An Overview of Artificial Intelligence for Smart Grid Optimization

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Abstract

This paper deals with a literature overview of the smart grid, specifically in the context of artificial intelligence (AI) technology. The paper is organized as follows. We begin with an overview of our papers through an explanation of our paper selection criteria before delving into five key areas of research: optimizing production, storage methods, distribution/scheduling, demand pricing, system maintenance, system ML attacks. For each theme, we **summarize the relevant papers within each section** before looking towards the future of the field. We then turn towards a discussion of the broader ethical implications of AI for energy waste and end with some concluding remarks.

Introduction

Smart grids are a type of energy grid that has been transformed through the use of digital tools. In accordance with the US Energy Information Administration, the typical electric grid is a complex network of individual facilities, machinery, and software components that transfer generated energy to the home. Upon generation of electricity, a transformer increases the voltage for transmission. Large towers called transmission lines carry the voltage to neighborhood-based transformers, which lower the voltage so it is safe for the end users to properly handle and consume. These neighborhood-based transformers are more formally called substations. Once the voltage is lowered, it is carried across smaller towers called distribution lines closer to the end location. These smaller towers have on their physical parts a series of small transformers that can adjust the voltage as necessary right before it meets the end consumer. In its entirety, the phases are summarized as follows: generation, transmission, substation, distribution, and end user.

Many parts of this process incur some software automation in a smart grid. Starting from the generation phase, organizations often employ software control and data acquisition technology (SCADA) so as to manage all equipment. During the substation phase, advancements have been made through the substation automation system (SAS), which incorporates a series of hardware and software components to monitor voltage switches. As an example, one piece of hardware called a remote terminal unit (RTU) may collect data and send it to a SCADA software control center to help automate the substation's next best action. During the distribution-line phase, smart load control switches and capacitor control systems are installed to ensure there is no overload or unnecessary distribution of energy to any of its endpoints. Once the energy reaches the end user, systems like smart meters are installed to measure the power consumption. This provides useful feedback to both the end user and the systems mentioned previously for regular updating. It is not just the individual steps that are altered by technology, however. Overarching to the energy grid is the need for communication across systems. GPS and satellite data have been useful in monitoring the grid geographically and sending data among all such systems.

Significance in Context of AI for Social Good

The automation of smart grids through artificial intelligence can substantially reduce overall waste throughout the energy production-to-home pipeline. Optimizing production can cut back on **environmental waste**. In accordance with Smart Energy Collaborative, statistics demonstrate how the introduction of a fully-optimized smart grid can cut air pollution from the electric utility sector as much as 30% percent by 2030. Maximizing storage plans of volatile energy production for long-term use can reduce **waste in the production** stage. After storage, optimally distributing the technology in relation to consumer demand and supplier transport can cut down on **market costs**. Throughout this process, optimally maintaining a system not only reduces **labor waste**, but may even create more jobs to help build the systems that automate this process. Statistics predict that nearly 280,000 new jobs can be created just from the creation and installment of Smart Grid technology (KEMA 2019). Finally, with the digitization of the system comes the threat of software attacks for personal gain. The usage of artificial intelligence to detect such situations can reduce **computation waste** in correcting successful attacks and also the computational power that was invested in steps prior to the attack.

Paper Selection

We went through two stages of paper selection to ultimately choose the 30 main papers that will be subsequently analyzed in this literature review. The process for paper selection is described below.

Stage 1 In the first stage, we started with an extensive search on Google Scholar, using the following keywords: ”energy grid,” ”energy waste,” and ”artificial intelligence.” We focused on the initial 60 papers that emerged from this search, prioritizing those with a minimum of ten citations and published between 2020-2024. This selection was systematically reviewed and categorized into six distinct themes relevant to waste reduction in the smart grid, namely: environmental waste, production waste, emission waste, market waste, labor waste, and computational waste.

Stage 2 From each of our six waste themes, we chose five papers based on a set of criteria. Each paper chosen was to be published between 2020-2024 and have 10+ citations. We analyzed Harvard’s Web of Science directory and included keywords to narrow down our search. We had for each theme two separate types of keywords. First, each search incorporated two general keywords, “energy grid” and “artificial intelligence.” General keywords were only to be pruned or slightly edited (for example, “energy” or “grid” instead of “energy grid”) if the resulting search did not produce enough papers. Second, each search included one to two special keywords related to the theme. In the end, the following search terms (both general and special) are shown below:

- Optimizing Production
  artificial intelligence, energy grid, renewable energy
- Storage Methods
  artificial intelligence, energy grid, storage
- Suppliers: Distribution/Scheduling
  artificial intelligence, energy, distribution
- Consumers: Demand Pricing
  artificial intelligence, energy grid, pricing, market waste
- System Maintenance
  artificial intelligence, grid, maintenance
- System ML Attacks
  artificial intelligence, energy grid, cyber attacks

All papers are project-specific and either came directly from the search result or came from a survey paper discovered during the search query, where that paper still adheres to the aforementioned criteria (citations, recent year of publish). The full list of 30 papers can be found in Figure 1, with links provided in the References section.

Number	Sections and Keywords Used	Waste	Year (2020-2024)	Citations	Specific Project from Query OR Specific Project from a an Overview	Title
1	1: Optimizing Production artificial intelligence energy grid renewable energy	environmental	2023	5	Specific Project	AI-enabled metaheuristic optimization for predictive management of renewable energy production in smart grids
			2022	80	Overview	Data-driven probabilistic machine learning in sustainable smart energy/ smart energy systems
2			2021	11	Specific Project	Novel AI Based Energy Management System for Smart Grid With RES Integration
3			2023	1	Specific Project	AI-based forecasting for optimised solar energy management and smart grid efficiency
4			2022	15	Specific Project	A Smart Microgrid System with Artificial Intelligence for Power-Sharing and Power Quality Improvement
5			2023	6	Specfic Project	An Artificial-Intelligence-Based Renewable Energy Prediction Program for Demand-Side Management in Smart Grids
	2: Storage Methods artificial intelligence energy grid storage	production	2020	130	Overview	Battery Digital Twins: Perspectives on the fusion of models, data and artificial intelligence for smart battery management systems
			2021	44	Overview	Artificial Intelligence to support the integration of variable renewable energy sources to the power system
1			2020	319	Specific Project	Closed-loop optimization of fast-charging protocols for batteries with ML
2			2020	277	Specific Project	Predicting the state of charge and health of batteries using data-driven machine learning
3			2022	29	Specific Project	Optimal Control of an Energy-Storage System in a Microgrid for Reducing Wind-Power Fluctuations
4			2020	21	Specific Project	AI-Aided MPC for Grid-Tied Wind-Hydrogen-Fuel Cell System
5			2020	75	Specific Project	Optimization Strategy Based on Deep RL for Home Energy Management
6			2021	80	Specific Project	Deep reinforcement learning for energy management in a microgrid with flexible demand
1	2: Suppliers: Distribution/Scheduling artificial intelligence energy distribution	emission	2023	17	Specific project	Short-term electricity load forecasting—A systematic approach from system level to secondary substations
2			2021	38	Specific project	Individualized Short-Term Electric Load Forecasting With Deep Neural Network Based Transfer Learning and Meta Learning
3			2021	164	Specific project	Intelligent multi-zone residential HVAC control strategy based on deep reinforcement learning
4			2022	22	Specific project	An occupant-centric control framework for balancing comfort, energy use and hygiene in hot water systems: A model-free reinforcement learning approach
5			2021	35	Specific project	Energy-Net: A Deep Learning Approach for Smart Energy Management in IoT-Based Smart Cities
1	4: Consumers: Demand/Pricing artificial intelligence energy grid pricing market waste	economic / market	2021	20	Specific Project	Data-driven Modeling of Energy Demand Response Behavior Based on Large-Scale Residential Trial
2			2022	22	Specific Project	Machine learning approach to uncovering residential energy consumption patterns based on socioeconomic and smart meter data
3			2022	16	Specific Project	Forecasting energy prices using a novel hybrid model with variational mode decomposition
4			2020	10	Specific Project	Modeling of frequency containment reserve prices with econometrics and artificial intelligence
5			2021	70	Specific Project	Multi-Objective Optimization for Smart Integrated Energy System Considering Demand Responses and Dynamic Prices
6			2021	51	Specific Project	Optimal dispatching strategy and real-time pricing for multi-regional integrated energy systems based on demand response
			2020	214	Overview	AI and ML Approach to Energy Demand-Side Response
1	5: System Maintenance artificial intelligence grid maintenance	labor-resource	2020	21	Specific Project	Intelligent maintenance frameworks of large-scale grid using genetic algorithm and K-Mediods clustering methods
			2021	32	Overview	The Current State of the Art in Research on Predictive Maintenance in Smart Grid Distribution Network: Fault’s Types, Causes, and Prediction Methods—A
3			2021	5	Specific Project	Research on Integrated Energy System of Power Grid Based on Artificial Intelligence Algorithm of Machine Learning
4			2021	59	Specific Project	Scientometric review of artificial intelligence for operations & maintenance of wind turbines: The past, present and future
5			2020	72	Specific Project	Integration of Novel Sensors and Machine Learning for Predictive Maintenance in Medium Voltage Switchgear to Enable the Energy and Mobility Revolutio
1	6: System ML Attacks artificial intelligence energy grid cyber attacks	computation	2021	12	Specific Project	CCPT Attack: Physical layer attack identification and localization in cyber-physical grid: An ensemble deep learning based approach
2			2020	12	Specific Project	Enhance BDD: Ensemble CorrDet with adaptive statistics for bad data detection
3			2022	54	Specific Project	False Data Injecttion (FDI) Attack: Detection of False Data Injection Attacks in Smart Grid: A Secure Federated Deep Learning Approach
4			2022	10	Specific Project	EDOS Attack: Artificial Intelligence Algorithm-Based Economic Denial of Sustainability Attack Detection Systems: Cloud Computing Environments
			2022	16	Overview	Cyber Threats to Smart Grids: Review, Taxonomy, Potential Solutions, and Future Directions
5			2020	14	Specific Project from Overview	DoS Attack: DoS attack detection model of smart grid based on machine learning method

Figure 1: An overview of the criteria-driven 30 papers selected for the literature review

Theme 1: Optimizing Production

In assessing the energy production process of smart grids with the overarching objective of minimizing waste, we focused on methods that integrate renewable energy systems into the grid—often referred to as hybrid energy systems. This approach is pivotal in reducing carbon emissions and aligning with global shifts towards sustainable energy. The push for renewable energy is increasingly urgent, underscored by global initiatives advocating for a sustainable transition. In the United States, numerous states (e.g., New Mexico, Washington, Nevada, and Colorado) have set ambitious goals, updating their renewable portfolio standards to mandate a 100% renewable energy target. Concurrently, more than ten publicly listed utility companies have declared 100% decarbonization targets [1], and a large portion of these utilities have established goals to lower carbon emissions to far under 80% of 2005 levels by 2050. However, the transition faces significant challenges, primarily due to the intermittent nature of renewable energy sources, specifically solar and wind power, whose outputs are highly weather-dependent. Integrating these sources as-is could compromise the grid’s reliability, heightening the risk of blackouts. Therefore, artificial intelligence is being leveraged to enhance the efficiency of the energy production phase, employing predictive models to anticipate the irregular production patterns of these renewable sources.

Overview of Existing Work

Renewable energy sources have significantly benefited from the recent increase in powerful AI models. The integration of sensor technologies has provided a wealth of data on wind and solar power production. Using this data, AI-driven strategies have been instrumental in reducing production costs, improving forecast accuracy, and maximizing portfolio returns, thereby bolstering the competitiveness of renewable energy sources. Considerable research efforts are focused on forecasting solar and wind energy, with deep learning models, particularly those based on Long Short-Term Memory (LSTM) techniques, gaining prominence. Given the intricate link between renewable energy production, its distribution, and the overarching energy management, our discussion will center on delineating the current trends in the integration of renewable energy within smart grids.

Hybrid Renewable Energy Systems Optimization Hybrid Renewable Energy Systems (HRES) integrate multiple renewable energy sources, such as solar, wind, and hydro, to provide a reliable, efficient, and sustainable power supply for smart grids. These systems enhance reliability by ensuring continuous energy production, even when individual sources might be inconsistent. They improve efficiency by optimizing the mix of renewable sources based on availability and demand. Moreover, the integration of HRES into smart grids presents a viable pathway toward sustainable energy systems, as such the subject of their optimization stands as a pivotal research focus.

