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Tutoring Machine Learning Algorithms in an Artificially Intelligent Environment: A Futuristic Approach for the Energy Sector

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ABSTRACT

In the realm of algorithms, Machine Learning is the epicenter of intelligent transactions. There are multiple approaches and kinds of algorithms, however in the legality of machine learning algorithms have emerged as a conundrum for regulators because of the way in which they 'behave' in artificially intelligent ambience. Issues concerning their structure, ownership, accountability mark a grey area for research and reflection. The first part of this paper aims to explain various approaches and supervision of algorithms. This is the quintessential first step to decide the accountability of algorithms. Second part addresses case studies and issues concerning algorithms and energy sector. India is undergoing a pragmatic shift of energy efficiency and sustainable development. It necessitates an in-depth look into the various instances which have been judicially decided, such that the policy makers can adapt respectively. The third part of this paper is a policy perspective on this issue, specifically to the energy sector in India. Fourth part deals with a comparative study between India and European Union for a futuristic analysis. Lastly, the paper deals with solutions for policy makers and regulators for an energy efficient India.

Keywords: *Machine learning, Machine Learning Algorithms, artificial intelligence, energy law, European Union, pricing algorithms*

I. INTRODUCTION

Most Machine learning is increasingly gaining priority in various sectors in their quest to harvest artificial intelligence for profit maximisation and efficiency. One key sector in this regard is the energy sector. It is ascertainable that renewable energy has benefitted from machine learning in past few years. Wind energy, solar energy, hydro energy as well as nuclear energy companies are utilizing it for bringing down their costs and increasing their returns in systems like smart grids. This particular trend is paving the way forward for interplay between

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artificial intelligence and energy efficiency. This paper intends to explore issues and challenges in this regard. Before delving into challenges faced by the industry, it enunciates various kinds of algorithms. It then proceeds to discuss policy perspectives like responsiveness of smart grids, power grids and posit solutions for harnessing it. Furthermore, it enlists certain case studies in India and the European Union in order to juxtapose what the future could hold for Indian policy makers and stakeholders.

II. Relevance of AI and Machine Learning Algorithms

AI comes from computer science. This subject tries to analyze the essence of human intelligence, and studies the way that computer or machine simulates human to analyze and recognize information, so as to expand human intelligence. In the past decades, AI has made great achievements in research and has been widely applied in various fields. According to the degree of applicability, AI can be divided into artificial narrow intelligence (ANI) and artificial general intelligence (AGI). ANI refers to AI applied in the situation of clear task, requirement and boundary. At present, ANI has made remarkable achievements, which are better than human in many applications. AGI refers to a system similar to human intelligence that can learn and evolve autonomously just like the human brain. However, for AGI, there are numerous problems to be solved, which cannot be realized for a long time. The wide application of artificial intelligence is a tendency. In the future, all industries will upgrade and change with AI, and more industries and emerging business models will be born. At present, AI in education, medical care, elderly care, environmental protection, urban management, judicial services and other aspects have been outstanding performance, and is gradually infiltrating into all aspects of life. Machine learning is a subdivision of AI, is one of the ways to achieve AI. Machine learning research is to create algorithms that enable computers to learn autonomously. Through the machine learning algorithm, the computer analyzes the existing laws of the existing data, and then uses the discovered laws to predict the similar situation. Machine learning algorithm abstracts real problems into mathematical models and applies mathematical methods to solve the models. By evaluating the mathematical model, researchers can check whether the model really solves the problem raised, or to what extent it solves the problem.[2]

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[2] Jian Jiao, "Application and Prospect of Artificial Intelligence in Smart Grid", *available at https://iopscience.iop.org/article/10.1088/1755-1315/510/2/022012/*pdf. (Last visited 11 January, 2022). See 4th International Workshop on Renewable Energy and Development (IWRED 2020). IOP Conf. Series: Earth and Environmental Science 510 (2020) 022012. doi:10.1088/1755-1315/510/2/022012.

