Time Series Forecasting Analysis for Tidal Power Potential

Group Members:

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GitHub Repository:

https://github.com/Ananya-2809/Swarup_Wu_Aggarwal_ENV797_TSA_FinalProject.git

Background and Motivation

Why Tidal Power?

- Relevance to our team members' environment concentrations (CAMS and EE)
- Clean, renewable energy source
- More reliability compared to wind and solar
- Currently undervalued (altenergymag.com)
- Potential to contribute to coastal energy resilience

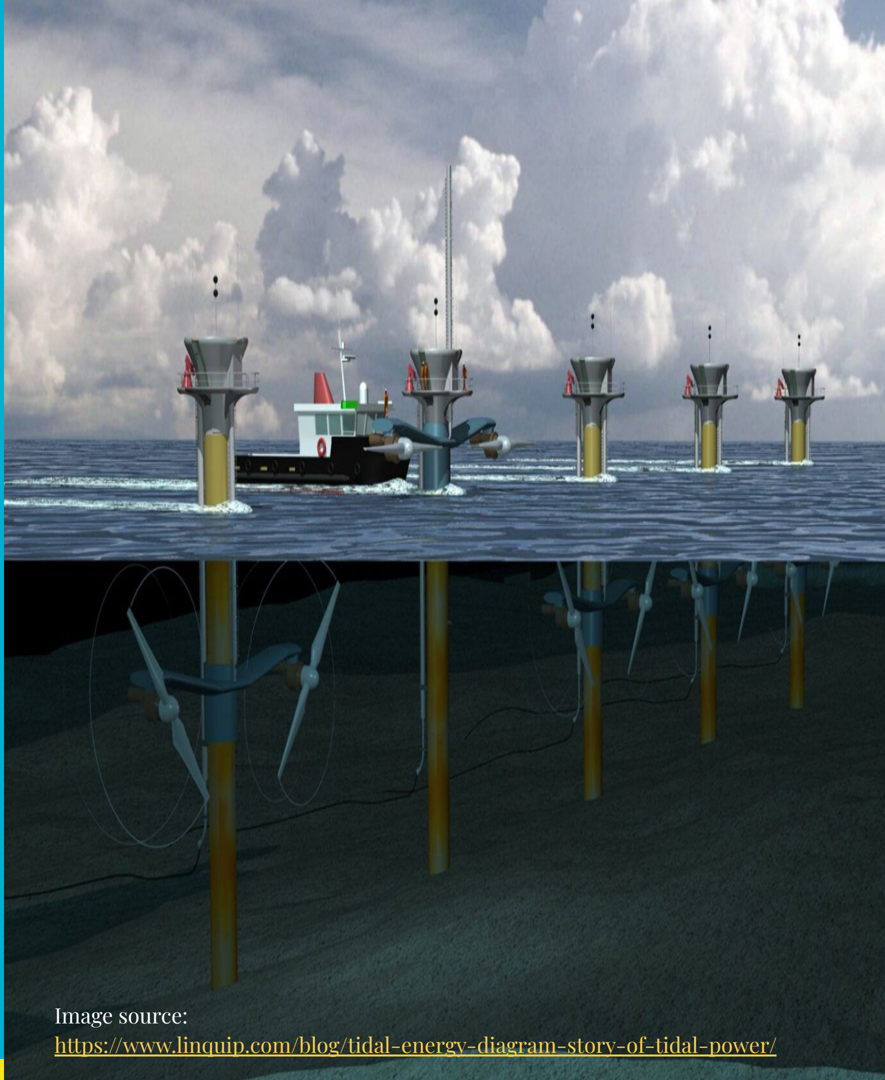


Image source: https://www.linquip.com/blog/tidal-energy-diagram-story-of-tidal-power/

Project Overview

Key Predictor Metric of Tidal Power

Wave Energy Flux (W/m^2)

