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A review for solar panels cooling techniques and efficiency enhancement: Numerical studies

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ABSTRACT

The efficiency and performance of photovoltaic (PV) solar panels are significantly impacted by elevated operating temperatures, with every degree Celsius increase potentially reducing conversion efficiency by (0.4-0.5) %. Numerical studies published during the last decade designated the cooling techniques to passive, active and hybrid strategies Although various numerical frameworks—including CFD, FEM, lumped-parameter, three-dimensional numerical, and equivalent circuit models—were employed and solved using ANSYS Fluent, COMSOL, MATLAB, and OpenFOAM, the thermal management performance was evaluated using unified performance indicators. These included module temperature reduction, maximum operating temperature, temperature uniformity, and the corresponding electrical efficiency improvement, enabling consistent cross-model comparison. This paper focuses on review the published paper in this context which performs numerical studies on PV panel cooling with a focus on computational techniques that allow for deep analysis and improvement of thermal management systems. The combination of detailed CFD simulations using advanced turbulence models and different software to solve them creates a complete framework for new ideas in PV thermal management.

1. Introduction

Mathematical frameworks and computational methodologies constitute the foundation of contemporary research into photovoltaic thermal management systems. Scholarly research employs theoretical frameworks grounded in heat transfer phenomena, thermodynamic principles, and fluid dynamic behaviors to formulate predictive algorithms capable of forecasting temperature distributions and cooling efficacy across diverse operational contexts. Figure 1 illustration of the photovoltaic–thermal (PVT) system showing the main energy transfer mechanisms. These computational methods use basic transport phenomena equations and set boundary conditions to make complete analytical frameworks. Such integration enables investigators to utilize numerical simulation techniques for analyzing thermal behavior patterns, thereby diminishing reliance on experimental laboratory measurements exclusively. The theoretical framework includes equations for energy conservation, correlations for heat transfer coefficients for both convective and conductive mechanisms, and governing equations for mass transfer. Together, these explain the complicated thermal phenomena that happen in photovoltaic systems [1], [2].

Ref. [1] propose a six-layer energy-balance model for a PVT collector and validate it experimentally under controlled laboratory conditions, demonstrating good agreement between simulations and measurements and showing that active heat extraction can recover about 16% of the thermal energy while reducing PV operating temperature and improving electrical performance. In contrast, [3] provide a comprehensive review of existing steady-state PV cell temperature correlations, identifying key governing parameters such as solar irradiance, ambient temperature, wind speed, and optical–electrical properties, and emphasizing best practices for temperature measurement and model validation. Together, the studies indicate that while detailed layer-based experimental modeling is effective for understanding and enhancing PVT performance, its applicability can be

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strengthened by adopting the parameter selection and validation strategies highlighted in broader temperature-correlation studies.

