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Impacts of different data averaging times on statistical analysis of distributed domestic photovoltaic systems

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Abstract

The trend of increasing application of distributed generation with solar photovoltaics (PV-DG) suggests that a widespread integration in existing low-voltage (LV) grids is possible in the future. With massive integration in LV grids, a major concern is the possible negative impacts of excess power injection from on-site generation. For power-flow simulations of such grid impacts, an important consideration is the time resolution of demand and generation data. This paper investigates the impact of time averaging on high-resolution data series of domestic electricity demand and PV-DG output and on voltages in a simulated LV grid. Effects of 10-minutely and hourly averaging on descriptive statistics and duration curves were determined. Although time averaging has a considerable impact on statistical properties of the demand in individual households, the impact is smaller on aggregate demand, already smoothed from random coincidence, and on PV-DG output. Consequently, the statistical distribution of simulated grid voltages was also robust against time averaging. The overall judgement is that statistical investigation of voltage variations in the presence of PV-DG does not require higher resolution than hourly.

Keywords: Time averaging; Photovoltaics; Domestic electricity demand; Distribution grid; Low voltage; Power flow

1 Introduction

Integration of distributed electricity generation (DG) in distribution networks is increasing steadily in many European countries and is expected to become more extensive in the future. High densities of DG in middle-voltage (MV) and low-voltage (LV) grids raise numerous issues, such as unintentional islanding, grid stability and power quality [1]. A major impact of DG introduction is voltage rise from excess on-site generation. Power injection can counteract voltage drops at high load situations, but at low load it can lead to violation of prescribed voltage limits. The matching between the local load and production is therefore of crucial importance.

Grid-connected photovoltaic (PV) systems have experienced a marked growth over the last decade, following the introduction of generous subsidy schemes [2]. A majority of the installed photovoltaic (PV) systems today are grid-connected distributed (PV-DG) systems [3]. Many of these are integrated at residential customers in low-voltage grids (0.4 kV), at the very end of the distribution system. A continuation of this trend could involve more extensive integration of PV in both existing and new low-voltage grids. Some areas around the world with large densities of PV-DG have been monitored and evaluated [4]. In many of these areas, however, the grid was specifically designed for high PV-DG penetrations. For studies of the impact of retrofitting large amounts of PV-DG into existing grids, simulations have to be performed for the actual grid.

Power-flow simulations to determine grid voltages are often based on worst-case scenarios, considering minimum load and maximum production [5, 6]. As the occurrence of worst and intermediate cases depends on both regular and stochastic variations in demand and production, this method can be too restrictive and result in overdimensioned grids or too restrictive limits to DG integration. Stochastic approaches take fluctuations into account to determine the probability for overvoltage events [7]. A variant of the latter approach is to construct detailed stochastic models of demand and PV generation that can be used in simulations of a specific LV grid. Examples include Thomson and Infield's study of a whole MV feeder with underlying LV grids in the UK [8] and simulations of MV grids by Paatero and Lund [9].

An important consideration is the choice of time resolution for the simulations. Thomson and Infield [8] performed high-resolution simulations on a 1-min time scale. Other separate studies of solar irradiation [10] and PV generation and demand [11] suggest that important fluctuations on short time scales (1-min or 10-min) may be overlooked when using data averaged over longer time intervals (1-hour). Since there are obvious practical drawbacks with higher resolution—longer data processing times, a lack of detailed meteorological data and a need for more advanced load models—it is important to determine the loss of precision that results from time averaging to avoid unnecessary complexity. Hourly time steps is also the usual resolution in simulations of photovoltaics and in most available meteorological data.

This paper investigates the impact of time averaging on statistics of demand and generation data and on the analysis of load matching and voltage levels in LV grids. The analysis is based on Swedish data, but since its main concern is the short-term variations in PV output and load, both of which are less related to the latitude than are annual and diurnal fluctuations, its results should be generally applicable. High-resolved measurements for domestic electricity load and irradiation constitute the basis for the analysis, and the effects on grid voltages are studied through power-flow simulation of a typical Swedish low-voltage feeder located in a residential area. Since the summer is the most critical period for load matching, with the PV output being at its highest and the domestic load at its lowest, the analysis is done for four consecutive summer weeks.