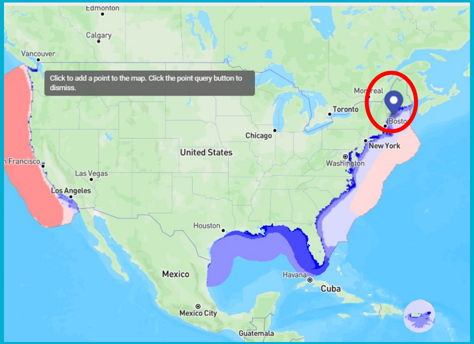
= Wave Power Density (J/m^3) * **Wave Energy Period (seconds)**

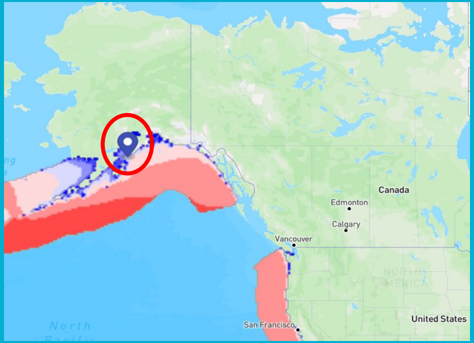
- Compare the Wave Energy Flux across the **3 sites** in different latitudes and coastal areas
- Identify the consistency of the model forecasting performance
- Compare seasonal and long-term trends

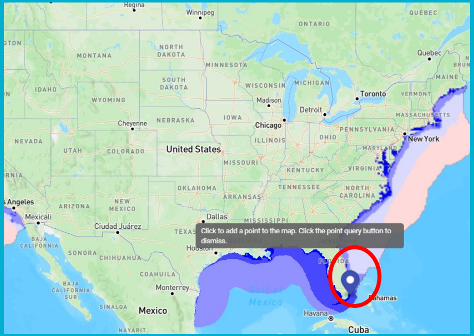
Pre-Modeling Data Selection

Three sites:

- Gulf of Maine (43.68° N, 69.77 ° W)
- ~ 3 km distance into ocean near Miami, Florida (25.74 ° N, 80.11 ° W)
- Cook Inlet, Alaska (59.37° N, 152.64° W)







Extracted data from: nrel.gov/marine-energy-atlas/data-viewer of the three sites with time range from year 1979-2010

Analysis Approach

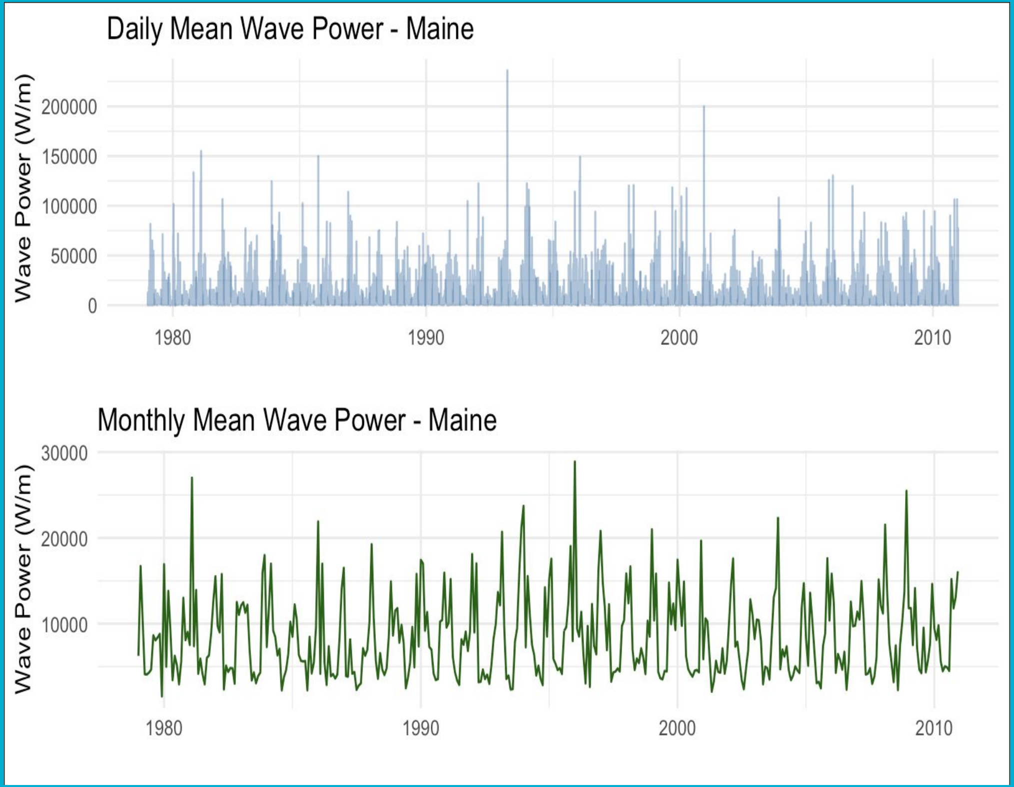
3 datasets (Alaska, Maine and Florida) containing data from 1979 to 2010 on hourly wave power

