Using Design Inversion on Building Energy Simulation (BES) Models to Investigate Variability with Integration of Renewable Energy: Part 1, TMY Analysis*

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Contents

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Abstract

We construct a building energy simulation (BES) model of a typical office building and use it to investigate the effects of solar PV and battery storage on realized demand to the electric power distribution grid. The paper focuses on realized variation in demand and on peak demand. The office building is modeled on an hourly basis for typical meteorological years in Riyadh, Saudi Arabia, and in Philadelphia, PA, United States. We obtain similar findings for these two very different locations, viz., that introduction of solar PV can, even without storage backup, (1) considerably reduce the variability of demand placed on the distribution grid and (2) reduce ('shave') realized peak loads. Our methodology, relying in the way it does on BES modeling, is novel and promises to ameliorate the data problem for distribution grid policy studies. BES modeling is mature and widely accepted for architectural design and engineering purposes. As such it is a credible surrogate in energy policy studies for actual usage data.

1 Preface

This document is the first of six projected working papers that explore using building energy simulation (BES) models to yield insight for policy making and planning in the area of renewable energy. Specifically, we are focused on the problem of managing grid volatility in consequence of the increasing presence of renewable energy sources in distribution grids.

1. In this, the first, paper we focus on a model of a 'typical' office building in Riyadh, Saudi Arabia, and in Philadelphia, PA. Here, we examine the model using a single year environmental data set from the IWEC (international weather for energy calculations) series prepared by ASHRAE (`https://www.ashrae.org/resources--publications/bookstore/international-weath-er-for-energy-calculations` and `http://www.equaonline.com/iceuser/ASHRAE_IWEC.html`). The data were prepared using the *typical meteorological year* (TMY) methodology. (See Appendix A for how a TMY is constructed.)

2. The second paper extends the analysis from the point estimates of peak demand and other measures of performance analyzed in the first paper. In this paper we develop and apply an innovative resampling method to the time series data used in the first paper. This affords an investigation of probabilistic variations in the measures of performance and their effects on the general findings of the first paper.

3. The third paper in the series reports on an extensive post-solution (aka: sensitivity) analysis of the models investigated in the first two papers. In undertaking this analysis we adopt the perspective of *solution pluralism* (Chou et al., 2014; Kimbrough and Lau, 2016), in which the models are systematically exercised to generate large numbers of solutions. We then use the use solutions to construct meta-models that execute rapidly to provide approximations of the behavior of BES models for many different buildings and building configurations.

4. The fourth paper considers the problem of designing buildings with integration of renewable sources of energy as a multi-objective constrained optimization problem. For example we consider the three-fold objective of minimizing demand variability presented to the grid, minimizing costs, and maximizing employment of renewable energy, subject to constraints of system performance.

5. The fifth paper explores policy options for electricity markets in light of the findings produced in the series of papers. We hint at examples in the concluding section of the present working paper.

6. The sixth paper in this series revisits the previous analyses now using *calibrated* BES models. Previously we will have explored hypothetical buildings in the context of real weather data and standard estimators of performance. These models are said to be *uncalibrated* because the buildings they model do not exist or exist but lack observational data for fitting the models. Calibrated models are models of actual buildings for which performance data have been obtained for fitting and tuning.

2 Introduction and Background

We undertook this exercise for three main reasons. First, we wish to gain insight on how solar PV can be integrated into electricity distribution grids and in particular on how potential problems of volatility of the grid might arise and be handled, in light of the basic variability inherent in solar PV. This is the principal focus of what follows. The second and third reasons are broadly methodological. We wish study the combined effects of solar PV and demand response regimes on grid stability and electricity costs and configurations. The present study is a step in that direction. Similarly, our third reason is to gain insight on the use of BES models for policy analysis in electric power systems generally. We envision modeling entire distribution grids and using calibrated BES models for each of the involved buildings in order to help understand energy demand at all levels. Again, the present study serves to produce knowledge that supports these more ambitious goals.

Focusing now on the consequences of the fact that renewable energy sources in the form of solar and wind are intermittent (hence variable, even volatile), we note that in general variability is costly. Insurance, hedging, portfolio diversification, and futures contracts are, among others, all widely used institutions for paying to ameliorate the consequences and costs of variability, arising from multiple sources. The problem is especially acute in the case of electric power systems, which have to be kept in balance over short periods of time (a few seconds to several minutes (Ellison et al., 2012)) in the presence of fluctuating demand. Because electric power systems are not purely financial entities, handling variability eventually comes down to manipulating physical components. There are in principle only a few kinds of options for managing the physical aspects of variability in electric power systems:

1. Ancillary services: spinning reserves (excess production that is grounded when not used), generating capacity with fast start up, and so on.

2. Storage: hydroelectric, battery, compressed air, super capacitors, etc.

3. Demand response: curtailing and/or shifting demand at times of high load; encouraging demand at times of low load.

4. Trade: using long distance transmission lines to exchange power with distant markets.

Each source of variability reduction has its own costs, which are often high, as well as operating and availability characteristics.

The problem of managing variability in electric power systems is exacerbated when the supply of power, as well as the demand, is also variable. Conventional sources of supply, such as coal, natural gas, hydroelectric, and nuclear plants, afford steady supply of power on a day-to-day basis. This changes with the introduction of renewable energy sources, raising the important question of how, at what cost and at what level, renewable energy sources can be incorporated into electric power systems. That is the main subject we address in the present paper.

It is well known that solar PV supply is highly variable, even during the day and even in such favorable circumstances as Saudi Arabia. Figure 1 on page 3 illustrates. Using data for a typical meteorological year in Riyadh, Saudi Arabia, the plot shows considerable daily output variation. As we shall see, if we zoom in and look at the variation by hour the variability appears even more problematic.

Renewable energy sources, such as solar and wind power, are said to be *intermittent* because they are not continually available, even approximately so. Their availability varies with time of day, with day of the year, and with local weather conditions. This elemental fact raises fundamental challenges for incorporating high levels renewable energy sources into electric power systems, which

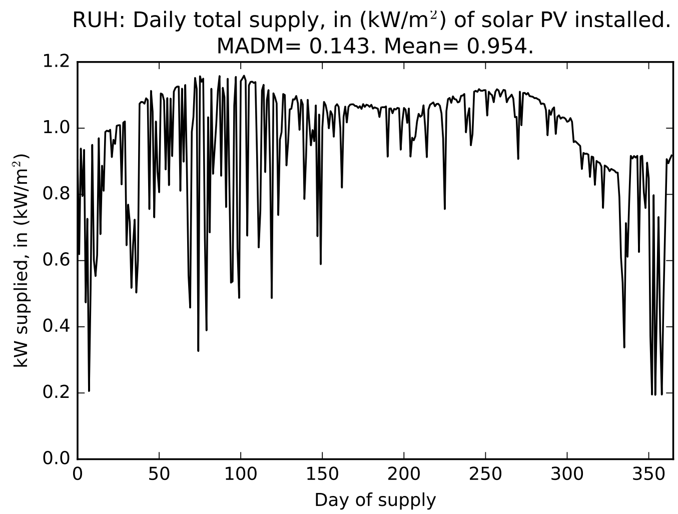


Figure 1: Total daily supply over 365 days per m^2 solar PV installed for Riyadh, Saudi Arabia, in a typical meteorological year.

must maintain supply and demand (load) balance at all times, within close tolerances. Were the cost of efficient electric storage negligible there would be no challenge, costs of the renewable sources themselves aside, for systems could be configured so as to provide real time availability to meet load demands from storage and to maintain an adequate buffer of storage to accommodate intermittent supply.

Alas, despite rapidly declining costs of solar energy, wind energy, and storage for electric power, integrating high levels of renewable energy sources and doing so at acceptable cost is a problem that will remain with us for the foreseeable future. This leads some authors, e.g., (Hall et al., 2014; Weißbach et al., 2013) to profoundly pessimistic conclusions about the future of renewable electric power. In any event, the prospect is for a continued need for careful design and optimization of heterogeneous energy systems if they are to be viable at all. These systems at least potentially incorporate renewable sources of electric power, fossil fuel sources (to be minimized insofar as possible), possibly nuclear, hydroelectric as well as other sources (e.g., geothermal, ocean waves), along with pricing regimes to encourage conservation and demand shifting (including demand response regimes), storage in multiple forms, and trade with regions in relative surplus or shortage (via transmission lines).

The design and optimization problem before us, then, is quite complex and will need to be approached in pieces and aspects. Further, the problem of finding adequate data to support this design and optimization process is itself daunting and at present not adequately solved. To state just some of the main factors, actual weather matters, insolation matters, wind profiles matter, design and use of buildings matter, incentives matter, human behavior matters, markets and institution designs matter, costs and operating characteristics of energy sources matter, and costs and operating characteristics of storage mechanisms matter. Not only are there no comprehensive benchmark data sets available, obtaining them is difficult and time-consuming, if it can be done at all. Even where it can be done, data from one location may be of questionable relevance for other locations. For example, full data for Riyadh from the Saudi Electric Company is hardly relevant for, say, Oslo, Singapore, or Seattle. Moreover, technical and market developments—services and their prices—are changing so rapidly that much of any given data set is at risk of being obsolete before it can be analyzed.

Given the foregoing as context, the work we report in this paper may be characterized (1) as addressing certain focused aspects of the design and optimization problem for integrating renewable energy, and (2) as making innovative use of an unusual and heretofore under-exploited source of relevant data.

Specifically, on (2) our unusual source of data is IES Virtual Environment (VE, `https://www.iesve.com/`, a BES modeling software package, along with meteorological and building data needed to drive building energy simulation (BES) modeling (also known as WBPA, whole building performance analysis modeling).[1] We designed a typical office building, placed it in Riyadh, Saudi Arabia, and in Philadelphia, PA, USA, and simulated its behavior, particularly its demand for electric power, on an hourly basis for a typical meteorological year for each location. In addition, we configured the building with solar PV of magnitude sufficient to make the building approximately energy neutral.

This at least is our baseline model, which we modify in the course of our analysis. BES models such as this basic model, whether undertaken with VE or other BES software (such as EnergyPlus andeQuest), afford very realistic sources of simulated data. They are sufficiently realistic that they are standardly used for designing and configuring buildings; real decisions are made based on these models and real money is spent implementing their designs. Our innovation is to begin with a standard design for a building, assume that its BES model is reasonably accurate, and then use the model, with varying inputs, to generate data we use for design optimization pertaining to electric power, specifically use of renewable energy. We call this general strategy by the name of *design inversion*, for we are, as it were, taking a design and turning it over to see how it works, and then modifying it.[2] Section 3 describes this baseline model in detail.

Regarding (1), focusing on only certain aspects of the design optimization problem, given that this is an inaugural study, we model as noted a typical office building placed in Riyadh and in Philadelphia, and consider various aspects of supplying it with solar PV.

In the baseline setup for our modeling and analysis, we situate a 'typical' office building in Riyadh, Saudi Arabia. The building is connected to the distribution grid and draws power from it. The building is also equipped with various forms of DER (distributed energy resources), in particular solar PV and electric battery storage.

We are interested in measures of performance having to do with the amount and variability of demand placed by the building on the distribution grid, and how these vary under different configurations of DER and operating policies. For example, without DER, what is the (yearly, daily, etc.) load placed on the grid by the building? What are the variability characteristics of this demand? How do these quantities change under different regimes of DER? And so on. The relevant design space is enormous and we cannot hope to canvass it thoroughly in a single paper. Instead, we focus on a number of especially interesting locations in the space where the findings constitute interesting contributions. In addition, the paper contributes methodologically in several ways, to be detailed below.

More specifically, we frame the problem conceptually as a constrained optimization problem,

[1]IES VE is a commercially available product. EnergyPlus is an important open-source alternative and is freely available. "EnergyPlus is a whole building energy simulation program that engineers, architects, and researchers use to model both energy consumption—for heating, cooling, ventilation, lighting and plug and process loads—and water use in buildings"—at `https://energyplus.net`, accessed 2015-12-07. eQuest `http://www.doe2.com/equest/` is another open source and freely available BES modeling tool, meant to be simpler and easier to use, "the QUick Energy Simulation Tool" as described on its Web page.

[2]Edwards (2010) uses the term inversion in a similar sense when discussing climate modeling. It has been necessary to "invert" meteorological models—to turn them over as it were and fiddle with them—to make them more useful for climate modeling.

whose multiple objectives include total demand to the public distribution grid (demand "in front of the meter"), peak demand, demand variability, and cost; all to be minimized. Constraints are present pertaining to satisfaction of demand, maintenance of adequate levels of comfort, and so on. Finally, decision variables include amounts of solar PV (photovoltaics), quantities of storage of various kinds, and demand response.

The principal questions we wish to address in our analysis have to do with the effects and trade offs of introducing various levels of solar PV, configurations of storage, and regimes of demand response on the several objectives mentioned above, particularly total demand from the distribution grid, peak demands, demand variability, and cost (although we focus a bit less on this, as it is so very much a moving target). Minimizing total demand, peak demand, and variability of demand on the distribution grid may each and all be seen as socially positive, ceterus paribus and in the long term. Reduced total demand may reduce the need for transmission facilities and other grid-level infrastructure as well as promoting a reduced carbon footprint. Reducing peak loads, as does reducing variability, presumably lessens reliance on special very expensive services, such as peakers, spinning reserves, and other providers of ancillary services. Thus, in general reducing these values creates positive network externalities and increasing them produces negative externalities. We wish to discover them, or rather learn something about them, through the present modeling effort.

Our main findings are that (i) adding even fairly large amounts of solar PV to the building reduces both peak demands and variability of demand as seen by the grid, (ii) if the solar PV is curtailed or redirected when in excess of immediately needed power, then very large amounts of solar PV can be added with continued reduction in demand variability as seen by the grid, and (iii) adding battery storage to the system results in modest reductions in variability but heavy reductions in peak demands during the summer.

The paper is organized as follows. §3 discusses our baseline model in detail. It and variations on it will be used throughout the paper. §4, "Initial Explorations," presents the fundamental facts of the nature of the demand (load) generated by the building, including totals, peaks, and variability. The section also presents corresponding findings on the supply side for solar PV. §5 "Effects of Adding Storage," examines the effects on our three primary measures of interest (grid-facing demand, peak demand, and demand variability) in the presence of various levels of solar PV, and in the presence of various levels of solar PV combined with various levels of storage.

§8, "Discussion and Conclusion," concludes the paper by summarizing our findings, commenting on their significance and pointing towards future research in which single building models, such as discussed here, may be proliferated for the sake of modeling entire distribution grids.

3 The Baseline Model

The model is designed to allow exploration and optimization of various ways to satisfy the building electricity demand using some combination of on-site renewables (PVs), storage, and the local power grid.

The energy model is used to predict the annual electricity demand of the office building at every hour over a year, given a year's worth of data. We used a typical meteorological year (TMY) for the data. Electricity is supplied either by PV arrays, from battery storage, or from the local electricity grid.

There are four high-level decision variables: The amount of PV, the amount of expensive storage, the amount of cheap storage, and the peak capacity of the local grid. The latter is not constraining in our results, so we do not discuss it further. In addition, the storage devices have parameters.

PV orientation is optimized to provide the maximum cumulative annual output at the location of the building.

There are two possible storage systems. An efficient, expensive battery and a cheaper, less efficient energy-storage system (e.g., hydrogen fuel cells.)

3.1 Building Demand control system / order of operations

This electricity demand can be satisfied from one or more of four sources at each moment. These sources are ranked in order of employment:

1. Directly from the PV array
2. Using the expensive battery (if it exists)
3. Using the cheap battery (if it exists)
4. From the local power grid

The building management system initially attempts to satisfy the raw demand from source (1), the PV array. If this is insufficient then it searches sequentially through the expensive battery to the cheap battery in search of the electricity required to meet the current demand. If the demand is still unmet by these sources then the system will satisfy the remaining demand by drawing electricity from the local grid. In this way renewable energy is used greedily. If the local grid is unable to supply the available power then the system reports an unmet electricity load.

3.2 PV control system / order of operations

Ideally the PV supplies energy to the building directly, but the array may supply more electricity than the building requires at any given moment over the year. In this case, the system will attempt to supply:

1. The expensive, high efficiency battery
2. The cheap, low efficiency battery
3. The local grid (although we also consider curtailing power at this point and not returning it to the grid)

Because the expensive battery is the most efficient, it is charged first. Only if this battery is already fully charged will the system attempt to charge to cheap battery at low efficiency. When building demand is fully satisfied and both batteries are charged, then any surplus electricity will be sold to the local grid at a lower price or curtailed.

Figure 2 presents a picture of the building energy model's geometry. Figure 3 shows the building's set points and operation hours. Figures 4 and 5 show schematics of the building's ground floor and an office floor.

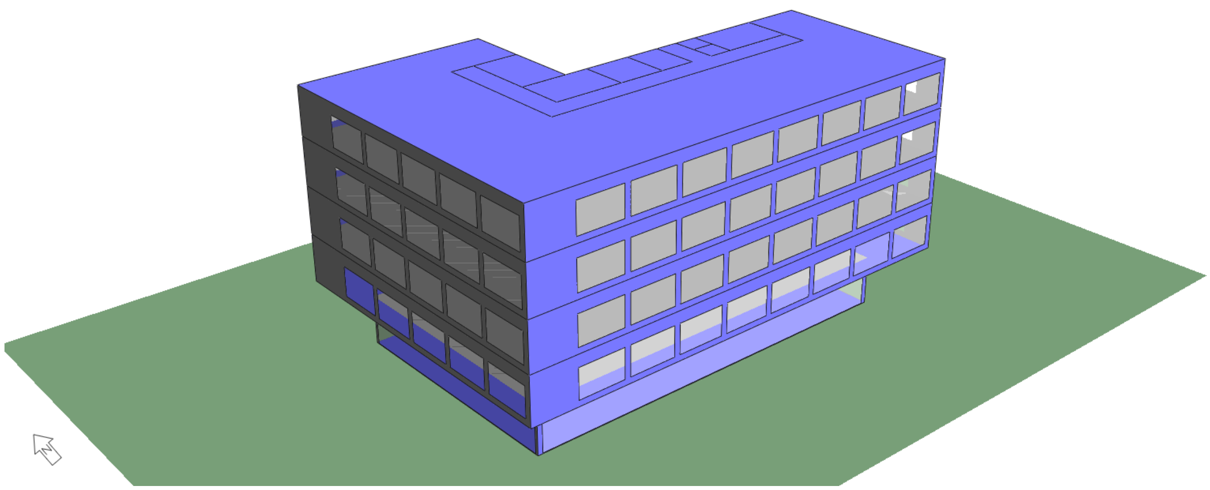


Figure 2: Building Model Geometry

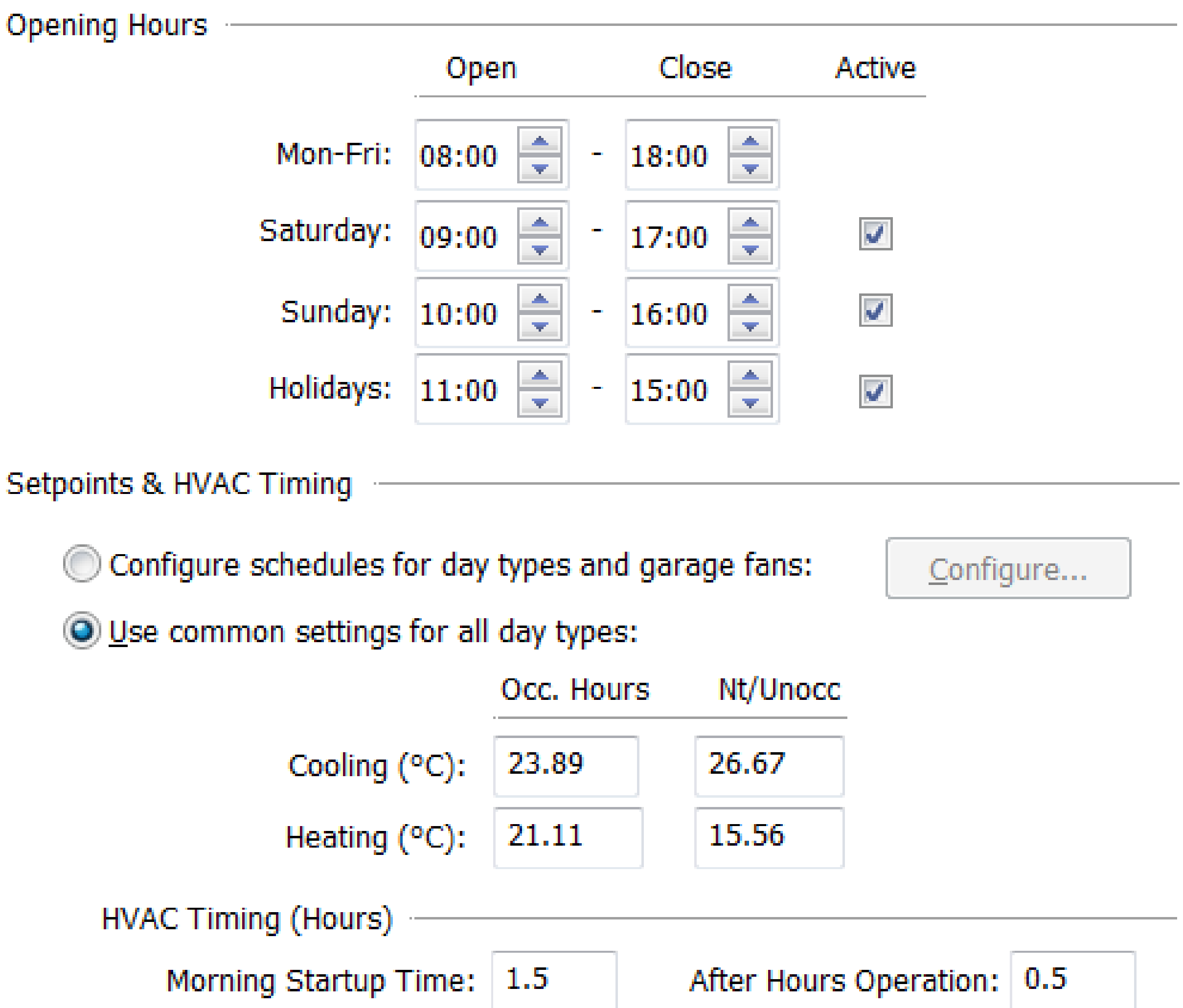


Figure 3: Building Model Set Points and Operation Hours

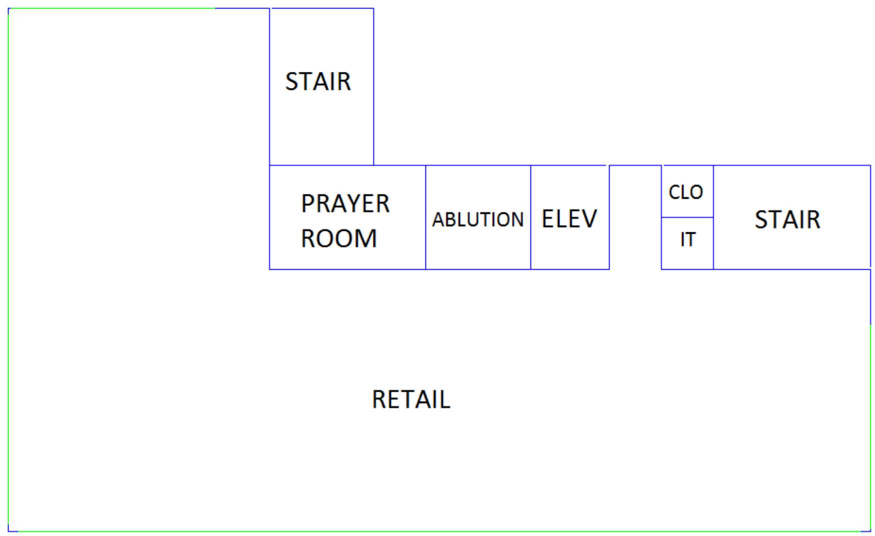


Figure 4: Schematic of ground floor.

