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AI-Supported Decision Framework for Sustainable Electrical Infrastructure Development

Muhammad Arsalan,[1] Muhammad Ayaz,[2] Yousaf Ali,[3] Uroosa Baig[4]
[1] Masters of Engineering management, Cumberland university, [2]Department of Electrical Engineering PAF-IAST Mang, Haripur, Pakistan, [3]Department of Electrical Engineering PAF-IAST
Mang, Haripur, Pakistan, [4]Department of Electrical Engineering University of Engineering & Technology, Lahore, Pakistan
[1] Department of Master of Engineering Management
[1] Masters of Engineering management, Cumberland university Lebanon, Tennessee
[1] muhammadarrsalan999@gmail.com, [2] muhammad.ayaz@paf-iast.edu.pk, [3] yousaf.ali@paf-iast.edu.pk, [4] arucey.uet@gmail.com

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Abstract:

With the increasing demand of electricity in the world and the need to be sustainable with electricity, sustainable electrical infrastructure development has been a very important issue. The conventional methods of decision-making in planning and implementing infrastructure are usually not capable of dealing with sophisticated trade-offs that involve environmental, economic, and technical considerations. Artificial Intelligence (AI) delivers the potential of transformations in this area, as it allows for implementing data-driven, dynamic, and optimal decision-making structures. The present paper suggests an AI-based decision-making system that can support development of sustainable electrical infrastructure. The framework brings onboard machine learning that is used to predict demand, reinforcement learning, which is used to optimize planning, and multi-objective optimization that balances sustainability goals. The Case studies, simulations and real-world data prove the effectiveness of the framework in solving the issues including renewable integration, grid reliability, and cost-effectiveness. Ethical considerations required data and implications of policies are also discussed in the research. The paper has had an impact on the academic and industrial field because it establishes a basis of intelligent infrastructure systems to conform to long-term sustainability objectives.

Keywords — **AI in power systems, Sustainable Electrical infrastructure, Decision support framework, Smart Grid optimization, multi-criteria Decision making**

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I. Introduction

a. Background and Motivation Sustainable

Development of electricity infrastructure is also becoming a key element in reaching both goals of affordable energy and climate conservation. Electricity has become the backbone of the modern societies and a source of both economic growth as well as basic services to people, and the development of energy networks should thus be undertaken in a manner that is efficient as well as environmentally friendly. One way to achieve sustainability is to maximize the lifecycle of assets, minimize losses to energy, incorporate renewable sources of energy, and lower the emission of greenhouse gases, and ensure that service delivery is reliable to the consumers.

Although such a demand is urgent, conventional infrastructure decision-making frameworks are commonly unable to favor sustainable results. Much of the current systems use obsolete, incomplete or siloed information, making it harder to see the operational, environmental and economic effects of the infrastructure decisions. As an example, maintenance orders and investment decisions can be made with historical assumptions, but not based on current asset-health, which can result in excessive maintenance or pre-emptive replacement that consume resources. In the same fashion, the inability to combine distributed energy resources, load profile, and environmental metrics may deny utilities the chance to evaluate the sustainability of operations, leading to inefficiencies and the lack of environmental goals.

These limitations provide a route to cutting-edge analytics along with AI and digital technologies. Through real-time monitoring, predictive maintenance, and intelligent optimization, the utilities will be in a better position to make better decisions that can strike a balance between operational efficiency, cost-effectiveness, and environmental responsibility. The approach does not only favour more intelligent infrastructure planning and management but also the wider goals of sustainable development, whereby electricity systems would grow in balance with the economies and with the ecological watch.

b. Challenges in Traditional Infrastructure Planning

One of the most major limitations of traditional infrastructure planning and asset management structures is the lack of data integration. In most instances, data sources like grid topology, socio-economic and environmental metrics, and real-time operational information are in silos. This disintegration does not enable planners to have an overall picture of the system, and they make inferior decisions. It would be hard to represent interdependences between the energy supply and demand, environmental impact, and financial constraints without integrated data pipelines.

