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Robust Dynamic Electricity Pricing under Uncertainty: A Stochastic-Behavioral Optimization Approach for Senegal

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Abstract

This study develops a stochastic and behavioral extension of a Pyomo-based mixed-integer linear programming (MILP) framework to optimize dynamic electricity tariffs in Senegal under uncertainty. Building on a previously established deterministic model for the 2022-2050 period, the proposed approach explicitly incorporates uncertainties related to electricity demand, fuel prices, renewable availability, and climate stress, while accounting for heterogeneous consumer responses to price signals. Three configurations are compared: a deterministic benchmark (M0), a stochastic model (M1), and a stochastic-behavioral model (M2). Results show that all configurations support a highly renewable transition by 2050, with renewable shares between 78% and 80%, but with different trade-offs between efficiency and robustness. While the deterministic benchmark achieves the lowest average cost under central conditions (68.9 FCFA/kWh), the stochastic-behavioral model provides the best overall performance under uncertainty, combining high renewable penetration (79.5%), competitive costs (≈69.5 - 70.0 FCFA/kWh), reduced subsidies (≈7.1%), and the highest peak reduction (15.8%). Under adverse scenarios, M2 consistently outperforms the other configurations, demonstrating superior resilience. Sensitivity analysis further identifies storage capacity, gas prices, and demand elasticity as key drivers of system robustness. Overall, the findings highlight that tariff design should be approached as an adaptive policy instrument integrating uncertainty management, demand flexibility, and social protection. The proposed Pyomo framework offers a reproducible tool to support predictive tariff regulation and resilient energy planning in Senegal.

Keywords

Pyomo, Stochastic Optimization, Dynamic Pricing, Demand Response, Renewable Energy Integration, Power System Resilience, Developing Countries

1. Introduction

Access to reliable, affordable, and sustainable electricity remains a major challenge in Sub-Saharan Africa. In Senegal, despite significant progress in electrification and renewable energy deployment, the power sector continues to face a triple constraint: expanding access, ensuring financial sustainability, and accelerating the energy transition. In this context, tariff design has evolved from a simple cost-recovery mechanism into a strategic instrument for coordinating demand, investment, and system flexibility [1]-[3].

Recent studies show that optimization-based approaches and dynamic pricing mechanisms can significantly improve tariff efficiency and facilitate renewable integration [4]. In particular, our previous work developed a Pyomo-based Mixed-Integer Linear Programming (MILP) model to optimize electricity tariffs in Senegal over the period 2022-2050, demonstrating that a dynamic hybrid tariff structure can reduce costs and subsidies while supporting high renewable penetration [1]. However, this framework relied on deterministic assumptions and did not explicitly account for uncertainties in electricity demand, fuel prices, and renewable generation.

Such assumptions are restrictive in a rapidly evolving power system. The Senegalese electricity sector is increasingly exposed to uncertainties related to demand growth, fuel price volatility, renewable intermittency, and climate variability. In addition, the effectiveness of dynamic pricing depends on heterogeneous consumer responses, which are often ignored in deterministic models. As a result, tariff structures optimized under average conditions may become fragile under adverse scenarios [5]-[7].

To address these limitations, this study extends the previous framework by introducing

1) A stochastic formulation to account for uncertainty;

2) A behavioral representation of demand based on heterogeneous consumer groups.

The objective is to design a dynamic electricity tariff that remains economically efficient, socially acceptable, and robust under uncertainty. This work contributes to the literature on dynamic pricing, optimization-based energy system modeling using open-source tools, and resilient tariff regulation in developing countries [6]-[9].

2. Literature Review

Research on electricity tariff design has evolved at the intersection of energy economics, regulation, and optimization modeling. The literature can be structured into four main strands: theoretical pricing frameworks, optimization-based energy system modeling, behavioral demand response, and uncertainty and resilience in power systems.

2.1. Theoretical Foundations of Tariff Design

Electricity pricing has historically relied on two main paradigms: average-cost pricing and marginal-cost pricing. The former prioritizes financial equilibrium and cost recovery, while the latter aims at allocative efficiency by reflecting the incremental cost of electricity consumption [10].

In systems with strong temporal variability, marginal-cost pricing provides more accurate signals for efficient resource allocation. However, in many developing countries, regulators still rely on increasing block tariffs and static pricing schemes. While these structures incorporate redistributive objectives, they often fail to reflect temporal cost variations and may distort incentives and subsidy allocation [11].

Dynamic pricing mechanisms—such as real-time pricing, time-of-use tariffs, and critical peak pricing—have been shown to improve cost recovery, reduce peak demand, and facilitate renewable integration when properly designed [12]-[14].

2.2. Optimization Models and Pyomo-Based Applications

The integration of mathematical optimization into energy planning has significantly improved the modeling of power systems. Linear programming (LP), nonlinear programming (NLP), and mixed-integer linear programming (MILP) are widely used to represent multi-technology systems under technical and economic constraints.

Open-source tools such as Pyomo have become increasingly important due to their flexibility, transparency, and reproducibility [8]. Recent studies show that MILP-based models implemented in Pyomo can support robust planning of generation systems, storage investments, dispatch strategies, and tariff design [9] [10].

Applications in emerging economies—including Morocco, South Africa, and Kenya—highlight the relevance of such approaches for data-constrained environments [10]-[12]. However, integrated frameworks combining tariff optimization, renewable integration, and demand-side behavior remain limited in West African contexts.

2.3. Consumer Behavior and Demand Response

A key limitation of many tariff optimization models lies in the simplified representation of demand. The effectiveness of dynamic pricing depends not only on price signals but also on the ability of consumers to adjust their consumption patterns.

Empirical studies emphasize the role of price elasticity in evaluating peak-load reduction and welfare effects [13]. More recent work shows that demand response is highly heterogeneous across consumer groups, depending on income levels, technological access, and usage constraints [14].

This heterogeneity is particularly relevant in African contexts, where low-income households often exhibit limited flexibility, while commercial and industrial users provide greater load-shifting potential. Consequently, tariff efficiency must be assessed alongside distributional impacts and social acceptability [12] [14].

2.4. Uncertainty and Climate Resilience

The increasing penetration of renewable energy has amplified the role of uncertainty in power system modeling. Deterministic approaches may underestimate risks associated with demand variability, fuel price fluctuations, renewable intermittency, and climate-related shocks.

Stochastic and robust optimization methods have therefore become central tools in energy planning [15]-[17]. Stochastic programming represents uncertainty through scenario-based approaches, while robust optimization seeks solutions that remain feasible under adverse conditions. Both approaches aim to avoid fragile optimal solutions.

In parallel, climate change has shifted attention toward system resilience. Extreme weather events, evolving demand patterns, and infrastructure stress increasingly affect system performance. Resilience is now defined as the ability of a system to anticipate, absorb, adapt, and recover from disruptions [18]-[21]. In this context, tariff design must be evaluated not only in terms of efficiency but also in terms of its contribution to flexibility and robustness.

2.5. Research Gap and Contribution

The literature reveals a persistent fragmentation. Studies on dynamic pricing often focus on efficiency without fully incorporating uncertainty. Stochastic optimization models rarely account for behavioral heterogeneity, while resilience studies are seldom linked to tariff design. These gaps are particularly pronounced in African contexts.

This study addresses these limitations by proposing a stochastic and behavioral extension of a Pyomo-based tariff optimization framework for Senegal. Building on a deterministic model [1], it integrates uncertainty in fuel prices, renewable generation, demand, and climate conditions, while explicitly modeling heterogeneous consumer responses. The contribution is both methodological and policy-oriented, supporting predictive tariff regulation and resilient energy governance.