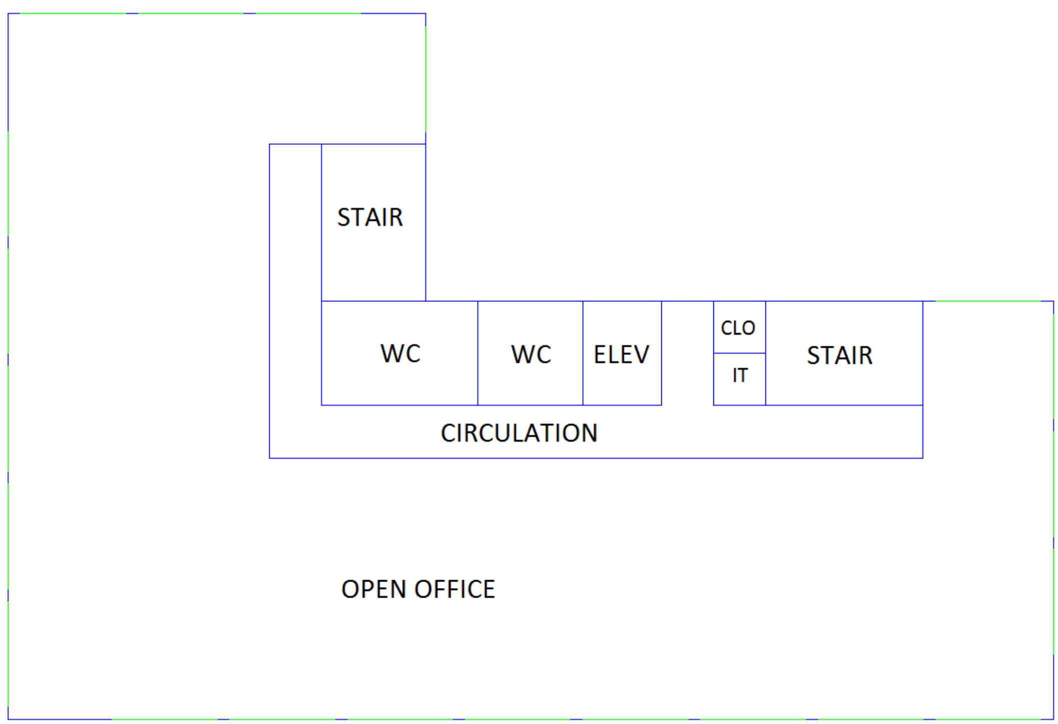


Figure 5: Schematic of office floor.

3.3 Typical Office Building in Riyadh - Description of the Energy Model

A typical building is used for the case study. The building is a mid-rise office building with 3810 m^2 of floor. All floors are used for offices, except the ground floor which is retail space. The cooling and heating is provided by terminal fan coil units with fresh air supplied by dedicated fresh air handling units. Fresh air demand is calculated according to ASHRAE 62.1. Internal gain values and profiles are based on ASHRAE 90.1 and the 90.1 User's guide.

Space use breakdown:

- 2520 m^2 open office plan space
- 438 m^2 retail space
- 312 m^2 corridor/transition space
- 20 m^2 electrical/mechanical space
- 20 m^2 inactive storage space
- 24 m^2 prayer room space
- 176 m^2 restroom and ablution space
- 240 m^2 stairs
- 60 m^2 elevators

The opaque walls have a U-value of 0.26 W/m^2-K (K is temperature Kelvin).[3] The window U-value is 1.7 w/m^2-K (including window frame). The windows have a solar heat gain coefficient (SHGC) of 0.4.[4] The roof has a U-value of 0.18 W/m^2-K.

The envelope allows an average outdoor air infiltration of 0.1 air-changes per hour (ACH) continuously. This reflects a good practice facade construction with pressure testing.

The annual weather data source for Riyadh is an ASHRAE IWEC typical year based on WMO weather station 404380.

The energy simulation is done using IES 2014.2.1, a whole building energy modelling software in compliance with ASHRAE standard 140. The energy model is run at peak conditions and dynamically over a typical year at a 1 minute time step. Each room in the building is represented as a thermal zone containing a certain volume of air at certain psychometric conditions. These thermal zones are adjacent to each other and, if they are on the edge of the building, to the ambient weather. The sun position is calculated over a year based on longitude and latitude. The intensity of solar radiation is based on the hourly data in the weather file.

3.4 Basic Description of the Philadelphia Model

A second office building energy model was created in Philadelphia. The layouts, constructions, fresh air requirements, lighting systems, small power loads, and occupancy density/profile are identical in the Philadelphia energy model. The heating and cooling terminal units and fresh air handling units have been resized based on the heating and cooling conditions of Philadelphia.

[3] U-value is a measure of heat transfer through a wall, roof, or window. Conduction heat gain in a building is the result of the U-value and temperature difference between inside and outside. U-value is the inverse of R-value: U-value = 1/R-value. More insulation translates to a lower U-value.

[4] Solar heat gain coefficient is a measure of solar heat transfer through a window. It is the ratio of the solar energy that actually enters the building through a window to the total solar energy falling that window.

4 Initial Explorations

In this section we undertake an exploratory analysis of the baseline model as driven by the typical meteorological data. Model outputs are by hour, of which there are 8760 over the course of 365 days. Our aim here is to display the main results of the model as they pertain to the problem of integrating solar PV and accommodating it into the distribution grid.

Figures 6 and 7 illustrate over two days the typical daily cycle of demand (load) for power, by hour in kW, and solar insolation per square meter. Demand and insolation broadly move on a common cycle, high during the day and low during the night, with insolation much more peaked than demand, which is fairly flat during the day. Notice, comparing the figures, that the natural match between demand for power and solar insolation varies somewhat by time of year.

Nevertheless, there is a stable congruence between demand for electric power in the building and ambient solar insolation, suggesting a good opportunity to use solar PV to meet the demand.

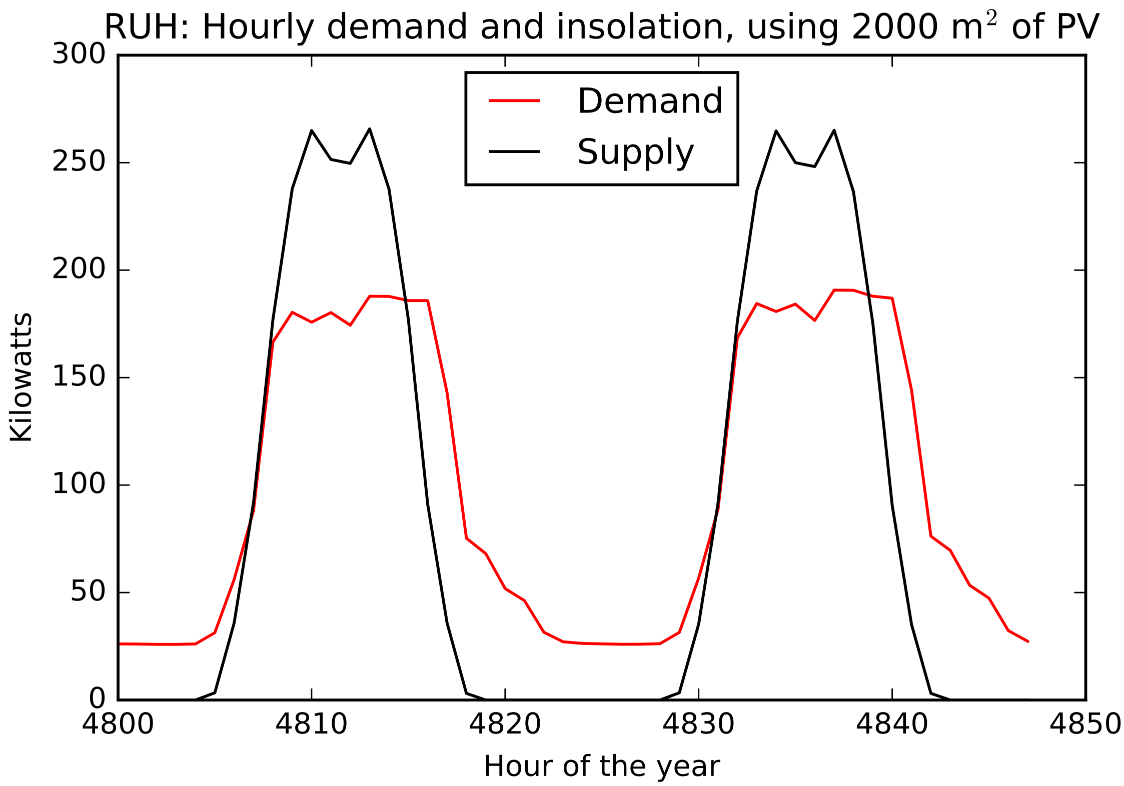


Figure 6: Demand and insolation, days 200 and 201.

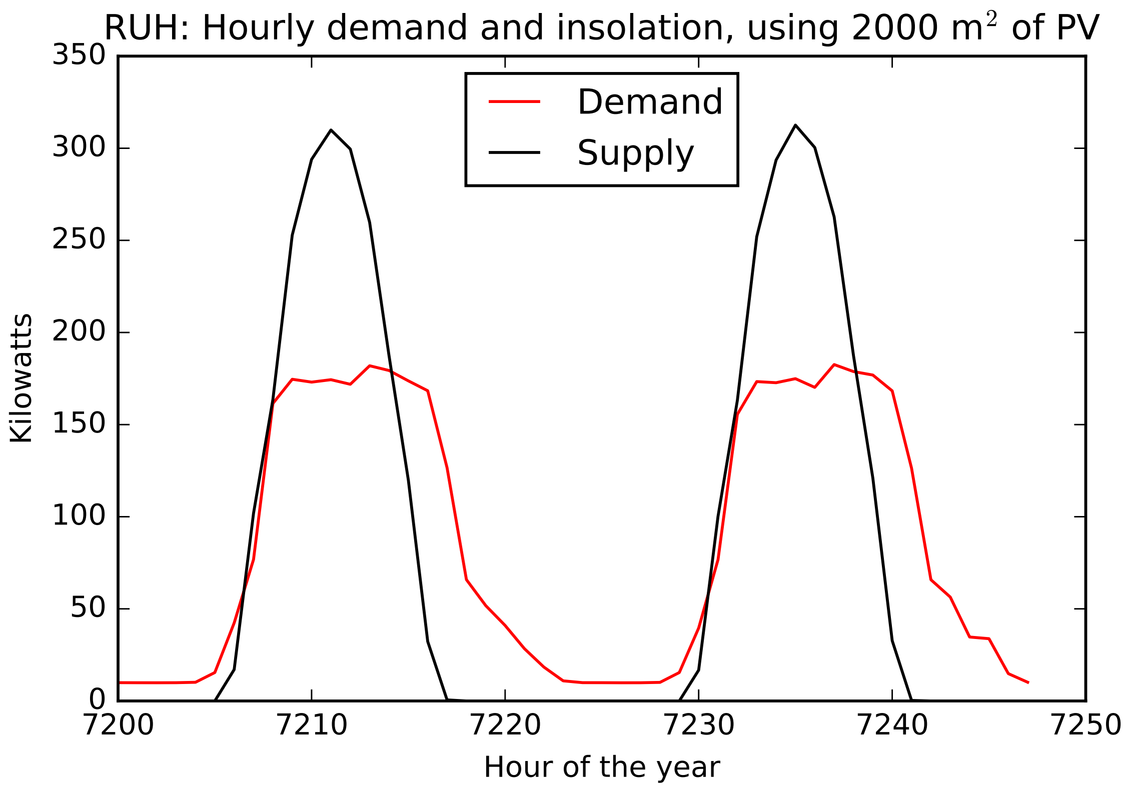


Figure 7: Demand and insolation, days 300 and 301.

Figures 8 and 9 present the analogous results for the Philadelphia office building.

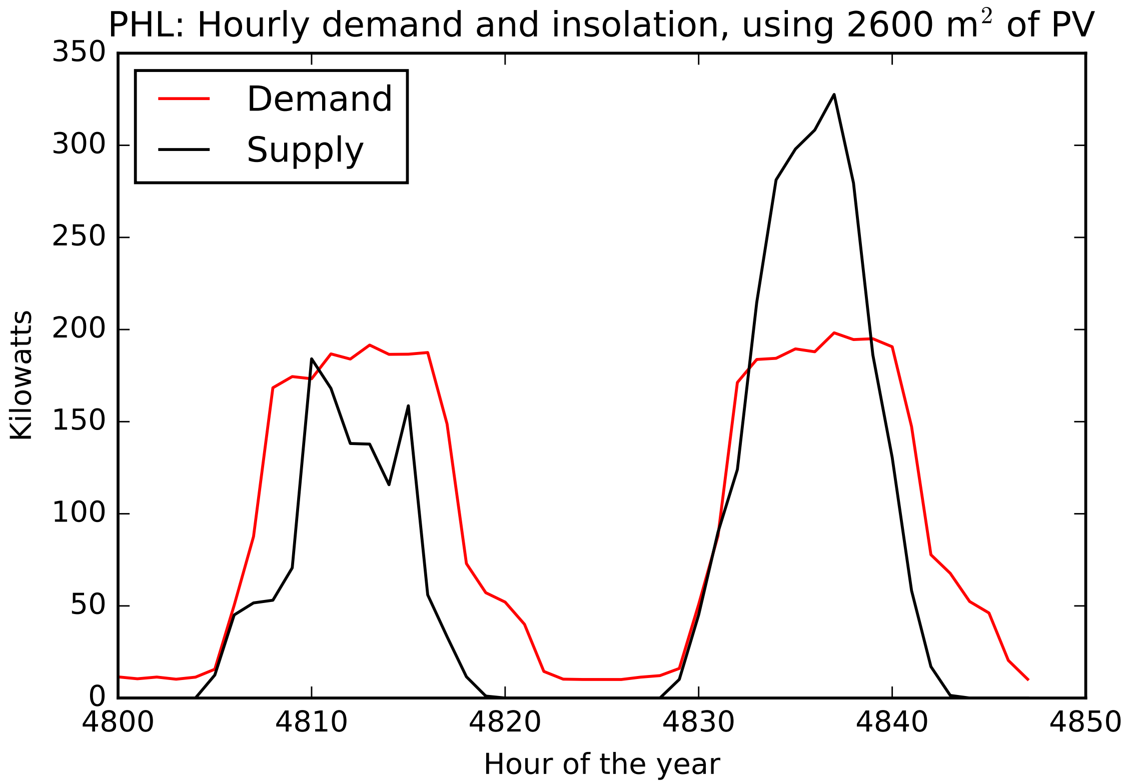


Figure 8: Demand and insolation, days 200 and 201.

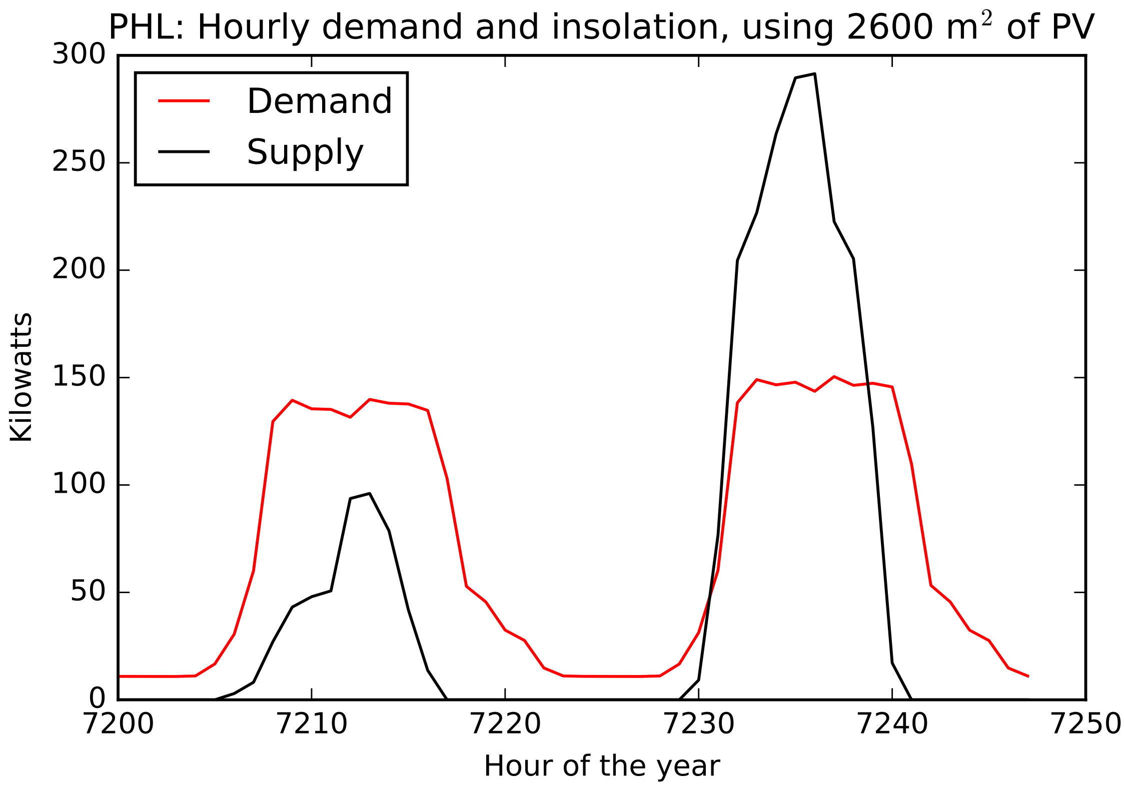


Figure 9: Demand and insolation, days 300 and 301.

4.1 Daily Highs and Lows of Demand

4.1.1 Peaks

The patterns of peak and minimum demand from the building are especially relevant to the matter of accommodating solar PV. Figure 10 displays the daily peak demands in Riyadh (top) and Philadelphia (bottom), measured over an hour, for the 365 days modeled.

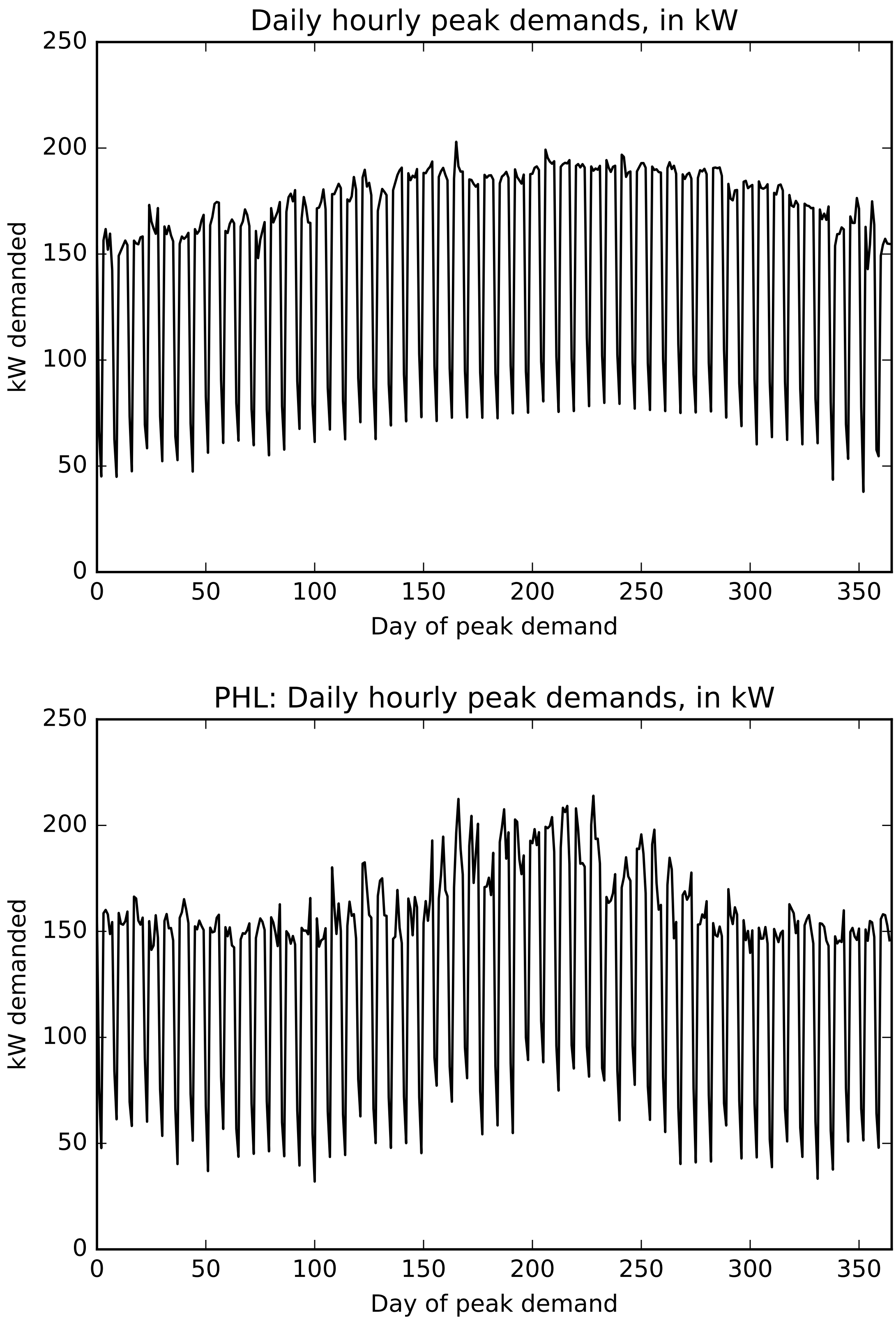


Figure 10: Peak hourly demands over 365 days (Riyadh, top, Philadelphia, bottom).