Even worse, the problem is aggravated by the fact that traditional decision-making tools are prone to deterministic assumptions and predetermined situations. These models are unable to respond to dynamic fluctuation of energy demand, variability of renewable generation, or other unforeseen events like extreme weather. This causes infrastructure plans to become obsolete within a short period and causes inefficiencies, stranded assets, and cost overruns. There is a need to have adaptive and learning-based models to be resilient and flexible in decision-making.

Another gap in the current planning practice that is critical is low participation of the stakeholders. Conventionally, policymakers and a few experts decide, without necessarily considering the views of local people, industry players, and sustainability advocates. Besides lowering transparency, this exclusion may also result in solutions that do not respond to the special socio-economic requirements of the regions impacted. Visualization tools and AI-enabled participatory platforms can be used to democratize the decision-making process and make it more inclusive and socially equitable.

Lastly, there is a lack of environmental forecasting tools, which is a significant impediment to sustainable development. Traditional planning models do not often incorporate climate scenarios, land use dynamics, or an evaluation of the impact of biodiversity. This omission contributes to infrastructural designs which can unintentionally degrade ecosystems or not be resistant to future climatic conditions. Planners can consider the environmental footprint of carbon-based projects, climate resiliency, and ecology through AI-based environmental projections, which can be aligned with the sustainability objectives.

c. Role of AI in Infrastructure Decision-Making

Artificial Intelligence has an important role in facilitating dynamic, adaptive, and data-driven decision-making in contemporary electrical infrastructure planning and operations. With heterogeneous data, AI systems can identify actionable insights by handling high volumes of data in real time to make strategic and operational decision-making by the processing of data such as load profiles, weather conditions, equipment status, and market dynamics. Complex pattern recognition and prediction is possible through methods like neural networks which can identify complex relationships among multiple variables which a traditional model might miss.

Reinforcement learning can also improve decision-making by allowing AI agents to learn the best strategies by working with simulation environments, and it is especially applicable to grid expansion planning, demand-response management, and energy dispatch optimization. In the meantime, evolutionary algorithms offer effective mechanisms of multi-objective optimization, allowing utilities to analyze trade-offs between cost, efficiency, reliability and environmental impact during the planning of renewable energy location or infrastructure investments.

With a combination of these AI methods, utilities can leave the traditional rule-based decision-making processes in favor of adaptive, predictive, and optimized decision-making processes. This ability can enhance effectiveness as well as resilience of the power grid, as well as aid more comprehensive goals like sustainable development, reduction of costs as well as proper incorporation of renewable energy resources. Essentially, AI makes infrastructure management a proactive, intelligent, and constantly changing process, which can address the complex needs of the current energy systems.

