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AI-Enabled Energy Policy for a Sustainable Future

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Abstract: The present time is a seminal decade for the transition of the energy sector through the deployment of green energy and the optimization of efficiencies using the power of automation and artificial intelligence (AI), which demands competitive policies to handle multidimensional endeavors via a single platform. The failure of energy policies can have far-reaching socioeconomic consequences when policies do not meet the energy and climate goals throughout the lifecycle of the policy. Such shortcomings are reported to be due to inadequate incentives and poor decision making that needs to promote fairness, equality, equity, and inclusiveness in energy policies and project decision making. The integration of AI in energy sectors poses various challenges that this study aims to analyze through a comprehensive examination of energy policy processes. The study focuses on (1) the decision-making process during the development stage, (2) the implementation management process for the execution stage, (3) the integration of data science, machine learning, and deep learning in energy systems, and (4) the requirements of energy systems in the context of substantiality. Synergistically, an emerging blueprint of policy, data science and AI, engineering practices, management process, business models, and social approaches that provides a multilateral design and implementation reference is propounded. Finally, a novel framework is developed to develop and implement modern energy policies that minimize risks, promote successful implementation, and advance society's journey towards net zero and carbon neutral objectives.

Keywords: AI-enabled energy policy; sustainable energy; energy policies management; policy development process; energy techno-economic analysis; policy failure; machine-learning-enabled energy policy

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Citation: Danish, M.S.S.; Senjyu, T. AI-Enabled Energy Policy for a Sustainable Future. *Sustainability* **2023**, *15*, 7643. https://doi.org/10.3390/su15097643

Academic Editor: Jack Barkenbus

Received: 25 February 2023
Revised: 31 March 2023
Accepted: 5 May 2023
Published: 6 May 2023

1. Introduction

Global warming and sustainable development are essential in the modern era and require multidisciplinary measures. Multiple aspects of sustainable energy impact at the regional and international levels and need specific metrics, indicators, tools, and techniques to measure energy poverty and sustainability pillars adapting based on supply and demand infrastructure [1]. The course of the action (policy and strategy) process should be transparent and inclusive to stakeholders within various multidimensional factors and historical trends [2]. Contemporary energy policy powered by AI and innovative technologies is indispensable in promoting energy sustainability and mitigating climate change.

Energy policy is a comprehensive set of laws, regulations, guidelines, and courses of action with limited flexibility for decision making that govern energy production, distribution, and consumption [3,4]. It addresses various issues, e.g., energy security, sustainability, affordability, accessibility, etc., through establishing goals and objectives, resource allocation, and standards for energy-related activities. Energy policy shapes the development of energy markets and the deployment of new technologies. It includes energy production and consumption targets, incentives for efficiency and renewable energy companies' regulations, research and development support, and other domains.

To prevent wide-ranging impacts on society caused by the failure of energy policies, it is crucial to promote fairness, equality, equity, and inclusiveness in energy policy development and project decision making. Timely and effective measures are necessary to prevent policy failures and ensure successful implementation while considering energy consumption and climate goals throughout the policy lifecycle [5].

Examining a comprehensive roadmap to address the shortcomings of energy policies and the integration of ML in energy policies while aligning with sustainability principles at the forefront of AI remains a top priority for research. This study thoroughly analyzes sustainability principles, efficiency (technical, technological, ecological, geopolitical, etc.), and global management practices to establish a novel paradigm [6]. The primary objective is to identify critical factors, establish viable indicators and metrics, and analyze the integration of AI in energy policies from various perspectives using innovative tools and techniques.

An interdisciplinary search of the recent literature on energy policy and the application of AI in energy sectors within substantiality requirements is briefly pointed out. A new formulation approach for sustainable replanting policies is proposed in [7], considering trade-offs between economic, social, and environmental factors using composite indicators and computer simulation tools. The proposed approach aims to find optimal replanting policies for different situations. In a study by [8], a novel framework for energy policy was developed from a strategic perspective. This method enhances the reliability and longevity of photovoltaic module cells by ensuring effective deployment.

Natural resource extraction has driven the world's rapid economic growth since the Industrial Revolution, with global material use tripling from 1970 to 96 billion metric tons in 2019. To balance finite resources and low-carbon demands with material modernization demands, the authors proposed a circular economy that prioritizes minimizing, reusing, recycling, and recovering materials as a solution for global economic sustainability. However, the current recycling rate is only 9% of global material demand, highlighting the need to address the gap in science, policy, and technology [9].

In [10], using a rough set approach to analyze the financial ratios of distressed companies in the solar energy industry in Taiwan from 2009 to 2014 is evaluated. The hypothetical approximations to maximize decision accuracy and certainty are applied. A novel pricing model for a sustainable supply chain consisting of an energy supplier and an efficient manufacturer is given in [11]. The model is based on a rebound effects theoretical approach for energy efficiency improvement in the production process and proposes a multi-stage model with tax deduction and subsidy scenarios as alternative energy policies. This study highlighted that tax deductions are more effective than subsidy schemes but subsidies provide better conditions for the government to control energy consumption. While setting policy objectives, it is essential to examine each case individually to ensure that the objectives are appropriate and achievable based on the specific circumstances.

A multi-objective optimization framework to provide decision makers with insights into the trade-offs between more robust decarbonization goals and higher costs in the European Union (EU) is discussed in [12]. The findings indicate that the maximum achievable reduction for the EU Effort Sharing sectors corresponds to a 35% target, which can be achieved with net social benefits. However, implementing a specific policy mix approach requires investments and public expenditures to accomplish this goal. Computer-aided decision making using AI and machine learning has become increasingly imperative in the energy sector [13]. This study supposed an optimization technique for energy systems to meet increasing demand while preserving resources and finds that AI and machine learning hold great promise for this purpose.

An AI deployment case study in the energy sector is reported in [14], where there is energy sector strain due to not fully leveraging AI. This study analyzed the role of AI and information management in India's energy transition and highlighted challenges and barriers. In general, limited incentives for AI in the energy sector, suggesting adaptive action from policymakers towards AI integration, are reported for this case study. Meanwhile, the energy sector transition and big data access call for a comprehensive AI policy. The impact of government incentive policies and residential choices in China's solar photovoltaic (PV) market using a Stackelberg game model is investigated in [15], suggesting that government subsidies are gradually becoming no longer needed for smaller-capacity PV investments when only economic benefits are considered.