Some examples of work in the area of HRES:

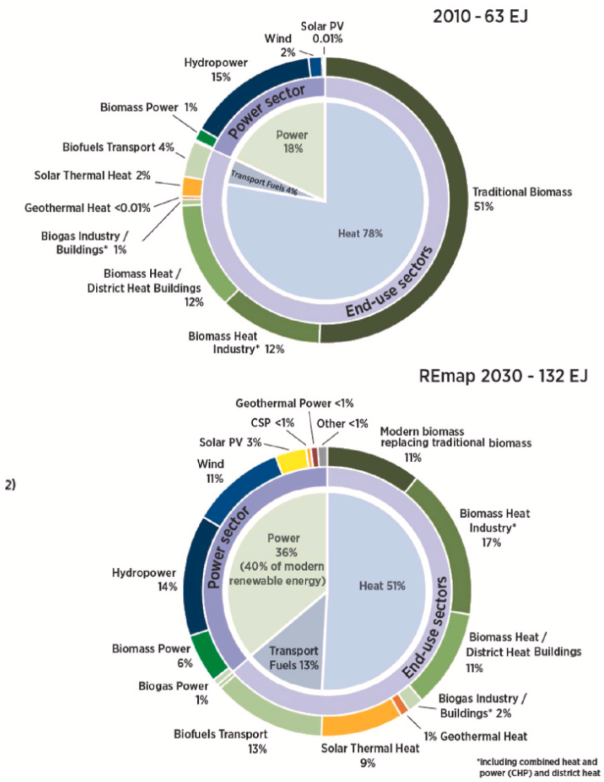

Figure 2: An overview of global renewable energy usage in 2010 and the renewable energy map 2030 projections, divided into technologies and sectors. *Renewable and Sustainable Energy Reviews 160 (2022) 112128*

- Tazay et al., (2020) [2] devised an autonomous HRES for a university in Saudi Arabia aimed at creating a stable energy supply by integrating solar and wind energy with battery storage. The system's effectiveness and economic viability were assessed via investment costs, operational expenses, and energy savings. The study applied advanced monitoring and control techniques to optimize the HRES's performance. It also examined challenges such as the unpredictability of renewable sources, battery constraints, and maintenance needs. The research highlighted the HRES's potential to significantly cut the university's carbon emissions while offering considerable economic gains.
- Abidi et al. (2019) [3] proposed a HRES to enhance power distribution and source resizing within an island microgrid for a petroleum platform in Tunisia. They recommended the integration of solar and wind power to reduce dependency on fossil fuels and improve sustainability. Their approach includes a more efficient energy distribution method using a hierarchical control system, ensuring stability and reliability across different load levels. Furthermore, they proposed an optimization model aimed at improving microgrid efficiency by determining the optimal sizing for energy sources.
- Said et al. (2018) [4] recommended a HRES with storage solutions to address intermittency and enhance grid integration. The paper discusses the advantages and challenges of these systems, shedding light on future research directions. It also emphasizes the accomplishments of Internet of Things (IoT)-enabled smart grid systems, highlighting strategies such as real-time energy monitoring and control, effective incorporation of renewables into the grid, and implementation of Demand Response (DR) programs that leverage AI.

Existing methods often blend various AI techniques or merge AI with optimization algorithms to manage demand response, load balancing, and renewable energy forecasting in HRES [5]. Notably, a variant of the Hybrid Long Short-Term Memory-Reinforcement Learning (LSTM-RL) model [6] has outperformed existing algorithms in forecasting and controlling renewable energy sources within smart grid contexts. We will examine this method in detail below.

An LSTM neural network is a powerful tool for analyzing sequential data, in our context, time series data for energy consumption patterns. Our review of the existing literature indicates that it's a prevalent AI technique in this domain as the method enables us to identify trends in historical energy usage and make accurate forecasts of future energy demands. LSTM on its own, however, falls short in devising the optimal demand response strategies for maximizing efficiency. This shortfall is addressed by integrating reinforcement learning (RL) algorithms. RL employs a trial-and-error approach to learn the formulation of optimal decisions, guided by rewards and penalties. The synergy of LSTM and RL harnesses the strengths of both methodologies: LSTM's proficiency in predicting energy demand patterns and RL's capability to fine-tune demand responses in alignment with the predictions. The particular model proposed by Sankarananth et al. (2023) [6] was motivated by the areas and research projects below:

- **Demand Response**: Hasan et al. (2019) [7] introduced the novel approach of combining LSTM and RL to forecast energy demand patterns and pinpoint demand response opportunities. This method analyzed various factors, including energy usage trends and weather conditions, to predict periods of high and low energy demand. Optimization algorithms can then be used to devise demand response strategies.
- **Load Balancing**: Ahmad et al. (2022) [8] demonstrated how RL could enhance load balancing in hybrid renewable energy systems. This AI technique analyzes both patterns of energy production and consumption, formulating strategies to evenly distribute energy loads across various sources. It employs metaheuristic optimization algorithms to continuously refine these strategies, adapting to evolving patterns of energy supply and demand.
- **Renewable Energy Forecasting**: Zhang et al. (2022) [9] explored the use of neural networks and decision trees for predicting renewable energy generation. Subsequently, metaheuristic optimization algorithms are applied to devise management strategies for renewable energy, optimizing the use of energy storage systems to harness excess energy during peak production times and compen-

sate when production drops to ensure balanced and efficient energy resource utilization.

Sankarananth et al. (2023) [6]'s paper introduces a unique method that combines three key techniques—demand response, load balancing, and energy usage forecasting—to enhance the optimization of HRES. Its innovation lies in demonstrating the benefits of integrating these elements, which have typically been examined in isolation in prior research [6]. The model considers the features: time, solar production, wind production, traditional production, energy demand, and energy storage level.

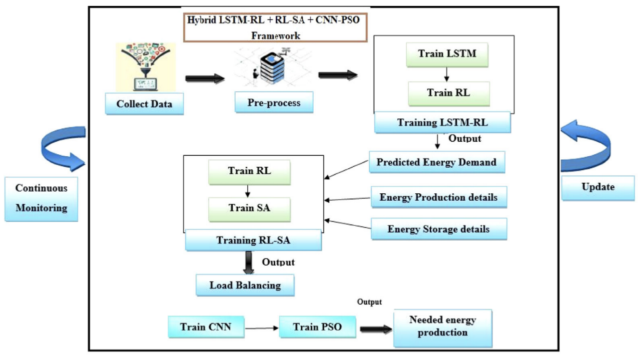

Figure 3: Hybrid LSTM-RL+RL-SA+CNN-PSO framework for smart grids. [6]

Model framework breakdown:

- Step 1: Pre-processing data on historical energy consumption, weather patterns, and other relevant variables.
- Step 2: LSTM-RL technique is used to predict energy demand patterns, RL-SA to develop best load balancing strategies, and CNN-PSO to forecast renewable energy production.
- Step 3: Actively introducing the optimal strategy into the energy system while monitoring its performance to ensure efficiency.

The model produced precision, recall, and accuracy scores of 0.92, 0.93, and 0.92 respectively, out-performing existing algorithms in forecasting energy production and demand. A summary of precision, recall and accuracy comparisons of the proposed model with existing algorithms is provided in Figure 3.

Impact Assessment

The integration of AI in optimizing renewable energy production significantly contributes to reducing carbon emissions. Reviewed papers demonstrated various AI interventions, like AI-enabled grid optimization [6], AI-based energy management systems [10], and predictive models for renewable energy forecasting [11], which collectively enhance the efficiency and reliability of renewable energy sources. By optimizing the balance between energy supply from renewable sources and demand, these AI systems reduce reliance on fossil fuels, thereby directly decreasing carbon emissions.

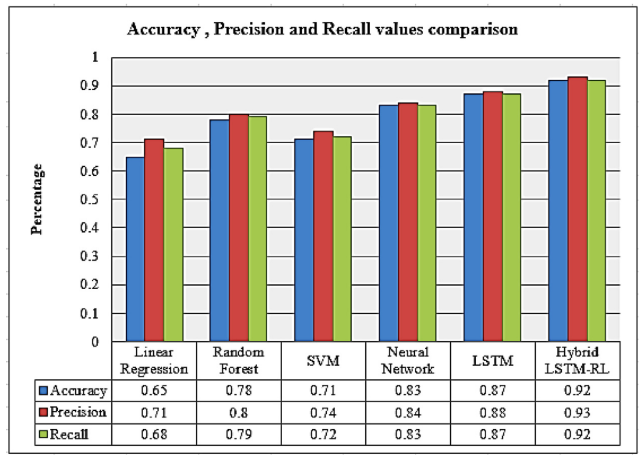

Figure 4: Comparison of the proposed hybrid LSTM-RL with existing techniques. [6]

The impact of AI interventions on reducing carbon emissions is typically measured via simulations that model the energy grid's operation with and without AI optimization. The metrics often include the amount of reduced carbon emissions, improvements in renewable energy penetration, and the efficiency of energy storage and distribution systems.

Several challenges exist in accurately assessing the impacts of AI interventions:

- **Data Availability and Quality**: Reliable historical and real-time data are critical for accurate modeling and forecasting energy systems' performance. Inconsistencies or gaps in data can lead to inaccurate assessments of carbon emission reductions.
- **Model Complexity**: Simulating the energy grid's dynamics, especially with the integration of intermittent renewable energy sources, is complex. Accurately reflecting the grid's behavior under various conditions to assess AI's impact is challenging considering the AI algorithms themselves are usually computationally demanding.
- **Scalability**: Models proven effective in simulations (commonly in the MATLAB-Simulink Environment [10]) or in microgrids [12] might not scale efficiently to larger grids due to increased variables, unpredictable operational challenges, or different grid configurations.

Overcoming these obstacles will require continuous efforts towards HRES research, however it will prove worth while as this technology has a tremendous potential to provide electricity access to the 1.2 billion deserving people [10], who do not have access to constant electricity.

Future of Field

The problems in integrating renewable energy into smart grids are far from being solved, offering plenty of room for innovation. While considerable progress has been made in enhancing renewable energy usage using AI, these advancements are mostly confined to smaller-scale applications like microgrids. The complexity of larger grid systems, coupled with the intermittent nature of renewable energy sources, presents ongoing challenges that require new solutions.

Our reviewed papers highlight several common hurdles in integrating renewable energy into smart grids, emphasizing issues like scalability [12], intermittency [6], and market constraints [13]. Scalability poses a significant challenge as transitioning from microgrid-level applications to broader grid systems requires new solutions to manage the increased computational demands and intricacies of larger, interconnected systems while preserving both model accuracy and efficiency. The intermittency of renewable energy sources further complicates this, as the variability inherent in sources like wind and solar requires robust models that can adapt to fluctuating conditions, needing data beyond historical patterns for improved performance. Moreover, market constraints are pivotal, with the regulatory landscape and evolving market structures presenting hurdles that must be navigated carefully to ensure the full potential of AI in this sector is realized. This requires technological advancements to be in sync with policy developments to encourage the broad adoption of these AI techniques.

To address these challenges, future advancements will likely focus on improving the interoperability between different renewable systems and the existing grid infrastructure. Innovations in grid architecture, such as the development of more modular grid designs, will facilitate the efficient incorporation of renewable energy sources at various scales. Moreover, we expect future research to concentrate on incorporating more data sources while reducing the need for quality data.

Theme 2: Optimizing Storage

Critical to the smart grid movement and the transition away from fossil fuels are robust storage systems and strategies. Unlike conventional power generators, the power production of wind turbines and solar panels is non-controllable and highly intermittent. The ultimate purpose of grid-scale and residential batteries is to store excess energy during times of peak production or limited consumption and discharge during times of limited production and peak consumption. Storage can therefore serve to flatten the demand curve, facilitating the transition towards non-controllable power generators. The success of storage systems in achieving this ambitious goal, though, is highly dependent on the quality of the batteries themselves and on the way in which they are integrated into the grid at large. If the previous section focuses on minimizing environmental waste during the production of energy, this section focuses on minimizing how much of that production ultimately goes to waste because of unpredictability and unreliability. As in each section, we give an overview of existing literature before analyzing its impact and offering perspectives on the future of the field.

Overview of Existing Work

In recent years, the application of AI methods to storage has become an active area of research, with promising results and tremendous potential for climate-saving impact. In the following section, we focus mostly on outlining the general trends of this large research direction, dividing the literature into three key initiatives: battery optimization, storage control, and energy management systems. Though overlap of course exists, these categories are ordered pseudo-chronologically; the battery optimization literature is generally older whereas the concept of an energy management system is quite new.