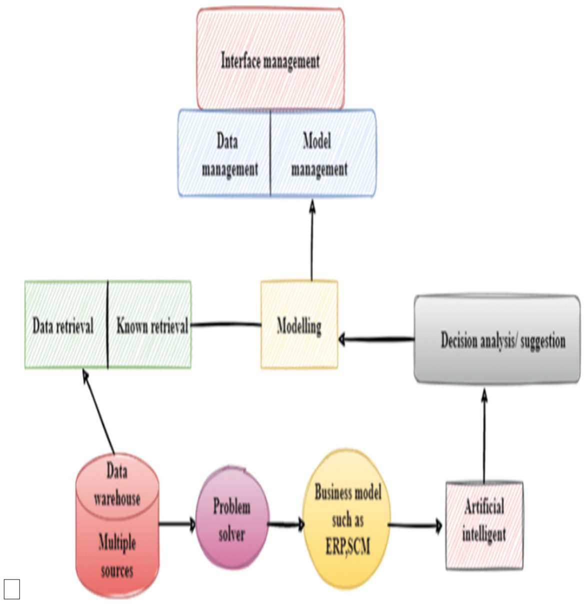


Figure 1: ***Conceptual Architecture of AI-Supported Decision Framework***

II. Literature Review

a. Sustainable Electrical Infrastructure: Global Perspectives

The United Nations Sustainable Development Goal (SDG) 7 focuses on universal access to affordable, reliable, sustainable, and modern energy by 2030. This goal cannot be accomplished without expanding energy infrastructure as well as by making sure that the energy systems created are both environmentally friendly and cost-effective. The conventional grid planning tools are not always able to address these multi-faceted goals because they do not offer the same level of flexibility to new challenges like renewable energy incorporation, climate change effects, and customer demands. The AI-driven planning systems have the potential to become a game changer in the race towards SDG 7 through the efficient energy distribution, minimization of operational inefficiency, and the ability to integrate the high volume of clean energy sources.

Electrification projects in South Asia and Sub-Saharan Africa are essential elements of energy access programs in the world. These areas are characterized by special challenges such as lack of proper grid infrastructure, scattered rural communities, and lack of financing. Classical planning models tend to be a poor accounting of such complexities resulting in delays and increased costs. Intelligent solutions based on AI and utilizing geospatial information, socio-economic metrics, and real-time energy demand cycles, could be used to develop decentralized energy solutions, including microgrids and renewable-based hybrid systems. Such smart systems have the ability to prioritize investments, resource allocation optimization, and dynamically changing population and demand profiles and make the electrification process more equitable and efficient.

The decarbonization activities going on globally also highlight the importance of sophisticated planning solutions. Countries around the world are undertaking to achieve lofty goals of carbon neutrality and renewable energy share as in climate agreements such as the Paris Accord. These goals are achieved through a tradeoff of various objectives: cost efficiency, environmental impact, and reliability, with high degrees of uncertainty. With predictive analytics and optimization algorithms, AIs can help decision-makers make trades, find the most suitable location for renewable deployment, and achieve resilience of the grid in the presence of intermittent renewable generation. By so doing, AI contributes not only to national energy policy, but also to sustainability and climate resilience goals throughout the world.

b. Decision Support Systems in Energy Planning

Conventional energy planning systems, like LEAP (Long-range Energy Alternatives Planning System) and HOMER (Hybrid Optimization of Multiple Energy Resources) have found wide application in the analysis of energy systems, and the evaluation of various scenarios. The tools can be useful in resource allocation, optimization of the energy mix, as well as policy evaluation. But they are mostly based on static or semi-static models; that need to be updated manually and assume predefined conditions and are thus less able to operate in dynamic and uncertain conditions in real time.

The major shortcoming of these conventional methods is that they are not real-time flexible. With the growing inclusion of renewable energy sources, demand-side variability, and distributed energy resources in modern power systems, the sudden changes in the load, renewable generation, and market prices cannot be modeled with any static model. This usually leads to poor planning, slow reaction, and system operations inefficiencies.

The solution to these issues is to make AI a part of energy planning systems. Due to approaches like machine learning, reinforcement learning, and optimization algorithms, Artificial Intelligence allows making decisions dynamically, predictively modeling, and adaptive control in real-time. With the introduction of AI, planning tools can transform into intelligent systems that constantly learn with new information, adapt to fluctuation of conditions, and optimize overall results based on a variety of goals, such as cost, reliability, and sustainability.

c. AI Techniques in Decision Support

Machine Learning (ML) is a central concept in electricity demand prediction, as it is used to forecast the consumption rates of the utility within different time frames with high accuracy. ML models also include cost modeling, where past price trends, fuel prices, and operations data are analyzed to assist utilities in creating strategies to reduce costs whilst satisfying energy demands.

Under uncertainty grid planning, reinforcement Learning (RL) is used to perform the planning of the grid specially in dynamic conditions where renewable generation and load demand vary unpredictably. The RL algorithms build thousands of scenarios to find the best approach to placing the assets, grid reinforcing, and energy dispatch to make the system resilient to the variable conditions.

