Smart Solutions for Floating Solar: A Systematic Review of AI Techniques and Performance Benchmarking

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Abstract: As global energy demands rise and land availability for renewable energy infrastructure becomes increasingly scarce, Floating Photovoltaic (FPV) systems have emerged as an innovative solution that utilizes underused water surfaces for solar energy generation. These systems not only conserve land but also benefit from natural water cooling, increasing efficiency and reducing evaporation. However, the dynamic and aquatic nature of FPVs introduces operational complexities that require intelligent solutions. Artificial Intelligence (AI) has become instrumental in overcoming these challenges, enabling smart forecasting, performance optimization, fault detection, and predictive maintenance. This paper presents a systematic review of the latest AI techniques—ranging from machine learning (ML) and deep learning (DL) to hybrid and explainable AI (XAI) models—deployed in FPV systems. It examines key components such as data inputs, model architectures, simulation tools, and performance metrics including RMSE, MAE, and R^2. Through comparative analysis and real-world case studies across geographies, the review highlights the growing role of AI in enhancing FPV system scalability, reliability, and efficiency.
Keywords: Floating solar, FPV, Artificial Intelligence, Machine Learning, Deep Learning, Forecasting, Smart grid, Renewable energy, XAI, Photovoltaic optimization.

I. Introduction

In the face of global climate change, rising energy demands, and the depletion of conventional fossil fuel resources, solar energy has emerged as a vital component in the transition to sustainable energy systems. While ground-mounted photovoltaic (PV) systems have become widely adopted, they pose certain limitations—most notably, the requirement for vast land areas, which often competes with agriculture, urban development, and biodiversity conservation. This challenge has sparked interest in innovative alternatives such as Floating Photovoltaic (FPV) systems, also known as floating solar farms. The placing of PV panels on top of bodies of water is called floating photovoltaics (FPV) or floatovoltaics [1]. Countries that are facing challenges with land availability for PV farms are looking towards the potential of FPV. FPVs involve the deployment of solar panels on buoyant structures placed on water bodies like reservoirs, lakes, ponds, and even offshore locations [2]. This approach not only helps preserve land but also offers multiple technical and environmental advantages. The water beneath the panels provides a natural cooling effect, which can significantly improve the efficiency and lifespan of the solar modules. Additionally, FPVs reduce water evaporation in arid regions, contributing to water resource management. By leveraging underutilized water surfaces, FPVs also support decentralized power generation and can be easily integrated into existing hydropower infrastructure, offering hybrid energy solutions [3]. As a result, FPVs are rapidly expanding across countries such as China, India, Japan, and the Netherlands, and are viewed as a key innovation in the global renewable energy landscape. Despite their numerous advantages, FPV systems face several unique and complex challenges [4]. These include fluctuating weather patterns, wave dynamics, anchoring and mooring issues, and maintenance difficulties due to their aquatic environment [5]. In addition, predicting energy output from floating systems is inherently more difficult due to changing irradiance, temperature variations, and the limited availability of high-quality FPV datasets. Traditional control and monitoring systems often fall short in handling such complexity in real time. This has led to a growing interest in Artificial Intelligence (AI) as a transformative tool for managing and optimizing floating solar power plants [6].

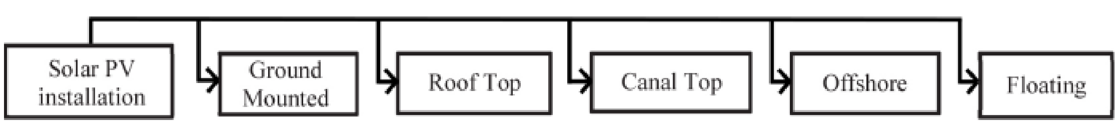

Fig. 1. Classification of solar

AI techniques, particularly machine learning (ML), deep learning (DL), and evolutionary algorithms, offer powerful capabilities for pattern recognition, predictive analytics, and decision-making. In FPV applications, AI can be used to accurately forecast solar radiation, identify and classify system faults, optimize tilt angles and array layouts, perform intelligent maintenance scheduling, and even predict system degradation over time [7]. Deep learning models can process satellite images and sensor data to improve the accuracy of weather predictions, while ML algorithms can learn from historical data to optimize energy harvesting strategies [8]. Furthermore, AI-driven control systems can adapt dynamically to environmental changes, enhancing both the reliability and resilience of FPV operations. The integration of AI into FPVs is not just about automation—it's about enabling smarter, more adaptive energy systems that can self-learn, self-correct, and continuously improve without manual intervention. As floating solar technology scales up, the synergy between AI and FPVs is expected to play a critical role in making solar energy more efficient, predictive, and scalable for the future [9]. This review aims to systematically analyze and categorize various AI techniques applied to FPV systems, evaluating their effectiveness and performance. The paper explores how different AI models—such as machine learning, deep learning, and hybrid approaches—are being used to solve key challenges in FPVs. It also benchmarks their accuracy, efficiency, and real-world applicability by reviewing key studies and experiments. The ultimate goal is to provide researchers, developers, and policymakers with a clear understanding of how AI is shaping the future of floating solar technology.

