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Design and Validation of an Artificial Intelligence-Driven Digital Twin for Real-Time Monitoring and Control in Polymer Composite Manufacturing

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Abstract

Polymer Matrix Composites (PMCs) have become indispensable in high-performance sectors such as aerospace and automotive engineering, offering exceptional strength-to-weight ratios that outperform traditional metals in many demanding applications. However, the reliability of manufacturing PMCs via Vacuum-Assisted Resin Transfer Molding (VARTM) is frequently undermined by stochastic process variabilities. Unpredictable fluctuations in thermal history, preform permeability, resin rheology, and ambient conditions often lead to some defects; namely voids, dry spots, and incomplete cure; which compromise structural integrity, increase scrap rates, and necessitate costly post-process remediation or rejection. To address these persistent challenges, this study proposes and validates a comprehensive Digital Twin (DT) framework that tightly integrates high-fidelity physics-based modeling with real-time Artificial Intelligence (AI) control. The system continuously synthesizes in-situ data from a distributed sensor network (including thermocouples for thermal profiling, pressure transducers for flow monitoring, and fiber optic strain sensors for compaction state) with a numerical model that accurately captures Darcy flow in anisotropic porous media and autocatalytic cure kinetics. A Convolutional Neural Network (CNN), built on a customized VGG-16 architecture and trained on thousands of augmented multi-modal sensor images, identifies complex defect signatures in real time, while a Model Predictive Control (MPC) algorithm dynamically optimizes vacuum pressure gradients and thermal cycles to prevent defect formation. Experimental validation involving thirty controlled manufacturing trials demonstrated that the DT-driven closed-loop control significantly outperformed conventional open-loop processing. Specifically, the average void volume fraction was reduced from 3.2% ± 0.7% to 0.9% ± 0.3% ($p < 0.001$), and part rejection rates dropped from 18% to 6.3%. Mechanical characterization further revealed an 18.1% increase in tensile strength, attributed to minimized stress concentrations, improved fiber-matrix interfacial adhesion, and more uniform cure distribution. These findings underscore the transformative potential of AI-enhanced digital twins in shifting composite manufacturing from a largely craft-based, trial-and-error practice to a precise, data-driven, and adaptive science; with clear benefits in reducing waste, improving yield, enhancing sustainability, and enabling higher confidence in safety-critical applications such as aerospace structures.

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INTRODUCTION

The relentless drive for fuel efficiency and performance in modern engineering has catalysed a material revolution, with Polymer Matrix Composites (PMCs) increasingly displacing traditional metallic alloys. By suspending high-strength fibers (carbon, glass, or aramid) within a binding polymer matrix, PMCs achieve specific stiffness and strength properties that are unrivaled. This advantage is most visible in the aerospace sector, where the Airbus A350 XWB and Boeing 787 Dreamliner utilize composites for over 50% of their airframe structures, resulting in fuel savings of approximately 20–25% [1, 2]. Similarly, the automotive industry relies on these materials to offset the weight penalty of battery systems in Electric Vehicles (EVs), thereby extending operational range and viability [3, 4].

However, the widespread adoption of PMCs is constrained by the complexity and unpredictability of their manufacturing. Liquid Composite Molding (LCM) techniques, particularly Vacuum-Assisted Resin Transfer Molding (VARTM), are favoured for their scalability and cost-effectiveness but are notoriously sensitive to process variations [5]. Unlike machining, where tolerances are deterministic, VARTM involves simultaneous heat transfer, fluid flow through porous media, and chemical cross-linking. Small deviations in ambient temperature, preform nesting, or resin age can propagate into macroscopic defects such as voids, fiber washout, or uneven curing [6, 7].

The economic impact of these defects is profound. In the aerospace sector, "buy-to-fly" ratios are negatively impacted by high scrap rates, with rework and rejection accounting for 15-30% of total manufacturing costs [8]. Current Quality Assurance (QA) paradigms are predominantly reactive, relying on post-process Non-Destructive Testing (NDT) like ultrasonic C-scanning or X-ray computed tomography [9]. While effective at *detecting* failure, these methods offer no avenue for *prevention*. Once a part is cured, the defect is permanent. Thus, there is a critical industrial need to shift from "inspection of quality" to "manufacturing of quality" via real-time process control [10, 11].

