



PennState

CELP

CENTER FOR ENERGY
LAW AND POLICY

Evaluating the Impact of Policy on Cost-Effectiveness of PV-Storage Systems

August 2023

Project Team (listed alphabetically):

Bhanu Babaiahgari, Assistant Professor of Engineering, Penn State Hazleton

Mesude Bayrakci-Boz, Assistant Professor of Engineering, Penn State Hazleton

Seth Blumsack, Professor, John and Willie Leone Family Department of Energy and Mineral Engineering; Earth and Environmental Systems Institute; Director, Center for Energy Law and Policy

Jingyu Guo, Ph.D. student in Public Administration, Penn State Harrisburg

Michael D. Helbing, Staff Attorney, Center for Energy Law and Policy

Daniel J. Mallinson, Assistant Professor, School of Public Affairs, Penn State Harrisburg

Hannah Wiseman, Professor, Penn State Law; Co-Director, Center for Energy Law and Policy

For correspondence about this White Paper, please contact Seth Blumsack at sab51@psu.edu.

About the Center for Energy Law and Policy

Penn State's Center for Energy Law and Policy (CELP) was founded in 2018 with a mission to harness interdisciplinary research strengths at Penn State and beyond to bring emerging science and scholarship to complex problems in energy law and policy. A major part of CELP's mission is to engage with stakeholders around energy policy issues in ways that drive and define interdisciplinary academic research problems and encourage ongoing interactions between researchers and practitioners. The Center for Energy Law and Policy is collaborative effort across Penn State's many disciplines, research centers and campuses, which makes it the only energy research center in the country that can fully harness the strengths of a leading land grant research university to assemble collaborative and interdisciplinary teams, providing Penn State with a unique opportunity to have a major impact. The University and its faculty also have a deep commitment to the kind of engaged and practitioner-informed scholarship that makes the Center for Energy Law and Policy a unique organization to serve the Commonwealth, the nation and the world.

Acknowledgements

This work was supported by Penn State's Commonwealth Campus Center Nodes (C3N) Program and the Center for Energy Law and Policy (CELP). The C3N program is designed to build collaboration between University Park-based research centers and Commonwealth Campus faculty nodes. More information about the C3N Program is available at <https://ccresearch.psu.edu/c3n/>. CELP is an interdisciplinary research initiative funded by multiple Colleges, Campuses, and Institutes at Penn State. More information on the Center's funding structure can be found at <https://celp.psu.edu>.

INTRODUCTION

As recently as 2014, academic scholars described energy storage as an area of regulatory “uncertainty.”¹ At this point in time, new forms of energy storage—beyond historically common pumped hydroelectric storage—were starting to emerge. Large-scale battery storage, in particular was becoming more common. Since that time, large-scale battery storage has grown rapidly. Based on recent installations and projections of continued trends, by the end of 2023, the grid will host ten times the amount of battery storage installed in 2019.² Small-scale storage is also becoming more common. Consumers increasingly install home battery systems to provide back-up to rooftop solar panels or blackout situations. Additionally, bidirectional electric vehicle (EV) systems are emerging, in which EV owners can sell electricity from their car battery to a utility. As municipal and state governments and the current federal government push toward zero-carbon generation in the United States, more intermittent renewable resources, primarily solar and wind energy, are being added to the grid. These resources do not produce a constant supply of electricity, requiring back-up power that can ramp up quickly. Batteries are a key back-up power source.

The policy environment for distributed energy and energy storage is also in flux. The Federal Energy Regulatory Commission substantially advanced storage opportunities when it issued Order 841 in 2018. This order directs grid operators—Regional Transmission Organizations (RTOs) and Independent System Operators (ISOs)—to write rules that allow energy storage resources to sell electricity and services in wholesale markets for electricity. FERC Order 2222 requires RTOs to establish rules for distributed energy resources to participate directly in wholesale power markets. Prior to Order 2222, these resources could only monetize their value to the grid indirectly, through wholesale aggregators or utilities. Although these regulatory actions open up many opportunities for energy storage, rules continue to raise barriers to energy storage in markets, such as requirements for minimum bid prices in some of the market run by RTOs and ISOs.³ Municipal and state regulations, as well as grid interconnection processes, can also pose regulatory challenges to energy storage deployment and market participation.

