The Role of Artificial Intelligence in Latin America's Energy Transition

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***Abstract*— Latin America's energy transition involves the massive integration of sustainable energy, different than hydro, at large and small scale, consumer empowerment, and the adoption of emerging information and communication technologies (ICT) in the entire electricity sector. These factors boost the usage of Artificial Intelligence (AI) to transform the traditional energy industry in a more complex cyber-physical ecosystem. But unlocking the full AI potential requires understanding working principles, current existing applications, and its comprehensive impact on the energy value chain. This paper discusses the role of AI in this context, emphasizing on the key factors for successful implementation in the region and proposes an AI maturity model for the energy transition that allow to determine the status and gaps for the AI adoption.**

***Index Terms*— Artificial intelligence, maturity model, energy transition, power systems, smart grid, machine learning, Latin America**

I. Introduction

Energy transition is marked by the so-called 3D paradigm: Decarbonization, decentralization and digitalization. Decarbonization refers to the integration of renewable energies into the energy matrix for the purpose of replacing the traditional fossil fuel-based resources with cleaner energy sources such as solar and wind power, characterized by low emissions and the usage of inverter-based technologies. On the other hand, decentralization refers to the massive integration of distributed energy resources (DERs) and Behind-the-meter technologies into distribution networks that aims at enabling a more active participation of electrical demand. Finally, digitalization implies transforming the current electricity business, through information and communications technologies (ICT), into a more efficient, intelligent, and consumer-oriented business.

Whereas the energy transition poses new challenges and opportunities to the electricity sector, it is necessary the study of key success factors that allow an effective evolution toward a more sustainable, resilient, and intelligent transmission and distribution networks in which ICT are playing an enabler role. Among the emerging ICT trends, Artificial Intelligence (AI) receives special attention in different fields of knowledge since it provides machine with human-like capabilities to perform a broad variety of specialized tasks, even outperforming model-based classical approaches.

Although AI applications for the energy industry have been developed since 1980s [1] (mostly rule-based, logic-based and experts systems approaches), those based on modern approaches are considered the most promising. Machine Learning techniques, a subset of AI studying the algorithms and models that allow machines perform a task without being explicitly programmed to achieve it, have a tremendous potential that could bring to power and distribution systems [2]: Grid flexibility, improved reliability and security, renewable resources integration, automated data analysis, fast and intelligent decision-making, efficient demand response, improved generation and demand forecast, and cost reduction from optimal operation. Such AI potential can support and accelerate the energy transition, provided that an understanding of the AI principles and enabling factors for developing and deploying AI applications for the energy transition exists.

However, despite its potential, AI's use in the energy sector is limited [3]. In Latin America, the lack of talent and high cost of technology have been identified as main obstacles to AI adoption [4]. Besides, recent advances in a fast-evolving AI industry altogether with the ongoing changes derived from the energy transition, make difficult to understand the comprehensive impact and potential of AI in this context, leading to misguided or incomplete strategies to cope with current and upcoming challenges. Such potential and impact are worth studying, specially emphasizing on the Latin America context for the purpose of accelerating the transition towards a greener energy future. Although energy transition brings new investments and new services markets in which AI can play a decisive role, this work is centered on the technical and technological aspects, providing valuable insights to understand where and how AI can be used in the energy value chain to address the challenges derived from the energy transition in the Latin America region.

Additionally, this paper presents an Artificial Intelligence Maturity Model for Energy Transition (AIMMET) to quantify the degree of AI adoption within companies of the electricity sector under the ongoing changes. AIMMET results aim at understanding how and where AI is used, but also about how fast or advanced is the adoption within a company in comparison to others in the sector.

This paper is structured as follow. Section II describes the challenges and relevant aspects of the Latin America's energy transition. Section III reviews modern AI methods and principles. Section IV discusses AI applications for energy transition, emphasizing the Latin America's energy industry. Section V presents the proposed AI maturity model for the energy transition. Finally, conclusions are presented in Section V.

