Import Relevant Packages and Custom Helper Functions

- Stored in `BoT_Exports/helper.py` to make code cleaner across .ipynb notebooks and .py scripts

In [1]:
```
from helper import *

# Ignore FutureWarning
warnings.simplefilter(action='ignore', category=FutureWarning)
pd.set_option('mode.chained_assignment', None)  # to avoid SettingWithCopyWa
```

Goal:

- Reseasonalize the Forecast back into actual scale
- Stitch back into:
  - `Level 0: Exports (BOP Basis)`

  \

  - `Level 1 (Custom Basis)` : weighted_Sum(Agriculture, Fishery, Forestry, Mining, Manufacturing, Other Exports, Re-Exports 1, Total Exports)
  - `Level 1 (BOP)` : weighted_Sum(Agriculture, Fishery, Forestry, Mining, Manufacturing, Other Exports, Re-Exports 1, Total Exports) + Coverage_Adjustment\

  \

  - `Level 2 (Custom Basis)` : weighted_Sum(weighted_sum_of_components) + Coverage_Adjustment
  - `Level 2 (BOP)` : weighted_Sum(weighted_sum_of_components) + Coverage_Adjustment

  \

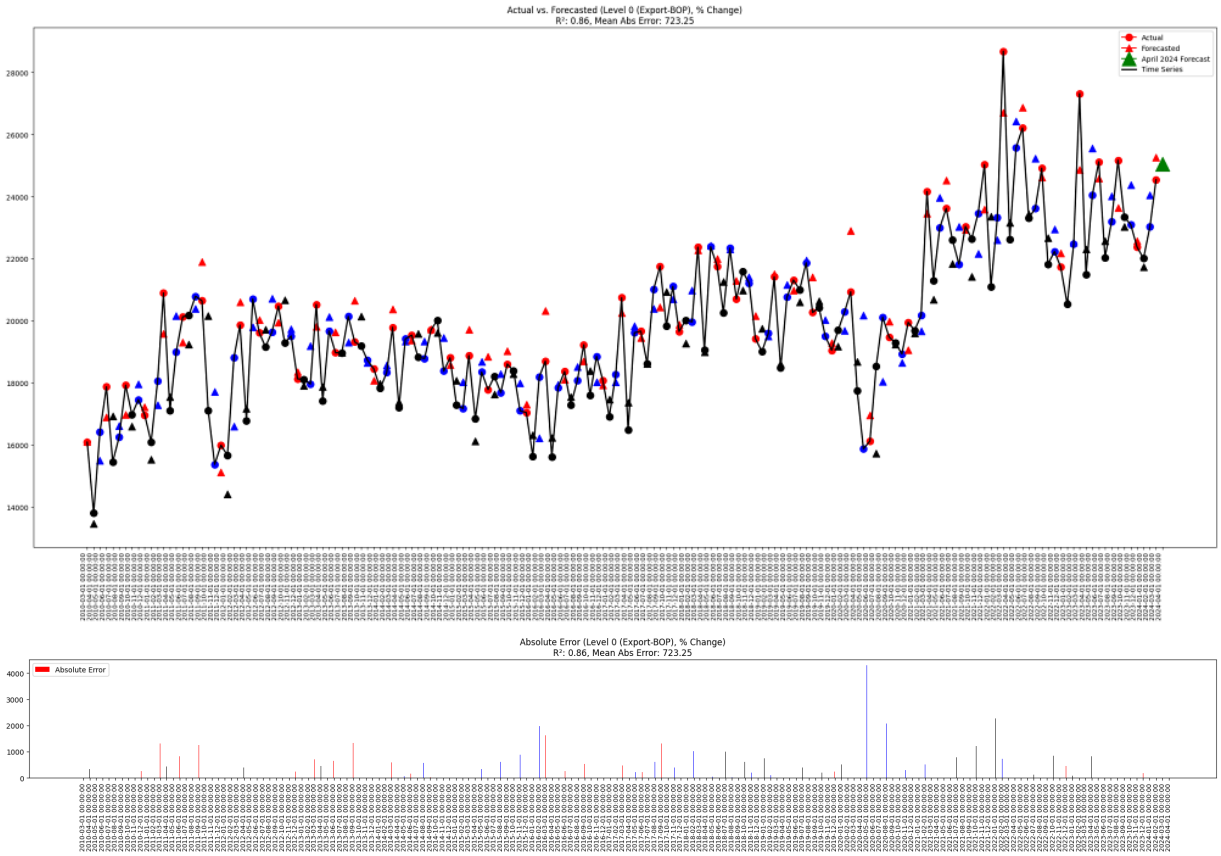
  - `Benchmark` (Exponential Moving Average)

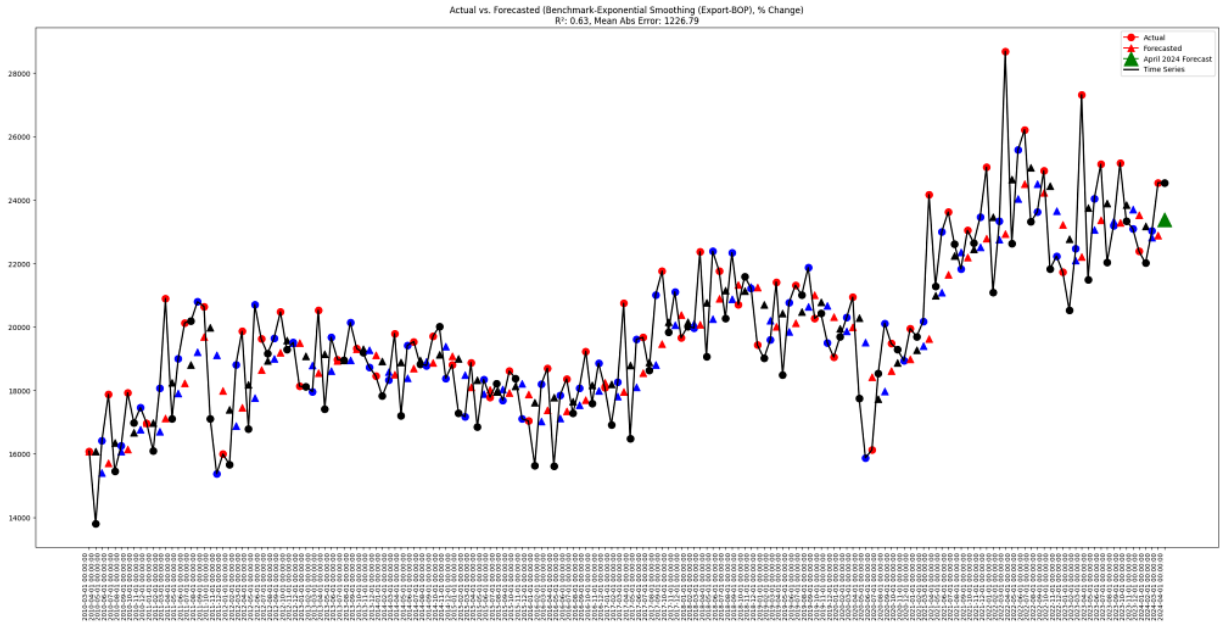
In [2]:
```
names = ['Agriculture', 'Rice', 'Rubber', 'Durian', 'Other_Fruits',
       'Horticultural_products,_n.i.e.', 'Animal_products', 'Fishery',
       'Crustaceans', 'Fish', 'Cuttlefish,_squid,_octopus',
       'Fishery_products,_n.i.e.', 'Forestry', 'Mining', 'Crude_oil',
       'Mineral_products,_n.i.e.', 'Manufacturing',
       'Agro-manufacturing_Products', 'Apparels_and_Textile_Materials',
       'Footware_and_parts', 'Electronics', 'Electrical_Appliances',
       'Metal_&_Steel', 'Automotive',
```

