Green Hydrogen as an Energy Vector for Mobility and Residential Buildings Needs in Urban Areas

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Abstract

Climate change and energy crises are among the most pressing threats. This work explores green hydrogen as an energy vector for mobility and residential buildings in urban areas, focusing on zero-energy cost buildings (nZEcB). We model annual energy consumption and photovoltaic production profiles for single-family homes in Central Europe, integrating PVGIS weather data and using pvlib. Additionally, we explore the role of solar-driven hydrogen production at the district level, aiming to optimize renewable energy storage and enhance energy self-sufficiency in urban environments.

Nomenclature

G	Irradiance, W/m^2
η_{inv}	Inverter efficiency
P_{DC}	DC power output, W
P_{AC}	AC power output, W
$\eta_{pv,ref}$	Reference panel efficiency
T_{cell}	Cell temperature, °C
T_{air}	Ambient air temperature, °C
T_{NOCT}	Nominal Operating Cell Temperature, °C
μ_{mp}	Maximum Power Point Temperature Coefficient, °C^{-1}
P_{tank}	Hydrogen tank pressure, Pa
V_{tank}	hydrogen tank volume, m^3
n_{H2}	Number of moles of hydrogen
$\dot{m}_{H2}$	Hydrogen production rate, kg/s
η_{elec}	Electrolyzer efficiency
P_{elec}	Power supplied to the electrolyzer, W
V_{H2}	produced hydrogen volume, m^3
HHV_{H2}	Higher Heating Value, J/kg
R	Universal gas constant, J/(mol·K)
T	Temperature, K
P_{FC}	Power output of the fuel cell, W
η_{FC}	Fuel cell efficiency
$P_{\mathrm{DC,ref}}$	DC reference power

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1. Introduction

Urbanization is a major driver of environmental and ecological pressures, contributing significantly to climate change through high CO2 emissions and energy consumption. Despite awareness and measurement of these impacts, implementing effective solutions remains challenging [1].

Climate change and energy crises are currently the most critical threats facing humankind. According to the Paris Agreement, governments accepted net-zero scenario strategies to control global warming by reducing carbon emissions and limiting the temperature increase to 1.5°C [2]. The extensive use of fossil fuels is a major factor contributing to the rapid rise in global temperatures and climate change [3, 4]. The CREST model, while advanced in simulating integrated thermal-electrical domestic demand through high-resolution stochastic analysis, does not address hydrogen production, a crucial element for sustainable urban energy systems. This study introduces a sophisticated model tailored for urban environments, enhancing the CREST framework by incorporating hydrogen production to optimize renewable energy use and storage. The objectives of the study are :

- Develop a comprehensive urban energy model that includes hydrogen production, offering a significant enhancement over existing models like CREST, which lack this capability.
- Evaluate how this integration impacts urban energy efficiency and CO2 emissions reduction, demonstrating clear advancements in managing the unique energy demands of densely populated areas.

1.1. Green Hydrogen as an Energy Vector

The findings indicate that hydrogen technology can store energy more than other storage systems. According to the hydrogen characterization, extending the storage capacity to 10 GW without storage limits is possible [5]. Also, green hydrogen plays a key role due to its double applicability as a direct fuel for conversion purposes by a chemical process or combustion and as an energy carrier for storing surplus energy from renewable sources [6].

Building energy demand requires efficient storage solutions, prompting exploration of various technologies. This study focuses on multi-energy systems for residential applications, incorporating a battery (BAT) and a water electrolyzer (EC) to utilize surplus electricity generated by solar photovoltaic (PV) panels for dihydrogen production.

The produced dihydrogen is subsequently used in a fuel cell (FC) to supply energy during periods of low solar irradiation.

1.2. Hydrogen Production Capacity in Urban Areas

Ulleberg et al. [7] were among the first to identify hydrogen as a future energy carrier, particularly for integrating intermittent renewables like solar and wind. They studied a 30 kW stand-alone PV/hydrogen system in Jülich over one year. The findings revealed that existing battery technology could not address long-term storage challenges, suggesting hydrogen energy storage as a viable alternative. Nasser et al. [8] investigated a hybrid hydrogen production system powered by solar and wind energy in Egypt. Using MATLAB/Simulink, they analyzed green H_2 production via electrolyzers, PV panels, wind turbines, and storage. The system yielded an average of 1912 kg of hydrogen annually, with energy and exergy efficiencies of 16.42% and 12.76%, respectively. Economic analysis estimated a payback period ranging from 7 to 13.85 years over the system's lifetime. Basiony et al. [9] analyzed a standalone solar-powered hybrid system in New Borg El-Arab, Egypt, integrating PV panels, an electrolyzer, and fuel cells with hydrogen storage. The system achieved efficiencies of 20.7% (PV), 68.2% (electrolyzer), and 34.6% (fuel cells), with an overall efficiency of 16.5% and a performance ratio of 2.61 for the MED-MVC unit. It effectively met electricity and water demands at an LCOE of $0.712/kWh.

