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Real-time carbon accounting and forecasting for reduced emissions in grid-connected processes

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ABSTRACT

Real-time carbon accounting is crucial for advancing policies that effectively meet sustainability objectives. This work introduces a carbon tracking tool specifically designed for the European electricity grid. The tool collects hourly data on electricity consumption and generation, cross-border power exchanges, and weather information to assess the real-time environmental effects of electricity use, employing locally-specific emission factors for the generation sources. It utilizes weather data from various stations across Europe to produce week-ahead forecasts of carbon intensity in the grid. Predictions are created using a random forest regressor, integrated within the optimal controller of an operational industrial batch process. This prediction-based optimizer seeks to reduce total emissions tied to the process schedule's electricity consumption by implementing a rolling horizon strategy. By leveraging enhanced energy flexibility, the controller provides significant opportunities for load shifting and emission reductions, though at a higher cost. An industrial batch process demonstration highlights the potential of this approach, showing environmental savings ranging from 4% in grids with low renewable energy to 32% in nations that incorporate a substantial proportion of renewable energy in their energy mix.

Keywords: Energy, Algorithms, Energy Systems, Industry 4.0, Modelling, Grid digitalization, Real-time emissions, Load shifting, Flexible operations

INTRODUCTION

European countries aim for carbon neutrality by 2050, driving a shift from fossil fuels to renewable energy and widespread electrification. Real-time carbon accounting is critical for effective green policies, while forecasting aids planning and operations [1]. The GHG Protocol [2] introduced a "location-based" method for reporting scope 2 emissions, improving accuracy over the market-based approach. In the same vein, Brander et al. [3] recommended this method to avoid misrepresenting responsibility.

However, the "location-based" method does not reflect real-time consumption emissions. Spork et al. [4] used real-time data to improve carbon reporting in Spain but faced boundary limitations. Significant improvements came from the introduction of input-output lifecycle assessment (IO-LCA) methods, as applied by Claus et al. [5], which expanded system boundaries for better accuracy and highlighted the importance of cross-border carbon transfers. More recently, Tranberg et al. [6] refined this with flow tracing, supporting dynamic carbon taxes.

A major objective with such approach is to be able to schedule operations in periods of low-carbon electricity. However, operational scheduling based on carbon forecasts remains uncommon. Models by Ma et al. [7] and Chen et al. [8] either assumed fixed carbon factors or focused solely on costs. More advanced models, like those by Zhang et al. [9], still lacked real-time carbon integration. Oftentimes, time-dependent carbon data is used in technology design studies, such as in Castro-Amoedo et al. [10].

Contributions

This study presents a dynamic life-cycle assessment framework for real-time carbon tracking in the

European electricity grid, expanding previous models by including ten more countries and using data from 200+ weather stations for week-ahead carbon forecasts. Key contributions include:

1. Optimized Industrial Operations: Using emission forecasts to control industrial batch processes, enabling load shifting and emission reductions.
2. Grid Digitalization: Emphasizing the need for granular electricity data to support broader carbon reduction strategies.

METHODOLOGY

The tool uses data provided by the ENTSO-E database [11] to quantify the impact of electricity consumption in each European country. It considers real-time electricity production mixes, electrical power exchanges across borders, and locally differentiated carbon intensities [12] of the energy sources to calculate current or past environmental indicators for each European country with a data granularity of one hour.

The implementation allows interfacing with optimization algorithms in such a way that the data stream indicators can be automatically fed into operation scheduling problems. As a result, the tool provides the basis for carrying out optimization with environmental objectives (i.e. minimization of the carbon footprint associated with production), or, alternatively, it can be used as a post-computation phase to assess the real-time environmental performance of a process by calculating its sustainability indicators. Our methodology includes :

3. Data Acquisition: Fetching real-time data on electricity production, consumption, and cross-border exchanges.
4. Data Validation: Ensuring accuracy by checking production limits, technology mix consistency, and eliminating invalid data.
5. Environmental Indicator Calculation: Computing indicators like carbon footprint, renewable energy share, and ecological impact.