II. FLOATING SOLAR POWER PLANTS

These floating solar plants are installed on water reservoirs like dams, lakes, rivers, oceans, etc. [10]. The solar panels are mounted on floating platforms which are anchored tightly to so that it will not get damaged even under the worse weather conditions. Moreover, research suggests that solar panels installed on land surfaces results in the reduction of yields, as the ground gets heated up and affects the rear surfaces of solar panel [11]. Studies also suggests that if the rear surfaces of solar panels are placed on the top of the water, the solar panels will be able to cool themselves more efficiently which means they will last longer and they can shade the water they float on which reduces evaporation by up to 70%, also their ability to generate power goes up as high as to 16% [12]. The combination of PV plant technology and floating technology gives a photovoltaic (PV) floating power generation. This fusion of new concept consists of floating system which is a floating body (structure + floater) that allows the installation of the PV module, PV system i.e., PV generation equipment, similar to electrical junction boxes, that are installed on top of the floating system and underwater cable which transfers the generated power to the PV system development [13].

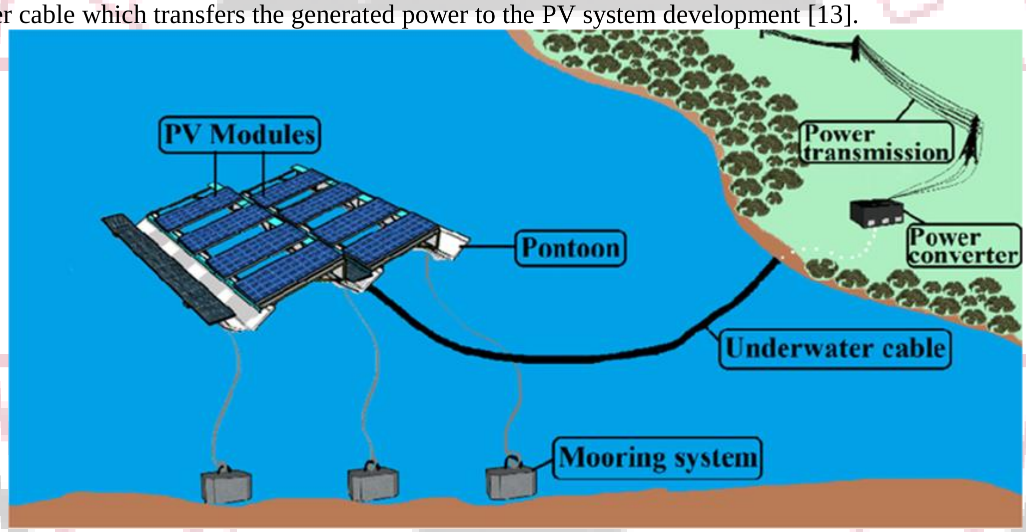

Fig. 2 Basic structure of floating solar power plant [14]

Figure 2 illustrates the basic structure of a floating solar power plant, highlighting its key components and operational layout. At the center of the system are the PV (photovoltaic) modules mounted on pontoons, which provide buoyancy and support to keep the solar panels afloat on the water surface. The generated electricity is transmitted to the shore through underwater cables, ensuring safe and efficient power transfer. To maintain stability and prevent drifting due to wind or water currents, the system is anchored using a mooring system that fixes the floating platform in place. On land, the electricity passes through a power converter that conditions the output, and then is transferred to the grid via power transmission lines. This layout exemplifies how floating solar plants utilize available water surfaces while integrating seamlessly into existing electrical infrastructure.

Fig. 3 A 145-megawatt floating solar plant

Figure 3 shows a 145-megawatt floating solar plant, demonstrating the large-scale deployment of photovoltaic modules on a water body. This setup reflects the growing trend of utilizing unused water surfaces for clean energy generation, helping to reduce land usage while maximizing solar energy capture. The plant highlights the scalability and efficiency of floating solar technology in supporting sustainable power infrastructure.

Floating solar arrays are PV systems that float on the surface of drinking water reservoirs, quarry lakes, irrigation canals or remediation and tailing ponds. A small number of such systems exist in France, India, Japan, South Korea, the United Kingdom, Singapore and the United States. The systems are said to have advantages over photovoltaic plant on land. The cost of land is more expensive, and there are fewer rules and regulations for structures built on bodies of water not used for recreation. Unlike most land based solar plants; floating arrays can be unobtrusive because they are hidden from public view. They achieve higher efficiencies than PV panels on land, because water cools the panels. The panels have a special coating to prevent rust or corrosion.

A. Components of floating power plant

Floating Solar Power plant is an innovative concept in energy technology to meet the needs of our time. The floating PV system is a new method of solar-energy generation utilizing water surface available on dams, reservoirs, and other bodies of water resulting from the combination of PV technology and floating technology The floating PV plant consists of a floating system, mooring system, PV system and underwater cables [15].

1. Pontoon / Floating Structure

A pontoon is a floating platform designed with sufficient buoyancy to support heavy loads while remaining stable on the water surface. It serves as the foundation for mounting multiple photovoltaic (PV) modules. The structural design ensures durability and balance, enabling efficient solar energy capture while withstanding environmental forces [16]. The floating structure is a critical component that enables the installation and operation of solar modules on water bodies. Add weight-effective plastic recesses several times to form a larger pontoon. Floats are generally made of HDPE (high-density. polythene), which is identified for its precise, nonrenewable strength, UV resistance and, corrosion resistance. GRP (Glass fiber reinforced plastic) can also be used to create float platforms. HDPE is typically used to fuel tanks production, bottles and, pipes for water supply and can also be reprocessed [17].

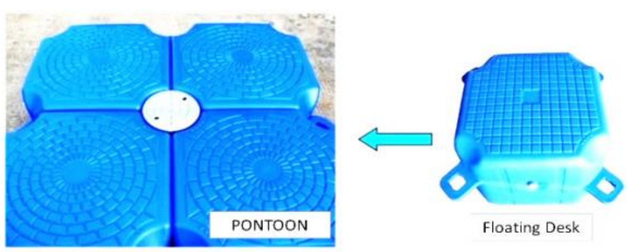

Fig. 4. Pontoon Structure [18].