Section 2 presents the model used for conversion of irradiance to PV system output, the power-flow simulations, and definitions for evaluation of averaging times. In Section 3 the applied demand, irradiance and LV grid data are described. The results are presented and discussed in Section 4 and conclusions are drawn in Section 5.

2 Methods and models

2.1 Photovoltaic system modelling

From global incident radiation I, the output of a PV system is calculated as

$$P_P = A_c I \eta_{mp} \eta_e \tag{1}$$

where A_c is the area of the photovoltaic array, η_{mp} is the maximum-power-point efficiency of the solar cells and η_e is the efficiency of additional equipment such as cables and inverters. While η_e is assumed constant, η_{mp} is temperature-dependent and is described as [12]:

$$\eta_{mp} = \eta_{mp,ref} \left[1 + \frac{\mu_{V_{oc}}}{V_{mp}} (T_a - T_{c,ref}) + \frac{\mu_{V_{oc}}}{V_{mp}} I \frac{T_{c,ref} - T_{a,ref}}{G_{ref}} (1 - \eta_{mp,ref}) \right] \tag{2}$$

where $\mu_{V_{oc}}$ is the temperature coefficient for the open-circuit voltage, V_{mp} is the voltage at the maximum power point, $T_{c,ref}$ is the reference cell temperature, T_a is the ambient temperature, $T_{a,ref}$ is the reference ambient temperature and G_{ref} is the reference global irradiance. Given a measured module size A_{ref}, the reference conversion efficiency is

$$\eta_{mp,ref} = \frac{I_{mp} V_{mp}}{G_{ref} A_{ref}} \tag{3}$$

where I_{mp} is the maximum-power-point current. All parameters are readily determined from standard solar cell parameters provided by module manufacturers. $T_{c,ref}$ is the Nominal Operating Cell Temperature (NOCT), normally measured at irradiance $G_{ref} = 800$ W/m^2, ambient temperature $T_{a,ref} = 20$ °C and AM1.5, together with corresponding values of V_{mp}, I_{mp} and $\mu_{V_{oc}}$. The applied parameter values are listed in Table 1.

System size is expressed in terms of peak power, evaluated at standard test conditions (STC). The system peak power is

$$\widehat{P}_P = G_{STC} A_c \eta_{mp} \tag{4}$$

where η_{mp} is evaluated at the STC irradiance G_{STC} and temperature T_{STC}. Normalised system output is defined as:

$$P_{norm} = \frac{P_P}{\widehat{P}_P} \tag{5}$$

When the PV profiles are used in the load-matching computations and grid simulations, the same PV output is used for all systems. Since all system output profiles are identical, possible coincidental smoothing of aggregate profiles is not taken into account. However, if all systems are confined within a sufficiently small area, they should experience similar meteorological conditions. In any case, the orientation of systems has only a limited impact on the hourly appearance of aggregate curves [13] and the impact on short-term fluctuations should be even smaller.

2.2 Power-flow simulations

Three-phase balanced power flow in the distribution grid was simulated with Newton's method [14] implemented in a Matlab script [15]. Power-flow simulations require a 'slack node' to be set as a constraint [14]. Thus, it will be assumed that at the root node, typically the MV/LV substation node for a LV grid, the voltage is assumed constant at 0.4 kV and the power flow into the LV grid is unconstrained. Consequently, possible voltage variation in the MV grid resulting from fluctuating load and production in this and other LV grids or directly connected to the MV grid is not taken into account. The results from the power flow simulations are voltages in each node of the network. From these node voltages, currents in the interconnecting lines can be calculated. Network losses are determined from the flow of current through the cable impedances.

2.3 Method for analysis

In the statistical analysis of loads, PV production and grid voltages, impacts of averaging on minima, maxima and standard deviation of the data were studied. Imports and exports of electricity in each household at different relative production and demand levels were estimated by calculating net production or load in each time interval. Network voltages and losses were derived from separate simulations with differently averaged load and generation data.

