Reducing Carbon Intensity in Household Electricity Consumption through Intelligent Decision Support

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Abstract

This paper proposes the idea to use real-time carbon intensity data to guide residential electricity usage, shifting the focus from price-based incentives to environmental impact. By integrating data from ElectricityMaps.com and applying constraint satisfaction algorithms, the system provides actionable insights to help users reduce their carbon footprint by optimizing electricity consumption based on time slots when the carbon emissions of the national electricity production are low. The proposed system offers both an API for smart home devices and a user interface for manual control, empowering individuals to make sustainable choices. This approach aims to drive behavioural change by making carbon reduction a central factor in energy consumption decisions.

Keywords

residential electricity usage, carbon emissions, behaviour change support, decision support sep smart homes

1. Introduction

The urgent need to reduce carbon emissions is now a central challenge in addressing climate change. Among the various sectors contributing to greenhouse gas emissions, electricity generation remains a major source, particularly when it is dependent on fossil fuels. Transitioning to a low-carbon electricity system is critical; however, it is equally important to optimize the way individuals and communities consume electricity. Reducing the carbon emissions associated with electricity usage not only supports national and global climate goals but can also lead to more resilient and efficient energy systems.

Despite widespread awareness of climate change, changing everyday behaviour around electricity usage remains difficult. One significant barrier is the lack of accessible, real-time insights into the carbon intensity of the electricity grid. It is generally difficult for people to know when their consumption has a higher or lower carbon impact. Furthermore, even when information is available, psychological factors —- such as cognitive overload, which hampers decision-making when individuals are confronted with complex or excessive information[1], habitual behaviors that persist even in the face of good intentions [1], and the perceived inconvenience of changing routines [2] —- limit individuals' efficacy in modifying their routines.

This short paper proposes a novel approach: using advanced algorithms to calculate and visualize the optimal times for electricity use based on real-time and forecasted carbon intensity. By providing clear, actionable insights, this system can empower individuals to make voluntary, informed choices about when to consume electricity in a way that minimizes their carbon footprint. Rather than relying on abstract encouragements to "use less energy", the proposed solution focuses on making the environmental consequences of daily actions visible, timely, and manageable. This integration of data-driven intelligence and behavioural nudges could significantly enhance the effectiveness of efforts to promote low-carbon living.

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[1]https://www.mayoclinichealthsystem.org/hometown-health/speaking-of-health/cognitive-overload

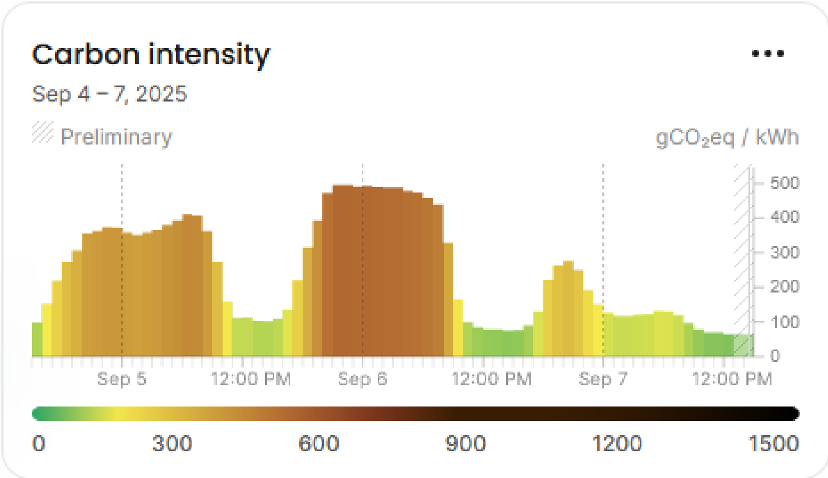

Figure 1: The fluctuations of the carbon intensity of electricity on the Dutch network. Within 18 hours, the intensity has shifted from 497 gCO_2eq/kWh to 76 gCO_2eq/kWh. (Taken from https://app.electricitymaps.com/zone/NL/72h/hourly).

2. Background

Electricity consumption does not have a constant carbon footprint. The carbon intensity of electricity fluctuates throughout the day depending on the availability of renewable sources and the use of fossil-fuel generation. These dynamics form an important background for the system proposed later in this paper, which seeks to align household electricity usage with periods of lower carbon intensity. This is discussed in Section 2.1.