Battery Optimization The increasing importance of storage units to the energy grid necessitates continual battery evolution and improvement. The key characteristics of batteries include energy density—the ratio of stored energy to physical space—battery lifetime, battery capacity, and battery performance, which is usually defined with respect to average and maximum charge and discharge speed [14]. Many of these objectives, though, are at odds with one another; repeated rapid discharges or battery over-charging can have an adverse effect on battery lifetime and long-term battery capacity, but optimizing only for battery lifetime by limiting battery discharges and imposing restrictions on charging compromises the usefulness of the battery. Furthermore, all of these objectives are intricately related to external factors like temperature and to the battery's intrinsic chemistry and physical design. The result is a system of significant complexity, but one that must be understood and optimized in order for the world to combat the ongoing climate crisis.

Traditionally, researchers and companies have relied on physics-based models to understand the interaction of various battery design parameters and how they can affect battery life and performance [14]. Crucial to these techniques, however, is accurate estimation of these various parameters as they evolve over time, which remains a significant challenge. Physics-based models are also inherently rigid and sometimes sensitive to unrealistic assumptions. Recently, though, machine learning models have emerged as viable alternatives as more batteries are deployed with sensors that can track voltage, current, and temperature, among other useful quantities.

The most obvious use of such models, already well-studied and seemingly mostly solved, is to provide a live estimate of battery state of health (SOH), state of charge (SOC), and remaining useful life (REU) [15]. Even before 2020, models were developed that accurately estimated SOH and REU within a single percentage point (0.1% and 0.6%, respectively), and SOC with an error of just 1.6% [16; 17; 18]. Each of these models was neural-network-based.

Machine learning models can also aid in the development of batteries before being released to market. Attia et al., for example, use closed-loop Bayesian optimization to accelerate research in battery design [19]. As discussed, the parameter space for battery design is quite large, and testing battery lifetime is an expensive, time-consuming process. Attia et al. thus develop both an early outcome prediction algorithm, which can decrease time per experiment, as well as design a Bayesian optimization algorithm to aid in choosing which parameters to test next. Their methods allow for 244 different charging protocols to be investigated in just 16 days, compared to the 500 necessary for the brute-force approach [19].

Storage Control Moving beyond the development of optimal storage units, there also exists substantial literature focused on the design of efficient control strategies for storage units when paired with renewable generation. For an illustrative example, consider a wind-turbine paired with a large, grid-scale storage unit. Under what production and load demand conditions should the turbine be charging the battery rather than sending energy directly to the power grid? When should the storage system be discharging its own energy? The answers to these questions depend, of course, on the optimization target.

In [20], the authors use classic control techniques to optimize a system comprising a wind-turbine power generator, a photovoltaic generator, a super-conductor, and a traditional battery. The control algorithm is designed with multiple objectives in mind:

1. reducing power output fluctuations,
2. maintaining the balance and status of energy charge, and
3. reducing network voltage changes and reducing the volatility of reactive power.

Their solution, based on a physical model of the battery, power generators, and super-conductor is shown to achieve the objectives during a short MATLAB simulation of 10 seconds.

In a more expansive example with probably greater potential for impact, Chen et al. use AI-enhanced model predictive control to optimize a wind-turbine-hydrogen-fuel-cell pairing with the goal of maximizing local usage of wind power on the microgrid scale (and therefore minimizing power exchanged with the grid) [21]. More specifically, upon constructing a smart grid on the campus of Guizhou University in China, the authors train an artificial neural network to accurately predict the power generated by the wind turbine based on historical, measured wind power data. The power forecasted by the neural network is then fed into a model predictive control scheme that comprises a genetic algorithm (a type of stochastic, global search algorithm) for optimization and a state space model which measures relevant quantities—measured wind output, predicted output, current charging and discharging state of the battery. These two components create a closed loop, as the power flow the genetic algorithm prescribes informs the state space model, the outputs of which are used by the optimization algorithm for next-step decision making.

The artificial neural network is able to predict the output generation over 24 hours, never exceeding a 5% error threshold and for the most part remaining within 2-3% of the true power. The root mean square error of the model is just 1.4%. The proposed power flow optimization algorithm is evaluated over four distinct days based on the power exchanged with the grid under this scheme compared to without optimization. Ultimately, the authors find that the developed MPC scheme increases usage of wind power by 45-90% while maintaining safe operation of the storage system. Demonstrating the paper's potential for real impact, the authors are implementing the developed strategy on an actual wind farm with fuel cell storage and constructing a full-scale experimental test rig.

Energy Management Systems The most recent development in the literature examining storage-related applications of artificial intelligence is in the design of *energy management systems* (EMS). Such systems aim to optimize load flow at the home or microgrid level, managing power interchange between storage units, fixed and controllable loads, distributed energy resources, and the power grid. Approaches to such systems can be broadly categorized into model-based and model-free learning and control techniques. Model-predictive control has been shown to be successful [21], but due to the ambitious scope of the control problem it is plagued by scalability issues that arise from reliance on accurate models and parameters for the home or microgrid system. A more attractive approach, then, is those that are model-free, methods that learn near-optimal control strategies based on the microgrid's operational data. A natural methodological choice for such a task is the reinforcement learning paradigm, in which an agent explores an unknown environment to find an optimal policy (in this case, a power control strategy). An additional advantage of the reinforcement learning paradigm is that it can be trained extensively using offline data, but also continue to learn while deployed, adapting to evolving conditions. The most flexible algorithms, which can learn even in scenarios where agents observe only part of the environment and when the environment is of high dimension, are so-called *deep reinforcement learning* (DRL) algorithms, which use an artificial neural network to approximate the state-reward mapping. Such algorithms can also learn the state-action transition probabilities, which are fundamental to the reinforcement learning approach.

In one illustrative example, researchers focus on the optimal management of home energy appliances [22]. The system included four controllable load components—an air conditioner, a heater, a dishwasher, and electric vehicles– as well as other, uncontrollable loads, a solar photovolatic generator, energy storage, and connection to the main grid. The actions available to the agent are thus to time-shift (delay the demand of) the heater, dishwasher, and electric car, power shift (decrease or increase the demand of) the air conditioner, as well as to charge or discharge the storage unit. The reward function is broadly to minimize cost to the consumer, but it factors in not only the real cost of purchasing energy from the grid at a price fixed by the local power operator but also integrates penalties for charging or discharging the storage unit (to preserve its lifetime), for selling photovoltaic output (to prioritize local consumption of renewable energy), and for shifting controllable demand away from consumer preference.

The paper demonstrates convergence of two deep reinforcement learning algorithms, deep q-learning and double deep Q-learning with the final policy lowering average consumer payments by 25%. By evaluating the algorithms on similar examples without electric vehicles or photovoltaic cells, the authors indicate their model's potential for generalization.

The EMS problem can also be studied at the microgrid scale. Nakabi and Toivanen, for example, consider a microgrid complete with distributed wind generation, a communal energy storage system, residential price-responsive loads, and a group of thermostatically controlled loads and examine the performance of seven state-of-the-art DRL methods [23]. The reward was again cost-based, defined to be the gross margin from operations—the revenue generated by selling energy to the external grid minus any costs associated with production, transmission, and purchases from the external grid, and the actions again concerned demand from controllable loads, the charging/discharing state the storage unit, and power to/from the external grid. Using historical data on demand and power production, the authors first evaluate each of the proposed algorithms on this model microgrid, concluding that a novel extension of the actor-critic algorithm performs best, before evaluating the method of choice against two baselines: the theoretically optimal solution assuming full information about consumption, prices, and temperatures throughout the day, and a theoretical retailer who buys the exact amount of energy necessary from the day-ahead market.

The results simultaneously demonstrate the promise of DRL algorithms for the EMS problem—the actor-critic algorithm outperforms the theoretical retailer by 24%—but also the tremendous room for growth—the actor critic still only achieves 50% of the profit promised by the theoretically optimal solution. Beyond total profits, the microgrid structure is also shown to increase grid resilience to local energy scarcity—with costs significantly lower than the theoretical retailer during days when wind generators under-produce.

Technical and Data Challenges

Model Building. In the field of AI for storage optimization, there exist substantial technical challenges for model building. These exist mostly for the newer, and more ambitious subfields. For energy management systems, for example, the complexity of the optimization problem at hand—coordinating power flow between dozens of smart energy components—means that methodologies struggle to generalize and are dependent on precise input data that is difficult to find in the real world. It remains to be seen whether deep RL methods can be applied efficiently and impactfully to problems of such high dimension and complexity. Furthermore, these EMS systems will need to work real-time on messy data captured by faulty sensors; substantial difficulties arise when models are implemented beyond simulated datasets.

Method Evaluation. Recall that from the perspective of AI for energy waste, the ultimate goal of the cited literature is to reduce production waste through optimization of storage methods and strategies. In most examples, though, this is not the explicit criteria by which the results are measured. Rather, methods are developed to, for example, decrease time and cost to companies for battery development or decrease consumer cost through home energy system management. Importantly, though, each of these studies does ultimately contribute to minimizing production cost in some way. A decrease in consumer cost, for example, can only be a result of a decrease in consumption from the main power grid, or at least a shift away from consumption during hours of peak demand; in either case, this means more efficient consumption of generated electricity. The misalignment between the explicit goals of the literature and the true opportunity for positive social impact does mean, however, that evaluating the social impact of research in this field can be challenging. This is made even more difficult by authors' tendency in the literature to focus mostly on simulated results and proofs of concept, rather than discuss ways in which their research will be or should be applied in real-world power grids. A notable exception to this trend is [21], which is moving to implement their AI-enhanced control methodology on a practical wind-farm with fuel cell energy storage and constructing a full-scale experimental test rig. The results of this implemented study, however, have seemingly not been published.

Future of Field

As evident by a lack of implemented methodologies, there remains substantial room for growth within the AI for storage methods literature. The potential for expansion is especially evident for the more ambitious of the initiatives; i.e. for storage control and even more so for energy management systems. We discuss each initiative in turn, starting with battery optimization.

Future of Battery Optimization. Battery optimization seems a more complete field, with much of the most relevant and impactful literature published before 2020. The existing literature, though, mostly focuses on the design and use of the standard lithium-ion battery [14; 15; 16; 17; 18]. Since development of other battery types, including superconductors and hydrogen fuel cells, is still an extremely active area [24; 25], it seems that there exists potential for existing ideas on optimizing and estimating state of health, state of charge, and remaining useful life to be extended beyond the lithium-ion battery into more cutting-edge and still developing technology.

Future of Storage Control. More ambitious than battery optimization, but falling short of the full complexity of the EMS problem, the future of storage control is in many ways exemplified by Chen et al.'s efforts to implement their AI-enhanced MPC algorithm for a live wind farm [21]. The addition of grid-scale storage units to renewable generators has great potential to increase the reliability of the grid and emphasize local usage of locally produced power in a way that is healthy for the grid at large. In many ways, it is an alternative solution to the emphasis on consumer-side storage units emphasized by microgrids and the EMS literature.

Future of Energy Management Systems. This is the field with the seemingly greatest potential and room for growth, but also the furthest away from immediate positive impact. The results of the cited literature further articulate this point, since though they do demonstrate some convergence of the deep reinforcement learning methods, the convergence often takes quite a long time—hundreds of episodes of training—

and exhibit policy instability even in the final stages of training [22; 23]. Nakabi et al., in particular, shows how much progress can still be made in this field, as the deep RL method achieves only 50% of the optimal controller's profits despite outperforming the baseline, unoptimized retailer by 24%. The room for growth may not be quite as large, the optimal controller has access to unrealistic, perfectly accurate information about the future demand and weather conditions and so is not an entirely fair comparison metric, but there is still clearly work that can be done.

Data and Collaboration

As discussed, much of the data is synthetic. The research is also focused in wealthier, developed countries with all of the real-world data coming either from China [21], the United States [22] or Finland [23].

Theme 3: Energy Distribution

Building on applications of AI to reduce waste in energy production and storage leads us to a natural discussion of AI for energy distribution. This occurs at grids of all scales — from microgrids managing the energy of small family homes, to national electrical grids as a whole. Although "distribution" can sometimes refer specifically to distribution grids in populated/industrial areas, with "transmission" referring to the (typically long-distance) travel of energy from production, in this section we will define distribution in the broader sense of any form of transportation of energy (whether it be directly to end users or right after production).

Given the rapid growth of renewable energy sources, as mentioned in the previous sections, along with the diminishing availability of fossil fuels and other non-renewable sources, optimization of energy distribution within a grid is establishing itself as a field in AI for social impact. This is a very intersectional field, in that distribution also occurs at a small scale within storage systems like EMS and is highly dependent on demand/response. AI for energy distribution allows for a uniquely standard and useful measure of impact – how much additional energy is being inefficiently distributed to places that do not need it?

