Novasinergia
Revista digital de ciencia, ingeniería y tecnología

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Research article

Urban Load Curve Transformation Driven by Energy Transition Policies: Electric Vehicles and Distributed Photovoltaics in Panama City

Transformación de la curva de carga urbana impulsada por políticas de transición energética: vehículos eléctricos y energía fotovoltaica distribuida en la ciudad de Panamá

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Citación: Boya-Lara, C.; Rivera-Caballero, O. & Galdámez-López, C., (2026). Urban Load Curve Transformation Driven by Energy Transition Policies: Electric Vehicles and Distributed Photovoltaics in Panama City. *Novasinergia. 9*(2). 06-23.

https://doi.org/10.37135/ns.01.18.01

Recibido: 30 enero 2026
Aceptado: 18 mayo 2026
Publicado: 08 julio 2026

Novasinergia
ISSN: 2631-2654

Abstract: This study analyzes how large-scale integration of electric vehicles (EVs) and distributed photovoltaic generation (PV DG), promoted through national energy transition strategies initiated in the early 2020s, transforms the urban electricity load curve in Panama City. The study applies a probabilistic, policy-oriented framework in which EV charging demand is simulated using copula-based modeling based on mobility data, while PV generation variability is represented using hour-specific kernel density estimation (KDE) calibrated to 689 days of measured PV output. Policy-aligned deployment scenarios are evaluated by constructing net load curves and computing operational indicators associated with peak concentration, ramping behavior, and peak-hour displacement. Results show a systematic shift of the peak hour from 12:00 to 19:00 across all scenarios (+7 h). The Power-Average Ratio (PAR) increases from 1.17 in S1 to 1.64 in S9, while the Hourly Ramp Rate (HRR) rises from 4.12 MW/h in S1 to 102.54 MW/h in S9. Net demand at 12:00 decreases across high-PV scenarios, with the largest reductions of −74.28% in S7 and −74.15% in S9, both relative to the 2024 baseline. Net demand at 19:00 increases with EV adoption, reaching +22.70% in S9. These results show that policy-driven EV and PV DG deployment reshapes the temporal structure of urban electricity demand and generates load-curve effects that are not captured by aggregate energy- or capacity-based policy targets.

Keywords: Load curve, Photovoltaic generation, Probabilistic modeling, Urban energy systems, Electric vehicles.

Resumen: *Este estudio analiza cómo la integración a gran escala de vehículos eléctricos (VE) y generación fotovoltaica distribuida (GD FV), impulsada por estrategias nacionales de transición energética iniciadas a principios de la década de 2020, transforma la curva de carga eléctrica urbana en la Ciudad de Panamá. El estudio aplica un marco probabilístico orientado a políticas públicas, en el cual la demanda de carga de VE se simula mediante modelos basados en cópulas derivados de datos de movilidad, mientras que la variabilidad de la generación fotovoltaica se representa mediante estimación de densidad kernel (KDE) calibrada con 689 días de datos medidos de generación FV. Los escenarios de implementación alineados con políticas energéticas se evalúan mediante la construcción de curvas de carga neta y el cálculo de indicadores operativos asociados con concentración de demanda, comportamiento de rampa y desplazamiento de la hora pico. Los resultados muestran un desplazamiento sistemático de la hora pico de 12:00 a 19:00 en todos los escenarios evaluados (+7 h). El índice Power-Average Ratio (PAR) aumenta de 1.17 en S1 a 1.64 en S9, mientras que la Hourly Ramp Rate (HRR) se incrementa de 4.12 MW/h en S1 a 102.54 MW/h en S9. La demanda neta a las 12:00 disminuye significativamente en escenarios con alta penetración fotovoltaica, alcanzando reducciones máximas de −74.28% en S7 y −74.15% en S9 respecto a la línea base de 2024. Por otro lado, la demanda neta a las 19:00 aumenta con la adopción de VE, alcanzando +22.70% en S9. Los resultados muestran que las políticas de despliegue de VE y GD FV modifican la estructura temporal de la demanda eléctrica urbana y generan efectos sobre la curva de carga que no son capturados mediante métricas agregadas de energía o capacidad.*

Palabras clave: *Curva de carga, Generación fotovoltaica, Modelado probabilístico, Sistemas energéticos urbanos, Vehículos eléctricos.*

1. Introduction

The global energy transition is driven by the need to reduce greenhouse gas emissions, meet rising electricity demand, and limit dependence on fossil fuels. The energy sector accounts for more than 75% of global greenhouse gas emissions, with transport and electricity contributing approximately 24% and 44%, respectively [1]. Within this context, electric vehicles (EVs) and distributed photovoltaic generation (PV DG) have been widely promoted as key technologies for decarbonization, particularly when supported by public policy instruments [2], [3].

Distributed renewable generation is commonly associated with increased resilience, energy democratization, and environmental benefits [4], [5]. Solar PV, in particular, stands out due to its declining costs and modular deployment. However, its variable and non-dispatchable nature introduces operational challenges at the system level, including voltage deviations, reverse power flows, and pronounced temporal imbalances between generation and demand. These effects are often summarized by the "duck curve" phenomenon, characterized by a midday demand trough followed by steep evening ramps [6], [7]. In parallel, large-scale EV adoption introduces clustered charging behavior that can intensify peak demand and increase operational stress if charging patterns are not explicitly characterized [8], [9].

