Estimating Marginal Carbon Emissions

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This note briefly reviews methods for estimating marginal carbon emissions: the change in carbon emissions caused by a unit increase or decrease of demand. Methods for estimating marginal CO2 emissions can be roughly divided into bottom-up simulation-based approaches and top-down data-driven approaches.

Bottom-Up Bottom-up approaches are simulation-based, aiming to replicate generator dispatch under different levels of demand [1]. This offers a highly granular analysis of carbon emissions, representing individual plants with unique heat rate curves and emissions factors. Furthermore, events not observed historically such as large load swings or introduction of new technologies can be simulated. Bottom-up approaches are capable of accounting for non-linear effects such as those encountered when an additional generator is dispatched.

Accurately simulating generator dispatch given multiple real-world power markets is highly complex, and bottom-up models require extensive calibration to achieve suitable accuracy. Furthermore, small inaccuracies in the modelled dispatch can result in large deviations between actual and modelled carbon intensity [2]. Simplified dispatch models have been used to estimate marginal emissions factors in the United States [3]. A simplified merit order stack is estimated for each week of the year, with enabling the marginal generator to be identified for a given load. Generator-specific heat rates and emissions factors are used to calculate carbon intensity.

Top-Down Top-down approaches rely on historical data to estimate marginal carbon intensity. The simplest models regress carbon emission (gCO2) against load (MWh), with the slope of the line representing the long-run marginal emissions intensity [4]. While valuable for long-term scenario analysis due to their low bias, these methods neglect exogenous factors impacting the dynamics of generator dispatch.

Binned approaches offer an improvement over these simplistic models by fitting a unique model for subsets of the data, such as time of day or season [5, 6]. Binning across temporal dimensions can help capture time-varying effects such as renewable generation patterns and the gradient of the demand curve.

More generally, statistical learning methods have been used to control for relevant variables such as time of day, market conditions, weather to predict fuel-specific generation and resulting carbon emissions [7]. This method offers benefits in flexibly exploiting large amounts of data, and harnessing machine learning methods to identify relevant features.

Summary Data-driven, top-down methods have been most widely applied to estimate marginal carbon intensity, and are most easily generalisable across regions with different levels of data availability. Bottom-up approaches, while offering greater granularity in practice, are more challenging to develop and calibrate. In general, the optimal dispatch calculated in a bottom-up model cannot be assumed to reflect reality, which can cause substantial model inaccuracies. Given widespread digitalisation in the energy system and increasing access to energy data, top-down approaches are likely to improve further in terms of accuracy.

Little research has been conducted into machine learning methods exploiting large amounts of data [7]. This can potentially offer comparable accuracy to bottom-up methods by learning highly complex dynamics between exogenous variables and generator behaviour. Furthermore, a systematic comparison of data-driven methods was not found in this review.

An additional concern of data-driven methods is limited interpretability. It is usually non-trivial to identify marginal impacts of predictors using black-box methods. In the prototype developed here, a generalised additive model (GAM) to address this limitation. GAMs allow for effects of multiple predictors to be decomposed, and produce smooth functions that are suitable for high-level analyses of marginal carbon intensity.

References

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