We undertook a program of interdisciplinary research to evaluate aspects of this emerging policy environment for distributed energy and battery energy storage in Pennsylvania, which is part of the multi-state PJM electricity market and thus subject to recent FERC orders on distributed energy and energy storage. One thread of the research considered the current policy environment for battery energy storage participation in regional power markets. The policy evaluation work involved a review of documents related to federal, state and local measures relevant to energy storage, including local zoning or other codes affecting battery energy storage deployment. This work helped to identify policy barriers to deployment and also highlight operational needs or requirements that are being written into policy measures.

The second thread of the proposed research involved a detailed simulation modeling of distributed energy systems with battery energy storage to identify needed performance and management

¹ See, e.g., Amy L. Stein, *Reconsidering Regulatory Uncertainty: Making a Case for Energy Storage*, 41 FLA. ST. U. L. REV. 697, 700-01 (2014).

² Energy Info. Admin., *Battery Storage in the United States: An Update on Market Trends at 1* (2021), https://www.eia.gov/analysis/studies/electricity/batterystorage/pdf/battery_storage_2021.pdf.

³ Sean Baur, *Going Beyond Order 841 to More Meaningful FERC Storage Policy*, *Utility Dive*, Sept. 1, 2020, <https://www.utilitydive.com/news/going-beyond-order-841-to-more-meaningful-ferc-storage-policy/584129/>.

capabilities that align with emerging policy requirements. Our research recognized that the management of these distributed systems would need to include control of the charge/discharge of battery energy storage during system disturbances to avoid deep battery discharge, which may interfere with market requirements and commitments. It tested the ability to optimize distributed energy systems internally to follow market dispatch orders.

DATA and PRELIMINARY ANALYSIS

1. Load Data

To obtain adequate residential load data that accurately describes the energy consumption behaviors of the United States population, we relied on a dataset from the United States Department of Energy (DOE) and made available by the Open Dataset Initiative.⁴ It comprises hourly load profile data for various building types, including 16 commercial building types based on the DOE commercial reference building models, as well as residential buildings based on the Building America House Simulation Protocols.

This dataset incorporates information from the Residential Energy Consumption Survey (RECS), which serves as a statistical reference for building types across different locations. Hourly load profiles are available for all TMY3 (Typical Meteorological Year 3) locations throughout the United States, providing a comprehensive understanding of energy consumption patterns.

The DOE website provides load information for these in the United States, categorized into three groups of measurements: BASE, LOW, and HIGH. This categorization allows for a more detailed understanding of energy consumption distribution in residential buildings. Furthermore, the load data is further classified into 13 different categories, providing additional insights into how energy consumption is distributed within residential buildings. These categories include:

- Electricity: Facility
- Gas: Facility
- Heating: Electricity
- Heating: Gas
- Cooling: Electricity
- HVAC Fan: Electricity
- Electricity: HVAC
- Fans: Electricity
- General: Interior Lights
- General: Exterior Lights: Electricity
- Appliance: Interior Equipment: Electricity

⁴ OPEN ENERGY DATA INITIATIVE, *Commercial and Residential Hourly Load Profiles for all TMY3 Locations in the United States*, doi: 10.25984/1788456, <https://data.openei.org/submissions/153> (last visited Aug. 1, 2023).

-Misc: Interior Equipment: Electricity

- Water Heater: Water Systems: Gas

For this analysis, we used the "base" load data for the city of Harrisburg, PA, because not all of the specific cities and towns (Lansdale, Ephrata, Elizabethtown, Mont Alto, New Wilmington, Middletown, and Kutztown) that were selected for analysis were listed in the dataset. Harrisburg was chosen as it is the closest surrounding city to the desired locations.