Panama has formally embraced this transition through its Energy Transition Agenda 2020–2030, supported by national strategies such as the Electromobility Strategy (ENME) and the Distributed Generation Strategy (ENGED). These initiatives promote rapid electrification of the transport sector and the expansion of distributed solar generation, targeting the electrification of up to 40% of the public transport fleet and more than 1.7 GW of PV DG by 2030 [10], [11]. As a result, EV adoption has increased from two vehicles in 2015 to more than 2000 units by 2025, while installed PV DG capacity expanded from 4.72 MW to about 190 MW between 2015 and 2025, with particularly rapid growth after 2023.

These developments have occurred within an electricity system characterized by limited regulatory and digital maturity [12]. Panama's electricity market continues to operate under a traditional Cost-of-Service (COS) framework, established by Law 6 of 1997, which lacks provisions for dynamic tariffs, bidirectional energy flows, or explicit demand-side flexibility mechanisms [13]. As a result, while EV and PV deployment targets are clearly defined in policy terms, their combined operational effects on the temporal structure of electricity demand have not been explicitly diagnosed. Panama also represents a particular environmental context, as it is internationally recognized as a carbon-negative country due to its forest coverage and land-use profile [14]. Although preserving this condition is not the objective of the present study, it constitutes an implicit system-level constraint that underscores the importance of understanding how electrification policies translate into operational demand patterns.

In this context, this study analyzes how energy transition policies promoting EVs and PV DG reshape urban electricity demand, using Panama City as a representative case. The city concentrates over half of the national population, approximately 42% of installed PV DG capacity, and nearly 79% of registered EVs [15], making it a suitable setting to observe the interaction between policy-driven deployment and system behavior in a tropical urban environment.

This study proposes a probabilistic analytical framework to diagnose load-curve transformation under multiple policy-aligned EV–PV scenarios. EV charging demand is modeled using copula-based methods, while PV generation variability is represented through kernel density estimation (KDE). Net load curves are then constructed and evaluated using system-oriented indicators that capture peak concentration, ramping behavior, and peak-hour displacement. The objective is to determine how the joint deployment of EVs and PV DG alters the temporal structure of urban electricity demand in Panama City and to identify operational effects not captured by aggregate energy- or capacity-based policy metrics.

2. Methodology

The modeling framework developed in this study is summarized in Fig. 1. Anchored in Panama's official energy transition policies, it provides a structured approach to simulating future electricity demand under varying levels of electric-vehicle and distributed photovoltaic adoption. The process begins by integrating the national targets outlined in ENME and ENGED to define penetration levels for EVs and PV DG. Based on these targets, synthetic EV charging demand is generated using a copula-based model that captures the statistical dependence between arrival time and daily travel distance. In parallel, PV generation profiles are simulated using KDE to capture hourly solar variability.

These probabilistic outputs are then combined to construct net demand curves for multiple policy-guided scenarios. The goal is to evaluate how different deployment pathways affect key operational indicators, such as peak demand, ramp rates, and load shifts, and to generate actionable insights that support regulatory modernization, infrastructure planning, and long-term sustainability goals.

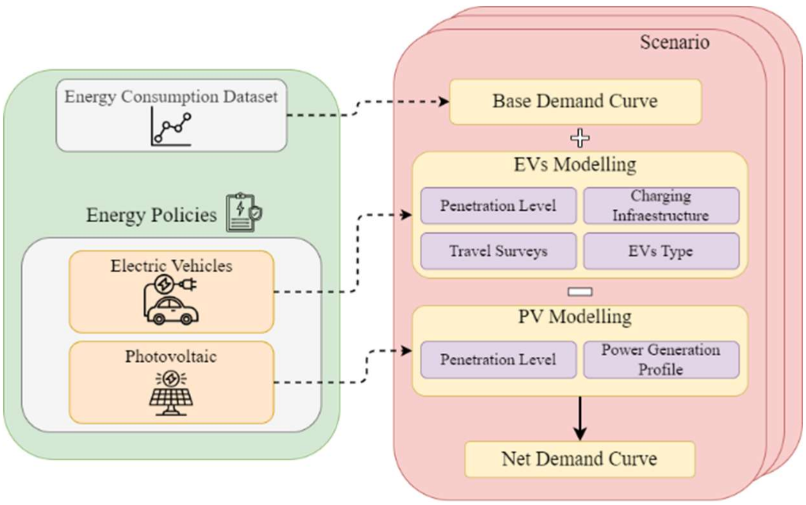

Figure 1. Methodological framework used to simulate EV charging demand, PV DG generation variability, and net load curves under policy-aligned deployment scenarios.

2.1. Policy-Aligned Penetration Levels for EV and PV Deployment

The definition of scenario boundaries in this study is guided by Panama's official energy transition targets. Specifically, the selected EV and PV DG deployment levels are based on the ENME and the ENGED, both of which are part of the ATE 2020–2030. In the case of distributed solar, ENGED outlines three policy-aligned penetration levels for 2030, 2%, 7%, and 14% of national electricity demand, representing trend, conservative, and optimistic adoption scenarios. These targets are grounded in a detailed technical and economic assessment developed for Panama's ENGED with support from the U.S. National Renewable Energy Laboratory (NREL). The assessment incorporated province-level satellite-based solar irradiance data, disaggregated user profiles, cost structures, tariff schemes, and investment recovery calculations. Based on this modeling, ENGED projects a potential installed capacity of up to 1,700 MW of PV DG by 2030 under the most optimistic pathway, aligned with an estimated national electricity consumption of 16,529 GWh/year and a total system demand of 2,449.3 MW. Panama's average daily solar resource, approximately 4.8 kWh/m^2/day [16], supports these projections, positioning the country as a high-potential environment for PV DG, particularly in urban areas where PV deployment can reduce stress on centralized infrastructure and promote the prosumer model.