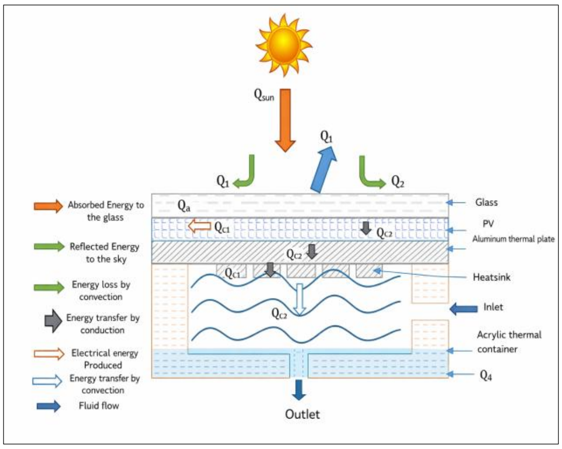

Figure 1 Principle of photovoltaic system

Academic studies utilize theoretical foundations rooted in heat transport mechanisms, energy conservation laws, and convective flow characteristics to develop computational algorithms that predict spatial temperature profiles and assess cooling performance under varying operational conditions.[4]. Theoretical modeling of photovoltaic cooling systems encompasses three fundamental frameworks that collectively enable accurate thermal performance prediction and optimization. Steady-state heat transfer modeling employs thermal resistance networks to establish robust temperature prediction capabilities for photovoltaic modules, where multi-dimensional thermal network nodal equations are formulated to capture conjugate heat exchange through both conduction and multi-node radiation mechanisms between composite surfaces [5],[6]. These thermal resistance networks utilize matrix solution procedures for formulating conduct and heat source matrices, enabling numerical solutions of heat conduction and transport equations that predict detailed temperature distributions across PV module layers with validated accuracy against experimental measurements [7]. Transient heat transfer analysis captures dynamic thermal behaviors through time-dependent temperature response models that incorporate varying environmental conditions via energy conservation equations, with particular emphasis on wind speed and direction effects using manufacturer data and literature-validated parameter [8]. Advanced dynamic modeling approaches integrate computational fluid dynamics (CFD) with finite element methods (FEM) and adaptive mesh refinement (AMR) techniques to resolve complex temporal and spatial thermal gradients, while machine learning algorithms optimize multi-physics modeling is a critical tool for enhancing computational efficiency and enabling predictive maintenance capabilities [9]. Within this framework, integrated multi-physics coupling frameworks facilitate the seamless integration of electro-thermal interactions through comprehensive opto-electro-thermal simulations. These simulations incorporate wavelength-dependent optical calculations, electrical output modeling, and multi-layer thermal resistance networks.

2. Numerical and theoretical models:

Computational Fluid Dynamics (CFD) simulation platforms have become essential instruments for evaluation and advancement of efficient cooling technologies in photovoltaic (PV) systems. A thorough examination in this domain typically entails evaluating the functionalities of premier simulation platforms, including ANSYS FLUENT, COMSOL Multiphysics, and OpenFOAM, to enhance photovoltaic thermal management solutions [10]. Significant matching between CFD and experimental data results was found in [11] which used CFD tool ANSYS Fluent 18. to run 3D steady in-compressible Reynolds Average Navier Stokes (RANS) simulations. These simulations looked at how different air-cooling techniques impact PV performance. The SST k-Omega turbulence model is employed to depict the turbulent flow. The semi-implicit method for the pressure-linked equation SIMPLE was utilized to resolve the RANS equations in conjunction with an upwind difference scheme. The results illustrate that using small backside fans for cooling PV can improve performance, yielding a maximum total enhancement of 2.1% in PV panel efficiency while reaching a 7.9% drop in energy consumption. Using the blower cooling method can boost the efficiency of PV panels by up to 1.34% and save energy by 4.2%.

2.1 Turbulence Modeling:

2.1.1 k-ε model:

This model is used in many researches, such as [12], [13], [14], [15], which utilize ANSYS Fluent as the primary CFD platform. Both [12] and [14] used passive cooling, [12] provided both computational fluid dynamics simulation and experimental validation of aluminum heat sink cooling for photovoltaic panels. The study showed that forced air convection at 1.5 m/s can lower the temperature from 85.3°C to 72.8°C (a drop of 12.5°C). The aluminum heat sink design increased the open-circuit voltage by 10% and the maximum power point by 18.67%, which made the electrical efficiency go from 8.51% to 11.11% (2.6% absolute gain). The experimental results confirmed theoretical results with great precision, utilizing 50 Wp polycrystalline panels and accurate measuring tools,[14] explored performance enhancement using heat sinks equipped with perforated fins, simulated by ANSYS-Fluent 2021-R1. This research systematically investigated and compared six distinct heat sink configurations, ultimately demonstrating that the design incorporating horizontal fins with 30 mm perforations reported the most effective cooling performance. Under demanding operating conditions (1000 W/m² irradiance, 35°C ambient temperature, and 1 m/s wind speed), the optimal configuration successfully elevated the power output from 83.33% to 88.74%, signifying a notable 6.49% enhancement in overall efficiency. Methodologically, numerical analysis employed the k-ε realizable turbulence model for fluid flow and Solar Ray Tracing for radiation modeling. Furthermore, the reliability of the results was ensured through rigorous mesh independence studies, involving computational grids of up to 5.5 million cells However,[15] investigated active cooling by combining experimental testing with CFD simulation to evaluate forced air-cooling enhancements using fins and baffles in a 150 W PV/T collector. The research demonstrates substantial performance improvements: exergy efficiency increased from 20% to 28% and thermal energy efficiency from 12% to 18% using longitudinal fins with inclined baffles. The methodology employed K-Epsilon turbulence model with SIMPLE pressure-velocity coupling, utilizing hexahedral mesh elements (2 million) and comprehensive experimental validation across multiple duct configurations. while the results of study [16] achieved 71.02% thermal efficiency compared to 53.61% for water, with exergy efficiency improvements from 20% to 36%. When they used Nano fluid-enhanced serpentine tube cooling using ANSYS Fluent with the k-ε turbulence model. an innovative hybrid prediction model that integrates Feedforward Neural Networks with the Archerfish Hunting Optimizer (FFNN-AHO) for jet-cooled photovoltaic-thermal (PVT) systems was used in [13] the FFNN-AHO model is quite good at making predictions. At its best flow rates (1.27 LPM), the jet-cooling system could lower the temperature by up to 11.76 K. It had a maximum electrical efficiency of 14.23%, a thermal efficiency of 54.43%, and an overall efficiency of 68.1%. The methodology utilized ANSYS ICEM and Fluent for CFD modeling using the RNG K-ε turbulence model, while MATLAB executed the FFNN-AHO optimization algorithm for performance forecasting.

