Review of artificial neural network applications for the optimization of photovoltaic-thermal systems integrated with phase change materials

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Abstract. The increasing world energy demand as well as environmental issues has made significant contributions to the necessity for the development of various renewable energy technologies, particularly solar energy systems. Within these areas of research hybrid photovoltaic-thermal (PVT) collectors stand out as possible sources for the simultaneous production of electricity and heat. This paper is a review of artificial intelligence applications in PVT systems employing phase change materials (PCM). It attempts to analyze, in a systematic manner, the ways in which artificial neural networks can be used to model, predict and optimize PVT-PCM systems. In doing this literature from 2015 through to 2024 is considered, in detail, to evaluate the ANNs used and their architectural efficiencies in terms of administering the complexities of the PVT-PCM systems. It is shown in this paper that multilayer perceptrons can give values of high accuracy for stage limits when the models reach a stage steady situation, and that recurrent networks, such as Long Short-Term Memory (LSTM) models give values which can explain adequately the dynamic behaviour characteristics of the thermal responses produced in this machine. This paper also describes the key variables which contribute to the overall performance of the systems and also describes the next stage in the direction of future research requirements in order that the viability and implementation of PVT-PCM systems can be achieved.

1 Introduction

The rapid depletion of fossil fuels and their harmful environmental impacts have made renewable energy sources, particularly solar energy, a vital focus for future sustainability [1,2]. Solar energy is abundant, clean, and eco-friendly, offering a promising solution to global energy challenges [3–6]. Technologies like solar thermal collectors, PV, and PVT systems are key to harnessing this resource [7].While PV panels convert only 15–20% of sunlight into electricity [8], PVT systems recover wasted heat, achieving combined efficiencies of 60–80% [9] . This dual output makes them significantly more efficient than standalone systems. However, their performance depends on cooling methods (e.g., water, nanofluids, or phase-change materials) and heat exchanger designs, which this review evaluates in detail [10,11].

The PV systems are fundamentally constrained by two critical limitations: significant thermal efficiency losses (0.3–0.5% per °C for crystalline silicon) and high spatial demands (5–7 m^2/kWp) [9]. These challenges are exacerbated in high-insolation environments, where module temperatures exceeding 60°C can precipitate annual energy losses of 10–25% [9,12]. The PVT systems present a transformative solution, synergistically generating electricity and recovering waste heat to elevate overall energy density and mitigate thermal degradation [13].

The efficacy of PVT systems is contingent upon advanced thermal regulation. Active cooling through integrated thermal collectors not only suppresses PV operating temperatures boosting electrical efficiency by 5-12% over conventional PV but also achieves concurrent thermal efficiencies of 40-70% [3,14]. Recent innovations focus on enhancing this heat transfer through nanofluid coolants (e.g., Al_2O_3, CuO) and PCMs, pushing combined peak efficiencies to 60–80% in optimized configurations [7,8].

PCMs, in particular, offer a paradigm for passive thermal management and storage. By absorbing latent heat during peak irradiation, PCMs stabilize PV cell temperature, improving electrical efficiency by 6-12% relative to standard PVT systems [11,15] . Subsequent solidification releases stored thermal energy for dispatchable use, smoothing output fluctuations and enhancing reliability. Advanced composite designs incorporating porous metal fins or nanoparticle-enhanced PCMs demonstrate further improvements in heat transfer rates and thermal regulation efficacy by up to 16% [16].

This confluence of higher energy yield per unit area and stable, dual-output generation solidifies the viability of advanced PVT systems, especially for building-integrated applications and industrial processes with concurrent energy demands. This review systematically evaluates these technological advancements to identify optimal PVT configurations across diverse operational contexts.

Traditional modeling methods often cannot accurately represent these complex interactions. They require many simplifications and need significant computational power [17]. This has led researchers to explore artificial intelligence (AI) approaches, particularly ANNs, for better system modeling [18] .ANNs can learn directly from system data without needing complex physical equations. They identify patterns between different input parameters and system performance, making them ideal for PVT-PCM system analysis [19] . Research shows that ANN models achieve excellent accuracy, with correlation coefficients above 0.99 for electrical efficiency [18] and errors below 5% for thermal predictions [20].

These models can handle changing weather conditions [21] and long-term performance changes [22] , helping to improve system management. This review paper examines how different ANN architectures can enhance PVT-PCM system modeling and contribute to better renewable energy systems. PVT systems with PCMs are complex because their heat and power output changes dynamically. This makes it difficult to create accurate performance models. The ANNs are powerful tools for this task in solar energy research [23]. However, most current studies use only basic types of ANNs, called Multi-Layer Perceptrons (MLPs) [23–25]. These studies often do not fully address the special ways that PCMs store and release heat, which affects system performance [26–28]. There is also a lack of research on newer, more powerful ANN types, like LSTM, GRU, and CNN models, for this specific application [27].

This review paper will address the situation of scarcity of research. We systematically investigate how advanced ANNs can be employed in predicting the performance of PVT-PCM systems. The central aims of this study are:

- To investigate and review various designs of ANN, with the explanation of how the more recent models are better than the elementary MLPs in the modeling of the unique thermal properties of PCMs.
- To evaluate and compare the accuracy of the single models and their combination (hybrid) models in prediction of output energy, including the factors occurring several hours later.
- To indicate and discuss the most important factors that affect the accuracy of prediction, such as weather conditions (sun, air temperature, wind), materials properties of the PCM.
- To summarize the present state of research and present clearly the existing problems and the systems of research in the future which appear to be the most encouraging.