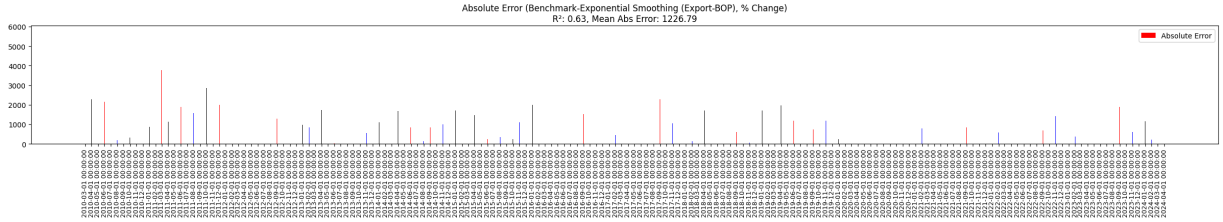
```
        'Aircrafts,_ships,_floating_structures,_and_locomotive',
        'Machinery_&_Equipment', 'Jewellery',
        'Chemicals_&_Petro-chemical_Products', 'Petroleum_products',
        'Photographic_&_cinematographic_instruments_&_supplies',
        'Medicinal_and_surgical_equipment_and_supplies',
        'Toiletries_and_cosmetics', 'Furniture_and_parts',
        'Other_Manufacturing_products', 'Other_Exports', 'Re-Exports_1',
        'Total_Exports_(Customs_basis)', 'Coverage_Adjustment',
        'Timing_Adjustment', 'Exports,_f.o.b._(BOP_basis)']
```

Level 0: Exports (BOP Basis)

In [3]:
```
## Level 0: BOP
name = "Exports,_f.o.b._(BOP_basis)"
# name = "Re-Exports_1"
# name = "Total_Exports_(Customs_basis)"


process_forecast_accuracy(name=name,
                          plot_show=True,
                          col_name="Level 0 (Export-BOP)",)
```




Actual vs. Forecasted (Benchmark-Exponential Smoothing (Export-BOP), % Change)
R²: 0.63, Mean Abs Error: 1226.79
Actual
Forecasted
April 2024 Forecast
Time Series
28000
26000
24000
22000
20000
18000
16000
14000


Absolute Error (Benchmark-Exponential Smoothing (Export-BOP), % Change)
R²: 0.63, Mean Abs Error: 1226.79
Absolute Error
6000
5000
4000
3000
2000
1000
0

Out[3]:
```
(              actual      forecast        error    abs_error  squared_erro
r  \
 2010-03-01  16088.22  16103.887847   -15.667847    15.667847   2.454814e+0
2
 2010-04-01  13804.62  13467.810703   336.809297   336.809297   1.134405e+0
5
 2010-05-01  16424.34  15498.108124   926.231876   926.231876   8.579055e+0
5
 2010-06-01  17871.67  16894.719461   976.950539   976.950539   9.544324e+0
5
 2010-07-01  15447.94  16929.517882 -1481.577882  1481.577882   2.195073e+0
6
 ...              ...           ...          ...          ...
...
 2023-12-01  22380.30  22567.179468  -186.879468   186.879468   3.492394e+0
4
 2024-01-01  22012.20  21730.407784   281.792216   281.792216   7.940685e+0
4
 2024-02-01  23036.45  24052.342575 -1015.892575  1015.892575   1.032038e+0
6
 2024-03-01  24543.84  25259.073457  -715.233457   715.233457   5.115589e+0
5
 2024-04-01       NaN  25058.037346          NaN          NaN            Na
N

             abs_percentage_error
 2010-03-01              0.000974
 2010-04-01              0.024398
 2010-05-01              0.056394
 2010-06-01              0.054665
 2010-07-01              0.095908
 ...                          ...
 2023-12-01              0.008350
 2024-01-01              0.012802
 2024-02-01              0.044099
 2024-03-01              0.029141
 2024-04-01                   NaN

 [170 rows x 6 columns],
               actual      forecast        error    abs_error  squared_erro
r  \
 2010-03-01  16088.22  16088.220000 -2283.600000  2283.600000   5.214829e+0
6
 2010-04-01  13804.62  16088.220000 -2283.600000  2283.600000   5.214829e+0
6
 2010-05-01  16424.34  15403.140000  1021.200000  1021.200000   1.042849e+0
6
 2010-06-01  17871.67  15709.500000  2162.170000  2162.170000   4.674979e+0
6
 2010-07-01  15447.94  16358.151000  -910.211000   910.211000   8.284841e+0
5
 ...              ...           ...          ...          ...
...
 2023-12-01  22380.30  23521.484792 -1141.184792  1141.184792   1.302303e+0
6
 2024-01-01  22012.20  23179.129354 -1166.929354  1166.929354   1.361724e+0
```

```
6
 2024-02-01  23036.45  22829.050548   207.399452   207.399452   4.301453e+0
4
 2024-03-01  24543.84  22891.270384  1652.569616  1652.569616   2.730986e+0
6
 2024-04-01  24543.84  23387.041269  1652.569616  1652.569616   2.730986e+0
6

            abs_percentage_error
 2010-03-01              0.165423
 2010-04-01              0.165423
 2010-05-01              0.062176
 2010-06-01              0.120983
 2010-07-01              0.058921
 ...                          ...
 2023-12-01              0.050991
 2024-01-01              0.053013
 2024-02-01              0.009003
 2024-03-01              0.067331
 2024-04-01              0.067331

 [170 rows x 6 columns])
```

Level 1 (Custom Basis) : weighted_Sum(Agriculture, Fishery, Forestry, Mining, Manufacturing, Other Exports, Re-Exports 1, Total Exports)

In [4]:
```
mapper = pd.read_pickle("data/cleaned/MAP_exports_FirstAnalysis.pkl")
mapper
```

Out[4]:

	Agriculture	Fishery	Forestry	Mining
0	Rice	Crustaceans	NaN	Crude_oil
1	Rubber	Fish	NaN	Mineral_products,_n.i.e.
2	Durian	Cuttlefish,_squid,_octopus	NaN	NaN
3	Other_Fruits	Fishery_products,_n.i.e.	NaN	NaN
4	Horticultural_products,_n.i.e.	NaN	NaN	NaN
5	Animal_products	NaN	NaN	NaN
6	NaN	NaN	NaN	NaN
7	NaN	NaN	NaN	NaN
8	NaN	NaN	NaN	NaN
9	NaN	NaN	NaN	NaN
10	NaN	NaN	NaN	NaN
11	NaN	NaN	NaN	NaN
12	NaN	NaN	NaN	NaN
13	NaN	NaN	NaN	NaN
14	NaN	NaN	NaN	NaN
15	NaN	NaN	NaN	NaN
16	NaN	NaN	NaN	NaN

In [5]:
```
map_l1 = mapper.iloc[:,[-1]].dropna()
name = map_l1.columns[0]
display(name)
display(map_l1)

constituents = map_l1[name].to_list()
display(constituents)
```

```
'Total_Exports_(Customs_basis)'
```

	Total_Exports_(Customs_basis)
0	Agriculture
1	Fishery
2	Forestry
3	Mining
4	Manufacturing
5	Other_Exports
6	Re-Exports_1

```
['Agriculture',
 'Fishery',
 'Forestry',
 'Mining',
 'Manufacturing',
 'Other_Exports',
 're-Exports_1']
```

In [6]:
```
with open("data/cleaned/forecasted_weights/dict_R2_cap_extreme_values.pkl",
    weights_r2 = pickle.load(f)[name]

display(weights_r2)

max_row_names = weights_r2.idxmax()

weight_technique_name_map = {"Lag-1": "Lag_1_",
                             "Exp Smooth": "Exp_Smooth_",
                             "DCR": "DCR_"}
REVERSE_weight_technique_name_map = {v: k for k, v in weight_technique_name_
max_row_names = max_row_names.map(weight_technique_name_map)
display(max_row_names)
```

	Agriculture	Fishery	Forestry	Mining	Manufacturing	Other_Exports	R Exports_
DCR	0.375374	0.163061	0.563713	0.252655	0.083092	0.004026	0.16053
Exp Smooth	0.454942	0.206607	0.692899	0.152601	0.052322	0.058823	0.20484
Lag-1	0.472380	0.539492	0.595167	0.261575	0.035167	-0.208714	-0.14272

```
Agriculture           Lag_1_
Fishery               Lag_1_
Forestry         Exp_Smooth_
Mining                Lag_1_
Manufacturing            DCR_
Other_Exports    Exp_Smooth_
Re-Exports_1     Exp_Smooth_
dtype: object
```