According to the classification criteria of learning mode and learning method, machine learning can be classified into distinct categories. For instance, based on the learning model, machine learning can be divided into supervised learning, unsupervised learning and reinforcement learning. Based on learning methods, machine learning can be divided into traditional machine learning and deep learning. Supervised learning is to establish a mathematical model for the labelled training data set through learning strategies, and then to mark the new data according to the established mathematical model. Typical supervised learning algorithms include regression algorithms and classification algorithms. Unsupervised learning is to describe the unmarked data and find out the rules hidden in the data. Typical unsupervised learning algorithms include single-class density estimation, single-class data dimension reduction, clustering, etc. Reinforcement learning is when the system maximizes the value of an output function by learning in some situations. Reinforcement learning has been successful in areas such as unmanned driving and robot chess. [3]

Algorithms applied to traditional machines include support vector machines (SVM) and bayesian methods. The traditional feature extraction of machine learning mainly depends on human, but the method of feature extraction and expression is not universal. Deep learning is a subdivision of machine learning, which is a data representation learning algorithm based on artificial neural network. Through feature transformation, deep learning transforms the feature representation of samples in the original space into a new feature representation, making it easier to classify or predict data. Compared with the method of constructing feature rules manually, deep learning method can describe data information more accurately.[4]

III. Exploring issues and challenges for the energy sector

The core of intelligent power grid lies in replacing manual operation with AI to obtain the advantage of high efficiency, reliability and low cost. There are corresponding application scenarios of AI in every link of power system, such as power generation, power transmission, power transformation, power distribution and power consumption.

(A) Power grid and its management

Smart grid is a combination of modern information system and the traditional power grid. Smart grid is the direction of power system development. It can solve the problems of the traditional power system such as low energy efficiency, poor interaction, and difficult security

[3] Id.
[4] Id.

and stability analysis. The increasing scale of the power grid, the access of renewable energy power plants and the reform of the electricity market make the power system increasingly complex, which brings a lot of uncertainty the operation of the power grid.[5]

Furthermore, the power system is closely related to other systems in such as information system, thermal energy system, transportation system, etc. The structure and composition of contemporary power grid are increasingly complex. When the power grid continues to produce a large number of high-dimensional and multi-type data, the traditional modelling, optimization and control technologies have many limitations, which put forward higher requirements on the power grid.

AI has become one of the fastest growing areas in technology and is expected to play an important role in energy, transportation, health care, security and other applications. Most of the problems in the power system are optimization and prediction. AI can provide unique solutions for energy production, power grid balance and energy consumption analysis. AI has become an important part of the power industry.

AI is an application process of self-learning and calculation. It can integrate human vision, perception, understanding, communication, adaptability and other abilities, and combine with the powerful data processing functions of computers. After summarizing the development of smart grid and AI, this paper will analyze some applications of AI in smart grid, such as the application of AI in the following situations: power load prediction, generation power prediction, power system stability control, power system fault diagnosis, and power network security protection.

However, the application of AI to smart grid also faces numerous challenges, which are also analyzed in this paper. Advancing towards a stable, well- distributed power grid based on renewable energy resources is becoming increasingly cumbersome and challenging. While the traditional power grid is capable of changing it into a smart grid by augmenting it with advanced information and communication technologies, and machine learning intelligence. The intervention of artificial intelligence, algorithmic machine learning can enable smart grid to make decisions that are more intelligent and respond to unprecedented changes in demands of consumers, outages of power, sudden drop and rise in the output concerning renewable energy or any other disastrous events. Machine learning can also assist in capturing certain crucial patterns like that of customer consumption, demand of energy and power generation of

[5] V. Venkatesh, "Fault classification and location identification on electrical transmission network based on machine learning methods," Master of Science Thesis, Virginia Commonwealth University, 2018.

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transient and intermittent sources, thereby predicting equipment failures. Currently, wireless technologies are being used in smart grid renders it vulnerable to cyber security threats Reinforced learning can aid in making energy dispatch decisions and activate demand management signals in order to maintain balance of power supply and demand.. With the increase in data volume, it is now possible to employ machine learning for the detection and prevention of anomalous behaviour, intrusion, cyber-attacks, and malicious activities as well as data authentication. This paper reviews the application of different machine learning approaches that aims at enhancing the stability, reliability, security, efficiency and responsiveness of smart grid. This paper also discusses some of the challenges in implementing machine learning solutions for smart grid.[6]

With the introduction of distributed and renewable energy sources, it is becoming increasingly difficult to maintain the balance between demand and supply of power as well as the quality of power in the electricity network. As the traditional power grid is not designed to handle bidirectional power flow, electricity networks are struggling to handle backflow of power from distributed generation sources such wind and solar. The intermittent nature of the renewable energy sources is also making it difficult to maintain stable power flow in the electricity network. The traditional power grid is transformable into an intelligent, automated and responsive power grid by augmenting it with information and communication technologies, and machine intelligence. This type of grid is often termed as smart grid. The motivation behind developing smart grid is to ensure stable, reliable, efficient, economical and sustainable generation, distribution and usage of conventional and renewable power.[7]

Smart grid can offer multifarious benefits to the operators of generation, transmission and distribution operators, and consumers as discussed below:

(B) Demand issues

The first and foremost positive outcome of the smart grid is that it allows customers and network operators to manage electricity consumption in order to reduce peak of demand and avoid network overloading.[8]

[6] Jian Jiao, "Application and Prospect of Artificial Intelligence in Smart Grid", *available at https://iopscience.iop.org/article/10.1088/1755-1315/510/2/022012/*pdf. (Last visited 11 January, 2022). See 4th International Workshop on Renewable Energy and Development (IWRED 2020). IOP Conf. Series: Earth and Environmental Science 510 (2020) 022012. doi:10.1088/1755-1315/510/2/022012.