2.1.2 k-w model:

Ref. [17] Focused on thermal optimization rather than electrical efficiency quantification, utilize active cooling mechanisms with ANSYS-CFX with the k-ω turbulence model to optimize forced air cooling through strategically positioned air guides. The study determines that 18 air guides positioned at 45° angles and 30mm from the PV cell base achieve optimal cooling performance at 0.01 kg/s mass flow rate.

Ref. [18] compared three cooling methods: air, water, and porous media with employs ANSYS suite (Design Modeler, Fluent, and Mechanical modules) with the k-ω turbulence model. This comprehensive study reveals water cooling as the most effective approach, reducing cell temperatures by over 35°C and achieving 30.9% net power output improvement, while porous media cooling provides a sustainable alternative with 26.3% improvement through passive evaporation.

The primary cooling technique investigated is passive air cooling and passive ventilation through natural convection in Ref. [19]. This method leverages buoyancy-driven natural convective currents generated by solar PV panels, which heat up due to solar radiation. The study explores how these currents can cool the PV panels and simultaneously ventilate the building's interior. The integration of the gap behind the PV panels into the building's interior allows for the generation of natural convective currents that entrain fresh air into the room through windows. This study utilized the Ansys Fluent (ANSYS 2021) computational fluid dynamics (CFD) package for 3D simulation of the building-integrated photovoltaic (BIPV) system. The unsteady Reynolds Averaged Navier-Stokes (URANS) approach was employed to obtain the thermal-fluid fields by solving mass, momentum, and energy conservation equations. The Shear Stress Transport (k-ω SST) model was used to model the natural convective flow, which is capable of predicting flow features with reasonable accuracy while being computationally less intensive than other methods like Large Eddy Simulation (LES) or Direct Numerical Simulation (DNS). Table 1 illustrates the typical application and strength of the turbulence models.

Both [20], [21] integrated thermal CFD results with electrical modeling using MATLAB/Simulink coupling and investigate phase change materials for passive thermal management study [20]. Focuses on nanoparticle-enhanced PCMs with porosity optimization while[21] study Emphasizes PCM-heatsink fin combinations for both mono- and polycrystalline panels, efficiency improved by (9.79%) through optimized nanoparticle-PCM systems comparing with (5-10% efficiency gains) in PCM-heat sink fin [21].

Table 1 Turbulence Models Used in PV Cooling Simulations

Turbulence model	**Typical application**	**Strengths**	**Limitations and computational aspects**
Laminar model	Low Reynolds number flows and preliminary analyses	Very low computational cost and fast convergence	Inaccurate for realistic outdoor PV cooling with turbulent air flow
k–ε (realizable)	Most common model for air-cooled PV and fined heat sinks	Good balance between accuracy and computational cost	Limited accuracy near walls and in strong flow separation regions
k–ω	PV systems with strong near-wall effects	Improved boundary-layer prediction compared to k–ε	Higher sensitivity to mesh quality and inlet conditions

2.2 Lumped Parameter Models:

Lumped parameter models represent complex thermal systems by discretizing temperature fields into representative nodes with concentrated thermal capacitances and resistances. These models assume uniform temperature distribution within each node while capturing heat transfer between nodes through thermal resistances, forming RC (resistor-capacitor) electrical circuit analogies that enable efficient computational analysis of transient thermal behavior as shown in figure (2) a and b [22], [23].