2 Methodology: Systematic Literature Review

This review employs a systematic literature review (SLR) protocol to ensure a rigorous and unbiased analysis of ANNs in PVT–PCM systems. The scope encompasses publications from 2015 to mid-2024 to capture evolving research trends. Literature was sourced from five major databases—Scopus, Web of Science, ScienceDirect, IEEE Xplore, and Google Scholar—using a Boolean query: ("photovoltaic thermal" OR PVT) AND ("phase change material" OR PCM) AND ("artificial neural network" OR ANN OR "machine learning"). The initial search yielded 387 records. A multi-stage screening process was applied: removal of duplicates and non-peer-reviewed sources; filtration by title and abstract relevance; and final full-text evaluation against strict inclusion criteria. Studies were required to focus on PVT–PCM systems, employ ANNs as a core methodology, and be peer-reviewed and in English. This process identified 89 high-quality publications for in-depth analysis, ensuring a reliable and comprehensive evidence base for this review.

3 Photovoltaic-Thermal Collectors

PVT collectors represent a hybrid technology designed to maximize solar energy conversion by concurrently generating electricity and useful thermal energy from a single interface [27,29–31]. The concept, initially proposed to mitigate the characteristic decline in PV efficiency at elevated operating temperatures [28], employs a coolant circuit integrated into a thermal absorber. This configuration actively regulates PV cell temperature to enhance electrical output while simultaneously capturing thermal energy for applications such as domestic water and space heating [32–34]. Consequently, this co-generation strategy enables PVT systems to achieve superior overall efficiencies, often exceeding 70%, demonstrating a more effective utilization of the solar spectrum compared to standalone systems [27].

4 Photovoltaic-Thermal Collectors with Phase Change Materials (PCM)

PCMs are critical in the thermal management of PVT systems, thereby greatly increasing energy efficiency and production [35,36]. Their application in solar technologies, first advanced by Telkes, capitalises on their ability to store and release large amounts of latent heat associated with isothermal phase changes with particular reference to the solid-liquid changes which occur [37,38]. This ability provides an extremely efficient means of temperature control in PV panels, maintaining a stable operating temperature and reducing efficiencies lost through overheating [35,39,40] . A variety of phase changes are possible (Fig.3), but the solid-liquid transition is optimal for thermal storage because of the high energy density and reasonable bulk volume stability that it affords over the liquid-gas transition. The solid-solid phase change is not suitable due to the very low latent heat available [41,42]. A PCM's efficacy is determined by its latent heat of fusion relating to the storage, and its thermal conductivity which controls its more rapid charging/discharging rate [43]. With a thermal storage capacity which is far in excess of that of water or air, the addition of a PCM layer behind a PV panel will therefore greatly limit overheating and lead to a significant improvement in thermal efficiency in the system [44].

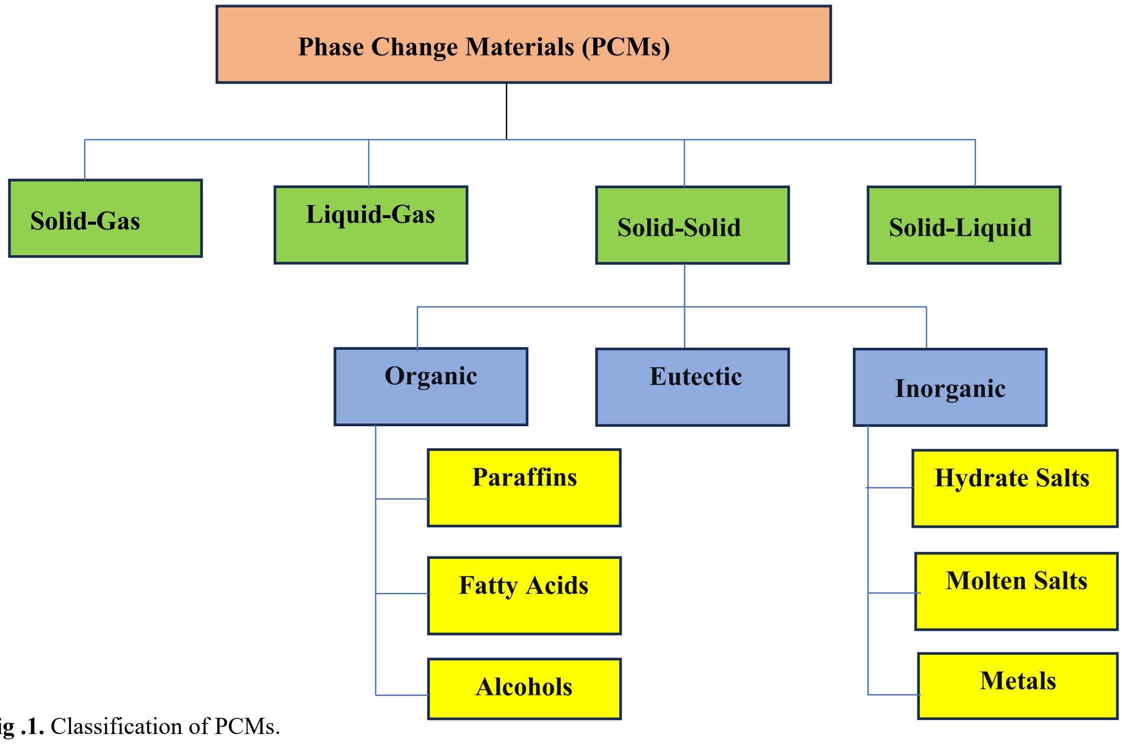

Fig .1. Classification of PCMs.

