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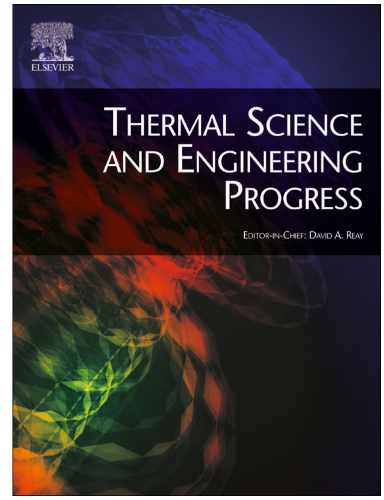

A comprehensive review of machine learning applications in liquid-based cooling solutions of PV/T systems

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Title: A Comprehensive Review of Machine Learning Applications in Liquid-Based cooling solutions of PV/T Systems

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A Comprehensive Review of Machine Learning Applications in Liquid-Based cooling solutions of PV/T Systems

Abstract: This paper presents a systematic review of machine learning (ML) applications in liquid-based photovoltaic-thermal (PV/T) systems, a topic that remains largely unaddressed in the existing review literature despite the growing importance of these hybrid systems in renewable energy. A total of 72 publications are analyzed and categorized across three methodological families: artificial neural networks (ANNs), ensemble methods, and other ML techniques. The review is complemented by a patent landscape analysis covering liquid-based PV/T technologies and a critical assessment of the experimental foundations underlying the reviewed ML models.

The analysis reveals that ANNs dominate PV/T modeling at 63% of reviewed studies, with Multilayer Perceptron being the most frequently applied architecture. Ensemble methods, particularly Random Forest and XGBoost, achieve the highest prediction accuracies with R^2 values up to 0.999. Across all ML categories, prediction accuracies exceed $R^2 = 0.95$ in most applications, confirming the effectiveness of ML in capturing the complex thermal-electrical interactions characteristic of PV/T systems. Nanofluid-enhanced and phase change material configurations consistently demonstrate significant performance improvements over conventional water cooling.

The review traces the evolution of ML methods in PV/T research from foundational ANN studies in 2012 through recent Transformer-based and reinforcement learning architectures in 2025. Critical research gaps are identified, including prevalent small dataset sizes in most studies, limited experimental validation of nanofluid ML models, and the absence of ML-related patent activity indicating a disconnect between academic research and commercial deployment. Future research directions are proposed covering standardized datasets, transfer learning, IoT integration for real-time control, and explainable AI for engineering interpretation.

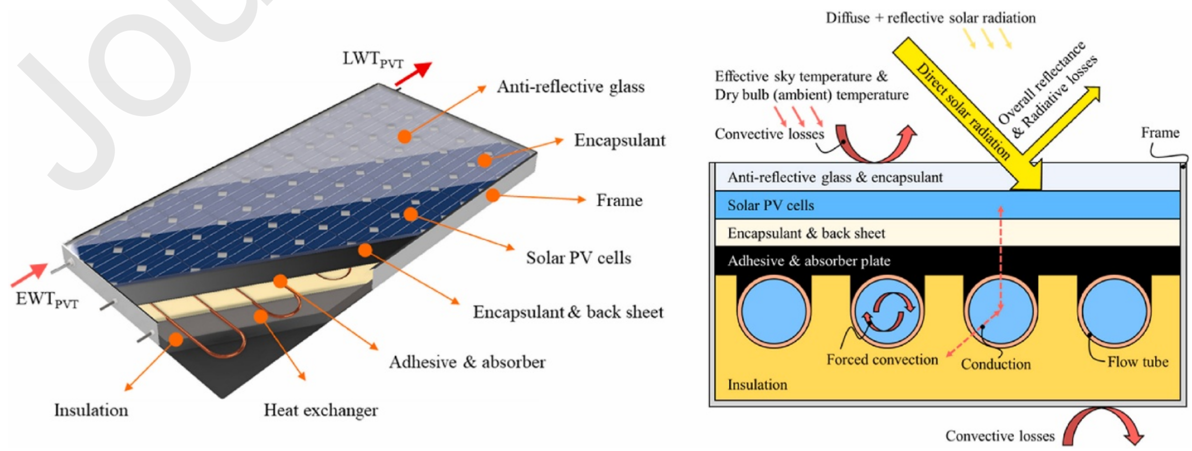
Keywords: Renewable energy; Photovoltaic-thermal; Working fluids; Machine learning; Neural networks; Ensemble methods

1. Introduction

The escalating global energy demand and environmental consequences of fossil fuel dependency have created an urgent need for a transition towards sustainable and renewable energy sources. Global additions to renewable power capacity rose 36% to a record 473 GW in 2023, marking the 22nd consecutive record year [1]. According to the IEA's outlook, renewable capacity is set to expand 2.7-fold by 2030, with solar photovoltaics alone providing around 80% of that additional capacity, and solar plus wind together contributing roughly 95% of total growth [2]. This expansion is reflected in generation data: global solar-PV output increased from 1,294 TWh in 2022 to 1,612 TWh in 2023 – a 25% rise in just one year [3]. Solar is projected to become the largest source of electricity by 2035 [3].

Despite this remarkable growth, conventional photovoltaic systems face significant thermal management challenges that substantially impact performance and longevity. Temperature significantly affects photovoltaic performance, with efficiency typically declining by 0.4% per 1°C increase in cell temperature for crystalline silicon modules [4,5], while alternative studies report rates of decline of 0.22% per degree Celsius [6]. Cooling interventions demonstrate substantial benefits, with temperature reductions of 20°C yielding electrical efficiency improvements of 9-12% [7]. Furthermore, prolonged thermal exposure accelerates degradation mechanisms, including delamination, EVA browning, junction deterioration, and diode failures [8,9], with annual degradation rates reaching 0.2-1.0% and initial losses up to 9.8% within the first year [10]. Empirical studies confirm that back surface temperature measurements provide superior correlation with real-time power output compared to ambient temperature data [11], emphasizing the critical importance of thermal management for maintaining photovoltaic efficiency and extending operational lifespan [9,12].

In response to these thermal challenges, hybrid photovoltaic-thermal (PV/T) systems have emerged as an innovative solution that simultaneously addresses temperature management while enhancing the efficiency of overall energy utilization. These systems provide dual benefits of electricity and thermal energy generation, utilizing solar energy more efficiently than conventional PV installations while maintaining cell temperatures within optimal operating ranges through active thermal management [13,14]. Fig. 1a illustrates the fundamental energy conversion processes in a typical liquid-based PV/T system, showing the integration of photovoltaic cells with thermal collection components and the various heat transfer mechanisms involved, including forced convection through the liquid cooling system and conductive heat transfer to the working fluid. PV/T systems respond to critical challenges such as redundant energy generation and grid mismatch during peak hours [15], offering integrated solutions with low levelized costs and reduced emissions that hold strong potential for driving decarbonization in diverse climate contexts [16–18].



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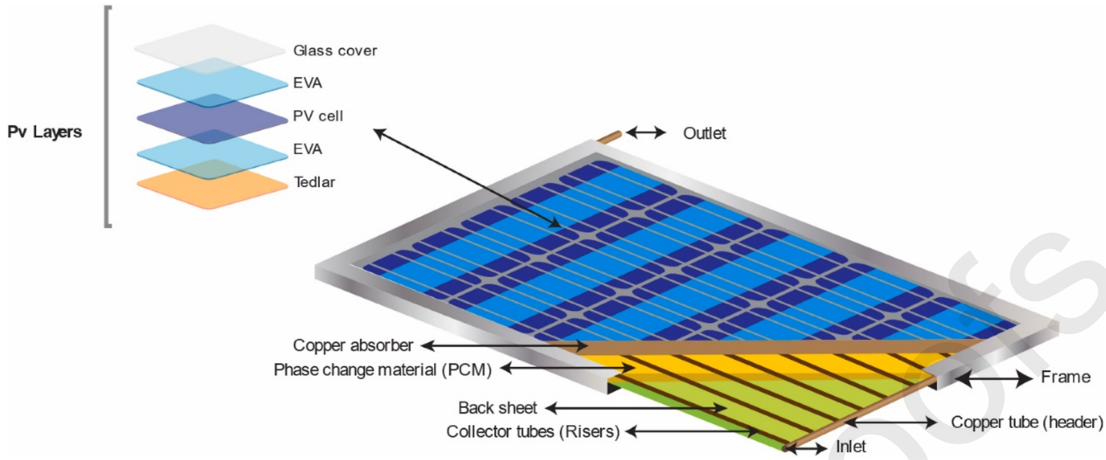

(b)

Fig. 1. Liquid-based photovoltaic-thermal (PV/T) system configurations: (a) Energy conversion processes and heat transfer mechanisms in basic PV/T systems [19]; (b) Advanced multi-layered PV/T system with phase change material (PCM) [20].

Comparative analysis reveals that liquid-based PV/T collectors consistently exhibit superior performance compared to air-based systems. Air-based PV/T systems offer advantages such as simpler construction and achieve thermal efficiencies of 20-60% with electrical efficiencies between 8-16% [21], and recent air-PVT concepts with fins/baffles and integrated PCM have been validated experimentally [22]. Water-based systems, though, outperform air-based collectors by 20.8–21.8% in thermal efficiency due to superior thermophysical properties [23,24]. Nanofluid-based systems offer even greater improvements, with electrical efficiency gains between 20.6% and 37.7% reported for different nanofluid-cooled designs [25]. Recent advances in nano-enhanced fluids and phase change materials have further improved system performance, with nano-PCM/nanofluid configurations achieving electrical and thermal efficiencies of 13.7% and 72.0% respectively, while binary nano-enhanced systems demonstrate thermal conductivity improvements of 179% and overall energy efficiencies reaching 83.65% for PVT-NePCM systems [26,27]. Three-dimensional CFD investigations have further demonstrated that hybrid nanofluids yield superior electrical and thermal performance compared to single-type nanofluids in novel PV/T collector geometries [28], with U-shaped channels filled with ternary nanofluid achieving exergy efficiencies of up to 14.6% and cell temperature reductions of 8.5 °C in coupled PV–TEG configurations [29]. A comparative study of hollow fins, wavy channels, and porous layer inserts reported temperature drops exceeding 37 °C relative to an uncooled reference panel, while artificial neural networks were successfully applied for performance estimation of the wavy channel system [30]. Fig. 1b demonstrates the evolution toward more sophisticated PV/T configurations, incorporating advanced thermal management systems with phase change materials (PCM) and multi-layered architectures, which significantly enhance heat transfer capabilities while simultaneously increasing system complexity and modeling challenges. Jarimi et al. [31] further support this trend toward liquid-based or dual-fluid PV/T configurations under varying climate conditions, justifying the focus of this review on liquid-based systems, particularly those using water and nanofluids as working media.

1.1. Research landscape and patent activity

Although numerous investigations have been conducted on PV/T systems, the extensive volume and diversity of studies have rendered the synthesis of findings challenging. Comprehensive analyses have been presented in numerous review articles examining system classifications, cooling methodologies, and material characteristics [14,21,32–34], with specific attention devoted to working fluid characteristics [25,35,36] and heat pump integration [37–41].

Beyond the academic literature, the development of PV/T technology can also be traced through patent activity. A search of Google Patents database identified 10 patents directly related to liquid-cooled PV/T systems, covering the period from 2011 to 2025 (Table 1). Three distinct categories are represented: PV/T collector design and operation (7 patents), building-integrated and geothermal PV/T (2 patents), and specialized applications (1 patent).

Table 1. Summary of identified patents related to liquid-based PV/T systems.

Ref.	Patent number	Key innovation
[42]	US10594255B2	Laminated PV/T module with absorber integrated into PV laminate and built-in fluid channels
[43]	US9219183B2	Microchannels and nozzles beneath photoactive layer for uniform coolant distribution
[44]	US9437766B2	Positioning mechanism for variable control of radiation ratio between electrical and thermal output
[45]	US11431289B2	Reverse flat plate collector with two-stage fluid heating and thermal storage
[46]	EP3866335B1	Vacuum-insulated multi-layer structure with improved bonding durability
[47]	WO2023073418A1	Coolant transparent in 400–1100 nm range; fluid acts as selective infrared absorber
[48]	WO2025191210A1	Thermoplastic spacers for hermetic insulation and improved cell-to-circuit thermal contact
[49]	US20110186109A1	Water/air cooling with building facade integration for domestic hot water
[50]	KR101568606B1	Metallic foam thermal interface coupled to ground source heat pump circuit
[51]	US9278315B2	PV/T waste heat recovery for seawater desalination

The largest category, collector design, reveals a clear evolutionary trend from simple pipe-based cooling towards fully integrated thermal-electrical structures. Early approaches positioned separate coolant pipes on the back surface of PV modules, whereas subsequent inventions embedded the absorber directly within the PV laminate with integrated fluid channels [42], or placed microchannels and distribution nozzles beneath the photoactive layer for controlled coolant delivery and reduced pumping losses [43,44]. More advanced configurations include a reverse flat plate collector with two-stage fluid heating and built-in thermal storage [45], vacuum-insulated multi-layer structures emphasizing bonding durability [46], and a transparent liquid collector in which the working fluid acts as a selective infrared absorber while remaining optically transparent across the 400–1100 nm range to preserve PV output [47]. The most recent patent, filed in 2025, employs thermoplastic spacers to improve hermetic sealing and thermal contact between cells and the cooling circuit [48].

The second category addresses system-level integration beyond the collector itself. One patent describes a building-facade configuration combining water and air cooling for domestic hot water production [49], while another couples the PV/T module to a ground source heat pump via a metallic foam thermal interface layer [50]. The single patent in the specialized applications category recovers PV/T waste heat to drive seawater desalination, extending the functional scope of liquid-cooled systems beyond electricity and heat supply [51].

A notable observation across all three categories is that every identified patent addresses hardware innovations, exclusively collector structures, cooling channel geometries, or system-level integration. No patents were identified that protect machine learning algorithms, predictive models, or data-driven optimization methods for PV/T systems.

1.2. Research gaps and novelty of this review

Despite this extensive research foundation, liquid-based PV/T systems continue to present complex nonlinear thermal-electrical interactions involving multiple coupled heat transfer mechanisms. These interactions, combined with variable flow dynamics and temperature-dependent material properties, create modeling challenges that exceed conventional analytical approaches. Machine learning (ML) techniques have emerged as powerful tools for addressing these modeling challenges, offering capabilities to identify complex patterns, optimize multivariable systems, and predict performance without explicit programming of underlying relationships.

A comprehensive review of recent machine learning research in PV and solar energy has revealed a significant gap concerning ML applications in hybrid PV/T systems. Recent studies [52–54] have focused primarily on conventional PV applications, presenting extensive overviews of ML techniques for PV control, fault detection, and power forecasting, but exclusively within electrical power generation contexts. Vakili and Salehi [55] explored ML applications in solar thermal collectors, briefly mentioning PV/T collectors but without providing ML-based analysis specific to these hybrid systems. Liu et al. [56] examined building-integrated PV optimization using hybrid ML techniques, while Alcañiz et al. [57] and Zaidi [58] conducted comprehensive analyses of ML trends in PV research, all excluding hybrid PV/T applications.

To systematically evaluate this research gap, a detailed analysis of existing ML reviews in solar energy systems has been conducted. Table 2 presents a comprehensive assessment of seven major review articles published between 2022 and 2024, examining their scope, focus areas, and treatment of PV/T systems. The analysis reveals a striking absence of comprehensive ML coverage for hybrid PV/T systems: six of the seven reviewed studies make no mention of PV/T systems whatsoever, while the single study acknowledging PV/T collectors [55] does not provide ML-based analysis specific to these hybrid configurations. This gap is particularly significant given the unique modeling challenges presented by PV/T systems, where complex thermal-electrical interactions, coupled heat transfer mechanisms, and temperature-dependent material properties create multidimensional optimization problems ideally suited to ML approaches. Unlike conventional PV systems focusing solely on electrical output optimization, PV/T systems require simultaneous modeling of thermal and electrical performance, heat dissipation dynamics, and fluid flow characteristics, challenges that conventional analytical methods struggle to address effectively.

Table 2. Research gap analysis in existing ML reviews for solar energy systems.