The figure shows a modest increased demand during the summer months, as would be expected. What is perhaps surprising is the overall shape of the plot, which resembles a thick band. This is due to weekly cycles, as illustrated in Figure 11, which zooms in on the macro pattern.

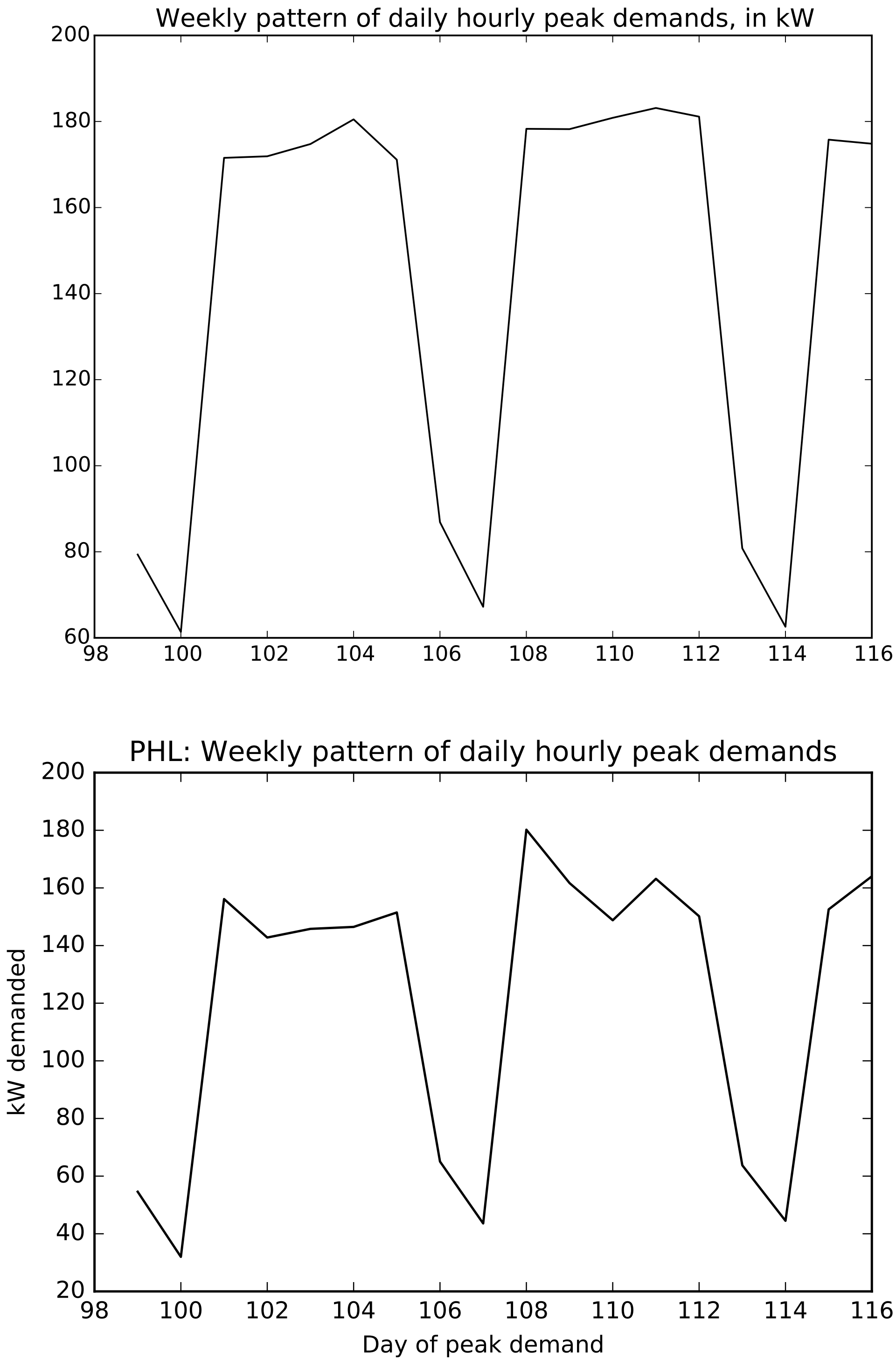
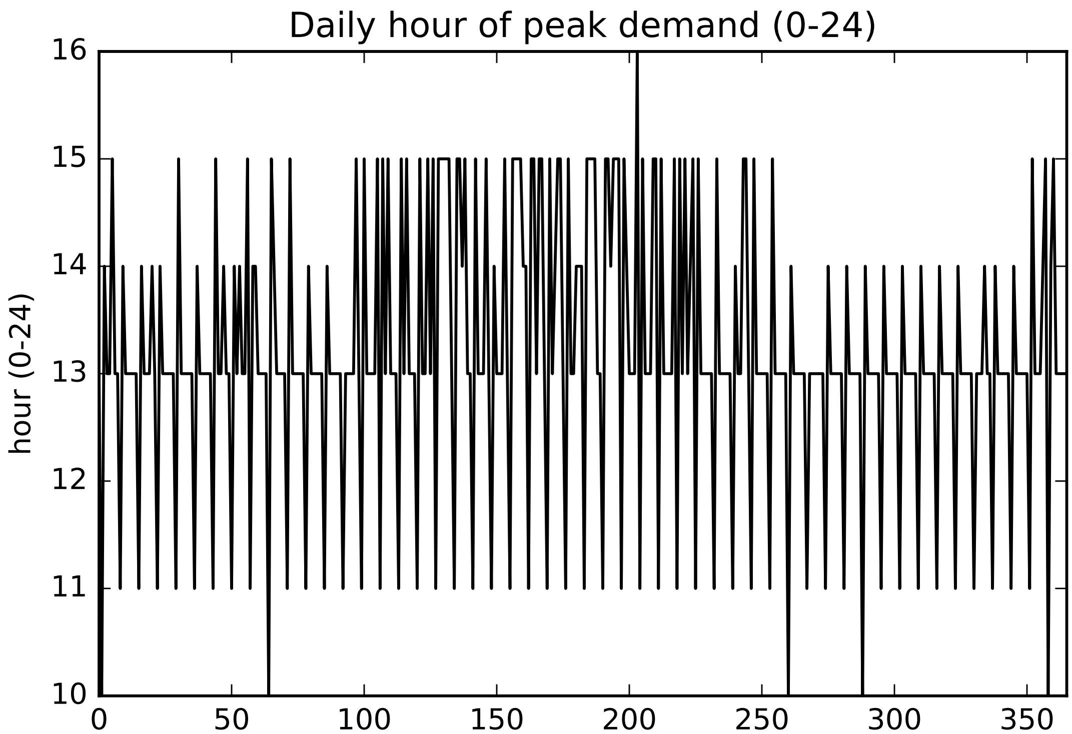


Figure 11: Peak hourly demands over 18 days (Riyadh, top, Philadelphia, bottom).

As modeled, the office building operates on a seven day cycle of 5 days of use followed by 2 days of non-use. (The model does not capture holidays and other events that result in deviations from this pattern.) Demand for electric power is high during the work week and low during the 2 weekend days. Days of the year are counted starting at 0, with day 0 being the last week day in a cycle, days 1–2 being weekend days, and days 3–6 being work week days. This pattern is maintained throughout the year. Looking at Figure 11, day 101 is the first day of a work week because `(101-3) % 7` (101-3 modulo 7) equals 0. Similarly, day D is the first weekend day of a week if `(D - 1) % 7` equals 0.

Next, we look at hours of the day in which the peak demands occur. See Figure 12.



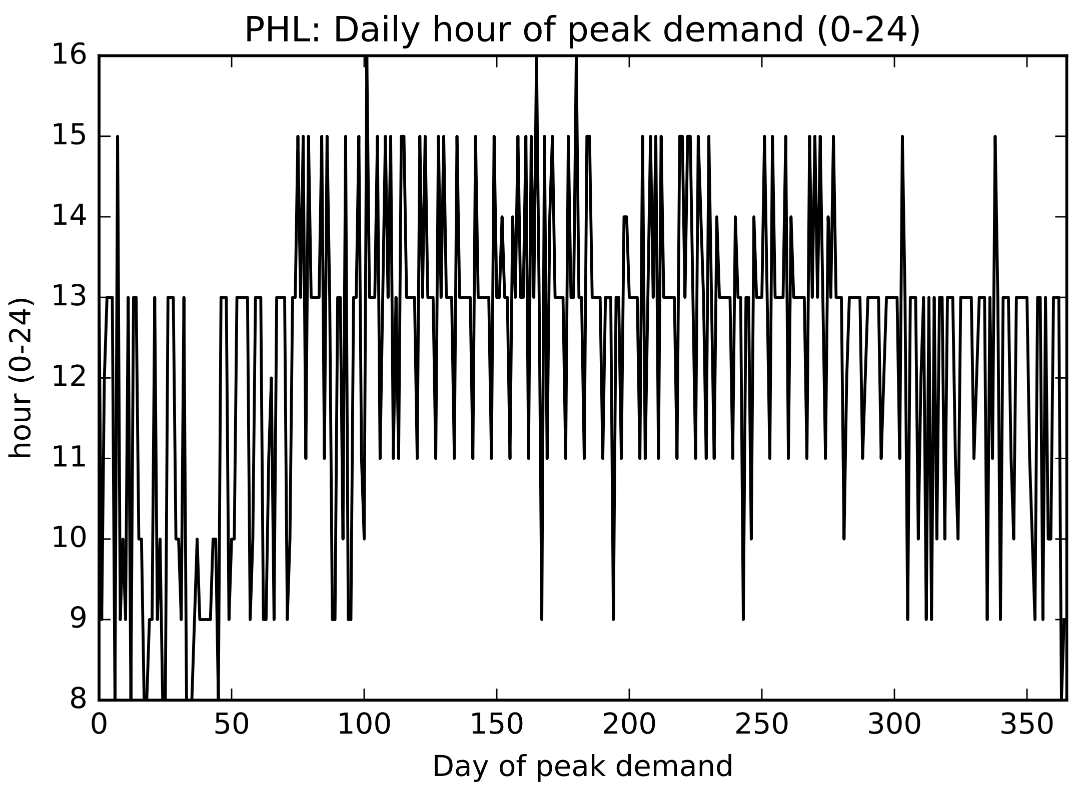


Figure 12: Hours of peak demands over 365 days (Riyadh, top, Philadelphia, bottom).

With just a few exceptions, the peak demands occur between 11:00 and 15:00, with an apparent concentration between 13:00 and 15:00.

Figure 13 zooms in as before on days 99–116. Notice that the 11:00 readings all occur on the first weekend days (99, 106, 113).

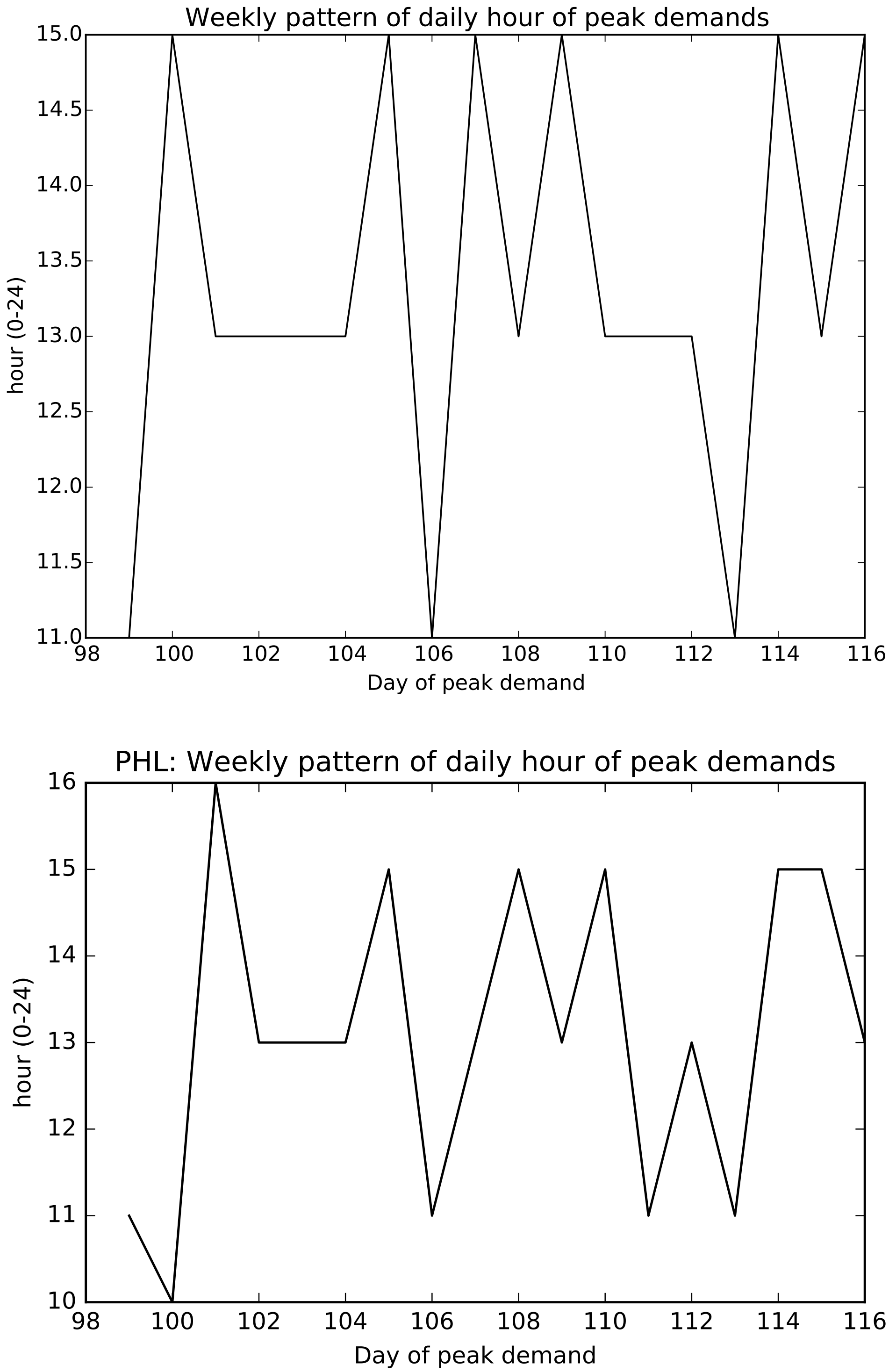
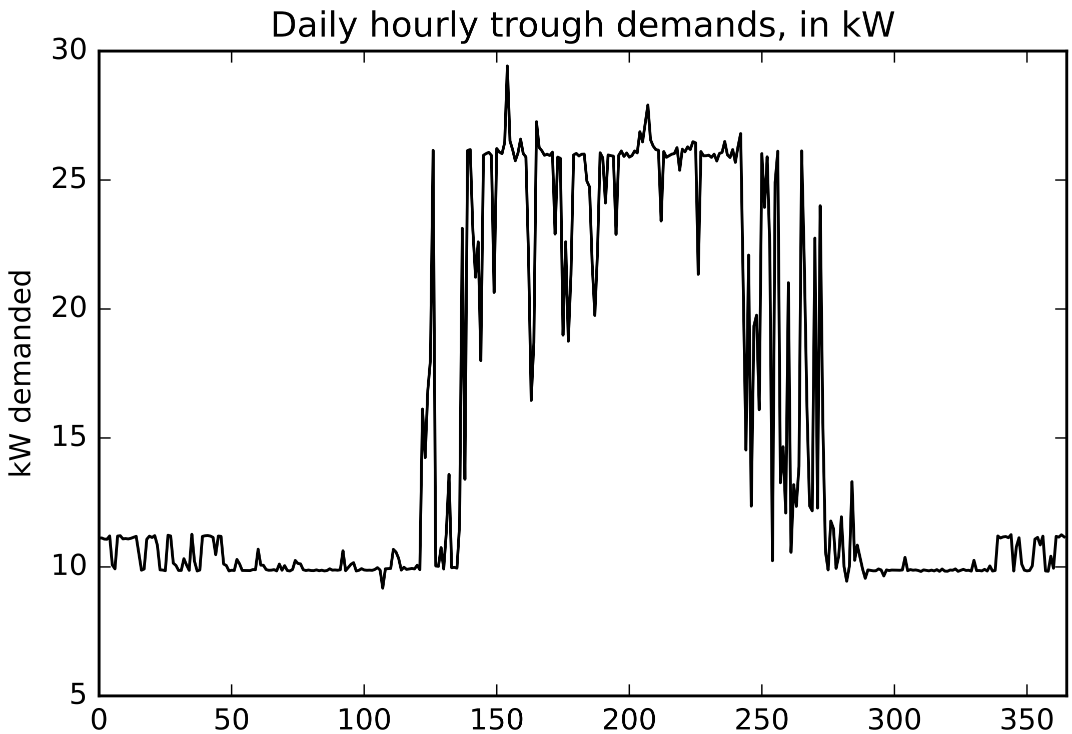


Figure 13: Hours of peak demands over 18 days (Riyadh, top, Philadelphia, bottom).

4.1.2 Troughs

We turn now from maximum demands to minimum demands, or troughs of demands. Figures 14–17 correspond to the previous Figures 10–13.

Figures 14 shows a remarkably different pattern than its analog for peaks, Figure 10. Troughs are relatively stable except during the middle of the calendar year (summer), when they increase substantially both in magnitude and variability.



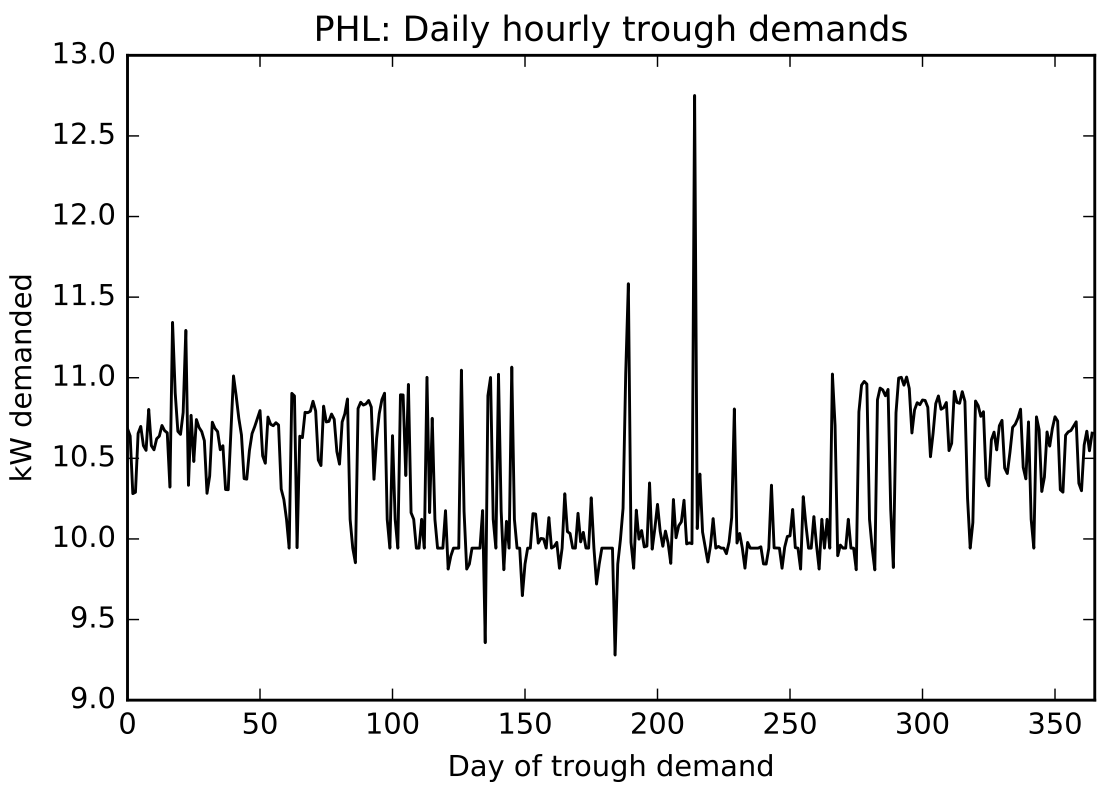


Figure 14: Trough hourly demands over 365 days (Riyadh, top, Philadelphia, bottom).

