

# GREEN CITIES: A TWO-STAGE STOCHASTIC APPROACH FOR RENEWABLE-ENERGY INTEGRATION AND GREEN-HYDROGEN STORAGE IN DEVELOPING REGIONS

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Received 11.06.2026.

Revised 10.09.2026.

Accepted 25.09.2026.

## Keywords:

*Two-stage stochastic programming,  
Renewable-energy integration, Green  
hydrogen, Hydrogen storage, Fuel  
cells, Energy-system planning,  
Ecuador*

## ABSTRACT

*This study develops a two-stage stochastic optimization model for planning solar photovoltaic generation, wind generation, electrolysis, green-hydrogen storage, and fuel-cell conversion in representative urban and industrial nodes of Ecuadorian Zone 1. The first stage determines investments in photovoltaic units, wind turbines, electrolyzers, hydrogen storage, and fuel cells before uncertainty is realized. The second stage determines scenario-dependent electricity dispatch, hydrogen production, industrial hydrogen delivery, storage operation, fuel-cell use, renewable curtailment, and unmet demand. Uncertainty is represented through joint variations in solar availability, wind availability, electricity demand, and industrial hydrogen demand across four quarterly periods with 96 operating instances per quarter. The model minimizes annualized investment, operating, and shortage costs. Results indicate that solar and wind generation cover 26–35% of the electricity demand in the represented rural and urban nodes. The integrated configuration produces up to 840,000 kg-H<sub>2</sub> per quarter for industrial districts and reduces the aggregate electricity deficit by 15%. Under constrained operating conditions, the shortfall indicator decreases by 94%. Hydrogen storage transfers renewable energy from high-resource periods to periods of lower renewable availability or higher demand. The framework supports low-carbon energy planning in developing regions.*



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## 1. INTRODUCTION

Ecuador's Zone 1 (Esmeraldas, Carchi, Imbabura and Sucumbíos) presents exceptional potential for energy transition due to its abundant renewable resources in

terms of high solar irradiation in Sucumbíos and optimal winds in Esmeraldas. There is also critical industrial demand in the petrochemical (Sucumbíos) and agricultural (Imbabura) sectors which require stable energy and clean gas (CELEC, 2025).

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The energy transition to 100% renewable systems faces a fundamental challenge: the intermittency of sources such as solar and wind, along with the historical dependence on fossil fuel-based power grids (Ali & Anufriev, 2020; Cabrera-Tobar et al., 2019; Fernández et al., 2019).

This work proposes a holistic approach to overcome these barriers by designing a closed system where surplus energy from solar and wind generation is transformed into green hydrogen (H<sub>2</sub>V) by electrolyzers, stored as a strategic energy vector.

During periods of deficit, fuel cells reconvert this hydrogen into electricity, closing the cycle and stabilizing the grid. This model not only addresses climate variability through dynamic storage, but also redefines the relationship between supply and demand, turning intermittency into an opportunity for resilience (Fernández et al., 2019; Žalėnienė & Pereira, 2021).

The abbreviations used throughout the manuscript are summarized in Table 1.

The deployment of renewable-energy systems in developing regions requires planning approaches that account for geographical heterogeneity, seasonal resource variability, industrial demand, and investment constraints. In Ecuadorian Zone 1, the energy transition cannot be represented only as a replacement of conventional electricity sources by solar or wind generation. The temporal mismatch between renewable availability and demand requires complementary technologies that can preserve energy and make it available when renewable output is lower than the demand to be served.

Green hydrogen is particularly relevant in this context because it connects electricity and industrial energy use. Electricity generated from renewable sources can be converted into hydrogen during periods of relative surplus. The hydrogen can then be used directly by industrial consumers, retained in storage, or reconverted into electricity by fuel cells. This multi-purpose role differentiates hydrogen from conventional short-duration electricity storage and makes it suitable for evaluating medium- and long-duration flexibility in systems characterized by variable renewable resources.

The central planning challenge is that infrastructure decisions and operating decisions are made under different information conditions. Investment in photovoltaic panels, wind turbines, electrolyzers, storage infrastructure, and fuel cells must be made before the future realization of solar irradiation, wind speed, electricity demand, and hydrogen demand is fully known. In contrast, the operating decisions of dispatching electricity, producing hydrogen, storing hydrogen, and using fuel cells can be adjusted after the operating

conditions are observed. This distinction motivates the use of a two-stage stochastic approach.

The objective of this study is to evaluate an integrated renewable-electricity and green-hydrogen configuration for representative urban and industrial nodes in Ecuadorian Zone 1. The proposed approach combines long-term investment decisions with adaptive operational decisions under uncertain renewable-resource and demand conditions. The study focuses on the role of hydrogen as an energy vector for improving system flexibility, reducing energy shortages, and increasing the use of renewable resources.

The contribution of the paper is threefold. First, it presents a system representation that jointly considers photovoltaic generation, wind generation, electrolysis, hydrogen storage, direct industrial hydrogen supply, and fuel-cell conversion. Second, it uses a two-stage stochastic structure to distinguish anticipatory investment decisions from scenario-dependent operating decisions. Third, it provides a computational case study for a developing-region context in which renewable-resource availability, electricity demand, industrial demand, and seasonal effects must be considered jointly. The remainder of the paper is organized as follows. Section 2 describes the conceptual framework and the architecture of the integrated energy system. Section 3 explains the two-stage stochastic approach and presents the mathematical formulation. Section 4 describes the computational implementation and the information available in the complementary repository. Section 5 discusses the principal results of the case study. Section 6 identifies the limitations of the study and future research directions. Finally, Section 7 presents the conclusions.

