From ANN Prediction to Closed-Loop PV Control: A Mini-Review of Thermal Management and Sun Tracking

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Abstract

Artificial neural networks (ANNs) are increasingly being used to improve photovoltaic (PV) performance under changing environmental conditions. However, good prediction accuracy does not always lead to effective real-time control. This mini-review examines the use of ANNs in PV thermal management and sun-tracking, with emphasis on how predictions are translated into operating decisions and physical control actions. Recent studies are compared based on their data sources, validation methods, control outputs, energy benefits, robustness, and level of practical implementation. The reviewed approaches are grouped into three stages: prediction, decision support, and closed-loop control. The analysis shows a clear gap between accurate ANN predictions and their reliable use in real operating systems. Many studies remain focused on prediction or optimization, while fewer demonstrate independent validation, real-time hardware operation, cross-site performance, or the energy consumed by cooling and tracking devices. Future work should focus on reliable models, low-cost implementation, net energy benefits, real-time validation, and combined thermal and tracking control. Overall, the key challenge is moving from accurate prediction to reliable and energy-efficient control of PV systems.

Keywords: Artificial Neural Networks (ANN); Photovoltaic Panel Efficiency; Thermal Management; Sun-Tracking Optimization; Smart Renewable Energy Systems; Machine Learning in Solar Energy

1. Introduction

Photovoltaic (PV) performance depends strongly on environmental and operating conditions, particularly module temperature and solar orientation [1–3]. High module temperature reduces electrical efficiency and has motivated cooling approaches including air and liquid cooling, phase-change materials (PCMs), nanofluids, and hybrid photovoltaic–thermal (PV/T) systems [18–24]. Recent studies have incorporated machine-learning methods to predict and optimize their thermal and electrical performance [14–17]. Similarly, solar tracking can increase incident radiation and electrical output by adjusting PV orientation throughout the day and across seasons [8–13]. However, tracking performance must also be considered alongside actuator energy, mechanical complexity, maintenance, and reliability. The availability of sensors, operating data, and low-cost computing has increased the use of artificial intelligence (AI) in PV modelling and control. Artificial neural networks (ANNs) are particularly useful for representing nonlinear relationships between environmental variables and PV-system responses. Earlier studies established ANN applications in renewable-energy and PV modelling, sizing, prediction, and control [1–3], while later reviews expanded their use to monitoring, diagnosis, optimization, and intelligent operation [4–7]. ANN-based methods have also been applied to solar-radiation and PV-power prediction [33–40], as well as thermal management and solar tracking [25–28]. Hybrid ANN approaches using genetic algorithms, particle swarm optimization, and fuzzy logic have further been investigated for PV control and MPPT [29–31]. However, **prediction accuracy alone does not demonstrate effective control**. An ANN may accurately predict temperature, power, irradiance, or tracking angle under known conditions but still fail when environmental conditions change or when its output must be converted into a physical actuator command. A practical PV controller must also account for training-data quality, independent-condition validation, response time, sensor uncertainty, actuator behaviour, auxiliary energy consumption, computational requirements, and robustness. These considerations are particularly important when models developed from laboratory experiments or simulations are transferred to outdoor systems [4–7]. The same issue applies to thermal management and solar tracking. An ANN that predicts an optimum tracking angle is fundamentally different from one that receives real-time measurements, generates a motor command, and operates under changing outdoor conditions [8–13,25–28]. Likewise, a cooling model that predicts temperature or efficiency is different from a controller that determines pump or fan operation while accounting for the energy consumed by the cooling system [14–24]. Thus, gross energy improvement or prediction accuracy alone may not represent the actual system-level benefit. Although previous reviews have examined AI in PV systems [4–7], solar tracking [8–13], thermal management [19–24], and broader PV power-enhancement strategies [13], the literature is commonly organized by technology, algorithm, or prediction performance. A recent systematic review has already covered major PV power-enhancement approaches, including MPPT, solar tracking, and thermal management [13]. Therefore, the novelty of this mini-review is not simply the combination of thermal management and solar tracking. Instead, it adopts a **prediction-to-control perspective**, examining how far ANN-based PV research has progressed from prediction to decision-making and physical actuation. This perspective highlights the **AI-to-actuation gap**: the difference between accurately predicting a PV-related variable and reliably converting that prediction into a timely and energy-efficient control action. Accordingly, this review focuses on ANN-based thermal management and sun-tracking control and evaluates studies according to their data sources, validation methods, control outputs, energy benefits, robustness, computational requirements, actuator integration, and evidence of real-time or hardware implementation.

The review addresses four questions:

1. How are ANNs used to support or directly control PV thermal management and solar tracking?
2. How far have ANN-based approaches progressed from offline prediction to decision-making and closed-loop control?
3. What factors limit the generalization, reliability, and deployment of ANN-based PV controllers?
4. What developments are needed for lightweight, adaptive, energy-aware, and deployment-ready control?

Overall, the review emphasizes **generalization, net energy benefit, real-time inference, hardware implementation, closed-loop validation, and integrated thermal–tracking control**, with the aim of shifting ANN-based PV research from prediction accuracy toward reliable and energy-efficient real-time control. The overall framework adopted in this review is illustrated in **Figure 1**, which links environmental sensing with ANN-based decision-making, physical actuation, and real-time feedback.