[7] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid—The new and improved power grid: A survey," IEEE Commun. Surveys Tuts., vol. 14, no. 4, pp. 944–980, 2011.

[8] . Awais, N. Javaid, N. Shaheen, Q. Z. Iqbal, G. Rehman, K. Muhammad, and I. Ahmad, "An efficient genetic algorithm based demand side management scheme for smart grid," in Proc. of 18th IEEE International Conference

However, in case there are swings in demand of energy, for countries it can turn into an expensive engagement while they shift towards green energy. Responding towards this fluctuation in demand is not easy. Countries like Germany have pledged to move towards renewable energy completely by 2050. The plausible repercussions of this decision could be high demand on certain specific days like festivals, etc. and volatility. In difficult weather conditions it is a challenge to maintain the supply of power. For instance on a windy or stormy day, it may not be plausible to continue the same flow of energy as in demand. Here comes the role of machine learning algorithms. The machine learning algorithms are trained hereby to utilize the data collected from wind turbines and solar panels to make forecast of weather and changes in power.[9]

(C) Stability and reliability of networking

Smart grid maintains the balance of supply and demand and regulates the voltage by varying generation and managing demand. Smart grid allows network operators to anticipate and locate faults and outages remotely that could lead to quicker restoration of power.

Smart grid is a complicated system with real-time perception, information service and dynamic control. The deep information flow interaction will make the power system face more potential threats. The network attack of the power system has the characteristics of strong concealment and long incubation period. Although the primary equipment is not directly damaged, the secondary system can be destroyed to attack the physical power grid. Deep learning can automatically identify network attack features, detect malware and intrusion, and provide network security protection for the power systems. The probability of power system being attacked is far less than that of normal operation, so the abnormal sample data of power network being attacked is far less than that of normal sample data. The training process of deep learning does not require sample labels, which can mitigate the impact of insufficient sample size.[10]

(D) Maintenance by Artificial Intelligence and Internet of Things (IoT)

Machine learning is a sub set of Artificial Intelligence. Employing artificial intelligence in this scenario, maintenance of power can be easily determined with machine learning techniques. Hence, operational time series data can be gathered from sensors employed at power lines,

on NetworkBased Information Systems (NBiS), 2015. doi: 10.1109/NBiS.2015.54

[9] N. Hajj and M. Awad, "A game theory approach to demand side management in smart grids," in Intelligent Systems'2014. Advances in Intelligent Systems and Computing, vol 323. D. Filev et al. Eds. Cham: Springer, 2014.

[10] Supra at 6.

stations and machinery.

Machine learning algorithms can then predict the life of a machine and tentative failures. The main purpose of putting these machine learning algorithms to work is such that they can help optimisation of maintenance, periodical functioning. Thereby reducing power cuts, failure of machines, blackouts and cost of maintenance.

For an example, USA is using phasor measurement units to track voltage, timestamps, device ID, location in microseconds. This prevents power failures. Hence, the maintenance mode is shifting pragmatically towards a predictive one instead of being reactionary.[11]

In an industry where equipment failure is common, with potentially significant consequences, AI combined with appropriate sensors can be useful to monitor equipment and detect failures before they happen, thus saving resources, money, time, and lives.[12]

Toshiba ESS has been conducting research on the use of IoT and AI to improve the efficiency and reliability of geothermal power plants. For example, predictive diagnostics enabled by rich data are used to predict problems that could potentially shut down plants. [13]

Preventive measures such as chemical agent sprays to avoid turbine shutdowns are optimized (quantity, composition, and timing) using IoT and AI. Such innovations are important in a country like Japan, which has the third largest geothermal resources in the world, especially in the face of decreasing costs of competing renewable sources such as solar power.[14]

(E) Consumption and exploration of energy

The clustering and identification ability of machine learning in AI can be utilized to analyze the power consumption behaviour of users, detect abnormal power consumption and non-invasive load monitoring. These analyses and tests provide theoretical support for the reasonable pricing of comprehensive energy system and the improvement of energy structure, and support two-way flexible interaction between energy supply and users. For example, based on the data of power, voltage and current measured by smart meters, AI clustering and data

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[11] Rob Toews, "Deep Learning's Carbon Emissions Problem", Forbes 17th June,2020. Available at https://www.forbes.com/sites/robtoews/2020/06/17/deep-learnings-climate-change-problem/?sh=370eadcc6b43. (Last visited 11 January, 2022).

