PyEMLab-AGG
Case Studies

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Introduction

PyEMLab can be used to answer a variety of questions and can be run both short term (< 1year) and longer term i.e. for 5 years. In all cases, parameters were varied incrementally so that comparison between cases could be made to provide an insight as to the effect of various key assumptions like social media propagation mechanics, social media network structure and assumptions on Agent Zero weights. Some of those effects are presented in the various subsections and figures below.

Long Term Case Parameters: Base Case

All cases use the same_Customer and aggregator input data. Parameters such as Agent_Zero weights, the number of bid buckets and the algorithm used (customer bids are aggregated into buckets) etc. can be changed by the users and used to simulate different scenarios or cases. All cases bar case 6 and 7 use equal number of bids in each bucket as the bucketing algorithm. The parameters used in these cases are listed below. Values for the bases case are given

Base Case Assumptions: Parameters

Balancing demand sensitivity factor = 1.5. # *Balancing demand is 50% higher than those presented in the input file*

Generation output sensitivity factor = 0.3 # *All generators produce 30% of the levels specified in the input file*

Domestic Customer flexibility sensitivity factor= 1 # *Multiplies supply of flex volumes for each customer as contained in input file*

Domestic Customer bid price sensitivity factor= 1 # *Multiples Marginal costs in input file by said factor - used in customer bidding values*

Aggregator_opx_CPX_sensi_factor= 1 # *OPX CPX*

Elasticity long term effects flag on = True # *Yearly effect*

Elasticity short term effects flag on = True # *Elasticity short term i.e. monthly effects*

Probability of domestic customer agent receiving message = 0.3

Stimulation adjustment factor =1 # *e.g. need 1 stim from neighbour to get a 1 one stim* *score sent to agent zero V*

agentzero_learn_rate=0.1

agentzero_V_wt=0.333

agentzero_P_wt =0.333

agentzero_S_wt = 0.333

Aggregator number of buckets=10

Number of aggregators = 6

Bucketing algorithm - Equal numbers of bids in each buckets

Frequency adjuster for demand =1

Domestic customer yearly expectation =£10/Year

Aggregator Risk - as per data input (3 with risk hedging on and 3 aggregators with off)

Aggregator Numbers = 6

Domestic customers = 50000

Industrial Customers = 4500

Table 1: Parameters – Base case

Longer Terms Simulations: Description & Summary Results from 14 Cases

During longer timeframe simulations used in the PSCC 2024 paper , aggregators can choose to change their business models and change contract offer terms and customers can change contracts many times. The current model will allow aggregators to exit the market and new ones to enter, but this functionality has been disabled in the simulations presented in the paper.

To show the effect of different assumptions on the longer-term evolution of the simulations, 14 cases are presented in Table 2 below.

Case Number	Brief Description	Assumptions/Parameters*	Average CP in year 5 £/Mwh	Average CP in year 1 £/Mwh	Average CP all years	Average Volatility in year 5 %	Average Volatility in year 1 %	Average Volatility all years %
1	Base Balancing Demand =1; OPX/CPX factor =0.4	Bal Demand Factor = 1, OPX/CPX factor =0.4, Yearly Elaticity = off	705	243	521	124%	180%	145%
2	Higher Balancing Demand; Higher customer expectations	Case 1 with higher Balancing Demand = 1.5 and customer expectation =£100/year	54	456	593	344%	143%	144%
3	Aggregator Risk Hedge On	As case 3 with all aggragtors with risk hedging On	62	457	600	314%	143%	143%
4	Aggregator Risk Hedge Off	As case 3 with all aggragtors with risk hedging Off	139	445	566	196%	145%	142%
5	Higher Balancing Demand and requires more stimulation from social interactyion to act	Bal Demand Factor = 1.7, Stimulation adjustment factor =5	1884	531	1127	54%	148%	99%
6	Astropy bucketing with Stimulation Factor of 5	Case 5 with Astropy Bucketing. Customer Expectations =£10/year Stimulation Factor =5	181	757	949	232%	123%	111%
7	Astropy bucketing with Stimulation Factor =1 . Different Fixed Price and Margin	Aggregators use Astropy bucketing algorithm to aggregate bids. Start FP=100 and initial aggragtor margin =0.3 , Stimulation adjustment factor =5; Balancing Demand Factor = 1.7; Stimulation Factor =1	228	727	944	177%	122%	110%
8	Customers use Marginal costs to bid No adjustmnet	As Case 3 but with with Domestic customer Expectations =£50/contract year; Start FP=100 and initial aggregator margin =0.3	233	223	294	200%	206%	199%
9	Customerts and Aggragtors both use Marginal costs to form bid	As Case 8 with Domestic customer Expectations =£50/contract year	233	223	294	200%	206%	199%
10	P=1; Logic preveails	Case3 assumptions but with balancing demand factor = 1.5 and P=1,V=0, S=0	1884	531	1127	54%	148%	99%
11	Domestic Customer follows Clear price rather than expectations	Domestic Customer Expectation = £10/yr, Balancing Demand =1.5	330	333	813	131%	161%	126%
12	Generation with Zip Trader rather than fixed Marginal Cost bidding	As Case x but Generators use a Clueraring Price following zip trader to alter bids.	137	446	547	199%	155%	148%
13	Domestic customer and Aggragator both follow CP rtaher set tragets in other ways	As Case 11 but with Aggregators and domestic customers following Clearing Price rather setting a target price based on expectations or profits	328	328	810	131%	161%	126%
14	V=1 Emotions prevail	As Case 10 but with P=0, V=1,S=0	181	462	553	120%	154%	1.498275

*Table 2: Five-year long-term simulation case summary (*see notes below)*

Table 2 also provides simulation summary values for average clearing price (CP), the volatility in those prices. Average CP's differ significantly from year 1 to year 5. This is not the case for case 8 and 9, where marginal costs are used to simulate clearing price output[1].

[1] This is the usual way to simulate clearing prices – e.g. as in SmartNet.