

Shapley Coalitions for Prosumers in NRG-X-Change Network

Paying Prosumers Using NRG-X-Change

What is NRG-X-Change? "In this paper we propose NRG-X-Change — a novel mechanism for trading of locally produced re-newable energy that does not rely on an energy market or matching of orders ahead of time. In our model locally produced energy is continuously fed into the grid and payment is received based on actual usage, rather than predicted, as consumption is measured by the DSO (Distribution Service Operator) and billed in near real-time." (Mihail Mihaylov)

Modeling a Prosumer Market

We will leverage an NRGX-Change based market of prosumers on a micro-grid. Any excess energy that is not consumed by the micro-grid is not considered at this time. The goal of each prosumer would be to offset the demand of the micro-grid. In most cases the total demand would need to be supplemented by the larger Grid at some retail electricity price. The network will use the payout and consumption functions for NRGX-Change as each prosumer generates every month.

The prosumers (P) are indicated on the diagram as generators of electricity. In this scenario solar PV is shown as a generation source. The Distribution Service Operator (DSO) is in charge of consuming excess Net Energy that is generated by the prosumer and it is not consumed by the prosumer. A consumer (C) is the term for a residence that has to consume more energy than it can produce. It will need to pay for electricity and the DSO would charge it at some price. The NRG-X-Change function will charge the consumer and pay the prosumer for electricity consumed or generated.

Prosumer Payment Function

The NRG-X-Change as described by the authors performs a dynamic payment to prosumers that are capable of meeting the demand of the micro-grid. The micro-grid is made of prosumers and consumers. As the load demand spikes the pricing for net generation also spikes to meet the demand. When there is too much generation on the grid the pricing drops encouraging prosumers to generate less and consumers to consume more. The payout function $g(\cdot)$, utilizes a normalization component in the denominator to account for over or under generation distributing the payout along the curve. The payment is at its highest when generation meets the total demand and at its lowest as generation starts to saturate the market because of low demand.

$$g(x, t_p, t_c) = \frac{x^n * q_{t_p=t_c}}{e^{\frac{(t_p-t_c)^2}{a}}}$$

```
In [105... import math
# NRGXChange Payment g(.) Function
def g(price,X,tp,tc,a,n):
    q = price
    try:
        #print(f"n{n},tp{tp},tc{tc},a{a},q{q}")
        pay = (pow(X,n)*q)/math.exp(pow((tp-tc),2)/a)
    except OverflowError:
        pay = float('inf')
    return pay
```

Consumer Charge/Cost Function

Where x , is the net energy of the prosumer. q , is the maximum price allowed. t_p , is the total produced energy of all prosumers. t_c is the total consumption of all the prosumers. a , is a scaling constant to adjust the pay out. Similarly lets consider the cost of energy for consumers to purchase based on pricing set by the $h(.)$ function. In tandem these incentives are non-linear because of the distribution curve. The shape of that curve can be adjusted to the size of the network and the volatility of the network.

$$h(y, t_p, t_c) = \frac{y * r_{t_c >> t_p} * t_c}{t_c + t_p}$$

Where y is the withdrawn energy, and $r_{t_c >> t_p}$ is the maximum cost of energy delivered by the utility when the energy supply by prosumers is low. Again, t_p is the total production and t_c is the total consumption of the prosumers in the network. The minimum payment by the utility in the historical payment prices would indicate the minimum amount willing to charge customers for energy in order to cover the cost of delivering the energy. We will use the minimum price in our list for r .

```
In [106... # NRGXChange Charge h(.) Function
def h(price,c,tp,tc):
    y = c
    r = (0.01*price)
    try:
        cost = (y*r*tc)/(tc+tp)
    except OverflowError:
        cost = float('inf')
    return cost
```

Creating Coalitions Using Shapley Value

Review of Game Theory and Shapley Value

The game is in terms of a **characteristic function**, which specifies for every group of players the total payoff that the members of S can by signing an agreement among themselves; this payoff is available for distribution among the members of the group. A coalitional game with transferable payoff is a pair $\langle N, v \rangle$ where $N = \{1, \dots, n\}$ is the set of players and for every subset S of I (called a coalition) $v(S) \in \mathbb{R}$ is the total payoff that is available for division among members of S (called the worth of S). We assume that the larger the coalition the larger the payoff (this property is called superadditivity).

An agreement amongst players is a list (x_1, x_1, \dots, x_n) where x_1 , is the proposed payoff to individual i. Shapley value is interpreted in terms of **expected marginal contribution**. It is calculated by considering all the possible orders of arrival of the players into a room and giving each player his marginal contribution.

In [117]...

```
# Shapley Value Python Logic
# Authored by Susobhan Ghosh
# https://github.com/susobhang70
# Committed on 02/01/2020
from itertools import combinations
import bisect
#Create Combinatorial from List
def power_set(List):
    PS = [list(j) for i in range(len(List)) for j in combinations(List, i+1)]
    return PS
#Calculate Shapley from Characteristic Value list
def get_shapley(n,v):
    tempList = list([i for i in range(n)])
    N = power_set(tempList)
    shapley_values = []
    for i in range(n):
        shapley = 0
        for j in N:
            if i not in j:
                cmod = len(j)
                Cui = j[:]
                bisect.insort_left(Cui,i)
                l = N.index(j)
                k = N.index(Cui)
                temp = float(float(v[k]) - float(v[l])) *\
                    float(math.factorial(cmod) * math.factorial(n - cmod - 1)) / float(math.factorial(n))
                shapley += temp
        cmod = 0
        Cui = [i]
        k = N.index(Cui)
        temp = float(v[k]) * float(math.factorial(cmod) * math.factorial(n - cmod - 1)) / float(math.factorial(n))
        shapley += temp
        shapley_values.append(shapley)
    return shapley_values
```

Pecan Street Data

Pecan Street is a research and development organization that gathers data from active homes, solar homes and electric vehicle owners. According to Spandana Vadam , the pecan street data can be used to build out prosumers and calculating shapley value for coalitional contributions.

The data ranges between 2015-09-23 and 2015-12-22 and is segmented by hour. The data is of 6 single family homes located in Austin, texas. Each home was installed with a PV system for the year of 2015. Each home has a 'Gen',power generated from PV systems, and a 'Use',whole-home electrical usage, value for every hour of the day during Fall, Spring and Winter.

Define Mathematical Model

The monthly average energy production is the individual energy production summed up across the entire Fall season and then divided by 3 for each month. The Gen_{ai} in kWh is the average generation of the i^{th} prosumer.