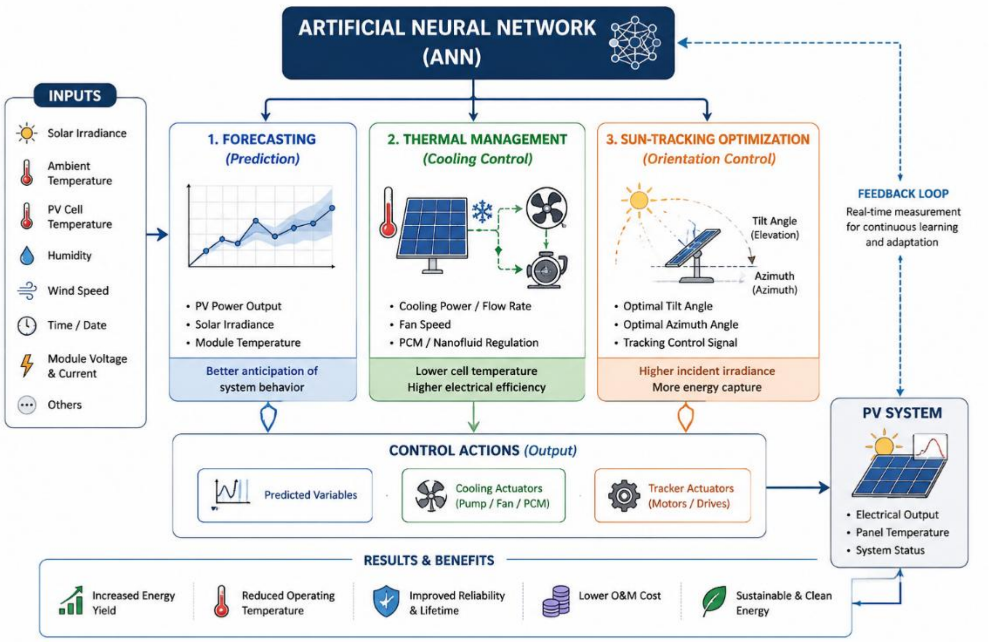

Figure 1. Conceptual framework of ANN-enabled photovoltaic system optimization, illustrating the integration of PV forecasting, thermal-management control, and sun-tracking optimization through environmental sensing, ANN-based decision-making, physical actuation, and real-time feedback.

2. Artificial Neural Networks as Enabling Models for Intelligent PV Control

Artificial neural networks (ANNs) are widely used in renewable-energy applications because they can capture nonlinear relationships between operating and environmental variables [1–6]. In PV systems, irradiance, temperature, wind, electrical conditions, and solar position interact continuously, making ANN-based modelling useful for prediction and control. However, for this review, the value of an ANN depends not only on prediction accuracy but also on how its output is used. ANN applications can range from prediction to decision support and, ultimately, closed-loop control.

2.1 ANN architecture and learning mechanisms

The multilayer perceptron (MLP) is a common ANN structure for nonlinear regression and classification. It maps inputs such as irradiance, temperature, wind speed, time, voltage, and current to outputs such as PV power, temperature, or control variables [1–6]. The general ANN relationship can be expressed as:

[Equation]

where the input variables represent measured or derived PV-system conditions, the output is the predicted variable, and the network parameters are learned during training. Temporal and deep-learning models can also capture time-dependent behaviour and have been applied to PV power and solar-radiation forecasting [33–40]. However, accurate forecasting does not by itself constitute real-time control.

2.2 From prediction to PV control

ANN applications in PV systems can be grouped into three levels:

- **Level I – Prediction:** estimation of variables such as irradiance, PV power, or module temperature [33–40].
- **Level II – Decision support:** prediction of operating conditions or control set-points, such as cooling conditions or tracking angles [14–17,25–28].
- **Level III – Closed-loop control:** real-time measurements are processed by the ANN to generate actuator commands, while the resulting PV response is fed back to the controller.

These levels represent increasing control maturity. Similar prediction metrics should therefore not be interpreted as equivalent evidence of practical control, since closed-loop operation also requires suitable response time, robustness, actuator compatibility, and stable operation under changing conditions [4–7,25–28].

2.3 ANN Applications in Thermal and Orientation Control

Two application pathways are central to this review.

Thermal management: ANNs can learn the relationships among environmental conditions, module temperature, cooling parameters, and electrical performance to support temperature prediction, cooling optimization, and, potentially, direct cooling control. Recent studies have applied machine-learning and AI approaches to nanofluid-cooled PV/T systems and other thermal-management configurations [14–17]. These data-driven approaches complement conventional thermal-management strategies based on nanofluids, phase-change materials (PCMs), and PV/T systems [18–24]. Recent work has further extended this direction through **physics-regularized neural prediction, physics-informed modelling of passive PV cooling, and field-based evaluation of passive cooling strategies**, illustrating the emerging connection between data-driven modelling, physical knowledge, and experimental validation [23,35,36]. **Sun tracking:** ANNs can estimate solar position or optimum module orientation using temporal, geographical, irradiance, and other environmental information. Their outputs can subsequently support tilt and azimuth control in single- and dual-axis tracking systems. Recent studies have demonstrated AI-based tracking in large-scale bifacial PV systems, deep-neural-network-based dual-axis tracking, and neural-network-assisted two-axis tracking [25–28]. Although these applications differ in their physical mechanisms, they share a common control principle: **using measured system and environmental information to generate an intelligent decision that produces a physical action capable of improving PV performance**. In thermal management, the action may involve regulating coolant flow or activating a cooling device; in sun tracking, it may involve adjusting the module orientation. This common prediction-to-action structure provides the basis for the control-oriented framework adopted in this review.

