Wave Farm Energy Prediction using Multi-Layer Perceptron Neural Networks

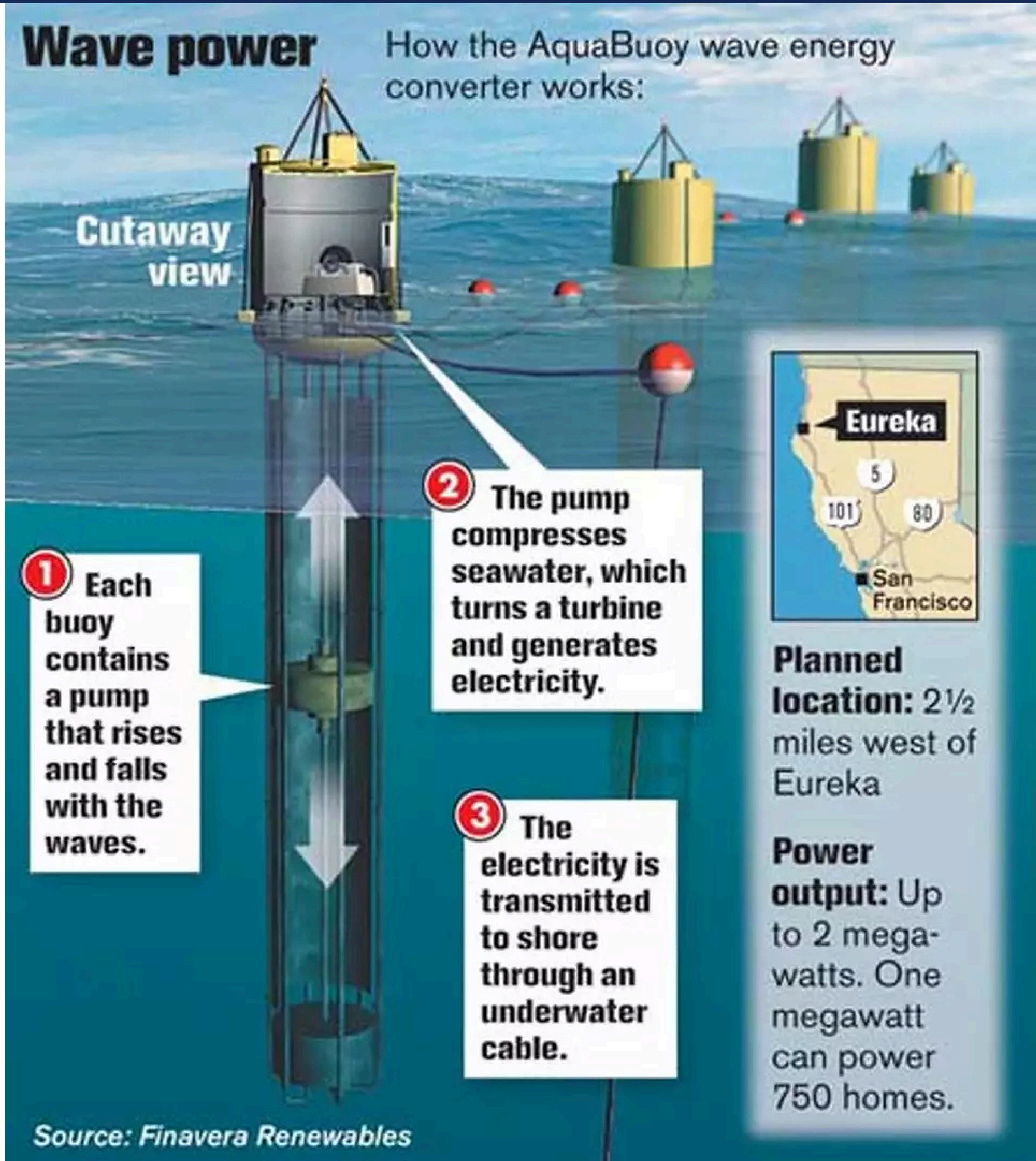
CUNANAN AND MAMOGKAT

DS100L – Applied Data Science

Focus: UN SDG 7 – Affordable and Clean Energy

INTRODUCTION

- Wave energy is a promising renewable source.
- But designing efficient buoy layouts is computationally expensive.
- Goal:
  - Predict a wave farm's energy output using only its buoy layout, skipping simulations.
- This enables faster decision-making during early design stages.