Building on the findings of these studies on hydrogen production systems, the methodology for energy modeling has progressively advanced, with the CREST demand model [10] emerging as a more flexible and scalable tool for addressing the complexities of modern energy systems.

2. Methodology

The CREST domestic energy demand model [10] is a widely recognized tool for generating high-resolution (1-minute) energy consumption and PV production profiles without requiring advanced expertise in building energy modeling. Initially a domestic occupancy model, it evolved to include electricity demand and thermal components like heating and cooling. Using stochastic methods, it incorporates factors such as weather, building characteristics, occupant behavior, and appliance usage, offering flexibility and accessibility with minimal inputs. However, it has notable limitations, including its daily simulation structure, slow VBA implementation, rigid inputs, and lack of integration with emerging technologies, making it less suitable for modern, large-scale, and flexible energy modeling needs.

2.1. Modeling Framework

The modeling framework is built upon the reimplementation of the CREST model in Python, transitioning from its original Excel VBA environment to enhance flexibility and scalability. This transition enables seamless integration with advanced simulation tools and easier modifications. The model supports multi-week simulations, ensuring long-term energy dynamics, temporal continuity, and accurate performance analysis in residential multi-energy systems.

For the need of the present study, this approach simulates energy consumption using stochastic activation profiles, enhances solar radiation forecasting with HMM, LSTM, and pvlib, and evaluates a dual-loop storage system with batteries for short-term storage and hydrogen for long-term storage.

Furthermore, hydrogen is assessed as a supplementary energy source for fuel cells and heating once residential demand is met. The study also considers EV charging integration to optimize hydrogen storage synergy and enhance energy efficiency. Future investigations will compare energy vectors to evaluate performance, feasibility, and efficiency, identifying optimal solutions for integrating renewable energy, hydrogen systems, and EVs in urban frameworks.

3. Models

3.1. Weather Model and Solar Radiation Estimation

Our model employs a hybrid approach that combines deterministic and machine learning techniques to generate high-resolution solar irradiation profiles, similar to the CREST model described by Richardson and Thomson [10]. Initially, the program computes an irradiance profile for a clear sky by first calculating clear-sky irradiance using the

Ineichen model [11], considering solar position and atmospheric conditions. However, the CREST model relies on pre-computed monthly transition matrices for cloud cover variations which is a a 101 × 101 transition matrix that requires high-resolution weather data (1-minute intervals) for parametrization. Our model dynamically estimates the clearness index using historical weather data obtained from PVGIS through the `pvlib` library [12]. This clearness index is further refined using a Hidden Markov Model (HMM) to capture state transitions in cloud cover. In addition, a Long-Short-Term Memory (LSTM) neural network [13] is trained to model short-term fluctuations and predict clearness index variations. While CREST relies on fixed probability transitions, our approach adapts to real-time conditions using minute-resolution data, Python typically employs deterministic models like Liu & Jordan [14] or Perez [15], making it more suitable for complex simulations and integration with machine learning techniques.

3.2. Photovoltaic Energy Production

The photovoltaic modeling approach integrates a physics-based simulation of the performance of the PV panel, aligned methodologically with the CREST model's electricity generation module [10]. it calculates plane-of-array (POA) irradiance using synthesized clearness index data, accounting for a panel tilt of 35 ° and an azimuth orientation of 180 ° (south). The power output calculation incorporates thermal effects through pvlib's Sandia Array Performance Model (SAPM), which estimates cell temperature considering ambient conditions and irradiance and directly affecting panel efficiency, as defined in Eq. (1).

The implementation adapts the PVWatts model to compute temperature-adjusted DC output in Eq. (2), factoring in a module power temperature coefficient ($\gamma_{pdc} = -0.004\,°C^{-1}$), while AC conversion follows inverter efficiency curves ($\eta_{inv} = 96\%$ nominal) to finally get the final usable AC output in eq (3).