Study	Main Focus	Key Topics Covered	PV/T Consideration?	Research Gap Identified
[52]	Review of ML applications in PV systems	ML for control, fault detection, diagnostics, irradiance forecasting, power estimation, site adaptation	No mention of PV/T	Focus on PV but lacks discussion on ML applications in hybrid PV/T systems
[53]	ML for smarter and cleaner PV systems	Fault detection, performance prediction, sustainability, future directions of ML in PV	No mention of PV/T	Emphasizes sustainability but does not address ML applications in PV/T systems
[54]	ML methods in PV power prediction	Comparison of ML models (ANN, SVM, RF, LSTM) for PV power forecasting	No mention of PV/T	Focuses on forecasting but does not explore ML-driven performance optimization in PV/T systems
[55]	ML for solar thermal collector modeling	Thermal efficiency prediction, optimization of collector design	Yes, mentions PV/T collectors but lacks ML-based analysis	Identifies ML potential in thermal collectors but does not apply ML for hybrid PV/T analysis
[56]	ML for PV system optimization in zero-energy buildings	ML for nanocomposite solar panels, energy efficiency in buildings, hybrid optimization techniques	No mention of PV/T	Focus on building-integrated PV, lacks discussion on hybrid PV-Thermal integration
[57]	Trends and gaps in PV power forecasting with ML	Review of 100 studies on ML for PV power forecasting, classification by ML family, location, forecast horizon	No mention of PV/T	No exploration of thermal aspects in ML-based PV forecasting
[58]	Bibliometric analysis of ML in PV and solar energy	Trends in ML research for solar energy, identification of key contributors and institutions	No mention of PV/T	Identifies research trends but does not address hybrid PV/T systems

To address this identified research gap, this review poses two fundamental research questions:

(1) Which ML techniques have been successfully applied in PV/T systems, and what specific modeling and performance prediction challenges do they address?

(2) How do different ML techniques perform across various liquid-based PV/T system configurations, and what factors influence their effectiveness?

The novelty of this review lies in providing the first comprehensive and systematic treatment of machine learning applications specifically in liquid-based PV/T systems, a topic that, as demonstrated in Table 2, remains unaddressed in the existing review literature. By systematically addressing the above research questions, this work offers the following original contributions:

- A structured taxonomy of ML techniques that categorizes applications across three methodological families (artificial neural networks, ensemble methods, and other approaches) and maps them onto specific PV/T cooling technologies including water, nanofluids, phase change materials, and refrigerants.
- A comparative analysis of ML technique effectiveness across different system configurations and working fluids, enabling researchers to identify the most suitable methods for their specific modeling needs.
- A critical assessment of the experimental foundations underlying the reviewed ML models, revealing important patterns in dataset characteristics, geographic distribution, and data collection practices.
- The identification of emerging methodological trends, from early MLP dominance through ensemble expansion to recent deep learning and Transformer-based architectures, tracing the technological maturation of the field from 2012 to 2025.
- A critical evaluation of current research limitations with evidence-based recommendations for future research directions aimed at accelerating the transition from laboratory-scale studies to commercial deployment.

This review is organized as follows: Section 2 presents the literature search methodology and screening criteria; Section 3 provides an overview of machine learning applications in PV/T systems; Sections 4 through 6 examine artificial neural networks, ensemble methods, and other machine learning approaches, respectively; Section 7 presents the experimental foundations of the reviewed ML models; Section 8 discusses the evolution of ML methods in liquid-based PV/T systems; and Section 9 provides conclusions and future research directions.

2. Literature search methodology

A systematic literature search was conducted to provide comprehensive coverage of machine learning applications in liquid-based photovoltaic thermal systems. The methodology employed a structured approach to ensure reproducibility and minimize bias in study selection and analysis.

2.1. Search strategy and data sources

The Scopus database was utilized as the primary source due to its extensive coverage of engineering, energy, and computational research domains. The search strategy employed multiple keyword combinations within title, abstract, and keywords fields. Three main groups were used: (1) "PV/T", "PV-T", "PVT", and "photovoltaic thermal" for comprehensive coverage of hybrid systems; (2) "liquid", "water", and "nanofluid" to filter liquid-based cooling techniques; and (3) "machine learning", "artificial neural network", "ensemble", and "regression" to target ML applications.

The search was conducted during June 2025 to ensure inclusion of the most recent developments in the field. As illustrated in Fig. 2, the methodological framework followed a systematic four-stage process: identification, screening, eligibility assessment, and final inclusion with data extraction and analysis.

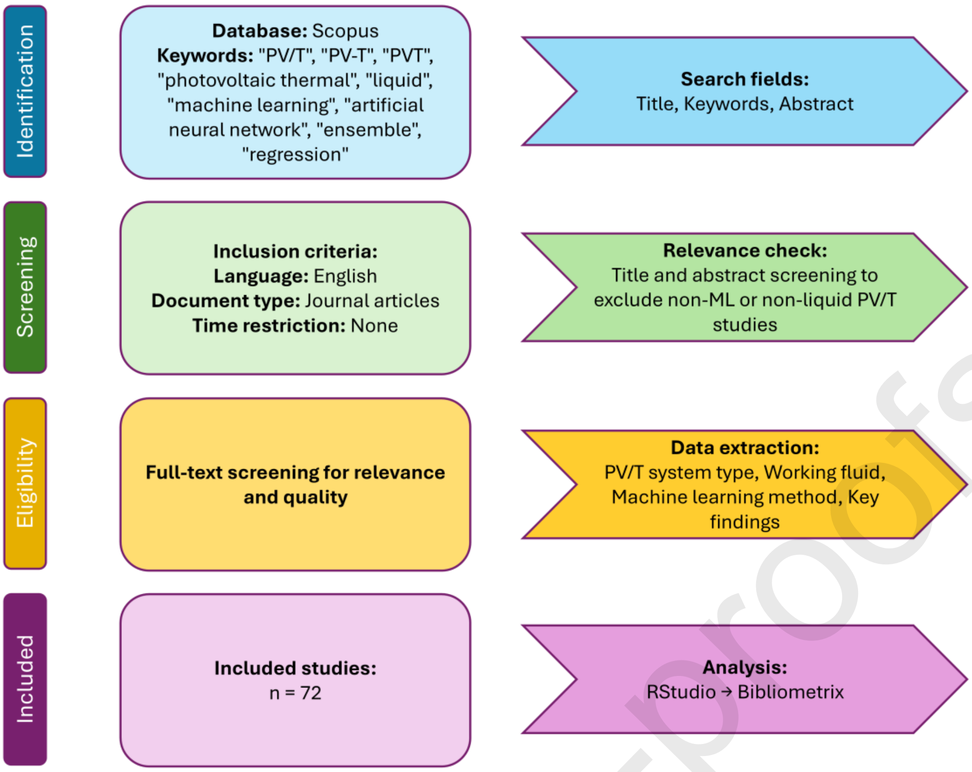

Fig. 2. Methodological framework of the systematic review and bibliometric analysis.

2.2. Selection criteria and screening process

The four-stage selection process was implemented following PRISMA guidelines to ensure study relevance and quality [59]. Initial database search used the defined keyword combinations within the title, abstract, and keywords fields of the Scopus database. Inclusion criteria were then applied, encompassing language restrictions (English), document type (journal articles), and no time restrictions. Title and abstract screening were conducted to exclude studies unrelated to ML applications in liquid-based PV/T systems.

Full-text screening for relevance and quality assessment followed, where studies were evaluated to verify application of ML models specifically to liquid-based PV/T systems. Exclusion criteria removed studies focused solely on conventional PV systems, air-cooled PV/T configurations, or general solar applications without ML-driven liquid-based PV/T analysis. This systematic process resulted in the final inclusion of 72 publications meeting all criteria, followed by systematic data extraction and bibliometric analysis using RStudio and the Bibliometrix package.

Each selected study was systematically analyzed to extract key information following a structured protocol. Data extraction focused on four primary categories as illustrated in Fig. 2: PV/T system type, working fluid characteristics, machine learning methodology employed, and key findings. Additional data extracted included input parameters utilized in ML models, prediction accuracy metrics (R^2, RMSE, MAPE), dataset characteristics, and validation methodologies. Performance benchmarks and comparative results between different ML approaches were systematically documented to enable a comprehensive analysis of technique effectiveness across varying system configurations.

2.3. Bibliometric analysis and publication trends

Bibliometric analysis was performed using the Bibliometrix package in RStudio [60], revealing significant growth in research activity from 2012 to 2025. The dataset demonstrates an annual growth rate of 22.5%, with publications distributed across 31 journals focusing exclusively on peer-reviewed articles. As illustrated in Fig. 3, publication frequency shows accelerating growth, particularly after 2020, with continued momentum through 2025.

Publication rates demonstrate significant growth over the study period. Monthly averages increased from near-zero levels in 2012-2017 to over 2.3 publications per month by 2025, with research activity peaking at 16 publications in 2024. This upward trend indicates that liquid-based PV/T systems integrated with machine learning have transitioned from a sporadic research interest to a sustained academic focus, suggesting the field has reached maturity in terms of research attention.

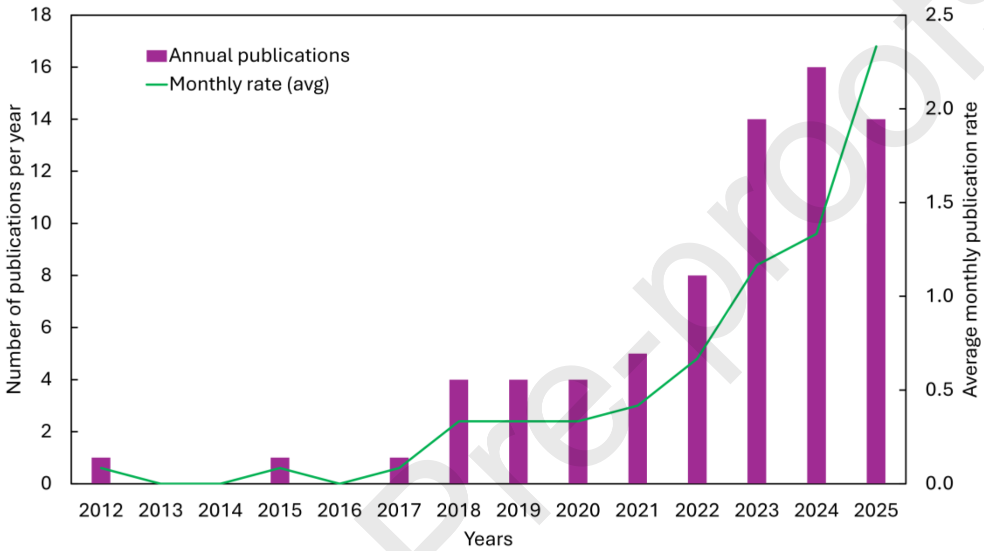

Fig. 3. Annual publication trends showing growth in machine learning applications for liquid-based PV/T systems from 2012 to June 2025.

The average citation rate of 24.6 citations per document indicates substantial research impact and growing interest in this domain. Fig. 4 presents the distribution of publications across different journals, where Renewable Energy, Applied Thermal Engineering, Case Studies in Thermal Engineering, and Engineering Analysis with Boundary Elements are the most frequently used journals. This distribution reflects the interdisciplinary nature of PV/T research, spanning renewable energy systems, thermal engineering, and computational analysis methods.

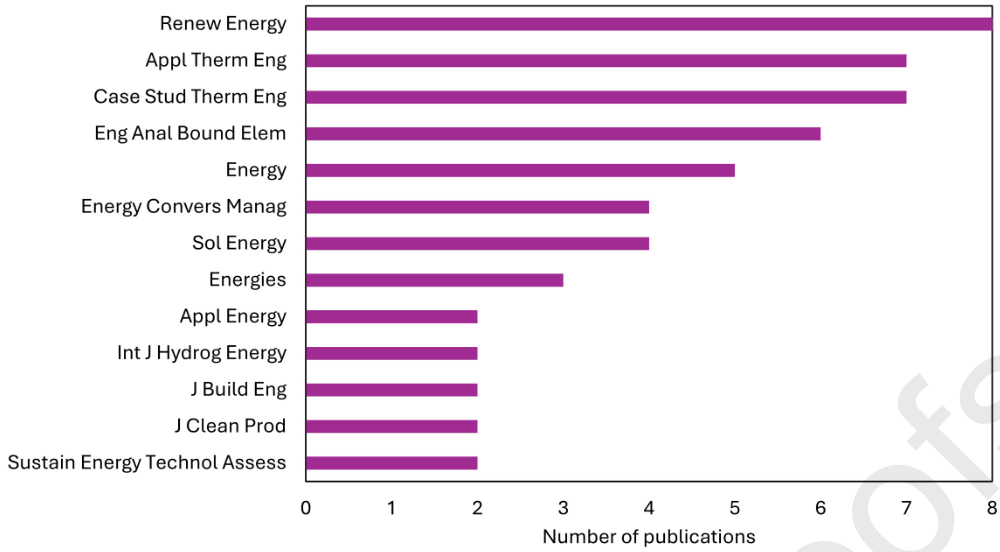

Fig. 4. Distribution of reviewed publications across scientific journals related to machine learning applications in liquid-based PV/T systems.

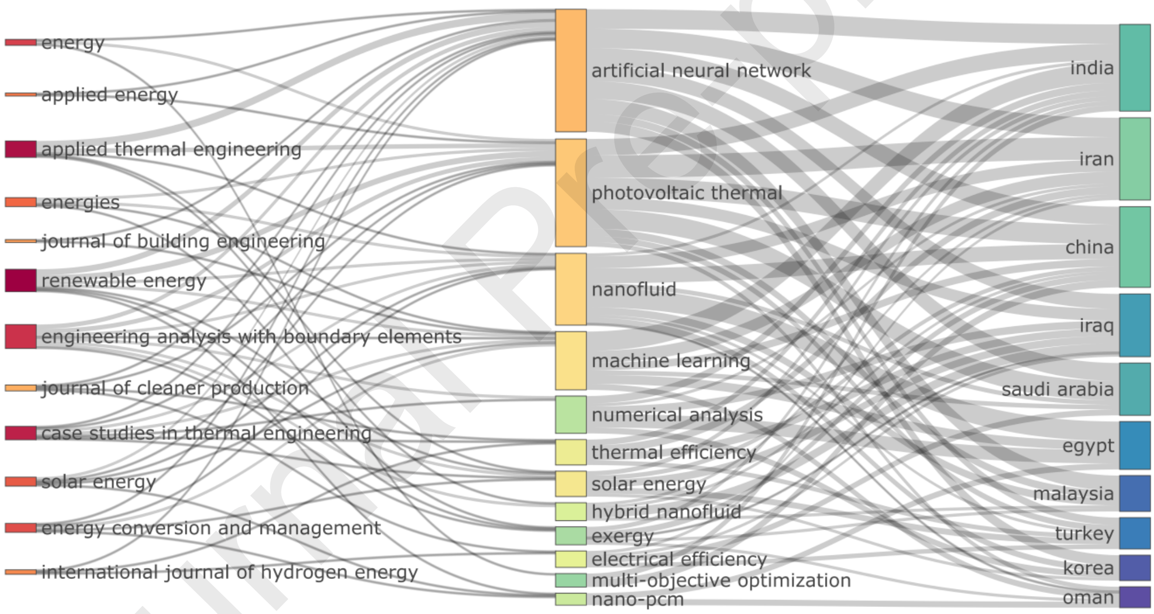

Fig. 5. Sankey diagram showing the connections between the publication source (left column), research keywords (middle column), and the authors' country (right column).

Fig. 5 presents a Sankey diagram illustrating the connections between publication sources, research keywords, and authors' countries, revealing the global distribution of research efforts. The analysis shows dominant contributions from Iran, India, Turkey, and China, with strong emphasis on keywords including "artificial neural network", "nanofluid", "photovoltaic thermal", and "numerical analysis". This geographical distribution indicates widespread international interest in ML applications for PV/T systems, with significant contributions from regions with high solar energy potential.

2.4. Limitations and scope

This review has several limitations. The exclusive use of the Scopus database may have resulted in the omission of relevant studies indexed in other databases. The focus was placed on liquid-based systems, excluding air-cooled PV/T applications. Non-English publications were also excluded, which may have omitted valuable research from international communities. The search was limited to peer-reviewed journals, excluding conference papers and technical reports that could offer innovative insights. The emphasis on ML as the primary focus may have missed studies using ML as a supporting analysis tool. Despite these constraints, the selected studies provide representative coverage of ML applications in liquid-based PV/T research. The systematic methodology ensures reproducibility and provides a basis for identifying research trends and future research directions.

3. Overview of ML applications in PV/T systems

The systematic analysis of 72 publications in liquid-based PV/T research reveals a structured landscape of machine learning applications organized around three distinct methodological categories. This categorization emerges naturally from the fundamental approaches to learning and prediction employed in ML techniques, each addressing specific modeling challenges inherent in PV/T systems.

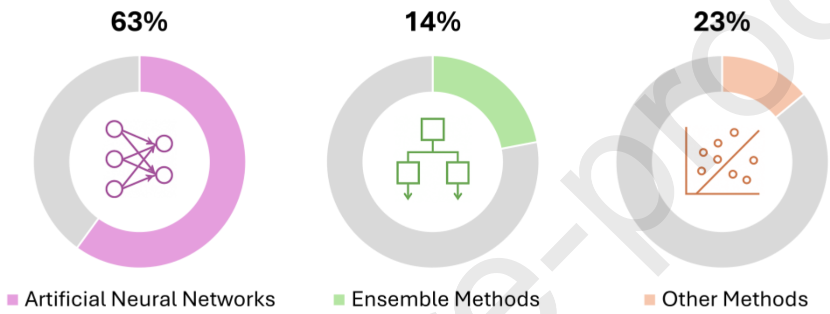

Fig. 6. Proportion of machine learning categories applied in PV/T system research.

