



This item was submitted to Loughborough's Institutional Repository (<https://dspace.lboro.ac.uk/>) by the author and is made available under the following Creative Commons Licence conditions.



CC creative commons
COMMONS DEED

Attribution-NonCommercial-NoDerivs 2.5

You are free:

- to copy, distribute, display, and perform the work

Under the following conditions:

 **Attribution.** You must attribute the work in the manner specified by the author or licensor.

 **Noncommercial.** You may not use this work for commercial purposes.

 **No Derivative Works.** You may not alter, transform, or build upon this work.

- For any reuse or distribution, you must make clear to others the license terms of this work.
- Any of these conditions can be waived if you get permission from the copyright holder.

Your fair use and other rights are in no way affected by the above.

This is a human-readable summary of the [Legal Code \(the full license\)](#).

[Disclaimer](#) 

For the full text of this licence, please go to:
<http://creativecommons.org/licenses/by-nc-nd/2.5/>

INTEGRATED SIMULATION OF PHOTOVOLTAIC MICRO-GENERATION AND DOMESTIC ELECTRICITY DEMAND: A ONE-MINUTE RESOLUTION OPEN-SOURCE MODEL

Ian Richardson and Murray Thomson,
CREST (Centre for Renewable Energy Systems Technology),
Department of Electronic and Electrical Engineering,
Loughborough University, Leicestershire, LE11 3TU, UK.

Corresponding author: Tel.: +44 1509 635326. Email: I.W.Richardson@lboro.ac.uk

ABSTRACT

Domestic photovoltaic (PV) generation can partially offset the electricity demand within an individual dwelling. The net demand may be readily estimated on an annual basis but modelling its import and export, with respect to time, is more complex. A key issue is that domestic electricity demand, particularly lighting, is significantly influenced by the outdoor light level, which of course also has a direct effect on PV generation. Thus, realistic time-step simulation of the net demand requires that the two components are modelled with respect to a common representation of the solar irradiance. This paper presents the construction of an integrated model that provides data at a one-minute time resolution, built upon a fully validated high-resolution electricity demand model. An open-source software implementation of the integrated model in VBA within Microsoft Excel is described and is available for free download.

INTRODUCTION

A domestic solar photovoltaic (PV) system will generate electricity that will partially offset electricity demand consumption at the dwelling. Naturally, both this generation and the demand vary considerably throughout the day: the PV output will relate closely to outdoor irradiance, while the demand consumption will reflect the occupants use of different appliances and electric lighting, which is also strongly influenced by the level of outdoor global irradiance.

Maximum generation will typically occur at solar noon, subject to atmospheric and weather conditions, which is also likely to be the time of least lighting demand. In contrast, maximum domestic demand often occurs in the early evening, and specifically in the case of lighting, the evening period after sunset. This timing mismatch should not be perceived as a fundamental problem with PV – the generation is still very valuable in offsetting demand elsewhere in the power system – but does serve to increase the ratio of minimum to maximum net demand for the individual dwelling and in the

local electricity distribution network. Such changes in typical demand profiles and in diversity have relevance in the design and operation of such networks and this is the motivation for the modelling presented here.

In order to properly represent the time correlation between PV generation and domestic lighting demand and PV output, it is necessary to use a common representation of outdoor irradiance. Earlier modelling, such as that presented by Thomson and Infield (2007), did not use a common input. The implication of this is that increases in lighting use, say during periods of heavy cloud cover during the day, will not correlate with decreases in PV output. In this case, there is a risk that the increased variance in net demand is under represented.

The contribution of this paper is to integrate demand and PV models in order to appropriately represent this correlation. The following components are considered important in the construction of such a model:

Simulation of domestic electricity demand

In order to properly simulate the spiky nature of electricity demand observed in individual dwellings the demand model should have a short time step (high-resolution). It should also represent the end-uses of electricity; in particular, the lighting demand should be explicitly and appropriately represented to vary according to outdoor irradiance. For the purpose of analysing electricity distribution networks, it is also important that the time coincidence of the demand both within, and between dwellings, is realistically represented.

Simulation of domestic PV

The size and efficiency of a PV installation are the first basis for estimating its electrical output, but the critical aspect for the modelling in hand is the variability of that output according to variation of outdoor irradiance.

