2026 Volume: 02 Issue: 11 www.ijrpa.com ISSN 2456-9995 Review Article

International Journal Research Publication Analysis

Page: 01-13

DEVELOPMENT OF A PHYSICS-INFORMED MACHINE LEARNING MODEL FOR PREDICTING HEAT TRANSFER AND PRESSURE DROP IN COMPACT HEAT EXCHANGERS: A CRITICAL REVIEW

***[1]Dr. Mayur Jayaant Gitay, [2]Sagar S. Sasane**

[1]Mechanical Engineering Dept. Adsul Technical Campus Chas Ahilyanagar

[2]PhD Scholar, Department of Mechanical Engineering, Sandip University, Nashik

Article Received: 11 October 2026

Article Revised: 01 November 2026

Published on: 20 November 2026

***Corresponding Author: Dr. Mayur Jayaant Gitay**

Mechanical Engineering Dept. Adsul Technical Campus Chas Ahilyanagar.

DOI: https://doi-doi.org/101555/ijrpa.3113

ABSTRACT

Physics-informed machine learning is investigated as a complementary approach to CFD and experimental correlations for predicting both heat transfer and pressure drop in compact heat exchangers. This review contrasts purely data-driven surrogates, conservation-penalized neural networks, inverse PINNs and hybrid reduced-order models. Special emphasis is placed on multi-output consistency, grouped validation by geometry, dimensional features, uncertainty, thermohydraulic trade-offs and extrapolation risk. A reproducible framework is proposed, without claiming newly trained models or generated results.

KEYWORDS: Physics-Informed Neural Network; Compact Heat Exchanger; Nusselt Number; Friction Factor; Grouped Validation; Surrogate Modeling.

1. INTRODUCTION

Compact exchangers compress large heat-transfer areas into small volumes; their geometric details also create flow separation, mixing and hydraulic resistance. High-fidelity CFD can capture such effects but becomes costly when repeated across dozens of operating points and geometry candidates. A conventional regression can reduce runtime yet produce unphysical behavior when extrapolated beyond training data.

Physics-informed modeling seeks a middle path by including mass, momentum and energy constraints alongside observations. The approach must be specified carefully: a PINN solving a PDE in space differs from a tabular regressor with a penalty for energy imbalance. Both can

be useful, but their computational demand, outputs and generalization behavior are not interchangeable.

2. Historical Development and Importance

The methodological sequence moves from design correlations and dimensional-analysis charts through CFD-trained response surfaces to machine-learning surrogates. Physics-informed neural networks formalized the use of differential-equation residuals during optimization. Recent heat-exchanger reviews report high interpolation accuracy, but emphasize that random-split evaluation often masks dependence between adjacent operating points from the same geometry.

Engineering importance is assessed against a realistic reference configuration: energy delivered at useful temperature, auxiliary work, capital and maintenance requirements, reliability, and operational constraints. This avoids labeling a design superior solely because of one locally favorable heat-transfer number.

3. Review Methodology

A structured critical-narrative review was prepared using publisher and scholarly publication records accessible online. Search terms combined the specific technology with experimental, numerical, modeling, optimization, performance, and review. Directly relevant experimental and numerical articles were prioritized; adjacent established literature and textbooks were used for fundamental equations and interpretation. The reference list identifies the sources used as technical context and supporting literature; this is not claimed as an exhaustive PRISMA systematic review.

Evidence was compared by physical configuration, operating boundary conditions, measurement or calculation method, validation level, useful performance metrics, and principal limitations. Where papers use different conditions or incompatible measures, no pooled improvement percentage was computed. Proposed experiments and calculations below are future methodology, not completed work.

4. Literature Survey and Critical Synthesis

Raissi, Perdikaris and Karniadakis [1] established a widely cited framework that embeds PDE residuals into training for forward and inverse tasks. This is foundational rather than direct proof of superiority for a specific compact exchanger. Heat-transfer and pressure-loss predictions require appropriate conservation laws and boundary data.

