Integrating AI, Machine Learning, and Cloud Computing to Drive Innovation in Renewable Energy Systems and Education Technology Solutions

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Abstract

This document contains a summary of all the problems that have arisen, from the design and selection of equipment, to its installation and configuration. The selection of physical systems has been performed such that they allow inexpensive energy generation models. Two physical systems have been considered in fixed installations in the range of 5–10 kW and in mobile installations with a capacity of 1500–1600 W. All wind turbines include an aerodynamically designed horizontal axis with two blades. The selected generation systems have been designed to allow future portability. The selection of the final site of the installation has been a difficult task due to the local orographic variables (terrain, obstacles, etc.) as well as the mechanical protection of the systems against high winds. Regarding the grid connection of the model, there are still many aspects to investigate. The hardware chosen allows connection with any devices that send data over OPC. Communication through REST or MQTT protocols, as well as OPC UA connections can be completed. The installation of physical systems in off-grid sites poses additional problems for their operation. The constant monitoring of such physical systems is achieved with specific knowledge of programming languages.

In renewable energy systems that use intermittent energy sources, it is essential to have autonomous systems capable of adequately governing this energy management without the intervention of specialists. A method for incorporating leakage power consumption in smart systems operating in a hybrid environment is presented. The Hybrid Petri Net has been presented as a formal modeling tool. An algorithm for automatic hybrid synthesis was proposed. Analyses were conducted on case studies of smart environments, including home, smart grid, urban, and renewable environments. The hybrid model of the smart city was composed of more than 1000 places and transitions. The prospects for further research include the significant complication of the structure of hybrid systems. Developers will need to consider new properties of hybrid systems. The addition of stochastic processes will require time notation and will complicate the analyzers and simulators. Additionally, a system-inspired approach to easily understandable models will be developed, adding more processes that can work regardless of each other.

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1. Introduction

Education has transformed dramatically in recent decades, especially due to the remarkable advancements of modern technologies such as Artificial Intelligence (AI) and Machine Learning (ML) technologies. In recent years, companies and researchers have been trying to improve the quality of teaching by utilizing AI. With immense resources in public and private sectors directed towards R&D and implementations, AI has shown the promise of altering how students engage in learning, educators instruct, and educational institutions function. From virtual teachers to being integrated into tablets and platforms, AI exists in various forms, providing personalized learning paths suited to each student . AI techniques can be utilized to substitute or notify the instructors of students who possess a greater risk of falling behind. Built-in analysis tools provide analysis and insights for both instructors and students, promoting the efficiency of educational institutions. Besides the mentioned effects and differences from traditional education, there are concerns about using AI in education.

The rapid growth of AI technologies comes with a price. Unfair AI recommender systems can affect students' mental health by creating echo chambers around them; the abuse of private information can harm users, and the stagnant settings of AI recommender systems can alienate students altogether. Besides, there are constraints on the accessibility of AI in education. Publicly available models often require fine-tuning with domain-specific data so that they can work properly, and high computational and engineering costs are required for such settings and implementations. Meanwhile, not all methods from one field are practical in another field. This research focuses on the intersection of literature studies and introductory texts to develop an economical solution and provide an optimal preparatory stage for further investigation into larger and more domain-specific data. This research aims to provide low-cost literature analysis methods across a wide range of institutions or disciplines that can be easily replicated with little local staff or knowledge. In addition, the developed methods can be adapted for other use cases as well. Finally, it is concluded that with a limited amount of domain-specific data, an elaborate examination of the quality of targeted educational materials can be automated, which leaves educators with more efforts on instruction and facilitates further expert exploitation of the resources of text genres looked at.

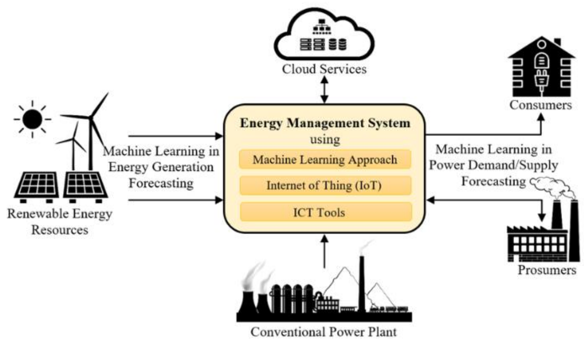

Fig 1: hybrid-renewable-energy system (HRES)

1.1. Background And Significance In recent years, Artificial Intelligence (AI) and Machine Learning (ML) have taken an overwhelming lead in various industries by providing faster solutions to challenging problems, supporting companies to enhance their operational systems and transitioning toward optimal operational situations. The convergence of AI, ML, Cloud Computing (CC), and the Internet of Things (IoT) provides a huge opportunity to analyze large sets of data from distributed sources. Furthermore, companies are turning to cloud service providers for infrastructure and software solutions to benefit from the rapid AI and ML developments while minimizing operational costs.