As illustrated in Fig. 6, Artificial Neural Networks dominate with 63% of applications, representing computational models that learn through interconnected processing units mimicking biological neural systems. Ensemble Methods account for 14% of applications, utilizing multiple learning algorithms combined to achieve superior predictive performance compared to individual models. Other Methods comprise 23% of applications, encompassing diverse approaches including statistical regression, support vector machines, and probabilistic methods that address specific requirements such as interpretability or uncertainty quantification.

This distribution reflects the complexity hierarchy of PV/T modeling challenges. Neural networks' dominance indicates their effectiveness in capturing the coupled thermal-electrical interactions that characterize PV/T systems, where temperature-dependent electrical performance, variable flow dynamics, and heat transfer mechanisms create highly nonlinear relationships. Ensemble methods' presence demonstrates growing recognition that combining multiple models can enhance prediction accuracy for systems with substantial parameter interdependencies. The significant proportion of alternative methods reflects the diverse requirements in PV/T research, from baseline performance modeling to specialized applications requiring transparent decision-making processes.

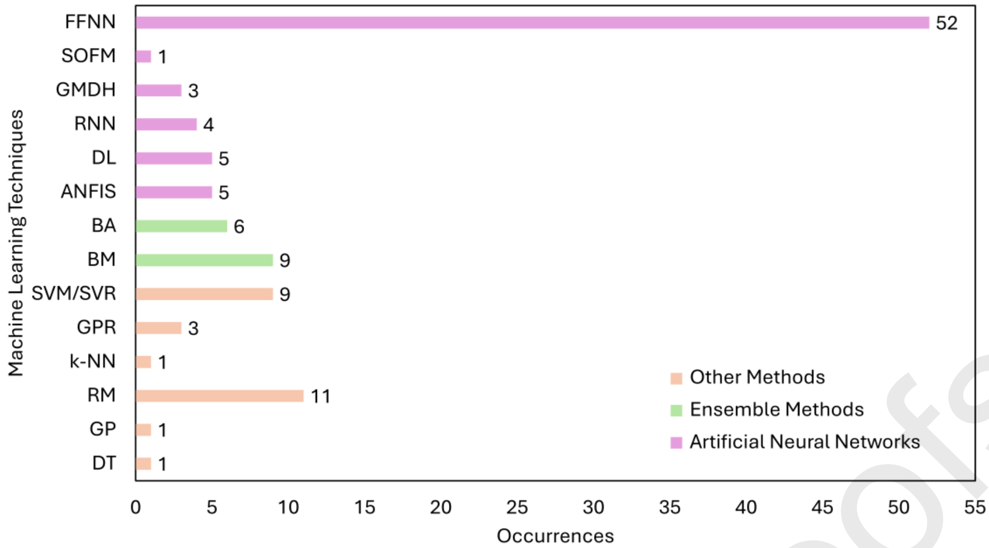

Fig. 7. Distribution of machine learning techniques used in PV/T system modeling.

Fig. 7 provides a detailed breakdown of individual techniques, revealing that Feedforward Neural Networks achieve widespread adoption with 52 occurrences, while Support Vector Machines/Regression and Boosting Methods each appear 9 times. Regression Methods show notable usage with 11 occurrences, demonstrating their continued relevance for baseline modeling. This pattern indicates both methodological preferences and the evolutionary nature of ML adoption in PV/T research, where established techniques provide reliable foundations while advanced methods address emerging system complexity.

The following sections examine each category systematically, providing a comprehensive analysis of applications, performance characteristics, and optimal use cases across different PV/T system configurations.

4. Artificial Neural Networks (ANN)

ANNs are advanced machine learning methods that are structured to mimic the information processing capabilities of biological neural systems. These computational models comprise interconnected artificial neurons organized in layers, where information is processed through weighted connections that are adjusted during training. In PV/T system modeling, ANNs are extensively utilized due to their exceptional ability to approximate complex nonlinear relationships between system parameters and performance metrics without requiring explicit physical equations. The core architectural approaches employed in PV/T applications are illustrated in Fig. 8, showing the fundamental structural differences between FFNN, ANFIS, RNN, and CNN as a representative DL approach. The adaptability of these machine learning approaches is particularly valuable for thermal-electrical systems where multiphysics interactions are challenging to model with conventional methods.

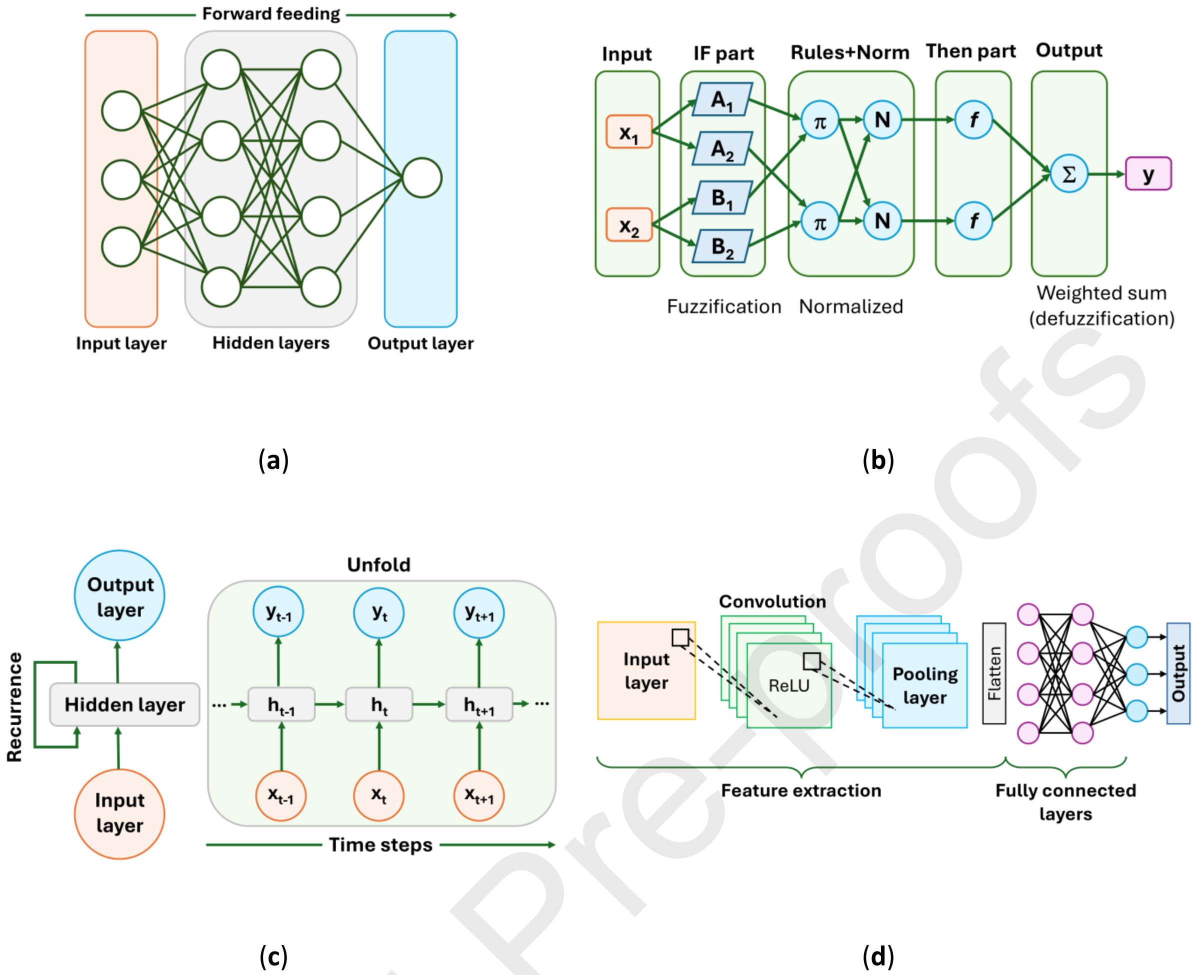

Fig. 8. Representative ANN models applied in PV/T systems: (a) FFNN; (b) ANFIS; (c) RNN; (d) CNN.

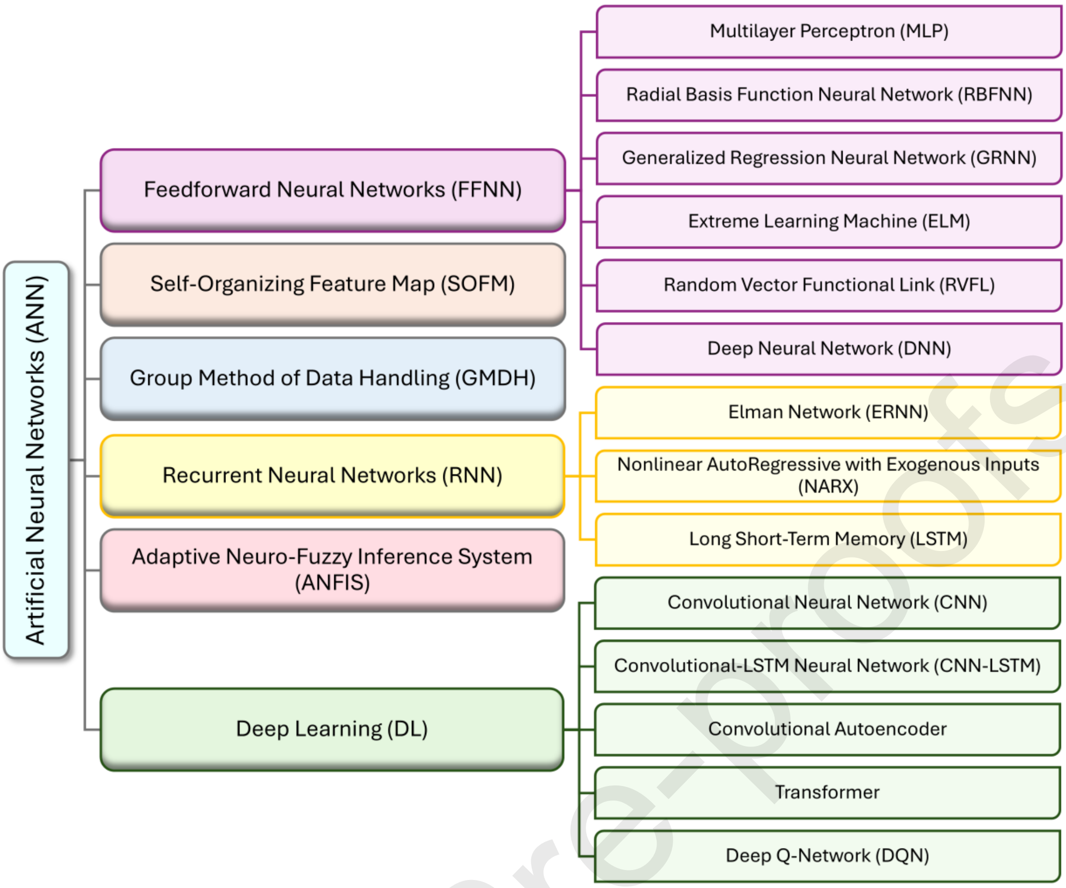

Fig. 9. Categorization of ANN models used in PV/T modeling.

As illustrated in Fig. 9, ANN methodologies applied in PV/T research are systematically categorized in several architectural classifications. Feedforward Neural Networks (FFNN) represent structures where information flows unidirectionally from input to output. Self-Organizing Feature Maps (SOFM) provide unsupervised learning capabilities for pattern identification in complex datasets. The Group Method of Data Handling (GMDH) offers self-organizing modeling where optimal structures are automatically discovered. Recurrent Neural Networks (RNN) incorporate feedback connections that enable temporal pattern recognition. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) combine neural learning with interpretable fuzzy logic rules. Finally, Deep Learning (DL) approaches leverage multi-layer architectures for advanced feature extraction and pattern recognition. This comprehensive taxonomy provides a structured framework for analyzing the application of machine learning methodologies across diverse PV/T system configurations.

4.1. Feedforward Neural Networks (FFNN)

Feedforward Neural Networks are characterized by a unidirectional information flow architecture wherein data is processed sequentially through input, hidden, and output layers without feedback loops or cyclical connections (Fig. 8a). These fundamental machine learning structures are widely implemented in PV/T system modeling due to their computational efficiency, reliable convergence properties, and well-established training methodologies. In PV/T applications, FFNNs are primarily utilized for performance prediction, parameter optimization, and system behavior analysis under varying operational and environmental conditions.

As shown in Fig. 9, several specialized FFNN architectures are examined in this study. MLP represents the most widely adopted approach, featuring multiple fully connected neuron layers trained through backpropagation. RBFNNs utilize distance-based activation functions for enhanced spatial pattern recognition. GRNNs employ one-pass learning algorithms, especially effective with limited training data. ELM architectures feature randomized input layer weights with analytically determined output weights for accelerated training. RVFL networks incorporate direct connections between input and output layers alongside hidden layer pathways. DNNs extend traditional architectures with multiple hidden layers for hierarchical feature extraction. These architectures are distinguished by their activation functions, training algorithms, computational requirements, and specific modeling capabilities, thereby offering complementary approaches for addressing the diverse challenges encountered in PV/T system analysis and optimization.

The subsequent sections examine each of these architectures in detail, beginning with the most extensively applied variant – MLP.

4.1.1. Multilayer Perceptron (MLP)

MLP is characterized as one of the most widely adopted artificial neural network architectures in PV/T modeling, representing 44 out of 72 reviewed publications. This feedforward network architecture comprises multiple neuron layers (input, hidden, and output), wherein connection weights are adjusted through backpropagation to minimize prediction error. MLP's effectiveness for PV/T systems is attributed to its capacity for capturing complex nonlinear relationships between diverse input variables and system performance metrics.

Despite some limitations – including requirements for large training datasets, computational intensity, and potential overfitting risks – MLP's strong predictive capabilities and adaptability have established it as the predominant machine learning approach for PV/T system analysis. The architecture has been successfully applied across diverse applications, from performance prediction and system design optimization to operational forecasting under varying environmental conditions.

Given the substantial number of MLP implementations in PV/T research, a structured classification framework has been developed to systematically analyze these studies. The primary organizing principle maintains this review's focus on machine learning methods while providing necessary categorization of the application domains. Publications are organized according to cooling medium type:

- Water-Cooled PV/T Systems (4.1.1.1): Further differentiated into standalone systems (where water circulates primarily for cooling) and integrated systems (where PV/T components are incorporated into larger energy infrastructures such as buildings, heat pumps, or combined cooling, heating, and power systems).
- Nanofluid-Cooled PV/T Systems (4.1.1.2): Categorized by nanofluid composition – simple metallic nanofluids, metal oxide nanofluids, hybrid nanofluids, and specialized formulations – reflecting the progressive evolution of thermal enhancement strategies.
- Alternative Cooling Methods (4.1.1.3): Encompassing emerging approaches such as phase change materials (PCM), refrigerant-based systems, and dual-fluid configurations.

This classification approach enables comparative analysis of MLP applications across different thermal management strategies while maintaining focus on the machine learning methodology. For each category, key input parameters, output metrics, and prediction accuracies are synthesized to identify methodological trends and performance benchmarks.

4.1.1.1. Water-cooled PV/T systems

Water-cooled PV/T systems are categorized into standalone and integrated configurations based on their implementation complexity and system integration level.

Standalone water-cooled PV/T systems are characterized by the primary function of heat extraction from PV modules to enhance electrical efficiency while capturing thermal energy. Extensive investigation of these systems using ML approaches has been conducted by multiple researchers [61–68].

In these studies, key input parameters typically include ambient temperature, solar irradiation, fluid inlet temperature, and coolant mass flow rate. High prediction accuracy has been achieved with MLP models, as evidenced by MSE values as low as 0.009 and R^2 values approaching 1.00. Advanced configurations incorporating evacuated tube collectors with compound parabolic concentrators have demonstrated exceptional performance when modeled using large datasets [69]. The optimization of coolant mass flow rate and meteorological variables has been identified as critical for enhancing both electrical and thermal performance.

Table 3 presents MLP-based predictions for standalone water-cooled PV/T systems, classified by the predicted output parameter. Studies are grouped into three categories: those focused on thermal efficiency prediction [61], electrical efficiency prediction [62,63], and comprehensive modeling of both parameters [64–69].

Table 3. MLP-based prediction of standalone water-cooled PV/T systems.

