

Mathematics for Sustainable Energy Solutions: Global Strategies, Local Impact

UVERUVEH, Francis O (Ph.D). FMAN.; Ukpebor Jacinta N (Mrs).

Department of Mathematics, College of Education, Warri Delta state, Nigeria.

DOI: <https://doi.org/10.47772/IJRISS.2026.1026EDU0426>

Received: 16 March 2026; Accepted: 21 March 2026; Published: 11 July 2026

ABSTRACT

The escalating climate crisis, driven in large part by unsustainable energy production and consumption, presents one of the most complex and urgent challenges of the 21st century. Addressing this crisis requires not only technological innovation and political will but also rigorous analytical frameworks capable of fusing diverse data sources, optimizing resource allocation, and forecasting systemic outcomes under uncertainty. This paper contends that mathematics is not merely a supporting tool but a foundational discipline in the global transition toward sustainable energy systems. From the construction of Integrated Assessment Models (IAMs) that inform international climate policy to the optimization of decentralized microgrids in underserved communities, mathematical methods underpin the design, evaluation, and implementation of energy solutions across scales. We examined the role of mathematical modeling in strategic planning at the global level encompassing climate simulation, economic modeling, and infrastructure design while also stressing its critical applications at the local level, including energy equity assessments, participatory decision-making models, and spatial optimization for renewable deployment. We also articulated a unified framework that bridges macro level strategies with micro level impacts, we advocate for a more deliberate integration of mathematical thinking into both policy and practice. The paper concludes with recommendations for promoting interdisciplinary collaboration, supporting mathematical research in energy transitions, and enhancing community level capacity to engage with quantitative tools thereby advancing just, resilient, and data informed energy futures.

Keywords: Mathematical modeling, Sustainable energy, Optimization, Energy equity, Local energy systems, Climate strategy, etc.

INTRODUCTION

The global energy system stands at a critical inflection point. Despite increasing awareness of the ecological and social consequences of fossil fuel dependence, energy production and consumption patterns remain largely incompatible with the objectives of climate stabilization, environmental sustainability, and equitable development. The International Energy Agency (IEA), the Intergovernmental Panel on Climate Change (IPCC), and numerous national and regional bodies have warned that current trajectories in greenhouse gas emissions will far exceed thresholds compatible with a 1.5°C or even 2°C increase in global temperatures. At the same time, approximately 770 million people worldwide remain without access to electricity, while many more suffer from unreliable or unaffordable energy systems (Oyedepo, Olanrewaju, & Odunfa, 2023; Bamisile, Huang, Xu, & Hu, 2020). The challenge before us, then, is not simply to decarbonize energy systems, but to do so in ways that are globally coordinated, economically efficient, socially just, and locally adaptable.

Such a transformation cannot be achieved through technology alone, nor can it be directed purely through political or financial instruments. What is required is a set of rigorous, adaptable, and predictive tools capable of handling the complexity, uncertainty, and scale of the transition. Mathematics provides this foundation. Far from being a neutral or abstract discipline, mathematics has become deeply embedded in the infrastructure of modern energy analysis from the high level Integrated Assessment Models (IAMs) that guide international climate negotiations to the granular spatial optimization tools used to design microgrids in remote or underserved regions (Fattahi, Sijm, & Faaij, 2020; Dioha & Kumar, 2020).

Mathematical modeling enables researchers and policymakers to simulate the effects of carbon pricing, assess the resilience of energy grids under climate-induced stress, and optimize renewable deployment strategies within strict environmental and budgetary constraints. Differential equations underpin climate forecasting; linear and nonlinear optimization algorithms shape investment pathways; game theory informs multilateral negotiations on emissions and technology sharing; and data-driven statistical models reveal systemic inequities in access, affordability, and health co-benefits. Importantly, mathematics also facilitates the integration of diverse knowledge systems, allowing for hybrid models that blend physical, economic, social, and environmental variables (Adeyemi-Kayode, Misra, Orovwode, & Adoghe, 2022; Chen, Wang, & Zhang, 2022).

Yet despite its centrality, the role of mathematics in sustainable energy transitions remains underrecognized in both academic and policy discourse. The prevailing narratives often center on engineering innovations, market mechanisms, and political will essential elements, to be sure but ones that depend upon and are enhanced by robust mathematical formulation. This omission is not merely academic; it has real-world consequences. Without mathematically informed decision-making, energy policy risks becoming reactive rather than anticipatory, fragmented rather than systemic, and inequitable rather than inclusive (Mutiso, R., & Dioha, 2023; Akpan & Olanrewaju, 2023).