Mathematical Approach

The carbon intensity arising from the consumption of electricity from the grid in each country is obtained by solving a linear system of equations representing the carbon flows in the European network [6]. The calculated values represent the greenhouse gas footprint of 1 kWh consumed inside a given country. The footprint is measured in gCO_2 equivalent, meaning that each greenhouse gas is converted into its carbon dioxide equivalent in terms of climate change potential. For each country i, the balance of eq. (1) can be written, where D_i is the total electricity demand, P_i is the total electricity production, and I_i and E_i are the total import and export of electricity, respectively.

$$\mathrm{D}_i = P_i + I_i - E_i \quad (1)$$

By extending eq. (1) to balance the carbon flows of country i, one obtains eq. (2), where x_i is the carbon intensity of electricity consumption, $e_{i,r}$ is the carbon intensity of resource r in country i, $P_{i,r}$ is the total electricity production using resource r, x_j is the carbon intensity of electricity imported from country j, $I_{i,j}$ is the electricity import to country i from j, and $E_{i,k}$ is the electricity export from country i to k.

$$x_i \mathrm{D}_i = \sum_r e_{i,r}\ P_{i,r} + \sum_j x_j\ I_{i,j} - \sum_k x_i\, E_{i,k} \quad (2)$$

Considering from eq. (1) that $D_i + E_i$ equates to $P_i + I_i$, and writing for each country, the following linear system results (eq. 3).

$$\begin{bmatrix} P_1 + I_1 & \cdots & -I_{1,n} \\ \vdots & \ddots & \vdots \\ -I_{n,1} & \cdots & P_n + I_n \end{bmatrix} \times \begin{bmatrix} x_1 \\ \cdots \\ x_n \end{bmatrix} = \begin{bmatrix} \sum_r e_{1,r}\ P_{1,r} \\ \cdots \\ \sum_r e_{n,r}\ P_{n,r} \end{bmatrix} \quad (3)$$

Where:

$$\mathrm{P}_1 = \sum_r P_{1,r}\ \ and\ \mathrm{I}_1 = \sum_j I_{1,j} \quad (4)$$

Because the CO_2 equivalent emissions of each country depend not only on its own electricity mix but also on that of its neighbours, the CO_2 mass flow balance of all countries must be addressed simultaneously. The same procedure was adopted to calculate other environmental indicators, such as renewable energy (RE) share.

The carbon intensities $e_{i,m}$ are location-dependent and specific to each energy resource. Such emission intensities account for the whole life cycle of electricity production, from plant construction and fuel treating, i.e. including all upstream activities, disposal and decommissioning. The impact of each resource r is calculated using all the technologies m associated with such a resource that is available in the country generation mix ($\mathbf{M}^r$). The impact factors $e_{i,m}$ are calculated by weighting each technology by the corresponding market share s_m [12](eq. 5).

$$e_{i,r} = \sum_m^{M^r} s_m \times e_{i,m} \quad (5)$$

Application to Case Study

A prediction-based optimizer with a weekly (168-hour) horizon is applied to an industrial batch process, simulated over one month with hourly rolling updates. The scheduling model, based on Mixed-Integer Linear Programming (MILP), is solved iteratively. The model is described in Santecchia et al. [13]. Unlike prior studies, this model focuses on minimizing emissions from electricity consumption rather than costs. The objective function is adjusted, extending the scheduling window from 72 to 504 time slots, corresponding to 20-minute intervals.

The predictive controller updates the process schedule hourly, retrieving electricity and weather data from ENTSO-E and the Visual Crossing API (Fig. 1). This data feeds a random forest regressor to update carbon intensity forecasts. The optimization is solved for each production line to meet minimum environmental impact goals, repeating hourly until the end of the month (N = 720).

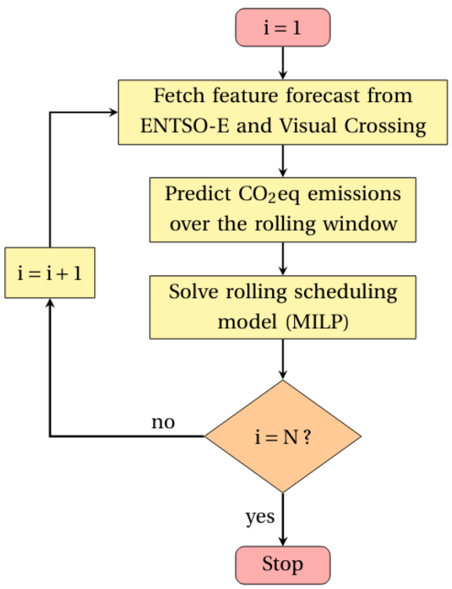

Figure 1. Flow diagram of the online scheduling algorithm with MPC approach.

