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DEVELOPMENT OF A PHYSICS-INFORMED NEURAL NETWORK FOR REAL-TIME PREDICTION OF HEAT EXCHANGER THERMAL PERFORMANCE: 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.

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

Mechanical Engineering Dept. Adsul Technical Campus Chas Ahilyanagar.

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ABSTRACT

This critical review evaluates pinn thermal twins as an emerging direction in mechanical engineering. Compact heat exchangers show strong coupling among conduction, convection, thermal capacity and flow conditions; temperature and flow sensors are often too sparse for reliable full-field reconstruction. The synthesis examines five linked research questions: inverse boundary-condition estimation, energy-balance residual constraints, sensor-sparse training, transient operating regimes, and performance validation. Instead of claiming new laboratory or numerical results, the paper compares methodological capabilities, limitations and validation requirements of reported and established approaches. A conceptual framework and comparative matrices are proposed for future investigations. The central conclusion is that physically meaningful baselines, leakage-resistant evaluation and uncertainty reporting are necessary before any claimed improvement can be accepted as transferable.

KEYWORDS: PINN thermal twins; mechanical engineering; modelling; validation; optimization; uncertainty; critical review.

1. INTRODUCTION

Compact heat exchangers show strong coupling among conduction, convection, thermal capacity and flow conditions; temperature and flow sensors are often too sparse for reliable full-field reconstruction. This creates a need for systematic comparison of engineering performance and practical deployability, rather than evaluation based on one favorable accuracy metric or a small number of selected cases.

The objective is to synthesize established methods and recent reported developments, clarify assessment criteria, and formulate a reproducible future study. The review considers the physical asset or material, the data acquisition or design variables, the computational method, and the validation target as a coupled system. Evidence is not treated as directly comparable when operating regimes or specimen conditions differ.

2. Historical Development and Importance

Classical effectiveness–NTU and finite-volume methods established interpretable equipment models; neural surrogates later accelerated repeated calculation; physics-informed training now combines both approaches. The historical progression is important because current computational tools should augment, not erase, the baseline physics, standardized tests and failure mechanisms established in earlier work.

Its engineering relevance lies in reducing physical prototyping or downtime while maintaining mechanical credibility. Performance must be judged by both direct outputs and implementation cost, including instrumentation, repeatability, inference resources, manufacturing variability and safety requirements. The literature remains uneven in reporting these factors.

3. Review Methodology

A focused narrative–critical review approach was adopted. Primary emphasis was placed on peer-reviewed articles and recognized technical books, supplemented by suitable engineering standards. Studies are grouped by modelling or fabrication route, performance variable, validation practice and application scale. The bibliography includes both topic-specific studies and methodological foundations; it should not be interpreted as a systematic database census.

Evidence extraction criteria include operating conditions, specimen or equipment scale, experimental controls, model inputs, test splitting, uncertainty, comparison baseline, and the extent to which governing principles are enforced. Studies lacking matched boundaries or adequate uncertainty description are treated as informative but not suitable for quantitative cross-study rankings.

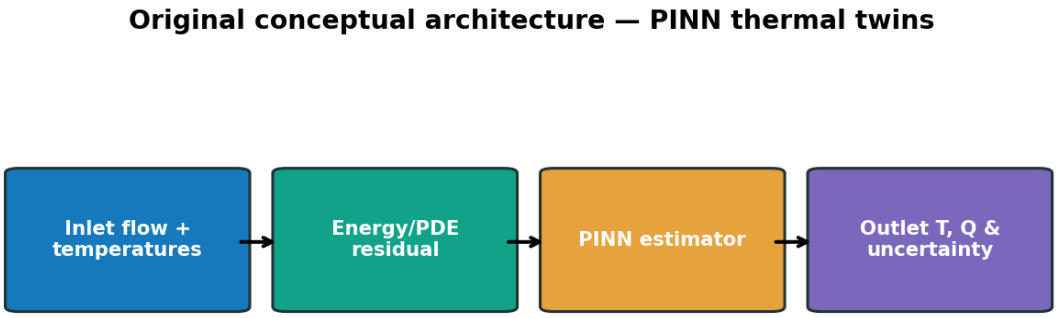

Figure 1. Original conceptual framework for pinn thermal twins (author-generated schematic).

4. Literature Survey and Critical Synthesis

Foundational modelling studies highlight the advantage of making the governing mechanisms explicit before adjusting complex algorithmic or design parameters. For pinn thermal twins, the particular issue of inverse boundary-condition estimation deserves attention. A robust investigation should identify a transparent reference baseline, document independent validation cases, report multiple performance measures and discuss whether the assumptions remain valid outside the tested range. This is especially important where large Biot-number gradients can bias the interpretation of observed differences.

Recent research increasingly combines high-dimensional sensing or design inputs with reduced-order surrogates or multi-variable analysis. For pinn thermal twins, the particular issue of energy-balance residual constraints deserves attention. A robust investigation should identify a transparent reference baseline, document independent validation cases, report multiple performance measures and discuss whether the assumptions remain valid outside the tested range. This is especially important where unknown fouling resistance can bias the interpretation of observed differences.

