IE3100R Systems Design Project

FORECASTING CARBON INTENSITY

NUS National University of Singapore | Department of Industrial Systems Engineering & Management
College of Design and Engineering

GIC

Group 15:
Chew Xun Yu Jaylen, Tan Yang Keat, Zhang Xiao, Chin Wei Herng, Gladys Phua Ying Xuan

Academic Advisors:
Dr Wang Zhiguo, A/Prof Ng Tsan Sheng, Adam

Industrial Advisors:
Lloyd Lee Wangru, Justin Choo Jie Hui

INTRODUCTION

This project is designed to enhance data-driven investment strategies by developing a robust emissions forecasting model. The model projects Scope 1 and 2 carbon intensity trajectories (tCO_2/\$revenue) for all MSCI ACWI Index constituents through 2050, enabling the calculation of portfolio-level weighted average carbon intensity (WACI) and assess climate-related financial risks.

DATA SOURCES

S&P Global

- Annual carbon emissions (tCO2) of Scopes 1-3, for more than 19,000 companies
- Total revenue of companies per fiscal year
- Classification of industries between companies

S&P TRUCOST ENVIRONMENTAL

MSCI

- Includes multiple emissions, intensity or energy reduction targets per company
- Coverage of emissions reduction efforts
- Scope of emissions reduction efforts

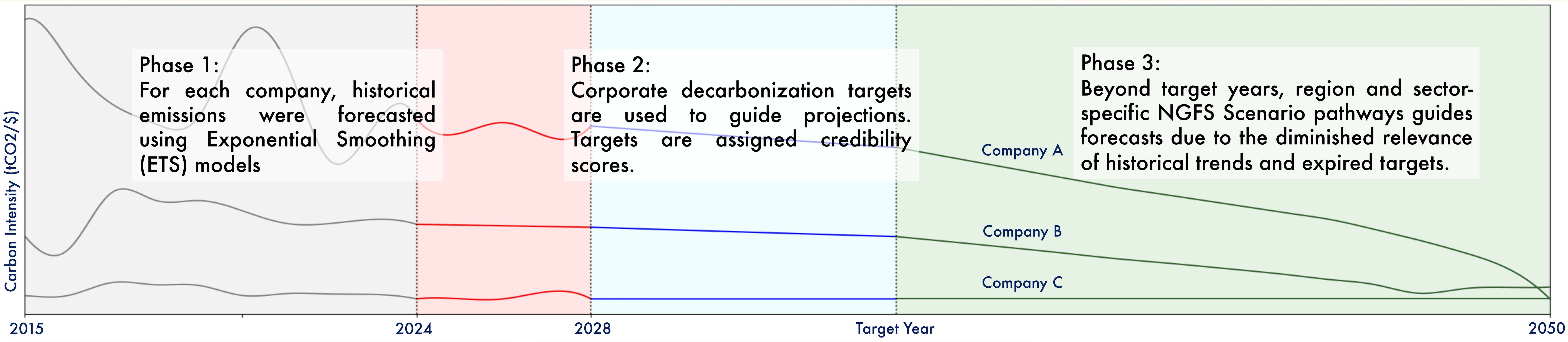
MSCI ESG TARGETS

NGFS

- Emissions trajectories of various scenarios: Net Zero 2050, Delayed Transition, Fragmented World, Current Policies
- Able to drill down by region and industry

NGFS SCENARIO EXPLORER

THREE-PHASE FORECASTING MODEL FOR CARBON INTENSITY



PHASE 1: HISTORICAL TREND

Time-Series Forecasting (ETS)