DATA SET - LAYOUT AS INPUT

Dataset by Neshat et al. (UCI Repository):

- **36,043** layouts from Perth wave conditions
- 49-buoy layouts → 98 input features (X1–Y49, Y1–Y49)
- Target: Total_Power (in watts)

X1	Y1	X2	Y2	X3	Y3	X4	Y4	X5	Y5
600	0	546.16	37.5	489.79	74.88	432.47	112.05	650	
593	12	546.16	37.5	489.79	74.88	432.47	112.05	644	
593	12	546.16	37.5	489.79	74.88	432.47	112.05	644	
593	12	546.16	37.5	489.79	74.88	432.47	112.05	644	
200	0	146.17	37.53	89.76	74.93	32.4	112.18	400	
600	0	546.17	37.53	489.76	74.93	432.4	112.18	200	20
600	0	546.17	37.53	489.76	74.93	432.4	112.18	800	
400	0	346.17	37.53	289.76	74.93	232.4	112.18	600	
800	0	746.17	37.53	689.76	74.93	632.4	112.18	1000	
800	0	746.17	37.53	689.76	74.93	632.4	112.18	1000	
800	0	746.17	37.53	689.76	74.93	632.4	112.18	1000	
800	0	746.17	37.53	689.76	74.93	632.4	112.18	1000	

EJ	EK	EL	EM	EN	EO	EP	EQ	ER	ES
Power42	Power43	Power44	Power45	Power46	Power47	Power48	Power49	qW	Total_Power
88867.92	98844.3	101283.6	98934.63	101624.6	100915	99625.68	96704.34	0.87	4102461
88896.55	98759.79	101346.1	98873.59	101629	100934.5	99606.13	96718.39	0.87	4103361
88919.83	98746.68	101346.2	98875.57	101618.3	100941	99611.35	96719.14	0.87	4103680
88855.14	98760.96	101338.6	98971.58	101632.3	100943.6	99589.25	96735.04	0.87	4105661
88005.3	98630.24	100432.7	98803.01	101064.5	100948.4	99028.87	96286.71	0.79	3752649
88409.39	98975.94	100999	99212.39	101773.6	101105.7	99172.6	96571.02	0.81	3820015
88076.2	98773.58	100568.5	98990.51	101199.1	100980.1	99199.7	96571.42	0.83	3938280
102602.3	101322.8	99491.77	99162.46	101280.7	100861.4	99126.7	96462.08	0.85	3993212
102533.6	101451.6	100040.6	98923.52	101203.8	100724.7	99030.73	96167.27	0.85	4037155
102606.4	101172	99952.16	99128.99	101332.8	100801.1	99120.43	96611.9	0.86	4047144

