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Decentralized renewable energy integration in the urban energy markets: A system dynamics approach

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Abstract

The ongoing transformation in complex energy systems, driven by factors such as the adoption of renewable energy, higher-quality data, and the decentralization of power grids, presents a significant opportunity to tackle climate change and promote environmental justice. At the heart of this shift lies the move toward decentralized energy production, enabled by microgrids, prosumer engagement, and localized energy solutions. These efforts aim to reduce transmission losses, increase grid resilience, and give communities greater control over their energy futures. The transition is also reshaping the role of utilities, which are pivoting toward renewable energy sources and adapting to decentralized grid architectures while integrating these innovations into traditional systems. However, the policy, regulatory, and urban planning components of this transition have not been equally explored, and this gap must be addressed to provide successful implementation. In this research, we apply system dynamics modeling to assess multiple scenarios that explore different energy pathways, from traditional, utility-centered models to more planning-driven approaches that consider customer choices and decentralized solutions. Our findings underscore the need for a multi-pronged approach that combines policy innovation, socio-economic benefits, carbon reduction strategies, and extended customer engagement. We emphasize the importance of adaptable energy policies, and this research identifies several key pathways, including the adoption of renewable energy technologies, energy efficiency programs, and design strategies such as compact urban development, that reduce energy demand. By simulating scenarios, ranging from Business-As-Usual to the Illinois Climate and Equitable Jobs Act, we estimate the impact of policies on carbon emissions, electricity prices, and economic stability. The findings reveal the strong potential of decentralized systems, such as community microgrids and prosumer-driven energy solutions, in creating a more resilient and equitable energy system. With results, we highlight the need for continued research into public acceptance, technology, design, and policy tools that can further accelerate progress.

Author summary

This research focuses on the ongoing transformation of energy systems, driven by the increasing use of renewable energy, improved data quality, and the decentralization of the power grid. This shift promises significant benefits for addressing climate change and promoting environmental justice. By moving towards decentralized energy production, such as prosumer engagement and microgrids, we aim to reduce energy losses and improve grid resilience. Our study examines how utilities are adapting to this new landscape, integrating renewable energy sources with existing grids. We also highlight a critical gap in the current approach: the need for more comprehensive policy and urban planning efforts. Using system dynamics modeling, we explore various scenarios, ranging from traditional utility-centered approaches to those driven by urban planning and customer choices. The findings emphasize the necessity of robust energy policies, the socio-economic advantages of this transition, significant carbon reductions, and active customer participation. By presenting these insights, we aim to guide future research and support the development of cleaner, more sustainable electricity solutions at both regional and local levels.

1. Introduction

Energy systems are now in a period of transition [1,2]. Many changes, such as access to new renewable energy sources [3], improved data quality [4], the development of cost-effective storage systems [5], and the overall decentralization of the grid [6,7], make energy systems more complex but also more flexible and adaptable. The primary benefit of these changes and opportunities is that they address the pressure of the climate crisis and create a new energy industry that helps cities and communities reduce pollution and advance environmental justice [8–10]. With a goal to limit global temperature rise, carbon emissions must be minimized. Cities heavily depend on fossil fuels, necessitating new energy production and consumption methods, such as small decentralized, non-carbon-based energy systems [11]. For consumption, demand-side management is required to improve the energy efficiency of the built environment [12,13]. New renewable technologies enable a shift in electricity flows, traditionally one-directional, from central utilities to consumers. Now, consumers can choose their energy sources, becoming prosumers by selling excess power [14,15] or participating in decentralized systems like microgrids [16,17] and nano-grids [18]. These approaches reduce reliance on long-distance transmission, increasing efficiency and resilience by localizing energy production [19]. The transition is moving toward smart grids with deregulated markets and flexible, cost-effective, and renewable technologies closer to consumers [20,21]. In this evolving “new” energy market, distributed generation, including leveraged renewables like wind and solar, has the potential to significantly cut global carbon emissions [22]. Distributed renewable generation faces two key challenges: intermittent power output due to varying sunlight and wind [23,24] and high upfront costs with long payback periods, which hinder adoption [25,26]. However, optimizing control systems can help balance supply and demand. Alongside decentralized community solutions, utilities are adapting by transitioning from fossil fuels to renewable energy sources. This transition improves grid integration [27], scalability, load prediction using historical data [28,29], investment in advanced technologies, and overall cost-effectiveness [30], thereby guaranteeing a smoother energy transition.

Despite the significance of the ongoing energy transition and the growing attention to distributed generation concepts, relatively little attention is given to the policy side and how current urban planning research reflects it [31–34]. Those policies are built around developing and approving a clear strategic plan at all governance levels (state, municipal, local), as well as other initiatives within, such as mandating solar panels on new buildings, offering financial incentives, setting clean energy targets, supporting community solar programs, and integrating renewables into city infrastructure and operations. It is commonly agreed upon in the literature that promoting renewable energy generation is critical for energy equity, availability, and overall sustainability [35–37]. However, the integration of energy and urban planning still faces key challenges: scaling solutions from building to city level [34], combining spatial and energy planning [38], improving communication across governance levels [7,39], coordinating with other infrastructures like transport and water [40,41], and enabling decentralized grid systems and municipal renewable energy policies mentioned earlier [42,43]. This research addresses these gaps by simulating multiple policy and planning scenarios to evaluate how different governance and decision-making models affect urban energy transitions. Specifically, we model both traditional utility-centered energy planning and more decentralized approaches that emphasize urban policy, spatial design, and customer decision-making. The existing literature on energy transition in urban areas focuses on several broader fields and points of focus that are incorporated into the framework of this study and scenario design. First, many cities are shifting toward renewable energy using diverse sources, though often through utility-centered solutions [44–46]. Second, because the transition requires major upfront investments, scenarios must account for socio-economic benefits like job creation and local revenue generation [37,47,48]. Third, scenarios consider carbon neutrality goals, emphasizing emissions reduction through both construction and operational changes, along with supportive policy and design strategies [37,49]. And finally, customer-driven scenarios reflect growing interest in decentralized energy, including prosumer participation, microgrids, and cost-saving behaviors [50–53]. Therefore, while existing research covers key aspects of urban energy transitions, gaps remain; and this research is looking at those gaps from the system perspective. There is limited exploration of how these factors interact across different urban contexts, as well as insufficient analysis of policy frameworks and planning frameworks that facilitate the adoption of decentralized energy. Furthermore, additional research is required to optimize environmental and financial models, thereby increasing the affordability and scalability of renewable solutions. To address these gaps, this study uses system dynamic modeling to evaluate whether and how traditionally structured energy system can become climate-neutral within a 50-year horizon and how the system will behave considering several scenarios to assess the combined effects of planning, policy, and user participation on long-term sustainable energy outcomes. A particular interest involves evaluating recent state-level policies and strategies toward achieving the goal of creating a sustainable energy future.

2. Materials and methods

The process of transition to clean, decentralized energy solutions in cities is a dynamically complex system, and System Dynamics (SD), as a modeling tool, provides benefits for investigating scenarios and time-varying trends [35,54]. Consequently, by applying the principles, rules, and theories of SD, this research constructs and investigates policies that facilitate a smooth energy transition in cities. After forming six scenarios of this transition (explained in detail in Section 2.4) and analyzing policy instruments, we were able to evaluate the scenarios and determine the most effective one from both environmental and economic perspectives. To answer the main research question mentioned earlier, a four-step methodology was employed. The conceptual methodological framework is presented in the diagram in Fig 1, and it partly follows

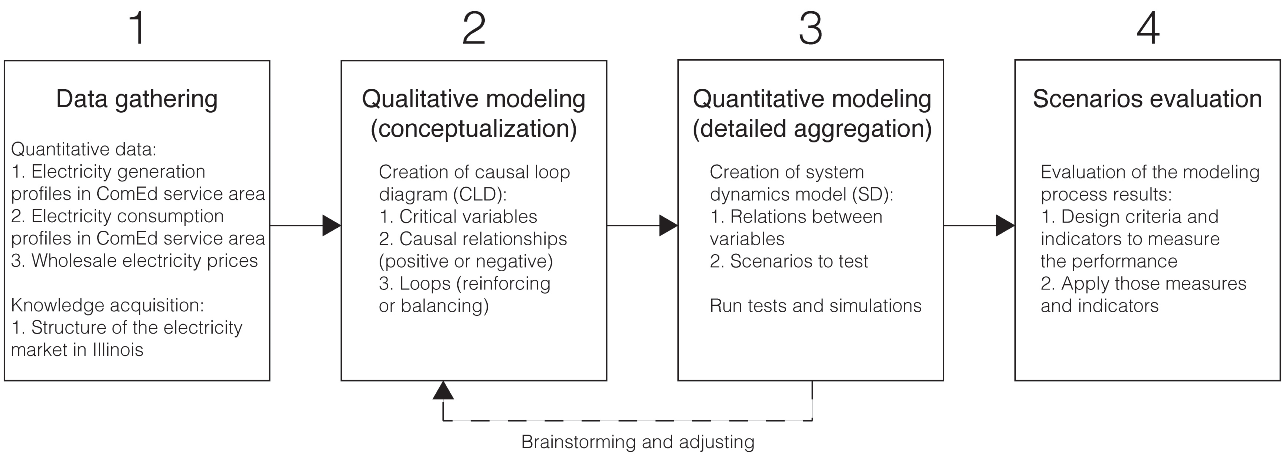

Fig 1. Conceptual methodological pipeline.

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the example workflow suggested by [55]. The methodological pipeline reflects the workflow, well-defined in the literature, from gathering data (fact-finding) to conceptualization (qualitative modeling – causal loop diagramming) with framing the main variables, their interaction, and potential testing scenarios based on diagrams explained in [56], to detailed aggregation (quantitative modeling – SD), guided by the relations between variables and scenarios to test [35,47,55,57]. In the end, the results of the modeling process were evaluated using criteria and indicators developed below to measure the performance of scenarios.

2.1. Data and area of study

The study area for this research is Northern Illinois (USA) – Commonwealth Edison (ComEd) service area (Fig 2), providing electric service to more than 4 million customers, with a significant variation in population profiles in the large metropolitan area (Chicago) from the east and other, more rural, areas from the west [58–60]. The motivation for focusing on the state of Illinois stems from a declaration of the intended transition to 100% renewable energy by 2050, as established by the Climate and Equitable Jobs Act and promoted as “establishing Illinois as a national leader on climate action” [7,61]. There are other states with similar goals, such as California (a carbon-free goal by 2045), Massachusetts (a net-zero greenhouse gas goal by 2050), and New York (a 100% carbon-free electricity goal by 2040) [62], so the approach could be easily generalized to those states and other territories. However, Illinois’ legislators explain the uniqueness of this new Illinois plan in terms of comprehensive solutions toward equitable and sustainable job opportunities, in addition to improving the energy sector, making it a unique case to explore.

Another reason why the ComEd service area was selected is due to the data availability provided by the utility to the general public, which is crucial for the replicability of the study and further investigations. ComEd’s Environmental Disclosure Reports are produced annually; for instance, [63–66] were used to model the distribution of different electricity sources supplied from 2017 to 2020 and then simulated for subsequent years. The electricity generation sources are listed in Table 1 and are primarily composed of natural gas-fired, nuclear, and coal-fired power, with a minimal penetration of renewable energy sources (wind, hydro, and solar).

In addition, accessible (for anyone for a fee) anonymized energy usage data in 30-minute intervals, representing the total electricity consumed in kWh within the city of Chicago and its surroundings [67], was used to create an averaged consumption profile of the customers. Based on EIA [68], the average Illinois customer (household) uses 8.7 MWh every year. However, due to a more urban and denser population with smaller housing units compared to other parts of the

Fig 2. Study area: state of Illinois and ComEd service area (highlighted in yellow) used in the modeling (figure created by the author using licensed Esri ArcGIS Pro 3.3 software). The shapefile for Illinois boundaries was obtained from the Census Bureau's open data portal (data.census.gov).

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Table 1. Sources of electricity supply for the 12 months in ComEd service area (in %), 2017-2020.

Source	2017	2018	2019	2020
Natural gas	27	34	38	39
Nuclear	36	34	35	34
Coal	32	26	22	21
Wind	3	3	3	3
Solar	0	0	0	1
Other (i.e., hydro, biomass, oil)	2	3	2	2

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state, and therefore lower electricity use [69], the consumption number is based on actual data from 2020 [66] and is 7.0 MWh per household. For example, in Fig 3, two yearly profiles for two zip codes are shown. The average household electricity consumption for these two areas is 6.1 MWh, with a clear difference defined by the predominant urban form. Zip code 60304 (green bars) is located in a suburban area with primarily single-family homes and limited mixed-use, while zip code 60608 (blue bars) is situated within the city of Chicago's boundaries and primarily consists of multifamily housing units. The design of wholesale electricity prices ($/MWh) was based on historical data from the PJM Interconnection [70], a regional transmission organization operating in multiple states, including the ComEd service area. The other data inputs were derived and aggregated from the literature and are mentioned in the article's text.

2.2. System dynamics (SD)

Causal loop diagrams (CLDs) are often aggregated to provide a strategic view of complex problems. They are used as a front-end model conceptualization tool before their extension to an SD simulation environment [55]. The CLDs explained earlier in [56] focus on the relations between main variables in the system, while for the full dynamic simulation, an SD

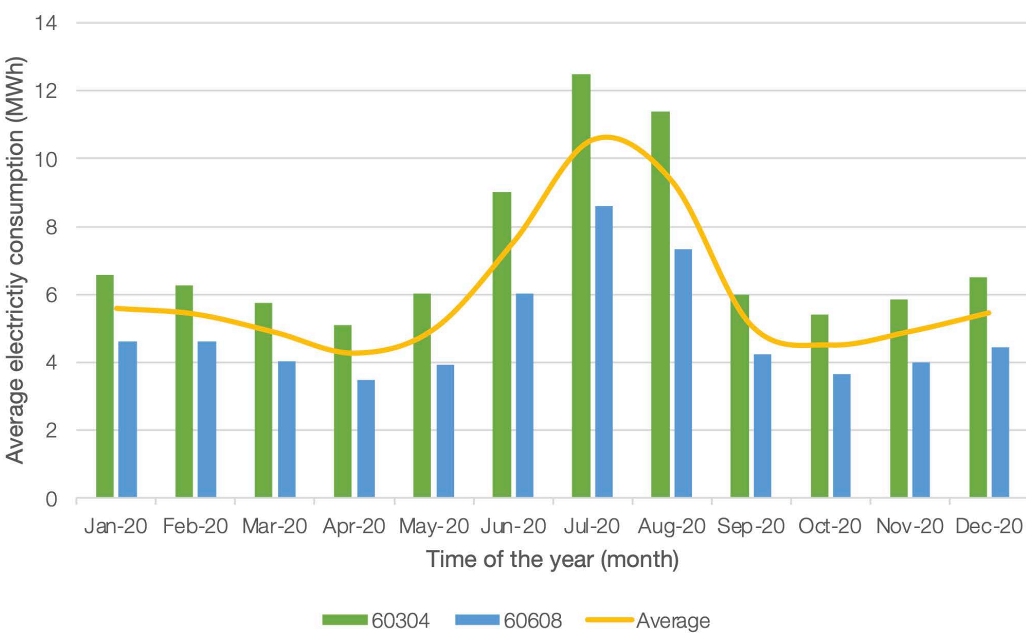

Fig 3. Base profiles for average yearly electricity consumption in two exemplary zip codes (60304 – green bars and 60608 – blue bars; yellow line represents the average consumption).