4.1 Classification (Organic, Inorganic, Eutectic)

PCMs can be classified in three major categories, based on their chemistry. Each category has its own advantages and disadvantages for thermal energy storage [44]. Organic PCMs, including paraffins and fatty acids, allow for congruent phase change, chemical stability, and non-corrosive characteristics. Their major disadvantages are low thermal conductivity and flammability [45]. Inorganic PCMs, such as salt hydrates, give good thermal conductivity and volumetric latent heat storage. They, however, usually exhibit problems of sub-cooling and phase segregation with cyclic operation [45]. Eutectic PCMs are mixtures of two or more substances which melt congruently at a specific minimum melting point. These mixtures allow specific thermophysical properties to be obtained a different combinations of organic and/or inorganic [46].

Consideration in the selection of PCM type must be made with respect to operable temperature range, thermal stability, conductivity requirements and the general application specific safety requirements. A full breakdown of the classification structure is given in Fig.1.

4.2 Synergistic Integration of PCM in PVT Systems

The introduction of PCMs within PVT systems is subject to considerable technical issues which result in diminished system performance and reliability. Some of the primary limitations are the poor thermal conductivity of standard PCMs which necessitates extensive enhancement measures for acceptable heat transfer rates [47,48]. The difficulty in the stabilization of phase change is compounded by the transient nature of the phase change which introduces substantial difficulty in thermal modelling and subsequent optimization of systems [49]. Also, systems feature long term operational problems which are of practical importance in their introduction, mainly problems of material stability under an expensive thermal cycling and also problems of containment for long periods of use [50,51] .The fundamental limitations in the characterization of PCMs and their consequent introduction into in

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PVT devices re-emphasizes the importance of new computer-based approaches. ANNs and their variants including MLPs, RNNs and Long Short-Term Memory networks give much scope for accurate prediction of performances of systems and effective system optimization as will be discussed in detail in subsequent sections.

5 Artificial neural networks

5.1 Short history: from perceptron to modern deep learning

The evolving designs of ANNs reflect an ongoing attempt to overcome their basic computational and theoretical limitations. After McCulloch and Pitts' neuron model was developed [52], the first wave of promise was followed by a clearer understanding of the linear restrictions of early models [53]. With the introduction of recurrent architectures, as represented by the Hopfield network, the introduction of energy-based dynamics for memory problems marked a landmark shift [54]. The possibilities were expanded during the 1980s when stochastic networks, such as the Boltzmann Machine, were examined [55]. However, the greatest advance was the introduction of backpropagation as a deployment procedure to enable the effective training of multilayer perceptrons [55]. These changes allowed one to start structural innovation, which is characteristic of modern deep learning. These include LSTM networks which are used to minimize the vanishing gradient problem in memorandum sequences [56], and Convolutional Neural Networks (CNNs), which are used for hierarchical extraction of spatio-theoretic features [57]. Another wave of structural development has occurred with bidirectional LSTMs [58], gated recurrent units [59], and Deep Residual Networks (ResNet), which use skip connections, allowing the training of very deep "supervised" models to take place in a stable way [60]. The culmination of these yields a collective use, as shown in the statistics in Fig.2. Models inspired by LSTM and CNNs account for the majority of models utilized for the approximation of complex nonlinear systems, like PVT systems.

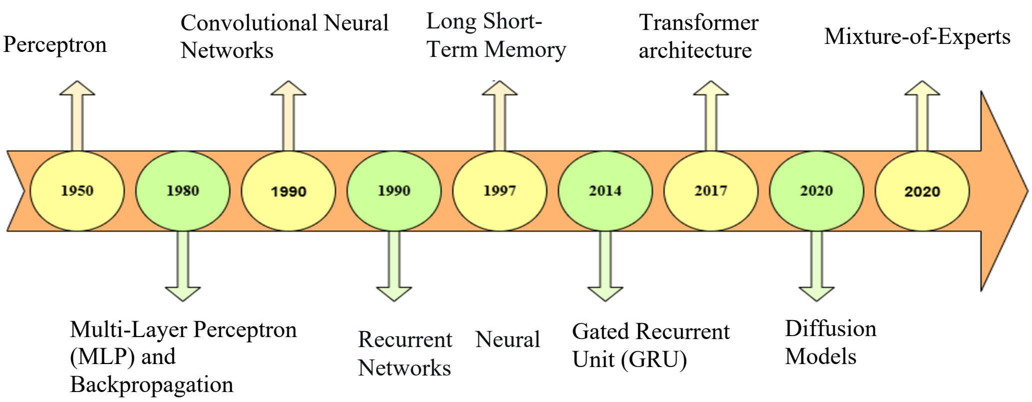

Fig.2: The architectural evolution of deep learning: from Single-layer perceptrons to modern generative and sparse models.

5.2 Types of ANNs Relevant to PVT-PCM Analysis

Artificial Neural Networks evolved through several specific forms to solve various classes of computational problems [61]. Some ANN architectures have shown particular relevance to the analysis of PVT-PCM systems. These include MLPs, RNNs including LSTM networks, CNNs, and hybrid types of architectures. Such computational devices have become significant to applications within the renewable energy field, most especially for purposes of predicting performance for PVT systems integrating PCMs. As shown in Fig.2, the ANN approach is the primary one employed since this has shown a significant degree of effectiveness. The research has also demonstrated a strong predictive capability for these networks in modelling complex systems such as those involving PCMs with finned devices [62], nanofluids enhancement effects [63] , and system design optimization [64]. These networks have also been effective in predicting heat transfer characteristics based on experimental data for PCMs [14].The effective and detailed discussions of the principal ANN architectures illustrated in Fig.2 will be discussed in more detail below. These sections will discuss their fundamental internal forms, how they operate, and their specific uses for performance prediction of PVT systems enhanced by PCMs.

