www.ijecs.in

*International Journal Of Engineering And Computer Science*
*Volume 10 Issue 12 December 2021, Page No. 25572-25585*
*ISSN: 2319-7242 DOI: 10.18535/ijecs/v10i12.4665*

# Transforming Renewable Energy and Educational Technologies Through AI, Machine Learning, Big Data Analytics, and Cloud-Based IT Integrations

**Venkata Narasareddy Annapareddy**

Sr Enterprise Application Developer, SunPower Corporation, Baltimore, ORCID ID:0009-0002-5385-5259

**Abstract**

This article presents the roles of artificial intelligence (AI) and Internet of Things (IoT) technologies in the renewable energy sector for the optimization and management of smart grids. With rapid advances in AI and IoT, there is enormous potential for developing smart energy systems that integrate clean energy sources and power generation, storage, and consumption. This has been an area of intense research and development activity and broad interest from governments and interested parties to adopt green energy sources and promote the use of electric vehicles (EVs). Affordable access to cloud computing platforms has enabled the development of intelligent technologies and architectures for data storage, processing, analytics, and machine learning with minimal costs. Cloud-based services can significantly reduce the price of sustainable energy systems and the risks associated with smart grid management by protecting the integrity of sensitive data and fostering collaboration among users. Smart meters and a growing number of individual IoT-based sensors and actuators at households, factories, parks, fleets, streets, and polluted areas collect data by constantly taking measurements. These data are transmitted to cloud servers for analytics, for developing AI-enabled algorithms for the prediction, optimization, and control of renewable energy systems.

Distributed energy resource (DER) systems introduce a significant challenge to managing and optimizing renewable energy systems. With the rapid rise of EVs, there is a need to integrate and manage the grid, battery EV charging stations, and solar panels, not only to maintain SWEs but also to optimize GWEs. Similar challenges exist in the management of charging stations and the optimization of distributed generating units, considering demand response. Lots of interesting contributions from control and optimization perspectives have focused on energy dispatching and flexible operations of these systems. However, these efforts are limited by centralized architectures that assume full knowledge of, and computations capabilities over, the grid and DER systems. New distributed approaches are necessary to implement the effectiveness of some beyond the state-of-the-art intelligence. These efforts should also go beyond just IT-enabled automation and augment human cognition. Smart energy systems must be distributed, with lots of computing happening at decentralized autonomous nodes and devices where data and decisions are generated. Such designs call for new machine learning and AI methods capable of constructing intelligent agents from minimal data and computing resources, as well as methods for automatically optimizing human-AI collaborative systems.

**Keywords:**Artificial Intelligence (AI), Machine Learning (ML), Big Data Analytics, Cloud Computing, Renewable Energy, Educational Technologies, Smart Grids, Solar Energy, Wind Energy, Intelligent Tutoring Systems, Personalized Learning, Digital Learning Platforms, Data-Driven Decision-Making, Internet of Things (IoT), Automation, Sustainability, Green Technology, Virtual Classrooms, Remote Learning, Digital Transformation, Energy Efficiency, Smart Education, Real-Time Monitoring, Optimization.

## 1. Introduction

Extreme weather events caused by climate change affect the reliability, stability, and efficiency of energy systems globally. Organizations competing for renewable energy and carbon neutrality often overlook the limitations of their systems and the likelihood of extreme weather events. Machine-learning frameworks using big-data analytics improve the reliability and stability of smart grids' renewable energy systems under unfamiliar and extreme weather events.

The introduction of renewable energy resources creates new applications of big data in the energy industry. Failures can arise from unfamiliar scenarios not included in the trained ML dataset, such as those generated from extreme weather events. Policymakers are understandably reluctant to implement ML coding-based very high unsutilized power rates because their oblivion can result in voltage fluctuations, smart grid control issues, actuated hardware failures, and even blackout safety incidents. In contrast, more acceptable and user-friendly prediction models still must account for sudden large loads and unexpected events like extreme weather events due to drop-offs in road traffic and visibility, resulting in unutilized power rates five times higher than suggested scheduling. A Digital Twin-based ML framework can provide user-friendly, ML-based support tools for safe operation management and troubleshooting decision making. By implementing input perturbations corresponding to the input uncertainty given a certain threshold, it is possible to generate a suitable dataset comprised of ordinary, familiar scenarios only containing small input uncertainty. The ability to interact with the physical counterpart's data of the digital replica opens up the infrastructure needed to incorporate additional robust mechanisms like schedule filtering and uncertainty quantification. DNN-based data-driven observation estimation models provide a direct impulse response of the physical counterpart

**Eq 01; Smart Grid Load Fore Casting Time Series Model.**

$$\hat{L}_{t+1} = f(L_t, L_{t-1}, ..., X_t)$$

- $\hat{L}_{t+1}$: Predicted load
- $X_t$: Exogenous variables (weather, demand patterns)
- $f$: Model function (e.g., LSTM, ARIMA)

The electricity industry is experiencing a transformative shift from a centralized approach to a more decentralized model. Alongside this transition, distributed generation of renewable energy has gained global traction and is increasingly being integrated into smart grids, autonomous grids, and microgrid networks. The scope and complexity of these systems have grown exponentially, giving rise to various challenges that hinder the operation and planning of the energy infrastructure. Due to pressing concerns about the climate crisis and volatile fossil fuel prices, there is a growing interest in harnessing advanced technologies, especially artificial intelligence and ML.