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approach was developed as a following step based on it, with a goal of understanding the causal interactions in the system over time through simulations. In SD, the system is represented in the form of a stock and flow diagram, and the main reason for using the SD approach is to get insights about feedback, delays, and other nonlinear interactions between elements and, therefore, provide help to decision-makers at the end [71]. By utilizing SD, we examine the long-term effects of various policy decisions and technological advancements on energy grids and markets. It is widely used in energy-related simulations, for example, in the diffusion of the photovoltaic energy market [72], the reciprocal relationships between technology, actors, economy, and institutions in urban energy systems [73], and the development of energy poverty policies [35,47].

The first step in developing the stock and flow diagram is to quantify CLD by adding equations, parameters, and inputs to the variables. At the core of the model is a conventional supply-demand concept for energy models [74,75], when energy generation addresses the needs of consumption at each moment. The entire stock and flow diagram is shown in Fig 4, which includes stock variables (rectangular shapes) representing the accumulation of materials, resources, and information that have accumulated over time, and flow variables (circular shapes connected by green lines) that change stocks [71]. Parameter variables (circular shapes) are designed to show the original value at the beginning of the simulation, as well as disturb flow variables in different scenarios using equations.

The SD model has five main components divided by the direction of analysis: electricity demand (consumption) – blue box, section (C), second from the right top corner; electricity supply (generation) – yellow box on the left, section (A); CO_2 emissions – green box, third from the right top corner, section (B); economics – red box in the lower right corner, section (E); and community decentralized energy perspectives – purple box in the upper right corner, section (D). Key stock and flow variables used in the diagram are listed in Table 2, along with brief descriptions. The model was created using the Silico App modeling framework and simulation tool. The list of main equations and parameters used in the model is available in S1 Appendix.

Fig 4C illustrates the electricity demand (consumption) represented by the main stock, "Electricity demand," in megawatt-hours (MWh), aggregated over time using the flow "Demand growth" in MWh per year. The demand is influenced by the population (number of households) and the average household consumption in MWh per year, which is informed by the real electricity data from ComEd, explained earlier, and can be adjusted based on real electricity data for any other territory or service area. Based on real data, the average household consumption has been growing over time (with the exception of the densification scenario, explained later), resulting in overall dynamic growth of demand. Additionally, density is a factor that can play a role in certain scenarios, impacting the total population and household consumption. Transmission losses, obtained from utility reliability reports, are factored in as an additional percentage of electricity added to the demand to ensure generation meets the required goals. Finally, the surplus represents instances where the supply exceeds demand at any particular point in time, offering opportunities for alternative utilization, such as selling to other regions or storing the excess.

The supply side of the model, depicted in Fig 4A, aims to accurately replicate the existing electricity generation market structure in the ComEd service area. At the core of this model component lies the "Central Electricity Generation" stock (MWh), representing the production of electricity over time. Inputs to this stock are represented by three primary flow components: electricity generation from carbon-based non-renewables (top of Fig 4A), nuclear power (middle of Fig 4A), and renewable energy sources (bottom of Fig 4A). The distribution of power plant types is determined based on real data (Table 1) or tested policies in different scenarios, with specific targets set for the share of each type by particular years (e.g., achieving 0% carbon-based plants by 2040). The supply side's main role is to provide supply-demand equilibrium based on demand requirements. The model incorporates the lifespan of different power plant types (30 years for carbon-based power plants, 20 years for nuclear power plants, and 25 years for renewables-based power plants), resulting in either new constructions or decommissioning of stations based on the scenario being tested. If the capacity of a

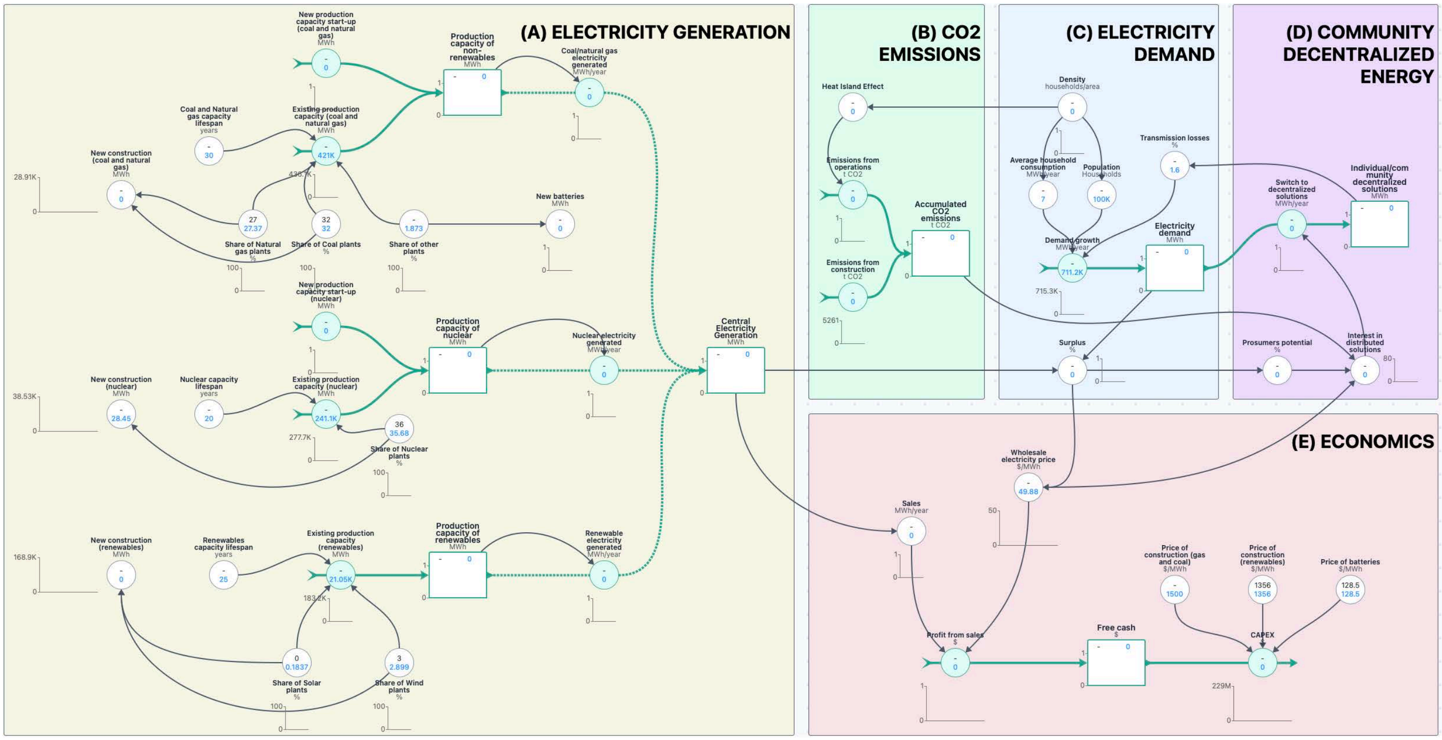

Fig 4. Stock and flow diagram of the energy market within the transition to a renewable-based decentralized energy system. (A): the large yellow box on the left represents the electricity generation profile based on the existing profile of ComEd in northern Illinois; **(B)**: the green box to the left from the "electricity demand" box is environmental measures from both operations and construction; **(C)**: the blue box on the top row in the middle represents an electricity demand side; **(D)**: purple box to the right from the "electricity demand" box is a community decentralized energy generation strategies; and, **(E)**: red box on the bottom right side is a finance measure with sales, electricity prices, etc., where free cash is a central measure.

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Table 2. Key stock and flow variables used in the diagram. In the table, "(…)" represents any source of generation, such as nuclear, coal, natural gas, wind, or solar.

Variable	Units	Description	Variable	Units	Description
Stock variables			**Flow variables**		
Accumulated CO_2 emissions	t CO_2	Total CO_2 emissions from operations and construction	Emissions from operations	t CO_2	Total CO_2 emissions from operations per year
Free cash	$	Cash generated after taking into consideration cash outflow (accumulation of free cash flow over time)	Emissions from construction	t CO_2	Total CO_2 emissions from new construction per year
Electricity demand	MWh	Total electricity demand	Demand growth	MWh	Total electricity demand per year
Central Electricity Generation	MWh	Total electricity supply from the power providers	Switch to decentralized solutions	MWh	Total electricity received from individual/ community solutions per year
Individual/ community decentralized solutions	MWh	Total electricity generated from small decentralized solutions	Profit from sales	$	Amount of income that remains after all expenses per year
Production capacity of (…)	MWh	Generation capacity from (1) non-renewables, (2) nuclear, (3) renewables	CAPEX	$	Capital expenditures for constructions per year
(…) electricity generated	MWh	Total amount of electricity produced by different sources	Existing production capacity (…)	MWh	A current capacity of various energy sources to produce electricity per year
			Central electricity generated	MWh	Total amount of electricity produced by all sources

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certain type of plant is no longer necessary in specific scenarios (e.g., after surpassing a designated threshold), construction of a different energy source commences.

The third component of the model focuses on the environmental impact of power generation (Fig 4B), with a central element being the "Accumulated CO_2 emission" stock, representing the cumulative t CO_2 emissions in the atmosphere resulting from power generation. This stock is influenced by two flows: emissions from operations, which can be influenced by the heat island effect discussed earlier, and emissions from construction activities. Evaluating the cleanliness of different electricity sources requires considering not only operational emissions but also emissions associated with the manufacturing and construction of plants, including high-emission, intensive production of batteries, solar panels, and wind turbines, as they are integral to the overall process. Emission factors are based on life cycle GHG assessments, calculated for operations, manufacturing, and fuel combustion [76–79], and the distribution of power generation sources in a given year is utilized to calculate the total emissions:

- Emission factors by source from operations and fuel combustion (in g CO_2/MWh): (1) natural gas = 595.6K; (2) coal = 918.8K; (3) nuclear = 20.9K; (4) solar PV = 12.3K; (5) wind = 8.3K
- Emission factors by source from construction (in g CO_2/MWh): (1) traditional power plants (averaged) = 3.1K; (2) renewables (averaged) = 31.1K; (3) batteries = 61.0M.

The accumulated CO_2 emissions stock serves as a significant measure and variable of interest in subsequent analyses.

The fourth component of the diagram focuses on the economic and financial aspects of the system (Fig 4E). It utilizes "Free cash" (measured in $) as the main stock, representing the accumulated cash generated by a company over time after accounting for operational and capital expenditures. The inflow of free cash is determined by the profit from sales, calculated by multiplying the annual electricity sales volume by the wholesale electricity price for residential customers in the corresponding year to capture the financial dynamics and revenue generation within the system, providing insights into the economic viability and performance of the company. In the real market, the wholesale price of electricity for residential consumers exhibits fluctuations over time due to various factors influencing the energy market [80], and these fluctuations occur due to changes in supply and demand dynamics, fuel costs, generation capacity, weather conditions, market regulations, and other variables. These price changes can occur on different timescales, ranging from intra-day fluctuations to seasonal or longer-term variations. To model these fluctuations for analytical purposes, fixed thresholds of 20, 40, 50, 60, 80, and 120 $ per MWh of electricity were used, representing the real prices in Illinois [81]. However, to account for the inherent randomness in the market, a random fluctuation of +/- $5 was introduced by drawing random samples from a normal (Gaussian) distribution to add a more realistic representation of market conditions in the modeling process. To accurately model the capital expenditure (CAPEX, $) flow, the construction amounts were derived from the supply component of the diagram, ensuring a realistic representation of infrastructure development. The prices used in the model are sourced from utilities' reports, reflecting actual market prices.

In the final component of the model, the focus is on customers' intentions to transition toward decentralized solutions, measuring the behavioral response to policies, which is explored through a separate scenario (Fig 4D). As discussed in [56] and [82], the decision to adopt distributed generation with community or individual-based solutions is influenced by various factors, with monetary considerations and environmental awareness identified as critical drivers. In this part, the interest in decentralized community energy systems is driven by three main components: prosumer potential, determined by the ability to sell surplus electricity; electricity prices; and accumulated CO_2 emissions, which are considered to become a visible factor due to climate change events. These factors are assumed to have equal weight in the decision-making process and are treated as such in the model. Once the switch to decentralized solutions occurs, customers begin generating electricity, resulting in decreased demand for conventional generation due to the independence of these systems from the main grid.

2.3. Model validation

The presented model was tested with several validation tests described in system dynamics literature [35,57,83–85]. As commonly emphasized in SD literature, such models prioritize understanding system behavior and dynamics over point predictions [83]. While SD models can provide insights into possible future trends or outcomes, the goal is more about understanding system behavior and testing "what-if" scenarios rather than making deterministic predictions. Therefore, the tests described later provide usefulness, are convincing, and inspire confidence in the model [86]. Historical data for electricity is available, dating back to the model's inception in 2017. Real data is available until 2025 (the last input available from ComEd reports is from June 30, 2025); historical tests were utilized in addition to operational and sensitivity tests to validate the model and achieve an acceptable level of simulation accuracy in the scenarios. Given the limited availability of data for statistical validation of other variables (emission and financial data are not disclosed by the utilities at the granular level needed for tests), our primary focus lies in conceptually validating the mechanisms within our model before projecting into the future and anticipating potential trajectories with cautious confidence. So, the model validation includes:

- operational and structural tests, including face validity and extreme condition testing
- historical behavior tests using real-world data (generation statistics from ComEd reports from 2017 to mid-2025)
- sensitivity analysis to test model robustness.

(a) Operational test. The operational test included the verification and analysis of the appropriateness of using the Silico software for this type of analysis, as well as general model verification and face validity. Variable units were checked to verify the equations, and this verification was performed to demonstrate that the scenario behaves as defined by the experiment. The approach of "face validity," originally defined by [84], was used to evaluate if all parameters and model structure make sense. For example, in our model, a hidden control variable (supply/demand equilibrium) is used to measure and ensure that fluctuations do not exceed a certain threshold [87]. Electricity demand is constantly changing, requiring suppliers to generate more energy during periods of high demand and less during periods of low demand. In the real environment, suppliers typically measure demand in 15-minute periods to effectively respond to changing electricity consumption patterns. During periods of low demand, such as during mild weather conditions, the supply of electricity can exceed demand, resulting in a surplus that can range from a few percentage points to a significant excess, potentially reaching double-digit percentages. Conversely, during periods of high demand or unexpected outages, the demand for electricity can exceed the available supply, resulting in a shortfall that can range from a minor shortage to a substantial gap, potentially reaching double-digit percentages. Managing the balance between supply and demand is crucial to avoid undersupply, which can lead to blackouts and brownouts, as well as oversupply, where excess energy may go to waste or be stored in batteries if certain technologies are available. As shown in Fig 5, the undersupply or oversupply is within the range between -300 GWh and 300 GWh (which is less than 1% of the total supply) with a few exceptions in the last years in one of the scenarios, where the fluctuations are within 5% of the total supply, which is also within the allowable threshold. That scenario, characterized by a high rate of decentralized energy and the highest oversupply (pink line in Fig 5), highlights a critical challenge where the rapid shutdown of power generators relying on traditional sources, such as nuclear power stations, is not immediately feasible, resulting in a time delay in the process.