1 Feed-Forward Networks & Multilayer Perceptron

The Multi-Layer Perceptron (MLP), which is one of the most fundamental forms of feedforward artificial neural network, is a very capable model for representing the dynamic behavior of PVT systems with a PCM [58]. The

MLP is distinctly different from a simple perceptron in so far as its hidden layers and the use of non-linear functions as its activation functions (such as ReLU and Sigmoid) enable it to learn and represent very complex non-linear patterns [59] which has been proved in similar energy related applications such as solar estimation [17,60]. These characteristics make the MLP an attractive tool for predicting PV power output. The process starts with inputs to the network which are fed in through the layers of the network, where each neuron applies a function to the weighted inputs, and the final output delivered at the output layer of the network will be the predicted output [61,62]. For example, Fig.3 shows a four-layer MLP which has input and output layers and 2 hidden layers. The model is presented with 'm' inputs (x_i) and produces 'p' outputs (y_l). The hidden layers contain 'n' [h_j] and 'o' [h_k] neurons respectively. The mathematical representation of the flow of computation through this network is given by the following equations:

- The output of the first hidden layer is calculated as $h_m= f_h (\sum_{i=1}^{m} xi\ wji+ a_i)$ (1)
- The output of the second hidden layer is computed as $h_o= f_h (\sum_{j=1}^{o} hj\ wkj+ b_j)$ (2)
- The final model output is given by $y_p = f_y (\sum_{k=1}^{p} hk\ wlk+ c_k)$ (3)

Here, w terms denote the connection weights (w_{ji},w_{kj},w_{lk}), a, b,and c are bias units, and f_h and f_y are the non-linear activation functions for the hidden and output layers.

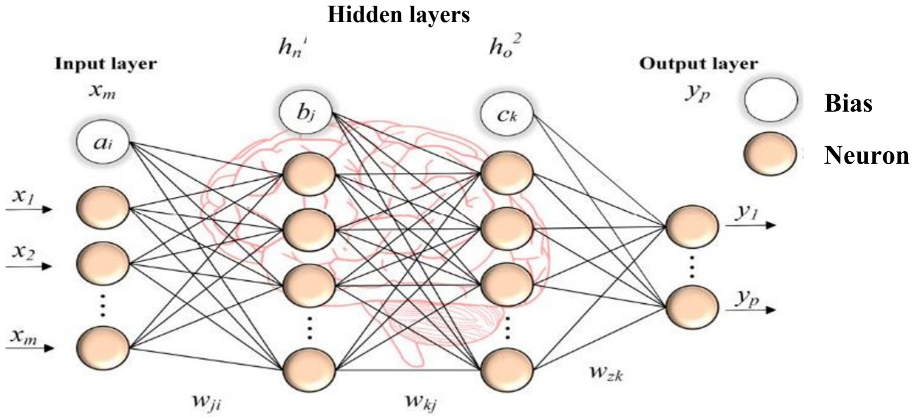

Fig.3. Multi-Layer Perceptron architecture [24].

2 Recurrent Neural Networks

Recurrent Neural Networks are a specialized class of artificial neural networks designed for sequential data, including time-series analysis and natural language processing [35]. Their core innovation lies in cyclic connections, which create an internal hidden state (h_n) that acts as a memory of previous inputs [60]. This allows the network to model temporal dynamics, unlike feed-forward architectures that process inputs in isolation.

The network's operation is governed by the iterative application of Equations (4) and (5) for a given input sequence ($x1,\ldots,xn$):

$$hn=fh\ (xn\ Whx+hn-1Whh+bh) \quad (4)$$

$$yn=fy(ht\ Wyh+by) \quad (5)$$

Here ,W denotes weight matrices,b are bias vectors, and f are activation functions [40]. The non-linear transformation of the hidden state provides the expressive power to capture complex temporal dependencies [70].

Despite this, a fundamental limitation of traditional RNNs is the difficulty in learning long-range dependencies due to the vanishing/exploding gradient problem during Backpropagation Through Time (BPTT) [40]. This instability hinders the network's ability to form reliable long-term memories, which directly motivated the development of more robust gated architectures like LSTM networks and GRUs [43].

3 Long Short-Term Memory and Gated Recurrent Unit

3.1 LSTM

LSTM networks are a powerful type of RNN made to learn from data over long periods [62]. They are especially useful for modeling PVT and PCM systems because they can track slow changes in temperature and energy storage [64].

The LSTM cell processes information through a series of gated steps, as shown in Fig.4. Each step is defined by a specific equation that controls the flow of information.