## 2. The Role of AI in Renewable Energy

AI, ML, and other data technologies will play a crucial role in training, operating, and evaluating various types of substantial renewable energy candidate systems, such as solar photovoltaic, wind, dynamic transmission, and battery systems. Some of their integrations and contributions are listed below.

(1) Data-driven analytics techniques based on semi-supervised, unsupervised, and transfer learning will be developed to analyze largescale and diversified data from hybrid renewable energy systems, e.g., wind and solar hybrid systems. New methods will be developed to identify critical operating conditions, evaluate performance metrics, discover implied causal interactions, and derive useful insights from hybrid renewable energy data streams obtained from high-fidelity simulations or real-world large-scale operations [1].

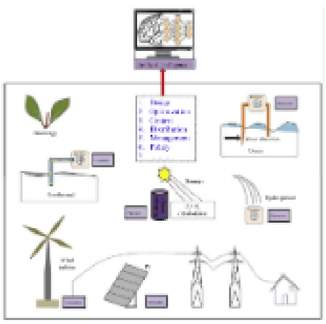


**Fig : 03 Schematic of application of artificial intelligence in renewable energy**

(2) Data-driven hybrid renewable energy system state identifications through synergies of accuracy-aware deep models and Bayesian optimization will be developed. A hazard alerts technology will be implemented to guarantee the robustness and improvement of threading operations. A commercialization conversion tool will be constructed to support the deployment of all data-driven technologies.

(3) Advanced hybrid renewable energy system bidding technologies based on interpretable deep learning methods, novel robustness assurance optimizations, and weather forecast ensemble systems will be developed to meet real-world industrial needs. Enhanced online bidding/operating ability will be achieved, and an effective and sustainable decision support system will be realized.

(4) Data-driven hybrid renewable energy system operating control coverings critical locations, operational time phases, and provide alerts will be developed. A cloud-based technology will be constructed and implemented to ensure the transparency and validity of data-driven technologies.

(5) Robust closed-loop bidding and operating technologies for hybrid renewable energy systems under stochastic modeling and data scrutiny will be developed. A cloud-computing auspice supervise platform will be constructed to validate and guarantee the framework.

### 2.1. AI Applications in Energy Generation

AI has begun to shine in energy forecasting models by advancing short-term, medium-term, and long-term forecast models. Novel approaches to wind and solar energy forecasting based on extreme learning machines (ELMs), adaptive neuro-fuzzy inference systems (ANFISs), ensemble learning techniques, and hybrid models for generating ensemble forecasts are developed. AI is also used to enhance demand response, a form of flexible load management. Models based on AI techniques with standalone or hybrid intelligence, such as artificial neural networks (ANNs), ANFIS, evolutionary support vector machines (ESVMs), and clustering methods have been developed to enhance the performance of DR. These models have been demonstrated to be able to reduce energy-related costs and contribute to system balancing, flexibility, and regulation .

AI is generally used to come up with optimal RES profiles to reduce $CO_2$ emissions and generation costs. AI techniques such as genetic programming (GP), genetic algorithms (GA), ant colony optimization (ACO) techniques, and particle swarm optimization (PSO) are frequently used. Models based on GPs have been modeled to generate P2P trading strategies for a micro-grid and the optimal sizing of electrical systems coupled with renewable sources. Furthermore, hybrid models based on a combination of various AI techniques have been applied to minimize trade costs, enhance the insurance services offered to agents from dysfunctional auctions, plan PV generation expansion for cost reduction, or make optimal use of energy locally generated profiles. However, the impact of climate and weather conditions on energy generation, and hence costs, has rarely been taken into account

**Eq 02: Student Performance Predicition Logisitic , Regression.**

$$P(\text{pass}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)}}$$

- $x_i$: Features (e.g., attendance, quiz scores)
- $\beta_i$: Model coefficients

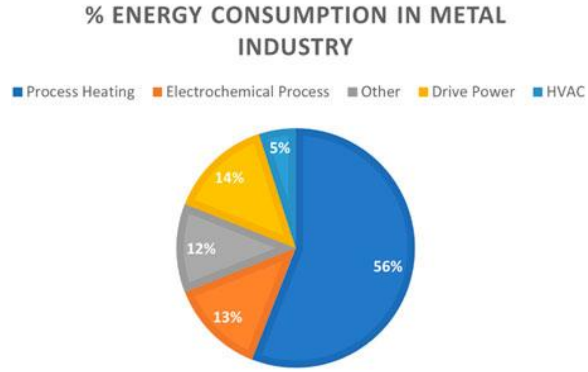
Finer-granularity approaches have been used to model multiple-network layers, hardware equipment technologies, cabling infrastructure, and the weather but time-consuming mixed-integer nonlinear programming techniques were used. AI has succeeded in modeling such larger networks, taking into account not just the operation of converters and their components in the time-domain, but also their involvement in short-term local electricity markets.

