Create Model Data for N-Number of Residential Solar-PV Prosumers in the Florida Power & Light Service Territory

Description:

Provide a simulation of prosumers (users that can provide generation), specifically for the FPL Territory by utilizing public government information. The methodology would take into account average curves in the published data and normalize it in order to simulate what an individual prosumers consumption and generation would be given averages states by common litterature. (i.e the average consumption of a typical home in south florida, and the generation capacity of the typical installation of PV solar). With the typical averages of a prosumer and the normalized curves we can synthesize a typical prosumer in the FPL territory. The final step would be to add variance to the consumption and generation profiles for each prosumer to simulate evironmental and behvaioural differences of each unique home. The final output would be a series of prosumers interacting with the grid to for consumption and providing net energy when solar generation is sufficient.

Steps:

1. Data Gathering

- Shows the steps taken to acquire the data from EIA.gov
- Validation of collected data with other resources , ie. NREL

2. Data Cleansing

- Conversion of units, normalization and joing of datasets

3. Build Model from Data

- Implement statistical variations to curves
- Create individual prosumer models and save to csv file

```
#import data from sources
import pandas as pd
from functools import reduce
import requests
import os
import pathlib
from datetime import datetime
import matplotlib.pyplot as plt
from numpy import random
```

```
from tabulate import tabulate
import math
```

Step 1: Data Gathering

1.1 Collecting Data Programatically from EIA

The Energy Information Administration (EIA) is the statistical agency of the Department of Energy. It provides policy-independent data, forecasts, and analyses to promote sound policy making, efficient markets, and public understanding regarding energy, and its interaction with the economy and the environment. They provide an API (Application Programmable Interface) for gathering historical data. The data is provided to users through the use of an API key and crafted URL queries. More information on the API and its query parameters can be found here (http://api.eia.gov/series/).

The simulation is focused on gathering datasets specifically from Florida. The datasets that the simulation will utilize are residential demand, generation from distributied photo-voltaic solar energy (roof-top solar), and residential price of electricity. The datasets provide these in particular formatting and scale that requires conditioning. THe condintioning step is referenced as "Data Wrangling" and is discussed further in latter sections.

- Call EIA.gov API
 - Set the api key
 - Set the start and end month in 'YYYYMM' format

```
In [95]:
          # Data Gathering Settings
          start = '201910'
          end = '202012'
          class Dataset:
              def __init__(self, name, query,start,end):
                  self.name = name
                  self.query = query
                  self.start =start
                  self.end = end
                  self.df = self.fetch()
              def plot(self):
                  self.df.plot(x='time',title=f"FL. Residential ({self.name})")
              def convert(self,unit):
                  self.df[self.name] = self.df[self.name].apply(lambda x: x*unit)
              def normalize(self):
                  self.df[self.name] = self.df[self.name].apply(lambda x: x/self.df[self.n
                  #self.df= self.df.sort values(by=['time'])
              def fetch(self):
                  eia url = 'http://api.eia.gov/series/'
                  api_key='d42ebe76b736d7815489e3298ff17079'
                  self.url = f'{eia url}?api key={api key}&series id={self.query}&start={s
                  data = requests.get(self.url).json()['series'][0]['data']
                  df = pd.DataFrame(data,columns=['time',self.name])
                  df['time'] = pd.to datetime(df['time'], format='%Y%m')
                  return df
```

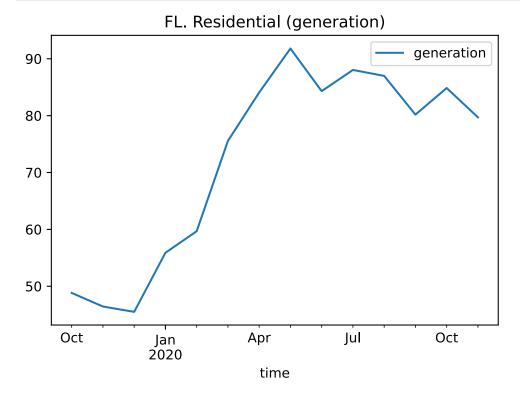
```
demand = Dataset(name='demand',query='ELEC.SALES.FL-RES.M',start=start,end=end)
generation = Dataset(name='generation',query='ELEC.GEN.DPV-FL-8.M',start=start,e
price = Dataset(name='price',query='ELEC.PRICE.FL-RES.M',start=start,end=end)
```

1.2 Validating Data

1.2.1 Net Generation of Residential Small-Scale PV Solar

The plot retreived from the generation data shows the peak of generation in Florida to be in the month of May. The data provided by the EIA is in accordance with reports collected by NREL DNI maps.