Due to the wide adoption of these technologies into the electricity industry, the need for educators to bring these advances into the classroom is quickly rising. Educators from engineering and computer science backgrounds need to collaborate with education specialists to fill the gap in a 3-tier view approach. The first tier focuses on educating engineering and programming skills, while on the second tier, students learn how to apply these skills on real-world problems such as Energy Management Systems (EMS), Distribution Management Systems (DMS), and so forth. Simultaneously, the upper tier builds curiosity toward the subject and motivates students to pursue related fields such as electrical engineering, autonomous programs, and AI and ML-infused studies. In their nature, these fields are very broad and require an interdisciplinary approach in their education. The infusion of computing abilities into various disciplines will engage students and provide them with industry-relevant skills.

This study focuses on renewable energy systems as a crucial part of the transformation toward a net zero-carbon goal. To succeed in this endeavor and drive innovative solutions, embracing AI and ML tools is a necessity. In parallel with the growing size and influence of energy systems, understanding these systems' behavior became more crucial than ever to uphold the security of supply, market efficiency, sustainability, and customer satisfaction. Traditional models for energy management system-related optimizations were proposed in various fields such as generation, demand forecasting, and pricing; however, most, if not all, are based on central optimization strategies with a lack of fairness in the computation process and the convergence to the global optimal solution .

Equ 1: Energy Trading Optimization

$$\max_{\mathbf{u}} \mathbb{E}\left[\sum_{t=0}^{T}(r_t \cdot u_t - C(u_t))\right]$$

Where:

- r_t is the revenue per unit of energy at time t
- u_t is the energy trading decision at time t,
- $C(u_t)$ is the cost associated with trading u_t

2. Overview of Renewable Energy Systems

Renewable energy systems on both microgrids and smart grids are crucial for curbing pollution and greenhouse gas emissions, as they help avoid using carbon-burning fossil energy sources and cut down carbon emissions. Renewable energy sources are environmentally friendly alternatives to fossil fuels and are unlimited and inexhaustible. These include biomass, wind, hydropower, geothermal, and solar energy. Renewable sources can produce electrical, thermal, hydraulic, and chemical energy. However, accurately forecasting renewable energy production is crucial since production depends on unpredictable and irregular weather conditions . Another challenge is that green energy production is not always aligned with conventional energy consumption. Renewable energy storage systems balance production and consumption. Energy storage management, just like renewable energy consumption modeling, is a combinatorial or multi-criteria optimization problem.

Machine learning methods are promising for dealing with uncertain scenarios, massively increased design space, and high data demand in renewable energy systems and energy management. Machine learning (ML) models have found widespread utility across various aspects of energy systems, particularly in forecasting electrical energy and renewable energy demand and consumption. These models offer pathways to enhance energy efficiency and reduce costs in the energy sector. Accurate energy consumption and demand predictions generated by ML models can be harnessed by building commissioning project managers, utility companies, and facility managers to implement energy-saving strategies. ML models also serve load forecasting, power generation prediction, power quality estimation, time series forecasting, wind speed projection, and power demand anticipation. The prediction of building energy consumption holds paramount importance in shaping decisions aimed at curbing energy usage and CO2 emissions. The developments of the Internet of Things (IoT), Cloud Computing, Big Data, Artificial Intelligence, and Cyber-Physical Systems have ushered in the Fourth Industrial Revolution. Systems' cyber and physical layers are integrated into a turnkey solution in M4IR, ushering in new energy and industrial transformation settings of smart energy and industry.