3. Methodology

3.1. General Framework

The proposed model is formulated as a multi-period stochastic optimization problem designed to determine a robust dynamic electricity tariff structure for Senegal over the period 2022-2050. It extends the deterministic Pyomo-based MILP framework developed in our previous study [1], which jointly optimized generation, storage, and tariff design under technical, economic, and social constraints.

Two major extensions are introduced. First, uncertainty is explicitly represented through a finite set of scenarios describing alternative trajectories of electricity demand, fuel prices, renewable availability, and climate-related stress. Second, the model incorporates a heterogeneous representation of demand by distinguishing multiple consumer groups characterized by different price elasticities, baseline consumption levels, and load-shifting capabilities.

Three model configurations are considered for comparison:

- **M0**: deterministic reference model;
- **M1**: stochastic model without behavioral segmentation;
- **M2**: stochastic-behavioral model with heterogeneous demand response.

The calibration of the present stochastic-behavioral framework ensures methodological continuity with the previous stages of this research while extending the model to account for uncertainty and heterogeneous demand behavior. The baseline parameter values are consistently inherited from the previously developed deterministic Pyomo-MILP optimization model and the comparative tariff-scenario analysis, which together established the empirical reference for the Senegalese power system over the 2020-2022 period and its projected transition toward 2050.

To guarantee full comparability across modeling approaches, the three configurations considered in this study: namely the deterministic benchmark (M0), the stochastic model (M1), and the stochastic-behavioral model (M2), share a common calibration point corresponding to the 2022 system conditions. These include an average electricity cost of 83.8 FCFA/kWh, a subsidy rate of 27.5%, and a renewable penetration level of 21.4%. This harmonized initialization ensures that differences in model outcomes can be directly attributed to the introduction of stochastic dynamics and behavioral response mechanisms.

The deterministic benchmark (M0) preserves the original tariff structure based on a three-period time-of-use scheme (off-peak, mid-peak, peak) defined at 65, 90, and 115 FCFA/kWh, respectively, combined with a social protection mechanism through a lifeline tariff of 65 FCFA/kWh applied to the first 50 kWh/month. Building upon this reference structure, the stochastic (M1) and stochastic-behavioral (M2) models introduce adaptive tariff signals and scenario-dependent adjustments, enabling improved robustness under uncertainty, particularly in the presence of demand variability, fuel price volatility, and renewable intermittency.

In addition to inherited parameters, the stochastic-behavioral extension introduces a set of explicitly defined variables governing intertemporal optimization and demand response. The discount rate is fixed at 8%, consistent with standard long-term energy planning practices in developing countries, as commonly adopted in the literature on energy system optimization. Storage system performance is characterized by charging and discharging efficiencies of 0.95, reflecting high-efficiency battery technologies. Demand elasticities are differentiated across consumer groups to capture heterogeneous responses to dynamic pricing, ranging from −0.05 for vulnerable households to −0.25 for industrial users. Hourly flexibility bounds are also introduced to reflect operational constraints, with values of 5%, 12%, 18%, and 22% for vulnerable, standard, commercial, and industrial users, respectively.

Uncertainty is represented through a discrete set of scenarios with associated probabilities defined as (0.40, 0.15, 0.15, 0.15, 0.15), assigning a higher likelihood to the central scenario while maintaining a balanced representation of adverse conditions. These scenarios are designed to capture a range of plausible future system conditions and to evaluate the robustness of investment and tariff decisions under uncertainty.

All calibration parameters are summarized in Table 1, which highlights both the continuity of the empirical and techno-economic framework and the extensions introduced in the stochastic and behavioral dimensions. For full transparency and reproducibility, the complete set of model parameters and scenario definitions are fully documented in the model input database and can be made available upon reasonable request for reproducibility purposes.

Table 1. Main calibration parameters retained for the stochastic-behavioral model.

Parameter	Symbol	Value	Unit	Source	Used in
Base-year average electricity cost	C_{2022}^{avg}	83.8	FCFA/kWh	Previous articles + Figure 2 code	M0, M1, M2
Base-year subsidy rate	Sub_{2022}	27.5	%	Previous articles + Figure 2 code	M0, M1, M2
Base-year renewable share	RES_{2022}	21.4	%	Previous articles	M0, M1, M2
Lifeline tariff	p^{soc}	65	FCFA/kWh	Previous deterministic article	M0, M1, M2
Lifeline threshold	L	50	kWh/month	Previous deterministic article	M0, M1, M2
Off-peak tariff benchmark	p^{off}	65	FCFA/kWh	Previous article + Figure 3 code	M0 reference
Mid-peak tariff benchmark	p^{mid}	90	FCFA/kWh	Previous article + Figure 3 code	M0 reference
Peak tariff benchmark	p^{peak}	115	FCFA/kWh	Previous article + Figure 3 code	M0 reference
Peak tariff (stochastic model)	p_{M1}^{peak}	124	FCFA/kWh	Figure 3 code	M1
Peak tariff (stochastic-behavioral)	p_{M2}^{peak}	121	FCFA/kWh	Figure 3 code	M2
Demand growth (2025/2035/2050)	g^{dem}	5.8/6.2/5.0	%/yr	Previous comparative article	Baseline path
Solar cost (2025/2035/2050)	c^{sol}	82/65/50	FCFA/kWh	Previous comparative article	Baseline path
Wind cost (2025/2035/2050)	c^{wind}	90/70/55	FCFA/kWh	Previous comparative article	Baseline path

Continued

Gas share in mix (2025/2035/2050)	Gas_t	25/20/10	%	Previous comparative article	Baseline path
Renewable share trajectory	RES_t	35/55/75	%	Previous comparative article	Baseline path
Renewable share in 2050	RES_{2050}	80.0/78.0/79.5	%	Figure 7 code	M0/M1/M2
Average cost in 2050	C_{2050}^{avg}	68.9/70.8/69.7	FCFA/kWh	Figure 2 and Figure 7 code	M0/M1/M2
Subsidy rate in 2050	Sub_{2050}	6.8/8.2/7.1	%	Figure 2 and Figure 7 code	M0/M1/M2
Peak reduction in 2050	PRR	13.0/14.2/15.8	%	Figure 4 and Figure 7 code	M0/M1/M2
Storage share in 2050	$Stor_{2050}$	10.0/11.0/11.0	% of mix	Figure 1 and Figure 7 code	M0/M1/M2
Emission reduction in 2050	$ERed_{2050}$	64.0/60.0/62.0	%	Figure 7 code	M0/M1/M2
Additional parameters	r, η^{ch}, η^{dis}, ϵ_g, $\overline{f}_g$, π_ω	$r = 8\%$; $\eta^{ch} = 0.95$; $\eta^{dis} = 0.95$; $\varepsilon_v = -0.05$; $\varepsilon_r = -0.12$; $\varepsilon_c = -0.20$; $\varepsilon_i = -0.25$; $\overline{f}_v = 5\%$; $\overline{f}_r = 12\%$; $f_c = 18\%$; $\overline{f}_i = 22\%$; $\pi = (0.40, 0.15, 0.15, 0.15, 0.15)$	—	Assumed calibration	M1, M2

3.2. Mathematical Formulation

3.2.1. Objective Function

The stochastic objective function minimizes the expected discounted total system cost across all scenarios. In the stochastic formulations (M1 and M2), the model follows a two-stage stochastic programming structure. First-stage decisions (here-and-now) are taken before the realization of uncertainty and are therefore identical across all scenarios. These include generation-capacity expansion, storage-capacity investment, and tariff-design variables defining the admissible dynamic pricing structure. Second-stage decisions (recourse decisions) are scenario-dependent and are adjusted after uncertainty realization. These include hourly generation dispatch, storage charging and discharging schedules, electricity demand by consumer group, and intra-day load shifting.

$$\min Z = \sum_{t \in T} \frac{1}{(1+\rho)^t} \left[\sum_{i \in I} C_i^{inv} X_{i,t} + \sum_{\omega \in \Omega} \pi_\omega Q_t(X, \omega) \right] \tag{1}$$

where:

- T is the set of time periods;
- I is the set of generation technologies;
- ρ is the discount rate;
- $X_{i,t}$ is the investment or installed capacity decision;
- C_i^{inv} is the investment cost;

- Ω is the set of scenarios;
- π_ω is the probability of scenario ω;
- $Q_t(X,\omega)$ is the recourse cost under scenario ω.