II. Energy Transition in Latin America

Energy transition in the 23 Latin American countries share the same global concerns on energy's decarbonization, decentralization and digitalization. Latin American Energy Organization (OLADE) has announced the regional renewable goal of 70% by 2030 [5], as evidence of the region commitment towards the environment. Although hydropower is the predominant energy source in Central and South America (approximately 60%), non-hydropower renewables (wind, solar photovoltaic and solar thermal) are gaining space by replacing fossil fuel-based resources, as seen in Fig.1. Brazil, México, and Uruguay lead the wind installed capacity in the region with more than 70% of the total, whereas Chile has the largest solar capacity installed (1 GW) in Latin America, taking advantage of the great potential of the Atacama Desert.

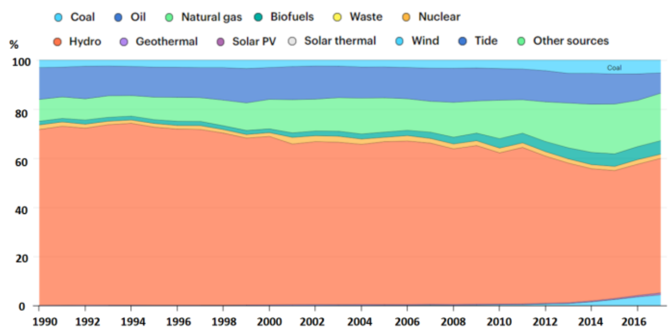

Fig. 1. Electricity generation by source in Central and South America [source: IEA (2019)].

From the regulatory perspective, policies to foster greener energy resources play a decisive role to attract investments and further development of market-based financing schemes for renewables. Power sector policies in the region include auctions, with over 54 renewable energy auctions identified in 12 countries, and grid access policies, identified in 13 countries [6]. However, a successful energy transition in Latin America implies to overcome other challenges, summarized in Fig.2., with singular characteristics for this region.

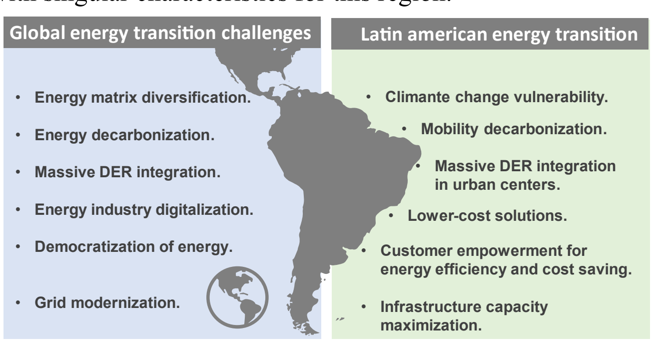

Fig. 2. Challenges in Lantin America Energy Transition.

Despite the vast area covered by the Latin America's countries that houses complex geography and a wide variety of climate, ranging from dry desert-like areas to humid forest, urban centers concentrate the largest density population thus largest centers of energy consumption, away from where generation resources are located, posing several challenges for large-scale transmission infrastructure installation across the countries. DERs emerge as an alternative to move the energy supply near to major load centers, minimizing transmission losses (around 16%, double the global average [7]) and congestions associated with long transmission corridors that connect remote areas with abundant natural resources to the main cities, or maximizing grid reliability of weakly interconnect or radial (single path of connection) systems, typically small distant villages, less-densely populated rural areas or industrial facilities. Although existing DERs in Latin America include already biomass, small-scale hydro or thermal, energy transition would integrate also solar and wind at distribution or household levels, where these resources would enable decentralized control and ancillary services provision. A research conducted by the firm Guidehouse Insights [7] conclude that the region has the world's fastest growing microgrid market, with regional capacity growing from 194.9 MW in 2019 to 2919.4 MW by 2028.

At the same time, urbanization means accessible digital services and the Internet coverage to more people, boosting the digitalization in several productive sectors, including electricity. According to the Organization for Economic Cooperation and Development (OECD) analysis about digital transformation in Latin America [8], countries in the region are taking policy actions to provide affordable access to the Internet with reasonable broadband speed, bringing the Internet to almost 270 million people in the region with no access by the end of 2016. On the other hand, electric mobility can greatly contribute to reduce the greenhouse gas emissions associated to air pollution in urban areas, the largest environmental risk for public health in the Americas [9], by replacing the fossil fuel-based vehicle fleet for cleaner technologies. Nevertheless, massive integration of electric vehicles (EVs) and electric buses into the network remain a challenge.