### 2.2. AI for Energy Consumption Optimization

The paradigms of artificial intelligence (AI) and machine learning (ML) have led to improvements in the automation of energy management. AI has widespread applications in both the manufacturing and the service sectors. It develops intelligent machines able to accomplish tasks that, for various reasons, were reserved for humans. Because of the advancement of AI, the automation of energy management improved significantly over the last decade. The smart grid framework consists of devices, equipment, and DRs that are embedded with intelligent measurement, monitoring, and control capabilities at variable locations and technologies to improve the efficiency and reliability of the power system. The smart energy management system is a concept based on a market mechanism, distribution, and other pricing signals to improve the economic operation of the power system. Two different paradigms of TM have been introduced: one based on centralized schemes and the other relying on multi-agent systems (MASs). Due to the ability of agents to operate both as individuals and within groups, the efficiency of the TM is improved. Several like-sided agents, such as customers, retailers, and FEDs, as well as different kinds of interactions, exist in a smart grid framework. The complexity arising from geographic dispersion and the temporal fluctuation of energy demand growth and generation, among others, must be addressed. MAS-based algorithms can be used to efficiently manage all resources in proximity with minimal communication and with no central authority. Various recent methods based on AI and ML techniques are already popular in the development of the TM for transactive energy systems. A more sustainable future is necessary for our world with an increasing energy demand due to the population growth, digitization, and development of new technologies. Decarbonization would be one option achieving this goal, which entails the replacement of fossil and contaminating fuels by renewable energies. However, a high penetration rate of renewable energies makes it hard to be integrated into the current grid, leading to the energy management problem. A new model of integration for the development of energy management facilities across a renewable energy fed ecosystem has been proposed as a solution. The model has resulted from the analyzed state-of-the-art of the consumption management domain and by the utilization of robust IoT communication protocols as well as state-of-the-art artificial intelligence paradigms. The new consumption management architecture proposed handles the classification, detection, prediction, and control of the global consumption and generation assets of the ecosystem. Artificial intelligence algorithms have been deployed at two levels to achieve this functional decomposition.

## 3.Machine Learning Techniques in Energy Management

Machine learning (ML) models have found extensive applications in energy management and systems. These instances encompass load forecasting, demand response, fault detection and diagnosis, detection of energy theft, determination of residential energy consumption, and the integration of renewable energy. ML models have become widely used in numerous aspects of energy systems. The introduction of different ML approaches in the aspect of energy systems took place dominantly in the last two decades, especially in the forecasting of electrical energy demand and renewable energy. Accurate generated predictions of energy consumption and energy demand with ML model results can be treasured by building commissioning project managers, utility companies, and facility managers in carrying out energy-saving procedures. Moreover, ML models have been found useful in other domains like load forecasting, power generation prediction, forecasting of power quality, forecasting time series, wind speed forecasting, and forecasting demand of electricity. The prediction of energy consumption of building holds a considerable importance in shaping decisions to reduce energy demand and lessening CO2 emissions. Efficient ML and AI techniques can help building occupants to save energy by determining random underlying factors governing energy consumption, and by some basic reduction in these parameters [2]. Unless the accurate selection of ML models, prediction of building energy consumption is still a rewarding challenge, because there are several determinants affecting it. Deep learning is a sort of machine learning that is able to discover inherent nonlinear features and high-level invariant structures in data. DL algorithms are appropriate to forecast renewable energy for data-driven prediction. In general, accurate prediction of supply and demand electricity is crucial for energy companies to optimize production and distribution, as it will lower costs and increase energy efficiency. Furthermore, ML models demonstrate their capability to address optimization problems such as energy control; planning for storage; dynamic energy pricing; estimating battery charging requirements; cost minimization; and peak load management. However, consumption and generation forecasting of renewable energy are a time severe challenge. Highly predictive energy modelling results could raise consumers' awareness on predicted use or production, and thus advance energy performance. Hybrid machine learning technique could be a suitable way to ameliorate the predictability of renewable energy consumption, as harnessing the strengths of dissimilar models, and thus yielding improved results.




**Fg : 05 frontiersin modeling energy consumption using machine learning.**

### 3.1. Predictive Analytics for Energy Demand

Energy serves as the cornerstone of human progress, as well as socio-economic and cultural advancement. It drives growth in sectors such as agriculture, commerce, healthcare, trade, and many others, while also being intrinsically linked to education and innovation. Sustainable energy systems are essential to curbing rising global temperatures and air pollution, thereby protecting the environment. Climate change now threatens to undermine much of the progress made over the past few decades in health, development, poverty eradication, and social equality. The international community recognizes the urgent need for the transition to reliable, affordable, and sustainable energy for all. In this regard, Sustainable Development Goal (SDG) 7 emphasizes the need for inclusive, equal access to reliable and affordable energy services, as well as an increase in the share of renewable energy sources in the global energy mix [3]. Energy is a vital commodity, and ensuring access to energy is one of the foremost global challenges that secure the standard of living of everyone on earth. The demand for energy is constantly growing, influenced by myriad factors ranging from urbanization and economic growth to natural disasters. A soaring demand for energy results in increased prices of fossil fuels and, subsequently, threatens energy security. Electricity being a form of usable energy is distributive in nature that, therefore, must be available when needed. It cannot be stored in bulk conveniently and only can be produced per demand [2].

Predicting the demand for energy services has become vital for employing effective energy management strategies for reducing peak load, ensuring reliability, addressing system instability, and reducing consumer expenditure. Accurate predictions of energy consumption and demand can empower stakeholders within the energy system with techniques that can be integrated into suitable business processes to meet challenging educational and environmental goals. In addition, accurate predictions of energy demand can facilitate optimal management of the power grid, improve the allocation and utilization of renewable energy sources, and reduce the reliance on nonrenewable sources. A predictive-based approach is proposed using a hybrid LM-RNN-LSTM model for accurately predicting short-term energy demand in energy-restricted communities.