[12] CBInsights. 2018. "5 Ways the Energy Industry is Using Artificial Intelligence." Research Briefs, March 8, 2018. https://www.cbinsights.com/research/ artificial-intelligence-energy-industry/.

[13] Richter, Alexander. 2018. "Toshiba Energy Systems & Solutions Corporation Has Launched a Research Program on Internet-of-Things and Artificial Intelligence Technology to Improve the Efficiency of Geothermal Power Plants. Think GeoEnergy, August 16, 2018. Available at https://www.thinkgeoenergy.com/ improving-efficiency-of-geothermal-plans-with-artificial-intelligence-and-iot-technology/. Last visited 11th January 2022.

[14] Baloko Makala and Tonci Bakovic, "Artificial Intelligence in the Power Sector", Note 81, April 2021. Available at EMCompass_Note_81-05-web.pdf (ifc.org). Last visited 11th January 2022.

mining can be used to identify the characteristics of electricity consumption behaviour of different user groups, realize scientific segmentation of customers, and then provide personalized marketing and services. Non-malicious factors (such as changes in electrical equipment, seasonal changes, changes in behavioural activities, etc.) can change power consumption patterns at short or long time scales and affect the accuracy of abnormal behaviour detection results. Therefore, it is necessary to identify and exclude the influence of these non-malicious factors. Power consumption analysis and abnormal behaviour detection can be summarized as the description of user characteristics, which can be solved mathematically by feature extraction or classification. The establishment of multi-hidden layer deep learning network can build a classifier with better performance.[15]

IV. Policy perspectives for sustainable energy management

Following are the few contours of policy perspectives that can be undertaken by stakeholders in order to progressively realize the best output using machine learning algorithms and AI.

(A) Prioritizing Long Time Memory Network (LTMN) technology

At present, artificial neural network technology has become one of the commonly used methods to predict power load. In the early stages, the back propagation algorithm (BP algorithm) used by the artificial neural network is a model containing only one hidden node. In the case of limited samples and computational elements, the model cannot fully describe complex functions. With the advance of technology, deep learning is widely used in power system load forecasting. The long and short time memory (LSTM) network is a common model in the field of deep learning. This model is an improved one based on recursive neural network (RNN). The characteristic of LSTM network is to use memory modules instead of common hidden nodes to ensure that the gradient will not disappear or expand after passing through many time steps, so as to overcome some difficulties encountered in traditional RNN training. LSTM is suitable for processing and predicting important events with relatively long intervals and delays in time series.

(B) Harnessing AI in energy sector and climate change

Recently, OpenAI announced it had built the biggest AI model in history known as GPT-3. Modern AI models consume a massive amount of energy, and these energy requirements are growing at a breathtaking rate. In the deep learning era, the computational resources needed to

[15] Supra at 14.

produce a best-in-class AI model has on average doubled every 3.4 months; this translates to a 300,000x increase between 2012 and 2018. GPT-3 is just the latest embodiment of this exponential trajectory.[16]

AI has a meaningful carbon footprint today, and if industry trends continue it will soon become much worse. Unless we are willing to reassess and reform today's AI research agenda, the field of artificial intelligence could become an antagonist in the fight against climate change in the years ahead.[17]

The problem with relying on ever-larger models to drive progress in AI is that building and deploying these models entails a tremendous amount of energy expenditure and thus carbon emissions. Emma Strubell estimated that training a single deep learning model can generate up to 626,155 pounds of CO_2 emissions—roughly equal to the total lifetime carbon footprint of five cars. As a point of comparison, the average American generates 36,156 pounds of CO_2 emissions in a year.