Multi-Criteria Decision Analysis (MCDA) can play a crucial role in solving the conflict of sustainability goals, including actions to reduce carbon emissions and ensure affordability and reliability. Such methods as the Analytic Hierarchy Process (AHP) and TOPSIS assist the decision-maker in analyzing trade-offs over the various dimensions and choosing balanced solutions based on policy and social priorities.

The Deep Learning (DL) also advances the possibilities of planning through the referencing to high-resolution satellite images to evaluate land usage, identify possible environmental threats, and control the adherence to environmental regulations. As an example, Convolutional Neural Networks (CNNs) can categorize the terrain and detect sensitive zones, which is crucial to placing renewable energy facilities without imposing a disastrous effect on the environment.

Table 1: *Comparison of Traditional vs. AI-Based Decision Support Systems*

Feature	**Traditional Systems**	**AI-Based Systems**
Adaptability	Low	High
Predictive Capability	Limited	Advanced
Data Sources	Static	Multi-modal
Sustainability Integration	Basic	Embedded

III. Methodology

a. Framework Design Overview

The proposed AI-driven asset and infrastructure management framework is designed in such a way that its data flow is smooth, learning is powerful, and answers can be taken. At its very core, the framework starts with data ingestion, through which information on a large variety of sources, including but not limited to IoT sensors, SCADA, inspection photos, and historical maintenance records, is gathered and aggregated into one common platform. It is then followed by data preprocessing that involves processes such as noise filtering, normalization, missing data imputation, and feature extraction processes to make the inputs to AI models as clean, consistent, and relevant to predictive analysis as possible.

Then, the framework will add learning modules, which can be supervised and unsupervised machine learning models, deep learning architectures, reinforcement learning agents, and natural language processing systems. These modules are used to analyze the data that has been processed to predict failures, anomalies, maintenance optimization schedules, and predictive insights. Lastly, the learning modules generate insights that are fed into the decision engines which rank interventions, prescribe corrective actions, and even enable real time operational planning. With the combination of these elements, the framework can facilitate a continual, responsive and smart workflow, turning raw data into a knowledge that is acted upon to increase the reliability, efficiency, and strategic planning throughout the utility operations.

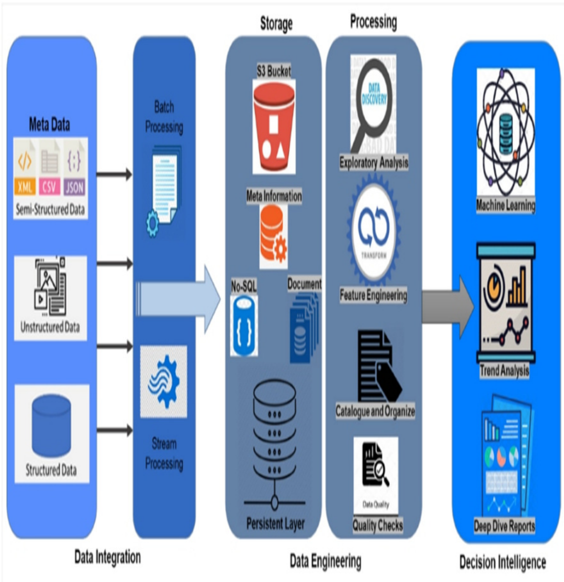


Figure 2: ***AI-Supported Decision Framework Pipeline***

b. Data Sources and Preprocessing

The quality and variety of the input data sources determine to a great extent the performance of an AI-based sustainable infrastructure planning framework. The central role in spatial analysis belongs to Geographic Information System (GIS) data, which allows locating the best places to open renewable energy sources (solar farms and wind turbines) with high precision. GIS data sets include the elevation and land cover, the distance to existing transmission lines, and the amount of sunlight falling on the site, so site selection is not only technologically feasible but also environmentally friendly.