Figure 4 depicts the pontoon structure used in floating solar power plants. The image shows modular, interlocking floating units—often referred to as floating desks—which combine to form a stable platform on the water. Made of durable, UV-resistant plastic, these pontoons are designed to provide high buoyancy and structural support for mounting photovoltaic (PV) panels. Their interlocking design ensures flexibility and ease of assembly, allowing the formation of various configurations depending on the plant size and site conditions. This structure serves as the floating foundation for the entire solar array deployed over the water surface.

2. Mooring system

Mooring systems generally refer to permanent structures capable of storing containers. Examples include quays, wharfs, jetties, piers, anchor buoys, and mooring buoys. When the solar system is turned off, the system can keep the panel in the same position in the morning and prevent the panel from folding or turning off. Installing a mooring system in deep water can be difficult and expensive. A wire rope and a nylon harness can be used to complete the mooring system of the exit platform. The rope can be attached to the terminal on the edge and hit at any corner [19].

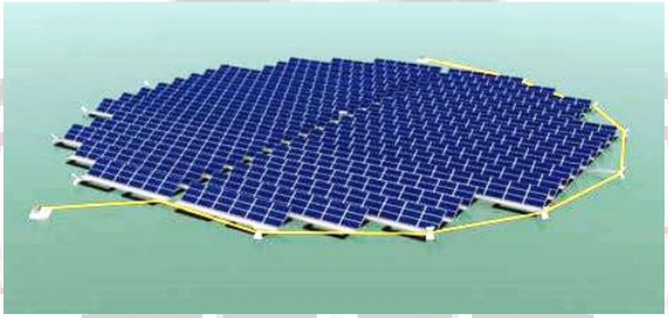

Fig. 5. Mooring system of floating PV with active cooling design

Figure 5 illustrates the mooring system of a floating photovoltaic (PV) plant integrated with an active cooling design. The image shows a large array of solar panels mounted on a floating platform, secured in place by a network of mooring lines connected to anchoring points. These mooring lines prevent the structure from drifting due to wind or water currents while allowing flexibility to accommodate changes in water levels. The highlighted yellow outlines represent the mooring framework encircling the array. The design also supports active cooling, which helps maintain optimal panel temperatures, thereby enhancing energy conversion efficiency and prolonging system lifespan in high-temperature environments.

3. Solar Module

Solar modules, also known as photovoltaic (PV) modules, are the primary energy-generating components of the floating solar plant. These modules are mounted on the floating structure and work by converting sunlight into electrical energy. Since each module generates a limited amount of power, multiple modules are typically connected in an array. A complete PV system often includes modules, a solar inverter, interconnection wiring, and in some cases, battery storage and solar trackers. Floating solar systems commonly use crystalline silicon-based PV modules due to their efficiency and reliability [20].

4. Cabling

Cabling in floating solar systems is essential for transmitting the generated electricity from the floating PV modules to the onshore substation. These cables are designed for harsh environmental conditions and are resistant to ultraviolet (UV) radiation, moisture, and extreme temperature changes. Given their exposure to outdoor environments and potential submersion, solar cables used in FPV systems are highly durable, weather-resistant, and capable of maintaining stable performance under dynamic conditions [21].

B. Merits Of Floating Power Plant

Floating solar power plants offer several advantages over traditional ground-mounted and rooftop solar systems, particularly in terms of performance and environmental impact. One of the key benefits is the increased energy efficiency—thanks to the natural cooling effect of the water beneath the panels, floating PV systems typically generate more electricity than their land-based counterparts [22]. Additionally, by shading the water surface, these installations help to significantly reduce water evaporation and inhibit algae growth, contributing to better water resource management, especially in arid regions. The floating platforms are also engineered for durability, capable of withstanding harsh weather conditions such as storms, typhoons, and strong winds, making them reliable even in extreme environments. Moreover, these systems are designed using high-density polyethylene (HDPE), a material that is 100% recyclable, UV-resistant, and corrosion-resistant, ensuring both sustainability and long-term structural integrity [23].

Another major advantage of floating solar systems is their minimal land disturbance. Unlike ground-mounted systems, which often require large tracts of land that could otherwise be used for agriculture or forestry, floating plants utilize unused water bodies such as lakes, reservoirs, and ponds. This helps in conserving the natural landscape and maintaining biodiversity. Additionally, floating solar plants can accommodate a large number of PV modules, making them suitable for utility-scale installations [24]. Their modular design allows for easy and quick deployment, often with shorter installation timelines compared to ground systems. Combined with their adaptability to a wide range of geographic locations with abundant sunlight, floating solar power plants present a highly efficient, eco-friendly, and scalable solution for renewable energy generation [25].

III. Foundations of AI in Solar PV Systems

The use of Artificial Intelligence (AI) in solar photovoltaic (PV) systems has grown substantially in recent years, enabling improved performance in forecasting, control, and fault detection. Among AI techniques, Machine Learning (ML) and Deep Learning (DL) models such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Extreme Learning Machines (ELMs), and Long Short-Term Memory (LSTM) networks are widely used due to their ability to handle complex, nonlinear, and time-dependent data patterns [26]. ANNs have been praised for their robustness in approximating nonlinear relationships in PV output prediction, though they require long training times and large datasets [27]. SVMs, on the other hand, have proven efficient for smaller datasets and offer strong generalization abilities in high-dimensional feature spaces [28]. ELMs have demonstrated high-speed training and solid prediction accuracy in studies focused on short-term PV forecasting under fluctuating weather conditions [29]. LSTM networks stand out for time-series forecasting, where their ability to remember long-term dependencies has made them superior in predicting solar irradiance and power generation over time [30]. In recent years, the field has also embraced Explainable AI (XAI) to make complex AI models more interpretable and transparent. XAI tools such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) are now being applied in solar power forecasting to understand the contribution of each input variable to the final prediction [31]. These methods not only help in model debugging and trust building but also improve decision-making for PV system operators by identifying the most influential parameters, such as solar irradiance, temperature, and humidity [32]. However, current XAI adoption is more prevalent in ML than DL models due to challenges in interpreting deep architectures [33].