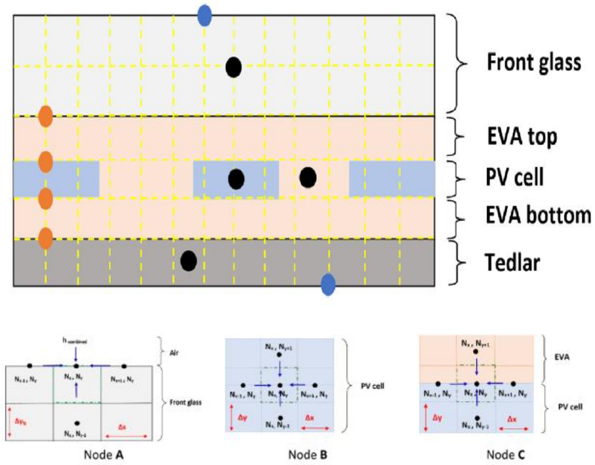

Figure 2 (a) Schematic representation of the nodes in PV layer (b) Schematic presentation of nodes heat balance).

Refs [22], [23], [24], [25] utilized lumped parameter approaches with RC circuit analogies, enabling efficient transient thermal analysis. MATLAB emerges as the usual software platform across [22], [23], [24], facilitated numerical integration and dynamic system modeling. Model verification approaches systematically evaluate computational predictions through comparison with experimental data, prioritizing thermal accuracy assessments [39],[40],[42]. Energy conservation laws constitute the theoretical foundation for thermal modeling frameworks, encompassing heat conduction, convective transport, and radiative exchange processes [22], [23], [24], [25].

Refs. [26] Mustafa et al. employed a three-dimensional numerical model to investigate the integration of phase change materials with nanofluid-filled tubes and different pin-fin configurations, providing deep physical insight into heat transfer mechanisms and phase transition behavior; however, the absence of extensive experimental validation limits the direct applicability of their findings. In contrast, [22] Aalloul et al. developed a coupled two-dimensional electro-thermal model based on a double-diode electrical representation and a finite-difference thermal scheme, with model parameters identified through optimization and validated experimentally, achieving strong agreement with measured data and demonstrating practical predictive capability. Meanwhile. Ref. [23] Cattarin focused on an experimentally validated lumped-parameter thermal model combined with local sensitivity analysis, showing that simplified formulations can still predict module temperature with high accuracy while clearly identifying the most influential parameters. Taken together, these studies highlight a clear trade-off between physical detail and practical applicability: high-fidelity three-dimensional models enhance fundamental understanding, whereas simplified and experimentally supported models offer robustness and efficiency for real-world photovoltaic performance assessment.

In [25] Presents a transient lumped-parameter thermal model for PV modules, solving differential energy balance equations iteratively. The model incorporates power-law convection correlations and load-dependent effects without requiring INOCT parameters. Implementation uses Euler numerical method for time integration, though specific software platforms are not explicitly mentioned.

It was found from above studies that temperature predictions show maximum deviations of <1°C for front glass and <1.5°C for Tedlar backsheet under varying loads and weather conditions [22]. Achieved validation with residuals typically within ±1°C and usually inside measurement uncertainty bands (±0.4°C). Local sensitivity analysis of 49 parameters identifies guard zone air temperature, initial envelope temperatures, and window dimensions as most influential factors affecting thermal predictions [23]. while in [24] focused on parametric analysis rather than experimental validation, demonstrating thermal mass effects on indoor climate. High thermal capacitance buildings can delay temperature responses by up to 10 days compared to low-mass structures, with heater performance coefficients reaching 99.97% when including radiation effects. Since validates against field measurements using identical PV modules in different operating modes study[25], achieving 100% accuracy within 3°C and typically <2.5°C deviations. Standard errors range from 1.02-2.00°C for the proposed model versus 4.91-12.85°C for conventional steady-state SNL models, with >90% of predictions within measurement uncertainty [25].

2.3 Equivalent Circuit Models:

Equivalent circuit models play a crucial role on fundamental tools in electronic and thermal engineering, representing complex physical systems through simplified electrical analogies by employing resistors, capacitors, and current sources to mimic real-world behavior, enabling accurate prediction and optimization of system performance.

[22] employed comprehensive experimental validation using thin-film PV panels, weather stations, and thermal imaging under varying load conditions presents a sophisticated double-diode equivalent circuit model coupled with thermal analysis. The electrical equivalent circuit comprises a photocurrent source in parallel with two diodes (representing different recombination mechanisms), series resistance (Rs), and shunt resistance (Rsh). The Artificial Hummingbird Algorithm (AHA) implemented in MATLAB 2022 a extracts seven key parameters, while Python handles the coupled electro-thermal simulation using two-dimensional finite difference methods. The thermal model employs explicit energy balance equations across multiple PV panel layers. The results demonstrate exceptional precision with relative errors below 2% for both electrical and thermal predictions, validated against experimental data using infrared thermography and thermocouple measurements.