Every PV Solar installation is different and will have a different net-generation curve. Systems can suffer from tree shading, orientation, and other external factors. According to the National Renewable Energy Labs' PVWATTS estimator, which takes decades of weather data and solar irradiance estimates to plot the output from a given solar energy system based on a set of assumption, the best time for solar energy production in Florida is spring. East facing systems will outperform a west facing system primarily because of afternoon rain showers in the late spring and summer. The east facing systems gather most of their energy in the relatively clear morning hours. An east facing system will produce about 9% less than a south facing system. A west facing system will produce about 11% less than a south facing system. Pitching panels in a manner that is not parallel to a roof surface costs more than the gains that would be achieved, and reduces total available roof space (because rows of pitched modules need to be spaced to

avoid shading) [1]. In summary the best time of year for solar power in Florida is spring, and the annual variation in solar production is dependent on the orientation of solar panels.

The National Renewable Energy Laboratory (NREL) specializes in the research and development of renewable energy, energy efficiency, energy systems integration, and sustainable transportation. They provide a DNI(Direct Normal Solar Irradiance) model that provides the generation expected from Solar at various areas in north america. Direct Normal Irradiance (DNI) is the amount of solar radiation received per unit area by a surface that is always held perpendicular (or normal) to the rays that come in a straight line from the direction of the sun at its current position in the sky. The maps shown provide annual average daily total solar resource using 1988-2016 data (PSM v3) covering 0.038-degree latitude by 0.038-degree longitude (nominally 4km x 4km). NREL The model from NREL confirms the assumptions that during the months of March, April and May are peak months for solar generation in almost the entire Florida region. A very sharp decline in DNI is seen during the month of June and other summer months. The counter-intuitive realization here is that even if summer days are longer and provide more exposure to the sun the irridiance is not as strong.

May DNI Map from NREL

Florida DNI

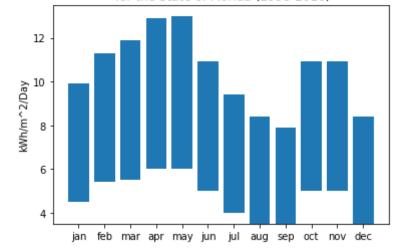
Analysis of just the state of florida can show us a trend of DNI over the year. This data was extracted and as an average range from the NREL DNI charts.

Florida DNI During The Month of May (Annualized 1998-2016)

May DNI Map from NREL

```
In [10]:
          fl dni plot title = 'Annualized Average Range of Direct Normal Solar Irradiance
          fl dni max data = [5.4,5.9,6.4,6.9,7.0,5.9,5.4,4.9,4.4,5.9,5.9,4.9]
          fl dni min data = [4.5, 5.4, 5.5, 6.0, 6.0, 5.0, 4.0, 3.5, 3.5, 5.0, 5.0, 3.5]
          fl dni x = ['jan','feb','mar','apr','may','jun','jul','aug','sep','oct','nov','d
          plt.bar(fl dni x,fl dni max data, bottom=fl dni min data)
          plt.ylabel('kWh/m^2/Day')
          plt.title(fl dni plot title)
          plt.show()
```

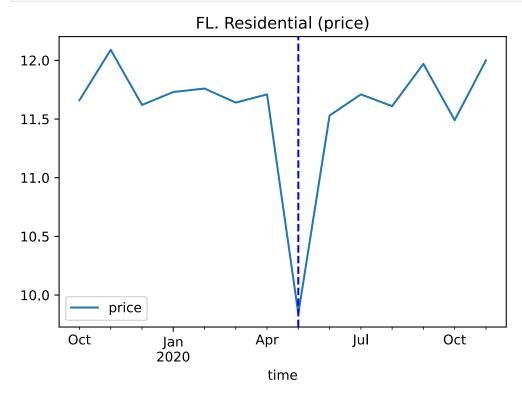
Annualized Average Range of Direct Normal Solar Irradiance for the State of Florida (1998-2016)