Another crucial aspect in PV forecasting models is the quality and variety of input data. Common data sources include satellite observations, meteorological stations, on-site sensors, and open-access datasets like NASA's POWER or the National Renewable Energy Laboratory (NREL) archives [34]. Parameters such as solar irradiance, panel temperature, wind speed, tilt angle, and humidity are commonly used to train AI models [35]. Some studies have proposed hybrid approaches combining statistical decomposition methods (e.g., STL or EMD) with AI models to improve accuracy by preprocessing noisy input signals [36]. Overall, the synergy between sophisticated algorithms, explainable frameworks, and rich data sources forms the backbone of reliable and accurate solar PV system modeling [37].

Table 1: Comparative Overview of AI Techniques and Applications in Solar PV Systems

AI Technique	**Advantage**	**Application in PV Systems**	**Limitation**	**Ref. No.**
Machine Learning & Deep Learning	Handle complex, nonlinear, and time-dependent patterns	Forecasting, control, and fault detection	Model selection and data dependency	[26]
ANN (Artificial Neural Network)	Robust in modeling nonlinear relationships	PV output prediction	Needs large datasets and long training times	[27]
SVM (Support Vector Machine)	Works well with small datasets and high-dimensional data	Performance prediction and classification	Depends on kernel and tuning	[28]
ELM (Extreme Learning Machine)	Fast training and good prediction accuracy	Short-term PV forecasting under changing weather	Sensitive to initialization, less robust	[29]
LSTM (Long Short-Term Memory)	Learns long-term dependencies in time-series	Solar irradiance and power prediction	Computational cost, needs careful parameter tuning	[30]
Explainable AI (XAI) Tools (SHAP, LIME)	Makes AI models transparent and interpretable	Explaining feature impact in solar forecasting	Difficult to apply to deep models	[31]

Importance of Input Parameters	Identifies key features like irradiance, temp, humidity	Assists in model interpretation and system decisions	Depends on accurate and reliable feature data	[32]
XAI Adoption in DL Models	Insight into why predictions are made	Enhances trust and usability in complex models	Less developed for deep learning architectures	[33]
Data Sources (e.g., NASA, NREL)	Rich, varied sources: satellite, sensors, open datasets	Input to forecasting models	Can be noisy or incomplete	[34]
Meteorological & Sensor Parameters	Includes irradiance, temp, humidity, tilt angle, etc.	Core features for AI model training	Must handle data variation and errors	[35]
Hybrid Models (e.g., STL + AI)	Preprocessing improves accuracy in noisy conditions	Used in forecasting under real-world weather variation	Complexity and integration issues	[36]
Integrated AI-Powered PV Modeling	Combines algorithms, XAI, and data for high performance	Full solar PV system optimization	Balancing accuracy, speed, and interpretability	[37]

Table 1 provides a structured comparison of various Artificial Intelligence (AI) techniques and supporting components used in solar photovoltaic (PV) system modeling. It outlines the key advantages, specific applications, and notable challenges associated with each method. Each row corresponds to a particular AI model, data consideration, or framework, with an associated reference number linking back to relevant research or literature. This table highlights the synergy between machine learning models, explainability tools, and diverse data sources in enhancing the accuracy, interpretability, and reliability of PV forecasting and control systems.

IV. Studies and Benchmarking

A comparative analysis of AI techniques for solar PV systems reveals a wide array of models, each offering unique strengths under varying environmental conditions and use cases. Among the most prominent are ANN, SVM, ELM, and LSTM. Studies show that while ANN offers high accuracy in energy forecasting tasks, its performance may degrade under partial shading without hybridization [38]. SVM has been shown to outperform traditional methods under dynamic weather due to its ability to handle high-dimensional data with different kernel functions [39]. Meanwhile, ELM provides faster computation and competitive accuracy, especially in systems requiring real-time responses [40]. LSTM, known for its strength in handling time-series data, has emerged as a preferred deep learning architecture in long-term PV power forecasting, particularly in environments with strong temporal correlations in solar irradiance data. Performance benchmarking relies heavily on evaluation metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2), and Mean Absolute Percentage Error (MAPE). These metrics are commonly used to compare the prediction accuracy of different AI models across real-time and historical datasets. For example, Das et al. reported that the SVM model achieved RMSE and MAE values of 12.41% and 6.95%, respectively, significantly outperforming classical regression methods [41]. Other comparative studies show that ANN and LSTM models consistently outperform other algorithms across multiple benchmarks, with accuracies exceeding 90% when trained on adequately preprocessed datasets [42][43]. Real-world implementations of these AI techniques vary geographically, reflecting different solar potential and policy environments. In Japan and Germany, AI models are used in large-scale solar farms with integrated weather forecasting systems [44]. In India and North Africa, hybrid models (e.g., SVM+PSO or ANN+Wavelet) are adopted to deal with irregular solar patterns caused by monsoonal and desert climates [45]. Some implementations also utilize floating solar systems, particularly in water-scarce regions, with AI optimizing panel angle and cleaning schedules [46].