MODEL AND TRAINING

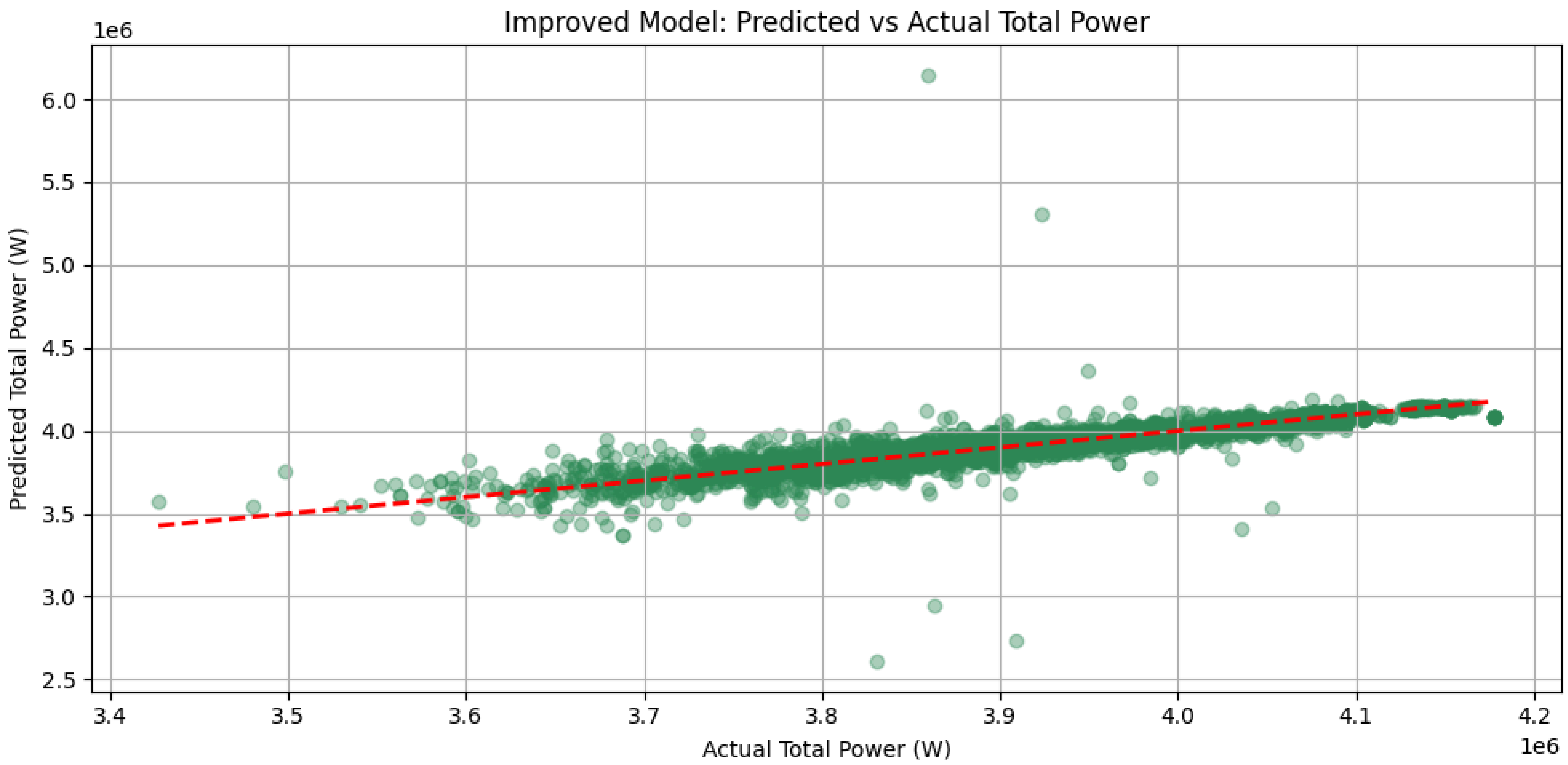
Model: Multi-Layer Perceptron Regressor (MLPRegressor – scikit-learn)

- 2 hidden layers: 128 & 64 neurons
- Best activation: **ReLU**
- Learning rate: 0.0005
- Epochs: 1000
- Features scaled with StandardScaler
- Train-test split: 80:20