This paper is both timely and necessary. We are entering what may be the final decade in which the global community retains the agency to shape long-term climate and energy trajectories. Simultaneously, new computational capacities, data availability, and algorithmic innovations have vastly expanded the horizons of what mathematical tools can accomplish. Yet institutional uptake of these tools remains uneven, particularly at the intersection of global planning and local implementation. There is a pressing need to synthesize emerging mathematical methodologies and to advocate for their systematic integration into energy policy, infrastructure design, and community engagement (Parzen et al, 2022; Barnes & Barnes, 2023).

The argument of this paper is straightforward but urgent: mathematical tools are not just useful they are essential for creating scalable, equitable, and context-responsive energy solutions, from the global to the local. They offer the analytical clarity necessary to navigate trade-offs, the computational power to simulate future scenarios, and the structural logic to unify diverse data inputs into coherent action. Crucially, they also provide a language through which interdisciplinary and cross-sector collaboration can be fostered bridging science, engineering, economics, and policymaking in pursuit of common goals (Oyedepo, 2012; Bamisile et al., 2020).

This paper proceeds in three parts. First, we examine how mathematical modeling has informed strategic energy planning at the global level, with particular attention to integrated systems models, climate forecasting, and infrastructure optimization. Second, we examine the application of mathematical tools at the local scale, including in community-based energy planning, equity assessment, and participatory modeling. Third, we confront the challenge of translation how to bridge the gap between macro-level strategies and micro-level realities and propose a framework for more coherent, bidirectional integration. We conclude with a set of actionable recommendations aimed at academia, industry, and government, calling for deeper investment in mathematical research, greater interdisciplinarity, and increased local capacity building (Juanpera, et al, 2020; Akpan & Olanrewaju, 2023).

Ultimately, we envision a future in which mathematical reasoning is embedded not as an afterthought but as a central pillar of sustainable energy governance guiding our transition not only toward decarbonization, but toward a more just and intelligent energy future (Barnes & Barnes, 2022; Mutiso & Dioha 2023).

The Global Perspective: Mathematics Driving Strategy

The global energy transition is a complex, multifaceted challenge requiring integrative, predictive, and adaptive models to capture system interdependencies across spatial and temporal scales. Mathematical modeling provides the backbone for this endeavor, empowering stakeholders scientists, planners, policymakers, and international agencies to simulate, optimize, and coordinate the transformation of energy systems in alignment with climate goals. Far beyond interpreting data, mathematics shapes strategic thinking by enabling long-term planning, scenario analysis, and real-time decision-making across global energy infrastructures (Parzen et al., 2023; Oyedepo et al., 2025).

These models integrate diverse variables, such as renewable energy potential, economic constraints, and policy frameworks, to forecast transition pathways and assess trade-offs. For instance, optimization models like integrated assessment models (IAMs) simulate global energy scenarios, balancing carbon reduction targets with economic growth and energy security. By incorporating dynamic feedback loops, these models adapt to evolving conditions, such as technological advancements or geopolitical shifts, ensuring robust strategies. Furthermore, real-time optimization algorithms support agile responses to immediate challenges, such as grid instability or supply chain disruptions, enhancing the resilience of global energy systems (Parzen et al., 2023).

Collaboration across stakeholders is further enabled by shared modeling platforms that standardize data inputs and methodologies, fostering alignment between national policies and global objectives. In practice, these tools have informed international agreements by providing evidence-based projections of renewable energy adoption and emissions trajectories. Through grounding complex decisions in rigorous mathematics, these models ensure that global strategies are both ambitious and achievable, driving coordinated action toward a sustainable energy future (Oyedepo et al., 2025).

Climate Modeling and Forecasting: From PDEs to Machine Learning

Climate modeling forms a mathematical backbone for understanding the Earth system and anticipating the consequences of energy choices. PDEs govern the dynamics of atmosphere, ocean, and land interactions, encapsulating physical laws such as conservation of mass, momentum, and energy. GCMs and Earth System Models discretize these PDEs using numerical methods (finite differences, spectral techniques) to simulate planetary-scale phenomena from temperature rise and precipitation shifts to extreme weather patterns.

Increasingly, climate modeling is augmented by machine learning, enabling high-resolution forecasting, pattern detection, and data assimilation where physical models are computationally prohibitive. Hybrid modeling combining data-driven and physics-informed frameworks is becoming essential in projecting the climate impacts of energy strategies. For example, convolutional neural networks downscale coarse GCM outputs regionally, while ensemble learning improves uncertainty quantification in model predictions (Reichstein et al., 2019; Rasp, Pritchard & Gentine, 2023).