Simulation of irradiance

As described above, a representation of outdoor irradiance is a critical input to both the electricity demand and PV models. Passing clouds can

cause rapid variations in PV output and thus the simulation of irradiance should also have a short time step. Furthermore, the model should be structured so that same irradiance data can be used for the simulation of correlated generation and demand in multiple dwellings in close geographic proximity.

MODEL ARCHITECTURE

The architecture of a model that meets the requirements set-out in the introduction is shown in Figure 1. The large white box represents a high-resolution model of whole-dwelling electricity demand. The construction and validation of this model is presented in earlier published work by the authors (Richardson et al., 2010). This model simulates the use of all the major types of domestic electrical appliances, including cold, cooking, and wet categories. The model is based upon active occupancy (defined as when people are at home and awake) as a key variable influencing domestic energy demand (Richardson et al., 2008). The simulation of the use of individual appliances is based upon activity profiles, constructed from time use data, which represents how people spend their time. Summing the demand from each appliance at a given time provides the aggregate dwelling demand, as is seen to the right of the inner box. This whole-dwelling demand model incorporates a model of domestic lighting (Richardson et al., 2009). Whilst there are many factors that may influence the use of domestic lighting (such as window and room orientation, and occupant preference), this model is constructed and

validated on the assumption that the occupant's tendency to use lighting is most significantly influenced by the level of outdoor global irradiance. The lighting demand also uses active occupancy as a key input variable.

The outer grey box represents the new integration work that is presented in this paper. With reference back to Figure 1, the net dwelling demand can be seen to be dependent on the output of a PV model and a demand model. Both the PV model, and the lighting components of the demand model, can be seen to use a common irradiance input. The construction of the new irradiance and PV models is described in the following sections.

CONSTRUCTION OF THE IRRADIANCE MODEL

Scope of the model

The domestic lighting demand model, introduced previously, was constructed using measured global irradiance data. This provides a constraint in that it is necessary to have available an appropriate high-resolution irradiance series, for long time periods, for the location being modelled. To increase the flexibility with regard to location, the new model is capable of generating synthetic irradiance data for any given geographic location.

A typical solar irradiance profile is shown in Figure 2. This profile shows the time varying one-minute global irradiance as measured at Loughborough University on 6th March, 2007 (Betts et al., 2007).

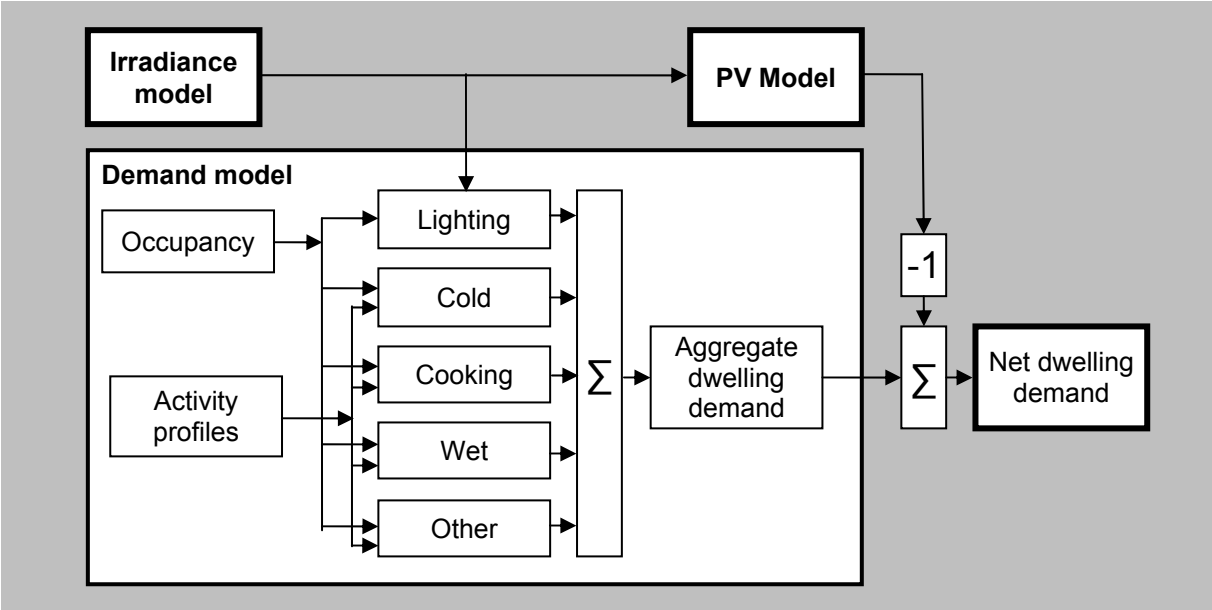


Figure 1 – Integrated PV and demand model architecture, using a common irradiance input