Focus	Studies	System Configuration	Input Parameters	Key Findings
Thermal Efficiency	[61]	Serpentine tube absorber	Inlet temperature, water flow rate, solar irradiation	$R^2 > 0.95$; inlet temperature and flow rate significantly impact heat transfer efficiency; good validation with experimental data
Electrical Efficiency	[62,63]	Variable pipe diameter collectors	Inlet temperature, flow rate, solar radiation, collector area, pipe diameter	$R^2 > 0.90$; pipe diameter and irradiance identified as key influencing factors; Random Forest outperformed MLP for out-of-range conditions in some configurations
Combined Performance	[64–69]	Grid-connected, hybrid, and actively cooled systems; U-shaped evacuated tube collectors with compound parabolic concentrators	Solar irradiance, ambient temperature, mass flow rate, wind speed, inlet temperature, thermal/electrical parameters	$R^2 > 0.95$ for both electrical and thermal outputs; MLP achieved $R^2 = 0.9982$ with 144,000-row dataset; mass flow rate critical for optimization; CPC-enhanced ETCs improved efficiency; ANN models outperform traditional regression techniques

Integrated water-cooled PV/T configurations are distinguished by their incorporation into larger energy systems, including building integration, heat pump coupling, and combined cooling, heating, and power (CCHP) systems. The increased system complexity necessitates advanced modeling approaches.

For building-integrated PV/T systems, a pioneering MLP model was developed wherein numerical simulation results were utilized to estimate PV yield for various flow configurations [70]. Computational time was significantly improved from hours to less than one second while high accuracy ($R \approx 0.98$) was maintained. Critical parameters such as array aspect ratio, fluid riser count, and flow direction were rapidly optimized.

Multiple studies have been conducted in heat pump integration applications. A 4-15-4 ANN architecture was employed to predict PV/T evaporator performance in solar-assisted heat pumps [71]. An innovative ANN-based predictive controller for hybrid ground source heat pump-PV/T systems was developed, achieving remarkable reductions in primary energy consumption (36%), operating costs (81%), and CO_2 emissions (36%) [72]. GSHP-PV/T system designs were optimized through coupled ANN models and genetic algorithms [73]. Large-scale implementations have been investigated where hybrid water-PV/T systems with multiple collectors were integrated with ground source heat pumps using multi-objective genetic algorithms [74]. Advanced MLP architectures with extensive input parameter spaces achieved significant performance improvements including COP enhancements and substantial CO_2 emission reductions. District heating applications were explored with an average coefficient of heating of approximately 2.95 reported [75].

Two notable approaches have been demonstrated for CCHP systems with PV/T components. ANN was utilized as a surrogate model for building-integrated CCHP systems, achieving 64.2% exergy efficiency while optimizing cost (5.78 $/h) and environmental performance [76]. Advanced ANN forecasting tools were developed with exceptional accuracy, demonstrating testing R^2 values from 0.991 to 0.999 [77].

Table 4 summarizes MLP applications in integrated water-cooled PV/T systems across three integration categories. Several trends are observed: 1) increased complexity in predicted output parameters, 2) expanded input parameter space including system-level variables, and 3) benefits extending beyond accuracy to computational efficiency and optimization capabilities.

Table 4. MLP-based prediction of integrated water-cooled PV/T systems.

Integration Type	Studies	System Configuration	Input Parameters	Key Findings
Building Integration	[70]	BIPV/T with water cooling	Array aspect ratio, mass flow rate, flow direction, number of risers	$R \approx 0.98$; computation time reduced from hours to <1 second; array geometry, coolant flow rate, and flow direction strongly influence performance; effective for rapid design optimization
Heat Pump Integration	[71–75]	SAHP (Solar-Assisted Heat Pump), GSHP (Ground Source Heat Pump), district heating systems; Large-scale hybrid water-PV/T + GSHP with 352 flat-plate collectors	Solar intensity, ambient temperature, wind speed, collector area, water flow rates, system load, multi-zone building parameters	Up to 81% operational cost reduction; 36% decrease in CO_2 emissions; 20% life-cycle efficiency improvement; $R^2 > 0.90$; COP ≈ 2.95 for PV/T heat pump systems; enhanced temperature stability with predictive control; COP improvements up to 41% (2.28-3.02 range); CO_2 reduction up to 144 t/yr
CCHP Integration	[76,77]	PV/T with thermal storage and absorption chillers	Solar radiation, ambient temperature, load	Exergy efficiency of 64.23%; cost rate optimization of 5.78 $/h; CO_2 index of 425.15 g/kWh; R^2 values 0.991-0.999 for

Integration Type	Studies	System Configuration	Input Parameters	Key Findings
			demands, system operational states	forecasting; improved design and operational predictability

4.1.1.2. Nanofluid-cooled PV/T systems

Nanofluid-cooled PV/T configurations have been extensively investigated due to their enhanced thermophysical properties and superior heat transfer capabilities compared to conventional water cooling. In these systems, base fluids with suspended nanoparticles provide improved thermal conductivity, convective heat transfer coefficients, and specific heat capacity. MLP models have been increasingly applied to predict and optimize these advanced systems.

The research in this area has been systematically categorized according to nanofluid type to highlight the progressive evolution of thermal enhancement strategies. Four main categories are examined: (1) simple metallic nanofluids, (2) metal oxide nanofluids, (3) hybrid nanofluids, and (4) non-metallic and specialized nanofluids.

Simple metallic nanofluids, primarily silver and copper-based, have been extensively investigated with significant thermal performance enhancements demonstrated when compared to conventional water cooling [68,78]. MLP models accurately predicted both thermal and electrical outputs with high reliability. Both Ag/water and Cu/water nanofluids exhibited superior performance characteristics across different system configurations.

Metal oxide nanofluids (ZnO, SiO_2, Al_2O_3, TiO_2) have been explored for various concentrations and flow conditions, where high MLP prediction accuracy was consistently achieved [78–81]. These nanofluids demonstrated significant improvements in electrical efficiency under optimal conditions. Geothermal cooling integration proved effective for temperature management. Advanced applications include greenhouse-integrated systems where multiple metal oxide nanofluids were evaluated [82]. MLP models demonstrated high predictive accuracy for optimized PV/T deployment in controlled agricultural environments.

The most recent advances have emerged in hybrid nanofluid applications. Mixtures like Al_2O_3–Cu/water and Ag-MgO/water have been utilized in sophisticated channel configurations with exceptional prediction accuracy achieved using ANN models [30,83–85]. Various channel designs including serpentine and wavy configurations were investigated. Tri-hybrid nanofluids combining MoS_2, graphene oxide, and multi-walled carbon nanotubes were applied in PV-HVAC systems [86]. Levenberg-Marquardt trained neural networks achieved exceptional prediction accuracy for modeling fluid dynamics and heat transfer behavior.

Specialized applications encompass oil-based nanofluids in concentrating PV/T systems and hexagonal boron nitride nanofluids [87,88]. MLP's effectiveness for modeling novel cooling approaches was demonstrated across diverse system configurations. These studies revealed optimal concentration ranges and performance trade-offs between thermal and exergy efficiencies.

Table 5 summarizes MLP applications in nanofluid-cooled PV/T systems by nanofluid type. This comparative analysis reveals that while all nanofluid types offer improvements over conventional water cooling, hybrid nanofluids in optimized channel designs provide the most significant performance enhancements, with MLP models serving as essential tools for prediction and optimization of these complex systems.

Table 5. MLP-based prediction of nanofluid-cooled PV/T systems by nanofluid type.

Nanofluid Category	Studies	System Configuration	Input Parameters	Key Findings
Simple Metallic	[68,78]	Water-based PV/T systems; PV/T systems with circular geometries for fluid flow channels	Solar radiation, ambient temperature, mass flow rate, nanoparticle concentration	$R^2 > 0.95$; Cu/water (5%, 0.0670 kg/s) optimal; MAPE: 4.98% thermal, 2.61% electrical efficiency; Ag/water nanofluid highly effective for electrical and thermal performance prediction
Metal Oxide	[78–82]	PV/T systems with circular geometries for fluid flow channels; PV/T collector integrated with geothermal cooling; Greenhouse-integrated PV/T systems	Environmental conditions, flow rate, nanoparticle parameters, greenhouse conditions, nanofluid concentration, Reynolds number, time	98% prediction accuracy; SiO_2/water (3 wt%) improved electrical efficiency by 27.7%; Al_2O_3/water with geothermal cooling maintained panel temperatures 32.1–36.5°C; MLP models effective for greenhouse applications; concentration optimization critical
Hybrid	[30,83–86]	80W PV with copper pipe/plate cooling system (1mm thickness); PV/T solar collector with single and double serpentine channels; PV panels with hollow fins, wavy channels, and porous layer inserts; Tri-hybrid nanofluids in PV-HVAC systems	Reynolds number, nanoparticle concentration, channel configuration, HVAC parameters, pipe diameter, heat flux, flow rate	R^2 up to 0.999; thermal efficiency up to 90.47% with double serpentine channels; temperature reductions up to 37.6°C with wavy channels; LMA-TNN achieved MSE as low as 10^{-11}; Cu/water-ethylene (70-30) optimal for copper pipe systems
Specialized	[87,88]	Solar concentrating photovoltaic thermal (CPV/T) collector with engine oil base; PV/T collector with hexagonal boron nitride cooling	Nanoparticle concentration, system geometry, radiation parameters, concentrator surface area, receiver specifications, flow rate, solar radiation intensity, nanoparticle diameter	Nanoparticle concentration increases thermal efficiency but may reduce exergy efficiency; optimal hBN ratio of 0.18; hBN/water shows 0.7% electrical and 3.01% thermal efficiency improvements; engine oil-based nanofluids effective in concentrating systems

4.1.1.3. Alternative cooling methods

Alternative cooling approaches for PV/T systems beyond conventional water cooling and nanofluids have been explored to further enhance thermal regulation and energy efficiency. Four primary categories of alternative cooling mechanisms are examined in this section: (1) phase change materials (PCMs), (2) refrigerant-based systems, (3) dual-fluid configurations, and (4) specialized heat transfer fluids. MLP models have been applied effectively to predict and optimize performance across these diverse cooling technologies.

PCM and nano-PCM systems represent the most extensively studied alternative cooling approach. The progressive evolution of this technology was demonstrated through sequential work by Al-Waeli and colleagues [89–92], where significant improvements in both electrical and thermal performance were achieved. Electrical efficiency was increased from 8.07% to 13.32% with nano-PCM cooling (incorporating SiC nanoparticles) compared to conventional methods. Recent advancements include MWCNT-enhanced PCMs [93], biochar-enhanced PCMs [94], and Glauber's salt PCM [95]. Advanced PCM integration with hydrogen generation systems was investigated through water-based spiral copper tube heat exchangers combined with paraffin wax PCM [96]. ANN modeling using the Levenberg-Marquardt algorithm achieved exceptional prediction accuracy (R^2 = 0.99972, MSE = 1.97E-01). Increasing water flow rate and incorporating PCM improved PV cooling, electrical output, and hydrogen production via electrolysis.

Refrigerant-based cooling has been investigated through roll-bond heat exchangers with refrigerants R134a and R22 [97,98]. Integration with heat pumps was optimized across different climate zones [99]. Advanced trifunctional DX-PV/T heat-pump systems were developed using 12 roll-bond PV/T modules acting as evaporator/condenser with two-stage vapor-injection heat pumps [100]. This system delivered PV electricity, domestic hot water, and chilled water via twin storage tanks. Enhanced Back-Propagation Neural Networks with hybrid optimizers (GA-PSO-BPNN-t) achieved superior prediction accuracy with MAPE 2.23% for electricity, 1.28% for heating, and 4.29% for cooling. MLP models effectively captured the complex thermodynamic interactions in these systems, enabling performance enhancements such as the 14.8% improvement in photoelectric conversion efficiency [97].

Dual-fluid approaches have been explored through several innovative configurations. The integration of thermoelectric coolers with PV/T systems using both air and water as working fluids was investigated, where aluminum-based PV/T-TEC water collectors were found to yield the highest daily electrical, thermal, and exergy gains [23]. Combined water-air cooling specifically designed for tropical climates was developed, demonstrating effective performance under high ambient temperatures [31].

Specialized heat transfer fluids represent the fourth category. Therminol-VP1 was investigated as a heat transfer medium for residential applications in the MENA region [101]. ANN models achieved high prediction accuracy (R^2 up to 0.99275) for this system, outperforming GPR models.

Table 6 summarizes MLP applications in PV/T systems with alternative cooling methods. PCM-based systems, particularly those enhanced with nanomaterials, demonstrate the most significant improvements in efficiency while maintaining relatively simple implementation. Refrigerant-based systems show particular promise for integration with existing HVAC infrastructure, while dual-fluid systems offer specialized solutions for specific climate conditions. Across all categories, MLP models have consistently achieved high prediction accuracy with R^2 values typically exceeding 0.9.

Table 6. MLP-based prediction of PV/T systems with alternative cooling methods.

Cooling Category	**Studies**	**System Configuration**	**Input Parameters**	**Key Findings**
PCM and Nano-PCM Systems	[89–96]	Various PV/T configurations utilizing PCM, nano-PCM (with SiC or MWCNT nanoparticles), biochar-enhanced PCM, Glauber's salt PCM, and hydrogen generation systems with paraffin wax PCM	Solar irradiance, ambient temperature, fluid temperatures, PCM properties, flow rate, water flow rate	High prediction accuracy (R^2 = 0.81-0.99972). Nano-PCM cooling increased electrical efficiency from 8.07% to 13.32% and achieved thermal efficiencies up to 72%. MWCNT-enhanced PCM reduced outlet temperatures to 37.72°C. PCM integration improved hydrogen production via electrolysis. Consistently outperformed conventional water cooling.

Refrigerant and Heat Pump Systems	[97–100]	PV/T systems with roll-bond heat exchangers and heat pumps using refrigerants (R134a, R22); Trifunctional DX-PV/T heat-pump systems with two-stage vapor-injection	Solar radiation, ambient temperature, refrigerant properties, heat pump parameters, frost/dew effects	14.8% improvement in photoelectric conversion efficiency. 14.19% photoelectric efficiency and 34.76% comprehensive thermal-electric efficiency achieved. Trifunctional systems: winter PV power 1.01 kW at 14.7% PCE, heating 7.46 kW with COP 3.64, summer cooling 4.07 kW. Enhanced BPNN achieved MAPE ≤ 4.29% across all functions.
Dual-Fluid Systems	[23,31]	PV/T collectors with dual-fluid configurations (PV/T-TEC with air/water; specialized water-air combinations)	Solar radiation, ambient conditions, flow rates, inlet temperatures, module type	Aluminum base PV/T-TEC water collector achieved highest electrical, thermal, and exergy gains. Water-air system demonstrated effective performance in tropical climates with minimal prediction error.
Specialized Heat Transfer Fluids	[101]	Grid-connected PV/T using Therminol-VP1 for MENA region applications	Solar radiation, ambient temperature, flow rate, inlet temperature	High prediction accuracy (R^2 up to 0.99275), outperforming GPR models. System proven economically and environmentally feasible for residential applications.

4.1.2. Alternative FFNN architectures

While MLP has been the predominant neural network architecture in PV/T system modeling due to its versatility and well-established training methods, several alternative feedforward architectures have emerged to address specific modeling challenges. These architectures provide distinct advantages in training efficiency, generalization capability, and suitability for particular aspects of PV/T performance prediction. Five principal alternative feedforward architectures are examined in this section: RBFNN, GRNN, ELM, RVFL, and DNN.

Table 7 provides a comparative overview of these architectures, highlighting their system applications, modeling capabilities, key advantages, and representative studies.

Table 7. Applications of alternative FFNN architectures in PV/T modeling.

Architecture	System Type	Main Applications	Key Advantages	Representative Studies
RBFNN	Water-cooling with cascade channels; Nanofluids (SiO_2, ZnO); Hybrid cooling with Nano-PCM	Temperature prediction; Thermal behavior modeling; Geometric optimization	Exceptional predictive capability (correlation up to 0.9997); Effective for nonlinear thermal processes; Captures complex geometric effects	[79,93,102,103]
GRNN	Water-cooled SPV/T systems	Transient performance prediction; Real-time modeling	One-pass learning algorithm; Minimal model complexity; Effective with limited training data	[104]

ELM	Hybrid cooling with Nano-PCM and finned collectors	Multi-parameter performance prediction; Thermal interaction modeling	Rapid training; Avoids local minima issues; Computational efficiency	[93]
RVFL	Integrated PV/T with electrolytic hydrogen production	Multi-physics system modeling; Comparative cooling media assessment	Complex multi-output prediction capability; Efficient model development; Handles integrated energy systems	[105]
DNN	Bi-fluid systems with variable fin configurations	Design parameter optimization; Performance comparison	Multi-layer feature extraction; Captures complex parameter interactions; Supports AI-driven design optimization	[106]

As demonstrated in Table 7, each architecture contributes unique capabilities to PV/T modeling. RBFNN demonstrates exceptional capability for modeling thermal processes across diverse cooling technologies, with particular effectiveness for temperature prediction and nonlinear heat transfer modeling. GRNN, though represented by a single study, shows remarkable promise for transient performance prediction with limited training data – addressing an important gap in steady-state modeling approaches that predominate in PV/T research.