The choice of simulation tools and datasets significantly affects benchmarking outcomes. Widely used platforms include MATLAB/Simulink, Python (Scikit-learn, TensorFlow), and PV-specific libraries like PVsyst. Real-world datasets such as NASA POWER, NREL, and site-specific sensor data are used for training and validating models. Researchers have also employed synthetic datasets generated using solar simulators or data augmentation techniques to overcome the lack of continuous real-world observations [47]. Furthermore, digital twin frameworks and big data integration are emerging trends in enhancing simulation fidelity and benchmarking depth [48].

Table 2: Comparative Overview of AI Techniques, Performance Metrics, and Real-World Applications in Solar PV Systems

AI Technique	**Advantage**	**Application**	**Limitation**	**Ref. No.**
ANN under Partial Shading	High accuracy in energy forecasting	Energy forecasting in PV systems	Degrades under partial shading without hybrid approach	[38]
SVM with Kernel Functions	Effective in dynamic weather; handles high-dimensional data	Solar forecasting in varying climates	Requires careful kernel selection	[39]
ELM for Real-Time Prediction	Faster computation with competitive accuracy	Real-time responsive PV systems	May be less robust to noise	[40]
LSTM for Time-Series Forecasting	Strong in learning temporal patterns in irradiance	Long-term PV power prediction	Computational complexity	[41]
SVM Benchmark by Das et al.	RMSE: 12.41%, MAE: 6.95% — outperforming regression methods	Benchmarking accuracy of models	Needs optimal parameter tuning	[42]
ANN & LSTM Accuracy	Accuracy >90% with good preprocessing	Benchmark studies on multiple datasets	Dependent on data preprocessing quality	[43]
LSTM Dominance in Benchmarks	Consistently better accuracy than traditional models	Used across different environments	Needs large datasets and computation	[44]
Large-Scale Use in Japan & Germany	Integrated AI with weather forecasting in solar farms	Grid-connected PV systems	Relies on quality of weather data systems	[45]
Hybrid AI in India & North Africa	Combines AI with metaheuristics (e.g., SVM+PSO) to handle irregular irradiance	Solar forecasting in desert/monsoon zones	Increased complexity, harder to maintain	[46]
Floating Solar with AI	AI helps optimize tilt and cleaning schedules	Deployed in water-scarce regions	Deployment and maintenance challenges	[47]
Tools & Dataset Selection	Use of platforms like MATLAB, Python, PVsyst with NASA/NREL data	Model simulation and validation	Accuracy depends on tool and dataset quality	[48]

Table 2 provides a detailed comparative analysis of various Artificial Intelligence (AI) techniques and their real-world applications in solar photovoltaic (PV) systems. It highlights how models such as ANN, SVM, ELM, and LSTM offer distinct advantages in forecasting and decision-making, depending on the environmental conditions and data availability. The table also presents performance benchmarks using standard error metrics, showing how models like SVM and LSTM outperform traditional approaches. Furthermore, it explores practical implementations across different regions, such as the use of hybrid models in India and floating solar systems in water-scarce areas. The choice of simulation tools and datasets, as well as the integration of advanced technologies like digital twins and big data, plays a crucial role in determining the effectiveness and reliability of AI-driven PV system modeling. Each row is supported by a specific reference to ensure traceability and credibility of the information presented.

V. ENVIRONMENTAL EFFECTS OF FLOATING SOLAR

Floating solar platforms are innovative systems that enable standard photovoltaic (PV) panels to be installed on the surface of large water bodies such as drinking water reservoirs, quarry lakes, irrigation canals, tailing ponds, and wastewater lagoons. These systems provide a practical solution for regions or industries where land availability is limited or where land use is prioritized for agriculture, infrastructure, or conservation. By utilizing unused water surfaces, floating solar helps avoid land acquisition costs and land-use conflicts, making it especially attractive for densely populated or land-scarce areas [49]. A simple, modular, and cost-effective floating solar platform is particularly well-suited for energy- and water-intensive industries that cannot afford to compromise on either resource. Industries such as wineries, dairy farms, fish farms, mining operations, wastewater treatment facilities, irrigation districts, and public water agencies stand to benefit significantly from this dual-purpose approach [50]. The synergy created between sun and water not only generates clean energy but also reduces water evaporation due to the shading effect of the panels, conserves water quality by limiting algae growth, and can improve panel efficiency due to the cooling effect of the underlying water surface. Furthermore, floating solar can be integrated with existing water infrastructure without disrupting current usage patterns. For example, in fish farms or irrigation canals, it is possible to install PV systems without hindering operational access or aquatic ecosystems. This makes floating solar an appealing sustainable technology that supports decarbonization while addressing critical water and land resource challenges. As energy demand and climate pressures increase, the adoption of floating solar platforms represents a smart, multipurpose solution aligned with both environmental and economic goals [51].