Experimental and industrial investigations reveal that accuracy measured on a narrow operating region is an unreliable indicator of transferable performance. For pinn thermal twins, the particular issue of sensor-sparse training deserves attention. A robust investigation should identify a transparent reference baseline, document independent validation cases, report multiple performance measures and discuss whether the assumptions remain valid outside the tested range. This is especially important where out-of-distribution flow rates can bias the interpretation of observed differences.

The mechanics–data interface remains an important source of error because discretization, material state, mounting conditions or boundary values are often uncertain. For pinn thermal twins, the particular issue of transient operating regimes deserves attention. A robust investigation should identify a transparent reference baseline, document independent validation cases, report multiple performance measures and discuss whether the assumptions remain valid outside the tested range. This is especially important where training stiffness can bias the interpretation of observed differences.

Evaluation practices vary considerably; these differences prevent a single ranking of approaches on the basis of reported percentage improvements. For pinn thermal twins, the particular issue of inference latency deserves attention. A robust investigation should identify a transparent reference baseline, document independent validation cases, report multiple performance measures and discuss whether the assumptions remain valid outside the tested range. This is especially important where large Biot-number gradients can bias the interpretation of observed differences.

A direct source anchor for the topic is as follows: Raissi et al. (2019) and Karniadakis et al. (2021) provide the governing framework for incorporating physical residuals into network training. These sources are used for their established contributions, not as evidence that the integrated research configuration has already been validated under all engineering conditions.

5. Proposed Methodology for Future Investigation

A future original research study should begin with a reproducible physical or computational reference. Define the system geometry, design factors and duty-cycle boundaries; obtain independently calibrated measurements or validated simulation reference cases; perform mesh/time-step or instrument sensitivity assessments; and divide the data by physically independent test groups. The proposed protocol is deliberately prospective: no new outcomes are claimed in this review.

The core workflow should compare a simple physical or empirical baseline, a more flexible statistical or numerical method, and a hybrid model or modified design. Include ablation studies to determine what additional value is provided by the proposed complexity. Where optimization is involved, treat conflicting objectives through Pareto analysis instead of combining them into an undocumented weighted score.

Methodological consideration 1: Inverse boundary-condition estimation should be examined under controlled shifts in boundary conditions or specimen properties. The independent test set should include the challenging case of large Biot-number gradients and the outcome

should be interpreted alongside physically plausible limits, computational expense and measurement uncertainty. Explicitly report repeatability rather than a single best trial.

Methodological consideration 2: Energy-balance residual constraints should be examined under controlled shifts in boundary conditions or specimen properties. The independent test set should include the challenging case of unknown fouling resistance and the outcome should be interpreted alongside physically plausible limits, computational expense and measurement uncertainty. Explicitly report repeatability rather than a single best trial.

Methodological consideration 3: Sensor-sparse training should be examined under controlled shifts in boundary conditions or specimen properties. The independent test set should include the challenging case of out-of-distribution flow rates and the outcome should be interpreted alongside physically plausible limits, computational expense and measurement uncertainty. Explicitly report repeatability rather than a single best trial.

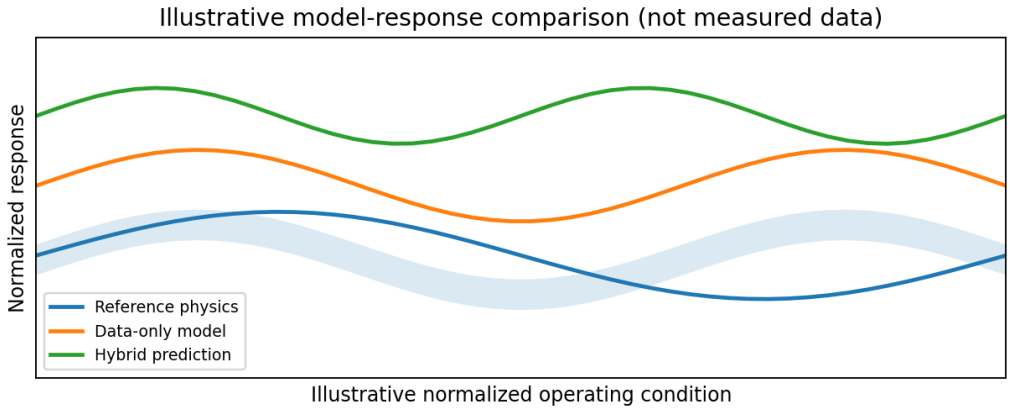

Figure 2. Original conceptual comparison or response visualization; all plotted curves are illustrative, not experimental measurements.

6. Comparative Discussion

Approach	Typical strength	Main limitation
ε–NTU/thermal circuit	Low cost; interpretable	large Biot-number gradients
FE/FV reduced order	Physics-aware representation	unknown fouling resistance
data-only neural network	Flexible nonlinear mapping	out-of-distribution flow rates
physics-informed neural network	Multi-variable capability	training stiffness

The comparison emphasizes that sophistication alone is not a measure of success. The preferred approach depends on the available data, computational budget and physical

interpretation required for a decision. For example, a simplified model may outperform a deep architecture outside its training envelope if its governing assumptions remain valid.