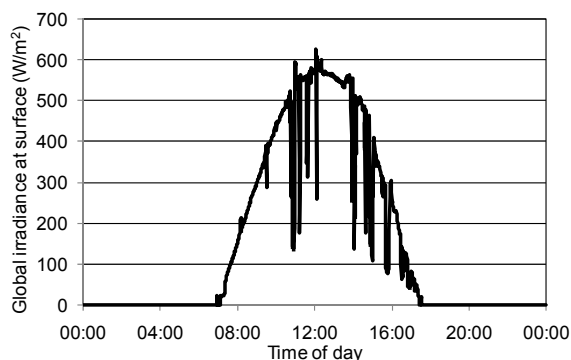


Figure 2 – Measured global irradiance profile

Figure 2 shows two clear characteristics. The first is its overall shape, which is a curve relating to the changing position of the sun in the sky through the day, and can be seen to peak at the middle of the day. The second is the spikiness where sharp falls in irradiance can be seen to occur. This is the result of changing weather conditions, particularly clouds passing overhead. The overall shape of the curve is clearly visible in this case and this is representative of a day with mostly clear skies.

In determining the level of outdoor irradiance at a particular location in this model, these two aspects of the irradiance profile are considered separately as follows:

- The modelling of the irradiance at the surface during clear sky conditions.
- The irradiance attenuation as a result of changing weather conditions, specifically passing overhead clouds throughout a day. Since the level of irradiance varies considerably from minute to minute, such as when clouds pass overhead, it is necessary for the synthetic data to approximate this variation.

Modelling the clear sky outdoor irradiance

The clear sky irradiance, at a given longitude and latitude, can be approximated through the calculation of solar position, given the day of the year and the time of day. It is necessary to take into account the local time, as well as, any time of year variations, such as British Summer Time (BST).

The irradiance model presented in this paper uses the approach presented by Dusabe, Munda and Jimoh (2009), together with the solar resource calculations in Masters (2004), where the calculations involved are clearly presented. As a brief summary, the clear sky solar irradiance at the surface is expressed as the sum of the direct, diffuse and reflected irradiance. Each of these components is

expressed as a function of the direct solar beam radiation from the sun at the surface.

The direct beam irradiance is dependent upon the extraterrestrial irradiance from the sun outside the Earth's atmosphere, as well as, the effect of the beam passing through the atmosphere. This latter effect is taken into account by the "optical depth" of the atmosphere: this is a coefficient that represents the distance travelled through the atmosphere, together with the level of beam scattering and absorption. In this case, the optical depth represents clear sky conditions without cloud.

In the integrated model described in this paper, the intensity of extraterrestrial irradiance from the sun at a point outside the atmosphere uses the equations defined in Yogi Goswami et al. (2000). This takes into account the distance of the Earth from the sun, as it varies throughout the year.

In order to provide a relationship between the time of solar noon and the actual local time at a given longitude, it is necessary to take into account the angle of the Earth's rotation and the orbit eccentricity. The Equation of Time is used to accomplish this and is adequately documented elsewhere (Honsberg et al., 2010, Australian government, 2010).

The output of the clear sky irradiance model is the clear sky beam irradiance at the horizontal surface, together with the solar altitude and azimuth.

A figure showing the output of the clear sky irradiance model for 6th March is shown in Figure 3, shown also with the measured data from Figure 2. The irradiance model is clearly providing a good representation of the clear sky level of outdoor irradiance.

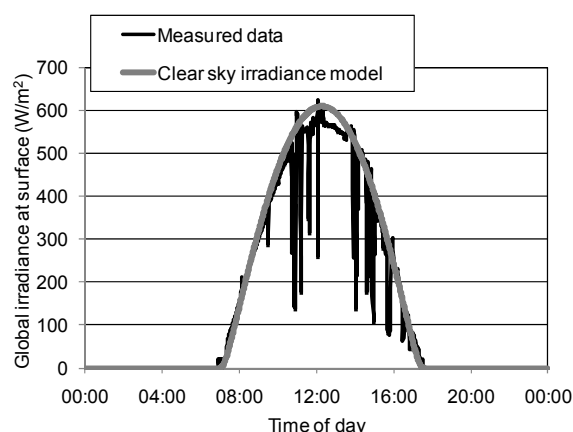


Figure 3 – Clear sky irradiance model output

However, the clear sky irradiance model alone does not take into account passing clouds, which is evident in the measured data. This aspect of the model is discussed next.