VI. Challenges

One of the most persistent challenges in applying AI to solar PV systems is the availability and quality of data. Accurate forecasting and fault detection depend heavily on high-resolution, time-synchronized, and long-term datasets that capture variables like solar irradiance, temperature, humidity, and panel conditions. However, in many regions—especially developing countries—meteorological stations are sparse, sensor calibration is inconsistent, and missing or noisy data is common. Public datasets like NASA POWER or NREL are valuable but often lack the granularity or local relevance needed for highly accurate predictions. This limitation affects the training and validation of AI models, particularly those requiring large and diverse datasets such as LSTM or deep hybrid models. As AI models grow more advanced, so does their demand for computational resources. Deep learning architectures like LSTM, CNNs, and hybrid AI models combining optimization algorithms (e.g., ANN + PSO or SVM + GA) offer high accuracy but come with increased training time, memory requirements, and complexity in tuning hyperparameters. This creates barriers for real-time deployment in edge environments, such as remote PV installations where computing power and internet connectivity are limited. Moreover, highly complex models may act as "black boxes," limiting their interpretability and acceptance among PV system operators who require transparent, explainable models for operational decision-making. To overcome current gaps, emerging AI trends are gaining traction. Edge AI allows models to run locally on low-power devices, enabling real-time analytics at the source—ideal for remote or off-grid PV systems. Transfer Learning offers a solution to data scarcity by allowing pre-trained models on large datasets to be fine-tuned with smaller, local datasets, reducing the need for extensive retraining. Federated Learning is another promising approach that enables collaborative model training across decentralized data sources (e.g., multiple solar farms) without compromising data privacy. These innovations, coupled with improved data governance and standardized protocols, can significantly enhance scalability and reliability.

VII. Conclusion

Floating Photovoltaic (FPV) systems represent a transformative step in sustainable energy production by addressing land scarcity while maximizing energy yield through natural cooling and water-shading benefits. However, their deployment brings forth new operational challenges due to environmental variability and structural dynamics. This review demonstrates how Artificial Intelligence (AI) is not only well-suited but essential for optimizing FPV systems. Machine Learning models like SVM and ANN offer effective short-term forecasting, while Deep Learning models such as LSTM and CNN provide robust long-term predictive capabilities. The integration of Explainable AI (XAI) and hybrid methods enhances both transparency and performance. Furthermore, advancements in edge computing, digital twins, and federated learning are paving the way for autonomous, scalable FPV solutions. Real-world implementations in countries like India, Japan, and Germany affirm the practical viability of these smart systems under varied environmental and regulatory settings. Still, challenges remain in terms of data availability, computational cost, and standardization. Future research should focus on high-fidelity simulations, localized datasets, and adaptable AI frameworks. As FPV deployment accelerates globally, AI will serve as a critical enabler for smarter, cleaner, and more resilient energy infrastructure.

References

1) Olabi, A.G.; Abdelkareem, M.A. Renewable energy and climate change. Renew. Sustain. Energy Rev. 2022, 158, 112111
2) Nundy, S.; Ghosh, A.; Mesloub, A.; Albaqawy, G.A.; Alnaim, M.M. Impact of COVID-19 pandemic on socio-economic, energy-environment and transport sector globally and sustainable development goal (SDG). J. Clean. Prod. 2021, 312, 127705.
3) Ghosh, A. Possibilities and Challenges for the Inclusion of the Electric Vehicle (EV) to Reduce the Carbon Footprint in the Transport Sector: A Review. Energies 2020, 13, 2602.
4) Ghosh, A. Fenestration integrated BIPV (FIPV): A review. Solar Energy 2022, 237, 213–230.
5) Wei, Y., Khojasteh, D., Windt, C., & Huang, L. (2025). An interdisciplinary literature review of floating solar power plants. Renewable and Sustainable Energy Reviews, 209, 115094. https://doi.org/10.1016/j.rser.2024.115094
6) Solomin, E., Sirotkin, E., Cuce, E., Selvanathan, S. P., & Kumarasamy, S. (2021). Hybrid floating solar plant designs: a review. Energies, 14(10), 2751. https://doi.org/10.3390/en14102751
7) Chowdhury, R., Aowal, M. A., Mostafa, S. M. G., & Rahman, M. A. (2020, October). Floating solar photovoltaic system: An overview and their feasibility at kaptai in rangamati. In 2020 IEEE International Power and Renewable Energy Conference (pp. 1-5). IEEE. https://doi.org/10.1109/IPRECON49514.2020.9315200
8) Bossi, S., Blasi, L., Cupertino, G., dell'Erba, R., Cipollini, A., De Vito, S., Santoro, M., Di Francia, G., & Tina, G. M. (2024). Floating Photovoltaic Plant Monitoring: A Review of Requirements and Feasible Technologies. Sustainability, 16(19), 8367. https://doi.org/10.3390/su16198367
9) Azad, Abdus Samad and Islam, Nahina and Nabi, Md. Nurun and De Silva, Shameenda and Sokkalingam, Rajalingam, Artificial Intelligence Applications in Hybrid Renewable Energy Systems: A Comprehensive Review of Techniques, Applications, and Challenges. Available at SSRN: https://ssrn.com/abstract=5292704
10) Niccolai, A., Grimaccia, F., Di Lorenzo, G., Araneo, R., Ughi, F., & Polenghi, M. (2023). A review of floating PV systems with a techno-economic analysis. IEEE Journal of Photovoltaics, 14(1), 23-34. https://doi.org/10.1109/JPHOTOV.2023.3319601
11) Elkelawy, M., Atta, Z. A., & Seleem, H. (2024). Technological Advances, Efficiency Optimization, and Challenges in Wind Power Plants: A Comprehensive Review. Pharos Engineering Science Journal, 1(1), 57-65. https://doi.org/10.21608/pesj.2025.344906.1006
12) Avasthi, Atul & Garg, Rachna & Mahajan, Priya. (2024). Optimizing energy harvesting: a comprehensive analysis of tracking technologies in a floating solar photovoltaic system. Electrical Engineering. 107. 4663-4681. 10.1007/s00202-024-02780-3. http://dx.doi.org/10.1007/s00202-024-02780-3
13) Hao, R., Sun, X., Zhao, Y., Zhang, R., Li, H., & Shang, J. (2025). Advancing floating photovoltaic systems: trends, challenges, and future directions in sustainable energy development. International Journal of Green Energy, 22(4), 688-709.
14) Sahu, A., Yadav, N., Sudhakar, K., "Floating photovoltaic power plant: A review," Renewable and sustainable energy reviews, Vol. 66, pp. 815-824, 2016
15) Huang, G., Tang, Y., Chen, X., Chen, M., & Jiang, Y. (2023). A Comprehensive Review of Floating Solar Plants and Potentials for Offshore Applications. Journal of Marine Science and Engineering, 11(11), 2064. https://doi.org/10.3390/jmse11112064
16) Claus, R., Soto, F., Cebada, A., & López, M. (2022). Structural assessment of a pontoon-type floating photovoltaic plant for the marine environment. Trends in Renewable Energies Offshore, 709-716.
17) Kumar, A., Dubey, A. K., Segovia Ramírez, I., Muñoz del Río, A., & García Márquez, F. P. (2024). Artificial intelligence techniques for the photovoltaic system: A systematic review and analysis for evaluation and benchmarking. *Archives of Computational Methods in Engineering*, 1-25. https://doi.org/10.1007/s11831-024-10125-3