In [7]:
```
forecast_df_original_dcr = pd.read_pickle(f"data/cleaned/forecasted_weights/
forecast_df_original_exp_smooth = pd.read_pickle(f"data/cleaned/forecasted_w
forecast_df_original_lag_1 = pd.read_pickle(f"data/cleaned/forecasted_weight

# Convert the PeriodDtype index to timestamps
forecast_df_original_dcr.index = forecast_df_original_dcr.index.to_timestamp
forecast_df_original_exp_smooth.index = forecast_df_original_exp_smooth.inde
forecast_df_original_lag_1.index = forecast_df_original_lag_1.index.to_times

#convert pd.to_datetime
forecast_df_original_dcr.index = pd.to_datetime(forecast_df_original_dcr.inc
forecast_df_original_exp_smooth.index = pd.to_datetime(forecast_df_original_
forecast_df_original_lag_1.index = pd.to_datetime(forecast_df_original_lag_1
```

```
display("forecast_df_original_dcr")
display(forecast_df_original_dcr)
display("forecast_df_original_exp_smooth")
display(forecast_df_original_exp_smooth)
display("forecast_df_original_lag_1")
display(forecast_df_original_lag_1)
```

'forecast_df_original_dcr'

	Agriculture	Fishery	Forestry	Mining	Manufacturing	Other_Exports	Re-Exports_1
2010-01-01	0.059828	0.009615	0.003298	0.006922	0.910358	0.009669	0.000311
2010-02-01	0.058623	0.009421	0.004346	0.006782	0.915440	0.005082	0.000305
2010-03-01	0.058245	0.009360	0.004778	0.006738	0.909528	0.011048	0.000303
2010-04-01	0.057699	0.009273	0.004144	0.006675	0.901009	0.020900	0.000300
2010-05-01	0.055815	0.008970	0.004752	0.007224	0.871590	0.020900	0.000290
...	...	...	...	...	...	...	...
2023-12-01	0.072646	0.005449	0.006575	0.003428	0.895598	0.015327	0.000977
2024-01-01	0.069014	0.005029	0.006548	0.003815	0.894287	0.020184	0.001122
2024-02-01	0.062080	0.004749	0.006573	0.003425	0.898328	0.023756	0.001090
2024-03-01	0.056775	0.004636	0.007422	0.003173	0.904796	0.022517	0.000680
2024-04-01	0.056775	0.004636	0.007422	0.003173	0.904796	0.022517	0.000680

172 rows × 7 columns

'forecast_df_original_exp_smooth'

	Agriculture	Fishery	Forestry	Mining	Manufacturing	Other_Exports	Re-Exports_1
2010-01-01	0.072152	0.009877	0.003401	0.008240	0.888141	0.017884	0.000305
2010-02-01	0.071383	0.009771	0.003582	0.008152	0.878674	0.028135	0.000302
2010-03-01	0.072388	0.009909	0.005029	0.008085	0.891040	0.013245	0.000306
2010-04-01	0.065901	0.009021	0.003951	0.007360	0.899407	0.014082	0.000278
2010-05-01	0.065163	0.008920	0.004408	0.007496	0.889335	0.024403	0.000275
...	...	...	...	...	...	...	...
2023-12-01	0.071353	0.005306	0.006119	0.003229	0.897928	0.015220	0.000846
2024-01-01	0.070010	0.004794	0.006428	0.003295	0.896379	0.018102	0.000993
2024-02-01	0.062975	0.004607	0.006817	0.003524	0.896797	0.024093	0.001186
2024-03-01	0.057785	0.004451	0.007534	0.003335	0.897296	0.028726	0.000873
2024-04-01	0.057785	0.004451	0.007534	0.003335	0.897296	0.028726	0.000873

172 rows × 7 columns

```
'forecast_df_original_lag_1'
```

	Agriculture	Fishery	Forestry	Mining	Manufacturing	Other_Exports	Re-Exports_1
2010-01-01	0.077335	0.008343	0.003512	0.005070	0.894888	0.009327	0.001525
2010-02-01	0.077689	0.008381	0.003925	0.005093	0.898979	0.004400	0.001532
2010-03-01	0.077069	0.008315	0.004622	0.005945	0.891811	0.010718	0.001520
2010-04-01	0.086701	0.009354	0.004224	0.008902	0.871099	0.018011	0.001710
2010-05-01	0.076795	0.008415	0.004116	0.006699	0.886231	0.016205	0.001539
...	...	...	...	...	...	...	...
2023-12-01	0.069067	0.005125	0.005789	0.002551	0.902586	0.013858	0.001024
2024-01-01	0.063152	0.004797	0.006714	0.003367	0.899579	0.021684	0.000708
2024-02-01	0.061800	0.005299	0.006777	0.003502	0.892903	0.028562	0.001157
2024-03-01	0.056838	0.004857	0.007693	0.004239	0.887934	0.037921	0.000519
2024-04-01	0.056838	0.004857	0.007693	0.004239	0.887934	0.037921	0.000519