2.4 Strengths and challenges of ANN-based control

ANNs can handle multiple interacting variables and nonlinear system behaviour while incorporating environmental, electrical, and temporal information [1–6]. Their data-driven nature also allows models to be updated as new operating data become available. However, these advantages do not guarantee better performance than conventional controllers. Results depend on data quality, model complexity, validation, and operating conditions [4–7]. Hybrid ANN approaches using genetic algorithms, particle swarm optimization, or fuzzy logic may improve optimization but can also increase computational and implementation requirements [29–31].

Thus, the key question for PV control is not simply **how accurately an ANN predicts**, but **whether it can convert measurements into a timely, robust, and energy-efficient control action under real operating conditions**.

2.5 Control-oriented evaluation criteria

ANN-based PV studies should therefore be evaluated using both prediction and system-level measures:

- **Prediction:** (R^2), RMSE, MAE, and related metrics.
- **Control effectiveness:** temperature reduction, electrical-power improvement, or increased irradiance capture.
- **Response time:** ability to operate within the required control interval.
- **Robustness and generalization:** performance under changing weather, shading, sensor noise, and unseen conditions.
- **Actuation and auxiliary energy:** compatibility with cooling and tracking hardware and the energy required to operate it.
- **Closed-loop validation:** evidence of real-time feedback and physical testing.
- **Deployment readiness:** inference time, computational requirements, and suitability for embedded or edge hardware.

This framework separates **model accuracy from control maturity** and provides the basis for assessing the transition from offline ANN prediction to validated, closed-loop, energy-aware PV control The prediction-to-control architecture adopted in this review is illustrated in **Figure 2**, showing the progression from real-time sensing and ANN-based prediction to decision-making, physical actuation, and feedback.

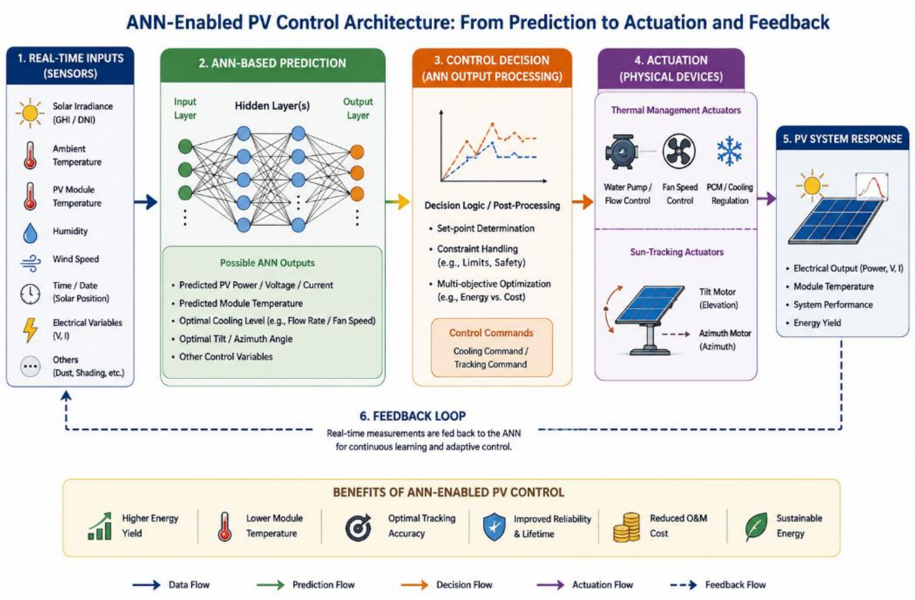

Figure 2. Prediction-to-control architecture of ANN-enabled photovoltaic systems, illustrating the progression from real-time sensing and ANN-based prediction through control decision-making and physical actuation to PV-system response and closed-loop feedback. The framework highlights thermal-management and sun-tracking control pathways and their potential benefits in energy yield, temperature regulation, tracking accuracy, reliability, and system-level efficiency.

3. ANN-Based Thermal Management of Photovoltaic Systems

3.1 Thermal losses and the need for intelligent management

PV module temperature strongly affects electrical performance, particularly under high irradiance and hot ambient conditions. This has led to a range of active and passive cooling methods, including air and water cooling, nanofluids, phase-change materials (PCMs), and photovoltaic–thermal (PV/T) systems [18–24]. However, effective thermal management is not simply a matter of reducing temperature. A practical system must balance temperature reduction, electrical output, thermal recovery, auxiliary energy consumption, complexity, and cost. Recent studies have therefore explored machine-learning methods for predicting and optimizing PV thermal and electrical performance [15,19–23].

3.2 ANN-based thermal modelling and control

The relationships among irradiance, ambient temperature, module temperature, wind, coolant conditions, and electrical output are highly nonlinear, making ANNs suitable for PV thermal modelling. Depending on the application, an ANN may predict module temperature or efficiency, or determine a control variable such as coolant flow rate or fan speed. For this review, an important distinction is made between **thermal prediction and thermal control**. A prediction model estimates system behaviour, whereas a control-oriented ANN uses real-time measurements to determine a cooling action and responds to the resulting PV behaviour. Shaban et al. investigated optimized deep-learning-based prediction and optimization of PV/T performance, while Diwania et al. examined machine-learning approaches for thermo-electrical performance in nanofluid-cooled PV/T systems [14]. These studies demonstrate the potential of AI for PV/T modelling and optimization, but strong prediction performance alone does not establish closed-loop cooling control.

