Feasibility and Impact of Converting UA's Surface Parking to Solar Power

Final Project for ME 591 - Sustainable Energy

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1 Introduction

To satisfy the ME-591 Sustainable Energy Project, students were asked to analyze a sustainable energy project. As it is an extremely open-ended topic, the professor gave a project centering on the University of Alabama (UA) as an example, and recommended to other students a project on powering UA buses with hydrogen gas.

Using UA as my centering object, my proposed project is powering UA's main campus with solar power. The land used for the solar panels will be the non-parking garage parking on campus. The parking lots were chosen for several reasons, but one was so that the scale of the solar project could be compared to land plots in our frame of reference. In reality, if UA were to use solar, they would likely buy a cheap plot of land outside of city limits.

The potential negatives of replacing parking with solar are initially glaring, i.e. where will people park? As such, I think it is important to address the parking fears before moving onto the energy analysis and economics. Replacing all of UA's *commuter* surface parking would reduce the amount of campus parking by **6,136 spots** (per email correspondence with the Transportation Services Department), which is a substantial amount.

In the time that I have been at UA (since 2015), multiple new parking lots have been constructed, showing that UA prioritizes on-campus parking. I think that this is a critical mistake. There is no data published by UA on the distance that the average student who parks on-campus commutes, but I would contend from personal experience that it is not far. While it is not in the scope of this project, I think interesting research could be done on the environmental benefit of replacing commuter trips with bus routes - buses that are used because an alternative is not available. In addition to the environmental benefits, built places centered on public transit and foot-traffic are generally more enjoyable. Anyone who travels to Europe notices that the best places also seem to be the hardest to get to via car. I would contend that there is correlation, and UA should experiment with designing a mostly car-free environment. It would be extremely hard to get faculty and staff on board with a transition to a "car-free" campus if their parking was eliminated, so parking garages in my plan would remain open, serving both staff as well as ADA parking and UA students who commutes a over a specific distance.

With the reduction in parking addressed (whether it was a sufficient argument or not being beyond the scope of this project), the remaining pages of this report cover the economics and environmental benefit of converting UA's surface parking to solar panel arrays. The first iteration of this report was created with the naive assumption that solar could power the entire campus, and thus calculations were also done for a hydro battery. After receiving UA's energy consumption data for an entire year, it was clear the converting the parking lots to solar arrays could not supply all of UA's power, instead it could only ever make up about 13% of the power requirements. This means that energy storage was not necessary, and therefore the calculations are not included in this iteration of the report.

A table summarizing the findings of this report can be seen below, where most of the values are given on a yearly basis. The "Solar" row highlights the metrics if solar were to be implemented, and the "No Solar" row can be taken as the current state of the University of Alabama.

	Cost [$]	Electric Cost [$]	CO2 [Mton]	Energy [GWh]	Power [MW]	Payback Per.	ROI [%]
No Solar	-	33,034,052	39,690,322	244	28	-	-
Solar	21,064,188	25,186,087	34,394,988	212	24	6.25	19.65

It's important to know that I generated below using Jupyter, Python and some Latex. It is likely un-orthodox, but conceivably one could copy my code below and check the results themselves. If you wish to run the code, I can supply the data sources.

2 Calculations

2.1 Python Imports

[1]:
```
import pint
import math
import numpy as np
import pandas as pd
from pytz import timezone
import pint_pandas
import atlite
import logging
import geopandas as gpd
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import plotly.io as pio

pio.templates.default = "ggplot2"
pio.renderers.default = "notebook+pdf"
logging.basicConfig(level=logging.ERROR)
ureg = pint.UnitRegistry(autoconvert_offset_to_baseunit = True)
pint_pandas.PintType.ureg = ureg
```

2.2 Assessing UA's Current Electricity Demand

To compare the solar potential of UA's parking lots to reality, I reached out to Energy Engineering department at UA. They graciously agreed to share UA's electricity consumption data in great detail. The data comes specifically from Will Stephens, an Energy Engineer with UA's Facilities and Grounds Department.

The data was in .CSV format and included four files - one for each substation on UA's main campus. The data was recorded every 15 minutes in power (kW) and listed at the end of the time period. Per Will's instruction, to get the power demand in kWh, one should multiple the power demand by 0.25. In a more verbose form:

$$E[\text{kWh}] = P[\text{kW}] \cdot 15\text{min} \cdot \frac{1\text{h}}{60\text{min}}$$

The rest of Section 2.2 covers importing and "cleaning" the data.