On the mobility side, the ENME envisions 10%-20% EV penetration in the private vehicle fleet by 2030, with more ambitious targets for public and institutional fleets. These goals are formalized through national legislation [10] and reinforced by fiscal incentives, infrastructure planning, and pilot programs to scale adoption. The targets are designed to reduce emissions from the transport sector, enhance urban air quality, and support energy diversification.

These strategy-aligned levels serve as the foundation for constructing realistic deployment scenarios in this study. Rather than assuming arbitrary technological growth, the analysis simulates adoption pathways that reflect Panama's institutional vision and planning capacity. Table 1 summarizes the combinations of EV and PV shares used to define the scenario matrix.

Table 1. Policy-aligned EV fleet share and PV DG share levels are used to construct the deployment scenarios.

Technology	Trend Scenario	Conservative Scenario	Optimistic Scenario
PV DG Share	2%	7%	14%
EV Fleet Share	10%	15%	20%

2.2. EV Charging Demand Modeling Using Copulas

To simulate realistic EV charging patterns, this study employs a copula-based approach to model the joint behavior of charging start time sct and daily travel distance dt. These variables exhibit statistical dependence: users with earlier or later arrival times may have different daily travel distances, which in turn affect both the charging start time and the required charging duration. The EV charging demand profile $D_i(t)$ for each EV i is estimated as follows [17]:

$$D_i(t) = \begin{cases} 0 & \text{if } t < sct_i \\ P_i & \text{if } sct_i \leq t \leq t_{fi} \\ 0 & \text{if } t > t_{fi} \end{cases} \tag{1}$$

where P_i is the charging power, sct_i is the charging start time, t_{fi} is the final charging time for each EV i. The variable t represents the discrete time intervals ($t = 1,2,3, \dots, T$), where T is the number of intervals. The final charging time is calculated as $t_{fi} = sct_i + tr_i$ and:

$$tr_i = \frac{B_i(1 - SOC_i)}{100\,\% P_i} \tag{2}$$

where B_i is the battery capacity and SOC_i is the state of charge after daily travel calculated as:

$$SOC_i = \left(1 - \frac{dt_i}{d_{max}}\right) \times 100\% \tag{3}$$

where d_{max} is the maximum distance that an EV can travel on a single charge and dt_i is the distance traveled by a user i.

The dependence structure between sct and dt is modeled using copulas. According to Sklar's Theorem [18], [19], a joint distribution $F_{X,Y}$ can be represented as:

$$F_{X,Y}(x, y) = C\big(F_X(x), F_Y(y)\big) \tag{4}$$

where F_X and F_Y are the marginal distributions and C is the copula function. In this study, a bivariate Gaussian copula is used to model the relationship between arrival time and daily travel distance [19]:

$$F_{sct,dt}(sct, dt) = C\big(F_{sct}(sct), F_{dt}(dt)\big) \tag{5}$$

where F_{sct} and F_{dt} are the empirical marginal distributions derived from mobility data. Synthetic EV user profiles are generated by sampling uniform pairs $(u, v) \in [0,1]^2$ from the copula C and transforming them using the inverse marginal distributions:

$$sct_i = F_{sct}^{-1}(u), \qquad dt_i = F_{dt}^{-1}(v) \tag{6}$$

Each pair (sct_i, dt_i) represents a simulated EV user. Repeating this process for N samples produce synthetic charging profiles $D_T(t)$, which are aggregated as:

$$D_T(t) = \sum_i^N D_i(t) \tag{7}$$

where $D_T(t)$ is the total EV charging demand at time interval t.

2.3. PV DG Generation Curve Simulation Using KDE

To simulate PV DG, this study applies KDE to model the probability distribution of PV power output for each hour of the day, using observations collected over multiple days. Instead of modeling a complete daily generation profile, the method constructs a separate KDE model for each hour i, e.g., 08:00, 09:00, ..., 17:00, based on the observed power output at that hour across M different days. This approach captures the intra-hour variability caused by dynamic atmospheric conditions, such as intermittent cloud coverage typical of tropical climates.

KDE is a non-parametric technique that estimates the probability density function of a random variable, providing a smooth representation of variability across time. For each hour i, the power output distribution $\hat{f}_i(x)$ was estimated as [20]:

$$\hat{f}_i(x) = \frac{1}{Mh}\sum_{j=1}^{M} K(\frac{x - x_{i,j}}{h}) \tag{8}$$

where $x_{i,j}$ represents the observed PV power output at hour i on day j, M is the number of observed days, $K()$ is the kernel function (typically Gaussian), and h is the bandwidth parameter controlling the smoothing level. A Gaussian kernel was used, and the bandwidth was selected using Silverman's rule-of-thumb method, providing a consistent smoothing criterion for each hourly PV output distribution. This method provides a probabilistic profile of PV output for each hour, incorporating the natural cloud variability over the year. The resulting distributions were then used to generate synthetic daily PV generation curves by sampling from each $\hat{f}_i(x)$, scaled according to the installed PV DG capacities defined for each scenario, and allocated across residential, commercial, and industrial sectors based on ENGED projections.

