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Evaluating self-consumption for domestic solar PV: simulation using highly resolved generation and demand data for varying occupant archetypes

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Abstract

A detailed study of the on-site consumption of domestic solar PV generated electricity has been undertaken in order to gain an insight in to the relationships between annual consumption, generation and grid injection and to explore the effect of factors such as orientation and occupant behaviour on self-consumption (SC).

Both empirical and simulated generation and export time series data for a large number of PV systems were analysed, and the degree to which SC is predicted by absolute generation and consumption and its variability have been quantified. SC is seen to be generally less than 50%, and the results illustrate the value of probabilistic models for predicting the socio-economic impacts of domestic PV. As such, the results are significant for evaluating both socio-economic impacts and distribution network load-flow implications.

Introduction

SC is generally viewed as favourable to household economics since solar PV generated electricity is produced at zero marginal cost and avoids the cost of imported electricity at domestic tariffs. Thus, the UK FiT subsidy regime, along with others that are not based on a full 'net-metering' model, incentivises SC rather than export. For tenant householders who are not owners of the PV system, financial benefit accrues solely due to the avoided grid electricity costs. The magnitude of SC therefore is pertinent to aspects such as domestic economics and fuel affordability. Knowledge of SC also has relevance for post-subsidy energy policy, and the impacts on the low-voltage network of high penetration of solar PV. Theoretical and empirical evaluations of the impact of load-shifting (McKenna, 2014), electric vehicle charging and electrical and thermal energy storage are examples of potential mitigating strategies benefiting from a detailed understanding of SC.

Definition and characterisation of SC

SC is defined as the fraction of renewable energy generated which is used to do meaningful on a site work, rather than being dumped or exported (Cao and Sirén, 2014). SC occurs when generation temporally matches or exceeds the load (the demand on a building's electricity supply due to the use of appliances). For this reason it is sometimes known as the load match index (Voss et al, 2010) or cover factor. The temporal load profile is dependent on the stochastic use of appliances, lighting, cooling and heating within the building (Richardson and Thomson). Similarly, the temporal profile of solar PV generation is subject to the unpredictability of the weather. This is demonstrated in figure 1 which shows an idealised demand profile (black dashed line) and a generation profile over 24 hours.

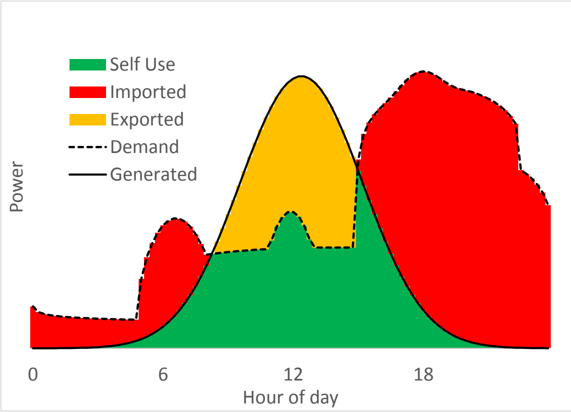

Figure 1. Idealised demand and generation profiles demonstrating self-consumption, resulting from matching of load to generation, and export of excess generation and import to make up the shortfall.

SC will tend to increase with both generation and demand since there will be more overlap between their profiles. In practice, even with very high demand, 100% SC is rarely attained without dedicated energy storage. This is due to rapid fluctuations in both electricity demand and generation at the domestic level (Richardson and Thompson, opt. cit.) as demonstrated by representative 1-minute resolution generation and demand profiles in figure 2. The 'spikey' behaviour of both generation, caused by rapid cloud movements, and demand, caused by the cycling of electric appliances, result in a lower than expected match between generation and demand due to a low probability of temporal coincidence of narrow sharp peaks in generation and demand respectively. Use of profiles with relatively coarse temporal resolution (as low as 5 minutes) has been shown to give errors as large as 80% (Cao and Sirén, opt. cit.).

The over estimation of SC exhibited by data with a course temporal resolution is well known (Wright and Firth, 2007). Thus one-minute data was used by Richardson and Thompson since it is commensurate with the temporal fine-structure of observed demand and generation profiles.

