motivate battery storage uptake and how this could translate into battery purchasing preferences. This research provides a foundation to better understand consumer motivations as the energy market transitions and will help inform policy and strategic decision making aimed at achieving optimal integration of the technology.

2. Theoretical approach – choice modelling

The choice modelling theoretical framework is based on the concept that any good can be described in terms of its attributes, or characteristics, and the different levels that these could take [24]. Choice modelling is a stated preference technique which involves asking respondents to choose a selection of product attributes and/or non-use values such as motivations so these preferences can be represented mathematically, modelled and/or used in simulations [25]. Two choice-modelling methods, best-worst scaling (BWS) and a discrete choice experiment (DCE), were used in this study to determine respondent product preference and non-use values and motivations. The theoretical application of these techniques is considered in more detail below.

2.1. Best-worst scaling

BWS can be used to determine consumer preferences and the strength of those preferences for various attributes in a statistically relevant manner [26]. BWS is grounded in Random Utility Theory which assumes that an individual's preference for item A compared with item B is a function of the frequency with which item A is chosen as better than, or preferred to B [26]. Effectively, BWS sees participants choosing the items that reflect the maximum difference in preference or importance, which over a number of choice sets provides much more information about the overall ranking of the items [27]. This is important as people are better at selecting for extremes than in trying to choose items that are more closely aligned or middle of the range [27]. As an extension of Thurstone's Law of Comparative Judgement [28], this theory allows 'scale values', which are measures of the position of each item on a subjective scale of interest [26].

Experimental design of BWS includes a number of steps. The first involves identifying the specific items being asked of respondents to be included in the study that will address the study's research objective. The second involves designing and displaying various choice sets. This requires an experimental design that maximizes frequency balance (where items appear an equal number of times) and orthogonality (where each item is paired with each other item an equal number of times) [27]. The most common way of achieving these requirements is by using statistical designs called Balanced Incomplete Block Designs [29]. In addition to achieving statistical rigor, this approach minimizes participant bias, particularly the possibility that respondents make assumptions about the items based on design elements [26]. BWS data can be presented as a hierarchy of preferences, or with regression analysis it can be used to infer possible consumer behavior based on preference.

2.2. Discrete choice experiment

DCEs have become one of the most important survey techniques to capture consumer choice and preference data [30]. In a DCE, participants respond to different descriptions of a product, differentiated by the levels of an attribute, and are asked to choose the product they most prefer [25]. An "attribute" is a product characteristic comprising a number of "levels" that define the attribute [30]. A "choice set" is the grouping of two or more product descriptions comprising attributes and level.

Discrete choice models represent an empirical application of Random Utility Theory in which choice probabilities change in response to individual choices made by consumers [31]. The theory assumes that consumers will always attempt to maximize individual utility [32]. The utility for an individual is conditional on a choice split into a deterministic and a stochastic component [33]. The stochastic components comprise all of the unknown factors that impact choice which reflect the variability in individual choice [31]. By observing how participants choose products in regards to different attributes and their levels, the impact of each can be used to estimate utilities. This can then be used to predict how consumers might respond to a product with any combination of levels, whether or not the actual product was used in the study [34].

Indirect utility according to Random Utility Theory takes the functional form [31]:

$$U_{in} = V_{in} + \varepsilon_{in}$$

Where:

U_{in} is the utility associated with an individual *n* choice of choosing option *i*.

V_{in} is the deterministic element of utility that individual *n* associated with option *i*.

ε_{in} is the stochastic element associated with individual *n*'s choice of option *i*.