Modelling attenuation due to clouds

Clouds reduce the level of irradiance reaching the surface. This reduction occurs on a random basis as a result of complex interactions in the atmosphere. There may be slow variation, in the case of grey overcast days, or rapid variation as patchy clouds move across the sky. The detailed modelling of the atmosphere involves complex meteorological science and is not required for the purposes of this paper.

Instead, a “clearness index”, as discussed by Skartveit and Olseth (1992), is one way of representing the additional attenuation that occurs as compared to clear sky conditions.

The clearness index can be used as a simple coefficient where an index of 1 represents a clear sky, and an index of 0.5 would be indicative of a cloudy sky resulting in only half the clear sky irradiance reaching the surface.

The clearness index will change frequently as clouds pass over and the weather conditions change. For the purposes of simulating rapidly changing clearness conditions, this model is required to be able to synthetically generate a realistic time-stepped series of clearness index values.

With a time-series of clearness index values, it is possible to calculate the outdoor irradiance at the surface as a proportion of that in the case of clear sky conditions. The calculation is shown in Figure 4.



Figure 4 – Calculation of outdoor irradiance given a clearness index

A synthetic series of clearness index values

In order to generate a synthetic series of minute to minute clearness index values, a first order Markov-Chain is utilised. This chain determines the clearness index at each time-step, based upon the index level at the previous time step. This method requires a probability distribution given a particular clearness index that can be used in conjunction with a random number to determine the value at the next step. (A similar use of this technique is presented in detail in Richardson et al., 2008).

The probability distribution of transition from each clearness state to each other possible state is defined in a Transition Probability Matrix (TPM). In this application, the TPM has a size of 101 x 101 elements, representing 100 bins

from “up to 0.01” to “up to 1.00”, as well as the clear sky index value of 1.

The first step in creating the TPM, is to generate a long time-series of clearness index values. This was constructed using the measured one-minute irradiance data set for Loughborough in 2007, in conjunction with the theoretical clear sky irradiance series from the irradiance model presented in the previous section. For each one-minute time step, the clearness index was calculated by dividing the measured irradiance value, against the theoretical clear sky irradiance, on that day, at that time. This yields a time-series of 525 599 values.

The TPM matrix is then constructed by calculating the likelihood of transition from each state to each other possible state. For example, the probability that the sky is clear in the next minute, given an already clear sky, can be determined by counting the number of times the sky is clear, and still clear at the next time step, and dividing by the number of times that the sky is clear.

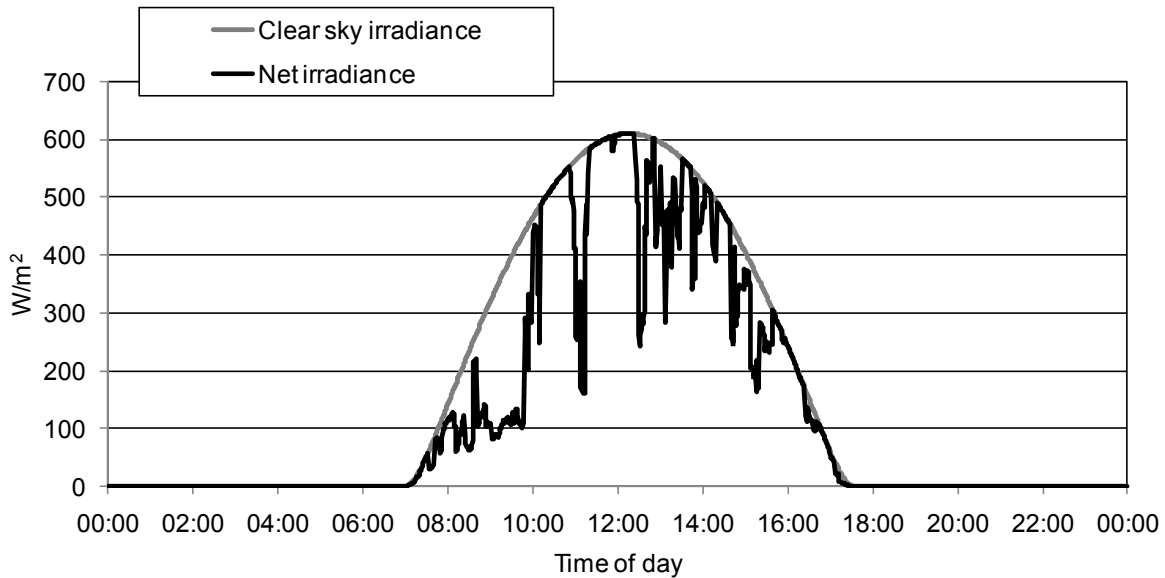
A partial representation of the TPM is shown in Table 1.