Climate change is also a common concern in the region, especially in countries with hydro-dependent systems in which the security risk and vulnerability of energy supply during extreme and longer-lasting dry seasons can be mitigated with solar and wind sources. However, technical challenges (e.g.: forecasting, inertia provision, frequency, and voltage control) associated with the variability and uncertainty of these Renewable Energy Resources (RES) must be tackled to achieve high level of integration.

Besides challenges associated with the energy transition in Latin America, additional efforts have been made to achieve regional energy integration. Central American Electrical Interconnection System (SIEPAC) connects six countries since 2014, mostly at 230 kV, to create a competitive regional market. In the Southern Cone, the Andean Electrical Interconnection System (SINEA) initiative plans to interconnect Chile, Colombia, Ecuador, Peru, and Bolivia, to form a sub-regional energy integration that could bring supply security and reduced renewable curtailment. More in the south, Brazil is the center of energy export/import among Paraguay, Argentina, Uruguay and Venezuela, trading energy surpluses through the existing interconnections without a regional market framework. Migrating towards a regional market can bring economic growth, increased flexibility, and benefits from renewable energy complementarity [10].

III. Modern AI

Artificial Intelligence can be defined as the field of computer science dealing with giving machines human-like cognitive, reasoning and behavior capabilities. Although this covers a wide range of applications in several knowledge fields, the present article emphasizes AI's modern approaches and applications in power systems and smart grids, disregarding classical AI like Experts Systems, rule-based systems and knowledge representation. From the practical perspective addressed in this paper, modern AI comprises a vast set of algorithms and techniques for solving problems which include reasoning, planning, natural language processing (NLP), learning, control, and robotics.

Machine Learning (ML), the study of algorithms with the ability of gaining knowledge or skills from experience, encompass a broad spectrum of approaches that can be grouped in three categories: Unsupervised learning, supervised learning, and reinforcement learning (RL). Unsupervised learning consists of deducing rules or structures from input data with approaches such as clustering, anomaly detection and association rule algorithms. In supervised learning, labeled data serve as expected output example for the training process. Supervised learning can predict numerical variables (regression) or categorical variables (classifiers). In contrast, reinforcement learning is a reward/punishment model relying on the interaction between software agents with the environment. A general overview of ML taxonomy is illustrated in Fig.3.

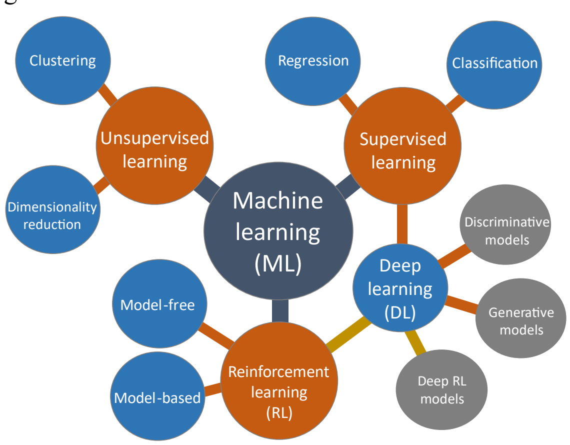

Fig. 3. Machine Learning taxonomy.

Among the modern AI methods stand out Artificial Neural Networks (ANN), an array of nodes (neurons or units) with activation functions that capture hidden behavior or patterns from input data. Nodes grouped at the same depth level are called layer. According to the number of layers, ANN can be shallow (a few layers) or deep (multiple hidden layers). When deep ANN are used for learning, it receives the name of Deep Learning (DL). DL models can be classified into three types of models: Discriminative models, generative models, and deep reinforcement models. While discriminative models learn the boundaries among classes by extracting relevant features from labeled input data, generative models can generate new data instances from training input data.