2.2.1 Loading the Data

[2]:
```
df_dict = {}
for direction in ["East", "West", "North", "South"]:
    df_dict[direction] = pd.read_csv(f"./UA Energy/{direction} Sub kW Demand␣
↪Info - 2019-01-01 - 2019-12-31.csv",
                                     skiprows=16,
                                     parse_dates=[['Date', 'Time']])
```

[3]:
```
for name, df in df_dict.items():
    if 'TOTAL - KW-TOT' not in df.columns:
        df['TOTAL - KW-TOT'] = df[[col for col in df.columns if col not in␣
↪['Date_Time']]].sum(axis=1)
    for col in df.columns:
        if col not in 'Date_Time':
            # Shift the data so that power consumption is associated with the␣
↪start time
            df[col] = df[col].shift(-1)
            # drop the last period
            df.drop(df.iloc[-1].name, inplace=True)
```

2.2.2 Creating the Total Dataframe

[4]:
```
total_df = df_dict['East'][['Date_Time', 'TOTAL - KW-TOT']].copy()
for name, df in df_dict.items():
    total_df[f'{name}-TOTAL'] = df['TOTAL - KW-TOT'].astype("pint[kW]")
    if name not in 'East':
        total_df['TOTAL - KW-TOT'] += df['TOTAL - KW-TOT']
total_df['TOTAL - KW-TOT'] = total_df['TOTAL - KW-TOT'].astype("pint[kW]")
```

2.2.2.1 Setting the Index to a Timezone-aware Datetime

[5]:
```
tz = timezone('US/Central', )
total_df['Date_Time'] = total_df['Date_Time'].apply(tz.localize, is_dst=False)
total_df.set_index('Date_Time', inplace=True, drop=False)
```

[6]:
```
for col in total_df.columns:
    if col not in 'Date_Time':
        total_df[col.split('-')[0] + " Energy"] = total_df[col] * 0.25 * ureg.
↪hour  # in kWh
```

2.2.3 Calculating UA's Total Power and Energy Consumption

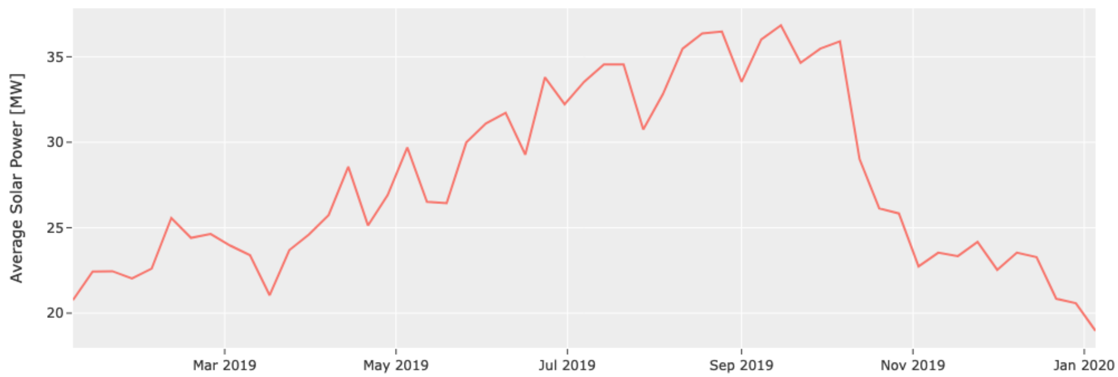
[7]:
```
total_df['TOTAL - KW-TOT'].mean()
```

[7]: 27877.04315930694 kilowatt

[8]:
```
total_df['TOTAL  Energy'].sum().to('GWh')
```

[8]: 244.15411325 gigawatt_hour

In summary, UA used 244 GWh of electricity throughout the year. Assuming that 2019 is representative of the average year at UA, this electricity usage peaks in late September / early October at 36.8 MW. To put that in context, the average house consumes 11,000 kWh per year [2]. UA's energy consumption is the equivalent of **22,181 homes.**



2.3 Solar Potential Calculation

After calculating UA's power and energy consumption, the analysis turned to analyzing the solar potential of UA's surface parking lots. The first part of this analysis was a simple one done using the formulas and values from this course's textbook, the Fundamentals and Applications of Renewable Energy [8]. Further down, a more detailed analysis was done using the atlite software [7].