3.3 Cooling technologies and the role of ANN

ANN-based methods have been applied to several cooling configurations:

- **Liquid cooling:** ANN models can relate flow conditions and environmental variables to thermal and electrical performance [14,15,18].
- **Nanofluid cooling:** Machine learning can link nanoparticle concentration, flow conditions, temperature, and PV/T performance [14,16].
- **PCM cooling:** ANN models can help predict thermal behaviour and identify suitable operating or material conditions [21–23].
- **Hybrid PV/T systems:** AI methods have been used to predict and optimize combined thermal and electrical performance [15–17].

The main opportunity is therefore not simply to maximize cooling, but to determine **when cooling is needed and how much cooling is worthwhile** while considering its overall energy cost.

3.4 Critical comparison of ANN-based thermal studies

Table 1 compares representative studies according to their AI role and control maturity. The comparison shows that most reported work remains focused on prediction, performance assessment, or optimization rather than direct closed-loop control.

Table 1. Representative ANN and AI approaches for PV thermal management

Study	Thermal configuration	AI/ANN approach	Main role	Key finding	Control maturity
Al-Waeli et al. [	Nanofluid/nano-PCM PV/T	Mathematical/experimental modelling	Thermal and electrical evaluation	Electrical efficiency ≈13.7%; thermal efficiency ≈72%	Baseline; not ANN control
Diwania et al.	Nanofluid PV/T	ANN, ANFIS, SVM	Thermo-electrical modelling	ML showed potential for PV/T performance prediction and improvement	Prediction/optimization

Shaban et al.	Water/air PV/T	Optimized DNN + metaheuristic optimization	Efficiency prediction/optimization	(R^2=0.9972), MAE = 0.0075, MSE = 0.00251	Prediction/optimization
Alhamayani	Nanofluid PV/T	Deep learning	Performance prediction	Demonstrated prediction of thermal and electrical behaviour	Prediction
Integrated ML PV/T study	Photo-thermal system	Machine learning	Thermal/electrical prediction	Demonstrated ML-based prediction of system outputs	Prediction
Selimefendigil et al.	PV–TEG with enhanced cooling channels	ML/CFD-assisted modelling	Design/performance assessment	Reduced computational burden through data-driven modelling	Design/model acceleration

Note: "Control maturity" indicates the role of AI in the reported study and is not a ranking of scientific quality.

The comparison highlights a clear pattern: **prediction and optimization are much more common than closed-loop ANN cooling**. For example, Al-Waeli et al. provided experimental evidence for nanofluid/nano-PCM PV/T operation, reporting approximately 13.7% electrical and 72% thermal efficiency, but the study was not an ANN control study. Similarly, Shaban et al. reported strong prediction performance, but their work focused on prediction and optimization rather than an ANN directly controlling a physical cooling system. Thus, the literature demonstrates that AI can represent complex PV/T behaviour, but considerably stronger evidence is needed to show that these models can make reliable cooling decisions under changing outdoor conditions.

3.5 From thermal prediction to intelligent cooling control

A practical ANN-based cooling system would use measurements such as irradiance, ambient and module temperature, wind speed, electrical output, coolant temperature, and flow rate to determine a cooling set-point or actuator command. The resulting PV response would then be fed back to the controller, allowing the cooling action to adapt to changing conditions. Performance should therefore be evaluated using **net energy benefit**, considering both the additional electrical energy obtained through cooling and the energy consumed by pumps, fans, valves, and control hardware. A system that produces greater temperature reduction may not provide the greatest overall benefit if its auxiliary energy demand is high.

3.6 Research gaps in ANN-based thermal management

The literature points to five main gaps:

1. **Limited closed-loop validation:** Most studies focus on prediction or optimization rather than complete sensor–ANN–actuator–feedback operation.
2. **Limited independent validation:** Models developed under restricted conditions may not generalize across climates, PV technologies, or weather conditions.
3. **Auxiliary energy is often overlooked:** Cooling benefits are commonly reported without fully accounting for pump and fan energy.
4. **Deployment complexity:** Deep and hybrid models can increase memory, computational requirements, and inference time.
5. **Limited system-level optimization:** Future controllers should consider electrical output, thermal recovery, auxiliary energy, cost, and component life together.

3.7 Key conclusions from the thermal-management literature

ANNs have expanded PV thermal management from conventional empirical modelling toward data-driven prediction and optimization [14–17]. However, most studies remain below the level of real-time closed-loop cooling. The main research need is therefore not another ANN with slightly better prediction accuracy, but a **lightweight, generalizable controller that can determine cooling actions in real time while accounting for auxiliary energy and overall system benefit**. Such development would move ANN-based thermal management from prediction toward practical PV control. The ANN-based thermal-management pathway is illustrated in

Figure 3, showing how real-time measurements are converted into cooling decisions and fed back through the PV system.