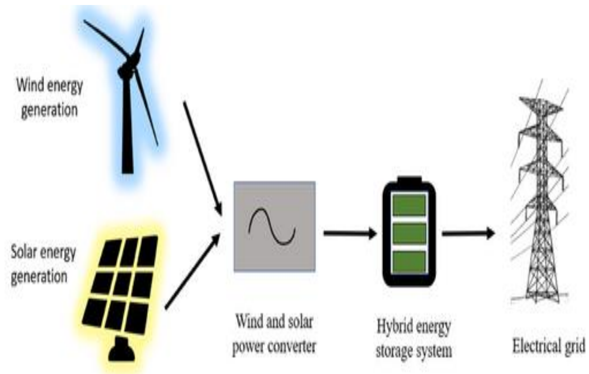

Fig 2: Overview of energy storage for renewable energy

2.1. Current Trends in Renewable Energy The World Energy Outlook Report indicates an enduring interest in renewable energy sources in contemporary societies. Despite widespread claims of a global shift in energy resources, fossil fuels continue to dominate, with nearly 86% reliance on fossil fuels and a mere 13% yielding from renewable sources in comprehensive energy production . Concerns regarding fossil fuel extraction and the consequent imminent exhaustion of resources have prompted a pursuit of alternative energy resources for the future. As a clean and inexhaustible resource, renewable energy is now receiving increasing attention globally. Nonetheless, it is primarily characterized by intermittent resource production and grid incompatibility. Therefore, it is imperative to enhance the reliability and sustainability of renewable supply systems and to develop more flexible production methods. Achieving competitive deployment of renewable energy resources is now on the agenda of governments and decision-makers all over the world. Organizational design, which directs a firm's structures, systems, and behaviors, can affect the industries' processes through its nutritional mechanisms and deployment factors. Business management boards, institutional design, the process of strategic performance dependencies, resource allocation decision-making, and external intervention have all been discussed. To achieve energy empowerment, it is imperative to have a strong design, governance, strategic orientation, and e-business model of foresight in urban energy systems. Would-be producers of decentralized energy and/or integrators of renewable energy resources should be cognizant of the stakeholder partnerships needed to be developed. Business examples of multi stakeholder partnerships in energy systems ought to be shared in education networks along with best-practice solutions.

2.2. Challenges in Renewable Energy Adoption Rising energy demands, environmental concerns, and climate change have forced industry and academia to seek alternative energy sources, especially renewable. Factors like abundant supply, continual availability, no environmental degradation during use, and low-impact manufacturing processes make renewables attractive. Renewable Energy Sources (RES) that satisfy these conditions include wind, solar, geothermal, hydropower, ocean waves, and biomass. Efforts are being made to harness and exploit RES via intelligent systems, new technologies, equipment, infrastructures, and integration mechanisms with existing energy systems .

Despite the significant benefits of Renewable Energy Strategies, such as reduced reliance on fossil fuels, safeguarding human wellbeing and environmental health, protection against resource shortages, and greater energy diversification, there are emerging challenges associated with their effective use and implementation. Scholars have attempted to address these issues, which are various in nature and require diverse solutions. Seven major challenges have been identified with significant effort put forth in academic literature to analyze and offer procedures or tools to effectively tackle them. Dealing with these challenges is crucial to deploying Renewable Energy Technologies solo or in hybrid configurations.

RE deployment technologies have complex economic considerations and market rules affecting their performance. These conditions increase the complexity of analyzing RE systems and designing and optimizing smart solutions. Smart solutions depend on the autonomous and effective operation of installations. However, there are many issues to be resolved to achieve complete autonomy, such as the lack of standard considerations, a precise model of how to perform autonomous decisions or actions, and rules governing the performance analysis and evaluation of autonomous upgrades.

Equ 2 :Predictive Maintenance

$$\hat{T}_{\text{failure}} = \int_0^{\infty} \left(\sum_{i=1}^{n} \lambda_i(t) \cdot \mathbf{S}_i(t) \right) dt$$

Where:

- $\hat{T}_{\text{failure}}$ is the estimated time to failure,
- $\lambda_i(t)$ is the failure rate of component i at time t,
- $\mathbf{S}_i(t)$ is the sensor data indicating the health of component i.

3. Introduction to AI and Machine Learning

Artificial Intelligence (AI) is a field of study in which machines are developed to mimic human capabilities such as reasoning, reasoning and thought, perception, sensory experiences, and movement. Researchers in AI explore how humans solve problems. With this knowledge, capability is embedded into machines. Broadly, machine learning is the sub-field of AI that provides tools necessary for computers to exhibit human capabilities. This requires data to represent the experience of the world and a learning algorithm to produce knowledge from the data. By studying and experimenting with machine learning, a computation-based system is tested for how much it can improve its experience at the real world task. The field has greatly flourished since then, as does its applications. Engineers in other fields now employ computational techniques which utilize machine learning. Such disciplines include, but are not limited to: oceans, the atmospheric sciences, traffic systems, power system management, geological processes, protein design, and medical diagnostics. There are several online teaching modules working on machine learning in education. Cloud providers provide free online tutorials on how to use their machine learning services. Some believed these online modules would expand the reach of this technology; however, demand for the education of how to utilise them, particularly for those who do not come from a computer science background, is increasing fast. In fact, a joint report states that machine learning engineering is the 4th largest growing field in the job market. AI can positively or negatively enable the 2030 Agenda for the United Nations Sustainable Development Goals (SDGs). An analysis of the positive capabilities includes better planet and climate management, better energy systems, good governance, and social justice. Negative impacts can include the denial of food because of geolocation, a perpetuation of prejudice in work or hiring systems, and the ability to further surveillance states through facial recognition systems. Academia will need to incorporate aspects of machine learning and/or data science into its curriculum pipelines. A future workforce trained in such a manner will be able to better integrate AI into engineering solutions that consider both the positive and negative impacts. AI will also be able to be better integrated into educational technology solutions.