[27] confirmed parameter extraction methodologies through stringent testing against recognized reference standards, namely the French RTC solar cell and Photowatt PWP 201 module, utilizing extensive statistical evaluation frameworks. The study focused solely on methodologies for extracting equivalent circuit parameters, systematically comparing single-diode model (SDM) and double-diode model (DDM) architectures. The research rigorously evaluates five metaheuristic optimization algorithms—AEO, GBO, GNDO, BO, and RTH—while concurrently analyzing three separate methodologies for current computation: approximation techniques, Lambert W function-based calculations, and Newton-Raphson iterative methods. Experimental results demonstrate the significant superiority of Newton-Raphson and Lambert W function methodologies in comparison to traditional approximation techniques. The study attains remarkable accuracy in parameter extraction, recording RMSE values as low as 6.93709×10^{-4} for the DDM configuration and 7.72986×10^{-4} for the SDM configuration using Newton-Raphson computational techniques, while [28] reported over 90% reduction in temperature prediction errors under aging conditions, with mean absolute errors typically below 2°C by combined finite element analysis simulations with experimental testing using commercial SEMIKRON IGBT modules and infrared temperature measurements, introduces an improved thermal equivalent circuit model for IGBT modules, incorporating real-time parameter correction to compensate for solder aging effects. The model uses thermal resistances and capacitances analogous to electrical components**.**

2.4 -3D Numerical Model

Three-dimensional numerical modeling approximates solutions of the partial differential equations that govern physical systems by discretizing the spatial domain into elements or control volumes and solving the resulting algebraic systems on a computational mesh, a formulation and workflow that underlie modern finite-element practice and its automation in preprocessing, mesh generation, assembly and postprocessing stages[29] .The finite element method (FEM) is the primary variational approach used in many 3D problems, while for conservation-law dominated flows finite-volume and stabilized finite-element formulations are commonly used and compared for accuracy and stability[30].

Hybrid photocell cooling system was examined in two study [31], [32]. the first study Utilizes ANSYS software for comprehensive 3D thermal modeling of hybrid PCM-forced convection cooling systems. The simulation encompasses detailed transient thermal analysis with sophisticated mesh generation, material property assignment, and validation protocols achieving simulation-experimental agreement within 1.2-4.06% error margins. while the second study Employs MATLAB 2021b for developing and validating a mathematical model incorporating transient energy balance equations for a hybrid photocell cooling system using heat pipes and PCM. The model integrates three interconnected components: photocell thermal dynamics, heat pipe thermal transport, and PCM phase-change behavior, with validation errors below 5.5%.

The results of experimental studies showed varying levels of thermal regulation performance. [31] represented a 4.26°C thermal reduction which mean dropped maximum panel operating temperatures from 109.26°C to approximately 105°C by used PCM-forced convection configurations In contrast, in[32] represented reveal enhanced cooling capabilities, with RT25 phase-change material delivering 8.7°C temperature decreases, outperforming RT35 and RT42 PCM formulations which achieved 7.5°C and 7.3°C reductions, respectively. Table 2 shows how different PV cooling Techniques compare.

It was shown that superior thermal management performance by using heat pipe strategy compared to copper fin heat sinks, achieving surface temperature reductions of 16.1 K in contrast to the 4.9 K decrease observed with copper fin [33]. The research employed computational fluid dynamics simulations using commercial finite element software with a discretized mesh containing approximately 2.3 million elements to investigate single-loop oscillating heat pipe (PHP) thermal management systems. Performance comparisons with conventional copper fin heat sinks were conducted through three-dimensional thermal analysis, revealing enhanced electrical output characteristics. Results demonstrated that PHP-based cooling configurations produced an 18% power output increase under 1000 W/m² solar radiation conditions, substantially outperforming copper fin cooling systems which yielded only 6% efficiency improvements.

Alternatively, the investigation utilized SolidWorks 2017 finite element analysis (FEA) platform for three-dimensional thermal modeling, establishing an innovative weighted moving-average computational framework that integrates equilibrium-state thermal predictions with dynamic heat capacity phenomena. The model is designed for integration with PVLIB Python package for widespread deployment in study[34] the focuses on temperature prediction accuracy rather than cooling system performance, achieving 0.17-0.58% improvements in PV energy modeling accuracy across different climatic conditions, with most temperature predictions within 2°C of measured values.