The graph demonstrates that the model maintains dynamic stability across most scenarios, with deviations emerging only under extreme decentralization conditions, indicating sensitivity to structural and policy-driven feedbacks. This outcome aligns with established SD validation principles, which emphasize behavioral and structural validation over exact numerical replication when empirical data are limited [83,85]. From a validation perspective, this behavior suggests that the model's structural integrity and feedback mechanisms are consistent with real-world system behavior, supporting its credibility for scenario-based policy exploration.

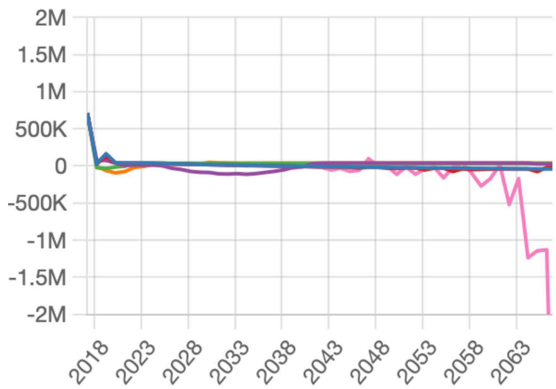

Fig 5. Electricity supply-demand equilibrium variable over the simulation timeframe.

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(b) Historical behavior tests. As mentioned earlier, due to the model's nature, it is challenging to conduct tests of multiple parameters and compare them with real historical data. However, to validate the model, we were able to compare generation patterns, which is one of the most important variables in the system, for the first nine years of the simulation with real-world data from the utility (Fig 6). We first identified a trendline formula from the observed utility data for 2017–2020 and used it to train the model. The model does not simply replicate that formula; instead, it learns the underlying patterns it represents and then generates its own simulated series. For this reason, we evaluate two cases: (i) in-sample backcasts for 2017–2020, where the simulated values need not exactly match the raw observations, but be able to be generalized from the trained model, and (ii) out-of-sample forecasts for 2021–2025. Therefore, the gaps in 2017–2020 arise because the learned simulation is based on a smoothed trend with modeling constraints (rather than point-by-point replication of noisy observations). In Fig 6, the numbers label the percent difference between the simulated series (green line) and the utility's reported values (orange points). Results show that the model can be considered robust, as the error between real and simulated data is small and falls within the 15% range (most of the simulated years within the 10% range, sometimes closer to 0% – exact alignment).

(c) Sensitivity analysis. In SD research, sensitivity analysis is not a substitute for model validation but rather a complementary step to assess model robustness and behavioral stability under uncertainty [83,85]. Following this principle, our sensitivity analysis was conducted after confirming face validity, operational integrity, and historical pattern replication, making sure that the model is both conceptually and empirically sound before testing its sensitivity boundaries and examining extreme situations. This type of analysis is typically understood as a method to alter the values of at least one factor, calculate and observe its impact on the results, and estimate the sensitivity of the results to that factor [83,88]. The sensitivity of tipping points to model parameters provides valuable insights into the factors that influence ripple effects and deadline stress. This information is particularly relevant for policymakers involved in managing large-scale projects, where rapid ripple effects and schedule pressures can emerge, to understand the critical parameters that should be considered when formulating policies to effectively manage large projects and mitigate the risks associated with ripple effects and schedule stress [89]. In this model, numerical sensitivity is employed to examine how changes in assumptions impact the mathematical values of the results [83]. As discussed earlier, the price of electricity is considered a critical component in the transition to decentralized systems at both individual and community levels [50,89–91]. The fluctuations in electricity prices depend on several key parameters, including market dynamics, prevailing fuel prices, generation capacity, available infrastructure, and weather conditions. In our model, based on historical data, the minimum price for electricity varies from \$20 per MWh to \$120 per MWh, using a random variable with a standard deviation of \$5, and is designed to primarily reflect market dynamics. In the sensitivity testing, we change the minimum price (\$20)

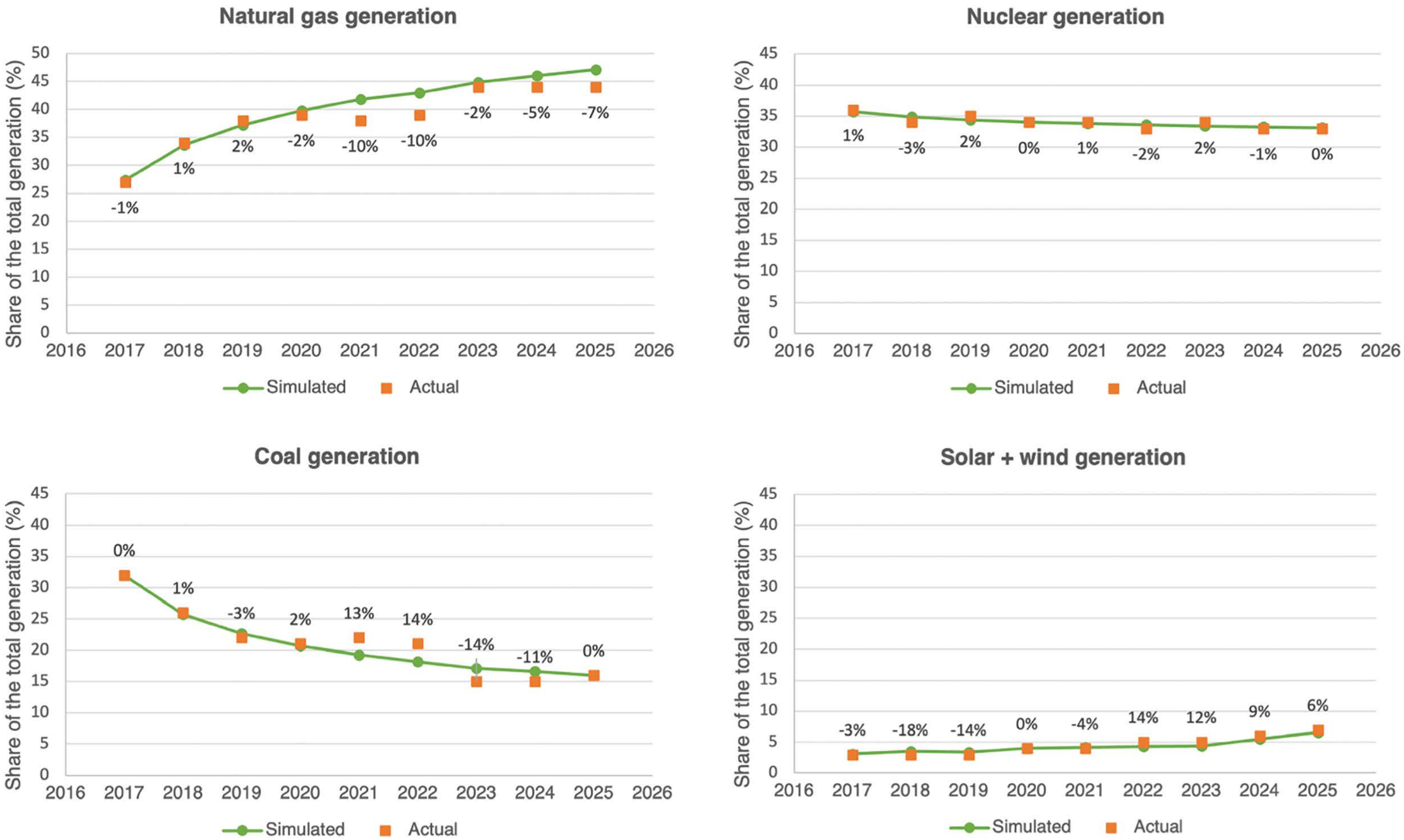

Fig 6. Historical test results for generation patterns in 2017-2025. The green color (lines and markers) represents simulated data, and the orange markers show real data. Numbers on the graph represent the difference (in %) between simulation and actual data.

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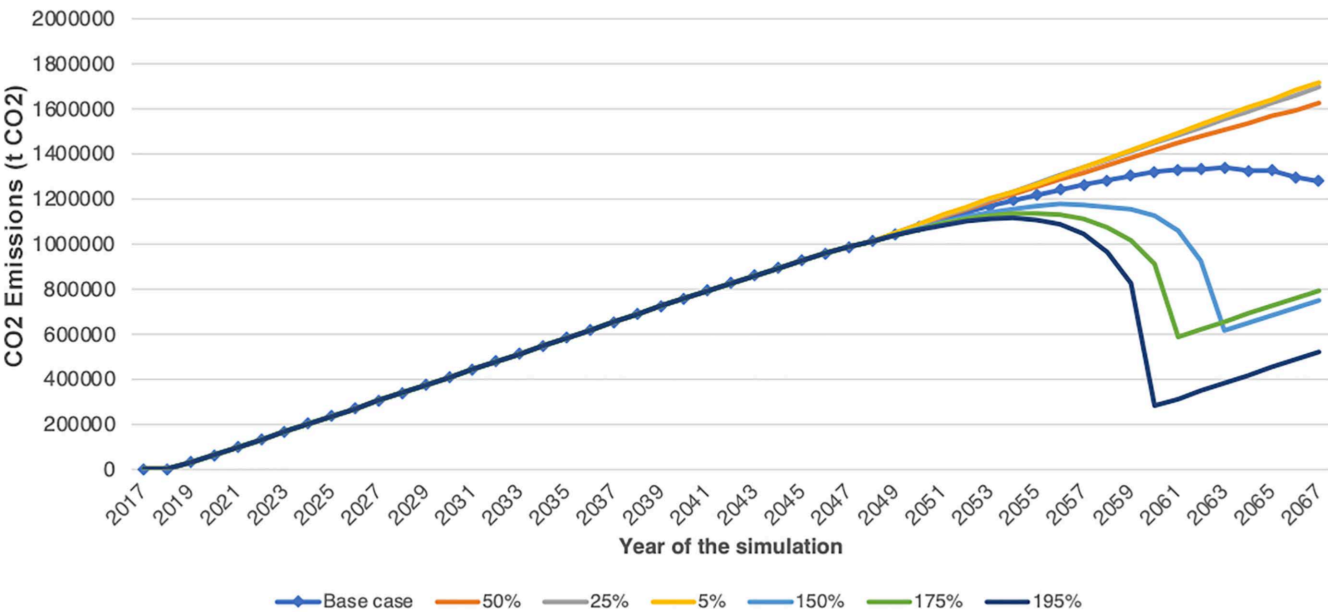
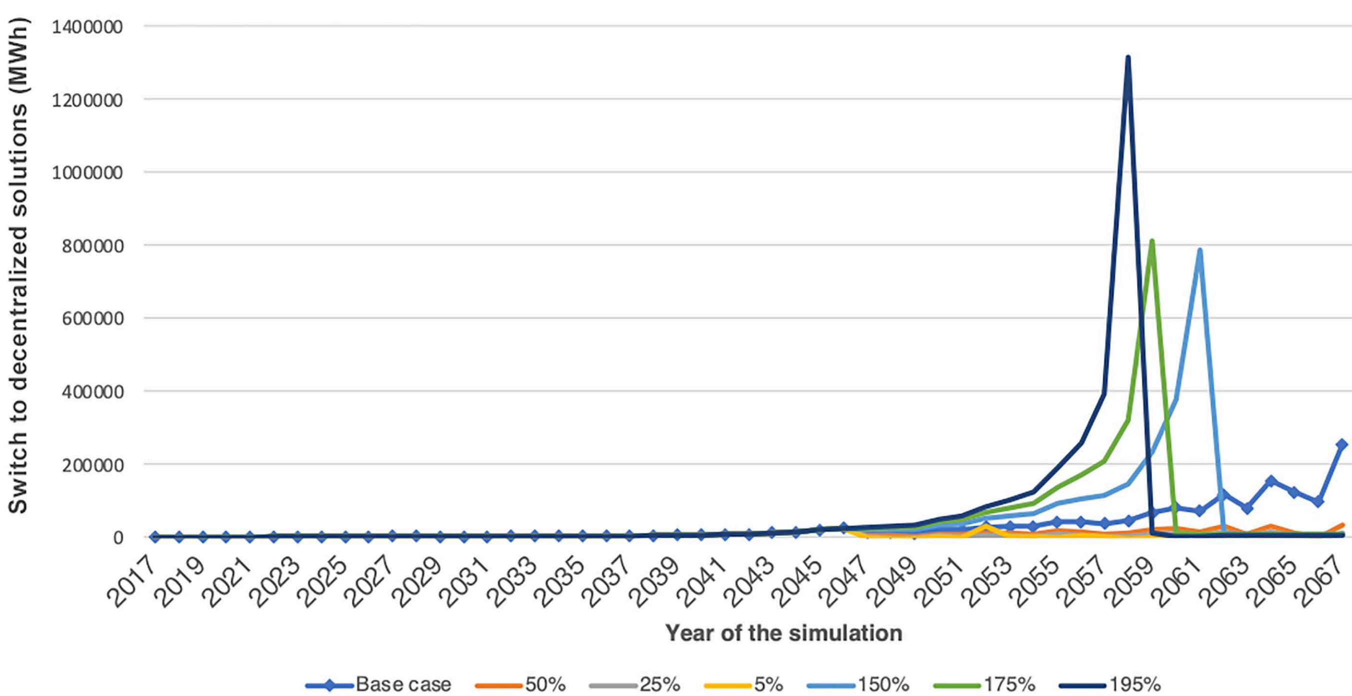
within the range [-95%; -75%; 50%; 150%; 175%; 195%] to see how two variables of interest (CO_2 emissions and switch to decentralized solutions) change over time with new inputs. The results presented in Fig 7 clearly show that the fluctuations of the minimum price for electricity affect the decision made to switch to a decentralized solution, even if it is only one component of the decision-making process, and, therefore, the overall CO_2 emissions due to a considerable change into more renewable solutions and less consumption of electricity from utility-based fossil fuel sources.

