

### Research Items

Relationship between Number of Segments and Profit Ratio

Optimal Profit ratios/Storage Type Table

Case Study 1.1: NYISO Data Hour Ahead

Case Study 1.2: NYISO Data Real Time

Case Study 2: Queensland Data Hour Ahead

Case Study 3: ERCOT Houston Hour Ahead

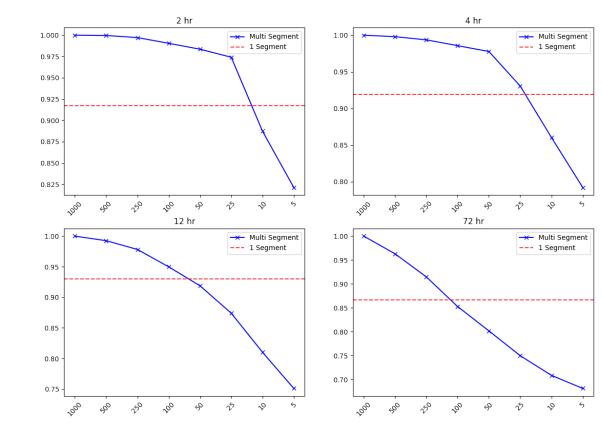
# Battery Parameters for All Case Studies

Capacity [MWh]	1
Marginal Cost	10
SoC Sample Granularity	0.001
efficiency	0.9
cinciency	0.3
Beginning/final SoC	0.5

- All lower segment value functions (eg 50, 10, 1) come from averaging 1000 segment value function
- All price data used was 5 minute frequency, except for ERCOT Houston which was 20 minute frequency

# Relationship Between Optimal Profit Ratio and Number of Segments





#### Num Segment

- graphs are produced using the optimal profits (perfect price valuation and arbitrage)
- Shows that for each battery type, there is a point at where one segment outperforms multi segment bidding

# Optimal Raw Profit Ratios for Different Energy Storage Duration

Opti	Optimal Profit Ratios of 10 Segment Relative to 50 segment optimal: 5min valuation					
Trial	NY I	LONGIL N	NORTH WEST	Γ		
2hr	82.34	88.76	80.92	90.22		
4hr	75.61	85.47	73.66	87.99		
12hr	74.27	85.66	70.51	88.16		

Or	Optimal Profit Ratios of 1 Segment Relative to 50 segment optimal: 5min valuation				
Trial	NY	LONGIL N	ORTH WE	ST	
2hr	94.84	93.43	94.77	93.24	
4hr	95.71	94.74	95.09	94.03	
12hr	108.43	100.38	107.35	101.22	

Opti	mal Profit	nal Profit Ratios of 10 Segment Relative to 50 segment optimal: 1hr valuation			
Trial	NY	LONGIL	NORTH	WEST	
2hr	81.86	86.49	83.34	4 85.51	
4hr	78.21	85.76	78.83	3 85.20	
12hr	77.32	86.55	73.26	6 87.09	

Op	Optimal Profit Ratios of 1 Segment Relative to 50 segment optimal: 1hr valuation				
Trial	NY I	LONGIL NO	ORTH WE	CST	
2hr	92.15	91.14	92.71	89.52	
4hr	93.18	92.07	94.25	90.00	
12hr	108.43	100.38	107.35	101.22	

- This was to check the correctness of the arbitrage and valuation code
- The hourly arbitrage was adapted directly from ArbSim\_noSoC on matlab
- 1 segment profit ratio increases with increasing energy storage duration (outperforming 50 segment for 12 hour, which aligns with the graph from earlier)
- 1 segment outperforms 50 segments for 12 hour, but doesn't outperform 1000 segments (in line with 1 and 1000 segment results from matlab)
- 10 segment does not have the same observable trend