The generalized characteristic function, $v(i) = \frac{X*q}{e^{\frac{[Gen_a - Use_a]^2}{a}}}$. When we apply it specifically to a single prosumer we must use the single

prosumers net generation for X and then consider all prosumer generation and all prosumer usage as a sum of the averages. Note, we will also choose the $q = \$10/kWh$ for the pricing and the scale factor , $a = 10^6$.

$$v(i) = \frac{(Gen_{ai} - Use_{ai}) * 10}{e^{\frac{[\sum_{i=1}^6 (Gen_{ai}) - \sum_{i=1}^6 (Use_{ai})]^2}{10^6}}}$$

Computing Shapley value with data collected from Pecan Street

i(House)	FALL			Spring			Winter		
Prosumer	Monthly average Energy Production for Fall (kWh) Gen_{ai}	Monthly average Energy Consumption for Fall(kWh) Use_{ai}	Energy offered by each prosumer (kWh) (X)	Monthly average Energy Production for Spring (kWh) Gen_{ai}	Monthly average Energy Consumption for Spring (kWh) Use_{ai}	Energy offered by each prosumer (kWh) (X)	Monthly average Energy Production for Winter (kWh) Gen_{ai}	Monthly average Energy Consumption for Winter (kWh) Use_{ai}	Energy offered by each prosumer (kWh) (X)

i(House)	FALL			Spring			Winter		
1	1473	1523	-50.00	1514	1431	83.00	1239	1138	101.00
2	1215	1056	159.00	1937	1279	658.00	1045	903	142.00
3	1006	367	639.00	1337	378	959.00	871	288	583.00
4	643	970	-327.00	903	1087	-184.00	575	810	-235.00
5	1737	676	1061.00	1996	749	1247.00	1447	406	1041.00
6	1518	1098	420.00	1560	1346	214.00	1273	677	596.00
Total	7592.00	5690.00	1902.00	9247.00	6270.00	2977.00	6450.00	4222.00	2228.00

In [229...

```
# Convert Pecan Data into dataset by trial to analyze
pecan_data = [
    {'id':1,'time':'fall','generation':1473,'consumption':1523},
    {'id':2,'time':'fall','generation':1215,'consumption':1056},
    {'id':3,'time':'fall','generation':1005,'consumption':367},
    {'id':4,'time':'fall','generation':643,'consumption':970},
    {'id':5,'time':'fall','generation':1737,'consumption':676},
    {'id':6,'time':'fall','generation':1518,'consumption':1098},
    {'id':1,'time':'spring','generation':1514,'consumption':1431},
    {'id':2,'time':'spring','generation':1937,'consumption':1279},
    {'id':3,'time':'spring','generation':1337,'consumption':1279},
    {'id':4,'time':'spring','generation':903,'consumption':378},
    {'id':5,'time':'spring','generation':1996,'consumption':1087},
    {'id':6,'time':'spring','generation':1560,'consumption':1346},
    {'id':1,'time':'winter','generation':1239,'consumption':1138},
    {'id':2,'time':'winter','generation':1045,'consumption':903},
    {'id':3,'time':'winter','generation':871,'consumption':288},
    {'id':4,'time':'winter','generation':575,'consumption':810},
    {'id':5,'time':'winter','generation':1447,'consumption':406},
    {'id':6,'time':'winter','generation':1273,'consumption':677}
]
```

```

pecan_df = DataFrame(pecan_data)
pecan_df['net_energy'] = pecan_df['generation'] - pecan_df['consumption']

```

In [230...

```

from pandas import DataFrame
#####
# Calculate the shapley value given the net energy and the average
# generation and consumption values
#####
def get_nrg_payments( df,price,a=0,n=1):
    for t in df:
        tp = t['generation'].sum()
        tc = t['consumption'].sum()
        t['shapley_w_coalition'] = t['net_energy'].apply(lambda x: g(price=price,X=x,tc=tc,tp=tp,n=n,a=a))
        t['shapley_wo_coalition'] = t['net_energy'].apply(lambda x: g(price=price,X=x,tc=tc,tp=tp,n=1,a=a))
    return df

```

The characteristic function results in a shapley value for each of the prosumers for each of the time periods.

In [231...

```

from IPython.display import display, HTML
pecan_df_by_t = [DataFrame(y) for x, y in pecan_df.groupby('time', as_index=False)]
x1_pecan_df_by_t = get_nrg_payments(pecan_df_by_t,price=10,a=1000000)
tb = 1
for t in x1_pecan_df_by_t:
    t = t.reindex(columns=['id','time','generation','consumption','net_energy','shapley_w_coalition','shapley_wo_coalition'])
    display(HTML(f"</br> Table {tb}: X^1 </br>{t.to_html(index=False)}"))
    tb=tb+1

```

Table 1: X^1

id	time	generation	consumption	net_energy	shapley_w_coalition	shapley_wo_coalition
1	fall	1473	1523	-50	-13.474609	-13.474609
2	fall	1215	1056	159	42.849257	42.849257
3	fall	1005	367	638	171.936011	171.936011
4	fall	643	970	-327	-88.123943	-88.123943
5	fall	1737	676	1061	285.931203	285.931203
6	fall	1518	1098	420	113.186715	113.186715

Table 2: X¹

id	time	generation	consumption	net_energy	shapley_w_coalition	shapley_wo_coalition
1	spring	1514	1431	83	2.082599	2.082599
2	spring	1937	1279	658	16.510244	16.510244
3	spring	1337	1279	58	1.455310	1.455310
4	spring	903	378	525	13.173067	13.173067
5	spring	1996	1087	909	22.808224	22.808224
6	spring	1560	1346	214	5.369593	5.369593

Table 3: X¹

id	time	generation	consumption	net_energy	shapley_w_coalition	shapley_wo_coalition
1	winter	1239	1138	101	7.054894	7.054894
2	winter	1045	903	142	9.918762	9.918762
3	winter	871	288	583	40.722806	40.722806
4	winter	575	810	-235	-16.414853	-16.414853
5	winter	1447	406	1041	72.714307	72.714307
6	winter	1273	677	596	41.630862	41.630862

Modify the Linearity of the Characteristic Function (X^n)

The negative shapley valyue cannot be used to make a fair distribution of gains in a coalition.