The potential of using renewable energy to meet energy needs and transition to both technically feasible and economically viable renewable energy sources is investigated in [16]. A range of policy recommendations to support the transition, including increased investment in renewable energy, establishing supportive regulatory frameworks, and developing renewable energy infrastructure, are discussed. Overall, these studies highlight the importance of considering the economic, social, and environmental factors in developing sustainable policies and the potential of using AI and machine learning to improve decision making and efficiency in a range of fields, including energy and environmental management. They also demonstrate the importance of transitioning to renewable energy technologies and improving energy efficiency to promote sustainable development and address global challenges, e.g., climate change, by shaping a viable policy roadmap.

This study aims to analyze the challenges and opportunities presented by integrating AI into energy sectors, focusing on energy policy processes. Specifically, this study examines the decision-making process during the development stage, the implementation management process for the execution stage, the integration of data science, machine learning, and deep learning in energy systems, and the requirements of energy systems in the context of sustainability. The study will also propose a novel framework for developing and implementing modern energy policies that minimize risks, promote successful implementation, and advance society's journey towards net-zero and carbon-neutral objectives. Whereas previous research has examined the integration of AI in energy sectors and energy policy processes, there is a lack of comprehensive analysis exploring the challenges and opportunities of integrating AI into all stages of energy policy processes. Furthermore, the existing research has not provided a detailed framework for developing and implementing modern energy policies that promote fairness, equality, equity, and inclusiveness in energy policy and project decision making. Therefore, this study aims to fill the gap by providing a multilateral design and implementation reference that integrates policy, data science and AI, engineering practices, management process, business models, and social approaches, thereby contributing to the energy transition towards net-zero and carbon-neutral objectives

This paper guides understanding of the complex landscape of energy transition and decarbonization scenarios, policy development, and decision-making processes. Section 1 provides an overview of the big picture of energy transition and decarbonization. Then, in Section 2 policy development and decision-making processes are explored. Section 3 deals with different energy policy scenarios. Section 4 answers "How will AI shape future energy policies". Policy building blocks are discussed in Section 5. Section 6 highlights AI and machine learning methods. Section 7 presents the proposed novel framework to realize modern energy policy exigency at the critical time of climate change. Finally, Section 8 wraps up with the key findings and future works.

2. Energy Transition and the Decarbonization Scenario at a Glance

The global energy sector transformation is knocked with electricity and hydrogen, which are expected to become the primary energy sources. According to studies [17], electricity and hydrogen's share of final energy consumption is estimated to reach 32% by 2035 and 50% by 2050. Despite a growing population, energy consumption is only forecasted to grow by 14% due to advancements in energy efficiency. Electrification is crucial for improving energy efficiency in vital sectors such as buildings, transportation, and industry, resulting in an anticipated doubling of electricity's share of final energy consumption from 20% to 40% by 2050 [17].

The use of hydrogen will also offset the use of fossil fuels. Power demand is predicted to triple by 2050 due to increased electrification and living standards, with 60% of the demand coming from appliances and space cooling in buildings [17]. Green hydrogen production will increase power demand, accounting for a 42% increase between 2035 and 2050. Renewables are expected to become the new baseline, making up 50% of the power mix by 2030 and 85% by 2050 [17]. However, current global emissions fall far short of the 1.5 °C pathway [17], and a policy documentation process is required to address the energy and climate change crisis.

Energy and climate data are crucial in developing effective energy policies, but data availability and systematicness limitations can pose challenges [18]. Scenario-based and case-by-case analyses are essential in providing a comprehensive understanding of the energy sector and its evolving trends, enabling informed policy decisions. The analysis assesses the efficacy of current policies, plans for future challenges and opportunities, evaluates policy options, and encourages collaboration among stakeholders, leading to a more sustainable and efficient energy future [19].

The International Energy Agency (IEA) [20] predicts that by 2050, fossil fuels will only account for 5% of the total energy supply. Electricity will become the primary energy source, providing over half the total final consumption. The report expects immense growth in low-emissions energy from solar and wind. The end-use sectors aim to deploy hydrogen and hydrogen-based fuels in heavy industry and long-distance transport and CO_2 capture in the industry and fuel transformation sectors to achieve the emissions reduction goal of 90% by 2050. The report requires a significant increase in investment in clean energy, with energy investment rising from 2% to nearly 4% of global GDP by 2030. However, policymakers need to do more to provide demand signals, develop a clean technology supply chain, and promote coordinated growth. Total energy sector employment is expected to increase to 90 million by 2030. Clean technologies are still the most cost-efficient option for new power generation despite the potential rise in borrowing costs. The IEA explores three energy future scenarios: The Stated Policies Scenario, the Announced Pledges Scenario, and the Net Zero Emissions by 2050 Scenario.

3. Policy Development and the Decision-Making Process

According to [21], energy sector policy development and the decision-making process involve several steps: agenda setting, policy formulation, adoption, implementation, and evaluation. During agenda setting, policymakers identify and prioritize issues that require attention; during policy formulation, they develop potential solutions or policy options. Once a policy is adopted, it is implemented and evaluated to assess its effectiveness and impact. The process requires input and feedback from various stakeholders, careful consideration of political, economic, and social factors, and may involve negotiation and compromise to ensure successful policy outcomes.

The concept of sustainability encompasses balancing five pillars—technical, economic, institutional, environmental, and social—to meet present needs without restraining future demand [22]. The criteria for sustainable energy system modeling include interpretive potential, simplicity, accuracy, scientific and theoretical validity, adaptability to changing trends, sensitivity to scenarios, and comparability with benchmarks through the integration of sustainability into decision-making processes at all levels of energy system development, including project, portfolio, policy-oriented, objective-oriented, and problem-oriented perspectives (Figure 1) [23].

Effective decision making is essential for any process and requires a systematic approach incorporating various phases. These phases include the conceptualization, assessment, excerption, ranking, consensus, and formulation, which are discussed as follows:

- Conceptualization Phase: This phase forms clear and abstract ideas of the concept or phenomenon, exploring further analysis.
- Assessment Phase: This phase evaluates the overall framework using relevant data to align with system parameters.