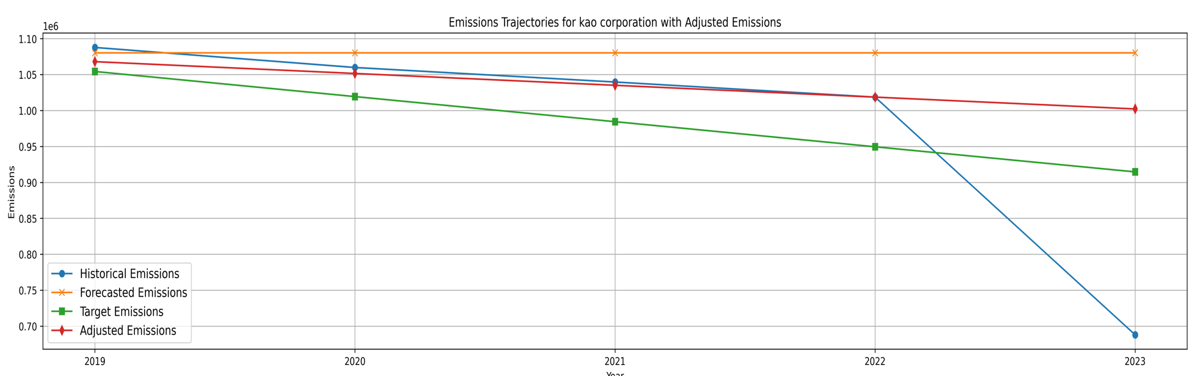
$$\hat{Y}_t = L_{t-1} + hB_n + SN_{n-L}$$

Where:

- $\hat{Y}_t$: forecast at time t
- L_{t-1} : smoothed level at $t-1$
- h : forecast horizons
- B_t: trend of the series
- SN_{t-L}: seasonal adjustment, offset by seasonal lag L

Each company's model is configured by minimizing the Akaike Information Criterion to balance pattern adaptation and avoid overfitting.

Optimization of Forecast Accuracy



This is an example of a suboptimal emissions forecast upon back-testing. Linear Programming is used to minimize the forecast error by blending both time-series and targets:

$$\text{Minimize} \quad \left(\frac{1}{N \times Y}\right) \sum_{n \in N} \sum_{y \in Y} \text{Absolute Percentage Error}(n, y)$$

Where:

- N: number of companies
- Y : Year 2019 - 2023

Optimizes for the ideal forecast and target emission weightage across the projection period

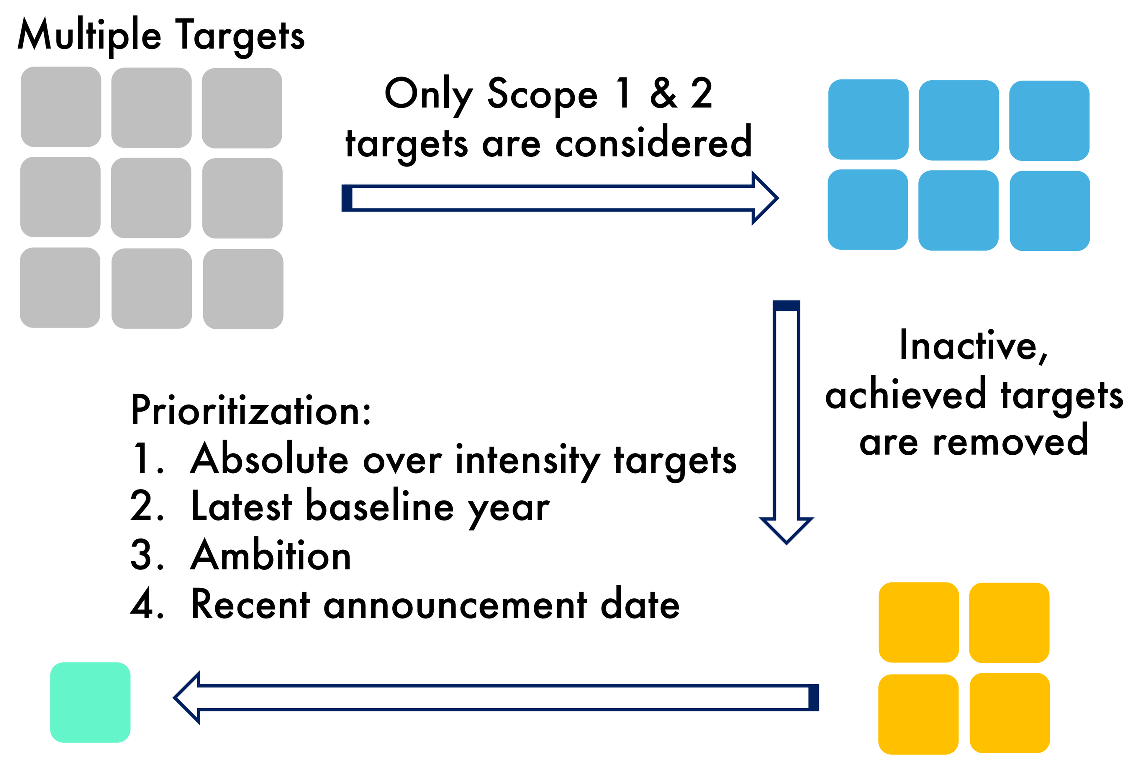
For each company: $E_{b,n} = E_{f,n} \times w_f + E_{t,n} \times w_t$