**Table 1.** Nomenclature.

| Abbreviation | Meaning                      |
|--------------|------------------------------|
| RES          | Renewable Energy Source      |
| EDC          | Electric Distribution Center |
| EU           | Electrolyzer Unit            |
| GLN          | Gas Load Nodes               |
| SN           | Storage Nodes                |
| FC           | Fuel Cells                   |
| H&N          | Here-and-Now                 |
| W&S          | Wait-and-See                 |

## 2. CONCEPTUAL FRAMEWORK AND SYSTEM DESCRIPTION

Figure 1 presents the conceptual structure of the integrated renewable-electricity and green-hydrogen system. The framework couples variable renewable generation with electrolysis, hydrogen storage, direct industrial hydrogen use, and fuel-cell conversion (Hren et al., 2023).

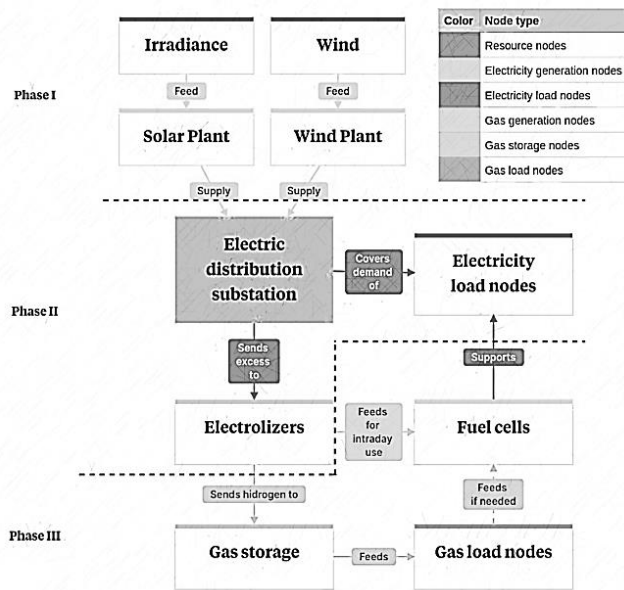


**Figure 1.** Conceptual structure of the integrated renewable-electricity and green-hydrogen system

The conceptual framework represents an integrated energy system in which electricity and hydrogen are treated as interconnected energy carriers. The electricity subsystem includes renewable generation from photovoltaic panels and wind turbines, as well as electricity demand from urban and industrial users. The hydrogen subsystem includes electrolysis, direct hydrogen consumption, storage, and electricity recovery through fuel cells. The interaction between both subsystems makes it possible to transform renewable electricity into hydrogen when generation is available and to use hydrogen when electricity or industrial energy demand becomes more difficult to satisfy.

The proposed architecture is intentionally designed as a planning-oriented representation. It does not attempt to reproduce every physical characteristic of an electricity transmission system or a hydrogen pipeline network. Instead, it identifies the principal energy flows and technological decisions that determine whether renewable resources can be converted into reliable energy services. This level of abstraction is appropriate for evaluating alternative infrastructure portfolios and for studying the role of hydrogen under renewable-resource and demand uncertainty.

The system architecture also reflects a hierarchy of energy use. Renewable electricity is primarily directed toward electric-load satisfaction. When renewable generation is available beyond the operational electricity requirement, it can be allocated to electrolyzers. The resulting green hydrogen can be assigned to industrial consumption, injected into storage, or reserved for fuel-cell conversion. This hierarchy permits the model to evaluate the competing uses of renewable electricity and hydrogen, rather than assuming that all renewable generation is immediately transformed into hydrogen. This model is divided into three main phases:

#### Phase I: Renewable Energy Generation

- Components: Solar and wind (RES) plants generate electricity using resources such as solar irradiation and wind speed.
- Function: The energy produced is sent to EDC for centralized management.

#### Phase II: Electricity Demand Satisfaction

- Process:
- EDC prioritizes meeting the electricity demand of cities and industrial districts.
- If generation exceeds demand, the surplus is directed to the Electrolyzer (EU) to produce green hydrogen.
- Objective: Minimize energy waste and maximize the use of renewable sources.

#### Phase III: Hydrogen Production and Management

- Conversion: The EU transforms excess electricity into hydrogen by electrolysis.
- Distribution:
- Gas Load Nodes (GLN): Hydrogen is delivered directly to industrial or transportation sectors.
- Storage Nodes (SN): Part of the hydrogen is stored for future use.
- Fuel Cells (FC): During periods of low renewable generation, stored hydrogen is converted back into electricity and fed back into the grid.

The three phases of the integrated model are structured hierarchically to optimize energy systems under uncertainty: Phase I focuses on renewable generation (solar and wind) through specialized nodes, guaranteeing primary supply to power distribution centers.

Phase II prioritizes urban and industrial electricity-demand satisfaction. When renewable generation is available beyond the electricity requirement represented in the model, the surplus can be directed to electrolyzers for green-hydrogen production. The model balances operating costs and shortage penalties through a two-stage stochastic structure that distinguishes here-and-now and wait-and-see decisions (Mulvey et al., 1995; Prékopa, 1995).

Phase III manages the hydrogen produced by allocating it to industrial hydrogen-demand nodes, storage facilities, or fuel cells. During low-renewable-generation conditions, fuel cells can convert available hydrogen into electricity and support the electric system (Babazadeh & Sabbaghnia, 2018; Escudero et al., 2009).

This framework combines anticipatory infrastructure-capacity decisions with adaptive scenario-dependent operational decisions, thereby addressing climate variability and demand fluctuations.

The relevance of this architecture lies in the complementarity between the technologies considered. Photovoltaic generation is driven by solar irradiation and tends to provide electricity during daylight hours, whereas wind generation may contribute under different meteorological conditions. Electrolyzers provide a controllable electricity demand that can use renewable energy when it would otherwise be curtailed. Hydrogen storage separates the moment of hydrogen production from the moment of consumption, while fuel cells make it possible to recover electricity from stored hydrogen during periods of limited renewable generation.