The MATLAB code that utilizes the base load data as input and generates hourly load data can be found in Appendix A.

2. Photovoltaic (PV) Data

We used the Systems Advisor Model (SAM) software to calculate the PV power data for the city of Harrisburg.⁵ The specific PV panels, PV design, and inverter assumptions utilized in the analysis can be found in Appendix B.

To account for various size possibilities of residential PV systems, the analysis considered 3 kW, 5 kW, 7 kW, and 10 kW configurations. Once the given assumptions were entered into the SAM software, the hourly power results were obtained and exported to Excel for further analysis.

3. Tariff (Electricity Price) Data

The residential tariff rates for utilities in the region were obtained. In this specific region, the selected cities have a consistent flat price throughout the year. As an example, the tariff rate for Middletown was chosen, which is \$0.116 per kWh [3].⁶

To analyze the impact of price variations, particularly time-of-use tariffs, two additional tariffs were identified and utilized for the optimization. One tariff was obtained from PPL, and another from PECO. Detailed information regarding these tariffs can be found in Appendix C.

Table 1. PPL Time-of-Use Tariff⁷

On-Peak	\$0.15626
Off-Peak	\$0.11182

On-Peak: Summer (6/1-11/30): 2:00 p.m. – 6:00 p.m. weekdays except select holidays.

Winter (12/1-5/31): 4:00 p.m. – 8:00 p.m. weekdays except select holidays.

Off-Peak: All the other hours on weekdays, weekends and select holidays.

⁵ NATIONAL RENEWABLE ENERGY LABORATORY, System Advisor Model (SAM), <https://sam.nrel.gov/> (last visited Aug. 1, 2023).

⁶ BOROUGH OF MIDDLETOWN PENNSYLVANIA, Electric, <https://middletownborough.com/services/electric/> (last visited Aug. 1, 2023).

⁷ PPL, Time of Use Program, <https://ppl electric.com/site/Ways-to-Save/Rates-and-Shopping/Time-of-Use-Plan> (last visited Aug. 1, 2023).

Table 2. PECO Time-of-Use Tariff⁸

Peak	\$1.04302
Off-Peak	\$0.26567
Super Off-Peak	\$0.17405

Peak: Weekdays (2:00 p.m. – 6:00 p.m.)

Off -Peak: Weekdays (6:00 a.m. – 2:00 p.m. & 6:00 p.m. – 12:00 a.m.)

Off-Peak: Weekends and Holidays (6:00 a.m. – 12:00 a.m.)

Super Off-Peak: All days (12:00 a.m. – 6:00 a.m.)

4. Optimization Code

We developed an optimization script to incorporate the PV system and energy storage. It aimed to determine the optimal cost for a given set of parameters. The script calculated the optimal cost and generated plots depicting the hourly changes in load, PV generation, and battery usage. The optimization script can be found in Appendix C.

5. Preliminary Results

Table 3 presents the optimal cost results for different sizes of PV systems. The optimal cost, represented in dollars (\$), is calculated based on the respective PV system size in kilowatts (kW).

Table 3. The optimal cost results for different size of PV systems

PV System Size (kW)	Optimal Cost (\$)
3	2898.1
5	3814.7
7	4740.7
10	9252.7

These results indicate that larger PV systems tend to have higher optimal costs. However, it is interesting to note that when the capacity increases from 3 kW to 7 kW, which is more than double the initial capacity of 3 kW, the corresponding optimal cost does not double. This finding highlights the importance of carefully analyzing the cost implications when considering different system sizes, especially with energy storage.

⁸ PECO, How Does Time-of-Using Pricing Work?, <https://www.peco.com/SmartEnergy/InnovationTechnology/Pages/TimeOfUsePricing.aspx>.