## Case Study 1.1: NYISO Data Hour Ahead Prediction

Profi	t Ratios of 10 S	Segment Re 5min val	lative to 50 segmen luation	t optimal:
Trial	NY LOI	NGIL NO	ORTH WEST	
2hr	67.17	70.65	65.15	78.27
4hr	62.13	70.40	56.36	77.19
12hr	56.92	73.67	47.80	79.14

Pro	ofit Ratios of 1 Segment Relative to 50 segment optimal: 5min valuation			
Trial	NY ]	LONGIL N	ORTH WES	ST
2hr	75.94	75.61	75.11	80.11
4hr	77.77	78.45	74.60	81.96
12hr	90.83	90.22	82.85	91.61

Profi	Fit Ratios of 10 Segment Relative to 50 segment optimal:  1hr valuation				
Trial	NY	LONGIL	NORTH	WEST	
2hr	40.53	40.55	42.6	2	55.68
4hr	41.53	45.86	46.4	3	59.54
12hr	44.69	55.32	46.8	9	74.43

Pro	Profit Ratios of 1 Segment Relative to 50 segment optimal: 1hr valuation					
		over ve		N. C.		
Trial	NY L	ONGIL NO	ORTH WES	ST		
2hr	40.94	41.38	47.00	52.69		
4hr	47.23	45.84	57.34	60.26		
12hr	61.13	63.58	77.74	82.65		

- Training/Prediction used 5 hour stack of RTP/DAP with 3 hour lookback in each row
- The hourly valuation was generated by predicting the 5 minute frequency value function and downsampling
- Would like to run future test on learning hourly valuation directly
- Poorer performance of hourly valuation tells us that there is a marked difference between downsampling price then valuating, as opposed to downsampling valuation
- One segment has the expected trend of increasing profit ratio with increasing energy storage duration
- Poorer performance of 10 segment makes sense according to graph 1 since it optimally achieves a lower ratio, and is harder for the network to learn, leading to overall poorer results



# Case Study 1.2: NYISO Data Real Time Prediction

Pro	Profit Ratios of 10 Segment Relative to 50 segment optimal: 5min valuation				Pr	ofit Ratios of 1	l Segment Rel mal: 5min val		egment
Trial	NY	LONGIL N	ORTH WI	EST	Trial	NY I	LONGIL N	NORTH V	VEST
2hr	70.69	75.00	66.26	82.23	2hr	82.95	82.03	80.26	86.15
4hr	64.04	73.20	60.40	79.38	4hr	82.68	82.60	78.94	82.20
12hr	55.49	73.19	46.89	78.11	12hr	84.43	84.56	83.39	92.26

- Training/Prediction using same data format as hour ahead
- Based on the results from 1.1, hourly valuation was not produced here
- Raw profits show expected trend (decreased raw profit but increased profit ratio with increasing duration), but network predictions achieve similar profit ratios across the board

# Case Study 2: Queensland Data Hour Ahead Prediction

Queensland 10 Segment Profit Ratios		
trials:	w.r.t 50 seg opt	
2hr	81.25	
4hr	79.79	
12hr	81.15	

Queensland 1 Segment Profit Ratios		
trials:	w.r.t 50 seg opt	
2hr	83.89	
4hr	82.91	
12hr	81.55	

- Training/Prediction Data structured as 5 hour stack of 5 hour look back RTP (no DAP used)
- Models trained on NYISO NYC data first, and then all layers except for output layer frozen and retrained on queensland data
- Similar Trend as NY Real Time prediction case

# Case Study 3: ERCOT Houston Data Hour Ahead Prediction

Queensland 10	<b>Segment Profit Ratios</b>	
trials:	w.r.t 50 seg opt	
2hr		62.33
4hr		68.26
12hr		76.05

Queensland 1 Segment Profit Ratios	
trials:	w.r.t 50 seg opt
2hr	70.90
4hr	60.32
12hr	68.30

- Training/Prediction Data structured as 5 hour stack of 5 hour look back RTP + 18 Hour DAP
- Model in general had more difficulty learning because of ¼ amount of data relative to 5 min market frequency cases
- Observable Trend not as clear