2.4. Load Curve Construction and Scenario Design

The modeling framework integrates multiple datasets and modeling stages to generate net demand curves for each policy-driven scenario. The overall workflow was illustrated in Fig. 1 and follows a modular structure with three main components: policy inputs, probabilistic modeling, and scenario-based aggregation.

- **Policy Inputs and Baseline Data**: ENME and ENGED provide the official targets for EV and PV deployment, which are used to establish technology penetration levels in each scenario. The baseline load curve is derived from hourly operational data for the Panamanian power system [21] and adjusted to reflect projected 2030 demand levels.
- **EV Modeling (Copula-Based)**: EV charging demand is simulated by modeling the joint distribution of arrival time and daily distance traveled, using a Gaussian copula. Empirical distributions are derived from local travel surveys (PIMUS) [22] and vehicle specifications. Based on this, time-varying charging loads are generated and scaled to the number of EVs specified for each scenario.
- **PV Modeling (KDE-Based)**: PV generation is modeled using KDE applied to historical power output data for each hour of the day. This enables the generation of

synthetic yet realistic PV output curves that reflect the typical variability of Panama City's tropical climate. These profiles are scaled to match the projected installed capacity for each scenario and sector (residential, commercial, industrial).

- **Scenario Integration and Net Load Curve Construction:** Each scenario combines a specific pair of EV and PV penetration levels (low, medium, or high). The net demand curve is calculated by subtracting hourly PV generation from the base demand and then adding the simulated EV load. This aggregation reflects realistic future electricity demand under policy-aligned technological pathways.

The resulting hourly curves are used to evaluate future load dynamics in 2030, including peak displacement, ramping conditions, and midday troughs.

This comprehensive modeling framework enables the evaluation of diverse decarbonization pathways and their operational consequences for Panama's urban electricity system.

2.5. Indicators and Evaluation Metrics

To assess the impact of each scenario on grid operation and planning, three key indicators are computed from the net demand curves:

- **Power-Average Ratio (PAR)**: This metric is defined as the ratio between the maximum hourly demand and the average demand over 24 hours. It quantifies the "peakiness" of the load curve. Higher PAR values indicate sharper peaks, which require greater generation and grid capacity, increasing infrastructure and operating costs. Scenarios with lower PAR are considered more grid-friendly.
- **Hourly Ramp Rate (HRR)**: This measures the largest change in demand between two consecutive hours. It reflects the grid's need for operational flexibility and the speed at which generation (or storage) must respond to changes in net load. High ramp rates may require fast-responding assets like batteries, flexible generation, or response mechanisms.
- **Peak Hour Shift (PHS)**: This indicator identifies when during the day the maximum demand occurs, allowing planners to detect structural shifts caused by technologies like PV and EVs. A shift from midday to evening peaks, for instance, may require different operational strategies and investment in evening-time flexibility resources.

These metrics provide a practical basis for comparing scenarios and supporting decision-making related to capacity planning, flexibility requirements, and policy design across diverse levels of EV and PV deployment.

3. Results

This section applies the modeling framework described above, including Copula and KDE-based components, to simulate future electricity demand scenarios in Panama City. The analysis focuses on how integrating EVs and PV DG, aligned with national energy transition policies, may reshape the city's load curve. By evaluating the impacts at an urban level, the study captures the localized effects of decentralized technologies on demand patterns, operational indicators, and grid flexibility needs.

3.1. Scenario Design

As described in the methodology, the baseline electricity demand curve is derived from historical hourly data for Panama City, scaled by a 15% projected growth rate between 2024 and 2030, informed by national planning assumptions [21]. EV adoption levels were defined using the policy targets established by the ENME and mobility information from the Plan Integral de Movilidad Urbana Sostenible (PIMUS). The PIMUS survey reports daily household mobility information, including trip origins and destinations, transport modes, trip purposes, and travel patterns. For this study, two variables were extracted from the survey structure: daily travel distance and residential arrival time. Daily travel distance was used to estimate the energy consumed by each vehicle during the day and, consequently, the required charging duration. Residential arrival time was used as the charging start time, assuming uncontrolled residential charging. These empirical distributions were used as marginal inputs for the copula-based model, allowing the generation of correlated synthetic EV charging profiles for the simulated fleet sizes in each scenario. This procedure enables large-scale EV demand simulation from survey data originally collected from a limited number of households.

The metropolitan area of Panama City has approximately 500,000 private vehicles [23]. EV modeling assumed the use of Level 2 AC chargers (240 V, 7.4 kW) and a 2024 Nissan Leaf S as the reference vehicle, with a 40 kWh battery and a 240 km range per full charge [24]. The analysis covered only light-duty private vehicles, excluding buses, taxis, and heavy-duty transport.

For PV generation, KDE models were trained using power output data from a utility-scale PV plant in Farallón, Coclé (8°22'57'' N, 80°06'49'' W), accessed through the CND [21]. The dataset covered 689 days and reflects the typical intra-day variability of PV output in tropical coastal conditions. Fig. 2 shows a subset of 334 hours used to illustrate the midday generation pattern and cloud-induced variability.