For generation and load powers and derived network voltages, the duration of power or voltage levels is the major statistic that should be preserved with time averaging. From a duration curve that orders the output from a system in each time step in decreasing order, the probability for different output levels can be estimated. For example, for a network voltage $V(k)$ where $k = 1, ..., N$ is the time step, the cumulative distribution function is defined as:

$$F_V(v) = \mathrm{Prob}(V \leq v) \tag{6}$$

Cumulative probability is estimated by dividing the number of time steps with a voltage less or equal than v, easily determined from the duration curve of the voltage, by the total number of time steps in the simulation period.

3 Data

3.1 Electricity demand data

Domestic electricity use has been monitored by the Swedish Energy Agency (SEA) in a measurement survey that was initiated in 2005 and finished in 2008 [16, 17]. The survey encompasses measurements on appliance level in 400 households with a 10-min time resolution. Both detached houses and apartments are covered, as well as different family sizes and age groups. Measurement series for a total of 13 households from the survey are used in this study. These data have been analysed previously in a behavioural study connected to the measurement survey [18] and for validation of the load models in refs. [19, 20, 21]. They have therefore been carefully examined for consistency and quality. The characteristics of the households are summarised in Table 2.

The analysed load data cover household electricity (no domestic hot water or space heating) during four weeks with a 10-min resolution. The available data comprise seven annual measurements and seven monthly measurements; however, one household was excluded because of measurement problems. Six households are detached houses, seven are apartments. Since detached houses in general use more electricity than apartments, this might lower the total demand somewhat compared to if all households had been detached houses, but the short-term variations are supposed to be unaffected. Monthly measurements were recorded in the autumn, while the summer is most interesting for this study. Thus, four whole summer weeks were picked from the annual measurements between 2006-06-05 and 2006-07-02, while four weeks of the monthly period were chosen for the other households. Total consumption was measured at the fuse boxes in all of the households. A majority of the end uses were also measured specifically. The aggregate annual demand is slightly lower than the standard figure of 5 MWh/year for detached houses in Sweden but higher than the preliminary figure of 4 MWh/year, as estimated in the SEA measurement survey [22].

For the power-flow simulations the reactive power demand of the households is needed.

This was calculated from the total active power demand assuming a constant power factor of 0.9.

3.2 Solar irradiance data

Global solar irradiance in a plane oriented due south and tilted 45° was measured with a 2-min resolution at the Ångström Laboratory, Uppsala University, Sweden (59° N, 17° E). The data were recorded with a pyranometer together with ambient temperature between 2007-06-01 and 2007-07-01. Due to measurement disturbances and interruptions from unloading the data logger on a few occasions, data for a few days were omitted. The final data series comprised 28 days.

3.3 LV distribution grid data

A simplified model for a 0.4 kV low-voltage (LV) distribution grid section was defined, based on a real LV grid in a district-heated area with detached houses in Uppsala, Sweden. The grid topology data were supplied by Vattenfall Eldistribution AB, Sweden. The grid topology is shown in Figure 1 and the impedances and lengths of the grid cables are listed in Table 3. The grid supplies 13 households and consists of four linearly interconnected buses (via 'bus cables' in Table 3) with three or four houses connected to each bus (via 'household cables' in Table 3). The grid is relatively small, the number of domestic loads is low and an overlying MV grid is not taken into account. Hence, no dramatic voltage fluctuations can be expected. Nevertheless, the relative impact of time averaging should be seen as clearly as on a weaker grid or a grid with more domestic end users.

The household loads were distributed among the household nodes 1–13 of the grid in the same order as in Table 2. Identical PV outputs calculated as in Section 2.1 were assigned to each household node. The system sizes were varied in three penetration level scenarios, shown in Table 4, by multiplying the normalised output in equation 5 by a desired peak power.