1.2.2 Validation of Residential Electricity Retail Monthly Price

The residential pricing plot shows a significant dip from above 11.5 cents to below 10 cents this correlates well with the pandemic relief provided by FPL (Florida Power & Light) for the month of May. The FPL utility provided 25% discount on electricity consumed in May. Sun-Sentinel

```
price.plot()
    # only one line may be specified; full height
    plt.axvline(x = '202005', color = 'b', label = 'May, Price Reduction (Pandemic R plt.show()
```

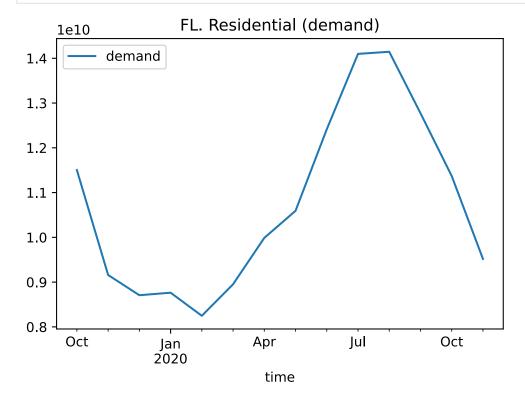


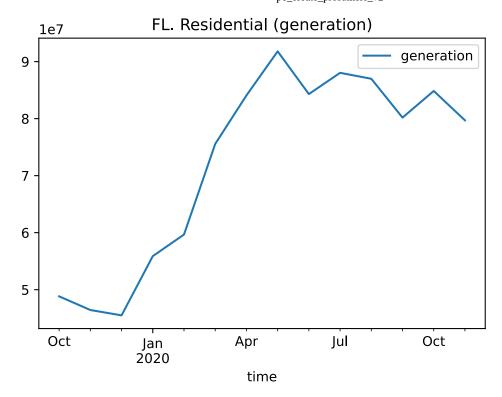
Step 2: Data Cleansing

2.1 Conversion of Units to kWh

- Average Consumption Dataset :
 - Retail sales of electricity, Florida, residential, monthly
 - Units in Million Kilowatthours
 - Conversion to kWh : X_kWh = (X * 10^6)
- Average Prosumer Generation Dataset :
 - Net generation, small-scale solar photovoltaic, Florida, residential, monthly
 - Units in thousand megawatthours
 - Conversion to kWh : X_kWh = (X 10^3 10^3)
- Average Price Dataset:
 - Average retail price of electricity, Florida, monthly
 - Units in cents per Kilowatthour
 - Conversion to cents/kWh : X_cents/kWh = X_cents/kWh

```
demand.convert(pow(10,6))
    generation.convert(pow(10,6))
    #price.convert(1) #No conversion required
    demand.plot()
    generation.plot()
```





2.2 Normalize & Join Data

How to combine? The datasets for generation, demand and price will be joined on the "time" stamp for year and month.

Why Normalize? The datasets are provided as an average of all of Florida. Since the simulation requires single prosumers to be synthesized from the average curve of all Florida residents the normalized curve will then be used to generate randomly an individuals curve about the normal curve. The statistical variance away from the normal curve can be adjusted to simulate the variability of a single prosumer. The same can be done for N number of prosumers.

Pricing? The prices for retial electricity each month will be used to create profits for the prosumers. These prices will be used as is and will not need to be normalized.

```
In [99]:
          # normalize the dataset from 0.0-1.0
          demand.normalize()
          generation.normalize()
          demand.plot()
          generation.plot()
          # merge the datasets by time column
          df = reduce(lambda left,right: pd.merge(left,right,on=['time'],how='outer'), [de
          print(df)
                  time
                           demand generation
                                                price
         0
            2020-11-01 0.672893
                                     0.868196
                                                12.00
         1
            2020-10-01
                        0.803816
                                     0.924304
         2
            2020-09-01
                        0.902985
                                     0.873409
                                                11.97
         3
            2020-08-01
                         1.000000
                                     0.947582
                                                11.61
            2020-07-01
                         0.996674
                                     0.958952
                                                11.71
                                                11.53
            2020-06-01
                         0.877596
                                     0.918344
```