To enhance the model's temporal adaptability, it integrates machine learning-predicted clearness indices from LSTM and HMM forecasts, allowing for multi-period simulations instead of single-day analyses.

$$T_{cell} = T_{air} + \frac{G}{G_{ref}} \times (T_{NOCT} - T_{air}) \tag{1}$$

$$P_{\text{DC}} = P_{\text{DC,ref}} \cdot \frac{G}{G_{\text{ref}}} \cdot [1 + \gamma_{\text{pdc}}\,(T_{\text{cell}} - T_{\text{ref}})] \tag{2}$$

$$P_{\text{AC}} = P_{\text{DC}} \times \eta_{\text{inv}} \tag{3}$$

As shown in Fig. 1, the irradiance comparison reveals significant variations in PV system output .

3.3. Consumption Pattern

3.3.1. Appliances model

This appliance load model, based on the CREST model, involves three key steps: stochastic appliance assignment, switch-on time estimation, and consumption calculation. Appliances are activated by daily activity profiles and operate for fixed or occupancy-based durations. Consumption is aggregated into hourly intervals with weekday and weekend variations. Regional adaptations adjust ownership rates, power cycles, and consumption using national datasets.

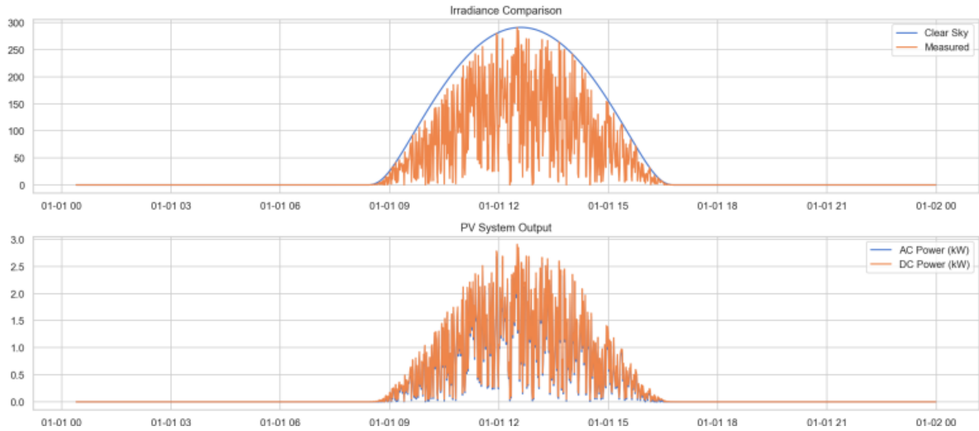

Figure 1: Comparison of Solar Irradiance and PV System Output over the Day

Figure 2 illustrates the hourly electrical demand distribution for various appliances, based on stochastic activation and usage patterns.

3.3.2. Lighting model

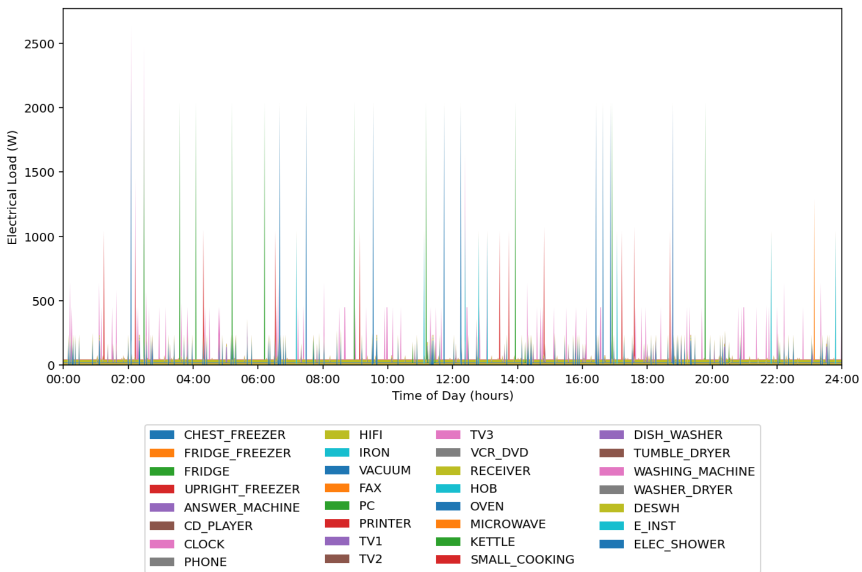

Figure 2: *Electric Load Profile of Selected Appliances*

The lighting consumption module, as detailed by Richardson et al. [16], assigns lighting fixtures to buildings using a predefined set of bulb configurations. During initialization, each building is randomly assigned one of a hundred possible configurations. At each time step, the probability of activation is determined by comparing a calculated value based on an irradiation threshold, occupancy patterns, calibration and usage factors with a randomly generated number (Eq. (4)).