The results of the sensitivity analysis are consistent with the real-life findings from the literature. The fluctuations in electricity prices are influenced by various parameters, including market dynamics, fuel prices, generation capacity, infrastructure availability, and weather conditions. In the model, the minimum price for electricity is initially set within a certain range based on historical data, reflecting market dynamics. The overall model is sensitive to price fluctuations in certain time periods within the simulation; however, it does not change significantly at the beginning of the modeling and at the very end of the simulation, when the variables of interest stabilize. The model's sensitivity to price fluctuations and its impact on the decision-making process can be explained by the economic dynamics at play: as electricity prices rise, the cost-effectiveness and competitiveness of decentralized solutions, such as solar or wind power, also increase. Additionally, the percentage of the increase (or decrease) of variables in the tested scenarios is not particularly high compared to the dramatic change in input, so the model can produce a tolerable output behavior. The relatively moderate percentage changes in the variables of interest compared to the dramatic changes in input indicate that the model produces output


CO2 Emissions (t CO2)
2000000
1800000
1600000
1400000
1200000
1000000
800000
600000
400000
200000
0
2017 2019 2021 2023 2025 2027 2029 2031 2033 2035 2037 2039 2041 2043 2045 2047 2049 2051 2053 2055 2057 2059 2061 2063 2065 2067
Year of the simulation
Base case
50%
25%
5%
150%
175%
195%

(a)


Switch to decentralized solutions (MWh)
1400000
1200000
1000000
800000
600000
400000
200000
0
2017 2019 2021 2023 2025 2027 2029 2031 2033 2035 2037 2039 2041 2043 2045 2047 2049 2051 2053 2055 2057 2059 2061 2063 2065 2067
Year of the simulation
Base case
50%
25%
5%
150%
175%
195%

(b)

Fig 7. **Results of the sensitivity analysis for accumulated CO_2 emissions (a) and switch to decentralized solutions (b).** The base case represents a modeled electricity price of $20/MWh; 50% – $10; 25% – $5; 5% – $1; 150% – $30; 175% – $35; 195% – $39.

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that aligns with expected behavior. This suggests that the model captures some of the complexity of the relationship between price fluctuations, the adoption of decentralized solutions, and resulting CO_2 emissions.

2.4. Scenario simulation

In this article, six scenarios were designed to test based on the literature and current energy market trends in Illinois. All scenarios were planned using real data inputs described earlier in their initial stages; however, the policies and strategies are unique to every single scenario. The modeling horizon spans 50 years, from 2017 to 2067, with each tick representing one year. The scenarios are presented in Table 3.

The selected scenarios were chosen to address the most pressing challenges and opportunities in urban energy markets by considering a mix of current utility strategies [56], policy-driven transitions [64], technological advancements [97,24], and consumer-driven changes. The BAU scenario serves as a benchmark, reflecting real utility data and projected trends, ensuring that all comparisons are grounded in actual market dynamics. The DENS scenario tests the well-documented correlation between urban densification and energy consumption patterns [92–95], which is the only urban planning-focused solution, and which has been shown to reduce per capita energy use through more efficient land use and infrastructure. This is illustrated by real-life examples, such as in Tokyo, Japan. Tokyo's high urban density has led to more energy-efficient buildings and infrastructure, resulting in reduced per capita electricity consumption. The city has implemented compact urban planning, which has improved public transport and energy efficiency, aligning with the DENS scenario's concept of increased population density and reduced household energy use. Policy-driven scenarios, such as CEJA and REN, enable the evaluation of regulatory impacts, particularly the feasibility and consequences of ambitious decarbonization goals, aligning with ongoing legislative efforts in Illinois and similar policies worldwide. Examples of similar strategies could be European policies [7], such as in Denmark (strategic planning), Germany (Energiewende strategy), or France's transition from nuclear power generation. The RENBS scenario is crucial for assessing the role of energy storage in mitigating the intermittency of renewables, a key technological challenge in transitioning to a low-carbon grid. This scenario takes into consideration the successful story of Moss Landing Energy Storage Facility in California, USA, which is one of the world's biggest storage projects. Finally, the DEC scenario acknowledges the growing interest in decentralized energy solutions, as identified in previous research, and explores the potential for prosumer participation to reshape electricity markets (for instance, Brooklyn Microgrid in New York, USA). Together, these scenarios provide a well-rounded analysis that accounts for both near-term transitions and long-term structural shifts in energy systems, informed by urban planning, energy engineering, and concrete policy strategies based on examples from around the world.

3. Results

A goal of this modeling process is to understand the complexity of the transition to the new electrical system through different scenarios and evaluate the environmental, economic, and technological sustainability of the designed system over the timeframe. This section provides the results from the simulations for all six scenarios described in the previous section. It is worth noting again that these SD simulations are not used to predict or forecast concrete numerical data, but rather to understand trends, patterns, and relative differences between scenarios, which can be used as input for assessing future policymaking processes. All simulations were made for an imaginary area with 100,000 residents located in northern Illinois. The results of the scenario simulations presented in this section can be combined into three broad categories of impact: electricity consumption and generation, finance, and environmental perspectives.

Table 3. Scenarios used in the model.

Scenario name	Description	Visualization
Business-as-usual scenario (BAU)	This scenario is based on the real ComEd data regarding shares of each source of energy in the total electricity generation profile and projected trends for the following years. This scenario includes a slow reduction of the share of coal-based power plants that mainly are changed to natural gas-based power plants following the current strategies of the utility.	The scenario uses blue color on graphs.
Densification scenario (DENS)	The densification scenario works under the concept of how electricity will be consumed based on the fact that the number of households in the region will increase, but the average consumption of the household will decrease because of the more compact urban form. The term "urban form" includes many characteristics of the built environment, such as density, orientation of the structures and streets, compactness, concentration, etc. It is based on the findings from [56], where the densification pattern is positively linked to the electricity demand. In the literature, a positive relationship between an increase in population density and a decrease in energy consumption have found [92–95]. The idea of this scenario is to represent the demand control using the tools and methods available to urban planners leading to denser neighborhoods. This scenario has the same generation patterns as BAU, with only changes in the consumption profile.	The scenario uses red color on graphs.
Illinois Climate and Equitable Jobs Act scenario (CEJA)	This scenario is based on a signed into law 2021 Illinois Climate and Equitable Jobs Act [61] which includes strategies of using about 90% of carbon-free sources by 2050 that will be achieved by having 50% of renewables by 2040 and keeping nuclear resources for the rest of the energy profile.	The scenario uses purple color on graphs.
Mostly renewables scenario (REN)	This scenario is similar to the previous scenario, but without using nuclear as a source of electricity generation and shutting down all nuclear stations over time. This scenario is based on renewables (both solar and wind) in addition to about 10% of other generation (such as natural gas) by 2035. As was discussed in [7], the nuclear lobby is significant in Illinois, and it is going to stay a vital part of the generation profile. However, taking into account nuclear disaster events that took place in several places, for example, Chernobyl or Fukushima, there is a strong need to test policies without high dependency on this source of power, following guidelines of many countries, such as Germany, shutting down the old nuclear reactors [96].	The scenario uses green color on graphs.
Mostly renewables and large battery storage scenario (RENBS)	This scenario is based on avoiding fossil fuels after 2040 and leaving only renewable sources and large batteries (storage) as a backup by 2040. The CLD analysis in [56] reveals the pivotal role of technological progress in the energy industry as both an initiator and disseminator of change. Notably, this progress has led to the cost reduction of batteries and improved customer accessibility for their installation. While the decreased prices of batteries have positive implications for their installation, it is essential to address the environmental drawbacks and upfront costs that remain significant concerns in the adoption of these technologies. This scenario will test a significant production of battery storage in several years with their further use in a generation profile.	The scenario uses orange color on graphs.
Individual and community-based decentralized solutions scenario (DEC)	This scenario is based on the assumption that consumers, if seeing clear benefits and opportunities to be involved in the electricity market (with primarily monetary potential, either in getting independence from the central utility and getting electricity with lower prices, or even becoming prosumers and selling a surplus of electricity back to the grid), consumers may decide to create an individual or community-based decentralized solution. This scenario tests the findings from the graph analysis from [56], which found the interest in decentralized solutions as a significant disseminator of change, directly connected with environmental concerns, electricity prices, opportunity for energy independence, and prosumer potential. All other parts of the model stay similar to the BAU scenario.	The scenario uses pink color on graphs.

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3.1. Electricity consumption and generation

Fig 8 shows results for all six scenarios from both the supply and demand sides of the electricity profile. Fig 8A illustrates the total generation managed by the centralized utility. Fig 8B shows the total electricity demand from the population that needs to be provided by the centralized utility. Fig 8C displays the pattern of switching to decentralized, individual, and/ or community-based solutions. Fig 8D–8F show the electricity generation for three major types of centralized electricity generation sources: thermal-power capacities (combining natural gas and coal-based technologies), nuclear-powered generation, and renewable-based technologies (combining wind and solar). The distinction between cumulative (stock; Fig

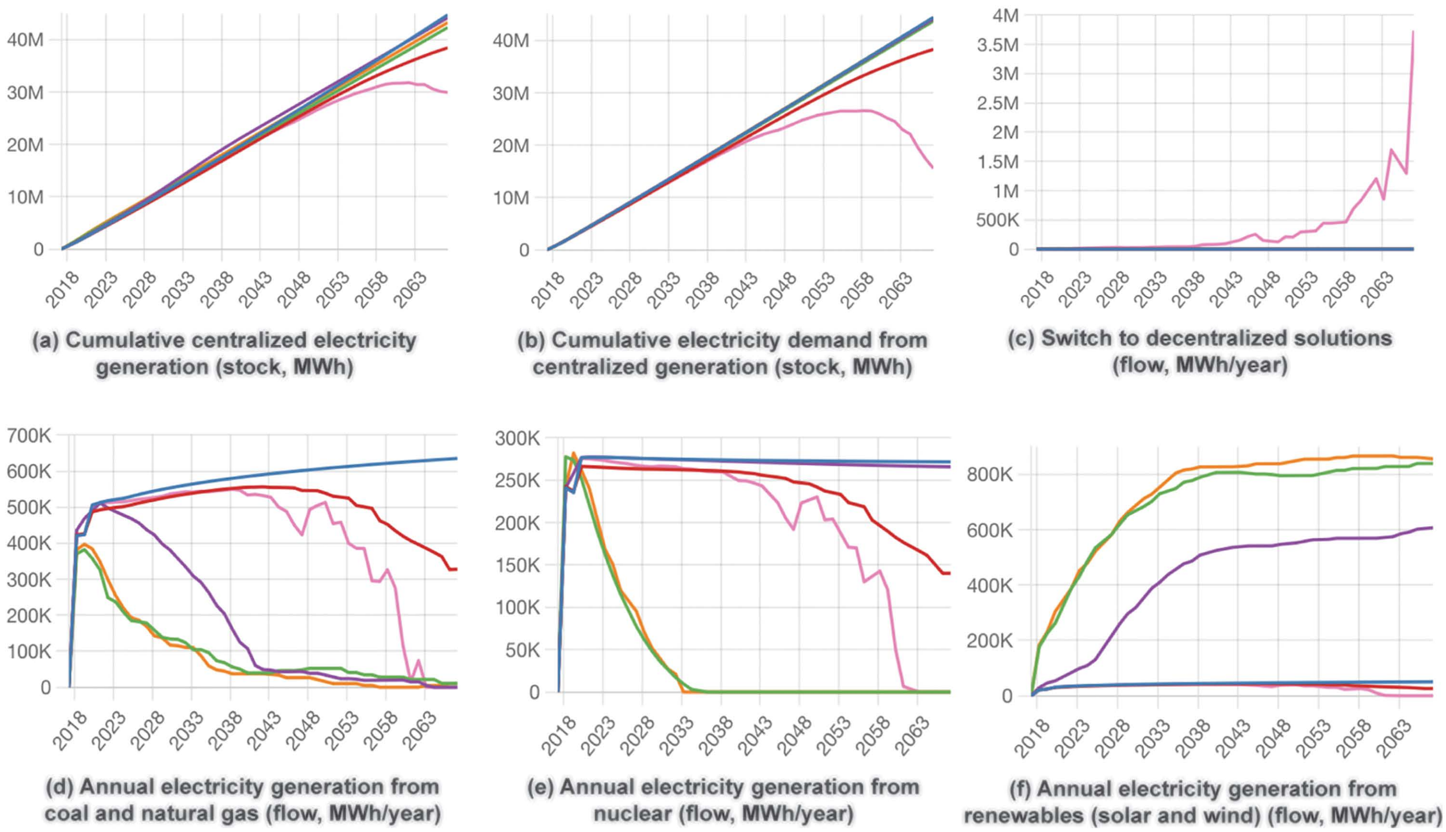

Fig 8. Comparison of simulation results for electricity supply and demand. The figures distinguish between stock variables (cumulative electricity generation and demand) and flow variables (annual generation and decentralized adoption).

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8A, 8B) and annual (flow; Fig 8C–8F) variables in this study follows established practices in SD modeling of energy transitions. Stock variables, such as cumulative centralized electricity generation and total demand, represent the aggregated state of the system over time, reflecting the long-term buildup of capacity and energy use. In contrast, flow variables, such as annual generation by source or yearly adoption of decentralized solutions, describe the rates of change and short-term dynamics that drive system evolution. Displaying both stock and flow perspectives allows for a more comprehensive understanding of the interrelations between accumulation, policy interventions, and transitional feedback effects [82,98,99]. This approach aligns with recent system dynamics and stock-flow consistent energy modeling literature, which emphasizes the importance of capturing both aggregated and rate-based system behaviors for realistic scenario analysis [82,100,–102].

The DEC scenario demonstrates a pronounced structural shift in the energy system, where decentralized adoption substantially modifies the supply-demand dynamics by reducing dependency on centralized generation and reshaping operational roles of utilities. As decentralized systems expand, centralized utilities increasingly function as backup capacity providers, supplying energy mainly during peak demand or unfavorable weather conditions. (i.e., windless day for the wind turbines-based systems). As decentralized systems expand, centralized utilities increasingly function as backup capacity providers, supplying energy mainly during peak demand or unfavorable weather conditions. This evolution also suggests a gradual realignment of utility operations, where retiring older, high-emission power stations becomes both economically viable and strategically beneficial. The model indicates that the most effective window for beginning large-scale decommissioning of centralized generation lies between 2045 and 2050, when decentralized capacity stabilizes, and investment returns for consumers improve (Fig 8D, 8E). The analysis revealed that this strategy provided a total reduction in generation at the end of the simulation of 28.9% compared to the BAU scenario (Table 4). Beyond the 50-year horizon, the trend becomes self-reinforcing – wider adoption of decentralized systems accelerates further investment through social and market feedbacks. This could be explained by the reinforcing nature of this process: results reveal a reinforcing feedback loop typical for socio-technical transitions. As decentralized adoption grows, centralized revenues decline, prompting tariff adjustments that, in turn, stimulate additional decentralized uptake. Such a behavioral-economic loop reflects the core feedback structure of the model and aligns with recent studies describing feedback-driven diffusion in distributed energy systems [82,101]. In the DEC scenario, over the last few years, there is no room for any other types of centralized generation; however, by 2062, some electricity will still be generated from centralized sources (mainly from natural gas- and nuclear-based stations).