AI for energy distribution can be split into two major subfields: AI for load forecasting and AI for scheduling/control. The former involves determining exactly how much energy will be needed at a given place and time (this could be as granular as an appliance within a home or as coarse as a distribution grid for a city), whereas the latter attempts to determine how to allocate and distribute energy across the grid for all of these appliances, smaller grids, and more, all at the same time. We will cover important, recent work from these two subfields individually, then discuss the ethical and social considerations that go along with these subfields more broadly, and then finally elaborate on future directions of AI for energy distribution research.

Load Forecasting

When it comes to energy distribution, the specific type of load forecasting that has proven crucial is **short-term load forecasting (STLF)**. This involves making predictions of energy need to the level of days, hours, or even minutes. Long-term load forecasting tends to be more important in energy production and demand planning/response, since it sets larger-scale goals for the amount of energy that will be necessary.

The majority of STLF done in practice still uses simple, analytical methods for predicting energy needs, since these have proven to be relatively accurate and easy to implement [26]. These include the autoregressive moving average (ARMA) and integrated, seasonal adaptations of it (ARIMA, SARIMA) — all highly interpretable since they build a moving average on just a few explanatory time series (like energy load trends and seasonality).

However, these models lack the ability to support "exogenous" variables like population demographics, temperatures, and more. As a result, they are not entirely optimal, and even marginal improvements can result in enormous energy reductions, since the models that predict how much energy is needed across an entire grid/nation have such a broad scope. We found two recent papers that provide significant improvements over the status quo alongside broader insights about AI for STLF:

- Pinheiro et al. argued that interpretability is still extremely important for models, so that we have access not only to predictions of energy needs but also the importance of certain variables (weather, demographics, economics) in determining these energy needs [26]. They used a new dataset to define the energy needs of all 100,000 secondary substations in Portugal (which service the grey regions in 5), and then tested several models that were more complex than ARIMA/SARIMA but still relatively interpretable — this included generalized linear and additive models (GLMs/GAMs) and gradient-boosted trees (XGBoost). They developed a GAM-based ensemble algorithm that used adjusted parameters for different seasons/holidays, and relative to the benchmark of moving-average models this performed extremely well (errors were reduced by nearly 50%). As a result, this solution was adopted by Portugal's distribution systems operator (DSO), and it can certainly be adjusted and re-applied to other countries' distribution systems as well. [26]
- Lee et al. found inefficiencies in the research trend of building STLF models that are broadly applicable to an entire grid or large subsystem (like secondary substations or all individual homes). Instead, they proved that individualized approaches to STLF can lead to important improvements in predictions of how much energy will be needed for specific customers (anything from industrial plants to single-family households). Lee et al. proposed that new models do not need to be created to adapt to these different circumstances/subsystems. Instead, they applied the notions of transfer learning (using a large, pretrained ML model used for a slightly different task, and then providing a small number of examples for the desired task) and meta-learning (training a ML model to learn from only a small number of examples) to prove that general, "one-for-all" methods for STLF

can be easily individualized to perform better. By applying these techniques to deep learning STLF models, Lee et al. showed that individualized multi-layer perceptrons (MLPs) could perform significantly (10-15%) better than standard methods such as ARIMA [27]. However, the results seem to not be as effective as Pinheiro et al.'s newer GAM-based ensemble algorithm, so it would be intriguing to see how the individualized MLPs proposed would compare to models introduced in the past year [26].

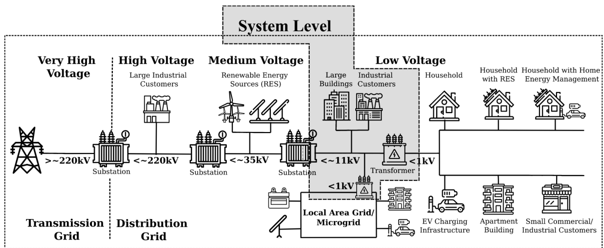

Figure 5: An overview of the path of energy distribution, from a national-scale grid down to individual homes. [26]

Scheduling and Control

Beyond the task of forecasting energy needed in various grid subsystems using STLF, which involves making useful predictions in advance, there exists complementary literature on scheduling and control in the distribution of energy. This is a very broad field, given that these algorithms must exist at every level of energy distribution, from nation-wide transmission systems to secondary substations (as mentioned in the previous section) and individual buildings and units.

This is a much more difficult technical task, since it requires near-immediate speed in deciding how much energy to transport to various destinations. Given the scale of distribution and transmission grids, data-focused approaches struggle to meet this criterion, necessitating the use of ML methods that stray from the recent trend towards broad application of deep learning techniques.

Given the discussion of energy management systems (EMS) in the scope of energy storage, we will develop the study of EMS further to discuss recent advancements in energy scheduling/control using ML. We focus on the smaller scale of local distribution grids and individual homes/neighborhoods, since larger-scale grids have already developed more technically-robust methods for control [28]. It is also important to note that various aspects of energy distribution ought to be considered as well, such as frequency regulation, voltage control, and several others. However, we maintain a focus on energy management since it has recently driven progress in scheduling/control and provides useful exemplars for this field. We consider three papers that present important progress in AI for scheduling/control, specifically in the scope of energy management:

- Almeida et al. studied the use of evolutionary algorithms to manage distributed energy resources (DERs). They noted that given the increased penetration of and reliance on unpredictable renewable energy generation (such as solar and wind power) and unpredictable energy use (anything from electric vehicles to smart homes), more complex algorithms are necessary to schedule power efficiently. They tested various evolutionary algorithms and found that, for a simulated model of a distribution network the size of a small neighborhood, two heuristic algorithms (CUMDANCauchy++ and HyDE-DF) provide superior results to evolutionary algorithms currently in use. The most notable contribution here is the conclusion that evolutionary algorithms can adapt much more easily to uncertainty, which will become increasingly crucial given the energy sources and consumers that will become more prevalent in the coming decades. [29]
- Du et al. examined ways to control heating, ventilation, and air conditioning in multi-zone residential units. This is a much smaller scale than Almeida et al.'s study of neighborhoods, and they also discussed control methods instead of scheduling methods (notably different because control requires much faster responses than in-advance scheduling). The paper found that deep deterministic policy gradients (DDPGs) are particularly impactful in not only reducing energy usage but also making sure that residents of a home have control over their heating/air conditioning [30; 29]. This can be generalized to larger-scale energy control as well, but it's unclear whether the impressive simulation results of 15% decreases in energy consumption and 80% improvements in comfort maintenance would generalize to larger models as well.
- Heidari et al. examined a similar system, albeit in a grid that is even more in development (water). They provided a double-deep Q learning approach, which expands over tabular and deep Q networks while remaining model-free. This was shown to provide a nearly 24% improvement in energy-saving compared to the rule-based approaches that would otherwise have been put in place for the real-world data provided by a home in Switzerland [31]. This is an even larger improvement than seen in Du et al., which may be related to inherent uncertainties and characteristics of hot water distribution but still shows impressive progress [30]. It's important to note that this strategy, along with the previous ones mentioned, is still purely theoretical (even if based on real-world data), but it may begin to be put in place as smart meters for electricity but also HVAC/water become more commonplace.

Ethical/Social Considerations

One important consideration is that the funding and inspiration for many of these projects comes from the corporate sector, instead of a more national/public source. One such example is Heidari et al.'s paper on RL for controlling hot water systems, which draws funding from Droople, a cleantech company [31]. These collaborations could encourage profit-driven energy distribution as opposed to efforts for pure energy efficiency. Thankfully, these goals are *typically* intersectional, since the cheapest option in terms of energy distribution is oftentimes the most efficient solution as well.

Another important ethical consideration is the introduction of smart meters for all kinds of household appliances and services, with research like Lee et al. showing how ML can be used to track variations in individual load [27]. This could result in aggressive pricing from energy providers, making it more expensive for individuals to pay for energy, regardless of whether it's generated renewably. Sharing of this newly-online data from energy providers could also make it more difficult for consumers to maintain privacy and autonomy in their own homes, which should be considered as well.

Future Directions

When considering future directions of research into AI for energy distribution, there are a few particularly important factors that must be considered:

- Renewable energy sources, such as wind or solar power, are climate-based and thus inconsistent at best and unreliable at worst. We are currently undergoing a major transition to these energy sources.
- There has been rapid development of new devices, vehicles, and more that will require significantly more electricity and other grid-dependent energy — this includes anything from smart home appliances to electric cars, trains, and planes.
- Energy grids are only growing more complex over time, as each individual household gains more power-dependent items, each microgrid/distribution network gains more households and businesses, and each country gains more distribution networks.

With these in mind, we consider the futures of load forecasting and scheduling/control as subfields of AI for energy distribution.

Future of Load Forecasting As the world's computing power scales significantly, our ability to deploy more complex models that encode granular data about energy needs improves. As a result, projects like Pinheiro et al.'s load forecasting of 100,000 substations are already possible, and soon enough we will be able to forecast the load of single home units and electric charging stations, not only in theoretical research but also in deployment [26].

Beyond this, significantly more work is needed in load forecasting outside of electricity — effectively all of the work in AI for load forecasting focuses on electrical grids, which is intriguing given that scheduling and control have already begun to examine water grids, HVAC grids, and more [31; 30]. That being said, much of load forecasting research is highly dependent on smart meters, which are becoming very available for electrical grids but are still being developed for water/HVAC/other grids. Consequently, ML for load forecasting can be expected to significantly expand to these types of grids within the next 5-10 years in research, and hopefully soon after in real-world application.

Despite this progress that can be made, it can be argued that load forecasting (especially short-term) is an overstudied field. Many of the improvements presented in recent years have been more marginal or application-focused, and the models used for load forecasting in electrical grids appear to be easily generalizable to other forms of energy as well. Thus, the pioneering research in AI for energy distribution likely lies outside of load forecasting, unless a revolutionary new ML framework is introduced that proves particularly applicable to load forecasting.

Future of Scheduling/Control As alluded to in the previous section, scheduling/control has made some advancements in AI targeted to grids that are not solely electrical. However, as smart meters are developed for non-electrical grids, studies and applications of scheduling/control algorithms for these new grids will certainly become more prevalent too.

AI for scheduling and control is also a much newer field than AI for load forecasting. Novel hardware (such as quantum computers) could allow the extremely complex problems to be solved with large, similarly complex models in negligible time. This is something that is presently impossible, specifically for the problem of energy control, which must rely on model-free approaches for the time being.

Still, AI for scheduling/control has clear room for expansion and further study via the methods being used today. Deep RL algorithms like those used by Du et al. and Heidari et al. show substantial improvements in not only energy saved but also in the comfort of the consumers whose systems rely on those algorithms [30; 31]. As the field of scheduling/control/energy management expands from both theoretical and application-based perspectives, it's very possible that we see these model-free approaches being implemented to solve these problems at all levels.

Theme 4: Energy Demand

For this section, the focus is on economic waste reduction through demand response programs. Generally, demand response is viewed as a way of adjusting various resources like loads and prices to balance or even out electricity demand. More specifically, waste reduction is typically done through lowering energy costs for consumers and operational expenses for suppliers, which tend to rely on the equilibrium price established by the grid's operating system. The economic approach of demand response is integral for load forecasting, as the ability to adjust distribution based on predicted demand – as costs vary with time – enhances the grid's capacity to reduce excess energy production. The discussion in this section focuses on three primary areas: price forecasting, customer segmentation, and incentive schemes. Thus, through the use of artificial intelligence in the economic side of demand response programs, there is potential for improved social welfare across all users.

Price Forecasting

Price forecasting is the practice of using historical data (prices, load demand, etc.) to predict future prices. Having future price knowledge then allows consumers and suppliers to make more informed decisions about when to produce and acquire energy. The use of machine learning models can help anticipate future prices based on understanding past trends, which can allow programs to respond better to current market fluctuations. Neural networks and other supervised learning approaches were the most common among the papers found, favored for their ability to model a non-linear and variable demand. These predictions are often able to incorporate uncertainty in future forecasts, which allows for more informative predictions than the traditional approaches (autoregressive integrated moving average, exponential smoothing, etc.) that assume a linear relationship between prices and input data [32]. Nonetheless, the use of deep learning in price forecasting can pose challenges, especially due to the computational intensity and the significant amount of feature engineering required to counteract this issue.