### 3.2. Machine Learning for Renewable Resource Assessment

This review article considers various machine-learning models to foresee the energy production of renewable energy sources – especially wind and solar energy applying Big Data Analytics for renewable resource assessment and AI-enabled conversion. The concepts of Big Data and machine learning are defined and categorized in depth using various essential parameters. Nevertheless, Big Data Analytics and machine-learning applications mostly focus on renewable resource investigation [2]. Although few attempts to investigate the Big Data Analytics applications of machine learning for renewable assessment have been made, these are less comprehensive. Therefore, a thorough overview of the machine-learning approaches applied for renewable resource assessment based on handling Big Data by reviewing various studies covering each state-of-the-art classification and machine-learning algorithm with their merits and demerits is necessary. Moreover, forecasting techniques for energy production with AI and cloud-based integrations have been studied. AI offers smart prediction for system users, improving their smart decision support systems by developing a general cloud-based model that combines supervised and unsupervised machine-learning techniques like decision trees, support vector machines, and artificial neural networks with evolutionary programming optimization methods. Furthermore, the cloud-based intelligently hybridized models with fuzzy modeling, the Gravitational Search Algorithm, Whale Optimization Algorithm, and doubly fed induction generator structures, enable users to efficiently foresee the hourly and daily energy generation from wind and PV systems at different geographical and meteorological sites.

**Eq : 03 Ai — Driven Adaptive Learning Rate Model**

$$\eta_t = \eta_0 \cdot \frac{1}{\sqrt{t+1}}$$

- $\eta_t$: Learning rate at iteration $t$
- Helps tune AI models for student learning adaptability over time

### 4. Big Data Analytics in the Energy Sector

Big Data Analytics (BDA) has recently gained remarkable attention in the energy sector and it is expected to be an effective solution for energy management and optimization. During the last decade, BDA has been confronted with the unprecedented growth of massive, diverse and complex data. The tremendous flows of data from sensors, equipment, social networks and other diverse data sources, which exceed the limit and treatment capacity of traditional database systems, have inspired the emergence of the concepts, technologies and techniques of Big data. Big data technologies are based on the three Vs characteristics: Volume, Variety and Velocity. Embedded in the 4V, the fourth characteristic Value has also been defined recently. The emergent of BDA has transformed technological and analytical environments in various sectors including finance, healthcare, transport, manufacturing and retail. To exploit the insights hidden in massive, complex and fast data, big data solutions based on both descriptive and predictive analytics have emerged. Data mining, operations research and machine learning are common used techniques in business optimization.

The energy sector is vital to economic growth of nations and security of resources and its aspects, such as energy generation, conversion, transportation, storage, dispatching and consumption, involve in diverse and large entities to create a complex interdependence system. Big Data technologies have revolutionized the industry of oil and gas, electricity market, renewable energies, energy consumption, smart grid system and laboratory simulation of energy storage media. The increasing penetration of interactive renewable generation systems, energy storage systems and electric vehicles, as well as internet of things technologies, has resulted in epic volume of Big Data in smart grid and Internet of Energy system. As a national critical infrastructure, cyber-security rapidly becomes a major issue in the energy sector with the implementation of Big Data and the inevitability of system guiding from centralized to decentralized decision making. To respond to the unprecedented need for multi-sources and multi-scale data processing, numerous studies have been conducted on cyber-physical systems and cloud-based BDA frameworks, platforms and structure to realize cloud services and ensure system security across entities.

Sorting the practical use cases of BDA and their contributions in the energy sector is of overarching significance to smart grid, Internet of Energy, security and privacy aware BDA as well as a step-further research agenda. There are several standard resources of energy data sources and some analytics tools for energy optimization. However, systematic reviews of data issues in the energy sector and tracking the practical application of BDA are still limited. As a response to these research gaps, an extensive scoping review methodology is conducted to investigate BDA practices in the energy sector in terms.

### 4.1. Data Collection and Management

A continuous rise in energy consumption, grounding emissions, and peak electricity demand has put the future of renewable energy (RE) at great risk. This has also pushed many nations to seek ways to transmute renewable energy sources in conjunction with sustained education. In such endeavors, it is significant to widen the realms of discipline on this subject matter. As a consequence, a grand challenge white paper has been drafted with a focus on proposing points with a focus on the potential transformative impacts of AI (artificial intelligence), ML (machine learning), data science, big data analytics, advanced analytics, and cloud-based IT integrations on renewable energy systems and educational technology for education data management in smart learning environments [4]. A mixed approach for qualitative and quantitative data collection is used in the study. The Mobil Home application is developed based on the Big Data architecture deployed on cloud services to monitor energy consumption and associated environmental and campus impacts based on Live Data, Batch Data, and Historical Data. The Data Collection and

Management phase is executed through an ETL process using automated scripts to filter and clean the data as well as to handle missing values. The data is then stored in a blob storage on the cloud and finally monitored by means of Power BI [5].