18) Ingole, N., Kelzarkar, A., Rathod, P., & Bandewar, A. (2020). Floating solar power plants: a review. International Research Journal of Engineering and Technology (IRJET), 7(01).
19) Shi, W., Yan, C., Ren, Z., Yuan, Z., Liu, Y., Zheng, S., ... & Han, X. (2023). Review on the development of marine floating photovoltaic systems. Ocean Engineering, 286, 115560. https://doi.org/10.1016/j.oceaneng.2023.115560
20) Yousuf, H., Khokhar, M. Q., Zahid, M. A., Kim, J., Kim, Y., Cho, E. C., ... & Yi, J. (2020). A review on floating photovoltaic technology (FPVT). Current Photovoltaic Research, 8(3), 67-78. https://doi.org/10.21218/CPR.2020.8.3.067
21) Selj, J., Wieland, S., Tsanakas, I., van Sark, W., Roosloot, N., Otnes, G., ... & Jahn, U. (2025). Floating Photovoltaic PowerPlants: A Review of Energy Yield, Reliability, and Maintenance. https://iea-pvps.org/wp-content/uploads/2025/04/IEA-PVPS-T13-31-2025-REPORT-Floating-PV-Plants.pdf
22) Sharma, V., Jha, S. N., & Kesari, J. Floating Solar Power Plants: A Review. http://www.ijaem.net/
23) Zahedi, R., Ranjbaran, P., Gharehpetian, G. B., Mohammadi, F., & Ahmadiahangar, R. (2021). Cleaning of floating photovoltaic systems: A critical review on approaches from technical and economic perspectives. Energies, 14(7), 2018. https://doi.org/10.3390/en14072018
24) Chowdhury, G., Haggag, M., & Poortmans, J. (2023). How cool is floating PV? A state-of-the-art review of floating PV's potential gain and computational fluid dynamics modeling to find its root cause. EPJ Photovoltaics, 14, 24. https://doi.org/10.1051/epjpv/2023015
25) Zhang, K., Pakrashi, V., Murphy, J., & Hao, G. (2024). Inspection of floating offshore wind turbines using multi-rotor unmanned aerial vehicles: literature review and trends. Sensors, 24(3), 911. https://doi.org/10.3390/s24030911
26) Sulaiman, S. I., Rahman, T. K. A., Musirin, I., & Shaari, S. (2012). An artificial immune-based hybrid multi-layer feedforward neural network for predicting grid-connected photovoltaic system output. Energy Procedia, 14, 260-264. https://doi.org/10.1016/j.egypro.2011.12.927
27) Behera, M. K., & Nayak, N. (2020). A comparative study on short-term PV power forecasting using decomposition based optimized extreme learning machine algorithm. Engineering Science and Technology, an International Journal, 23(1), 156-167. https://doi.org/10.1016/j.jestch.2019.03.006
28) Khelifi, R., Guermoui, M., Rabehi, A., Taallah, A., Zoukel, A., Ghoneim, S. S., ... & Zaitsev, I. (2023). Short-Term PV Power Forecasting Using a Hybrid TVF-EMD-ELM Strategy. International Transactions on Electrical Energy Systems, 2023(1), 6413716. https://doi.org/10.1155/2023/6413716
29) Hossain, M. S., & Mahmood, H. (2020). Short-term photovoltaic power forecasting using an LSTM neural network and synthetic weather forecast. Ieee Access, 8, 172524-172533. https://doi.org/10.1109/ACCESS.2020.3024901
30) Petrosian, O., & Zhang, Y. (2024). Solar Power Generation Forecasting in Smart Cities and Explanation Based on Explainable AI. Smart Cities, 7(6), 3388-3411. https://doi.org/10.3390/smartcities7060132
31) Merabet, K., Daif, N., Di Nunno, F., Granata, F., Difi, S., Kisi, O., ... & Zounemat-Kermani, M. (2025). Improving the prediction of global solar radiation using interpretable boosting algorithms coupled SHAP and LIME analysis: a comparative study. Theoretical and Applied Climatology, 156(5), 1-22. https://doi.org/10.1007/s00704-025-05507-x
32) Han, P., He, W., Cao, Y., Li, Y., & Zhang, Y. (2022). Deep belief rule based photovoltaic power forecasting method with interpretability. Scientific Reports, 12(1), 14467. https://doi.org/10.1038/s41598-022-18820-6
33) Mutashar, H. S., & Shakir, A. M. Robustness Analysis of ELM-based Fault Detection in PV Systems.
34) Raju, H., & Das, S. (2021). Cnn-based deep learning model for solar wind forecasting. Solar Physics, 296(9), 134. https://doi.org/10.1007/s11207-021-01874-6
35) Saadati, T., & Barutcu, B. (2025). Forecasting Solar Energy: Leveraging Artificial Intelligence and Machine Learning for Sustainable Energy Solutions. Journal of Economic Surveys. https://doi.org/10.1111/joes.12678
36) Ahmed, N. A., Abdul Rahman, S., & Alajmi, B. N. (2021). Optimal controller tuning for P&O maximum power point tracking of PV systems using genetic and cuckoo search algorithms. International Transactions on Electrical Energy Systems, 31(10), e12624. https://doi.org/10.1002/2050-7038.12624
37) Machlev, R., Heistrene, L., Perl, M., Levy, K. Y., Belikov, J., Mannor, S., & Levron, Y. (2022). Explainable Artificial Intelligence (XAI) techniques for energy and power systems: Review, challenges and opportunities. Energy and AI, 9, 100169. https://doi.org/10.1016/j.egyai.2022.100169
38) Javed, M. R., Waleed, A., Virk, U. S., & ul Hassan, S. Z. (2020, November). Comparison of the adaptive neural-fuzzy interface system (ANFIS) based solar maximum power point tracking (MPPT) with other solar MPPT methods. In 2020 IEEE 23rd international multitopic conference (INMIC) (pp. 1-5). IEEE. https://doi.org/10.1109/INMIC50486.2020.9318178