Where:

- w_f : weightage of forecasts
- w_t : weightage of targets
- $E_{b,n}$: blended emissions at year n
- $E_{f,n}$: forecasted emissions at year n
- $E_{t,n}$: target emissions at year n

PHASE 2: TARGET-DRIVEN

Target Selection Methodology



Credibility Assessment Matrix

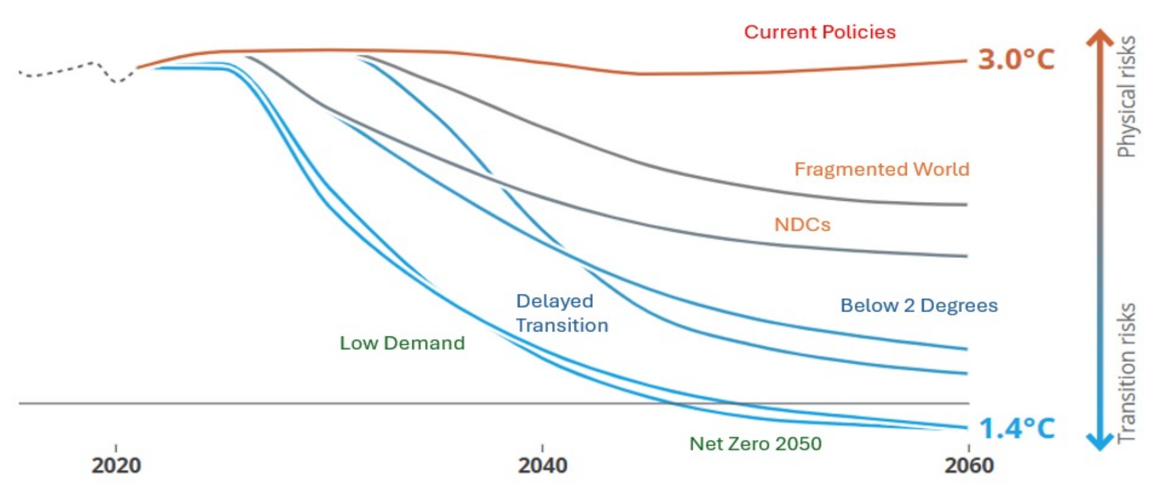
Description	Credibility Weight	Target before 2032	Target After 2032	Has SBTI Approved Target	Has Committed to SBTI Target
No SBTI validated targets	25%	✅/❌	✅/❌	❌	✅/❌
Has SBTI validated long-term targets, without a transition plan	50%	❌	✅/❌	✅	❌
Has SBTI validated short-term targets, without a transition plan	75%	✅	✅/❌	✅	❌
Has both short and long-term SBTI targets supported by a transition plan	100%	✅	✅/❌	✅	✅

$$\text{Emissions}_t = \text{Emissions}_{t-1} - \text{Targeted Carbon Reduction} \times \text{Credibility Score}$$