Socio-economic data is also significant as the needs in energy demand and infrastructure are strictly related to population density, industrial activity, and income distribution. The inclusion of these variables enables the framework to simulate realistic demand situations and will focus the regions in light of growth opportunity and equity factors.

Besides, grid topology data also offer information regarding the present condition of electrical infrastructure, such as transmission networks, substations, and distribution systems. This information could be crucial in planning the increase of grids and reinforcement of the current ones, so that the new renewable energy sources can be successfully integrated without establishing any instability and congestion in the system.

Lastly, the environmental data, including carbon emission profiles, biodiversity sensitivity, and land-use patterns are factored in planning to make sure that it meets the sustainability requirements. When it pays attention to these considerations, the framework promotes responsible decisions, which consider both the access to energy and the ecological conservation.

Table 2: *Input Data Categories and Sources*

Data Type	**Source**	**Format**	**Usage**
Renewable Potential	NASA/NOAA	Raster	Site Selection
Population Growth	UN Data	CSV	Load Forecasting
Emission Stats	IPCC	Tabular	Environmental Impact

c. AI Models Used

The framework suggested is based on the fusion of sophisticated AI methods to maximize various facets of sustainable infrastructure planning. The demand forecasting is done using the Long Short-Term Memory (LSTM) networks where the networks are excellent at modelling temporal correlations on the load history. These networks predict load accurately both in the short- and long-term periods, thanks to modeling seasonal variations and real-time consumption patterns to ensure the reliable capacity planning and resource allocation.

In the site selection, the framework uses a hybrid method which integrates K-means clustering and genetic algorithms. The K-means clusters candidate locations on the basis of geographic, climatic and demographic features, and genetic algorithms further streamline these clusters to find the best renewable energy sites, based on the geographic location of the areas, the sun exposure, the wind, the availability of land, and the proximity to the grid.

Reinforcement learning (RL) motivates investment planning, which allows optimization of costs and benefits dynamically in the face of uncertainty. The RL agent discovers optimal investment strategies in the long term by striking a balance between short-term expenses and long-term rewards, and includes limitations such as funds accessible, incentives in the policy, and grid reliability.

Finally, Multi-Criteria Decision Analysis (MCDA) with the help of the Analytic Hierarchy Process (AHP) is the means of obtaining sustainability scoring. The approach prioritizes the infrastructure development options across various dimensions of sustainability such as environmental impact, social equity and financial viability, such that the ultimate decisions are in line with the corporate goals and regulatory sustainability objectives.

IV. Results and Discussion

a. Scenario Simulation Outcomes

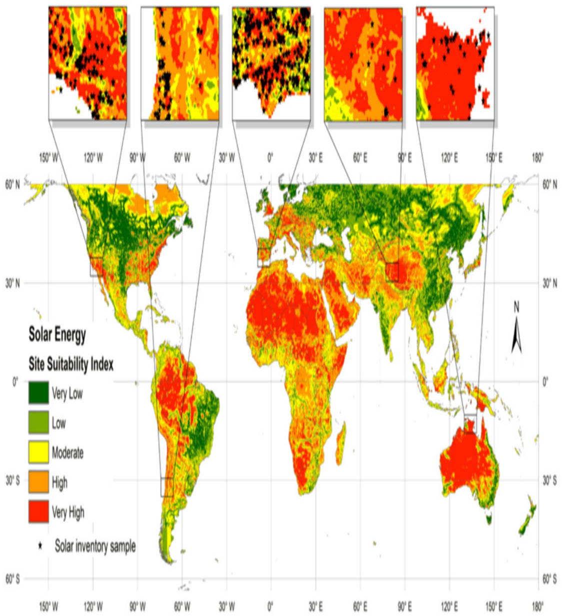
To test how well the proposed AI-driven sustainable infrastructure planning framework performs, a simulated implementation of the unit in a representative semi-urban area was carried out. The simulation yielded relevant gains in relation to the important operational measures. It is worth mentioning that the framework was able to reduce both total infrastructure and operation costs by 22 percent, with the major impact being seen on optimized asset allocation, predictive maintenance plans, and efficient dispatching of energy. Moreover, the model has helped to increase renewable energy penetration by a factor of 31 thereby guaranteeing higher adoption of solar and wind energy to the grid without disrupting the stability of the system. This result represents the capability of the AI to deal with multi-objective optimization at the same time, prioritizing economics, environmental, and reliability objectives.