- Averaged to a daily and monthly view
- Split (using the 80/20) rule into training and test datasets
- Data visualization was done on entire dataset

EDA (1): Data Visualizations

Daily vs Monthly Wave Power

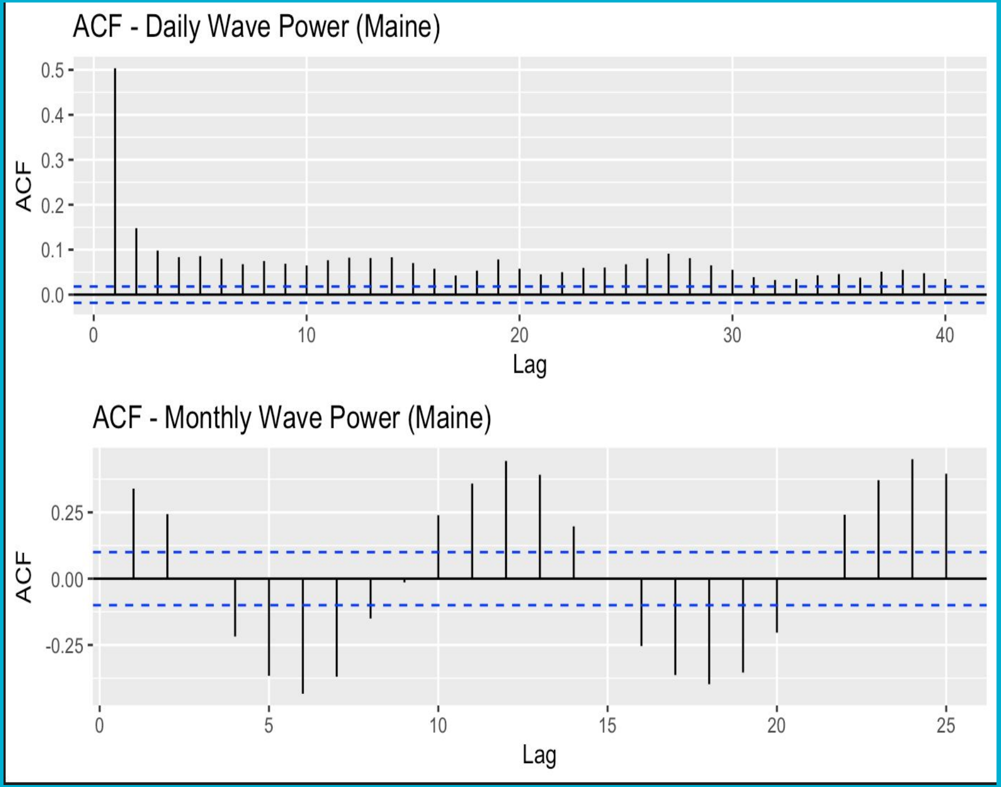
- Hard to discern seasonality in daily trends
  - Clearer trends in monthly series
- Averaging to a monthly view reduces influence of outliers
- Stability of monthly series



EDA (2): ACF Plots

Daily vs Monthly Wave Power

- Sharp drop after lag 1 for daily wave power
  - strong seasonality shown for monthly wave power (good for forecasting longer-term)
- Strong short-term autocorrelation ⤳ AR models
  - SARIMA models (or other models with seasonal components) may be a good fit based on monthly series