Typical DL generative models use cases are generation of scenarios, synthetic time-series, synthetic audio or synthetic images/videos, and missing data imputation. In contrast, typical DL discriminative models use cases are NLP, artificial vision, clustering, anomaly detection, feature extraction, prediction, and forecasting.

On the other hand, the Deep Reinforcement Learning (DRL) models combines DL with RL principles to provide algorithms capable of improving the performance in conducting a task with a trial-and-error approach, applied to robotics, optimal controllers of systems and decision-making systems. DRL enables decentralized AI architecture with distributed intelligence through Multi-Agent Systems (MAS), multiple intelligent and autonomous entities (agents) interacting each other in a coordinated way to solve common objectives.

Finally, Nature Inspired Intelligence (NII) take advantage of the way biological and natural systems work collectively to find solutions or adapt to overcome limitations. Common uses for NII are optimization and searching, carrying out exploration and exploitation of the search space in an iterative way, especially useful with complex or non-convex problems. More popular NII stochastic optimization algorithms can be divided in three groups: Evolutionary algorithms (EA), Swarm Intelligence algorithms and Physics/chemistry-based algorithms. EA are exploration-based algorithms that search the best solutions with best-agent selection inspired in Darwin theory of evolution. Swarm-based algorithms are exploration-based algorithms that search the solution moving simple agents around the solution or parameter space, until a global intelligent behavior emerges. Physics/chemistry-based algorithms use a single agent iteratively improving by moving through the search space.

IV. AI Applications for Energy Transition

AI applications are proliferating in the entire energy value chain, leveraging the increasing amount of data and the deployment of new ICT infrastructure. Energy value chain involves manly three activities: Generation, transmission and distribution, and electricity demand. The AI impact on each of these activities in this context has been studied in [11]–[13], highlighting applications related to wind and solar generation maximization with less curtailment, demand-side management for cost and congestion reduction, sustainable energy infrastructure and reliable energy supply. Fig.4. summarizes the AI applications for addressing the energy transition challenges from a systemic and technical point of view.

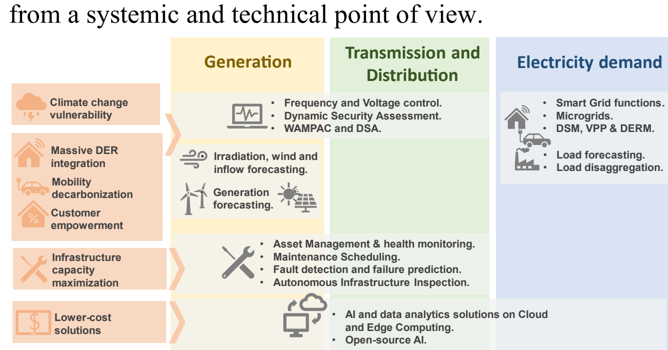

Fig. 4. AI applications for energy transition.

A. Forecasting

Forecasting refers to predict the future from past and present data for a given time horizon that can vary from very short-term (up to an hour) to long-term (more than 1 year). Forecasts are valuable inputs to real-time operation, day-ahead unit commitment, operation planning and adequacy assessment studies.

1) Load/demand Forecasting: Electricity load forecasting applications encompass prediction of peak demand, active and reactive power profile curves, and energy consumption patterns for different time horizons. In this context, AI provides an alternative to deal with the additional complexity to obtain accurate forecasts in scenarios of massive behind-the-meter resources integration. Data-driven and AI-based models can be classified as [14]: Time series analysis-based models, regression models, ANN models, Support Vector Machines (SVM) and Genetic Algorithms (GA). Other applications such as prediction of user behavior consumption, activities of daily living, current or next location and price forecasting, are summarized in [15] for smart home applications. ANN-based methods are used for load profile disaggregation [16]. These AI-based approaches enable to improve energy efficiency, demand-side programs, and system optimization.