Feature selection

The framework generates day-ahead and week-ahead carbon emission forecasts using data on projected generation, consumption, solar and wind output, cross-border electricity flows, and day-ahead market prices from the ENTSO-E database. To extend forecasts beyond one day, it integrates weather data (wind speed, direction, temperature, precipitation, cloud cover) from over 200 European weather stations via the Visual Crossing API.

To reduce computational demands, a statistical feature selection method evaluates the relationship between input variables and carbon emissions. This involves constructing a normalized covariance matrix over 1–3 years using Pearson Correlation Coefficients (PCC). Features with strong correlations are flagged as redundant, while weakly correlated ones are removed, ensuring efficient modelling without significant data loss. A PCC of 0.6 was chosen as threshold to distinguish strong and weak correlations, and was not subject to optimization.

Prediction algorithms

Due to feature selection reducing the dataset - sometimes to as few as two variables - various learning algorithms were tested, including simpler models. These included linear regression with batch and stochastic gradient descent for error minimization, along with LASSO (L1 regularization), Ridge regression (L2 regularization), and their combination through Elastic Net Regression to mitigate overfitting. Multivariate polynomial regression was explored for modeling non-linear relationships, and the RANSAC algorithm was applied to detect outliers.

While these simpler methods aimed to avoid unnecessary complexity, they often lacked sufficient prediction accuracy or failed with high-dimensional data. To address this, advanced models like artificial neural networks (Multi-layer Perceptron, Dense networks) and random forests were implemented. Despite higher computational demands, these models delivered greater accuracy with minimal data pre-processing and tuning. Random forests outperformed other algorithms in early evaluations and were chosen for prediction tasks due to their robustness with complex datasets and resistance to outliers. To further prevent overfitting, hyperparameter tuning was systematically applied using a combinatorial search approach. For random forests, key hyperparameters such as the number of trees, tree depth, and minimum samples per leaf were optimized to balance model complexity and generalization. A grid search and random search were employed to explore different hyperparameter combinations, followed by k-fold cross-validation to evaluate model stability and prevent data leakage. Additionally, cross-validation techniques were employed to assess model performance and ensure that the selected hyperparameters led to robust predictions on unseen data.

RESULTS

Accuracy improvements on carbon accounting standards

The real-time carbon tracking method offers greater accuracy than traditional approaches used by organizations for carbon accounting. Typically, impact factors in scope 2 reporting (GHG Protocol Corporate Standard) are based on annual electricity production data. Fig. 3 illustrates the potential improvement of real-time tracking, showing the mean relative error reduction across various time scales (hourly, daily, weekly, monthly). These values estimate the reporting errors in indirect emissions from purchased electricity.

Since the exact real-time environmental impact is unknown, the tool's indicators are treated as accurate. The improvement is assessed using bootstrapping, where random samples from the 2023 environmental impact database are repeatedly drawn to measure deviations from the annual average. This process uses a sample size of 1,000 and is repeated 10,000 times to approximate the accuracy distribution.

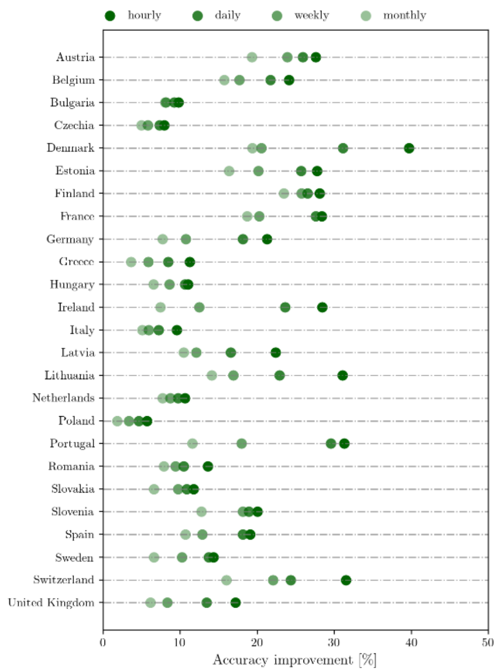

Fig 3 - Accuracy improvement of real-time carbon tracking compared to current accounting standards, showing average relative improvements across hourly, daily, weekly, and monthly intervals.