		Next State						
		Clearness Index	Up to 0.01	Up to 0.02	Up to 0.03	...	Up to 0.99	Up to 1.00
Current State	Up to 0.01	0	0	0		0	0	0
	Up to 0.02	0	0.667	0.333		0	0	0
	Up to 0.03	0	0.025	0.828		0	0	0
	...							
	Up to 0.99	0	0	0		0.249	0.128	0.172
	Up to 1.00	0	0	0		0.132	0.248	0.317
	Clear Sky	0	0	0		0.07	0.012	0.910

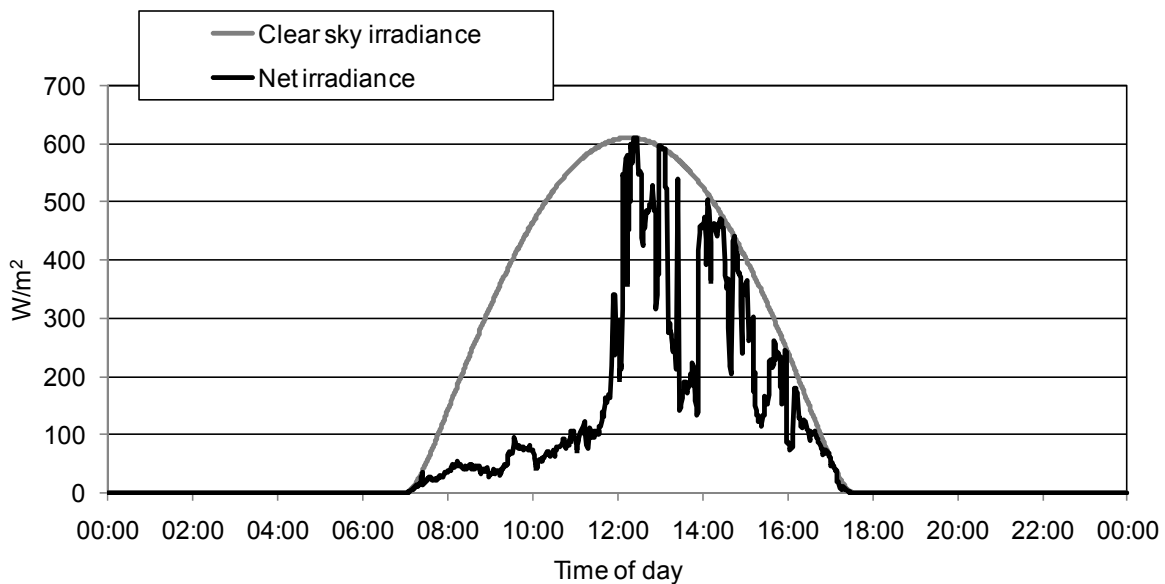
Table 1 - Clearness index TPM

The TPM shows that the clearness index is very likely to stay the same in the next minute, rather than change significantly. For example, if the conditions are clear, then there is a 91% likelihood that they will remain clear in the next minute. This is evident in that the diagonal terms in the TPM have relatively higher values.

The tendency for the conditions to remain the same mean the TPM is sparse and has many zero values in the off diagonal elements. This is a reason why it is appropriate to use a matrix of discrete values, rather than probability density derived through a curve fitting approach, since it is not a smooth surface.