- Excerption Phase: Handles identification and selection of obvious or decisive solutions to remove from further evaluation in the cycle.
- Ranking Phase: This phase involves arranging the different decision options in order of priority to assist in the weighting process.
- Consensus Phase: Reaching an agreement among previous phases to determine key performance indicators and assign weights.
- Formulation Phase: Synthesizing the process, creating a structured framework from the raw inputs/parameters for the given process.

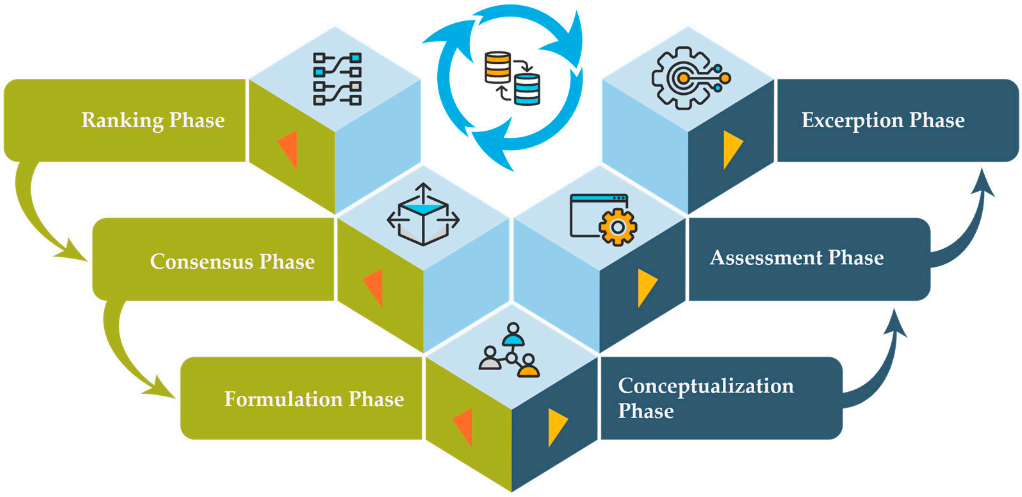

Figure 1. Steps for energy policy development.

A combination of technical, managerial, and policy expertise is required to ensure successful policy and process development. Several multi-criteria decision-making methods based on the weighing approach have been proposed, including the best–worst method, weights scoring, and decision-making matrix [24,25]. Other techniques, such as qualitative and generic decision-making frameworks, have also been applied for specific purposes [26]. Overall, the decision-making process for energy policy development can be represented through a diagram, as depicted in Figure 2.

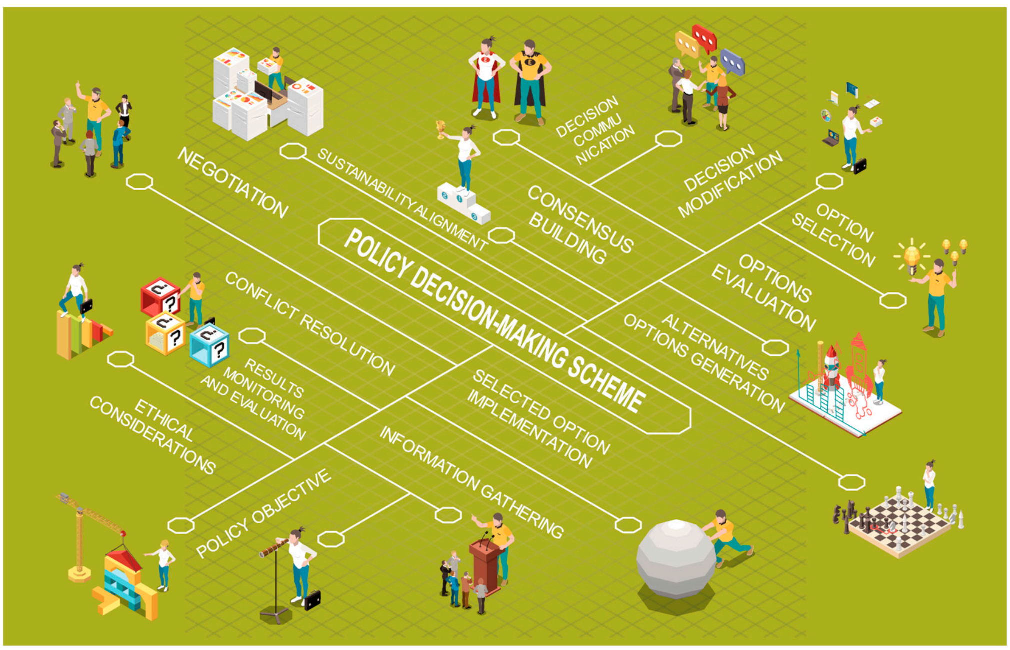

Figure 2. The landscape of decision-making building blocks for energy policy development.

The weighting approach is one of the most used methods in decision making that can be demonstrated in various ways based on specific objectives [27]. The weighing process can be categorized into verbal judgment and a numerical value. However, in some cases, it needs further formulation to adapt to the target problem. Supporting information and detailed formulations for the weighing methodology are given in [28].

4. Energy Policy Scenarios

Figure 3 analyzes high-level structural scenarios for energy policy building blocks using functional domain approaches within the energy policy paradigm [8,16,29–33]. The scenarios showcase the significant roles that different functional domains can play within the scope of policy and targeted objectives. Policy development is not a fixed endeavor but a flexible process throughout the lifecycle, from policy initiation to implementation, monitoring, and adjustment. Various scenarios present multiple options and policy building blocks that can be incorporated into high-level structural scenarios by utilizing functional domain perspectives. These approaches enable policymakers to understand how different aspects of the energy system interact and identify potential areas for improvement in their energy policy.