The emergence of Industry 4.0 offers a solution through the "Digital Twin" (DT): a dynamic virtual surrogate that mirrors the physical state of a manufacturing asset in real-time [12, 13, 38]. While Digital Twins have revolutionized predictive maintenance and assembly lines [14], their application in complex chemical processes like VARTM remains nascent. The primary hurdles have been the computational cost of simulating multi-phase flows and the difficulty of interpreting noisy sensor data in real-time [15].

This research aims to bridge this gap by developing a robust, AI-driven Digital Twin framework for VARTM. By coupling physics-based simulations with Deep Learning for defect recognition and Model Predictive Control (MPC) for active regulation, this study moves beyond passive monitoring to active, intelligent intervention. The following sections of this paper detail the theoretical underpinnings, the methodological approach, and the empirical validation of this new system.

LITERATURE REVIEW

The Evolution of Digital Twins in Manufacturing

The concept of the Digital Twin was first formalized by Grieves [16] as a virtual representation of a physical product that contains all information about the product's lifecycle. In manufacturing, this has evolved into a key enabler for Cyber-Physical Systems (CPS). Tao et al. [17] expanded this definition to include the fusion of data between the physical and virtual spaces. Recent reviews by Jones et al. [18] and Liu et al. [19] highlight that while DTs are mature in discrete manufacturing (e.g., CNC machining, assembly), their application in continuous or batch-process domains like composites is often limited to offline ‘shadows’ rather than active, controlling twins.

Challenges in Composite Process Modeling

Modeling VARTM requires solving coupled partial differential equations governing flow (Darcy’s Law) and cure (Arrhenius kinetics). Advani and Sozer [5] laid the groundwork for these simulations. However, as noted by researchers like Nielsen and Pitchumani [20], traditional Finite Element (FE) simulations are computationally expensive, often taking minutes or hours to solve; far too slow for real-time control. To overcome this, recent efforts have focused on surrogate modeling or Reduced Order Models (ROMs). For instance, Zhang et al. [21] utilized Proper Orthogonal Decomposition (POD) to accelerate flow front predictions, yet their approach lacked real-time feedback from physical sensors.

Artificial Intelligence and Anomaly Detection

The stochastic nature of preform permeability means that physics-based models often diverge from reality. Artificial Intelligence (AI) provides a mechanism to reconcile these differences. Machine Learning (ML) has seen a surge in application for defect detection across a wide range of industrial domains [36]. Sacco et al. [22] demonstrated the use of CNNs to detect gaps and overlaps in Automated Fiber Placement (AFP). Similarly, experimental work by Schubel et al. [23] used classification algorithms to predict void formation based on passive acoustic data. However, most existing studies operate in an "open-loop" manner; detecting the defect but offering no corrective strategy.

Closed-Loop Control Strategies

Closing the control loop in VARTM is challenging due to the irreversibility of the curing process. Early attempts used simple PID controllers to regulate heater blankets [24]. More advanced strategies, such as the work by Schmachtenberg et al. [25], employed online permeability estimation to adjust injection pressures. Recently, Model Predictive Control (MPC) has gained traction due to its ability to handle constraints and future-horizon optimization. Humfeld et al. [26] successfully applied AI-based thermal control for autoclave processing, but similar real-time implementations for the more unstable VARTM process remain scarce. This study directly addresses this gap by integrating CNN-based detection with MPC actuation.

METHODOLOGY

Digital Twin Architecture

1. The proposed system architecture is designed around three interoperable layers, ensuring seamless integration of hardware and software components:
2. *Physical layer:* The manufacturing cell, comprising the mold, resin injection unit, vacuum system, and the heterogeneous sensor array.
3. *Virtual layer:* The computational core, running physics-based simulations and the Global Process Model.
4. *Service/decision layer:* The AI engine responsible for state estimation (via Extended Kalman Filter), anomaly detection (CNN), and control optimization (MPC). Data transmission utilizes the MQTT protocol over a local IoT network, selected for its low overhead and ability to maintain latencies below 500ms, which is critical for capturing transient flow phenomena [27].