Figure 1. Hourly Load, PV generation and battery storage from July 19 to July 24

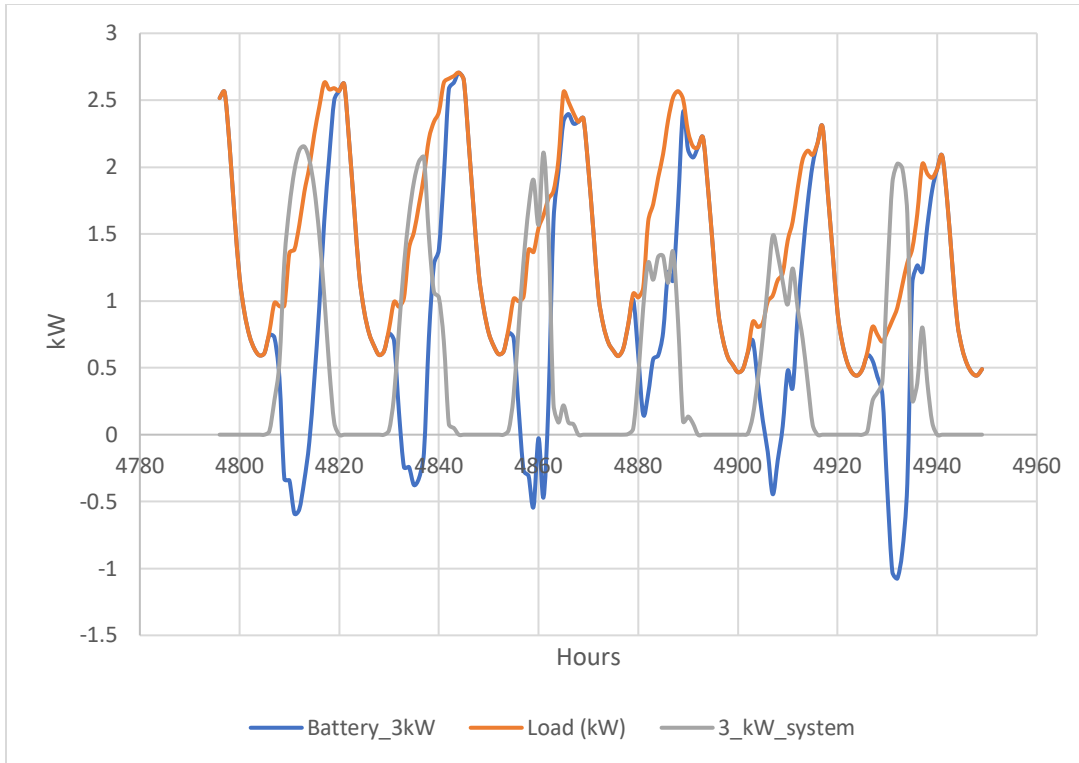


Figure 2. Hourly Load, PV generation and battery storage on June 25.