(C) Equitable access to computational resources to academia

Academic researchers need equitable access to computation resources. Recent advances in available compute come at a high price not attainable to all who desire access. Most of the models studied in this paper were developed outside academia; recent improvements in state-of-the-art accuracy are possible thanks to industry access to large-scale compute.[18]

The supervised learning algorithms require fully labelled data for training purposes; however, fully labelled data is either limited or difficult to obtain.[19] In case of predicting power outage events, the scarcity and imbalance of event data poses a significant problem as power grid failures are quite rare. For example, distribution feeders have different kinds of failures and there are few training examples available for each kind.[20] The failure pattern may change rapidly and the model for prediction may be obsolete after some time. If deep learning algorithms are used for modelling problems in smart grid, the efficacy of modelling will depend on the availability of vast amount of quality data. It is possible to generate high resolution synthetic data for training by modelling and sampling, but this is not without challenges. The

[16] Supra at 14 .
[17] *Id.*
[18] Emma Strubbel, Ananya Ganesh, Andrew McCallum, "Energy and Policy Considerations for Deep Learning in NLP".Available at https://arxiv.org/pdf/1906.02243.pdf.(Last visited 11th January, 2022).
[19] Y. Zhou, R. Arghandeh, and C. J. Spanos, "Partial knowledge data-driven event detection for power distribution networks," IEEE Transactions on Smart Grid, vol. 9, no. 5, 2018.
[20] C. Rudin et al. "Machine learning for the New York city power grid," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 34, no. 2, 2012.

challenges mentioned in are: (1) high dimensionality, (2) large number of observations, (3) non-Gaussian marginal probability of individual.[21]

V. INDIA AND EUROPEAN UNION

(A) India's global leadership in renewable energy

India has continued to rise in the Global Innovation Index (GII) rankings to 46 among 132 nations.[22] Recently at COP 26, India has committed itself towards climate friendly energy perspectives. It has also been the torch- bearer and founding nation for International Solar Alliance as well as building disaster resilient infrastructure.[23]

India receives a great deal of attention for embracing renewable energy and setting aggressive deployment targets. Nationally, India has over 35 gigawatts (GW) of installed capacity from wind power sources with another 25 GW from solar power sources—representing 60 GW of India's total of 75 GW from renewable sources. India aims to go further in the coming years with a goal to reach 175 GW of renewable energy in the electric power sector by 2022. [24]

Adding to this, recent statements made by central government officials at an International Renewable Energy Agency meeting suggest the government would like to rachet its ambition up to deploy 500 GW of renewable energy by 2030. However, states are struggling to use all the power generated from renewable sources despite regulations requiring state utilities to dispatch power generated from those sources ahead of that produced by thermal power plants.[25]

As Prime Minister Narendra Modi's government strives to reach its ambitious target , it faces many challenges in crafting regulations that will shape the market to incentivize and optimize existing and future power generation assets, including allowing renewable sources to penetrate and expand in the power generation mix of various states. One set of tools India's states and the central government should pursue to address these hurdles lies in artificial intelligence through machine learning applications.[26]

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[21] M. Sun, I. Konstantelos, and G. Strbac, "A deep learning based feature extraction framework for system security assessment," IEEE Transactions on Smart Grid, 2018. doi:10.1109/TSG.2018.2873001

[22] Global Innovation Index 2021 Report. Available at https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2021/in.pdf.

[23] Ministry of External Affairs Media Center, "National Statement by Prime Minister Shri Narendra Modi at COP 26 Summit in Glasglow". Available at https://www.mea.gov.in/Speeches-Statements.htm?dtl/34466/National+Statement+by+Prime+Minister+Shri+Narendra+Modi+at+COP26+Summit+in+Glasgow. Last visited 11th Januray,2022.

[24] Jeffrey D. Bean and Kartikeya Singh, "Optimizing India's Electricity Grid for Renewables Using AI and Machine Learning Applications". Available at https://www.csis.org/analysis/optimizing-indias-electricity-grid-renewables-using-ai-and-machine-learning-applications. Last visited 11th January,2022.

[25] Id.

[26] Id.

The National Institution for Transforming India (NITI Aayog), the official policy think tank for the government of India, released a National Strategy for Artificial Intelligence, which identified artificial intelligence (AI) as one technology India could use to make the adoption of renewables more cost effective and increase the efficiency of existing solar and wind power sources. It is not enough to point AI at the problem in the future—India's states need to start laying the groundwork for AI now to maximize the efficiency of the renewable sources they plan to create and reduce renewable energy power curtailment. Machine learning can provide better predictive electricity grid load management and maintenance for renewable sources permitting states to enhance their collective energy security.[27]

1. Renewables and Their Challenges

Renewable energy sources have many clear benefits. They are climate friendly, minimize air and water pollution, require only a one-time capital expenditure for infrastructure (coupled with regular maintenance costs) and no recurring fuel costs, offer new jobs, and reduce the import of hydrocarbon fuel sources. However, absent adequate energy storage options, the output from these renewable sources is often less predictable because it varies based on the weather, season, and time of day. Renewable energy sources thus require enhanced forecasting and scheduling of power resources to effectively manage the grid.[28]