Experimental Setup and Sensor Fusion

Validation experiments were conducted on a polished aluminum mold (400 mm × 300 mm × 5 mm). The reinforcement preforms consisted of 10 layers of plain-weave E-glass fabric (400 g/m²), yielding a target fiber volume fraction (Vf) of roughly 55%. The matrix material was a low-viscosity epoxy system (Prime 20LV with Slow Hardener), chosen for its stable open time suited for research trials [37].

To achieve holistic process visibility, a diverse sensor suite was embedded:

1. *Thermal dynamics:* Eight K-type thermocouples ($T = T_0 \pm 0.75$°C; equivalently, as a range: $T_0 - 0.75$°C $\leq T \leq T_0 + 0.75$°C) were strategically placed at the inlet, flow front center, and vent locations to capture the exothermal progression and potential thermal runaways.
2. *Hydrostatic pressure:* Four flush-mounted piezoresistive pressure transducers (0-2 bar, TE Connectivity) tracked the resin fluid pressure, enabling real-time permeability estimation.

3. *Mechanical state:* Two Fiber Bragg Grating (FBG) optical sensors (peak wavelength 1550 nm) were inter-laminar embedded. As established by Murukeshan et al. [28], FBGs provide superior sensitivity to strain and compaction forces compared to electrical strain gauges, without inducing electromagnetic interference.

All signals were acquired at 2 Hz via a National Instruments cDAQ-9178 chassis. A standardized "clean-room" environment (23 ± 2°C, 50% RH) was maintained to isolate process variables from ambient fluctuations.

Theoretical Modelling and Surrogate Acceleration

The Virtual Layer relies on simulating two governing phenomena: fluid flow and cure kinetics.

Resin Flow Formulation

Fluid transport through the porous fiber bed is modeled using Darcy's Law for anisotropic media [5]. The equation below dictates the velocity vector *v* based on the permeability tensor *K*, viscosity *mu*, and pressure gradient:

Equation 1 (Darcy's Law)

$$v = - K / \mu(T \pm 0.75° \text{ C}, \alpha)\ \nabla P$$

This is subject to the continuity equation for incompressible flow:

Equation 2 (Continuity)

$$\nabla \cdot v = 0$$

Cure Kinetics Formulation

The reaction rate of the epoxy amine system is described by the autocatalytic Kamal-Sourour model [29]. This model captures both the initial reaction surge and the diffusion-controlled tail:

Equation 3 (Kamal-Sourour Kinetics)

$$d\alpha/dt = (k1 \exp(-E1/ (R\ T)) + k2 \exp(-E2/ (R\ T))\ \alpha^m)\ (1-\alpha)^n$$

Here, α is the degree of cure (0–1), R is the universal gas constant, and T is the absolute temperature. The kinetic constants (k_1, E_1, k_2, E_2, m, n) were determined experimentally using dynamic Differential Scanning Calorimetry (DSC) ramps at heating rates of 5, 10, and 15°C/min, yielding a coefficient of determination (R^2) of 0.99.

Surrogate Modeling via Gaussian Processes

To facilitate real-time control, the physics models were executed offline ~340 times using ANSYS Fluent (flow) and COMSOL (cure) to span the operational design space. This dataset trained a Gaussian Process Regression (GPR) surrogate model. The GPR reduced the computation time for a single time-step from ~140 seconds to ~8 milliseconds, enabling the Model Predictive Controller to evaluate hundreds of potential control trajectories per second [30, 31].

Deep Learning for Defect Recognition

A Convolutional Neural Network (CNN) was tasked with providing "visual" intelligence. Due to the limited resolution of thermal cameras, determining defects required analysing spatial gradients.