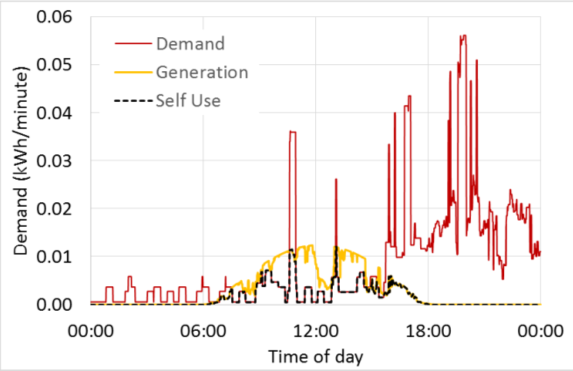

Figure 2. Domestic electricity demand and PV generation profiles at 1 minute resolution

In summary there are several distinct features to consider when evaluating SC:

- The overlap between load and generation is determined by the magnitude of both the energy generation and the energy demand. The greater the magnitude of either, the greater is the probability of overlap and therefore the greater the SC.
- The stochastic nature of demand and yield mean that the load match is not a readily modelled deterministic problem; rather it requires a probabilistic analysis.
- The temporal frame for the stochastic events occurs over high resolution time-frames, but the socio-economic impacts are generally modelled over much larger time-frames, typically one year.

The challenges of garnering data to evaluate SC are considerable. The range of annual electricity consumption needs to match typical empirical domestic electricity consumption ranges and for each annual demand a wide range of solar PV generation needs to be sampled to deliver a granular joint probability distribution (JPD) of the form: $P\ (Consumption, Generation, Selfuse)$

Two approaches to creating this JPD are considered in the following sections.

Domestic field Trials

Insights yielded by the UK's domestic field trials (DFT) (Munzinger et al, 2006) were investigated using 135 PV systems with 23 months of 5 minute time resolution data. System ratings, typically 1 kWp, are considerably lower than the systems now deployed in the UK. Measured specific yields are also lower than those reported for today's systems (Colantuono et al., 2014). In addition the households in the DFT sample exhibited somewhat lower consumption than that of the national population.

Whilst the decade-old DFT data are in a limited parameter space (low generation, low consumption) compared to contemporary PV deployment contexts, the DFT self-consumption analysis does demonstrate hypothesised trends; figure 3 shows an increase in SC with both annual household electricity demand and solar PV generation. The scatter of the data also supports the premise of highly stochastic data resulting from a wide variety of occupant behaviours.

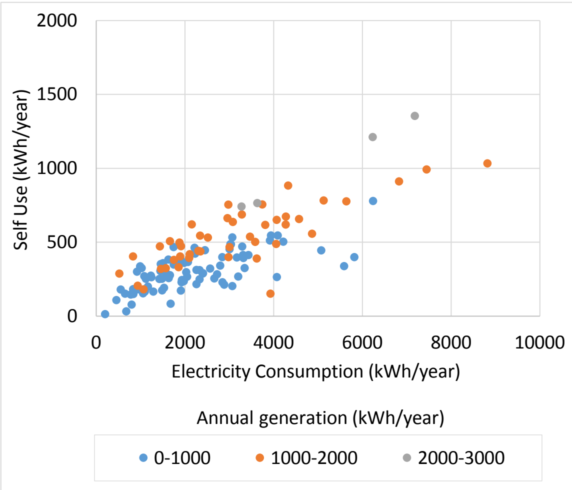

Figure 3. Annual self-consumption as a function of annual electricity consumption segmented by annual system yield (generation) from the DFT data.

The comparisons of specific yield, rating, annual electricity consumption suggest that the DFT data may not be representative of the wider national population. In this context, the DFT did not use a wide, random sample of PV adopters but a purposeful selection of new-build social housing (Munzinger et al, opt. cit.).

Whilst the dataset reliably yields general trends, this 5-minute data does not deliver SC of the correct magnitude; to address this problem, the high resolution stochastic model was adapted to analyse SC over the long term using 1-minute time series and consistent dwelling configurations. This is presented in the next section.

Simulation of Self Use

The Richardson-Thomson model simulates daily electricity load profiles based upon minute time-step aggregated demand data from a set of household appliances randomly assigned to the dwelling based on published statistics of appliance ownership and ratings. Appliances are categorised into several groups: those that run all the time, consuming a base load such as a freezer, and those operated by an active occupant performing a particular activity. Active occupancy and activity profiles within the dwelling are simulated stochastically using temporal probabilities derived from the UK's time-use survey (TUS) for between 1 and 5 residents. Separate probability data are used for weekdays and weekends. The model also features a seasonally linked lighting simulation module (Richardson et al., 2009).