For computationally efficient modeling, ELM offers significant advantages through its non-iterative training approach, maintaining good prediction accuracy while dramatically reducing model development time. The more advanced architectures – RVFL and DNN – demonstrate particular value for emerging frontiers in PV/T research: RVFL for integrated multi-physics energy systems, and DNN for complex design optimization challenges involving multiple interacting parameters.

This analysis reveals that neural network architecture selection should be guided by specific modeling challenges, with consideration given to system complexity, cooling mechanism, data availability, and critical performance aspects. As PV/T technology evolves toward more sophisticated designs with multiple integrated components, these alternative architectures will likely play an increasingly important role alongside traditional MLP approaches, offering complementary capabilities that address the growing complexity of advanced thermal-electrical systems. The following sections examine each architecture in detail.

4.1.2.1. Radial Basis Function Neural Networks (RBFNN)

RBFNN is characterized by radial basis functions, typically Gaussian, as activation functions in the hidden layer. A three-layer structure is employed: an input layer connecting to the feature space, a hidden layer with radial basis function neurons, and an output layer computing weighted sums of hidden layer outputs. Hidden neurons respond most strongly to inputs near their center points, whereby localized patterns in data are effectively captured. Advantages for PV/T performance prediction include faster training, improved nonlinear relationship handling, and enhanced interpolation capability.

RBFNN has been applied across diverse PV/T cooling technologies. A PV/T system with SiO_2-water nanofluid was modeled, wherein nanoparticle shape effects (spherical, blade, cylindrical, and brick) were uniquely investigated alongside volume fraction and environmental parameters [102]. RBFNN's capability to capture subtle nanoparticle morphology effects on system performance was demonstrated.

An innovative geometric design was examined featuring rectangular cascade channels in water-cooled PV/T systems [103]. Heat transfer enhancement through novel channel configurations was addressed, highlighting RBFNN's strength in modeling complex geometric parameters.

Multiple neural network architectures for zinc-oxide/water nanofluid PV/T systems have been evaluated, wherein RBFNN was found to excel specifically in fluid outlet temperature prediction [79].

The most sophisticated application involved modeling a hybrid cooling system combining water cooling with nano-PCM containing MWCNT nanoparticles and finned collectors [93]. RBFNN's capability to model multi-mechanism cooling technologies was thereby demonstrated.

Exceptional predictive capability was exhibited across these studies, with correlation coefficients reaching 0.9997. RBFNN's localized activation function proved particularly suitable for modeling nonlinear thermal transfer processes in advanced PV/T systems.

4.1.2.2. Generalized Regression Neural Network (GRNN)

GRNN is characterized as a specialized feedforward architecture designed for function approximation and regression tasks. This architecture performs a one-pass learning algorithm, enabling rapid training even with limited datasets. The four-layer structure (input, pattern, summation, and output layers) facilitates convergence to underlying regression surfaces without iterative training or extensive parameter tuning. Each pattern neuron functions as a memory unit representing a training example, whereby a weighted average of all training outputs is computed with weights determined by input vector distances from training samples.

GRNN was applied to predict system performance under transient, real-world conditions for a solar photovoltaic thermal water collector (SPV/T-WC) [104]. This research addressed the temporal dimension of PV/T performance that is frequently overlooked in steady-state modeling approaches. Two complementary GRNN models were developed using a minimalist design approach: one dedicated to overall power output prediction and another focused on efficiency prediction.

Despite utilizing only two input parameters for each model, remarkable prediction accuracy was achieved, with 95.36% and 96.22% alignment with real-time experimental results over a continuous four-day period. This parsimonious approach highlighted GRNN's ability to extract maximum information from limited input data. The research methodology emphasized real-world validation through continuous data collection across varying environmental conditions, demonstrating GRNN's exceptional capability for transient performance prediction in practical PV/T applications where operating conditions continuously fluctuate with weather patterns.

4.1.2.3. Extreme Learning Machine (ELM)

ELM is characterized by a distinctive training approach wherein input weights and biases are randomly assigned and remain fixed, while only output weights are analytically determined in a single step. This architecture consists of a single hidden layer feedforward neural network with randomized input weights creating a fixed feature mapping. Training time is dramatically reduced compared to backpropagation methods, often by orders of magnitude, while competitive prediction accuracy is maintained. Local minima issues inherent in gradient-based optimization are avoided by eliminating iterative weight adjustments.

ELM was applied to model an advanced hybrid cooling system for PV/T applications [93]. The system studied combined multiple heat transfer mechanisms: conventional water cooling, phase change materials (PCM) enhanced with multi-walled carbon nanotube (MWCNT) nanoparticles, and finned collectors for an increased heat transfer surface area. The inherently low thermal conductivity of phase change materials was addressed by incorporating MWCNT nanoparticles in the PCM.

An unusually comprehensive set of performance parameters was predicted by the developed ELM model, including thermal aspects (melted PCM fraction, surface temperature, coolant outlet temperature) and electrical performance. Model inputs encompassed standard parameters (solar radiation, ambient conditions) as well as nanoparticle mass fraction.

Significant cooling improvements were achieved in the modeled system, with outlet temperature reduction to 37.7°C and electrical efficiency enhancement up to 13.9%. ELM's computational efficiency and ability to avoid local minima issues were demonstrated, highlighting its value for applications requiring rapid model development or real-time performance prediction.

4.1.2.4. Random Vector Functional Link (RVFL)

RVFL networks are characterized by direct connections between input and output layers alongside traditional hidden layer pathways. In this architecture, input weightings and biases are randomly assigned and remain fixed throughout training, while only output layer weightings are optimized. Advantages of this approach include reduced overfitting risk, faster training, and enhanced generalization capabilities.

RVFL was applied to an innovative integrated energy system [105]. This research examined a Photovoltaic Thermal Collector combined with an Electrolytic Hydrogen Production system (PV/TC-EHP), wherein thermal collection and hydrogen generation were integrated. This multi-physics system incorporated a spiral tube thermal collector and Hoffman electrolysis unit, representing an advance in solar energy utilization beyond conventional PV/T applications.

A comparative assessment of cooling media impact was conducted using air and water as cooling fluids. Performance differences between cooling configurations were successfully captured by the RVFL model, which accurately predicted the water-cooled system's superior performance across all metrics, including significantly higher hydrogen production (4.41 kg/day vs. 3.60 kg/day for air). RVFL's capability to model complex multi-vector energy systems with interacting thermal, electrical, and chemical processes was thereby demonstrated.

4.1.2.5. Deep Neural Networks (DNN)

DNNs are characterized by multiple hidden layers – typically exceeding three – whereby hierarchical representations of input data are learned. Complex patterns and nonlinear relationships that might be challenging for simpler networks are effectively captured through this architectural depth. Automatic feature extraction is performed through successive data transformations, wherein each hidden layer learns progressively more abstract features based on previous layer outputs.

A bi-fluid PV/T system utilizing both water and air as cooling mediums simultaneously was modeled to address the fundamental challenge of optimizing the balance between electrical and thermal efficiency [106]. Three different fin configurations (no fins, 20 fins, and 40 fins) were systematically examined to assess extended surface area impact on system performance.

The intricate relationships between geometric parameters, operating conditions, and performance metrics were effectively captured through the DNN's multi-layer architecture. The 40-fin design was identified as providing optimal performance across all evaluated metrics. DNN's potential for addressing complex design optimization challenges in advanced PV/T systems was thus demonstrated, wherein the exploration of large parameter spaces is efficiently conducted with accurate performance prediction.

4.1.3. Other ANN architectures

Alternative neural network architectures beyond feedforward networks have been extensively investigated for PV/T system modeling applications. These specialized architectures address specific challenges in thermal-electrical performance prediction that traditional networks cannot effectively capture. Five principal alternative architectures are examined in this section: SOFM, GMDH, RNN, ANFIS, and advanced DL techniques.

Table 8 provides a comparative overview of these architectures, highlighting their primary applications, key advantages, and representative studies.

Table 8. Applications of other ANN architectures in PV/T system modeling.

Architecture	System Type	Main Applications	Key Advantages	Representative Studies
SOFM	Hybrid cooling systems comparing conventional, PCM, and nano-enhanced approaches	Exploratory analysis of novel cooling technologies	Autonomous pattern identification without labeled data; Effective for comparing multiple cooling technologies	[89]
GMDH	Nanofluid-based systems (conventional and building-integrated); PCM-based PV/T systems	Geometric optimization; Exergy analysis; Multi-objective optimization with decision-making	Automatic model complexity discovery; Exceptional prediction accuracy ($R^2 > 0.996$); Integration with multi-criteria decision-making ($R^2 > 0.999$)	[20,107,108]
RNN	Nanofluid-cooled systems; Hybrid PCM configurations; Greenhouse-integrated systems; Multi-objective hybrid systems	Temporal performance prediction; Thermal dynamics modeling; Multi-variable efficiency prediction; Performance benchmarking	Effective capture of time-dependent phenomena; Suitable for systems with thermal inertia and phase transitions; NARX achieves exceptional accuracy ($R^2 = 0.99795$); Superior temporal relationship modeling	[82,93,109,110]
ANFIS	Diverse systems: water-cooled, nanofluid-based, and hybrid PCM	Parameter optimization; Electrical efficiency prediction; Multi-objective optimization	Interpretable modeling through fuzzy rules; Broad applicability across cooling technologies (R^2 up to 1.00)	[61,62,79,80,111]
DL	Nanofluid optimization; Integrated systems with heat pumps; U-shaped evacuated tube collectors; PV/T-heat pump fault detection;	Comprehensive optimization; Adaptive control strategies; Comparative architecture analysis; Real-time fault	Combined spatial-temporal modeling capabilities; Economic performance optimization; High accuracy comparison (CNN $R^2 = 0.9980$); Robust anomaly detection (95.75% accuracy);	[69,110,112–114]

detection; Multi-objective system optimization	Advanced Transformer performance ($R^2 \approx 0.93$-0.97)

As demonstrated in Table 8, each architecture contributes unique capabilities to PV/T modeling: unsupervised learning for exploratory analysis of novel cooling technologies (SOFM), automatic discovery of optimal model complexity (GMDH), effective capture of time-dependent thermal behavior (RNN), transparent reasoning through fuzzy rule representation (ANFIS), and advanced spatial-temporal modeling for performance optimization and control (DL). These approaches collectively enhance PV/T modeling capabilities beyond conventional techniques, particularly for complex configurations involving nanofluids, phase change materials, and dynamic operating conditions. The following sections explore each architecture in detail, demonstrating how they can be strategically selected based on specific modeling requirements in PV/T research.

4.1.3.1. Self-Organizing Feature Map (SOFM)

SOFM is characterized as an unsupervised learning approach whereby high-dimensional data is projected onto a lower-dimensional grid while topological relationships are preserved. Patterns and relationships within input data are autonomously identified, without requiring labeled training data. This capability is particularly valuable for clustering and exploratory analysis of complex system behaviors.

SOFM was applied to model an advanced PV/T system incorporating multiple cooling technologies [89]. Three distinct cooling configurations were compared: a conventional water-filled tank with water flow, a PCM-filled tank with water flow, and an innovative hybrid approach using nano-PCM (nano-SiC) combined with nano-fluid (water-SiC).

The superior performance of the nano-enhanced system was demonstrated through systematic evaluation of conventional versus advanced cooling approaches. Two critical aspects of PV/T thermal management were addressed by incorporating both nano-PCM and nano-fluid: effective heat absorption during peak operation and efficient heat transfer away from PV cells. The performance enhancements achieved with the advanced cooling system were successfully captured by the SOFM model.

The architecture's potential value for exploratory analysis of novel cooling technologies is highlighted by this application, particularly where complex interactions between multiple materials may not be fully understood through theoretical models alone.

4.1.3.2. Group Method of Data Handling (GMDH)

GMDH is characterized as a self-organizing modeling approach where complex models are automatically constructed from simpler components. Optimal partial models are iteratively generated and selected, then combined into increasingly complex structures. Overfitting is avoided through validation-based selection. Automatic discovery of optimal model complexity is enabled by this unique approach, which is particularly valuable for systems where underlying variable relationships are not well-defined theoretically.

Advanced thermal management approaches using nanofluids have been the focus of recent GMDH applications in PV/T research. A PV/T unit featuring an innovative corrugated serpentine absorber tube filled with Al_2O_3/water nanofluid was modeled, demonstrating GMDH's effectiveness for complex geometric configurations [107]. Multiple aspects of thermal management were simultaneously addressed through this combination of geometric optimization and nanofluid enhancement.

GMDH application was extended to building-integrated photovoltaic thermal (BIPV/T) systems, where an Al_2O_3/water nanofluid-cooled collector designed for architectural integration was comprehensively examined [108]. The growing interest in building-integrated solar technologies was addressed by this research, where system design and performance are constrained by additional aesthetic and structural requirements.

Phase change material integration represents another significant GMDH application area. Multi-objective optimization of PCM-based PV/T systems was achieved through GMDH-type artificial neural networks predicting electrical power, thermal power, and entropy generation [20]. Exceptional accuracy was demonstrated with $R^2 > 0.999$ for all outputs. The framework was integrated with Multi-objective Thermal Exchange Optimization and PROMETHEE decision-making methods. This combination of machine learning with multi-criteria decision-making demonstrates GMDH's versatility for complex optimization scenarios.

Reynolds number and nanoparticle concentration were utilized as key input parameters in nanofluid studies, and GMDH's capability to capture complex fluid dynamics is indicated. GMDH's effectiveness for modeling advanced thermal management approaches is demonstrated by the exceptionally high accuracy achieved across all applications. A valuable tool for system optimization is thus provided, particularly where experimental testing of all possible configurations would be prohibitively expensive.

4.1.3.3. Recurrent Neural Networks (RNN)

RNNs are distinguished from feedforward architectures by their feedback connections that create internal memory (Fig. 8c). This feature enables temporal dependencies to be captured, which is particularly valuable for systems where past states influence current behavior. In PV/T systems, where thermal mass and time-dependent conditions are significant factors, RNNs offer notable advantages for performance modeling.

Multiple RNN architectures have been applied to PV/T systems: ERNN, LSTM, and NARX. ERNNs utilize a context layer to retain information from previous states, enabling temporal pattern recognition with relatively low computational requirements. ERNN was applied to a PV/T system with a sheet-and-serpentine tube collector cooled by water-magnetite nanofluid [109]. Exceptional prediction accuracy was achieved for thermal efficiency (R=0.9973). This application demonstrates ERNN's effectiveness for modeling time-dependent thermal behavior in systems where thermal inertia affects performance.

LSTM networks, a more sophisticated RNN variant, were designed to address the vanishing gradient problem when modeling extended temporal dependencies. Their specialized cell structure enables selective information retention through input, output, and forget gates. This architecture was employed to predict the performance of an advanced cooling system combining water-based cooling with nano-PCM containing MWCNT nanoparticles and finned collectors [93]. The application of LSTM was particularly appropriate for this system, as phase change materials introduce time-dependent behavior through transition processes. Comparative studies have demonstrated LSTM performance benchmarks against advanced architectures, where frequency-enhanced Transformers achieved superior accuracy in multi-objective optimization scenarios [110].

NARX networks represent another significant RNN variant that incorporates both autoregressive and exogenous input capabilities. These networks demonstrated exceptional predictive accuracy when applied to greenhouse-integrated PV/T systems using nanofluid cooling [82]. Various nanofluids including Al_2O_3, SiO_2, and hybrid Al_2O_3–SiO_2 formulations were evaluated for predicting electrical, thermal, and overall efficiency. NARX achieved the highest performance among tested models (R^2 = 0.99795, RMSE = 0.1062), highlighting its capability for capturing complex temporal relationships in multi-variable PV/T systems.

As PV/T research increasingly incorporates thermal storage and dynamic operating strategies, recurrent architectures are expected to become more significant for accurate performance modeling. All RNN variants studied demonstrated exceptional capabilities for capturing the temporal aspects of PV/T thermal behavior, with potential applications in both performance prediction and control optimization.

4.1.3.4. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is characterized as a hybrid methodology. Neural networks' learning capabilities are integrated with the interpretability offered by fuzzy logic systems in this approach. Complex nonlinear relationships are effectively modeled while transparency is simultaneously maintained through the implementation of interpretable fuzzy rules. The structural organization is typically established as a five-layer network (Fig. 8b). A Takagi-Sugeno fuzzy inference system is implemented within this framework. Parameter optimization is achieved through the application of neural network learning algorithms.

ANFIS has been extensively applied in PV/T research across various cooling technologies and system configurations. A conventional water-cooled PV/T system was modeled with baseline performance predictions established with exceptional accuracy (MSE of 0.009 and R^2 of 1.00) [61]. The effectiveness of ANFIS for basic thermal management strategies was thus demonstrated, providing a foundation for comparative analysis with more advanced approaches.