The DENS scenario also provides a slight reduction in both consumption and production patterns. In this case, the total generation decreases moderately (-14.1% from BAU) (Table 4), but the benefits of compact urban form are partially offset by reduced potential for on-site renewable generation due to building height, shadowing, and limited rooftop space [94,103]. This indicates that densification alone cannot ensure sustainability unless supported by integrated spatial-energy planning strategies. In dense urban settings, maximizing renewable generation potential requires joint consideration of architectural form, solar access, and urban energy infrastructure, a finding that links energy modeling with spatial planning and policy design. Scenarios CEJA, REN, and RENBS exhibit similar trends to BAU over time, allowing for reductions of 1.3%, 5.4%, and 3.3% of the total generation, respectively (Table 4). Their trajectories demonstrate that renewable growth alone, without active demand-side measures or decentralized governance, is insufficient for achieving long-term decarbonization. This reinforces the study's main argument that transformative energy transitions depend on policy integration, behavioral feedbacks, and urban planning coordination rather than isolated technological interventions.

3.2. Finance

In Fig 9, five financial variables simulated in the model are presented. Fig 9A represents the total sales of electricity in MWh. Fig 9B shows the wholesale electricity prices in $/MWh based on historical data with artificially created random fluctuations, and Fig 9C therefore shows the total profit from sales based on sales and the average electricity price. Fig 9D represents CAPEX, which refers to "capital expenditure" and represents the funds invested in acquiring, upgrading, or expanding fixed assets or infrastructure (in our model, this includes capital construction of new power generation plants or energy storage systems). The price for capital construction varies throughout the entire simulation period and takes into account predictions regarding fluctuations in the market price for different types of renewable infrastructure and batteries

Table 4. Electricity consumption and generation for the different scenarios at the end of the simulation (year = 2067) and a comparison with a BAU scenario (change in % to the base run).

	Centralized electricity generation		Electricity demand from centralized generation		Electricity generation from coal and natural gas		Electricity generation from nuclear		Electricity generation from renewables (solar and wind)	
	MWh	Change (%)	MWh	Change (%)	MWh	Change (%)	MWh	Change (%)	MWh	Change (%)
BAU	*44,771,576*	–	*44,464,356*	–	*635,170*	–	*271,625*	–	*50,477*	–
DENS	38,461,175	-14.1	38,329,563	-13.8	327,743	-48.4	140,157	-48.4	26,046	-48.4
CEJA	44,210,127	-1.3	44,138,040	-0.7	0	-100	265,825	-2.1	607,588	1,103.7
REN	42,338,314	-5.4	43,716,887	-1.7	10,879	-98.3	0	-100	839,866	1,563.9
RENBS	43,292,019	-3.3	44,382,601	-0.2	10,207	-98.4	0	-100	856,269	1,596.4
DEC	31,820,998	-28.9	25,598,894	-42.4	0	-100	0	-100	0	-100

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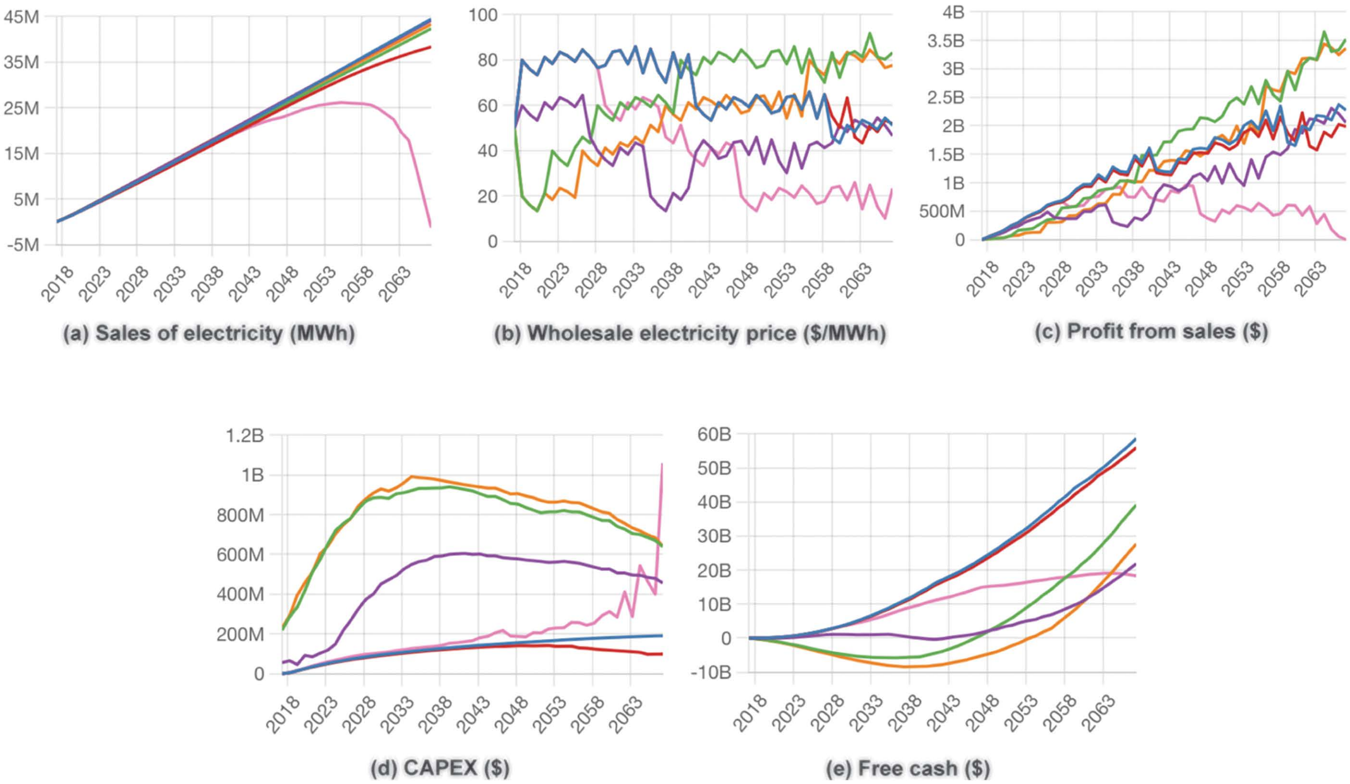

Fig 9. Comparison of simulation results for economic factors.

https://doi.org/10.1371/journal.pcsy.0000083.g009

[68,104,105]. Finally, Fig 9E illustrates the free cash measure, which represents the amount of cash generated by a utility from its operations after accounting for capital expenditures and working capital requirements. Free cash flow is generally considered a valuable measure for all finance because it provides insights into the financial sustainability of strategies and allows us to see potential scenario profitability.

The sales of electricity graph shown in Fig 9A is almost identical to the plot shown in Fig 8A, representing a centralized electricity generation pattern. Usually, all produced electricity goes to the grid and is sold; however, since sometimes there is a surplus of electricity, utilities have to manage it with different scenarios such as selling to other utilities, saving it to the storage if available, incentivizing consumption through demand response mechanisms or time-of-use pricing, or use curtailment as a last option when surplus generation exceeds storage and demand capacity. However, profit from sales (Fig 9C) varies a lot since it is highly linked with wholesale electricity prices (Fig 9B). In BAU and DENS scenarios, electricity prices remain relatively stable due to the absence of new construction, low capital expenditure, and steady consumption trends, resulting in minimal tariff pressure. In contrast, REN and RENBS scenarios show gradual price increases (to $83 and $78/MWh by 2067), primarily reflecting cost recovery mechanisms for renewable infrastructure investments. The DEC scenario exhibits an inverse market response: as customer migration toward decentralized systems accelerates, utilities reduce output and operational costs, thereby lowering prices to remain competitive. This reflects a balancing feedback between market share loss and cost reduction, where price adaptation acts as a temporary stabilizing mechanism within a declining utility revenue base. Consequently, the end price in 2067 for the DEC scenario is $23/MWh. As seen in Table 5 and Fig 9C, REN and RENBS scenarios yield the highest nominal revenues in terms of revenue generated from electricity sales; however, the CAPEX for those scenarios is very high, too (Fig 9D). The higher CAPEX is only in the DEC scenario

Table 5. Economics for the different scenarios at the end of the simulation (year = 2067) and a comparison with a BAU scenario (change in % to the base run).

	Sales of electricity		Profit from sales		CAPEX		Free cash	
	MWh	Change (%)	$	Change (%)	$	Change (%)	$	Change (%)
BAU	44,462,233	–	2,274,812,166	–	190,589,062	–	58,652,521,327	–
DENS	38,329,110	-13.8	1,988,132,518	-12.6	98,369,974	-48.4	55,978,774,846	-4.6
CEJA	44,137,922	-0.7	2,053,779,770	-9.7	456,832,448	139.7	21,853,517,805	-62.7
REN	42,338,313	-4.8	3,521,654,910	54.8	638,874,341	235.2	39,157,495,804	-33.2
RENBS	43,292,019	-2.6	3,360,497,537	47.7	641,991,028	236.8	27,661,301,256	-52.8
DEC	0	-100	0	-100	1,059,166,015	455.7	18,312,826,962	-68.8

https://doi.org/10.1371/journal.pcsy.0000083.t005

with a significant construction of individual or community-based solutions. In the DEC scenario, however, investment responsibilities are distributed among actors (municipalities, cooperatives, and public–private or citizen–private partnerships [97,106]), indicating a systemic redistribution of financial risk and ownership. This structure may improve long-term resilience, even if short-term profitability declines. BAU and DENS have almost no CAPEX due to the minimal construction and improvements.

Free cash used in the model allows one to measure how efficiently utilities generate operational liquidity after deducting all expenses related to CAPEX. In our model, as shown in Fig 9E, we clearly observe that the BAU and DENS scenarios are the most profitable because they maintain stable operations and low reinvestment needs. Since utilities are well-regulated and their business structure has remained largely unchanged for decades, the safer option is to stick with existing mechanisms and infrastructure, renewing only the basic poles and wires. It is important to note that in some U.S. states, such as Illinois, generation and transmission are legally unbundled but often corporately integrated, allowing financial outcomes to remain aligned between production and distribution arms. This vertical alignment partially explains why the BAU and DENS scenarios sustain high free cash flow despite limited innovation.

3.3. Environmental metrics

In Fig 10, major environmental metrics are shown. Fig 10A represents the total accumulated CO_2 emissions over 50 years of the simulation coming from two sources: operations (Fig 10B) and new construction (Fig 10C).

The BAU scenario has the most considerable environmental impact due to the monotonously increasing amount of CO_2, which aligns with real-world emission trajectories for fossil-fuel-dependent systems reported in both empirical and modeling studies [107–109]. DENS exhibits a similar behavior; however, since the overall amount of electricity produced is lower, the total amount of emissions is also lower. A pronounced reduction in operational emissions is observed in scenarios where coal and natural gas generation are progressively replaced by renewable sources, confirming the direct sensitivity of total CO_2 emissions output to the system's generation mix. Among all cases, REN achieves the most substantial cumulative emission reduction (-78.9% vs. BAU; Table 6), reflecting an aggressive renewable expansion strategy with limited thermal back-up. CEJA performs comparably well but shows residual emissions from ongoing infrastructure construction, indicating that policy-driven transitions, while impactful, may still involve embedded carbon costs in new investments. The RENBS scenario exhibits a distinctive construction-phase emission spike (Fig 10C) primarily driven by battery manufacturing, which is known for high embodied carbon intensity. This short-term increase, however, is followed by long-term operational benefits once storage assets reduce curtailment and reliance on fossil sources. Emission factors applied in the model reflect lifecycle assessments: traditional thermal power plants (averaged for natural gas and coal) – 3.1 Kg CO_2/ MWh; renewables (averaged for wind and solar) – 31.2 Kg CO_2/ MWh; and batteries – 61 Kg CO_2/ MWh. DEC scenario performs favorably in operational emissions due to the gradual phase-out of centralized fossil generation, while construction-related emissions remain moderate given the distributed nature of investments. Although total

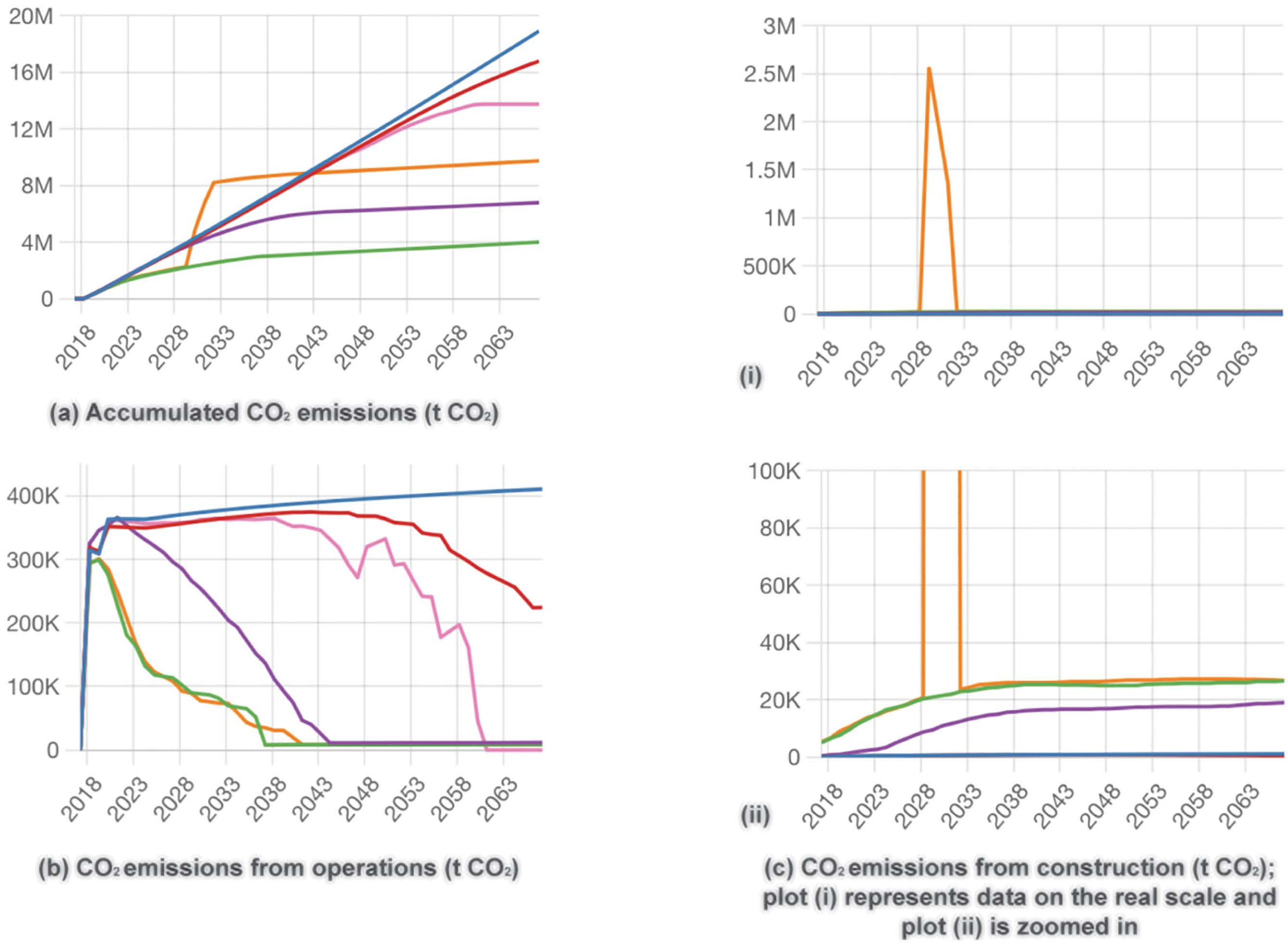

Fig 10. Comparison of simulation results for environmental factors.

https://doi.org/10.1371/journal.pcsy.0000083.g010

Table 6. Total CO_2 emissions for the different scenarios at the end of the simulation (year = 2067) and a comparison with a BAU scenario (change in % to the base run).

