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Research article

Analysis of installed photovoltaic capacity in Mexico: A systems dynamics and conformable fractional calculus approach

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Abstract: This study develops a new estimation method within the system dynamics (SD) framework, incorporating fractional calculus (FC) to conduct a sensitivity analysis on photovoltaic capacity growth in Mexico. The primary goal is to address the need to model energy transitions accurately and realistically, considering Mexico's advantages in renewable energy, particularly solar power. The study explores the use of FC to improve the precision of simulations and provide valuable insights into the growth of photovoltaic installations under different market conditions and policies.

The methodology is structured in three phases. Initially, an exponential growth model is developed to simulate the early stage of photovoltaic capacity expansion, incorporating key variables such as public investment, subsidies, and the effects of rural loss on the adoption of renewable technologies. In the second phase, a sigmoidal growth model is applied to represent more realistic capacity limits, considering market saturation and structural limitations. The differential equations governing the growth were solved using the conformable derivative, which captures the complexity of the system's dynamics, including memory effects.

The sensitivity analysis performed on both the exponential and sigmoidal models reveals that the fractional parameter $\alpha = 0.8652$ provides the best fit to the actual data from 2015 to 2023, reducing the average error to 16.52%. Projections for the period from 2023 to 2030 suggest that Mexico's installed photovoltaic capacity could range between 23,000 and 25,000 MW, with α values varying between 0.8 and 1, aligning with the expected market dynamics and national energy goals.

This study emphasizes the importance of using system dynamics combined with FC as an innovative tool for energy planning in Mexico. The ability to simulate multiple scenarios and perform sensitivity analyses is crucial for optimizing energy resources, designing policies that promote renewable technologies, and ensuring a successful transition to a sustainable energy future.

Keywords: renewable technologies; solar irradiance; sensitivity analysis; system dynamics; fractional conformable derivative; installed photovoltaic capacity

1. Introduction

One crucial international commitment to fight climate change is the Paris Agreement, which has been in force since 2020. The Participating countries, including China and Turkey, have committed to increasing the share of non-fossil energy in their respective energy matrices. For example, China has committed to reducing the increase in its carbon emissions [1, 2]. Turkey committed to reducing greenhouse Gasses (GHGs) emissions by 21% by 2030 compared with the current situation [3]. However, the withdrawal of the US from the agreement in 2018 raised uncertainty about the economic and environmental consequences of not meeting targets for non-fossil energy consumption [4].

Mexico has evolved considerably in installed photovoltaic capacity over recent years, driven by the new government's energy policies, which are focused on transitioning to renewable sources. The country set a target to ensure that by 2030, 35% of the energy generated will come from clean sources, including solar energy, according to the Ministry of Energy [5]. A series of incentives created by the Mexican government has facilitated the transformation of installed photovoltaic capacity. The results were significant between 2015 and 2019 [6]. This increase in renewable energy has been successful, and the dependence on fossil fuels has been reduced [7].

In addition to expanding photovoltaic capacity, decarbonization is an essential component in meeting the international agenda for reducing carbon dioxide emissions by 2030 and 2050. Solar energy offers opportunities to produce green hydrogen and sustainably meet future energy demands. In Mexico, regions with high potential for renewable energy production, such as the western part of the country and Oaxaca, have been identified as having significant capabilities for solar and wind power generation. These renewable resources could be integrated into hydrogen production processes, such as photocatalysis and photoelectrochemical cells, which have potential applications in sectors such as transportation, heating, and industry [8].

In this context, various studies have analyzed the implementation and use of solar energy in Mexico, highlighting both opportunities and challenges. Silva and Andrade [9] conducted a comprehensive review of how solar energy is harnessed and implemented in the country, noting that although photovoltaic technology is still relatively novel, both public and private entities are collaborating to build sustainable options. On the other hand, Pérez and Hansen [10] conducted a life cycle assessment of a grid-connected photovoltaic system in Mexico City, concluding that this technology represents one of the cleanest energy sources with the lowest environmental impacts throughout its life cycle. These findings underscore the importance of broader technological deployment, which could accelerate the transition toward a sustainable and diversified energy future.

However, there is a clear need to improve justice and sustainability in the implementation of renewable energy projects. In rural communities of developing countries, where diesel-fueled power generation is common, hybrid renewable energy systems (HRESs) offer an environmentally and economically attractive alternative. A recent study analyzed the feasibility of implementing an HRES based on photovoltaic technology to meet the power demand in rural areas. The study compared different power systems, including a diesel generator with battery storage, a photovoltaic system with storage, and a photovoltaic system with a diesel generator and battery storage. The results indicated that the photovoltaic/diesel generator/AGM battery hybrid power system was the most feasible, offering the lowest cost of energy (COE) at USD 0.14/kWh. This demonstrates that it is possible to meet the electricity demand of rural communities at a reasonable and accessible cost [11].

Uncertainty in private investment and government policy changes affect the growth of photovoltaic development rate [12, 13]. In this context, robust predictive models are needed to simulate different scenarios under changing conditions, such as using system dynamics in policy formulation. System dynamics is based on the use of causal loop diagrams and differential equations to represent interactions between different components of the system and to understand the system's evolution over time, enabling the simulation of future scenarios and identification of effective policies.

System dynamics models have proven to be valuable tools across various fields, providing analytical frameworks for strategic decision-making. In the energy sector, they have been used to forecast the growth in electricity consumption of data centers and assess the impact of factors such as the end of Moore's Law and the rise of the Industrial Internet of Things [14]. In the industrial sector, they have been applied to analyze and predict emergency situations in oil refineries, improving safety management systems [15]. In environmental studies, these models have facilitated the understanding of water pollution caused by tourism, emphasizing integrated strategies for mitigation [16]. Similarly, they have been instrumental in flood risk management through participatory approaches involving communities and experts in the development of mitigation strategies [17]. Lastly, in the construction sector, system dynamics models have been employed to simulate the impact of environmental policies on carbon emission reductions in the prefabricated building supply chain, highlighting the effectiveness of economic incentives and environmental regulations [18].

Models like MEDEAS allow for the analysis of interactions among energy availability, the investments needed for the energy transition, and biophysical constraints, providing a dynamic assessment of potential mineral scarcities and the impacts of climate change on energy systems [19]. Furthermore, the model presented by Capellán-Pérez et al. [20] shows that a decline in fossil fuel is crucial for planning future energy scenarios; otherwise, the current projections could be overly optimistic.

A system dynamics model simulates different investment scenarios, allowing companies to adapt to uncertain policies and maximize their long-term benefits [21]. This approach also applies to energy management in buildings, where the implementation of energy management systems allows for the optimization of electricity usage and reduced demand in a context of increasing consumption [22]. These models address the uncertainties inherent in the energy transition, facilitating the development of sustainable strategies for the future.

The fundamental purpose of this research is to establish an estimation method that fits within the framework of system dynamics. This method is based on FC and is used as a tool to carry out a sensitivity analysis. As a practical case, this methodology is applied to examine the growth of photovoltaic installation capacity in Mexico, a topic of great relevance given the increasing importance of renewable energies in the current energy context of the country.

Improving the performance of a dynamic model is based on designing several scenarios and changes in key parameters of the model to understand how they affect outcomes and provide information for better decision-making. This allows for the identification and classification of the most influential parameters, typically varying one at a time, which can limit the analysis by failing to adequately capture nonlinear growth or other complex behaviors that are difficult to analyze [23, 24]. Unlike conventional sensitivity analyses, this fractional approach allows the observation of the system's behavior as a function of both the fractional parameter α and the time t, generating a variety of adjustable scenarios according to different values of α [25]. The use of conformable FC introduces additional flexibility, significantly expanding the modeling possibilities to predict solar capacity growth in response to changes in policies and market conditions.

