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(Review Article)

Leveraging Digital Twin Technology and Predictive Maintenance for Optimizing Solar PV and Battery Storage Systems

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Abstract

The most significant role in the context of the modernization of energy infrastructures is the adoption of renewable sources of energy, solar photovoltaic (PV) systems, and battery storage. However, conventional methods of maintaining facilities can be considered quite responsive in nature and result in the emergence of inefficiencies, unexpected downtimes, and higher expenditure. In this paper, the application of Digital Twin technology and Powered by Artificial Intelligence (AI) and Machine Learning (ML) as a Predictive Maintenance (PdM) solution is examined as the means to reach the maximum performance and availability of the solar PV and battery storage system. Digital Twin designs the online representation of the physical objects, which allows supervising the assets over the net and performing the anticipatory analytics to improve the functioning of the mechanism and foresee the breakdowns. In the meantime, it pertains to the application of AI/ML algorithmics to treat past and operational data to aid in the forecasting of any possible interference, in order to take preventive measures and keep it in reserve. Such technologies go far to increase the uptime of systems, increase resiliency, and lower the costs of the lifecycle. Furthermore, in this paper, the current research, methods, and applications, which represent successful instances of the Digital Twin and PdM model application to the energy systems sector, are reviewed. It also gives how they have been modified to the new smart grids and micro grids, to decentralize the integration of the energy resources. The results indicate that the innovations not only resolve the key issues of the solar and storage systems, but also make it possible to have more sustainable, adaptive, and cost-effective energy infrastructure to drive the future of renewable energy systems to the forefront.

Keywords: Battery; Digital; Maintenance; Optimizing; Predictive; Solar

1. Introduction

Solar photovoltaic (PV) systems and battery storage have come to be an inseparable part of clean energy generation and the power supply in a world that is increasingly moving towards renewable energies. Nevertheless, the optimization

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and maintenance of such systems remain a challenging problem, and in many cases, the conventional approach to maintenance is reactive, leading to expensive downtime and ineffectiveness. To solve this problem, Digital Twin technology and Predictive Maintenance (PdM) driven by AI/ML offer a high-level solution to enhance the system performance. Digital Twin develops a 3D implementation of real-time monitoring, simulation, and predictive analytics to prevent failures and optimize each operation optimization. Simultaneously, the AI/ML analyzes vast amounts of data to predict the system's behavior and streamline the maintenance schedule. In this paper, the algorithm of Digital Twin and AI/ML-based PdM adoption to achieve better uptime, resilience, and lifecycle cost-reduction of solar PV systems and battery storage systems, particularly regarding smart grids and microgrids, is discussed, in an attempt to develop more efficient, sustainable, and cost-effective energy systems in the end. Recent articles have indicated that due to the application of Predictive Maintenance (PdM) and Digital Twin technologies to solar PV and battery storage systems, it is possible to reduce operational costs by 15-20% at least, through a decrease in downtimes and optimized maintenance plans. Moreover, the Levelized Cost of Energy (LCOE) of solar systems can be decreased by up to 10-12 percent by having the advantages of the proactive identification of system inefficiencies and breakage.

2. Overview of Digital Twin Technology

Digital Twin technology can be defined as the creation of an imaginary replica of a real physical system, asset, or process that reports on the real-time performance. A Digital Twin is a dynamically simulated digital representation of physical systems when used with solar photovoltaic (PV) systems, battery storage systems, and will be constantly updated with real information. According to Kull et al. (2025), this virtual model is capable of simulating the condition of the physical version since it incorporates the data presented by Internet of Things (IoT) device and sensors that check the factors of power output, battery condition, and system wear and tear. The advantage of the real-time simulation is that it will give the operators the capacity to learn and predict the system behavior, it maximizes the performance, and enables people to know beforehand the maintenance.

Real-time simulation of the system will give the opportunity to optimize the work and reach efficiency, and guarantee the reliability of the system in the long run. Njoku et al. (2025) append that by assisting with Digital Twin, operators can anticipate failures and inefficiency in the functioning before they happen, hence sparing them time (downtime) and money (mending the machine). The testing and simulation of the work under various conditions make it possible to find out the most efficient settings of the system, and the work of solar PV and battery storage will be ensured in the most effective manner. Recent simulations conducted by Njoku et al. (2025) indicate that implementing the Digital Twin approach to solar PV systems has increased the use of the technology to enhance by 13 percentage of energy generation during peak times and particularly through the modification of the settings based on the current real-time environmental conditions such as temperature and sunlight intensity. In addition, the battery storage systems have indicated 15% growth in lifespan thanks to real-time monitoring and predictive analytics that aware of their maintenance requirements and anticipate their major failure.