The remaining analysis uses values from the SunPower's datasheet. SunPower panels were chosen for this analysis as they are one of the most widely adopted brands and had informative documentation on their website. Specifically, the P-Series panels were selected as they are SunPower's utility-scale panels. The most important value from the datasheet is the efficiency of the panels, which for the SunPower P-Series is around 19%.

2.3.1 Simplistic, from the book

The book provides average solar radiation values ($\frac{MJ}{m^2 \cdot day}$) for many cities in the U.S. The nearest city to Tuscaloosa that has values is Birmingham, Alabama, so it is used as an analog.

[175]:
```
G_solar = list(map(lambda x: x * ureg.MJ / (ureg.m ** 2 * ureg.day), [9.20, 11.
↪92, 13.67, 19.65, 21.58, 22.37, 21.24, 20.21, 17.15, 14.42, 10.22, 8.40]))
G_solar = {i + 1: {'G': g, 'D': (30 if i % 2 else 31) * ureg.day} for i, g in␣
↪enumerate(G_solar)}
# Manually Correcting Feb. Days
G_solar[2]['D'] = 28 * ureg.day
```

Using Google Maps measure tool, I calculated the surface area of all the considered parking lots and saved it to a CSV, along with the GPS coordinates to each of the parking lots centers.

[12]:
```
parking_lots = pd.read_csv("ParkingLotArea.csv")
parking_lots.head()
```

[13]:
```
parking_lots['Area (ft)'] = parking_lots['Area (ft)'].astype("pint[ft^2]")
```

2.3.1.1 Calculating the Theoretical Energy per Day

Using the 19% efficiency of the SunPower P-series panels (N_{pv}), the power in terms of $\frac{MJ}{day}$ can be calculated for every month of the year. The equation is as follows:

$$P_{\text{parking lot}_{\text{month}}} = A_{\text{parking lot}} \cdot G_{\text{month}} \cdot N_{pv}$$

The loop below calculates the power for each parking lot and for each month in the year.

[176]:
```
N_pv = 0.19 # the efficiency of SunPower P-series
```

[177]:
```
for month, inner_dict in G_solar.items():
parking_lots[f'P_{month}'] = (parking_lots['Area (ft)'] * N_pv *␣
↪inner_dict['G']).pint.to("MJ / day")
```

2.3.1.2 Average Daily per Lot and Total

Using the monthly power calculated in Section 2.3.1.1, the yearly average values can be found for each parking lot by taking the weighted average of each months' average power, where the weights are the days in the month.

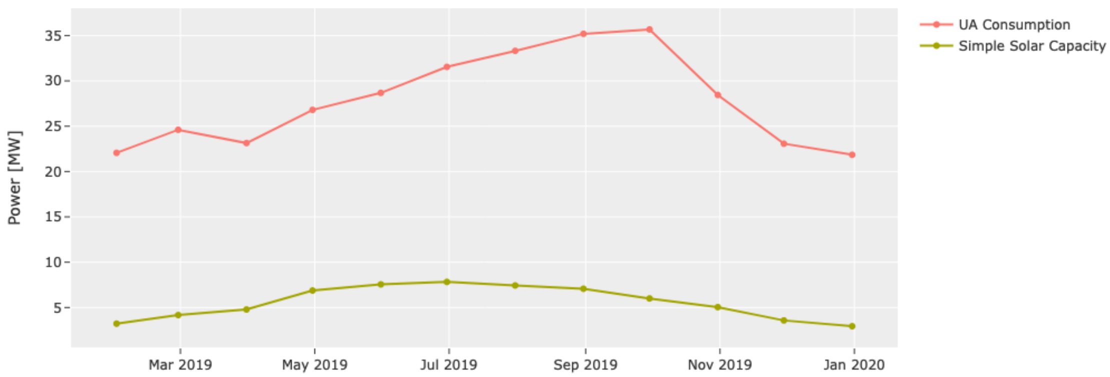
[16]:
```
parking_lots['P_avg'] = 0
parking_lots['P_avg'] = parking_lots['P_avg'].astype('pint[MJ / day]')

for month, inner_dict in G_solar.items():
    parking_lots['P_avg'] += parking_lots[f'P_{month}'] * inner_dict['D'] / (365␣
↪* ureg.day)
```

[17]:
```
parking_lots['P_total'] = (parking_lots['P_avg'] * 365 * ureg.day)
```

2.3.1.3 Plotting the Calculated Solar Power vs. Monthly Power Consumption

In the figure below, the simple solar power calculations from the book are plotted against UA's power demand throughout the year.