Conformable FC is a valuable tool for modeling nonlinear phenomena with short-term memory effects, making it particularly suitable for improving system dynamics models applied to electric markets and capacity projections. By incorporating this approach, it is possible to address the volatility and uncertainty of the system more accurately, providing a realistic view of future behavior [26]. This calculus has been applied in fields such as viscoelastic theory [27], fractional cosmology [28], and stability analysis [29], and it is especially useful in the energy sector for modeling renewable energy growth and assessing the impact of policies on infrastructure [30].

This method has broad applications, including the analysis of electrical circuits that exhibit dynamic and nonlinear behaviors [31], as well as modeling complex systems like soliton profiles and Korteweg–de Vries equations [32].

This research focuses on the development of system dynamics models to evaluate the growth of photovoltaic energy capacity in Mexico, integrating both the public and private sectors into the analysis. To conduct this study, a system dynamics model was used to simulate the installed photovoltaic capacity growth in Mexico between 2015 and 2030. This approach allows for the analysis of installed capacity evolution on the basis of multiple key variables, considering both the initial exponential growth and the subsequent sigmoidal stabilization of the system.

The model was developed using the Vensim platform and is based on differential equations representing two growth patterns: exponential and sigmoidal. During the first phase (2015–2023), the model describes exponential growth driven by the initial adoption of photovoltaic technologies. Subsequently, for the period 2023–2030, a sigmoidal behavior is introduced, reflecting market saturation and the physical and economic limits of installed capacity expansion.

To improve the estimation of photovoltaic growth, FC techniques were incorporated through the use of the fractional conformable derivative, employed as a new estimator in system modeling. Additionally, an innovative sensitivity analysis was developed on the basis of this approach, adjusting the alpha parameter in different scenarios to evaluate its impact on the model projections. Comparing the results with historical data allowed for optimization of the model's accuracy and provided a more detailed characterization of the evolution of installed capacity in Mexico.

The model also considers key economic and energy factors. Elements influencing the profitability of photovoltaic systems were analyzed, such as installation and operational costs, generation efficiency, and the impact of public and private investments. Furthermore, the analysis included capacity losses in rural areas, where photovoltaic systems represent a key solution for electrification but face risks of disconnection or underutilization.

This methodology provides a comprehensive vision of photovoltaic capacity growth in Mexico, serving as a useful tool for energy policy formulation and strategic decision-making in the renewable energy sector.

In the existing literature on system dynamics models, the behavior of various energy transitions has been understood, and tools have been developed to simulate complex scenarios. However, SD models do not offer a formal methodology for parameter estimation. Instead of providing adjustment techniques based on historical data, SD focuses on emulating systemic behaviors through differential equations and predefined causal relationships.

The deficiencies of SD as an estimation method: include the following:

- Lack of a formal estimation methodology: SD models are not designed to automatically adjust the parameters to historical data.
- Manual calibration: the parameters are usually adjusted empirically, which can introduce biases into the results.
- Limited capacity for statistical validation: Unlike other approaches such as econometrics or machine learning, SD does not offer standard metrics to evaluate the quality of the fit.

The main contributions of this study are summarized as follows:

- FC-based growth modeling: Development of exponential and sigmoidal models using fractional and conformable derivatives to describe different phases of PV capacity growth;
- Dynamic transition representation: Integration of fractional exponential and sigmoidal models to capture the transitions between growth stages dynamically;
- Sensitivity and predictive analysis: Use of fractional functions to assess key factors (e.g., costs, investments) and improve the prediction of installed PV capacity's evolution;
- Application to the Mexican context: Implementation of the proposed methodology in Mexico, considering urban and rural dynamics to generate scenarios that support energy planning.

This work is organized as follows: Chapter 2 presents the materials and methods, including a literature review of historical installed photovoltaic capacity, basic concepts of system dynamics and conformable calculus, and the implemented methodology. Chapter 3 details the development of the study and the results obtained. Subsequently, Chapter 4 presents the conclusions of the work. Finally, Chapter 5 contains the references used in this study.

In Table 1, the variables used throughout the document can be seen, along with their capacity units. Table 1 presents the key variables used in this study, including their descriptions and corresponding units. These variables are fundamental for understanding the photovoltaic capacity models analyzed in this work.

Table 1. Key variables in the photovoltaic capacity models.

Variable	Description	Unit
$C_i(t)$	Installed photovoltaic capacity at time t	MW
$A_{pu}(t)$	Public deployment of photovoltaic capacity	MW/year
$B_{pr}(t)$	Private deployment of photovoltaic capacity	MW/year
$L_{ru}(t)$	Loss of rural users	MW/year
k_1	Adjusted growth rate considering market saturation	MW/year
$C_{\max}$	Maximum projected photovoltaic capacity	MW
P	System profitability	Adimensional
$R(t)$	Revenue from produced energy	USD/year
C_{total}	Total installation and operation costs	USD
α_{base}	Base parameter for private deployment	MW/year
$\frac{dC_i(t)}{dt}$	Rate of change in installed capacity	MW/year
$\frac{1}{C_{\max}}$	Normalization factor in the logistic equation	1/MW

2. Materials and method

This section presents the data, the system dynamics model, and the FC methods used in this study to analyze and model the growth of installed PV capacity in Mexico. The data for this analysis were gathered from official sources such as Statista [33] and the National Institute of Statistics and Geography (INEGI) [34], covering the period from 2015 to 2023. Additionally, the methodology integrates system dynamics for simulating the evolution of PV capacity, alongside the use of conformable FC for a more accurate prediction of future growth.

2.1. Data

This section presents the data gathered from official sources such as Statista [33] and the INEGI [34], illustrating the growth of installed photovoltaic capacity in Mexico in recent years. Some of the primary sources of renewable energy in the country are solar energy, due to the excellent solar irradiance conditions across various regions.

2.1.1. Installed Photovoltaic Capacity (2015–2023)

The plot of the Figure 1 shows the growth of installed photovoltaic capacity in Mexico between 2015 and 2023, measured in megawatts (MW):

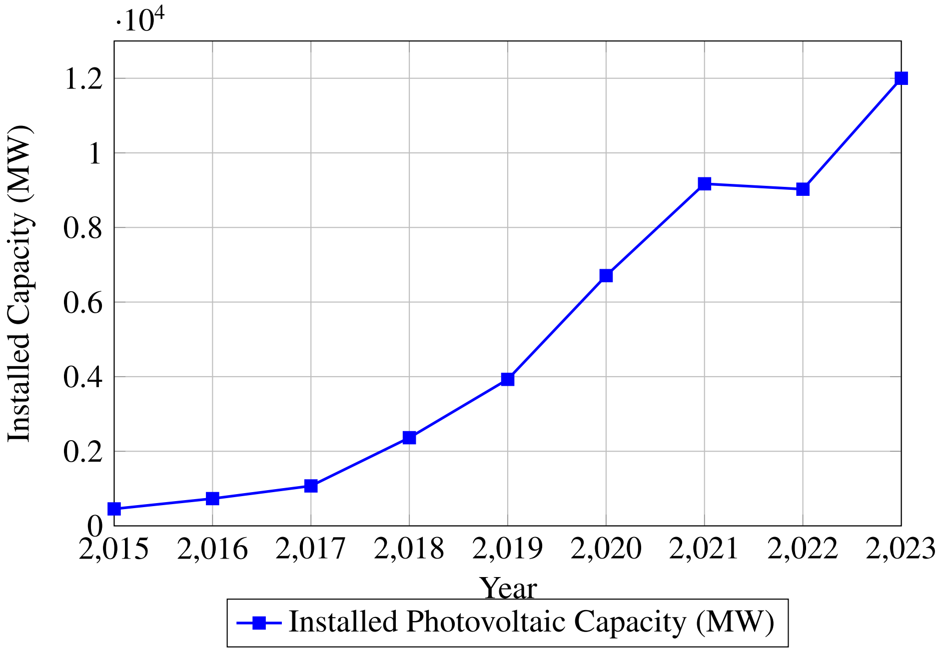

Figure 1. Installed photovoltaic capacity in Mexico (2015-2023). Source: Statista [33], INEGI [34].