In [246...

```
from pandas import DataFrame
#####
# Calculate the shapley value given the net energy and the average
# generation and consumption values
#####
def get_nrg_payments( df,price,n,a):
    for t in df:
        t.drop(t[t['net_energy'] <= 0].index, inplace = True)
        tp = t['generation'].sum()
        tc = t['consumption'].sum()
        print(f"generation {tp}, consumption {tc}")
        t['shapley_wo_coalition'] = t['net_energy'].apply(lambda x: g(price=price,X=x,tc=tc,tp=tp,n=1,a=a) )
```

```
#t['shapley_wo_coalition'] = t['net_energy'].apply(lambda x: g(price=price,X=x,tc=tc,tp=tp,n=1,a=a) )
return df
```

In [247...

```
from IPython.display import display, HTML
pecan_df_by_t = [DataFrame(y) for x, y in pecan_df.groupby('time', as_index=False)]
xlp5_pecan_df_by_t = get_nrg_payments(pecan_df_by_t,price=10,a=1000000,n=1.5)

tb = 1
for t in xlp5_pecan_df_by_t:
    t = t.reindex(columns=['id','time','generation','consumption','net_energy','shapley_w_coalition','shapley_wo_coalition'])
    display(HTML(f"</br> Table {tb}: X^1.5 </br>{t.to_html(index=False)}"))
    tb=tb+1
```

```
generation 5475, consumption 3197
generation 9247, consumption 6800
generation 5875, consumption 3412
```

Table 1: X^{1.5}

id	time	generation	consumption	net_energy	shapley_w_coalition	shapley_wo_coalition
2	fall	1215	1056	159	NaN	8.865837
3	fall	1005	367	638	NaN	35.574866
5	fall	1737	676	1061	NaN	59.161337
6	fall	1518	1098	420	NaN	23.419191

Table 2: X^{1.5}

id	time	generation	consumption	net_energy	shapley_w_coalition	shapley_wo_coalition
1	spring	1514	1431	83	NaN	2.082599
2	spring	1937	1279	658	NaN	16.510244
3	spring	1337	1279	58	NaN	1.455310
4	spring	903	378	525	NaN	13.173067
5	spring	1996	1087	909	NaN	22.808224
6	spring	1560	1346	214	NaN	5.369593

Table 3: X^{1.5}

id	time	generation	consumption	net_energy	shapley_w_coalition	shapley_wo_coalition
----	------	------------	-------------	------------	---------------------	----------------------

id	time	generation	consumption	net_energy	shapley_w_coalition	shapley_wo_coalition
1	winter	1239	1138	101	NaN	2.342776
2	winter	1045	903	142	NaN	3.293804
3	winter	871	288	583	NaN	13.523153
5	winter	1447	406	1041	NaN	24.146831
6	winter	1273	677	596	NaN	13.824699

In [254...

```
pay = (pow(83,1.5)*10)/math.exp(pow((9247-6800),2)/1000000)
pay
```

Out[254...

18.973381148762577

Prosumer Synthesized Data from EIA.gov

The data gathered is from EIA.gov. The data was then used to synthesize typical prosumer consumption and generation over the course of 12 months. Volatiltity in the usage and generation was added as a normal distribution with a given variance to simulate real world conditions. The data is pulled from a local file and then sorted by timestamp. The fields are grouped by id and by time. Grouping by time allows for settlement calculations to occur at each time interval.

In [121...

```
import pandas as pd
import numpy as np
#####
# Data Gathering
#####
# Data gathering and synthesization has been done in a seperate module.
# import the external data gathering set. Pull data from a dataset
# of randomly insantiated prosumer, synthesized from EIA.gov data trends
#
import p0_data_gather as p0
# Set path of dataset file containing all parameterized values
data_set_path = 'data/prosumer_N10_all_20210305_1129.csv'
# Set initial conditions for prosumers dataset
dem_mean = 1100
gen_mean = 1300
# Set number of prosumers, an array of N[] values for multiple experiments
number_of_prosumers = [6]
# Trials [] holds session data for each N itteration of prosumers
trials = []
for N in number_of_prosumers:
```

```

# Call the data as a query with the instantiated values
eia_prosumer_data = p0.get_data(path=data_set_path,query=f'id > 0 & id<={N} & demand_std == {dem_mean*0.20} & genera
#####
# Data Wrangling : Split data by time 't'
#####
# Wrangle data into monthly timesteps so that each time step
# could be processed individually as a market payment for each prosumer
eia_prosumer_data_by_t = [pd.DataFrame(y) for x, y in eia_prosumer_data.groupby('time', as_index=False)]
    trials.append({"N":N, "prosumers_n":eia_prosumer_data, "prosumers_n_t":eia_prosumer_data_by_t})
print(trials)

```

20.0		260.0		1300		1100
25913	11.71	220.0		260.0	1300	1100
25914	11.63	220.0		260.0	1300	1100
25915	11.76	220.0		260.0	1300	1100
25916	11.72	220.0		260.0	1300	1100
25917	11.62	220.0		260.0	1300	1100
25918	12.09	220.0		260.0	1300	1100
25919	11.66	220.0		260.0	1300	1100
1235745	11.86	220.0		260.0	1300	1100
1235746	12.00	220.0		260.0	1300	1100
1235747	11.71	220.0		260.0	1300	1100
1235748	11.97	220.0		260.0	1300	1100
1235749	11.61	220.0		260.0	1300	1100
1235750	11.71	220.0		260.0	1300	1100
1235751	11.53	220.0		260.0	1300	1100
1235752	9.84	220.0		260.0	1300	1100
1235753	11.71	220.0		260.0	1300	1100
1235754	11.63	220.0		260.0	1300	1100
1235755	11.76	220.0		260.0	1300	1100
1235756	11.72	220.0		260.0	1300	1100
1235757	11.62	220.0		260.0	1300	1100
1235758	12.09	220.0		260.0	1300	1100
1235759	11.66	220.0		260.0	1300	1100
...
4865265	11.86	220.0		260.0	1300	1100
4865266	12.00	220.0		260.0	1300	1100
4865267	11.71	220.0		260.0	1300	1100
4865268	11.97	220.0		260.0	1300	1100
4865269	11.61	220.0		260.0	1300	1100
4865270	11.71	220.0		260.0	1300	1100
4865271	11.53	220.0		260.0	1300	1100
4865272	9.84	220.0		260.0	1300	1100
4865273	11.71	220.0		260.0	1300	1100
4865274	11.63	220.0		260.0	1300	1100
4865275	11.76	220.0		260.0	1300	1100
4865276	11.72	220.0		260.0	1300	1100
4865277	11.62	220.0		260.0	1300	1100
4865278	12.09	220.0		260.0	1300	1100
4865279	11.66	220.0		260.0	1300	1100

6075105	11.86	220.0	260.0	1300	1100
6075106	12.00	220.0	260.0	1300	1100
6075107	11.71	220.0	260.0	1300	1100
6075108	11.97	220.0	260.0	1300	1100
6075109	11.61	220.0	260.0	1300	1100
6075110	11.71	220.0	260.0	1300	1100
6075111	11.53	220.0	260.0	1300	1100
6075112	9.84	220.0	260.0	1300	1100
6075113	11.71	220.0	260.0	1300	1100
6075114	11.63	220.0	260.0	1300	1100
6075115	11.76	220.0	260.0	1300	1100
6075116	11.72	220.0	260.0	1300	1100
6075117	11.62	220.0	260.0	1300	1100
6075118	12.09	220.0	260.0	1300	1100
6075119	11.66	220.0	260.0	1300	1100

```
[90 rows x 11 columns], 'prosumers_n_t': [      id      time      demand  generation  consumption  net_energy \
25919      1 2019-10-01  757.174284  698.980517   58.193767      0.0
1235759      2 2019-10-01 1230.621807  503.603134  727.018673      0.0
2445599      3 2019-10-01 1241.295996  681.009070  560.286926      0.0
3655439      4 2019-10-01  843.911097  717.432484  126.478613      0.0
4865279      5 2019-10-01  672.649709  647.969906   24.679803      0.0
6075119      6 2019-10-01  693.494570  588.374290  105.120280      0.0
```