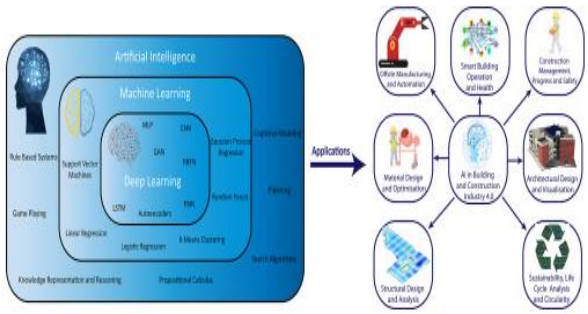

Fig 3: AI and Machine Learning

3.1. Fundamentals of AI Artificial intelligence (AI) is transforming our lives from several perspectives, impacting every aspect of our daily lives and reshaping the future in and outside of the classroom . However, the fast-growing applications of AI in business, industry, and community practices are far ahead of the education curricula, which fall short in addressing education on AI creation rather than consumption. This creates a huge gap between education and industry practice, leading to many students being unprepared to be AI creators, practitioners, and engineers in the future. Consequently, the ability to create advanced intelligent algorithms and architectures is to be defined as a 21st-century core competency equivalent to math and computer programming literacy. However, the existing algorithms and frameworks for achieving such a definition require a lengthy period of training, valuable experience accumulation, and large resources to practically implement AI in valuable systems.

Making the deployment progressively smoother and easier while maintaining the created models even without coding knowledge is of utmost importance to aiming for accelerated AI education. To start educating AI from scratch in ways that anyone can create deep learning contracts while learning fundamental principles, heartly understanding black boxes, and such massive work products can be effectively designed in 21st century K-12 education. However, the first step to such a tremendous effort, which is comprehensive research of K-12 AI projects or tools worldwide, has been little effort so far. This proposal aims to fill this software gap in the existing literature by gathering and presenting interactive projects that are useful for teaching and learning AI-related topics at early education levels and programming knowledge levels.

3.2. Machine Learning Algorithms This section provides a review of the fundamentals of machine learning algorithms. An online approach is presented to decrease the electricity consumption of energy-driven or data-center-driven systems. Almost avoidance of meetings or delaying a meeting while knowing that such a time interval has no free resources is suggested as rules. For this purpose, linear programming with multiple constraints is combined with a heuristic random search algorithm. A central resource manager tries to autonomously do maximum possible efforts to minimize the consumption. However, it is shown that such autonomic strategies may behave in a greedy manner and will possibly cause disorder in meeting serial scheduling. Therefore, a concept of fairness, where pursuing the Global Optimum and computing all resources can be the perfect solution to an optimization problem, is discussed. Its relation to controllability is elaborated. In contrast, most states of a system are bad states, and the actual state of such systems tends to approach the Bad State Traffic Jam is discussed in detail .

The energy consumption level of a meeting-holding system with shared resources is formulated as a multistate resource consumption polynomial. Two cases of exact, possibly ill-posed, and heuristic polynomial systems are theoretically investigated to ensure that the hardness might come not only from causality. Swarm intelligence of users in data-center-driven systems and smart grid consumption in collaboration of teams of engineers faces the tradeoff between efficiency and fairness. It is finally discussed that the lack of incentives could lead to emptiness of newly available meeting times, and either due to selfishness or stigmatization a division of a collaborative group might form. Many questions remain on how to scale up the soft constraints implemented in this work, like how to tune models for fairness, or how to implement a load-balancer with thresholds, and to preassign room credentials. Much larger, faster, and more scalable models could also be built from basic recursive equations on degree level with explicit state transitions. Enjoy smooth meetings with your colleagues!

4. Cloud Computing in Modern Applications

Cloud computing provides computing storage, and processing power as services over a network. Resources are shared and thus more elastic which means customers are charged according to demands . Based on the location of services, the cloud can be segregated as public, private, and hybrid clouds. Public clouds offer services to various clients, while private clouds are operated within a single organization. A hybrid cloud is a combination of public and private clouds. Direct connection to the private cloud is provided via leased and secure lines, while the public cloud is connected via a direct Internet connection.

The significant advantage of cloud computing is “Pay per use”, where a client can rent or lease a service from the cloud provider. This means clients can scale their business without making upfront infrastructure investments. On the other hand, cloud computing raises concerns over security, scalability, and reliability.