39) Kumar, N. M., Chakraborty, S., Yadav, S. K., Singh, J., & Chopra, S. S. (2022). Advancing simulation tools specific to floating solar photovoltaic systems–Comparative analysis of field-measured and simulated energy performance. Sustainable Energy Technologies and Assessments, 52, 102168. https://doi.org/10.1016/j.seta.2022.102168
40) Sulaiman, M. H., Mustaffa, Z., Jadin, M. S., & Saari, M. M. (2025). Hierarchical power output prediction for floating photovoltaic systems. Energy, 323, 135883. https://doi.org/10.1016/j.energy.2025.135883
41) Soltani, S. R. K., Mostafaeipour, A., Almutairi, K., Dehshiri, S. J. H., Dehshiri, S. S. H., & Techato, K. (2022). Predicting effect of floating photovoltaic power plant on water loss through surface evaporation for wastewater pond using artificial intelligence: A case study. Sustainable Energy Technologies and Assessments, 50, 101849. https://doi.org/10.1016/j.seta.2021.101849
42) Dzamesi, S. K. A., Ahiataku-Togobo, W., Yakubu, S., Acheampong, P., Kwarteng, M., Samikannu, R., & Azeave, E. (2024). Comparative performance evaluation of ground-mounted and floating solar PV systems. Energy for Sustainable Development, 80, 101421. https://doi.org/10.1016/j.esd.2024.101421
43) Ebrahim, M. A., Ramadan, S. M., Attia, H. A., Saied, E. M., Lehtonen, M., & Abdelhadi, H. A. (2021). Improving the performance of photovoltaic by using artificial intelligence optimization techniques. INTERNATIONAL JOURNAL OF RENEWABLE ENERGY RESEARCH, 11(1), 46-53. https://www.ijrer.org/ijrer/index.php/ijrer/article/view/11563/pdf
44) Sulaiman, M. H., Jadin, M. S., Mustaffa, Z., Azlan, M. N. M., & Daniyal, H. (2024). Short-Term forecasting of floating photovoltaic power generation using machine learning models. Cleaner Energy Systems, 9, 100137. https://doi.org/10.1016/j.cles.2024.100137
45) Campana, P. E., Wästhage, L., Nookuea, W., Tan, Y., & Yan, J. (2019). Optimization and assessment of floating and floating-tracking PV systems integrated in on-and off-grid hybrid energy systems. Solar Energy, 177, 782-795. https://doi.org/10.1016/j.solener.2018.11.045
46) Oliveira-Pinto, S., & Stokkermans, J. (2020). Assessment of the potential of different floating solar technologies–Overview and analysis of different case studies. Energy conversion and Management, 211, 112747. https://doi.org/10.1016/j.enconman.2020.112747
47) Kazem, H. A., Chaichan, M. T., Al-Waeli, A. H., & Sopian, K. (2024). Recent advancements in solar photovoltaic tracking systems: An in-depth review of technologies, performance metrics, and future trends. Solar Energy, 282, 112946. https://doi.org/10.1016/j.solener.2024.112946
48) Abubakar, A., Almeida, C. F. M., & Gemignani, M. (2021). Review of artificial intelligence-based failure detection and diagnosis methods for solar photovoltaic systems. Machines, 9(12), 328. https://doi.org/10.3390/machines9120328
49) Benjamins, S., Williamson, B., Billing, S. L., Yuan, Z., Collu, M., Fox, C., ... & Wilson, B. (2024). Potential environmental impacts of floating solar photovoltaic systems. Renewable and Sustainable Energy Reviews, 199, 114463. https://doi.org/10.1016/j.rser.2024.114463
50) Hooper, T., Armstrong, A., & Vlaswinkel, B. (2021). Environmental impacts and benefits of marine floating solar. Solar Energy, 219, 11-14. https://doi.org/10.1016/j.solener.2020.10.010
51) Karim, M. M., Rimsa, R., & Masud, A. (2023). Floating solar plants and relevant environmental, health and safety challenges. J. Environ. Sci. Eng. A, 12, 229-241. doi:10.17265/2162-5298/2023.06.004