2.2. System dynamics

How the behavior of complex systems over time develops is measured via the methodology of system dynamics, feedback loops, stocks, and flows that characterize these systems. A stock represents the accumulation of a certain quantity over time, while a flow refers to the rate at which the stock increases or decreases. The general equation governing the change in a stock is given by:

$$S(t) = S_0 + \int_0^t (\text{inflow}(s) - \text{outflow}(s))\, ds, \tag{2.1}$$

where $S(t)$ is the stock at time t, S_0 is the initial value of the stock, and inflow(s) and outflow(s) are the rates of flow into and out of the stock at time s, respectively. This integral equation captures the dynamic nature of the system by representing how stocks accumulate over time on the basis of the inflows and outflows.

Systems dynamics models are widely applied in fields such as economics, environmental studies, and energy systems. Input and output rates influence changes in reservoirs or critical variables, thus creating complex interactions within the system. For example, Sterman (2002) emphasized that understanding feedback structures is crucial for effective decision-making in complex systems, as they can lead to unintended consequences if not properly managed [35].

The interaction between renewable energy sources and consumption patterns in energy models illustrates the importance of the dynamics in their behavior. As Meadows et al. (1972) pointed out, adaptive strategies in policy formulation using feedback loops to create oscillations and delays in response to changes in supply or demand are needed [36]. Dynamic models help simulate various scenarios and understand the implications of different policy options on energy systems and resource management in climate change.

The presence of delays requires careful consideration in the design and analysis of the model to be developed. These delays can affect the overall behavior of the system, leading to non-linear responses and oscillatory behavior. Moreover, the sensitivity analysis of a system dynamics model can be developed with the proposed methodology, allowing researchers to explore the possible outcomes of the various scenarios. For example, sustainability studies in system dynamics models have made it possible to examine the long-term effects of different energy policies on resource depletion and environmental impact [37, 38].

Overall, system dynamics provides a comprehensive framework for understanding the complexities of interconnected systems and their temporal dynamics, making it an essential tool for researchers and policy-makers alike.

2.3. Fractional conformable derivative

The notion of derivatives and integrals of non-integer orders generalizes the classical theory of calculus. In particular, FC is important in the study of the dynamics of processes where the use of integer-order operators does not satisfactorily describe the phenomena. Specially, the FC allows for the description of systems with memory or historical effects [39]. Among the various definitions of fractional derivatives, the conformable fractional derivative has gained attention due to its simplicity and versatility in modeling dynamic systems.

The conformable fractional derivative of order α is defined as:

$$T_\alpha(f)(t) = \lim_{\epsilon \to 0} \frac{f(t + \epsilon t^{1-\alpha}) - f(t)}{\epsilon}, \tag{2.2}$$

For all $t > 0$, where $f : [0, \infty) \to \mathbb{R}$ is a function and $\alpha \in (0, 1]$ is the non-integer order. When $\alpha \to 1$, $f^{\alpha}(t) \to f'(t)$.

The evolution of dynamic systems allows for a deeper understanding using the flexibility of conformable FC. For example, the dynamics of memory systems are captured with fractional derivations using variations from classical calculus [40]. Energy policies and changes in installed capacity are strengthened in modeling energy systems, where a more robust approach is required to understand long-term effects.

This flexibility allows the conformable fractional derivative to effectively model complex growth processes, such as the deployment of photovoltaic capacity over time, which involves strategic planning and memory effects [41]. Conformable FC is a valuable tool for theoretical analysis and practical applications in various problems in physics, engineering, and energy systems.

This study uses a systems dynamics model to simulate the growth of installed photovoltaic capacity in Mexico from 2015 to 2030, focusing on the interactions among key variables to model the behavior of complex systems over time (See Figure 2).

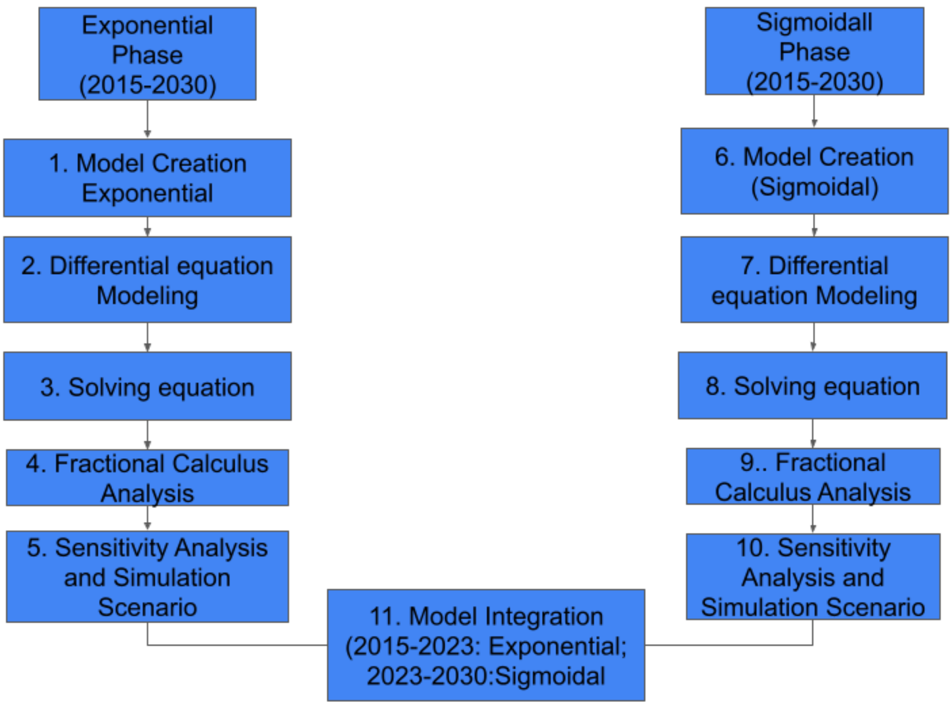

Figure 2. Compact block diagram of the methodology.

2.4. Phase 1: Modeling and simulation of exponential growth (2015–2030)

1. **Development of the system dynamics model in Vensim:** A simulation model is created to describe the growth of installed photovoltaic capacity in Mexico. In this model, the system's variables are defined, such as the installed photovoltaic capacity.
2. **Definition of the differential equation model:** The differential equation representing the exponential growth of installed capacity is formulated. The related variables are explained.
3. **Analytical solution of the model:** The resulting differential equation is solved analytically,

providing an explicit expression that describes how installed capacity varies over time.

4. **Solution of the fractional model using conformable derivative:** The integer order operator is replaced by a fractional order one, then the fractional order differential equation is solved using the properties of the fractional conformable derivative, capturing complex dynamics that include memory effects and non-local behavior in the growth of installed capacity.
5. **Sensitivity analysis and scenario simulation: A comparison of Errors with historical data:** Simulations are performed by varying the values of the alpha parameter across different scenarios. The projected installed capacity is compared with historical data, analyzing the error and precision of the model.