A 50% credibility score means the company is expected to achieve half its stated emissions reduction

PHASE 3: POST-TARGET

NGFS Scenarios Used



$$\text{Blended Scenario Decarbonization Rate}(t) = s_1 \times w_1 + s_2 \times w_2 + s_3 \times w_3 + s_4 \times w_4$$

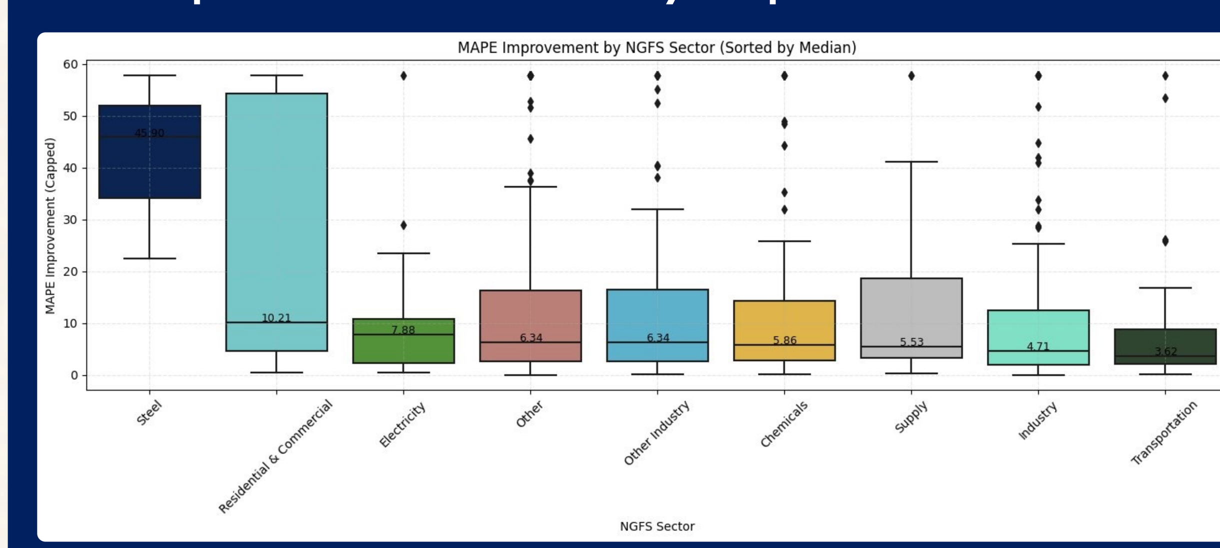
w_1, w_2, w_3, w_4, are equally weighted by default

1. Net Zero 2050 (S_1): A fast, coordinated transition to limit warming to 1.5°C, reaching net zero by 2050
2. Delayed Transition (S_2): Emissions increase till 2030, resulting in strong policies to limit warming to 2°C
3. Fragmented World (S_3): Delayed and divergent climate policy ambition globally, leading to high physical and transition risks
4. Current Policies (S_4): Assumes that only currently implemented policies are preserved, leading to high physical risks

RESULTS (Phase 1)

Adjustment	Median RMSE	Median MAE	Median MAPE (%)
Pre-Optimization	118,435.005	103,424.033	28.190
Post-Optimization	94,372.364	77,635.636	24.909

Post-optimization accuracy improvements:



ACHIEVEMENTS

- Delivered a robust projection model for over 2000 companies across 50+ industries
- Procured and utilized industry-leading data sources, ensuring scalability of model in the future
- Developed in conjunction with ESG experts at GIC

SKILLS APPLIED

Python | Project Management | Time-Series Forecasting | ESG & Climate Modelling