2) Generation Forecasting: Due to the intermittent nature of RES, additional variability and uncertainty are impacting the operational reliability and flexibility. In addition to the technical impacts, saving cost from reducing the renewable energy curtailment, start and shutdown of non-renewable plants, network congestion and ancillary services requirements are also associated with forecasting accuracy [17]. In the case of renewable resources, wind speed/power and solar irradiance forecasting methods can be mainly divided in physical approaches, statistical and data-driven approaches, and hybrid approaches [18]. Although the data-driven and AI-driven methods are not an atmospheric phenomena model per se, they can capture the nonlinear interactions between variables, solving this physical model's limitation, covering a statistically significant portion of the solution space [19]. Several ANN-based models have been proposed in literature for wind and solar forecasting [20], [21].

Among Latin America's system operators, wind forecasting is obtained with physical models in most cases, as summarized in Table I [22]–[26], using Model Output Statistics (MOS) post-processing techniques on data collected from physical models such as WRF (Weather Research and Forecasting), GFS (Global Forecast System) or NWP (Numeric Weather Prediction). However, generation forecasting error analysis [27]–[30] has shown notable inaccuracy, leaving researchers an opportunity for proposing improvement on existing tools and techniques.

TABLE I
SOLAR AND WIND FORECASTING METHODS BY COUNTRY

Country	Methods	Type of Model
Argentina	Physical	MOS with WRF and GFS input data
Brazil	Hybrid	WEOL: Weighted Average with NWP input data
Chile	Physical, Hybrid, AI	MOS with NWP input data Proprietary's AI and ML-based Tools
Colombia	Hybrid, Statistical	MOS with NWP input data, and Ordinary Least Square (OLS)
Dominican Republic	Physical	Proprietary model
Mexico	Hybrid, Statistical	Proprietary atmospheric models and adaptive statistical techniques
Uruguay	Physical	MOS with WRF input data

Regarding solar forecasting, it has been identified as one of the technical barriers for solar massive deployment in Chile, altogether with the harsh environment conditions and the lack of access to water, due to the location of solar resources in the middle of the Atacama desert [31]. Solar forecasting is a relative few explored field in Latin America, so further research on AI-driven and data-driven techniques are recommended for low-cost solutions development, especially regarding video and photo analysis of clouds and other climatic variables (e.g. the low-cost solution with DL-based artificial vision proposed in [32] for cloudy weather detection).

B. Smart Grid Applications

Grid modernization is not relied only on high-voltage infrastructure changes, distribution and lower voltage levels networks are also facing challenges derived from the integration of cleaner energy sources, energy storage systems (ESS), electric transportation technologies and Advanced Metering Infrastructure (AMI) that enable active participation of small-scale energy resources, cogeneration and electricity demand in the wholesale, ancillary service and capacity markets, bringing additional benefits to market's participants, power system operators, transmission operators and distribution operators. Smart Grid (SG) concept encompasses a wide variety of subjects, but this section is centered on how AI is making distributed Smart Grids smarter. The adoption of these technologies could bring energy democratization, efficient energy use and energy cost reduction.

Brazil, Colombia and Chile are the leaders in Smart Gird infrastructure planned investments in South America over the next decades [33], focusing their efforts on nationwide AMI rollout, grid automation, DERs connectivity, IT and utility-scale storage, seeking at minimizing current high non-technical losses, facilitating DERs integration and bringing more services to customers. However, improving the efficiency of the grid and empowering users is only possible if intelligent functions and data-driven decision making are integrated into the systems.

AI techniques applied to SG are reviewed in [34]–[37], addressing applications in every SG domain. Nonetheless, there is one application that serves as mechanism to integrate AI into SG: Energy and DER Management Systems (EMS and DERMS). SG EMSs are evolving to intelligent and autonomous management systems where AI-based technologies enable enhanced functionalities in every SG domain as summarized in Table II [38]–[48].