[26], Fluent andaddressed PV thermal management to enhance both electrical and thermal performance and employ comprehensive heat and mass transfer equations, considering conduction, convection, and radiation mechanisms, utilize time-dependent modeling to capture dynamic thermal behavior under varying environmental conditions but each study used different Numerical Approach, Custom implicit finite difference method with Thomas algorithm and Gauss-Seidel iteration used in [35] which investigated Air inlet quantity and chimney configuration optimization and Commercial COMSOL 6 FEM software with two-phase mixing technique in [26] which examined Pin fin shape optimization (circular, triangular, square, rectangular), while [36] used Analytical ODE solution via MAPLE with CFD validation using ANSYS Fluent, and used

PCM thickness optimization (1-5 cm) and fin arrangement studies. The results show 68% of the thermal efficiency increase and 5% electrical efficiency improvement through multi-inlet design in [35]. And 13% maximum temperature decrease and 3.4% electrical efficiency increase with 5 cm PCM thickness in [36] while, [26] showed Variable temperature reduction depending on pin fin geometry, with circular fins providing optimal panel cooling.

Table (2) Comparison of PV Cooling Techniques [16], [32], [36]

Cooling technique	Reported performance	Efficiency impact	Computational cost	limitations
PCM cooling (e.g., RT25)	Cell temperature reduction up to ~8–9 °C	Electrical efficiency improvement up to ~5%	High computational cost when transient phase-change is modeled (small time steps, nonlinear enthalpy method)	Performance strongly depends on melting temperature and PCM thickness
PCM cooling (RT35, RT42	Temperature reduction ~7 °C	Electrical efficiency gain ~4–5%	Moderate-to-high CFD cost; grid and time-step sensitivity remain critical	Less effective than RT25 under similar conditions
Heat pipe cooling	Improved heat dissipation from PV rear surface	Indirect electrical efficiency improvement	Requires conjugate heat transfer modelling; moderate CFD cost	Recovered heat often unused, reducing overall system benefit
Hybrid heat pipe–PCM cooling	Enhanced temperature uniformity and peak temperature reduction	Higher electrical and thermal efficiency than single techniques	Very high computational cost due to coupled PCM and heat-pipe physics	Numerical stability and convergence are challenging
Natural air cooling (passive)	Limited temperature reduction	Marginal efficiency improvement	Low computational cost (steady or laminar models)	Insufficient for hot climates with high solar irradiance

3. Numerical software and methods:

3.1 ANSYS

ANSYS is a very important computer program that is often used to improve thermal management systems in photovoltaic (PV) solar panel applications, and Its Fluent module is the main platform for these kinds of studies. Engineers and researchers use this software to run very accurate three-dimensional computational fluid dynamics simulations. This lets them look closely at How heat moves through and around photovoltaic panel parts and how cooling media, whether gas (air) or liquid, moves through and around them. A critical challenge confronting solar panel technology lies in the progressive decline of conversion efficiency corresponding to elevated operating temperatures. Researchers gain important information about the physical processes that cause this performance drop-off with temperature through these computer analyses. Studies found that using a cooling system based on air or water flow, which was studied with ANSYS, made the temperature of the PV panel drop significantly as the flow rate of the fluid increased. This simulation helps plan and test new cooling systems, such as micro-heat pipes or heat sinks, to see how well they work before they are built. This, in turn, helps make cooling systems that are good for the environment and don't cost too much [37],[12]. Computational fluid dynamics studies have demonstrated that the strategic incorporation of adiabatic extensions in rear-mounted cooling channels can significantly enhance heat dissipation. Specifically, outlet extensions three times the panel height resulted in a 65% increase in mass flow rate, a 13.4% improvement in average Nusselt number, and an 11% decrease in maximum panel temperature at modified Rayleigh numbers of 10^6 [38].

Ref. 19], [38] Both studies investigate passive air cooling of photovoltaic (PV) panels driven by natural convection, but with complementary scopes and modeling approaches. Ahmadi Moghaddam et al. employed a three-dimensional URANS CFD model of a building-integrated PV (BIPV) system to evaluate the coupled effects of roof emissivity, solar heat flux, and ambient conditions on PV temperature and indoor ventilation, showing that increasing roof emissivity enhances buoyant flow, reduces the mean PV temperature by about 3 K, increases mass flow by up to 34%, and yields noticeable gains in efficiency, lifespan, and air-change rates. In contrast, [38]Badi and Laatar conducted a two-dimensional numerical analysis of an inclined PV air channel, focusing on geometric parameters such as Rayleigh number, tilt angle, aspect ratio, and inlet/outlet extensions, and demonstrated that an optimal aspect ratio (~0.1) and outlet extensions (~2H) can increase mass flow by up to 65% and reduce maximum panel temperature by around 11%. Taken together, the results indicate that both surface radiative properties and channel geometry are effective and complementary design strategies for enhancing passive PV cooling.