The process begins with the forget gate. This gate looks at the current input (xt) and the previous hidden state (h_{t-1}). It uses these to decide what information from the long-term memory cell (C_{t-1}) should be kept or discarded. It produces a value between 0 (completely forget) and 1 (completely keep) for each piece of information.

$$f_t = \sigma_f \left(w_f \cdot [h_{t-1}, x_t] + b\right) \quad (6)$$

Next, the input gate works in two parts. First, it decides which new information is important enough to be remembered. Second, it creates a new candidate value ($\boldsymbol{N_t}$) that holds the potential new memories.

$$i_t=\sigma_i(w_i.[h_{t-1},x_t]+b) \quad (7)$$
$$N_t= \tanh(w_c .[h_{t-1}, x_t] + b) \quad (8)$$

The long-term memory is then refreshed. The old cell state (C_{t-1}) is multiplied by the forget gate's decisions, removing unwanted information. Then, the new candidate values (N_t) are scaled by the input gate's decisions and added to the memory, updating it for the current step.

$$C_t = C_{t-1} * f_t +N_t * i_t \quad (9)$$

Finally, the output gate determines what the LSTM unit will reveal as its final output (h_t). This gate uses the current input and previous hidden state to filter the newly updated memory (C_t). The memory is scaled to a$_{-1}$ to 1 range using a tanh function and then multiplied by the output gate's signal.

$$O_t=\sigma \left(w_o [h_{t-1}, X_t] + b\right) \quad (10)$$
$$h_t = O_t * \tanh(C_t) \quad (11)$$

This step-by-step process allows the LSTM to carefully manage information over long sequences, making it highly effective for forecasting complex trends in PVT and PCM systems where past conditions heavily influence future performance.

3.2 GRU

GRU is a efficient type of recurrent network that solves the problem of learning from long sequences proposed in 2014 [64] ,making it highly suitable for forecasting in PVT and PCM systems [61,62]. As shown in Fig.4, the GRU simplifies the LSTM by using only two gates. The update gate (ut) decides what information from the past should be carried forward, effectively combining the roles of the LSTM's forget and input gates. The reset gate (rt) determines how much of the past history is relevant for understanding the current input.

The mathematical process is as follows. First, both gates are calculated using the new input and the previous hidden state:

$$r_t=\sigma \left(W_r\cdot[h_{t-1}, xt]+b\right) \quad (12)$$

$$u_t=\sigma \left(Wu\cdot[h_{t-1}, xt]+b\right) \quad (13)$$

Next, the reset gate is used to create a candidate for the new hidden state, which mixes the new input with a controlled amount of past memory:

$$h't = \tanh \left(wh'\cdot[h_{t-1}, x_t] + b\right) \quad (14)$$

The final step updates the network's state. The update gate acts as a blend knob, creating the new hidden state as a mix between the old state and the new candidate:

$$h_t= (1 - u_t) * h_{t-1} + u_t * h't \quad (15)$$

This streamlined process allows the GRU to effectively model long-term trends in energy data like thermal performance, while its simpler design makes it faster to train and less likely to overfit than more complex models [47].

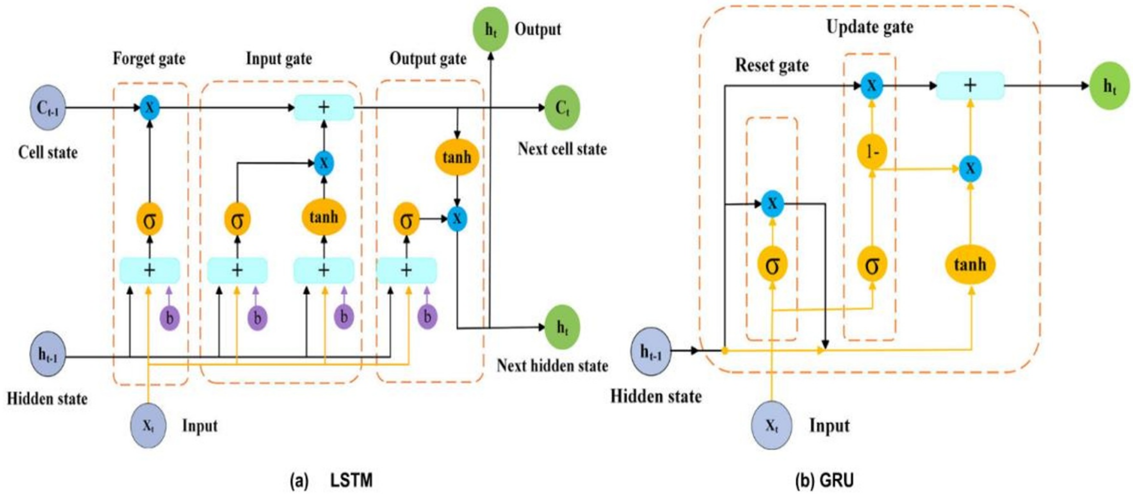

Fig. **4**. The architecture and flow of data in LSTM and GRU .

4 Convolutional Neural Networks

The CNNs offer a powerful framework for analyzing data with an inherent spatial structure, such as images. Their architecture is defined by a hierarchical stack of convolutional and pooling layers, which work in concert to automatically learn and consolidate complex feature representations directly from input data. This makes CNNs exceptionally well-suited for interpreting nuanced patterns in energy systems, for example, by detecting thermal anomalies in PVT panels or analyzing the heterogeneous phase distribution in PCMs [24,52]. As depicted in Fig.4, the computational process involves convolutional filters that identify local features, followed by pooling operations that spatially downsample these features to ensure robustness and computational efficiency [53]. The resulting abstract representations are subsequently transformed and passed to a series of fully-connected layers, which perform the final task-specific computations, such as predicting system efficiency or classifying operational states [54]. Through this structured, hierarchical approach to feature learning, CNNs provide a sophisticated and effective methodology for advancing predictive modeling in solar energy and thermal management research [55] .