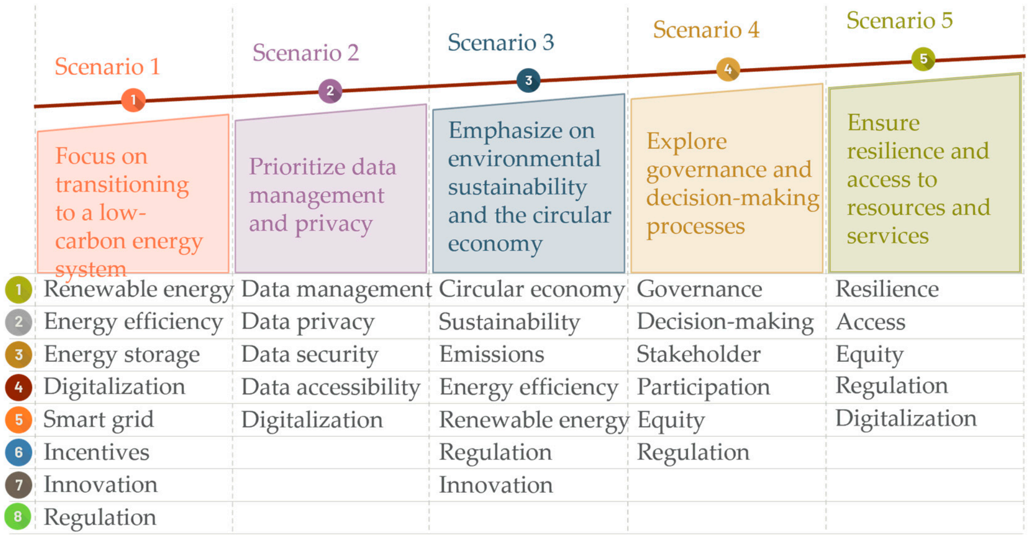

Figure 3. Analysis of high-level structural scenarios for energy policy using functional domain approaches, showcasing the significant role of different domains and the flexibility of policy development throughout the lifecycle.

5. How Will AI Shape Future Energy Policies?

Shaping the present and future of energy systems through critical decisions about resource allocation and technology development is considerably influenced by energy policy formulation and implementation. Besides its primary function, energy policy knowledge facilitates optimizing energy systems in line with policy objectives and data as the input, where goals and objectives are defined, policy constraints are incorporated, and policy impacts are evaluated through a clear roadmap. The energy systems optimization models can integrate policy objectives (e.g., minimizing the carbon footprint to reduce greenhouse gas emissions), constraints (e.g., renewable portfolio standards that mandate a specific percentage of renewable energy sources), and a huge volume of other critical performance indicators of different policy scenarios to ensure that the resulting energy system is aligned with the objectives [34].

Modeling energy systems in the context of AI and machine learning deployment is challenging and time consuming due to their complex interdependencies and non-linear patterns [35]. Operation and reliability can be improved by enabling system-parameter-based analysis using data-driven methods. However, there is a need for benchmarking among different methodologies, tools, and techniques due to the lack of standardization to transform system-parameter-based models into data-driven models. Establishing robust frameworks and benchmarking protocols is crucial to evaluate performance, comparability, and generalizability [36]. Therefore, transitioning to data-driven models is essential to align energy systems from the initial stage of policy development by allocating enough financial, technical, and human resources to align the fast-growing technologies of AI. Feature engineering methods are widely used for data-driven model analysis among many machine learning techniques [37].

Solving a data-driven machine learning model is an iterative process (some steps can be added or repeated based on different scenarios) organized hierarchically. The stages in developing an AI model to support energy policy are outlined in Figure 4 [38–40], where the identification of necessary datasets is the first. Planning for collecting and cleaning the data follows. Patterns and relationships between the input and output variables can be identified by exploring the collected data. A suitable data-driven model can then be selected and trained on the collected data. The model's performance evaluation is recommended on a separate dataset and fine-tuned as necessary. Finally, predictions are expected and recommendations for optimization are developed based on the model's predictions. The last steps are reporting and highlighting to summarize the research, including the methods, results obtained, conclusions, and essential findings and recommendations.

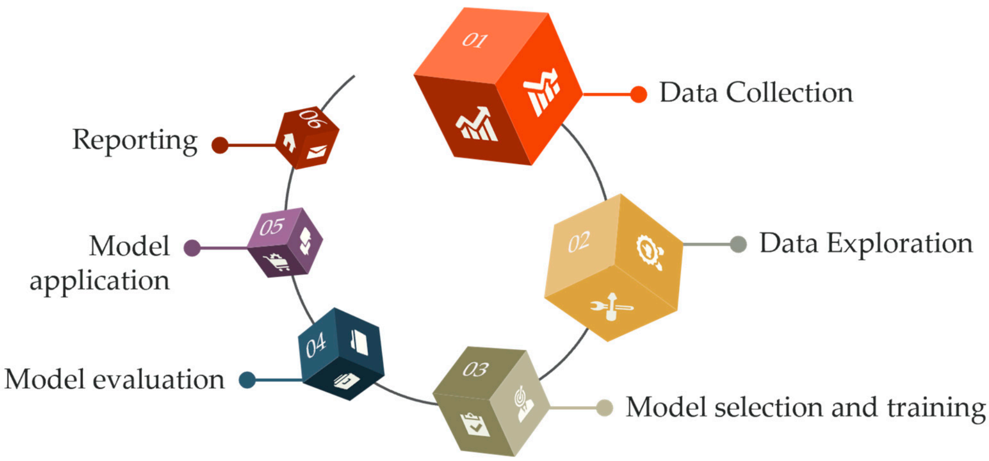

Figure 4. The high level of hierarchical stages of the workflow for developing an AI model for energy policy applications.

1. Data Collection:
   The first step in developing a data-driven model for energy facilities involves identifying the necessary datasets for training and testing the model. This may involve developing a plan for data collection, which can include utilizing publicly available datasets, partnering with other organizations to collect data, or creating a synthetic dataset. Once the dataset has been identified, it must be collected and cleaned to ensure accuracy, representativeness, and quality.
2. Data Exploration:
   After data collection, the next step is to analyze the data to identify patterns and relationships between the input variables and output. This involves performing any necessary data pre-processing, such as feature scaling or normalization.
3. Model Selection and Training:
   Once the data is explored, a suitable data-driven model, such as an artificial neural network, can be selected to be trained on the collected data.
4. Model Evaluation:
   After the model is trained, its performance requires a separate dataset. If necessary, the model can be fine-tuned to improve its performance.