4 Results: Impacts of time averaging

4.1 Load data

The impact of time averaging on the electricity demand data (active power) is shown with an example in Figure 2. The figure shows the 10-minutely and hourly power demand for one day in one individual household and for all households in the data set. The original demand pattern in the individual household in (a) is fluctuating heavily between high and low power levels. In the night, there is a low base load and a cyclic component, corresponding to standby power and fluctuating load from cold appliances. When there is activity in the household, especially during the evening, the demand increases due to increased need for lighting and active use of various appliances. The demand peaks are reduced heavily and some low power levels are raised when hourly averages are formed, but the more low-frequent demand variations are preserved. The aggregate demand in (b) is subject to random coincidence of the individual household loads. This has a smoothing effect on the demand, which results in lower variations in comparison to the mean load and a more evident general daily pattern. Time averaging has a smaller relative impact on the aggregate curve, since it is already smoothed considerably from random coincidence.

These observations are confirmed when all households are considered. Table 5 shows the impact of time averaging on descriptive statistics for the demand data over the whole four-week measurement period. With hourly averages the maximum power is lowered and the minimum power is increased throughout. The general variation decreases, as indicated by the lower standard deviation for hourly averages. The maximum and minimum powers, and the impact of averaging on these, differ considerably between households. For the aggregate demand the relative impact is smaller. Note, though, that the effect on maxima and minima show the most extreme impacts.

A more revealing picture of the averaging impacts is given by the duration curves of the power demand for one and all households in Figure 3. For the individual household in (a) it is clearly seen that the high power levels are lowered by hourly averaging while lower power levels are raised. For the aggregate demand the same effect can be noticed, but it is negligible for almost all power levels but the very highest.

4.2 Photovoltaic system output

As for the demand data, Figure 4 shows an example of normalised PV system output during one day of the modelled four-week period. Here, data obtained with 2-min, 10-min and 60-min averaging times are shown. The general pattern, following the insolation pattern over the day, is clearly visible for all averaging times. For the 2-min data, some high-frequent fluctuations are occurring, a typical effect of moving clouds. These individual power dips are decreased heavily already by 10-min averaging of the data series, and furthermore by hourly averages. It should be noted that this relatively smooth example pattern corresponds to a day with a rather undisturbed beam insolation. With fractional cloud movement the power fluctuations should be higher.

Nonetheless, the impact of averaging is much smaller than on both individual and aggregate household loads. This is shown for the maximum output power and the standard deviation in Table 6. Minimum power is not studied, as it will be zero regardless of averaging time (except for extremely long ones). The duration curve, shown in Figure 5, clearly shows that averaging has a very small and negligible impact on the distribution of power output levels.

An important observation is that all fluctuations are power dips due to different forms of shading of the incident radiation. Contrary to the household power demand, the power thus fluctuates down from a rather well-defined predictable cyclic pattern. In particular, there is a predictable upper limit to the PV system output since the installed peak power will never be exceeded. This is also predictable for every single moment in time since the pattern of maximum insolation is known. Fast dips and subsequent surges from cloud movement can be studied separately with constructed cases, but for the general distribution of power output levels no significant improvement is made with high-resolution insolation data.

4.3 Net demand and production

With on-site generation at every household the fluctuating nature of load and generation affects the proportions of demand and generation that are delivered to and from the distribution grid. Since time averaging decreases fluctuations in generation and more so in demand, the matching between load and generation is likely to be overestimated with longer averaging times. Consequently, the exported and imported proportions would be underestimated. That this is the case is shown in Table 7. For some households the impacts of averaging are quite large, such as for exports with PV penetration scenario A in households 1 and 6. In general, in the lower penetration level scenario the exported proportions are more severely underestimated than the imported proportions. In scenario B both exported and imported proportions are less affected.

The explanation is that in scenario A the power production is about the same magnitude as the power demand during daytime. Thus the fluctuations in both demand and production cause variation in the overproduced power. In general, power is imported during night-time (cfr. Figure 2) and thus the imported proportion is marginally affected by the production which occurs during daytime. In the second scenario the PV output powers are in general higher than the mid-day load and thus the fluctuations in demand affect the overproduction less. Random fluctuations on short time scales are therefore only of importance when production and load are about the same magnitudes. With PV this would be the case for low system peak powers; however in those cases the power levels submitted to the grid would be small and have a low impact.