2.3.2 Complicated Capacity Estimate

In Section 2.3.1, the average daily sun power that reaches the parking lot surfaces was calculated, which ignores several details. In this section, the atlite Python package is utilized to estimate the actual available solar power with more accuracy Hofmann et al. [7].

2.3.2.1 Calculating the installed capacity, using the available area and Sun Power's Datasheet

One of the inputs to the atlite solar calculations is the *installed capacity*, which is different than average power used in Section 2.3.1. The total solar capacity is calculated as

$$\text{Capacity}_{\text{solar}} = N_{panels} \cdot \dot{W}_{panel} * N_{\text{ac/dc}}$$

where N_{panels} is the number of panels that can fit on the parking lots and $\dot{W}_{panel}$ is the nominal max power of the panel, which comes from the datasheet. For the P-series panel, the nominal power is 335 Watts. Because solar panels generate DC power and UA uses standard AC power, an inverter would per required. $N_{\text{ac/dc}}$ represents the inverter efficiency and is assumed to be 90%.

The formula that I used to find the number of panels for each parking lot is below:

$$N_{panels} = \text{floor}\left(\frac{A_{\text{parking lot}}}{A_{\text{solar panel}}} \cdot N_{\text{area}}\right)$$

where N_{area} is a scaling factor < 1 to account for the fact that not 100% of the parking lot surface area can likely be utilized by solar panels, as there will be transformer hardware etc.

[181]:
```
P_pv = 355 * ureg.watt
A_pv = 81.4 * 39.3 * ureg.inch ** 2
N_ac_dc = .9
N_area = 0.95  # estimating that not all surface area will be covered by panels
 ↪due to geometry constraints etc.
```

2.3.2.2 Determining the number of SunPower P17 Panels that can fit on each surface

[182]:
```
parking_lots['# of Panels'] = (parking_lots['Area (ft)'] / A_pv * N_area).pint.
  ↪to('dimensionless')
parking_lots['# of Panels'] = np.floor(parking_lots['# of Panels'])
parking_lots['# of Panels']
```

[182]:

Lot	# of Panels
NE of NE Commuter	10038
Cent. of NE Commuter	8833
S of NE Commuter	4820
Frat of NE Commuter	12121
Cyber Hall Parking	4189
Yellow Zones	4910
Bryce Hospital	5730
West Commuter	7924
SE Commuter Coleman	9089
SE Commuter Law	5600

[183]:
```
parking_lots['PV Capacity'] = parking_lots['# of Panels'] * P_pv * N_ac_dc
parking_lots['PV Capacity'] = parking_lots['PV Capacity'].astype('pint[W]')
parking_lots['PV Capacity'] = parking_lots['PV Capacity'].pint.to('MW')
# parking_lots['PV Capacity']
```

[184]:
```
parking_lots['PV Capacity'].sum()
```

[184]: 23.404653 megawatt

Using the constants above, the total installed capacity is 23.4 MW, which was cross-referenced by visiting NREL's PVWatts website [4]. Both PVWatts and my calculations above agree.

2.3.2.3 Using the ERA5 Dataset

The atlite package relies on the ERA5 dataset for it's solar calculations. The data has been collected since 1979 and provides hourly estimates of a large number of atmospheric, land and oceanic climate variables [6]. For this project, the relevant dataset is solar radiation at the earth's surface.

Data from 2015 was used in the calculations below as it was the most recent year with data for the state of Alabama. This is an assumption that would matter more the finer the time resolution of the analysis is, but for the scope of this project I felt that it was an okay assumption.

[186]:
```
bl = 32.988320041698074, -87.79145924201974
tr = 33.473235950702524, -87.32768306322347

cutout = atlite.Cutout(path="Alabama.nc",
                       module="era5",
                       x=slice(bl[1], tr[1]),
                       y=slice(bl[0], tr[0]),
                       time="2015"   # "2018-12")
                       )
```

2.3.2.4 Downloading ERA5 Data for the specified cutout

[24]:
```
cutout.prepare()
```

2.3.2.5 Finding the Cutout Cell Nearest to the UA Parking Lots

The ERA5 data is partitioned into "cut-outs" that are larger than the parking lots themselves. To account for this, all of the parking lots considered for this project where assigned to the nearest ERA5 cell below.