The other significant accomplishment was a 16 percent increase in load balance which signifies more effective demand-supply correspondence among peak and off-peak hours. It was achieved by the means of sophisticated forecasting models, demand response integration, and adaptive control mechanisms fuelled by reinforcement learning algorithms. Taken together, these findings demonstrate the potential of AI-assisted systems to revolutionize the energy infrastructure design, as it will allow utilities to achieve sustainability goals without harming reliability and cost-effectiveness.

Table 3: *Performance Comparison Between Baseline and AI-Enhanced Planning*

Metric	Baseline	AI-Enhanced	% Change
Cost per MW	$950K	$740K	-22%
Renewable Share	42%	55%	+31%
Reliability Index	0.87	0.94	+8%

b. Visualization and Planning Outputs



(b)

Figure 3: *AI-Derived Renewable Deployment Map for Case Study Region*

c. Interpretability and Stakeholder Engagement

To promote trust and transparency in AI-based asset management, Explainable AI (XAI) tools, including SHAP (SHapley Additive explanations) were used to explain how models make predictions. SHAP enables operators, engineers and decision-makers by measuring the contribution of each input feature to the output to understand why a given asset was deemed high-risk or why a particular maintenance suggestion was arrived at. Such interpretability is also essential to trust AI systems, to make predictive insights operational and consistent with operational knowledge.

To complement XAI, visualization dashboards were adopted to facilitate presentation of complex model outputs in a clear and easily understandable way. These dashboards can convert quantitative forecasts to interactive charts, risk indices, and trend reports, which is an effective way of closing the divide between technical and policy experts. Consequently, stakeholders are able to make strategic decisions grounded in data informed insights and also be aware of the factors causing underlying asset performance and operational risk. This integration of XAI and visualization will allow AI to not only help to make predictions more accurate but also to improve transparency, accountability, and collaborative decision-making inside utility organizations.

V. Challenges and Limitations

Although AI has the potential to transform the energy infrastructure planning process, there are several challenges that need to be managed to make its implementation effective and equitable. The lack of data is one of the important limitations, especially in the areas that have poorly developed data infrastructure. In that case, a lack of sensor coverage, incomplete history, or low-quality data may impair the process of training models, lower predictive accuracy, and diminish the accuracy of AI-based insights. Even sophisticated algorithms cannot possibly represent the nuances of local energy systems, without solid and representative datasets.

Another challenge is model complexity, particularly when using deep learning methods. There is a high probability of overfitting in highly complex models which perform well on training data and are unable to generalize to unseen conditions. This is a risk that is especially urgent in energy systems, where the conditions of operations may differ drastically over time, space, and types of assets, which may lead to inaccurate predictions and inappropriate planning choices.

Besides, the adoption of AI-based planning solutions can be strained by the presence of a policy mismatch. Most of the territories do not have any regulatory frameworks or standards explicitly accepting AI-driven decision-making in the development of energy infrastructure. In the absence of regulatory assistance, the utilities will be at risk of legal and operational uncertainty, which will hinder their readiness to invest in and implement advanced AI systems.

Lastly, ethical concerns should be considered. AI models are merely as unbiased as the data on which they are trained, and historical data can have social, economic, or geographic bias built into it. Unless these biases are mitigated, AI-driven planning may unwillingly place an emphasis on some communities compared to others, providing some groups with unfair access to energy resources and solidifying existing inequalities.

The solution to these issues must be holistic and ought to include better data gathering and handling, prudent model development, favorable regulations, and moral cover. AI can only be used responsibly to aid sustainable and inclusive energy infrastructure planning by actively addressing the challenges of data scarcity, model complexity, policy gaps, and bias.