5.3 Why ANNs are Ideal for PVT-PCM Systems?

The ANNs offer distinct benefits for modeling PVT systems with PVT-PCM. These systems exhibit complex thermal and electrical interactions that challenge conventional modeling approaches. ANNs address these limitations through three key attributes.

First, ANNs effectively model non-linear system behavior. PVT-PCM systems demonstrate complex dynamics including phase-change hysteresis and variable thermal gradients. ANNs learn these patterns directly from operational data, providing accurate predictions without requiring complete physical governing equations [62,55].

Second, ANNs provide substantial computational advantages. While detailed simulations demand extensive processing resources, trained ANN models generate predictions rapidly. This efficiency enables comprehensive parameter studies and optimization procedures that would be impractical using conventional simulation methods [35].

Third, ANNs serve as effective surrogate models. They emulate system behavior with sufficient accuracy while requiring minimal computational resources compared to high-fidelity simulations. This capability significantly accelerates research and development cycles for PVT-PCM system optimization [58].

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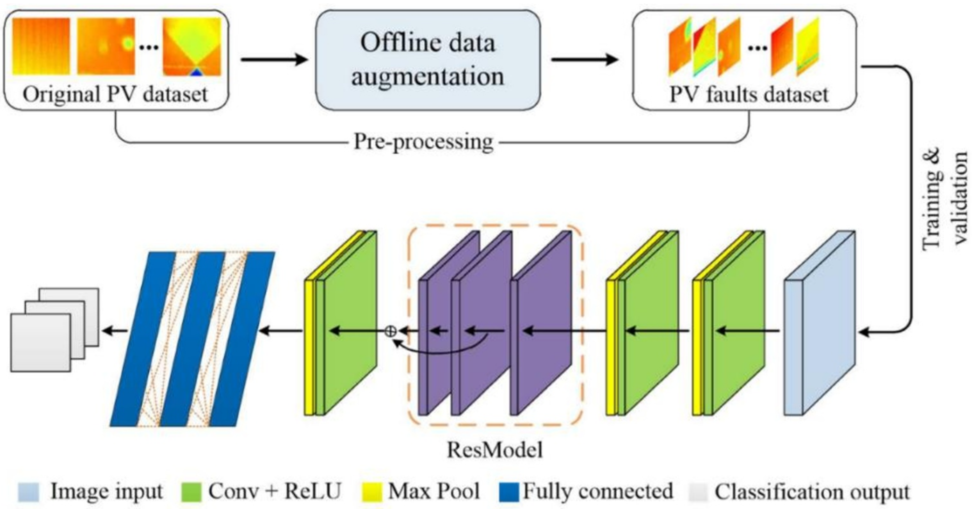

Fig .5. The structure of PV cell faults classification method [56].

Table. 1. Correspondence between ANN characteristics and PVT-PCM modeling requirements

ANN Characteristic	PVT-PCM Challenge	Research Application
Non-linear mapping [58,61]	Complex thermal-electrical dynamics with hysteresis effects	System performance prediction without complete physical models
Computational efficiency [57]	Prohibitive computational requirements for detailed simulations	Parameter optimization and sensitivity analysis
Surrogate modeling capability [58]	Limited capacity for design space exploration with conventional tools	Rapid system evaluation and performance prediction

6 Critical Analysis of ANN Applications in PVT-PCM Systems (2015-2024)

The ANNs effectively predict PVT system performance under different environmental conditions [52]. These networks identify complex relationships between weather data and system operation to forecast electrical and thermal output . This predictive ability helps engineers create better system designs and verify performance.

Recent studies show ANN applications in various PVT designs identified , including building-mounted systems and specialized cooling configurations [20,60]. Improved methods combining ANNs with optimization algorithms show better accuracy than basic neural networks [61]. The growing use of computer models in solar thermal systems appears in successful implementations of multiple algorithm types and enhanced networks for systems with phase-change materials [32].

While computer models show strong potential for advancing PVT systems, researchers note the continued need for experimental testing and better adaptation to weather changes. This study expands current knowledge by combining physical measurements with computer modeling to develop more efficient and reliable hybrid solar energy systems.

Table .2. ANN for Prediction and Modeling of PVT-PCM Systems.

Ref.	Year Location	Method	PVT technology	Error	Accuracy	Critical findings
[55]	2016 Trieste, Italy	ANN MLP	Grid-connected PV System (Note: This foundational study focuses on PV, establishing the ANN methodology later	MAE = 0.063	$R^2 = 0.987$	This seminal research demonstrated the efficacy of Artificial Neural Network (ANN) models, specifically a Multilayer Perceptron (MLP), in achieving high-accuracy, short-term solar forecasts.