Infrastructure as a service (IaaS), Platform as a service (PaaS), and Software as a service (SaaS) are the three service models offered by a cloud with IaaS being the lowest level service. SaaS applications run in a cloud environment that is in control of the cloud provider and the end-user only interacts with the service via the Internet or thin clients and browsers. PaaS provides a platform to the development team for developing, testing, and delivering applications without worrying about storage, backups, or operating systems. IaaS provides hardware components as a service i.e. computing resource storage and networking.

With the growth in the Internet of Things, many smart devices like watches, smart air conditioners, and LED bulbs have become a part of one's life. These smart devices monitor health parameters, air and water quality, and power consumption via sensors. A cloud-based application is hosted on a cloud, which is used to store and process health-related data. With the user consent, the data gets shared with various organizations for research and analysis. Users can view the processed data on the cloud or on a mobile application. All computation is performed on an end-user device. Thus all the processing is done using the device memory and users do not need to rely on clouds to process their data.

Fig 4: Artificial Intelligence(AI) in Cloud Computing applications

4.1. Cloud Service Models The cloud computing paradigm serves as the foundation for providing cloud-based services and is emerging as a new business model that empowers the energy management of smart grid infrastructures. A cloud service acts as a single service that provides accessibility, storage, scalability, and interoperability to a vast number of utility companies and vendors worldwide . The rapid deployment of cloud services leads utility companies to store enormous data from smart grid infrastructures in the cloud to be processed as a service. A typical smart grid is a complex system for linkable infrastructures collecting a huge amount of complex data worldwide. With enough data processing, the cloud can provide an intelligent and strategic advantage in the competitive smart grid market to make predictions that significantly improve the maintenance and operation for smart grids.

A smart grid is based on interoperable technological devices, electronic equipment, and worldwide standards so that all services can be harmonized and easily managed. A set of cloud services capable of optimizing interoperability through the automatic and dynamic configuration of API connections among intelligent devices deployed worldwide must also be provided by the cloud service provider. The cloud must enable (1) monitoring consumption worldwide, (2) defining services that use energy monitoring consumption data, (3) automatic extraction of clients, (4) specification of connection parameters, (5) use of APIs for providing optimized driver connection, (6) simplification of communications, and (7) monitoring of services worldwide. The issues of smart grid monitoring and services are the focus of the design and implementation of cloud services, aiming to provide a model for managing consumption information stored in the cloud.

Historically, cloud computing has been a significant technology trend in Information Technology (IT) processes and reshaping the IT marketplace. Cloud computing signifies a model that allows on-demand network access to a shared pool of configurable computing resources to store applications and services that can be rapidly provisioned and released with low management effort or service provider interaction . At a service level, the cloud provides hosted services and applications over the Internet. Cloud-enabled solutions offer significant cost reduction by sharing resources, increasing efficiency and flexibility, and optimizing the business model.

4.2. Benefits of Cloud Computing Benefits of cloud computing for educational institutions such as schools, colleges and universities is discussed in this paper. Education today is becoming a more significant part of Information Technology for content delivery, communication, collaboration than ever before. The need of Servers, storage, and Software is very demanding in universities, colleges and schools. Cloud Computing is an Internet based Computing, whereby shared resources, Software and information are provided on-demand. IaaS, PaaS and SaaS are the business models for Cloud Computing. The paper reviews the features an educational institution can use from the cloud computing providers to benefit its students and teachers. The usage of Information Technology particularly Computers, Network, Internet, and Intranet by universities, colleges and schools for imparting Computer awareness, training programs, teaching and learning process is sharply increasing. For this, mainly Institutions have started investing in Infrastructure, Platform and Software. The infrastructure required is large i.e. Storage, Servers and Networking. Due to this demand, it is required to select the Hardware, Operating systems, Installation and Network Security etc by highly skilled System Admins. Education is entering into a very interesting world of Technology, where now they have started investing in Infrastructure, Platform, Software and Web Technologies. Information Technology for content delivery, communication and collaboration is becoming a more significant part of Education than ever before. Students' expectation is to view information on PDA, Tablets and Mobile Phones .

Equ 3: Energy Generation Forecasting

$$\hat{P}_{t+1} = f(\mathbf{X}_t, \mathbf{W})$$

Where:

- $\hat{P}_{t+1}$ is the predicted power output at time $t+1$,
- $\mathbf{X}_t$ is the input feature vector at time t,
- $\mathbf{W}$ represents the model weights.