Unlike the definition used for large-scale EMS, this term also describes several types of distributed Smart Grid solutions aiming at visualization, aggregating, monitoring, control and

TABLE II
SUMMARY OF AI APPLICATIONS FOR EMS

EMS Types	AI Applications
Electric Vehicle EMS	Vehicle to grid (V2G): Fair energy provision or market bidding optimization. Grid to vehicle (G2V): Charge schedule or congestion management.
Home, Building & Factory EMS	Multi-objective optimization with nature inspired algorithms for management for energy efficiency, cost reduction, improved comfort, and productivity. DRL applied to energy optimization allows to develop on-line applications by overcoming the heuristic optimization processing time limitation. Demand Response (DR) with ML, ANN, MAS and RL. Designing DR pricing mechanism with NII optimization. Customer segmentation and categorization with several types of clustering algorithms.
Microgrid, EMS & DERMS	Optimal dispatch, Voltage/frequency control, Real/reactive power control, Device specific functions with AI under cloud-based and centralized approaches.

forecast of energy supply and demand to unlock potential value through energy efficiency, cost saving, improved reliability, and demand response programs. With multiple of these management systems interacting each other in the Smart Grid environment, approaches based on coordinated and hierarchical intelligence, such as MAS, will gain relevance.

EMS functions imply collecting, processing, and analyzing a significant amount of data from sensors and utility-scale and/or household-scale resources, transmitted through traditional or Internet of Things (IoT) infrastructure. If data is on the Internet, public or private Cloud Computing platforms are available with on-demand AI and data analytics solutions. Another IoT-based solution is Edge Computing, on-premises solutions that offload cloud server by processing data on the device, entity, or user itself when low latency or timely decision-making is required. IoT-based architectures with intelligent edge computing [47] or with customized ML and AI models [48] have been studied in literature. These state-of-the-art solutions will constitute the basis for smart cities and other innovation in the electricity sector.

C. Frequency and Voltage Control

Frequency and voltage control are two of the main functions at system operators control centers. Both control processes imply scheduling and operating the resources necessary to meet the system performance requirements that are constantly changing due to the load fluctuations, VER variations and unexpected events that affect the grid. The emerging generating and transmission technologies in the energy industry are introducing uncertainty in both the operation and the models, but at the same time, enabling new services and markets. Data-driven approaches emerges as an alternative to cope with the challenges associated with the massification of these technologies.

1) Frequency Control: AI-based techniques proposed to solve some challenges associated with frequency control can be group in three use cases: Reserve requirements [49]–[51], frequency control performance monitoring and evaluation [52], [53], and AI-based control techniques [54]–[58] for Automatic Generation Control (AGC), Load Frequency Control (LFC) or Fast Frequency Response (FFR).

Non-linear dynamic behavior can be captured with data-based models much simpler than traditional complex system models, facilitating the development of practical tools. As regards frequency control performance evaluation, alternative ML-based solutions have been proposed by the Colombian System Operator in [52], [53], using different metrics than NERC's Control Performance Standard (CPS) metrics which it is not necessarily assessing the requirements for Latin America's countries, characterized by few interconnection links and fast dynamics.

2) Voltage Control: Main objective in voltage control is to maintain the voltage within operational and control limits at the grid's nodes. System-level voltage control is commonly performed manually at Latin America's control centers and, in most of the cases, giving priority to switching on/off the compensation devices and changing the transformers' tap (discrete control actions), over changing generators setpoints. In contrast, voltage control in Europe, Asia, and Australia is based on generator's voltage regulation capability (continuous control actions) and thus solutions from these countries are not entirely suitable for the Latin American region.

Modern AI and data-driven approaches offers new alternatives to perform autonomous voltage control in power system and distribution grids using Multi-agent DRL [54], DRL [59]–[61], data-driven online system identification with regression techniques [62] and support vector machines [63]. A DRL agent for automatic voltage control in [64], shows how the ANN can learn the proper control actions by interacting with the power system.

D. Wide Area Monitoring, Protection and Control (WAMPAC)

WAMPAC systems employ synchronized Phasor Measurement Units (PMUs) for disturbance detection/prediction and localization, system states monitoring, islanding detection, and Dynamic Security Assessment (DSA), gaining relevance in low-inertia scenarios with a considerable number of DER and RES.