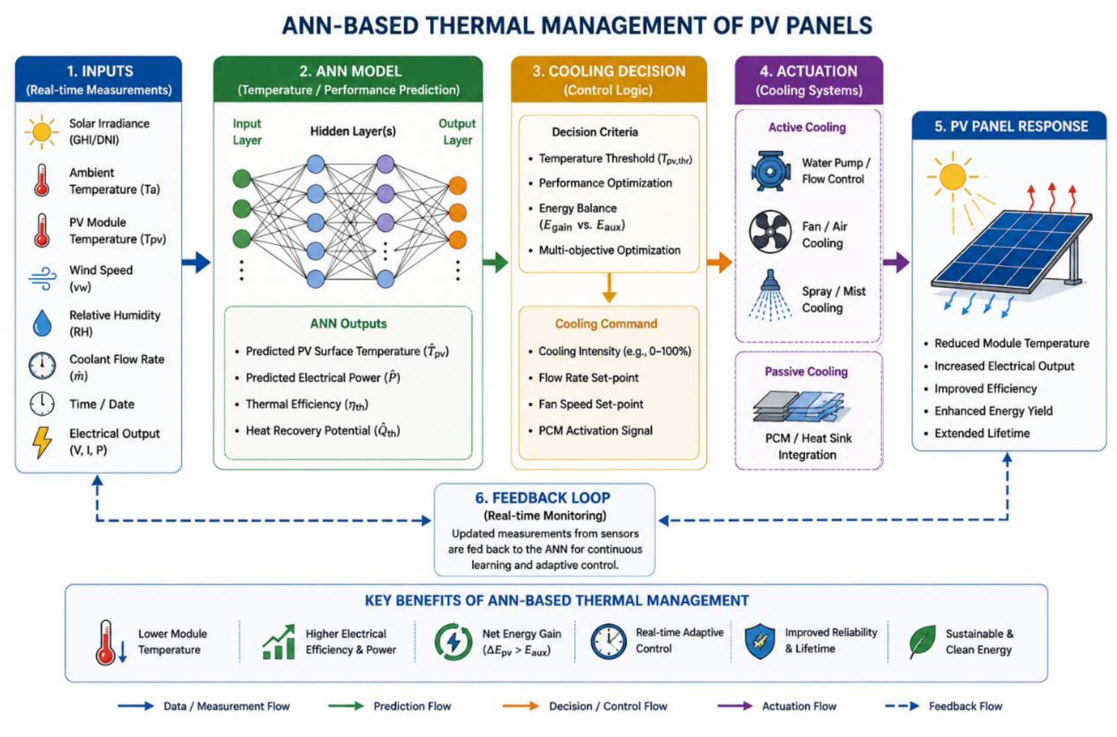

Figure 3. ANN-based thermal-management framework for photovoltaic panels, illustrating the progression from real-time environmental and PV measurements through ANN-based thermal prediction and cooling decisions to active/passive cooling actuation, PV response, and closed-loop feedback for adaptive control.

4. ANN-Based Sun-Tracking Optimization

4.1 Fixed-tilt versus dynamic tracking

The orientation of a PV module directly affects the solar radiation it receives and, consequently, its electrical output. Fixed-tilt systems cannot follow the changing solar position, whereas single- and dual-axis trackers adjust module orientation throughout the day and year [8–13]. However, greater tracking accuracy does not necessarily mean greater overall benefit. Tracking performance should also consider energy gain, actuator consumption, reliability, cost, and operating conditions [9–13]. For ANN-based systems, the objective should therefore be **maximum net energy gain rather than minimum angular error**.

4.2 ANN-based solar-position prediction and tracking control

Conventional trackers commonly use astronomical calculations, light sensors, or predefined schedules. ANN-based methods instead learn the relationship between variables such as time, location, irradiance, and temperature and the required tracker position. An ANN tracker can operate at three levels: **solar-position prediction, decision support, and closed-loop control**. At the first level, the ANN predicts the solar position or optimum angle. At the second, this prediction is converted into a tracker set-point. At the third, real-time measurements are used to generate actuator commands and provide feedback. Thus, accurate solar-position prediction alone does not demonstrate effective tracker control, since response time, stability, actuator energy, and changing weather conditions must also be considered.

4.3 Recent ANN-based tracking approaches

Recent studies show a gradual move from prediction toward practical tracking. Masoumi et al. [27] used neural-network modelling for two-axis solar-position prediction, demonstrating the feasibility of data-driven tracking. Santos de Araújo et al. [25] went further by applying AI-based tracking to a large-scale bifacial PV plant, using weather, diffuse irradiance, plant geometry, and bifacial characteristics. The system achieved an average gain of about 1.2% over a commercial tracker, increasing to 7.83% under cloudy conditions. Tahtah et al. [28] combined ANN-based solar-position prediction with sliding-mode control, showing how an ANN can serve as a prediction layer within a feedback controller. Ayu et al. [26] used a deep neural network for performance estimation in a dual-axis tracking system.

Together, these studies show that ANN-based tracking is progressing from angle prediction toward prediction-assisted control and system optimization.