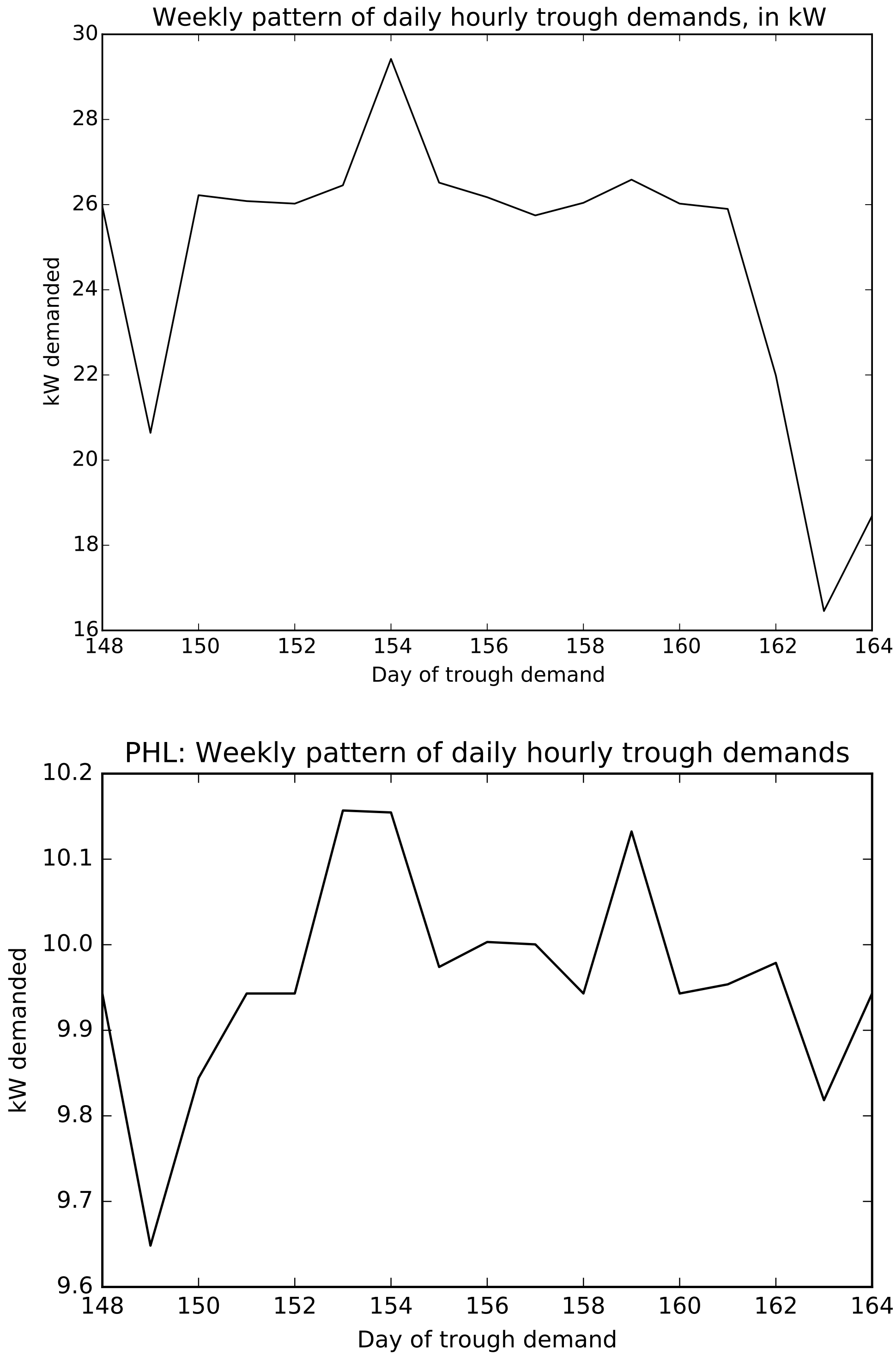


Figure 15: Trough hourly demands over 18 days (Riyadh, top, Philadelphia, bottom).

Zooming in to days 148–164 (during the summer; day 148 is the first of two weekend days) we see a fairly steady trough during week days.

Next, we look at hours of the day in which the peak demands occur. See Figure 16.

Figure 17 zooms in on days 148–164. Notice its similarity with Figure 13.

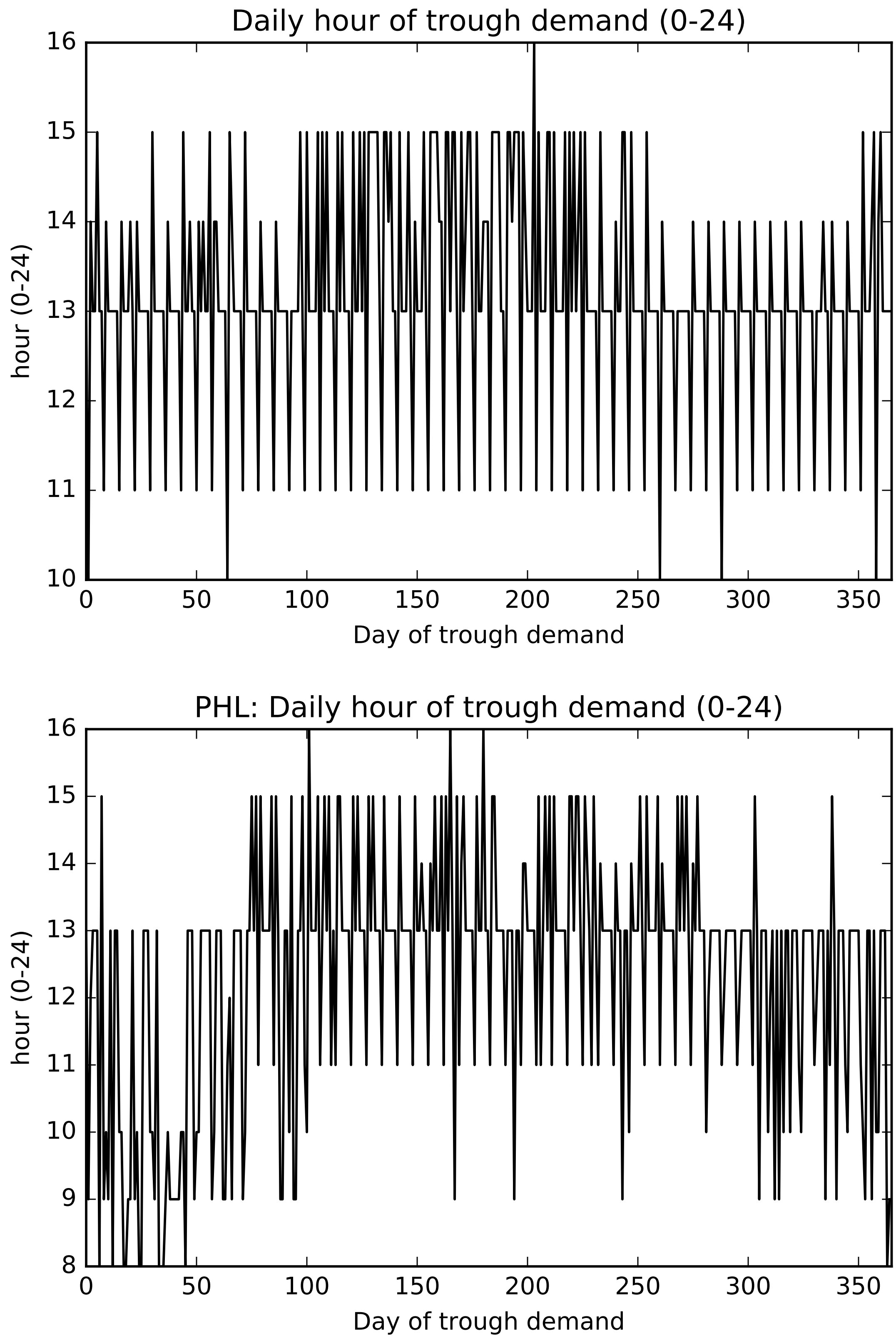
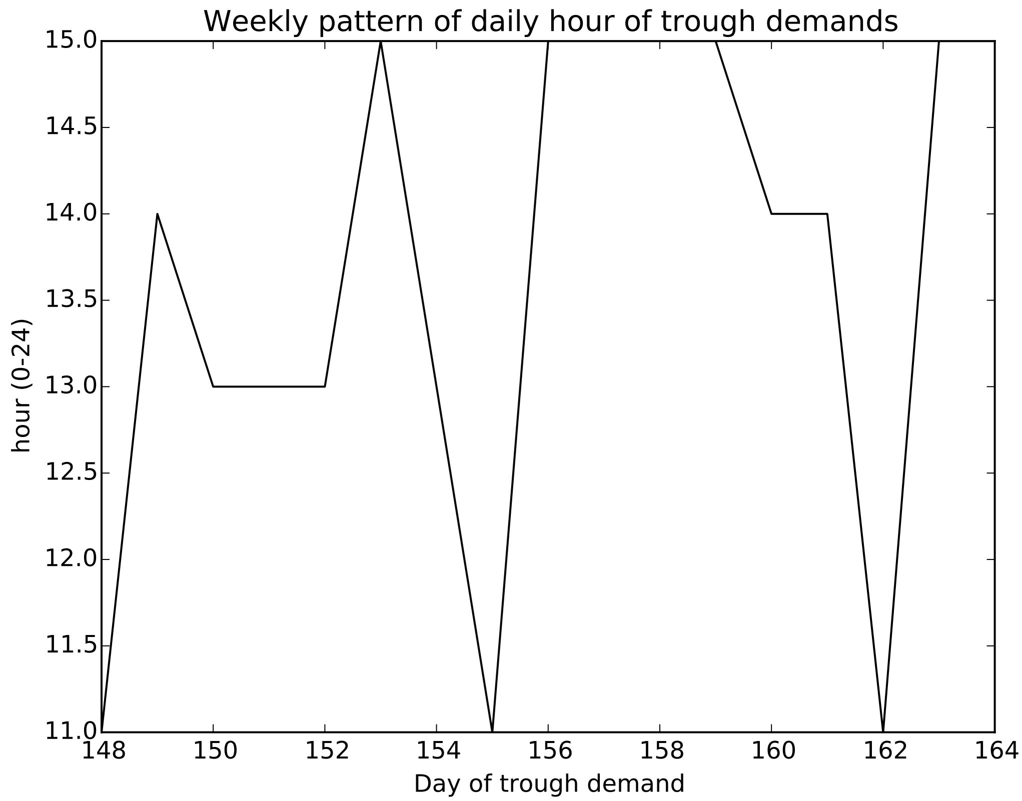


Figure 16: Hours of trough demands over 365 days (Riyadh, top, Philadelphia, bottom).



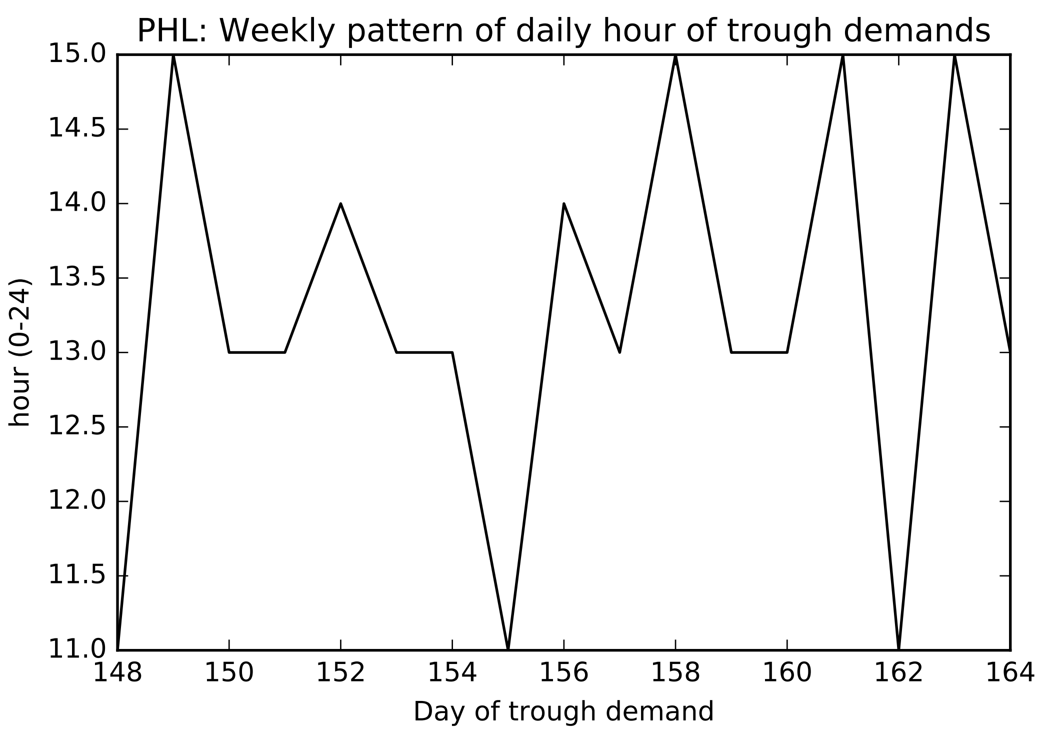


Figure 17: Hours of trough demands over 18 days (Riyadh, top, Philadelphia, bottom).

4.1.3 Total Demand

Figure 18 plots the total demand by day. Note its strong similarily in pattern with the plot of peak hourly demands in Figure 10.

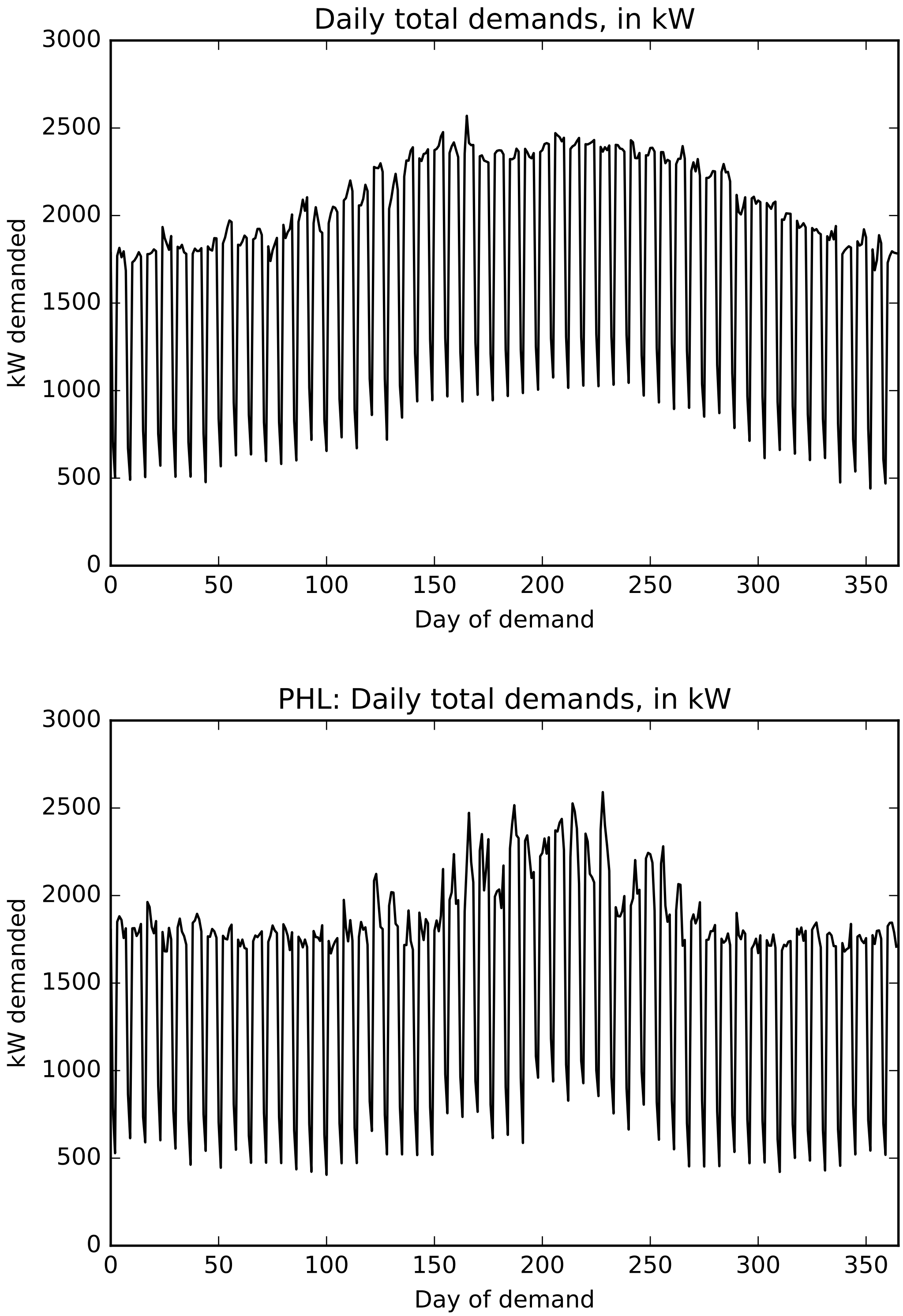


Figure 18: Total hourly demands over 365 days (Riyadh, top, Philadelphia, bottom).

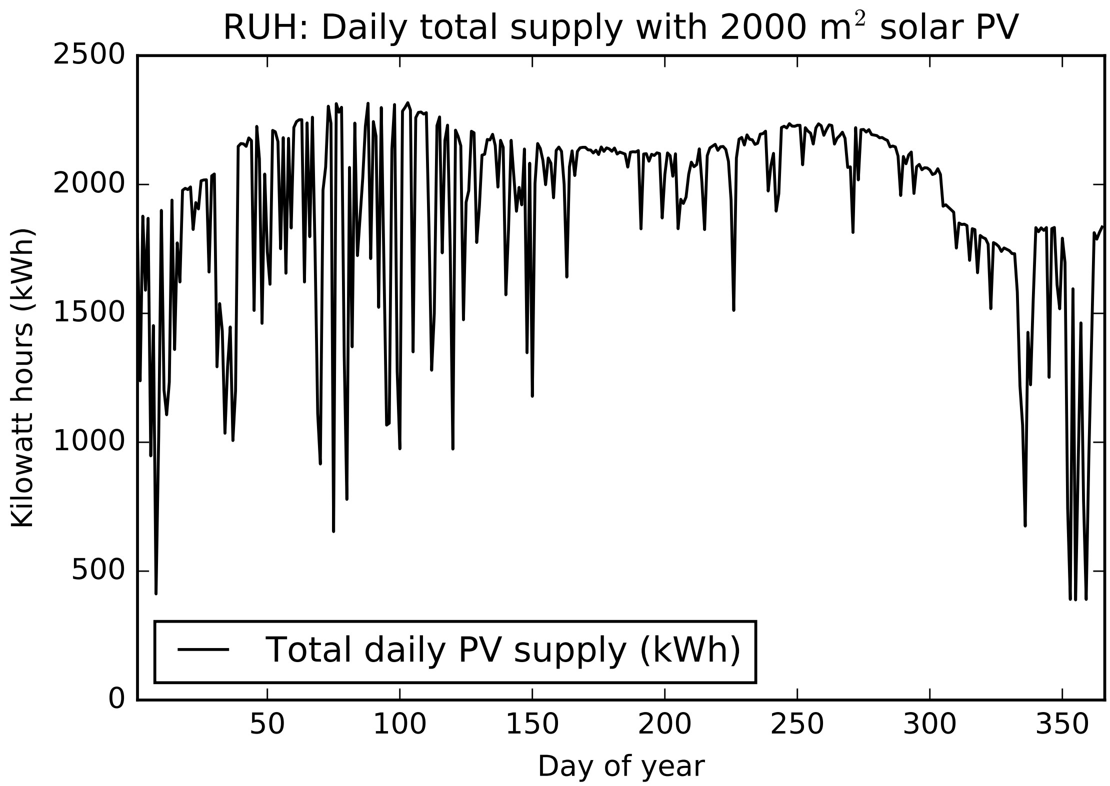
4.1.4 Discussion: Variability of Demand

This exploratory analysis reveals a robust pattern of demand variability on a weekly basis, with generally high demand on weekdays and low demand on weekends. This variability is much in excess with variability introduced by time of year, although that too is substantial.

4.2 Variability and Solar PV

Figure 19[5] shows considerable daily output variation evident in our data for a typical meteorological year. If we zoom in and look at the variation by hour over, say 5 arbitrary days of a representative period during the year we get Figure 20 and, with less regularity, Figure 21.

[5]This echoes Figure 1 but now shows the output produced according to the model with 2000 m^2 installed solar PV.