2.1. Application of Digital Twin in Battery Storage and Solar PV

The main application of the Digital Twin technology in the solar PV and battery storage is that of real-time optimization of the system and continuous monitoring of the system. According to Njoku et al. (2025), under the simulated behaviour of the system in different conditions, the Digital Twin will give valuable information about system output in terms of energy, battery life, and the system conditions. To take one of them as an example, a digital Twin of a solar PV system can be assumed, which can predict the potential impact of some uncontrollable factors like cloud cover or temperature changes on the energy production. The same can also be applied to Digital Twin to predict battery to charge and discharge in a battery storage system to test the optimum battery health, as well as to increase the overall storage capacity.

2.2. Integration of IoT and Sensors

The IoT devices and sensors are important to provide digital Twin technology with additional opportunities to monitor the physical system continuously and draw conclusions regarding it. Padmawansa et al. note that these types of sensors read such vital values as temperature, voltage, current, and energy output, and the information is transmitted to the Digital Twin model in real-time. This type of integration enables the virtual model to project the health of the system at any given point in time, which enables the operators to observe the performance of the system and the inefficiencies in the system, as well as to anticipate any possible malfunction in the system.

IoT devices can also monitor the system conditions that are viable to affect the performance of the systems, such as temperature changes. To give an example, according to Padmawansa et al. (2023), the solar panels shall be automated with sensors related to the IoT to identify the sun's light intensity and weather conditions and utilize it to activate a

Digital Twin model. With the understanding of the effect of the environmental factors, the system operators will be able to tune the system settings, providing maximum energy production. Equally, in the case of battery storage systems, the health of the particular battery cells can be monitored with the help of IoT sensors, and the Digital Twin can forecast the battery degradation and enable replacement of the failing components in time by preventing more significant failures of the system.

2.3. Digital Twin applications

The Digital Twin technology has large applications in the renewable energy systems and, in particular, in the solar PV. According to Padmawansa et al. (2023), the whole solar energy production system may be simulated with the help of a Digital Twin to optimize the performance depending on the information about the environment and operational indicators in real time. As an example, using Digital Twin simulates the interface of different amounts of solar irradiance, customers can predict how solar panels will act in different circumstances, allowing operators to set the configuration so that maximum amounts of energy are produced. Digital Twin technology has been instrumental in battery management with respect to energy storage. According to Njoku et al. (2025), the Digital Twin model can be described as a form of simulating the individual cell performance and health of a battery, as well as the monitoring of performance specifically. It is through Digital Twin that the charge/discharge cycles can be even more controlled through continued checking on the health of the battery, and thus it extends the life-cycle of the battery system and ascertains that the battery system has been made to operate in the best possible manner.

2.4. Predictive Maintenance in Solar PV and Battery Storage Systems

Predictive Maintenance (PdM) is one of the modern methods of maintenance that is characterized by using data analysis, Artificial Intelligence (AI), and Machine Learning (ML) algorithms to predict the likelihood of a system breakdown and preemptively maintain it. Unlike the old-fashioned reactive maintenance, when the problems occur, which are only noted, PdM is proactive in addressing these issues because it will constantly analyze the operational data offered by sensors on the systems of solar PV and battery storage. According to Kull et al. (2025), PdM enables optimizing the performance and life of important components, including solar panels, inverters, and battery cells, predicting their possible failure or declining performance. Such a predictive opportunity allows planning the maintenance only in case of necessity and carrying out interventions at the most suitable time to avoid unnecessary spending and interruptions of the system. Moreover, PdM helps to reduce operational fluctuations and eradicate the idea of performing costly emergency repairs, and this makes it one of the essential tools of providing a reliable and efficient renewable energy-related framework.

According to recent simulations by Njoku et al. (2025), the deployment of the Digital Twin approach to solar PV systems has boosted the utilization of the technology to improve by 13 percent of energy production during peak hours and especially by altering the settings based on the prevailing real-time weather, such as temperature levels and sunlight intensity levels. Moreover, the battery storage systems have reported 15% extend in lifetime courtesy to real time tracking and predictive analytics which comprehends its service needs and foresees its significant breakdown.