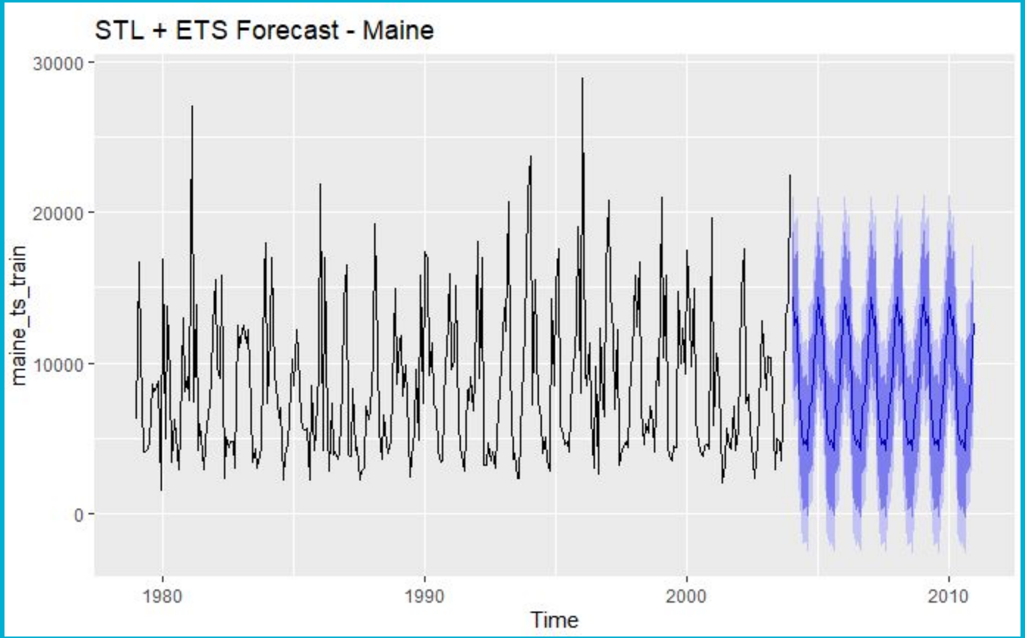
Full Model List

Forecast Accuracy for Monthly Wave Power - Maine

	ME	RMSE	MAE	MPE	MAPE	ACF1	Theil's U
SNAIVE	-822.52074	4290.692	3202.526	-19.62825	42.60721	0.06549	0.89498
SARIMA	-217.59468	4026.117	3221.739	-29.70686	50.01054	0.32049	0.83462
STL+ETS	-192.97893	3730.735	2709.232	-17.21843	36.39588	0.18831	0.70042
ARIMA+Fourier	736.38317	3690.025	2601.569	-5.30294	31.99013	0.20083	0.72561
ES	-3467.10238	4906.397	3481.704	-66.83019	67.08750	0.45623	1.12238
StructTS	4686.01400	5864.526	4762.718	78.82107	80.54519	-0.00122	1.84991
TBAT	569.08601	3728.780	2690.142	-8.37019	33.99924	0.17281	0.70592
NN	18.86256	4046.358	2813.138	-13.09440	36.32380	0.17590	0.72400