The recourse function is defined as:

$$Q_t(X,\omega)=\sum_{h\in H}\left[\sum_{i\in I}C_i^{op}E_{i,t,h,\omega}+C^{stor}\left(S_{t,h,\omega}^{in}+S_{t,h,\omega}^{out}\right)+C^{sub}Sub_{t,\omega}+C^{ls}LS_{t,h,\omega}\right] \quad (2)$$

3.2.2. Supply-Demand Balance

The operation of the electricity system must satisfy a fundamental balance between supply and demand at each time step. This constraint ensures that total electricity generation and storage discharge meet total consumption and storage charging for every period, hour, and scenario.

$$\sum_{i\in I}E_{i,t,h,\omega}+S_{t,h,\omega}^{out}=\sum_{g\in G}D_{g,t,h,\omega}+S_{t,h,\omega}^{in} \quad \forall t,h,\omega \quad (3)$$

where:

- G denotes the set of consumer groups,
- $E_{i,t,h,\omega}$ is the electricity generated by technology i in period t, hour h, under scenario ω;
- $S_{t,h,\omega}^{out}$ is the electricity discharged from storage in period t, hour h, under scenario ω;
- $D_{g,t,h,\omega}$ is the final electricity demand of consumer group g in period t, hour h, under scenario ω;
- $S_{t,h,\omega}^{in}$ is the electricity charged into storage in period t, hour h, under scenario ω.

3.2.3. Capacity Constraints

The electricity production of each technology is limited by its installed capacity and its availability, which may vary across time and scenarios.

$$E_{i,t,h,\omega}\le CF_{i,t,h,\omega}\cdot X_{i,t} \quad \forall i,t,h,\omega \quad (4)$$

where $CF_{i,t,h,\omega}$ represents the capacity factor of technology i.

3.2.4. Storage Dynamics

Energy storage is modeled through an inter-temporal balance equation linking the state of charge across successive time steps, accounting for charging and discharging efficiencies.

$$S_{t,h,\omega}=S_{t,h-1,\omega}+\eta^{in}S_{t,h,\omega}^{in}-\frac{1}{\eta^{out}}S_{t,h,\omega}^{out} \quad \forall i,t,h,\omega \quad (5)$$

The storage level is bounded by its physical capacity:

$$0\le S_{t,h,\omega}\le\overline{S} \quad \forall t,h,\omega \quad (6)$$

where:

- $S_{t,h-1,\omega}$ is the state of charge at the previous time step;
- η^{in} is the charging efficiency ($0<\eta^{in}\le 1$);

- η^{out} is the discharging efficiency ($0 < \eta^{out} \le 1$);
- $\overline{S}$ is the maximum storage capacity.

3.2.5. Renewable Share Constraint

To ensure consistency with national energy transition objectives, a minimum share of renewable energy is imposed in the electricity mix.

$$\frac{\sum_{h \in H} \sum_{i \in R} E_{i,t,h,\omega}}{\sum_{h \in H} \sum_{i \in I} E_{i,t,h,\omega}} \quad \forall t, \omega \tag{7}$$

where $R \subset I$ denotes the set of renewable technologies and α_t the target share.

3.2.6. Dynamic Pricing Equation

Electricity prices are endogenously determined based on marginal system costs, allowing temporal differentiation of tariffs.

$$P_{t,h,\omega} = P_t^{base} + \delta_h \left(C_{t,h,\omega}^{marg} - C_{t,\omega}^{marg} \right) \ \forall t, h, \omega \tag{8}$$

To ensure affordability and regulatory consistency, tariff bounds are imposed:

$$P_t^{\min} \le P_{t,h,\omega} \le P_t^{\max} \quad \forall t, h, \omega \tag{9}$$

where $P_{t,h,\omega}$ is the electricity price, P_t^{base} the base tariff, δ_h a time differentiation factor, and $C_{t,h,\omega}^{marg}$ and $C_{t,\omega}^{marg}$ denote the instantaneous and average marginal costs, respectively. $P_t^{\min}$ and $P_t^{\max}$ represent regulatory tariff bounds.

3.2.7. Behavioral Demand Module

To better capture real-world consumption patterns, demand is modeled as a function of price signals and behavioral parameters.

$$D_{g,t,h,\omega} = D_{g,t,h,\omega}^{ref} \left[1 - \epsilon_g \frac{P_{t,h,\omega} - P_t^{ref}}{P_t^{ref}} \right] + \Gamma_{g,t,h,\omega} \tag{10}$$

where:

$D_{g,t,h,\omega}^{ref}$ is baseline demand;

ϵ_g is price elasticity;

$\Gamma_{g,t,h,\omega}$ captures exogenous effects.

To preserve essential consumption needs, a minimum demand level is enforced:

$$D_{g,t,h,\omega} \ge D_g^{\min} \ \forall g, t, h, \omega \tag{11}$$

Load shifting behavior is represented as:

$$D_{g,t,h,\omega} = D_{g,t,h,\omega}^{ref} - S_{g,t,h,\omega}^{out} + S_{g,t,h,\omega}^{in} \quad \forall g, t, h, \omega \tag{12}$$

with daily energy conservation:

$$\sum_{h \in H} S_{g,t,h,\omega}^{in} = \sum_{h \in H} S_{g,t,h,\omega}^{out} \quad \forall g, t, \omega \tag{13}$$

and bounds on flexibility:

$$S_{g,t,h,\omega}^{out} \le \beta_g D_{g,t,h,\omega}^{ref} \quad \forall g, t, h, \omega \tag{14}$$

3.2.8. Social Protection Constraint

To ensure affordability for vulnerable consumers, a social tariff mechanism is incorporated into the model.

$$P_{t,h,\omega} \le P^{social} \quad \text{for the first } Q^{life} \text{ kWh/month} \tag{15}$$

where P^{social} denotes the regulated social tariff and Q^{life} the lifeline electricity consumption threshold to which this tariff applies.

This constraint guarantees that essential electricity consumption remains accessible under dynamic pricing.

3.3. Scenario Structure

Uncertainty is represented through a finite set of discrete scenarios, each associated with a probability:

$$\sum_{\omega \in \Omega} \pi_\omega = 1, \ \pi_\omega \ge 0 \tag{16}$$

Each scenario ω is defined by a vector of uncertain variables:

$$u_\omega = \left(Dem_{t,\omega}, FP_{t,\omega}, CF^{sol}_{t,h,\omega}, CF^{wind}_{t,h,\omega}, Temp_{t,h,\omega}, l_{t,\omega} \right) \tag{17}$$

where:

- $Dem_{t,\omega}$: electricity demand level;
- $FP_{t,\omega}$: fuel prices;
- $CF^{sol}_{t,h,\omega}$, $CF^{wind}_{t,h,\omega}$: solar and wind capacity factors;
- $Temp_{t,h,\omega}$: ambient temperature;
- $l_{t,\omega}$: system stress or shock indicator.