3.2 COMSOL

As a commercial multi-physics platform, COMSOL Multiphysics provides a consistent framework for linking flow equations with other physical phenomena [17]; it had already been successful in turbulence studies and experimental benchmarks [39]. Practical guidelines and performance assessments show that using turbulence models and multi-phase flow modules in COMSOL gives results that converge toward reference data and meet strict numerical verification standards [40].

[41] used COMSOL Multiphysics 5.1 as the main computational platform. By employed the finite element method with tetrahedral meshing, where linear elements (P1) break up temperature and pressure fields and quadratic elements (P2) break up velocity fields. Numerical stabilization uses both streamline and crosswind methods. It also uses separate solvers and damped Newton methods to make sure that conjugate heat transfer problems converge. [42] similarly employed COMSOL software but utilizes the Galerkin Least Squares finite element method with AcuSolve Solver implementation, maintaining second-order spatial accuracy in discretizing Navier-Stokes equations for natural convection analysis around multidirectional tapered fin heat sinks

The thermal performance results showed additional details about how to cool PV panels [41] reported that ribbed microchannels achieved 1.6-1.8 times higher Nusselt numbers compared to smooth channels, maintaining solar cell temperatures below 301 K under high concentration conditions (CF = 1000), though at the cost of 2.3-3.9 times higher friction factors while, [42] achieved 8.61% temperature reduction using multidirectional tapered fin heat sinks compared to bare modules, with maximum temperatures reaching 56.73°C, demonstrating superior performance across varying wind orientations with over 10% temperature reduction in real-world conditions. These results indicate that active liquid cooling (188) provides the most precise temperature control, passive solutions [42]. Offer practical advantages in terms of maintenance requirements and energy consumption.

3.3 OPEN FOAM software:

OpenFOAM is the most flexible platform because its C++ toolbox framework provides strong solutions for complicated thermal phenomena like conduction, convection, and radiation heat transfer. There are many specialized tools in the software ecosystem, such as PALABOS for lattice Boltzmann methods in multiphase thermal flows, Elmer for coupled multi-physics thermal-structural problems, and Code_Saturne for turbulent heat transfer in industrial settings. These open-source platforms utilize finite volume and finite element discretization methods to solve the Navier-Stokes equations coupled with energy equations, enabling accurate prediction of temperature distributions and thermal boundary layer behavior. The workflow typically integrates geometry modeling tools (CAD), advanced meshing capabilities (Gmsh, Netgen), CFD simulation engines, and post-processing visualization platforms (ParaView) to deliver comprehensive thermal analysis results. Validation studies demonstrate comparable accuracy to commercial software like ANSYS Fluent, making these open-source solutions highly viable for academic research and industrial thermal engineering applications [43], [44].

3.4 MATLAB software

[32], [45] both employed MATLAB as software to investigate potential for enhancing solar energy conversion efficiency across different climatic conditions by implementing PCM as passive cooling. But [32] used transient Energy Balance by 1D lumped-parameter model, while [45] used Enthalpy method and 1D heat conduction model. With the selection of appropriate PCM melting temperatures emerging as a critical design parameter. It was shown that PCMs with lower melting points achieve superior thermal regulation and electrical performance improvements compared to higher melting point alternatives [39],[40]. Phase-change material configurations utilizing substances with transition temperatures within the 21-26°C range exhibit remarkable thermal regulation capabilities, achieving maximum photovoltaic cell temperature decreases of 27-39% while enhancing electrical performance by 5.3-6% relative to standard cooling approaches [39], [40]. The coupling of heat pipe mechanisms with PCM-based thermal control systems yields additional cooling enhancements, where RT25-integrated hybrid designs demonstrate 8.7°C temperature reductions and attain thermal efficiencies of 48.9% during summer operational periods [39]. Comprehensive optimization studies across multiple hot climate zones, including locations in Pakistan, India, and the United States, have validated that RT21 PCM consistently outperforms higher melting point alternatives (RT35, RT42, RT44) in terms of electrical output enhancement, achieving improvements of up to 16% in power generation while maintaining optimal thermal regulation [40]. These results collectively demonstrate that strategic PCM selection, informed by local climatic conditions and operational temperature ranges, constitutes a feasible approach for passive photovoltaic thermal management. This method yields significant performance enhancements through efficient heat dissipation and temperature stabilization mechanisms that maintain semiconductor junction efficiency under heightened solar irradiance conditions.[39], [40].