$$P_{\text{ract}} = \text{flag}_{\text{irrad}} \cdot \text{factor}_{\text{occupancy}} \cdot \text{factor}_{\text{relative usage}} \cdot \text{factor}_{\text{calibration}} \tag{4}$$

This domestic lighting model simulates the minute-by-minute behavior of household lighting by combining en-

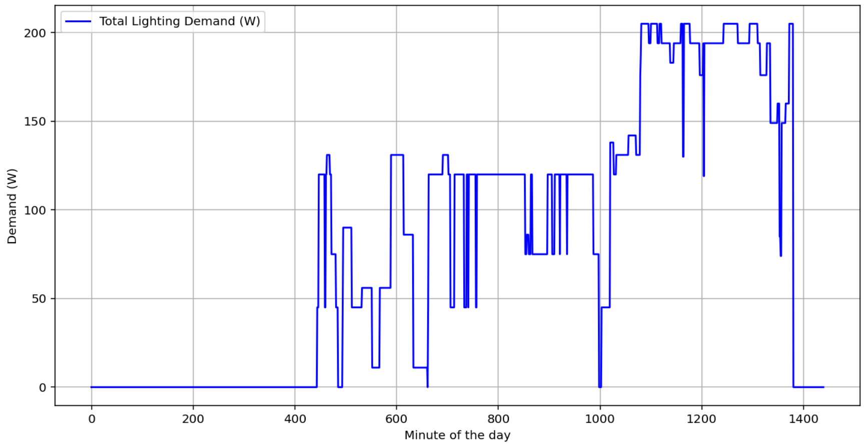

Figure 3: *Total Lighting Demand over the Day*

vironmental conditions, occupancy, and stochastic elements. By using Monte Carlo-based threshold generation and a time-step simulation loop, the model captures the probabilistic nature of lighting usage, approximating complex user-driven behaviors in a structured energy framework. Fig . 3 shows the total daily lighting demand, with variations driven by occupancy, environmental conditions, and stochastic factors.

3.4. Energy Consumption and Photovoltaic Production Profiles

At the system level, habitations prioritize self-consumption. A high-resolution simulation of energy consumption, photovoltaic (PV) production, and battery storage for a single-family home in Belfort, France, uses one-minute resolution to capture detailed energy dynamics. The demand for appliances and lighting follows occupancy-based modeling aligned with local legal time, peaking in the morning and evening. PV generation, based on solar time, peaks around solar noon .

4. Hydrogen Production Modeling

At the system level, habitations prioritize self-consumption. Consequently,energy generated by photovoltaic panels is initially allocated to meet the building's requirements. Surplus PV energy is first directed to charge the battery until it reaches full capacity. If excess energy remains, and the hydrogen tank is not full, it is converted into hydrogen via the electrolyzer. The control strategy dynamically manages this allocation using real-time power balance and the battery's state of charge (SOC), with key thresholds at 0.3, 0.8, 0.85, and 1. When power is needed, the system prioritizes battery discharge; if SOC drops below 30 and hydrogen is available, the fuel cell is activated. Grid import occurs only when both battery and fuel cell are unable to meet the demand, ensuring a resilient and self-sufficient energy flow as shown the Fig. 4.

The electrolyzer absorbs surplus electricity to convert water into hydrogen via the process of electrolysis. The anticipated hydrogen production rate, $\dot{m}_{H_2}$ (kg/s), is calculated using eq (Eq. (5)) extracted from Ref [17]

$$\dot{m}_{H_2} = \frac{\eta_{elec} \cdot P_{elec}}{V_{H_2} \cdot HHV_{H_2}}, \tag{5}$$

The electrolyzer produces hydrogen at a pressure of 50 bars which is commonly used for stationary applications.