1.0

0.9

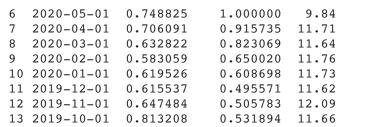
8.0

0.7

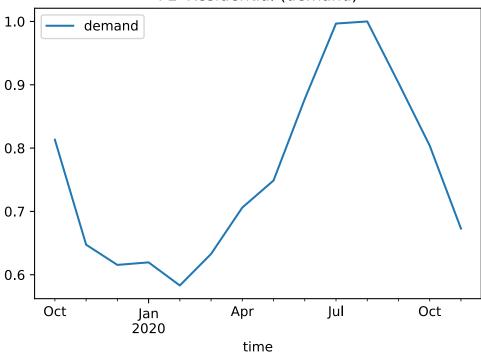
0.6

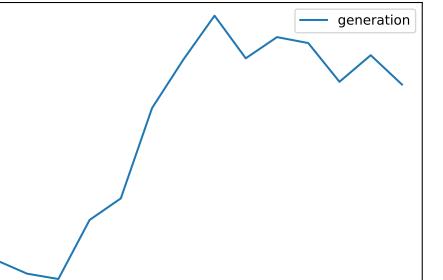
0.5

Oct



FL. Residential (demand)





Jul

Oct

FL. Residential (generation)

Step 3: Build Model from Data

Jan 2020 Apr

time

3.1 Synthesizing Individual Prosumer Data From Ensemble Datasets

Typical individual consumption per month in florida: 1100kWh/mo.

The datasets collected are monthly averages rolled up for the entire state of florida. The florida data can be used as a baseline to show variations each month from a norm. The average consumer demand in florida was estimated to be 1100kWh a month. Since we have a percentage of the average home usage we can use it as our baseline deviation from norm.

Typical individual solar generation per month in florida : (10kW) 4hr30days = 1200kWh/mo.

Most florida prosumers are using residential PV installations that are considered Tier 1, less than 10kW AC capacity. By multiplying the possible generation accross the hours of optimum daylight each day (assumption made from surveys) (4 hours * ~30days) we can arrive at an approximate normal capacity for a typical home at around 1200kWh a month. The florida regulations for net metering prohibits the generation of more than 115% of the homes consumption. This limitation fits the benchmarks chosen for an everage prosumers generation, in this case (1,125kWh/mo.).

The randomized curves are generated from the normalized curve. The function "get_random_curve" shows how the new curves for the prosumers will be created.

3.1.1 Define Prosumer

• The prosumer object can be designed to have the generation, demand, consumption, netenergy curves as properties. The first two would be generated from the normal curves randomly while the last two will be calculated from the previous ones.

3.1.2 Calculate Prosumer Net-Energy Data

 Create net-energy values by taking difference in the generation and demand for each prosumer that is positive. This represents the prosumers excess generation to the grid.

3.1.3 Calculate Prosumer Consumption Data

• Create consumption values by taking the negative values of the difference between the generation and demand. This represents the prosumers consumption from the grid to meet the required demand for the prosumer that is not met by the solar production.

```
class Prosumer:
    def __init__(self, id, gen, dem, price):
        self.id = id
        self.generation = gen
        self.demand = dem
        self.price = price
        diff = self.demand['demand'] - self.generation['generation']
```

```
consumption = [max(x,0) \text{ for } x \text{ in } diff]
    net energy = [\min(x,0) for x in diff]
    self.consumption = pd.DataFrame(list(zip(self.generation['time'],consump
    self.net_energy = pd.DataFrame(list(zip(self.generation['time'],net_ener
    self.data = reduce(lambda left,right: pd.merge(left,right,on=['time'],ho
def table(self):
    #print(f"\nProsumer:{prosumer['id']}")
    print(tabulate(self.data, headers = 'keys', tablefmt = 'github', showinde
def data_w_id(self):
    data_w_id = self.data
    data_w_id["id"] = self.id
    return data w id
def plot(self):
    # plot all curve associated with prosumer
    self.data.plot(x='time',y=['demand','generation','consumption','net_ener
```

```
In [108...
          # Given statistical arguments , converts an original dataframe curve with 'time
          # randomly sampled equivalent given the args['std'],args[llim],args[ulim],args[
          def get_random_curve(args,curve):
              c = [max(args['llim'], min(args['ulim'], random.normal(loc=args['mean'], scale=
              return pd.DataFrame(list(zip(curve['time'],c)),columns=['time',args['type']]
```