	Accumulated CO_2 emissions	
	t CO_2	Change (%)
BAU	18,923,049	–
DENS	16,792,876	-11.3
CEJA	6,794,217	-64.1
REN	4,001,477	-78.9
RENBS	9,750,673	-48.5
DEC	13,961,390	-26.2

https://doi.org/10.1371/journal.pcsy.0000083.t006

cumulative emissions (-26.2% vs. BAU) are higher than in centralized renewable cases, the trend stabilizes and begins to decline in later simulation years, suggesting that decentralized systems may achieve deeper reductions over extended horizons once infrastructure turnover stabilizes. This trajectory reflects a structural lag common in socio-technical transitions, where emission reductions accelerate only after cumulative system restructuring reaches maturity.

4. Discussion

The simulation reveals both similarities and differences among the scenarios in various metrics. For example, the BAU and DENS scenarios, based on actual ComEd data, exhibit similarities in certain parameters, such as free cash, although they differ in terms of demand formation principles. Similarly, the CEJA, REN, and RENBS scenarios share similarities in generation patterns due to their significant reliance on renewable energy. On the other hand, the DEC scenario exhibits behavior that varies across the relevant metrics, as it is the only scenario that focuses on independently produced energy outside of central power providers.

Under the ***BAU scenario***, the system exhibited a well-balanced equilibrium between electricity supply and demand, with slight fluctuations in price, relatively stable profits from sales, and growing free cash. These results support the current electricity market in northern Illinois, which has a low penetration of renewable energy resources, a high dependence on nuclear power, and thermal-powered capacities (coal and natural gas). However, this scenario has the highest CO_2 emissions throughout the entire simulation period, reflecting the structural inertia of centralized, fossil-based systems. This persistence is not only due to limited utility action but also the absence of strategic integrative regulatory planning between market and policy actors [7,110,111]. Also, although in today's circumstances, natural gas is commonly viewed as a "bridge fuel," the BAU scenario highlights that even transitional reliance on it locks the system into sustained emission trajectories, an insight that aligns with current empirical evidence.

The DENS scenario shows similar trends over time; however, with lower produced electricity and, therefore, lower CO_2 emissions from operations, as well as total emissions at the end of the simulation. The DENS case differs fundamentally from BAU by focusing solely on urban design interventions that indirectly influence energy demand. Essentially, this scenario operates under the theory that the average household consumption decreases due to the densification of neighborhoods. Densification (sometimes called urban infill) leads not only to some benefits in the electricity sector but was demonstrated to improve land use to a more efficient [112], increase social interaction [113], promote affordable housing [114], and provide cost savings to other public infrastructure such as roads, public transportation, etc. [115] if adequately monitored and regulated. There are many potential strategies that could be employed in the process, for instance, changes in zoning regulations and designating zones for more mixed-use purposes, implementation of transit-oriented developments (TODs), urban redevelopment targeting underutilized or vacant areas within cities (infill development), or providing incentives, such as tax breaks or expedited permitting processes, to developers who build higher-density and energy efficient projects with incorporating affordable housing units. Following the principles discussed in [7], a new strategic municipal planning framework with connections between municipalities and energy planning entities, involving stakeholders at various levels, from local communities to national entities, has become a crucial basis. This scenario highlights a key gap: urban planning and design can significantly reduce consumption, but cannot alone transform the energy supply structure, underscoring the need for integrated urban-energy planning.

REN **and** ***RENBS scenarios*** have relatively similar patterns in most of the metrics and represent technologically driven decarbonization pathways. Those scenarios play a significant part in reaching the goal of decreasing carbon emissions and are a good possibility for utilities to convert their business toward a more sustainable way. Both scenarios achieve major CO_2 reductions through rapid renewable expansion, replacing nearly all thermal generation. The REN scenario is the best case in terms of CO_2 emissions (~4x lower than BAU), while RENBS introduces short-term emission spikes due to the carbon intensity of large-scale battery production. This trade-off illustrates a classic rebound in life-cycle emissions, where construction-phase impacts temporarily offset operational gains. Electricity prices in these cases follow investment cycles: rising during infrastructure build-out (2030–2035) and stabilizing afterward (~$80/MWh) with some fluctuations to $40–60/MWh. However, with very high CAPEX, some years are not profitable, and free cash shows negative values mid-simulation. This gap might be covered by long-term strategic government or state initiatives and programs (such as tax credits, financing programs, and state partnerships), which were found to be an important lever in the CLD in [56], and it is clearly not possible to fill with only tariff mechanisms or utilities-centered initiatives and could be solved only with significant collaboration between levels of governance. Utilities in Illinois are required to provide a "reliable, environmentally safe and least-cost" delivery of electricity [116]; however, without proper planning and control, they can fit within the law without spending at all, just providing "demand response" programs, for example, rewarding customers who use do not use energy when there is a high demand [117]. However, there is an interest in utilities being involved in less cost-effective projects, as they can collect an additional percentage as a profit. Moreover, more costly solutions (even if not very environmentally friendly) can potentially generate more revenue as a result. It supports the fact that even though REN and RENBS solutions are outstanding in terms of CO_2 emissions, they might not be as desirable by utilities' stakeholders who are incentivized to make more expensive investments (such as physical infrastructure and costly thermal power generators) due its higher potential to generate revenue if not properly controlled by regulators (who may target cheaper solutions, e.g., energy efficiency programs). It is worth noting that in the modeling, we did not distinguish between decentralized and centralized renewable solutions in these scenarios, so both are possible. The decision will be based on the particular needs of the municipality, the geographical uniqueness of the area, and overall strategic goals. For example, on-site generation or community solar subscription solutions are successful examples of decentralized options managed by utilities or other power providers.

The CEJA scenario, which reflects real legislative action as a test case, yields robust results, situating itself between the radical and conservative scenarios. It achieves meaningful emission reduction and cost stability with limited CAPEX, confirming the practical viability of gradual, policy-driven transitions. It also maintains competitive prices ($18–50/MWh range) without profitability losses, illustrating that moderate decarbonization can align with economic resilience. Moreover, CEJA demonstrates how regulatory alignment, rather than a technological leap, can drive significant change, a key insight for policymakers. Beyond CEJA, further integration with federal incentives, carbon pricing, and decentralized support schemes (e.g., feed-in tariffs, net metering) would likely amplify its outcomes, especially when coordinated with municipal-scale planning (while not simulated in this model). For example, the Investment/Residential Tax Credit has played a crucial role in driving solar energy adoption, and similar financial incentives could further advance these strategies by increasing the economic feasibility of decentralized energy solutions. Additionally, net metering policies, like those implemented in many states, have encouraged prosumers to invest in rooftop solar by allowing them to sell excess energy back to the grid at competitive rates. However, regulatory barriers, such as interconnection challenges, permitting delays, and utility resistance to distributed generation, remain significant hurdles. Addressing these barriers through streamlined permitting processes and standardized interconnection regulations, as seen in Germany's approach to integrating decentralized renewable energy sources, is crucial. Furthermore, policies promoting demand-side management, such as time-of-use pricing and demand response programs, could complement CEJA by optimizing electricity consumption patterns and reducing peak loads, ultimately leading to a more resilient and cost-effective energy system. In this work, these initiatives and motivations are captured in the "Interest in distributed solutions" variable, but they should be explored further in future studies. Additionally, even though it was not designed as a separate scenario, combining the DENS solution with it yields an even higher drop in CO_2 emissions and electricity prices; however, this requires a comprehensive framework of collaboration between the energy market and urban planners.

Finally, while the previously discussed solutions partly have common trends over time, the ***DEC scenario*** demonstrates a unique pattern in comparison to all other scenarios. Here, individual and community actors emerge as key energy producers, leading to a redistribution of market power and a shift in utility functions. DEC shows high CAPEX, low sales, and, therefore, low free cash, yet it achieves the lowest end-user prices ($15–20/MWh) and a structural decline in emissions due to distributed renewables. The scenario reveals and confirms a paradox: what is least profitable for utilities may be most beneficial for consumers and the environment. Successful decentralization thus depends on active utility participation in distributed networks through new business models, such as shared storage services, microgrid operation, and energy-as-a-service. The DEC case uniquely demonstrates how decentralization can become a systemic stabilizer rather than a disruptive threat when properly integrated into policy frameworks. As discussed earlier, the increased interest in these solutions is based on the benefits each customer sees in this transition, so there might be various strategies to increase the willingness of utilities to switch from the centralized solutions to become a significant part of the decentralized transition, for instance, those that we already discussed earlier. Interestingly, at the end of the simulation, there is a complete shift to decentralized solutions from central utilities, assuming sufficient funding is available to implement these strategies. Thus, it might seem beneficial for utilities, in order to stay in the market and not lose customers, to become a part of that decentralized community micro- or nano-grids transition by providing, first of all, funding, as well as solutions, such as energy storage services, smart controllers, or enabling bidirectional energy flow. In addition, if the goal is to make BAU and DENS scenarios more profitable and sustainable, utilities and municipalities can participate in their development, ultimately achieving better outcomes.

Comparing across all scenarios reveals complementary strengths rather than isolated solutions. BAU represents the persistence of legacy infrastructure; DENS adds spatial efficiency but limited decarbonization; REN and RENBS demonstrate technical feasibility with short-term cost volatility; CEJA bridges policy and economics; and DEC redefines the system boundary by introducing consumer-driven feedbacks, but poses financial and operational challenges for traditional utilities (which have significant inertia, as discussed in [40]), requiring strong policy interventions to facilitate integration. Together, they illustrate that the transition toward a sustainable energy system is not linear but multi-path, dependent on how governance, technology, and social behavior interact. Overall, this research provides an integrated perspective linking urban form, energy systems, and policy feedbacks within a single modeling framework – a unique contribution rarely explored in urban energy transition literature. Following insights from scenario simulations, as electricity consumption continues to outpace decarbonization efforts, it becomes crucial to transition from centralized, capital-intensive projects to decentralized and intelligent small-scale energy production initiatives, as seen from the simulations. Additionally, the recognition that the aging state of centralized energy infrastructures, often poorly maintained by power providers, which come with high environmental costs, further necessitates this shift. Grid stability becomes a major concern as decentralized generation introduces variability in supply, which can potentially lead to frequency and voltage fluctuations. Power quality issues, such as harmonics and voltage sags, can arise due to the intermittent nature of renewable energy sources and bidirectional energy flows. Additionally, effective storage solutions are crucial for balancing supply and demand; however, they come with constraints related to efficiency, cost, and lifespan. Given the rapid pace of advancements in renewable energy and battery storage technologies, the model incorporates mechanisms to adapt to emerging trends, particularly in source efficiency, enabling regular updates to key assumptions based on new data and technological breakthroughs. By adjusting parameters and conducting new scenario analyses, the model can account for varying technological trajectories, making sure that it remains relevant and accurately reflects the dynamic nature of the energy sector over time. This approach enables continuous refinement as new advancements emerge. Advanced grid management strategies, including smart inverters, demand response mechanisms, and improved forecasting techniques, can help mitigate challenges over time. Incorporating a more detailed discussion of these technical aspects in future research would provide a more comprehensive understanding of the feasibility and scalability of decentralized energy transitions.

In this model, we diligently assess our energy consumption patterns. From the simulations and historical data, it is clear that the overall electricity demand is not decreasing now, and it will not in the following decades, so moving away from careless energy consumption and acknowledging the substantial costs of energy production, we can embrace a mindset that treats energy as a product, every customer should care about. Understanding the factors that influence consumer behavior, such as economic incentives, environmental concerns, and social norms, can provide additional insights into how communities may respond to renewable energy solutions. In our model, we have employed a generalized index, "Interest in distributed solutions," to capture this consumer behavior, building on previous insights [56]. However, a more detailed exploration of public acceptance could help refine this index and improve the accuracy of our assumptions in future work. Those factors might include financial incentives such as tax credits or subsidies, perceived environmental benefits, the reliability and affordability of renewable energy sources, local community engagement, peer recommendations, and concerns about the aesthetics or disruption caused by renewable energy infrastructure. Those factors play an important role in various pilot programs worldwide. Future research will incorporate these case studies and technological advancements to enhance the model's predictive capabilities and better reflect the complexities of real-world energy transitions. Finally, the very cost-intensive REN and RENBS solutions demonstrate their clear benefits in terms of CO_2 emission reduction and meeting the region's environmental targets. On this basis, we conclude that these solutions, with more renewables in energy systems than in any other scenario, demonstrate reasonable security of electricity generation, even at lower costs than some thermoelectricity-based scenarios. By capturing the interactions between decentralized adoption, policy design, and urban densification, the model offers new insights into how cities and utilities can co-evolve toward low-carbon, resilient energy futures.

5. Conclusions

In summary, this article provides insights into the potential of utilizing decentralized renewable energy in northern Illinois and beyond, contributing to the practice by increasing understanding of regional decentralization and decarbonization dynamics. The model examines the current scenario utilities have today (BAU), as well as the CEJA strategy – a recently signed into law Illinois Climate and Equitable Jobs Act [61], and several imaginary scenarios with more deep-seated solutions. Rather than restating that BAU is economically stable yet environmentally unsustainable, a widely recognized trade-off, the model here quantifies the magnitude of that imbalance and frames it against dynamic policy and consumer-driven alternatives. This allows a deeper understanding of why systemic inertia persists and how policy design can accelerate transformation. On the other hand, the CEJA scenario appears sustainable and desirable for Illinois in the long term: it is well-balanced in terms of free cash, CAPEX, and environmental benefits. Unlike BAU, it demonstrates the potential for a self-sustaining, policy-driven transition that preserves financial stability while sharply reducing emissions. Based on the simulations, it is evident that the best smaller solutions can be applied to existing strategies and scenarios. For example, densification from the DENS scenario can clearly bring some reduction in electricity demand, which, in addition to decarbonization, is an important issue. However, the integration of such urban design measures with decentralized energy policies is what creates a novel insight of this study; the spatial dimension of decarbonization is rarely modeled within SD frameworks and can substantially amplify emission reductions when aligned with energy transition planning.