(a) Example simulation run 1 – global irradiance for a relatively clear sky day



(b) Example simulation run 2 – global irradiance with significant morning cloud cover

Figure 5 – Simulation output

The full TPM is provided in a freely downloadable example which is introduced later. It is noted that the values in the rows sum to one, as expected, with the exception of the first row. This is because there are no states with a clearness index of less than 0.01. The low clearness index values are rare, and since they are based on measured data over the period of a year, are likely to be the result of times when the solarimeter was blocked from the sun entirely, perhaps during maintenance.

With reference back to Figure 2, two example simulations are presented in Figure 5 for March 6th. The clear sky irradiance shows the maximum irradiance that could be expected on that day of the year. The net irradiance takes

into account the changing clearness index on a minute to minute basis. As a stochastic simulation, the output will be different each time the model is run. Figure 5(a) shows a relatively clear day, whereas, Figure 5(b) shows a day with heavy cloud cover in the morning. The model can be seen to be appropriately representing the minute to minute variation.

Although the irradiance model works well, a number of limitations in the approach are acknowledged as follows:

The clearness index chain is constructed without regard to the changing patterns of weather over time. In reality, cloud cover will change by season and on longer time scales. A whole year of data was used to construct a single TPM.

This means that in this model, the probability of clearness index change in January is the same as in June. Future research could assess the extent to which time varying TPMs would improve the simulation.

Furthermore, the TPM was constructed with data from just one location (Loughborough, UK), and the extent to which probabilities may vary with respect to geographic location has not yet been assessed.

The model does not take atmospheric refraction into account at sunrise or sunset, and further does not include spectral effects, which can be significant in the prediction of long-term PV system performance (Gottschalg et al., 2005).

Lastly, the simulation starts each day with a clear sky. However, since this is at midnight and there will be several hours of Markov-chain simulation before sunrise, the overall effect should be negligible.

MODELLING OF PV GENERATION

The PV model used in the integrated simulation presented in this paper uses a simple system energy conversion coefficient that requires inputs of incident irradiance subject to panel orientation, as well as, the surface area of the PV panel array. This approach has been used elsewhere (Paatero and Lund, 2007) and is shown in Figure 6.

The orientation of the panel is taken into account by using the tilt angle and azimuth of the panel array, using the calculations detailed in Dusabe, Munda and Jimoh (2009).

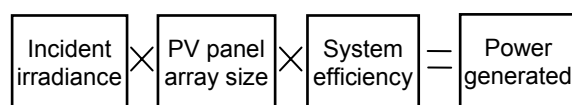


Figure 6 – Simplified PV system model

It is acknowledged that this approach does not explicitly represent the thermal characteristics of the PV, any localised shading effects, or any variable losses in the inverter or other balance of plant. However, these aspects are considered relatively constant in comparison to the volatility of the changing level of irradiance and thus the simple conversion coefficient is appropriate for the application in hand.

SIMULATION OUTPUT

The output from an example simulation run, for the 1st July, is shown in Figure 7. In this example, the electricity demand in the dwelling

totalled 10.8 kWh, it generated 4.8 kWh and exported 1.3 kWh.

The occupancy and irradiance simulations are shown in Figure 7(a). In this simulation run, there is considerable cloud cover during the middle of the day, perhaps as the result of a summer storm. The dwelling has four total residents in this simulation, and there is active occupancy throughout the day from just after 07:00 in the morning.

The lighting demand in the dwelling is shown in Figure 7(b). As a summer day, little demand for lighting can be seen in the early and mid morning periods. However, as the irradiance level drops after 11:00, the increased lighting demand is clearly visible. As the irradiance increases throughout the afternoon, the demand for domestic lighting falls. As would be expected, it rises again in the evening as the sun sets.

The aggregate domestic electricity demand and the net electricity demand, the latter taking into account the PV generation, are shown in Figure 7(c). During the night time, through to 05:30, the aggregate demand and net demand are the same. There is no PV generation at this time, and two refrigeration appliances can be seen to cycle.

As the irradiance level increased beyond 05:30, the dwelling can be seen to export electricity as the net demand becomes negative. The aggregate and net demands diverge due to the PV generation offsetting the electricity demand in the dwelling.