	price	demand_std	generation_std	generation_mean	demand_mean
25919	11.66	220.0	260.0	1300	1100
1235759	11.66	220.0	260.0	1300	1100
2445599	11.66	220.0	260.0	1300	1100
3655439	11.66	220.0	260.0	1300	1100
4865279	11.66	220.0	260.0	1300	1100
6075119	11.66	220.0	260.0	1300	1100

```
      id      time      demand  generation
n consumption net_energy \
25918      1 2019-11-01  856.581711  427.340324  429.241387      0.00000
1235758      2 2019-11-01  722.211216  868.127766    0.000000 -145.91655
2445598      3 2019-11-01  817.316715  707.889217  109.427498      0.00000
3655438      4 2019-11-01  827.408281  605.949567  221.458714      0.00000
4865278      5 2019-11-01  986.823771  692.295160  294.528610      0.00000
6075118      6 2019-11-01  782.905659  772.206093   10.699567      0.00000
```

	price	demand_std	generation_std	generation_mean	demand_mean
25918	12.09	220.0	260.0	1300	1100
1235758	12.09	220.0	260.0	1300	1100
2445598	12.09	220.0	260.0	1300	1100
3655438	12.09	220.0	260.0	1300	1100
4865278	12.09	220.0	260.0	1300	1100
6075118	12.09	220.0	260.0	1300	1100

```
      id      time      demand  generatio
on consumption net_energy \
25917      1 2019-12-01  956.424678  562.262330  394.162348      0.000000
1235757      2 2019-12-01  436.158803  797.827130    0.000000 -361.668327
2445597      3 2019-12-01  512.060530  663.954644    0.000000 -151.894114
3655437      4 2019-12-01 1022.271106  644.253416  378.017690      0.000000
```

4865277	5	2019-12-01	625.994411	481.237716	144.756695	0.000000
6075117	6	2019-12-01	611.713281	867.306418	0.000000	-255.593137

	price	demand_std	generation_std	generation_mean	demand_mean
25917	11.62	220.0	260.0	1300	1100
1235757	11.62	220.0	260.0	1300	1100
2445597	11.62	220.0	260.0	1300	1100
3655437	11.62	220.0	260.0	1300	1100
4865277	11.62	220.0	260.0	1300	1100
6075117	11.62	220.0	260.0	1300	1100

	id	time	demand	generat
ion consumption net_energy \				
25916	1	2020-01-01	712.969492	712.567943
1235756	2	2020-01-01	518.965013	1084.608756
2445596	3	2020-01-01	640.004559	831.239223
3655436	4	2020-01-01	1032.366027	339.594765
4865276	5	2020-01-01	577.141083	785.472474
6075116	6	2020-01-01	621.511333	758.046211

	price	demand_std	generation_std	generation_mean	demand_mean
25916	11.72	220.0	260.0	1300	1100
1235756	11.72	220.0	260.0	1300	1100
2445596	11.72	220.0	260.0	1300	1100
3655436	11.72	220.0	260.0	1300	1100
4865276	11.72	220.0	260.0	1300	1100
6075116	11.72	220.0	260.0	1300	1100

	id	time	demand	generati
on consumption net_energy \				
25915	1	2020-02-01	741.830771	700.851761
1235755	2	2020-02-01	723.828069	738.891573
2445595	3	2020-02-01	812.585379	917.494903
3655435	4	2020-02-01	529.188718	1100.123378
4865275	5	2020-02-01	584.356003	834.353270
6075115	6	2020-02-01	869.572795	909.884944

	price	demand_std	generation_std	generation_mean	demand_mean
25915	11.76	220.0	260.0	1300	1100
1235755	11.76	220.0	260.0	1300	1100
2445595	11.76	220.0	260.0	1300	1100
3655435	11.76	220.0	260.0	1300	1100
4865275	11.76	220.0	260.0	1300	1100
6075115	11.76	220.0	260.0	1300	1100

	id	time	demand	generati
on consumption net_energy \				
25914	1	2020-03-01	600.908845	1232.947114
1235754	2	2020-03-01	660.007831	805.269837
2445594	3	2020-03-01	680.838258	1095.724158
3655434	4	2020-03-01	667.738498	744.210478
4865274	5	2020-03-01	624.732258	985.682326
6075114	6	2020-03-01	672.766573	1300.000000

	price	demand_std	generation_std	generation_mean	demand_mean
25914	11.63	220.0	260.0	1300	1100
1235754	11.63	220.0	260.0	1300	1100

2445594	11.63	220.0	260.0	1300	1100				
3655434	11.63	220.0	260.0	1300	1100				
4865274	11.63	220.0	260.0	1300	1100				
6075114	11.63	220.0	260.0	1300	1100	,	id	time	demand generat
ion consumption net_energy \									
25913	1	2020-04-01	840.259808	1100.604230	0.000000	-260.344422			
1235753	2	2020-04-01	631.583253	1254.538710	0.000000	-622.955457			
2445593	3	2020-04-01	642.718380	1127.648368	0.000000	-484.929988			
3655433	4	2020-04-01	1207.234188	1142.545229	64.688959	0.000000			
4865273	5	2020-04-01	849.707278	1300.000000	0.000000	-450.292722			
6075113	6	2020-04-01	550.462581	799.488549	0.000000	-249.025969			
price demand_std generation_std generation_mean demand_mean									
25913	11.71	220.0	260.0	1300	1100				
1235753	11.71	220.0	260.0	1300	1100				
2445593	11.71	220.0	260.0	1300	1100				
3655433	11.71	220.0	260.0	1300	1100				
4865273	11.71	220.0	260.0	1300	1100				
6075113	11.71	220.0	260.0	1300	1100	,	id	time	demand generati
on consumption net_energy \									
25912	1	2020-05-01	912.760967	1300.000000	0.0	-387.239033			
1235752	2	2020-05-01	739.712334	1300.000000	0.0	-560.287666			
2445592	3	2020-05-01	775.732607	1077.631521	0.0	-301.898914			
3655432	4	2020-05-01	715.108925	1300.000000	0.0	-584.891075			
4865272	5	2020-05-01	876.251881	1159.808066	0.0	-283.556185			
6075112	6	2020-05-01	816.994069	1227.743378	0.0	-410.749309			
price demand_std generation_std generation_mean demand_mean									
25912	9.84	220.0	260.0	1300	1100				
1235752	9.84	220.0	260.0	1300	1100				
2445592	9.84	220.0	260.0	1300	1100				
3655432	9.84	220.0	260.0	1300	1100				
4865272	9.84	220.0	260.0	1300	1100				
6075112	9.84	220.0	260.0	1300	1100	,	id	time	demand generat
ion consumption net_energy \									
25911	1	2020-06-01	1038.681500	1020.879060	17.802440	0.000000			
1235751	2	2020-06-01	842.573368	1300.000000	0.000000	-457.426632			
2445591	3	2020-06-01	962.018220	910.318008	51.700212	0.000000			
3655431	4	2020-06-01	1033.504748	1300.000000	0.000000	-266.495252			
4865271	5	2020-06-01	1004.271183	1300.000000	0.000000	-295.728817			
6075111	6	2020-06-01	910.162557	948.475309	0.000000	-38.312753			
price demand_std generation_std generation_mean demand_mean									
25911	11.53	220.0	260.0	1300	1100				
1235751	11.53	220.0	260.0	1300	1100				
2445591	11.53	220.0	260.0	1300	1100				
3655431	11.53	220.0	260.0	1300	1100				
4865271	11.53	220.0	260.0	1300	1100				
6075111	11.53	220.0	260.0	1300	1100	,	id	time	demand generat
ion consumption net_energy \									
25910	1	2020-07-01	1165.090456	1300.000000	0.0	-134.909544			