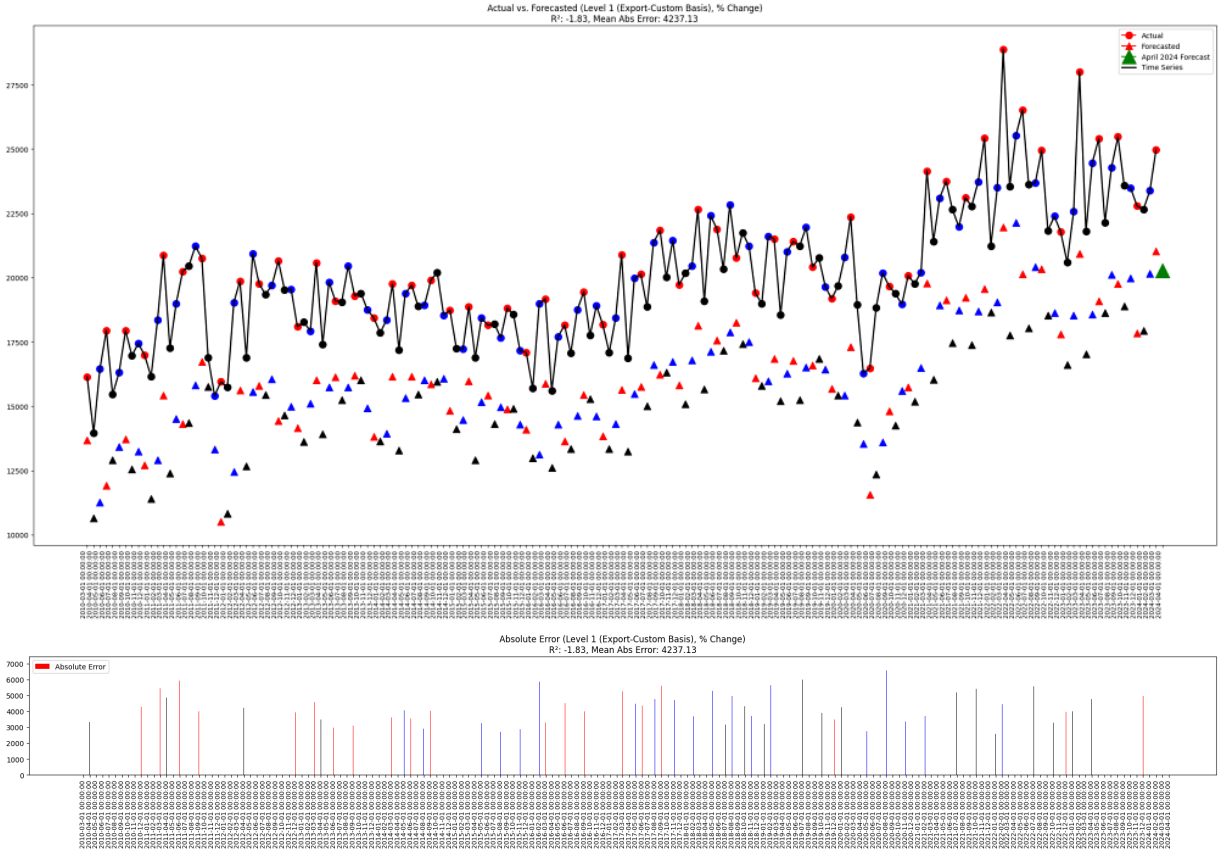
172 rows × 7 columns

In [8]:
```
#weighted sum
df_weighted = pd.DataFrame()

for i in constituents:
    #get weights
    best_r2 = max_row_names[i]
    w = convert_period_index_to_datetime(pd.read_pickle(f"data/cleaned/forec
    #get forecast returns
    forecast, benchmark = process_forecast_accuracy(name=i,
                                                    plot_show=False)
    forecast = forecast["forecast"]

    #reindex to the shorter length
    if len(w) > len(forecast):
        w = w.reindex(forecast.index)
    else:
        forecast = forecast.reindex(w.index)

    df_weighted[i] = forecast * w

#drop the na rows
df_weighted = df_weighted.dropna().sum(axis=1).dropna()
```

```
df_actual, _ = process_forecast_accuracy(name=name,
                                         plot_show=False)
df_actual = df_actual["actual"]

# reindex to the shorter length
if len(df_weighted) > len(df_actual):
    df_weighted = df_weighted.reindex(df_actual.index)
else:
    df_actual = df_actual.reindex(df_weighted.index)

df_accuracy = calculate_accuracy_metrics(actual=df_actual,
                                         forecast=df_weighted)
display(df_accuracy)

plot_actual_vs_forecast(df_accuracy=df_accuracy, col_name="Level 1 (Export-C
```

	actual	forecast	error	abs_error	squared_error	abs_percentage_er
2010-03-01	16142.69	13690.545677	2452.144323	2452.144323	6.013012e+06	0.151
2010-04-01	13964.05	10657.468361	3306.581639	3306.581639	1.093348e+07	0.236
2010-05-01	16447.98	11256.543127	5191.436873	5191.436873	2.695102e+07	0.315
2010-06-01	17942.68	11910.646263	6032.033737	6032.033737	3.638543e+07	0.336
2010-07-01	15456.20	12902.011271	2554.188729	2554.188729	6.523880e+06	0.165
...	...	...	...	...	...	
2023-12-01	22791.55	17836.941877	4954.608123	4954.608123	2.454814e+07	0.217
2024-01-01	22649.88	17936.698094	4713.181906	4713.181906	2.221408e+07	0.208
2024-02-01	23384.86	20162.683337	3222.176663	3222.176663	1.038242e+07	0.137
2024-03-01	24960.55	21038.438273	3922.111727	3922.111727	1.538296e+07	0.157
2024-04-01	NaN	20280.668523	NaN	NaN	NaN	N

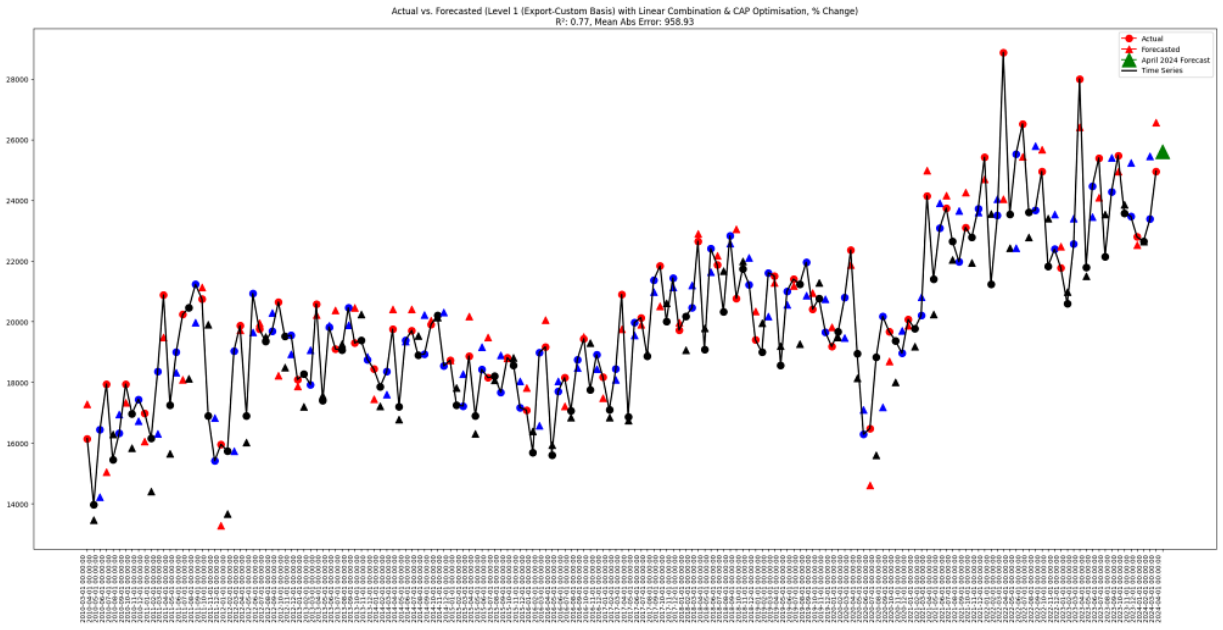
170 rows × 6 columns

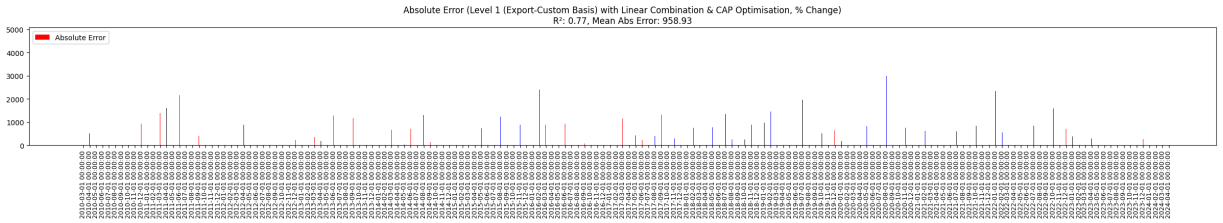


The above result from the stiched forecast looks bad, however, I can see a trend which looks like a speculative linear combination of the actual. This means that Linear combination Optimisation can be done over a rolling scale to optimise (minimize the MAE). In the future, I will implement a rolling optimisation but for the current stage, the computation is too expensive given the deadline, and the optimisation here with be a rough representation and experiment

In [9]:
```
df = df_accuracy.copy(deep=True)
df["forecast"] = cap_extreme_values(df[["forecast"]])["forecast"]

#objective function to minimize (linear combination of forecast)
def objective(params, actual, forecast):
    a, b = params
    adjusted_forecast = a * forecast + b
```

```
    error = np.mean(np.abs(actual - adjusted_forecast))  # Mean Absolute Err
    return error

# Initial guess for a and b
initial_params = [1, 0]

# Perform the optimization
result = minimize(objective, initial_params, args=(df['actual'], df['forecas

# Extract the optimal parameters
a_opt, b_opt = result.x

# Apply the optimal parameters to adjust the forecast
df['forecast'] = a_opt * df['forecast'] + b_opt

df = calculate_accuracy_metrics(actual=df['actual'], forecast=df['forecast']
plot_actual_vs_forecast(df_accuracy=df,
                        col_name="Level 1 (Export-Custom Basis) with Linear Combinat
display(df)
'''
This will be implented as a function for future levels
'''
```





	actual	forecast	error	abs_error	squared_error	abs_percentage_e
2010-03-01	16142.69	17289.544762	-1146.854762	1146.854762	1.315276e+06	0.071
2010-04-01	13964.05	13459.294910	504.755090	504.755090	2.547777e+05	0.036
2010-05-01	16447.98	14215.822289	2232.157711	2232.157711	4.982528e+06	0.135
2010-06-01	17942.68	15041.840942	2900.839058	2900.839058	8.414867e+06	0.161
2010-07-01	15456.20	16293.762763	-837.562763	837.562763	7.015114e+05	0.054
...	...	...	...	...	...	
2023-12-01	22791.55	22525.722997	265.827003	265.827003	7.066400e+04	0.011
2024-01-01	22649.88	22651.697773	-1.817773	1.817773	3.304298e+00	0.000
2024-02-01	23384.86	25462.730516	-2077.870516	2077.870516	4.317546e+06	0.088
2024-03-01	24960.55	26568.656895	-1608.106895	1608.106895	2.586008e+06	0.064
2024-04-01	NaN	25611.725314	NaN	NaN	NaN	