2.5. Artificial Intelligence and Machine Learning in Predictive Maintenance

The addition of AI and ML algorithms gives a lot of expansive success in predictive maintenance as it assists the systems to learn from vast data of operation to be successful in long-term predictions. Vichare and Gaikwad (2025) note that the AI-based models might be used to collect data on the historical performance of the solar PV and battery storage system and real-time sensor data to identify the patterns that suggest failure or inefficiency in these systems. Based on this data, the AI models will be capable of forecasting the remaining useful life (RUL) of components deployed in the system, like the battery cells or the solar inverters and allow operators to plan to undertake the maintenance or replacements. In their study article, Shittu and Shittu (2024) note that such predictive functionality can assist operators of solar farms to manage their assets in a more efficient way, such that not only failures in the system can be prevented, but also uptime is maximised. Still, the rate of prediction of an energy generation with AI-driven models is approximately 95% and regulates how the solar panels work depending on the environmental changes, such as cloud cover and temperature variations. Likewise, in a study, optimization of inverters with the assistance of AI led to higher efficiency and efficiency of the system; specifically, when the sunlight was variable.

2.6. Benefits of Predictive Maintenance

There is a broad spectrum of operational and financial advantages associated with the application of predictive maintenance in solar PV and battery storage systems. Considering the definition given by Kull et al. (2025), it means that PdM allows repairing or replacing the operations by predicting the potential failures prior to them interfering with the operations, therefore limiting the chances of the operation discontinuation. This is a proactive measure to make sure that the energy production will not cease, which enhances the uptime of the system significantly. Additionally, predictive maintenance would help in lowering the overall cost of maintenance. PdM will help minimize the costs of parts replacement and labour costs as now only the necessary measures are taken instead of carrying out routine and urgent repairs on parts that are not urgent (Qureshi et al., 2024).

3. Artificial Intelligence and Machine Learning Framework for Performance Optimization

3.1. AI/ML Models for Optimization

The work of solar photovoltaic (PV) and energy storage requires improvements with the help of Machine Learning (ML) and Artificial Intelligence (AI). Through the analysis of an increasing amount of information generated by the IoT sensors and system operations, AI/ML models will have the opportunity to identify the most optimal system settings, anticipate energy generation, and optimize the efficiency of solar PV and battery storage systems in general. As shown by Ebrahim et al. (2021), works involving machine learning, such as supervised learning and neural networks, can be applied to maximize solar panel performance through analyzing sun radiation and temperature levels as environmental representations. To use AI as an illustration, the behavior of inverters could be programmed by AI models based on the estimated availability of solar energy to generate the maximum possible amount of power under the most optimal conditions. This is the precision part of the system, with the assistance of the real-time data, which will enable the smooth operation and balance of the solar PV systems even in the presence of variations in the given environmental parameters.

3.2. AI/ML in Energy Forecasting and Load Prediction

Among the main advantages of the combination of AI and ML and solar PV and battery storage, one may mention the possibility of optimizing the energy forecast and load estimation. According to Abedi et al. (2023), AI and ML have the capabilities of processing large amounts of data that are gathered at the grid and the environment to predict the energy production trends, storage needs, and consumption trends. Using historical data on energy generation and real-time weather forecasts, AI algorithms are able to determine the quantity of energy that a solar PV system will create across the day, considering diverse elements including cloudy regions, temperature adjustments and season. Also, the use of AI-based forecasting models can be used to optimize battery storage by estimating the extent of energy storage required and the time to release the energy, thus streamlining the entire energy system and lowering the need to use external sources of energy.

3.3. Predictive Analytics for Battery Storage Systems

AI/ML models are applied in battery storage systems to enhance the efficiency of charge/discharge processes so that batteries can be optimized to offer long-term application even before being compromized. Predictive analytics is applied to determine the health and useful life (RUL) of battery cells by analyzing the behavior of each battery cell, predicting when either cell could start degrading or malfunctioning, as explained by Padmawansa et al. (2023). By monitoring such factors as charging cycles, changes in temperature, and patterns of discharge, machine learning models are able to foresee battery behaviour and foresee maintenance before the system failure occurs. This optimization must be necessary in that way, in order that battery storage systems can provide back-up power delivery to energy grids in an effective way, especially during periods of high demand or unpredictable solar production. In addition, predictive models will allow balancing the charge/discharge cycles of batteries such that they are not overcharged but are neither discharged too much, which would otherwise cause a shorter lifespan. Predictive analytics can increase the operational lifespan of energy storage systems and make them more reliable by precisely forecasting when they need to replace their operational parts or provide maintenance.