Applications of ANFIS have been extended to nanofluid-based PV/T systems by multiple researchers. When various neural network architectures were compared for a zinc-oxide/water nanofluid system, ANFIS was found to provide the most accurate predictions specifically for electrical efficiency [79]. This capability for electrical performance prediction is particularly valuable when electrical generation is prioritized in PV/T systems. Further demonstration of ANFIS's modeling capabilities was provided for silica nanofluid cooling effects, where substantial performance improvements were achieved under specific radiation and flow conditions [80].

The most sophisticated application involved a hybrid cooling system combining nanofluids with nano-enhanced phase change materials [111]. Optimal operating parameters were effectively identified, including PCM layer thickness, heat transfer fluid mass flow, and nanoparticle mass fractions, to maximize both thermal energy output and exergy efficiency.

A comparative assessment of ANFIS was conducted against other machine learning approaches for water-cooled PV/T collectors, revealing important performance characteristics [62]. Although Least Squares Support Vector Machine (LSSVM) slightly outperformed ANFIS in their specific application, ANFIS's competitive performance was demonstrated, particularly in situations where experimental data is limited.

The widespread adoption of ANFIS across diverse PV/T applications emphasizes its versatility and effectiveness for thermal-electrical system modeling. Its unique combination of learning capability and interpretability is particularly valuable for engineering applications where understanding underlying relationships is essential for system design optimization.

4.1.3.5. Deep Learning Techniques (DL)

Sophisticated DL approaches have recently emerged in PV/T modeling, where multiple neural network architectures are combined to address complex challenges in performance prediction, fault detection, and system control (Fig. 8d). These advanced techniques are utilized to model spatial-temporal patterns and implement adaptive control strategies through complementary architectural strengths.

Multiple DL architectures have been applied to PV/T systems, ranging from fundamental CNN to advanced hybrid models and Transformer-based approaches. Comparative analysis between deep learning architectures revealed performance differences when applied to complex PV/T configurations. CNN was evaluated against MLP for hybrid systems integrating U-shaped evacuated tube collectors with compound parabolic concentrators [69]. Both models were trained on a comprehensive 144,000-row dataset for predicting thermal and electrical parameters. CNN achieved high accuracy (R^2 = 0.9980) for modeling the complex interactions within CPC-enhanced evacuated tube systems, where outlet temperatures increased by approximately 10°C.

CNN-LSTM hybrid models integrate spatial feature extraction capabilities with temporal dependency modeling. This architectural fusion proves particularly valuable for processing data with both spatial and temporal dimensions, such as evolving temperature distributions in PV/T systems. CNN-LSTM hybrid modeling was applied to evaluate various nanofluids for PV/T cooling in Riyadh's challenging hot climate [112].

Advanced fault detection capabilities have been demonstrated through Convolutional Autoencoders combined with Residual Bi-directional GRU [114]. This architecture achieved robust performance for anomaly detection in PV/T-heat pump systems (95.75% normal vs. 4.25% faulty detection). Weak supervision enabled adaptive, low-cost diagnostics for real-time sensor data monitoring, maintaining operational efficiency in refrigerant-based PV/T systems.

Transformer-based architectures represent the latest advance in PV/T optimization. FEDformer, a frequency-enhanced Transformer, was employed for multi-objective optimization of hybrid PV/T-GSHP systems [110]. The model achieved exceptional performance ($R^2 \approx 0.93$–0.97) while processing 116 samples per millisecond, significantly outperforming LSTM and standard Transformer baselines. This approach enabled comprehensive system optimization, reducing grid electricity consumption by 70.8% and lifecycle costs by 54.6%.

Deep Q-Networks with LSTM layers provide reinforcement learning capabilities for adaptive control optimization. Applied to PV/T systems integrated with brine-to-water heat pumps, this approach achieved an approximately 4% reduction in operating costs during training and 3% during validation [113].

These applications demonstrate the potential of advanced deep learning techniques not only for modeling PV/T performance but also for actively improving system operation through intelligent control. As PV/T integration with building energy systems and smart grids increases, such adaptive control approaches will become increasingly significant for maximizing installation value in real-world environments.

5. Ensemble methods

Ensemble methods represent an advanced machine learning approach where multiple models are combined to achieve superior predictive performance compared to individual learners. These techniques address limitations of single-model approaches by leveraging collective intelligence to reduce prediction variance, improve generalization, and enhance robustness across diverse operating conditions.

The aggregation of predictions from multiple base models is particularly valuable for PV/T systems, where performance is influenced by numerous interdependent variables and complex nonlinear relationships between thermal and electrical processes. Enhanced model stability and reduced overfitting risk are achieved through this multi-model integration, enabling more accurate representation of intricate system dynamics.

Three principal ensemble strategies have been applied to PV/T system modeling: Bootstrap Aggregating (Bagging), Boosting, and Stacking. As illustrated in Fig. 10, BA involves training multiple models in parallel on bootstrapped datasets, where variance is reduced through prediction averaging (Fig. 10a). BM utilizes sequential model training, where each iteration corrects errors from previous models to progressively enhance accuracy (Fig. 10b). Stacking represents a meta-learning approach that combines predictions from multiple base models through higher-level learners (Fig. 10c).

Fig. 11 presents the categorization of these strategies and their specific implementations in PV/T research. RF and ETR represent predominant Bagging approaches, while Boosting methods include GBR, XGBoost, LightGBM, BRT, and AB. Stacking represents the third major ensemble category. These specialized techniques have been successfully implemented in PV/T system modeling applications.

The following sections examine these ensemble approaches in detail, highlighting their applications, performance characteristics, and contributions to PV/T system modeling accuracy.

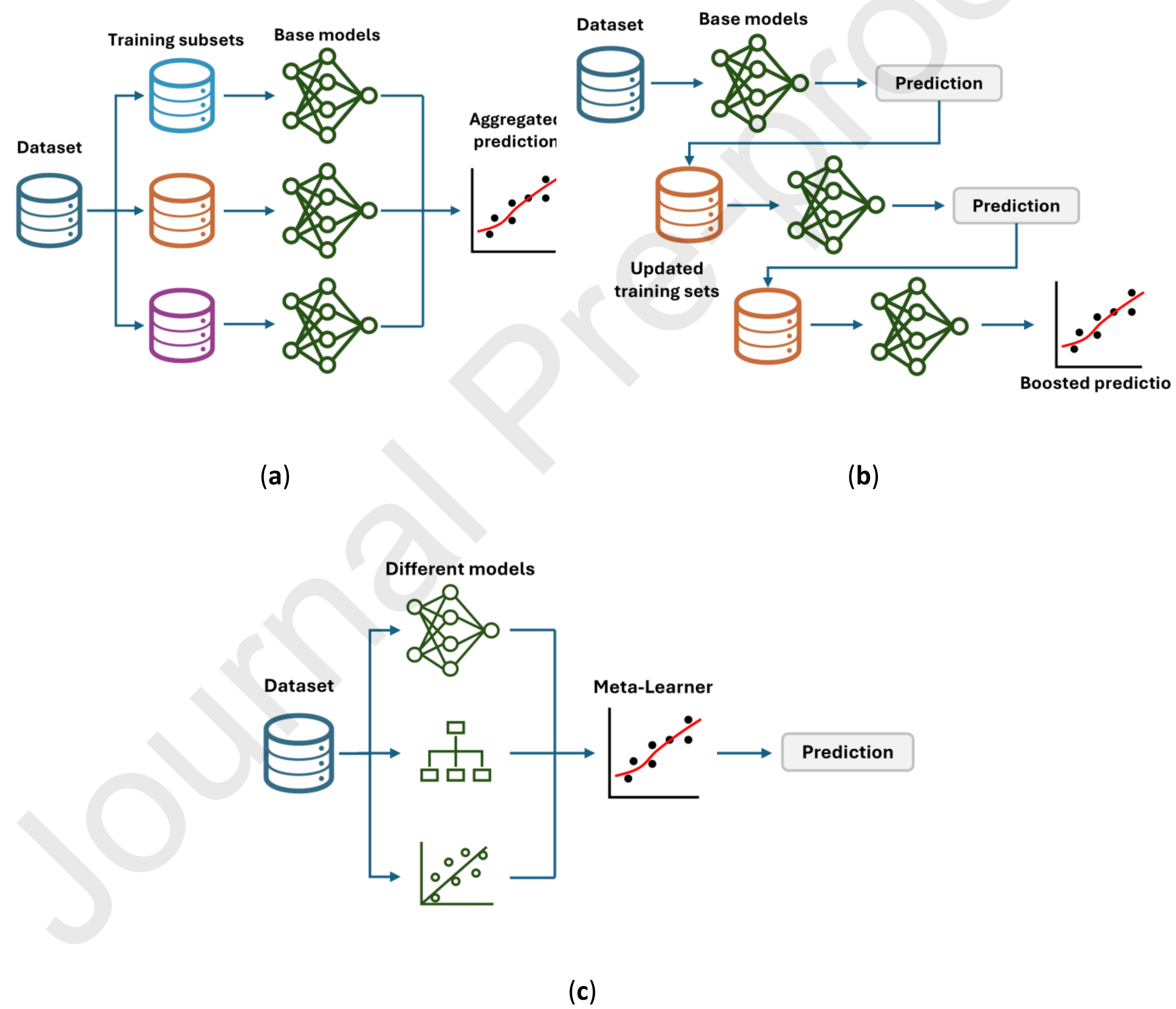

Fig. 10. Schematic representation of ensemble learning strategies: (a) Bagging; (b) Boosting; (c) Stacking.

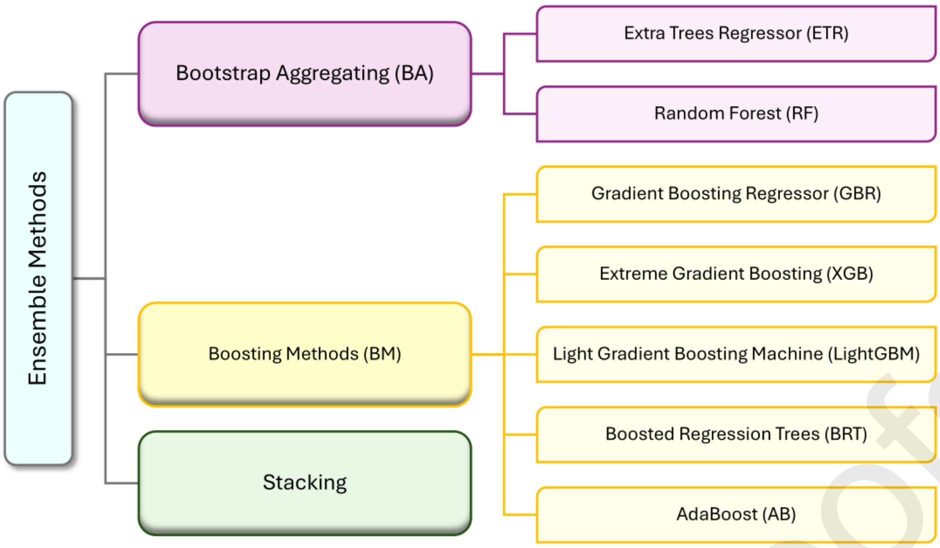

Fig. 11. Categorization of ensemble machine learning methods used in PV/T modeling.

5.1. Bootstrap Aggregating (BA)

BA reduces variance and improves model stability through training multiple models on bootstrapped data subsets. Final predictions are obtained through averaging for regression tasks or majority voting for classification. This approach effectively reduces overfitting and enhances robustness in complex datasets. RF and ETR are most widely utilized in PV/T system modeling due to their capability to capture nonlinear dependencies and improve predictive accuracy.

RF constructs multiple decision trees on bootstrapped samples, where predictions are aggregated to reduce overfitting and improve generalization, particularly in high-dimensional datasets. RF was applied to predict PV/T system electrical efficiency, outperforming SVR and MLP [63]. Energy and exergy efficiencies in a nanofluid-based PV/T system were evaluated using RF, demonstrating its ability to model nonlinear interactions between Reynolds number, nanoparticle concentration, and efficiency metrics [115]. Optimal RF performance was found to depend on hyperparameter tuning, where Grid Search significantly improved accuracy [95].

Advanced applications of RF have been demonstrated in hybrid energy systems. RF was applied alongside other ensemble methods for hydrogen production prediction in riser-optimized PV/T systems coupled with Hofmann electrolysis [116]. The novel riser tube geometry with natural circulation enhanced thermal and electrical outputs, resulting in approximately 12.5% higher hydrogen yield compared to conventional systems. RF was utilized for multi-objective optimization of PV/T-thermoelectric systems, contributing to sustainability assessment alongside other regression methods [117].

ETR builds upon RF principles by introducing additional randomness during tree construction. Unlike RF, which selects optimal split points based on criteria such as Gini impurity, ETR chooses split points randomly from the full feature value range. This added diversity often results in lower variance and improved generalization. ETR was applied alongside XGB and k-Nearest Neighbors to predict PV/T system efficiency using nanofluid cooling [118]. ETR outperformed KNN and delivered performance comparable to XGB, demonstrating robustness in handling large, high-dimensional datasets.

Despite their strengths, Bagging-based models require careful hyperparameter tuning and sufficiently large datasets to prevent overfitting. Computational cost increases with the number of base models, making efficiency considerations crucial.

Table 9 summarizes key applications and performance metrics of Bagging-based models in PV/T system modeling.

Table 9. Applications of BA methods in PV/T system modeling.

Method	System Type	Main Applications	Key Advantages	Representative Studies
RF	Electrical efficiency prediction systems; Nanofluid-based PV/T with needle-finned serpentine channels; General PV/T prediction systems; Riser-optimized PV/T with hydrogen production; PV/T-thermoelectric systems	Electrical efficiency prediction; Energy and exergy efficiency evaluation; Hyperparameter optimization; Hydrogen production prediction; Multi-objective sustainability optimization	Captures nonlinear dependencies effectively; Outperforms SVR and MLP; Benefits significantly from Grid Search optimization; High prediction accuracy (R^2 up to 0.9952); Effective for multi-physics applications	[63,95,115–117]
ETR	Nanofluid-cooled PV/T systems	Electrical and thermal efficiency prediction; Comparative performance assessment with ensemble methods	Additional randomness reduces variance; Improved generalization in high-dimensional datasets; Performance comparable to XGB; Superior to KNN	[118]

5.2. Boosting methods (BM)

Boosting sequentially trains models where each iteration corrects errors made by previous models, refining weak learners into strong predictive models. Various boosting techniques have been applied to PV/T system modeling, each requiring careful hyperparameter tuning to balance learning rate, tree depth, and regularization to prevent overfitting.

GBR builds decision trees sequentially, with each tree correcting previous errors, making it effective in high-dimensional datasets. However, computational intensity remains a limitation. GBR was used to predict PV/T efficiency using geothermal cooling and nanofluids, successfully modeling nanofluid concentration and Reynolds number [81]. GBR and LightGBM were compared for power prediction in water-based PV/T systems, where LightGBM demonstrated superior thermal efficiency while MLP performed best in electrical efficiency prediction [68]. Additionally, GBR was applied for optimizing PV/T systems with battery storage and electric vehicles, improving energy management [119].

XGB integrates regularization techniques to enhance generalization, making it more robust against overfitting than traditional gradient boosting while efficiently handling large datasets. XGB was applied to a PV/T system utilizing Al_2O_3-water nanofluid as the cooling medium, achieving the highest accuracy and outperforming both ETR and KNN models [118]. XGB significantly outperformed AdaBoost in a hybrid system integrating photovoltaic panels with solar still technology and Glauber's salt PCM [95]. Advanced ensemble applications were demonstrated using XGB for hydrogen production prediction in riser-optimized PV/T systems, where ensemble approaches enabled accurate modeling of complex thermal-electrical-chemical interactions [116].

AB iteratively adds weak learners and adjusts weighting to focus on misclassified examples from previous rounds. Although effective for combining weak base learners, AB demonstrates sensitivity to noise and outliers, achieving lower performance metrics compared to XGB across different training-testing splits [95].

LightGBM uses a leaf-wise growth strategy for faster computation and reduced memory usage. LightGBM was found to be superior to GBR in predicting thermal efficiency for water-based PV/T systems [68]. BRT sequentially enhances weak learners to capture nonlinear dependencies. BRT was used to evaluate energy and exergy efficiencies of a concentrating PV/T system, effectively modeling heat transfer enhancements [120].

Among the studies reviewed, GBR was the most frequently applied method. However, XGB demonstrated superior balance between accuracy and computational efficiency.

Table 10 summarizes Boosting-based models and their performance in PV/T system modeling.

Table 10. Applications of BM in PV/T system modeling.