Daily PV generation profiles are simulated by calculating the clear-sky irradiance for every minute of the day. A clearness index is used to attenuate the clear-sky irradiance due to clouds (Skartveit and Olseth, 1997). Richardson and Thomson (opt. cit.), using a one-minute time-series of empirical horizontal irradiance data recorded in Loughborough, England, over a whole year (Betts and Gottschalg), created a transition probability matrix (TPM) which allows the stochastic prediction of the clearness index at time t_{n+1}, given the clearness index at time t_n. In this way, the TPM is used to generate a one-minute time series for clearness index for a whole day. Multiplying each corresponding minute's clearness index by the clear sky irradiance delivers a realistic time series of horizontal irradiance. The tilt and azimuth of the plane of array are taken into account to calculate the irradiance in the plane-of-array (Dusabe et al, 2009) and a simple system efficiency method is used to convert the irradiance into an estimation of the minute-by-minute AC electrical output of the system.

Modifications to the Simulation Software

The simulation requirement is to generate an aggregated SC over a whole year for appropriate combinations of annual consumption and PV generation. If the maximum range for these were taken to be 10 and 5 MWh/year respectively, and SC were assumed to maximise at 100% (i.e. also 5 MWh/year) and 1 MWh sampling intervals are required, then an average sampling rate of 100 simulations per bin requires 25,000 simulations. This would require ten years of CPU time on a standard desktop computer. A modification to the application code resulted in a 50-fold increase in computing speed of calculating the clear sky irradiance, thus making the attainment of a reasonable number of simulations in a short time feasible. This was further extended by running the modified application on several PCs and combining the results for analysis.

The application was further extended to automatically cycle through every day of a whole year with a fixed set of start parameters to represent a dwelling, occupant and appliances. The automatic entry of these is carried out by selecting a random value between an upper and lower limit for each of the parameters (table 1) and using a random allocation of appliances and lighting loads.

Table 1 Starting parameters and ranges used in simulations

	Lower	Upper	Selected
Calibration	1	1	1
Resident Count	1	5	3
System Rating	1	5	3
Azimuth	-90	90	40
Slope	20	45	35
Day	1	365	n/a
Occupancy Archetype	1	6	5

The aggregated demand, generation and export values are determined for each day and added to a running total for the year. After the last day of the year, the running annual totals are saved along with the start parameters and the simulation repeats for another whole year with a new set of random start parameters.

Simulation Results

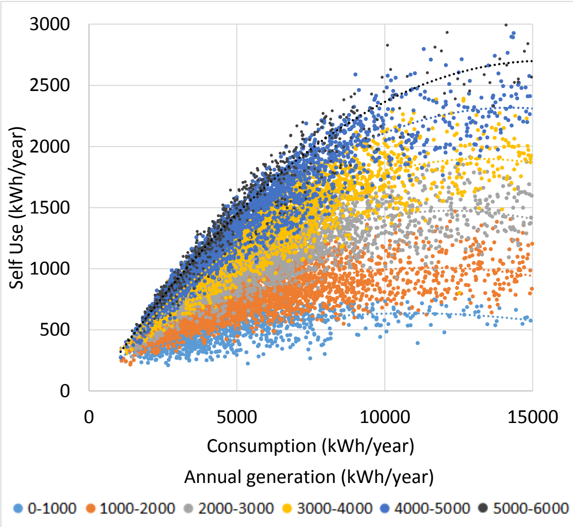

Figure 4. Annual self-consumption as a function of annual electricity consumption segmented by annual system yield for simulated data.

Figure 4 shows the result of 30 whole-year worth of 1-minute simulations. The dataset exhibits a broad range of annual electricity demand and generation values, as might be observed in the general population although it is apparent that the stochastic simulation model under-represents low electricity consumers. This could be due to over-estimation of occupancy, energy consuming activities or appliance ownership all of which mitigate against the observation of low electricity consumption.

There is good agreement with the DFT data and the general trends concur with the hypothesis that both generation and consumption are strong predictors of SC with an expected large variability. The effect of orientation was analysed and is shown in figure 5.

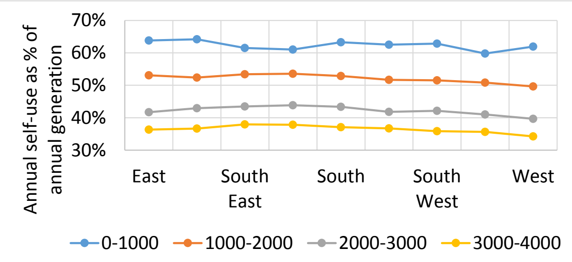

Figure 5 Average annual self-consumption as a percentage of generation as a function of system orientation. Each curve represents a generation band.

No discernible effect of orientation upon SC is observed, countering the normative view that East and West facing modules contribute to higher SC during higher average occupancies at the 'breakfast surge' and evening homecoming respectively, in comparison to those facing directly South, as illustrated in figure 6.