2.5. Phase 2: Modeling and simulation of sigmoidal growth (2015–2030)

1. **Development of the system dynamics Model in Vensim:** A simulation model is created to describe the sigmoidal growth of installed photovoltaic capacity in Mexico. In this model, the system variables are defined, including installed photovoltaic capacity, the maximum capacity of the system, and factors influencing the adoption of photovoltaic technologies.
2. **Definition of the differential equation model:** The differential equation representing the sigmoidal growth of installed capacity is formulated. This section explains the related variables, including the growth rate and the limits affecting the system's behavior.
3. **Analytical solution of the logistic solution:** The differential equation is solved analytically, providing an explicit expression that describes how installed capacity varies over time in a sigmoidal context.
4. **Conformable fractional logistic solution:** The integer order operator is replaced by a fractional order one, then the fractional order differential equation is solved using the properties of the fractional conformable derivative, capturing complex dynamics that include memory effects and non-local behavior in the growth of installed capacity.
5. **Sensitivity analysis and scenario simulation: A comparison of errors with historical data:** Simulations are performed by varying the values of the parameter across different scenarios. The projected installed capacity is compared with historical data, analyzing the error and precision of the model in representing sigmoidal growth.

2.6. Phase 3: Integration of models and sensitivity analysis through FC (2015–2030)

1. **Integration of models:** The results of the exponential and sigmoidal models are combined. The analytical solution of the exponential model is used for the period from 2015 to 2023, capturing the initial rapid growth of installed capacity. For the period from 2023 to 2030, the analytical solution of the sigmoidal model is used, reflecting the stabilized growth of the system. This approach also allows for the development of a sensitivity analysis, where variations in the alpha parameter of the model can be evaluated through FC techniques.
2. **Transition and sensitivity analysis:** This integration phase not only allows for the analysis of the transition between the two growth behaviors but also facilitates a sensitivity analysis using fractional functions obtained through conformable calculus. Different scenarios are explored to assess how changes in the alpha parameter affect the dynamics of the system over time. This provides a deeper understanding of the interactions under various conditions.

3. Results

3.1. Development of the system dynamics model in Vensim

This study developed a system dynamics model to analyze and predict the exponential growth of installed photovoltaic (PV) capacity in Mexico during the period 2015–2023. Transitioning to renewable energy, particularly solar photovoltaic systems, has become an essential strategy for reducing greenhouse gas emissions and promoting sustainable energy use. In this context, system dynamics serves as a robust methodology for studying and simulating the complex interactions among public policies, economic factors, and technological adoption.

The increasing adoption of PV systems holds great significance for energy security and sustainability. By harnessing abundant solar resources, Mexico can reduce its dependency on fossil fuels and stabilize electricity costs for both urban and rural populations. The model helps assess the factors driving this transformation, such as the cost of PV installation, the availability of investment, and the operational efficiency of solar systems.

3.1.1. Key energetic and economic considerations

A central focus of the model is the profitability of PV systems, which determines their attractiveness to private investors and their long-term sustainability in public deployments. To evaluate profitability, several factors are analyzed.

- **Installation and operational costs:** The capital cost of PV systems, combined with their annual operational costs, represents a significant determinant of system's profitability. While global trends have seen a decline in PV installation costs, achieving profitability remains challenging without substantial efficiency improvements or favorable policies.
- **Energy production potential:** The installed capacity is measured in megawatts (MW), and it is assumed that PV systems operate for approximately 8,760 hours per year. However, due to inherent inefficiencies, the capacity factor—typically around 20% for solar systems—limits the actual energy produced. This efficiency directly impacts the financial returns of the system, as it determines the revenue generated from energy sales.
- **System profitability threshold:** For private investment to be sustainable, the profitability of the system (P) must exceed a value of 1. When profitability is low, private entities are unlikely to invest, necessitating greater public intervention to drive PV deployment.
- **Rural energy access and losses:** In rural areas, PV systems often represent the most viable energy source due to the lack of access to public electricity infrastructure. However, rural installations are subject to higher risks of disconnection or underutilization, leading to capacity losses over time. These dynamics are modeled as a steady outflow from the installed PV capacity.

Public sector investment faces the dual challenge of achieving economic viability while meeting social and environmental objectives. Public investment in PV systems can be justified not only by its economic returns but also by its alignment with goals such as reducing energy poverty, decarbonizing the grid, and fostering rural development. By incorporating these considerations, the system dynamics model provides a comprehensive framework for evaluating the growth and sustainability of PV capacity in Mexico. Figure 3 illustrates the structure of the system dynamics model used to analyze photovoltaic capacity deployment in the country, highlighting key variables and interactions within the system.

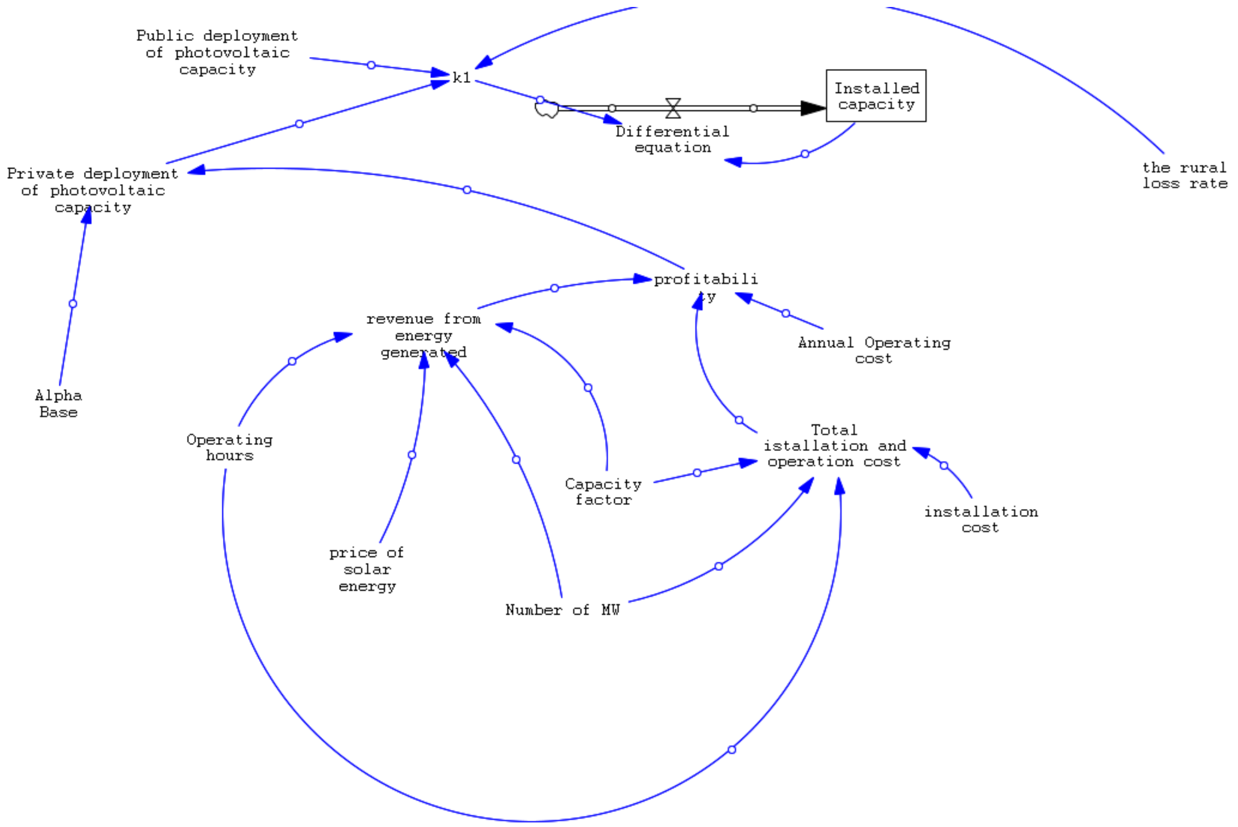

Figure 3. System dynamics model for photovoltaic capacity deployment in Mexico.