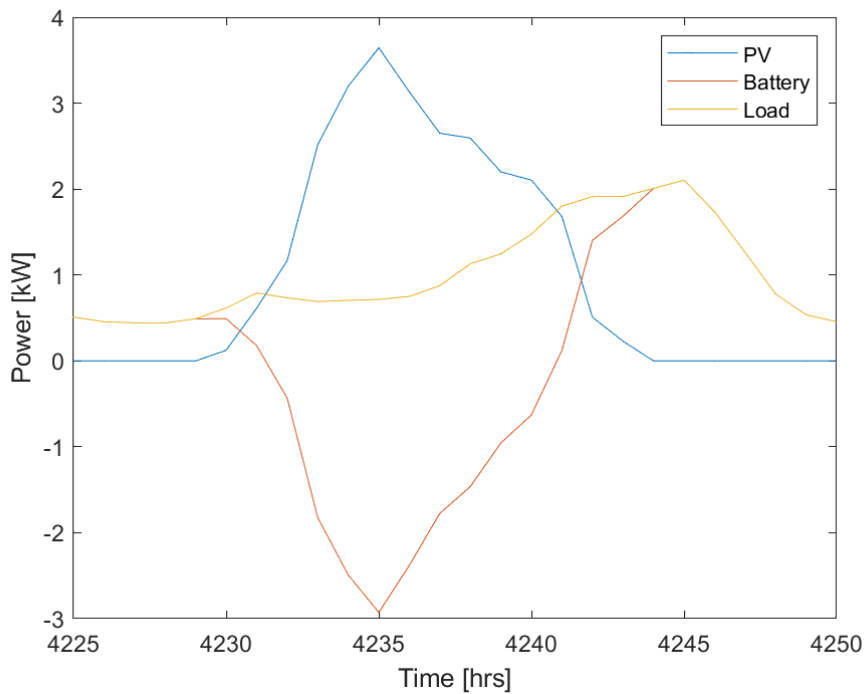


Figure 1 illustrates the hourly changes in load, PV generation, and battery usage over a period of six days, from July 19 to July 24, for a 3 kW PV system. Additionally, the hourly changes for June 25 with a 5 kW system are shown in Figure 2 as examples. It can be observed that when the PV system is producing electricity, the battery is being charged. This is indicated by negative values for battery usage, which signify the charging process. On the other hand, during the evening and night hours, the battery starts discharging. This discharge provides electricity to meet the load demand during those hours.

Table 4 presents the optimal cost comparison for a 3 kW and 7 kW PV system, considering both the flat price and time-of-use tariff options.

Table 4. Optimal cost with different tariff options for 3 kW and 7 kW PV systems

3 kW		7 kW	
Tariff	Optimal Cost (\$)	Tariff	Optimal cost (\$)
Flat Price	2892.1	Flat Price	4740.7
PPL_Time-of-Use	2902.8	PPL_Time-of-Use	3850.5
PECO_Time-of-Use	3870.5	PECO_Time-of-Use	2892.1

These results demonstrate that the impact of the time-of-use tariff option differs depending on the PV system size. The time-of-use option does not make sense with a 3 kW PV system since it leads to an increase in the overall cost. However, with a 7 kW PV system, the optimal cost decreases when the time-of-use option is considered.

This can be explained by considering the load and the interaction between PV power output, load and battery usage.

With a 3 kW system considering load is around 4-5 kW, the PV power output is generally sufficient to meet the demand without relying heavily on the battery. In this case, the time-of-use option may not provide significant benefits and may even lead to increased costs due to the higher tariff rates during peak hours.

On the other hand, with a 7 kW system, the PV power output exceeds the load, creating an opportunity to charge the battery during periods of excess generation. The stored energy in the battery can then be utilized during peak hours when the electricity price is higher. This strategy allows for better utilization of the PV system's capacity and can result in cost savings.

Therefore, the decision to opt for a time-of-use option depends on factors such as the size of the PV system, load, and the availability of excess generation for battery charging.

APPENDIX A.