4.4 Grid voltage levels

The impact of time averaging on LV grid voltages is illustrated in Figure 6, showing the voltage variation with PV penetration scenario A during one example day at household node 13, which has the largest voltage fluctuations. As expected, the voltage variations are not very large, far from the prescribed limit voltages that define the window of permissible variation, typically between ±5 % or ±10 % within nominal voltage (0.4 kV in this case) [23]. The mean low-load voltage at the node when there is no PV production (night-time) is lower than nominal voltage, due to a voltage drop resulting from the aggregate load along the feeder. With net PV production during the day the voltage rises and decreases in the evening due to net demand. There are fluctuations in the 10-min data that are reduced with hourly averages; however due to low load and an excess of less variable PV during daytime, the fluctuations are low until the evening when large load fluctuations result in a more varying voltage.

The duration of voltage levels in the same household over the whole four-week period is shown in Figure 7. The curves can be divided roughly into three areas. To the left, there is a voltage rise above nominal voltage due to excess PV production. This level, which is an effect of overproduction that would become more problematic with a weaker grid or one with more household loads, increases in proportion to the PV penetration level. In the middle, there is a voltage rise reducing the voltage drop, which is beneficial from grid point of view. This level increases between the default scenario and scenario A but insignificantly between scenarios A and B. This is because with larger systems, generation in the time intervals with reduction of demand goes from mainly reducing demanded power to overproducing power. To the far right the maximum voltage drop, resulting from high demand levels, is unaffected by PV as it occurs during night-time. In all cases the duration curves are insignificantly affected by time averaging.

The latter observation suggests that the cumulative probability distribution of the voltage, estimated from the duration curve, would be rather unaffected by hourly time averaging. That this is the case is shown in Table 8 for a number of voltage levels. The estimated probabilities are very close, differing at maximum by one percentage point.

Voltages affect losses in the grid. A counteracted voltage drop from PV would thus decrease losses. The calculated losses at the different PV penetration scenarios are shown for different averaging times in Table 9. The losses are low compared to the total load on the grid because of the low voltage variations. With PV scenario A, the losses decrease, while with scenario B the losses increase and exceed those in the default case as the total power flow in the grid increases. The difference between averaging times is 1 kWh throughout, which is a quite large relative difference for the lowest values. However, what is of importance when PV penetration levels are considered is the relative improvement between different scenarios, which seems to be reproduced with longer averaging times.

5 Conclusions

A number of conclusions can be drawn from the analyses. Regarding the impact of time averaging on demand data there is a relatively high impact on the demand of individual households, in particular on extreme values but less on the distribution of demand over the whole four-week period. It is important to note that aggregate demand is less affected by averaging than individual loads because of smoothing from random load coincidence.

For the investigated data, averaging has less impact on PV system output than on demand. Averaging also has an overall low impact on the statistical distribution of power levels over time and consequently the distribution of voltage levels is also robust to averaging. In particular, voltage rise from PV is insignificantly affected by time averaging.

This suggests that statistical investigation of probabilities for different voltage levels, especially when the main concern is voltage rise from PV, should not require higher resolution than hourly. Very extreme situations, such as high load and generation cases and sudden power dips and surges, e.g. from cloud movement, can be studied with deterministic cases.

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Table 1: PV system model parameters.

Parameter	Value
$\mu_{V_{oc}}$	-0.064 [V/°C]
V_{mp}	15.2 [V]
I_{mp}	3.51 [A]
$T_{c,ref}$	46 [°C]
$T_{a,ref}$	20 [°C]
G_{ref}	800 [W/m^2]
A_{ref}	0.56 [m^2]
η_e	0.8
T_{STC}	25 [°C]
G_{STC}	1000 [W/m^2]

Table 2: Properties of the domeestic electricity demand measurements. For monthly measurements the annual demand is estimated (*).