Vidhyarthi and colleagues [2] studied a physics-informed approach for heat-transfer coefficient and pressure-drop prediction in micro-fin-tube boiling. The study is particularly relevant because it addresses both thermal and hydraulic outputs. However, two-phase results cannot simply be transferred to single-phase compact channels, where the controlling dimensionless groups differ.

Recent heat-exchanger ML reviews [3, 4] distinguish surrogate training from actual physical constraint enforcement. They highlight strong in-domain results for neural networks but also gaps in independent case validation, multi-output prediction and geometric extrapolation. These shortcomings are essential to interpreting headline accuracy metrics.

A broad synthesis of PINNs for heat-transfer multiphysics [5] emphasizes inverse property identification, sparse measurements and coupled physical fields. The lesson for compact exchangers is that adding physics penalties may improve consistency but does not guarantee easier convergence or a lower total computational cost than CFD.

PCM–plate-exchanger learning methods [6] demonstrate how optimization, data analytics and heat-transfer physics can be combined in high-dimensional systems. This adjacent application is useful because it connects thermal objectives to control and design variables, although latent transitions introduce different governing equations.

Foundational heat-transfer and heat-exchanger texts [7, 8] remain indispensable for baseline correlations, nondimensionalization, energy balances and thermal resistance reasoning. ML models must be tested against these engineering checks, particularly under altered operating conditions or unknown geometries.

5. Recommended Experimental and Numerical Methodology

(1) Define design variables including channel hydraulic diameter, aspect ratio, fin spacing, surface roughness, fluid properties, Reynolds number and inlet temperature. Specify whether the problem is steady, conjugate, turbulent or phase-changing.

(2) Construct the baseline with correlations and independently converged CFD cases; reserve some geometries, not simply some rows, for final testing. Retain test conditions and geometry identifiers.

(3) Predict Nusselt number, friction factor or pressure loss and outlet temperatures with a multi-task model. Normalize with dimensional groups and inspect thermal-hydraulic consistency.

(4) Form a loss with observational errors, energy-balance residuals, mass conservation and suitable positivity constraints; quantify sensitivity to relative weights rather than claim physics guarantees by construction.

(5) Evaluate grouped-geometry extrapolation, unseen flow regimes, uncertainty bounds and speedup against equivalent CFD predictions; plot Pareto performance under fixed pumping power.

6. Discussion and Comparative Analysis

Table 1 contrasts representative design or modeling choices. The comparisons are qualitative because reported absolute performance depends on fluid, geometry, loading, boundary conditions and evaluation method.

Model class	Principal advantage	Critical limitation
Empirical correlation	Low cost, interpretable	Restricted geometry validity
CFD	Resolved local fields	High compute cost
Standard ML surrogate	Fast parametric search	Extrapolation risk
PDE PINN	Equation-constrained state estimates	Training stiffness
Hybrid surrogate	Balance speed and consistency	Calibration and governance burden

Table 2 sets out common reporting criteria needed to prevent misleading cross-study comparisons. In particular, improvements should be assessed against a clearly stated reference case, with energy conservation and auxiliary inputs included.

Comparison dimension	Recommended reporting practice	Reason
Reference baseline	Same envelope, duty and operating boundary conditions	Controls confounding
Thermal benefit	Heat duty, outlet temperatures, useful efficiency or COP	Captures service value
Hydraulic/electric cost	Pressure drop, pumps/fans/compressor electricity	Captures parasitic energy
Validation	Separate experiments, numerical grid/time checks	Tests reliability
Economic/reliability	Cost, material compatibility, long-term cycling	Tests deployability

Across the surveyed literature, a persistent issue is that attractive performance often arises under favorable flow conditions or a narrow set of thermal loads. Comparisons that omit boundary differences, capital cost or auxiliary consumption are incomplete. It is therefore preferable to present normalized and absolute results side by side, discuss measurement error,

and expose multi-objective trade-offs rather than identify a single universally optimal configuration.