5. Model Application:
   The next step is to use the trained model to make predictions and analyze the variables under different scenarios. Based on the model's predictions, recommendations for optimization can be developed.
6. Reporting:
   Finally, the study's results are summarized in a report that includes the methods used, results obtained, and conclusions drawn. Additionally, a presentation can be prepared to highlight the essential findings and recommendations to relevant stakeholders. Following these steps, a data-driven model can be developed and utilized to optimize energy facilities and improve energy efficiency.

6. AI-Driven Policy Development Building Blocks

A modern energy policy integrated map represents a thorough and collaborative approach to energy policy and AI implementation, considering the sustainability pillars (technical, economic, institutional, environmental, and social) along with specific domains of system data, policy building blocks, and stakeholder engagement.

The proposed modern energy policies focus on sustainability, decarbonization, efficiency, and integrating renewable energy technologies. AI-driven energy policy takes a step further by utilizing AI and machine learning techniques to boost the trends by optimizing energy systems for maximum efficiency, performance, cost savings, etc. A structured roadmap of AI-enabled energy policy is drawn in five high levels (including continuous improvement), as shown in Figure 5 (adapted from [41,42]).

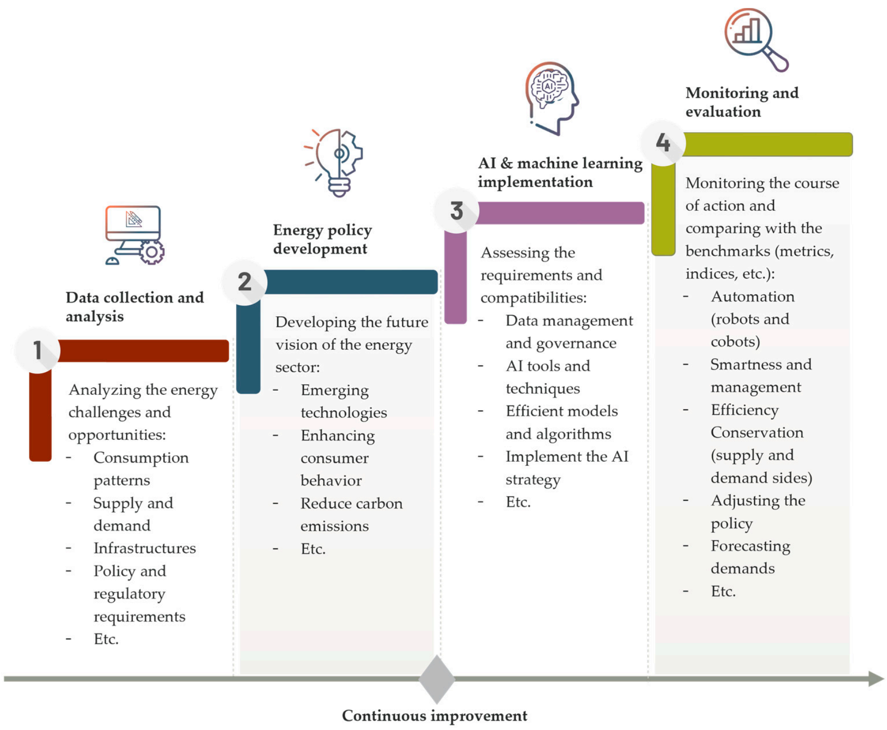

Figure 5. A structured roadmap of AI-enabled energy policy formulation and implementation (high level).

In successfully leveraging AI to support energy policy development and implementation, several critical components are essential for harmonizing harmoniously (Figure 6) [43,44]. These components include data platforms and infrastructure to collect and analyze energy data, specific AI algorithms and models to generate insights and recommendations, policy and regulatory frameworks to ensure compliance and accountability, stakeholder engagement to promote collaboration and address concerns, and communication and dissemination platforms to share results with relevant parties. Utilities or governments can create an effective and efficient AI-enabled energy policy that addresses all stakeholders' needs and ensures the energy sector's long-term sustainability by incorporating each element into an integrated system.

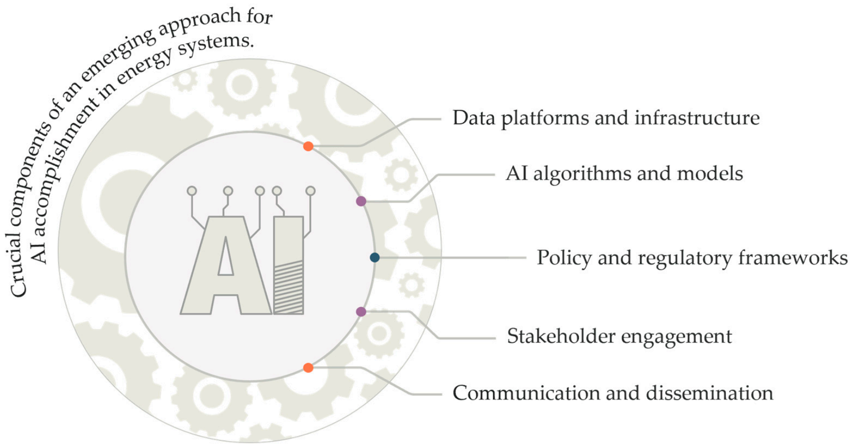

Figure 6. Crucial components of an emerging approach for AI accomplishment in energy systems.

7. AI and Machine Learning Methods for Integration in Energy Systems

The literature has extensively discussed and categorized data science, AI, machine learning, and deep learning from multiple perspectives and viewpoints [8,10,45–52]. However, this classification can sometimes overlook the overlapping and interconnectivity of certain methods and tools, leading to a generalization that may not fully capture the nuances and complexities of these methods.

Machine learning methods can be classified into four categories for their application in the energy sector. Class 1 methods involve classification, which helps identify patterns and categorize data into groups and can be applied to predict patterns. Class 2 consists of regression methods that predict numerical values and can be useful in forecasting and optimizing scenarios. Class 3 represents the association analysis and clustering for identifying relationships between variables and grouping similar data points to identify patterns. The methods in Class 4 are associated with various techniques, including reinforcement learning, network and graph analysis, and generative methods for multi-purpose applications.