Lin et al. propose a novel decomposition-ensemble method for forecasting future energy prices [33]. As mentioned previously, many of the traditional approaches in energy forecasting fail to capture the complexities across factors like market demand and changes in supply. Through a decomposition approach, the authors sought to isolate underlying patterns of price dynamics. As shown in the figure 6, the authors started by decomposing the prices based on frequencies using variational mode decomposition (VMD). They then used a different model based on the frequencies, utilizing autoregression for long-term trends (low frequency) and Elman neural networks or improved bidirectional long short-term memory models (IBiLSTM) for short-term fluctuations (high frequency). The authors suggest that the use of iBiLSTM can counteract the limitations of other neural networks that lack the ability to remember and use past information to predict future information. Subsequently, the authors reassembled the original signal through the optimal set of modes and frequencies via Lagrange multipliers. As a result of the study, the authors found that their mean squared error, mean absolute error, and mean absolute percentage error values were all lower than for traditional models. Thus, the performance of the VMD-IBiLSTM seemed to mirror the complex, non-linear dynamics of energy prices. The implications of this paper can then allow governments and companies to make more informed decisions. Additional accuracy in these decisions can also allow for more optimal resource allocation.

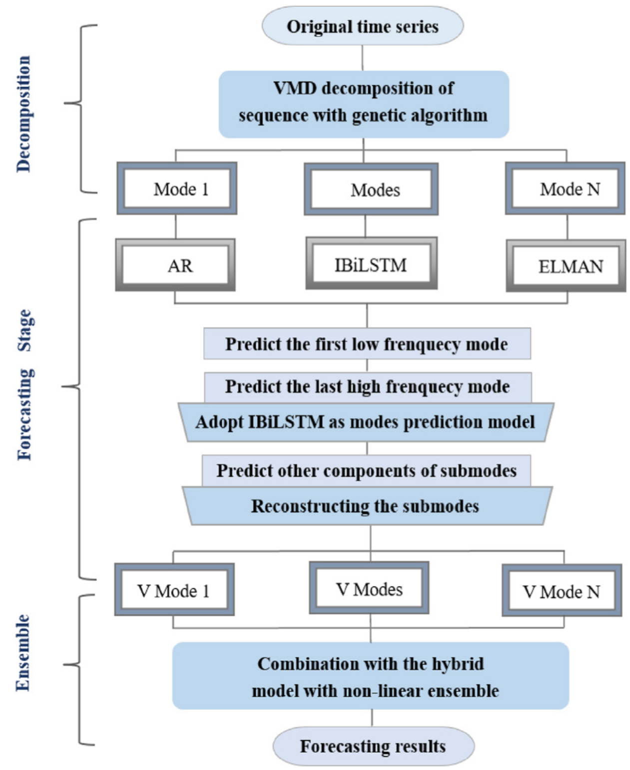

Figure 6: Proposed novel decomposition-ensemble method using VMD. [33]

Another approach by Kempitiya et al. employs an AI framework to develop strategies for market participants to determine the quantity of energy to offer and the price [34]. This occurs within the ”frequency market,” typically associated with the electricity market segment where grid frequency services are traded. The bidding strategies often activate during high-price periods, enabling market participants to propose their energy injection or withdrawal capacity to help balance the grid's frequency. The authors delineate three AI-driven bidding strategies to address the corresponding optimization challenges:

- Strategy 1: The first strategy is dedicated to non-reschedulable reserve resources, aiming to bid in day-ahead markets predicted to have high prices. If these bids are unsuccessful, the strategy shifts to the hour-ahead market as a secondary option.
- Strategy 2: An enhancement of Strategy 1, the second strategy also targets non-reschedulable reserves but avoids bidding in day-ahead markets if higher prices are anticipated in the hour-ahead market. It bids in the day-ahead market only if prices exceed a certain threshold; otherwise, it opts for the hourly market to secure better prices just before the demand arises.
- Strategy 3: The third strategy applies to reschedulable reserve resources, necessitating the scheduling of resource use during times of peak predicted prices. An example of this can be large-scale batteries, which can store energy and then release or use it at optimal times. This strategy then can use the ability of scheduling energy usage to align with the peak pricing periods.

Additionally, the authors integrated an AI prediction model that leverages Bayesian neural networks for market price forecasting and Monte Carlo Dropout to manage the uncertainty in these forecasts. The findings indicated that Strategy 3 outperformed the others, underscoring the advantage of adaptable and data-informed methods. The significance of this study lies in its contribution to real-time supply and demand balancing. The application of AI in these strategies potentially enhances the market participants' profitability and efficiency, thereby minimizing economic waste and unnecessary production.

Customer Segmentation

Customer segmentation is the identification of distinct groups based on energy usage patterns or responsiveness to price changes to enable more tailored demand-response programs. Generally, the papers found in this area focus on unsupervised learning techniques given the limited amount of labeled consumer data that currently exists. The process of customer segmentation requires extensive pre-processing like to harness the various sources of data effectively. This process then allows for a better understanding of consumption patterns that might occur within each customer segment.

One data source utilized was smart meter data, analyzed by Tang et al. to uncover the link between load patterns and socioeconomic traits [35]. The authors employed the subsequent steps to identify the socioeconomic features most correlated with these load patterns:

1. The data were pre-processed, segmenting the dataset into weekdays and weekends using the date stamps. Each day was further divided into 24 one-hour intervals.
2. Considering the real-world, imperfect nature of the data samples, the K-Medoids method was chosen to identify the most representative sample within each cluster. This method is less sensitive to outliers and noise compared to K-Means.
3. Feature selection was then applied to eliminate redundant and irrelevant features through an entropy-based filter method, enhancing the interpretability of the consumption behavior analysis.
4. Finally, the authors developed K distinct deep learning neural network models with the chosen features as inputs to predict the probability of certain load patterns.

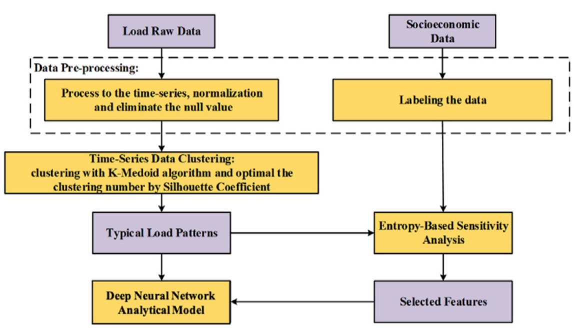

Figure 7: Methods used to combine load patterns and socioeconomic factors. [35]

Figure 7 illustrates these steps graphically. The authors determined a significant correlation between load patterns and specific socioeconomic features, such as age and education level. Their deep learning model outperformed traditional methods like XGBoost and convolutional neural networks. These insights allow utilities to devise more tailored energy efficiency programs, leveraging detailed knowledge of consumer characteristics.

An alternative method for consumer segmentation involves examining participation in demand response programs. The study done by Antonopoulos et al. looked into how specific household characteristics, such as heating system type, internet connectivity, and air-conditioning availability, influence residential demand response actions, utilizing data from the Smart Grid Smart City (SGSC) trial [36]. This trial, one of Australia's most extensive smart grid experiments, encompassed data on electricity usage, generation, grid performance, and consumer feedback from over 50,000 residential and business sites. Similar to the previous study, this research required thorough data pre-processing and clustering to classify consumer behaviors and identify shared attributes for participant selection. Subsequently, the team applied machine learning techniques, including gradient boosting regression and random forest to navigate complex data structures, alongside dense neural networks to capture nonlinear relationships within the data. These methods were compared against baseline linear models for performance evaluation. From this study, the key results showed that internet access, air-conditioning presence, and appliance usage most influenced the propensity to respond to demand response events.

Thus, the combined insights from these studies underscore the value of consumer segmentation in energy management. By understanding the drivers behind response behaviors and the impact of specific programs on different consumer groups, energy providers can tailor their initiatives more effectively. This strategic approach not only enhances the efficiency of demand response programs but also contributes to more sustainable energy consumption patterns, aligning with broader goals of energy efficiency and conservation.

Incentive Schemes

Incentive schemes, by leveraging insights from price forecasting and customer segmentation, aim to optimize the alignment between the objectives of all stakeholders and the grid's operational efficiency. These schemes commonly employ reinforcement learning and game theory to address the complexities of multi-objective optimization. Through the dynamic adaptation of pricing and incentives, the system ensures that the interests of stakeholders are aligned with the grid's efficiency and operational goals.

One approach to developing an incentive scheme is through multi-objective optimization to achieve optimal system performance. The two challenges that Zhang et al. addresses are that conventional models often overlook the interdependence of energy sources, and the prevalent fixed price strategy struggles to accommodate all stakeholders [**?**]. The authors introduce a 2D demand response model, which integrates both spatial and temporal aspects, allowing consumers to adjust their usage over time and suppliers to optimize availability. Meanwhile, the supplier aims to maximize their revenue.

The optimization model employs an iterative solution process with the CPLEX solver, where the minimum and maximum values of the objectives are sequentially optimized and recorded to guide subsequent steps, achieving a Pareto optimal solution. The results found by the authors demonstrate the feasibility and efficiency of the proposed model in balancing the complex demands of energy supply and con-

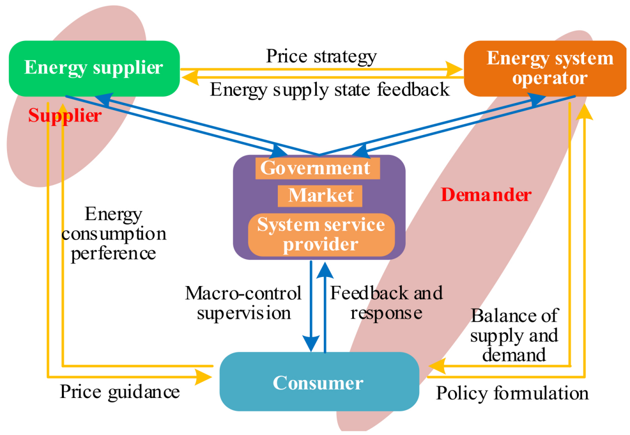

Figure 8: Framework of stakeholders impacted by energy pricing.

sumption. This can be significant for the energy sector, indicating that a more dynamic and responsive pricing model can lead to better resource utilization and satisfaction of different stakeholders' needs.

Another approach to addressing multi-objective optimization issues is through a bilevel programming model, where the upper level, representing the supplier, aims to maximize profit, and the lower level, the regional integrated energy system (RIES), focuses on enhancing overall social welfare. Guanxiu et al. utilized this hierarchical structure and converted it into a mixed integer quadratic programming model that ran on synthetic data from the Lingang Area in Shanghai [37]. By employing real-time pricing in this model, social welfare, reflecting the economic benefits for both the RIES and suppliers, increased by 14.12% compared to traditional methods. This improvement also resulted in a 16.99% decrease in the peak-to-valley power load difference and a 5.7% reduction in carbon emissions. AI was more implicitly used in this paper to allow for complex optimization and predictive modeling. Thus, this study provided a proof-of-concept for a more dynamic and efficient energy management system that can respond to real-time market conditions. The successful application of the model in a synthetic environment underscores its potential for real-world implementation. Therefore, incentive schemes in the energy grid are crucial for motivating stakeholders to optimize their energy usage and production, leading to enhanced grid stability, increased energy efficiency, and a reduction in negative environmental impact.

Ethical Considerations

Much of the research in demand response programs has been concentrated in developed countries, especially China, partly due to the availability of data on energy consumption and established frameworks. This could exacerbate socioeconomic disparities, as the developed areas are better positioned to leverage AI for increased efficiency and reduced costs. Nonetheless, the environmental benefits of using AI in demand response programs still offer a compelling case for its advancement but would need more development in other areas to create a more balanced benefit distribution. Along the same lines, funding and resource allocation is a major aspect of these programs, especially given that the benefits are economical. Over two-thirds of the papers surveyed in this section had some funding from a scientific institute or university in their respective country. In recent years, however, many AI startups have been created to leverage AI in the energy sector and take advantage of the profit and environmental opportunities.

Regulation seems to be less of a focus across the papers read due to the fact that most of the mechanisms suggested in the literature have not been implemented in a real-world context. One issue with integrating these changes into the system is security concerns for the smart grid and potential biases with regards to customer segmentation. Customer segmentation also benefits from having customer feedback which would require additional data collection and cleaning in order to incorporate this into later stage models.

Future of AI in Demand Response Programs

The future of AI in demand response programs appears to be focused on improving the existing algorithms and expanding their applications. While most of the focus has been predominantly on price and load forecasting due to the availability of data, there is growing recognition of the need to broaden the scope of the research to incorporate other aspects. For example, recent 2022-2023 has been focused on the integration of decentralized financial systems into the smart grid, improving the economics of energy distribution and consumption, and then using AI to optimize the problems presented. Other areas for further research have been participatory pricing models. One example is the use of adaptive clustering-based customer segmentation, where the pricing strategies differ across groups while simultaneously maximizing retailer profit [38]. The main limitation in this area is that the quality and availability of economic data varies across geographic regions, and the personalization of schemes can be difficult given legal considerations. Nonetheless, the use of AI in this sector can allow for more consumer-centric and economically efficient demand response strategies.