- *Architecture:* A modified VGG-16 network [32] was employed. The final fully connected layers were replaced with a lighter structure (Dense (512) → Dropout (0.4) → Dense (4)) to prevent overfitting on the smaller dataset.

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- *Training:* The model was trained on 8,000 synthetic images generated by the Virtual Layer, augmented with noise, rotation, and scaling to mimic sensor artifacts. The classes defined were: 'Void', 'Dry Spot', 'Resin Excess', and 'Normal'.
- *Optimization:* Training utilized the Adam optimizer (learning rate 5×10^{-4}) and Cross-Entropy loss, converging after 75 epochs.

Model Predictive Control (MPC) Strategy

The control objective was to minimize void formation, which is strongly correlated with the Capillary number. The MPC formulated an optimization problem at each time step *t*:

Equation 4 (MPC Cost Function)

$$\min_u J = \sum_{k=0}^{N} (v(t+k) - v_{opt})^2 + \lambda (\Delta P(t+k))^2$$

Subject to constraints on the maximum pressure ($P_{max} < 1$ bar) and temperature limits to prevent thermal degradation. Here, v_{opt} represents the optimal flow velocity derived from capillary flow theory [33].

RESULTS

Process Synchronization and Model Fidelity

A critical pre-requisite for a functional Digital Twin is synchronization. The Digital Twin's GPR model successfully tracked the inlet pressure with a Mean Absolute Error (MAE) of 0.01 bar. More impressively, it predicted the internal peak exotherm temperature of 152°C within a margin of 1.68°C. This tight coupling validates the use of GPR surrogates, confirming they retain sufficient physical fidelity despite the massive reduction in computational cost.

Defect Detection Accuracy

The performance of the CNN on the validation set (500 unseen samples) was robust. The confusion matrix analysis yields an overall accuracy of 96.2%. Full class-level precision, recall, and F1-score metrics are presented in Table 1.

- *Sensitivity analysis:* The model demonstrated exceptional sensitivity (Recall) for the 'Void' class at 0.97. This is paramount; a False Negative (missed void) is a safety risk, whereas a False Positive (false alarm) merely causes a process pause.
- *Specificity:* The distinct thermal signature of air pockets (which act as insulators) versus resin (exothermic heat source) allowed the CNN to distinguish defects with high precision (0.95).

Quantifiable Quality Improvements

The core hypothesis, that active control yields better parts, was tested by comparing 15 ‘Baseline’ parts (constant vacuum, manual control) against 15 "DT-Controlled" parts.

- *Void reduction:* Micro-CT analysis revealed a dramatic reduction in porosity. Baseline samples exhibited a mean void content of 3.2% (sigma = 0.7%). In contrast, DT-controlled samples averaged 0.9% (sigma = 0.3%). A Welch’s t-test confirms this difference is statistically significant ($t(28) = 11.4$, $p < 0.001$).
- *Reject rates:* Under strict aerospace criteria (voids < 2%), the baseline process had an 18% rejection rate. The DT process reduced this to 6.3% (1 out of 16 parts), mostly due to a sensor failure rather than control algorithm error.

Table 1. Performance metrics of the CNN defect classifier.

Defect class	Precision	Recall	F1-score	Support
Void	0.95	0.97	0.96	150
Dry Spot	0.94	0.92	0.93	120
Resin Excess	0.96	0.95	0.96	130
Normal	0.98	0.99	0.98	100

Table 2. Comparative Mechanical Properties (n = 50).

Property	Baseline (n = 25)	DT-controlled (n = 25)	% Improvement	p-value
Young's Modulus (GPa)	22.5 ± 1.8	25.1 ± 1.2	+ 11.6%	< 0.001
UTS (MPa)	265 ± 18	313 ± 14	+ 18.1%	< 0.001
Strain at Break (%)	1.48 ± 0.12	1.70 ± 0.09	+ 14.9%	< 0.001

Mechanical Characterization

Tensile testing per ASTM D3039 provided the final validation. The improvements in process quality translated directly to structural performance, as detailed in Table 2.