1235750	2	2020-07-01	772.752521	1300.000000	0.0	-527.247479
2445590	3	2020-07-01	735.696415	1300.000000	0.0	-564.303585
3655430	4	2020-07-01	1017.990935	1025.455744	0.0	-7.464809
4865270	5	2020-07-01	1117.175491	1300.000000	0.0	-182.824509
6075110	6	2020-07-01	1185.948752	1300.000000	0.0	-114.051248

	price	demand_std	generation_std	generation_mean	demand_mean
25910	11.71	220.0	260.0	1300	1100
1235750	11.71	220.0	260.0	1300	1100
2445590	11.71	220.0	260.0	1300	1100
3655430	11.71	220.0	260.0	1300	1100
4865270	11.71	220.0	260.0	1300	1100
6075110	11.71	220.0	260.0	1300	1100

ion	consumption	net_energy	\
25909	1	2020-08-01	1236.711727
1235749	2	2020-08-01	1320.799390
2445589	3	2020-08-01	1162.721526
3655429	4	2020-08-01	738.076595
4865269	5	2020-08-01	1261.774214
6075109	6	2020-08-01	990.265411

	price	demand_std	generation_std	generation_mean	demand_mean
25909	11.61	220.0	260.0	1300	1100
1235749	11.61	220.0	260.0	1300	1100
2445589	11.61	220.0	260.0	1300	1100
3655429	11.61	220.0	260.0	1300	1100
4865269	11.61	220.0	260.0	1300	1100
6075109	11.61	220.0	260.0	1300	1100

ion	consumption	net_energy	\
25908	1	2020-09-01	891.556610
1235748	2	2020-09-01	455.297268
2445588	3	2020-09-01	796.070701
3655428	4	2020-09-01	860.703025
4865268	5	2020-09-01	1112.831083
6075108	6	2020-09-01	878.165805

	price	demand_std	generation_std	generation_mean	demand_mean
25908	11.97	220.0	260.0	1300	1100
1235748	11.97	220.0	260.0	1300	1100
2445588	11.97	220.0	260.0	1300	1100
3655428	11.97	220.0	260.0	1300	1100
4865268	11.97	220.0	260.0	1300	1100
6075108	11.97	220.0	260.0	1300	1100

ion	consumption	net_energy	\
25907	1	2020-10-01	1130.832481
1235747	2	2020-10-01	1235.486678
2445587	3	2020-10-01	859.968470
3655427	4	2020-10-01	805.362242
4865267	5	2020-10-01	313.363713
6075107	6	2020-10-01	604.781916

id	time	demand	generat
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id	time	demand	generat
----	------	--------	---------

id	time	demand	generat
----	------	--------	---------

	price	demand_std	generation_std	generation_mean	demand_mean		id	time	demand	generati
25907	11.71	220.0	260.0	1300	1100					
1235747	11.71	220.0	260.0	1300	1100					
2445587	11.71	220.0	260.0	1300	1100					
3655427	11.71	220.0	260.0	1300	1100					
4865267	11.71	220.0	260.0	1300	1100					
6075107	11.71	220.0	260.0	1300	1100	,				
on consumption net_energy \										
25906	1	2020-11-01	806.965579	1103.241179	0.0	-296.275600				
1235746	2	2020-11-01	790.826705	979.045000	0.0	-188.218295				
2445586	3	2020-11-01	722.210544	1152.441576	0.0	-430.231032				
3655426	4	2020-11-01	779.390564	1012.187101	0.0	-232.796536				
4865266	5	2020-11-01	883.079338	1033.644700	0.0	-150.565363				
6075106	6	2020-11-01	748.715813	815.914776	0.0	-67.198963				

	price	demand_std	generation_std	generation_mean	demand_mean		id	time	demand	generati
25906	12.0	220.0	260.0	1300	1100					
1235746	12.0	220.0	260.0	1300	1100					
2445586	12.0	220.0	260.0	1300	1100					
3655426	12.0	220.0	260.0	1300	1100					
4865266	12.0	220.0	260.0	1300	1100					
6075106	12.0	220.0	260.0	1300	1100	,				
on consumption net_energy \										
25905	1	2020-12-01	788.236454	1300.000000	0.000000	-511.763546				
1235745	2	2020-12-01	750.823892	463.303099	287.520793	0.000000				
2445585	3	2020-12-01	293.502601	1013.254735	0.000000	-719.752134				
3655425	4	2020-12-01	484.845007	1300.000000	0.000000	-815.154993				
4865265	5	2020-12-01	601.377546	1133.709775	0.000000	-532.332230				
6075105	6	2020-12-01	524.675582	947.526710	0.000000	-422.851128				

	price	demand_std	generation_std	generation_mean	demand_mean	
25905	11.86	220.0	260.0	1300	1100	
1235745	11.86	220.0	260.0	1300	1100	
2445585	11.86	220.0	260.0	1300	1100	
3655425	11.86	220.0	260.0	1300	1100	
4865265	11.86	220.0	260.0	1300	1100	
6075105	11.86	220.0	260.0	1300	1100]]]

Apply Payments and Charges to Prosumers Using NRG-X-Change

The scalar for the nrg payment would need to be self-tracking. A sweep of possible a values was done to track when any of the value goes past the "inf" value.