Method	System Type	Main Applications	Key Advantages	Representative Studies
GBR	Geothermal cooling with nanofluids; Water-based PV/T systems; Battery storage and EV integration systems	PV/T efficiency prediction; Power prediction; Energy management optimization	Effective in high-dimensional datasets; Successfully models nanofluid concentration and Reynolds number; Improves energy management strategies	[68,81,119]
XGB	Nanofluid-cooled PV/T systems; PV/T-solar still systems with PCM integration; Riser-optimized PV/T with hydrogen production	Electrical and thermal efficiency prediction; Performance comparison and optimization; Hydrogen production prediction	Enhanced generalization through regularization; Superior accuracy compared to ETR and KNN; Outperforms AB; Robust against overfitting; Effective for multi-physics modeling	[95,116,118]
AB	PV/T systems with solar still and PCM integration	Performance prediction and comparative assessment	Assigns higher weights to misclassified samples; Lower performance than XGB due to noise sensitivity in PV/T applications	[95]
LightGBM	Water-based PV/T systems	Thermal efficiency prediction; Comparative performance assessment	Leaf-wise growth strategy for faster computation; Reduced memory usage; Superior thermal efficiency prediction compared to GBR	[68]
BRT	Concentrating PV/T systems with heat transfer enhancements	Energy and exergy efficiency analysis; Heat transfer optimization	Sequential enhancement of weak learners; Effective modeling of nonlinear dependencies; High accuracy and interpretability	[120]

5.3. Stacking methods

Stacking represents a meta-learning approach that combines predictions from multiple base models through a higher-level learner. This technique differs from bagging and boosting by training a meta-model to learn optimal combination weights for base model predictions. Enhanced predictive performance is achieved through leveraging the strengths of diverse algorithms while minimizing individual model weaknesses.

Advanced stacking applications were demonstrated for predicting hydrogen production in riser-optimized PV/T systems [116]. Multiple base models including RF and XGBoost were combined through a meta-learner to predict complex thermal-electrical-chemical interactions. Exceptional accuracy was achieved with R^2 = 0.9986 and AAPRE = 0.1837%, demonstrating superior performance compared to individual learners. This approach proves particularly valuable for multi-physics systems where diverse modeling strengths can be leveraged to capture complex system behaviors.

6. Other methods

Alternative machine learning approaches other than ANNs (Section 4) and Ensemble Methods (Section 5) have been investigated for PV/T system modeling applications. These complementary techniques address specific modeling challenges where neural networks or ensemble methods may not be optimal, including scenarios requiring model interpretability, uncertainty quantification, or computational efficiency. Six principal alternative methods have been applied to PV/T research, each offering distinct advantages based on system complexity, dataset characteristics, and computational requirements.

As illustrated in Fig. 12, these methods include different machine learning approaches: SVM/SVR for high-dimensional nonlinear regression tasks, GPR for probabilistic predictions with uncertainty quantification, k-NN for distance-based learning from historical data, traditional RM including linear and regularized approaches, GP for evolutionary symbolic regression, and DT for transparent rule-based modeling.

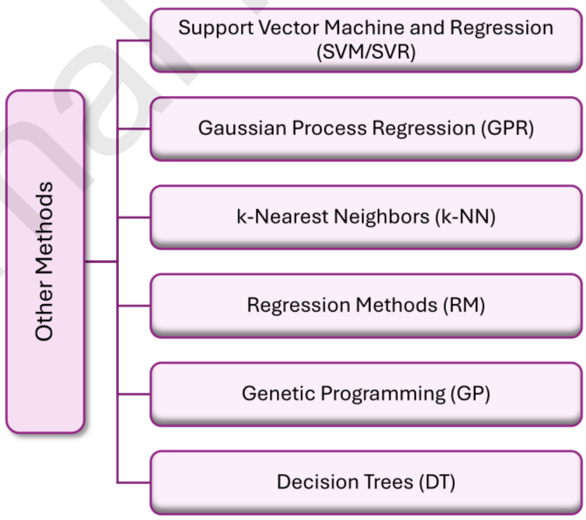

Fig. 12. Categorization of additional machine learning methods used in PV/T modeling.

These techniques have been strategically employed to address specific challenges in PV/T modeling, including nonlinearity handling, data sparsity management, and computational cost optimization. Applications range from baseline performance prediction using traditional regression methods to sophisticated symbolic model development through genetic programming. The interpretability offered by methods such as decision trees and genetic programming is particularly valuable for engineering applications where understanding underlying relationships is essential for system design optimization.

Table 11 provides a comparative overview of these methods, highlighting their primary applications, key advantages, and representative studies in PV/T research. The following sections examine each method in detail, demonstrating their contributions to the comprehensive machine learning toolkit available for PV/T system analysis and optimization.

Table 11. Applications of other ML methods in PV/T system modeling.

Method	System Type	Main Applications	Key Advantages	Representative Studies
SVM/SVR	Various configurations: nano-PCM and nanofluid cooling; water-based PV/T; Gulf region climate systems; hybrid SCPP-PV/T power plants	Nonlinear regression; Performance prediction; Comparative analysis with ANN/ensemble methods; Multi-objective optimization	Robust with limited datasets; Strong generalization properties; Effective extrapolation beyond training data; Exceptional accuracy with hybrid kernels (R^2 = 0.996)	[61–63,65,67,80,89,95,121]
GPR	Grid-connected PV/T systems; Nanofluid-based cooling with Fe/water nanofluids; PV/T-thermoelectric hybrid systems with water-based nanofluids	Performance forecasting; Uncertainty quantification; Day-ahead prediction; Multi-objective sustainability optimization; CO_2 mitigation prediction	Probabilistic predictions with uncertainty estimation; Non-parametric approach; Valuable for energy planning under variable conditions; Highest accuracy for environmental impact prediction	[101,117,122]
k-NN	PV/T collector with nanofluid-based cooling	Thermal and electrical efficiency prediction; Distance-based learning	Captures complex interactions without explicit functional forms; No assumptions about data distribution; Simple implementation	[118]
RM	Standard PV/T collectors; PV/T with nano-PCM and nanofluids; Ternary hybrid nanofluids; PV/T-thermoelectric systems; Concentrating PV/T with mirrors; PV/T-heat pump combinations; Nocturnal cooling systems; Low-concentration PV/T systems	Baseline modeling; Sensitivity analysis; Explicit formula derivation; Multi-objective optimization; Real-time control; Performance forecasting; Environmental factor analysis; Clustering-based control; Parameter ranking	Computational efficiency; High interpretability; Valuable for sensitivity analysis; Good baseline comparison; Probabilistic predictions with uncertainty; Real-time applicability; Enhanced stability through regularization	[19,81,91,92,95,117,123–127]
GP	Concentrating PV/T (CPV/T) with engine oil-based nanofluids	Symbolic regression; Mathematical model derivation; Efficiency prediction	Interpretable mathematical formulations; No predefined equations required; Clear parameter influence understanding	[87]

DT	PV/T with nanofluid-based geothermal cooling	Performance prediction; Parameter influence analysis; Rule-based modeling	High interpretability with clear decision rules; Handles mixed data types; Minimal preprocessing requirements	[81]

6.1. Support Vector Machines and Regression (SVM/SVR)

SVM and SVR are characterized by their capability to project input data into higher-dimensional spaces through kernel functions, enabling effective modeling of nonlinear relationships in PV/T systems. Robust performance with limited training samples and strong generalization properties are demonstrated by these methods, making them valuable for PV/T applications where experimental data collection is costly.

Computational limitations are encountered with large datasets due to intensive matrix operations, while performance dependency on hyperparameter tuning remains significant. Despite these constraints, successful implementation in PV/T modeling has been achieved across multiple studies. SVM effectiveness was demonstrated by Al-Waeli et al. [89] for nano-PCM and nanofluid cooling systems, though ANN approaches provided superior performance. Strong electrical current estimation with correlation coefficient $R = 0.92$ was reported by Yousif & Kazem [65] for PV/T systems under Oman climatic conditions.

Advanced kernel variations have been explored to enhance modeling accuracy. Hybrid SVR incorporating multiple kernel functions was applied to optimize combined solar chimney-photovoltaic thermal power plant performance [121]. Linear, Polynomial, Gaussian, and Hybrid kernels were evaluated within the HSVR framework. Exceptional accuracy was achieved with $R^2 = 0.996$ for the hybrid SCPP-PV/T system. The optimized system outperformed standalone PV modules by up to 4.8%, with electrical generation ranging from 6.90-8.36 MW depending on weather conditions.

Error minimization capabilities achieving the lowest MAPE of 0.0358 were confirmed by Kazem et al. [67] compared to alternative methods. Advanced LSSVM variations have been utilized to enhance accuracy and computational efficiency. Superior performance over ANN and ANFIS models was demonstrated by Zamen et al. [61] achieving $R^2 = 1.00$ and Ahmadi et al. [62] with $R^2 = 0.991$ and RMSE = 0.055 for thermal and electrical efficiency prediction. Competitive results with $R^2 = 0.938$ with nanofluid-cooled PV/T collectors were achieved by LS-SVR as reported by Cao et al. [80].

Recent comparative studies have investigated hybrid approaches and feature selection techniques. Competitive performance with $R^2 = 0.9935$ and RMSE = 0.5087 after hyperparameter tuning was maintained by SVR when compared with ensemble methods by Ganesan et al. [95]. Effectiveness in extrapolating beyond training data achieving $R^2 = 0.7639$ was emphasized by Gharaee et al. [63] through SHAP analysis.

A strong potential in PV/T modeling has been demonstrated by SVM/SVR methods, offering robust nonlinear regression capabilities with good generalization properties. These approaches remain valuable when interpretability, generalization, and data efficiency are prioritized over complex modeling approaches.

6.2. Gaussian Process Regression (GPR)

GPR is characterized as a non-parametric machine learning method where probabilistic distributions over possible functions are defined rather than fixed functional forms being assumed. Both predictions and uncertainty quantification are enabled through this approach, making it advantageous for PV/T modeling where performance varies with environmental conditions. However, computational expense is encountered, particularly with large datasets.

Key performance metrics including electrical and thermal efficiency, reference yield, and final yield have been forecasted using GPR in PV/T applications. A 3.0 kWp grid-connected PV/T system to be installed in 18 cities in the MENA region was evaluated by Adun et al. [101], where GPR's predictive capability was compared with Artificial Neural Networks. Reasonable estimates were produced by GPR, however superior performance was demonstrated by ANNs in modeling nonlinear dependencies.

Day-ahead forecasting of PV/T performance under nanofluid-based cooling was explored by Diwania et al. [122] using historical data from Roorkee, India. System efficiency was modeled with pure water and Fe/water nanofluid as working fluids. PV cell temperature reductions up to 9.47°C were achieved through increased nanofluid mass flow rates, with electrical efficiency enhanced by 7.11% and overall efficiency by 9.84% compared to water-cooled systems.

Advanced applications of GPR have been demonstrated in hybrid PV/T-thermoelectric systems. Anisi et al. applied GPR alongside other regression methods for multi-objective optimization of PV/T-TEG systems cooled with water-based hybrid nanofluids [117]. The highest accuracy was achieved by GPR with $R^2 = 0.9937$ for CO_2 mitigation prediction, enabling optimization that increased CO_2 mitigation from 11.15 to 53.17 tonnes while improving economic return from –$74 to $737.

Accurate performance predictions closely matching real-world data were demonstrated by GPR across diverse applications. However, limitations compared to ANN-based models in capturing highly nonlinear system behavior were highlighted. GPR remains valuable for performance forecasting when prediction confidence understanding is crucial, particularly for sustainability optimization and energy planning under variable conditions.

6.3. Regression methods (RM)

RMs have been applied to predict thermal and electrical performance of PV/T systems, focusing on efficiency estimation and optimization. Linear regression, a fundamental method assuming linear relationships between input and output variables, was utilized to develop prediction models for power productivity in PV/T systems incorporating nano-phase change materials and nanofluids. Computational efficiency was demonstrated despite limited accuracy with $R^2 = 0.500$ and RMSE = 0.658 compared to nonlinear approaches [91]. Similar limitations were observed in multi-objective PV/T-TEG system optimization, where linear regression provided computational efficiency but demonstrated reduced accuracy compared to more sophisticated approaches [117].

Multiple linear regression models have been extensively applied across diverse PV/T configurations. Solar irradiance, ambient temperature, and cell temperatures were mapped to output parameters using multiple-linear-regression models in low-concentration PV/T systems, achieving R^2 values between 0.87-0.98 [125]. Statistical approaches employing multiple regression analysis with backward calculation methods demonstrated prediction accuracy of 91.09% for water-cooled PV/T systems using minimal variables [127].

Ordinary Least Squares (OLS) regression was applied to model PV power generation, wherein solar irradiance and ambient temperature were effectively captured as key predictors. While high accuracy with R^2 ranging from 0.874 to 0.990 was achieved, superior adaptability to complex nonlinear relationships was demonstrated by ANN [92]. Simplified regression modeling using least squares methods proved effective for nocturnal cooling applications, achieving mean absolute errors of 0.74±0.91 K with $R^2 = 0.911$ correlation [126]. Real-time regression-based approaches were integrated with proportional controllers for dynamic heliostat angle adjustment in concentrated PV-T systems, demonstrating practical implementation capabilities for thermal optimization [124].

In comparative studies, Linear Regression was evaluated alongside SVM, DT, and MLP for PV/T system modeling. Computational efficiency was maintained by LR, though difficulties in capturing nonlinear dependencies resulted in lower accuracy with $R^2 = 0.690$ compared to tree-based and neural network models [81].

Regularization techniques including Ridge Regression, Lasso Regression, and Elastic Net were introduced to address these limitations. Model stability was improved through penalization of large coefficient values to control overfitting, particularly in high-dimensional datasets. However, superior predictive accuracy was maintained by ensemble learning models despite these refinements achieving R^2 values between 0.775 and 0.874 [95]. Polynomial Regression within clustering-based frameworks achieved $R^2 > 0.95$ for flow-rate optimization in hybrid PV/T-heat pump systems [19].

Hyperparameter tuning via Grid Search was applied by Ganesan et al. [95] to optimize multiple regression models, wherein improved model stability was achieved but ultimate superiority was demonstrated by ensemble methods. Advanced regression models utilizing supervised machine learning techniques were developed to derive explicit performance equations for PV/T efficiency, wherein key parameters such as fluid force and Nusselt number were successfully modeled with mean absolute errors as low as 0.0003 for efficiency prediction [123].

Despite refinements, limitations in capturing nonlinear dependencies were maintained by linear regression methods. Nevertheless, the value for baseline PV/T modeling, sensitivity analysis, and system design evaluations were demonstrated, particularly where interpretability and computational efficiency were prioritized.

6.4. Less frequently applied methods

Several machine learning approaches have been explored in PV/T modeling with limited representation in the current literature. Three distinct techniques are examined together due to their singular application in PV/T research: k-NN, GP, and DT.

K-NN regression was implemented for predicting thermal and electrical efficiencies of a PV/T collector with nanofluid-based cooling by Margoum et al. [118]. Predictions were established through K closest neighbors, wherein feature relationships were determined via distance metrics. Complex interactions between nanofluid concentration, Reynolds number, and mass flow rate were captured without explicit functional forms being required. However, computational limitations were encountered due to training data storage requirements. Performance degradation was observed with increased input features. R^2 values of 0.96996 and 0.99522 were achieved for electrical and thermal efficiencies respectively, whereby inferior performance to ensemble methods was indicated.

Multi-Gene GP was utilized to predict efficiencies in a concentrative PV/T solar collector [87]. First-law and second-law efficiencies were modeled through this evolutionary approach. Mathematical models were derived without predefined equations. Engine oil-based nanofluids with six nanoparticle concentrations were investigated across multiple parameters. MGGP achieved correlation coefficient $R = 0.99284$ and $RMSE = 0.00930$ for first-law efficiency, and $R = 0.98244$ and $RMSE = 0.00656$ for second-law efficiency. Higher predictive accuracy was achieved by ANNs, however advantages were offered through interpretable mathematical formulations.

DT modeling for PV/T collector efficiency prediction was implemented by Jakhar et al. [81]. Input features were segmented into structured hierarchies. Clear visual representations of parameter influences were provided through the model's interpretable nature. Competitive performance was demonstrated with $R^2 = 0.92$, whereby SVM and linear regression were outperformed.

These specialized approaches provide valuable insights through distinct algorithmic characteristics, particularly when model transparency or specific computational requirements are prioritized.

7. Experimental foundations of reviewed ML models

Of the 72 publications included in this review, 33 were based fully or partially on data collected from physical PV/T installations. The remaining studies used numerically generated datasets from validated CFD simulations or analytical models. This division is not uniform across system types and has direct consequences for the generalizability of the reported ML models. Table 12 summarizes the experimental characteristics grouped by system category.

Table 12. Experimental PV/T studies underlying the ML models reviewed in this work, grouped by system category.