From a system-planning perspective, this architecture creates a set of economic and technical trade-offs. Increasing renewable capacity can reduce the dependence on conventional energy sources, but it may also increase renewable curtailment if flexible demand or storage capacity is insufficient. Increasing electrolyzers capacity can increase hydrogen production, but it also competes with direct electricity demand for available renewable generation. Similarly, storage and fuel-cell capacity can improve reliability, but they require additional investment and are associated with energy-conversion losses. The optimization model is used to identify a configuration that balances these competing effects.

The conceptual structure is applicable to regions in which renewable-resource potential is geographically dispersed and demand is heterogeneous. For Ecuadorian Zone 1, the framework provides a way to examine how solar-resource conditions, wind-resource conditions, urban demand, industrial demand, and hydrogen infrastructure may be coordinated. The model therefore supports strategic analysis of energy-transition alternatives rather than the detailed engineering design of a specific generation plant, storage cavern, or distribution network.

The proposal is presented below (García & Peña, 2018; Goerigk, 2012; Mulvey et al., 1995; Shahbazi et al., 2021).

### 3. TWO-STAGE STOCHASTIC APPROACH

The mathematical approach is based on a two-stage stochastic decision framework. This framework is appropriate when certain decisions must be made before uncertain conditions are observed, while other decisions can be adjusted after uncertainty is realized. In the present study, uncertainty is associated with the variability of solar irradiation, wind availability, electricity demand, and industrial hydrogen demand.

The first stage represents strategic or here-and-now decisions. These decisions define the infrastructure that will be available to the regional energy system, including renewable-generation technologies, electrolyzers, and fuel cells. Since these decisions are made before the realization of the operating conditions, they are common

to all possible scenarios. Their purpose is to establish the capacity of the system to generate renewable electricity, produce hydrogen, store energy, and provide backup electricity.

The second stage represents operational or wait-and-see decisions. Once a specific realization of renewable-resource availability and demand is observed, the model determines how the installed infrastructure should be operated. These decisions include renewable-electricity dispatch, green-hydrogen production, hydrogen delivery to industrial nodes, storage injection, storage withdrawal, fuel-cell operation, and the management of shortage variables.

The two-stage structure is relevant because a deterministic planning model based solely on average renewable-resource values may underestimate the consequences of adverse operating conditions. A system designed for average solar irradiation, average wind availability, and average demand may not provide adequate service when low renewable output and high demand occur simultaneously. By distinguishing between anticipatory investment decisions and adaptive operating decisions, the model incorporates this uncertainty directly into the planning process.

#### Two-stage structure

##### i. Main Indexes

- $b \in \mathcal{B}$ : Types of solar panels (e.g., small, medium, large).
- $w \in \mathcal{W}$ : Types of wind turbines (e.g., Enercon E-115, Vestas V150).
- $l \in \mathcal{L}$ : Solar nodes (e.g., Sucumbíos, Imbabura).
- $m \in \mathcal{M}$ : Wind nodes (e.g., Esmeraldas, Carchi).
- $o \in \mathcal{O}$ : Hydrogen-generation nodes.
- $t \in \mathcal{T}$ : Time periods in Quarters of the year.
- $i \in \mathcal{I}$ : Operating instances within each quarterly period.
- $j \in \mathcal{J}$ : Cities.
- $k \in \mathcal{K}$ : Industrial Districts

The index sets define the spatial, technological, and temporal structure of the case study. The sets of solar nodes and wind nodes represent the geographical locations in which renewable technologies can be installed. The sets of cities and industrial districts represent the electricity and hydrogen demand points. The time and instance indices capture the temporal variation that arises throughout the year, while the scenario index represents the uncertain combination of renewable-resource conditions and demand levels.

The scenario index  $\omega$  is especially important in the proposed model. A scenario does not represent only a change in a single variable; rather, it represents an operating condition characterized by a particular combination of irradiation, wind availability, electricity

demand, and hydrogen demand. This allows the model to evaluate the system under favourable, intermediate, and constrained operating conditions. The scenario-dependent variables in the second stage ensure that electricity and hydrogen flows can respond to the conditions observed in each case.

## ii. Stage I: Investment Decisions (“Here & Now”) Decision variables:

The first-stage variables define the number of photovoltaic panels of type  $b$  installed at solar node  $l$ , the number of wind turbines of type  $w$  installed at wind node  $m$ , the number of electrolyzers installed at hydrogen-generation node  $o$ , and the number of fuel cells installed at node  $n$ .  $(x_{(l,b)}^s)(x_{(m,w)}^{wt})(x_o^e)(x_n^{fc})$

### Objective Function H&N:

$$\underset{x^s, x^w, x^e, x^{fc}}{\operatorname{argmin}} \left\{ \sum_{l,b} x_{(l,b)}^s + \sum_{m,w} x_{(m,w)}^{wt} + \sum_o x_o^e + \sum_n x_n^{fc} \right\} \quad (1)$$

The first-stage objective minimizes the installed quantities of the selected technologies, subject to the capacity, environmental, and backup constraints described below. The resulting infrastructure portfolio is subsequently evaluated through the scenario-dependent operational objective.