3.4. AI/ML in Energy Storage Optimization

AI and ML play a significant role in optimization of the energy storage system, specifically in making storage more reliable and efficient. Shittu and Shittu (2024) note that AI can be used to rationalize the dynamic of the energy storage systems in a variety of circumstances, which will be used to simulate how a variety of storage capacities and charge cycles will influence the efficiency of the system with time. It is through this information that AI algorithms will be able to optimize storage and retrieval of energy where the appropriate energy is stored during excess supply and is released in efficient manner when people demand the most energy. These systems will assist in decreasing energy wastage and the economic viability of renewable energy sources due to the ability to store the energy. The systems of AI also enhance the unity between the energy storage and the renewable source, where there is the availability of energy even at times when specific sources, such as solar, are not producing much energy.

4. Enhancing Uptime and Resilience with Predictive Maintenance

4.1. Improving System Uptime

Predictive Maintenance (PdM) is important in improving the functioning of systems in order to minimize the occurrence of unplanned failures. PdM enables advanced detection of the possible failure of the system through the application of AI and Machine Learning (ML) while preventing its subsequent failures or replacement beforehand. PdM can use IoT sensors to continuously monitor the health of such components in the systems, such as inverters and battery cells, to provide valuable insights and ensure that a system runs without problems and interruptions (Kull et al., 2025). Anticipating a failure can prevent missing out on opportunities that come before failure, so that the PV and storage released by the sun can maintain strong availability to prevent losing valuable time where the failure will happen, even though they operate at high cost, also adding to the reliability of the system, in general.

4.2. Increasing Resilience of Energy Systems

Predictive Maintenance (PdM) contributes to the resiliency of energy systems in that the system does not fail because of unfavourable conditions. As Al-Shetwi et al. (2025) note, the Digital Twin technology combined with PdM can be used to simulate the real-time behaviour of the system in different environmental and operating conditions. The feature allows operators to understand how the external changes, like the alteration in the temperature or grid instability, will influence the functioning of the system. PdM allows the stable production of power by solar PV and energy storage systems even under unpredictable conditions by preventing possible breaks and supporting the timely reaction, preventing disturbing factors, improving the ability of the system to respond to the emergence of unforeseen difficulties and ensuring reliability.

4.3. Key Performance Indicators (KPIs) for Resilience

Key Performance Indicators (KPIs) can be used to measure the effectiveness of predictive maintenance and can be defined as the performance and resilience of the system across time. Qureshi et al. (2024) discuss that the key KPIs of solar PV systems are availability, mean time between failures (MTBF), and mean time to repair (MTTR). These KPIs also allow one to monitor system health and downtime rate, which are important to determine the point at which PdM is reducing disruptions. In the case of battery storage system, the KPIs such as cycle life, efficiency, state of health (SOH) are utilized in order to track the integrity and performance of the system to allow predictive analytics to handle its maintenance requirements and enhance its operational lifespan.

4.4. Operational Benefits of Increased Resilience

Both solar PV and battery storage systems have significantly increased operational benefits through increased resilience in predictive maintenance. Shittu and Shittu (2024) explain that more resilient systems have a higher energy yield because they have fewer failures and downtimes, thus they can continue performing even during poor conditions. PdM also assists in the lengthening of systems life-span especially in the energy storage systems in the optimization of charge/discharge and alleviates overuse or deterioration of separate cells. Predictive maintenance increases the long-term operational expenses and enhances the financial viability of the renewable energy projects since it prevents the premature failure of the components and increases the need to make emergency repairs. All these benefits make PdM a necessity to gain the prospects of maximum energy output and efficiency of operation.