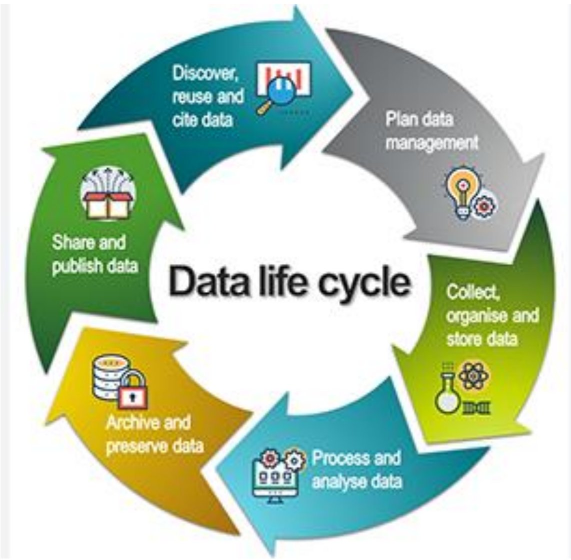



**Fig : 02 Data Management.**

The proposed topics outline the key research challenges associated with the re-transmogrification of RE systems and educational technologies and the cognition of the research realms of both interdisciplinary and transdisciplinary research. The focal aim of the study is to analyze research challenges and opportunities that AI, ML, data science, big data analytics, and cloud-based IT integrations placed on renewable energy systems and education data management systems in potential smart learning environments. The aftermaths of the study put forward research challenges and solutions with an aim of screening the focus domains of awareness discovery, which is envisaged to serve as a guiding principle for educational institutions, industry, researchers, and policy makers in hardihood of ascending re-ennead of RE energies in combination with sustained twentieth education. Finally, recommendations for future findings and applications of the proposed study are presented.

### 4.2. Insights from Big Data for Policy Making

The findings uncover new potentials for Big Data applications in public sector. Moreover, they indicate considerable chances of policy innovation, productivity enhancements, and efficiency gains across the whole of government. As such, they highlight how big data integrations into the public sector can be relevant for policy making and address the associated technological, ethical, organizational, and political challenges [6].

Presently most of the government research on big data and AI focuses on a limited range of applications based on a narrow number of data science techniques. There is still public sector opportunity space for big data cross-fertilization from science areas where advanced analytical methods exist; and compliance with ethical and governance regimes that ensure effective data handling, proper data analytics use, and avoidance of harms to the value of data assets built up over years. This means that policymakers can benefit in terms of innovation and productivity from recognizing and addressing governance and ethical problems from other fields and introducing relevant compliance measures [7]. Modernization without big data is a looming risk for administrators as the ICT competition is expected to continue. The decreasing returns to scale in the use of traditional administrative data are making the public sector trust more on new forms of digital info, which governments may not want to be overstabilized. Busyness of governments with big data may shake the established view of the public data space. Contentions may arise about the accountability of new actors, data hoarding, and use of computational power for further discrimination of publics. While policymakers catch up with these problems introduced, efficacious management of crisis and risks depends on closing understanding gaps about the new technologies.

### 5. Cloud-Based IT Integrations

The Cloud is the fastest growing supporting technology for whichever businesses today. The finest example for cloud computing service is Google, as classroom and documents provided by Google help universities to focus more on content, delivery, communication and collaboration, putting less effort in waiting a machine to process the data. Cloud computing is the integration of service-oriented architecture, grid computing, utility computing and software as a service. It is the next evolution of Internet services. Essentially the Cloud is the same concept as "Software as a Service," except that it is more flexible and vast. The Amazon Cloud is one of the best examples of the SaaS model. The cost of processing, storage, alerts and notifications are provided as per the requirement of end-users. Education today is becoming completely associated with Information Technology. Learning is now no longer limited to a particular locality. In this society, where a mobile device is treated as soon as the birth certificate, the content delivery is expected any time and anywhere. Cloud Computing is an Internet-based computing, whereby shared resources, software and information are provided to computers and devices on-demand [8].

Cloud computing offers services in three different environments, which are Infrastructure as a service (IaaS), Platform as a service (PaaS) and Software as a service (SaaS). By availing these services from cloud computing providers, it is possible to cut short the cost for investing in transitory and ever changing hardware and software. The investment will also automatically get increased as the number of users or requirement of software and hardware increases. As these are handled by cloud service providers, there is no concern from users' side, which increases the productivity and profit merging. Though, educational institutions have taken a new shape from a conventional institute of sitting at class, but to be up to date and meet the needs of coming generation there is always a significant need to enhance the facilities. Currently, and in the coming decades, cloud services such as storage, platform, and software are best suited for educational institutions to be on par with the education delivery style in developed countries and for the proper training of the trained and trained trainers.

### 5.1. Benefits of Cloud Computing in Energy Systems

Cloud computing improves the quality of service in energy systems and creates a new opportunity that was previously impossible with traditional formats. Cloud computing takes advantage of a distributed infrastructure for storing, managing, and processing data across a big network of servers, leading to lower costs and more efficient utilizations. The cloud computing environment can also improve the quality of service (QoS) of energy data transportation and service by using the more mature, reliable, and robust expertise in the IT sector in a complete supply chain [9]. The cloud computing-transformed services/products can outperform traditional services/products in terms of energy consumption, cost, and capacity. The significant benefits of cloud computing transformation in energy and energy education systems are illustrated in this section [2].