### Key constraints:

The constraints (2.r1) and (2.r2) represent the capacity limits with respect to available area and ecological constraints, (2.r3) the synergy of hydrogen generation and (2.r4) the industrial back-up for peak demand (Bertsimas & Brown, 2009; Goerigk & Schöbel, 2011; Rosenhead et al., 1972).

$$\left\{ \begin{array}{l} \mathbf{r}_1: \sum_{l,b} x_{(l,b)}^s \leq X_{(l,b)}^{s,max} \quad \forall l \in \mathcal{L} \\ \mathbf{r}_2: \sum_{m,w} x_{(m,w)}^{wt} \leq X_{(w)}^{wt,max} \quad \forall w \in \mathcal{W} \\ \mathbf{r}_3: \sum_o x_o^e \leq \eta^e (\sum_l \bar{G}_l^s + \sum_m \bar{G}_m^{wt}) \quad \forall o \in \mathcal{O} \\ \mathbf{r}_4: \sum_n x_n^{fc} \leq \gamma \cdot \max_{t,i} \{ D_{(k,t,i)}^{elec} \} \quad \forall k \in \mathcal{K} \end{array} \right\} \quad (2)$$

Here,  $X_{(l,b)}^{s,max}$  is the Maximum Solar Capacity per Node,  $X_{(w)}^{wt,max}$  the Maximum Wind Capacity per Node, and  $\eta^e (\sum_l \bar{G}_l^s + \sum_m \bar{G}_m^{wt})$  the Green Hydrogen Production Limit being  $\bar{G}_l^s$  expected average solar generation at node  $l$  (MWh/year) and  $\bar{G}_m^{wt}$  the expected average wind generation at node  $m$  in (MWh/year) with electrolyzer efficiency factor ( $\eta^e$ ) of 0.72 while  $\gamma$  is the Redundancy Factor for Backup that guarantees that the fuel cells cover extreme events with an Industrial Electric Demand ( $D_{(k,t,i)}^{elec}$ ).

The first-stage constraints are intended to prevent the model from selecting infrastructure capacities that exceed spatial, technical, or environmental limits associated with candidate locations. In this manner, optimization does not treat renewable-generation and conversion capacities as unlimited. The limits reflect practical considerations such as available area for photovoltaic deployment, feasible wind-turbine installation, maximum electrolyzers capacity, and the level of backup capacity required to address periods of high industrial electricity demand.

The first-stage decisions also determine the range of operational choices available in the second stage. For example, installing additional photovoltaic capacity can increase the amount of renewable electricity available under favorable irradiation conditions, but it cannot guarantee energy availability during low-irradiation periods. Similarly, installing electrolyzers capacity permits greater hydrogen production when surplus renewable electricity exists, whereas fuel-cell capacity determines the potential contribution of stored hydrogen to electricity supply during constrained periods. The value of these investments is therefore evaluated through their expected performance across the modeled operating conditions.

## iii. Stage II: System Operation (“Wait & See”) Decision variables (scenario $\omega$ ):

$y_{(l,t,i,\omega)}^s$  represents the solar energy sent to the grid (MWh),  $y_{(m,t,i,\omega)}^{wt}$  wind energy generated (MWh),  $h_{(o,t,i,\omega)}^{H_2}$  produced green hydrogen ( $GH_2$ ),  $h_{(o,k,t,i,\omega)}^{ind}$   $GH_2$  shipped directly to industry (kg),  $H_{(t,i,\omega)}^{fc}$   $GH_2$  used in fuel cells (kg). For  $GH_2$  Storage we have the following variables:  $\theta_{(a,t,i,\omega)}^{in}$   $GH_2$  injected into storage (kg),  $\theta_{(a,t,i,\omega)}^{out}$   $GH_2$  extracted from storage (kg),  $I_{(a,t,i,\omega)}$  Inventory of stored  $GH_2$ . The Deficits (Penalties) variables are as follows:  $\delta_{(j,t,i,\omega)}^+$  electricity deficit (MWh),  $\delta_{(k,t,i,\omega)}^{H_2}$  industrial hydrogen deficit (kg). The variable curtailed  $D_{(t,i,\omega)}^{curt}$  electrical demand (MWh) is defined as non-essential load disconnected to release energy to electrolyzers.,  $\omega \in \Omega$  is the set of the scenarios.

### Objective Function W&S:

$$\underset{y^s, y^{wt}, h^{H_2}, \theta^{in}, \theta^{out}, \delta^+, \delta^{H_2}}{\operatorname{argmin}} \mathbb{E}_\omega \left\{ \sum_{t \in T} \sum_{i \in I} \left( \underbrace{A}_{\text{Operational costs}} + \underbrace{B}_{\text{penalties}} \right) \right\} \quad (3)$$

- 3.A is defined as:

$$\sum_l c_{op}^s y_{(l,t,i,\omega)}^s + \sum_m c_{op}^{wt} y_{(m,t,i,\omega)}^{wt} + \sum_o c_{op}^e h_{(o,t,i,\omega)}^{H_2} + \sum_a c_{op}^{st} (\theta_{(a,t,i,\omega)}^{in} + \theta_{(a,t,i,\omega)}^{out})$$

- 3.B is defined as:

$$\sum_{j \in J} \pi_{e(\omega)} \delta_{(j,t,i,\omega)}^+ + \sum_{k \in K} \pi_{H_2(\omega)} \delta_{(k,t,i,\omega)}^{H_2}$$

The second-stage objective represents the operating consequences of the infrastructure selected in the first stage. It incorporates the costs associated with renewable generation, green-hydrogen production, and storage movements, together with penalties for unsatisfied electricity and industrial hydrogen demand. The shortage penalties are included to ensure that the model explicitly recognizes the importance of energy reliability. They should be interpreted as reliability parameters that discourage unmet demand, rather than as observed market prices for electricity or hydrogen.

The expected-value structure of the objective function evaluates the operational performance of the system over the set of possible scenarios. Consequently, the selected investment plan is not based exclusively on a single favorable or unfavorable realization of renewable resources and demand. Instead, it reflects the trade-off between infrastructure cost and the expected ability of the system to satisfy demand, use renewable resources, produce hydrogen, and manage shortages across the operating conditions represented in the model.

#### Key constraints ( $\forall \omega$ ):

The constraints  $r_1$  and  $r_2$  represent the capacity limits with respect to available area and ecological constraints,  $r_3$  the synergy of hydrogen generation and  $r_4$  the industrial back-up for peak demand.

This module dynamically minimizes operational costs (solar/wind generation,  $\text{GH}_2$  production and storage management) and penalties for electricity shortfall ( $\pi_e = 10,000$  USD/MWh) and industrial hydrogen ( $\pi_{h2} = 5,000$  USD/kg) through adaptive decisions to  $\omega$ -weather scenarios.