5. Case Studies and Real-World Applications

5.1. Case Study 1: Predictive Maintenance in a Large-Scale Solar PV Farm

Predictive maintenance was implemented in the large-scale solar PV farm in California with the use of the machine learning (ML) algorithms as a way of maximizing the work of the system. Badreldien et al. (2021) assert that the farm had IoT sensors on the inverters and panels that the farm used to acquire real-time data on important variables, such as the solar irradiance and panel voltage. Such points have been input into machine learning algorithms that could anticipate problems of failures or underperformance even before they occur. Predictive maintenance implementation enabled an opportunity to increase the energy production by 15% of the previously aided rate because the farm could react proactively to components that were performing poorly. Reducing the downtime that is not necessary and, in case of an emergency, no repairs were necessary, the farm could not only make the process more efficient, but also save significantly on the actual costs of operation, which demonstrated the potent influence of AI-based predictive maintenance. At a solar farm in California, the predictive maintenance also minimized the downtime rate by 30% and hence led to a 15 percent growth in the energy production and a subsequent saving of half a million dollars in the costs per year. With the help of predictive models that were created with the help of AI, the farm was capable of predicting the failures of the system before they became necessary, which resulted in fewer emergency-related repairs and better overall efficiency of the system.

5.2. Case Study 2: AI-based Predictive Maintenance to Battery Storage Optimization

An AI-based predictive maintenance system was applied to a battery storage facility to enhance its operations in the U.K. The system in question was constantly tracking individual battery cells, where Padmawansa et al. (2023) mention monitoring such variables as charge cycles, temperature, and voltage. The system was capable of predicting the remaining useful life (RUL) of the battery cells with the assistance of machine learning, so that the degradation patterns could be anticipated, and replacements would still be made in time. This maintenance proactivity model contributed to the enhancement of the operating efficiency of the facility, minimization of the chances of unexpected failures, and the increase of the total battery lifetime by 20%. Through maintenance that is only done when necessary and through optimization of charge/discharge cycles, the facility saved a lot in terms of costs and the reliability of the systems was also enhanced, hence the facility would make a steady supply of energy. Predictive maintenance was able to increase the battery life of a battery storage facility in the UK by 20%. The system predicted battery degradation very accurately, making it possible to replace the batteries in time and was able to save about 300,000 in maintenance and replacement costs.

5.3. Case Study 3: Microgrid Artificial Intelligence and Digital Twin

In Japan, an AI and Digital Twin microgrid project optimized the functioning of the distributed energy resources (DERs). The Digital Twin framework, as discussed by Shittu and Shittu (2024), modelled the real-time performance of a number of solar PV systems and battery storage units inside the microgrid. The AI algorithms enabled them to forecast the energy generation through the analysis of the collected data via sensors of IoT and optimize the use of energy distribution, according to the demand, efficiently. This synergy resulted in the 25 percent improvement of system reliability as well as greater energy yields through minimization of energy loss and load variation. Real-time simulation of different operational conditions allowed making decisions proactively and resulted in a more robust microgrid in general, which became more flexible to new environmental conditions and demand trends.

5.4. Data and Performance Comparison

Table 1 Performance Comparison Before and After Digital Twin and PdM Implementation

Metric	Before Implementation	After Implementation	% Improvement
Downtime (hours/year)	500	350	30% reduction
Energy Production (MWh/year)	1,000	1150	15% increase
Maintenance Costs ($/year)	$1,000,000	$750,000	25% reduction
Battery Life (years)	8	10	20% increase
LCOE ($/MWh)	$50	$45	10% reduction

5.5. Predicting Battery Health and Remaining Useful Life

The integration of AI and ML allows predicting the battery health and the remaining useful life (RUL) of battery cells, which is vital in the practical storage of energy. Ebrahim et al. (2021) state that AI models take into account such factors as the charge cycles, the voltage and the temperature and predict when a battery is likely to fail. Predictive maintenance can be applied by ensuring that the RUL is accurately predicted, hence replacing/repairing the batteries before they deteriorate severely. This not only maximizes the performance of the battery storage but also minimizes the maintenance expenses that are usually caused by unexpected failures, making the battery storage system serve systems work efficiently with increased durations.

5.6. Load Balancing and Grid Integration

AI and ML are very crucial in energy loads and efficient incorporation of battery storage plants with respect to the electric grid. The research indicated that AI algorithms, which are based on the review of the needs generated by the source of solar power, forecast the demand on the grid and optimize the sources (Odunaiya et al., 2021). The AI-enabled systems have the capability of detecting when to store the energy produced by the solar PV systems or release it to the grid, based on the Demand, which changes with time. It can stabilize the grid, especially when the level of solar generation or demand is high. Through optimal energy exchange between the solar storage systems and the grid, AI maximizes the resilience of the system, minimizes the amount of wasted energy, and facilitates the transition of energy towards sustainability.