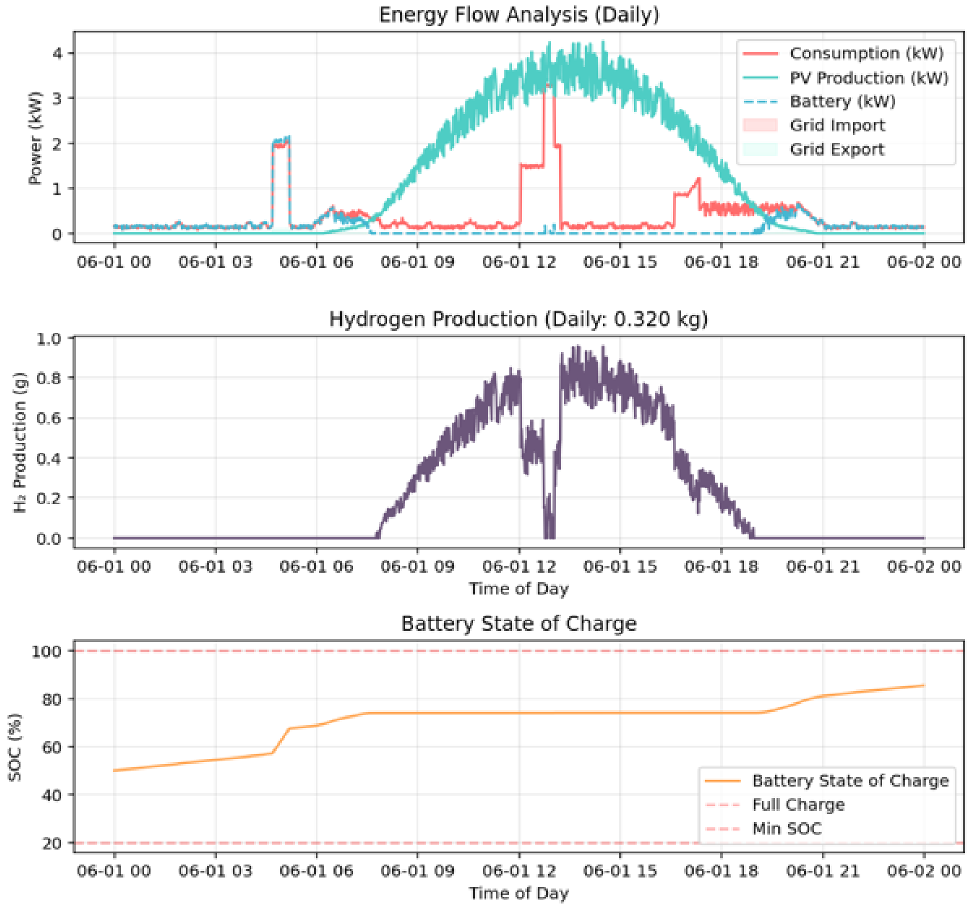

Figure 4: *Energy Consumption, PV Production, Battery Storage, and Hydrogen Production for a Single-Family Home*

The compressed hydrogen tank stores the hydrogen at this same pressure. Therefore, in general, additional energy losses associated with hydrogen compression or the hydrogen tank are not considered. At this pressure and ambient temperature, hydrogen behaves approximately as an ideal gas, (compressibility factor $Z \approx 1$). Thus, the storage process can be expressed by the ideal gas law as given in Eq. (6):

$$P_{tank}V_{tank} = n_{H_2}RT, \tag{6}$$

Stored hydrogen will subsequently be reconverted into electricity and heat using a proton exchange membrane fuel cell (PEMFC). The electrical power output of the fuel cell is given by:

$$P_{FC} = \eta_{FC} \cdot \dot{m}_{H_2} \cdot HHV_{H_2}, \tag{7}$$

A Python-based model was first developed at the building scale, integrating PV, battery storage, and hydrogen systems with time-series simulations and control strategies to maximize self-consumption,with future extension to the neighborhood scale to evaluate the benefits of decentralized hydrogen production and energy sharing.

5. Results and Analysis

The simulation results demonstrate the technical feasibility of a small-scale solar-to-hydrogen system. With a daily photovoltaic (PV) energy production of 23.7 kWh, the system yields 3.14 Nm^3 of hydrogen per day, equivalent to approximately 0.282 kg. This corresponds to an average hourly production of 0.131 Nm^3/h, with a peak of 0.39 Nm^3/h during high solar irradiance. The overall system efficiency is 59.8%, confirming that the energy conversion from solar to hydrogen is both realistic and efficient for residential or microgrid applications.

Furthermore, transitioning to a Python-based implementation, we can address these limitations, enabling seamless annual simulations, and high-resolution modeling.

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