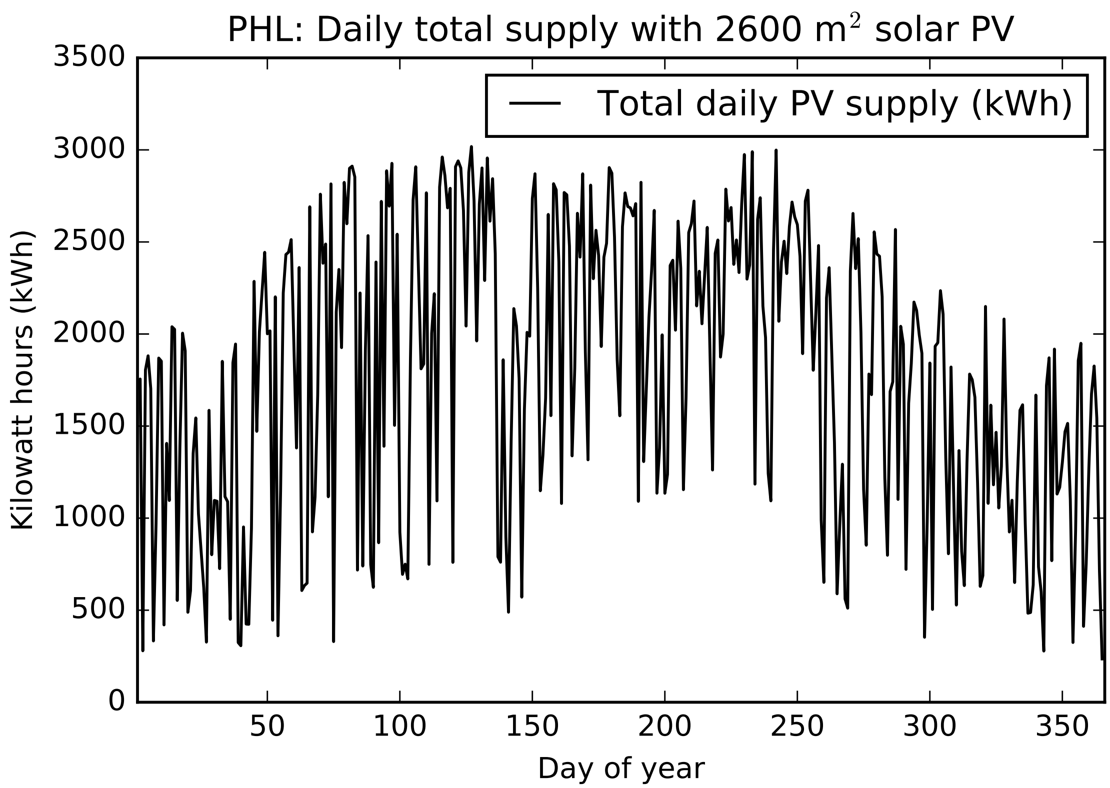


Figure 19: Total daily supply over 365 days with 2000 m^2 installed of solar PV.

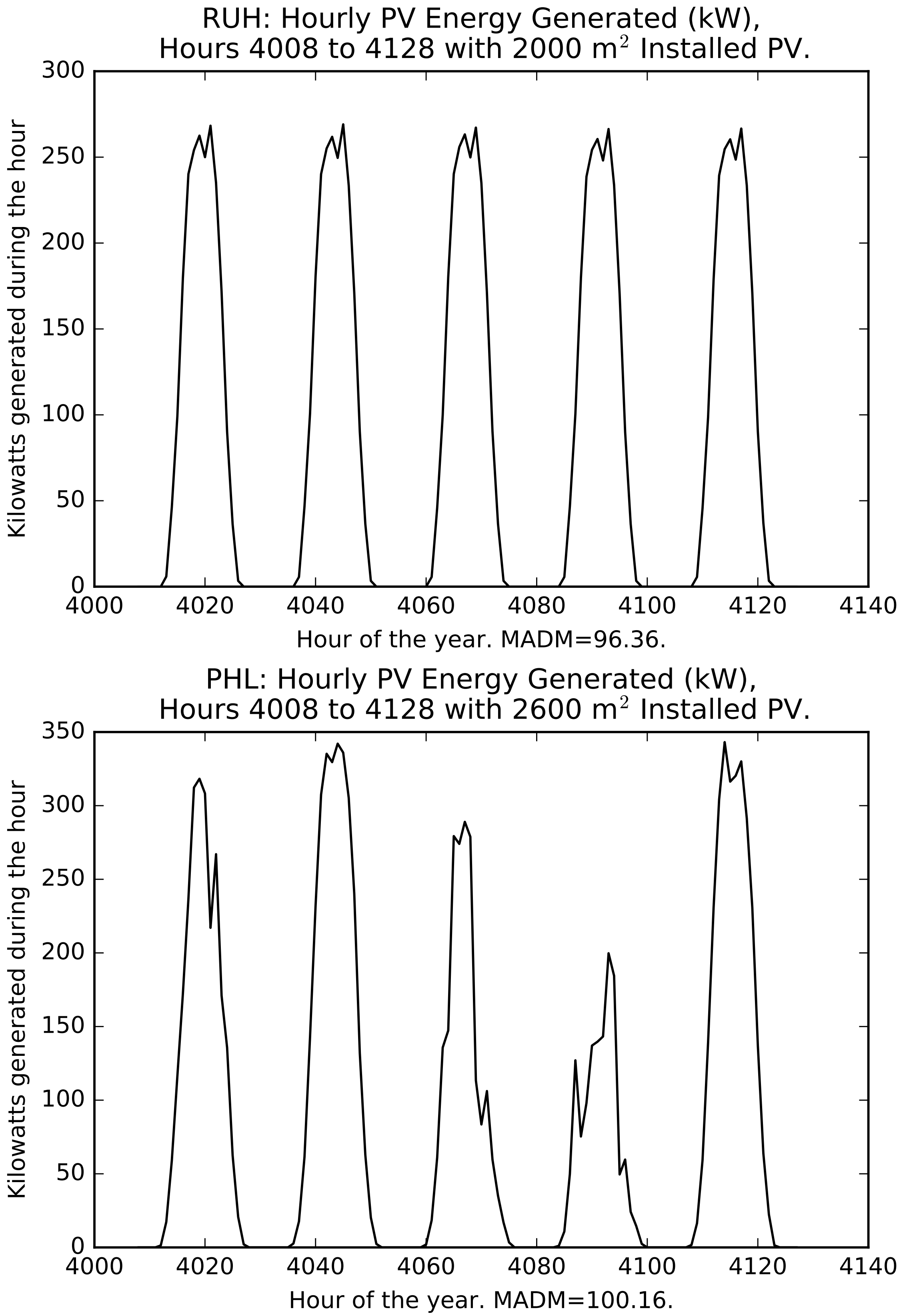


Figure 20: Hourly PV Supplied

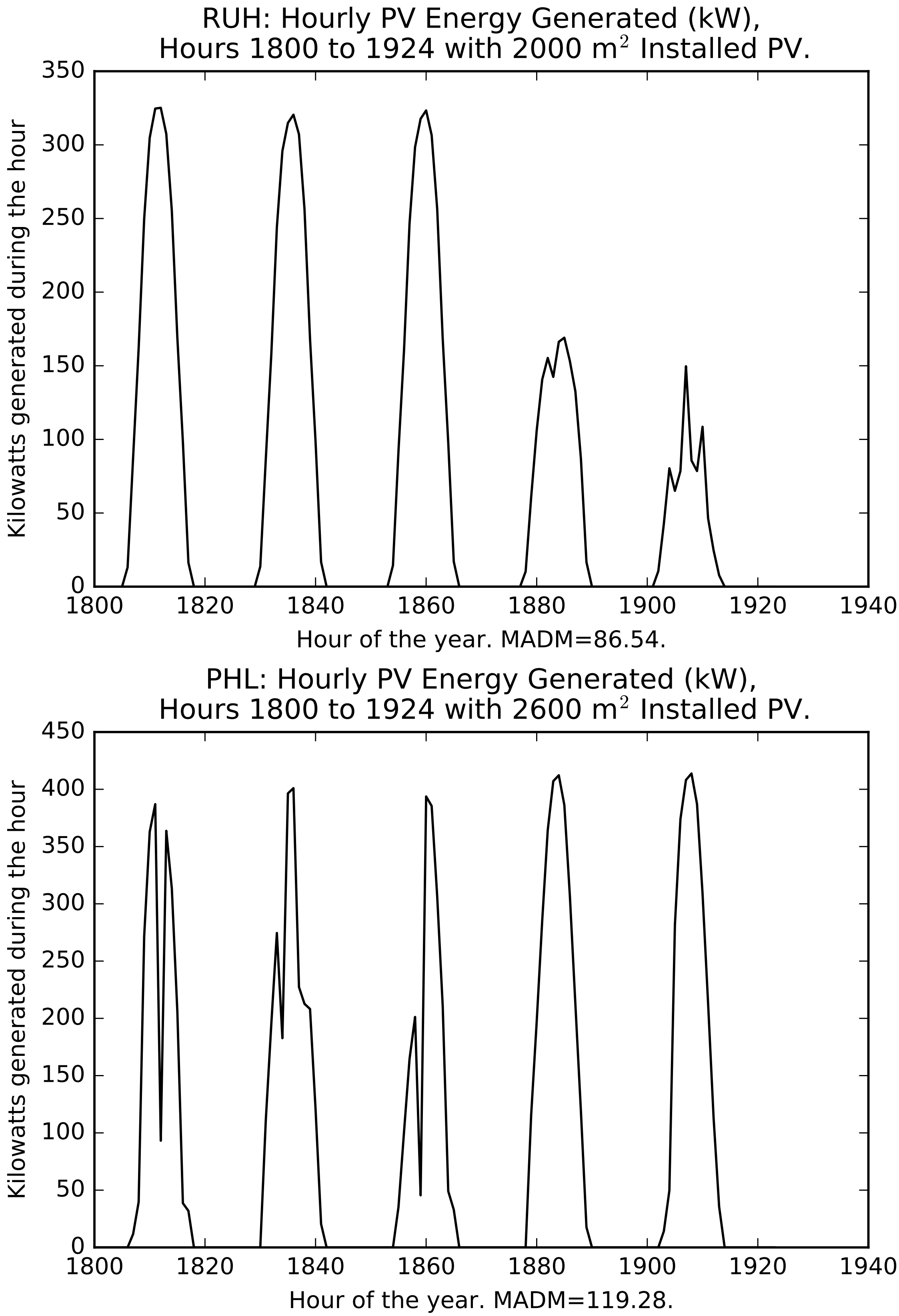


Figure 21: Hourly PV Supplied

The mean absolute deviation about the mean (MADM pronounced "madame") is an appropriate measure of the variability of demand (load) over a year.

$$\text{MADM} = \sum_{i=1}^{n} \frac{|x_i - \bar{x}|}{n} \tag{1}$$

We coded in Python and used:

```
def MADM(aSeries):
    '''
    Mean absolute deviation from the mean.
    Given a Series, aSeries, calculates and returns the mean
    absolute deviation from the mean of the series.
    '''
    return ((aSeries - aSeries.mean()).abs()).mean()

print(MADM(PVPower['Energy Demand (kW)']))
```

The model's value is 55.54 for Riyadh and 53.46 for Philadelphia, which is to say that on average over the year the realized demand for power during a given hour differs from the average demand by 55.54 kW in Riyadh and 53.46 in Philadelphia.

With the baseline case solar PV configuration for Riyadh, if we apply generated solar power against demand at the time of generation but do not put excess supply back to the grid, we have MADM = 21.01, a very considerable reduction. If, however, we put the excess solar product back on the grid we get 50.64, which amounts to only a slight decline in variation seen by the grid, although the total demand drops from 642,652 kWh to 203,136 kWh.

Here an important measure is FIU, for fraction immediately used. If we apply the solar PV power to the building's immediate (hourly) demands and neglect any power not used for this purpose we get the FIU. In the present baseline case (Riyadh), FIU = 0.66, that is, of the total solar PV generated over the year, above 669,487 kWh, about 66% can be immediately used (without storage) by the building. This produces the MADM above of 21.01, compared to 55.54 without any solar PV supply. Thus, *if* the cost of the installed solar PV times $\text{FIU}^{-1} = 1.52$ is economically viable for the 439,516 kWh actually used, then it would be economically viable to install the solar PV and discard ("curtail") the 229,972 kWh of over supply. Depending on the costs of alternatives to solar (we should also factor in air pollution and health costs) and the value of *reducing* variability, it may well be attractive to do this. Even so, there remains the possibility of using the over supply and gaining value from it. So we now we will examine that.

With our baseline case expensive battery configuration this drops considerably in Riyadh, `MAD(CB['Unmet Demand']-EB['Excess PV eletricity after charging'])` = 23.02, which is only slightly higher than the 21.01 we get by keeping all of the solar PV off of the grid. Thus the variability of grid-side demand is less than half of what it is without solar and without the battery.

When we introduce our base case cheap battery we get `MAD(CB['Unmet demand'] - CB['Excess PV eletricity after charging'])`=10.30, a quite considerable drop from the original 55.54. With this configuration the net annual demand on the grid is not only considerably reduced, but the variability of the demand has dropped considerably. This has some positive value, ignoring the cost, a subject we consider in the sequel.

Figure 22 compares the daily total PV supply and building demand for the baseline cases in Riyadh and Philadelphia. In both cases, and especially in Philadelphia, we see considerable volatility of solar supply. Figure 24 shows for Riyadh the hourly total demand for a 1000 hour period.

Considerable variation is present, with a regular pattern of reduced demand on the weekends. Figure 24 shows for Riyadh the hourly demand, net of solar supply, for the same period. The overall pattern resembles that of Figure 24 (total demand), but has reduced magnitude and MADM.

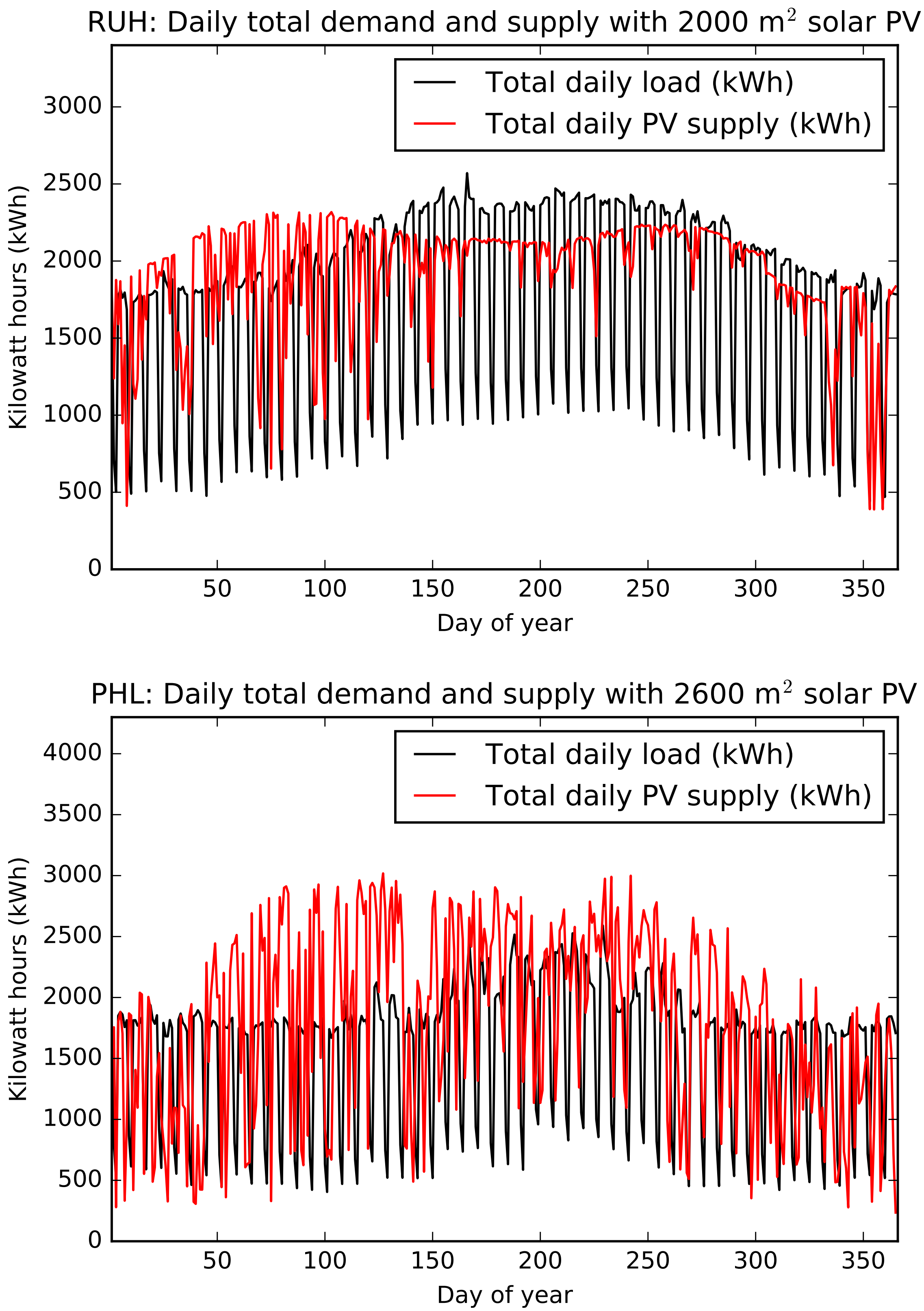


Figure 22: Total hourly supply over 365 days of solar PV compared to demand.

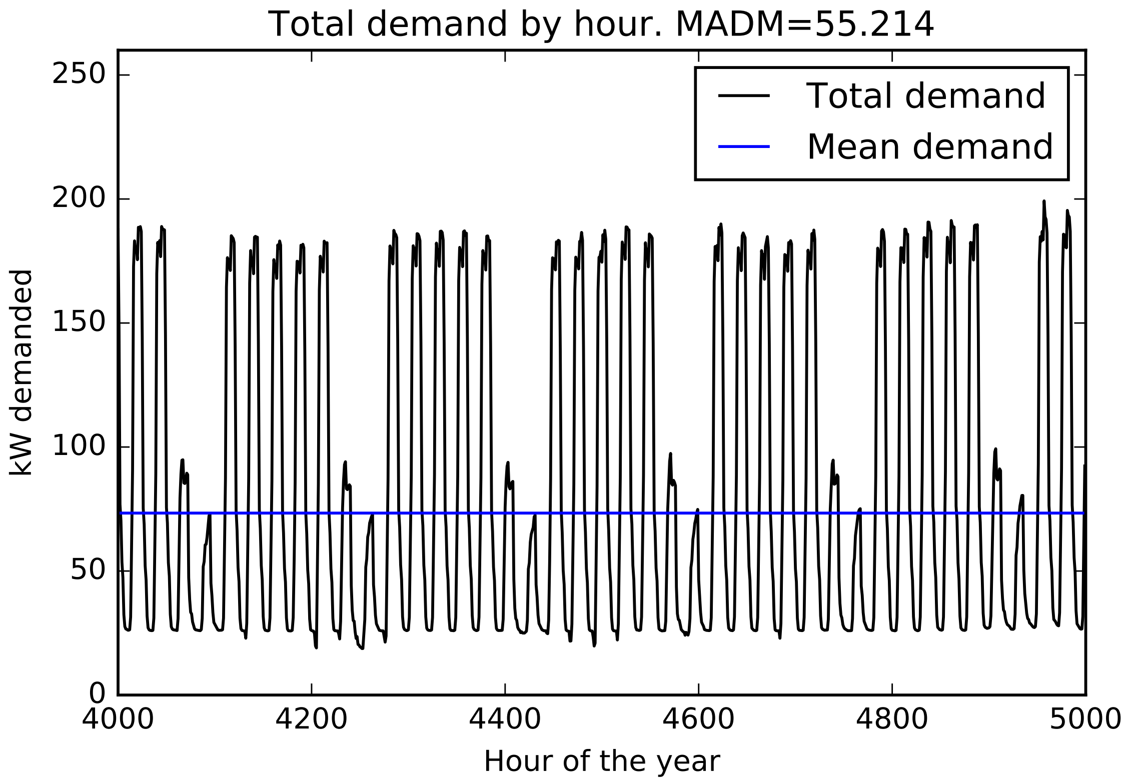


Figure 23: Hourly demand for hours 4000-4999.

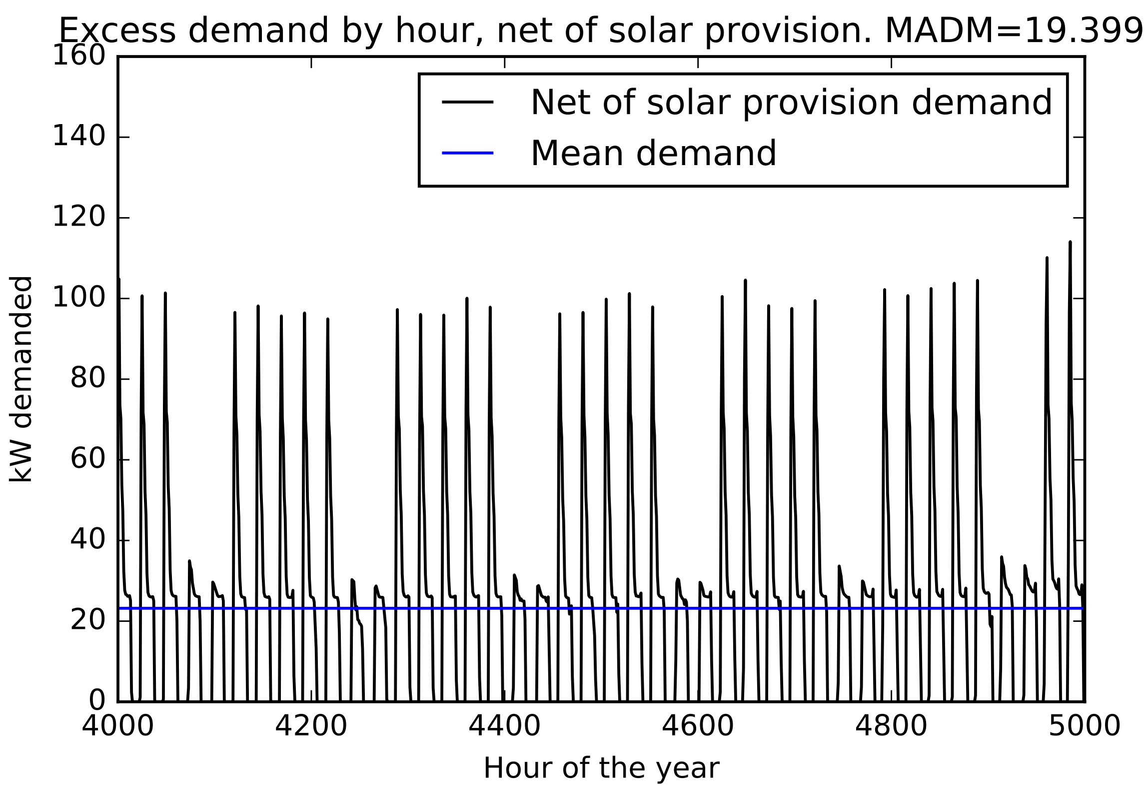


Figure 24: RUH: Hourly demand net of solar for hours 4000-4999.