5.7. Cost Efficiency and Financial Sustainability

AI and ML also play an important role in cost-effectiveness of renewable energy systems and their financial sustainability, and especially optimization of battery storage. The authors note that AI-driven predictive models reduce maintenance and operation expenses because they extend the lifecycle of the battery systems achieved through optimization of charge/discharge cycles (Al-Shetawi et al., 2025). Energy storage can prevent expensive replacement of batteries that are used for high power consumption by making sure that the batteries are used efficiently to enhance the reliability of the system. In addition, predictive maintenance decreases downtime, meaning that renewable energy systems are always open, which will make them more cost-effective and the need to be dependent on external and costly energy sources will be minimized.

6. Challenges and Future Directions

Technological and Implementation Barriers: Although the application of AI, ML, and Digital Twin technologies to solar PVs and battery storage has great potential, it is important that a number of challenges are overcome before the technologies are introduced. Al-Shetwi et al. (2025) note that one of the most critical challenges can be the data quality and availability, which are needed to train the AI models. Poor predictions resulting in low predictive maintenance of equipment and performance optimization can be caused by inaccurate or inadequate data of the IoT sensors. Besides, the integration of the systems may be complicated, because such developed technologies should have a smooth interaction with the current infrastructure. An interoperability of new AI models with old systems, as well as communication protocols, is a typical obstacle that needs to be broken. Another complexity that factors into their cost is that the process of developing and maintaining these advanced systems requires a high number of skilled staff who are capable of handling the systems.

High Startup Cost and Operational Cost: The other primary concern of implementing AI/ML and Digital Twin technologies is that the startup costs are very high. The installation of sophisticated sensors, AI-based techniques creation, and Digital Twin models related expenses can be costly, particularly in the case of smaller energy projects or developing nations (as Kull et al., 2025, note). Although the technologies have potential to save the firms in long run; optimized performance and lower maintenance costs, lack of upfront financing forms a hindrance to most organizations. Also, operations can be a further burden on budgets due to the cost of maintaining and updating such technologies. The return on investment (ROI) and a proper comprehension of the payoff in terms of long-term benefit should be considered to ensure that the financial viability of such systems is guaranteed.

Input in Data privacy and Data security: A significant concern that the implementation of AI, ML, and Digital Twin technologies in the energy systems introduces is the question of the privacy and security of data. According to Odunaiya et al. (2021), the volumes of information that are being collected by IoT sensors and processed by AI models are incredibly sensitive as they are very large. The usage of the data will lead to the breach of privacy or dominate the work of the energy systems illegally. Such data should be strengthened in the example of solar and battery storage because cyber attacks may derail the system and lead to inconveniences or inefficiency. To deploy those technologies in a secure and trustworthy manner, there will be the need to make sure that they are highly cyber safe and data integrity. There is a need to come up with a series of uniform data protection models that ultimately align with numerous laws, including the General Data Protection Regulation (GDPR), when attempting to overcome such issues.

7. Conclusion

The introduction of Artificial Intelligence (AI), Machine Learning (ML), and Digital Twin into the solar photovoltaic (PV) system and battery storage is one of the largest advances in the performance, reliability, and cost-efficiency maximization of the renewable energy systems. The systems based on AI/ML can predictively maintain, optimize energy storage, and monitor performance in real-time, mitigate the level of downtime, enhance the uptime of the system, and add to the lives of important assets. In addition, Digital Twin technology can be used to simulate the energy systems dynamically with the aim of making superior predictions and managing the resources. Regardless of these benefits, there exist issues like high cost of initial investment rates, data, and elaborate system integration security problems. Nevertheless, as edge computing is developed, quantum computing and 5G will enable their scalability and effectiveness to improve. Such technologies are expected to produce a more autonomous energy system, which will be smarter, more resilient, and sustainable energy infrastructure. The trend of renegotiable energy and the implementation of AI/ML and

Digital Twin technologies will also become the key to the future in the sphere, and will have a beneficial contribution to the efficiency and sustainability of the sphere. Finally, the combination of AI, ML and Digital Twin technologies has been shown to be revolutionizing the optimization of solar PV and battery storing systems. These technologies have shown as much as 20% of operational cost recessions, 15-20 percent energy generation growth and 10-12 percent LCOE. Moreover, according to case studies, these solutions can not only increase the reliability of the energy systems, but provide substantial cost-saving through the amplification of the lives of key elements of the system and overall systems efficiency.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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