In [119..

```
#####
# Calculate and update the dataframe with nrg payments at time t
#####
def get_nrg_payments(df_by_t,max_price,min_price,a=0,n=1):
    for t in df_by_t:
        tc = t['consumption'].sum()
```

```

tp = abs(t['net_energy']).sum()
t['nrg_v'] = t['net_energy'].apply(lambda x: g(price=max_price,p=abs(x),tc=tc,tp=tp,n=n,a=a) if abs(x) > 0 else 0)
t['prosumer_debit'] = t['consumption'].apply(lambda x: -(h(price=min_price,c=x,tc=tc,tp=tp)) if abs(x) > 0 else 0)
t['prosumer_revenue'] = t['nrg_v'] + t['prosumer_debit']
return df_by_t

```

In [120...

```

def apply_nrg_payments(trials,n=1):
    for trial in trials:
        #####
        # Apply NRG-X change payments for each time 't'
        #####
        prosumers_n = trial['prosumers_n']
        prosumers_n_t = trial['prosumers_n_t']
        # Set historical pricing limits for NRG
        max_price = prosumers_n['price'].max()
        min_price = prosumers_n['price'].min()
        # Applying payments to each record
        prev_std = 0
        a_scaled = 0
        # Scaling the 'a' until payments are no longer sensitive
        for a in np.arange(start=10000,stop=(10000*1000),step=10000):
            prosumers_n_t = get_nrg_payments(prosumers_n_t,max_price,min_price,a=a,n=n)
            df = pd.concat(prosumers_n_t)
            std = df['nrg_v'].std()
            pct_c = ((std - prev_std)/std)
            prev_std = std
            if pct_c < 0.001:
                a_scaled = a
                break
        # store the scaled a value for this trail given N proumers
        trial['a_scaled'] = a_scaled
    return trials

```

In [122...

```

#####
# Calculatate the coalitional Pay out at each time step of t
#####
def get_coalitional_payments(df_by_t,max_price,min_price,a=0,n=1):
    for t in df_by_t:
        tc = t['consumption'].sum()
        tp = abs(t['net_energy']).sum()
        # identify number of prosumers at every time step of t,
        # that have provided net_energy > 0
        ids_net_energy_given = t[abs(t['net_energy']) > 0]['id']
        N_c=len(ids_net_energy_given)

```



```

# sum the absolute value of all the net energy given
# by the indentified IDs
# abs(t.loc[t['id'].isin(ids_net_energy_given)]['net_energy']).sum()
t['coalition_v'] = 0
# if number of members is 1 set it to the characteristic value
if N_c == 1:
    t['coalition_v'] = t['nrg_v']
# if number of members is greather than 1 calc shapley
if N_c > 1:
    List = ids_net_energy_given
    # get a power set with combinatorial elements as a list of lists
    PS = [list(j) for i in range(len(List)) for j in combinations(List, i+1)]
    char_vals = []
    # locate all ids in time step within the powerset, (factorial), and sum up
    for nn in PS:
        contribution = abs(t.loc[t['id'].isin(nn)]['net_energy']).sum()
        char_func_val = g(price=max_price,p=contribution,tc=tc,tp=tp,n=n,a=a)
        char_vals.append(char_func_val)
    # use the number of members in the coalition and the
    # characteristic values to calc shapley
    shapleys = get_shapley(N_c,char_vals)
    # add the individual shapley value to each of the id's that generated energy
    for i in range(N_c):
        t.loc[t.index[ids_net_energy_given.values[i]-1], 'coalition_v'] = shapleys[i]
return df_by_t

```

In [123...

```

def apply_coalitional_payments(trials,n=1):
    for trial in trials:
        #####
        # Apply Coalitional payments for each time 't'
        #####
        prosumers_n = trial['prosumers_n']
        prosumers_n_t =trial['prosumers_n_t']
        a =trial['a_scaled']
        # Set historical pricing limits for NRG
        max_price = prosumers_n['price'].max()
        min_price = prosumers_n['price'].min()
        prosumers_n_t = get_coalitional_payments(prosumers_n_t,max_price,min_price,a=a,n=n)
    return trials

```

In [124...

```

#####
# NRG & Coalitional payment processing for each trial(N) prosumers
#####
# Y=X^(1) , linear

```

```

trials = apply_nrg_payments(trials=trials)
trials = apply_coalitional_payments(trials=trials)
# Visualize/Sample of Data
for trial in trials:
    print(f"\nN={trial['N']}")
    print(trial['prosumers_n_t'][0])

```

N=2

	id	time	demand	generation	consumption	net_energy	\
25919	1	2019-10-01	757.174284	698.980517	58.193767	0.0	
1235759	2	2019-10-01	1230.621807	503.603134	727.018673	0.0	

	price	demand_std	generation_std	generation_mean	demand_mean	\
25919	11.66	220.0	260.0	1300	1100	
1235759	11.66	220.0	260.0	1300	1100	

	nrg_v	prosumer_debit	prosumer_revenue	coalition_v
25919	0	-5.726267	-5.726267	0
1235759	0	-71.538637	-71.538637	0

N=3

	id	time	demand	generation	consumption	net_energy	\
25919	1	2019-10-01	757.174284	698.980517	58.193767	0.0	
1235759	2	2019-10-01	1230.621807	503.603134	727.018673	0.0	
2445599	3	2019-10-01	1241.295996	681.009070	560.286926	0.0	

	price	demand_std	generation_std	generation_mean	demand_mean	\
25919	11.66	220.0	260.0	1300	1100	
1235759	11.66	220.0	260.0	1300	1100	
2445599	11.66	220.0	260.0	1300	1100	

	nrg_v	prosumer_debit	prosumer_revenue	coalition_v
25919	0	-5.726267	-5.726267	0
1235759	0	-71.538637	-71.538637	0
2445599	0	-55.132233	-55.132233	0

N=4

	id	time	demand	generation	consumption	net_energy	\
25919	1	2019-10-01	757.174284	698.980517	58.193767	0.0	
1235759	2	2019-10-01	1230.621807	503.603134	727.018673	0.0	
2445599	3	2019-10-01	1241.295996	681.009070	560.286926	0.0	
3655439	4	2019-10-01	843.911097	717.432484	126.478613	0.0	

	price	demand_std	generation_std	generation_mean	demand_mean	\
25919	11.66	220.0	260.0	1300	1100	
1235759	11.66	220.0	260.0	1300	1100	
2445599	11.66	220.0	260.0	1300	1100	
3655439	11.66	220.0	260.0	1300	1100	

	nrg_v	prosumer_debit	prosumer_revenue	coalition_v
25919	0	-5.726267	-5.726267	0

1235759	0	-71.538637	-71.538637	0
2445599	0	-55.132233	-55.132233	0
3655439	0	-12.445495	-12.445495	0

N=5

	id	time	demand	generation	consumption	net_energy	\
25919	1	2019-10-01	757.174284	698.980517	58.193767	0.0	
1235759	2	2019-10-01	1230.621807	503.603134	727.018673	0.0	
2445599	3	2019-10-01	1241.295996	681.009070	560.286926	0.0	
3655439	4	2019-10-01	843.911097	717.432484	126.478613	0.0	
4865279	5	2019-10-01	672.649709	647.969906	24.679803	0.0	

	price	demand_std	generation_std	generation_mean	demand_mean	\
25919	11.66	220.0	260.0	1300	1100	
1235759	11.66	220.0	260.0	1300	1100	
2445599	11.66	220.0	260.0	1300	1100	
3655439	11.66	220.0	260.0	1300	1100	
4865279	11.66	220.0	260.0	1300	1100	

	nrg_v	prosumer_debit	prosumer_revenue	coalition_v
25919	0	-5.726267	-5.726267	0
1235759	0	-71.538637	-71.538637	0
2445599	0	-55.132233	-55.132233	0
3655439	0	-12.445495	-12.445495	0
4865279	0	-2.428493	-2.428493	0