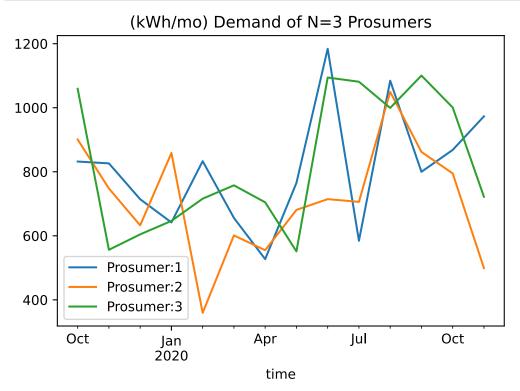
```
In [109...
          # Generate prosumers based on normalized curves from data gethering stage
          def get_prosumers(N,gen_args,dem_args,gen_df,dem_df,price_df):
              prosumers = []
              for n in range(N):
                  prosumers.append(
                      Prosumer(id=n+1,
                               gen=get_random_curve(args=gen_args,curve=gen_df),
                               dem=get random curve(args=dem args,curve=dem df),
                              price=price df))
              return prosumers
```

```
In [110...
          # Generate a collection of prosumers
          N = 3 # Number of prosumers to create
          prosumers = get prosumers(N,
                               gen args= {
                               'type': 'generation',
                               'mean':1200,
                               'std': 1200 * 0.2, #20% of mean,
                               'ulim':1200, # upper limit (capacity),
                               'llim':0 # lower limit
                               },
                               gen df=generation.df,
                               dem_args= {
                               'type': 'demand',
                               'mean':1100,
                               'std': 1100 * 0.2, #20% of mean
                               'ulim':1100 * 2, # upper limit (max load),
                               'llim':1100 * 0.1 # lower limit (constant load)
                               },
                               dem df=demand.df,
                               price df=price.df)
```

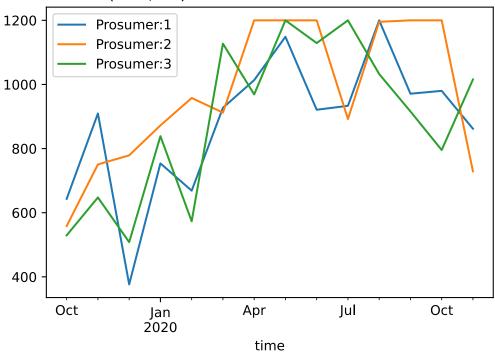
3.2 Analysis of Prosumer Data

3.2.1 Validating Generated Data for All Prosumers

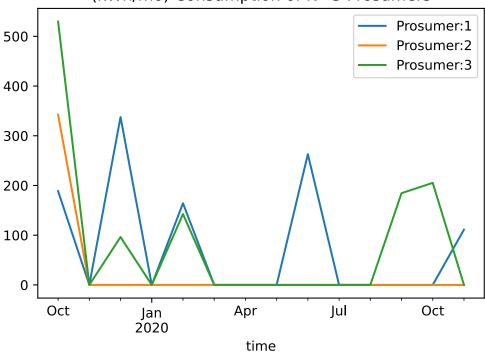
- Demand curves follow the mean demand curve for the ensemble data collected.
- Generation curves are bounded by upper bound parameters set for the simulation to act as maximum capacity of the solar PV system.
- Consumption curves are positive values that show the required energy consumed by the prosumer from the Grid.
- Net-Energy curve is negative indicating the power put back on the grid, this power would be subject to profit from net-metering.