3.1.2. Definition of the differential equation model

The growth of installed photovoltaic capacity during the period 2015–2023 can be described by the following differential equation:

$$\frac{dC_i(t)}{dt} = K_1 C_i(t), \tag{3.1}$$

$$K_1 = A_{pu}(t) + B_{pr}(t) - L_{ru}(t). \tag{3.2}$$

where:

- $A_{pu}(t)$ is public deployment of photovoltaic capacity,
- $B_{pr}(t)$ is private deployment of photovoltaic capacity, dependent on profitability,
- $L_{ru}(t)$ is loss of rural users.

State variables

$$B_{pr}(t) = \begin{cases} \alpha_{\text{base}} \cdot (P-1) \cdot C_i(t), & \text{if } P > 1, \\ 0, & \text{if } P \leq 1, \end{cases} \tag{3.3}$$

where:

- α_{base} is the base parameter for private deployment;

- P is the system's profitability.

$L_{ru}(t)$ is the loss of rural users (in MW/year). This flow represents the rate at which installed capacity is reduced due to rural users disconnecting from their solar systems:

$$L_{ru}(t) = \beta \cdot \tag{3.4}$$

where:

- β is the parameter representing the rural loss rate.

3.1.3. Auxiliary variables

- **System profitability** (P): Profitability is defined as:

$$P = \frac{R(t)}{C_{\text{total}}}, \tag{3.5}$$

where $R(t)$ represents the revenue generated by the energy, calculated as:

$$R(t) = \text{operating hours} \times \text{price of solar energy} \times \text{MW} \times \text{capacity factor}. \tag{3.6}$$

For the calculation, 1 MW is used.
- **Total installation and operation costs** (C_{total}): This variable reflects the total costs related to the installation and operation of the photovoltaic system, calculated as:

$$C_{\text{total}} = (\text{capacity factor} \times \text{number of MW} \times \text{operating hours} \times \text{installation costs}) + \text{annual operating costs}. \tag{3.7}$$

3.1.4. Analytical solution of the model

We start from the differential equation:

$$\frac{dC_i(t)}{dt} = k_1 \cdot C_i(t), \tag{3.8}$$

where the coefficient k_1 is defined as:

$$k_1 = A_{pu0} + \alpha_{\text{base}}(P - 1) \bullet \beta. \tag{3.9}$$

The general solution to this equation is:

$$C_i(t) = C_0 \cdot e^{k_1 \cdot t}. \tag{3.10}$$

where C_0 is the initial installed photovoltaic capacity, taken from real data.

3.1.5. Solution of the fractional model using conformable calculus

When we apply a conformable fractional derivative of order α, the differential equation becomes:

$$\frac{d^{\alpha}C_i(t)}{dt^{\alpha}} = t^{1-\alpha}\frac{dC_i(t)}{dt} = k_1 \cdot C_i(t), \quad 0 < \alpha \leq 1. \tag{3.11}$$

Separating the variables and solving the equation, we obtain:

$$\frac{dC_i(t)}{dt} = t^{\alpha-1} \cdot k_1 \cdot C_i(t). \tag{3.12}$$

The general solution to the conformable fractional differential equation is:

$$C_i(t) = C_0 \cdot e^{\frac{k_1}{\alpha} \cdot t^{\alpha}}, \tag{3.13}$$

where C_0 is the initial installed photovoltaic capacity.

3.1.6. Sensitivity analysis and scenario simulation: a comparison of errors with historical data

The fractional function obtained through the conformable derivative provides a framework for analyzing a fractional reinforcement loop in system dynamics. Conducting a sensitivity analysis by varying α allows us to explore different scenarios within the Euler model. The analysis of the 2015–2023 period shows that the traditional system dynamics model ($\alpha = 1.0000$) yields a 23.30% error. However, optimizing α significantly improves accuracy, with $\alpha = 0.8652$ reducing the error to 16.52%. Other values, such as $\alpha = 0.8500$, also outperform the conventional model.

Table 2 presents the results of the sensitivity analysis, showing the error rates for different values of α. These findings highlight the advantages of incorporating fractional system dynamics for more precise estimations, particularly in modeling photovoltaic capacity in Mexico. Additionally, Figure 4 illustrates the impact of different α values on the model's accuracy, highlighting the improvements achieved with optimized parameters.

Table 2. Average percentage errors for different alpha values (2015–2023).

Alpha value	Average percentage of error
$\alpha = 1.0000$	23.30%
$\alpha = 0.9500$	19.92%
$\alpha = 0.9000$	17.63%
$\alpha = 0.8652$	16.52%
$\alpha = 0.8500$	16.90%
$\alpha = 0.8000$	20.37%

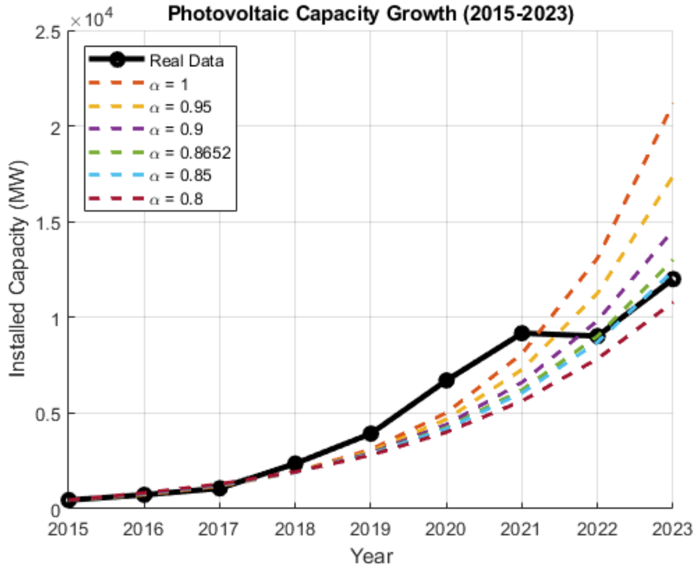

Figure 4. Analysis of α values from 2015 to 2023.

Scenario 2015–2030: Projections indicate capacities ranging from 100,000 to 700,000 MW, which seem illogical given market saturation and the increasing competition from other renewable energy sources, such as wind power. The behavior observed in the 2015–2023 period is deemed appropriate and reasonable, especially considering that the value of α with the lowest error is 0.8652. In contrast, the projection of reaching between 25,000 and 30,000 MW in Mexico by 2030 appears unrealistic, given the excessively high projected growth rate. Figure 5 illustrates these photovoltaic capacity projections for the 2015 to 2030 period.