In addition to these dynamics, it is useful to review existing approaches that have sought to influence electricity consumption patterns. Two widely studied examples are dynamic pricing mechanisms, which encourage residential users to shift consumption in response to fluctuating electricity prices, and industrial load management strategies, such as peak shaving, which redistribute electricity usage to reduce grid strain. Although these approaches are not primarily designed to reduce carbon emissions, they provide valuable insight into the opportunities and limitations of changing consumption behaviour—insights that inform the design of the proposed system.

2.1. Fluctuations in Carbon Intensity of Electricity

The carbon intensity of electricity — usually measured in grams of CO_2-equivalent per kilowatt-hour (gCO_2eq/kWh) — can vary significantly throughout the day, reflecting the intermittency of renewable generation. Solar production peaks around midday on sunny days, while wind generation is more pronounced during windy periods. In contrast, periods of low renewable output are often balanced by fossil-fuel generation, leading to a higher carbon intensity of electricity consumed.

In Germany, for example, grid carbon intensity has been observed to fluctuate between 100 and 350 gCO_2eq/kWh over the course of a day, depending on renewable availability and demand levels [3]. In California, detailed analyses of hourly carbon intensity show intra-hour variability of about 2.4%, while intra-annual variation can reach 31%, reflecting seasonal and weather-driven changes in renewable output [4]. A similar dynamic is observed in the Netherlands, where electricity supply is heavily dependent on wind and sun conditions. On windy winter days, the Dutch grid can operate at below 80 gCO_2eq/kWh, while on calm and cloudy days with higher reliance on natural gas, intensity levels sometimes even exceed 500 gCO_2eq/kWh [5]. Also the intra-day dynamics can be quite high. Figure 1 provides an example of the carbon dynamics in the Netherlands during three consecutive days.

Tools such as Electricity Maps (app.electricitymaps.com) provide real-time visualization of these fluctuations, showing the contribution of each generation source, the resulting CO_2 emissions, and the aggregate carbon intensity per country. These platforms rely on the standardized measure of

gCO_2eq/kWh and make the dynamics of grid emissions visible to end-users[2] [5]. Such tools highlight the opportunities for aligning electricity consumption with periods of lower carbon intensity, thereby enabling households to reduce their environmental impact through informed behavioral changes.

2.2. Dynamic Pricing and Consumer Behaviour

Dynamic energy pricing contracts, where electricity prices vary hourly based on real-time market conditions, have become an increasingly popular tool to influence consumer behaviour [6]. By exposing users to fluctuating costs, these contracts incentivize shifting electricity usage to periods of low demand and high supply. Since periods with high supply are generally characterized by a high level of renewable energy production (e.g. by photovoltaic solar and wind power), these periods are often also the moments when the carbon intensity of the electricity production is low. However, several studies have shown that the response of consumers to price incentives is limited [7, 8, 9]. Dynamic electricity prices combined with residential energy management systems (i.e. smart homes) are hypothesized to contribute to more balanced energy use and a reduction in carbon emissions related to power production [10]. In these cases, automated systems (like smart thermostats and other connected appliances) can adjust consumption patterns without active user intervention. However, for many residential users, the correlation between electricity price and carbon intensity is not always straightforward, and price incentives alone may not align perfectly with environmental goals. In addition, the complexity of constantly changing tariffs can lead to disengagement, especially when users lack the time, interest, or tools to interpret and act on information effectively.

2.3. Load Management and Peak Shaving in Industrial Contexts

In industrial and commercial settings, sophisticated analyses of electricity usage patterns are often employed to manage demand more strategically. Techniques such as peak shaving, which reduces electricity consumption during periods of maximum demand, help facilities lower energy costs, reduce the strain on the grid, and prevent net congestion.

These strategies often rely on detailed monitoring and forecasting, enabling facilities to schedule or shift load based on anticipated peaks. For example, in industrial refrigeration, strategic load shift combined with optimized compressor operation sequencing can lead to energy savings of up to 20% compared to traditional control methods [11]. Similarly, in a systematic case study of a food manufacturing facility, the integration of solar PV, battery energy storage, and demand response resulted in reductions of approximately 6.9% in energy costs and 8.6% in CO_2 emissions [12].

Despite these proven benefits, the technical complexity and infrastructure requirements, such as energy storage systems, smart controls, and forecasting models, limit their applicability in residential settings. These solutions typically require high upfront investments and ongoing operational expertise, making them less accessible to individual households without substantial simplification or automation.