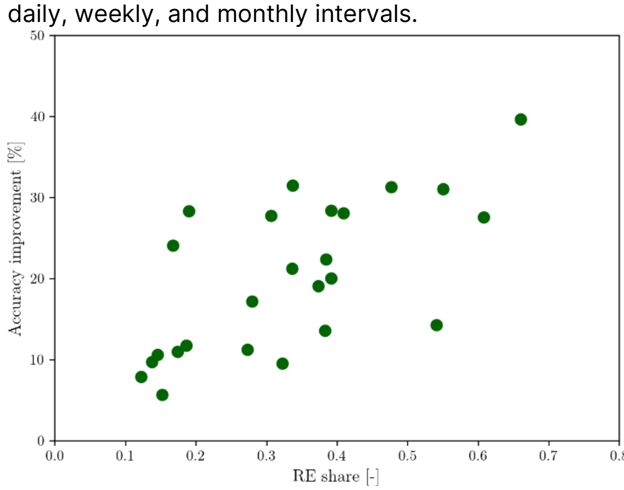

Fig 4 - Accuracy improvement [%] of the real-time carbon tracking method as a function of the RE share [-] by country.

Hourly accuracy improvements vary by country and are more significant in grids with high renewable energy penetration (Fig. 4). The method shows the smallest benefit in Poland (6%) due to its reliance on coal (15% renewable share) and the largest in Denmark (40%), where renewables account for 66% of electricity. This correlation highlights that greater variability in renewable generation leads to more accurate carbon accounting. Implementing real-time carbon tracking is essential for accurately estimating indirect emissions in renewable-heavy grids, supporting Europe's transition to a decarbonized energy system.

Emissions forecast with Random Forest

The random forest regressor is trained on the emissions database, split into 80% for training and 20% for testing. While it offers high predictive accuracy, it risks overfitting. A balanced dataset size is essential—too large, and the model overfits past grid data; too small, and it misses key grid patterns. Testing datasets of 1–2 years, closest to the prediction window, ensures optimal accuracy.

Fig. 5 illustrates a week-ahead CO_2 prediction (January 1–7, 2023) for Germany. The model accurately tracks carbon intensity trends, with a mean absolute error (MAE) and an R^2 value of 0.86.

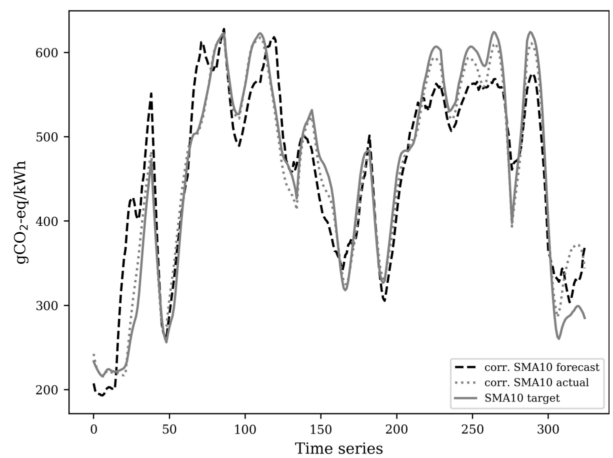

Fig 5 - Week-ahead prediction trend in Germany (January 1–7, 2023) using a random forest regressor trained on 2020–2022 data. The SMA10 tracks prediction accuracy, with the 'actual' curve showing model output. Key metrics: MAE (19.4 actual, 54.9 forecast) and R^2 (0.952 actual, 0.728 forecast).

Reducing emissions in a batch process

Fig. 6 presents the cumulative average emission profiles for two rolling schedules. In the first scenario (process 1d), emissions are minimized using day-ahead grid carbon intensity predictions with a 24-hour rolling window, limiting the ability to anticipate favorable conditions beyond that period. This approach results in an 11.6% reduction in emissions compared to the baseline scenario (BAU, shown in red).

