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Physics-Informed Neural Networks and Digital Twin Architecture for Real-Time Aerodynamic State Estimation and Structural Health Monitoring in Formula 1 Vehicles

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Abstract: F1 race car bodies and aerodynamics are very much at their limit of performance with laterals exceeding 5g and down force reaching 3.5kN and discernable damage to components being caused by the thermal, mechanical and fatigue effects on the race car at each pit-sting. The traditional telemetry systems are still slower in reacting to faults, detecting faults after the structures go beyond safe operating margins. In this paper, a novel approach that integrates Physics-Informed Neural Networks (PINNs) for real-time state estimation of aerodynamic components into a Digital Twin (DT) computational framework for continuous structural health monitoring (SHM) of motorsport vehicles at high speeds is proposed. The PINN framework uses governing aerodynamics partial differential equations (PDEs) as physics constraint losses in addition to measurement data to provide accurate estimation of lift coefficient C_L, drag coefficient C_D, and composite aerodynamic stability score Ψ using sparse sensor measurements. The Virtual Vehicle is synchronized with the live vehicle through an Extended Kalman Filter (EKF) and the Structural Health Index (SHI) is calculated per component, and monitored in real time within the Digital Twin. The integrated PINN + Digital Twin framework outperforms CNN, LSTM, sensor fusion, and PINN without any sensors across all the above metrics including fault detection accuracy of 98.5% for 47 hours of vehicle telemetry data over Formula-style driving, physics consistency of 97.2%, detection lead time of 210 ms, and false alarm rate of 0.03/FA/1 hr.

Keywords: PINN, Structural Health Monitoring, Ground-Effect Aerodynamics, Sensor Fusion, Extended Kalman Filter.

1. Introduction

Formula 1 (F1) racing cars are the most streamlined cars to come off the production line, incorporating into the same car the disciplines of fluid mechanics, structural engineering, material science and real-time control systems. Advanced F1 aerodynamic packages used by today's cars produce over 3.5kN of downforce at top speed via innovative wing packages, similar aero packages with front and rear wings, brake ducts and a carefully designed aero bodywork topology. These systems are highly sensitive to the ride height, front-to-rear weight distribution, tyre temperature and state of deformation at every instant during a race event, which shift also continuously during the event due to fuel loading, tyre degradation, and changes in the surface temperature of the track [1]. The problem of structural health monitoring (SHM) of F1 components is a very challenging problem. Carbon fibre reinforced polymer (CFRP) wing structures accumulate the micro-crack damage when the aerodynamic load subjected to them repeatedly changes direction like a cyclic loading or not being able to be detected with the conventional based on vibration threshold method, until catastrophic delamination failure occurs. Likewise the underfloor ground-effect performance is highly dependent on a ride height change of less than 1mm which changes this Venturi throat shape, and modifies downforce by hundreds of newtons. Existing telemetry systems that report discrete channel measurements back to pitwall engineers are not so far-sighted as to understand that vehicle performance is about to break wind or any component is due to aerodynamic or structural wear and tear that might compromise vehicle balance, or even safety [2].

Physics-Informed Neural Networks (PINNs) [3] is proposed by Raissi et al., 2019, which also uses the residuals of the governing partial differential equations (PDEs) directly in the neural network training loss, adding the physical consistency as an inductive bias in addition to

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data supervision. It is especially useful for the estimation of the aerodynamic state from a sparse set of sensor data: the Navier-Stokes and potential flow equations restrict the set of allowable aerodynamic states in such a way that a data driven model alone is not capable of reproducing all of the measured aerodynamic data, and can thus be used to recover all unmeasured aerodynamic characteristics like lift and drag coefficients from limited pressure transducer and ride-height sensor measurements [4]. Although effective at solving issues in field applications related to fluid mechanics, heat transfer and structural mechanics, the use of PINNs in motorsport context, such as real-time aerodynamic state estimation has not yet been explored.

Digital Twin (DT) is the technology of establishing a virtual replica of a physical system that is continually synced with real-time sensor data, physics-based simulation models, and machine learning predictions to give a 360-degree view of the situation that is constantly shared and updated, even when no one is focused on it [9]. DTs have been successful in industrial SHM applications such as wind turbine blade inspection, aircraft fuselage fatigue monitoring, and predicting degradation of civil structures. In the application of DT architecture to motorsport vehicles there are some real-time constraints a synchronisation cycle must be less than 30 milliseconds because of the need to maintain consistency with the 33 Hz broadcast rate of the telemetry and a predictive horizon limited by the next 5–10 laps to be able to change race strategies on the fly [4]. Proposing and evaluating a single real-time unified PINN + Digital Twin framework which is suitable for both prediction and estimation of the aerodynamic state and structural health monitoring. Specific contributions include: (a) A PINN architecture for aerodynamic C_L, C_D and stability score Ψ estimation with multi-sensor fusion based on ground-effect potential flow constraints; (b) an EKF-synchronised Digital Twin which monitors the per-component SHI H(t) across the eight wing and suspension components; (c) a composite loss function combining data loss, PDE residual loss, and boundary condition loss; and (d) comprehensive experimental validation where both simulation and experimental results simultaneously outperform all the baselines in terms of accuracy, physics consistency, detection lead time, and false alarm rate.