Class 1:

- Classification: Naive Bayes, Support Vector Machines (SVM), decision trees, neural networks, induction rules, k-nearest neighbors.

Class 2:

- Regression: Linear and logistic regression, polynomial regression, CART (Classification and Regression Trees);
- Time series forecasting: Autoregression (AR), Mean Absolute Percentage Error (MAPE), Moving Average (MA), exponential smoothing, ARIMA (Auto Regressive Integrated Moving Average).

Class 3:

- Association analysis: A priori algorithm, ECLAT (Equivalence Class Transformation) algorithm, FP-growth algorithm;
- Clustering: k-Means, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), hierarchical clustering, XRF Spectral-Based Sorting (SBS);
- Anomaly detection: Isolation forest, distance-based, density-based, LOF (Local Outlier Facto), one-class SVM, Z-score;
- Feature selection: Recursive feature elimination, lasso regression, random forest;
- Ensemble methods: Random forest, gradient boosting, AdaBoost.

Class 4:

- Deep and transfer learning: Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs);
- Text mining: Natural Language Processing (NLP), Term Frequency–Inverse Document Frequency (TF-IDF), sentiment analysis;
- Computer vision: Image classification, object detection, segmentation;
- Natural language generation: GPT-3 (Generative Pretrained Transformer 3), OpenAI, ELMo (Embeddings from Language Models), OpenAI Gym;
- Dimensionality reduction: Principal Component Analysis (PCA), Singular Value Decomposition (SVD), Linear Discriminant Analysis (LDA);
- Reinforcement learning: Q-Learning, SARSA (State–Action–Reward–State–Action), Deep Q-Networks (DQN);
- Generative methods: Variational Autoencoders (VAE), Generative Adversarial Networks (GAN), Boltzmann machines;
- Network and graph analysis: Centrality measures, community detection, link prediction, PageRank;
- Recommender systems: Matrix factorization, neighborhood-based collaborative filtering, deep-learning-based recommender systems.

8. The Proposed Framework

The decision-making scenario for energy policy options is a valuable tool that enables policymakers to make informed decisions regarding energy policy development. By prioritizing policy objectives and considering various scenarios the proposed scheme in Figure 7 (adapted from [4,20,23]) facilitates a structured approach to decision making based on the energy sector’s specific needs and priorities. The scheme provides a clear roadmap for developing energy policy aligned with sustainability and efficiency criteria, as well as considering the potential impact on various stakeholders and the broader community. The proposed framework in Figure 8 will contribute to optimizing policy objectives by assessing and prioritizing many objective options, resulting in a transparent, accountable, and inclusive energy policy. Meanwhile, having clear objectives as the input/output can accelerate transferring a system-parameter-based model to a data-driven model in the context of AI applications.

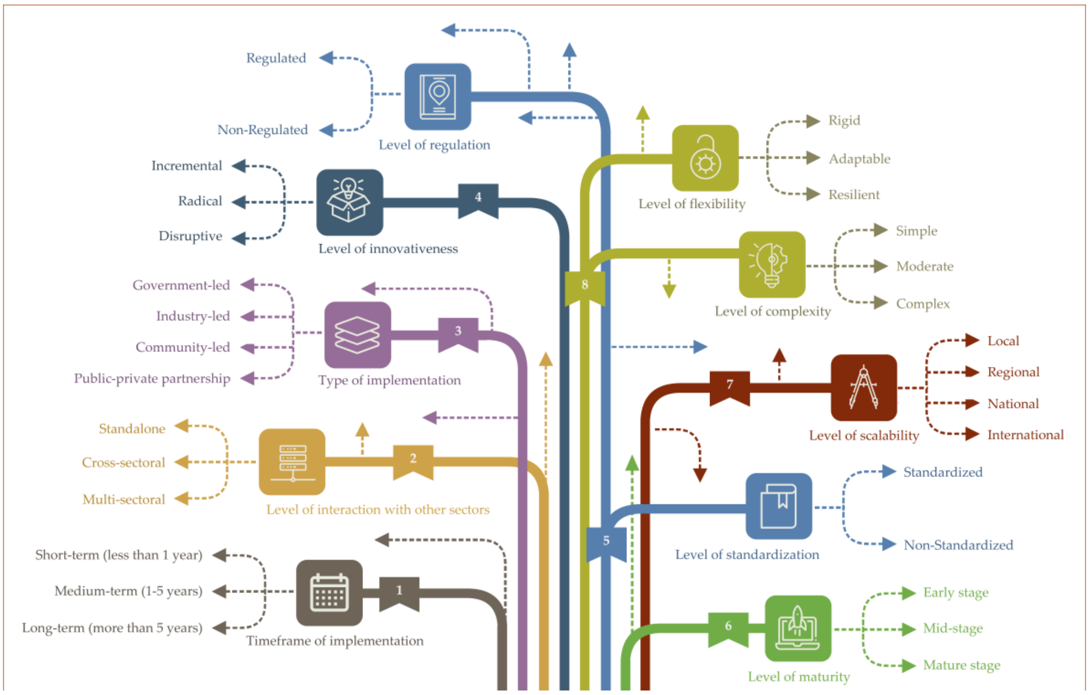

Figure 7. A decision-making scenario scheme for energy policy options based on policy objectives and priorities, helping to facilitate informed decision making in the energy sector.