4.2.1 Sweep of installed solar PV

The baseline amount of installed solar PV is 2000 m^2 in Riyadh and 2600 in Philadelphia. Table 1 reports data from a sweep with solar PV areas ranging from 0 to 2500 for Riyadh. Table 2 reports on a sweep for Philadelphia.

PV (m^2)	MADM total demand	PV generated	PV used	MADM of demand, net of PV used	MADM of demand, no PV curtailment
0.00	55.54	0.00	0.00	55.54	55.54
500.00	55.54	174127.69	171382.95	40.34	40.57
750.00	55.54	261191.53	245604.89	33.04	34.43
1000.00	55.54	348255.38	312156.43	27.28	30.30
1250.00	55.54	435319.22	368476.64	23.92	30.04
1500.00	55.54	522383.06	406895.25	22.41	34.49
1750.00	55.54	609446.91	429278.50	21.49	43.31
2000.00	55.54	696510.75	444447.73	20.87	53.65
2250.00	55.54	783574.60	454565.45	20.32	64.35
2500.00	55.54	870638.44	461838.34	19.79	75.27

Table 1: RUH: Sweep of installed PV (m^2).

PV (m^2)	MADM total demand	PV generated	PV used	MADM of demand, net of PV used	MADM of demand, no PV curtailment
0.00	53.46	0.00	0.00	53.46	53.46
500.00	53.46	124896.23	121896.58	42.59	42.85
750.00	53.46	187344.35	175072.49	37.39	38.46
1000.00	53.46	249792.46	223436.23	33.21	35.40
1250.00	53.46	312240.58	265844.43	30.33	34.05
1500.00	53.46	374688.69	298910.18	28.33	34.47
1750.00	53.46	437136.81	322676.66	26.75	35.95
2000.00	53.46	499584.93	340281.12	25.35	40.44
2250.00	53.46	562033.04	354236.07	24.11	47.89
2500.00	53.46	624481.16	365815.75	22.97	55.58
2750.00	53.46	686929.27	375681.60	21.92	63.47

Table 2: PHL: Sweep of installed PV (m^2).

Figure 25 plots data from Tables 1 and 2. Specifically how MADM varies with area of PV installed and whether curtailment is in effect. Most interestingly, we see in both cases that variability (MADM) of demand as seen by the grid declines with increasing amounts of solar PV. This holds for amounts up to about 1250 m^2 in Riyadh and 1500 in Philadelphia, with and without curtailment. At these levels, solar PV looks to provide a positive network externality for the grid.

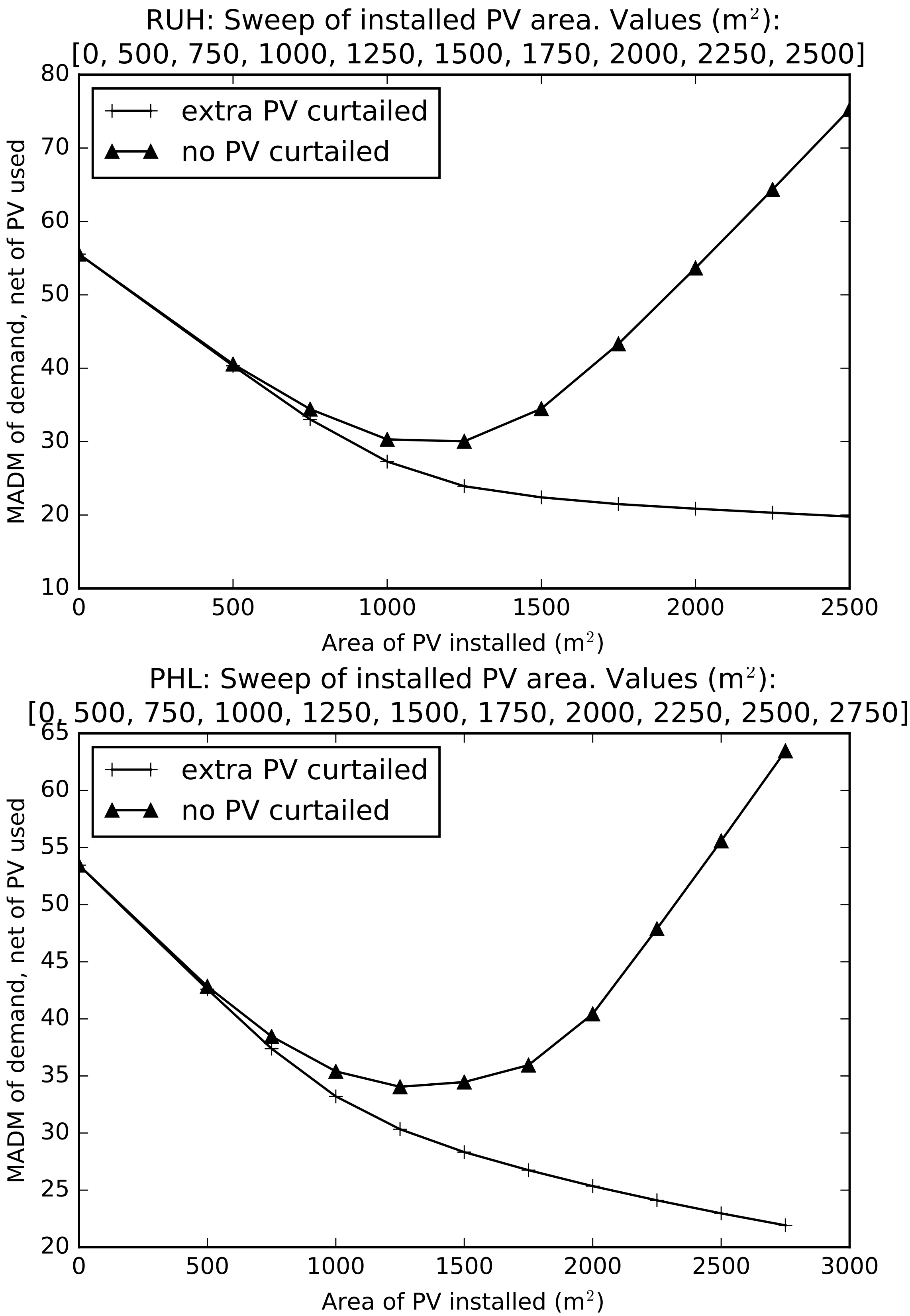
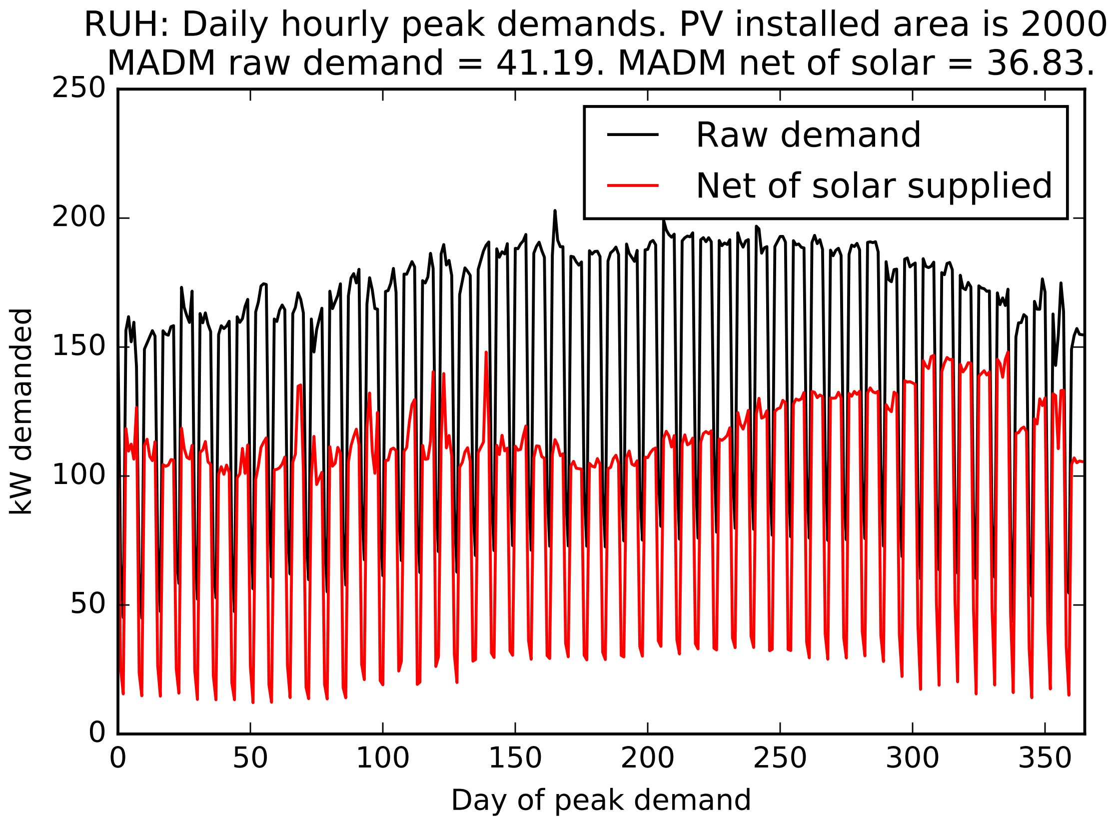


Figure 25: Sweep of solar PV area installed.

Finally, what is the effect of the solar PV on peak demand? In Figure 26 we see a substantial amount of "peak shaving" as well as about an 11% decline in MADM. Solar PV is not only reducing variability, as measured by MADM, it is also reducing peak demand. This holds both for Riyadh, where the effect is larger, and for Philadelphia.



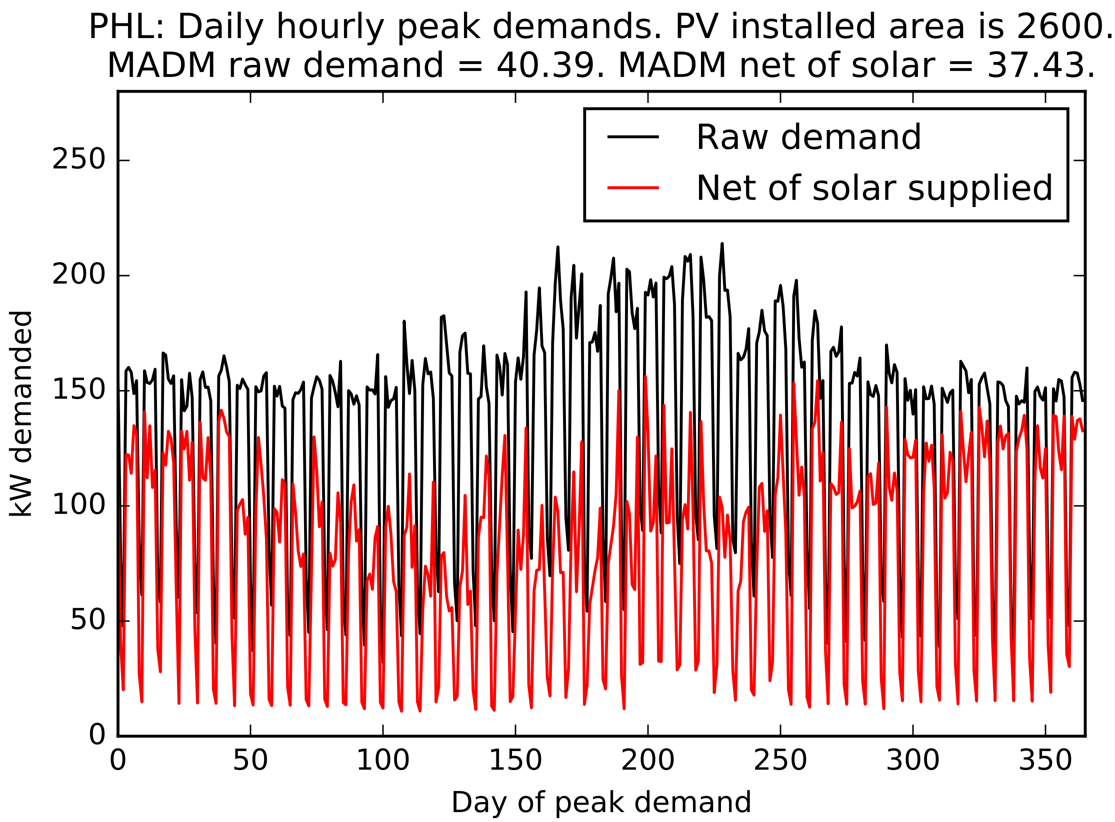


Figure 26: Daily peak demands by hour, raw demand and net of PV supplied.

5 Effects of Adding Storage

Given that only about 64% of the solar PV power generated could be used by the building at the time (during the hour) of generation in the case of Riyadh and 57% in the case of Philadelphia, we modeled the effects of adding battery storage. We did this with two kinds of batteries. Our expensive batteries, used first, have a charging efficiency of 0.99 and an extraction efficiency of 0.95. The baseline configuration has a battery capacity of 500 kWh of expensive batteries. Our cheap batteries, used last, have a charging efficiency of 0.30 and an extraction efficiency of 0.99. The baseline configuration has 1000 kWh of these cheap(er) batteries.

Considering only the application of the expensive batteries, the MADM of the hourly demand seen by the grid is 12.78. Adding in the cheap batteries yields a MADM of 9.85 in Riyadh. For Philadelphia these numbers are 15.41 and 11.55.

Figure 27 presents comparisons of the hourly *peak* demands for raw demand and net of solar PV and the expensive battery. Interestingly, there is much more peak shaving in Riyadh than in Philadelphia, where there is also actually an increase in MADM of the hourly peak demands.

Figure 28 presents comparisons of the hourly *peak* demands for raw demand and net of solar PV, the expensive battery, and the cheap battery. That is, Figure 28 is what we get when we add the cheap battery to the configuration of Figure Figure 27. For both Riyadh and Philadelphia much more peak shaving is in evidence.

It is interesting to see that peak shaving is generally more extensive during the summer months. We note that for Riyadh (Philadelphia)

MADM(PVPower['Energy Supply (kW)']) = 89.08 (88.85)

and

MADM(PVPower['Energy Demand (kW)']) = 55.54 (53.46).

Supply is much more variable than demand and basically increases a more than demand during the summer.

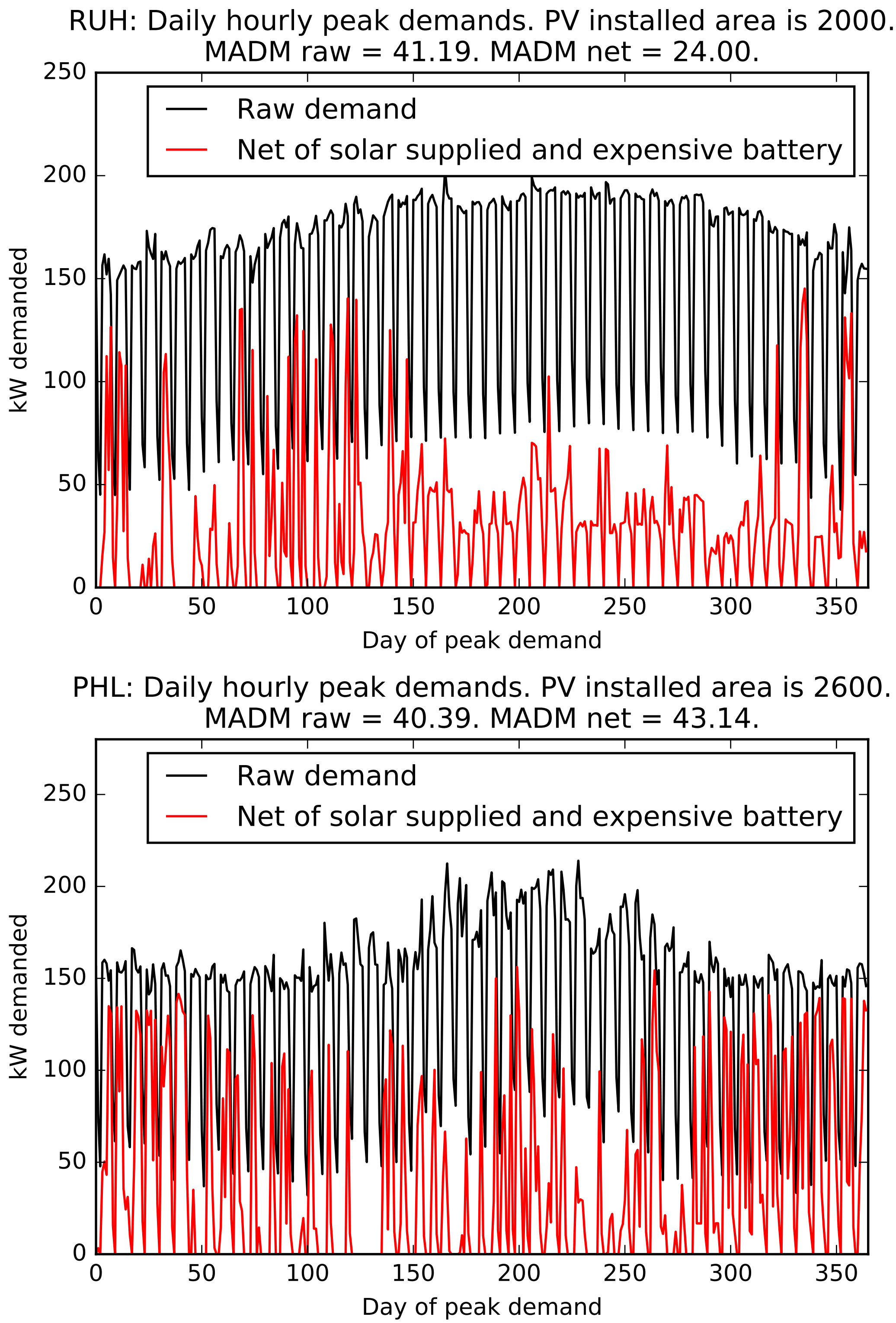
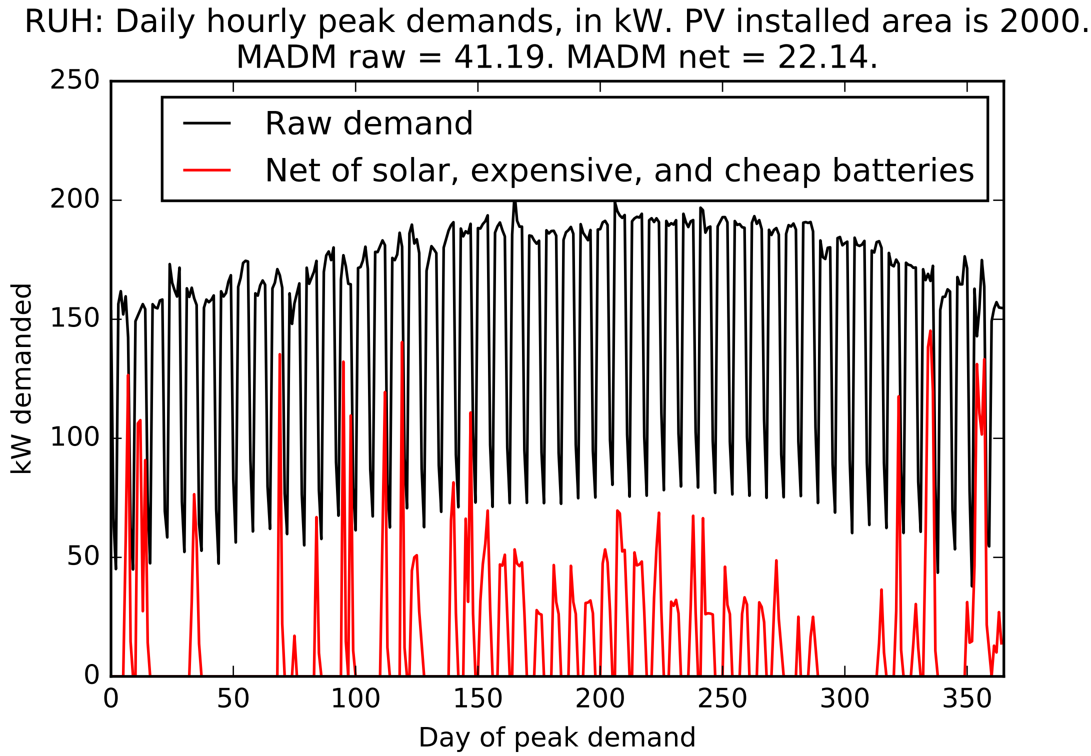


Figure 27: Daily peak demands by hour, raw demand and net of PV supplied and use of expensive batteries.