[187]:
```
cells = gpd.GeoDataFrame({'geometry': cutout.grid_cells,
  'lon': cutout.grid_coordinates()[:,0],
  'lat': cutout.grid_coordinates()[:,1]})
```

[188]:
```
nearest_cell = cutout.data.sel({'x': parking_lots.Lon.values,
                                'y': parking_lots.Lat.values},
                               'nearest').coords
```

[189]:
```
# Map capacities to closest cell coordinate
parking_lots['lon'] = nearest_cell.get('lon').values
parking_lots['lat'] = nearest_cell.get('lat').values
```

[190]:
```
parking_lots['PV Capacity'] = parking_lots['PV Capacity'].pint.magnitude
```

[29]:
```
new_data = parking_lots.merge(cells, how='inner')

# Sum capacities for each grid cell (lat, lon)
# then: restore lat lon as columns
# then: rename and reindex to match cutout coordinates
new_data = new_data.groupby(['lon','lat']).sum()

layout = new_data.reset_index().rename(columns={'lat':'y','lon':'x'})\
                    .set_index(['y','x'])['PV Capacity']\
                    .to_xarray().reindex_like(cutout.data)

layout = layout.fillna(.0).rename('Installed Capacity [MW]')
```

The atlite package allows the user to configure the orientation of the solar panels. Because the class did not explicitly cover solar panel orientation calculations, I chose to let atlite calculate the optimal orientation given the latitude of Tuscaloosa, Alabama.

[30]:
```
pv = cutout.pv(panel="CSi", orientation='latitude_optimal', layout=layout)
```

2.3.2.6 Put the data into a DataFrame and fixing the timezone

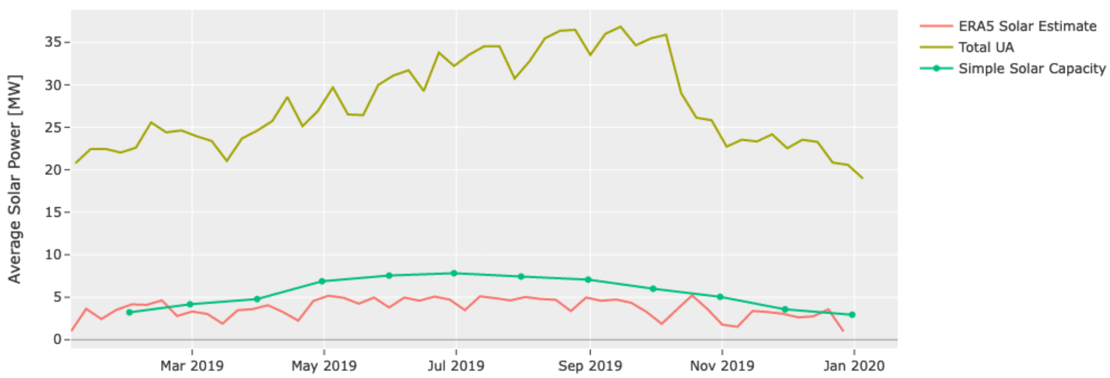
[31]:
```
pv_df = pd.DataFrame(pv.squeeze().to_series())
```

```
[32]: tz = timezone('GMT', )
pv_df['Date_Time'] = pv_df.index.values
pv_df['Date_Time'] = pv_df['Date_Time'].apply(tz.localize, is_dst=False)
pv_df['Date_Time'] = pv_df['Date_Time'].dt.tz_convert(timezone('US/Central'))

pv_df.set_index('Date_Time', inplace=True)
```

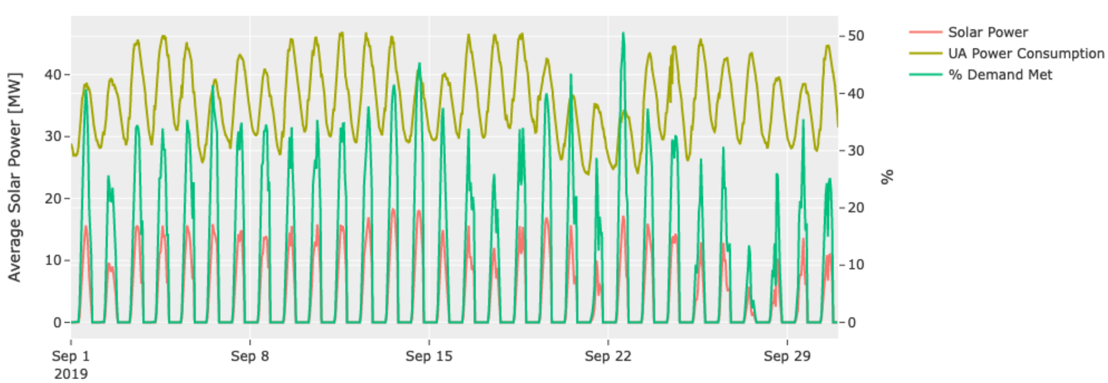
2.4 Plotting In-depth Solar vs. UA Power Consumption vs. Simple Solar Calculation

2.4.1 Average Weekly Power



2.4.2 Daily in September

The plot below shows that the daily peaks in both solar power generation and UA's power consumption actually coincide in September.