Goal: learn mapping from buoy positions → total power output

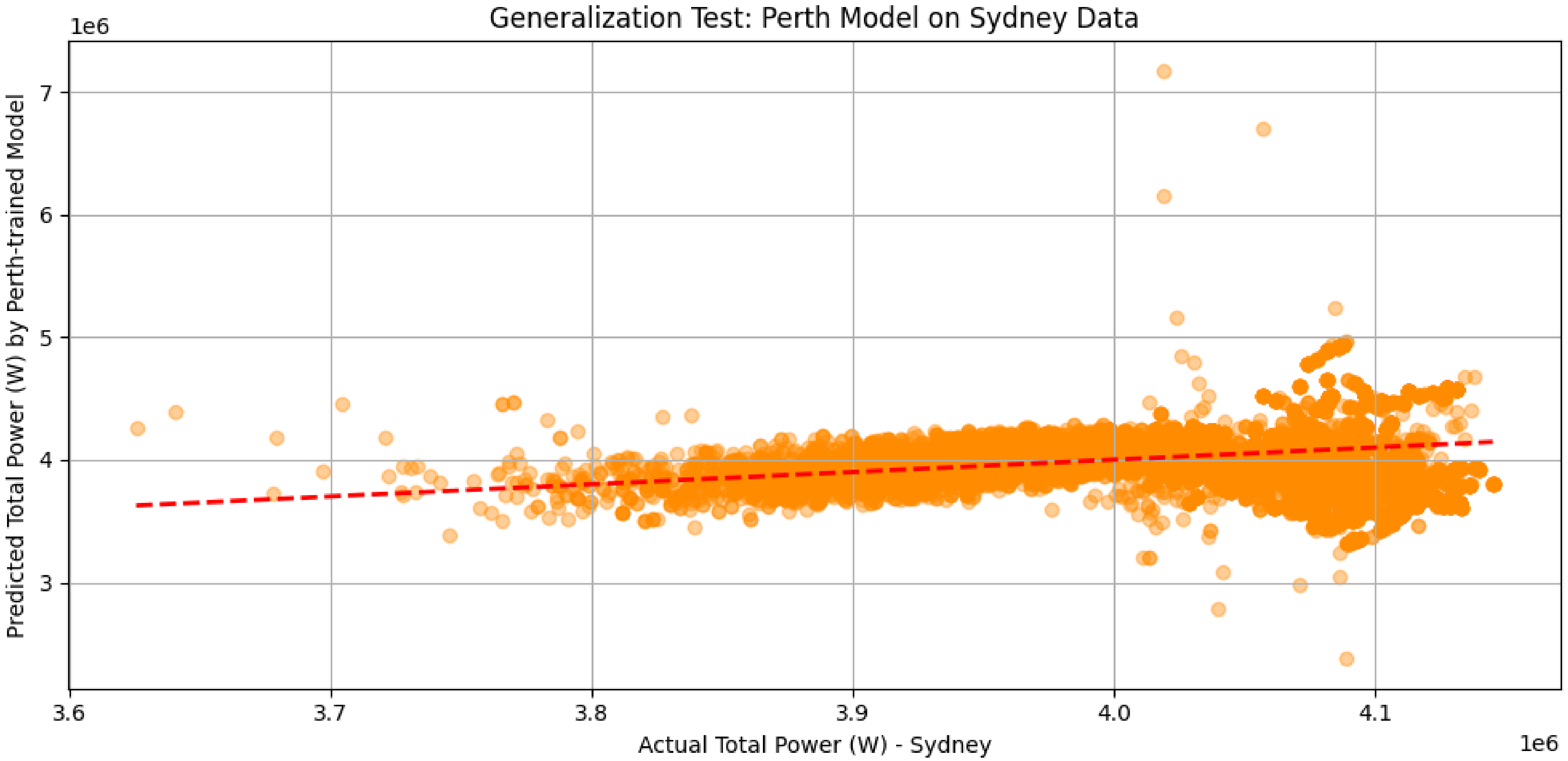
RESULTS – PERTH TEST SET

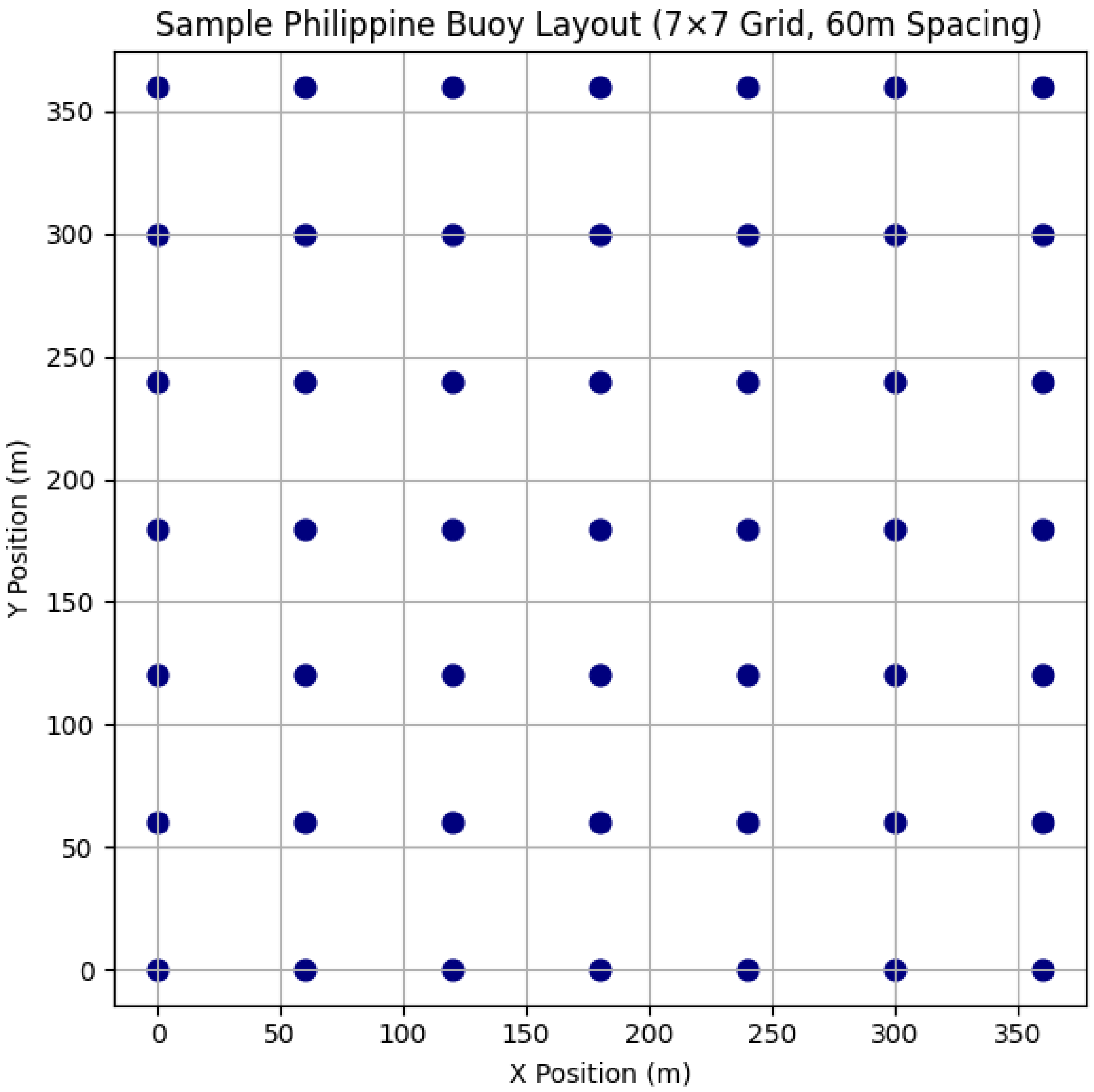
- After tuning:
  - MAE: **25,062 W**
  - Percent Error: **0.64%**
- Insight:
  - MLP can accurately model layout-energy relationships
- Before tuning:
  - ~1.12% error → tuning had major impact