A baseline set of scenarios is considered:

1) reference (central) scenario;
2) high-demand scenario;
3) fuel price shock scenario;
4) low renewable generation scenario;
5) combined climate-fuel shock scenario.

The comparison of M0, M1, and M2 shows that uncertainty does not change the long-term direction of the energy transition but significantly affects the optimal tariff path. While M0 is the least costly under central conditions, M1 improves robustness by accounting for uncertainty, and M2 further enhances it through demand flexibility. This highlights that integrating behavioral response in tariff design reduces the economic cost of uncertainty and improves adaptability under adverse conditions.

To represent deviations from reference conditions, any exogenous variable x is defined as:

$$x_{t,h,\omega} = x^{ref}_{t,h} \left(1 + \nu_{x,\omega} \right) \tag{18}$$

where $\nu_{x,\omega}$ represents the relative deviation under scenario ω.

Climate effects are explicitly modeled through their impact on demand and renewable availability:

$$D^{clim}_{t,h,\omega} = D_{t,h} \left[1 + k \max\left(0, Temp_{t,h} - Temp^{ref} \right) \right] \tag{19}$$

$$CF_{t,h,\omega}^{clim} = CF_{i,t,h}^{ref}\left(1-\psi_{i,t,h,\omega}\right) \tag{20}$$

where:

- κ : temperature sensitivity coefficient of demand;
- $Temp^{ref}$: reference temperature;
- $\psi_{i,t,h,\omega}$: climate-induced degradation factor.

Each scenario is associated with a probability reflecting its likelihood of occurrence. The central scenario is assigned the highest probability (0.40), while the remaining four scenarios are each assigned a probability of 0.15.

Scenario deviations are defined relative to the baseline trajectory. Demand shocks represent variations in annual consumption and peak load, fuel-price shocks affect thermal generation costs, renewable shocks impact solar and wind capacity factors, and climate effects influence both demand and system stress.

3.4. Peak Reduction Metric

The impact of dynamic pricing on peak demand is evaluated using the Peak Reduction Ratio (PRR), defined as:

$$PRR = \frac{D_{\max}^{ref} - D_{\max}^{dyn}}{D_{\max}^{ref}} \times 100 \tag{21}$$

where:

- $D_{\max}^{ref}$: maximum demand under the reference tariff;
- $D_{\max}^{dyn}$: maximum demand under dynamic pricing.

3.5. Data Sources and Implementation

The model calibration relies on multiple validated data sources. Historical calibration is anchored in SENELEC observations for the period 2020-2022, including hourly load curves, generation data, tariff structures, and network losses. These data are complemented by SENELEC annual reports, which provide information on average revenues, total system costs, net margins, renewable shares, and production costs, forming the empirical baseline of the model.

Techno-economic projections are derived from IRENA and IEA databases. In particular, solar generation costs are assumed to decrease from 82 FCFA/kWh in 2025 to 65 FCFA/kWh in 2035 and 50 FCFA/kWh in 2050, while wind generation costs decline from 90 to 70 and 55 FCFA/kWh over the same milestones. Macroeconomic assumptions and fuel-price trajectories are based on World Bank data. Regulatory tariff structures and social-protection parameters are obtained from CRSE sources.

In the optimization phase, the temporal structure is based on representative time slices constructed from hourly load data. This aggregation reduces computational complexity while preserving demand variability, peak demand patterns, and seasonal effects.

The model is implemented in Python 3.11 using Pyomo 6.5.2. Data preprocessing and visualization are performed using pandas and matplotlib. The implementation extends a previously developed deterministic Pyomo-based MILP framework, ensuring full reproducibility through explicit parameterization and standardized data-model separation.

The main calibration parameters are defined based on national energy planning assumptions and consistent with empirical data sources and regulatory frameworks in Senegal. The discount rate is set to 8%, in line with standard practice in long-term energy planning in developing countries and consistent with World Bank and IEA guidelines. Tariff bounds range between 65 and 125 FCFA/kWh, reflecting CRSE regulatory structures. The renewable penetration target is set between 78% and 80% by 2050, in accordance with national energy transition objectives. Storage charging and discharging efficiencies are assumed to be 95% and 95%, respectively, consistent with typical lithium-ion battery performance. The lifeline consumption threshold is fixed at 50 kWh/month, based on social tariff policies. Demand elasticities vary across consumer groups, ranging from −0.05 for vulnerable households to −0.25 for industrial users, while load-shifting flexibility is limited to ±20% of baseline demand.

All parameters are derived from SENELEC reports, CRSE regulatory documents, IRENA and IEA techno-economic databases, and World Bank projections, ensuring consistency with the empirical and policy context of the Senegalese power system.

3.6. Evaluation Indicators

To ensure consistency with previous stages of the project, four core performance indicators are used and extended to the stochastic framework.

First, the average electricity cost is defined as the ratio of total system cost to total electricity supplied over the planning horizon. This definition is consistent with baseline values of 83.8 FCFA/kWh in 2022 and 68.9 FCFA/kWh in 2050 reported in the deterministic model.

Second, the subsidy rate is defined as the share of total system cost not covered by tariff revenues. This indicator captures the financial sustainability of the electricity system and the burden on public finances.

Third, the renewable energy share is computed as the ratio of electricity generated from renewable technologies to total electricity generation. This indicator reflects the progress of the energy transition and aligns with long-term policy targets.

Fourth, emissions reduction is measured as the relative decrease in direct power-sector CO_2 emissions compared with the 2022 baseline.

For stochastic models (M1 and M2), these indicators are reported as expected values across scenarios, whereas for the deterministic model (M0), they correspond to a single trajectory.

4. Results and Analysis

This section presents the main outputs of the Pyomo-based model applied to the Senegalese power system over the period 2022-2050. Unlike the previous study, which compared tariff scenarios within a deterministic framework, the present analysis focuses on three structural model configurations:

- **M0**: deterministic benchmark;

- **M1**: stochastic optimization without behavioral segmentation;
- **M2**: stochastic-behavioral optimization.

The analysis is structured along seven key dimensions, including system composition, cost dynamics, tariff structure, peak reduction, stress robustness, sensitivity analysis, and overall performance indicators.

4.1. Evolution of the Energy Mix

Figure 1 illustrates the evolution of the electricity mix between 2025 and 2050 across the three model configurations.

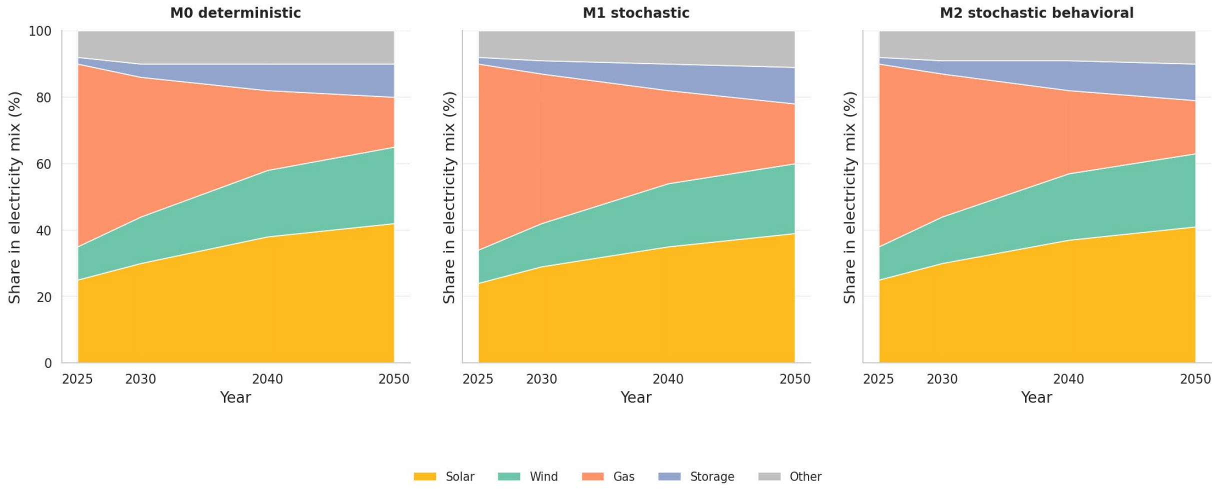

Figure 1. Evolution of the electricity mix under models M0, M1, and M2 from 2025 to 2050.