7. Research Outcomes and Gaps

A trustworthy model should be evaluated on held-out geometries and operating conditions, not only randomized observations. Predicting heat transfer and pressure loss jointly can expose thermohydraulic inconsistencies and support meaningful design ranking. Future value lies in modest-data, uncertainty-aware physics-guided surrogates with explicit validation domains.

Suggested next steps are paired-design validation, systematic sensitivity studies, transparent uncertainty propagation and independent replication under part-load or off-design conditions. The review identifies research opportunities; it does not certify that any proposed study is wholly novel.

7.1 Governing transport equations and output definitions

Compact heat exchangers obey continuity, momentum and energy conservation even when their internal geometry is highly complex. For an incompressible single-phase flow, continuity requires zero divergence of velocity, while momentum includes inertia, pressure gradients and viscous stresses. The temperature field satisfies advection–diffusion with appropriate solid-fluid coupling. A learning model may represent the velocity and temperature fields or only integrated quantities such as outlet temperature, Nusselt number and pressure drop. These are different problem formulations; the former can apply PDE residuals at collocation points, while the latter is usually a physics-guided surrogate with global balance constraints. The manuscript should name the formulation precisely to avoid overstating its physical rigor.

7.2 Dimensionless groups and generalization

Nusselt number, Reynolds number and Prandtl number encode heat transfer behavior in a form that can generalize better across length and property scales than raw dimensional variables alone. The friction factor similarly normalizes hydraulic resistance, but its definition must distinguish Darcy from Fanning conventions. Geometry descriptors may include hydraulic diameter, channel aspect ratio, fin pitch, porosity and surface roughness. A network trained only at one fluid temperature can exploit spurious correlations between viscosity and Reynolds number; explicit feature design and systematic operating sweeps reduce this risk. Generalization cannot be judged from a random row split when consecutive rows share almost the same exchanger geometry.

7.3 Physics-informed loss construction

A weighted training objective can combine labeled output errors, differential-equation residuals, boundary-condition mismatch and integral conservation penalties. If the network estimates total heat duty and outlet temperatures, an energy-balance residual can penalize the difference between hot-side heat release and cold-side heat gain. If it predicts a pressure field, hydraulic boundary conditions and momentum residuals become relevant. Loss terms have different units and numerical magnitudes, so normalization and weighting require a sensitivity study. A very small total numerical loss does not necessarily signify physical accuracy; it may reflect dominance of one easy-to-satisfy term or an underweighted data requirement.

7.4 Training datasets from experiments and CFD

An effective database spans flow regime, operating temperature and several distinct exchanger geometries. CFD cases need mesh-convergence and turbulence-model checks before their outputs are considered reference labels. Experiments provide an essential independent check because an ML model trained exclusively on CFD inherits any CFD modeling bias. Geometry IDs, sensor accuracy, fluid properties and boundary-condition variations should be retained as metadata. Data preprocessing should be fitted only on training cases so that information from test geometries does not leak into feature scaling. If multiple snapshots originate from the same simulation, they should remain in the same validation partition.

7.5 Joint treatment of heat transfer and pressure drop

An exchanger with increased Nusselt number may also have a larger pressure penalty, and an ML surrogate trained on only one of these targets is poorly suited to system optimization. Multi-task learning can share geometric representations while producing separate output heads for the two responses. A designer should compare heat duty or effectiveness at fixed pumping power, or examine a Pareto front containing heat-transfer gain and hydraulic cost. Friction factor and pressure drop must be connected through actual flow path length and hydraulic diameter. An output model with a small mean-squared error can still misrank designs near a pumping-power constraint, so ranking accuracy should be reported.