Theme 5: System Maintenance

Impact Assessment

With the intersection between the IOT (Internet of Things) and the IOE (Internet of Energy), together with the growing field of AI, the information gathered from the IOE and IOT have been better utilized and delivered a bigger impact to the field of maintenance than before. In every stage of the power grid, from the power generation phase, to the transformer stage, to the transmission stage, distribution stage and eventual usage stage, there are the presence of maintenance to make sure the outage will be monitored, detected and dealt to the fastest speed, avoiding larger economic and social impact.

In the realm of wind energy (together with other forms of renewable energy), the application of AI techniques has been pivotal in evolving operations and maintenance (OM) strategies. The shift towards AI, particularly deep learning, has been instrumental in transitioning from conventional signal processing methods to more advanced predictive and performance assessment models. Techniques like Empirical Mode Decomposition (EMD) and Spectral Kurtosis (SK) have laid the groundwork for the incorporation of sophisticated ML models such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). This transition signifies the potential of AI to enhance the reliability and efficiency of wind energy sources, advocating for ongoing research and development to fully exploit data-driven decision-making in the sector. [39]

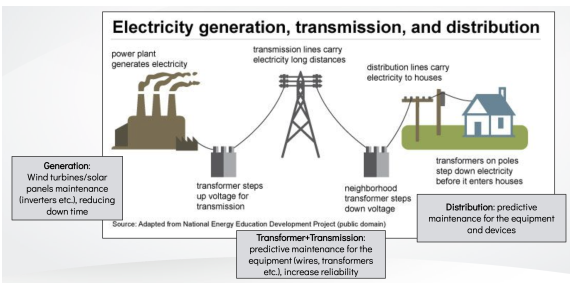

Figure 9: Maintenance in Different Stages of the Grid That Could Be Optimized by AI
[40]

The complete evaluation of smart grid technology emphasizes the utilization of AI across various facets along with operation and management, upkeep and lifespan management, grid making plans and layout, and metering. Machine studying fashions which include Support Vector Machines (SVM) and Neural Networks had been highlighted for their roles in predictive analytics and fault detection, alongside the use of big information analytics for dealing with the records inflow from smart meters and sensors. This research underscores the significance of advancing AI applications inside smart grids to enhance grid reliability, performance, and interoperability among additives thru requirements like IEC 61850.

In predictive protection for smart grid distribution networks, the innovation delivered with the aid of IoT and the importance of smart grids in catering to the escalating global energy demand have been diagnosed. The systematic overview underscores the evolution of predictive maintenance in alignment with the Industry 4.0 revolution. It delineates the journey from conventional techniques together with Infrared Thermography-Based Techniques and Impedance-Based Methods to superior ML processes which includes SVM, ANN, Random Forest, and RNN. These advancements signify a paradigm shift towards enhancing predictive preservation techniques, highlighting the importance of sensors for continuous tracking and the crucial function of statistics analysis in preserving grid stability and reliability.

The incorporation of genetic algorithms and K-Medoids clustering methods in huge-scale grid protection underscores the necessity for progressive answers to deal with the challenges posed via the complexity of smart grid systems. The adaptive genetic algorithm and custom designed K-medoids clustering method exemplify the systematic technique to smart grid protection, prioritizing essential maintenance, optimizing useful resource usage, and minimizing operational disruptions. This research contributes drastically to the smart grid preservation domain, providing sensible, information-pushed answers to enhance the energy distribution network's reliability and performance, for that reason reinforcing the crucial role of AI in transforming power structures renovation. With the research and the experiment behind, we've seen the AI have been providing values to each stage of the power grid's maintenance process, bringing real-life improvement to make the grid robust.

Experimental Evaluations

Different stage of the power grid could have their improvement of maintenance with the help of the introduction fo the AI. The exploration and validation of AI strategies for boosting smart grid preservation have ended up enhancing machine reliability, performance, and sustainability. The integration of ML algorithms and deep gaining knowledge of models into the protection protocols of strength systems gives a promising avenue for addressing the complicated challenges associated with device preservation and failure prevention [39]. This subsection delves into the experimental reviews which have been carried out to check the suitability and effectiveness of numerous AI strategies in transforming conventional renovation processes into predictive, AI-driven paradigms [41].

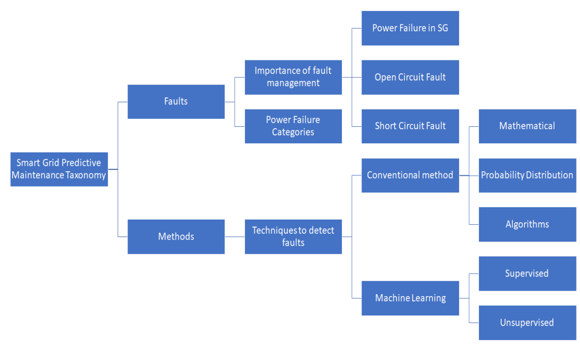

Figure 10: Smart grid predictive maintenance taxonomy [42]

1. Maintenance Task Dispatchment There are not just equipment that could be maintained better with the help of AI, human and human-related tasks could also be optimized with the usage of my intelligent dispatchment system. There are frameworks aim to optimize worker dispatch by ensuring all workers are fully utilized, prioritizing the repair of devices with the highest severity levels, and minimizing the overall travel distance/time. We can also see there is the usage of 2 systems, Large-Scale Grid Using Genetic Algorithm and K-Medoids Clustering Methods:

- **Genetic Algorithm-Based Maintenance Framework (GAMF):** This framework employs an adaptive genetic algorithm to determine the optimal working path for each maintenance crew. It seeks to maximize the overall severity level of addressed faults while simultaneously minimizing the total travel time. By iteratively assigning workers one at a time, the GAMF ensures that the most critical devices are addressed efficiently, balancing the need for prompt repairs with the logistical constraints of travel time and distance.

- **With the K-Medoids Clustering-Based Maintenance Framework (KMCMF):** , This framework utilizes a customized K-medoids clustering method to group faulty devices into clusters based on their geographic location and severity level. Each cluster is designed to contain one of the top k severity level devices, ensuring that repairs are prioritized according to the criticality of the faults. This framework aims to distribute maintenance tasks among available crews in a manner that minimizes travel time and maximizes the efficiency of the repair process. [43]

As demonstrated by experiments conducted on real-world datasets from five different locations in eastern China: The K-Medoids Clustering-based Maintenance Framework (KMCMF), in particular, showed a slight advantage over the Genetic Algorithm-based framework (GAMF) in terms of eliminating aggregated severity levels of faults. For instance, in Hangzhou city, the KMCMF achieved an aggregate severity level reduction of 210 at a 20 km/h movement speed, compared to 204 by the GAMF. Similarly, in Cixi city, KMCMF managed an aggregate severity level reduction of 213, showcasing its efficiency in addressing severe faults more effectively than other strategies, including traditional methods like Highest Severity First (HSF) and Shortest Path First (SPF).

2. Energy Generation

There are multiple sources of energy generation. Not only could the AI empower the traditional fossil-based power plants, renewable sources such as the wind power, AI could bring positive change to their improvement. We can see in the case of wind turbines, we know that wind energy is recognized as a crucial renewable energy source, but it faces challenges in operations and maintenance (OM) due to operational inconsistencies and the complex nature of wind turbines. The research highlights the importance of condition-based monitoring (CBM) and performance assessment for effective OM planning and cost reduction. It notes the shift from traditional signal processing methods to the application of AI techniques, particularly deep learning, in the wind industry over the last decade.

Initially, the focus was on signal processing and vibration analysis for turbine health monitoring, utilizing techniques like Empirical Mode Decomposition (EMD) and Spectral Kurtosis (SK) for fault detection. This period saw limited AI application in performance assessment rather than fault prediction. There has been a significant shift towards using AI, especially machine learning and deep learning models, for both CBM and performance assessment. This includes regression and classification techniques for predicting operational parameters and identifying faults, as well as deep learning models like Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) for more sophisticated data analysis and prediction. There's also an exploration of Natural Language Generation (NLG) for generating human-intelligible maintenance reports and reinforcement learning for OM planning and optimization. The research with the wind turbines emphasizes the potential of AI to revolutionize OM practices in the wind industry by making wind energy sources more reliable and efficient. It calls for continued research and development in AI applications, addressing existing challenges to fully harness the benefits of data-driven decision-making in the wind sector. [39]

3. Overall Lifespan Management of Grid

If we zoom out to the see the entire grid, with regard to operation and control, maintenance and lifespan management, grid planning and design, and metering in Smart Grids, there are extensive references to the use of AI, including machine learning models like support vector machines (SVM) and neural networks for predictive analytics and fault detection. The application of big data analytics for handling the vast amount of data generated by smart meters and sensors. Simulation tools and optimization algorithms, such as mixed integer linear programming, are discussed for grid planning and design decisions.The research also highlights the use of communication standards like IEC 61850 for interoperability among smart grid components.

It also emphasizes the significance of asset management and monitoring, exploring strategies for maintenance and risk management to enhance grid reliability and efficiency. The metering section examines the advancements in metering technologies and control equipment, focusing on demand response strategies and the interactions between metering systems and customer installations. This includes an in-depth analysis of the impact of smart metering on utility operations and customer engagement. [44]

4. Grid Fault Type and Occurrence Prediction When it comes to detecting the fault types including common occurrences, such as a line-to-line fault (LLF), a three-phase-to-ground fault (LLLGF), a single line-to-ground fault (SLGF), and a double line-to-ground fault (DLGF) (each with its unique characteristics and implications on grid performance), AI can also help improving the prediction,

We can see the increasing reliance on Internet of Things (IoT) innovations and the critical role of smart grids in meeting the global surge in energy demand. Through a systematic review spanning eight years (2012-2020) and analysis of 65 selected studies, the research whos the evolution and significance of predictive maintenance in line with the Industry 4.0 revolution. Traditionally, there are:

- **Infrared Thermography-Based Technique with Multilayered Perceptron (MLP):** A non-destructive method utilizing AI to analyze infrared thermal images for early fault detection.
- **Traveling Wave Fault Location:** Utilizes the principle of wave reflection and transmission to pinpoint fault locations, requiring precise data capture devices and GPS for effective fault localization.
- **Impedance-Based Method:** A commonly used technique for fault location through the analysis of

impedance measurements, notable for its simplicity and cost-efficiency, etc.

Right now with the introduction of Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest, and Recurrent Neural Networks (RNN): These methods offer advanced capabilities for fault prediction and classification by learning from vast amounts of data, showing promise for enhancing predictive maintenance strategies.SVM has a noteworthy coefficient of assurance esteem of 0.75.[42]

5. Hardware Equipment Predictive Maintenance

One of the most commonly used components is the Voltage Switchgear. This could be a symbol of how the AI might help the hardware maintenance. When it comes to Medium Voltage Switchgear, there are also many innovative approaches to help with their predictive maintenance. The approach outlined in the research involves the integration of various types of novel sensors that monitor different aspects of switchgear condition, such as thermal, mechanical, and partial discharge indicators. These sensors enable continuous condition monitoring of critical grid assets, providing a wealth of data that reflects the real-time state of the switchgear. To process and analyze this data, the research advocates for the use of machine learning algorithms. These algorithms can sift through the collected data to identify patterns, anomalies, and predict potential failures before they occur. By doing so, the research suggests that predictive maintenance strategies can be significantly improved, leading to enhanced grid reliability and efficiency.

The technical algorithms and tools discussed in the research are centered around machine learning for predictive maintenance, specifically highlighting the use of Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest, and Recurrent Neural Networks (RNN) for advanced data analysis and fault prediction. These machine learning methods are capable of processing complex and varied data from sensors to make accurate predictions about equipment health and the likelihood of future failures. This predictive capability allows for maintenance to be scheduled proactively, reducing downtime and preventing catastrophic failures. [41]

Meanwhile, Terminal equipment also shares similarities in the benefits it get from AI. Within an integrated energy system (IES), which has become increasingly complex with the incorporation of renewable energy sources, active loads, and the need for large-scale regional interconnection, terminal equipment also has a high stake in running smoothly. Deep learning models such as Convolutional Neural Networks (CNN) and other unsupervised learning models like Deep Belief Networks (DBN), Stacked Autoencoders (SAE), and Restricted Boltzmann Machines. These models are applied to predict and evaluate the health status of integrated energy systems, focusing on aspects such as terminal equipment operation and fault diagnosis.