5. Integrating AI and Machine Learning in Renewable Energy

The importance of renewable energy is growing rapidly as it plays a significant role in meeting global energy demand and ensuring sustainable development. New topics, challenges, advancements, and updates related to various aspects of renewable energy systems and grid optimization. The implications for the future of renewable energy are substantial. Based on the distribution, demand, and other characteristics of renewable energy sources, available data will be gathered. This data is used to formulate an appropriate network structure, followed by the application of a specific training algorithm to fine-tune the network's performance. Their assessment is conducted using test data, and their superior performance, as compared to other methods, is confirmed through a series of test processes.

With the rising concern regarding depletion of fossil fuels and growing environmental issues, there has been increasing interest in integrating renewable energy sources such as wind and solar into the conventional electric grid. The integration of renewable energy sources depends on the electricity production forecast of these resources in the next few hours. The influence of machine learning on energy systems spans various dimensions, with particular attention towards solar energy and wind power. Also, wind power production has garnered significant attention due to its advanced utilization in renewable sources. Accuracy in the prediction of wind speed and wind power production has a significant effect on the production and reliability of electric energy systems.

On the other hand, among renewable energy systems, accurately predicting solar power generation is crucial for managing energy quality, enhancing reliability, and providing quality power in grid-connected networks. Significant achievements have been made in forecasting solar power production based on supervised learning techniques, particularly using statistical and machine learning methodologies that have proved to be effective . Machine Learning techniques such as Deep Neural Networks, Support Vector Machines, and Random Forest models are effectively utilized to enhance the prediction of solar irradiance. Most of these models, however, necessitate sample datasets for training, which usually leads to longer training durations. ML models, particularly Artificial Neural Networks, play a pivotal role in monitoring solar energy systems and facilitating optimization.

Fig 5: AI/ML in Renewable Energy Systems

5.1. Predictive Analytics for Energy Production Energy consumption predictions are important for conserving energy and depend on internal and external factors affecting energy consumption patterns. Accurate energy consumption forecasting is at the core of energy sustainability and attains the two following significant essential benefits: achievement of green buildings and reduction of energy waste. Control and auditing of consumption by increasing the accuracy of energy consumption prediction systems in offices can lead to reduced energy waste. This section first reviews the relevant literature on energy consumption prediction tasks and briefly explains each category of approaches. Regression-based energy consumption forecasting is highly effective with notable results. Artificial neural networks are the most commonly utilized methods in deep learning and are partially explained, especially recurrent neural networks (RNNs). RNN models can learn the sequential features of time-series data efficiently, but previous RNN models experience prediction deviation—a common issue in time-series forecasting problems. The waterfall and significant drop in the prediction accuracy curve are the first issues faced by energy consultants. A solution is proposed based on the opening of a new research line with a focus on the design of robustness-assisted-trained deep learning models for the time-series energy consumption prediction. There are also large opportunities for the application of explainable AI (XAI) techniques to reinforce the efficiency and transparency of energy consumption predictions/rendering systems.

Energy forecasters should apply the proper energy prediction model based on the nature of the necessary prediction process taken into account by flexibility in definition, the expected amount of input/output data, and computational tools . Large amounts of various data are owned and handled. Thus, the model focusing on this concept should be adaptive and flexible. The scratch process must be conducted on the pre-process level when collected data change. Accordingly, the required amount of computed historical data falls under municipal duties, especially in officially run and overseen buildings. Using the previously developed model throughout municipal territory may also create this other limitation. Future prediction horizons also vary significantly. Day-based predictions are not applicable for several-studied systems of less than an hour range, so re-training makes a model unable to regard this flexibility dimension. Another effective consideration is to define the ability of anticipated models to operate in real time. The expedition of building information modelling (BIM)-based plans for cottage forecasters, mechanical excitements, or a more generalized perspective on eventual co-design adopted on real-time energy behavior.

5.2. Optimization of Energy Systems Energy has been harvested from renewable sources, as well as energy storage considering fewer emissions and carbon footprints. Other issues like efficiency, fuel price, and market supervision become essential. Collecting as much information about the energy systems in an ecosystem is also needed for optimization. Internet of Things (IoT) and BlockChain based approaches can be discussed from both energy harvesting and efficiency, as systems need to be analyzed as a whole. Therefore, both energy management and predictive maintenance, as the mathematical and machine learning models, have been considered, with more emphasis on the latter one.

Energy systems have been optimized using heuristic algorithms also, but preferably more efficient and less cumbersome ones like particle swarm, cuckoo search or hybrid methods combining both optimization and trajectory prediction for Microgrids. Any paradigm can be used to collect and process data. Agents are commonly used to distribute the complex computational tasks. The agent can be either centralized or distributed per site or per sector, obtaining a balance between computational complexity and transmission data.

Hybrids of both grid and renewable systems are to be analyzed. Some major paradigms can also be mentioned. On grid systems mostly Condition Monitoring INformation (CMIN) is used as Centralized, Client-Server based architectures with compatible communication standards. This approach eases modularity and visualization at the expense of introducing multi-tier communication.