			applied to PVT systems)			The reliable data generated under mid-latitude climatic conditions is a crucial prerequisite for the performance modeling and prediction of advanced hybrid PVT systems.
[49]	2017 Malaysia	Deep Belief Network (DBN)	PV System (Methodology applicable to PVT)	RMSE = 0.0234, MAE = 0.0187	-	Demonstrated that Deep Belief Networks can effectively capture complex temporal patterns in PV power generation, providing more accurate forecasts compared to traditional shallow networks. This deep learning approach shows promise for PVT system forecasting.
[55]	2017 Iran	Hybrid PSO-ANN	Nanofluid-cooled PVT Collector (SiO_2/water nanofluid)	–	PSO-ANN: R^2 = 0.998 Standard ANN: R^2 = 0.993	This pioneering hybrid model demonstrated that metaheuristic optimization (PSO) could significantly enhance ANN prediction accuracy for nanofluid-based PVT systems. The PSO-ANN hybrid achieved superior performance in forecasting the exergetic performance, a critical metric for system optimization.
[7]	2018 Oman	ANN	Hybrid Nanofluid & Nano-PCM PVT System (SiC/Water Nanofluid + Nano-enhanced PCM)	–	$R^2 > 0.98$	This study demonstrated the superior predictive capability of ANNs over traditional regression methods for a complex, dual-enhanced PVT system. It validated ANNs as a reliable tool for modeling systems that integrate multiple performance-enhancing technologies (nanofluids and nano-PCMs).
[55]	2020 Kuwait	hybrid PSO–ANN technique	integrated PVT (BIPV/ T) system	PSO RMSE = 0.010274 ANN RMSE = 0.006112	PSO R2 = 0.9968 ANN R2 = 0.9989	A comparative analysis of model performance indicated a slight but consistent superiority of the Particle Swarm Optimized-Artificial Neural Network (PSO-ANN) over its standard ANN counterpart, as evidenced by lower error metrics.
[56]	2020 Iran	ANN	Grid connected PVT system (GCPVT)	MSR = 1864.93	R = 0.9771	The optimized ANN model accurately forecast the output energy of the GCPVT system, a conclusion supported by low error (MSE) and high correlation coefficients. Key operational

						parameters were identified through an analysis of variance. The model's predictions showed strong concordance with simulated values, registering marginal discrepancies of 9.38% for thermal energy and 8.83% for electrical power.
[18]	2020 Malaysia	ANN	PVT system cooled by water, nanofluid and nanofluid nano-PCM	MSE = 0.0223 RSME = 0.149	R2 = 0.8742	Linear models enable fast, low-error solar system prediction and optimization. Neural networks can expedite this process, with the most accurate PV forecasts relying on solar irradiance and temperature inputs.
[56]	2020 Iran	ANN	BIPVT collector	RSME = 1.5237	R2 = 0.99970.9999	The exergetic performance of a BIPVT complex was forecasted using an ensemble of machine learning models. After evaluating techniques from linear regression to advanced neural networks and decision trees, the Random Forest (RF) algorithm demonstrated superior predictive capability over all other tested models.
[58]	2020 India	ANN	Conducting (copper/ aluminium) base PVT collector	MSE = 0.0748	R = 0.999	The ANN model was trained on meteorological data from four Indian cities. An architecture with two hidden layers (10 neurons) and using the Levenberg-Marquardt algorithm yielded predictions closely matching analytical results, demonstrating a faster and more efficient approach than conventional methods.
[60]	2021 Saudi Arbia	ANN	Circular tube fitted with novel corrugated spring tape PVT	–	R2 = 0.98	An ANN model accurately predicted thermo-hydraulic performance (Nusselt number, efficiency η) with 97% accuracy on test data. This reliable tool can be directly applied to the design of heat exchangers and the analysis of heat transfer enhancement techniques.
[59]	2021 France	ANN LS-SVM	Air cooled PVT system	MAE = 0.0078 MAE = 2.69	R = 0.86 R = 0.80214	A comparative analysis revealed that the ANN model achieved higher accuracy in forecasting

						the thermal and electrical efficiency of the PVT air system than the LS-SVM approach.
[61]	2022 Turkey	LSTM and MLF	PVT based on natural zeolite plates	MSE = 0.1	R2 = 0.996	The study employed an LSTM model for energy yield prediction and an MLF algorithm to accurately isolate and calculate the impact of temperature on PVT panel performance.
[61]	2022 Iran	CFNN and MGGP	PVT cooled by oil based nanofluid	RMSE = 0.00930	R = 0.982443	A comparative analysis between CFNN and MGGP for predicting receiver tube efficiencies revealed CFNN's higher accuracy. However, MGGP offered a distinct advantage by generating transparent, mathematical relationships from the six input parameters, facilitating diagnostic insight.
[15]	2023 Saudi Arabia	GMDH	PVT system cooled by hybrid nanofluids	RMSE = 0.0015	R2 = 0.9961	With a determination coefficient of R^2 = 0.9962, the GMDH neural network exhibited remarkable reliability in estimating total entropy generation, confirming its robustness for modeling thermodynamic irreversibility in BIPVT systems.
[62]	2024 Iran	GA-ANN	PVT system cooled by nano-PCM and porous foam gradient	RMSE = 0.0885	R2 = 0.9857	A hybrid genetic algorithm-artificial neural network (GA-ANN) model was developed to forecast electrical efficiency, achieving a high coefficient of determination of R^2 = 0.9857.