Extending predictions to a week ahead leads to a greater reduction in emissions. With improved insight into future grid conditions, the optimizer schedules operations more effectively, especially during periods of high carbon intensity (e.g., between 10:00 and 15:00). Unlike the short-term model, the week-ahead schedule shifts energy-intensive tasks to low-emission periods, reducing CO_2 emissions by 17.5% compared to BAU and 6.6% compared to the day-ahead scenario.

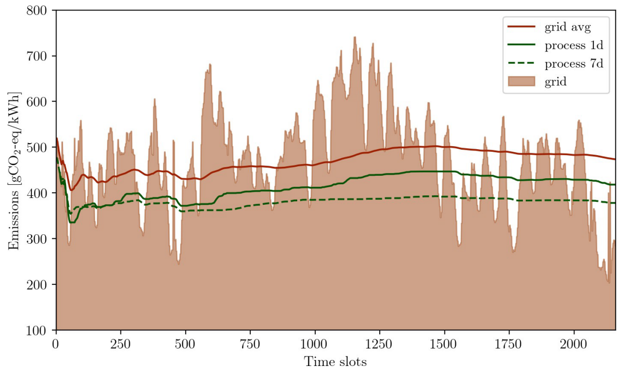

Fig 6 - Cumulative average emissions of the MPC for an industrial batch process in Germany, comparing day-ahead (solid green) and week-ahead (dashed green) predictions. The shaded area shows hourly grid intensity, and the red line represents the BAU scenario.

Benefits of optimal operations scheduling with emission targets in Europe

The process was simulated across various European countries using 1-day and 7-day prediction windows. Results in Table 1 show that emission reductions vary by country. Significant improvements occur in nations with high renewable energy use, like Denmark (-28.6%) and Lithuania (-32.4%), while countries reliant on fossil fuels, such as Czechia (-9.2%) and Poland (-4.4%), see smaller gains. This difference stems from the greater variability in carbon intensity within renewable-heavy grids, allowing long-term planning to be more effective. On average, carbon emissions dropped by 15%.

Table 1: Results of the MPC simulations by country, showing emission reduction for both the short- (daily) and long-term (weekly) optimizers.

	Emissions (gCO_2/kWh)			%
Country	Grid	Process 1d	Process 7d	Max reduction
Austria	271.1	253.8	235.6	-13.1%
Czechia	763.5	731.2	692.8	-9.2%
Denmark	207.0	180.4	147.8	-28.6%
Estonia	583.0	567.5	517.1	-11.3%
Finland	191.7	181.3	172.5	-10.0%
Germany	473.5	418.4	390.6	-17.5%
Greece	666.0	614.3	523.5	-21.4%
Italy	382.9	358.9	334.7	-12.6%
Lithuania	227.9	189.3	154.1	-32.4%
Poland	947.4	925.4	905.3	-4.4%
Spain	232.5	215.6	201.3	-13.4%
Sweden	37.4	34.1	30.8	-17.7%
UK	270.8	248.3	203.1	-25.0%

CONCLUSIONS

This study introduces a real-time carbon tracing method for the electricity grid, using hourly data on electricity consumption, generation, cross-border power flows, and weather conditions to calculate environmental impacts with locally differentiated emission factors. This method improves accuracy over traditional carbon accounting, with emission reporting improvements ranging from 6% in Poland to 40% in Denmark, especially in grids with high renewable energy penetration.

The framework also generates day-ahead and week-ahead carbon emission forecasts based on projected generation, consumption, renewable output, electricity trade, prices, and weather data from ENTSO-E and Visual Crossing APIs. To enhance efficiency, a feature selection algorithm removes redundant data using Pearson Correlation Coefficients.

A random forest algorithm is used for forecasting, with hyperparameter tuning to prevent overfitting. Training the model on one to two years of data achieved reliable carbon intensity predictions (R^2 = 0.86).

This model is integrated into a mixed-integer linear programming (MILP) optimizer for an industrial batch process in Germany, reducing emissions by 17.5% and increasing renewable energy use by 9.7 percentage points compared to BAU. Simulations across Europe show greater benefits in countries with high renewable energy shares (-32.4%) and smaller gains in fossil-fuel-dependent countries (-4.4%).

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