170 rows × 6 columns

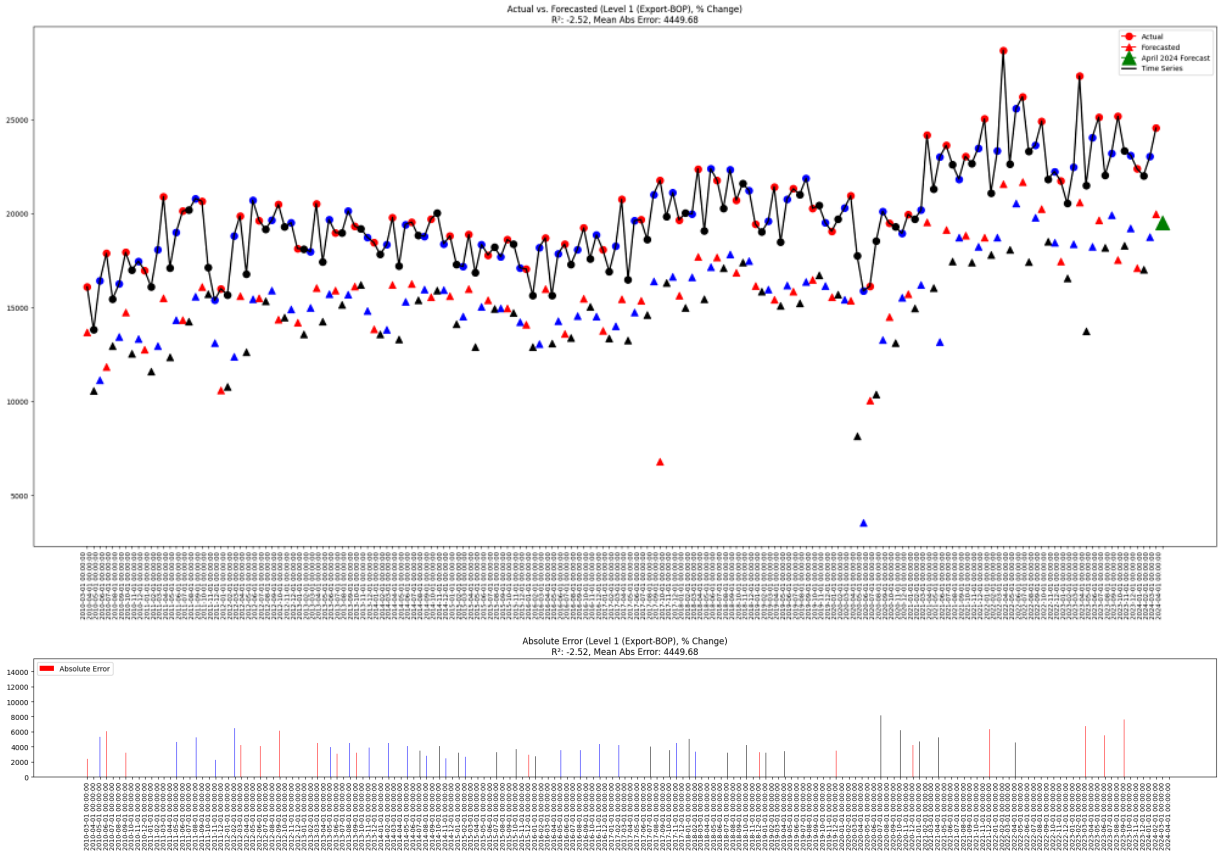
Out[9]: '\nThis will be implented as a function for future levels\n'

Level 1 (BOP) : weighted_Sum(Agriculture, Fishery, Forestry, Mining, Manufacturing, Other Exports, Re-Exports 1, Total Exports) + Coverage_Adjustmen

w/o Linear Combination Optimisation

In [10]:
```
name = "Exports,_f.o.b._(BOP_basis)"

df_Coverage_adj, _ = process_forecast_accuracy(name="Coverage_Adjustment",
                                               plot_show=False)
df_Coverage_adj = df_Coverage_adj["forecast"]

# reindex to the shorter length
if len(df_weighted) > len(df_Coverage_adj):
```

```
    df_weighted = df_weighted.reindex(df_Coverage_adj.index)
else:
    df_Coverage_adj = df_Coverage_adj.reindex(df_weighted.index)

df_weighted = df_weighted + df_Coverage_adj

df_actual, _ = process_forecast_accuracy(name=name,
                                         plot_show=False)
df_actual = df_actual["actual"]

# reindex to the shorter length
df_actual = df_actual.reindex(df_weighted.index)

df_accuracy = calculate_accuracy_metrics(actual=df_actual,
                                         forecast=df_weighted)

plot_actual_vs_forecast(df_accuracy=df_accuracy, col_name="Level 1 (Export-B
```

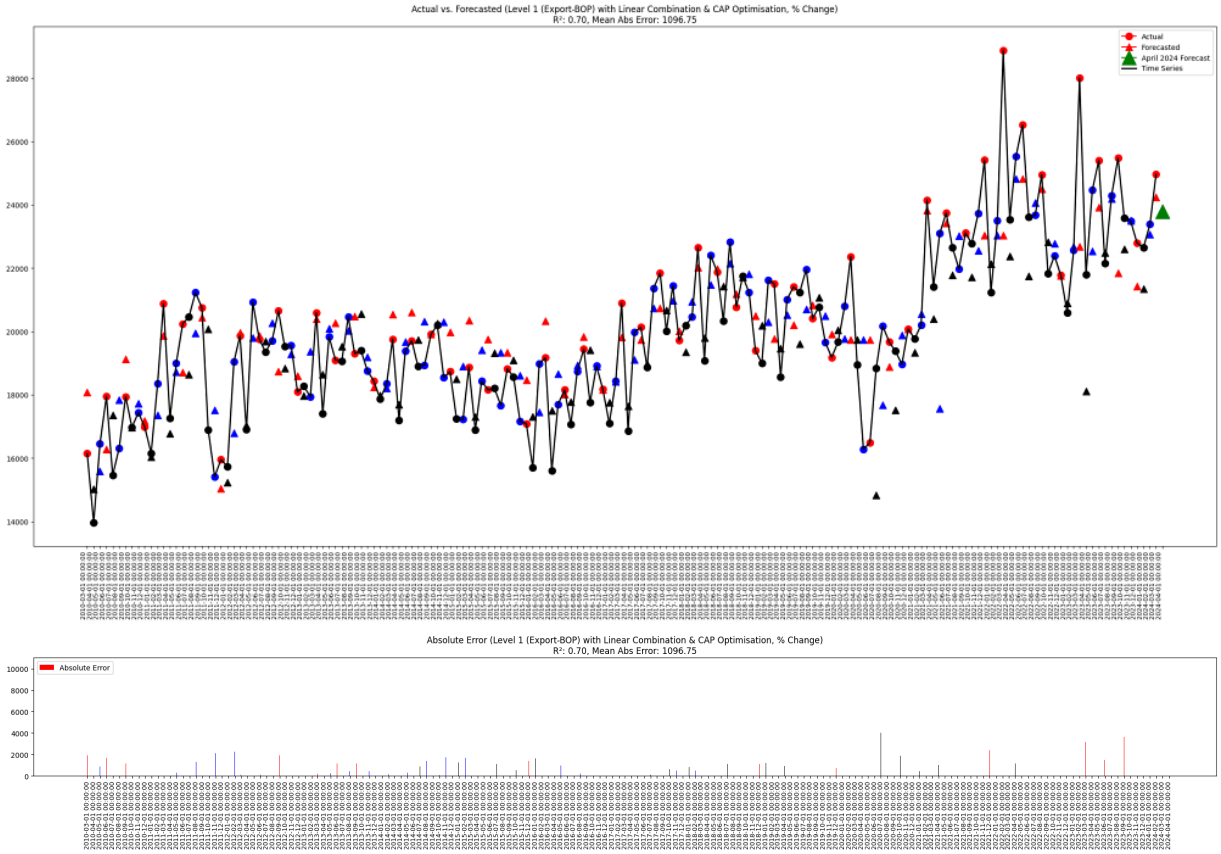


The above is now placed into functions for easier constituent stitching

In [11]:
```
name2 = "Coverage_Adjustment"
mapper_path = "data/cleaned/MAP_exports_FirstAnalysis.pkl"
weights_path = "data/cleaned/forecasted_weights/dict_R2_cap_extreme_values.p
```