2.4.3 Determining the actual area required for solar panels to power UA's campus

UA's average power consumption peaks in September at a value of 35675 kW. In order for solar to **completely** supply UA's campus with power, the monthly average solar power would have to be greater than this value. Assuming that both solar radiation and solar panel efficiency are fixed, this calls for more area devoted to solar panels. The calculations below determine roughly the area required, though the simple calculation over-estimates the solar power available, and a correction factor, C_f, will be applied, which is simply $\frac{\text{era5 estimate}_{\text{September}}}{\text{simple estimate}_{\text{September}}}$. The actual area required is calculated as

$$A = \frac{P_{desired}}{N_{pv} \cdot G \cdot C_f}$$

The AC/DC convererter efficiency is not explicitly included in the formula as it is included in the C_f calculation.

Its important to note that this calculation does not take into consideration the energy lost in electricity storage. If UA were to be completely powered by solar panels, there would have to be an energy storage system as well - which has its own inefficiencies.

[35]:
```
total_required_power = total_df.loc[total_df.index.month == 9, 'TOTAL - KW-TOT'].
↪pint.to('MW').mean()
total_required_power
```

[35]: 35.67570416666667 megawatt

2.4.3.1 Correction Factor

[36]:
```
corr_factor = pv_df[0].loc[pv_df.index.month == 9].mean() / parking_lots[f"P_9"].
↪sum().to('MW').magnitude
corr_factor
```

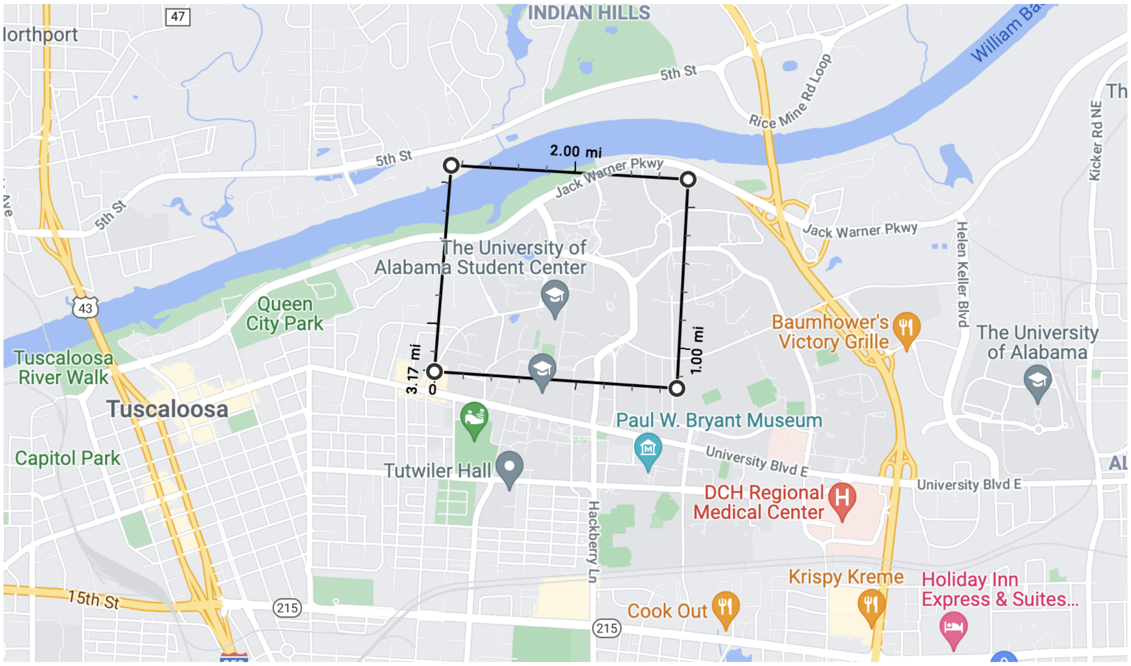
[36]: 0.677499185567263

2.4.4 The Total Area Required

[37]:
```
A = total_required_power / (N_pv * G_solar[9]['G'] * corr_factor)
A.to('m^2')
```

[37]: 1396239.0932734653 meter^2

To put the amount of area required into perspective, the image below shows a box with equivalent area drawn on top of UA's main campus.