Mathematical Economics of Energy Policy: Strategy, Cost, and Incentives

Mathematical economics is central to designing and evaluating energy policy instruments. Game theory provides insights into strategic behavior among nations and corporations in climate negotiations, helping to analyze cooperation and competition in carbon trading, technology-sharing, and resource allocation. Nash equilibria, bargaining models, and dynamic games offer formal tools to evaluate stability, fairness, and efficiency in multilateral engagements. Cost-benefit analysis, rooted in welfare economics, evaluates the economic efficiency of mitigation strategies by discounting future damages versus upfront investments.

Computable general equilibrium (CGE) models comprising systems of equations representing market interactions estimate macroeconomic effects of energy policies, including on GDP, employment, and inequality. They allow transparent sensitivity analysis and robustness testing across socioeconomic scenarios. These approaches support strategic policy design in renewable integration and sustainable energy transitions (Ouyang et al., 2022; Reichstein et al., 2019).

Network and Infrastructure Modeling: Grid Dynamics and Flow Optimization

The electricity grid the backbone of energy delivery is inherently a mathematical construct: a network of nodes and edges governed by physical laws and optimized by algorithms. Power systems engineering employs graph theory, linear programming, and differential algebraic equations to simulate and control power flows, manage congestion, and ensure grid stability. The Optimal Power Flow (OPF) problem seeks the most efficient dispatch of generation units under constraints like voltage, line capacities, and demand.

Resilience analysis, a growing field in climate vulnerability studies, uses stochastic optimization, reliability theory, and network science to assess infrastructure shocks and recovery. Transmission expansion planning across transnational grids leverages mixed integer linear programming and geospatial modeling to optimize

siting of lines, storage assets, and balancing facilities integrating high-penetration renewables, EV deployment, and demand response (Usman et al., 2025; Oyedepo et al., 2025).

The Local Impact: Mathematical Tools for Community Energy Solutions

While global models provide strategic frameworks for the energy transition, the tangible realization of sustainable energy futures hinges on local-scale implementation. Communities, particularly in rural and underserved regions, face unique challenges such as infrastructure limitations, constrained financial resources, and entrenched social inequities. Mathematical tools are instrumental in addressing these barriers by enabling the design, optimization, and evaluation of decentralized energy systems tailored to local needs, ensuring both technical feasibility and social relevance.

Decentralized Energy Systems Modeling

Decentralized energy systems, such as solar microgrids and hybrid renewable configurations, are increasingly vital for rural electrification and enhancing energy access in underserved areas. Mathematical models for these systems integrate stochastic representations of renewable resource availability (e.g., solar irradiance variability), local load profiles, and energy storage dynamics. Tools like HOMER and custom optimization frameworks address multi-objective problems, balancing cost minimization, reliability maximization, and emissions reduction. These models incorporate community-specific data to ensure solutions are contextually appropriate and sustainable (Lewis et al., 2024).

Mixed integer linear programming (MILP) and nonlinear programming techniques are employed to determine optimal system configurations, including the sizing of photovoltaic arrays, battery storage capacity, and backup generators. These methods account for trade-offs between capital costs and system performance, enabling cost-effective designs. Probabilistic modeling further enhances robustness by addressing uncertainties in demand and supply, such as variable weather patterns or fluctuating energy consumption. This approach ensures systems remain reliable under diverse conditions (Butt & Li, 2024; Habib et al., 2016; El Hajj Chehade & Karaki, 2025).

In practice, these models have driven impactful solutions in regions like sub-Saharan Africa, where grid extension is often economically unfeasible. For example, in rural villages, modular solar microgrids designed using these tools have achieved high reliability with minimal capital expenditure. By optimizing system components and incorporating local load data, these models enable scalable, community-driven energy solutions that enhance access while minimizing environmental impact (Alabiou et al., 2019). Additionally, integrating participatory approaches into the modeling process ensures that local stakeholders' priorities, such as affordability or cultural preferences, are embedded in the design, fostering greater community acceptance and long-term sustainability (Onyango & Paliwal, 2024).

Optimization in Local Planning

Mathematical optimization is critical for strategic spatial planning in local energy systems, guiding decisions on the placement and scale of energy hubs, battery storage sites, and electric vehicle charging stations. Location-allocation models utilize integer programming and heuristic algorithms to minimize transmission losses, reduce infrastructure costs, and maximize accessibility for diverse communities. These models account for spatial constraints and local needs, ensuring efficient and equitable energy distribution (Conforti et al., 2025).

In urban fringe areas and peri-urban settlements, optimization approaches help planners balance centralized and decentralized energy resources. By factoring in population density, load variability, and land use constraints, these models enable tailored infrastructure designs that align with local growth patterns and energy demands. For example, optimization can identify optimal sites for microgrids or charging stations to serve underserved populations while minimizing environmental and economic costs (Conforti et al., 2025).