Off-grid renewable plants usually have lower cost and custom-build microcontrollers post-processing data locally and periodically sending them to analyze via a constrained-bandwidth communication channel. Programmable Logic Controllers (PLC), Energy Supervisory Control and Analysis Systems (ESCADA), or similar systems are popular. Narrowband communication standards and other protocols are beneficial for power-constrained, high-growth markets but should be analyzed from mobility, price, network longevity, security, and feasibility perspectives.

6. The Role of Cloud Computing in Renewable Energy

Virtualization technology also has precise intrusions to traditional infrastructures. It aids to create distributed architectures and server farms for small clustering-based data centers including virtualization software as an operating system kernel. The concept of commodity has pursued successfully a digital object successively with deeper abstractions. On the basis of virtual machine snapshots can easily be viewed on a commodity browser and the resource of distant computation is accessible to the user without arrangements of infrastructure. The software inventories may enhance visual advantages of usage allowing users to run the appliances without involving the existence of hosting. Cloud computing plays an important role to diminish computation cost and update elasticity and reliability. Virtualization technology is used in cloud computing which takes a variety of altered categories of computing assets as distracted facilities to users.

In renewable energy systems, integration with cloud computing can offer a range of benefits, including improved data storage and management, accessibility and collaboration, enhanced analytics and insights, cost savings, and scalability. This integration can empower renewable energy systems by improving data analysis speed and the accuracy of decisions. The use of cloud computing also allows for remote access and management, scalability, and cost savings. The underpinning technologies of cloud computing are virtualization, SOA, and web services. Cloud services can be divided into three categories: infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS). Cloud computing faces problems such as expectancy and connectivity issues, resource distribution, reliability, rapid resources misallocation, and recovery of appliances and fault tolerance.

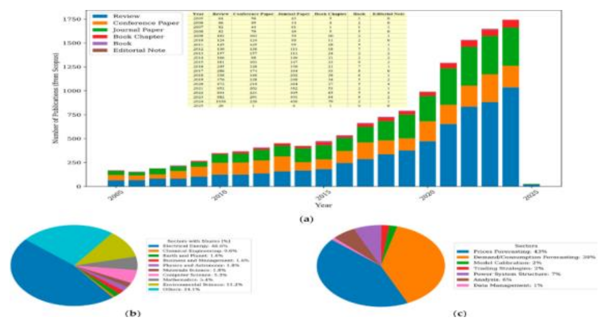

Fig : Energy Intelligence A Systematic Review of Artificial Intelligence for Energy Management

6.1. Data Storage and Processing The proposed approach integrates AI, machine learning tools, and cloud computing to analyze educational data through big data detection. Predictive analytics with auto-chart extraction is carried out based on the operational standards of educational institutions. Data is processed on non-binary content towards a Cloud Multi-Agent System (CMAS) architecture to improve educational services. Cloud storage systems facilitate the process by storing and sharing the educational data with their Cloud Agent (CA)-dedicated system. A cloud-based analysis is detailed to contain the entire processing of operational standards utilizing two base systems, Safety Assessment Cloud System (SACS) and Big Data Knowledge Enhancement Cloud System (BEKECS). Big Data engines in BD KEC perform AI-assisted vector extraction of textbooks to depict students' focus on ideas and knowledge across the PDF file of textbooks. The proposed platform combines AI and cloud computing to identify and analyze learning contents based on big data tools and visualize the analysis results with an AI-based intelligent discourse engine (AIDE).

Training the ChatGPT AI platform on education-related classes proceeded after collecting text data. An architecture is developed to cover an educational Cloud Multi-Agent System (CMAS) structure used to assess the educational domain and decide on the generated response texts to inquiries. Planning is the core part of each agent in this platform, and the Travel Algorithm is improved to work with Waze traffic in Iran. Road safety and traffic state are computed in Cloud dispatching agents using CA algorithms. A Cloud Multi-Angle Real-time Vision System (CMARVS) is supplied to extract multi-angle external views of monitored vehicles. On top of that, several Cloud vehicle detection and classification agents process camera images to control insurance and rescue aspects for safer city vehicles.