By using cloud computing, big data, and federated Machine Learning (ML), energy systems can achieve the synergy of QoS improvement and energy cost reduction in one transformation. Cloud computing services can offer an IT-IT gateway to transport energy data with better QoS and lower costs. A group of energy utilities can collaboratively find better knowledge without transferring their data. Cloud computing offers the chance for the knowledge/ML model to be continually trained, including during co-usage. By using big data technologies, the knowledge production cost can be significantly reduced, and ground truth knowledge can be obtained automatically from consumptive behavior using data mining technologies.

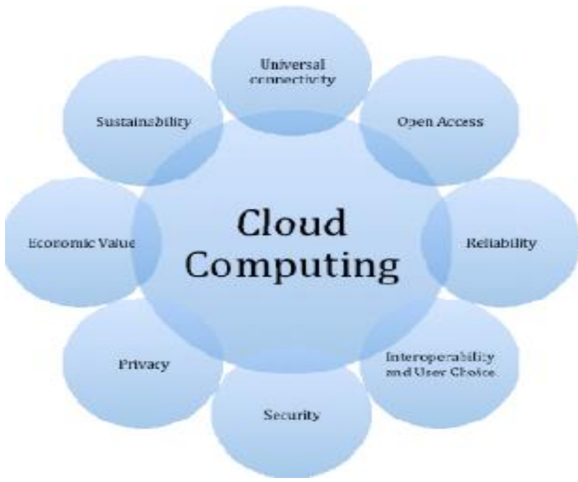



**Fig : 01 The 8 Fundamental Elements of Cloud Computing**

The state of the energy systems' reactance can be monitored more accurately using cloud technologies and transfer learning technology compared with traditional systems, helping to significantly reduce energy and production costs. Using federated ML techniques, without exchanging data, cloud computing can be used to find the optimum demand dispatch and consumption plans at power/grid users, significantly reducing electricity costs while increasing service utility. Cloud computing and data mining/ML help to monitor up to 1,000 multiple buildings' performance in cities, responding to blackouts automatically and quickly.

### 5.2. Case Studies of Cloud Implementations

Cloud solutions have taken the academic world by storm, and universities are investing time and effort in implementation, just like the business world. Cloud computing is revolutionizing educational technology solutions to provide improved services to faculty, staff, and students. The Dominican University of California's IT infrastructure is all cloud-based, from the learning management system (LMS) to the business operations systems. Institutions exploring cloud-based solutions can benefit from exploring a case application at the Dominican University of California. Before any design or implementation occurs, consideration should be given to the institution's educational technology needs and challenges, available solutions, cloud vendors, and cloud service models. The selected solution(s) should then be piloted. Piloting the cloud service helps ensure a precise fit for the institution's needs, and modifications can be requested for cloud service usage to alleviate specific pain points. Full implementation is only recommended after individual services have been piloted, and a scalable and secure implementation plan must be developed when transitioning from an on-premise service to the cloud.

In practice, though, there are many cases in academia documenting successful cloud implementations [5]. In this study, the application of the cloud to the performance monitoring of a smart campus is presented as an acceptable real-world case in academia documenting the need for, design of, and investment in a cloud-based solution. This example is relevant not only to institutions considering a rudimentary cloud solution but also to those already implementing cloud services, as there are many nuances in academia. As institutions contemplate broader applications of the cloud, the intangible considerations might take precedence before the cloud service itself can be examined in detail. It is critical for institutions to discover and understand these subtleties as they apply cloud services to their own environments. The implementation of a broadband-based campus network as a stage-one recommendation is included, as an institution's current state and vision relative to what the cloud solution involves can impact the design

## 6. Educational Technologies Leveraging AI and Big Data

Information and communication technologies (ICT) such as the internet, clouds, and smart mobile devices are revolutionizing human society and everyday life [7]. Unfortunately, schools and other educational institutions have a hard time coping with these changes. Even though new ICT have been adopted by teachers in classroom teaching, and young people, in particular, are avid users of smart and social media technology, many educational institutions dwindle in information poverty. School leaders and teachers are generally not ready to exploit the potential that new technology can bring to education in learning, teaching, management, and administration. Hence, the pedagogics of ICT in general and big data and AI applications in particular still have to start with a clean slate in K-12 education and in many ways also in higher education. Moreover, new kinds of training and on-going education must be developed, designed, and offered to ensure the readiness of teacher educators, in-service teachers, and other educational administrators to effectively adopt and deploy new ICT.

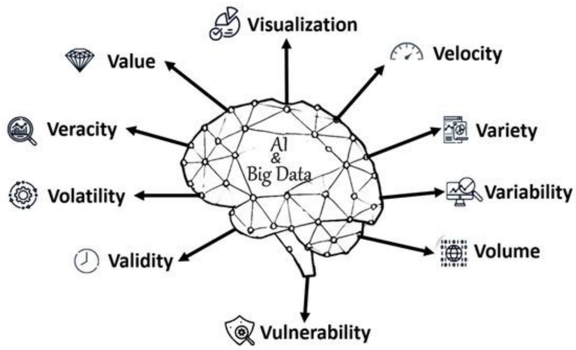



**Fig : 04 The AI Powered Evolution of Big Data**

It is not too much to claim that the current rapid growth of big data and AI has raised significant challenges to the educational community worldwide. In particular, questions have arisen regarding what big data and AI terminology, technologies, and tools mean with regard to assessment and education; how they are being, could be, and should be used to shape electronic learning environments, to promote self-regulated and group-based knowledge construction, to support critical thinking and creative learning; whether and how new technologies could be and should be integrated with traditional learning and teaching activities, environments, and tools; how they would impact educational quality and equity; and what policies and environments are needed to enable the successful adoption, deployment, and use of big data and AI applications in education.