The integrated energy management system described in the research encompasses both the energy integrated management and control center system and the monitoring system for distributed energy sources and load monitoring, including building energy management and control systems, charging station monitoring systems, and user energy consumption monitoring systems. The system aims to improve the overall energy efficiency, economy, and stability of regional energy systems by enabling multi-energy complementation and optimal dispatching. [45]

Collaboration and Regulation

The global landscape of AI research and deployment in smart grid maintenance exhibits disparities, with higher socio-economic countries often at the forefront due to greater access to financial and technical resources [43]. This imbalance underscores the importance of fostering interdisciplinary collaboration as a means of democratizing AI advancements in smart grid maintenance [41]. By bridging diverse fields of expertise, such collaborative efforts ensure that the transformative potential of AI is realized across different regions, thereby enhancing global energy resilience and sustainability [45].

The regulatory and policy frameworks governing the use of AI in smart grid maintenance are critical for ensuring that these advancements are leveraged responsibly and ethically [39]. As AI technologies become integral to smart grid operations—predicting failures, optimizing maintenance schedules, and automating control processes—the need for stringent oversight to address data privacy, security concerns, and ethical implications becomes paramount [42]. Regulatory bodies are thus challenged to keep pace with technological advancements, crafting policies that not only foster innovation but also safeguard public interest and promote equity in AI's application to smart grid maintenance [43].

AI's empowerment of smart grid maintenance offers a pathway to revolutionizing how energy systems are managed and operated [41]. By leveraging AI and ML algorithms, energy providers can transition from reactive to predictive maintenance strategies, minimizing downtime, extending the lifespan of grid components, and ensuring a stable energy supply [45]. However, achieving this vision requires a concerted effort to address the ethical considerations inherent in AI deployment, such as algorithmic bias, data privacy, and the socio-economic impacts of automation [39]. Stakeholder engagement and ethical guidelines are essential for navigating these challenges, ensuring that AI solutions are developed with transparency, accountability, and fairness at their core [44].

Communal and Ethical Considerations

The adoption of AI for predicting system failures, refining maintenance schedules, and boosting the overall efficiency and reliability of smart grids introduces ethical dimensions that necessitate meticulous scrutiny [43]. Addressing the inherent biases in AI algorithms, protecting data privacy and security, and contemplating the socio-economic effects of automation on the workforce are imperative [44]. These issues underscore the necessity for a holistic deployment strategy of AI in smart grid maintenance that thoughtfully balances technological innovation with ethical considerations and the well-being of society.

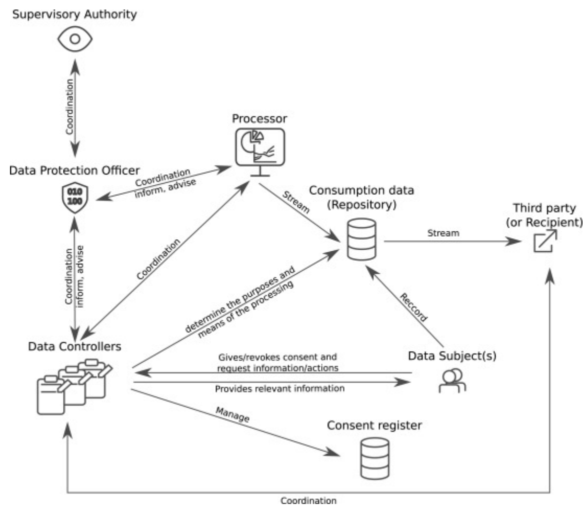

Figure 11: The ethical smart grid: Enabling a fruitful and long-lasting relationship between utilities and customers [46]

In response to these ethical challenges, the formulation and implementation of AI solutions in smart grid maintenance are progressively being steered by comprehensive ethical guidelines. These guidelines aim to emphasize the significance of transparency in AI decision-making processes, allowing stakeholders to comprehend the basis of decisions fully. The accountability for the outcomes of AI systems represents another fundamental aspect of these guidelines, necessitating those behind AI deployment to take responsibility for their actions and any unforeseen consequences. Moreover, ensuring fairness in AI applications is critical, preventing the perpetuation of existing inequalities or the introduction of new forms of discrimination.

Achieving these ethical objectives mandates engaging with a wide array of stakeholders. This involvement includes regulatory bodies, consumer advocacy groups, employees, and the general public in dialogues regarding AI's deployment in smart grid maintenance. Such engagement is crucial for developing AI solutions that not only satisfy technical and operational requirements but also resonate with societal values and expectations. It guarantees that the advantages of AI are equitably shared across society and that the employed technologies reflect a consensus on ethical standards and societal objectives.

Furthermore, as AI reshapes smart grid maintenance, there lies an opportunity to reassess and bolster the ethical frameworks guiding technological innovation in the energy sector. Encouraging open discussions among technologists, policymakers, and the public, the sector can navigate the ethical complexities associated with AI and machine learning. This collaborative approach is vital for fostering trust in AI solutions and ensuring that the shift towards AI-enhanced smart grid maintenance is universally perceived as a step forward towards a more efficient, dependable, and sustainable energy future.

In summary, the communal and ethical considerations tied to deploying AI in smart grid maintenance are of utmost importance. They necessitate a concerted effort to ensure that AI technologies are developed and implemented in ways that are transparent, accountable, fair, and aligned with societal values. As the energy sector increasingly relies on AI to improve smart grid maintenance, it is imperative to steadfastly adhere to these principles, ensuring that technological progress positively impacts society and upholds the highest ethical standards.

Future of Field

The research discusses the ongoing challenges of data availability and quality, the lack of transparency in AI models (referred to as the "black-box" type), and the challenges of more sophisticated models using it for real-time decision support Strategies to address these issues include improving the quality of the data, interpretable AI techniques Improved scalability and ability to integrate AI models to air turbine OM real-time. [39]

The combination of AI and smart grid maintenance is not just a step up but a leap toward a future in which energy systems are more reliable, efficient, and inherently sustainable [39]. This emerging field of AI-powered systems maintenance faces significant change, with the promise of AI technology to [44] redefine traditional maintenance paradigms as we look ahead to this field, which is as important as AI The potential for improvement is clear, with the promise of better maintenance options, increased reliability of the power system, and significant [42] reductions in operating costs.

The future of this industry is also ripe with opportunities that extend beyond technology, into the legal and ethical aspects of implementing AI as AI technologies become more integrated into energy systems, ensuring delivery AI will play a role in ethics, protecting data privacy, AI The need for a robust regulatory framework that also protects against potential biases in algorithms is growing Addressing these challenges requires strategies diversity combining technical expertise with insights from legal, ethical and social issues

In the future, the advancement of AI in smart grid maintenance is anticipated to play a pivotal role in shaping a sustainable and efficient future for energy systems. By leveraging AI to enhance predictive maintenance, energy providers can significantly reduce operational costs, improve system reliability, and minimize environmental impact. This vision for the future underscores the importance of continuous innovation, skilled AI professionals, and collaborative efforts across various stakeholders to navigate the complexities and realize the full potential of AI in energy system maintenance.

In conclusion, the integration of AI into system maintenance represents a paradigm shift towards a more sustainable, efficient, and reliable future for energy systems. The journey towards achieving this future is multifaceted, encompassing technological advancements, regulatory and ethical considerations, and the need for cross-disciplinary collaboration. As the field of AI-driven maintenance continues to evolve, it promises to usher in an era of unprecedented efficiency and sustainability in energy system management, marking a significant milestone in the quest for a more sustainable and resilient energy future.

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Broader Ethical Implications

Ethical Consideration: Digital Security

In looking at the smart grid as a whole, one must undertake ethical evaluations of energy digitalization and system optimization through artificial intelligence. Its implications are widespread: in accordance with the Global and United States Smart Grid Cyber Security Market Report, the cybersecurity industry specifically for defending electrical grids is expected to grow from $4.729 billion in 2022 to $8.562 billion by 2028. This security increase is primarily due to the lucrative amount of business being conducted through electrical networks, which has subsequently seen an increase in the amount of attacks in recent years. A report by the United States' Department of Energy (DOE) claimed to have seen a rise in physical attacks over 77% in 2022 [47], and IBM recently released a Threat Intelligence Index report, which stated that the energy sector was the fourth most cyber-attacked industry (Gregory, 2023).

The introduction of artificial intelligence research into the energy sector can help alleviate a good proportion of the manual inspection it takes to uncover attacks. Such **impacts** can be more quantitatively measured by the usage of performance indicators (precision, recall, AUC) against benchmarks, such as existing mathematical models used within the smart grid or digitally-unrealized electrical grid simulations. The **challenge** of such an impact, however, relates to the relatively volatile and quick-evolving nature of machine learning as a field. Concerns have risen with respect to the attacker's ability to read about grid detection attack countermeasures through online literature. While such information can be privatized, this only makes entry into the field more difficult for its application and individual study. Therefore, AI models and their impact predictions should take into account attackers' responses during training phases.

While there are many ways to integrate AI into electrical systems to detect cyber attacks, the methods ultimately chosen need to be computationally inexpensive. Two main methods that have been explored include supervised machine learning and deep learning algorithms. While deep learning (DL) is on average able to compute more granular features from the input compared to shallow ML models, it requires much more data and layers in order to produce such results, thereby increasing its overall computational power. Therefore, it is worthwhile to research what kinds of AI models are best suited for specific kinds of cyber attacks.

Experimental evaluations are often split up by the type of cyber attack. Figure 12 summarizes some of the most common attacks featured in the literature [48]:

Attack	Abbrev.	Description
False Data Injection	FDI	Inject false data or interfere with meter measurements on the grid: can evade bad data detection (BDD) systems
Denial of Service	DoS	Limit grid communication: manipulate protocols or flood device/channel with data
Coordinate Cyber-Physical	CCPT	Physically trip a transmission line, forge an output signal from that line
Dataframe	DFA	Confuse control center about where an attack is coming from
Man in the Middle	MitM	Interrupt measurement, modify its data, and pass it off as the sender
False Command Injection	FCIA	Inject control commands that disrupt operations
Replay	RA	Steal information on a line to then sell that data

Figure 12: Types of Researched Attacks and their Descriptions

The most commonly-studied types of attacks include some form of malware injection or denial of service. For FDI attacks specifically, **experimental evaluations** when applied with AI have found that deep learning has some of the more provided promising results [48]. However, because neural networks rely on more transmissions to and from a data center to operate on a large scale, this situation is prone to data leaks. Subsequent literature has desired to find a distributed approach to help with this. One promising evaluation tested a model that served as a combination between transformers and federated learning. Using a dataset comprised of weak attacks, which often go undetected due to their relative similarity to normalized data, the results proved to be effective, achieving a precision and recall score of 0.9995 and 0.9938 respectively [49]. Research of AI integration has gone just beyond the direct detection of the attack, however. In relation to FDI attacks, existing detection mechanisms such as bad-data-detection (BDD) models are not able to fully detect all injections. This is partially due to the fact that FDI attacks operate on supervisory control and data acquisition (SCADA) systems, which have numerous interconnected components. Attackers can inject false data into any one of these points or make their adaptive measurements look legitimate, which often makes it difficult to decipher. One model in particular suggests the usage of an Ensemble CorrDet, which is sophisticated in that it is tested against real-life systems, specifically using the IEEE 118-bus system. By using matrix identities and adaptive statistics, the algorithm achieves a 99.35% accuracy [50].

Denial of Service (DoS) attacks are another widely studied attack due to their popularity among perpetrators and also the variance by which they can be employed. Such attacks can be targeted to a single agent (DoS) or multiple agents (DDoS), and the underlying attack can compromise one or more types of protocols being used by that energy grid's region, including TCP, UDP, and HTTP. Researchers even go as far as to split up these attacks into whether they attack the cloud-based data (EDoS) communication protocols or the application itself (ADoS). Due to their consistent upbringing in cyber-security, more simplified pattern recognition models in the realm of supervised machine learning have often worked well for DoS attacks [51]. This result was discovered after Aldhyani's team led an experiment that analyzed the best way to discover EDoS attacks. The group looked over a variety of methods, including supervised learning (SVM), unsupervised learning (KNN), reinforcement learning, and deep learning (LSTM Neural Networks). In the end, the results demonstrated that supervised SVM achieved the highest accuracy for multi-classification of DoS attacks, around 97.56% . An additional study was done to expand beyond EDoS classification and into other forms of Denial of Service attacks. The group tested SVM, decision tree and naive Bayesian network classification algorithms to discover that, similarly, supervised learning models such as SVM proved better over neural network approaches [52].