4.4 Comparative assessment of representative studies

Table 2. Representative ANN-based approaches for photovoltaic sun-tracking optimization

Study	Configuration	ANN role	Main inputs	Output	Validation	Key finding	Control maturity
Abu Hussein and Musa	Single-axis	Performance comparison	Time, location, PV conditions	Tracker orientation	Experimental	Tracking improved performance over fixed orientation	Baseline
Masoumi et al.]	Two-axis	Solar-position prediction	Day, time	Zenith/azimuth	Experimental tracker + ANN	ANN represented solar movement effectively	Prediction + optimization
Santos de Araújo et al.]	Large-scale bifacial	AI tracking optimization	Weather, diffuse irradiance, geometry	Tracking/backtracking command	Real PV plant	≈1.2% average gain; up to 7.83% under cloudy conditions	Practical control
Ayu et al. [26]	Dual-axis	Deep neural network	Solar/tracking variables	PV power estimation	Tracker evaluation	Demonstrated DNN-based tracker performance estimation	Prediction/support
Tahtah et al.	Dual-axis	ANN + sliding-mode control	Time/date	Solar altitude/azimuth	Control assessment	Hybrid ANN–SMC approach for tracking	Prediction + closed-loop architecture

Note: "Control maturity" describes the role of the ANN in the reported study and is not a ranking of scientific quality.

The studies shown in table 2 differ considerably in control maturity. Some focus mainly on solar-position or power prediction, whereas others integrate ANN outputs into a control architecture [26–28]. The Santos de Araújo et al. study is particularly relevant because it was tested at a real large-scale PV plant [25]. Reported energy gains should nevertheless not be compared directly because climate, tracker type, baseline controller, PV technology, diffuse radiation, test duration, and actuator energy can all affect performance.

4.5 From angle prediction to closed-loop tracking

A deployment-ready ANN tracker should progress through four stages:

prediction → decision → actuation → feedback

The ANN first estimates the solar position or optimum orientation. This estimate is converted into a tracker command, the motor adjusts the PV module, and measurements of PV output, irradiance, or angular error are returned to the controller. This separates **ANN-assisted tracking**, where the ANN mainly provides a reference angle, from **ANN-controlled tracking**, where it forms part of the feedback loop. Tracking should also be evaluated using **net energy gain**. Motor, drive, sensor, and control-system energy must be considered alongside the additional PV energy obtained. Frequent small corrections may reduce angular error while consuming more actuator energy, reducing the overall benefit.

4.6 Critical limitations and research gaps

The main gaps are:

1. **Limited closed-loop validation:** Many studies remain focused on angle or power prediction rather than long-term outdoor control.
2. **Limited cross-site validation:** Models trained at one location may not perform equally well under different climates, cloud conditions, shading, or diffuse radiation.
3. **Context-dependent energy gains:** AI benefits depend strongly on the baseline tracker and weather conditions. The larger gains reported under cloudy conditions by Santos de Araújo et al. [25] suggest that adaptive tracking may be most useful under non-ideal conditions.
4. **Actuator energy is often overlooked:** Gross PV-energy gain should be separated from the net gain after tracker energy consumption.
5. **Robustness:** Sensor errors, cloud transients, mechanical backlash, communication delays, and operating constraints can affect ANN performance.
6. **Embedded implementation:** Larger models may increase inference time and hardware requirements without providing a meaningful control benefit.

4.7 Key insights from ANN-based sun-tracking research

ANNs can support solar tracking through solar-position prediction, optimum-angle estimation, PV-power prediction, and hybrid feedback control [25–28]. However, current evidence does not show that ANN trackers universally outperform conventional astronomical or sensor-based systems. Their main advantage may instead be the ability to incorporate information such as weather, diffuse irradiance, bifacial behaviour, and site-specific conditions [25]. Future studies should therefore move beyond minimizing angular error and evaluate **net energy gain, response time, robustness, actuator consumption, cross-site generalization, and real-time hardware performance**. The ANN-based sun-tracking pathway is illustrated in **Figure 4**, showing the progression from environmental measurements and solar-position prediction to tracking decisions, actuator control, and real-time feedback.