The deterministic benchmark (M0) leads to a rapid transition toward a renewable-dominated system. By 2050, the mix consists of 42% solar, 23% wind, 15% gas, 10% storage, and 10% other sources. This result is consistent with previous findings, where dynamic tariff optimization enabled renewable penetration to reach approximately 80% of total generation [1].

Introducing uncertainty (M1) slightly moderates this transition. The share of solar and wind decreases to 39% and 21%, respectively, while gas increases to 18%. This shift reflects a precautionary strategy: the model retains more dispatchable capacity to hedge against unfavorable scenarios such as low renewable output or demand surges.

When behavioral flexibility is incorporated (M2), the system regains most of its renewable ambition. The shares of solar and wind rise again to 41% and 22%, respectively, while gas decreases to 16%. This indicates that demand-side flexibility partially substitutes for thermal backup capacity. In other words, behavioral response reduces the need for conservative capacity expansion under uncertainty.

4.2. Evolution of Costs and Subsidies

Figure 2 compares the evolution of average electricity cost and subsidy rates across the three configurations.

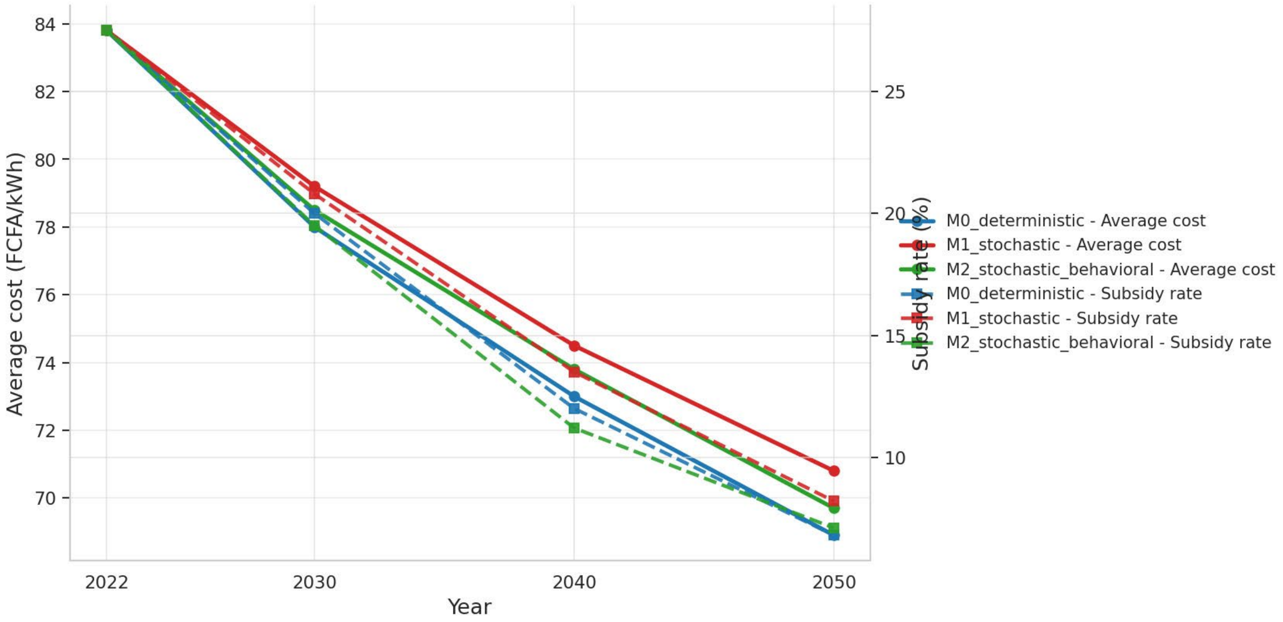

Figure 2. Evolution of the average electricity cost and subsidy rate under the three model configurations.

The deterministic model (M0) yields the lowest average cost trajectory, decreasing from 83.8 FCFA/kWh in 2022 to 68.9 FCFA/kWh in 2050, in line with previous results [1]. The subsidy rate also declines significantly, from approximately 27.5% to around 7%.

The stochastic model (M1) exhibits a slightly higher cost, reaching 70.8 FCFA/kWh in 2050. This increase should not be interpreted as inefficiency but rather as the cost of robustness. By internalizing uncertainty, the model adopts more conservative investment and dispatch strategies.

The stochastic-behavioral model (M2) mitigates this effect. The average cost decreases to 69.8 FCFA/kWh, while the subsidy rate stabilizes around 7.2%. Demand response reduces reliance on expensive peak generation and improves storage utilization, thereby offsetting part of the cost of uncertainty.

Overall, these results indicate that the cost of robustness remains limited when uncertainty management is combined with demand-side flexibility.

4.3. Structure of Dynamic Tariffs

Figure 3 presents the hourly tariff structures generated by the three model configurations.

The deterministic model (M0) reproduces the standard three-period tariff structure identified in previous work: 65 FCFA/kWh during off-peak hours, 90 FCFA/kWh during intermediate periods, and 115 FCFA/kWh during evening peak hours [1].

The stochastic model (M1) produces a more differentiated tariff profile. While off-peak prices remain similar, prices increase more gradually throughout the day, reaching a higher peak of approximately 124 FCFA/kWh. This reflects the need to manage consumption during periods of high system stress and uncertainty.

In contrast, the stochastic-behavioral model (M2) maintains strong temporal differentiation but with a slightly lower peak, around 121 FCFA/kWh. This suggests that incorporating behavioral responses allows the system to achieve demand adjustment without requiring extreme price signals.

Hence, behavioral modeling not only improves realism but also enhances tariff efficiency by reducing the need for excessive price peaks.

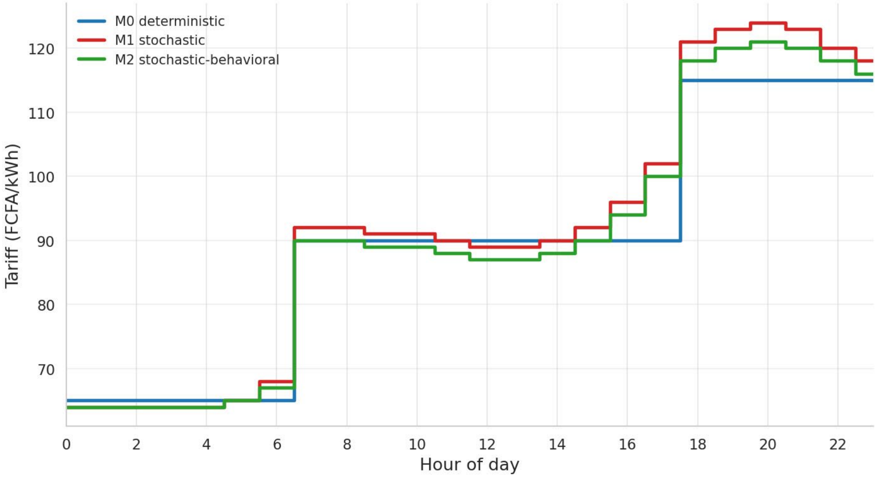

Figure 3. Optimal hourly structure of dynamic electricity tariffs under models M0, M1, and M2.