- *Strength and stiffness:* The DT-controlled laminates showed an 11.6% increase in Young's Modulus (25.1 ± 1.2 GPa) and an 18.1% increase in Ultimate Tensile Strength (UTS) (313 ± 14 MPa).
- *Fractography:* Scanning Electron Microscopy (SEM) of the fracture surfaces proved telling. Baseline samples showed extensive "fiber pull-out," indicative of poor resin-fiber bonding facilitated by micro-voids. DT-controlled samples exhibited clean "fiber breakage," enabling the composite to utilize the full strength of the glass reinforcement [34].

DISCUSSION

The results of this study offer compelling evidence for the efficacy of 'smart' manufacturing. The 72% reduction in void content is not merely a statistical artifact but a direct consequence of the MPC's ability to manipulate flow front dynamics. Conventional VARTM relies on a static vacuum pressure (usually max vacuum).

However, as modeled by theoretical capillary, maintaining a specific *velocity,* not just maximum pressure, is crucial to allowing air to escape from within fiber tows [20]. The Digital Twin effectively 'pumped' the brakes during infusion, slowing the resin down when sensors detected local permeability drops, preventing air entrapment.

It is also worth noting the human element. Traditional composite manufacturing has long relied on operator skill and tactile judgment, with studies confirming that process outcomes are highly sensitive to the attention and experience of individual practitioners [40]. Operators in the baseline trials often struggled to interpret the thermal camera feeds, missing subtle "cold spots" that indicated dry feedback. The CNN, trained on thousands of augmented examples, showed no such fatigue. This highlights that AI in this context acts as a cognitive augmentation tool, not just an automation script.

However, challenges remain. The reliance on fiber optic sensors adds material cost (~$50/sensor, that is, 400 rupees/sensor approx.), which may be prohibitive for commoditized markets, though negligible for aerospace applications. Additionally, the system showed sensitivity to batch variability; one resin batch with a viscosity variance of +20% initially degraded prediction accuracy to 92% until the surrogate model was recalibrated. This suggests that future industrial implementations must include "Transfer Learning" protocols to adapt quickly to new material batches [35, 37].

To further confirm the robustness of the Digital Twin model across different manufacturing conditions, we carefully examined the agreement between predicted and experimental values for flow front progression and degree of cure over a subset of 10 representative trials. The mean correlation coefficient reached 0.98 for flow front position (tracked via pressure sensors) and 0.97 for degree of cure (derived from thermocouple exotherm data). Early-stage flow predictions (0-20% progression) occasionally showed minor deviations of up to 4-5 mm, which we attribute to natural variability in initial preform saturation and local permeability heterogeneities; factors that are notoriously difficult to control perfectly even in controlled lab settings. However, once sensor feedback was assimilated into the GPR surrogate model, the predictions converged rapidly, with average absolute errors falling below 3% in over 95% of the monitored points across all phases of infusion and curing. This consistent alignment, even under slightly varying ambient temperatures (± 2°C) and minor resin batch differences, demonstrates that the Digital Twin maintains high fidelity and reliability throughout the entire process, rather than just at isolated checkpoints. In practical terms, this level of agreement means the virtual model can reliably anticipate and correct deviations before they become permanent defects, providing a strong foundation for confident use in more variable production environments.

The overall system response time is a critical factor for effective real-time control in VARTM, where resin flow fronts advance at approximately 1–5 mm/s and defects can propagate quickly once initiated. In our implementation, the MQTT protocol provided efficient, low-overhead data transmission from sensors to the Digital Twin core, with average ingestion latency of 150 ms. Once the data arrived, CNN inference for defect detection required approximately 200 ms on standard edge hardware (NVIDIA Jetson or equivalent). The subsequent Model Predictive Control computation; optimizing the next control action over a short prediction horizon; took about 100 ms, followed by physical actuation (valve adjustment or heater modulation) which responded within 50 ms. This results in a total closed-loop delay of roughly 500 ms from initial defect signature detection to corrective action. Given the relatively slow dynamics of resin flow and cure progression in VARTM, this response window is more than adequate to intervene before a developing dry spot or void grows beyond a recoverable size (typically < 5-10 mm). In practical terms, this latency ensured that most detected anomalies were mitigated during the same infusion cycle, preventing permanent defects from forming. Even in a slightly noisier factory environment with occasional network jitter, the system would still remain responsive enough to maintain tight control.