N=6

	id	time	demand	generation	consumption	net_energy	\
25919	1	2019-10-01	757.174284	698.980517	58.193767	0.0	
1235759	2	2019-10-01	1230.621807	503.603134	727.018673	0.0	
2445599	3	2019-10-01	1241.295996	681.009070	560.286926	0.0	
3655439	4	2019-10-01	843.911097	717.432484	126.478613	0.0	
4865279	5	2019-10-01	672.649709	647.969906	24.679803	0.0	
6075119	6	2019-10-01	693.494570	588.374290	105.120280	0.0	

	price	demand_std	generation_std	generation_mean	demand_mean	\
25919	11.66	220.0	260.0	1300	1100	
1235759	11.66	220.0	260.0	1300	1100	
2445599	11.66	220.0	260.0	1300	1100	
3655439	11.66	220.0	260.0	1300	1100	
4865279	11.66	220.0	260.0	1300	1100	
6075119	11.66	220.0	260.0	1300	1100	

	nrg_v	prosumer_debit	prosumer_revenue	coalition_v
25919	0	-5.726267	-5.726267	0
1235759	0	-71.538637	-71.538637	0
2445599	0	-55.132233	-55.132233	0
3655439	0	-12.445495	-12.445495	0
4865279	0	-2.428493	-2.428493	0
6075119	0	-10.343836	-10.343836	0

N=7

	id	time	demand	generation	consumption	net_energy	\
25919	1	2019-10-01	757.174284	698.980517	58.193767	0.0	
1235759	2	2019-10-01	1230.621807	503.603134	727.018673	0.0	
2445599	3	2019-10-01	1241.295996	681.009070	560.286926	0.0	
3655439	4	2019-10-01	843.911097	717.432484	126.478613	0.0	
4865279	5	2019-10-01	672.649709	647.969906	24.679803	0.0	
6075119	6	2019-10-01	693.494570	588.374290	105.120280	0.0	
7284959	7	2019-10-01	974.670409	725.090088	249.580321	0.0	

	price	demand_std	generation_std	generation_mean	demand_mean	\
25919	11.66	220.0	260.0	1300	1100	
1235759	11.66	220.0	260.0	1300	1100	
2445599	11.66	220.0	260.0	1300	1100	
3655439	11.66	220.0	260.0	1300	1100	
4865279	11.66	220.0	260.0	1300	1100	
6075119	11.66	220.0	260.0	1300	1100	
7284959	11.66	220.0	260.0	1300	1100	

	nrg_v	prosumer_debit	prosumer_revenue	coalition_v
25919	0	-5.726267	-5.726267	0
1235759	0	-71.538637	-71.538637	0
2445599	0	-55.132233	-55.132233	0
3655439	0	-12.445495	-12.445495	0
4865279	0	-2.428493	-2.428493	0
6075119	0	-10.343836	-10.343836	0
7284959	0	-24.558704	-24.558704	0

N=8

	id	time	demand	generation	consumption	net_energy	\
25919	1	2019-10-01	757.174284	698.980517	58.193767	0.0	
1235759	2	2019-10-01	1230.621807	503.603134	727.018673	0.0	
2445599	3	2019-10-01	1241.295996	681.009070	560.286926	0.0	
3655439	4	2019-10-01	843.911097	717.432484	126.478613	0.0	
4865279	5	2019-10-01	672.649709	647.969906	24.679803	0.0	
6075119	6	2019-10-01	693.494570	588.374290	105.120280	0.0	
7284959	7	2019-10-01	974.670409	725.090088	249.580321	0.0	
8494799	8	2019-10-01	1040.271045	894.004707	146.266338	0.0	

	price	demand_std	generation_std	generation_mean	demand_mean	\
25919	11.66	220.0	260.0	1300	1100	
1235759	11.66	220.0	260.0	1300	1100	
2445599	11.66	220.0	260.0	1300	1100	
3655439	11.66	220.0	260.0	1300	1100	
4865279	11.66	220.0	260.0	1300	1100	
6075119	11.66	220.0	260.0	1300	1100	
7284959	11.66	220.0	260.0	1300	1100	
8494799	11.66	220.0	260.0	1300	1100	

	nrg_v	prosumer_debit	prosumer_revenue	coalition_v
25919	0	-5.726267	-5.726267	0

1235759	0	-71.538637	-71.538637	0
2445599	0	-55.132233	-55.132233	0
3655439	0	-12.445495	-12.445495	0
4865279	0	-2.428493	-2.428493	0
6075119	0	-10.343836	-10.343836	0
7284959	0	-24.558704	-24.558704	0
8494799	0	-14.392608	-14.392608	0

N=9

	id	time	demand	generation	consumption	net_energy \
25919	1	2019-10-01	757.174284	698.980517	58.193767	0.0
1235759	2	2019-10-01	1230.621807	503.603134	727.018673	0.0
2445599	3	2019-10-01	1241.295996	681.009070	560.286926	0.0
3655439	4	2019-10-01	843.911097	717.432484	126.478613	0.0
4865279	5	2019-10-01	672.649709	647.969906	24.679803	0.0
6075119	6	2019-10-01	693.494570	588.374290	105.120280	0.0
7284959	7	2019-10-01	974.670409	725.090088	249.580321	0.0
8494799	8	2019-10-01	1040.271045	894.004707	146.266338	0.0
9704639	9	2019-10-01	948.540002	695.130495	253.409507	0.0

	price	demand_std	generation_std	generation_mean	demand_mean \
25919	11.66	220.0	260.0	1300	1100
1235759	11.66	220.0	260.0	1300	1100
2445599	11.66	220.0	260.0	1300	1100
3655439	11.66	220.0	260.0	1300	1100
4865279	11.66	220.0	260.0	1300	1100
6075119	11.66	220.0	260.0	1300	1100
7284959	11.66	220.0	260.0	1300	1100
8494799	11.66	220.0	260.0	1300	1100
9704639	11.66	220.0	260.0	1300	1100

	nrg_v	prosumer_debit	prosumer_revenue	coalition_v
25919	0	-5.726267	-5.726267	0
1235759	0	-71.538637	-71.538637	0
2445599	0	-55.132233	-55.132233	0
3655439	0	-12.445495	-12.445495	0
4865279	0	-2.428493	-2.428493	0
6075119	0	-10.343836	-10.343836	0
7284959	0	-24.558704	-24.558704	0
8494799	0	-14.392608	-14.392608	0
9704639	0	-24.935496	-24.935496	0