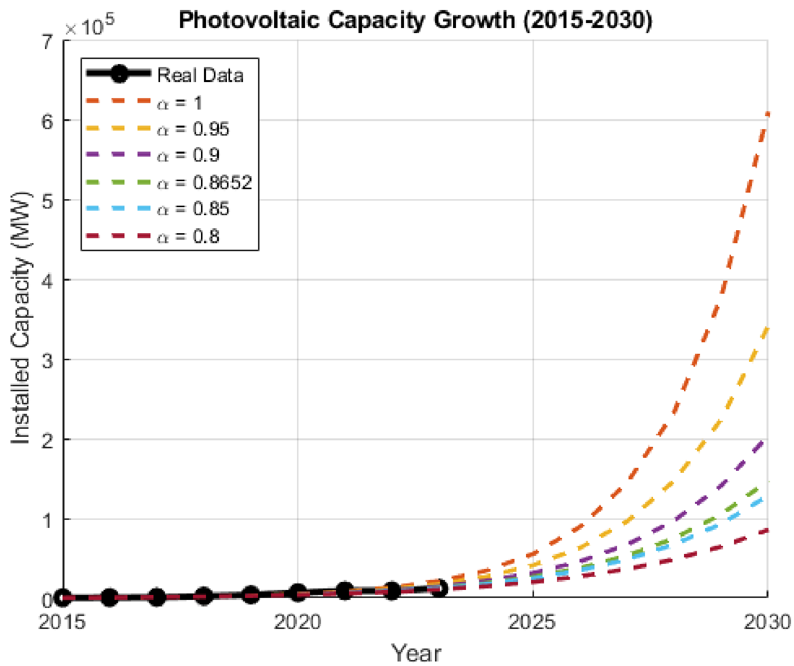

Figure 5. Projections for photovoltaic capacity from 2015 to 2030.

Therefore, it is important to emphasize that this is not the definitive estimator but rather a test of the 2015–2030 period using a purely exponential model. While the behavior observed from 2015 to 2023 appears reasonable and aligns with historical data, the projections for 2023 to 2030, such as those from Secretary of energy of Mexico (SENER), seem less adequate due to unrealistic growth expectations. This highlights the need to integrate another basic system dynamics model in the next stage to obtain more precise and realistic projections.

The results obtained for the 2023–2030 period are neither acceptable nor accurate concerning the country's policies. Therefore, the exponential modeling approach is not suitable for this period, reinforcing the need to adopt a different modeling strategy that aligns with realistic growth expectations and policy frameworks.

3.2. Transition to a logistic growth model

3.2.1. Development of the system dynamics model in vensim

The sigmoidal growth model extends exponential growth by incorporating a balancing feedback loop that accounts for market saturation and structural limitations. For Mexico's photovoltaic capacity, this model aligns with SENER's 2030 goal of 25,000 MW, ensuring a realistic and sustainable transition. A limiting factor slows growth as capacity nears this target, optimizing resource allocation and directing investments toward infrastructure and efficiency improvements. By integrating this constraint into the system dynamics model, the approach ensures that photovoltaic expansion remains both feasible and aligned with environmental and energy policies. Figure 6 illustrates the Vensim model developed to represent this growth dynamics.

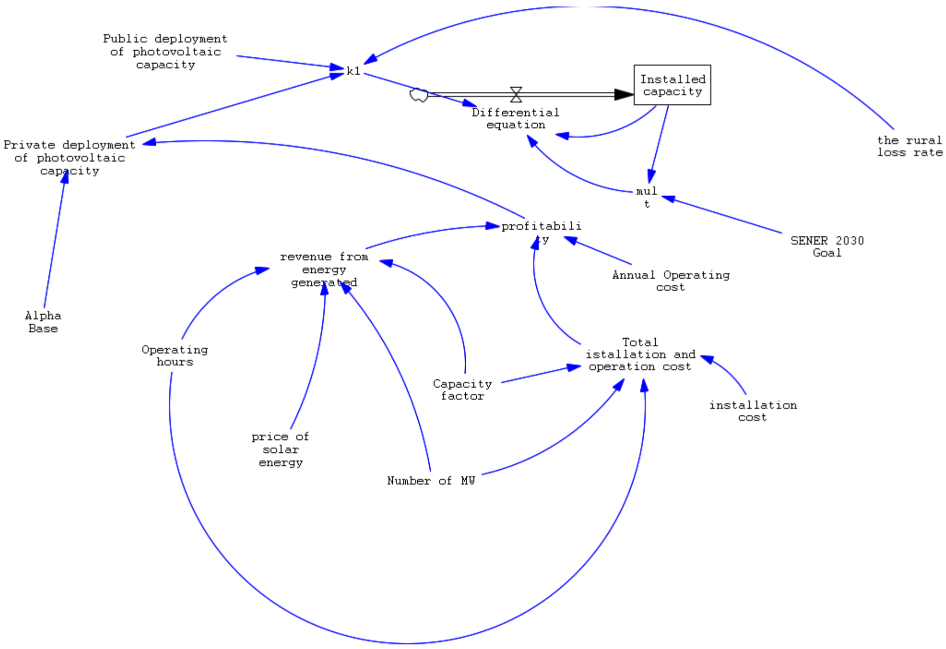

Figure 6. Vensim model for photovoltaic capacity growth.

The sigmoidal model used to describe the growth of photovoltaic capacity is based on the growth rate parameter k_1, consistent with the model derived from Euler's method. With the recent target set by SENER and adjustments in the feedback loops of the system dynamics model, the dynamics of the sigmoidal model are further refined to ensure a more accurate representation of market conditions.

3.2.2. Definition of the differential equation model

The sigmoidal model can be expressed as follows. The logistic growth model, expected as the photovoltaic market matures, is described by the following differential equation:

$$\frac{dC_i(t)}{dt} = k_1 \cdot C_i(t)\left(1 - \frac{C_i(t)}{C_{\max}}\right) \tag{3.14}$$

where:

- k_1 is the Adjusted growth rate that considers market saturation and is consistent with the previous model derived from Euler's method;
- $C_{\max}$ is the projected maximum capacity for the photovoltaic market, estimated at 25,000 MW.

3.2.3. Analytical solution of the logistic differential equation

Logistic differential equation: The logistic growth model is represented by the equation:

$$\frac{dC_i(t)}{dt} = k_1 \cdot C_i(t)\left(1 - \frac{C_i(t)}{C_{\max}}\right) \tag{3.15}$$

Rearranging the equation: To separate variables, the equation is rewritten as

$$\frac{dC_i(t)}{C_i(t)\left(1 - \frac{C_i(t)}{C_{\max}}\right)} = k_1\, dt. \tag{3.16}$$

Integrating both sides: The left-hand side requires partial fraction decomposition

$$\frac{1}{C_i(t)\left(1 - \frac{C_i(t)}{C_{\max}}\right)} = \frac{A}{C_i(t)} + \frac{B}{1 - \frac{C_i(t)}{C_{\max}}}. \tag{3.17}$$

To determine A and B, we solve the equation

$$A\left(1 - \frac{C_i(t)}{C_{\max}}\right) + B \cdot C_i(t) = 1. \tag{3.18}$$

By solving for A and B, we find

$$A = \frac{1}{C_{\max}}, \quad B = \frac{1}{C_{\max}}.$$

Thus, the equation becomes

$$\frac{1}{C_{\max}} \int \left(\frac{1}{C_i(t)} + \frac{1}{1 - \frac{C_i(t)}{C_{\max}}}\right) dC_i(t) = k_1 \int dt. \tag{3.19}$$

Integration: The left-hand side integrates to

$$\frac{1}{C_{\max}}\left(\ln|C_i(t)| - \ln\left|1 - \frac{C_i(t)}{C_{\max}}\right|\right) = k_1 t + C. \tag{3.20}$$

Combining the logarithmic terms gives

$$\ln\left|\frac{C_i(t)}{1 - \frac{C_i(t)}{C_{\max}}}\right| = k_1 C_{\max} t + C. \tag{3.21}$$

Exponentiating: Taking the exponential of both sides

$$\frac{C_i(t)}{1 - \frac{C_i(t)}{C_{\max}}} = e^{k_1 C_{\max} t + C}. \tag{3.22}$$

Final Form: Rearranging gives the final logistic growth equation

$$C_i(t) = \frac{C_{\max}}{1 + \left(\frac{C_{\max}}{C_0} - 1\right) e^{-k_1 t}}. \tag{3.23}$$

where:

- $C_{\max}$ is the maximum projected capacity for the photovoltaic market (estimated at 25,000 MW);
- C_0 is the initial installed capacity at the start of the logistic growth phase.