Category	References	Locations	Campaign and dataset character	Primary measured quantities
Water-cooled flat-plate PVT	[61,62,65–69,104,126,127]	Turkey, Oman, India, Italy, USA, Korea, Iran	Wide range: from three-day rooftop comparisons and parametric noon-hour sweeps (fewer than 100 measurements) to seven-month continuous monitoring yielding over 15,000 data points; interval typically 5–60 minutes	Fluid inlet and outlet temperatures, panel surface temperature, coolant flow rate, solar irradiance, ambient temperature, electrical voltage and current, thermal and electrical efficiency
PVT integrated with heat pump	[19,71,75,97–100,119]	India, China, Belgium, Korea	Longest campaigns in the review: 60-day laboratory trials (Gunasekar) to one-year continuous building-scale monitoring (Rehman, Dalian series); one-minute logging resolution typical for heat pump studies; dataset sizes range from hundreds to tens of thousands of records	Refrigerant temperatures and pressures, compressor power consumption, PVT array electrical output, coefficient of performance, storage tank temperatures, solar irradiance, ambient temperature and relative humidity
Nanofluid-cooled PVT	[78,79,82]	Iran	Short campaigns of 3–10 days under defined solar window conditions; typically 100–130 interval measurements at 30-minute resolution; dataset sizes rarely exceed 200 points	Fluid inlet and outlet temperatures, panel surface temperature, solar irradiance, coolant flow rate, electrical current and voltage, thermal and electrical efficiency
PCM and nano-PCM PVT	[89–92,94,95]	Malaysia, India	Highly variable: from 41-sample reproducibility benchmarks (Ganesan) to multi-month outdoor campaigns with simultaneous four-configuration logging (Al-Waeli series); dataset size not reported in most studies; 15-minute acquisition intervals typical	Panel and PCM container temperatures, solar irradiance, coolant flow rate, electrical voltage and current, thermal and electrical efficiency

PVT for hydrogen production	[96,105,116]	India	Short campaigns of 3–20 days, typically seven hours of daylight operation per day; absolute sample counts not stated in most studies; small datasets	Electrical voltage and current, solar irradiance, ambient temperature, fluid temperatures, hydrogen volume collected in graduated electrolysis tubes
Concentrating and dual-fluid PVT	[31,69,124,125]	Malaysia, Iran, Switzerland	Moderate duration: from single-day standardized test sequences to 28-day and four-month seasonal campaigns; ASHRAE 93-2003 and ASHRAE 2010:93 standards applied in two studies; IoT-based continuous logging in one field installation in Switzerland	Fluid outlet temperature, solar irradiance, mirror or tracking angles, concentration ratio, thermal and electrical efficiency; wind speed and ambient temperature as meteorological covariates

Water-cooled flat-plate systems provide the broadest experimental base. Early studies by Zamen et al. [61] and Ahmadi et al. [62] collected around 100 data points from parametric sweeps under quasi-steady noon conditions. These small datasets limited the architectures that could be applied to simple MLP and ANFIS models. Kayri [66] carried out a more systematic 13-day campaign in Batman, Turkey, varying mass flow rate across seven levels at five-minute logging intervals. Sridharan [104] designed a four-day experiment specifically for transient GRNN prediction. At the upper end, Safae et al. [68] provided 15,450 continuously logged samples from a commercial WISC installation in Catania, enabling comparative ensemble modelling with LightGBM and GBR. Yousif and Kazem [65] and Kazem et al. [67] used short three-day campaigns from the same rooftop at Sohar University across two years. Almoatham et al. [126] contributed a nocturnal cooling dataset from Dayton, Ohio, while Jo et al. [127] monitored a factory rooftop system in Dangjin, Korea across two seasonal periods.

PV/T systems integrated with heat pumps represent the most sustained experimental effort in this review. The Dalian University of Technology group published five studies between 2021 and 2025 [75,97–100], all based on the same building-scale roll-bond PV/T heat pump platform with one-minute logging resolution. These studies underpin the refrigerant-based ML results, including BP neural networks and GA-PSO-optimized models. Rehman et al. [119] provided the only year-long dataset, collected from 81 channels in a residential system in Belgium for gradient boosting applied to energy management. Chae et al. [19] used continuous data from an office building in Busan for clustering-based flow rate control. Gunasekar et al. [71] trained a 4-15-4 ANN on a 60-day R134a heat pump campaign from Coimbatore, one of the earliest ML applications to a PV/T heat pump evaporator.

The PCM category is dominated by four publications by Al-Waeli et al. [89–92], based on a platform in Bangi, Malaysia that tested four configurations simultaneously: conventional PV, water-cooled PV/T, nano-PCM, and nanofluid using a shared data acquisition system. These studies document the progression from nano-PCM characterization to ANN-assisted optimization. Deka et al. [94] provided experimental data for neural network modelling of a biochar-based PCM system in Guwahati, India. Ganesan et al. [95] used only 41 samples for a multi-model comparison including XGBoost, RF, and regularized regression, which is the smallest dataset in this review.

Three studies coupled PV/T collectors with electrolytic hydrogen production. Abd Elaziz et al. [105] provided experimental data for the RVFL model comparing air and water cooling for hydrogen yield. Senthilraja et al. [96] combined paraffin wax PCM with Hofmann electrolysis over three days in Chennai. Mohan [116] used a 20-day outdoor campaign comparing conventional and novel riser tube geometries to validate ensemble models.

Concentrating and dual-fluid configurations were investigated in four studies. Daghigh and Arshad [69] used experimental measurements for validation while training MLP and CNN models on synthetic data from their ETC+CPC platform in Iran. Ramezani et al. [125] characterized a low-concentration PV/T following ASHRAE 2010:93 standard at Semnan University. Moradi et al. [124] operated a dual-axis tracking CPV-T system in Granges, Switzerland using IoT infrastructure for continuous monitoring. Jarimi et al. [31] tested a dual-fluid collector under tropical conditions in Arau, Malaysia following EN 12975 and ASHRAE 93-2003 standards.

The nanofluid category deserves a separate comment. Despite the large number of nanofluid ML publications, only three studies were based primarily on experimental nanofluid data: Kalani et al. [79], Singh et al. [78], and Pour et al. [82]. The studies by Al-Waeli et al. [89–92] also collected nanofluid measurements, although these publications are classified under the PCM category due to their primary research focus. The majority of remaining nanofluid ML models were trained on numerically generated datasets. This approach allows wider parameter exploration but may limit applicability under real operating conditions.

Several structural patterns can be observed. Geographically, India, Iran, China, Malaysia, and Oman account for most contributions. Western Europe appears only in Rehman et al. [119] and Safae et al. [68], North America only in Almoatham et al. [126]. Nearly all experiments used single panels or small arrays. Building-integrated systems were tested only by the Dalian group and Rehman et al. Dataset size remains the most persistent constraint. Most studies used fewer than 100 samples as a direct result of short campaign durations. Parametric sweeps of three to ten days were the norm until approximately 2019, after which continuously monitored installations began producing datasets large enough for advanced architectures and multi-output ensemble methods.

8. Evolution of ML in liquid-based PV/T systems

Machine learning deployment in liquid-based PV/T systems has been examined across four developmental phases spanning 2012-2025, with technological maturation patterns captured in Table 13.

Initial viability was established during the foundational period (2012-2017), when ANNs dominated experimental frameworks. ANFIS, RBFANN, and LS-SVM were tested comparatively against conventional approaches. Water-cooled BIPV/T and heat pump configurations constituted primary test beds, while preliminary nanofluid trials were conducted. Computational advantages over traditional numerical simulation were demonstrated conclusively.

Methodological expansion characterized the 2018-2019 period. While ANN and ANFIS applications persisted, phase change materials, thermoelectric cooling, and ground source heat pumps were systematically integrated. Nanofluid formulations were diversified to include various oxide compositions, and nano-PCM incorporation was attempted. Performance quantification was achieved through enhanced modeling, enabling preliminary operational parameter optimization.

Sophisticated control strategies emerged between 2020-2022. Ensemble methods and LSTM architectures were deployed alongside reinforcement learning for autonomous operation, while fault detection capabilities were developed concurrently. Concentrating collectors and complex channel geometries were investigated, with refrigerants tested as alternative working fluids. Multi-objective optimization frameworks were implemented to balance economic, environmental, and thermodynamic performance metrics.

Current developments (2023-2025) demonstrate pervasive AI integration across all system aspects. CNN, Transformer, and refined ensemble architectures have been implemented, with model interpretability enhanced through explainable AI techniques. Ternary hybrid nanofluids and trigeneration configurations represent unprecedented system complexity. Digital twin construction has enabled autonomous energy management, establishing machine learning as a fundamental infrastructure for next-generation PV/T optimization.

Table 13. Evolution of machine learning methods applied to liquid-based PV/T systems, highlighting the progression of ML techniques, working fluids, and application contexts.

Phase	Key ML Methods	Dominant Fluids and Systems	Primary Goals and Applications
2012–2017: Foundations and Proof of Concept	ANN as a primary tool; Introduction of ANFIS, RBFANN, and LS-SVM for comparative analysis	Systems: Simple Building-Integrated PV/T (BIPV/T) and PV/T-Heat Pump (PV/T-HP) systems; Fluids: Primarily water; initial tests with nanofluid (ZnO/water)	Proof of Concept: Demonstrating that ML can accurately predict performance, serving as an alternative to complex and time-consuming numerical simulations
2018–2019: New Materials and Hybridization	Continued use of ANN and ANFIS; Comparative analysis of different model architectures	Systems: Hybridization with Phase Change Materials (PCM), Thermoelectric Cooling (PV/T-TEC), and Ground Source Heat Pumps (PV/T-GSHP); Fluids: Broader investigation of nanofluids (SiO_2, SiC) and nano-PCM	Benefit Quantification: Using ML to evaluate the performance impact of new materials (nanofluids, PCM); Preliminary Optimization: Applying models to analyze parameters and identify optimal operating conditions
2020–2022: System Optimization and Control	Emergence of Ensemble Methods (RF) and early Deep Learning (LSTM); Application of Reinforcement Learning for control; Development of fault detection models	Systems: First Concentrating PV/T (CPV/T) systems; integration with district heating and EVs. Studies on advanced channel geometries (e.g., wavy); Fluids: Continued use of water, development of nanofluids (e.g., Al_2O_3, TiO_2), and initial tests with refrigerants (R134a)	Multi-Objective Optimization: Simultaneous optimization for Life Cycle Cost (LCC), CO_2 emissions, and energy/exergy efficiency; Increased Rigor: Trend towards using larger and more comprehensive datasets for model training and validation
2023–2025: AI-Driven Systems and Autonomy	Widespread adoption of DL: CNN, RNN (LSTM, Bi-GRU), Transformers; Refinement of Ensemble Methods (XGBoost); Explainable AI (XAI, e.g., SHAP) for model interpretability	Systems: Advanced trigeneration systems; complex geometries (twisted tape turbulators, porous media); integration with agriculture and hydrogen production; Fluids: Ternary hybrid nanofluids (e.g., Al_2O_3-Cu/water); further tests with refrigerants (R22)	Decision Support: Creating "digital twins" for simulation and optimal system design selection; Autonomous Energy Management: Designing intelligent, self-adaptive control systems to minimize costs and maximize energy self-sufficiency

9. Conclusions

A systematic review of 72 publications on machine learning applications in liquid-based PV/T systems was conducted. The main findings are summarized below.

1) ANNs were found to be the dominant ML category, representing 63% of all reviewed studies. MLP was the most widely applied architecture, used in 44 publications. In the great majority of cases, R^2 values above 0.95 were reported.
2) Ensemble methods accounted for 14% of applications. Despite their lower representation in the literature, these methods achieved the highest prediction accuracies overall (RF and XGBoost models reached R^2 values up to 0.999).
3) Other ML techniques, including SVR, GPR, and linear regression, were applied in 23% of studies. These methods proved particularly useful when datasets were limited or when uncertainty quantification was required alongside point predictions.
4) Water-cooled PV/T systems were the most extensively studied configuration. Among enhanced cooling technologies, nanofluid-based systems demonstrated thermal efficiency improvements reaching 90.47%, while PCM-based systems showed electrical efficiency gains between 8.07% and 13.32%.
5) Advanced deep learning architectures have entered PV/T research in recent years. CNN-LSTM hybrids, Transformer-based models, and reinforcement learning agents were applied for performance prediction, fault detection, and adaptive control, representing a clear shift from static offline modeling toward active system management, although validation under variable field conditions remains at an early stage.
6) A patent landscape analysis was conducted as part of this review. All identified patents addressed hardware-level innovations: collector design, cooling configurations, and system integration. No patents protecting ML methodologies for PV/T applications were found. This gap between academic activity and commercial protection of ML-based solutions appears significant.
7) Fewer than half of the 72 reviewed studies were based on authors' own experimental measurements. The remainder relied on numerically generated data from CFD simulations or analytical models. Strong geographical concentration was observed, with India, Iran, China, Malaysia, and Oman contributing the majority of experimental work. Contributions from Western and Northern Europe remain sparse.
8) Most studies used datasets of fewer than 100 samples. This increases overfitting risk, restricts model generalization, and limits applicability to diverse climatic conditions and commercial-scale installations.

9.1. Future research directions

Based on the gaps identified throughout this review, the following directions are proposed:

1) Development of open-access, standardized PV/T databases is needed, covering diverse system configurations, working fluids, and climatic zones. Without such resources, fair model comparison and reproducibility of results will remain difficult to achieve.
2) Transfer learning methods should be explored to enable model adaptation across geographical locations and system scales without extensive retraining. This is considered especially relevant given the geographical concentration identified in the current literature.
3) Integration of ML models with IoT sensors and edge computing platforms should be pursued. Real-time data acquisition and adaptive operation under varying environmental conditions are prerequisites for practical autonomous control.
4) Multi-criteria optimization frameworks require further development. Most reviewed studies optimize a single performance metric; simultaneous consideration of energy efficiency, levelized cost of energy, and carbon emissions would yield more realistic and deployable results.

5) Explainable AI techniques should be systematically applied to deep learning models used in PV/T research. Improved interpretability of predictions would support engineering decision-making and is likely to facilitate broader industry acceptance.
6) Reinforcement learning for adaptive flow control and dynamic operation remains largely unexplored in this field. Development of self-optimizing PV/T systems through this approach represents a promising and underutilized direction.
7) Long-term validation studies are necessary. Although the short campaign durations documented in this review make this difficult to meet, models should be tested across multiple seasons and degradation cycles to confirm reliability under real operating conditions.
8) Standardized performance metrics and evaluation protocols are required to allow meaningful comparison between ML approaches. Their absence continues to slow technology development and complicates commercialization efforts.

These developments are considered essential for moving ML-based PV/T optimization from controlled research settings toward real-world deployment. As PV/T systems become increasingly integrated into building energy networks and district heating infrastructure, machine learning is expected to serve as a key tool for their intelligent operation and system-level optimization.

List of Abbreviations and Nomenclature

Machine Learning Methods:

AB	AdaBoost
ANN	Artificial Neural Networks
ANFIS	Adaptive Neuro-Fuzzy Inference Systems
BA	Bootstrap Aggregating
BM	Boosting Methods
BRT	Boosted Regression Trees
CNN	Convolutional Neural Networks
DL	Deep Learning
DNN	Deep Neural Networks
DT	Decision Trees

ELM	Extreme Learning Machine
ERNN	Elman Networks
ETR	Extra Trees Regressor
FFNN	Feedforward Neural Networks
GA-PSO	Genetic Algorithm-Particle Swarm Optimization
GBR	Gradient Boosting Regressor
GMDH	Group Method of Data Handling
GP	Genetic Programming
GPR	Gaussian Process Regression
GRNN	Generalized Regression Neural Networks
GRU	Gated Recurrent Units
k-NN	k-Nearest Neighbors
LightGBM	Light Gradient Boosting Machine
LS	Least Squares
LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Error
MGGP	Multi-Gene Genetic Programming
ML	Machine Learning

MLP	Multilayer Perceptron
MSE	Mean Squared Error
NARX	Nonlinear AutoRegressive with Exogenous Inputs
OLS	Ordinary Least Squares
R^2	Coefficient of Determination
RBFNN	Radial Basis Function Neural Networks
RF	Random Forest
RM	Regression Methods
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Networks
RVFL	Random Vector Functional Link
SOFM	Self-Organizing Feature Maps
SVM	Support Vector Machines
SVR	Support Vector Regression
XGB	XGBoost

System Configurations and Technologies:

BIPV/T	Building-Integrated Photovoltaic-Thermal
CCHP	Combined Cooling, Heating, and Power

COP Coefficient of Performance

GSHP Ground Source Heat Pump

HVAC Heating, Ventilation, and Air Conditioning

PCM Phase Change Materials

PV/T Photovoltaic-Thermal

SAHP Solar-Assisted Heat Pump

TEC Thermoelectric Cooler

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used *Claude Sonnet 4* in order to improve the language quality, fluency, and readability of the manuscript, as the authors are not native English speakers. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Highlights

- First systematic review of machine learning in photovoltaic thermal systems
- Identifies major research gap in hybrid solar energy system modeling approaches
- Machine learning techniques achieve excellent prediction accuracy in applications
- Provides systematic guidance for optimal machine learning method selection
- Nanofluid systems demonstrate superior performance over conventional cooling

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