3.5 Finite Element Method (FEM)

The Finite Element Method (FEM) is a powerful framework for 3-D thermal analysis of photovoltaic (PV) modules, providing high-fidelity resolution of coupled heat-transfer processes and spatial temperature fields that underpin the assessment and optimization of cooling strategies. In FEM-based thermal models, the multilayer PV stack is meshed into finite elements and the transient heat equation

It is solved over the domain, with α the thermal diffusivity, Q the volumetric heat source and ρ, cp material properties assigned per layer (glass, EVA, silicon cells, back sheet) to capture spatial heterogeneity. State-of-the-art implementations treat Multiphysics coupling by resolving conduction through the stratified materials, applying natural/forced convection boundary conditions informed by Reynolds- and Nusselt-number correlations, and modeling radiative exchange with the sky and ground via view factors and surface emissivities—together enabling predictive evaluation of cooling performance under realistic operating scenarios. The computational accuracy of FEM approaches depends critically on mesh quality, with typical implementations requiring element sizes on the order of millimeters to capture thermal gradients accurately, particularly at material interfaces where thermal resistance concentrations occur. Three-dimensional FEM models enable comprehensive evaluation of cooling system configurations, including heat sink geometries, fluid flow patterns in liquid cooling systems, and phase change material integration, providing detailed temperature field predictions with spatial resolutions unattainable through simplified modeling approaches. Recent studies demonstrate FEM's capability to predict hot-spot formation, thermal stress distributions, and cooling system optimization parameters, with validation studies showing agreement within 3-5% of experimental measurements when appropriate boundary conditions and material property temperature dependencies are incorporated [42], [46].

4. Limitations of numerical studies

Simplified analytical and lumped-parameter models require negligible computational resources and can be solved within seconds, making them suitable for preliminary assessments; however, they fail to capture spatial temperature gradients and detailed heat transfer mechanisms. In contrast, two-dimensional CFD models provide a reasonable balance between accuracy and efficiency, typically involving tens of thousands of mesh elements and moderate simulation times, while still neglecting some three-dimensional flow and thermal effects. Fully transient three-dimensional CFD models, particularly those incorporating phase change materials and advanced radiation schemes, impose significantly higher computational demands, often requiring hundreds of thousands to millions of mesh elements, small time steps, and high-performance computing resources, resulting in simulation times extending from several days to months. Consequently, because of PCM or heat-pipe physics (strongly nonlinear latent heat, moving melt fronts, or coupled conjugate heat transfer) increases stiffness and DOFs, the choice of numerical approach represents a trade-off between accuracy and computational cost, highlighting the importance of selecting an appropriate model complexity based on the objectives and available computational resources of the study. [16], [17], [18], [27], [36], [42], [46]

Conclusion

- Theoretical and numerical investigations provide good value for cost-effective and powerful tools for optimizing solar cooling technologies, enabling systematic parametric analyses and accurate performance predictions while minimizing dependent on expensive experimental prototyping.
- This review highlights the most common study use of Reynolds-Averaged Navier–Stokes (RANS) turbulence models, particularly the k–ε and k–ω formulations, for simulating photovoltaic cooling systems.
- These models are widely implemented within advanced computational platforms, including ANSYS Fluent, COMSOL Multiphysics, OpenFOAM, and MATLAB, which support coupled thermo-fluid simulations, multiphasic integration, extensive parametric studies, and control-oriented modeling frameworks.
- Despite their effectiveness, inconsistencies in modeling assumptions, boundary conditions, and validation approaches significantly limit the comparability and reproducibility of results across existing studies.
- Future research should prioritize the development of standardized numerical frameworks, long-term validation against experimental and field data, climate-specific performance assessments, and the integration of techno-economic evaluations and control optimization strategies.
- Addressing these research gaps is essential to accelerate the deployment of scalable, reliable, and high-performance photovoltaic cooling solutions

Declaration of Competing Interest

The authors declare no conflicts of interest.

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