6.2. Remote Monitoring and Control The development of monitoring systems within the renewable energy infrastructure has significantly increased over the last decade. Sensors are easily integrated into any renewable system to achieve the required monitoring parameters, and the connection to the cloud is facilitated by a wide range of IoT protocols. However, making sense of the huge number of data points that can be collected from the sensors of the renewable energy infrastructure, understanding which ones are correlated, and deciding on the next operation steps are still open problems. Assisting engineers with AI-based agents to find these correlations and detect abnormal readings from sensors, proposing easy next operation actions, and finally executing the actions proposed are hot topics in AI and ML research. Therefore, any additional development in AI techniques for edge computing, data mining techniques in this area can be efficient, and advancements in advanced AI applications for decision making (automated decision making) and hybrid AI systems for orchestrating traditional systems with AI agents are highly anticipated for multiple applications [5]. Although the techniques for treatment of time series data using ML methods are widely known, another area that can benefit from the application of AI techniques is the indication of the state of the PVE using weather, maintenance, and monitoring parameters. Using modern signal processing techniques combined with supervised learning, PVE malfunctions can be detected at an early stage, and thus maximize PVE performance before complete failure. It allows construction of an indirectly supervised PVE monitoring system that gives actionable insights regarding the PVE operability in a cost-effective staggered form. Initially, monitoring the availability of the cooling circuit is proposed, and further developments can be conducted across a wider set of topics and respective malfunctions. The new hybrid model integrates AI and monitoring systems that process a wide range of monitoring parameters, focusing on new scalable AI techniques that can be applied throughout a wide bandwidth system. Their future evolution and digitization can follow. It covers an operational use case prior to deployment, with potential application in various renewable areas. It will cover educational engagement and content definition, co-designing new PVE monitoring systems with universities across a bi-annual boot camp, and engagement of partner universities in running the new AI-based monitoring systems to gauge the educational potential of the collaboration.

7. Conclusion

This paper discussed how Artificial Intelligence (A.I.), Machine Learning (M.L.), and Cloud Computing can transform Renewable Energy Systems (R.E.S.) and Education Technology (Ed Tech) solutions. Specifically, it analyzed new developments in A.I. and M.L. can empower consumers to form Distributed Solutions in R.E.S., create analytics tools for data-driven Ed Tech solutions, and process long-term commercial flight data and renewables availability.

R.E.S. is becoming widespread but has faced technical and economic challenges on consumer-level smart grids. With increased consumer-prosumer connectivity, the new A.I. Edge-Cloud scheme uses federated M.L. to create an efficient data-driven forecasting tool that empowers controlled co-generation of localized aggregated energy loads and production. In Ed Tech solutions, data accessibility has led to more focus on analytics tools to interpret the data and improve educational performance. Combined with new A.I. developments, there is a huge opportunity to create Ed Tech solutions that generate adaptive questions for exam preparation. These customized questions are generated through a Multi-Task Recursive Hierarchical Vector Quantization with visual representations on the inference server and multiple batches on the consumer side. Finally, major commercial flights collect and store large volumes of data. The Edge-Cloud scheme uses A.I. Edge processing to consolidate trade-off capability indexes on the aircraft and report them on the cloud with correlated sensitivity grades. This multi-class risk-feeding A.I. the model also assesses performance on control engines in the cloud.

Overall, A.I. with M.L. and cloud computing opens the door to a myriad of Virtual Power Plant-like R.E.S., Intelligent Systems for Ed Tech solutions, and smart aircraft architecture worldwide. With consideration for the environment, effective and efficient use of resources for successful partnerships and large-scale deployment should be addressed.

7.1. Future Trends The integration of AI, machine learning (ML), and cloud computing is rapidly transforming various sectors, including renewable energy systems and education technology solutions. This explores the future trends and developments in these fields and emphasizes their impact on fostering innovation. Instances of developing AI-ML-based cloud solutions are described in the domains of renewable energy systems and education technology solutions. Future trends such as transferring solutions from the energy domain to the smart grid domain, adopting new machine learning techniques, improving visualization and UX in EdTech solutions, and providing paid solutions are discussed as potential pathways for expanding the current solutions. To promote the green economy in many countries, the integration of renewable energy sources such as wind, solar, and biomass into distribution networks is sustainable. In order to understand and optimize the performance of the energy system and provide better decisions for electric utilities, the development of data-driven solutions is instrumental due to the ever-increasing amount of data generated by smart grid infrastructures. The development of cloud-based AI and ML solutions in the domain of renewable energy systems has been considered. First, the energy domain has an enormously growing market in renewable energy after the hardware infrastructure of the power and energy systems is upgraded with smart meters and data collection infrastructures. An immediate advantage of cloud computing with a flourishing ecosystem is that otherwise costly solutions can be delivered in the form of SaaS through the internet. As another development, current solutions, mainly based on RNN and ANN, can be advanced through the modification of neural network topologies. For instance, developing a hybrid machine learning method is a way to enhance the predictability of renewable energy consumption by benefiting from different models. In addition, the interpretability and explainability of existing models can be advanced through techniques such as LIME and SHAPE. Integration of additional factors based on feedback from the end users can enhance the transparency of the existing renewable energy models.

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