Key constraints ensure that renewable generation (4.r1/r2) does not exceed weather potential or installed capacity; that  $\text{H}_2\text{V}$  (4.r3) is produced exclusively from renewable surpluses net of curtable demand; that the electricity balance (4.r4) meets demand through renewable sources and conversion of  $\text{H}_2\text{V}$  to fuel cells; that the allocation of  $\text{H}_2\text{V}$  for electricity (4.r5) does not compete with direct industrial supply; that industrial demand for  $\text{H}_2$  (4.r6/r7) is met by direct delivery or storage withdrawal; and that the inventory (4.r8) manages storage flows and losses.

The operational constraints link the physical availability of renewable resources with the dispatch, conversion, storage, and demand-satisfaction decisions. The solar and wind constraints limit renewable generation according to resource conditions and installed capacity. The hydrogen-production constraints ensure that green hydrogen is obtained from renewable electricity supplied to the electrolyzers. The electricity-balance constraints account for the contribution of renewable generation and fuel-cell conversion to the satisfaction of electricity demand.

The hydrogen-related constraints regulate the allocation of produced hydrogen among industrial delivery, storage, and fuel-cell operation. The inventory balance ensures that hydrogen withdrawn from storage is limited by the amount that was previously injected, after accounting for storage losses. This structure permits the model to represent the temporal role of hydrogen: renewable energy can be captured in one operating instance and used in a later instance when direct renewable generation is less available.

$$\left\{ \begin{array}{l} r_1: y_{(l,t,i,\omega)}^s \leq \phi_b^s \cdot Irr_{(l,t,i,\omega)} \cdot x_{(l,b)}^s \\ \quad \forall (l, t, i, \omega) \in \{L \times T \times J \times \Omega\} \\ r_2: y_{(m,t,i,\omega)}^{wt} \leq \frac{1}{2} \rho \cdot C_p \cdot (Wind_{m,t,i,\omega})^3 x_{(m,w)}^{wt} \\ \quad \forall (m, t, i, \omega) \in \mathcal{M} \times T \times J \times \Omega \\ r_3: h_{(o,t,i,\omega)}^{H_2} \leq \eta^e \left( \sum_l y_{(l,t,i,\omega)}^s + \sum_m y_{(m,t,i,\omega)}^{wt} - D_{(t,i,\omega)}^{curt} \right)^+ \\ \quad \forall (o, t, i, \omega) \in \mathcal{O} \times T \times J \times \Omega, (\cdot)^+ = \max(\cdot, 0) \\ r_4: \sum_n y_{(n,t,i,\omega)}^s + \sum_m y_{(m,t,i,\omega)}^{wt} + \eta^{fc} H_{(t,i,\omega)}^{fc} = D_{(j,t,i,\omega)}^{elec} + \delta_{(j,t,i,\omega)}^+ \\ \quad \forall (j, t, i, \omega) \in \mathcal{J} \times T \times J \times \Omega \\ r_5: H_{(t,i,\omega)}^{fc} \leq \sum_o h_{(o,t,i,\omega)}^{H_2} - \sum_k h_{(o,k,t,i,\omega)}^{ind} \\ \quad \forall (t, i, \omega) \in T \times J \times \Omega \\ r_6: \sum_k h_{(o,k,t,i,\omega)}^{ind} + \theta_{(a,t,i,\omega)}^{out} \geq D_{(k,t,i,\omega)}^{H_2} - \delta_{(k,t,i,\omega)}^{H_2} \\ \quad \forall (k, t, i, \omega) \in \mathcal{K} \times T \times J \times \Omega \\ r_7: \sum_k h_{(o,k,t,i,\omega)}^{ind} \leq h_{(o,t,i,\omega)}^{H_2} \\ \quad \forall (o, t, i, \omega) \in \mathcal{O} \times T \times J \times \Omega \\ r_8: I_{(a,t,i,\omega)} = I_{(a,t,i-1,\omega)} + \theta_{(a,t,i,\omega)}^{in} - \theta_{(a,t,i,\omega)}^{out} - \lambda_{(a)} I_{(a,t,i-1,\omega)} \\ \quad \forall (a, t, i, \omega) \in \mathcal{A} \times T \times J \times \Omega \end{array} \right\} \quad (4)$$

The shortage variables preserve feasibility under severe combinations of renewable availability and demand. Their values provide a direct measure of the extent to which the modeled system cannot satisfy electricity or industrial hydrogen demand with the installed infrastructure. Therefore, the reduction of shortage variables after incorporating hydrogen storage and fuel-cell operation is a central indicator of the resilience contribution of the integrated system.

Under the constrained operating conditions represented in the computational experiments, this integration reduces the shortfall indicator in Zone 1 by 94%, which supports the role of green hydrogen as a flexibility resource for renewable-dominated systems.

## 4. COMPUTATIONAL IMPLEMENTATION

### 4.1. Algebraic modelling and solution environment

Algebraic modelling languages provide a structured environment for representing optimization problems through sets, parameters, variables, objective functions, and constraints. Their use is especially useful in energy-system planning because the model must integrate multiple technologies, geographical locations, temporal

instances, demand categories, and uncertainty scenarios within a single decision framework.

The computational implementation of the proposed model was developed in AIMMS Academic Version 4.81. AIMMS (2025) was used to define the two-stage stochastic structure, manage the input data associated with renewable resources and demand, formulate the decision variables and constraints, and execute the optimization runs. The implementation supports the representation of photovoltaic generation, wind generation, electrolysis, hydrogen production, storage operation, fuel-cell conversion, electricity-demand satisfaction, and industrial hydrogen-demand satisfaction.