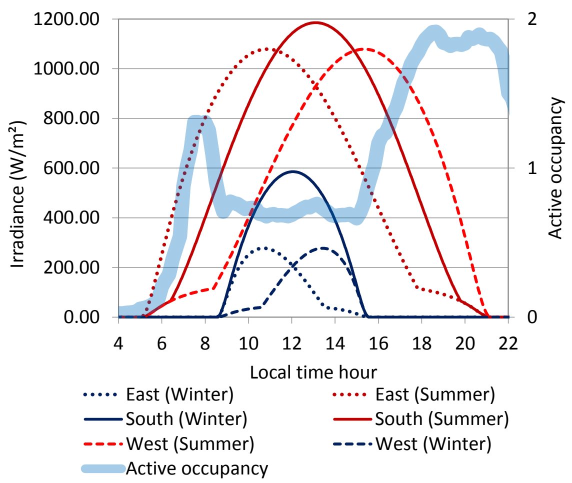

Figure 6. Average weekday occupancy superimposed on clear-sky irradiance for different aspects and seasons.

Yao and Steemers (2005) proposed five domestic load archetypes related to active occupancy (table 2). Instead of using the stochastically generated occupancy patterns a set of idealised patterns were created for each of these archetypes plus one extra, namely all day unoccupied. This allowed the sensitivity of SC to occupancy parameters to be studied.

Table 2. Typical appliance load profiles for average domestic household related to occupancy archetypes with the average simulated self-consumption observed

Load Pattern Archetype	Average SC (%)
Unoccupied 9:00 – 13:00	44
Unoccupied 9:00 – 16:00	25
Unoccupied 9:00 – 18:00	19
Unoccupied 13:00 – 18:00	47
All Day Occupied	69
All Day Unoccupied	15

For these simulations, a consistent 3kWp PV system was used. The results, also in table 2, exhibit little difference between morning and afternoon absence. Home-comers at 16:00 self-consume 25% compared to 19% for 18:00 returners. In contrast, full-time occupancy achieves 69% SC.

Conclusion

A simulated joint probability distribution for consumption, generation and SC has been quantified. Consumption and generation are strong predictors of SC which is highly variable. The variability is shown to be due to different occupant behaviours as demonstrated by the use of idealised occupancy archetypes to quantify SC.

The distribution will be useful in probabilistic or Monte-Carlo modelling applications which require the probabilistic prediction of SC given domestic generation and demand. It has been used in integrated modelling of domestic PV for the evaluation of socio-economic impacts using Bayesian Networks (Leicester et al 2014)

Bibliography

Betts TR and Gottschalg R., (2007) Irradiance data: solar irradiation data for Loughborough. Centre for Renewable Energy Systems Technology (CREST), Loughborough University, UK.

Cao, S. and Sirén, K. (2014). Impact of simulation time-resolution on the matching of PV production and household electric demand. Applied Energy, 128, pp.192-208.

Colantuono, G., Everard, A., Hall, L. and Buckley, A. (2014). Monitoring nationwide ensembles of PV generators: Limitations and uncertainties. The case of the UK. Solar Energy, 108, pp.252-263.

Dusabe D., Munda J. and Jimoh A., (2009) Modelling of cloudless solar radiation for PV module performance analysis,.J Electr Eng, 60(4), pp 192–197.

Leicester P.A., Goodier C., Rowley P., (2014) Evaluating the contribution of PV to Social, Economic and Environmental Aspects of Community Renewable Energy Projects, PVSAT-10 conference, Loughborough, UK.

Munzinger, M., Crick, F., Dayan, E., Pearsall, N., Martin, C., (2006). PV Domestic Field Trial: Final Technical Report.

Richardson, I. and Thomson, M. (2012). Integrated simulation of photovoltaic micro-generation and domestic electricity demand: a one-minute resolution open-source model. Proc. of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy, 227(1), pp.73-81.

Richardson, I., Thomson, M., Infield, D. and Delahunty, A. (2009). Domestic lighting: A high-resolution energy demand model. Energy and Buildings, 41(7), pp.781-789.

Voss K, Sartori I, Napolitano A, Geier S, Goncalves H, Hall M, et al. Load matching and Grid Interaction of Net Zero Energy Buildings. EuroSun, Graz Austria, September 29th-October 1st; 2010.)

Skartveit A. and Olseth J.A., (1992). The probability density and autocorrelation of short-term global and beam irradiance, Sol Energy, 49(6), pp 477–487.

Wright, A. and Firth, S. (2007). The nature of domestic electricity-loads and effects of time averaging on statistics and on-site generation calculations. Applied Energy, 84(4), pp.389-403.

Yao, R. and Steemers, K. (2005). A method of formulating energy load profile for domestic buildings in the UK. Energy and Buildings, 37(6), pp.663-671.