In [12]:
```
# with linear combination optimisation
name = "Total_Exports_(Customs_basis)"
df_accuracy = calculate_weighted_forecast(name=name,
```

```
                                            mapper_path=mapper_path,
                                            weights_path=weights_path,
                                            plot_show=False)
df_weighted = df_accuracy["forecast"]
df_accuracy_CA = calculate_weighted_forecast_with_coverage_adjustment(name=r
                                                                      df_weight
                                                                      mapper_pa
                                                                      weights_p
                                                                      plot_show
opt_df_accuracy_CA = optimize_forecast(df_accuracy_CA,
                                       plot_show=False)

opt_df_accuracy_CA["forecast"] = cap_extreme_values(opt_df_accuracy_CA[["for

plot_actual_vs_forecast(df_accuracy=opt_df_accuracy_CA,
                        col_name="Level 1 (Export-BOP) with Linear Combinati

display(opt_df_accuracy_CA)
```



	actual	forecast	error	abs_error	squared_error	abs_percentage_e
2010-03-01	16142.69	18073.227635	-1930.537635	1930.537635	3.726976e+06	0.119
2010-04-01	13964.05	15024.728189	-1060.678189	1060.678189	1.125038e+06	0.075
2010-05-01	16447.98	15588.316987	859.663013	859.663013	7.390205e+05	0.052
2010-06-01	17942.68	16273.782147	1668.897853	1668.897853	2.785220e+06	0.093
2010-07-01	15456.20	17346.749815	-1890.549815	1890.549815	3.574179e+06	0.122
...	...	...	...	...	...	
2023-12-01	22791.55	21426.031065	1365.518935	1365.518935	1.864642e+06	0.059
2024-01-01	22649.88	21347.662797	1302.217203	1302.217203	1.695770e+06	0.057
2024-02-01	23384.86	23057.819053	327.040947	327.040947	1.069558e+05	0.013
2024-03-01	24960.55	24245.115256	715.434744	715.434744	5.118469e+05	0.028
2024-04-01	NaN	23787.264231	NaN	NaN	NaN	

170 rows × 6 columns

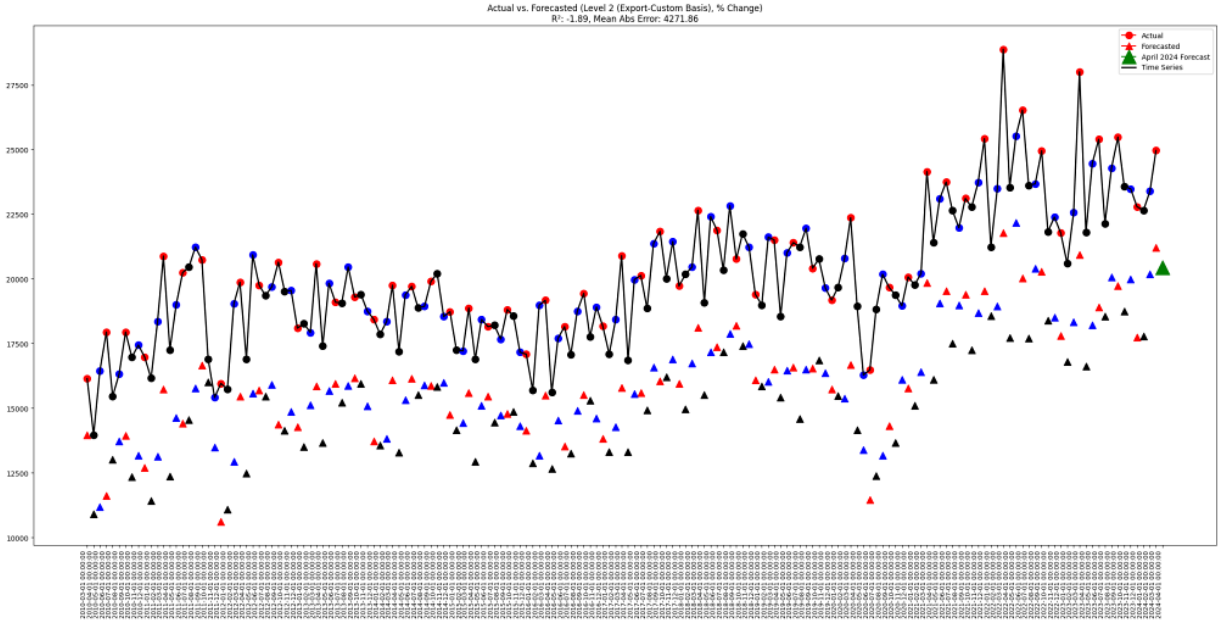
Level 2 (Custom Basis) : weighted_Sum(weighted_sum_of_componen + Coverage_Adjustment

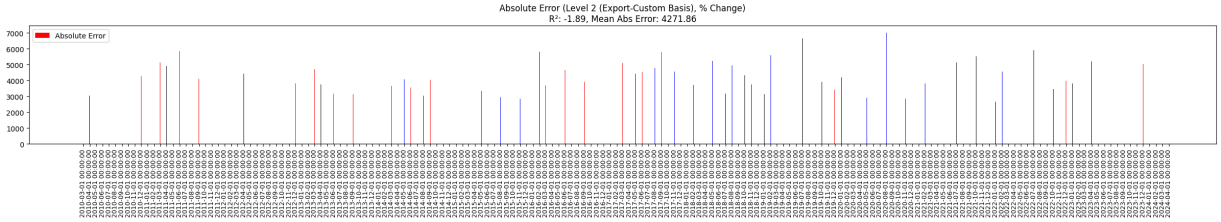
In [13]:
```
name = 'Total_Exports_(Customs_basis)'
```