4.4. Peak Reduction by Consumer Group

Figure 4 reports peak demand reduction across consumer groups as well as at the aggregate system level.

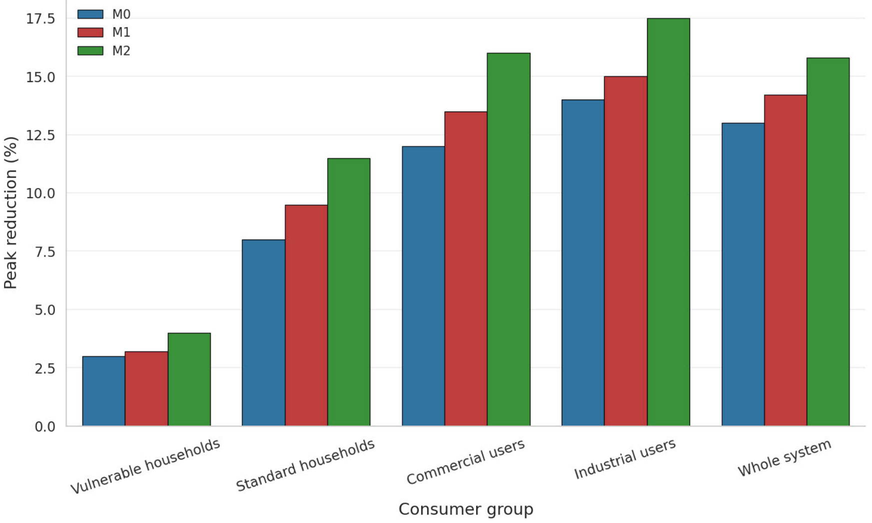

Figure 4. Peak reduction by consumer group under the different model configurations.

The deterministic benchmark (M0) achieves a system-wide peak reduction of 13.0%, consistent with the 12% - 15% range reported in previous work [1]. This performance improves to 14.2% under the stochastic model (M1) and reaches 15.8% when behavioral heterogeneity is incorporated (M2).

Disaggregated results reveal strong heterogeneity in demand flexibility. Vulnerable households contribute only marginally to peak reduction, with reductions of 3.0% (M0), 3.2% (M1), and 4.0% (M2). This limited response reflects the high share of essential and non-shiftable consumption in this group.

By contrast, standard households, commercial users, and industrial consumers provide the bulk of system flexibility. Under M2, peak reduction reaches 11.5% for standard households, 16.0% for commercial users, and 17.5% for industrial consumers.

These results highlight a key policy-relevant insight: system-level flexibility can be significantly improved without imposing disproportionate adjustment efforts on vulnerable consumers. Demand-side heterogeneity therefore plays a central role in achieving both efficiency and equity objectives.

4.5. Robustness under Stress Scenarios

Figure 5 compares the average electricity cost across five stress scenarios.

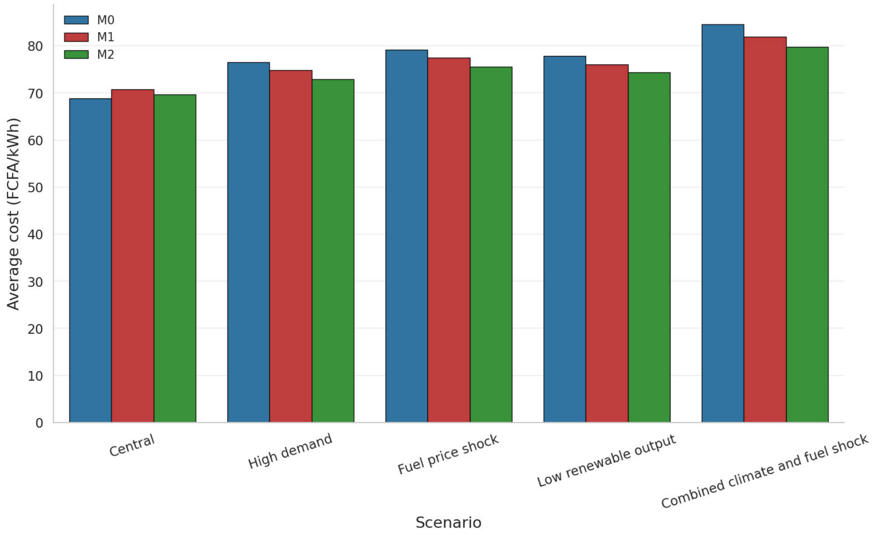

Figure 5. Comparative performance of the models under energy and climate stress scenarios.

In the central scenario, the deterministic model (M0) remains the least costly configuration (68.9 FCFA/kWh), compared to 70.8 FCFA/kWh for M1 and approximately 70.0 FCFA/kWh for M2. However, this ranking systematically reverses under adverse conditions.

Under high demand, average costs increase to 76.8 FCFA/kWh in M0, compared to 75.0 FCFA/kWh in M1 and 73.0 FCFA/kWh in M2. Similar patterns are observed across all stress scenarios. Under fuel price shocks, costs reach approximately 79.5 (M0), 77.5 (M1), and 76.0 FCFA/kWh (M2). Under low renewable generation, the corresponding values are 78.0, 76.2, and 74.5 FCFA/kWh. In the combined climate and fuel shock scenario, costs rise sharply to 84.5 FCFA/kWh in M0, compared to 82.0 in M1 and 80.0 in M2.

These results clearly demonstrate that the deterministic benchmark is optimal only under expected conditions. Once uncertainty materializes, both stochastic configurations outperform it, with the stochastic-behavioral model (M2) consistently delivering the best performance.

This confirms that the primary contribution of the proposed framework lies not in marginal improvements in average performance, but in substantial gains in system resilience under adverse conditions.

4.6. Sensitivity Analysis

Figure 6 presents the sensitivity of the M2 model to key techno-economic and behavioral parameters.

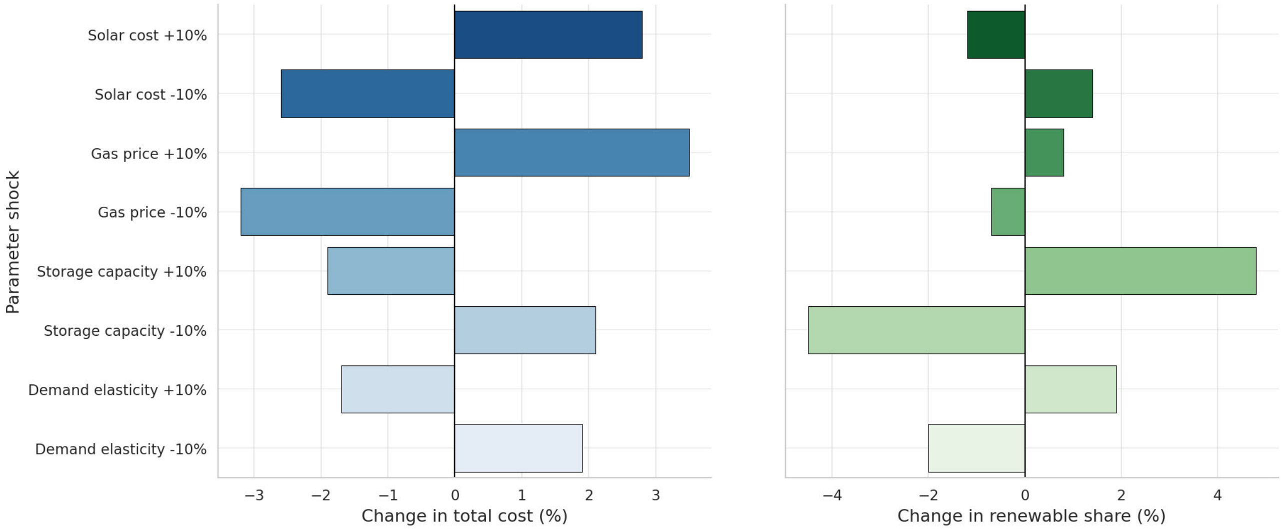

Figure 6. Sensitivity analysis of model M2 results with respect to key techno-economic and behavioral parameters.