**6.1. Personalized Learning Experiences**

Personalized learning experiences are customized educational approaches that cater to the individual needs, preferences, and learning styles of students. With the rise of digital technology, the potential for improving the quality of teaching and learning in an education system is limitless. This paper looks at the ways the calibration of the English as a Foreign Language (EFL) teaching and learning approaches with Artificial Intelligence (AI) can potentially facilitate a smart transformation of the aforementioned approaches, fostering a personalized and engaging experience in teaching and learning among the stakeholders of the education system. A framework named EFL Big Data Ecosystem, based on Big Data, Analytics, Machine Learning, and cluster domain of EFL teaching and learning contents, is focused in this paper. The framework has been developed on the basis of the theory that machine learning algorithms can cull out the patterns, similarities, and differences existing in the contents of the domains. These machine learning algorithms can apply these already identified patterns to perform new tasks on open Big Data platform and identify similar contents to be stored in the respective cluster domain of EFL Bigdata Ecosystem [10] without being supervised. Theoretically, the structured and semi-structured data are to be prepared skill-wise, attribute-wise, method-wise, and preference-wise to accommodate the personalized preferences and diverse teaching and learning needs of different individuals. The ultimate goal is to optimize the learning experience. By selecting the most suited piece of content for the situation, it prefers the Machine Learning paradigm of AI.

**6.2. Data-Driven Decision Making in Education**

The latest development of Artificial Intelligence (AI) for educational technologies has made it easily accessible to students and educators for managing digital and physical classrooms [7]. Educators can now start a teaching session by simply giving a voice command, and learning materials, quizzes, assignments, and reports can be created automatically. Besides classroom management, learning management has also improved dramatically. Now AI can automatically assign different levels of learning materials, quizzes, and assignments based on an in-class performance analysis of each individual student. Additional learning materials are automatically shared with slow learners who have failed in review quizzes. Even physical classroom education can be transformed by simply installing AI sensors on classroom walls. These sensors automatically create a learning report of each student. The implementation of these AI solutions has almost no related cost at the start-up phase as already available technologies can be purchased and used for creating this integration. But for using the education-related data generated through these technologies for big data analytics, proper attention has not yet been paid. Since these solutions have no learning objective, the data generated by using these solutions have no meaning. So, it is required to train educators on the proper implementation of education technologies which will also enhance the effectiveness of the learning system. An automatic analysis of the huge amount of education-related big data can give valuable information to take effective educational decisions, fix the gaps of the learning management technologies, and ensure the proper implementation of technology in the classroom.

Big data refers to large, complex data sets generated from many sources that are difficult to analyze. Data analytics is the process of examining this data to discover patterns, correlations, and trends. In education, big data analytics can be used to gather and analyze data on learner and instructor behaviors and preferences to improve educational effectiveness [10]. The Education Data Mining (EDM) and Learning Analytics (LA) fields focus on the creation, research, and implementation of data mining and analytics systems to measure, analyze, and understand learning. This chapter briefly explains these two methods, their scope in the educational sector, possible applications, and their challenges and prospects. Through optimized application of education-related big data analytics and these related technologies, the development of adaptive and personalized learning management technologies can be ensured. Education-related big data analytics can also be used to improve the efficiency of the education system and quality control of the resources while ensuring the proper use of education-related records.

## 7. Future trends

Data have become increasingly relevant in understanding the immense complexity of environmental systems and behaviours, as well as in generating predictions of these and associated hazards. Transforming these data into actionable knowledge necessitates analytical frameworks, technologies, and algorithms that can be used by different stakeholders in a coherent, easy-to-follow manner [7]. Current research trends in big data analytics and machine learning that aim to make the models emerging from AI technologies a more actionable addition to existing knowledge entail targeted developments in IT technology and on integrating these two very different fields.

Easy-to-use platforms that democratize the use of such technologies are the next frontier for the deep learning community, taking care to disseminate knowledge widely and correctly, avoid misinformation, and bridge the technological divide that is anticipated to become a wider rift than that created by the digital divide. Collaboration is also key in this development, so that future tools can reflect the scale of knowledge and analytical approaches brought by increasing data volumes and types. AI-driven big data analytics has many potential educational uses, but there are also significant implementation challenges to adoption, including disparities in computational resources, staff expertise, and students' digital competencies.

Still, the findings of this literature survey are encouraging. Given recent technological developments and the rise of open-source and cloud-based software environments for educational technologies, opportunities exist to further integrate readily available resources, making it feasible to implement learning systems that take advantage of lower-priority educational data and foster interconnected learning. The tremendous strides in big data approaches and technologies are essential to understanding and acting upon societal decisions.

## 8. Conclusion

This paper proposes transformations of renewable energy and educational technologies from data and processing methodologies, utilizing AI, ML, big data analytics, cloud-based integration, etc. To address various issues in renewable energy generation, utilization technologies, and educational technologies, various data-driven methodologies are reviewed including regression, clustering, kernel methods, ANNs, LSTMs, CNNs, etc. The deep learning algorithms are proposed for large-scale data transformation of renewable energy technologies. Regarding small-scale and non-data hungry problems in educational technologies, cloud-based IT integration methodologies are proposed. Transformation ideas of renewable energy technologies are presented based on wind and solar energies as examples.