A key facet of the challenge is that India's power distribution companies (discoms) and load managers at times curtail renewable energy power as a result of scheduling and cost challenges, transmission inefficiencies, and a lack of interstate balancing and power transfers. Renewable energy power curtailment for wind power in Tamil Nadu reached as high as 50 percent in the past and averaged around 20-25 percent for the state's largest operator in 2018. On the solar power side in Tamil Nadu, curtailment reached as high as 100 percent on certain days in 2017, although state regulations have subsequently been passed to limit curtailment from solar pants.[29]

Moreover, some states have reached power surpluses at times due to a surge in power generation assets, but the assets need to be managed efficiently, as state governments want to both ensure their energy security and make money to recuperate costs. Currently, the rubber meets the road in terms of power distribution within India at state load dispatch centers

[27] Id.

[28] OECD "Climate Resilient Infrastructure" OECD Environment Policy Paper Number 14. Available at https://www.oecd.org/environment/cc/policy-perspectives-climate-resilient-infrastructure.pdf. Last visited 11th January,2022.

[29] Id.

(SLDCs) and regional load dispatch centers (RLDCs). Load dispatch centers should be aided in the effort of efficiently integrating renewable generated power into the grid via newly planned collocated Renewable Energy Management Centers (REMCs) modeled after European systems to provide more robust renewable energy forecasting, scheduling, and monitoring capabilities. These centers, established as part of the Green Energy Corridor, an eight-state partnership focused on increasing intra- and interstate transmission for renewable energy, would benefit from the granular and advanced forecasting that machine learning tools can offer.[30]

In addition, leaders of India's states widely support developing additional storage to make managing their power needs more achievable and reduce the effects of curtailment. Wind and solar power can be used to charge large-scale batteries (including pumped storage) that in turn can be used as on-demand power sources. Storing renewable energy into batteries for future use requires significant upfront planning and investment on its own, and AI tools can enhance its efficacy. Currently, only one battery storage pilot is active outside Delhi, operated by Tata Power Delhi Distribution Limited and developed in collaboration with AES and Mitsubishi, but other pilot efforts for battery storage are planned, including in Andhra Pradesh. There are, however, several pumped storage sites in India, including in the states of West Bengal, Maharashtra, Andhra Pradesh, and Tamil Nadu, and several more are being planned or under construction.[31]

Maximizing optimization in each of these areas for renewables, however, currently requires detailed prior planning and/or intensive monitoring. This is a clear focus for many Indian states. For example, the Gujarat Electricity Regulation Commission recently announced new regulations that permit day-ahead and intra-day scheduling changes for renewables—up to 9 times a day for solar generators and up to 16 times a day for wind generators. With this, Gujarat has joined Maharashtra, Uttar Pradesh, Punjab, Telangana, Haryana, Andhra Pradesh, Gujarat, Tamil Nadu, and Meghalaya in issuing regulations for the forecasting, scheduling, and deviation settlement for solar and wind generation.[32]

2. Bring on the Narrow AI

Machine learning tools, including deep learning applications, can process large datasets of past weather, generation output history, and operational electricity requirements in specific

[30] Id.
[31] Supra at 28.
[32] Id.

locations. These machine learning applications offer potential solutions for forecasting and scheduling that would allow states and specifically SLDCs to better manage their renewable (and non-renewable) power load and in turn their entire electricity grids. There are projects underway now in the United States and Europe that have made progress in AI-based applications for real-time and short-term predictive modeling using machine learning techniques. Deepmind, a subsidiary of Google, has leveraged machine learning algorithms via a neural network to process local weather data and historical wind turbine output for 700 megawatts (MW) of wind power capacity in the central United States. This allowed Deepmind to optimally manage hourly power delivery commitments a day in advance—claiming to boost the value of their wind turbine output "by roughly 20 percent." In a similar vein, the firm Ayata offers predictive technology software for wind and solar power applications using AI programs.[33] The European software firm Peltarion has also developed an AI cloud-based predictive software (Deep Weather) for weather and energy grid management and applied it for the Swedish energy group Tekniska verken. Researchers at the Department of Energy's Argonne National Laboratory are building machine learning programs along the same lines to make the U.S. electric grid smarter. While these applications are still in the nascent stage, they show tremendous promise and potential savings to consumers and utilities.

Machine learning based applications for renewables are not limited to load management and forecasting—they can also aid in maintenance and remote equipment monitoring. In the United States, a number of utility companies claim to utilize machine learning from companies such as SpaceTimeInsight to monitor equipment to reduce wind turbine failure rates and shape maintenance schedules to reduce costs. In addition, AI researchers at the Thapar Institute of Engineering and Technology of Punjab developed a program that can predict when solar photovoltaic (PV) panels will require maintenance before their performance deteriorates. PV maintenance and reliability is a big issue in India—a study in *Energy & Environmental Science* showed that in Delhi over a two period, "average annual attenuation of solar panel output was about 12 percent" due to air pollution leading to as much as $20 million in lost revenue per year.