Hourly Load Data Script

```
clear
%% import the data
opts = delimitedTextImportOptions("NumVariables", 14);

% Specify range and delimiter
opts.DataLines = [2, Inf];
opts.Delimiter = ",";

% Specify column names and types
opts.VariableNames = ["DateTime", "ElectricityFacilitykWhHourly",
"GasFacilitykWhHourly", "HeatingElectricitykWhHourly", "HeatingGaskWhHourly",
"CoolingElectricitykWhHourly", "HVACFanFansElectricitykWhHourly",
"ElectricityHVACKWhHourly", "FansElectricitykWhHourly",
"GeneralInteriorLightsElectricitykWhHourly",
"GeneralExteriorLightsElectricitykWhHourly",
"ApplInteriorEquipmentElectricitykWhHourly",
"MiscInteriorEquipmentElectricitykWhHourly", "WaterHeaterWaterSystemsGaskWhHourly"];
opts.VariableTypes = ["double", "double", "double", "double", "double", "double",
"double", "double", "double", "double", "double", "double", "double"];

% Specify file level properties
opts.ExtraColumnsRule = "ignore";
opts.EmptyLineRule = "read";

% Specify variable properties
opts = setvaropts(opts, "DateTime", "TrimNonNumeric", true);
opts = setvaropts(opts, "DateTime", "ThousandsSeparator", ",");

% Import the data
load_data_complete = readtable("C:\Users\mzb187\OneDrive - The Pennsylvania State
University\C3N\Harrisburg_Base_Load.csv",opts);
load_data_complete = table2array(load_data_complete);
clear opts

%% FINDING YEARLY DATA
load_data_complete(:,1)=[1:8760]; % adding time sequence
total_load_data_hourly=load_data_complete(:,1:2);

i = 1;

while i <= 24;
    total_load_data_hour = total_load_data_hourly(i:24:8760,2);
    average_day(1,i) = mean(total_load_data_hour);

    max_hour_yearly = max(total_load_data_hour);
    max_day(1,i) = max_hour_yearly;

    min_hour_yearly = min(total_load_data_hour);
    min_day(1,i) = min(total_load_data_hour);
end
```

```

        i = i+1;
end

hours = 1:24;
figure (1)
plot(hours, average_day)
hold on
plot(hours, max_day)
hold on
plot(hours, min_day)
title('Load Profile Representative of Year')
xlabel('hour')
ylabel('kW')

i = 1;

while i <= 8760;

    day = total_load_data_hourly(i:i+23,2);

    err = sqrt(immse(average_day,day'));
    err_avg_day(1,i) = err;

    p_err = abs((day' - average_day) ./ average_day*100);
    p_err_avg = sum(p_err)/24;
    p_err_avg_day(1,i) = p_err_avg;

    i = i + 24;

end
err_day = sum(err_avg_day)/365
p_err_day = sum(p_err_avg_day)/365

```

APPENDIX B: SAM Assumptions.

**Same PV panels and inverter were used for all different sizes, PV design was changed.

Module Characteristics at Reference Conditions

Reference conditions: Total Irradiance = 1000 W/m², Cell temp = 25 C

SunPower T5-SPR-327

Nominal efficiency	20.0555 %	Temperature coefficients	
Maximum power (Pmp)	327.106 Wdc	-0.386 %/°C	-1.263 W/°C
Max power voltage (Vmp)	54.7 Vdc		
Max power current (Imp)	6.0 Adc		
Open circuit voltage (Voc)	64.9 Vdc	-0.273 %/°C	-0.177 V/°C
Short circuit current (Isc)	6.5 Adc	0.062 %/°C	0.004 A/°C

Bifacial Specifications

Module is bifacial

Transmission fraction	0.013	0-1
Bifaciality	0.65	0-1
Ground clearance height	1	m

Efficiency Curve and Characteristics

SMA America: SB2500HFUS-30 [240V]

Number of MPPT inputs: 1

CEC weighted efficiency: 96.725 %
European weighted efficiency: 96.294 %

Datasheet Parameters

Maximum AC power	2530 Wac
Maximum DC power	2620.36 Wdc
Power use during operation	15.4278 Wdc
Power use at night	0.759 Wac
Nominal AC voltage	240 Vac
Maximum DC voltage	480 Vdc
Maximum DC current	6.31412 Adc
Minimum MPPT DC voltage	100 Vdc
Nominal DC voltage	415 Vdc
Maximum MPPT DC voltage	480 Vdc

Sandia Coefficients

C0	-8.55649e-06	1/Wac
C1	-3.3e-05	1/Vdc
C2	0.000132	1/Vdc
C3	-0.000457	1/Vdc

Note: If you are modeling a system with microinverters or DC power optimizers, see the Losses page to adjust the system losses accordingly.

CEC Information

CEC name: SMA America: SB2500HFUS-30 [240V] CEC hybrid: empty CEC type: Utility Interactive CEC date: n/a

AC Sizing

Number of inverters: 1

DC to AC ratio: 2.07

Size the system using modules per string and strings in parallel inputs below.

Estimate Subarray 1 configuration

Sizing Summary

Nameplate DC capacity	5.234 kWdc	Number of modules	16
Total AC capacity	2.530 kWac	Number of strings	2
Total inverter DC capacity	2.620 kWdc	Total module area	26.1 m ²

DC Sizing and Configuration

To model a system with one array, specify properties for Subarray 1 and disable Subarrays 2, 3, and 4. To model a system with up to four subarrays connected in parallel to a single bank of inverters, for each subarray, check Enable and specify a number of strings and other properties.