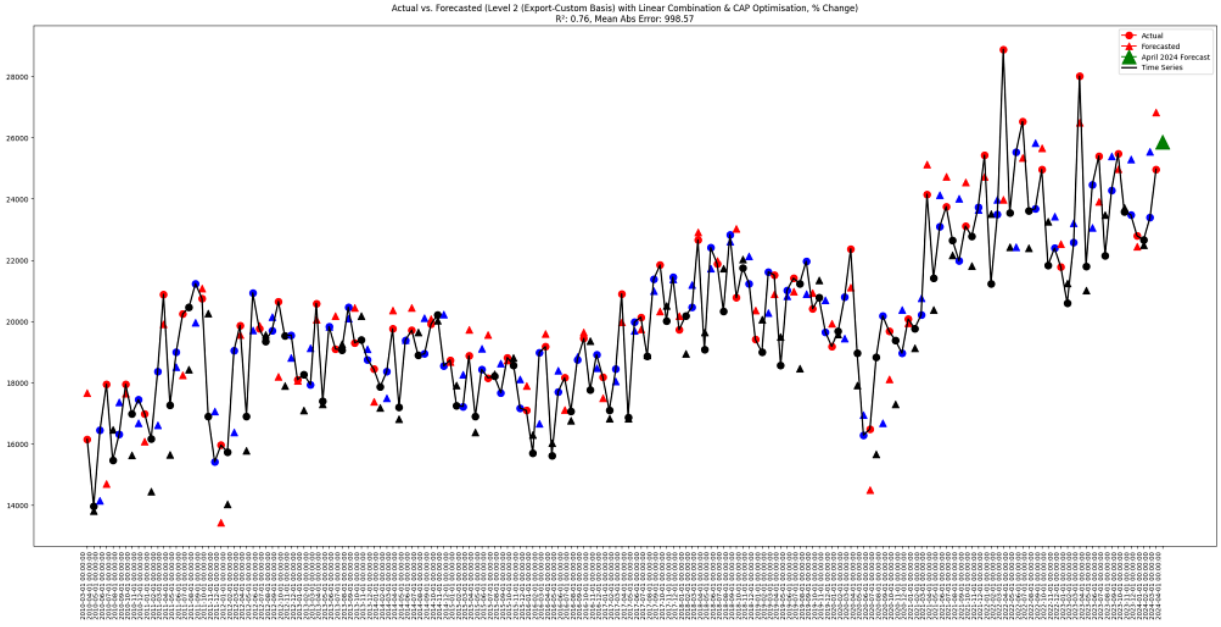
In [14]:
```
max_row_names
```

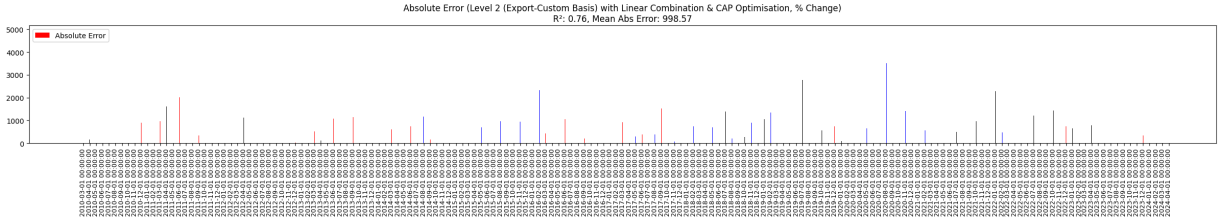
Out[14]:
```
Agriculture          Lag_1_
Fishery              Lag_1_
Forestry         Exp_Smooth_
Mining               Lag_1_
Manufacturing          DCR_
Other_Exports    Exp_Smooth_
Re-Exports_1     Exp_Smooth_
dtype: object
```

In [15]:
```
df_weighted = pd.DataFrame()

for major_col in mapper.columns[:-1]:

    df_accuracy = calculate_weighted_forecast(name=major_col,
                                              mapper_path=mapper_path,
                                              weights_path=weights_path,
                                              plot_show=False)
    forecast = df_accuracy["forecast"]
    with open(weights_path, "rb") as f:
        weights_r2 = pickle.load(f)[name]
    max_row_names = weights_r2.idxmax()
    weight_technique_name_map = {"Lag-1": "Lag_1_", "Exp Smooth": "Exp_Smoot
    max_row_names = max_row_names.map(weight_technique_name_map)
    best_r2 = max_row_names[major_col]
    w = convert_period_index_to_datetime(pd.read_pickle(f"data/cleaned/forec

    if len(w) > len(forecast):
        w = w.reindex(forecast.index)
    else:
        forecast = forecast.reindex(w.index)

    df_weighted[major_col] = forecast * w

df_weighted = df_weighted.dropna().sum(axis=1).dropna()
df_actual, _ = process_forecast_accuracy(name=name, plot_show=False)
df_actual = df_actual["actual"]
df_actual = df_actual.reindex(df_weighted.index)
df_accuracy = calculate_accuracy_metrics(actual=df_actual, forecast=df_weigh
# display(df_accuracy)
plot_actual_vs_forecast(df_accuracy=df_accuracy, col_name="Level 2 (Export-C


#with Linear Optimisation and CAP Adjustment
df_accuracy["forecast"] = cap_extreme_values(df_accuracy[["forecast"]])["for
df_accuracy_CA = optimize_forecast(df_accuracy=df_accuracy,
                                   plot_show=True,
                                   col_name="Level 2 (Export-Custom Basis) w
display(df_accuracy_CA)
```


Actual vs. Forecasted (Level 2 (Export-Custom Basis), % Change)
R²: -1.89, Mean Abs Error: 4271.86
Actual
Forecasted
April 2024 Forecast
Time Series


Absolute Error (Level 2 (Export-Custom Basis), % Change)
R²: -1.89, Mean Abs Error: 4271.86
Absolute Error


Actual vs. Forecasted (Level 2 (Export-Custom Basis) with Linear Combination & CAP Optimisation, % Change)
R²: 0.76, Mean Abs Error: 998.57
Actual
Forecasted
April 2024 Forecast
Time Series


Absolute Error (Level 2 (Export-Custom Basis) with Linear Combination & CAP Optimisation, % Change)
R²: 0.76, Mean Abs Error: 998.57
Absolute Error

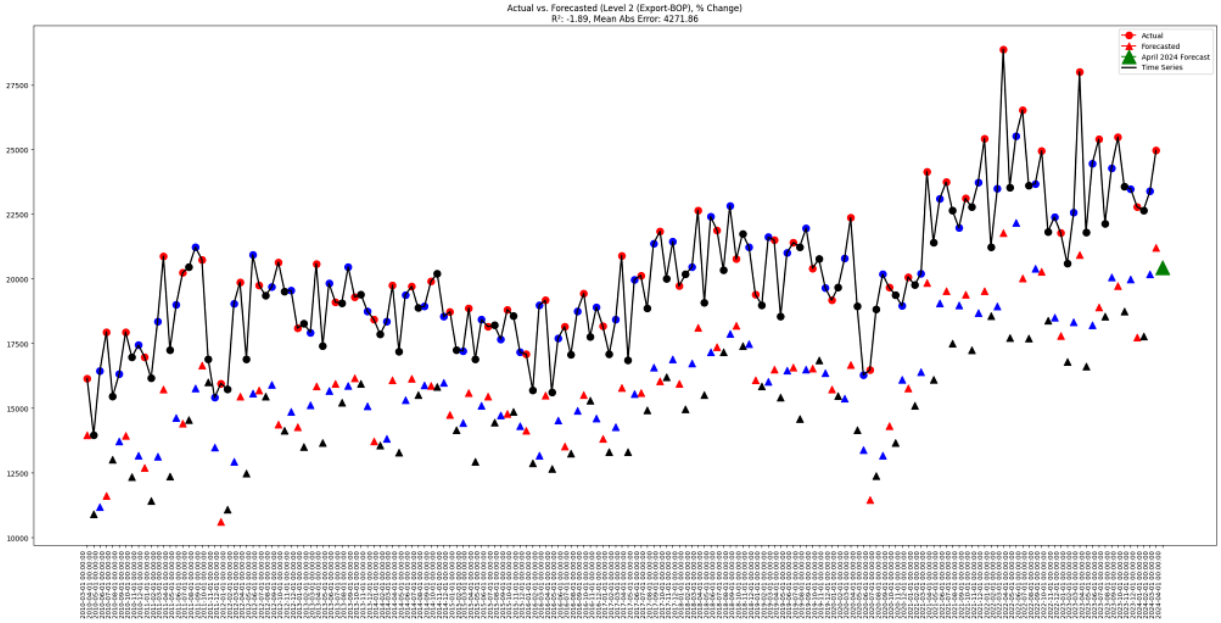
	actual	forecast	error	abs_error	squared_error	abs_percentage_e
2010-03-01	16142.69	17660.116174	-1517.426174	1517.426174	2.302582e+06	0.094
2010-04-01	13964.05	13812.936386	151.113614	151.113614	2.283532e+04	0.010
2010-05-01	16447.98	14138.004915	2309.975085	2309.975085	5.335985e+06	0.140
2010-06-01	17942.68	14688.608134	3254.071866	3254.071866	1.058898e+07	0.181
2010-07-01	15456.20	16465.638936	-1009.438936	1009.438936	1.018967e+06	0.065
...	...	...	...	...	...	
2023-12-01	22791.55	22446.419626	345.130374	345.130374	1.191150e+05	0.015
2024-01-01	22649.88	22494.782111	155.097889	155.097889	2.405536e+04	0.006
2024-02-01	23384.86	25538.984843	-2154.124843	2154.124843	4.640254e+06	0.092
2024-03-01	24960.55	26830.219890	-1869.669890	1869.669890	3.495665e+06	0.074
2024-04-01	NaN	25863.852496	NaN	NaN	NaN	