3.2.4. Conformable fractional logistic solution

Conformable fractional formulation: The application of the conformable fractional derivative of order α to the logistic growth model gives

$$t^{1-\alpha}\frac{dC_i(t)}{dt} = k_1 C_i(t)\left(1 - \frac{C_i(t)}{C_{\max}}\right). \tag{3.24}$$

Separating variables: Rearranging and separating variables yields

$$\frac{dC_i(t)}{C_i(t)\left(1 - \frac{C_i(t)}{C_{\max}}\right)} = k_1 t^{\alpha-1} dt. \tag{3.25}$$

Integration: As in the ordinary case, the left-hand side is decomposed using partial fractions

$$\frac{1}{C_{\max}}\int\left(\frac{1}{C_i(t)} + \frac{1}{1 - \frac{C_i(t)}{C_{\max}}}\right) dC_i(t) = \int k_1 t^{\alpha-1} dt. \tag{3.26}$$

The right-hand side of the integral equates to:

$$\int k_1 t^{\alpha-1} dt = \frac{k_1 t^{\alpha}}{\alpha} + C. \tag{3.27}$$

Final Solution: Substituting back and simplifying yields the following fractional logistic solution

$$C_i(t) = \frac{C_{\max}}{1 + \left(\frac{C_{\max}}{C_0} - 1\right) e^{-\frac{k_1 t^{\alpha}}{\alpha}}}. \tag{3.28}$$

where:

- C_{max} is the maximum projected capacity for the photovoltaic market;
- C_0 is the initial installed capacity at the start of the logistic growth phase;
- α is the fractional order parameter reflecting memory effects in the system.

3.2.5. Sensitivity analysis and scenario simulation: comparison of errors with historical data

The sigmoidal growth model, unlike the exponential one, incorporates a balancing feedback loop that limits growth as the market reaches saturation. Given that photovoltaic capacity in Mexico faces technological, economic, and regulatory constraints, this model allows for a more realistic evaluation of its evolution.

The sigmoidal model is now applied to analyze photovoltaic growth in two periods, namely 2015–2023, (where a clear trend has been observed), and 2023–2030, to assess how suitable it is compared with existing projections. This will help determine whether this approach provides a more accurate estimation aligned with market conditions.

Average percentage errors

The model was evaluated over two significant time periods: 2015–2023 and 2023–2030. The average percentage errors for various values of α during the period from 2015 to 2023 are shown in Table 3.

Table 3. Average percentage errors for different alpha values (2015–2023).

Alpha value	Average percentage error
$\alpha = 1.00$	25.07%
$\alpha = 0.95$	27.09%
$\alpha = 0.90$	29.31%
$\alpha = 0.87$	30.76%
$\alpha = 0.85$	31.37%
$\alpha = 0.80$	33.27%

3.3. Analysis of photovoltaic capacity growth scenarios

The following analysis examines different scenarios for the periods 2015–2023 and 2015–2030. The division at 2023 is based on data availability and allows for an assessment of the transition towards future growth. In the second period, the projected capacity approaches 25,000 MW, which aligns with SENER's projections. This suggests that this scenario could more accurately represent the system's evolution, considering both the physical limits of expansion and the need for strategic adjustments in energy production to meet national sustainability goals.

Figure 7 illustrates the photovoltaic capacity growth using the Euler model for the period 2015–2023, while Figure 8 presents the growth using the sigmoidal model for the period 2015–2030.

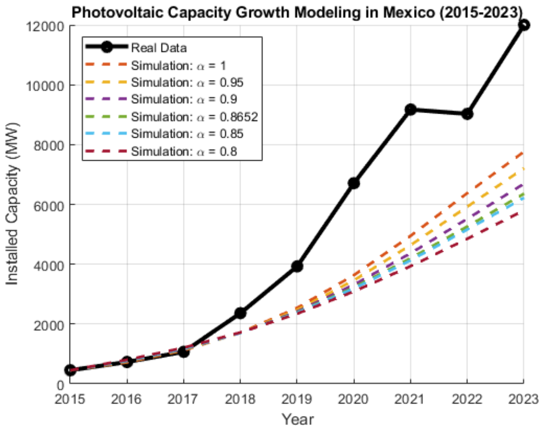

Figure 7. Photovoltaic capacity growth using the Euler model (2015–2023).

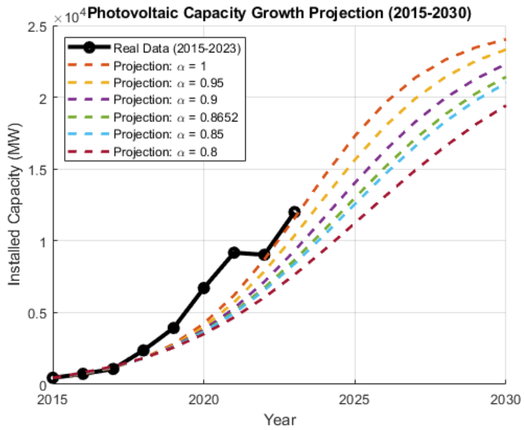

Figure 8. Photovoltaic capacity growth using the sigmoidal model (2023–2030).

The sigmoidal model does not exhibit an adequate fit for the 2015–2023 period, showing a high error percentage. However, for the 2023–2030 period, the model aligns well with expectations, particularly with SENER's projection of reaching 25,000 MW. This suggests that the sigmoidal approach better represents future capacity growth, capturing the stabilization effect as the system approaches its expected limit.

4. Phase 3: Integration of models and sensitivity analysis through FC (2015–2030)

4.1. Integration of models

In the analysis of the evolution of photovoltaic capacity in Mexico between 2015 and 2023, we initially observe exponential growth, reflecting rapid adoption of the technology, driven by factors such as the availability of incentives and the beginning of infrastructure expansion. However, as the market matures and more users begin to adopt solar energy, the growth dynamics adjust, showing a transition to a sigmoidal model. This shift in growth behavior reflects the progressive saturation of the market, where the adoption rate slows as capacity limits and structural barriers, such as space availability or installation costs, are approached.

The sigmoidal model captures this transition more realistically, incorporating the idea that in the early stages, the adoption of new technologies is faster (exponential), but as the technology becomes established and the market reaches its maximum capacity, growth slows down (sigmoidal). This approach is key to understanding that the growth of photovoltaic capacity does not follow an indefinitely accelerated trajectory but adjusts to market conditions and the natural limitations of the system.

The integration of this analysis with FC allows for greater accuracy in modeling this nonlinear behavior, providing a more robust framework to anticipate the future evolution of installed capacity. By simulating different scenarios, we can explore how variations in market conditions, government policies, and infrastructure investments affect the rate of adoption and sustained growth of photovoltaic technology.

4.2. Transition and sensitivity analysis

This integrated approach, combining insights from the exponential growth model with the sigmoidal framework, indicates that the short-term challenges facing the sector are manageable. The results suggest that reaching these targets is feasible, particularly when considering supportive governmental policies and market conditions.

Thus, this study, along with the fractional sensitivity analysis, provides a more realistic perspective on the future growth of photovoltaic capacity, adapting to both historical data trends and expected developments while offering a perspective of various scenarios, which could be *N* scenarios. Figure 9 illustrates the modeling of photovoltaic capacity growth in Mexico from 2015 to 2030.