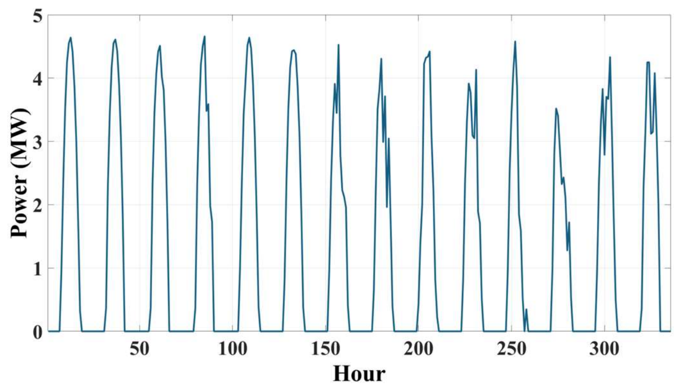

Figure 1. Hourly PV power output (MW) from the Farallón utility-scale solar plant over 334 operating hours used for KDE calibration.

The EV-PV scenario matrix includes three levels of technology penetration, aligned with targets from the ENME and ENGED strategies:

- EV adoption: Low (10%, 50,000 EVs), Medium (15%, 75,000 EVs), High (20%, 100,000 EVs)
- PV DG installed capacity: Low (105 MW), Medium (399 MW), High (714 MW)

Table 2 summarizes the configuration of the nine scenarios evaluated.

It is important to clarify that ENGED sets a national target of 1,700 MW of distributed photovoltaic (PV) capacity to be installed by 2030, whereas the maximum PV deployment level modeled in this study is 714 MW. This is because the simulation framework focuses exclusively on the urban context of Panama City, which currently concentrates approximately 42% of installed PV systems. This modeling choice ensures internal consistency between the study's spatial resolution and the empirical deployment patterns that underpin national energy strategies.

Table 2. EV adoption levels (thousands of vehicles) and PV DG installed capacity (MW) define the nine deployment scenarios evaluated for the 2030 horizon.

Scenario	EV adoption (thousands)	PV DG Installed (MW)
S1	Low (50)	Low (105)
S2	Medium (75)	Low (105)
S3	High (100)	Low (105)
S4	Low (50)	Medium (399)
S5	Medium (75)	Medium (399)
S6	High (100)	Medium (399)
S7	Low (50)	High (714)
S8	Medium (75)	High (714)
S9	High (100)	High (714)

3.2. *Load Curve Impacts*

Before evaluating the future scenarios, it is essential to characterize the baseline used for comparison. This reference curve, shown as the dashed blue line in Fig. 3, represents the projected demand for 2030, assuming no additional EV or PV DG integration. It is derived from operational data for the Panamanian grid and adjusted to reflect a 15% increase in demand from 2024 levels. This baseline exhibits a PAR of 1.25, with a demand peak around 12:00. Demand then declines steadily throughout the afternoon, reaching a mild plateau between 20:00 and 21:00 before tapering off during nighttime hours. This profile reflects expected trends under conventional commercial and residential consumption patterns in urban areas, without the influence of new distributed technologies.

In contrast, Figure 3 presents the net demand curves for the nine EV–PV deployment scenarios projected for 2030. A clear structural shift emerges as early as S1:

- Midday demand drops progressively due to PV generation, reaching a 74.15% reduction in S9.
- Evening demand increases due to EV charging, up to +22.7% in S9 at 19:00.
- PAR grows from 1.17 (S1) to 1.64 (S9), indicating steeper peaks and higher system stress.

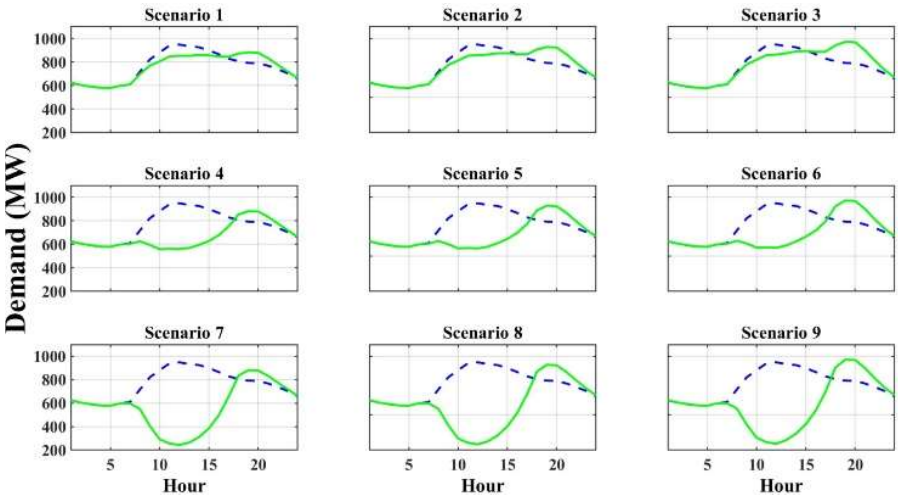

Figure 2. Projected hourly net demand curves (MW) for scenarios S1–S9. The dashed blue line represents the projected 2030 baseline demand without additional EV or PV DG integration, while the solid green lines represent net demand including simulated EV charging and PV DG.

Interestingly, Scenario S1 exhibits a lower PAR than the 2024 baseline (1.17 vs. 1.25), despite integrating 50,000 EVs and 105 MW of PV DG. This counterintuitive result is explained by the structural shift in peak demand from midday (12:00) to the evening (19:00). The modest level of PV generation in S1 reduces midday demand enough to offset the evening peak added by EV charging. Consequently, although total consumption increases, the net load curve becomes smoother than in the previous period, resulting in a lower PAR. This finding highlights the potential of distributed PV—even at low penetration levels—to mitigate peakiness in urban electricity demand.

Table 3. Operational indicators for scenarios S1–S9 relative to the 2024 baseline.