México, Brazil, Uruguay, Chile, Ecuador, Colombia, and Argentina have deployed PMUs for monitoring and protection schemes purposes. For example, in the case of the SIEPAC network, a wide-area protection scheme detects unstable operating conditions and opens the interconnection with El Salvador to isolate the Guatemalan power system from the rest of Central America before a general blackout occurs [65]. However, other functions for guarantying frequency stability and control under low-inertia scenarios are required. With the existing models, model-based techniques may not be reliable in small-signal dynamic analysis and coherency identification due to the non-linear behavior of the system in presence of wind power [66] and other inverter-based resources. To overcome these and other challenges and limitation, model-free alternatives or measurement-based methods for the above-mentioned applications are summarized in Table III [67]–[74].

TABLE III
SUMMARY OF AI APPLICATIONS FOR WAMS

Application	Techniques
State Estimation	Kalman filtering algorithms, the traditional Least Square approaches, ANN and Belief Network algorithms.
WAMS (Coherency identification, Event Localization and Dimensionality Reduction)	Clustering algorithms, Principal and Independent Component Analysis (PCA & ICA), Local Outlier Factor (LOF), RNN and CNN.
WACS	RL-based damping control.
DSA	Decision Tree, Anomaly Detection algorithms and density-based clustering (DBSCAN).

AI-based Wide-Area Control System (WACS), focus mainly on voltage stability and oscillation damping control, has shown better transient and damping response under non-linear and non-stationary power system dynamics in the presence of uncertainties [75] and to low-frequency oscillation damping control under solar power uncertainty shows better performance than conventional control techniques [73].

E. Asset Management and Health Monitoring

The term asset management defines the systematic process that aim at maximizing the value of assets during their whole life cycle, involving assets operation and upgrade, asset/health monitoring and maintenance scheduling. The metering and sensing systems installed across the grid generate enough data from the fleet of assets to allow seeing the bigger picture of the entire system in time horizons near to real time, but also the health of each equipment.

The role of AI in the asset's lifecycle management is reviewed in [76], highlighting the following applications: ML and DL to predict asset performance, ANN and other supervised learning algorithms to improve predictive maintenance, and the potential use of Genetic Algorithms (GA)-based simulation-optimization approach to find optimal solutions of asset spare provisioning and replacement to minimize the cost.

Machine learning methods for wind turbine condition monitoring are reviewed in [77], addressing both diagnosis (fault detection) and prognosis (fault prediction) approaches by intrusive or non-intrusive monitoring methods.

F. Robotics

Both physical and software robots are autonomous systems designed with problem-solving capabilities to carry out complex tasks . In energy industry, besides the physical robots employed in the manufacture sector, unmanned aerial vehicles (UAV) with artificial vision and other AI algorithms can facilitate the infrastructure inspection in the Latin America's complex geography, without interrupting the operations, reducing cost, and increasing efficiency.

V. AI MATURITY MODEL

The proposed AI Maturity Model for the Energy Transition (AIMMET) consists of measuring the level of usage of AI within companies of the electricity sector based on six domains: AI readiness, forecasting and prediction, decision support tools, planning and operation, smart grid, and asset management. These domains result after overviewing the AI applications for energy transition (twenty-seven functions were identified as seen in Fig.5.), grouped in five broad technical categories. An additional domain (AI readiness) is proposed to measure how prepared is the organization and the available ICT infrastructure to AI adoption. The level of maturity for each domain can fall into one of the following categories with their corresponding value associated: Non-existent (0), planned (1), implementing (2), partially implemented (3), and fully implemented (4).

The proposed AIMMET is not exclusive for the Latin America region use since it was derived from a review of the state of the art in AI, but for illustrative purposes, it was tested on actual survey data from four Latin American companies: Two ISOs (Independent System Operators), one TSO (Transmission System Operator) and one DSO (Distribution System Operator). Although this number of system operators may not be a representative sample, these were the only answers received after requesting information from several system operators in the region.