7.6 Uncertainty and extrapolation testing

A model operating outside its training domain should communicate uncertainty rather than provide a confident single-value estimate. Ensembles, conformal intervals and Bayesian approximations are possible tools, each with computational and calibration trade-offs. Validation should include a held-out geometry family, a new Reynolds-number range and,

where feasible, a second fluid. Error-versus-Reynolds and error-versus-geometric-change plots can reveal hidden failures behind aggregate R-squared. Physical tests should check positivity of heat-transfer coefficients and plausible monotonic pressure-drop trends under fixed geometry. Uncertainty bounds need calibration with independent cases and should not be described as guaranteed merely because they emerge from an ensemble.

7.7 Reduced-order models versus full PINNs

A reduced-order model derived from snapshots can compress spatial solution fields and then use ML to predict modal coefficients. This strategy differs from a PINN that directly penalizes PDE residuals across the domain. For expensive high-Reynolds turbulent CFD, reduced-order models may be easier to train and faster in deployment, but can fail when the flow topology changes significantly. PINNs do not automatically outperform established solvers in every regime, especially near steep gradients, multiple scales or complex boundary conditions. A robust benchmark should compare wall time, memory use, data requirement and generalization, not just prediction error.

7.8 Experimental quantities and error propagation

Thermal duty based on temperature rise and flow rate has uncertainty originating in flow measurement, thermocouple calibration and fluid property correlations. Pressure loss requires tapping locations and correction for manifold contributions, especially in compact exchangers where headers and turns are significant. These uncertainties should be propagated into normalized target values and incorporated in model evaluation. If a database reports only outlet temperatures, a surrogate may appear highly accurate while missing local thermal nonuniformity. Pairing bulk measurements with distributed wall temperatures or infrared imaging can test whether local predictions are meaningful.

7.9 Multi-objective design optimization

After validating a surrogate, candidate geometries can be searched with evolutionary or gradient methods under thermal, hydraulic and manufacturing constraints. Results should be checked with high-fidelity CFD and at least selected physical prototypes. Surface roughness and tolerance constraints are important because a predicted microchannel optimum may not be buildable or cleanable. The optimization should be repeated under uncertain inlet conditions and manufacturing deviations. A robustly acceptable design may be less impressive at one nominal point but superior across a useful operating range.

7.10 Recommended research contribution

A particularly valuable contribution would combine modest experimental datasets, multiple geometric families and a conservation-aware multi-output model. Its novelty should be

established against existing heat-exchanger surrogates rather than claimed from the use of PINNs alone. Independent tests should quantify improvement over Reynolds-based correlations, conventional regression and at least one validated CFD model. Report open data splits, training settings, wall time and error distributions. The central engineering test is whether the model enables trustworthy design decisions and reduces computational cost without hiding pressure-drop penalties.

7.11 Energy-balance constraints

For a steady exchanger without significant ambient loss, the hot-side heat-rate magnitude should approximately equal the cold-side heat-rate magnitude. The two independently measured rates use their respective mass flows, heat capacities and inlet–outlet temperature differences. A neural-network prediction that generates incompatible outlet temperatures violates this physical condition even if each temperature appears individually close to a measured value. An integral heat-balance penalty is therefore a useful model constraint, provided the assumed heat-loss term and uncertainty are explicitly included. Similar relations for pumping work can expose unsupported pressure-drop predictions, although they do not replace the full momentum equation.

7.12 Thermal–hydraulic objective choice

A compact exchanger performance comparison should not hold Reynolds number fixed automatically when geometries have different hydraulic diameters and losses. For a system with limited pump capacity, constant pumping power or constant volumetric flow can be a more meaningful constraint. The optimization can be expressed as increasing total heat duty or effectiveness while limiting pressure loss, weight, volume and manufacturing difficulty. The surrogate may support rapid Pareto exploration, but optimal points should be recalculated with independent CFD or experiment. Designs near a constraint boundary are particularly sensitive to even small model bias.