Scenario	PAR	Δ Net Demand @ 12:00 (%)	Δ Net Demand @ 19:00 (%)	HRR (MW/h)	Peak Hour
S1	1.17	-10.08	+11.31	4.12	19:00
S2	1.21	-9.52	+17.14	9.96	19:00
S3	1.25	-9.00	+22.70	15.55	19:00
S4	1.33	-41.08	+11.31	46.05	19:00
S5	1.37	-40.51	+17.14	51.88	19:00
S6	1.41	-39.99	+22.70	57.47	19:00
S7	1.55	-74.28	+11.31	91.12	19:00
S8	1.60	-73.71	+17.14	96.94	19:00
S9	1.64	-74.15	+22.70	102.54	19:00

These changes are quantified in Table 3, which presents PAR and HRR as key indicators of load concentration and flexibility needs. Additionally, the table includes percentage changes in net demand at 12:00 and 19:00, referenced to the 2024 baseline. While all scenarios peak at 19:00, this represents a +7-hour displacement from the original system peak, a structural transformation that must be addressed in planning.

It is important to highlight that all percentage variations and comparative indicators reported in Table 3 are referenced to the historical 2024 baseline. In contrast, the dashed blue curve shown in Fig. 3 represents the projected 2030 baseline demand without additional EV or PV DG integration. It is used only for visual comparison of future demand profiles.

To complement the detailed scenario analysis, Fig. 4 presents a heatmap summarizing the normalized impact of each EV–PV deployment scenario on two key operational indicators: PAR and HRR. The color intensity reflects the relative stress induced by each configuration, with darker shades indicating greater operational challenges. While the absolute metrics are reported in Table 3, this visual summary facilitates a quick comparison of scenario severity and enables a clearer identification of threshold scenarios. Notably, all cases produced a consistent shift in peak demand from 12:00 to 19:00 (+7h), which, although invariant across configurations, signals a structural transformation in grid operation. This increasing operational stress is further compounded by load curve variability, which is explored in the following section.

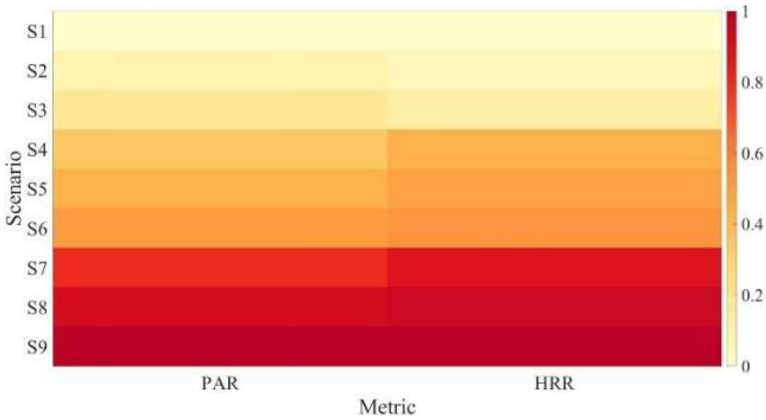

Figure 3. Normalized operational indicators (PAR and HRR) for scenarios S1–S9.

3.3. *Load Curve Variability*

Beyond changes in total demand and peak magnitude, the joint deployment of EVs and PV DG introduces operational volatility due to hourly load variability. A key metric for quantifying this effect is the HRR, defined as the steepest change in net demand between two consecutive hours. As shown in Table 3, HRR increases sharply across scenarios—from 4.12 MW/h in S1 to over 102 MW/h in S9—indicating a growing need for flexible resources such as battery storage, fast-ramping generation, and demand response mechanisms. This trend is especially prominent between 17:00 and 19:00, when solar generation wanes and residential EV charging intensifies.

Although all future scenarios peak at 19:00, this corresponds to a +7-hour structural shift from the 2024 baseline peak at 12:00. While this PHS is constant across scenarios and therefore excluded from Table 3 as a separate column, it nonetheless signals a fundamental change in the timing of system stress, with critical implications for grid operation and planning.

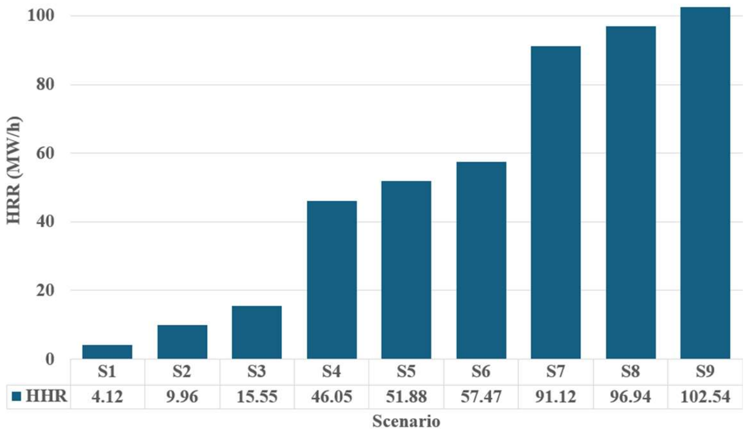

Figure 4. Hourly Ramp Rate (HRR, MW/h) values for scenarios S1–S9. Each bar represents the maximum absolute inter-hour variation in net demand for the corresponding EV–PV deployment scenario.