Fig.5. shows a stacked bar chart with AIMMET results that allows to easily compare which domains have higher maturity levels than others, or which companies have higher level of AI adoption. This example illustrates how AIMMET allow to identify the low level of AI adoption at the DSO in almost every domain, but at the same time, the ISOs strengths in the AI readiness and forecasting & prediction domains. Weaknesses and strengths identified with AIMMET could serve as baseline

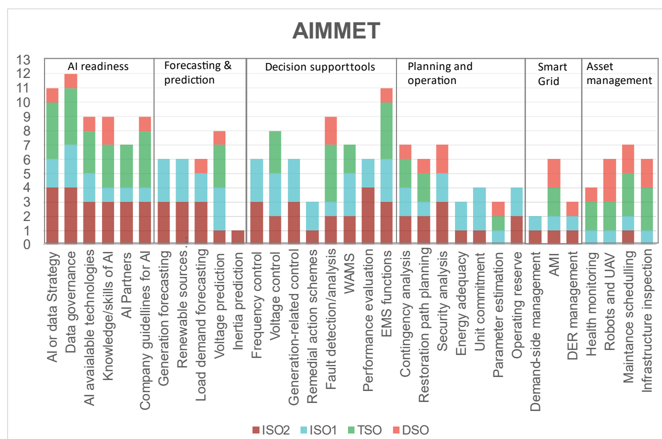

Fig. 5. AIMMET stacked column chart.

of future improvements plans.

A. Key Enablers for AI Adoption

AIMMET results serve as input to define an AI for energy transition roadmap in which the following key enablers to guarantee a successful adoption should be considered according to [11], [78]: Data, technology, organization, and regulatory framework.

1) Data: Extracting the full value of this important asset implies guarantying its proper handling with the FAIR (Findable, Accessible, Interoperable and Reusable) principles, counting on high-quality structured data across the business, and data exchanging among information systems. Harmonizing and implementing standards related to data exchange or data sharing in Latin America could facilitate regional integration, as well as cross sector operations, e.g., energy and gas or electricity and transport. Currently, several countries in the region have already open data portals (under the internet domains *datos.gov.xx, datos.gob.xx* or *datosabiertos.gob.xx)* with available information corresponding to energy consumption, prices, and generation.

2) Techonology: The ICT trends that enable AI adoption are IoT (for enabling Internet connection), AMI (metering), AI frameworks (software), and virtualization of infrastructure (such as cloud and edge computing) technologies. Ongoing AMI deployment projects in Brazil, Mexico, Colombia, Chile, and Peru, are bringing an unprecedent opportunity to introduce new services/products, roles, and actors in these countries' energy industry. Cloud and edge computing facilitates the scalability of solutions without physical infrastructure deployment. Open-source AI frameworks can reduce the costs of developing tools, avoiding dependency on cloud providers.

3) Organization: Digital transformation is putting users and customers in the center of business with technology as the foundational basis. This disruption is forcing companies to adapt the organizational structure, culture, processes, technology, and capabilities to emerging trends. Building a data management and data governance in the company, reskilling and upskilling current professional with AI-related skills and developing a data-driven culture are some challenges to tackle.

4) Regulatory framework: Argentina, Brazil, Chile, Colombia, Costa Rica, México, and Perú have adopted the OECD's principles on AI, the first international standards agreed by governments for the responsible stewardship of trustworthy AI. According to OECD's AI observatory data, the policy initiatives registered in the Latin America territory covering the strategy for national digital transformation and AI national plans by country are Colombia (30), Argentina (11), Chile (10), Brazil (10), Perú (9), Costa Rica (7), México (6) and Uruguay (4). In general terms, OECD's recommendations for policy makers include: Investing in AI research and development, fostering a digital ecosystem for AI, building human capabilities, and preparing for labor market transformation and international co-operation.

VI. Conclusion

Latin America's energy transition implies wind and solar power integration at different scales into hydro-dominant systems aiming at reducing climate change vulnerability, customer empowerment for cost reduction, and infrastructure capacity maximization. AI can accelerate these changes by providing smarter capabilities in the entire energy chain value. The proposed AI maturity model for energy transition has shown to be suitable to identify the current AI status and gaps in the adoption of the state-of-the-art AI applications in the energy transition.

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