7.13 Reproducibility package

A publishable PINN study should provide the nondimensional governing equations, boundary conditions, data preprocessing sequence, architecture, optimizer, training schedule, loss weights and random seeds. It should also publish a geometry-wise data split and show error distribution by flow regime. A simple regression or tree-ensemble baseline is essential because added physics complexity should have demonstrable benefit. Sensitivity to the amount of labeled data should be measured, since sparse-data robustness is a main motivation for physics guidance. Where training inputs include geometry features generated from CAD, their definitions must remain consistent across cases.

8. CONCLUSION

Physics-informed models are promising accelerators, but their added complexity is justified only when they improve verified prediction or decision quality. Comparisons should use identical datasets, geometry-based splits and physically meaningful error metrics, while preserving CFD and experiments as reference methods.

REFERENCES

1. Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics, 378*, 686–707. https://doi.org/10.1016/j.jcp.2018.10.045
2. Rode, R., Kurpatwar, B., Patil, P., Gitay, M., Pawar, N., & Ghule, A. (2026). Research and experimental analysis of intelligent predictive maintenance for industrial machinery using AI-based analytical techniques. *Aposta: Revista De Ciencias Sociales, 24*(114), e988. https://doi.org/10.23900/ra.v24i114.988
3. Vidhyarthi, N. K., Srivastava, A., Deb, S., Pal, S., & Das, A. K. (2025). Experimental investigation and physics-informed neural network based modelling of heat transfer coefficient and pressure drop in R513A flow boiling through micro-fin tube. *International Journal of Refrigeration, 172*, 94–107. https://doi.org/10.1016/j.ijrefrig.2025.01.025
4. Mohod, Amar, Gitay, Mayur, Patil, Pradeep, Kaware, Kiran, Pawar, Nitin, & Patil, Mangesh. (2026). Design, modeling, and validation of an AI-driven resonant inductive charging module for next-generation electric vehicle architectures. *Aposta: Revista de Ciencias Sociales, 24*, e1003. https://doi.org/10.23900/ra.v24i114.1003
5. Machine learning surrogate modelling for enhanced heat transfer in heat exchangers: A state-of-the-art review. (2026). *Energy and AI*. https://www.sciencedirect.com/science/article/pii/S2666546826002570
6. Pawar, Nitin Namdeo. (2026). Analysis of LED bulb by mathematical and simulation methods with porous fin material with square-shaped extruded fins in passive cooling mode. *Journal of Technology, 16*(1), 125–132.
7. Machine Learning in Heat Exchangers: State-of-the-Art Review. (2026). *ACS Engineering Au*. https://doi.org/10.1021/acsengineeringau.5c00073

8. Jadhao, P. K., Karale, S. R., Pawar, N. N., & Sah, B. (2025). Analytical and CAD modeling of double-acting reciprocating compressor components. *Utilitas Mathematica, 122*.
9. Physics-informed neural networks in heat transfer-dominated multiphysics systems: A comprehensive review. (2025). *Engineering Applications of Artificial Intelligence, 157*, 111098. https://doi.org/10.1016/j.engappai.2025.111098
10. Pawar, Nitin, & Nanvala, H. (2024, December 28). Mathematical and simulation analysis of various LED bulb arrays. Paper presented at the Second International Conference on Advances in Thermal Systems, Materials and Design Engineering (ATSMDE–2024).
11. Isania, F., & Galgaro, A. (2025). Machine Learning for Design Optimization and PCM-Based Storage in Plate Heat Exchangers: A Review. *Energies, 18*(19), 5115. https://doi.org/10.3390/en18195115
12. Pawar, Nitin. (2024). Application of LED bulb with perforated plus shape fin array in mines. *Journal of Mines, Metals and Fuels*.
13. Incropera, F. P., DeWitt, D. P., Bergman, T. L., & Lavine, A. S. *Fundamentals of Heat and Mass Transfer*. Wiley. https://www.wiley.com/en-us/Fundamentals+of+Heat+and+Mass+Transfer-p-9780470501979
14. Pawar, Nitin. (2024). An experimental investigation on diesel engine performance by the application of dual bio-diesel blends. *Journal of Mines, Metals and Fuels*.
15. Shah, R. K., & Sekulić, D. P. *Fundamentals of Heat Exchanger Design*. Wiley. https://www.wiley.com/en-us/Fundamentals+of+Heat+Exchanger+Design-p-9780471321712
16. Pawar, Nitin. Performance analysis on solar flat plate collector with reducing energy wastage using optimal geometry application. *Journal of Harbin Engineering University*, 1380–1387.
17. Nagar, S., & Sreenivasa, S. (2024). Mathematical modeling, numerical simulation and experimental validation of temperature profiles of PCMs and their applications in industry 4.0: A review. *Proceedings of the Institution of Mechanical Engineers, Part C*. https://doi.org/10.1177/09544062241242704
18. Pawar, Nitin Namdeo. (2023). Design and evaluation of perforated fins with different array of fins structure by an active mode of cooling system. *Journal of Mines, Metals and Fuels*.