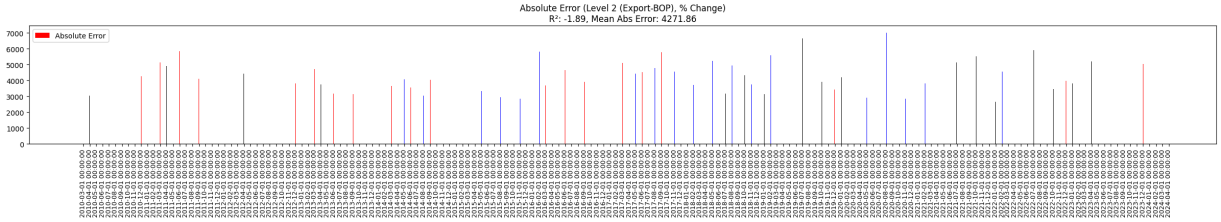
170 rows × 6 columns

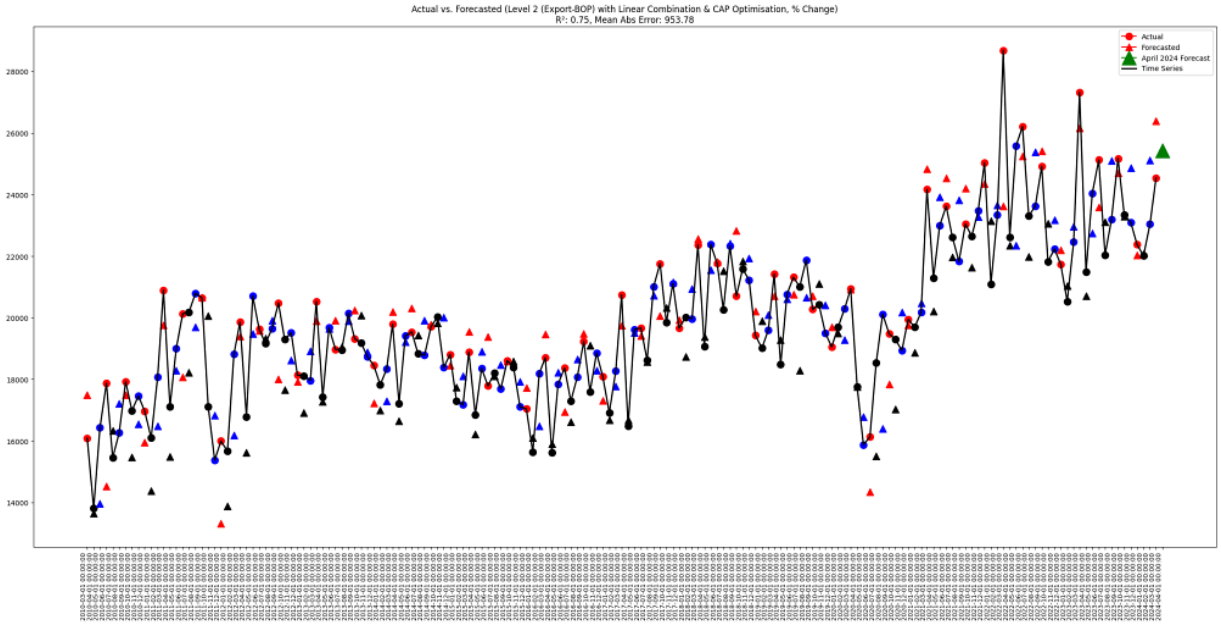
Level 2 (Export-BOP) : weighted_Sum(weighted_sum_of_componen + Coverage_Adjustment

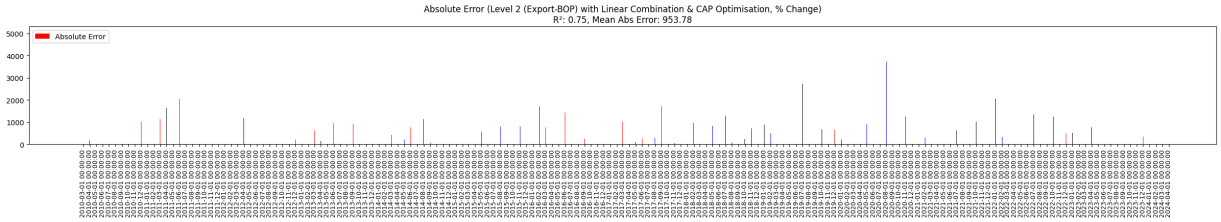
In [16]:
```
df_weighted = pd.DataFrame()

for major_col in mapper.columns[:-1]:

    df_accuracy = calculate_weighted_forecast(name=major_col,
                                              mapper_path=mapper_path,
                                              weights_path=weights_path,
                                              plot_show=False)
    forecast = df_accuracy["forecast"]
    with open(weights_path, "rb") as f:
        weights_r2 = pickle.load(f)[name]
    max_row_names = weights_r2.idxmax()
    weight_technique_name_map = {"Lag-1": "Lag_1_", "Exp Smooth": "Exp_Smoot
    max_row_names = max_row_names.map(weight_technique_name_map)
```

```
    best_r2 = max_row_names[major_col]
    w = convert_period_index_to_datetime(pd.read_pickle(f"data/cleaned/forec

    if len(w) > len(forecast):
        w = w.reindex(forecast.index)
    else:
        forecast = forecast.reindex(w.index)

    df_weighted[major_col] = forecast * w

df_weighted = df_weighted.dropna().sum(axis=1).dropna()
df_actual, _ = process_forecast_accuracy(name=name, plot_show=False)
df_actual = df_actual["actual"]
df_actual = df_actual.reindex(df_weighted.index)
df_accuracy = calculate_accuracy_metrics(actual=df_actual, forecast=df_weigh
plot_actual_vs_forecast(df_accuracy=df_accuracy, col_name="Level 2 (Export-E


#with Linear Optimisation and CAP Adjustment
df_accuracy["forecast"] = cap_extreme_values(df_accuracy[["forecast"]])["for
df_accuracy_CA = optimize_forecast(df_accuracy=df_accuracy,
                                   plot_show=False,
                                   col_name="Level 2 (Custom Basis) with Lir

df_Coverage_adj, _ = process_forecast_accuracy(name="Coverage_Adjustment",
                                               plot_show=False)
df_Coverage_adj["forecast"] = cap_extreme_values(df_Coverage_adj[["forecast"
df_Coverage_adj = optimize_forecast(df_Coverage_adj,
                                    plot_show=False,
                                    col_name="Level 2 (Total Export-BOP) wit

df_actual, _ = process_forecast_accuracy(name="Exports,_f.o.b._(BOP_basis)",
                                               plot_show=False)

df_actual["forecast"] = df_accuracy_CA["forecast"] + df_Coverage_adj["foreca
df_actual["forecast"] = cap_extreme_values(df_actual[["forecast"]])["forecas
df_actual = optimize_forecast(df_actual,
                              plot_show=True,
                                col_name="Level 2 (Export-BOP) with Linear C
display(df_actual)
```


Actual vs. Forecasted (Level 2 (Export-BOP), % Change)
R²: -1.89, Mean Abs Error: 4271.86
Actual
Forecasted
April 2024 Forecast
Time Series


Absolute Error (Level 2 (Export-BOP), % Change)
R²: -1.89, Mean Abs Error: 4271.86
Absolute Error


Actual vs. Forecasted (Level 2 (Export-BOP) with Linear Combination & CAP Optimisation, % Change)
R²: 0.75, Mean Abs Error: 953.78
Actual
Forecasted
April 2024 Forecast
Time Series


Absolute Error (Level 2 (Export-BOP) with Linear Combination & CAP Optimisation, % Change)
R²: 0.75, Mean Abs Error: 953.78
Absolute Error

	actual	forecast	error	abs_error	squared_error	abs_percentage_e
2010-03-01	16088.22	17495.763580	-1407.543580	1407.543580	1.981179e+06	0.087
2010-04-01	13804.62	13640.445631	164.174369	164.174369	2.695322e+04	0.011
2010-05-01	16424.34	13954.519382	2469.820618	2469.820618	6.100014e+06	0.150
2010-06-01	17871.67	14519.186492	3352.483508	3352.483508	1.123915e+07	0.187
2010-07-01	15447.94	16325.733039	-877.793039	877.793039	7.705206e+05	0.056
...	...	...	...	...	...	
2023-12-01	22380.30	22034.010002	346.289998	346.289998	1.199168e+05	0.015
2024-01-01	22012.20	22082.117495	-69.917495	69.917495	4.888456e+03	0.003
2024-02-01	23036.45	25110.269597	-2073.819597	2073.819597	4.300728e+06	0.090
2024-03-01	24543.84	26394.696576	-1850.856576	1850.856576	3.425670e+06	0.075
2024-04-01	NaN	25433.424378	NaN	NaN	NaN	

170 rows × 6 columns