Electrical Configuration	Subarray 1	Subarray 2	Subarray 3	Subarray 4
	(always enabled)	<input type="checkbox"/> Enable	<input type="checkbox"/> Enable	<input type="checkbox"/> Enable
Modules per string in subarray	8			
Strings in parallel in subarray	2			
Number of modules in subarray	16			
String Voc at reference conditions (V)	519.2			
String Vmp at reference conditions (V)	437.6			

APPENDIX C: Optimization Code_Flat Price

```
clear;
clc;

PV_Power_3kW = xlsread('Optimization_Data.xlsx',1,'B2:B8761');
Electricity_Price = xlsread('Optimization_Data.xlsx',1,'F2');
Load_kW = xlsread('Optimization_Data.xlsx',1,'G2:G8761');
x=xlsread('Optimization_Data.xlsx',1,'A2:A8761')
n = length(Load_kW);

soc_min = 20; % Minimum State of Charge for Battery %
soc_max = 100; % Maximum State of Charge for Battery %
k_b = 1000; % Battery Capacity in Ah %
v_b = 12; % Battery voltage in Volts %
c_b = 0.30; % Cost of battery in dollars/Ah ($/Ah) %
c_extra = 1; % Cost to dissipate extra power %
time = 1; % Battery discharging/charging time frame (hr)%
c_pv = Electricity_Price; % Cost of PV in dollars/KW ($/KW) %
soc_init = 100; % Initial Battery State of Charge %

prob = optimproblem('ObjectiveSense','min');

p_pv = optimvar('p_pv',n,'LowerBound',0);
p_b_disch = optimvar('p_b_disch',n,'LowerBound',0,'UpperBound',12);
p_b_ch = optimvar('p_b_ch',n,'LowerBound',0,'UpperBound',12);
batt_control =
optimvar('batt_control',n,'Type','integer','LowerBound',0,'UpperBound',1);
soc = optimvar('soc',n,'LowerBound',soc_min,'UpperBound',soc_max);
p_extra = optimvar('p_extra',n,'LowerBound',0);

prob.Objective = c_pv*sum(p_pv) + c_b*sum(p_b_disch + p_b_ch) + c_extra*sum(p_extra);

cons1 = optimconstr(n);
for i = 1:n
    cons1(i) = p_pv(i) + p_b_disch(i) - p_b_ch(i) >= Load_kW(i);
end

cons2 = optimconstr(n);
for i = 1:n
    cons2(i) = p_pv(i) == PV_Power_3kW(i);
end

cons3 = soc(1) == soc_init;

cons4 = optimconstr(n-1);
for i = 1:n-1
    cons4(i) = soc(i+1) == soc(i) + ((p_b_ch(i) - p_b_disch(i))/(v_b*k_b))*time*100;
end

cons5 = optimconstr(n);
for i = 1:n
    cons5(i) = p_extra(i) == p_pv(i) + p_b_disch(i) - p_b_ch(i) - Load_kW(i);
end
```

```

prob.Constraints.cons1 = cons1;
prob.Constraints.cons2 = cons2;
prob.Constraints.cons3 = cons3;
prob.Constraints.cons4 = cons4;
prob.Constraints.cons5 = cons5;

[sol,fval,exitflag,output] = solve(prob);
pv_power = sol.p_pv;
battery_power_disch = sol.p_b_disch;
battery_power_ch = sol.p_b_ch;
battery_soc = sol.soc;
extra_power = sol.p_extra;

Optimal_cost = fval % Optimal cost in dollars ($) %

Battery=battery_power_disch-battery_power_ch

%plot(x,pv_power,x,Battery,x,Load_kW);
%grid on;
%legend('PV','Battery','Load')
%xlabel('Time [hrs]'); ylabel('Power [kW]');

%%%%%%%%%%%%to zoom into specific days%%%%%%%%%%%%
% Assuming you have a figure already plotted
% Get the handle of the current figure

%fig = gcf;

% Set the x-axis limits to the desired range
%xlim([4225, 4250]);

% Optionally, you can adjust the y-axis limits as well
% ylim([y_min, y_max]);

% Update the figure display
%drawnow;