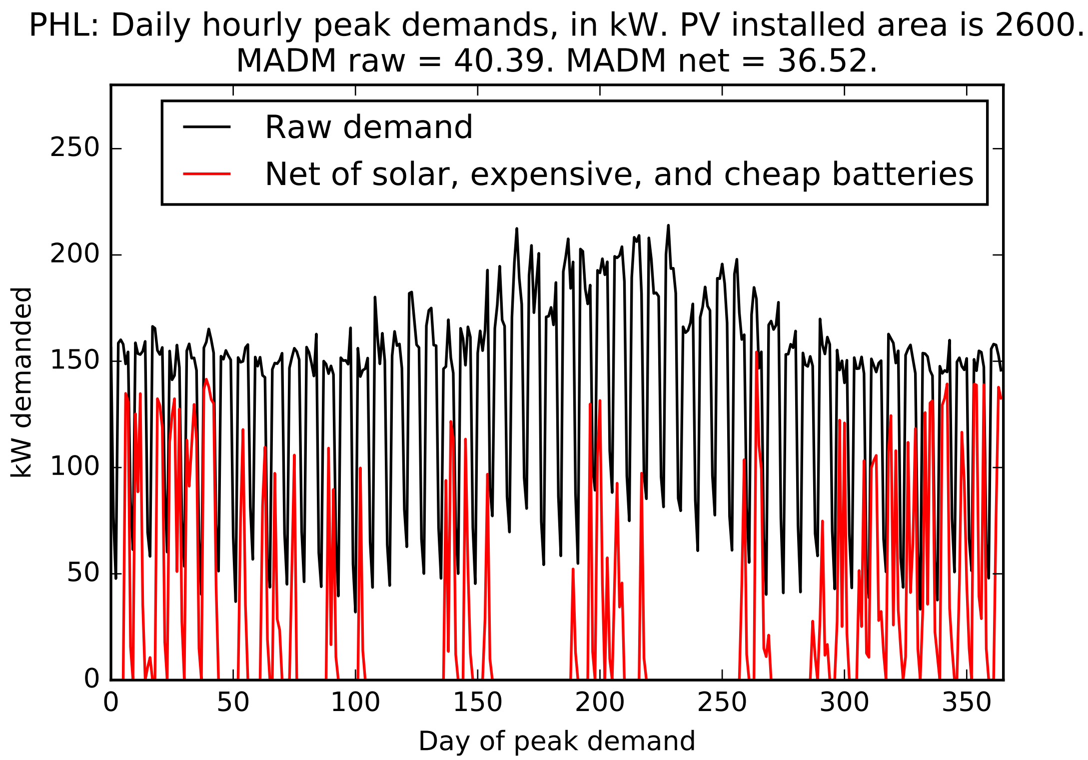


Figure 28: Daily peak demands by hour, raw demand and net of PV supplied and use of both expensive and cheap batteries.

6 A Villa in Riyadh

For purposes of doing further comparison we modeled a representative (somewhat upscale) villa in Riyadh. /* Give size, etc. characteristics */ Over the course of a year the villa's demand for electricity is 98,150 kWh. Configured with 300 m^2 of solar PV, installed so as to maximize energy production over the year, the building produces 104,477 kWh of power, so it is approximately net-zero energy. We used eQUEST as our tool for doing the WBPA simulation model.

Figure 29 shows hourly demand and solar PV production for two two-day periods, one in the summer, one in fall. It is evident that there is considerable mismatch between supply of solar power and demand for power by the villa.

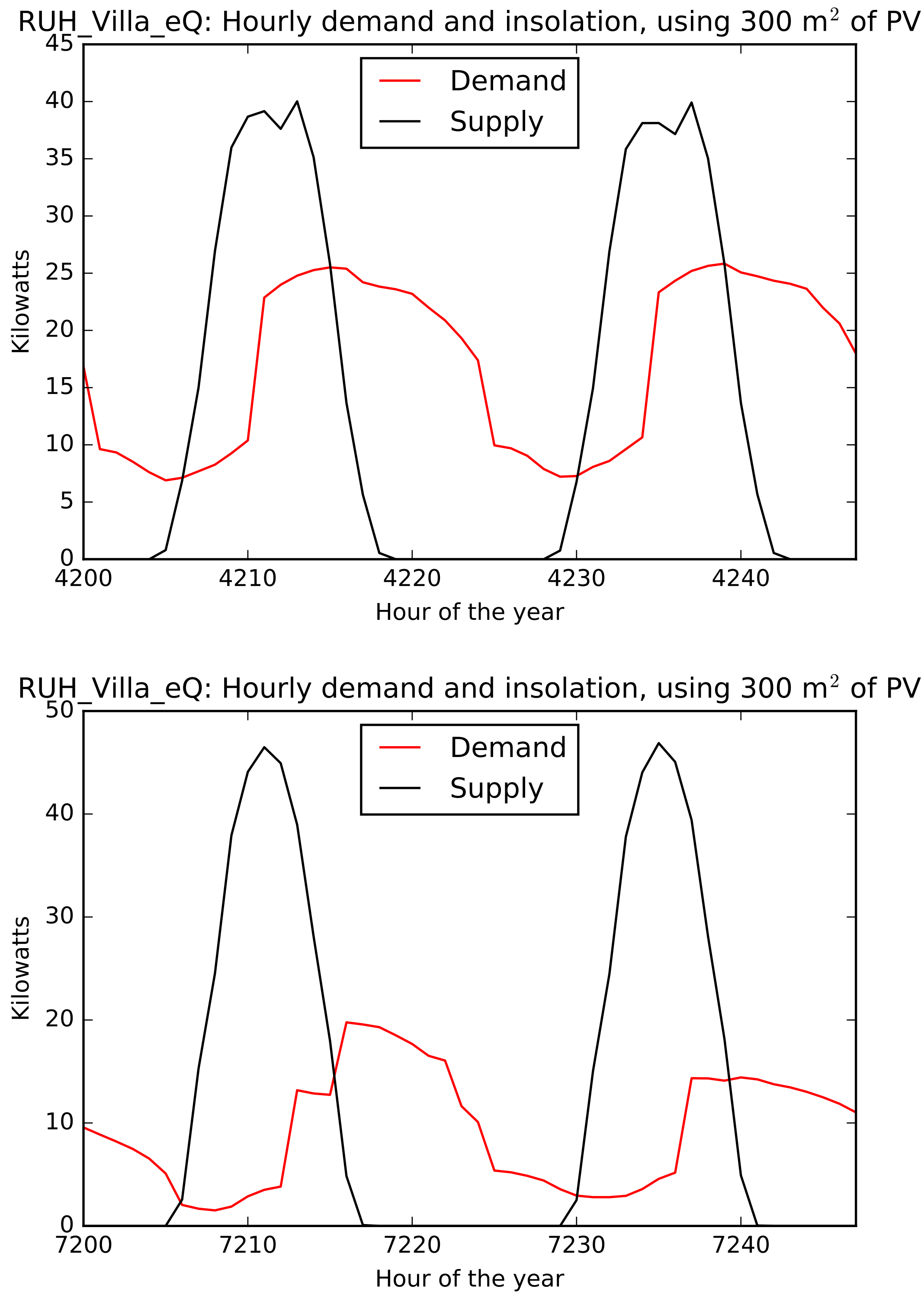


Figure 29: Hourly demand by a villa in, and insolation for, Riyadh, two two-day periods.

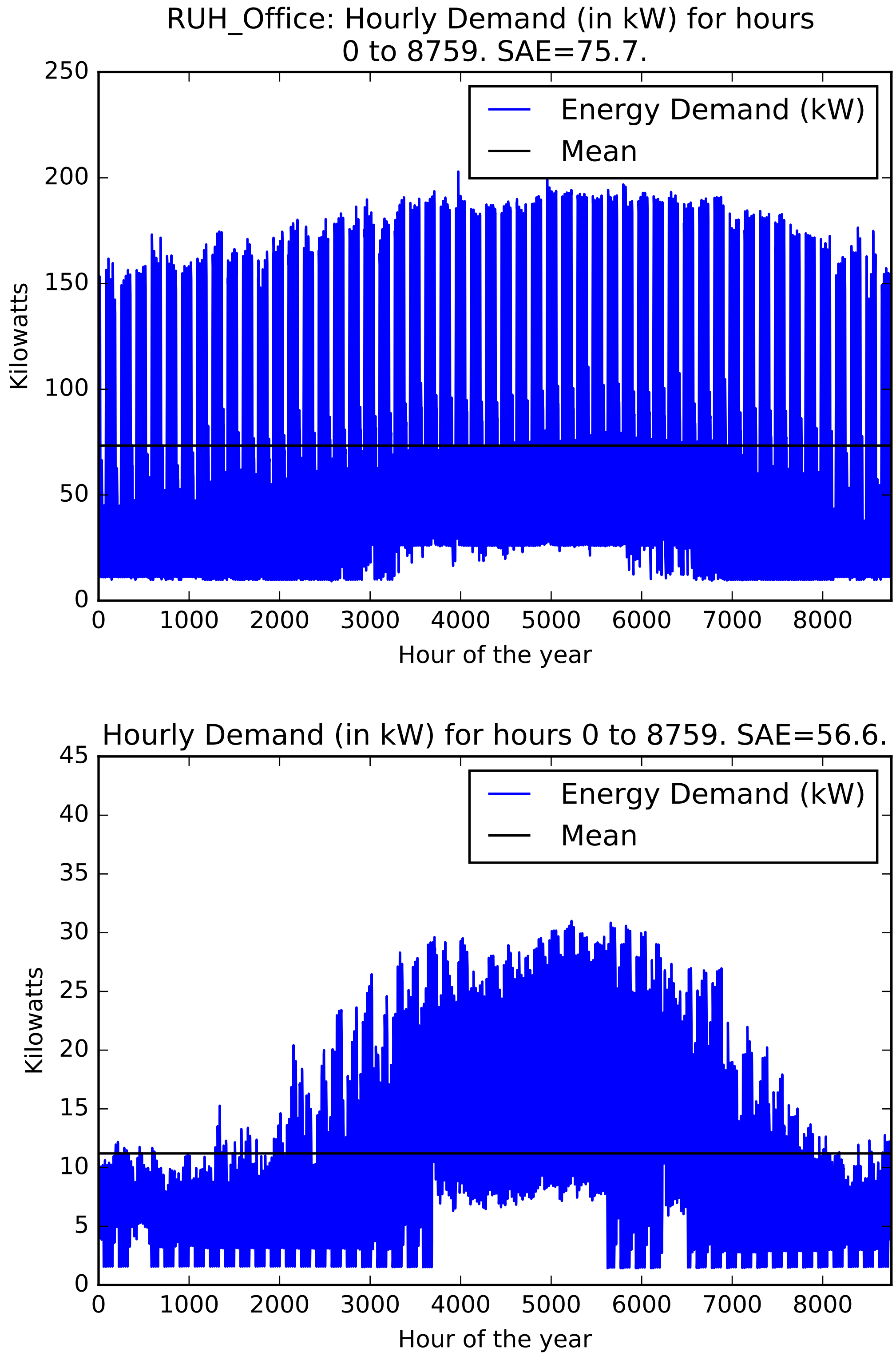


Figure 30: Demand by hour over a full year for an office building (top) and a villa (bottom) in Riyadh.

Comparing Figure 30 just above to Figure 10, page 16, for the office building in Riyadh, we see much greater variability in demand from the villa. (Even though Figure 10 is hourly peak demands, the point is well taken.) What does this mean for the effects of solar PV?

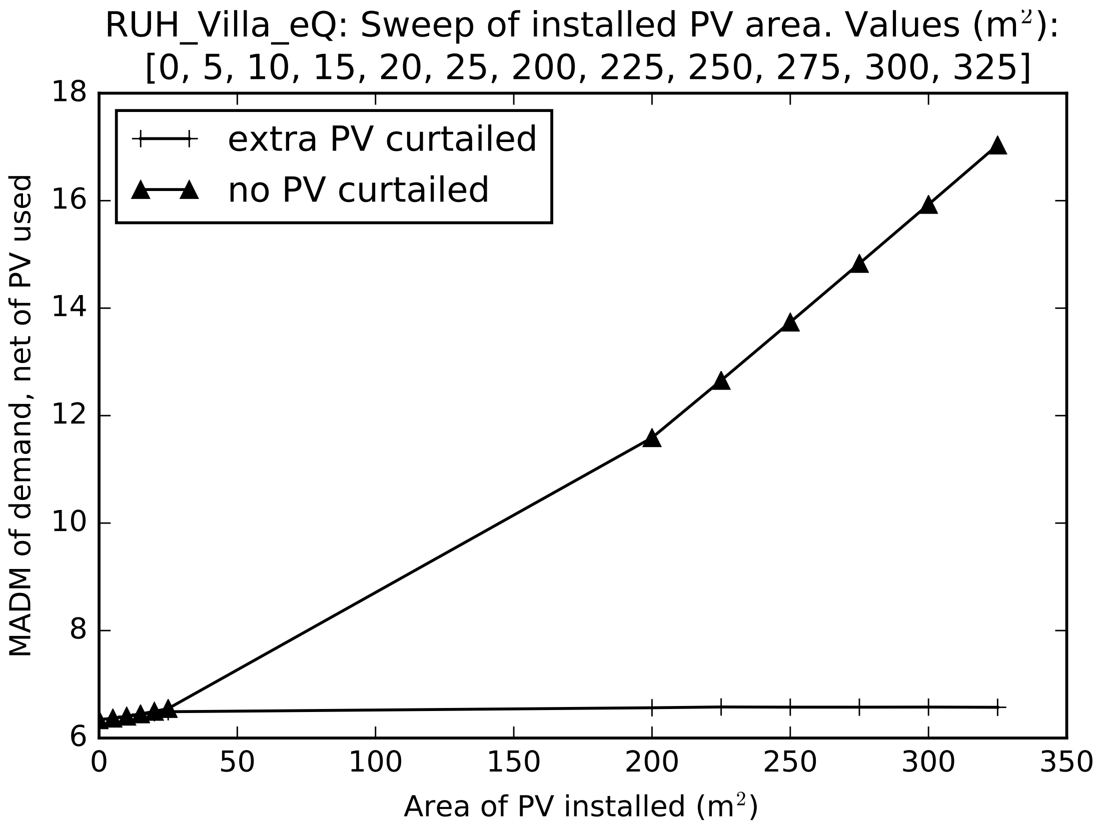


Figure 31: Demand by hour over a full year for a villa in Riyadh.

The sweep on area of installed PV for the villa, shown just above in Figure 31, is quite different from the sweeps for the office building, show in Figure 25, on page 41.

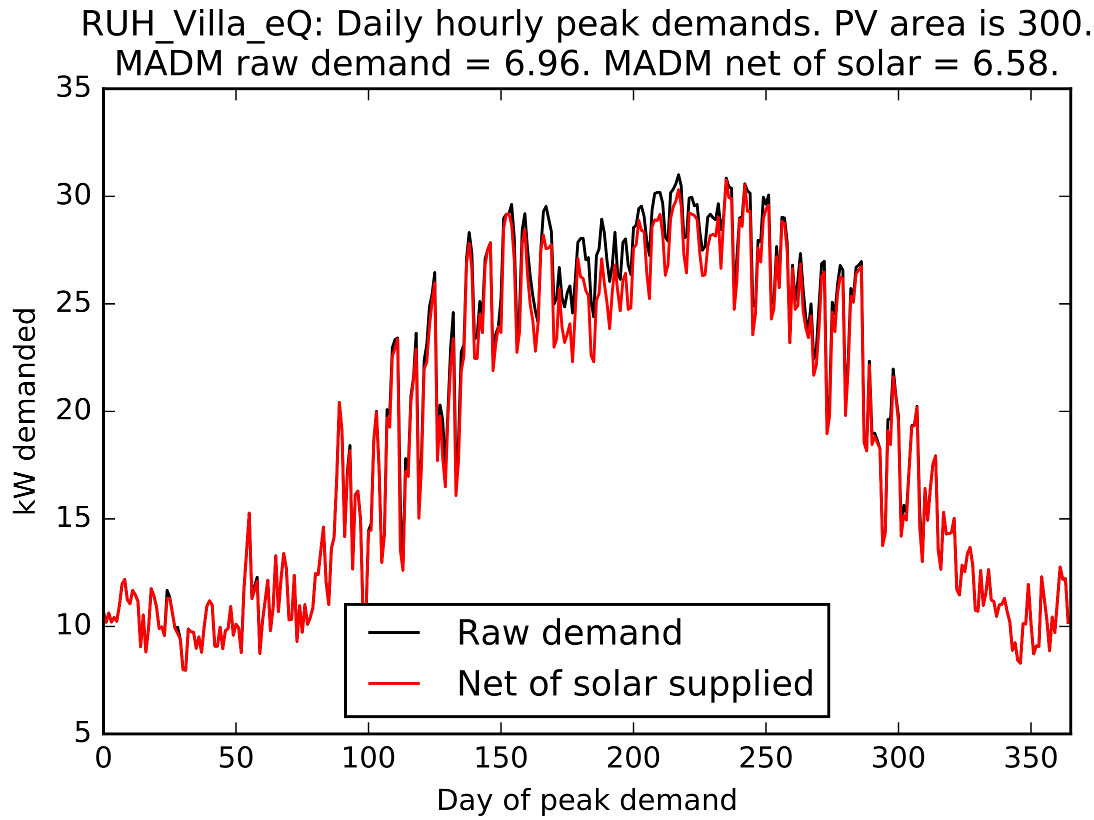


Figure 32: Daily peak demands by hours, raw demand and net of PV supplied for a villa in Riyadh.

Figure 32 above tells us that there is very little peak shaving by the 300 m^2 of solar PV for the villa. This contrasts strongly with what we saw for the office building in Figure 26, page 43.

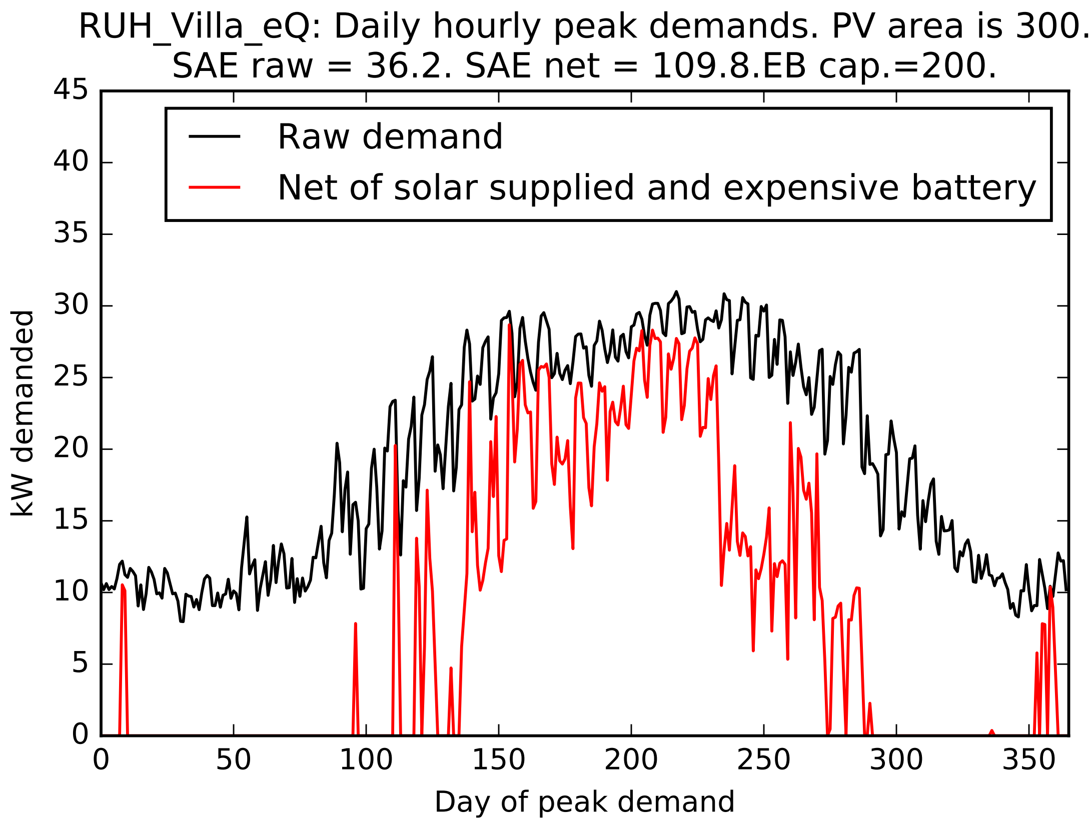


Figure 33: Daily peak demands by hours, raw demand and net of PV supplied and expensive battery for a villa in Riyadh.

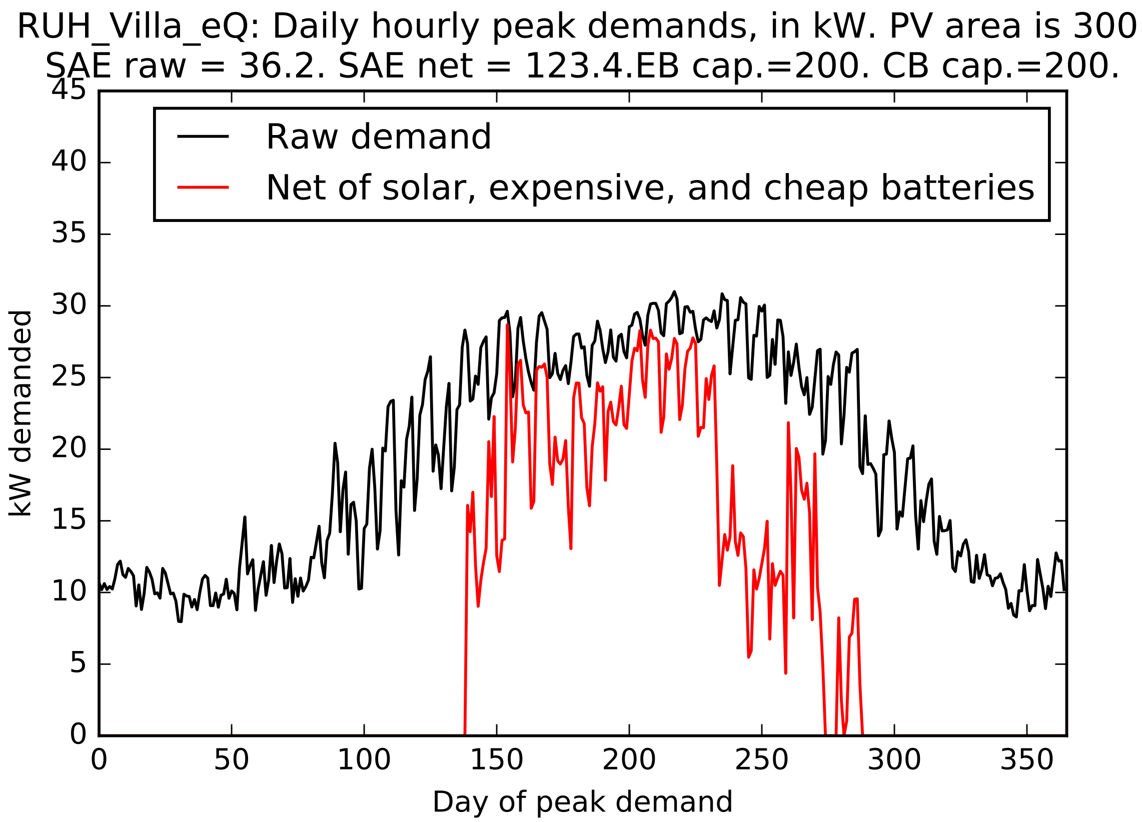


Figure 34: Daily peak demands by hours, raw demand and net of PV supplied, expensive battery, and cheap battery for a villa in Riyadh.