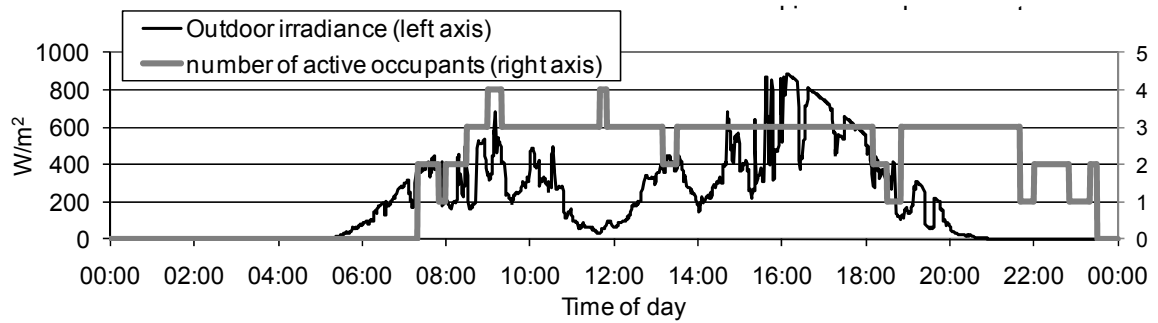
However, during the late morning period, PV generation falls as the irradiance drops, and the dwelling demand is seen to increase, particularly as a result of the increased lighting demand, which forms part of the aggregate demand.

The dwelling does not significantly export electricity again until mid-afternoon at 15:00, beyond which the aggregate and net demand profiles gradually converge, as PV generation falls towards sunset.

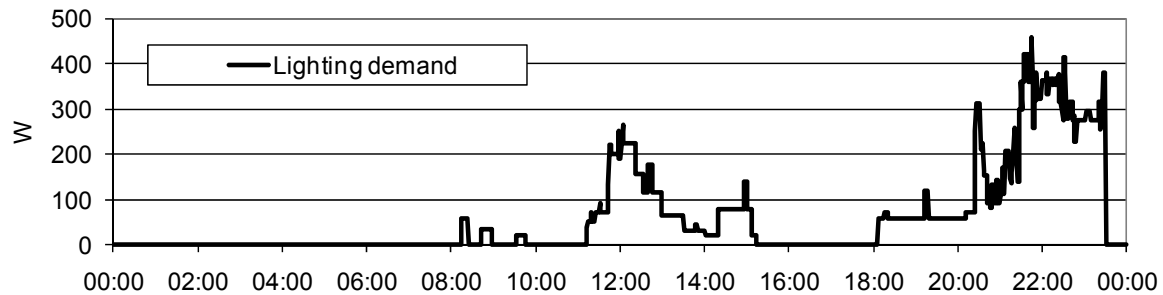
FREELY DOWNLOADABLE MODEL

A freely downloadable model has been made available that provides a one-day simulation example for a single dwelling (Richardson et al., 2010). It is constructed in VBA using Microsoft Excel. It incorporates the previously developed whole-dwelling electricity demand model, also freely available, that has been modified to use the common irradiance data as input.

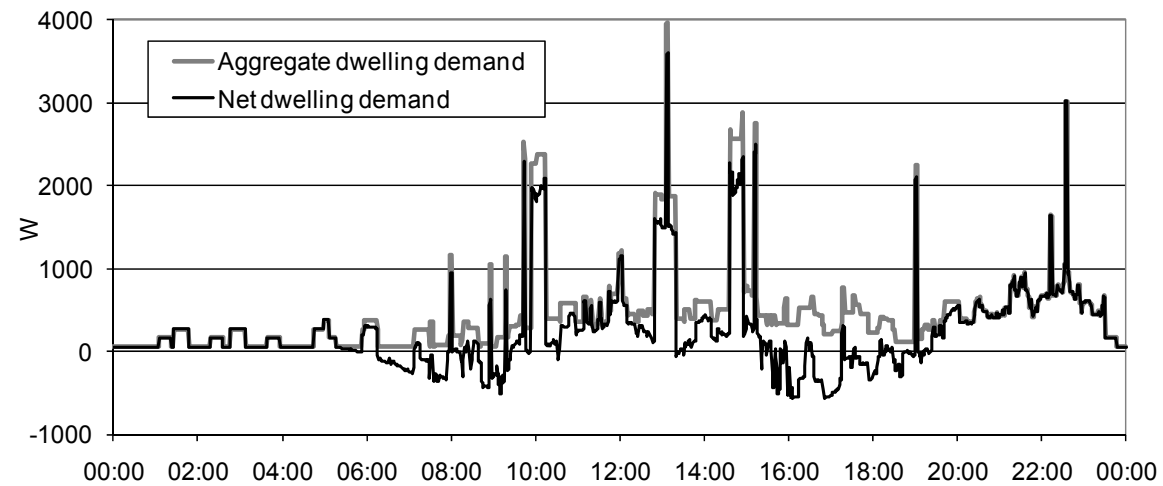
installation of PV is typically coincident with demand reduction through both technical