2.5 Hydro Battery Calculations

I was going to do hydro-battery calculations for my proposal, as some storage device is necessary to capture the full potential of solar power if it is to be the main power source. Given UA's power demand though, storage is not required. Even during peak-sun periods, the solar panels do not provide excess power that needs to be stored.

If there was an excess energy provided by the panels, I think an interesting storage solution would be a hydro-battery. UA's main campus has two geological advantages for a hydro-battery: a river 500m from campus and ~100ft of elevation change between campus and the river. The river provides ample water for a battery to operate with relatively little impact down / upstream, with a flow rate of 2000 cubic feet per second (from TODA1 gauge of NWS's Advanced Hydrological Prediction Service). The natural change in elevation means that water could be pumped to a reservoir on UA's campus and stored with little investment in infrastructure.

There is of course the glaring question as to why both the solar and hydro-storage have to be on UA's campus and not instead on land else where. The answer is simply that for the class we were asked to propose a project related to the campus and using campus as the "land source" provided a good sense of scale for the area that solar power requires.

3 Economics of the Proposal

This section is dedicated to analysing the economics of implementing solar panels on UA's campus. As a reference point to the installation cost of solar, I looked up the cost of the new Tutwiler Hall being built on campus. Its current expected cost in **$144,900,659.00** per Building Bama's website [1].

For the engineering economics calculations in this section, the assumed interest rate is 6%. As a caveat, it is likely that the University of Alabama has access to lower interest rates, but I could not find better information on it.

[99]:
```
i = 0.06
```

3.1 Solar Implementation Cost

Per the Solar Energy Industries Association (SEIA), the average cost of utility-level solar projects in Q3 of 2021 is $0.90 per watt of DC power [9]. This value is used for the cost analysis in this section, but it is likely that UA would have access to discounted rates (through government rebates) given that it is a public research institution.

[85]:
```
parking_lots['PV Capacity'].sum()
```

[85]:
```
23.404653
```

[83]:
```
C_solar = 0.9 / ureg.W
cost_solar = parking_lots['PV Capacity'].sum() * ureg.MW * C_solar
cost_solar = cost_solar.to('dimensionless')
cost_solar.magnitude
```

[83]:
```
21064187.700000003
```

The turn-key installation cost is $21,064,187. In comparison to the cost of the new Tutwiler Hall construction, this would be a relatively small project for the university.

3.2 Cost of Electricity

Using my monthly power bill in Tuscaloosa, Alabama, I found the cost of electricity to be $0.1353 per kWh. It is likely that UA receives discounted rates from the local utility company. Without having the information on UAs effective cost of electricity, I use the consumer cost of electricity.

[86]:
```
c_p_kwh = 13.53 / 100 / ureg.kWh
```

3.3 Determining UA's Yearly Power Bill

[87]:
```
yearly_elec = total_df['TOTAL  Energy'].sum()
```

[88]:
```
yearly_elec.to('kWh') * c_p_kwh
```

[88]: 33034051.522725

Using the assumptions alluded to above, UA pays $33,034,051 per year in electricity costs.

3.4 Solar's Yearly Savings

To find the total energy that the solar panels would provide in a year, the numerical integral of the atlite power estimate throughout the entire year was calculated.

[89]:
```
yearly_solar_electricity = (np.trapz(pv_df[0], dx=3600) * ureg.MW * ureg.s).
↪to('kWh')
```

Multiplying the amount of solar energy that the parking lots would capture by the cost of electricity, the yearly savings to UA can be calculated.

[90]:
```
yearly_solar_electricity_savings = yearly_solar_electricity.to('kWh') * c_p_kwh
```

Converting the parking lots to solar installations could save UA $4,407,000.00 per year on electricity.

3.5 Present Value of Annual Savings

The present value calculation relies on the installation lifetime. I could not find great data on SunPower's website for the actual lifetime of the panels, but they have a 25 year warranty. Going forward, I will use 25 years as the lifetime of the project, n.

The formula for present value of annual savings, P, is below

$$P = U\left[\frac{1-(1+i)^{-n}}{i}\right]$$

where U is the yearly savings calculated in Section 3.4, and i is the interest rate.