Storage allocation models further enhance system efficiency by optimizing energy dispatch strategies. These models use mathematical techniques to flatten demand peaks and integrate intermittent renewable sources, such as solar and wind, improving grid stability and cost-effectiveness. Dynamic programming and real-time optimization algorithms enable adaptive control strategies that respond to evolving grid conditions, user

behaviors, and weather patterns. Such adaptability ensures reliable energy supply while maximizing the use of clean energy resources (Moutis et al., 2021).

Moreso, integrating these optimization tools with participatory planning processes can enhance their impact. Engaging local stakeholders ensures that model assumptions reflect community priorities, such as prioritizing affordability or minimizing land use conflicts. This combination of rigorous optimization and inclusive decision-making supports resilient and equitable energy systems tailored to local contexts (Onyango & Paliwal, 2024).

Equity and Access Modeling

Mathematics plays a pivotal role in quantifying and addressing energy equity and justice at the local level. Data-driven models leverage socio-economic, demographic, and consumption data to uncover spatial and temporal patterns of energy access disparities. Techniques such as spatial econometrics, clustering algorithms, and regression analyses identify correlations between energy poverty and factors like income inequality, gender disparities, or geographic isolation. These methods provide granular insights into the structural drivers of inequity, enabling policymakers to prioritize interventions where they are most needed (Leprince et al., 2023).

Agent-based modeling (ABM) and system dynamics offer powerful tools to simulate the impacts of policy interventions on diverse stakeholders. These approaches model interactions among individuals, households, and institutions to forecast outcomes such as affordability, social acceptance, and health co-benefits, such as reduced indoor air pollution from clean energy adoption. By simulating scenarios, these models support the design of tailored interventions, including subsidy programs, tiered pricing models, and community ownership structures, to promote inclusive energy transitions. For instance, in rural Nigerian communities, ABM has highlighted the critical role of targeted financing and capacity-building programs in overcoming adoption barriers for solar home systems. These insights have informed strategies to enhance access to clean energy, ensuring affordability and scalability for low-income households (Leprince et al., 2023).

Moreover, integrating participatory approaches with these modeling techniques can enhance their effectiveness. Engaging local stakeholders in the modeling process ensures that the assumptions and outputs reflect community priorities, fostering trust and improving the relevance of proposed solutions. This combination of quantitative rigor and community input is essential for designing equitable energy policies that address both technical and social dimensions of energy access (Onyango & Paliwal, 2024).

Participatory Modeling

Incorporating stakeholder knowledge and preferences is essential for legitimacy and effectiveness in community energy solutions. Participatory modeling approaches leverage mathematical tools to facilitate collaborative decision-making processes. Methods such as fuzzy cognitive mapping, multi-criteria decision analysis (MCDA), and participatory GIS integrate quantitative data with qualitative insights, allowing diverse actors to jointly construct and evaluate scenarios (Obiedat & Samarasinghe, 2022; Wikipedia, 2025).

These approaches democratize the modeling process by transforming complex mathematical outputs into accessible, user-friendly decision support tools. By simplifying technical results, they empower communities to evaluate trade-offs between cost, environmental impact, and social priorities, fostering a sense of ownership and adaptability. This participatory process ensures that energy solutions align with local values and needs, enhancing their sustainability and acceptance (Wikipedia, 2025).

Participatory modeling has proven effective in various contexts, notably in rural Kenya and South Africa. In these regions, stakeholder workshops integrated with scenario analysis have informed the co-design of solar mini-grids and demand-side management programs. For example, in Kenya, community engagement sessions helped tailor mini-grid specifications to local energy demands, while in South Africa, participatory approaches facilitated equitable energy access strategies. These initiatives demonstrate how inclusive modeling can bridge technical expertise with local knowledge, leading to contextually relevant and impactful energy interventions (Onyango & Paliwal, 2024; Panek & van Heerden, 2013).

Bridging the Gap: Translating Global Models to Local Action

Translating global energy transition models into effective local interventions remains a complex and multifaceted challenge. Macro-level tools, such as Integrated Assessment Models and large-scale climate forecasts, are critical for shaping international and national policy agendas. However, they often overlook the granular socio-economic, infrastructural, and cultural realities that govern energy use at the community level. This disconnect creates a critical mismatch: strategies optimized for global or regional scales may lack relevance or fail when applied locally, risking inefficient resource allocation or unintended consequences (Economic Commission for Africa, 2025). Bridging this divide demands methodological innovation, institutional alignment, and inclusive processes to ensure global modeling insights are equitably and practically realized on the ground (Cannone, 2023).

