Hitachi-Imperial Centre for Decarbonisation and Natural Climate Solutions

IMPERIAL
Ada Lovelace Academy
FACULTY OF ENGINEERING

Optimising Demand Response Strategies for Carbon-Intelligent Load Shifting

by
Daniel Kaupa

Supervisors:
Dr. Gareth Collins Dr. Mirabell Mûuls Dr. Shefali Khanna

The Data

Household electricity consumption data for Tata Power Customers in Delhi and Mumbai

The Question

Can we significantly reduce emissions by shifting household electricity use to different times of the day?

The Background

Marginal and Average Emission Factors:

- Marginal ≠ average emission factors
- Average emissions tell you the carbon intensity of all electricity generated, while marginal emissions tell you the carbon intensity of the next unit of electricity
- Marginal emission factors are **preferred** when evaluating impact of specific actions

but of course...

- Marginal emission factors are:
  - not readily available
  - hard to evaluate for accuracy
  - often require complex models to estimate

Project Aims

1. Develop an interpretable, public-data-based methodology for estimating marginal emission factors
2. Develop an optimisation algorithm that finds emission-reducing shifts while respecting real-world constraints.

Methodology

Strategy

Before estimating marginal emissions (how CO_2 changes with an incremental change in demand), we first fit a model of emissions given net load, weather, time, and mix cues to absorb everything else.
Then we take the partial derivative with respect to net load, holding those other variables fixed, to obtain the marginal emissions rate, and calibrate it against observed short-horizon ramps.

1a. Process & Join Public Data

GRID DATA
Tons of CO₂, Generation (MW) by source, MW demand

ERA 5
Solar radiation, temperature, precipitation, cloud cover

1b. Make the Model (PyGAM)

$$Y = \beta_0 + f_Q(Q_{std}) + f_T(T_{std}) + f_W(W_{std}) + f_S(log(1 + S_{raw})_{std}) + x_{lin}^{\top}\beta + \varepsilon.$$

Where: Y is tons of CO_2; Q: is net load (demand – renewable generation); T, W, S are temperature, wind speed, solar radiation; Xlin are linear context terms including temporal variables, wind direction & boolean flags; each f(.) is a spline learned jointly with the others by penalised least squares; an L2 penalty smooths the curve, reduces overfitting, and stabilises our derivative.

1c. Compute the derivative

$$\widehat{ME}_t = \frac{\partial \hat{Y}}{\partial Q}\big|_{Q=Q_t, X=X_t}.$$

1d. Calibrate

$$s_i = a + bME_i^{mid} + \varepsilon_i$$

$$\widehat{ME}_{cal} = \hat{a} + \hat{b}\widehat{ME}$$

2a. Make the Optimisation Algorithm

$$\max_{q \geq 0} \sum_{i \in I} \sum_t \sum_s (m_t - m_s) q_{i,t \to s}$$

Greedy flow: a move reallocates $q_{i,t \to s}$ kWh from a higher-MEF slot t to a lower-MEF slot s within a short time window $|t \to s| \leq W$ where $i \in I$ indexes customers (households), $t, s \in T = \{0, \ldots, 47\}$ index half-hour slots in a day with t as the source time slot and s as the destination time slot, and $m_{s\, or\, t}$ is the marginal emission factor at that slot in grams CO_2/kWh.

2b. Set the Constraints

Constraint	Value used
Maximum Shift Time Window	±2 hours
Maximum Shifts per Customer per Day	1
Maximum Shifts per Customer per Week	3
Maximum Shift out of Peak Hours	≤ 25% of baseline in peak hours
City destination anti-spike	≤ 25% uplift vs baseline
Maximum Regional Shift Percentage per Day	≤ 10% of daily city load
Minimum Usage per Slot	max{hour-of-day/day-of-week minimum, 10% × robust maximum, ε}

Join and Run Optimiser

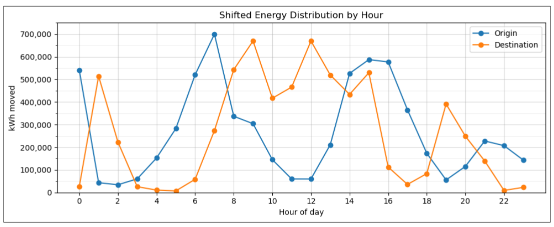
Marginal Emission Factors

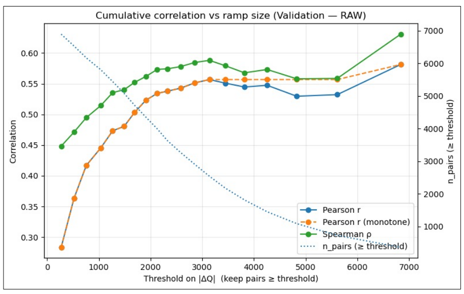
Meter Readings

Results

93.6% of shifts ran on medium confidence estimates

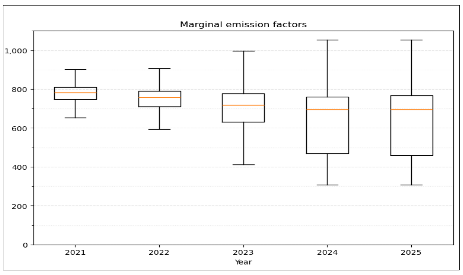
$R^2 \approx 0.9840$, RMSE ≈ 755 (t CO_2)





The optimiser moved ≥ 1.1 MWh and processed ≥ 40 households per second

Each shift moved an average of 0.428 kWh and 44 g CO_2 per move



Time Period	Average CO_2 emissions per household (kg)	Average CO_2 savings (kg)	Impact
Week	17.227	0.129	0.75% reduction
Year	895.845	6.344	0.71% reduction

Conclusions

Public-data → MEFs: A penalised GAM + partial derivative gives a usable marginal signal.
Ramp-tested, calibrated: Stronger at typical–large ramps; scale aligned to observed changes.
Actionable, not absolute: Best for **ranking hours** and steering small shifts—not inventories.
Insignificant savings with constraints: Little potential for reductions with provided constraints.
Applicability: average shift is about equivalent of re-timing laundry loads on an efficient machine.

We build a transparent public-data pipeline that turns grid and weather feeds into half-hourly marginal emission factors (MEFs) for India and test whether they can steer real-world load shifting. A penalised GAM fits emissions vs. net load and context; its derivative yields a raw MEF we linearly calibrate against short-horizon ramps and map to ramp-based confidence. Correlations are modest on small ramps and stronger ≥1 GW—good enough to rank hours. Midday MEFs often exceed AEFs, consistent with PV saturation and fossil margins. A conservative ±2 h greedy scheduler over ~238k customers moves an average of 0.43 kWh per shift; per-home savings are small, yet MEFs change accounting (+313% vs AEFs). The method is reproducible and portable.

References
Bracht, F., Khanna, S., Martin, R., & Muûls, M. (2025) ; Cohen, J. (2013) ; Siler-Evans, K., Azevedo, I. L., & Morgan, M. G. (2012) ; WattTime. (2022)