On the hardware side, these forecasting services utilize AI chips, including field programmable grid arrays and application specific integrated circuits, or ASICs, which are of bespoke design for the machine learning tasks at hand, maximizing the efficiency in which the programs can be trained. And the datasets required to train these applications—weather data in a specific

[33] Id.

location and solar/wind generation history—are becoming more readily available as renewable energy operators track temperature, barometric pressure, precipitation, output, and numerous other variables in routine course of their operation as they are weather dependent. Existing monitoring requirements in India for grid stability also provide a natural platform for grid management data if it is saved digitally and curated properly.

3. Powering Up: Takeaways

In the Center for Strategic and International Studies' recent survey of state power distributors, only two states, Tamil Nadu and Gujarat, prioritized predictive load balancing. Yet the takeaways for India's states are multifold. India's state power regulators and utilities should explore adoption of machine learning based predictive management and require companies to demonstrate the efficiency of their applications through pilot projects at select SLDCs and REMCs. There are already Indian firms in this space utilizing machine learning like Climate Connect that could be considered.

States should pass legislation requiring that discoms save and archive renewable generation and transmission data so that it can be analyzed in future machine learning applications to reduce cost (this data provides grist for the machine learning mill). They should also analyze any gaps in the data they are currently collecting, for example on transmission network weaknesses.

State-owned utilities should also explore the use of sensor networks and machine learning applications in remote monitoring for reducing equipment failure and maintenance costs. This will serve a double benefit for India's newly expanded service network— part of the universal electrification scheme, "Saubhagya."

Finally, states and the central government should explore opportunities for engagement with the United States, including utility to utility partnerships that share the similar scope of renewables in their power mix where U.S. firms are using AI or connecting SLDCs to U.S. utilities that service cross-state, areas such as Xcel Energy. Facilitation of deeper engagement on machine learning in the power sector between U.S. and Indian universities and the U.S. Department of Energy labs through a "power and energy efficiency pillar" under the new U.S.-India Strategic Energy Partnership might be one way to put this into action.

In the long term, if machine learning proves an effective tool for India's grid management, the wider adoption and implementation of these technologies will likely lower the cost of renewables and maximize efficiency by reducing renewable energy curtailment.

(B) European Union

The EIA process in EU Member States, has been strengthened by an amendment to the EIA Directive (2014/52/ EU amending 2011/92/EC), which places a stronger emphasis on climate change adaptation and resilience across the screening, scoping and assessment process.

The new AI regulation will make sure that Europeans can trust what AI has to offer. Proportionate and flexible rules will address the specific risks posed by AI systems and set the highest standard worldwide. The Coordinated Plan outlines the necessary policy changes and investment at Member States level to strengthen Europe's leading position in the development of human-centric, sustainable, secure, inclusive and trustworthy AI.[34]

The new rules will be applied directly in the same way across all Member States based on a future-proof definition of AI. They follow a risk-based approach:

Unacceptable risk: AI systems considered a clear threat to the safety, livelihoods and rights of people will be banned. This includes AI systems or applications that manipulate human behaviour to circumvent users' free will (e.g. toys using voice assistance encouraging dangerous behaviour of minors) and systems that allow ‘social scoring' by governments.[35]

High-risk: AI systems identified as high-risk include AI technology used in:

- Critical infrastructures (e.g. transport), that could put the life and health of citizens at risk;
- Educational or vocational training, that may determine the access to education and professional course of someone's life (e.g. scoring of exams);
- Safety components of products (e.g. AI application in robot-assisted surgery);
- Employment, workers management and access to self-employment (e.g. CV-sorting software for recruitment procedures);
- Essential private and public services (e.g. credit scoring denying citizens opportunity to obtain a loan);
- Law enforcement that may interfere with people's fundamental rights (e.g. evaluation of the reliability of evidence);

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[34] European Commission, “Excellence and Trust in Artificial Intelligence”. Available at https://ec.europa.eu/info/strategy/priorities-2019-2024/europe-fit-digital-age/excellence-trust-artificial-intelligence_en
[35] Id.

- Migration, asylum and border control management (e.g. verification of authenticity of travel documents);
- Administration of justice and democratic processes (e.g. applying the law to a concrete set of facts).