GENERALIZATION TEST – SYDNEY

- Trained on Perth, tested on Sydney layouts
- Error increased to **4.14%** (from 0.64%)
- Insight: Model is layout-sensitive but wave-condition-dependent





SAMPLE PHILIPPINE LAYOUT TEST

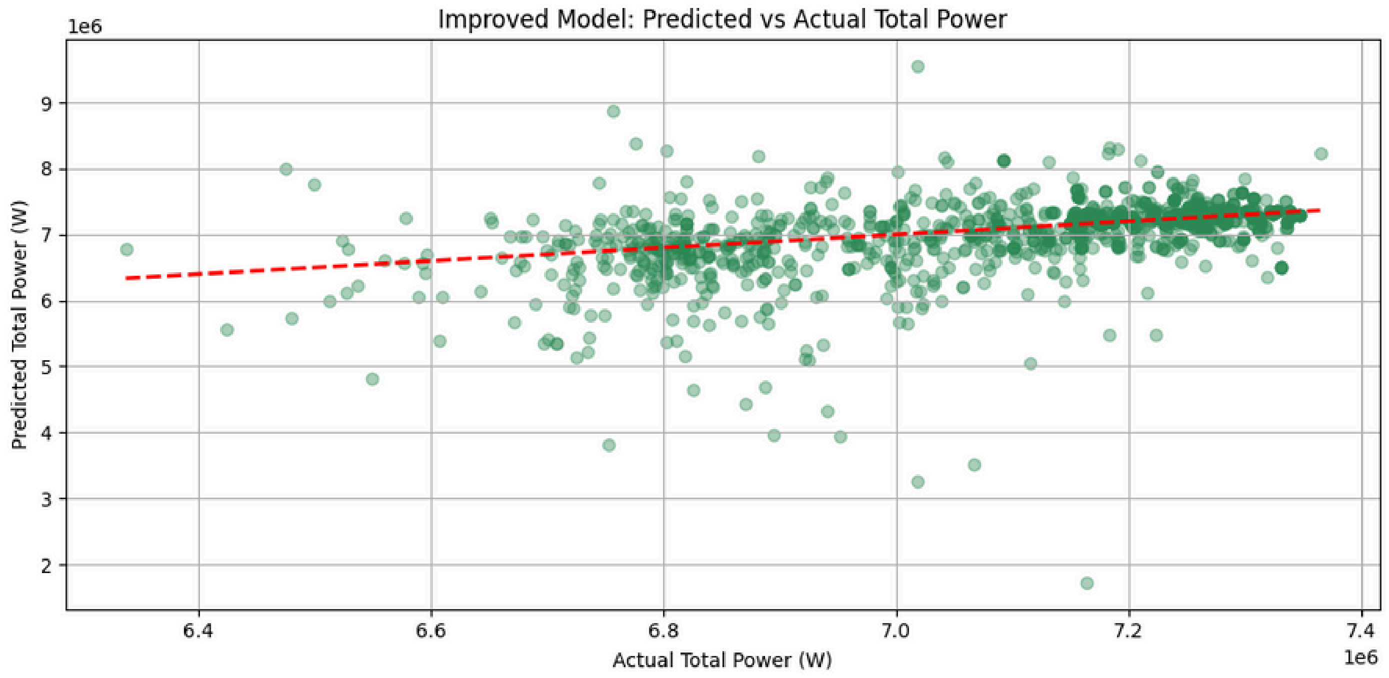
- 7x7 buoy grid (60m spacing), inspired by potential PH use
- Trained on Perth data — assumes Perth-like waves
- Predicted Output: **5.35 MW**
- Perspective: Enough to power **32,700 Philippine homes**
  - Based on Department of Energy (2024), Summary of 2023 Power Statistics