The model was evaluated using quarterly operating periods and 96 instances per quarter. This temporal resolution was selected to capture seasonal variation while maintaining a computationally manageable set of instances. The solution procedure produced satisfactory optimization results, with reported solution times of no more than 30 seconds per scenario. These computational times indicate that the formulation can be used as a planning-support tool for analyzing alternative configurations of renewable and hydrogen infrastructure. The optimization model was solved with the CPLEX solver included in the AIMMS distribution, using its default branch-and-cut settings, on a personal computer equipped with an Intel Core i7 processor, 16 GB of RAM, and the Windows 11 operating system.

The model implementation includes the technical and spatial limits used in the case study. For example, the maximum photovoltaic deployment considered in Esmeraldas was 460 units. The model also incorporates an electrolyzer efficiency parameter of 0.72 and a hydrogen-storage cost of 1.2 USD/kg-H<sub>2</sub>/year. These assumptions permit the analysis of trade-offs between renewable generation, hydrogen conversion, storage operation, fuel-cell backup, and demand satisfaction.

The computational model, input data, and extended outputs are documented in the associated public repository. The repository contains the extended numerical material used to complement the concise presentation of principal findings in this article. It is intended to support transparency, reproducibility, and further examination of the scenario-dependent results, while the present manuscript reports the central methodological structure and the main conclusions of the case study.

## **4.2. Data and results availability**

The computational material associated with this study is available in a public GitHub repository (Fernández et al., 2025): <https://github.com/johncortes117/greencities-twostage-stochastic-optimization>. The repository includes model-related materials, extended results, and

documentation associated with the computational experiments.

The repository is provided as supplementary reproducibility material. It allows interested readers to examine the extended outputs that cannot be fully reproduced in the main text because of space limitations. In particular, the repository documents the scenario-dependent behavior of renewable generation, hydrogen production, storage operation, and demand-satisfaction indicators.

The main article remains self-contained with respect to its research question, system architecture, two-stage stochastic approach, computational environment, principal parameter values, and central findings. The repository extends this presentation by making additional numerical details available to readers who wish to reproduce, inspect, or further develop the computational case study.

## **4.3. Artificial intelligence use declaration**

During the revision of this manuscript, ChatGPT (OpenAI; GPT-4 class model, version accessed in September 2026) and Perplexity (Perplexity AI; version accessed in September 2026) were used exclusively to assist with English-language editing, translation of author-prepared text, improvement of readability, and preliminary organization of the written material. No artificial intelligence tool was used to generate, manipulate, or interpret the study data; to execute the AIMMS optimization model; to determine the final mathematical formulation; or to make scientific decisions. All AI-assisted text was critically reviewed, revised where necessary, and approved by the authors. The authors take full responsibility for the accuracy, originality, and integrity of the manuscript. No artificial intelligence system is listed as an author or co-author.

## **5. RESULTS AND DISCUSSION**

### **5.1. Renewable contribution and hydrogen production**

The numerical results show that photovoltaic and wind technologies make a relevant contribution to the electricity supply of the modeled urban and rural demand nodes. Across the evaluated locations and quarterly instances, renewable generation covers between 26% and 35% of electricity demand. This result reflects the fact that the contribution of renewable generation is conditioned by the spatial distribution of solar irradiation, wind availability, and demand.

The coverage range indicates that renewable generation alone is not sufficient to guarantee demand satisfaction under all operating conditions represented in the model. The remaining demand must be addressed through the flexibility provided by the integrated hydrogen system,

the shortage variables used to preserve feasibility, or other energy resources that are outside the scope of the present planning representation. This result highlights the relevance of evaluating renewable generation together with technologies that can transfer energy across time.

The model indicates that electrolyzer operation can produce up to 840,000 kg-H<sub>2</sub> per quarter in the industrial districts included in the computational case study. This production is generated from renewable electricity that can be allocated to electrolysis under the operational conditions of the model. The magnitude of this production demonstrates that green hydrogen can play a dual role: it can be delivered as an industrial energy carrier and can support electricity reliability through storage and fuel-cell conversion.

The reported hydrogen-production level should be interpreted in relation to the temporal and spatial assumptions of the case study. It is not a universal production estimate for the entire region, but an output of the modeled infrastructure configuration, renewable-resource conditions, demand profiles, and technical parameters. Its principal significance is that it demonstrates the capacity of the integrated system to use renewable electricity beyond immediate electricity-demand satisfaction.

The integration of hydrogen storage reduces the aggregate energy deficit by 15%, highlighting its technical and economic relevance. Table 2 summarizes the principal computational results and model parameters of the Ecuadorian Zone 1 case study.

**Table 2.** Summary of the main results of the Ecuadorian Zone 1 case study

| Indicator / parameter                        | Value   | Unit                        |
|----------------------------------------------|---------|-----------------------------|
| Operating instances                          | 96      | instances/quarter           |
| Renewable electricity coverage               | 26–35   | % of demand                 |
| Maximum green-hydrogen production            | 840,000 | kg-H <sub>2</sub> /quarter  |
| Aggregate electricity-deficit reduction      | 15      | %                           |
| Shortfall reduction (constrained conditions) | 94      | %                           |
| Seasonal operating variation                 | 10–15   | %                           |
| Hydrogen-storage unit cost                   | 1.2     | USD/kg-H <sub>2</sub> /year |
| Electrolyzer efficiency parameter            | 0.72    | —                           |
| Electricity shortage penalty                 | 10,000  | USD/MWh                     |
| Industrial hydrogen shortage penalty         | 5,000   | USD/kg-H <sub>2</sub>       |

## 5.2. Storage, reliability, and shortage reduction

The integration of hydrogen storage improves the capability of the modeled system to manage the temporal mismatch between renewable generation and electricity demand. The case-study results indicate that the storage

and fuel-cell configuration reduce the aggregate energy deficit by 15%. This result is associated with the use of stored hydrogen during periods in which instantaneous photovoltaic and wind generation are insufficient to supply the demand represented in the model.