During the modeling process, several limitations were identified and might be addressed in further research. In addition to some factors discussed in earlier sections, the scarcity of available data at a higher level to conduct a complete model validation is another factor, with future work focusing on developing a more comprehensive validation method. It was possible to partially complete this article with the available data; however, having it for a longer perspective and evaluating it over time would be beneficial. Secondly, the competitive behavior between various stakeholders was not taken into account in this model, implying that we assumed this model reflects equitable access to information and a broader goal of developing the grid from its current state. Additionally, the geography was considered in isolation from other interconnections, so any electricity exports or imports were excluded. As a general limitation for many models, not all relationships between variables can be fully recreated, so some degree of subjectivity is inherent to this model. Additionally, only a simplified version of urban planning policies (densification) was considered. The further development of the model may include specific actions or strategies that planners and policymakers, legislators, and utilities may want to address together. In particular, incorporating competition and cooperation among stakeholders could provide a more realistic representation of the governance dynamics influencing grid evolution. However, these actions require more in-depth modeling, potentially using other methods that can consider the spatial component in the simulation. Also, in future analyses, the inclusion of demand control scenarios will broaden the scope of the analysis. These scenarios will encompass options for beneficial electrification (replacing direct fossil fuel use such as propane, heating oil, and gasoline with electricity), energy efficiency programs (e.g., demand response during peak periods), leveraging technological advancements available to consumers (e.g., energy efficiency rebate programs or smart grid technologies like real-time monitoring), and behavioral simulations (e.g., educational campaigns and outreach program) to further expand the densification scenario. By incorporating these aspects, a more comprehensive understanding of the potential energy efficiency gains and the impact of consumer behavior on the system can be attained. We recognize the crucial role of emerging technologies, such as smart grids, advanced energy storage systems, and AI-driven grid management, in facilitating the successful integration of decentralized energy systems. These technologies are particularly relevant for our study, as they can enhance grid stability, improve power quality, and enable real-time optimization of energy distribution, which is crucial for scaling up decentralized solutions. However, due to the limitations in available data, particularly from the region analyzed, we were unable to incorporate these technologies with detail into our current model, as they were not the main focus of this study (while on a more general level, they are included in the "Community Decentralized Energy" and "Electricity demand" parts of the model). While these technologies are critical for overcoming many of the challenges associated with decentralized energy systems, the nature of the SD model we used focuses more on high-level policy scenarios and broader energy transition pathways. We plan to explore these technologies in greater detail in future research based on more comprehensive data and advanced data analysis techniques. Moreover, further analysis with more in-depth examination of the electricity consumption and generation data can create additional criteria for model evaluation, as well as a more detailed simulation of the microgrids compared to the current overly aggregated scenario, to determine their role in the overall transition. Also, for future research, the created SD model could be tested in other geographies (states, regions, or countries) where the electricity profile is different from Illinois to understand strategies regarding the electricity market development. Finally, as was discussed in [7], the strategic regulatory incentives and multilevel connections in the energy planning process in the transitional period may be considered a promising aspect of future model development. This multi-scalar adaptability (allowing the model to be applied across different jurisdictions) underscores its contribution as a transferable framework for exploring decentralized transition dynamics under varying policy and infrastructural conditions.

In conclusion, this work advances current understanding by integrating urban form, policy design, and decentralized energy adoption within a unified systems framework. Rather than prescribing a single optimal pathway, it provides a decision-support perspective for policymakers, revealing the structural and behavioral feedbacks shaping long-term energy transitions. The model demonstrates that meaningful decarbonization depends not only on technological adoption but also on aligning spatial planning, stakeholder incentives, and policy frameworks, a contribution that distinguishes this study from existing SD models and supports its practical value for decision-makers.

Supporting information

S1 Appendix. List of main equations used in the system dynamics model.
(DOCX)

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References

1. Creutzig F, Simoes SG, Leipold S, Berrill P, Azevedo I, Edelenbosch O, et al. Demand-side strategies key for mitigating material impacts of energy transitions. Nat Clim Chang. 2024;14(6):561–72. https://doi.org/10.1038/s41558-024-02016-z
2. Carley S, Konisky DM. The justice and equity implications of the clean energy transition. Nat Energy. 2020;5(8):569–77. https://doi.org/10.1038/s41560-020-0641-6
3. Hoang AT, Pham VV, Nguyen XP. Integrating renewable sources into energy system for smart city as a sagacious strategy towards clean and sustainable process. J Clean Prod. 2021;305:127161. https://doi.org/10.1016/j.jclepro.2021.127161
4. Rind YM, Raza MH, Zubair M, Mehmood MQ, Massoud Y. Smart Energy Meters for Smart Grids, an Internet of Things Perspective. Energies. 2023;16(4):1974. https://doi.org/10.3390/en16041974
5. Zhou J, Xu Z. Optimal sizing design and integrated cost-benefit assessment of stand-alone microgrid system with different energy storage employing chameleon swarm algorithm: A rural case in Northeast China. Renew Energy. 2023;202:1110–37. https://doi.org/10.1016/j.renene.2022.12.005
6. Dokk Smith I, Kirkegaard JK, Szulecki K. A functional approach to decentralization in the electricity sector: learning from community choice aggregation in California. J Environ Plan Manag. 2022;66(6):1305–35. https://doi.org/10.1080/09640568.2022.2027233
7. Rozhkov A. Harnessing European policies for energy planning in Illinois: Overcoming barriers and transitioning to a climate-neutral society. Sustain Cities Soc. 2023;98:104803. https://doi.org/10.1016/j.scs.2023.104803
8. Abbass K, Qasim MZ, Song H, Murshed M, Mahmood H, Younis I. A review of the global climate change impacts, adaptation, and sustainable mitigation measures. Environ Sci Pollut Res Int. 2022;29(28):42539–59. https://doi.org/10.1007/s11356-022-19718-6 PMID: 35378646
9. Shivanna KR. Climate change and its impact on biodiversity and human welfare. ProcIndian Natl Sci Acad. 2022;88(2):160–71. https://doi.org/10.1007/s43538-022-00073-6
10. Guerrero J, Blaabjerg F, Zhelev T, Hemmes K, Monmasson E, Jemei S, et al. Distributed Generation: Toward a New Energy Paradigm. EEE Ind Electron Mag. 2010;4(1):52–64. https://doi.org/10.1109/mie.2010.935862
11. Wehkamp S, Schmeling L, Vorspel L, Roelcke F, Windmeier K-L. District Energy Systems: Challenges and New Tools for Planning and Evaluation. Energies. 2020;13(11):2967. https://doi.org/10.3390/en13112967
12. Heydari AH, Khoshkhoo RH, Zahedi R, Noorollahi Y. Demand side management optimization and energy labeling of multi-purpose buildings. J Build Eng. 2024;88:109143. https://doi.org/10.1016/j.jobe.2024.109143
13. Kumar M, Chokkalingam B, Devakirubakaran S. Demand side management using optimization strategies for efficient electric vehicle load management in modern power grids. PLoS One. 2024;19(3):e0300803. https://doi.org/10.1371/journal.pone.0300803 PMID: 38512967
14. Silva WN, Henrique LF, Silva AFP da C, Dias BH, Soares TA. Market models and optimization techniques to support the decision-making on demand response for prosumers. Electric Power Syst Res. 2022;210:108059. https://doi.org/10.1016/j.epsr.2022.108059
15. Kesting S, Bliek F, Sioshansi F. From consumer to prosumer: Netherland's Power Matching city shows the way. Energy Efficiency. Academic Press; 2013. p. 355–73.
16. Warneryd M, Håkansson M, Karltorp K. Unpacking the complexity of community microgrids: A review of institutions' roles for development of microgrids. Renew Sustain Energy Rev. 2020;121:109690. https://doi.org/10.1016/j.rser.2019.109690
17. Soshinskaya M, Crijns-Graus WHJ, Guerrero JM, Vasquez JC. Microgrids: Experiences, barriers and success factors. Renew Sustain Energ Rev. 2014;40:659–72. https://doi.org/10.1016/j.rser.2014.07.198
18. Burmester D, Rayudu R, Seah W, Akinyele D. A review of nanogrid topologies and technologies. Renew Sustain Energ Rev. 2017;67:760–75. https://doi.org/10.1016/j.rser.2016.09.073
19. Cao Y, Wang X, Li Y, Tan Y, Xing J, Fan R. A comprehensive study on low-carbon impact of distributed generations on regional power grids: A case of Jiangxi provincial power grid in China. Renew Sustain Energ Rev. 2016;53:766–78. https://doi.org/10.1016/j.rser.2015.09.008
20. Samadi S, Fischer A, Lechtenböhmer S. The renewables pull effect: How regional differences in renewable energy costs could influence where industrial production is located in the future. Energ Res Soc Sci. 2023;104:103257. https://doi.org/10.1016/j.erss.2023.103257
21. Osorio-Aravena JC, Aghahosseini A, Bogdanov D, Caldera U, Ghorbani N, Mensah TNO, et al. Synergies of electrical and sectoral integration: Analysing geographical multi-node scenarios with sector coupling variations for a transition towards a fully renewables-based energy system. Energy. 2023;279:128038. https://doi.org/10.1016/j.energy.2023.128038

22. Descateaux P, Astudillo MF, Amor MB. Assessing the life cycle environmental benefits of renewable distributed generation in a context of carbon taxes: The case of the Northeastern American market. Renew Sustain Energ Rev. 2016;53:1178–89. https://doi.org/10.1016/j.rser.2015.09.022
23. Yekini Suberu M, Wazir Mustafa M, Bashir N. Energy storage systems for renewable energy power sector integration and mitigation of intermittency. Renew Sustain Energ Rev. 2014;35:499–514. https://doi.org/10.1016/j.rser.2014.04.009
24. Nyangon J, Byrne J. Estimating the impacts of natural gas power generation growth on solar electricity development: PJM's evolving resource mix and ramping capability. Wiley Interdiscip Rev Energ Environ. 2023;12(1):e454. https://doi.org/10.1002/wene.454
25. Stigka EK, Paravantis JA, Mihalakakou GK. Social acceptance of renewable energy sources: A review of contingent valuation applications. Renew Sustain Energ Rev. 2014;32:100–6. https://doi.org/10.1016/j.rser.2013.12.026
26. Nyangon J, Akintunde R. Principal component analysis of day-ahead electricity price forecasting in CAISO and its implications for highly integrated renewable energy markets. Wiley Interdiscip Rev Energ Environ. 2024;13(1):e504.
27. Iweh CD, Gyamfi S, Tanyi E, Effah-Donyina E. Distributed Generation and Renewable Energy Integration into the Grid: Prerequisites, Push Factors, Practical Options, Issues and Merits. Energies. 2021;14(17):5375. https://doi.org/10.3390/en14175375
28. Kaur A, Nonnenmacher L, Coimbra CFM. Net load forecasting for high renewable energy penetration grids. Energy. 2016;114:1073–84. https://doi.org/10.1016/j.energy.2016.08.067
29. Rozhkov A, Movahedi A, Derrible S. A machine learning framework to assess the impact of the COVID-19 pandemic on electricity consumption patterns. Cities. 2023;143:104639. https://doi.org/10.1016/j.cities.2023.104639
30. Steffen B, Karplus V, Schmidt TS. State ownership and technology adoption: The case of electric utilities and renewable energy. Res Policy. 2022;51(6):104534. https://doi.org/10.1016/j.respol.2022.104534
31. Asarpota K, Nadin V. Energy Strategies, the Urban Dimension, and Spatial Planning. Energies. 2020;13(14):3642. https://doi.org/10.3390/en13143642
32. Cajot S, Schüler N. Urban energy system planning: Overview and main challenges. In: Urban energy systems for low-carbon cities. 2019. p. 19–49.
33. De Pascali P, Bagaini A. Energy Transition and Urban Planning for Local Development. A Critical Review of the Evolution of Integrated Spatial and Energy Planning. Energies. 2018;12(1):35. https://doi.org/10.3390/en12010035
34. Cajot S, Peter M, Bahu J-M, Guignet F, Koch A, Maréchal F. Obstacles in energy planning at the urban scale. Sustain Cities Soc. 2017;30:223–36. https://doi.org/10.1016/j.scs.2017.02.003
35. Che X, Geng P, Wang D, Fan C, Yuan Y. Integrated decision-making about China's energy poverty alleviation based on system dynamics. Energ Strategy Rev. 2023;45:101011. https://doi.org/10.1016/j.esr.2022.101011
36. Lu Y, Khan ZA, Alvarez-Alvarado MS, Zhang Y, Huang Z, Imran M. A Critical Review of Sustainable Energy Policies for the Promotion of Renewable Energy Sources. Sustainability. 2020;12(12):5078. https://doi.org/10.3390/su12125078
37. Gielen D, Boshell F, Saygin D, Bazilian MD, Wagner N, Gorini R. The role of renewable energy in the global energy transformation. Energ Strategy Rev. 2019;24:38–50. https://doi.org/10.1016/j.esr.2019.01.006
38. Stoeglehner G, Neugebauer G, Erker S, Narodoslawsky M, Stoeglehner G, Narodoslawsky M, et al. Processes and Tools for Integrated Spatial and Energy Planning. Springer International Publishing; 2016. p. 91–110. https://doi.org/10.1007/978-3-319-31870-7_6
39. Große J, Fertner C, Groth NB. Urban Structure, Energy and Planning: Findings from Three Cities in Sweden, Finland and Estonia. Urban Plan. 2016;1(1):24–40. https://doi.org/10.17645/up.v1i1.506
40. Rozhkov A, Zellner M, Murphy JT, Massey D. Identifying leverage points for sustainable transitions in urban – rural systems: Application of graph theory to participatory causal loop diagramming. Environ Sci Pol. 2025;164:103996. https://doi.org/10.1016/j.envsci.2025.103996
41. Chauhan RS, Sutradhar U, Rozhkov A, Derrible S. Causation versus prediction: Comparing causal discovery and inference with artificial neural networks in travel mode choice modeling. npj Sustain Mobility Transp. 2025;2:5.
42. Sperling K, Hvelplund F, Mathiesen BV. Centralisation and decentralisation in strategic municipal energy planning in Denmark. Energy Policy. 2011;39(3):1338–51. https://doi.org/10.1016/j.enpol.2010.12.006
43. Petersen J-P. The application of municipal renewable energy policies at community level in Denmark: A taxonomy of implementation challenges. Sustain Cities Soc. 2018;38:205–18. https://doi.org/10.1016/j.scs.2017.12.029
44. Hoicka CE, Conroy J, Berka AL. Reconfiguring actors and infrastructure in city renewable energy transitions: A regional perspective. Energ Policy. 2021;158:112544. https://doi.org/10.1016/j.enpol.2021.112544
45. Thellufsen JZ, Lund H, Sorknæs P, Østergaard PA, Chang M, Drysdale D, et al. Smart energy cities in a 100% renewable energy context. Renew Sustain Energ Rev. 2020;129:109922. https://doi.org/10.1016/j.rser.2020.109922
46. Ngar-yin Mah D, Wu Y-Y, Ronald Hills P. Explaining the role of incumbent utilities in sustainable energy transitions: A case study of the smart grid development in China. Energ Policy. 2017;109:794–806. https://doi.org/10.1016/j.enpol.2017.06.059
47. Garces E, Franco CJ, Tomei J, Dyner I. Sustainable electricity supply for small off-grid communities in Colombia: A system dynamics approach. Energy Policy. 2023;172:113314. https://doi.org/10.1016/j.enpol.2022.113314