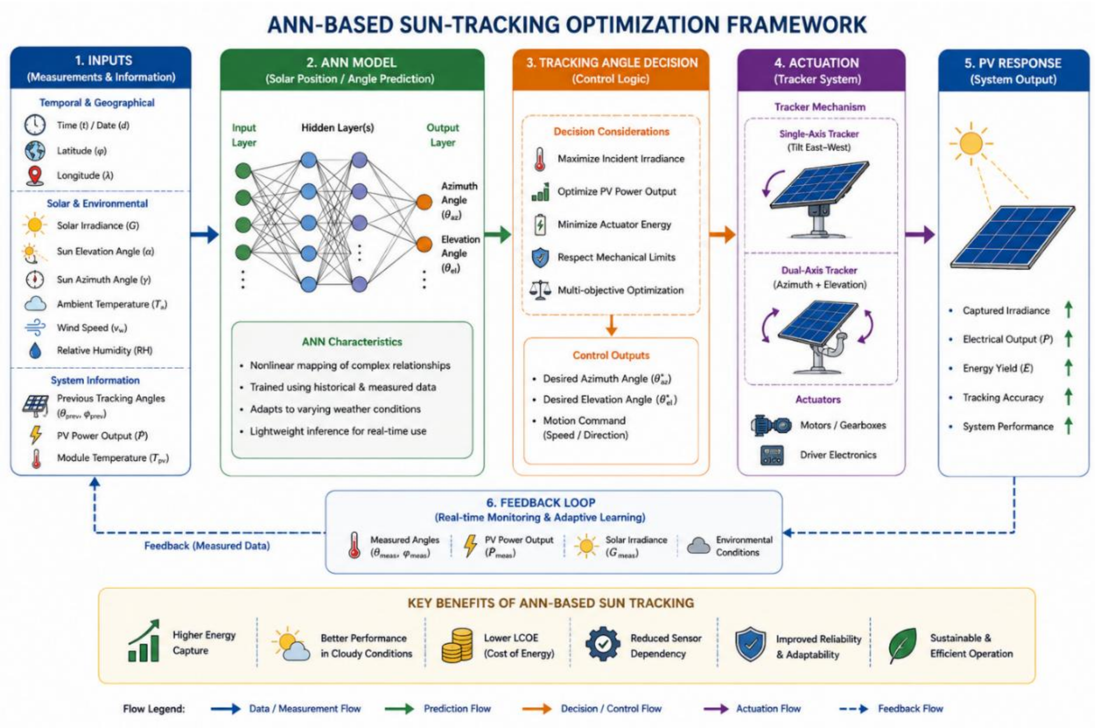

Figure 4. ANN-based sun-tracking optimization framework, illustrating the progression from temporal, geographical, solar, and environmental measurements through ANN-based solar-position prediction and tracking-

angle decision-making to single- or dual-axis actuator control, PV-system response, and real-time feedback for adaptive tracking.

5. Hybrid AI Models for PV Optimization

Hybrid AI methods combine ANNs with optimization or rule-based techniques to improve PV control. They have been used mainly for maximum power point tracking (MPPT), where changing irradiance and partial shading create highly nonlinear operating conditions [29–31]. Their main benefit is improved adaptability, but the added algorithms can also increase computational and implementation requirements.

5.1 ANN–Genetic Algorithm approaches

Genetic algorithms (GAs) can optimize ANN parameters or controller settings. Zhang et al. [29] developed a hybrid genetic algorithm–simulated annealing–BP neural network–fuzzy logic approach for MPPT under varying irradiance and temperature. The method improved convergence and reduced oscillations around the maximum power point. However, the additional optimization stage increases computational cost and may limit embedded implementation.

5.2 ANN–Particle Swarm Optimization approaches

Particle Swarm Optimization (PSO) can similarly optimize ANN parameters and control strategies. Dennai and Tedjini [30] reported a PSO–ANN MPPT approach with improved convergence and stable power extraction under changing conditions. Although PSO can efficiently search nonlinear parameter spaces, repeated optimization may be unsuitable for controllers with strict response-time requirements.

5.3 ANN–Fuzzy and ANFIS approaches

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) combine neural learning with fuzzy rules, allowing nonlinear relationships to be learned while retaining a rule-based control structure. ANFIS-based MPPT methods have been investigated under partial shading and rapidly changing irradiance [29–31]. Their main advantage is the combination of learning and rule-based control, although large rule sets and numerous membership functions can increase model complexity.

5.4 Comparative assessment and research implications

Table 3 Representative hybrid AI approaches for PV optimization

Study	Hybrid approach	Application	Main finding
Zhang et al.	GA–SA–BPNN–FLC	MPPT	Improved convergence and reduced oscillations under varying conditions
Dennai & Tedjini et al	PSO–ANN	MPPT	Improved convergence and stable power extraction
Worku et al.	PSO–ANFIS	MPPT under partial shading	Improved tracking performance and dynamic response

Overall, hybrid methods as shown in table 3 can improve **optimization, adaptability, and rule-based control**, but greater complexity does not necessarily mean better control. Additional optimization layers may increase training time, memory use, inference time, and sensitivity to parameter selection. Therefore, hybrid models should be assessed not only by MPPT efficiency or convergence speed but also by **computational cost, response time, auxiliary energy, robustness, and hardware feasibility**.

6. Evaluation Metrics and Dataset Considerations

The reliability of an ANN-based PV model depends on both **how it is evaluated and how well the dataset represents real operating conditions**. High accuracy on a limited dataset does not necessarily mean that the model will perform well under unseen weather, thermal, or operating conditions. Evaluation should therefore cover both prediction accuracy and practical control performance.

6.1 Evaluation metrics

Common metrics include RMSE, MAE, , and MAPE. RMSE emphasizes larger errors, MAE gives the average magnitude of error, indicates how well the model explains the observed variation, and MAPE expresses error relative to the measured value.

The appropriate metrics depend on the application. PV prediction can be assessed using RMSE and MAE, while tracking also requires angular error, response time, and energy gain. Thermal control should additionally consider temperature reduction, electrical-power improvement, and cooling energy consumption.

For this review, the main evaluation criteria are:

- **Prediction:** RMSE, MAE, , and MAPE.
- **Thermal control:** temperature reduction, electrical-power improvement, and net energy gain.
- **Sun tracking:** angular error, response time, tracking accuracy, and additional energy captured.
- **System level:** auxiliary energy, computational latency, robustness, and reliability.

Thus, a high alone should not be taken as evidence of a better PV controller.

6.2 Dataset sources and quality

ANN-based PV studies generally use **experimental, simulated, or public datasets**. Experimental data provide realistic measurements but are often limited in size and location. Simulated data can provide larger and more controlled datasets, although their accuracy depends on the assumptions of the underlying models. Public datasets improve reproducibility and comparison, but differences in sensors, sampling rates, locations, and PV technologies must be considered when combining them. For PV control, **dataset diversity is often more important than dataset size**. A smaller dataset covering different seasons, irradiance levels, temperatures, cloud conditions, and operating states may provide better generalization than a much larger dataset collected under nearly identical conditions.