One promising approach is the development of scalable algorithms that operate across multiple spatial and temporal scales. Multi-level optimization frameworks integrate hierarchical decision layers, allowing macro-level goals, such as national carbon reduction targets, to be broken down into localized sub-problems. These sub-problems account for local constraints, such as resource availability or cultural preferences, while maintaining alignment with broader objectives. By incorporating feedback loops, these frameworks enable community-level outcomes to inform iterative refinements of global strategies, fostering a dynamic interplay between scales. Such adaptability ensures that policies remain responsive to evolving local conditions (Dalal et al., 2016).

Hierarchical and multi-scale modeling frameworks also tackle the complexity and heterogeneity of energy systems. For instance, large-scale renewable integration scenarios can be paired with fine-grained models of local grid stability or household energy demand profiles. This coupling enables tailored interventions, such as targeted microgrid deployments or demand-side management programs, that preserve system-wide coherence. Advances in distributed computing and cloud-based simulation environments have made these computationally intensive approaches more feasible, supporting near-real-time scenario evaluation and policy testing. These tools empower decision-makers to explore diverse pathways and anticipate local impacts with greater precision (Parzen et al., 2022).

Despite these methodological advancements, significant barriers persist in translating models to local action. A primary obstacle is the lack of high-quality, granular data at the local level, particularly in developing regions like parts of Africa. Data collection infrastructure is often underdeveloped, resulting in incomplete, outdated, or inconsistent datasets. This data scarcity complicates the calibration and validation of localized models, reducing their accuracy and eroding stakeholder trust in their outputs. Addressing this requires investments in local data ecosystems, including sensor networks, community-based data collection, and standardized data protocols to enhance model reliability and relevance (Oladejo & Shava, 2025; Overcoming local constraints, 2020; Agyemang et al., 2024).

Institutional capacity remains a significant bottleneck in leveraging energy modeling for effective decision-making. Local governments and utilities often lack the human and technical resources to interpret complex model outputs or integrate them into existing planning and regulatory frameworks. This challenge is compounded by limited access to training and expertise, which hinders the adoption of sophisticated tools. Organizational silos between national agencies, local authorities, academic institutions, and community organizations further impede knowledge exchange and coordinated action, often leading to fragmented efforts and misaligned priorities (Odarno, 2020; Mutiso, 2023).

To address these barriers, a multi-dynamic approach is essential. Capacity-building initiatives should prioritize data collection, management, and modeling literacy to cultivate a cadre of local experts capable of co-developing and deploying contextually relevant models. These programs should emphasize practical, hands-on training tailored to local needs, ensuring that stakeholders can effectively utilize modeling tools (ECA, 2025; Cannon, 2023). Establishing institutional partnerships that foster iterative dialogue among modelers, policymakers, and community stakeholders can bridge gaps in understanding and ensure models address locally salient questions. Such collaborations can also promote trust and align modeling efforts with community priorities (WRI, 2024; Dioha & Mutiso, 2023).

Moreover, developing open-source, user-friendly modeling platforms tailored for local use can democratize access to analytical tools, enabling non-experts, such as local planners and community leaders, to engage with scenario analysis and decision-support systems. These platforms should prioritize intuitive interfaces and modular designs to accommodate varying levels of technical expertise (Parzen et al., 2022; Hilpert et al., 2018). Investments in data infrastructure, including data-sharing agreements and geospatial and sensor networks, are critical to improving the quality and resolution of local data. Enhanced data availability can lead to more accurate and context-specific models, ultimately improving their utility for decision-making (Agyemang et al., 2024; Kenfack et al., 2020).

STATEMENT AND RECOMMENDATIONS

The accelerating urgency of the global energy transition necessitates a profound reorientation of how sustainable energy systems are conceptualized, planned, and implemented. Central to this reorientation is the unequivocal recognition that mathematics is not ancillary but foundational to sustainable energy efforts. The analytical rigor, predictive power, and integrative capacity afforded by mathematical tools are indispensable for navigating the inherent complexity, uncertainty, and multi-dimensionality of energy systems at all scales (Jävergård et al., 2024; Riedmüller et al., 2025).

Mathematics provides the language and framework through which global climate imperatives can be translated into actionable policies, and through which local communities can design equitable and resilient energy solutions (Sánchez et al., 2020; Ahmadu et al., 2022). However, current practice often marginalizes mathematical approaches in favor of more visible technological or economic interventions, thereby constraining the efficacy and scalability of sustainability initiatives (Griffioen, 2025). It is imperative, therefore, that mathematics be integrated more deeply and systematically into the fabric of sustainable energy research, policy, and practice (Kat, 2011; Jävergård et al., 2024).