7 All Saudi Arabian Demand

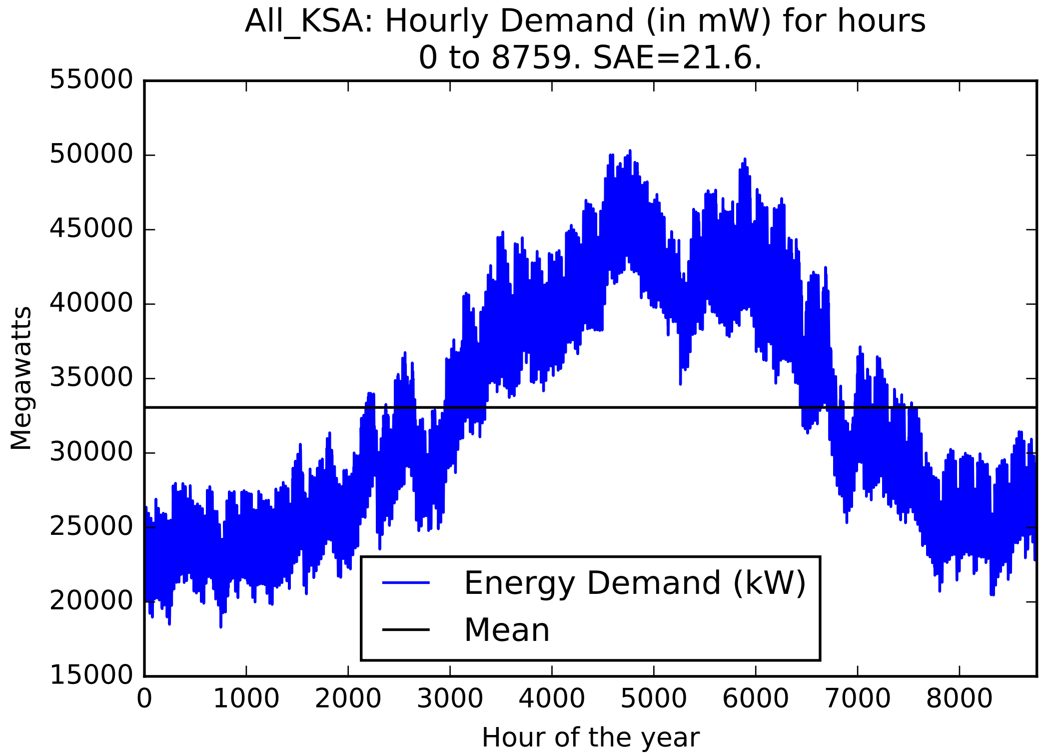


Figure 35: Demand by hour over a full year (2013) for all of KSA. Source: Saudi Electric Company.

8 Discussion and Conclusion

The perhaps surprising most fundamental findings of this study are that introduction of solar PV can, even without storage backup, (1) considerably reduce the variability of demand placed on the distribution grid and (2) reduce ('shave') realized peak loads. The findings are for a similar building placed in two very different meteorological locations, Riyadh and Philadelphia.

Other buildings and other locations will of course need to be studied, but we expect the findings will obtain broadly because the underlying causal dynamics are clear. Variability is measured as MADM. Above average demands are positively associated with above average solar insolation. Using the solar energy to meet these demands will tend reduce them, resulting in lower MADM. To the extent that solar energy is applied to reduce below-mean demand, MADM will tend to increase. Further, unused electric power that is placed onto the grid in effect creates a negative demand, so the effect is to increase MADM of demand as seen by the grid. That the net effect seen is a reduction is of course an empirical matter, depending on when the supplies and demands are realized, whether or not there is curtailment, and with storage, when the solar energy is actually applied. This is why we do the modeling. The conditions obtaining in our models that lead to the found reductions (in variability and peak loads) will, we think, obtain very generally, although it very much remains to be seen what the general magnitude of the effect is.

Our findings are, we believe, rich in relevance for policy making, especially when combined with other investigations, such as studies of the value of reductions in load variability. A comprehensive policy analysis, including alternative market designs, is surely called for. These are matters beyond the scope of this initial foray, which merely seeks to present material that can be used for such analyses. We do, however, want to offer two comments pertaining to policy making and market design.

First, although the setup as discussed encourages us to think in terms of a building with solar panels attached, this is hardly required. Alternatively, the utility or perhaps a third party might build solar capacity nearby and connected to the grid. This could likely be done much more cheaply than by putting the panels on the building. It suggests an interesting avenue for a business model for utilities in the future, roughly as follows. Building owners contract with solar PV suppliers for a certain amount of solar PV. Production is monitored along with demand from the building as placed on the grid. Besides a basic production price for the solar PV, a tariff is paid for the amount of variability reduction realized (with another tariff for increases in variability). Base load power, in virtue of its constancy, can do little to decrease the need for ancillary services that respond to changes in load. The variability of solar PV can be, in this regard, an asset and could be compensated as such.

Second, as we have seen throughout, demand in our office buildings drops dramatically on the weekends, resulting in a surplus that in the case of curtailment goes unused. See Figures 36 and 37. Smarter storage policies than the greedy one we have investigated might be employed to capture weekend surplus and deliver it strategically during the week to reduce peaks and variability more effectively. Alternatively, special markets or tariffs might be organized to consume the power when it is captured on the weekends. For example, relatively time insensitive uses might be identified (e.g., filling water towers, supplying residences) and undertaken when the buildings are not in work day use. Might an organized market for this spur creative and productive applications? This would seem to be a reasonable hope.

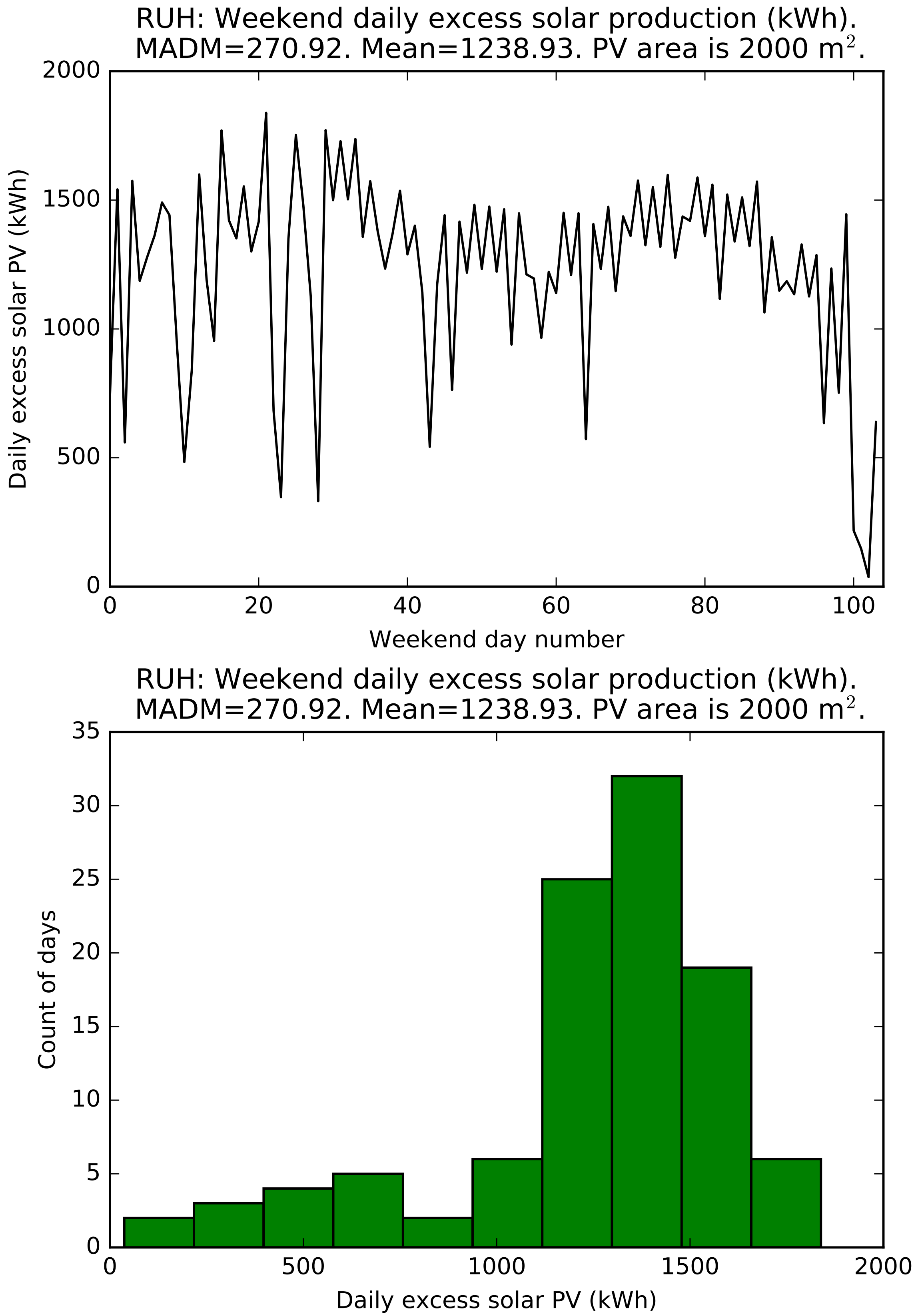
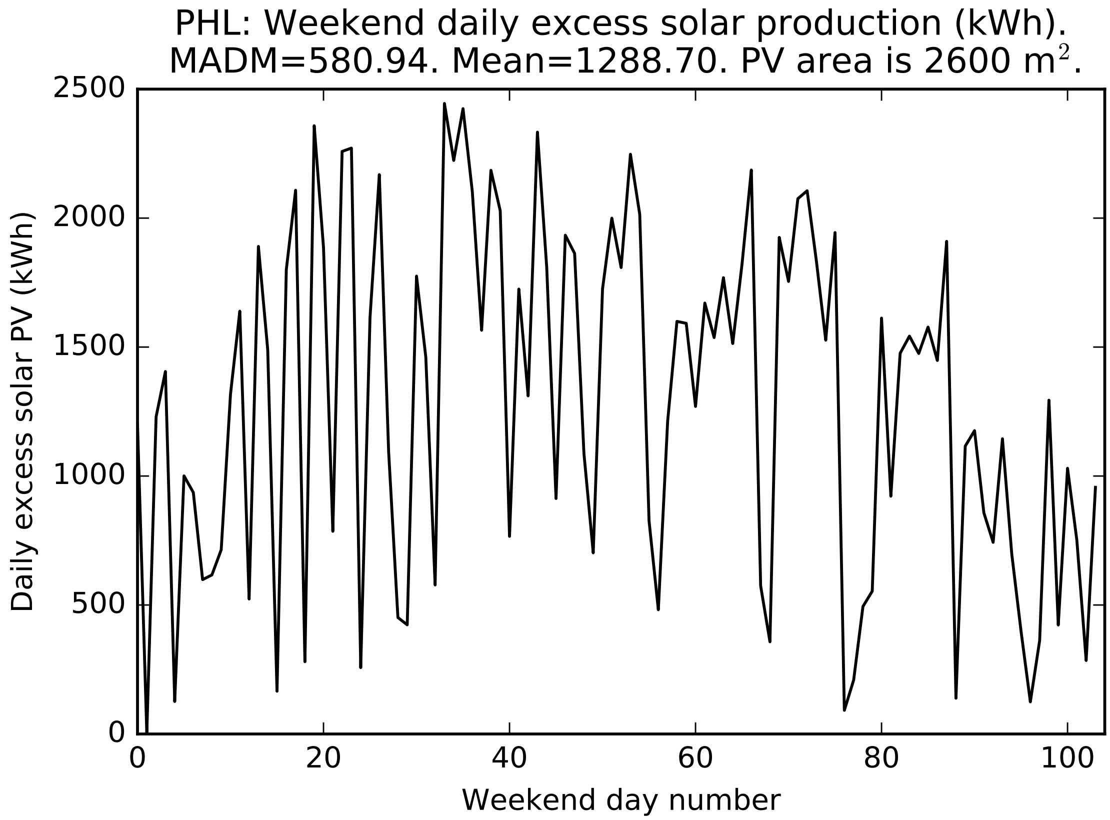


Figure 36: Daily peak demands by hour, raw demand and net of PV supplied.



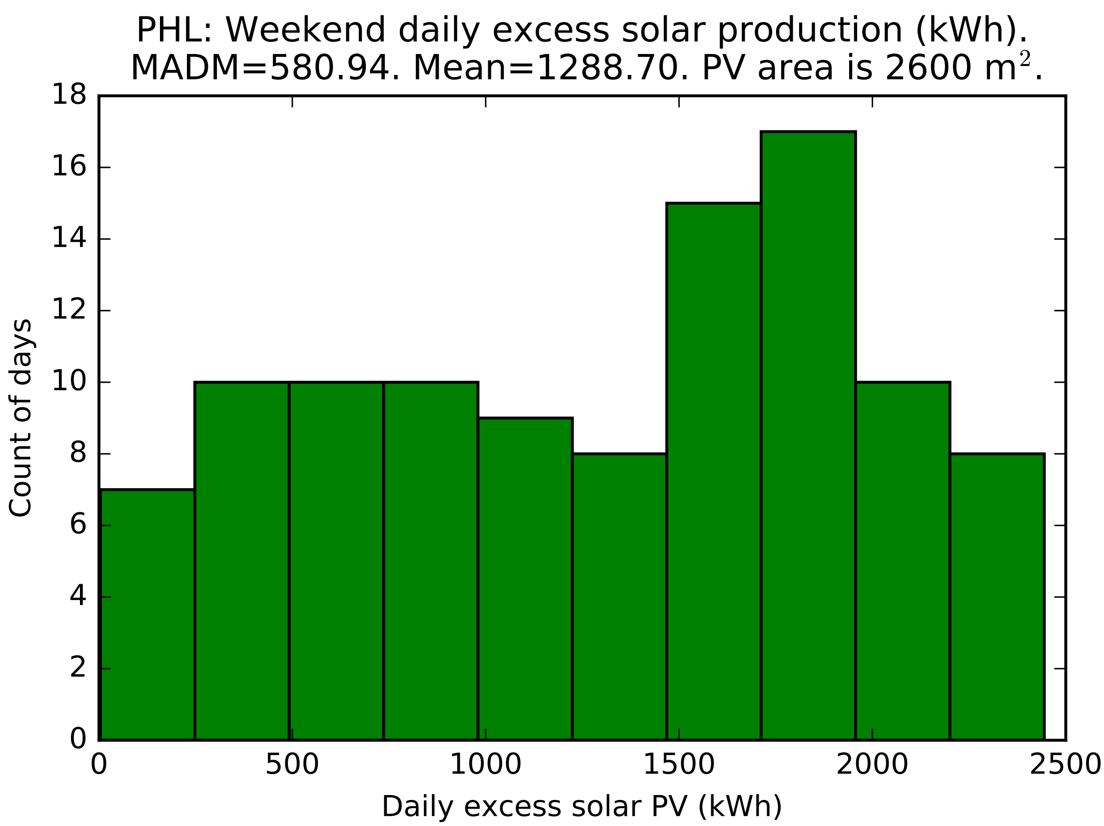


Figure 37: Daily peak demands by hour, raw demand and net of PV supplied.

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A The Typical Meteorological Year

According to "TYPICAL METEOROLOGICAL YEAR USER'S MANUAL TD-9734 Hourly Solar Radiation-Surface Meteorological Observations" (file *C00045_TD-9734-TMY-manual-1981.pdf*, URL `http://www1.ncdc.noaa.gov/pub/data/metadata/documents/`) there are two steps involved in creating a TMY data series: "The first step was to select five candidate years. The second step was to select the TMM [typical meteorological month] from the five candidate years."

A.1 Selection of five candidate years

For each of the twelve calendar months the procedure involved selecting the five years that were "closest" to the composite of all 23 years. This was done by comparing the cumulative distribution function (CDF) for each year with the CDF for the long term composite of all 23 years for each of the 13 indices. (The CDF gives the proportion of values which are less than or equal to a specified value of an index.) Many statistics are available for comparing CDFs. Reference [3] lists six of them and gives some of the properties of the statistics. The statistic selected to measure the closeness of each year's CDF to the long term composite for a given index was the FinkelsteinSchafer (FS) statistic. See reference [2]. The CDF for the variable X is estimated by S (x) where:

$$S_n(x) = \begin{cases} 0 \text{ for } x < x_{(1)} \\ (k - .5)/n \text{ for } x_{(k)} \le x \le x_{(k+1)} \\ 1 \text{ for } x > x_{(n)}, \end{cases}$$

Where $x_{(k)}$ is the k^{th} ordered (from smallest to largest)

Figure 38:

observation and n is the number of observations on the variable x, (if the month is May, n = 31). S (x) is a monotonically increasing step function which is boilnded by zero and one. The steps are of size 1/n and occur at the values of x(k). See Figure 2 for a plot of typical CDFs for mean daily wind velocity. The station is Albuquerque and the month is May. The long term CDF is based on 23 years of data - 713 daily observations. The CDFs labeled 1958 and 1953 are each based on 31 daily observations. The FS statistic for comparing the long term CDF and the month/year CDF for the variable x is given by

$$FS = \frac{1}{n} \sum_{i=1}^{n} \delta_i$$

Where:

δ_i = the absolute difference between the long term CDF and the month/year CDF at $x_{(i)}$ $(i = 1, \ldots, n)$.

n = the number of daily readings in the month.

The closer the two CDFs the smaller the value of FS.

Figure 39:

It is noted in passing that some solar practitioners have attempted to pick representative months by matching the mean and standard deviation of a month/year combination to the long term mean and standard deviation. It is felt that using the CDF and a statistic such as FS is a better selection procedure because the first two moments of two distributions can be close and yet the distributions can be quite different. A statistic such as FS is more sensitive to differences. For each year, thirteen FS statistics were computed, one for each index. As mentioned above, the matching of certain distributions of some indices is more impcrtant than matching those of other indices. How to order groups (the years) of thirteen FS statistics in which some statistics are more important than others is an open question. One way to perform the ordering is with a weighted sum of the thirteen FS statistics,

$$WS = \sum w_i \ FS_i$$

Figure 40:

where the FS values associated with important statistics would receive relatively larger weights than the less important statistics. Choosing these weights (w.) is not clear cut but would depend on the ultimate applitation of the generated typical year. In the generation of these TMY's, it was determined that the three range statistics and the minimum of wind velocity were of little or no value in the selection process, so these statistics were omitted, i.e., assigned zero weight. The maxima and minima of dry bulb and dew point temperatures were assigned the minimum non-zero weight, the means of those statistics and the mean and maximum of wind velocity a weight twice that minimum, and daily total global solar radiation was assigned the maximum weight. The actual weighting scheme used for the TMY's follows:

A value for WS was computed for each year and the five years with the smallest values for WS were selected as candidate years for the month in question.

	Temperature								
	Dry Bulb			Dew Point			Wind Velocity		Solar Radiation
	Max	Min	Mean	Max	Min	Mean	Max	Mean	
W_i:	1/24	1/24	2/24	1/24	1/24	2/24	2/24	2/24	12/24

Figure 41:

A.2 Final Selection of TMM

The final selection of the TMM from the five candidate years involved examining statistics and persistence structure associated with mean daily dry bulb temperature and daily total global solar radiation. The statistics examined were the FS statistic and the deviations of the monthly mean and median from the long term mean and median. Persistence was characterized by frequency and run length (RL) above and below fixed long term percentiles. For mean daily dry bulb temperature the frequency and run length above the 67th (consecutive warm days) and below the 33rd (consecutive cool days) long term percentile were computed. For solar radiation the frequency and run length below the 33rd long term percentile (consecutive days with low radiation) were computed. Table A-III in Appendix A is an example of the runs information calculated for daily total global solar radiation. Persistence was considered important because it was thought that in some cases a given year's CDF could be quite close to that for the long term composite yet there still could be atypically long runs of cloudy or warm or cool days. An unusual run structure is of particular importance with regard to solar energy systems.

The final selection of a TMM was somewhat subjective. However, an attempt was made to select years with small WS values, small deviations, and "typical" run structures. The summary statistics calculated for each month/year combination are included with this report on microfiche. Appendix A describes the computer output that was generated and gives some examples of output. Typical wind years (TWY) were also characterized. Maximum and mean daily wind velocity were the only indices used in the selection of the TWY. The selection of the five candidate years for the TWY was similar to that used for the TMY. These may be found in Appendix Table A-I. It should be noted that no adjustments were made in the wind velocity data due to changes in anemometer heights during the period of record. If appropriate adjustments were made to compensate for anemometer height changes, different TWYs would probably have been chosen.

B Files

The output from the BES/WBPA simulations is recorded in two Excel files, *Philly_Typ_Office_clculator_rev06.xlsx* and *Riyadh_Typ_Office_clculator_rev06.xlsx*. Python modeling, which was validated against the Excel files, was done in the files *PhillyTypOfficeExplore.ipynb*, *RiyadhTypOfficeExplore.ipynb* and *RiyadhTypOfficeInit.py*. The latter file makes the basic calculations for hourly results. The other two files read in *RiyadhTypOfficeInit.py*, and use it as a library for creating the plots and other calculations. These files were then generalized to *BuildingExplore.ipynb* and *BuildingInit.py*. Copies of all these files are present in `https://www.dropbox.com/sh/rrubq4lttpolviv/AABzcEdS3XLf-f2d5aMpEPlTa?dl=0/KAPSARC/BESRiyadhPhiladelphia1/`.