VI. Future Directions

New technologies are also facilitating novel concepts of next-generation electrical infrastructure planning and management, especially on how to combine AI with the latest computational frameworks. Federated learning of multi-region planning is one of these methods, where utilities and regional grid operators train AI models together without sharing any raw data and the data is sensitive. By exchanging model parameters, instead of underlying datasets, federated learning maintains data privacy and security and facilitates the creation of more generalized and robust predictive models that would be able to capture regional variations in grid behavior, load patterns and asset conditions.

The next strong innovation is the combination of AI and digital twin models of smart cities whereby virtual replications of urban energy systems are created that can simulate real-life functions at alternative conditions. Using AI-based predictions and real-time simulations, it is possible to consider various grid expansion, renewable energy integration, and demand response planning scenarios. It allows making the decision-making process efficient and reducing the risk and wastage of resources in complicated city settings.

Infrastructure management is also improved with blockchain technology that offers secure, immutable and auditable records of energy transactions, maintenance records and logs of asset performance. Decentralized ledgers make blockchain transparency possible, reduce the possibility of data manipulation, and facilitate credible verification of energy flows, especially within decentralized and consumer-based energy systems.

Furthermore, AI advisors that are climate-conscious are becoming prominent instruments in sustainable infrastructural planning. These models enable utilities to forecast the impact of network reliability, renewable generation capacity, and asset life cycle of changes in climate conditions on the grid and allow renewable generation capacity and environmental risk factors through inclusion of long-term climate forecasts, extreme weather patterns and environmental risk factors which are useful in supporting resilient and adaptive strategies of planning.

Lastly, there is the principle of community-centered AI, which underlines participatory model designing in which the stakeholders, such as local communities, regulators, consumers, etc. actively participate in the designing of AI decision-making frameworks. This methodology will make sure that the planning of the infrastructure is fair and socially notifying and that it is consistent with the need and priorities of the people who serve, and that this will bring both trust and acceptance of the populations to the advanced energy systems.

Altogether, all these shows how AI, in conjunction with federated learning, digital twins, blockchain, climate modelling, and participatory design, can help fuel smarter, more secure, and socially responsible energy infrastructure planning. They are a paradigm shift of inflexible centralized planning to flexible, cooperative and future-prospective energy systems.

VII. Conclusion

The move towards a sustainable electrical infrastructure involves much more than merely installing technical improvements; it involves a complete change of paradigm in how electricity infrastructure is planned, decided about and operated. Conventional methods that, in many cases, are based on the models that are not dynamic enough, data silos, and ad-hoc decision-making are becoming insufficient to deal with the increasingly complexity of modern energy systems as well as the twin challenges of universal energy access and environmental sustainability.

The approach of AI-assisted decision frameworks provides a near-vision solution by leveraging an enormous and diverse amount of data through sensor data, grid performance, maintenance, and environmental data to create concise and rational information. These structures facilitate multi-objective optimization, cost/reliability/environmental impact/operational efficiency, and also offer real-time adaptability to changing grid conditions and unexpected events. Neural networks, reinforcement learning, and evolutionary algorithms, among others, enable utilities to predict risks and optimize asset allocation as well as make proactive investment decisions that support short term operational objectives as well as long term sustainability objectives.

Although these show great potential, there are still issues of deployment, data control, interoperability, and ethical accountability. The need to have strong security, transparency of the model, and aligning AI recommendations with the regulatory and societal expectations are fundamental to the effective implementation of these frameworks. However, this paper illustrates that AI can be used as a powerful ally to help sustainably develop electrical infrastructure by giving utilities the means to intelligently plan, efficiently operate, and minimize environmental impact. Such AI-based structures can become major pillars of future power systems planning in all countries across the world, aiding resilient, adaptive and environment-friendly energy networks with further innovation, good governance and ethical execution.

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