Hydrogen storage is modeled as a strategic flexibility resource rather than only as a destination for hydrogen production. In operating periods with higher renewable availability, available electricity can be transformed into green hydrogen and retained in storage. In periods with lower renewable availability or higher electricity demand, stored hydrogen can be withdrawn and allocated either to industrial use or to fuel-cell conversion. The fuel cells then provide an additional source of electricity, reducing the dependence of the system on instantaneous renewable generation.

The extended output also reports a reduction of 94% in the shortfall indicator under constrained operating conditions. This indicator reflects the ability of the integrated configuration to reduce the most severe shortages represented in the computational experiments. The aggregate deficit reduction of 15% and the 94% reduction in the constrained-condition shortfall indicator describe different aspects of system performance and should not be interpreted as identical measures.

The storage cost assumption used in the simulations is 1.2 USD/kg-H<sub>2</sub>/year. Under this assumption, the model evaluates whether the reliability benefits associated with storing hydrogen justify the additional cost of storage and conversion. The results suggest that storage can contribute to energy-system resilience when it is coordinated with renewable generation, electrolyzer operation, and fuel-cell backup.

The quarterly analysis revealed system-level operating variations of approximately 10–15%, reflecting changes in renewable-resource availability, electricity demand, hydrogen production, storage operation, and fuel-cell utilization. Extended scenario-dependent outputs and computational documentation are available in the public GitHub repository associated with this study (Fernández et al., 2025): <https://github.com/johncortes117/greencities-twostage-stochastic-optimization>.

## 5.3. Seasonal variation and operational interpretation

The quarterly analysis reveals that seasonal conditions influence the operating behavior of the integrated electricity-hydrogen system. The results indicate variations of approximately 10–15% across the quarterly instances. These variations are associated with changes in solar irradiation, wind availability, electricity demand, and the utilization of electrolyzers, storage facilities, and fuel cells. Figure 2 summarizes the principal performance indicators reported for the case study.

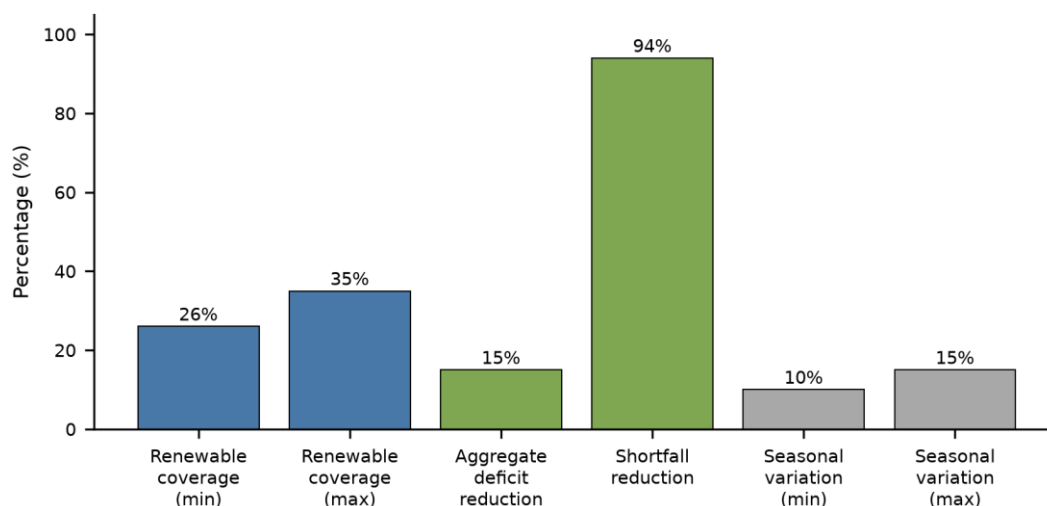


**Figure 2.** Principal performance indicators of the Ecuadorian

Zone 1 case study: renewable electricity coverage, aggregate deficit reduction, shortfall reduction under constrained operating conditions, and seasonal operating variation.

The observed seasonal variation demonstrates the limitations of planning on the basis of average annual conditions alone. An infrastructure configuration that appears sufficient under average resource conditions may experience shortages when solar and wind output decrease simultaneously or when demand increases. Conversely, periods with high renewable availability can generate energy surpluses that can be used for hydrogen production and storage.

The two-stage approach is useful in this context because it permits operational decisions to adapt to the conditions represented in each instance. During favorable conditions, the model can allocate renewable electricity to demand satisfaction and electrolysis. During constrained conditions, it can use the available stored hydrogen to support industrial demand or fuel-cell electricity generation. The scenario-dependent operation therefore transforms renewable variability from a purely limiting factor into a condition that can be managed through coordinated infrastructure and operational decisions.

The seasonal results should be interpreted as a system-level operating variation, not as a change in the intrinsic efficiency of the technologies. The electrolyzer efficiency parameter remains fixed in the model, whereas the realized contribution of each technology varies according to the renewable-resource and demand conditions represented in the quarterly instances.

#### 5.4. Discussion and extended repository results

The results show that the value of green hydrogen in the proposed framework does not arise solely from hydrogen

production. Its main value is related to flexibility. Electrolyzers can absorb renewable electricity during periods in which generation exceeds immediate electricity requirements. Storage can preserve the resulting hydrogen, and fuel cells can convert hydrogen back into electricity during periods of restricted renewable availability. This sequence creates a mechanism for transferring renewable energy across time.

The results also illustrate the importance of considering both urban and industrial demands. Direct hydrogen delivery may contribute to industrial energy requirements, while fuel-cell operation can contribute to electricity-demand satisfaction. The allocation between these uses is determined by the operating conditions and by the cost and shortage parameters specified in the optimization model. This integrated perspective is particularly relevant for regions seeking to use renewable electricity not only for grid supply but also for industrial decarbonization.