Household	Type	Time period	Period demand [kWh]	Annual demand [kWh]
1	Detached house	060918-061015	339	3401 (*)
2	Detached house	060925-061022	258	2689 (*)
3	Detached house	061016-061112	417	3362 (*)
4	Detached house	060605-060702	594	2164
5	Detached house	060605-060702	460	5382
6	Detached house	060605-060702	284	5252
7	Apartment	060904-061001	216	3330 (*)
8	Apartment	061030-061126	237	4248 (*)
9	Apartment	060918-061015	105	6354 (*)
10	Apartment	060605-060702	286	5902
11	Apartment	060605-060702	125	8996
12	Apartment	060605-060702	89	2184
13	Apartment	060605-060702	143	1786
Average			273	4235

Table 3: Grid cable properties.

Cable	Length [m]	Resistance [Ω/km]	Reactance [Ω/km]
Bus cables	100	0.300	0.080
Household cables	50	1.800	0.090

Table 4: PV penetration level scenarios.

Scenario	Peak power ($\widehat{P}_P$) [kW]	A_c [m^2]	Period production [kWh]
Default	0	–	–
A	1	8.7	131
B	2	17.4	262

Table 5: Impacts of time averaging on electricity demand statistics.

Household	Max power [W]		Min power [W]		Standard deviation [W]	
	10 min	60 min	10 min	60 min	10 min	60 min
1	5675	3086	42	123	555	420
2	3586	1664	42	139	383	296
3	4940	2811	121	167	598	525
4	5470	2441	15	559	314	231
5	5237	2484	28	265	458	336
6	5881	2588	67	68	582	428
7	4507	2235	16	73	395	331
8	2902	1341	87	89	190	177
9	2323	963	29	98	135	96
10	3385	2297	46	83	489	435
11	2671	1304	33	63	187	141
12	3488	1414	29	65	151	112
13	2569	1523	20	92	255	190
Aggregate	14912	10991	2180	2698	2024	1818

Table 6: Impacts of time averaging on PV system output statistics.

Max power [W/W_p]			Standard deviation [W/W_p]		
2 min	10 min	60 min	2 min	10 min	60 min
0.825	0.810	0.803	0.249	0.243	0.238

Table 7: Impacts of time averaging on period export and import of electricity.

Household	PV scenario A (1 kW_p/hh)				PV scenario B (2 kW_p/hh)			
	Export [kWh]		Import [kWh]		Export [kWh]		Import [kWh]	
	10 min	60 min	10 min	60 min	10 min	60 min	10 min	60 min
1	53	41	261	249	155	140	231	216
2	62	58	188	184	175	170	169	165
3	36	33	322	319	125	119	279	273
4	2	1	465	464	64	60	396	392
5	22	19	351	347	106	97	303	295
6	57	49	210	202	161	149	183	170
7	70	65	155	150	181	176	134	129
8	53	51	159	157	165	163	140	138
9	87	84	60	57	209	206	51	48
10	47	43	202	198	150	144	173	167
11	75	72	69	66	195	192	57	55
12	92	89	49	47	216	213	42	39
13	72	66	83	77	189	184	69	64
Aggregate	500	470	2345	2316	1862	1824	1999	1961

Table 8: Impacts of time averaging on the cumulative probability for different voltage levels at household node 13.

Voltage [V]	PV scenario A (1 kW_p/hh)		PV scenario B (2 kW_p/hh)	
	10 min	60 min	10 min	60 min
397	0.00	0.00	0.00	0.00
398	0.02	0.01	0.02	0.01
399	0.25	0.25	0.22	0.22
400	0.76	0.75	0.64	0.64
401	0.93	0.94	0.76	0.76
402	1.00	1.00	0.85	0.86
403	1.00	1.00	0.95	0.96

Table 9: Impacts of time averaging on aggregate period network losses.