A 10% increase in solar costs leads to a 2.8% increase in total system cost and a 1.2% decrease in renewable share. Conversely, a 10% cost reduction decreases total cost by 2.6% and increases renewable penetration by 1.4%. While solar costs remain important, their influence is moderate compared to other parameters.

Gas prices emerge as a more critical driver. A 10% increase in gas prices raises total system cost by 3.7% and slightly increases renewable share (+0.8%). Conversely, a 10% decrease reduces total cost by 3.1% but slightly lowers renewable penetration (−0.7%). This confirms that gas remains a key determinant of system economics, even in a highly renewable pathway.

Storage capacity appears as the most influential lever for renewable integration. A 10% increase in storage capacity reduces total cost by 1.9% and increases renewable share by 4.8%, while a 10% decrease produces the opposite effect.

Finally, demand elasticity emerges as a critical parameter in the extended model. A 10% increase in elasticity reduces total cost by 1.7% and increases renewable share by 1.9%, whereas a decrease produces symmetric effects. This highlights the strategic importance of improving empirical knowledge of consumer behavior for effective tariff design and system planning.

4.7. Synthesis of Key Performance Indicators

Figure 7 provides a consolidated comparison of the main performance indicators in 2050 across the three model configurations.

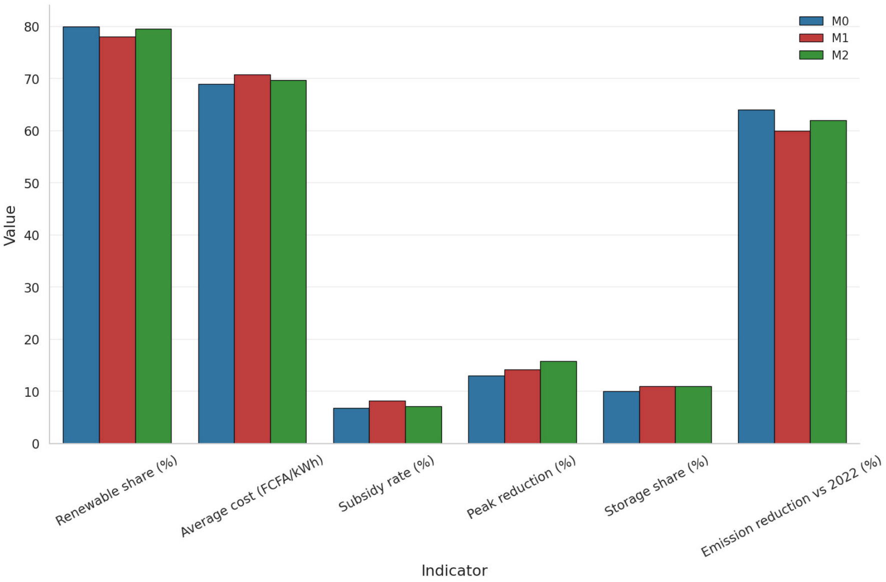

Figure 7. Summary comparison of key performance indicators across models in 2050.

The deterministic benchmark (M0) delivers the best performance under central conditions. It achieves the highest renewable share (80%), the lowest average electricity cost (68.9 FCFA/kWh), the lowest subsidy rate (6.8%), and the largest emission reduction relative to 2022 (−64%). However, these advantages come at the expense of system flexibility and robustness, as reflected in its lower peak reduction performance and weaker resilience under stress scenarios.

The stochastic model (M1) adopts a more conservative strategy. It achieves a renewable share of 78%, with a higher average cost (70.8 FCFA/kWh) and a higher subsidy rate (8.2%). This reflects the cost of explicitly accounting for uncertainty, leading to more cautious capacity and dispatch decisions.

The stochastic-behavioral model (M2) provides the most balanced outcome. It reaches a renewable share of 79.5%, while maintaining an average cost in the range of 69.5 - 70.0 FCFA/kWh and a subsidy rate of approximately 7.1%. In addition, it achieves the highest peak reduction (15.8%) and a significant contribution of storage (11%) to system flexibility.

Overall, M2 emerges as the most efficient compromise between economic performance, demand-side flexibility, and robustness to uncertainty. These results highlight the critical role of integrating both stochastic dynamics and behavioral responses in the design of resilient electricity tariff systems.

5. Discussion and Policy Implications

The results obtained from the stochastic-behavioral Pyomo model highlight the transformative potential of dynamic electricity pricing when both uncertainty and consumer heterogeneity are explicitly accounted for. This section discusses the implications along four complementary dimensions: economic sustainability, social equity, institutional governance, and long-term system resilience.

5.1. Economically Sustainable Yet More Robust Transition

The comparison between M0, M1, and M2 shows that accounting for uncertainty does not fundamentally alter the long-term direction of the energy transition, but significantly reshapes the nature of the optimal solution.

While the deterministic benchmark (M0) achieves the lowest average cost under central conditions, it proves fragile under adverse scenarios. In contrast, the stochastic framework (M1) internalizes uncertainty, resulting in slightly higher expected costs but substantially improved system stability.

Importantly, the stochastic-behavioral model (M2) demonstrates that part of this “cost of robustness” can be offset through demand-side flexibility. This is a key result: robustness does not require a major sacrifice in average performance when tariff design is combined with realistic behavioral modeling.

From a policy perspective, this suggests that integrating demand response into tariff reforms can significantly reduce the economic trade-off traditionally associated with uncertainty management.

5.2. Social Impacts and Energy Equity

Tariff reforms often raise concerns about affordability, particularly for low-income households. The results clearly show that vulnerable consumers contribute only marginally to peak reduction compared to other groups.

This implies that dynamic pricing should not be applied uniformly across all consumers. Instead, it should be accompanied by targeted social protection mechanisms, such as lifeline tariffs and differentiated response expectations across user categories.

Crucially, preserving social protection does not undermine system efficiency. On the contrary, the results from M2 indicate that substantial flexibility can be mobilized from more responsive consumer groups—such as commercial and industrial users—without imposing excessive burdens on vulnerable households.

This finding reinforces the idea that equity and efficiency are not necessarily conflicting objectives in tariff design, provided that heterogeneity is explicitly considered.

5.3. Institutional Strengthening and Predictive Regulation

The effectiveness of dynamic pricing depends not only on model design but also on regulatory capacity. Transitioning from static tariff structures to predictive, data-driven pricing requires stronger institutional frameworks.

In the Senegalese context, the Electricity Sector Regulatory Commission (CRSE) would need to rely on higher-frequency data, scenario-based tariff simulations, and systematic integration of uncertainty into tariff-setting processes.

These results support the argument, already advanced in previous work [1], that tariff regulation should evolve toward a more anticipatory and model-based approach. Establishing dedicated institutional structures—such as a Tariff Optimization Unit (TOU) and a National Observatory for Energy Pricing (NOEP)—could provide the operational backbone for such a transition.