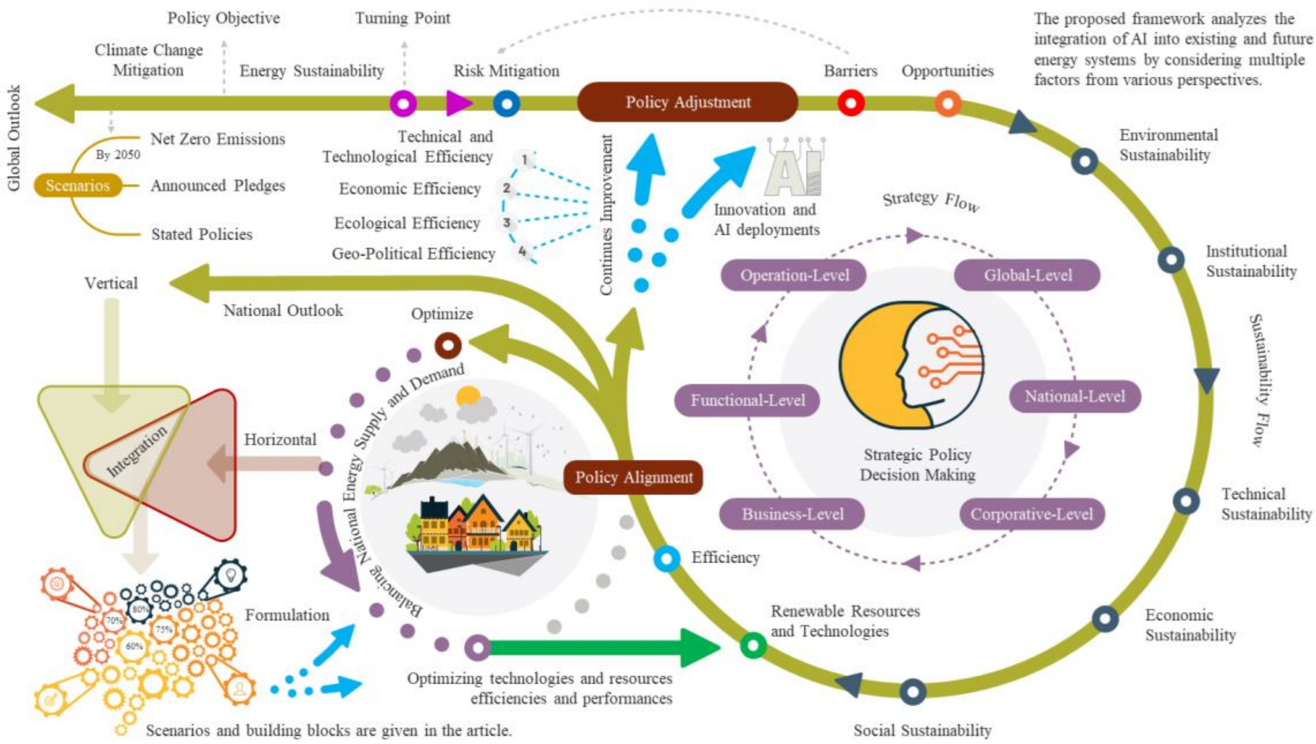

Figure 8. The proposed multidimensional framework for analyzing the integration of AI into existing and future energy systems examines multiple influencing factors from various perspectives.

1. Timeframe of implementation:
   - Short-term: The energy policy tool or technique is expected to be implemented for less than one year and obtain results within this period. Short-term solutions have an implementation period of less than one year. They often address immediate or urgent energy-related issues, e.g., emergency power generation during natural disasters, load-shedding programs to reduce peak demand, etc.
   - Medium-term: Medium-term solutions have an implementation period between one and five years. These solutions usually address intermediate energy-related issues and lay the foundation for long-term solutions, e.g., energy efficiency programs for buildings and appliances.
   - Long-term: Long-term solutions are implemented for periods over five years. These plans address long-term energy-related issues, e.g., transitioning to a low-carbon energy system, developing large-scale renewable energy projects, deploying carbon capture and storage technologies, etc.
2. Level of interaction with other sectors:
   - Standalone: Implemention by a single sector without potentially impacting other sectors. Projects such as energy efficiency programs for buildings and appliances, development of small-scale renewable energy projects, etc.
   - Cross-sectoral: A multi-task or multi-beneficiaries project design to be implemented in collaboration with other sectors. These solutions are implemented considering their impact on different industries and aim to achieve multiple objectives. Cross-sectoral solutions include integrating electric vehicles into the transportation sector, using energy storage to enhance the reliability of the electric power grid, etc.
   - Multi-sectoral: Involves multiple sectors with various stakeholders impacted differently and interchangeably. These solutions aim to achieve multiple objectives and are implemented in collaboration with different sectors, e.g., integrating

renewable energy into the industrial sector, deploying smart grid technologies to enhance the reliability of the electric power grid, etc.

3. Type of implementation:
   - Government-led: Primarily implemented by government agencies or entities through regulations, subsidies, or other forms of government support, e.g., building energy codes and standards, renewable energy portfolio standards, etc.
   - Industry-led: Governing by private industry or businesses using market-based mechanisms or voluntary agreements between industry and government, e. g., feed-in tariffs, energy efficiency programs for buildings and appliances, etc.
   - Community-led: Directed by communities or local organizations conducting community-based initiatives, e.g., energy cooperatives or community-based renewable energy projects, etc.
   - Public–private partnership: Collaboration of public and private sectors and associations between government agencies, private industry, and local organizations, e.g., development of large-scale renewable energy projects, deployment of smart grid technologies, etc.
4. Level of Innovativeness:
   - Incremental: Existing infrastructures or setups show a gradual improvement over existing solutions. These solutions are typically low-risk and have a relatively low level of uncertainty.
   - Radical: Emerging technologies demonstrate a significant departure from existing solutions. These solutions have a higher level of risk and uncertainty than incremental solutions.
   - Disruptive: This class is based on new or emerging technologies or practices that fundamentally change the energy system and disrupt existing markets and technologies. These solutions can potentially create new opportunities and transform the energy system but also come with high risk and uncertainty. For instance, disruptive solutions include deploying blockchain technology for energy transactions and integrating artificial intelligence for energy system management.
5. Level of Maturity:
   - Early stage: At the early stages of development or implementation and having high uncertainty.
   - Mid-stage: At the middle stages of growth and after examining the solutions; demonstrates some level of validation but is not yet fully mature.
   - Mature stage: At the fully developed stage and has been implemented and validated in multiple settings. These solutions have a low level of uncertainty and have been proven effective.
6. Level of complexity:
   - Simple: Easy to understand and implement with a low level of complexity, fewer components, easy to replicate, e.g., energy-efficient lighting systems, public awareness campaigns, etc.
   - Moderate: A moderate level of complexity with more components that may require more resources to implement and maintain, e.g., energy efficiency programs for buildings and appliances, development of small-scale renewable energy projects, etc.
   - Complex: Highly complex with many components and requires significant resources to implement and maintain, e.g., the development of large-scale renewable energy projects, the deployment of smart grid technologies, etc.
7. Level of scalability:
   - Local: Implemented at a local level within a specific city or community, tailored particular needs of the local area and having a limited impact in the broader