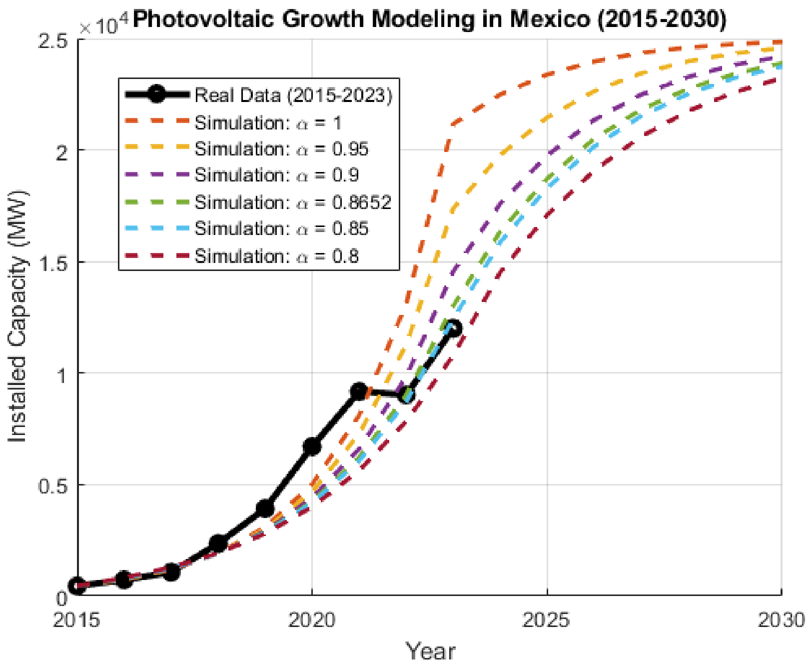

Figure 9. Photovoltaic capacity growth modeling in Mexico (2015–2030).

The exponential model effectively represents the 2015–2023 period, accurately capturing the initial growth, phase based on real data. However, due to market saturation and the inherent limitations of continuous exponential growth, this approach becomes less suitable for long-term projections. For the 2023–2030 period, the sigmoidal model provides a more realistic representation, as it incorporates the stabilization effect that naturally occurs when an energy market reaches capacity constraints. This transition ensures a more accurate forecast, aligning with expected market behavior and regulatory goals.

5. Limitations and future work

Despite the promising results, some limitations need to be addressed in future research. The proposed model assumes relatively stable economic and political conditions, which may not accurately reflect the impact of abrupt regulatory changes or economic crises. Additionally, external factors such as supply chain disruptions, technological advancements, or changes in consumer behavior are not explicitly included in the current framework. Future studies could integrate more refined economic models, stochastic elements, or machine learning techniques to improve the accuracy of predictions.

This project is based on basic system dynamics models, specifically the sigmoid and exponential models, as well as their integration. Future work could also explore other fundamental system dynamics models and further integrate them to enhance estimations.

Furthermore, enhancing the representation of spatial heterogeneity in the adoption of photovoltaic energy adoption considering regional differences in solar radiation, grid capacity, and socioeconomic factors—could increase the model's applicability. Expanding the methodology to include hybrid energy systems and storage solutions would provide a better understanding of Mexico's renewable energy transition.

The main weakness of the model lies in certain transitions across specific years, where slight deviations occur. However, an error margin of 16% is acceptable within system dynamics models, representing a good starting point for estimation and trend analysis in this context.

This study highlights the importance of using system dynamics combined with FC as an innovative tool for energy planning in Mexico. The ability to simulate multiple scenarios and perform sensitivity analysis is crucial for optimizing energy resources, designing policies that promote renewable technologies, and ensuring a successful transition to a sustainable energy future.

The choice of the conformable fractional derivative over other fractional approaches, such as Caputo or Riemann–Liouville, is primarily due to its simplicity and ease of interpretation for the reader. Unlike Caputo derivatives, which often require special functions like Mittag–Leffler functions for their solution, the conformable derivative retains a structure that is more similar to classical calculus, making its application and understanding more straightforward. However, future research could explore alternative fractional formulations to assess their impact on the model's accuracy and behavior, incorporating more complex methodologies if necessary.

6. Conclusions

This research developed an innovative estimation method within the system dynamics framework, based on FC, aimed at performing sensitivity analyses in the context of photovoltaic capacity growth in Mexico. This study demonstrates the effectiveness of the estimation method and sensitivity analysis through the combined use of system dynamics and the conformable fractional derivative of order

$0 < \alpha \leq 1$, to evaluate the growth of installed photovoltaic capacity in the country. The applied methodology was structured in three phases. In the first phase, a system dynamics model was developed to simulate the exponential growth of installed capacity, with a focus on key variables such as investment and government subsidies. During this phase, the fractional parameter $\alpha = 0.8652$ was optimized, which reduced the average percentage error to 16.52% when compared to actual installed capacity data from 2015 to 2023.

Following this, a sigmoidal growth model was explored, providing a deeper analysis of the system's capacity limits and the factors influencing the adoption of photovoltaic technologies. Differential equations capturing this behavior were developed, and the conformable fractional derivative of order $0 < \alpha \leq 1$, was applied to reflect complex dynamics and memory effects in the growth trajectory of installed capacity. The resulting projections for the period 2023 to 2030 suggest that installed capacity could range between 23,000 and 25,000 MW, with the fractional parameter α varying from 0.8 to 1. This range points to a more sustained and realistic growth pattern, aligning with the expected market conditions, national policies, and Mexico's renewable energy goals.

The sensitivity analysis of both the exponential and sigmoidal models allows an examining of the transition between different growth behaviors, providing a more comprehensive understanding of the system. The methodology proposed in this study, which combines system dynamics with FC, provides a powerful tool for energy planning and decision-making in Mexico's energy sector. By integrating exponential and sigmoid growth models, this approach allows for the simulation of various photovoltaic capacity expansion scenarios, offering valuable insights into how variables such as public investment, government subsidies, and energy policies impact the adoption rate of renewable technologies. The ability to simulate multiple scenarios and perform sensitivity analyses is crucial for the formulation of effective public policies, as it enables the anticipation of potential futures, the adjustment of strategies, and the optimization of resources allocated to the energy transition. Moreover, given Mexico's significant role in the global sustainability context and its commitment to international agreements like the Paris Agreement, this methodology helps align national goals with market trends, promoting a more realistic and sustainable growth of photovoltaic capacity in the country.

The models developed in this study can be applied to the markets of other countries as long as the necessary data are available to adjust the relevant parameters. To adapt these models to other countries, it is essential to collect specific information, such as installed photovoltaic capacity, public investment, subsidies, and local energy market conditions. Once these data are integrated, the model is adjusted by updating key parameters, including the fractional exponent α, which has proven to be crucial in the sensitivity of the results. Furthermore, this methodology is not limited to the photovoltaic sector but can be applied to any other simulation model in different sectors, offering a flexible tool for energy planning and resource optimization in various national contexts.

Use of AI tools declaration

The authors declare that they have not used artificial intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this paper. No financial or personal relationships that could influence the work were reported.

Author contributions

Conceptualization, B.J.M.; methodology, B.J.M., B.R.; software, B.J.M., M.L.; validation, B.J.M., B.R., M.L.; formal analysis, B.J.M., B.R.; investigation, B.J.M., B.R.; resources, B.R.; data curation, B.J.M., M.L.; writing—original draft preparation, B.J.M., M.L., B.R.; writing—review and editing, B.J.M., B.R., M.L.; visualization, B.J.M., M.L.; supervision, B.R.; project administration, B.R.

All authors contributed to the work, declared no conflicts of interest, and approved the submitted version.

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