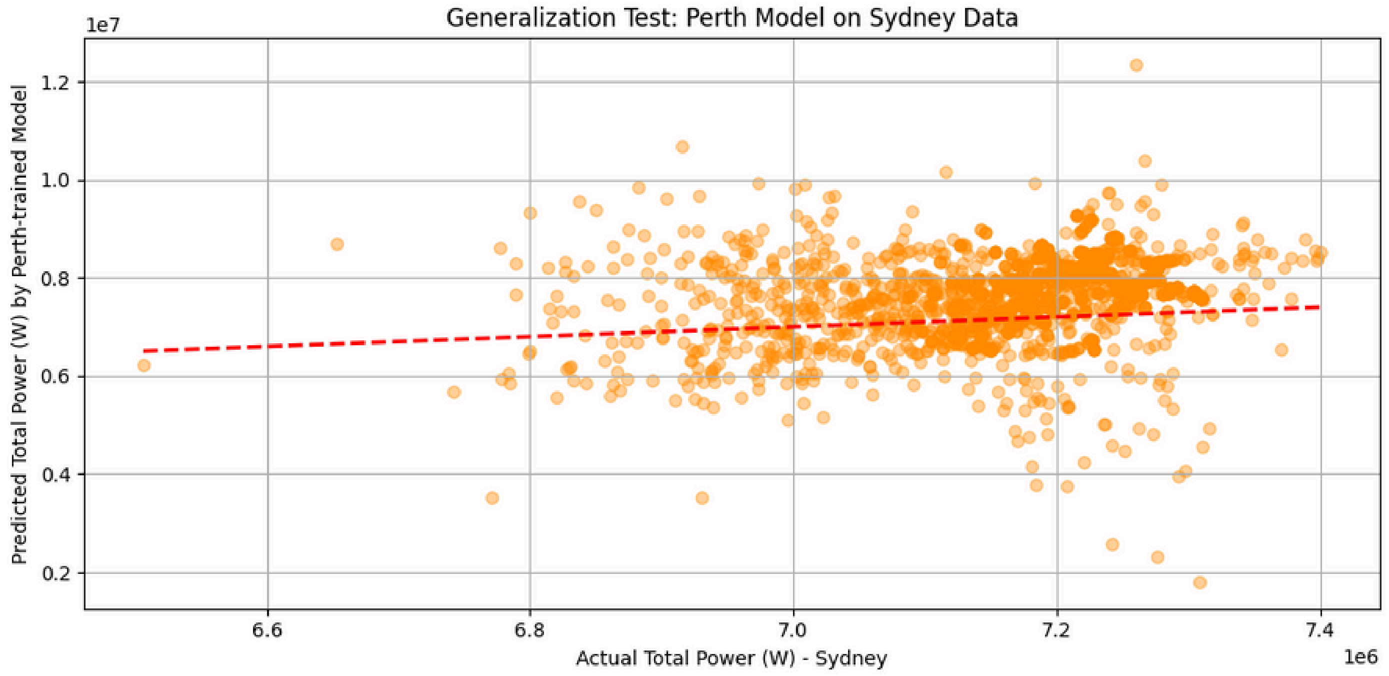
EXTENSION – 100-BUOY LAYOUTS

- Retrained MLP on 100-buoy Perth dataset (7,277 layouts)
- Performance dropped:
  - Perth: 3.67% error
  - Sydney: 10.18% error
- Reason: More inputs, fewer samples → harder to generalize

TABLE III
100-Buoy Model Generalization Performance

Model	Train Data	Test Layout	% Error
100-Buoy	Perth (7,277)	Perth	3.67%
100-Buoy	Perth	Sydney (100-buoy)	10.18%





CONCLUSION

- MLP can estimate energy output from layout alone
- Accurate on Perth, but generalization limited
- Useful for early design phases before simulation
- Future works
    - Use PH-specific wave data & layout optimization

QUESTIONS & ANSWER