Attacks need not be purely software-based. CCPT attacks are an additional growing attack that combines a physical attack to cause more chaos across longer-sourced sectors of the energy grid. Because detection of such attacks requires the fine-tuning attention span of identifying forged data while also studying the macro-levels of systems across the entire grid, ensemble methods between machine learning and deep learning have proven beneficial for this field. One study in particular proposed an Ensemble Representation Learning Classifier (ERLC), which uses a decision tree classifier, a random forest classifier, and a feed-forward artificial neural network. In examining the performance of this model on dozens of attacks and fault scenarios, ERLC was able to achieve a classification accuracy that was 2.63% higher than standalone classifiers, such as random forest [53].

Due to the field's importance and the sudden popularity of AI model integration, detection of energy attacks has been mostly solved and explored in recent years. Regardless, **future explorations** of digital security managed by ML and DL models can be examined from a variety of different lenses. Some attacks, such as Load-Altering Attacks, are less present in the literature and as such have the potential to be further explored. Moreover, most of the incorporation of AI into energy security has been for detection and less for the automation of finding the perpetrator and updating software in light of the information gathered around the attack. Such mechanisms can be further explored through interdisciplinary collaboration with feedback across industries. Within detection itself, most of the proposed models can only identify one or a subset of the dozens of types of attacks that have been defined in the literature. Such algorithms can be expanded upon to detect many attacks at once and operate under spatio-temporal changes (seasons, natural energy fluctuations/surges).

This continual exploration of AI revolves around research proposals and collaboration. One key challenge pertaining to the proliferation of knowledge aimed at detecting cyber attacks on energy grids is the potential for the perpetrator to find out about the defense mechanisms being researched and employed. This is especially an issue considering that many publications are available to the public. The primary act of defense against this is keeping research results encrypted behind authenticated access portals or restricted access control, by which a paper is only available through a trusted institution. In terms of securing data beyond just research protocols, many countries have suggested a wide variety of defense mechanisms to be implemented into the core structure of smart grids.

- **United States** The passage of the Energy Independence and Security Act provides the Federal Energy Regulatory Commission (FERC) and the National Institute of Standards and Technology (NIST) the ability to standardize smart grid security guidelines [54]. Some examples of this include anti-corruption task forces in resource-rich countries, monitoring any alterations related to energy grid changes in communication or electrification, and summarizing security reports.
- **Europe** A report offered by the European Parliamentary Research Service (EPRS) has found vulnerabilities in their continental energy grid systems, which have in recent decades begun to switch towards distributed renewable energy, sector coupling, and flexible demand algorithms [55]. The group recommends the energy sector be transformed into a more secure system characterized by the following: regular encrypted updates and audits, security and emergency plans for personnel, authentication protocols for physical and data storage, duplicated systems, a private network via which operations are carried over, and sharing when attacks happen with overhead figures so as to allow for a continuous feedback loop of recommendation and renewal.
- **Asia** The territories that cover Asia-major vary widely in their approaches to their respective energy sectors, yet complement one another in their challenges for security. Electrification of the area has become very rapidly adopted, however Asia's widely varying geographical features can cause many of these systems to be susceptible to disasters [56].

Figure 13: Precedence Research, Smart Grid Market Size in the U.S. 2023 To 2032

Despite its challenges, the field of AI integration into the energy sector does indeed pose many opportunities for the smart grid. With many of the proposed models successfully monitoring digital security, smart grids have been able to readily expand and receive investment in countries around the world. The United States, in accordance with Precedence Research, is predicted to grow its smart grid size by around 400% in the next 10 years [57]. Worldwide, cybersecurity advancements have been projected by Statistica to increase overall revenue by 10.56% annually [58]. Moreover, with nearly 67% of organizations worldwide reporting staff shortages (Smith, 2024), there exists large room for employment and job growth to enter into the industry to maintain security for the energy sector.

Ethical Consideration: Research Collaboration

Another ethical consideration relates to the funding itself. Because a large percentage of the aforementioned research has originated from countries that have the resource-capability to fund such experiments, the majority of the reference papers received funding through national grants and foundations. Inter-regional collaboration is more common than across larger continental boundaries. Those that do exist across continents are often divided between Western-European, Eurasian, or Asian-Pacific connections.

A large proportion of this skewed collaboration is due to the relevance of the energy sector in each region at the time of the research proposal.

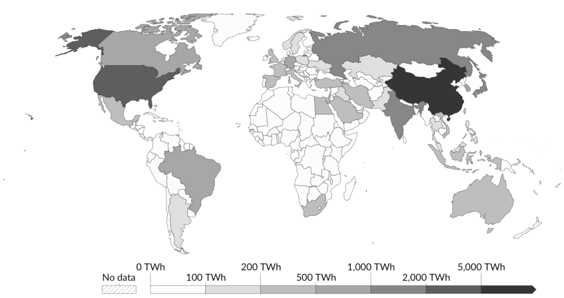

Figure 14: Our World in Data, Current Primary Energy Consumption, 2022 measured in terawatt-hours, using the substitution method.

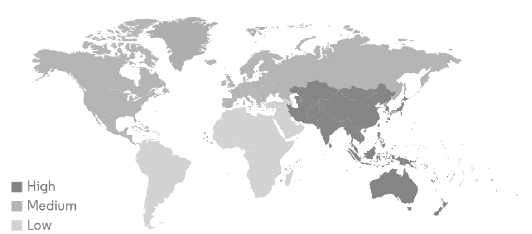

Figure 15: Fig. Mordor Intelligence, Smart Grid Network Market Growth Rate Projection by Region, 2022-2027

At the same time, research beyond regional borders is critical to the overall vitality of findings. The areas most lacking in pioneering research are predominantly found in the Global South, where the electrical grids operate under different standards and geographical constraints compared to other continental regions. On that note, research is also more prominent in the Global North as it geographically correlates

Region	Oil/Gas/Goal	Nuclear	Hydro	Wind	Solar
Asia	87.15%	2.16%	5.85%	2.66%	2.18%
Africa	90.30%	0.45%	7.29%	1.11%	0.85%
Austr.	86.15%	0%	2.71%	5.00%	6.14%
Europe	77.48%	8.79%	6.59%	4.95%	2.20%
N. America	81.74%	6.93%	5.51%	3.96%	1.85%
S. America	65.89%	0.08%	27.13%	4.28%	1.89%

Figure 16: A breakdown of each region's consumption of energy in the year 2022 averaged over available country data. Measured as a percentage of all the categories listed, rounded to the hundredths. Source: [60]

with being the source of the majority of emissions. A report published by the IEEE demonstrated how South American countries faced higher levels of distribution losses due to the stagnation of quality-service indices since the 2000s [59]. Nicaragua, for example, had losses that incurred around 1.7% of their GDP. With many research publications centered around high-tech solutions related to physical **storage and distribution** materials and methods, there also needs to be discussion related to how this can be achieved at low cost and with existing infrastructure that has not necessarily been updated.

Beyond physical system health, there exists noticeable variability in electricity sources across countries, as seen in Figure 16. If we look at non-fossil fuel sources, some countries focus heavily on specific kinds over others, such as how Australia favors solar power and South America favors hydropower. Therefore, if research was mainly concerned with optimizing energy production on sources that favored the continents that the research was done in, areas with less research may be unfavorably affected. In other words, the research being done can't extrapolate its findings to other regions of the world because that research did not broadly relate to other kinds of geography, economic zones, and production types. As an example, because South America heavily invests in hydropower compared to other regions of the world, any research from Europe or North America that focuses on another source such as nuclear would not be as beneficial to the South American countries. Australia focuses a large proportion of its renewable energy on solar power, though this would be less studied in Asia where research into renewable energies and materials is more prominent, thereby creating an imbalance in demand.

Beyond just inter-regional differences, there is also a division within socio-economic contributions, as more wealthier countries are more predominant in the research, distribution, and scaling process, with other countries following behind. This often lends itself to an ever-growing issue of stifled innovation in less well-off countries, where existing research published is less monetarily feasible. Such nations often rely on imports of commodities that are researched and manufactured in order to utilize them efficiently, but the costs of development are partially reflected in the expensive import prices, thereby again reducing the ability of these nations to gain traction in these sectors.

Regardless of these differences, interdisciplinary collaboration that does exist does indeed play a nontrivial role in advancing AI for social good for smart grids. In its essence, it provides an adequate exchange of knowledge across varying cultures, economic status levels, and geographical constraints that allow for a more broad and in-depth consideration of the integration of artificial intelligence into the varying sectors of the energy grid.

Ethical Consideration: Regulation

The rapid expansion of artificial intelligence and subsequent innovation has outpaced legislation in recent decades. Regardless, ensuring fair foundational grounds for competition and business practice is crucial to the long-term viability of an economy. Therefore, the incorporation of artificial intelligence into the smart grid should be regulated within certain stages of the smart-grid pipeline.

Because industrial policies are best made or at least inspired by those who have knowledge of the sector the regulation is being imposed in, several research groups have proposed initial guidelines to help governmental figures in developing AI policies for the energy sector. One group proposes a visual decision-tree framework that entices policymakers to consider breaking up regulation into themes such as the type of AI implementation; level of innovation and interaction with other industries; overall timeline of the energy-AI proposal; existing regulation relating to the project of interest; and the level of flexibility, scalability, and complexity [61]. Regulation can be defined to either be adaptable to circumstances or more rigid, and the parameters being regulated can be overseen by governmental figures, voluntary industrial agreement, or a blend of both. The ultimate goal of such introductory frameworks is to help policymakers and stakeholders understand the rapidly evolving nature of the energy sector in relation to digitization. As with all regulations, such proposals should be cognizant of the potential upbringing of market failures (such as market power) and the need for their legislation to have the flexibility to combat these issues.

Beyond generalized regulation comes the need to understand more specific considerations such as the individual users and suppliers. For users, artificial intelligence policies should focus more on the demand side in offering **fair pricing** to all individuals. Within Europe, there can be proposals to extend the European Competition Law and EU General Data Protection Regulation to the domain of artificial intelligence for the continuation of fair pricing. In North America, this is already underway through a proposed Algorithmic Accountability Act of 2023, which requires organizations to assess all usage of artificial intelligence systems, which in the context of smart grid-based companies can extend to price predictions. While Asian countries vary wildly in their economic models, the ASEAN establishes guidelines for fair market pricing, which subsequently extends to the energy sector through machine-aided distribution.

The other consideration related to the supply-side should consider policies relating to the potential for **labor externalities** to occur. If machine-aided models suggest an optimized proposal for a new production location or more investment into certain production facilities, it can uproot certain communities whose lives revolved around that production site in the name of renewable development, economic prosperity, or a blend of the two. Automation has always been a looming threat to existing ways of labor. One particular publication by the International Labor Office of Geneva investigates this issue in depth and concludes that the best way to protect labor while optimizing production is to allow for workers to consult and manage job alterations and offer collective dismissals [62]. The European Economic and Social Committee's Opinion on Artificial Intelligence likewise proposes a "human-in-command" approach where any new incorporation of machines still allows for existing workers to be involved in the creation and operation of such technology [63]. Despite these regulations, innovations in ML will often occur before policies are enacted, and as such these policies need to be consistently and routinely updated to handle the ever-growing nature of technical accomplishments and threats.

Conclusion, Future of the Field

In its entirety, artificial intelligence integration into the smart grid offers a variety of benefits to its users and in all stages of the system. Several fields, such as optimizing production and energy storage, offer plenty of room for innovation in terms of perfecting the volatile nature of renewable sources. Other themes, such as demand response and digital security, are more focused on improving existing algorithms. Many of these optimizations must be explored on a variety of different layouts and scopes of grids. For example, decentralized grids, also known as autonomous energy grids (AEG), are a type of microgrid that can reduce the strain on centralized networks by allowing for smaller ports of energy consumption within a closer proximity to the end user. The advancements made in automating large grids across their varying energy sources can be succinctly applied to these smaller grids, but with an added need for digital security protection and discussion as to whether to standardize such decentralized systems. The future of smart grids is ultimately in the hands of individuals and companies who desire to see a change in the way our energy is produced, and as such machine learning can become a valuable aid in its ultimate progression.

Contributions

- **Madison Davis** Introduction, Paper Selection Version 2, Broader Ethical Considerations, Conclusion
- **Jerry Huang** Theme 5 System Maintenance
- **Andrew Palacci** Theme 3 Energy Distribution
- **Avery Park** Theme 4 Energy Demand, Paper Selection Version 1
- **Phevos Paschalidis** Theme 2 Optimizing Storage
- **Yiyi Wang** Theme 1 Optimizing Production

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