To better visualize the increasing operational volatility, Fig. 5 illustrates the HRR across all scenarios. The results confirm a nonlinear increase in ramping requirements: while low-deployment scenarios remain within manageable limits (<20 MW/h), high-penetration configurations (S7–S9) require the grid to handle hourly swings exceeding 90 MW/h. This level of demand fluctuation is significant for a developing urban grid such as Panama City's. As the country currently lacks utility-scale storage and real-time demand response infrastructure, such ramping magnitudes would strain the existing generation fleet and increase the risk of imbalances.

Although the peak demand hour (19:00) remains constant across scenarios, this represents a +7-hour structural shift from the historical peak at 12:00. Such displacement concentrates operational stress in the evening period, when solar generation is no longer available. This reinforces the case for flexibility investments targeted toward post-sunset demand ramps. These findings confirm that increased EV and PV DG penetration not only shifts peak demand to the evening but also amplifies hourly variability, stressing grid flexibility requirements.

In parallel, these patterns of volatility and structural load shifts underscore the need for regulatory foresight and anticipatory planning. Without institutional mechanisms to enable flexibility, price signals, and coordinated resource integration, even moderate deployment trajectories could strain system stability in ways that conventional planning may underestimate.

4. Discussion

4.1. Technical Implications

The combined deployment of EVs and PV DG in Panama City produces a substantial transformation of the urban electricity demand profile. Results from multiple policy-aligned scenarios reveal structural effects with direct implications for grid operations and long-term planning.

The load curve exhibits a systematic shift in the PH from midday (12:00) to the evening period (19:00) across all evaluated scenarios. This temporal displacement shifts when system stress concentrates, reducing the contribution of solar generation during peak-demand hours and increasing reliance on fast-ramping or dispatchable resources in the post-sunset period. This shift reflects a change in the temporal organization of demand rather than a marginal variation around historical patterns.

This peak displacement is accompanied by a pronounced increase in operational stress, as reflected in the growth of PAR and HRR. As EV and PV penetration levels rise, demand becomes more concentrated in time, and inter-hour variability intensifies. These trends indicate that large-scale, unmanaged deployment of EVs and PV DG increases flexibility requirements and challenges existing operational practices, particularly in electricity systems with limited digitalization and real-time control.

These dynamics extend beyond grid engineering considerations. Panama's recognition as a carbon-negative country establishes an implicit system-level constraint, as increased evening demand may require additional fossil-based dispatch depending on marginal generation availability. Although emissions are not explicitly modeled in this study, the observed shift of demand toward periods with limited renewable availability highlights a potential tension between deployment-focused policies and operational sustainability.

The diagnosed load-curve transformations point to the relevance of flexibility resources capable of addressing temporal mismatches between generation and demand. Battery energy storage systems, demand response programs, and future vehicle-to-grid integration represent potential mechanisms for managing the identified stress patterns. These options are not evaluated in this work, but the results provide a quantitative basis for assessing their necessity under continued EV and PV expansion.

The analysis demonstrates that even moderate levels of EV and PV DG penetration reshape urban load curves in ways that challenge conventional planning assumptions. Without an explicit temporal diagnosis and corresponding regulatory adaptation, energy transition policies risk introducing new sources of operational stress in urban electricity systems. The framework developed in this study enables the identification of these structural effects in data-constrained contexts and supports more informed evaluation of policy-driven electrification pathways.

4.2. *Policy Implications*

The technical findings indicate that Panama's electricity system may experience increasing operational stress as EVs and PV DG expand under current energy transition policies. While national strategies such as ATE 2020–2030, ENME, and ENGED clearly define deployment targets, the electricity market continues to operate under a COS regulatory model. This framework limits demand-side participation, dynamic pricing, and bidirectional energy flows, constraining the system's ability to respond to the temporal effects identified in the load-curve analysis.

The diagnosed transformation of the urban load curve highlights a gap between policy objectives expressed in terms of capacity and adoption rates and the operational behavior of the electricity system. In particular, the absence of regulatory mechanisms that explicitly address peak timing, ramping behavior, and flexibility requirements reduces the system's capacity to accommodate the combined effects of EV and PV deployment. As a result, policies focused solely on technology diffusion may increase operational stress if temporal impacts are not incorporated into planning and regulation.

International experience illustrates how regulatory frameworks can evolve to address similar challenges. Time-of-use (TOU) tariffs and demand response (DR) programs have been implemented in countries such as Chile and Colombia to manage peak demand and improve system flexibility [25], [26], [27], [28]. Performance-based regulation in Brazil has been used to incentivize investment in grid modernization and operational flexibility [29], [30]. At the same time, Mexico has introduced incentive schemes and regional TOU structures to support private-sector participation [31]. High EV-penetration contexts such as Germany and Norway further illustrate the role of digital infrastructure and active consumer participation in system balancing [32], [33].

Within Panama's institutional context, these experiences point to the need for a phased regulatory transition that incorporates temporal and operational diagnostics into policy design. The recommendations outlined in Table 4 build on existing national roadmaps [12] and are informed by the load-curve transformations identified in this study. Rather than prescribing specific control strategies, they emphasize enabling conditions for flexibility, coordination, and system observability, allowing future interventions to be evaluated against diagnosed operational needs.

Table 4. Phased regulatory transition measures (short-, medium-, and long-term) proposed to address operational impacts associated with EV and PV DG deployment.