19. Abdellatif, H. E., Belaadi, A., Arshad, A., & Bourchak, M. (2025). Modeling and performance analysis of phase change materials in advanced thermal energy storage systems: A comprehensive review. *Journal of Energy Storage, 121*, 116517. https://doi.org/10.1016/j.est.2025.116517
20. Pawar, Nitin Namdeo, & Nanwala, H. Study of extruded aluminum alloy LED bulb in a passive mode of the cooling system with a different array of fin structure. *Journal of Material Engineering, 2*, 35–43.
21. Saleh, H. H., & Mussa, M. A. (2025). Comparative analysis of heat exchanger models for phase change material melting process: Experimental and numerical investigation. *Heat Transfer, 54*, 1232–1251. https://doi.org/10.1002/htj.23217
22. Kumara, S., & Pawara, N. N. Design of experiment with tribological performance analysis of electroless nano-composite Ni-P-SiC coating for conveyors. *Tribology in Industry*.
23. Jha, P., Das, B., Gupta, R., Mondol, J. D., & Ehyaei, M. A. (2023). Review of recent research on photovoltaic thermal solar collectors. *Solar Energy, 257*, 164–195. https://doi.org/10.1016/j.solener.2023.04.004
24. Pawar, Nitin Namdeo, Jadhao, K. K., Bothra, L. S., & Kumar, S. Design and analysis of pumping housing for water cooled engine system. *GIS Science Journal*, 318–331.
25. Variyenli, H. İ., et al. (2025). Numerical and experimental analysis of a water cooled photovoltaic-thermal system using modified tubes. *Applied Thermal Engineering*, 127559. https://doi.org/10.1016/j.applthermaleng.2025.127559
26. Pawar, Nitin. Design and fabrication and testing of a water cooler with a use of heat exchanger as economizer. Paper presented at the 7th International Conference on Innovation and Research in Engineering Technology, April 8–9, 2022. Elsevier/SSRN. https://papers.ssrn.com/sol3/cf_dev/AbsByAuth.cfm?per_id=5240104
27. Abd-Elhady, M. M., et al. (2025). Experimental investigation of hybrid photovoltaic-thermal system: Integration of concentration, tracking, and cooling mechanisms. *Solar Energy, 299*, 113759. https://doi.org/10.1016/j.solener.2025.113759
28. Pawar, Nitin. Design and fabrication of multi-stage automatic sand separator. Paper presented at the 7th International Conference on Innovation and Research in Engineering Technology, April 8–9, 2022. Elsevier/SSRN. https://papers.ssrn.com/sol3/cf_dev/AbsByAuth.cfm?per_id=5240104