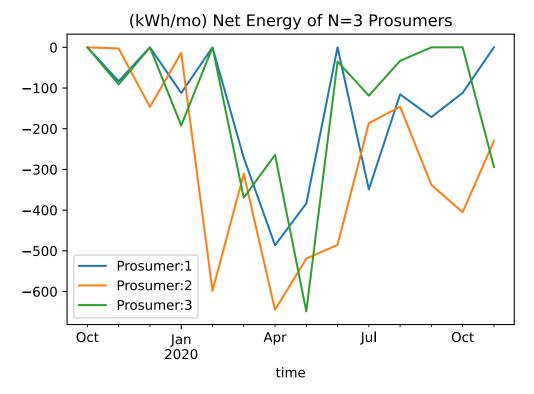


(kWh/mo) Generation of N=3 Prosumers



(kWh/mo) Consumption of N=3 Prosumers

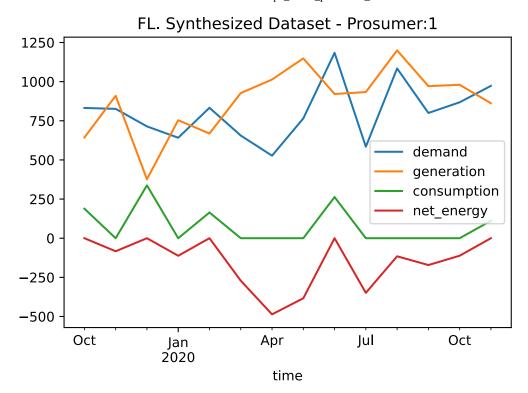


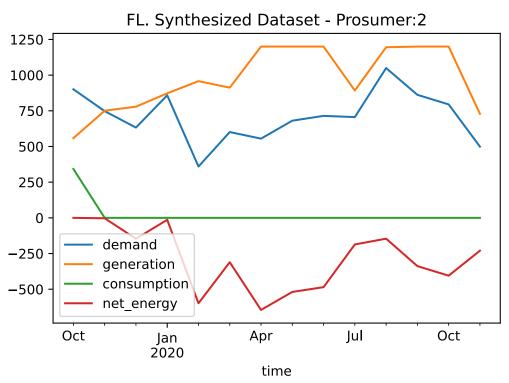


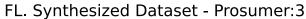
3.2.2 Validating Individual Prosumer Data

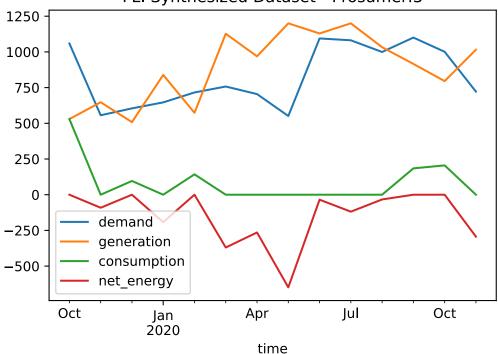
- The variance from the normal curve is within the set tolerances
- The average demand and generation coincide with the ensemble data
- The net energy is opposite to the consumption for each home
- The average performance of generation seems logical and consistent with the claims made for residential solar PV system (able to offset most of the homes usage but not all)

```
for prosumer in prosumers:
    prosumer.plot()
```









In [113... all

```
all_prosumers_data = pd.DataFrame({})

for prosumer in prosumers:
    prosumer.table()
    all_prosumers_data = all_prosumers_data.append(prosumer.data_w_id(), ignore_

#Export the data to local csv
all_prosumers_data.to_csv(f'data/prosumer_N{N}_model_{datetime.today().strftime()})
```

time		demand		generation	consumption		net_energy	-
price								
			-	-				-
	'		'			'		'
2020-11-01	00:00:00	973.134		861.974	111.16		0	
12								
2020-10-01	00:00:00	868.242		980.065	0		-111.823	
11.49								
2020-09-01	00:00:00	799.849	1	971.203	0	1	-171.355	
11.97		, , , , , , , ,	1	3,10200	·	1	1,1000	'
2020-08-01	00:00:00	1084.41		1200	0		-115.585	- 1
11.61	'		'	'		'		'
2020-07-01	00:00:00	584.39	1	933.458	0	I	-349.069	- 1
11.71			'			'		'
2020-06-01	00:00:00	1184.07		921.13	262.939		0	- 1
11.53			'			'		'
2020-05-01	00:00:00	765.169	1	1148.75	0	I	-383.583	1
9.84		,03.103	1	1110073	v	1	505.505	- 1
2020-04-01	00:00:00	527.143	1	1013.55	0	I	-486.41	1
11.71		327110	1	1010100	v	1	100011	'
2020-03-01	00:00:00	655.802	1	927.165	0	I	-271.363	1
11.64	00.00.00	033.002	ı	327.103	v	1	271.303	ı
2020-02-01	00.00.00	833.084	1	668.772	164.312	ı	0	1
	00.00.00	033.004	ı	000.772	104.512	ı	U	ı
11.76	00.00.00	641 761	1	752 06 1	0	1	110 000	1
2020-01-01	00:00:00	641.761	ı	753.86	0	1	-112.099	
11.73								
2019-12-01	00:00:00	714.284		376.561	337.723		0	
11.62								