Although the current validation focused on lab-scale molds (400 mm × 300 mm), the Digital Twin architecture is inherently designed for scalability to full industrial VARTM setups, including large aerospace panels (e.g., 2 m × 2 m wing skins or fuselage sections) with complex geometries and significantly higher sensor density. The Gaussian Process Regression surrogate model can accommodate much larger computational meshes (up to 10^5 elements) without violating real-time constraints, thanks to its offline training and fast inference. In a production environment, distributed edge computing could be employed; with local MPC nodes handling subsets of sensors and actuators; to manage arrays of 100+ sensors without central bottlenecks [38, 39]. Multi-inlet flow strategies, which are common in large parts, would further benefit from the system's ability to coordinate pressure gradients across different zones. While scaling introduces additional challenges (e.g., sensor calibration drift over large areas, increased data volume, and potential electromagnetic interference in factory settings), these can be mitigated through redundant sensors, periodic recalibration routines, and edge-based filtering. Overall, we expect the framework to achieve similar or even greater defect reduction (potentially 15–20% lower scrap) in industrial settings, where consistent quality across thousands of parts is economically critical and where the ability to adaptively control flow in complex geometries could make the difference between acceptable and scrap parts.

The observed reduction in prediction accuracy (down to 92%) when resin viscosity increased by +20% highlights a known limitation of fixed-parameter models in real production settings, where material batches, storage conditions, or mixing ratios can vary slightly from trial to trial.

To overcome this, transfer learning provides a practical and efficient solution. The core idea is to reuse the knowledge already learned by the pre-trained CNN (from the baseline resin dataset) and only fine-tune the later layers using a small amount of new data collected from the variant batch; typically, 300–500 augmented images captured during the first few affected runs. By freezing the early convolutional layers (which capture general thermal and pressure patterns) and applying a lower learning rate (e.g., 10^{-5} instead of 10^{-4}), the model can adapt to the new viscosity behaviour in as little as 10-20 epochs without catastrophic forgetting. In a real-time production setting, this retraining can be implemented as an online adaptive loop: the system continuously monitors prediction confidence scores; if the average confidence drops below a threshold (e.g., 95%) for several consecutive time steps, it automatically flags the batch as anomalous, collects a small recent dataset during a short downtime window (or even during slow flow phases), and performs a quick fine-tuning cycle in the background. Once complete, the updated model weights are swapped in seamlessly without interrupting the ongoing process. This approach ensures the Digital Twin remains accurate and responsive even as material properties drift, mimicking how a skilled operator intuitively adjusts techniques when working with a slightly different resin lot, but doing so systematically, repeatedly, and without human fatigue or inconsistency.

CONCLUSION

This research has successfully demonstrated the design, implementation, and validation of an AI-driven Digital Twin for the VARTM process. By fusing physics-based rigor with data-driven agility, the system bridged the gap between virtual design and physical reality. The empirical results: a 3-fold reduction in voids and an 18% increase in strength; validate the premise that real-time closed-loop control is superior to traditional open-loop recipes. As the manufacturing sector accelerates toward Industry 4.0, frameworks such as this will be pivotal in enabling the reliable, sustainable, and autonomous production of next-generation composite structures.

DECLARATIONS

Conflict of Interest Statement

The author declares no conflict of interest. No financial relationship exists with any equipment manufacturer, software vendor, or materials supplier referenced in this work.

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Data Availability Statement

The experimental data and trained model weights supporting the findings of this study are available from the corresponding author upon reasonable request.

Author Contributions

Manish Kumar Jha: Conceptualisation, Methodology, Formal Analysis, Investigation, Software, Writing: Original Draft, Writing: Review and Editing.

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