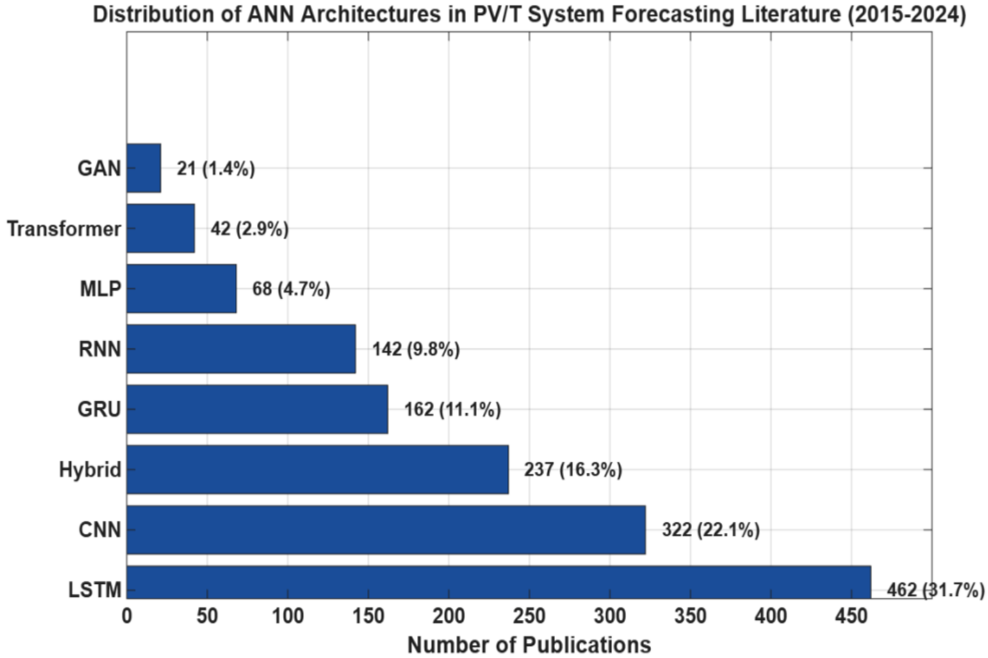

Fig.6. Distribution of artificial neural network architectures in PVT System forecasting literature (2015-2024).

7 Limitations and Critical Gaps in the Current Body of Literature

Although this systematic review identifies the main trends in the application of ANNs to PVT-PCM systems, it has several limitations. A major constraint is the methodological heterogeneity of the primary studies examined, which hinders any direct quantitative comparison of model performance. Neural network architectures, from simple Multi-Layer Perceptrons (MLPs) to complex recurrent structures such as LSTMs and GRUs, were evaluated using disparate datasets, validation protocols, and performance metrics. In particular, the ability of MLPs to capture complex temporal dynamics is often overestimated in suboptimal experimental configurations, while the superiority of LSTMs/GRUs in this regard is offset by their substantial data requirements, a detail that is frequently underreported. Similarly, the application of CNNs to time series, while promising, lacks standardized frameworks in the literature, leading to ad hoc adaptations that complicate the assessment of their true effectiveness. Consequently, this synthesis is naturally limited by the lack of robust comparative data and unified benchmarks in the field, a gap that future research must address.

8 Conclusions and recommendations

This paper systematically examines the application of ANNs for modeling and predicting the performance of PVT systems integrated with PCM. By synthesizing findings from recent literature, this work consolidates the current understanding of ANN architectures, their predictive accuracy, and their evolving role as an indispensable tool for simulating these complex energy systems identified in Fig 6. The following sections present the principal conclusions derived from this analysis and propose targeted recommendations for future research:

- Consensus on high predictive accuracy: The scholarly consensus indicates that ANN models deliver exceptionally accurate predictions for the energy output of PVT-PCM systems. This is robustly demonstrated by consistently high coefficients of determination (R^2) frequently exceeding 0.98 and minimal error metrics across a wide range of system configurations and climatic conditions [7,25,62].
- Paradigm shift towards hybrid modeling: A dominant trend is the evolution from standalone ANNs to hybrid models that leverage metaheuristic optimization algorithms. The integration of techniques such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) has consistently yielded superior predictive performance compared to conventional ANN architectures, establishing a new benchmark for model accuracy [55,61] .
- Architectural diversification for enhanced capability: The field is witnessing a strategic diversification beyond the standard MLP. Specialized architectures, including DBNs for capturing complex feature hierarchies and LSTM networks for temporal sequence modeling, are proving more effective for specific forecasting tasks, indicating a move towards bespoke AI solutions [61,62].

- Demonstrated versatility and generalizability: ANN frameworks have proven to be remarkably adaptable, successfully modeling the complex, non-linear thermodynamics of advanced PVT systems. Their efficacy spans configurations enhanced with nanofluids, nano-PCMs, porous media, and novel heat exchanger geometries, underscoring their generalizability as a universal modeling paradigm [55,56] .
- Evolution from predictive to diagnostic tools: The utility of ANNs is expanding beyond performance forecasting to encompass system design and diagnostic analysis. Advanced implementations are capable of quantifying the influence of individual operational parameters and performing sensitivity analyses, thereby providing valuable insights for engineering optimization [53,60].

Based on the reviewed literature, the following research avenues are proposed to advance the field of ANN modeling for PVT-PCM systems:

- Develop explainable AI models. Future work should focus on creating "explainable AI" (XAI) that provides clear, understandable reasons for its predictions. This will build trust and offer deeper physical insights for system designers.
- Integrate physics into neural networks. A key direction is using Physics-Informed Neural Networks (PINNs). These models incorporate fundamental physical laws during training, improving their accuracy and reliability, especially when experimental data is scarce.
- Establish public benchmark datasets. The research community should collaborate to create open-source, high-quality datasets from various PVT-PCM systems. Standardized data is crucial for the fair comparison and validation of new AI models.
- Create advanced hybrid algorithms. There is significant potential in developing next-generation hybrid models. Research should explore novel combinations of AI (like deep learning) with powerful optimization algorithms to achieve new levels of predictive performance.
- Implement AI for real-time control. Future efforts should shift from offline modeling to real-time applications. Using accurate ANNs for live system control and "digital twins" can actively optimize energy output and manage system operation.

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