			P1-	_create_prosumers_v2					
2019-11-01 12.09	00:00:00	826.204		909.504		0		-83.2994	
2019-10-01	00:00:00	831.948		643.255		188.693		0	
11.66 time		demand		generation		consumption		net_energy	
price 			- -		· –		-		
2020-11-01	00:00:00	499.003		729.044		0		-230.041	
12 2020-10-01	00:00:00	794.903		1200		0		-405.097	
11.49 2020-09-01	00:00:00	861.938		1200		0		-338.062	
11.97 2020-08-01	00:00:00	1049.51		1195.37		0		-145.857	
11.61 2020-07-01	00:00:00	705.952		892.281		0		-186.329	
11.71 2020-06-01	00:00:00	714.539		1200		0		-485.461	
11.53 2020-05-01	00:00:00	680.852		1200		0		-519.148	
9.84 2020-04-01	00:00:00	554.988		1200		0		-645.012	
11.71 2020-03-01	00:00:00	601.231		912.11		0		-310.88	
11.64 2020-02-01	00:00:00	359.469		957.83		0		-598.361	
11.76 2020-01-01	00:00:00	858.732		872.346		0		-13.6134	
11.73 2019-12-01	00:00:00	632.552		778.964		0		-146.412	
11.62									
2019-11-01	00:00:00	747.771		750.591		0		-2.82005	
12.09 2019-10-01		747.771		750.591 558.506		0 342.305		-2.82005 0	
12.09		'	1	558.506			'	0	
12.09 2019-10-01 11.66		900.81	1	558.506	 -	342.305	'	0	
12.09 2019-10-01 11.66 time	00:00:00	900.81 demand	 -	558.506 generation	 -	342.305	'	0 net_energy	
12.09 2019-10-01 11.66 time price 2020-11-01 12	00:00:00	900.81 demand	 -	558.506 generation 1015.51	 -	342.305 consumption	'	0 net_energy	
12.09 2019-10-01 11.66 time	00:00:00	900.81 demand 721.915 1000.83	 -	558.506 generation 1015.51 795.56	 - - 	342.305 consumption 0 205.271	'	0 net_energy293.593 0	
12.09 2019-10-01 11.66 time	00:00:00 00:00:00 00:00:00 00:00:00	900.81 demand 	·	558.506 generation 1015.51 795.56 915.891	 - 	342.305 consumption 0 205.271 184.507	'	0 net_energy	
12.09 2019-10-01 11.66 time	00:00:00 00:00:00 00:00:00 00:00:00	900.81 demand 721.915 1000.83 1100.4 999.403	·	558.506 generation 1015.51 795.56 915.891 1032.53	 - 	342.305 consumption 0 205.271 184.507	'	0 net_energy293.593 0 0 -33.1227	
12.09 2019-10-01 11.66 time	00:00:00 00:00:00 00:00:00 00:00:00 00:00:00	900.81 demand 721.915 1000.83 1100.4 999.403 1081.22	·	558.506 generation 1015.51 795.56 915.891 1032.53 1200	 - 	342.305 consumption 0 205.271 184.507 0 0	'	0 net_energy293.593 0 0 -33.1227 -118.783	
12.09 2019-10-01 11.66 time price 2020-11-01 12 2020-09-01 11.97 2020-08-01 11.61 2020-07-01 11.71 2020-06-01 11.53	00:00:00 00:00:00 00:00:00 00:00:00 00:00:00	900.81 demand 721.915 1000.83 1100.4 999.403 1081.22 1094.31	·	558.506 generation 1015.51 795.56 915.891 1032.53 1200 1129.14		342.305 consumption 0 205.271 184.507 0 0	'	0 net_energy293.593 0 0 -33.1227 -118.783 -34.8326	
12.09 2019-10-01 11.66 time price 2020-11-01 12 2020-09-01 11.49 2020-08-01 11.61 2020-07-01 11.71 2020-06-01 11.53 2020-05-01 9.84	00:00:00 00:00:00 00:00:00 00:00:00 00:00:00 00:00:00	900.81 demand 721.915 1000.83 1100.4 999.403 1081.22 1094.31 551.245	. - -	558.506 generation 1015.51 795.56 915.891 1032.53 1200 1129.14 1200		342.305 consumption 0 205.271 184.507 0 0 0	'	0 net_energy293.593 0 0 -33.1227 -118.783 -34.8326 -648.755	
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