#3 : STL + ETS

Seasonal-Trend decomposition using LOESS + Error-Trend-Seasonality



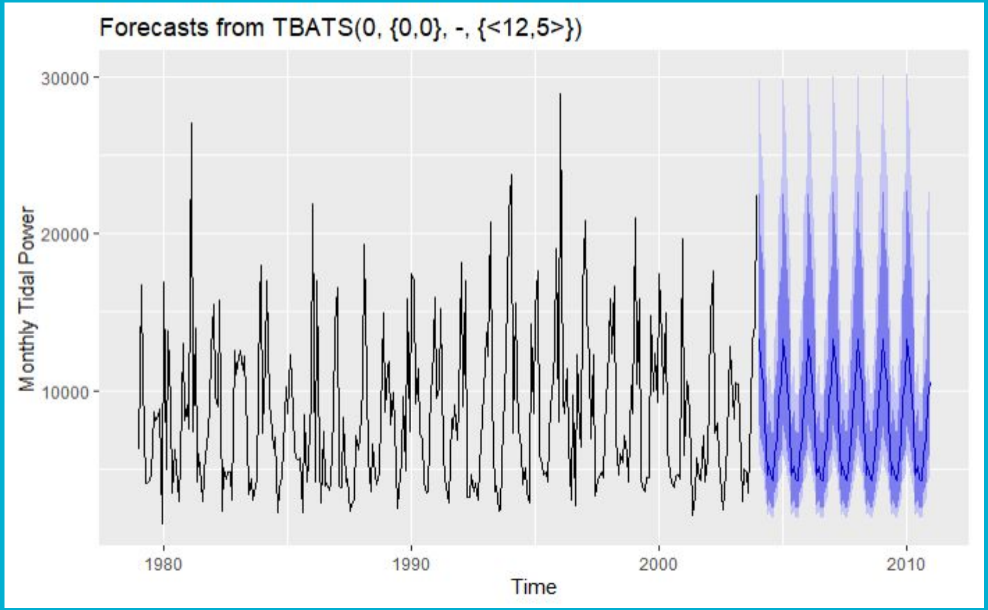
Strengths - Works well with pronounced seasonality and is robust to outliers

Performance for Maine Data:
MAPE: 36.40% ; RMSE: 3730.74

Has a slightly negative bias, and doesn't capture the peaks well, even with the confidence intervals

#2 : TBAT

Trigonometric Box-Cox transform, ARMA errors, Trend, and Seasonality

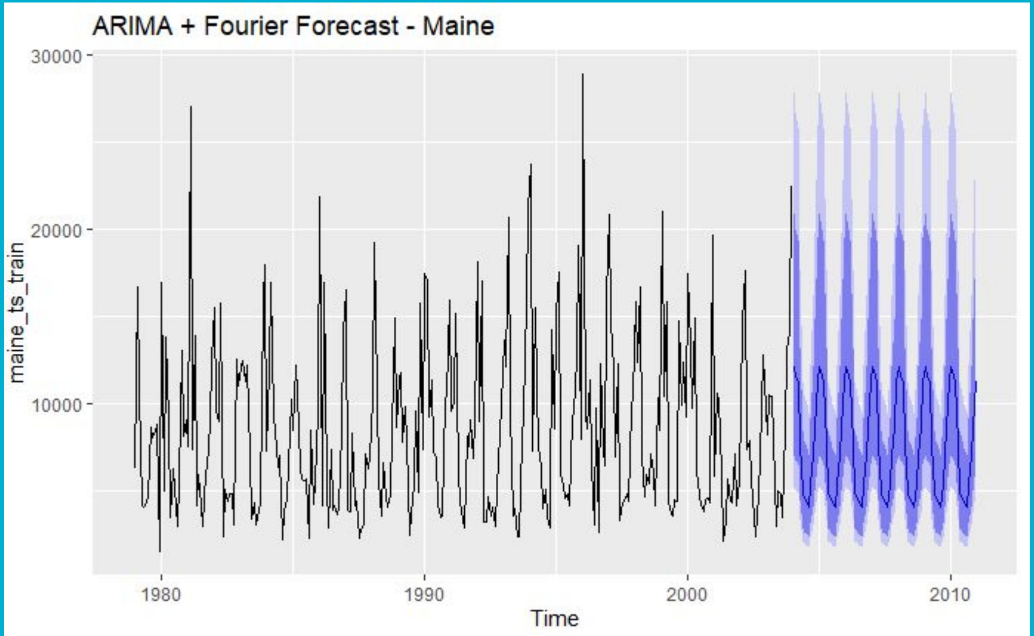


- Identifies and isolates multiple seasonal patterns (ideal for tidal power)
- Models leftover noise (ARMA errors)
  - Also ideal for tidal power, with the number of variables that affect ocean current direction and speed

- Performance for Maine Data:
  MAPE: 34.00% ; RMSE: 3728.78

#1 : ARIMA + Fourier

AutoRegressive Integrated Moving Average with Fourier terms (best fit : K = 4)