```

Optimization Code_TOU Options:

```

clear;
clc;

PV_Power_10kW = xlsread('Optimization_Data.xlsx',1,'B2:B8761');
Electricity_Price = xlsread('Optimization_Data.xlsx',1,'H2:H8761');
Load_kW = xlsread('Optimization_Data.xlsx',1,'G2:G8761');
x=xlsread('Optimization_Data.xlsx',1,'A2:A8761')
n = length(Load_kW);

soc_min = 20; % Minimum State of Charge for Battery %
soc_max = 100; % Maximum State of Charge for Battery %
k_b = 1000; % Battery Capacity in Ah %

```

```

v_b = 12; % Battery voltage in Volts %
c_b = 0.30; % Cost of battery in dollars/Ah ($/Ah) %
c_extra = 1; % Cost to dissipate extra power %
time = 1; % Battery discharging/charging time frame (hr)%
c_pv = Electricity_Price; % Cost of PV in dollars/KW ($/KW) %
soc_init = 100; % Initial Battery State of Charge %

prob = optimproblem('ObjectiveSense','min');

p_pv = optimvar('p_pv',n,'LowerBound',0);
p_b_disch = optimvar('p_b_disch',n,'LowerBound',0,'UpperBound',12);
p_b_ch = optimvar('p_b_ch',n,'LowerBound',0,'UpperBound',12);
batt_control =
optimvar('batt_control',n,'Type','integer','LowerBound',0,'UpperBound',1);
soc = optimvar('soc',n,'LowerBound',soc_min,'UpperBound',soc_max);
p_extra = optimvar('p_extra',n,'LowerBound',0);

prob.Objective = sum(c_pv.*p_pv) + c_b*sum(p_b_disch + p_b_ch) +
c_extra*sum(p_extra);

cons1 = optimconstr(n);
for i = 1:n
    cons1(i) = p_pv(i) + p_b_disch(i) - p_b_ch(i) >= Load_kw(i);
end

cons2 = optimconstr(n);
for i = 1:n
    cons2(i) = p_pv(i) == PV_Power_10kW(i);
end

cons3 = soc(1) == soc_init;

cons4 = optimconstr(n-1);
for i = 1:n-1
    cons4(i) = soc(i+1) == soc(i) + ((p_b_ch(i) - p_b_disch(i))/(v_b*k_b))*time*100;
end

cons5 = optimconstr(n);
for i = 1:n
    cons5(i) = p_extra(i) == p_pv(i) + p_b_disch(i) - p_b_ch(i) - Load_kw(i);
end

prob.Constraints.cons1 = cons1;
prob.Constraints.cons2 = cons2;
prob.Constraints.cons3 = cons3;
prob.Constraints.cons4 = cons4;
prob.Constraints.cons5 = cons5;

[sol,fval,exitflag,output] = solve(prob);
pv_power = sol.p_pv;
battery_power_disch = sol.p_b_disch;
battery_power_ch = sol.p_b_ch;
battery_soc = sol.soc;
extra_power = sol.p_extra;

```

```

Optimal_cost = fval % Optimal cost in dollars ($) %

%Battery=battery_power_disch-battery_power_ch

%plot(x,pv_power,x,Battery,x,Load_kW);
%grid on;
%legend('PV','Battery','Load')
%xlabel('Time [hrs]'); ylabel('Power [W]');

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%to zoom into spesific days%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Assuming you have a figure already plotted
% Get the handle of the current figure

%fig = gcf;

% Set the x-axis limits to the desired range
%xlim([4225, 4250]);

% Optionally, you can adjust the y-axis limits as well
%ylim([y_min, y_max]);

% Update the figure display
%drawnow;

```