[101]:
```
n = 25

pv_as = yearly_solar_electricity_savings.magnitude * (1 - (1 + i) **(-1 * n)) / i
pv_as
```

[101]: 56339815.92712577

3.5.1 Present Value of the Maintenance Costs

Just as there is a present value of the savings, there is also a present value of the maintenance costs of the solar project. Solar maintenance mainly involves cleaning the panels and I found an estimate online for $11.50 per kWh [3].

[50]:
```
C_repair = parking_lots['PV Capacity'].sum() * ureg.MW * 11.50 / ureg.kW
C_repair = C_repair.to('dimensionless')
```

[102]:
```
pv_repair = C_repair.magnitude * (1 - (1 + i) **(-1 * n)) / i
pv_repair
```

[102]: 3440685.1731863804

3.5.2 Net Present Value

[105]:
```
npv = pv_as - pv_repair
npv
```

[105]: 52899130.75393939

The net present value of the project is the difference between the present value of savings the present value of repair. For this project, the net present value is $52.9 million.

3.6 ROI

```
[112]: roi = (yearly_solar_electricity_savings - C_repair) / cost_solar
       roi.magnitude * 100
```

```
[112]: 19.645312005848915
```

The return on investment is 19.6%, which would be generally thought of as a good investment.

3.7 Payback Period

Knowing the up-front cost of the solar panels, the yearly electric savings, and the yearly solar panel maintenance cost, we can calculate the payback period, n_{dpb}, with the equation below.

$$n_{dpb} = \frac{\log \left[1 - (\frac{P}{U})i\right]^{-1}}{\log(1+i)}$$

```
[79]: P = cost_solar.magnitude
      U = (yearly_solar_electricity_savings - C_repair).magnitude
      i = 0.06
```

```
[80]: n_dpb = np.log((1 - (P / U) * i) ** (-1)) / np.log(1 + i)
```

```
[81]: n_dpb
```

```
[81]: 6.254497071824046
```

The projects payback period is 6.25 years using the discounted payback period equation.

3.8 Final Results

```
[148]: ## Alabama's Carbon Intensity: From https://www.eia.gov/environment/emissions/
        ↪state/
       al_co2 = (47.6423949721341 * ureg.kg / (1e6 * ureg.BTU)).to('kg/kWh')
       al_co2
```

[148]: $0.16256 \ \frac{\text{kilogram}}{\text{kilowatt\_hour}}$

The US Energy Information Administration publishes the carbon intensity of every states electricity grid [5]. By using Alabama's, I can estimate the carbon emissions that UA would save by adding solar panels. The saved carbon emissions are displayed in the table below, which also appears in the Introduction 1.

The following table has been generated to summarize the project. It's important to note that this table is generated via the Jupyter code cells not shown, and won't execute where it is at. Probably not great programming practice, but it had to be in the introduction to satisfy the project requirements.

	Cost [$]	Electric Cost [$]	CO2 [Mton]	Energy [GWh]	Power [MW]	Payback Per.	ROI [%]
No Solar	-	33,034,052	39,690,322	244	28	-	-
Solar	21,064,188	25,186,087	34,394,988	212	24	6.25	19.65

4 Conclusion

The amount of electricity that UA's campus uses is striking. Comparing it to solar area really puts it into perspective. I'm sure that UA has considered energy saving efforts before, but as I write this I am sitting in a library that is cooled into the low 60s. That feels excessive, but it is also beyond the scope of this project.

Replacing UA's on-campus parking with solar is a project that was doomed to fail from the start. Its not so much cost prohibitive as it is public-approval prohibitive. That being said, adding utility-level solar to UA's campus would be a good investment. Alabama gets sufficient solar radiation to make large investment in a solar project worthwhile. Depending on the levels of government grants, incentives, etc., the cost could even be quite a bit less than my estimates. If UA had access to equivalent plots of unused land it's almost a no-brainer. The publicity from a solar project of this magnitude would likely drive funding to faculty as well, essentially reducing the cost of the project further.

While solar would be a good investment, the analysis in this project proves that completely decarbonizing the power sector is a daunting task. Solar is one of the most mature renewable energy technologies, and to power UAs campus with it would require a footprint the size of UAs campus itself (see Section 2.4.3). It is going to take clever solutions to free even the University of Alabama from coal / natural-gas fired power plants. I am confident that humanity will solve the problem, but we need to see more investment and experimentation from the government and private sector.

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