The renewable energy generation processes, utilization technologies, and their integration systems are complex and large-scaled, and the information processing large and high-dimensional. The transformation ideas based on renewable energy data and integration methods of various data mining algorithms are proposed and reviewed, from filtering, regression, and clustering methods to deep learning algorithms. Data-driven methodologies are able to transform renewable energy technologies through theory modelling adjustments based on partial data, computational cost reductions with representative selections, and parameters predictions from physics-based models. AI, big data analytics, econometric theory, data mining, Internet of things, and etc. are integrated into commercialized products.

On the education side, the educational technologies are complex, wide-ranging, and diverse, while dealing with small-scale and non-data hungry problems in various countries and regions. This paper proposes transformation pathways based on limited data and their cloud-based integration methodologies. Low-cost learning approaches are employed to address the artificial intelligence models under non-data hungry situations on account of high projection ability with few neutron-channels of ANNs. Various cloud-integrated IT infrastructures based on RDBMS and NoSQL are utilized for knowledge across educational computing resources, courses, and content, and knowledge mining cloud-based systems are illustrated.

**References:**


1. Chava, K., Chakilam, C., Suura, S. R., & Recharla, M. (2021). Advancing Healthcare Innovation in 2021: Integrating AI, Digital Health Technologies, and Precision Medicine for Improved Patient Outcomes. Global Journal of Medical Case Reports, 1(1), 29–41. Retrieved from https://www.scipublications.com/journal/index.php/gjmcr/article/view/1294
2. Nuka, S. T., Annapareddy, V. N., Koppolu, H. K. R., & Kannan, S. (2021). Advancements in Smart Medical and Industrial Devices: Enhancing Efficiency and Connectivity with High-Speed Telecom Networks. Open Journal of Medical Sciences, 1(1), 55–72. Retrieved from https://www.scipublications.com/journal/index.php/ojms/article/view/1295
3. Avinash Pamisetty. (2021). A comparative study of cloud platforms for scalable

infrastructure in food distribution supply chains. Journal of International Crisis and Risk Communication Research , 68–86. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2980
4. Anil Lokesh Gadi. (2021). The Future of Automotive Mobility: Integrating Cloud-Based Connected Services for Sustainable and Autonomous Transportation. International Journal on Recent and Innovation Trends in Computing and Communication, 9(12), 179–187. Retrieved from https://ijritcc.org/index.php/ijritcc/article/view/11557
5. Balaji Adusupalli. (2021). Multi-Agent Advisory Networks: Redefining Insurance Consulting with Collaborative Agentic AI Systems. Journal of International Crisis and Risk Communication Research , 45–67. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2969
6. Singireddy, J., Dodda, A., Burugulla, J. K. R., Paleti, S., & Challa, K. (2021). Innovative Financial Technologies: Strengthening Compliance, Secure Transactions, and Intelligent Advisory Systems Through AI-Driven Automation and Scalable Data Architectures. Universal Journal of Finance and Economics, 1(1), 123–143. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1298
7. Adusupalli, B., Singireddy, S., Sriram, H. K., Kaulwar, P. K., & Malempati, M. (2021). Revolutionizing Risk Assessment and Financial Ecosystems with Smart Automation, Secure Digital Solutions, and Advanced Analytical Frameworks. Universal Journal of Finance and Economics, 1(1), 101–122. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1297
8. Gadi, A. L., Kannan, S., Nandan, B. P., Komaragiri, V. B., & Singireddy, S. (2021). Advanced Computational Technologies in Vehicle Production, Digital Connectivity, and Sustainable Transportation: Innovations in Intelligent Systems, Eco-Friendly Manufacturing, and Financial Optimization. Universal Journal of Finance and Economics, 1(1), 87–100. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1296
9. Cloud Native Architecture for Scalable Fintech Applications with Real Time Payments. (2021). International Journal of Engineering and Computer Science, 10(12), 25501-25515. https://doi.org/10.18535/ijecs.v10i12.4654
10. Pallav Kumar Kaulwar. (2021). From Code to Counsel: Deep Learning and Data Engineering Synergy for Intelligent Tax Strategy Generation. Journal of International Crisis and Risk Communication Research , 1–20. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2967
11. Chinta, P. C. R., & Katnapally, N. (2021). Neural Network-Based Risk Assessment for Cybersecurity in Big Data-Oriented ERP Infrastructures. Neural Network-Based Risk Assessment for Cybersecurity in Big Data-Oriented ERP Infrastructures.
12. Katnapally, N., Chinta, P. C. R., Routhu, K. K., Velaga, V., Bodepudi, V., & Karaka, L. M. (2021). Leveraging Big Data Analytics and Machine Learning Techniques for Sentiment Analysis of Amazon Product Reviews in Business Insights. American Journal of Computing and Engineering, 4(2), 35-51.
13. Routhu, K., Bodepudi, V., Jha, K. M., & Chinta, P. C. R. (2020). A Deep Learning

Architectures for Enhancing Cyber Security Protocols in Big Data Integrated ERP Systems. Available at SSRN 5102662.

14. Chinta, P. C. R., & Karaka, L. M.(2020). AGENTIC AI AND REINFORCEMENT LEARNING: TOWARDS MORE AUTONOMOUS AND ADAPTIVE AI SYSTEMS.