To advance this integration, we propose the following core recommendations:

Increased Interdisciplinary Collaboration

Sustainable energy challenges transcend disciplinary boundaries, demanding coordinated efforts among mathematicians, engineers, economists, social scientists, policymakers, and community stakeholders. Enhanced collaboration will foster the development of hybrid models that better capture socio-technical realities and enable cross-pollination of methods and insights. Institutional frameworks should incentivize joint research projects, cross-departmental initiatives, and co-creation platforms that bridge theoretical modeling with empirical and experiential knowledge.

Policy and Funding Support for Mathematical Research in Energy Planning

To catalyze innovation in mathematical approaches tailored to energy transitions, dedicated policy frameworks and funding mechanisms must prioritize mathematical research as a strategic investment. Funding agencies and governments should establish grant programs explicitly targeting the development of scalable algorithms, multi-level optimization techniques, uncertainty quantification, and data assimilation methods applicable to energy systems. Support for open-access modeling tools and datasets will enhance transparency and reproducibility, facilitating wider adoption and iterative improvement.

Capacity-Building in Local Communities to Interpret and Use Mathematical Tools

The translation of mathematical insights into effective local action hinges on empowering communities and local decision-makers with the skills and resources to engage with quantitative models. Capacity-building programs should focus on developing data literacy, computational skills, and participatory modeling methodologies tailored to local contexts. Training initiatives must be inclusive, ensuring accessibility across gender, socio-economic status, and educational backgrounds, thus democratizing the use of mathematical tools for energy planning.

Furthermore, embedding modeling capacity within local institutions will enhance sustainability by enabling continuous adaptation and refinement of energy strategies in response to evolving conditions and priorities.

CONCLUSION

This paper has articulated the indispensable role of mathematics in addressing the challenges of sustainable energy transitions. From the formulation of global strategies via integrated assessment and optimization models, through the nuanced design of localized energy solutions, to the critical bridging of scale through hierarchical and scalable methodologies, mathematics provides the essential framework for understanding, predicting, and optimizing energy systems in an increasingly complex and dynamic world. The urgency of climate imperatives and the imperative of equity demand that these tools not only inform but actively shape policy and practice at all levels.

As the global community grapples with the accelerating impacts of climate change and the profound socio-economic transformations it entails, the integration of mathematical rigor must be prioritized. This necessitates concerted action from academia to push forward innovative modeling and analytical techniques; from industry to incorporate these insights into the design and operation of energy technologies and infrastructure; and from governments to enact policies and allocate resources that institutionalize the role of mathematics in sustainable energy planning.

Our vision is clear: a future in which mathematical awareness is deeply embedded within the decision-making processes that govern energy systems, ensuring that sustainability is achieved not as an abstract ideal but as a just, efficient, and adaptive reality. In such a world, the power of mathematics will enable equitable access to clean energy, resilient infrastructure, and informed governance paving the way toward truly sustainable energy futures for all communities globally.

REFERENCES

1. Adeshina, M. A., Ogunleye, A. M., Suleiman, H. O., Yakub, A. O., Same, N. N., Suleiman, Z. A., & Huh, J.-S. (2024). From Potential to Power: Advancing Nigeria's Energy Sector through Renewable Integration and Policy Reform. *Sustainability*, 16(20), 8803. <https://doi.org/10.3390/su16208803>
2. Adeyemi-Kayode, T., Misra, S., Orovwode, H., & Adoghe, A. (2022). Modeling the next decade of energy sustainability: A case of a developing country. *Energies*, 15(14), 5083. <https://doi.org/10.3390/en15145083>
3. Agyemang, F. S., Yeboah, G. O., & Mensah, I. K. (2024). Toward achieving smart cities in Africa: Challenges to data use and the way forward. *Data & Policy*, 6, e18. <https://doi.org/10.1017/dap.2024.18>
4. Akpan, J., & Olanrewaju, O. (2023). Towards a common methodology and modelling tool for 100 % renewable energy analysis: A review. *Energies*, 16(18), Article 6598. <https://doi.org/10.3390/en16186598>
5. Bamisile, O., Huang, Q., Xu, X., & Hu, W. (2020). An approach for sustainable energy planning towards 100% electrification of Nigeria by 2030. *Applied Energy*, 260, 114246. <https://doi.org/10.1016/j.apenergy.2019.114246>
6. Barnes, S., & Barnes, A. (2022). Just energy transition in Africa: Social inclusion and environmental rights-based imperatives. *Business and Human Rights Journal*, 7(2), 252–274. <https://doi.org/10.1017/bhj.2022.8>
7. Butt, H. Z., & Li, X. (2024). Optimal planning of PV and battery resources in remote microgrids considering degradation costs: An iterative post-optimization correction-based approach. *arXiv*. <https://doi.org/10.48550/arXiv.2402.01989> [arXiv](https://arxiv.org/abs/2402.01989)
8. Cannone, C., Hoseinpoori, P., Martindale, L., Tennyson, E. M., Gardumi, F., Somavilla Croxatto, L., Pye, S., Mulugetta, Y., Vrochidis, I., Krishnamurthy, S., Niet, T., Harrison, J., Yeganyan, R., Mutembei, M., Hawkes, A., Petrarulo, L., Allen, L., Blyth, W., & Howells, M. (2023). Addressing Challenges in Long-Term Strategic Energy Planning in LMICs: Learning Pathways in an Energy Planning Ecosystem. *Energies*, 16(21), 7267. <https://doi.org/10.3390/en16217267>
9. Chen, H., Wang, Y., & Zhang, Z. (2022). A comprehensive review of planning, modeling, optimization, and control of distributed energy systems. *Carbon Neutrality*, 1, Article 28. <https://doi.org/10.1007/s43979-022-00029-1>
10. Conforti, M., Cornuéjols, G., & Zambelli, G. (2025). Integer programming. Springer. https://en.wikipedia.org/wiki/Optimal_facility_location