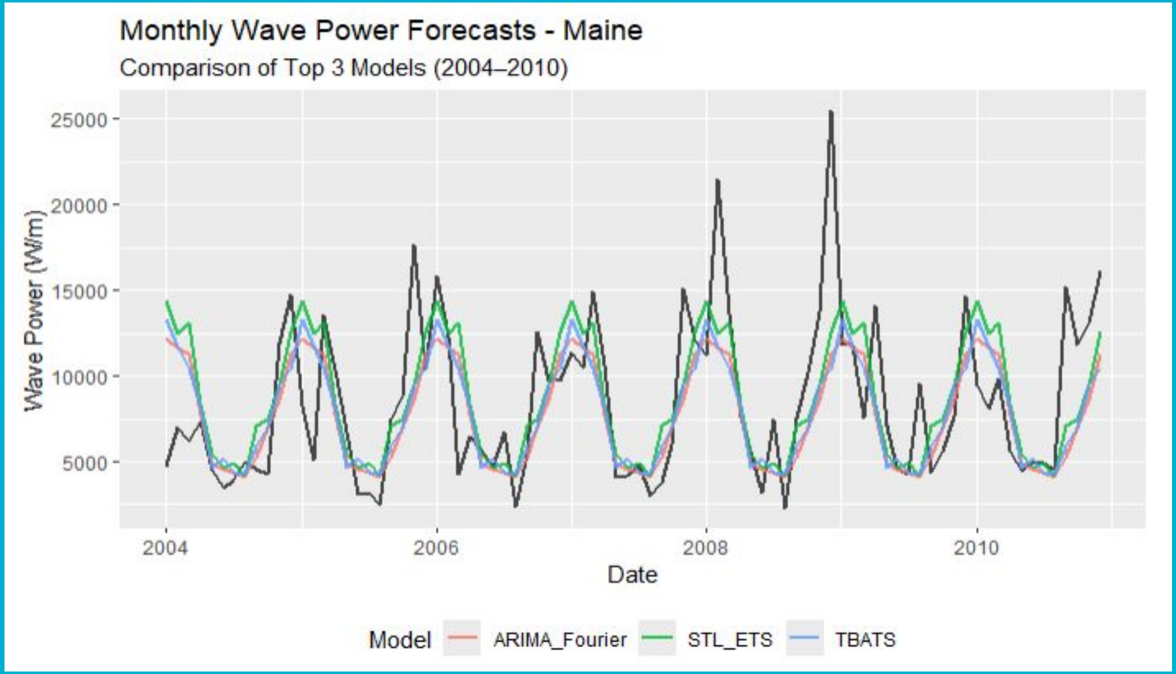


Strengths - Is more flexible than standard seasonal ARIMA and is good for data with strong cyclical components
- Good for ocean wave data that can have shifting cycles

- Performance for Maine Data:
MAPE: 31.99% (lowest among all models)
RMSE: 3690.03

Observation on Confidence intervals - We don't see the typical funnel pattern in either of the models, which shows that strong seasonality drives the variance rather than trend. This helps with more precise long-term forecasting

Comparing the Top 3 Models with Actuals:



All models capture the seasonality, but underestimate the highest peaks on average; more dependable for minimum power generation forecasting, while considering ‘safe’ lower bounds on the maximum capacity

Next steps

- Continue tweaking model parameters
- Explore incorporating El Niño and La Niña (or other variables like sea surface temperature)
- Shortlist 2-3 models
  - Forecast for Alaska and Florida and make site recommendations
  - Potentially look into a different site for Alaska
- Political Climate

Sources/Datasets

- Marine Energy Atlas - (if you want to play around with other sites!) https://maps.nrel.gov/marine-energy-atlas/data-viewer/download?vL=WavePowerMerged&b=%5B%5B-150.717111%2C43.537926%5D%2C%5B-114.418117%2C51.672586%5D%5D
- https://www.altenergymag.com/article/2024/10/evaluating-the-present-and-future-potential-of-tidal-power-in-the-us/43464
- https://www.linquip.com/blog/tidal-energy-diagram-story-of-tidal-power/

THANK YOU!