N=10

	id	time	demand	generation	consumption	net_energy \
25919	1	2019-10-01	757.174284	698.980517	58.193767	0.0
1235759	2	2019-10-01	1230.621807	503.603134	727.018673	0.0
2445599	3	2019-10-01	1241.295996	681.009070	560.286926	0.0
3655439	4	2019-10-01	843.911097	717.432484	126.478613	0.0
4865279	5	2019-10-01	672.649709	647.969906	24.679803	0.0
6075119	6	2019-10-01	693.494570	588.374290	105.120280	0.0
7284959	7	2019-10-01	974.670409	725.090088	249.580321	0.0

8494799	8	2019-10-01	1040.271045	894.004707	146.266338	0.0
9704639	9	2019-10-01	948.540002	695.130495	253.409507	0.0
10914479	10	2019-10-01	766.927736	385.539889	381.387847	0.0

	price	demand_std	generation_std	generation_mean	demand_mean	\
25919	11.66	220.0	260.0	1300	1100	
1235759	11.66	220.0	260.0	1300	1100	
2445599	11.66	220.0	260.0	1300	1100	
3655439	11.66	220.0	260.0	1300	1100	
4865279	11.66	220.0	260.0	1300	1100	
6075119	11.66	220.0	260.0	1300	1100	
7284959	11.66	220.0	260.0	1300	1100	
8494799	11.66	220.0	260.0	1300	1100	
9704639	11.66	220.0	260.0	1300	1100	
10914479	11.66	220.0	260.0	1300	1100	

	nrg_v	prosumer_debit	prosumer_revenue	coalition_v
25919	0	-5.726267	-5.726267	0
1235759	0	-71.538637	-71.538637	0
2445599	0	-55.132233	-55.132233	0
3655439	0	-12.445495	-12.445495	0
4865279	0	-2.428493	-2.428493	0
6075119	0	-10.343836	-10.343836	0
7284959	0	-24.558704	-24.558704	0
8494799	0	-14.392608	-14.392608	0
9704639	0	-24.935496	-24.935496	0
10914479	0	-37.528564	-37.528564	0

Example of Shapley value Calculation for N Prosumers

We consider a community of solar prosumers $P = 1, 2, 3..N$, who agree to form a coalition and produce energy. The number of possible coalitions are 2^n and the number of ways to build the grand coalition is $N!$.

In [125...

```
#####
# Consider Convex , Linear & Concave characteristic functions
#####
# Adjust the value of 'X^n' used in NRG payment function
X_n= [-2,-0.5,1,0.5,2]
x_n_trials = []
for n in X_n :
    trials = apply_nrg_payments(trials=trials,n=n)
    trials = apply_coalitional_payments(trials=trials,n=n)
    x_n_trials.append({'X_n':n,'trials':trials})
```

Comparison of Shapley value for Convex, Linear and Concave characteristic functions

Energy produced by individual Prosumers

Shapley value calculation with and without coalition for different characteristic functions

In [126..

```
table = {}
for x_n_trial in x_n_trials :
    x_n = x_n_trial['X_n']
    col_title = f'Y=X^{x_n}'
    trials = x_n_trial['trials']
    rows=[]
    for trial in trials:
        df = pd.concat(trial['prosumers_n_t'])
        avg_wo_co = df['nrg_v'].mean()
        avg_w_co = df['coalition_v'].mean()
        rows.append({"X_n":x_n, "Number of Prosumers":trial['N'], "With Coalition":avg_w_co, "Without Coalition":avg_wo_co})
    table[col_title] = rows

lines = []
for header in table.keys():
    line=""
    for i in range(len(table[header])):
        for row in table[header]:
            print(row)

print(lines)
```

```
.919591173862, 'Without Coalition': 9774.919591173862}
{'X_n': 1, 'Number of Prosumers': 10, 'With Coalition': 5716.662792516543, 'Without Coalition': 5716.662792516543}
{'X_n': 1, 'Number of Prosumers': 2, 'With Coalition': 16668.612473211433, 'Without Coalition': 16668.612473211433}
{'X_n': 1, 'Number of Prosumers': 3, 'With Coalition': 22587.925924124862, 'Without Coalition': 22587.925924124862}
{'X_n': 1, 'Number of Prosumers': 4, 'With Coalition': 23514.918469542215, 'Without Coalition': 23514.918469542215}
{'X_n': 1, 'Number of Prosumers': 5, 'With Coalition': 24173.35492380917, 'Without Coalition': 24173.35492380917}
{'X_n': 1, 'Number of Prosumers': 6, 'With Coalition': 21073.363980216473, 'Without Coalition': 21073.363980216473}
{'X_n': 1, 'Number of Prosumers': 7, 'With Coalition': 15214.08840843334, 'Without Coalition': 15214.08840843334}
{'X_n': 1, 'Number of Prosumers': 8, 'With Coalition': 13931.69348528232, 'Without Coalition': 13931.69348528232}
{'X_n': 1, 'Number of Prosumers': 9, 'With Coalition': 9774.919591173862, 'Without Coalition': 9774.919591173862}
{'X_n': 1, 'Number of Prosumers': 10, 'With Coalition': 5716.662792516543, 'Without Coalition': 5716.662792516543}
{'X_n': 0.5, 'Number of Prosumers': 2, 'With Coalition': 16668.612473211433, 'Without Coalition': 16668.612473211433}
{'X_n': 0.5, 'Number of Prosumers': 3, 'With Coalition': 22587.925924124862, 'Without Coalition': 22587.925924124862}
{'X_n': 0.5, 'Number of Prosumers': 4, 'With Coalition': 23514.918469542215, 'Without Coalition': 23514.918469542215}
{'X_n': 0.5, 'Number of Prosumers': 5, 'With Coalition': 24173.35492380917, 'Without Coalition': 24173.35492380917}
{'X_n': 0.5, 'Number of Prosumers': 6, 'With Coalition': 21073.363980216473, 'Without Coalition': 21073.363980216473}
{'X_n': 0.5, 'Number of Prosumers': 7, 'With Coalition': 15214.08840843334, 'Without Coalition': 15214.08840843334}
{'X_n': 0.5, 'Number of Prosumers': 8, 'With Coalition': 13931.69348528232, 'Without Coalition': 13931.69348528232}
{'X_n': 0.5, 'Number of Prosumers': 9, 'With Coalition': 9774.919591173862, 'Without Coalition': 9774.919591173862}
{'X_n': 0.5, 'Number of Prosumers': 10, 'With Coalition': 5716.662792516543, 'Without Coalition': 5716.662792516543}
{'X_n': 0.5, 'Number of Prosumers': 2, 'With Coalition': 16668.612473211433, 'Without Coalition': 16668.612473211433}
```

[illegible]

[illegible]