region (country), e.g., community-based renewable energy projects, energy efficiency programs for local buildings and appliances, etc.
- Regional: Designed for the regional level for a specific state or province with a more significant impact on a region, e.g., the development of small-scale renewable energy projects, the deployment of smart grid technologies in a specific area, etc.
- National: Deployed on a national scale with a significant impact on the energy system and put into action through national policies and regulations, e.g., renewable energy portfolio standards, energy conservation standards for appliances and buildings, etc.
- International: Draws in a big picture at the international level across multiple countries, having a global impact pursued through international agreements and frameworks, e.g., the deployment of carbon capture and storage technologies, international cooperation on energy and climate policy, etc.

8. Level of Flexibility:
    - Rigid: This applies to an inflexible system with predefined rules and parameters that cannot be adjusted quickly and are less adaptable to changing circumstances.
    - Adaptable: Refers to a flexible system that can be adjusted to changing circumstances with more adaptability to the evolving circumstances and customizability to suit specific needs.
    - Resilient: A system to withstand and recover from disturbances with a robust condition and withstand disruptions to the energy system.
9. Level of Regulation:
    - Regulated: Subject to government regulations and oversight, implemented by government mandates, e.g., building energy codes and standards, that are closely monitored to ensure compliance.
    - Voluntary: Refers to a voluntary agreement between industry and government that is implemented based on mutual agreement, e.g., energy efficiency programs for buildings and appliances, and relies on self-regulation and market-based mechanisms.
    - Hybrid: Demonstrates a combination of regulated and voluntary measures, using a combination of government mandates and incentives, voluntary agreements, and market-based mechanisms.
10. Level of Automation:
    - Manual: Operating manually requires human intervention for operation with less efficiency and may have higher costs.
    - Semi-automatic: Possesses some level of automation but still requires human intervention for operation; more efficient than manual and may have lower costs.
    - Automatic: Automation with minimal human intervention is the most efficient and cost-effective method due to high production and low error rates.

The proposed framework employs a multidimensional approach to analyze the integration of AI into existing and future energy systems. The proposed framework examines multiple influencing factors from various perspectives. This approach allows for a more comprehensive understanding of the energy policy development and implementation process, including factors such as the timeframe of implementation, level of interaction with other sectors, type of implementation, level of innovativeness, complexity, scalability, flexibility, regulation, and standardization. Furthermore, the framework facilitates the breakdown of the energy system into smaller, more manageable segments, enabling an in-depth understanding of the system and facilitating the system's transformation from a parameter-based to a data-driven approach. This leads to increased accuracy in the planning and performance of a system. Additionally, the framework identifies potential synergies and areas for further research and development. The proposed framework is based on previous concepts [4,20,23] but has been reinterpreted and enriched with recent trends and AI and machine learning application options.

The proposed framework establishes interlinked relations among the most involved domains that provide a systematic roadmap in a synergetic manner. This framework enables potential implementation and estimation of the required resources (human, budget, tools, techniques, procedures, and methodologies) at different stages of strategy development within the approaches of various scenarios. Indeed, all these levels are competing or overlapping conceptual interactions to achieve a goal, relying on circular economy circulation in the context of feedback and reprocessing policy adjustment and revision. This framework tries to innovatively integrate domains and draw the level of the interactions by level based on viable scenarios. At different levels, various indicators and measures can be defined to adapt to the strategic goals within the optimum allocation of resources and utilization of technologies, especially AI. Emerging strategic processes, sustainability requirements, and efficiency criteria within innovative technologies deployment can lead to comprehensive strategic policy decision-making endeavors.

Due to the broadness of the proposed multidimensional approach, an exhaustive investigation of this subject will be conducted in the future. At this point, the salient points are exposed within the limited elaboration of details.

9. Conclusions and the Way Forward

This study provides a multidimensional analysis of energy policy development and the integration of AI options. It emphasizes the importance of a transdisciplinary approach and the role of policymakers and energy experts in making sustainable long-term decisions. The study covers various topics, such as decision-making processes, high-level structural scenarios, and a hierarchical workflow for developing an AI model. It also proposes a groundbreaking and structured roadmap for AI-enabled energy policy formulation and a decision-making scenario scheme based on policy objectives and priorities. This study proposes a multidimensional framework for analyzing and integrating scenarios into existing and future energy trends. The framework considers various factors, including policy, technology, economics, and social aspects, to comprehensively explore energy trends and their potential impact on sustainability. Overall, this study highlights the importance of sustainability-oriented perspectives in energy policy development and the potential role of AI and machine learning in policy formulation. As a result, it has significant implications for real-world application and serves as a multilateral reference for students, researchers, scholars, and practitioners in related fields. Moreover, this study has outlined various avenues for further research, exploring the management and implementation processes of energy policies, addressing concerns related to energy system modeling approaches from system-parameter-based to data-driven-based models, elaborating metrics and indices, and benchmarking the improvement potential and limitations of modern AI-enabled energy policy application options.

Author Contributions: Conceptualization, M.S.S.D. and T.S.; methodology, M.S.S.D. and T.S.; software, M.S.S.D.; validation, M.S.S.D. and T.S.; formal analysis, M.S.S.D.; investigation, M.S.S.D. and T.S.; resources, M.S.S.D.; data curation, M.S.S.D.; writing—original draft preparation, M.S.S.D.; writing—review and editing, T.S.; visualization, M.S.S.D.; supervision, T.S.; project administration, M.S.S.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: We would like to express our heartfelt gratitude to all those who contributed to the completion of this article. Your unwavering support, insightful comments, and invaluable guidance, especially during critical moments, have been instrumental in shaping this work. We sincerely appreciate your contributions and willingness to join us on this journey. Thank you for your time, effort, and dedication to making this article successful.

Conflicts of Interest: The authors declare no conflict of interest.

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