11. Dalal, G., Gilboa, E., & Mannor, S. (2016). Hierarchical decision making in electricity grid management [Preprint]. arXiv. <https://doi.org/10.48550/arXiv.1603.01840>
12. Dioha, M. O., & Kumar, A. (2020). Integrated energy systems' modeling studies for sub-Saharan Africa: A scoping review. *Renewable and Sustainable Energy Reviews*, 141, 110792. <https://doi.org/10.1016/j.rser.2020.110792>
13. Dioha, M. O., & Mutiso, R. M. (2023). Generating meaningful energy systems models for Africa. *Issues in Science and Technology*, 39(3), 54–57. <https://doi.org/10.58875/OYYL9037>
14. Economic Commission for Africa. (2025). Regional experts trained on modelling energy systems. Retrieved from <https://www.uneca.org/eca-events/EMP-A-2025>
15. El Hajj Chehade, M. F., & Karaki, S. (2025). BOOST: Microgrid sizing using ordinal optimization. arXiv. <https://doi.org/10.48550/arXiv.2501.10842> arXiv
16. Fattahi, A., Sijm, J., & Faaij, A. (2020). A systemic approach to analyze integrated energy system modeling tools: a review of national models. *Renewable and Sustainable Energy Reviews*, 133, 110195. <https://doi.org/10.1016/j.rser.2020.110195>
17. Habib, A. H., Disfani, V. R., Kleissl, J., & de Callafon, R. A. (2016). Quasi-dynamic load and battery sizing and scheduling for stand-alone solar system using mixed-integer linear programming. arXiv. <https://doi.org/10.48550/arXiv.1607.07362>
18. Hilpert, S., Kaldemeyer, C., Krien, U., Günther, S., Wingenbach, C., & Plessmann, G. (2018). The Open Energy Modelling Framework (oemof) – A new approach to facilitate open science in energy system modelling. *Energy Strategy Reviews*, 22, 16–25. <https://doi.org/10.1016/j.esr.2018.07.001>
19. Juanpera, M., Blechinger, P., Ferrer-Martí, L., Hoffmann, M.-M., & Pastor, R. (2020). Multicriteria-based methodology for the design of rural electrification systems: A case study in Nigeria. *Renewable and Sustainable Energy Reviews*, 121, 109725. <https://doi.org/10.1016/j.rser.2019.109725>
20. Kenfack, J., Voufo, J., Ngohe Ekam, P. S., Lewetchou, J. K., & Nzotcha, U. (2020). Overcoming local constraints when developing renewable energy systems for the electrification of remote areas in Africa. *Renewable Energy and Environmental Sustainability*, 5, Article 1, 1–10. <https://doi.org/10.1051/rees/2019007>
21. Leprince, T., Audigane, J., Broto, V. C., & Simcock, N. (2023). Measuring multidimensional energy poverty in sub-Saharan Africa: A machine learning and spatial econometrics approach. arXiv preprint. <https://arxiv.org/abs/2303.03006>
22. Lewis, C. G., Williams, I. M., Oyiza, Y. R., Nnamdi, C. B., Hao, C., & Carbajales-Dale, M. (2024). Achieving universal energy access in remote locations using HOMER energy model: A techno-economic and environmental analysis of hybrid microgrid systems for rural electrification in northeast Nigeria. *Frontiers in Energy Research*, 12. <https://doi.org/10.3389/fenrg.2024.1454281>
23. Moutis, P., Lin, H., & Khargonekar, P. P. (2021). Dynamic optimization and real-time control of distributed energy resources. arXiv preprint. <https://arxiv.org/abs/2105.06096>
24. Mutiso, R. M. (2023). African energy transitions should be driven from the ground up. *Science*, 382, ead13462. <https://doi.org/10.1126/science.adl3462>
25. Mutiso, R., & Dioha, M. O. (2023). Generating meaningful energy systems models for Africa. *Issues in Science and Technology*, 39(4), 54–57.
26. Nabiliou, A., Kodjo, K. M., Amoussou, K., & Ajavon, A. S. A. (2019). Optimization of the sizing of hybrid wind, solar photovoltaic, biodiesel and storage systems using the integer linear programming method. *International Journal of Advanced Research*, 7(6), 871–882.
27. Obiedat, R., & Samarasinghe, S. (2022). Fuzzy cognitive mapping for participatory modeling in environmental decision-making. arXiv preprint. <https://arxiv.org/abs/2208.05103>
28. Odarno, L. (2020, July 29). Missing links between electricity access and development priorities in Africa. World Bank. <https://www.worldbank.org/en/news/feature/2020/07/29/missing-links-between-electricity-access-and-development-priorities-in-africa>
29. Onyango, G. O., & Paliwal, R. (2024). Participatory GIS and community engagement in solar mini-grid design: Case studies from rural Kenya and South Africa. *International Journal of Energy Research*, 48(2), 345–361. <https://doi.org/10.1002/er.7654>
30. Ouyang, T., Lu, J., Hu, X., Liu, W., & Chen, J. (2022). Multi-dimensional performance analysis and efficiency evaluation of paper-based microfluidic fuel cell. *Renewable Energy*, 187, 94–108. <https://doi.org/10.1016/j.renene.2022.01.060>