3. Outline of Proposed System

While dynamic pricing encourages residential users to adapt their electricity usage primarily for cost savings, it does not directly address the carbon intensity of electricity consumption. Industrial load management strategies, such as peak shaving, are effective but too complex for household application. Finally, although the dynamics of carbon intensity throughout the day is increasingly visible through platforms such as Electricity Maps, this information has not yet been translated into practical guidance for individual users. To address these gaps, this article proposes a system that leverages smart algorithms to provide simple, actionable information, enabling households to adapt their usage patterns based on carbon intensity rather than price.

[2] https://www.zerofy.net/2022/09/08/how-much-co2-grid-electricity.html

1	continuous use (minutes)	/lowcarbonhours?horizon=<hours>&duration=<minutes>
2	continuous use (percentage)	/lowcarbonhours?horizon=<hours>&usage_perc=<perc>
3	intermitted use (start time)	/islowcarbonhour?start=<time>&horizon=<hours>&usage_perc=<perc>
4	intermitted use (end time)	/islowcarbonhour?start=<s-time>&end=<e-time>&duration=<minutes>

Table 1
Two REST resources that can be used for different appliance usage patterns.

3.1. Appliance Usage Patterns

To develop the system, we first categorize different types of electricity usage scenarios. Some appliances, such as dishwashers, require continuous operation for a fixed duration (e.g., 1.5 hours) within a flexible window of time (e.g., the next 12 hours). Other devices, such as heat pumps and refrigerators, operate intermittently, using electricity for short periods (e.g., 10 minutes every half hour) but can tolerate some temporary interruptions without affecting their functionality.

3.2. REST API

Based on these scenarios, we develop a JSON-based REST API that allows specification of usage constraints, such as “20% runtime within the next 4 hours” or “1.5 hours continuous operation within the next 12 hours.” The system integrates ElectricityMaps.com forecast data on carbon intensity in the coming hours. Using these predictions, it calculates optimal usage patterns that meet the specified constraints and returns them in JSON format, along with the associated estimated carbon emissions.

The REST API provides two resources; both can be used in two different ways. Table 1 lists the REST commands.

1. **Continuous use (minutes)**: Can be used for scenarios in which an appliance needs to run for at least <minutes> in the next upcoming <hours> (e.g. a dishwasher). The command returns a time slot that results in the lowest carbon emissions.
2. **Continuous use (percentage)**: Alternative formulation of the scenario above, but allowing for the specification of a duration in <perc>% of the time.
3. **Intermitted use with start time**: Returns whether it is *currently* a time slot with low carbon intensity, when an appliance needs to be on within <hours> from <time> for at least <perc>% of the time. This is useful for appliances such as refrigerators
4. **Intermitted use with end time**: Returns whether it is *currently* a time slot with low carbon intensity, when an appliance needs to be on for at least <minutes> between <s-time> and <e-time>. This is useful for applications such as charging an electric vehicle.

This API can be used directly by smart household appliances or integrated into home energy management systems such as HomeAssistant[3] or Domoticz[4]. Additionally, the aim is to develop a user-friendly web interface where end-users can manually specify their appliance usage patterns. This interface should provide clear visualizations showing the best times to operate their devices, the total CO_2 emissions associated with their choices, and the carbon savings achieved by adapting their behaviour.

4. Conclusions and Future Work

The proposed system offers a new pathway for individuals to actively contribute to climate goals by aligning their electricity usage with periods of lower carbon intensity, without sacrificing comfort or convenience. Translating complex data into simple, actionable choices reduces psychological and informational barriers to sustainable behaviour change.

[3]https://www.home-assistant.io/
[4]https://www.domoticz.com/

In the future, the system could evolve to support fully autonomous optimization, where appliances and home energy systems intelligently adapt in real time. Based on measurements of appliance electricity usage, AI algorithms can be used to automatically detect usage patterns and automatically control devices. Furthermore, aggregating anonymized user data could enable broader insight into consumption trends, helping utilities and policymakers design smarter, more sustainable energy infrastructures. Given the extremely high fluctuations in carbon intensity of electricity, empowering large numbers of users with these tools could ultimately drive meaningful reductions in carbon emissions at scale.

At the same time, realizing this potential will require addressing challenges such as interoperability with various household appliances, protecting user privacy, and ensuring that recommendations are considered trustworthy and transparent. If successfully integrated, the system could also complement existing grid management strategies by aligning household flexibility with renewable generation peaks, thus not only reducing emissions but also supporting grid stability. In this way, carbon-aware consumption at the residential level can become a meaningful contributor to the broader transition toward a low-carbon energy system.

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Declaration on Generative AI

During the preparation of this work, the author used Writefull and GPT-4o mini in order to do: Grammar and spelling check, Paraphrase and reword, and Improve writing style. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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