48. Essletzbichler J. Renewable Energy Technology and Path Creation: A Multi-scalar Approach to Energy Transition in the UK. European Plan Stud. 2012;20(5):791–816. https://doi.org/10.1080/09654313.2012.667926
49. Kabeyi MJB, Olanrewaju OA. Sustainable Energy Transition for Renewable and Low Carbon Grid Electricity Generation and Supply. Front Energy Res. 2022;9:1032. https://doi.org/10.3389/fenrg.2021.743114
50. Bögel PM, Upham P, Shahrokni H, Kordas O. What is needed for citizen-centered urban energy transitions: Insights on attitudes towards decentralized energy storage. Energy Policy. 2021;149:112032. https://doi.org/10.1016/j.enpol.2020.112032
51. Parag Y, Sovacool BK. Electricity market design for the prosumer era. Nat Energy. 2016;1(4):1–6. https://doi.org/10.1038/nenergy.2016.32
52. Vanadzina E, Mendes G, Honkapuro S, Pinomaa A, Melkas H. Business models for community microgrids. In: Paper presented at the *2019 16th International Conference on the European Energy Market (EEM)*, 2019. p. 1–7.
53. An J, Lee M, Yeom S, Hong T. Determining the Peer-to-Peer electricity trading price and strategy for energy prosumers and consumers within a microgrid. Appl Energ. 2020;261:114335. https://doi.org/10.1016/j.apenergy.2019.114335
54. Brinkerink M, Shivakumar A. System dynamics within typical days of a high variable 2030 European power system. Energ Strategy Rev. 2018;22:94–105. https://doi.org/10.1016/j.esr.2018.08.009
55. Voinov A, Jenni K, Gray S, Kolagani N, Glynn PD, Bommel P, et al. Tools and methods in participatory modeling: Selecting the right tool for the job. Environ Model Softw. 2018;109:232–55. https://doi.org/10.1016/j.envsoft.2018.08.028
56. Rozhkov A. Applying graph theory to find key leverage points in the transition toward urban renewable energy systems. Appl Energ. 2024;361:122854. https://doi.org/10.1016/j.apenergy.2024.122854
57. Kubli M, Ulli-Beer S. Decentralisation dynamics in energy systems: A generic simulation of network effects. Energ Res Soc Sci. 2016;13:71–83. https://doi.org/10.1016/j.erss.2015.12.015
58. Zellner M, Massey D, Rozhkov A, Murphy JT. Exploring the Barriers to and Potential for Sustainable Transitions in Urban–Rural Systems through Participatory Causal Loop Diagramming of the Food–Energy–Water Nexus. Land. 2023;12(3):551. https://doi.org/10.3390/land12030551
59. Rozhkov A, Zandiatashbar A, Massey D, Shin J, Smith J, Zellner M. Effectiveness variation of different census outreach activities: An empirical analysis from the state of Illinois using machine learning and user interface technologies for participatory data collection. Appl Geogr. 2023;154:102928. https://doi.org/10.1016/j.apgeog.2023.102928
60. Shin J, Zandiatashbar A, Massey D, Rozhkov A, Smith J, Zellner M. Intrastate applicability of National Census Response Rate Models: The case of the 2020 Census in the state of Illinois, United States. Populat Space Place. 2022;28(8):e2608.
61. State of Illinois. Gov. Pritzker signs transformative legislation establishing Illinois as a national leader on climate action [press release]. 2021 [cited May 15, 2024]. Available from:https://www.illinois.gov/news/press-release.23893.html
62. Clean Energy States Alliance. Summaries of State 100% Clean Energy Plans. 2023 [cited May 15, 2024]. Available from: https://www.cesa.org/projects/100-clean-energy-collaborative/guide/state-summaries/
63. ComEd. Environmental disclosure report. 2018.
64. ComEd. Environmental disclosure report. 2019.
65. ComEd. Environmental disclosure report. 2020.
66. ComEd. Environmental disclosure report. 2021.
67. ComEd. Anonymous data service product offering. 2021. [cited May 15, 2024]. Available from: https://www.comed.com/SmartEnergy/Innovation-Technology/pages/anonymousdataservice.aspx
68. U.S. Energy Information Administration. U.S. EIA/ Illinois: State Profile and Energy Estimates. 2022 [cited March 27, 2024]. Available from: https://www.eia.gov/state/print.php?sid=IL
69. Movahedi A, Parsa AB, Rozhkov A, Lee D, Mohammadian AK, Derrible S. Interrelationships between urban travel demand and electricity consumption: a deep learning approach. Sci Rep. 2023;13(1):6223. https://doi.org/10.1038/s41598-023-33133-y
70. U.S. Energy Information Administration. U.S. EIA/ Electricity Data Browser. 2023 [cited March 27, 2024]. Available from: https://www.eia.gov/electricity/data/browser/
71. Meadows DH. Thinking in systems: A primer. Chelsea Green Publishing; 2008.
72. Movilla S, Miguel LJ, Blázquez LF. A system dynamics approach for the photovoltaic energy market in Spain. Energ Policy. 2013;60:142–54. https://doi.org/10.1016/j.enpol.2013.04.072
73. Manfren M, Caputo P, Costa G. Paradigm shift in urban energy systems through distributed generation: Methods and models. Appl Energ. 2011;88(4):1032–48. https://doi.org/10.1016/j.apenergy.2010.10.018
74. Zhou K, Chu Y, Hu R. Energy supply-demand interaction model integrating uncertainty forecasting and peer-to-peer energy trading. Energy. 2023;285:129436. https://doi.org/10.1016/j.energy.2023.129436
75. Balasubramanian S, Balachandra P. Effectiveness of demand response in achieving supply-demand matching in a renewables dominated electricity system: A modelling approach. Renew Sustai Energ Rev. 2021;147:111245. https://doi.org/10.1016/j.rser.2021.111245
76. Hondo H. Life cycle GHG emission analysis of power generation systems: Japanese case. Energy. 2005;30(11–12):2042–56. https://doi.org/10.1016/j.energy.2004.07.020

77. Degen F, Schütte M. Life cycle assessment of the energy consumption and GHG emissions of state-of-the-art automotive battery cell production. J Clean Prod. 2022;330:129798. https://doi.org/10.1016/j.jclepro.2021.129798
78. Li H, Jiang H-D, Dong K-Y, Wei Y-M, Liao H. A comparative analysis of the life cycle environmental emissions from wind and coal power: Evidence from China. J Clean Prod. 2020;248:119192. https://doi.org/10.1016/j.jclepro.2019.119192
79. Liu CM, Sandhu NK, McCoy ST, Bergerson JA. A life cycle assessment of greenhouse gas emissions from direct air capture and Fischer–Tropsch fuel production. Sustain Energ Fuel. 2020;4(6):3129–42. https://doi.org/10.1039/c9se00479c
80. Allcott H. Rethinking real-time electricity pricing. Res Energ Econ. 2011;33(4):820–42. https://doi.org/10.1016/j.reseneeco.2011.06.003
81. PJM Interconnection. Price-ticker. 2023 [cited May 15, 2024]. Available from: https://www.pjm.com/about-pjm/learning-center/price-ticker.aspx
82. Bhattacharya S, Rousis AO, Bourazeri A. Trust & Fair Resource Allocation in Community Energy Systems. IEEE Access. 2024;12:11157–69. https://doi.org/10.1109/access.2024.3351376
83. Sterman J. Business dynamics: Systems thinking and modeling for a complex world. 2000.
84. Ford FA. Modeling the environment: An introduction to system dynamics models of environmental systems. Island Press; 1999.
85. Barlas Y. Formal aspects of model validity and validation in system dynamics. Syst Dyn Rev. 1996;12(3):183–210. https://doi.org/10.1002/(sici)1099-1727(199623)12:3<183::aid-sdr103>3.0.co;2-4
86. Greenberger M, Crenson M, Crissey B. Models in the policy process. New York: Russell Sage Foundation; 1976.
87. Eicke A, Ruhnau O, Hirth L. Electricity balancing as a market equilibrium: An instrument-based estimation of supply and demand for imbalance energy. Energ Econ. 2021;102:105455. https://doi.org/10.1016/j.eneco.2021.105455
88. Li W, Jiang R, Wu H, Xie J, Zhao Y, Song Y, et al. A System Dynamics Model of Urban Rainstorm and Flood Resilience to Achieve the Sustainable Development Goals. Sustain Cities Soc. 2023;96:104631. https://doi.org/10.1016/j.scs.2023.104631
89. Hekimoğlu M, Barlas Y. Sensitivity analysis of system dynamics models by behavior pattern measures. 2010.
90. Szeberényi A, Rokicki T, Papp-Váry Á. Examining the Relationship between Renewable Energy and Environmental Awareness. Energies. 2022;15(19):7082. https://doi.org/10.3390/en15197082
91. Muhammad I, Shabbir MS, Saleem S, Bilal K, Ulucak R. Nexus between willingness to pay for renewable energy sources: evidence from Turkey. Environ Sci Pollut Res Int. 2021;28(3):2972–86. https://doi.org/10.1007/s11356-020-10414-x
92. Li C, Song Y, Kaza N. Urban form and household electricity consumption: A multilevel study. Energ Build. 2018;158:181–93. https://doi.org/10.1016/j.enbuild.2017.10.007
93. Næss P. Urban structure matters: Residential location, car dependence and travel behaviour. Routledge; 2006. https://doi.org/10.4324/9780203099186
94. Ko Y. Urban form and residential energy use: A review of design principles and research findings. J Plan Lit. 2013;28(4):327–51. https://doi.org/10.1177/0885412213491499
95. Ratti C, Baker N, Steemers K. Energy consumption and urban texture. Energ Build. 2005;37(7):762–76. https://doi.org/10.1016/j.enbuild.2004.10.010
96. Wittneben BBF. The impact of the Fukushima nuclear accident on European energy policy. Environ Sci Policy. 2012;15(1):1–3. https://doi.org/10.1016/j.envsci.2011.09.002
97. Vanadzina E, Mendes G, Honkapuro S, Pinomaa A, Melkas H. Business models for community microgrids. In: Paper presented at the 2019 16th International Conference on the European Energy Market (EEM), 2019. p. 1–7.
98. Yang X, Hu M, Tukker A, Zhang C, Huo T, Steubing B. A bottom-up dynamic building stock model for residential energy transition: A case study for the Netherlands. Appl Energ. 2022;306:118060. https://doi.org/10.1016/j.apenergy.2021.118060
99. Jacques P, Delannoy L, Andrieu B, Yilmaz D, Jeanmart H, Godin A. Assessing the economic consequences of an energy transition through a biophysical stock-flow consistent model. Ecol Econ. 2023;209:107832. https://doi.org/10.1016/j.ecolecon.2023.107832
100. Jackson A, Jackson T. Macroeconomic, sectoral and financial dynamics in energy transitions: A stock-flow consistent, input-output approach. Ecol Econ. 2025;230:108507. https://doi.org/10.1016/j.ecolecon.2024.108507
101. Zhou W, Moncaster A, Reiner DM, Guthrie P. Developing a generic System Dynamics model for building stock transformation towards energy efficiency and low-carbon development. Energ Building. 2020;224:110246. https://doi.org/10.1016/j.enbuild.2020.110246
102. Selvakkumaran S, Ahlgren EO. Review of the use of system dynamics (SD) in scrutinizing local energy transitions. J Environ Manage. 2020;272:111053. https://doi.org/10.1016/j.jenvman.2020.111053
103. Cheng V, Steemers K, Montavon M, Compagnon R. Urban form, density and solar potential PLEA2006 - the 23rd Conference on Passive and Low Energy Architecture. 2006.
104. International Renewable Energy Agency (IRENA). The cost of financing for renewable power. Abu Dhabi. 2023.
105. Cole W, Frazier AW, Augustine C. Cost projections for utility-scale battery storage: 2021 update. NREL; 2021 [cited May 15, 2024]. Available from: https://www.nrel.gov/docs/fy21osti/79236.pdf
106. Batidzirai B, Trotter PA, Brophy A, Stritzke S, Moyo A, Twesigye P, et al. Towards people-private-public partnerships: An integrated community engagement model for capturing energy access needs. Energ Res Social Sci. 2021;74:101975. https://doi.org/10.1016/j.erss.2021.101975

107. Androniceanu A, Georgescu I. The Impact of CO2 Emissions and Energy Consumption on Economic Growth: A Panel Data Analysis. Energies. 2023;16(3):1342. https://doi.org/10.3390/en16031342

108. Hasan MM, Chongbo W. Estimating energy-related CO2 emission growth in Bangladesh: The LMDI decomposition method approach. Energ Strategy Rev. 2020;32:100565. https://doi.org/10.1016/j.esr.2020.100565

109. Zapata S, Castaneda M, Franco CJ, Dyner I. Clean and secure power supply: A system dynamics based appraisal. Energ Policy. 2019;131:9–21. https://doi.org/10.1016/j.enpol.2019.04.028

110. Krog L. How municipalities act under the new paradigm for energy planning. Sustain Cities Soc. 2019;47:101511. https://doi.org/10.1016/j.scs.2019.101511

111. Krog L, Sperling K. A comprehensive framework for strategic energy planning based on Danish and international insights. Energ Strategy Rev. 2019;24:83–93. https://doi.org/10.1016/j.esr.2019.02.005

112. Koroso NH, Lengoiboni M, Zevenbergen JA. Urbanization and urban land use efficiency: Evidence from regional and Addis Ababa satellite cities, Ethiopia. Habitat Int. 2021;117:102437. https://doi.org/10.1016/j.habitatint.2021.102437

113. Teller J. Regulating urban densification: what factors should be used? Buildi Cities. 2021;2(1):302–17. https://doi.org/10.5334/bc.123

114. Debrunner G, Hartmann T. Strategic use of land policy instruments for affordable housing – Coping with social challenges under scarce land conditions in Swiss cities. Land Use Policy. 2020;99:104993. https://doi.org/10.1016/j.landusepol.2020.104993

115. Næss P, Saglie I, Richardson T. Urban sustainability: Is densification sufficient? European Plan Stud. 2020;28(1):146–65.

116. Illinois General Assembly. Public Utilities Act (220 ILCS 5/8-401). 2020.

117. Kibbey JC. Utility accountability 101: How do utilities make money? 2021 [cited 2024 May 15]. Available from: https://www.nrdc.org/bio/jc-kibbey/utility-accountability-101-how-do-utilities-make-money