More broadly, this shift reflects a move from reactive regulation toward predictive governance in energy systems.

5.4. Energy Transition, Flexibility, and Climate Resilience

All three model configurations converge toward a highly renewable electricity system by 2050, confirming the technical feasibility of a low-carbon transition in Senegal. However, the comparison reveals that the key issue is not only the final share of renewables, but the robustness of the pathway leading to that outcome.

Storage emerges as a central pillar of system resilience, as confirmed by the sensitivity analysis. However, the results clearly indicate that storage alone is insufficient. Its effectiveness critically depends on its interaction with dynamic pricing and demand-side flexibility. In this respect, the most resilient system is not simply the one with the highest renewable penetration or storage capacity, but the one in which generation, storage, and demand response are coherently coordinated.

Furthermore, the stress scenario analysis demonstrates that climate and fuel uncertainties must be treated as intrinsic components of tariff design. A system that appears optimal under deterministic average conditions can become economically fragile when exposed to heatwaves, demand surges, fuel price shocks, or temporary reductions in renewable generation.

From this perspective, the stochastic-behavioral configuration (M2) provides the most policy-relevant outcome, as it combines a robust low-carbon trajectory with improved performance under adverse conditions.

5.5. Limitations and Future Research Directions

While the proposed framework represents a significant improvement over the deterministic benchmark, several limitations should be acknowledged.

First, the behavioral representation of demand remains stylized. The segmentation of consumer groups and the use of elasticity parameters provide a useful approximation but do not substitute for detailed micro-econometric estimates of actual consumer responses to dynamic pricing in the Senegalese context.

Second, the scenario-based treatment of uncertainty necessarily simplifies the range of possible future trajectories. The results should therefore be interpreted as a structured approximation of robustness rather than a fully exhaustive representation of uncertainty.

Third, several technical constraints of the electricity system remain aggregated. The model does not yet explicitly capture network congestion, spatial constraints, strategic interactions among market actors, or the full range of regulatory implementation frictions.

Future research could address these limitations by:

1) incorporating richer empirical estimates of demand response;

2) coupling stochastic optimization with machine learning-based forecasting tools;

3) integrating more detailed climate-energy interaction modules;

4) extending the framework to regional-scale analyses within the ECOWAS power system.

6. Key Findings and Policy Implications

6.1. Synthesis of Main Results

The simulations conducted over the 2022-2050 period yield five major insights.

First, all model configurations converge toward a highly renewable electricity mix by 2050, with renewable shares ranging from 78% to 80%, confirming the technical feasibility of a low-carbon transition in Senegal.

Second, while the deterministic benchmark remains the least costly under central conditions, the stochastic-behavioral model preserves most of this economic advantage while significantly improving system robustness.

Third, demand-side flexibility emerges as a key driver of system performance. Explicit behavioral modeling increases peak reduction from 13.0% in the deterministic case to 15.8% in the stochastic-behavioral configuration.

Fourth, the stochastic-behavioral model consistently outperforms the deterministic benchmark under all adverse scenarios, highlighting the importance of explicitly accounting for uncertainty.

Fifth, system resilience is shaped by a combination of storage capacity, fuel price dynamics—particularly gas—and demand elasticity, which jointly determine the system's ability to adapt to variability and stress.

Taken together, these findings indicate that tariff design should not be assessed solely on its performance under average deterministic conditions, but rather on its capacity to remain efficient, flexible, and socially sustainable under uncertainty.

6.2. Policy Recommendations

Based on the model results, several strategic recommendations can be formulated.

First, a robust dynamic pricing structure should be progressively implemented, with clear differentiation between off-peak, intermediate, and peak periods, while explicitly incorporating uncertainty into tariff calibration.

Second, tariff regulation frameworks should evolve toward scenario-based approaches, replacing single-trajectory planning with multi-scenario analysis to better capture uncertainty.

Third, demand-side flexibility should be mobilized as a central policy instrument, with priority given to commercial, industrial, and flexible residential consumers.

Fourth, social protection mechanisms must be preserved and better targeted. Lifeline tariffs should remain a core component of any dynamic pricing reform to protect vulnerable consumers.

Fifth, investment strategies should jointly prioritize storage and demand flexibility, recognizing their complementarity rather than treating them as substitutes.

Sixth, institutional and data capabilities must be strengthened. The CRSE, SENELEC, and the Ministry of Energy should enhance their capacity in data collection, tariff analytics, and predictive modeling.

Finally, the framework could be extended to support future regional integration within ECOWAS, particularly in areas such as reserve sharing, storage pooling, and tariff harmonization.

6.3. Strategic Implications and Outlook

The integration of stochastic and behavioral optimization into tariff regulation marks a shift from static tariff administration toward predictive and adaptive energy governance. It redefines electricity pricing as a strategic instrument capable of anticipating cost evolution, demand variability, and environmental stress.

In the Senegalese context, this implies that tariff policy should become a central pillar of the energy transition strategy rather than a downstream regulatory adjustment. The results show that the most effective tariff architecture is neither purely deterministic nor purely risk-averse, but rather an adaptive framework combining uncertainty management, demand flexibility, and social protection.

Such an approach offers a pathway to align tariff regulation with broader objectives of financial sustainability, renewable integration, and climate resilience.

7. Conclusions

This study demonstrates that extending dynamic electricity tariff optimization from a deterministic Pyomo-MILP framework to a stochastic and behavioral model significantly enhances its relevance for public policy. By jointly integrating uncertainty, generation planning, storage, and heterogeneous demand responses, the proposed framework provides a more robust basis for electricity pricing design in Senegal.

Three main conclusions emerge. First, the deterministic benchmark remains a useful reference and delivers the lowest average cost under central conditions, confirming the technical feasibility of a highly renewable and less subsidized electricity system. Second, the stochastic model highlights that robustness to uncertainty comes at a moderate cost, yielding a system that is more conservative but significantly less vulnerable to adverse shocks. Third, the stochastic-behavioral model provides the best overall trade-off, combining high renewable penetration, competitive costs, improved peak reduction, and superior performance under stress scenarios. This confirms that demand-side flexibility constitutes a key system asset alongside storage and dispatchable capacity.

From a scientific perspective, the study shows that tariff design should be framed as a robustness problem rather than a purely deterministic efficiency exercise. From a policy standpoint, it suggests that electricity regulation in Senegal should evolve toward a more adaptive, data-driven, and predictive approach.

Future research could further strengthen this framework by improving empirical estimation of demand response, integrating machine learning-based forecasting tools, refining network constraints, and extending the analysis to regional electricity markets in West Africa.

Ultimately, the most effective dynamic tariff is not the one that minimizes average cost in a deterministic setting, but the one that remains economically efficient, socially acceptable, and technically robust under uncertainty. The stochastic-behavioral Pyomo framework developed in this study provides a reproducible analytical foundation to support such a transition.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Abbreviations

SENELEC	National Electricity Company of Senegal
CRSE	Electricity Sector Regulatory Commission
IRENA	International Renewable Energy Agency
IEA	International Energy Agency
ECOWAS	Economic Community of West African States
Pyomo	Python Optimization Modeling Objects
MILP	Mixed-Integer Linear Programming
LP	Linear Programming
NLP	Nonlinear Programming
DR	Demand Response
PV	Photovoltaic
FCFA	Franc CFA
kWh	Kilowatt-hour
MWh	Megawatt-hour
LCOE	Levelized Cost of Electricity
TOU	Tariff Optimization Unit
NOEP	National Observatory for Energy Pricing
M0	Deterministic benchmark model
M1	Stochastic model
M2	Stochastic-behavioral model