6.3 Training and validation challenges

Several issues can reduce the reliability of ANN-based PV models.

Overfitting is a major concern, particularly with small or highly correlated datasets. Cross-validation, regularization, dropout, early stopping, and independent test data can help reduce this problem.

Data leakage can occur when time-series measurements are randomly divided, allowing highly similar observations from the same operating period to appear in both training and test sets. Chronological or condition-based validation is therefore more appropriate for many PV applications.

Distribution shift is another important issue. Changes in climate, season, shading, PV technology, cooling conditions, or tracker hardware can affect model performance. Cross-day, cross-season, cross-site, and cross-system validation therefore provide stronger evidence of generalization than a single random split.

Finally, **computational requirements** become important when ANN models are intended for real-time control. Model size, inference time, memory requirements, and processor demand should be reported alongside conventional accuracy metrics, particularly for embedded and edge deployment.

Overall, reliable ANN evaluation should progress from **prediction accuracy → independent-condition validation → real-time and system-level assessment**, rather than relying on a single train–test result.

7. Research Gaps and Future Directions

ANNs have shown strong potential for PV modelling and optimization, but important challenges remain before they can be used reliably in real operating systems. The main issue is no longer whether ANNs can model nonlinear PV behaviour, but whether their predictions can be converted into robust, efficient, and reliable control actions [4–7].

7.1 From offline models to adaptive control

Most ANN models are trained using data collected under limited operating conditions. Their performance may decrease when irradiance, temperature, shading, cooling conditions, or tracker behaviour changes. Future studies should therefore consider online learning, transfer learning, and adaptive control, with validation under unseen seasons, weather conditions, and operating regimes.

7.2 Lightweight and embedded deployment

Real PV controllers require fast response, limited memory, and low computational demand. Complex ANN and hybrid models can make deployment difficult. Model pruning, quantization, knowledge distillation, and compact architectures could support implementation on microcontrollers and edge devices. Studies should report inference time, memory use, processor demand, and controller energy consumption alongside prediction accuracy [4–7].

7.3 Integrated thermal–tracking control

Thermal management and sun tracking are usually studied separately, although both directly affect PV energy output. A more useful control strategy could jointly maximize net energy:

$$E_{net} = E_{PV} - E_{cooling} - E_{tracking}$$

while maintaining acceptable module temperature, tracker movement, and system operating limits. This would shift the focus from optimizing individual subsystems to improving overall PV-system performance.

7.4 Generalizable and standardized datasets

Site-specific datasets remain a major limitation for ANN generalization. Future datasets should combine irradiance, ambient and module temperature, wind, electrical output, cooling conditions, tracker position, and actuator energy across different seasons and locations. Public datasets with consistent sampling, metadata, and predefined training and testing protocols would improve reproducibility and comparison between models [4–7].

7.5 Explainable and trustworthy PV control

High prediction accuracy does not necessarily mean that an ANN makes reliable control decisions. Explainable methods such as SHAP and LIME can help identify the variables influencing model outputs. Future work should go further by explaining why a controller changes cooling intensity or tracker position and by combining explainability with uncertainty estimates and physical constraints.

7.6 Digital twins and adaptive PV systems

Combining ANN controllers with digital twins and edge–cloud systems could support continuous monitoring, model updating, predictive maintenance, and system optimization. An edge ANN could handle fast control locally, while a digital twin and cloud platform could support longer-term analysis and model improvement. Practical implementation will nevertheless require attention to communication delays, data quality, cybersecurity, and reliable model updates.

7.7 Priority research directions

Overall, the literature points toward a clear progression:

Offline prediction → Adaptive decision-making → Closed-loop control → Edge deployment
→ Autonomous PV operation

The key research priority is to move along this pathway while maintaining generalization, low computational cost, net-energy awareness, robustness, and reliable physical operation. This would help bridge the gap between promising ANN models and practical intelligent PV systems.

8. Conclusion

Artificial neural networks (ANNs) offer useful opportunities for improving photovoltaic (PV) performance under changing operating conditions. This mini-review examined their use in thermal management and sun tracking, focusing on the transition from prediction to practical control. The literature shows that ANNs can effectively model nonlinear relationships involving irradiance, temperature, weather, and PV operating conditions. However, prediction accuracy does not necessarily indicate control effectiveness. Most studies remain focused on prediction or optimization, while fewer demonstrate complete sensor–ANN–actuator–feedback operation under realistic outdoor conditions. The review also highlights the importance of evaluating net energy benefit. Thermal-management studies should account for the energy consumed by pumps and fans, while tracking studies should consider actuator energy, response time, and actual energy gain rather than angular accuracy alone. Limited and site-specific datasets, weak independent validation, computational demands, and insufficient hardware testing continue to restrict practical deployment. Future research should focus on lightweight and generalizable ANN models, independent-condition validation, closed-loop hardware testing, integrated thermal–tracking control, uncertainty-aware decision-making, and edge deployment. Digital twins and edge–cloud systems may further support adaptive operation and long-term monitoring. Overall, the field needs to move beyond increasingly accurate offline models toward generalizable, closed-loop, energy-aware, and experimentally validated controllers. Closing the AI-to-actuation gap from sensing and prediction to decision, actuation, and feedback will be essential for developing reliable and practical intelligent PV systems**.**

Conflict of Interest

The author declares that there is no conflict of interest.

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