The main manuscript reports the central results required to interpret the case study: renewable coverage of 26–35%, maximum hydrogen production of 840,000 kg-H<sub>2</sub> per quarter, 15% reduction in aggregate energy deficit, 94% reduction in the constrained-condition shortfall indicator, and seasonal operating variation of 10–15%. Extended results, including scenario-dependent computational outputs and model documentation, are available in the public GitHub repository associated with this study.

The repository provides supplementary numerical detail and supports transparency and reproducibility. It is particularly useful for readers interested in examining the computational outputs underlying the analysis, including the configuration of renewable resources, hydrogen-production behaviour, storage operation, and scenario-related performance indicators. The repository should be

consulted as complementary material to the methodological explanation and principal findings reported in this article.

These findings are consistent with previous studies on stochastic and robust planning of energy systems under uncertainty. Shahbazi et al. (2021) show that hybrid stochastic/robust formulations improve the resilience of distribution networks against extreme weather conditions, and the present results likewise indicate that scenario-dependent operation reduces the most severe shortages rather than only the average deficit. Hren et al. (2023) report that the environmental and economic performance of hydrogen depends strongly on the production, storage, and transport configuration, which supports the interpretation adopted here that the value of hydrogen arises from its coordination with renewable generation and not from production capacity alone. In comparison with the supply-chain design model of Babazadeh and Sabbaghnia (2018) and the multistage stochastic formulation of Escudero et al. (2009), the proposed model retains the here-and-now versus wait-and-see separation but applies it to a coupled electricity–hydrogen system with explicit industrial hydrogen demand in a developing-region context. The main difference with respect to these contributions is therefore the joint treatment of renewable investment, electrolysis, storage, and fuel-cell backup within a single regional planning framework.

## 6. LIMITATIONS AND FUTURE RESEARCH

The present study is subject to limitations that define the scope of the reported results. First, the model is a strategic planning representation of an integrated electricity and hydrogen system. It does not include detailed electrical power-flow equations, voltage constraints, transmission congestion, hydrogen-pipeline hydraulics, compressor operation, electrolyzer ramping, fuel-cell degradation, or start-up and shut-down dynamics. The results therefore support comparative planning analysis but do not replace a detailed engineering design for a specific facility.

Second, the temporal representation is based on quarterly periods with 96 operating instances per quarter. This structure captures relevant seasonal variation while maintaining a manageable computational formulation. However, it does not reproduce all sub-hourly, hourly, or extreme-event dynamics that may be relevant for real-time system operation. The estimated contribution of storage and fuel cells is therefore conditional on the time resolution and the scenarios used in the case study.

Third, the cost and technical parameters are aggregated assumptions. Actual investment costs, operating costs, technology efficiencies, financing conditions, renewable-resource availability, and hydrogen-storage requirements can vary across locations and projects. The

hydrogen-storage representation should therefore be interpreted as a planning assumption rather than as confirmation of the technical, geological, environmental, or regulatory feasibility of a particular storage site.

Fourth, the results are obtained for the selected regional context and modelled demand structure. The reported coverage, hydrogen-production, deficit-reduction, and shortfall-reduction values should not be generalized automatically to other regions. Their interpretation depends on the available renewable resources, industrial-demand characteristics, infrastructure constraints, and assumptions used in the model.

Future research can improve the proposed framework by incorporating higher-frequency resource and demand data, network-constrained electricity flows, detailed hydrogen-transport infrastructure, alternative storage technologies, demand growth, market-price uncertainty, and extreme weather conditions. Further extensions may include life-cycle emissions, water availability, land-use constraints, and social or regulatory criteria. Multi-stage stochastic and robust optimization approaches could also be used to examine longer planning horizons and more severe forms of uncertainty.

## 7. CONCLUSIONS

This study presented a two-stage stochastic approach for the integrated planning of photovoltaic generation, wind generation, green-hydrogen production, hydrogen storage, and fuel-cell conversion in a representative energy system for Ecuadorian Zone 1. The model distinguishes between long-term infrastructure decisions and scenario-dependent operating decisions, allowing the evaluation of renewable-resource variability and demand uncertainty within a single planning framework.

The computational analysis considered four quarterly periods and 96 operating instances per quarter. The results indicate that solar and wind technologies cover between 26% and 35% of the electricity demand represented in the rural and urban nodes of the case study. The model also indicates green-hydrogen production of up to 840,000 kg-H<sub>2</sub> per quarter in the industrial districts considered.

The integration of hydrogen storage and fuel-cell conversion improves the flexibility of the system by connecting renewable-energy surpluses with periods of lower renewable availability or higher demand. Under the assumptions of the computational case study, the integrated configuration reduces the aggregate energy deficit by 15%. In constrained operating conditions, the shortfall indicator is reduced by 94%. These results show that the principal contribution of hydrogen lies in its ability to transfer renewable energy across time and between electricity and industrial energy uses.

The study contributes a planning-oriented methodology for evaluating the coordinated use of solar energy, wind energy, electrolysis, hydrogen storage, and fuel cells in developing regions. The results are conditional on the selected regional context, resource profiles, demand structure, technology assumptions, and cost parameters. Therefore, the model should be interpreted as a decision-support framework rather than a detailed design or investment recommendation for a specific energy project.

Extended computational materials, including scenario-related outputs and model documentation, are made available through the associated GitHub repository. Future research should incorporate more detailed network constraints, higher-frequency data, site-specific storage assessments, local technology-cost validation,

and environmental and social criteria in order to strengthen the model's applicability to implementation-oriented energy-planning decisions.

**Acknowledgement:** The following research is a tribute to:

- Research Department of the Universidad Politécnica Estatal del Carchi, Tulcán, Ecuador.
- Complements of Robust Optimization of the current Doctoral thesis development in Mathematical Sciences (2022-2027), University of Havana, Havana, Cuba: Modelos de Optimización Matemática para manejo de emergencias meteorológicas en presencia de incertidumbres

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