Phase	Recommendation
Short term	Enable TOU tariffs for EV users.
	Launch aggregator pilot programs for coordinated smart charging.
	Update net billing schemes to reflect real-time valuation of distributed generation and consumption.
Medium term	Invest in digital metering and control infrastructure to support real-time flexibility.
	Develop technical and regulatory protocols for V2G integration.
	Strengthen interoperability standards for sector-wide data sharing and coordination.
Long term	Modernize the institutional framework for electricity sector governance.
	Foster inter-agency collaboration and public engagement.
	Integrate emissions monitoring to align system operation with climate commitments.

4.3. *Limitations and future work*

This study provides a diagnostic assessment of how large-scale integration of EVs and PV DG reshapes the urban electricity load curve. Still, several limitations must be acknowledged to guide interpretation and future research. As a scenario-based modeling effort, the analysis reflects trade-offs between analytical depth, data availability, and policy relevance. While the proposed framework captures structural effects in the temporal organization of demand, certain simplifications were required to preserve tractability, transparency, and replicability.

First, EV charging behavior and PV generation patterns are represented using probabilistic models calibrated with available mobility surveys and historical PV production data from a utility-scale plant. This approach supports realistic, policy-aligned scenario construction but does not capture the full range of behavioral heterogeneity or microclimatic variability within the urban area. A specific limitation of the PV modeling is that generation profiles were derived from a utility-scale PV plant and used as a proxy for distributed urban PV behavior. This may introduce bias because rooftop systems can differ in orientation, tilt, shading, self-consumption patterns, and geographic dispersion. Therefore, the PV profiles used in this study should be interpreted as representative of tropical solar variability rather than as a full spatial model of urban distributed generation. Future work should incorporate rooftop-level measurements, spatial diversity factors, or synthetic urban PV profiles to better represent distributed PV deployment across Panama City. As higher-resolution mobility, charging, and solar datasets become available, the framework can be refined to improve spatial and temporal granularity.

Second, the scope of the study is limited to light-duty private vehicles and excludes other electrification vectors, such as public transportation, commercial fleets, or building electrification. Extending the analysis to additional demand sectors would provide a more comprehensive view of the impacts of urban electrification. Still, the current focus allows the isolation of EV–PV interactions that are directly targeted by existing national strategies.

Third, emissions impacts are not explicitly quantified. While Panama's carbon-negative status provides an important contextual backdrop, the study focuses on diagnosing temporal changes in demand rather than estimating emissions outcomes. Future research could couple the diagnosed load-curve changes with marginal generation models to assess emissions implications under different dispatch assumptions.

Finally, limited access to high-resolution operational data (e.g., AMI or SCADA) constrains model calibration. This limitation reflects structural conditions, including legacy metering infrastructure, restricted data-sharing mandates, and incomplete digitalization. In this context, the framework's low-data-demand design enables policy-relevant analysis despite these constraints and enhances its applicability to other data-scarce urban systems.

Future work may increase analytical resolution through integrated grid simulations, sector coupling, or agent-based approaches, enabling deeper exploration of interactions among users, technologies, and regulatory structures in rapidly transitioning urban energy systems.

5. Conclusions

This study analyzed how policy-driven EV and PV DG deployment transforms the temporal structure of urban electricity demand in Panama City under data-constrained conditions. The results show that evaluating energy transition policies solely by aggregate capacity or energy targets is insufficient, as operational effects emerge through the timing of demand, the displacement of the peak hour, and increased ramping requirements.

The results show that even moderate levels of EV and PV integration produce structural changes in the temporal organization of urban electricity demand. Peak demand systematically shifts from midday to evening hours, while indicators such as PAR and HRR increase with rising deployment levels. Although distributed PV reduces net demand during midday, the temporal concentration of EV charging intensifies evening stress and ramping requirements, revealing operational effects not captured by aggregate energy- or capacity-based policy metrics.

These findings demonstrate that energy transition policies focused on deployment targets alone are insufficient to characterize their system-level consequences. Without an explicit temporal diagnosis of demand, policy-driven electrification and distributed generation can translate into increased operational stress, particularly in electricity systems governed by legacy regulatory frameworks and limited digitalization. In this context, scenario-based analysis provides a practical tool for connecting policy objectives to physical system behavior when high-resolution operational data are unavailable.

The framework developed in this study is transferable to other urban systems undergoing rapid electrification, especially in the Global South. By incorporating temporal and operational diagnostics into planning processes, policymakers and system planners can better anticipate load-curve transformations induced by EV and PV deployment and evaluate future regulatory or infrastructural responses on a physically grounded basis.

Author Contributions

Conceptualization, C.B.-L.; methodology, O.R.-C. and C.G.-L.; software, C.B.-L.; formal analysis, C.G.-L. and O.R.-C.; investigation, C.B.-L., O.R.-C. and C.G.-L.; data curation, O.R.-C.; writing—original draft preparation, O.R.-C. and C.G.-L.; writing—review and editing, C.B.-L.; visualization, O.R.-C.; supervision, C.B.-L.; funding acquisition, C.B.-L. All authors have read and approved the published version of the manuscript.

Acknowledgments

The authors gratefully acknowledge the support of the National Secretariat of Science, Technology, and Innovation of Panama (SENACYT) and the Specialized Higher Technical Institute (ITSE).

Conflict of Interest

The authors report no conflicts of interest related to this research.

Generative Artificial Intelligence (AI) Use Statement

Generative artificial intelligence tools were used exclusively for language revision and editorial assistance. All scientific content, analysis, modeling, and conclusions were developed and validated by the authors.

Funding Sources

This work was supported by Secretaría Nacional de Ciencia, Tecnología e Innovación (SENACYT) and the Sistema Nacional de Investigación (SNI) de Panamá.

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