High-risk AI systems will be subject to strict obligations before they can be put on the market:

- Adequate risk assessment and mitigation systems;
- High quality of the datasets feeding the system to minimise risks and discriminatory outcomes;
- Logging of activity to ensure traceability of results;
- Detailed documentation providing all information necessary on the system and its purpose for authorities to assess its compliance;
- Clear and adequate information to the user;
- Appropriate human oversight measures to minimise risk;
- High level of robustness, security and accuracy.

In particular, all remote biometric identification systems are considered high risk and subject to strict requirements. Their live use in publicly accessible spaces for law enforcement purposes is prohibited in principle. Narrow exceptions are strictly defined and regulated (such as where strictly necessary to search for a missing child, to prevent a specific and imminent terrorist threat or to detect, locate, identify or prosecute a perpetrator or suspect of a serious criminal offence). Such use is subject to authorisation by a judicial or other independent body and to appropriate limits in time, geographic reach and the data bases searched.

Limited risk, i.e. AI systems with specific transparency obligations: When using AI systems such as chatbots, users should be aware that they are interacting with a machine so they can take an informed decision to continue or step back.

Minimal risk: The legal proposal allows the free use of applications such as AI-enabled video games or spam filters. The vast majority of AI systems fall into this category. The draft Regulation does not intervene here, as these AI systems represent only minimal or no risk for citizens' rights or safety.

In terms of governance, the Commission has proposed that national competent market surveillance authorities supervise the new rules, while the creation of a European Artificial

Intelligence Board will facilitate their implementation, as well as drive the development of standards for AI. Additionally, voluntary codes of conduct are proposed for non-high-risk AI, as well as regulatory sandboxes to facilitate responsible innovation.

Coordination will strengthen Europe's leading position in human-centric, sustainable, secure, inclusive and trustworthy AI. To remain globally competitive, the Commission is committed to fostering innovation in AI technology development and use across all industries, in all Member States.

First published in 2018 to define actions and funding instruments for the development and uptake of AI, the Coordinated Plan on AI enabled a vibrant landscape of national strategies and EU funding for public-private partnerships and research and innovation networks. The comprehensive update of the Coordinated Plan proposes concrete joint actions for collaboration to ensure all efforts are aligned with the European Strategy on AI and the European Green Deal, while taking into account new challenges brought by the coronavirus pandemic. It puts forward a vision to accelerate investments in AI, which can benefit the recovery. It also aims to spur the implementation of national AI strategies, remove fragmentation, and address global challenges.

The updated Coordinated Plan will use funding allocated through the Digital Europe and Horizon Europe programmes, as well as the Recovery and Resilience Facility that foresees a 20% digital expenditure target, and Cohesion Policy programmes, to:

- Create enabling conditions for AI's development and uptake through the exchange of policy insights, data sharing and investment in critical computing capacities;
- Foster AI excellence 'from the lab to the market' by setting up a public-private partnership, building and mobilising research, development and innovation capacities, and making testing and experimentation facilities as well as digital innovation hubs available to SMEs and public administrations;
- Ensure that AI works for people and is a force for good in society by being at the forefront of the development and deployment of trustworthy AI, nurturing talents and skills by supporting traineeships, doctoral networks and postdoctoral fellowships in digital areas, integrating Trust into AI policies and promoting the European vision of sustainable and trustworthy AI globally;
- Build strategic leadership in high-impact sectors and technologies including environment by focusing on AI's contribution to sustainable production, health by

expanding the cross-border exchange of information, as well as the public sector, mobility, home affairs and agriculture, and Robotics.

VI. Conclusion

The use of AI in the power sector is now reaching emerging markets, where it may have a critical impact, as clean, cheap, and reliable energy is essential to development. The challenges can be addressed over time by transferring knowledge of the power sector to AI software companies. When designed carefully, AI systems can be particularly useful in the automation of routine and structured tasks, leaving humans to grapple with the power challenges of tomorrow. Access to energy is at the very heart of development. Universal access to affordable, reliable, and sustainable modern energy is one of the Sustainable Development Goals (SDGs). Yet it will remain just that—a goal—unless innovative solutions and modern technologies can overcome.

The many energy-related obstacles that plague emerging markets, from a lack of sufficient power generation, to poor transmission and distribution infrastructure, to affordability and climate concerns. In addition, the diversification and decentralization of energy production, along with the advent of new technologies and changing demand patterns, create complex challenges for power generation, transmission, distribution, and consumption in all nations. Artificial intelligence, has the potential to cut energy waste, lower energy costs, and facilitate and accelerate the use of clean renewable energy sources in power grids worldwide. AI can also improve the planning, operation, and control of power systems. Thus, AI technologies are closely tied to the ability to provide clean and cheap energy that is essential to development.

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