31. Oyedepo, S. O. (2012). Energy and sustainable development in Nigeria: The way forward. *Energy, Sustainability and Society*, 2, Article 15. <https://doi.org/10.1186/2192-0567-2-15>
32. Oyedepo, S. O., Waheed, M. A., Abam, F. I., Dirisu, J. O., Samuel, O. D., Ajayi, O. O., Somorin, T., Popoola, A. P. I., Kilanko, O., & Babalola, P. O. (2025). A critical review on enhancement and sustainability of energy systems: Perspectives on thermo-economic and thermo-environmental analysis. *Frontiers in Energy Research*, 12, 1417453.
33. Panek, J., & van Heerden, J. H. (2013). Participatory GIS for community resource management and gender equity: Lessons from South Africa. ILRI. <https://www.ilri.org/news/empowering-every-voice-participatory-gis-can-transform-resource-management-and-gender>
34. Parzen, M., Abdel-Khalek, H., Fedorova, E., Mahmood, M., Frysztacki, M. M., Hampp, J., Franken, L., Schumm, L., Neumann, F., Poli, D., Kiprakis, A., & Fioriti, D. (2022). PyPSA-Earth: A new global open energy system optimization model demonstrated in Africa [Preprint]. arXiv. <https://doi.org/10.48550/arXiv.2209.04663>
35. Parzen, M., Abdel-Khalek, H., Fedorova, E., Mahmood, M., Frysztacki, M. M., Hampp, J., Kiprakis, A., et al. (2022). PyPSA-Earth: A new global open energy system optimization model demonstrated in Africa. *Applied Energy*, 316, 119031. <https://doi.org/10.1016/j.apenergy.2022.119031>
36. Rasp, S., Pritchard, M., & Gentine, P. (2023). Machine learning for numerical weather and climate modelling: A review. *Geoscientific Model Development*, 16, 6433–6453. <https://doi.org/10.5194/gmd-16-6433-2023>
37. Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, 566(7743), 195–204.
38. Ugwoke, S. U., Nnaji, C. C., & Iloeje, O. C. (2024). Socioeconomic modeling of adoption barriers for solar home systems in Nigerian rural communities. arXiv preprint. <https://arxiv.org/abs/2401.14499>
39. Usman, B. M., Johl, S. K., & Khan, P. A. (2025). Enhancing energy sector sustainability through robust green governance mechanisms for carbon neutrality. *Discover Sustainability*, 6, Article 216. <https://doi.org/10.1007/s43621-025-00196-3>
40. Wikipedia contributors. (2025, July 30). Participatory modeling. In Wikipedia, The Free Encyclopedia. Retrieved July 13, 2025, from https://en.wikipedia.org/wiki/Participatory_modeling