	Network losses [kWh]	
PV scenario	10 min	60 min
Default (0 kW_p)	11	10
A (1 kW_p)	9	8
B (2 kW_p)	16	15

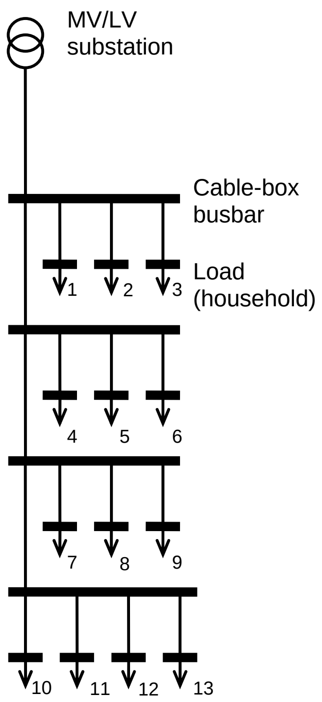

Figure 1: LV grid model overview.

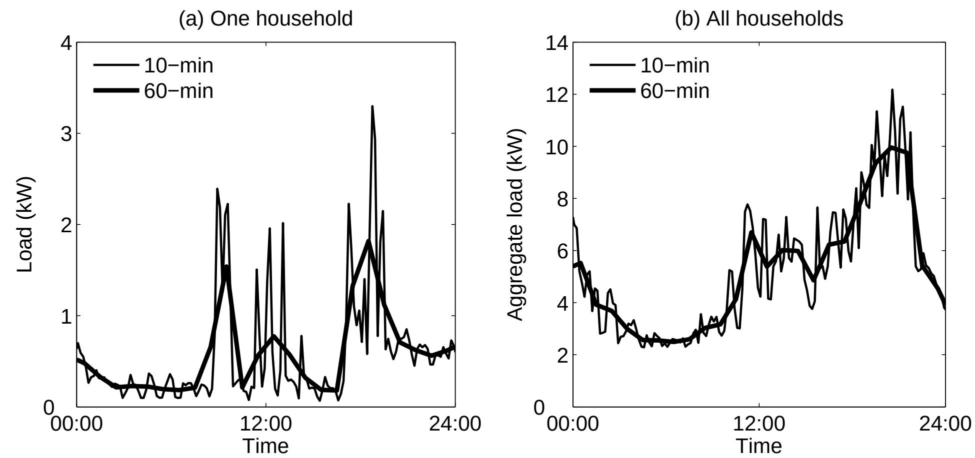

Figure 2: Example of electricity demand during one day with 10-min and 60-min averaging times. (a) shows the demand for an individual household and (b) shows the aggregate demand for all 13 households.

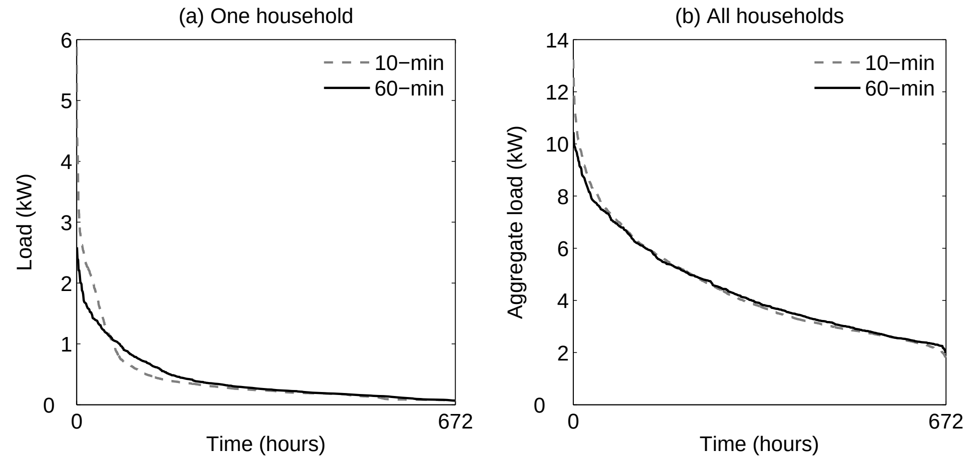

Figure 3: Duration curves for the electricity demand of an individual household (a) and aggregated for all 13 households (b) over the whole four-week period with different averaging times.