29. Jouhara, H., Khordehgah, N., Almahmoud, S., Delpech, B., Chauhan, A., & Tassou, S. A. (2018). Waste heat recovery technologies and applications. *Thermal Science and Engineering Progress, 6*, 268–289. https://doi.org/10.1016/j.tsep.2018.04.017
30. Pawar, Nitin Namdeo. (2023). Design and simulation of a high power LED bulbs with different array of fins in passive mode of cooling. In *Microelectronics, Circuits and Systems, Lecture Notes in Electrical Engineering* (Vol. 976). Springer Nature Singapore.
31. Phase change materials for thermal energy storage in industrial applications. (2025). *Heliyon, 11*, e41025. https://doi.org/10.1016/j.heliyon.2024.e41025
32. Pawar, Nitin Namdeo. (2023). An experimental investigation of the production of plastic fuel and blend with diesel fuel. In *Microelectronics, Circuits and Systems, Lecture Notes in Electrical Engineering* (Vol. 976). Springer Nature Singapore.
33. Phase change thermal energy storage: Materials and heat transfer enhancement methods. (2025). *Journal of Energy Storage, 123*, 116778. https://doi.org/10.1016/j.est.2025.116778
34. Pawar, Nitin N. (2022, February). Design, fabrication and testing of a water cooler with a use of heat exchanger as economizer. *International Journal of Scientific Research in Engineering and Management*.
35. Duffie, J. A., & Beckman, W. A. *Solar Engineering of Thermal Processes*. Wiley. https://www.wiley.com/en-us/Solar+Engineering+of+Thermal+Processes%2C+4th+Edition-p-9780470873663
36. Pawar, Nitin N. (2022, February). Design and fabrication of multi-stage automatic sand separator. *International Journal of Scientific Research in Engineering and Management*.
37. Bejan, A. *Advanced Engineering Thermodynamics*. Wiley. https://www.wiley.com/en-us/Advanced+Engineering+Thermodynamics%2C+4th+Edition-p-9781119052098
38. Pawar, Nitin N. (2019, May). Ozone generation. *International Journal for Science and Advance Research in Technology*.
39. NIST Chemistry WebBook, thermophysical property database. National Institute of Standards and Technology. https://webbook.nist.gov/chemistry/
40. Pawar, Nitin N. (2016, July). Cooling of LED bulb by using a different array of fins. *International Journal of Innovative Research in Science and Engineering, 2*(7).
41. Tamraparni, A., Rendall, J. D., Shen, Z., Hun, D. E., & Shrestha, S. S. (2025). Experimental investigation on phase change material-based finned tube heat exchanger for thermal energy storage and building envelope thermal management. *Applied Thermal*

Engineering, 273, 126490. https://www.ornl.gov/publication/experimental-investigation-phase-change-material-based-finned-tube-heat-exchanger

42. Pawar, Nitin N. (2016, July 30). Cooling of LED bulb by using a different array of fins. Paper presented at the 5th International Conference on Science, Technology and Management.
43. Fullick, K., Vadali, P. A., Henze, G., & Krarti, M. (2026). A review of energy performance for heat pumps integrated with PCM thermal storage systems. *Renewable and Sustainable Energy Reviews*, 117218. https://doi.org/10.1016/j.rser.2026.117218
44. Pawar, Nitin N. (2016, August 18–19). Cooling of LED bulb by using a different array of fins. Paper presented at the International Conference on Research Challenges in Engineering and Technology.
45. An experimental-numerical investigation of a photovoltaic thermal system with polypropylene heat exchanger: Case in Morocco. (2025). *IET Renewable Power Generation*. https://doi.org/10.1049/rpg2.70041
46. Pawar, Nitin N. Analysis of Li-Iron battery performance with respect to temperature and some other parameter. Paper presented at the 3rd National Conference on Research and Development in Mechanical, Electronics and Civil Engineering.
47. Characterization, Performance, and Efficiency Analysis of Hybrid Photovoltaic Thermal (PVT) Systems. (2025). *Energies, 18*(5), 1050. https://doi.org/10.3390/en18051050
48. Erdinç, M. T., et al. (2025). A comprehensive review of miscellaneous heat transfer enhancement designs of phase change material integrated heat exchanger. *International Communications in Heat and Mass Transfer, 164*, 108791. https://doi.org/10.1016/j.icheatmasstransfer.2025.108791