(a) Irradiance and active occupancy



(b) Lighting demand



(c) Dwelling aggregate and net demand

Figure 7 – Simulation output

CONCLUSIONS

An integrated model of PV generation and domestic electricity demand that provides a good representation of the rapidly varying net demand of a whole dwelling has been presented. The validity of the model rests primarily on that of the previously validated sub-models from which it is constructed, and is considered an adequate basis for its intended application in the study of power flows in electricity distribution networks. The model may find further application, for example in evaluating import/export tariffs averaged over different time intervals. Further validation is ongoing but is constrained by the low availability of un-skewed demand data for dwellings that have PV: the

ACKNOWLEDGMENT

This work was supported by the Engineering and Physical Sciences Research Council, UK, within the Supergen HiDEF (EP/G031681/1) project, and the Transition Pathways to a Low Carbon Economy project (EP/F022832/1).

REFERENCES

Australian Government, IPS Radio and Space Services, The Equation of Time, <http://www.ips.gov.au/Category/Educational/The%20Sun%20and%20Solar%20Activity/General%20Info/EquationOfTime.pdf> (Consulted 1st December, 2010).

- Betts, T.R. et al. 2007, Irradiance data: Solar Irradiation Data for Loughborough, Centre for Renewable Energy Systems Technology (CREST), Loughborough University, UK.
- Dusabe, D. , Munda, J., Jimoh 2009 A., Modelling of Cloudless Solar Radiation for PV Module Performance Analysis, Journal of Electrical Engineering 60 (4) 2009 192-197.
- Gottschalg, R., Betts, T. R., Infield, D. G., Kearney M. J. 2005, The effect of spectral variations on the performance parameters of single and double junction amorphous silicon solar cells, Solar Energy Materials and Solar Cells 85 (3) (2005) 415-428.
- Honsberg, C., Bowden, S., 2010 PVEducation.org, <http://www.pveducation.org/pvcdrom/properties-of-sunlight/solar-time> (Consulted 1st December, 2010).
- Masters, G. 2004 Renewable and Efficient Electric Power Systems, John Wiley & Sons, New Jersey.
- Paatero, J., Lund, P. 2007, Effects of large-scale photovoltaic power integration on electricity distribution networks, Renewable Energy 32 (2007) 216-234.
- Richardson, I., Thomson, M., Infield, D., Clifford, D. 2010, Domestic electricity use: A high-resolution energy demand model, Energy and Buildings 42 (10) (2010) 1878-1887.
- Richardson, I., Thomson, M., Infield, D. 2008, A high-resolution domestic building occupancy model for energy demand simulations, Energy and Buildings 40 (8) (2008) 1560-1566.
- Richardson, I., Thomson, M., Infield, D., Delahunty, A. 2009, Domestic lighting: A high-resolution energy demand model, Energy and Buildings 41 (7) (2009) 781-789.
- Richardson, I., Thomson, M., Infield, D. 2008, A high-resolution domestic building occupancy model for energy demand simulations, Energy and Buildings 40 (8) (2008) 1560–1566.
- Richardson, I., Thomson, M. 2010 Domestic Electricity Demand Model—Simulation Example, Loughborough University Institutional Repository, 2010, <http://hdl.handle.net/2134/5786>
- Richardson, I., Thomson, M. 2010, Domestic Electricity Demand Model—Integrated Domestic Electricity Demand and PV Micro-generation Model, Loughborough University Institutional Repository, 2010, <http://hdl.handle.net/2134/7773>
- Skartveit, A., Olseth, J. A. 1992, The probability density and autocorrelation of short-term global and beam irradiance, Solar Energy 49 (6) 477-487.
- Thomson, M., Infield D. 2007. Network Power-Flow Analysis for a High Penetration of Distributed Generation, IEEE Transactions on Power Systems 22 (3) (2007) 1157-1162.
- Yogi Goswami, D., Kreith, F., Krieder J. F., 2000, Principles of Solar Engineering, 2nd Edition Taylor & Francis.