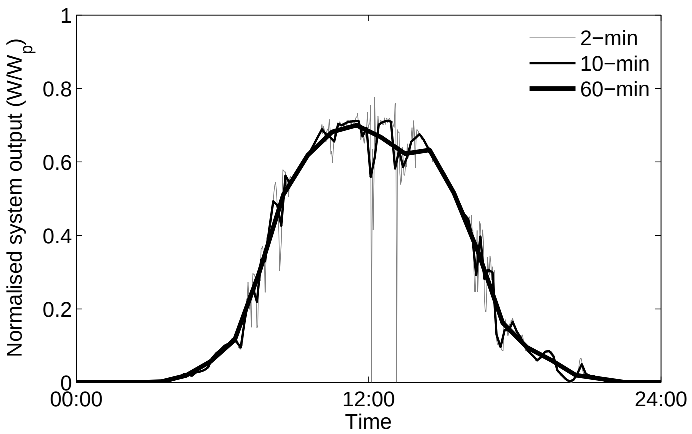

Figure 4: Example of normalised PV system output during one day with different averaging times.

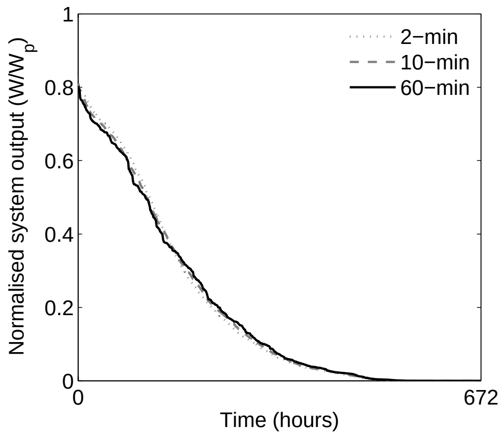

Figure 5: Duration curve for the normalised PV system output over the whole four-week period with different averaging times.

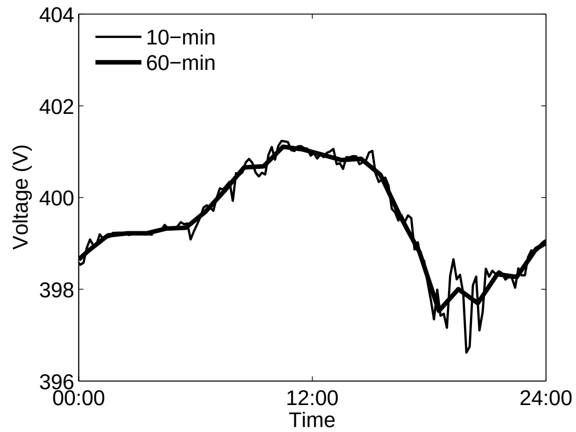

Figure 6: Example of grid voltage during one day at one household node (node 13) with the 1 kW_p scenario and different averaging times.

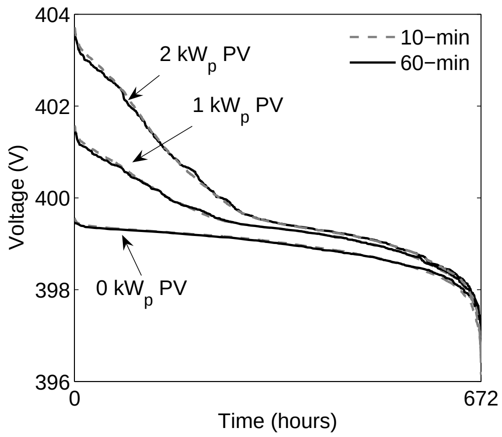

Figure 7: Duration curve for the grid voltage at an individual household node (node 13) over the whole four-week period with different averaging times and at different PV penetration level scenarios.