Assessment domain	Recommended measure	Critical reporting requirement
Primary performance	Temperature MAE	Matched baseline and independent validation
Secondary performance	Heat-duty error	Matched baseline and independent validation
Physical consistency	Energy residual	Matched baseline and independent validation
Practical deployment	Inference latency	Matched baseline and independent validation

7. Outcomes, Research Gaps and Future Scope

The literature synthesis indicates four recurring research opportunities: (i) evaluate multiple operating regimes and boundary conditions; (ii) represent uncertainty and measurement errors; (iii) compare low-complexity baselines with physics-guided or optimized alternatives; and (iv) connect performance improvement to durability, life-cycle cost or deployment constraints. These are proposed gaps requiring a systematic database-specific novelty check before submitting a new original research article.

Future experiments should pre-register the primary response variables and employ repeated tests when feasible. Dataset provenance, model code, geometry files and exclusion criteria should be documented. For application-oriented work, performance improvements should be assessed in absolute engineering units instead of relying exclusively on percentage changes.

7.1 Detailed Validation and Benchmark Design

A defensible benchmark for pinn thermal twins should make the effect of inverse boundary-condition estimation observable rather than merely inferred. The investigator should define the reference state, independent variable, measurement instrument or numerical solution pathway, uncertainty interval and acceptance criteria before executing the experiment. Whenever possible, the benchmark should contain paired cases in which only one controllable factor changes. This facilitates causal interpretation and reduces the chance that gains are attributable to large Biot-number gradients instead of the intervention. Repeated runs and independent operating states are essential for distinguishing reproducible behavior from model or manufacturing noise. Comparison with published work should only occur after normalizing units, duty conditions and baseline geometry or sample preparation.

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A defensible benchmark for pinn thermal twins should make the effect of transient operating regimes observable rather than merely inferred. The investigator should define the reference state, independent variable, measurement instrument or numerical solution pathway, uncertainty interval and acceptance criteria before executing the experiment. Whenever possible, the benchmark should contain paired cases in which only one controllable factor changes. This facilitates causal interpretation and reduces the chance that gains are attributable to training stiffness instead of the intervention. Repeated runs and independent operating states are essential for distinguishing reproducible behavior from model or manufacturing noise. Comparison with published work should only occur after normalizing units, duty conditions and baseline geometry or sample preparation.

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7.2 Mechanistic Interpretation and Evidence Quality

The inverse boundary-condition estimation question has a physical dimension as well as a statistical or procedural dimension. The first task is to identify which governing mechanism should control the response, then determine whether the selected sensors or characterization technique can observe that mechanism. For example, a predictor may correlate with an outcome but may not distinguish alternative causes when large Biot-number gradients is present. A review therefore should not interpret high cross-validation accuracy or favorable average properties as conclusive validation. Strong evidence also requires an explicit external case, documented failure examples, sensitivity to uncertain parameters and error distributions rather than just a single mean metric. Researchers should explain the conditions in which the proposed approach performs no better than the simplest baseline.

The energy-balance residual constraints question has a physical dimension as well as a statistical or procedural dimension. The first task is to identify which governing mechanism should control the response, then determine whether the selected sensors or characterization technique can observe that mechanism. For example, a predictor may correlate with an outcome but may not distinguish alternative causes when unknown fouling resistance is present. A review therefore should not interpret high cross-validation accuracy or favorable average properties as conclusive validation. Strong evidence also requires an explicit external case, documented failure examples, sensitivity to uncertain parameters and error distributions rather than just a single mean metric. Researchers should explain the conditions in which the proposed approach performs no better than the simplest baseline.

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7.3 Translating the Findings Into Engineering Decisions

For implementation, evidence on inverse boundary-condition estimation should be connected to a decision such as accepting a design, selecting maintenance timing, changing a process parameter or approving a simulation surrogate for operational use. Engineers need to know the magnitude of risk associated with a false decision, not merely the average predictive or mechanical-performance gain. A practical acceptance matrix should include Temperature MAE, the fourth metric (Inference latency), repeatability, cost of implementation, robustness to unavailable inputs and the consequences of drift. If decision thresholds are optimized on the same samples used to report success, the apparent benefit may be overstated. External replication and uncertainty-aware thresholds are therefore priorities for publishable future research.

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8. CONCLUSION

This review identifies pinn thermal twins as a promising, but methodologically demanding, route for modern mechanical engineering. The most defensible next step is a matched-baseline investigation coupling physical reasoning with independent validation, explicit uncertainties and application-specific costs. Reported benefits cannot be generalized without checking large Biot-number gradients, unknown fouling resistance and operating-range transferability. The present contribution is a structured critical synthesis and proposed framework, not a presentation of newly performed tests or simulations.

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