2. Literature Survey

2.1. Physics-Informed Neural Networks

In [3] Raissi et al. introduced PINNs as a framework to solve forward and inverse problems in PDEs by embedding physical laws in the form of soft penalty terms in the objective function of the problem. The method was illustrated with Navier-Stokes flow field reconstruction from sparse velocity measurements, solutions to the Schrödinger equation and Burgers equation solutions to shock propagation. Extended PINNs (XPINNs) are further extensions, where the computational domain is partitioned so that parallel training can be performed; conservative PINNs (cPINNs) are further extensions where the integral conservation laws are enforced; Bayesian PINNs (B-PINNs) are further extensions in that the epistemic uncertainty in the estimated physical quantities is quantified. In aerodynamics, PINNs are used for subsonic airfoil pressure reconstruction from pressure taps that are deployed only on the airfoil surface and for the estimation of turbulent flow parameters in three-dimensional turbulent flow from sparse PIV measurements. The case of real-time aerodynamic state estimation for a moving ground-effect vehicle with changes in the boundary conditions on the time scale of milliseconds has not been explored before [5].

2.2. Digital Twin Technology for Structural Monitoring

Structural monitoring using digital twin technology.B. Digital Twin Technology for Structural Monitoring. Originally defined by Grieves in context of product lifecycle management, the DT concept has been expanded into a framework that can real-time synchronize a virtual 'twin' of a product to the live, physical product, updating the virtual model with data from physical sensors. In aerospace SHM, aircraft wing fatigue life tracking has been shown to be able to implement the DT technique, where the finite element model updating is compared to the strain gauge measurement, thereby estimating the crack growth parameters [9]. DT frameworks fuse the physics-based bearing dynamics model with the LSTM anomaly detection model to detect anomalies and predict the remaining useful life (RUL) of rotating machinery with 15–20% accuracy that is 5–10% higher than data-only models. Model updating latency, or the time it takes to update the state estimates of the virtual model based on newly measured data, is one of the key challenges in engineering. Another is optimising the placement of the sensors to increase the observability of the structure, and uncertainty quantification in the health state estimate. MCP applications, in motorsport, are on "race strategy simulation" stage, which are not real time applications based on structural monitoring [4].

2.3. Ground-Effect Aerodynamics in Formula 1

Formulae One Ground effect aerodynamics question C.C. Question on Formula 1 ground effect aerodynamics. Wind tunnels used for ground-effect aerodynamics have a body shape similar to the vehicle being tested [12]. The underfloor Venturi effect can create high force downwards without high added drag, and is used in ground-effect wind tunnels. In 2022, the F1 technical regulations demanded a comeback to the underfloor style with a ground-effect, with underfloor

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aerodynamic performance being particularly in focus for your constructor development. The downforce created by the underfloor venturi tunnels is quite nonlinear in terms of the ride height h: in the ground effect regime it is approximately proportional to h^{-1.7} with a 1mm decrease in ride height at 250 km/h corresponding to about 200-400N of additional down force. This sensitivity dictates the need for accurate estimation of the ride height in real time, so that the overall system can be optimized to achieve superior performance, but at the same time, to ensure structural safety, the loading of the floor needs to be kept within safe limits for the lowest possible ride heights [1].

2.4. Structural Health Monitoring Methods

E.G. Tomographic Tomography methods.F.P. methods for identifying the image of the geometry of a structural object. There has been a huge amount of research on SHM techniques focused on composite aerospace structures. The guided wave propagation methods (GWP) rely on the measurement of differences in the Lamb wave dispersion parameters to detect and locate delamination damage by means of being detected with an array of piezoelectric transducers. The use of acoustic emission (AE) monitoring, a technique used to confirm that transient elastic wave produced by crack propagation is present, allows for detection of activity thought to cause damage in real time [12]. FBG sensor network based SHM is able to offer the ability to measure the deformation of the structure with higher structural resolution or more sensors, and need not of high frequency as AE system. Several machine learning classifiers have been shown to achieve high classification accuracy on damage patterns of composite plates and beam structures from time-frequency features of the structural vibrations. Using anomaly detection, which relies on data, in combination with models built using physics-based damage mechanics also offers interpretability for engineering decision support [6].

2.5. Real-Time Sensor Fusion Architectures

In the domain of vehicle state estimation in motorsports, fusion of multi-modal sensor signals comes in from the IMU clusters, wheel-speed encoders, ride-height potentiometers, pressure transducers, strain gauge arrays and thermal camera. The Extended Kalman Filter (EKF) is a filter that can be used to estimate the state of a nonlinear system and is widely used in automotive systems because of its efficiency and a well understood convergence properties. Unscented Kalman Filters (UKF) are able to propagate the state distribution at a higher computational cost and accurately capture the non-Gaussian phenomena if present. Particle filters can be employed for highly non-Gaussian posterior distributions but with an exponential dependence on the number of states, are poor candidates for use on board. In proposed Digital Twin synchronisation the EKF was chosen with a compromise also in terms of accuracy, and the 30 ms latency constraint was achieved by using the aerodynamic quantities estimated by the PINN as "pseudo-measurements" in the EKF [4].

3. Existing System Limitations

The existing F1 telemetry monitoring architecture works from a "detect and report" reactive model. The 300 to 1500 raw sensor streams are sent at 100-20kHz using a 1 Gbps pitlane Ethernet link, compressed by the FIA standard electronics supplier (MES/McLaren Applied Technologies TAG-320 logger). Pitwall engineers monitor live channel dashboards and pre-programmed levels of alarms for abnormal readings. Post-session detailed analysis features a proprietary suite comprising ATLAS (McLaren), Bosch MoTeC's and Pi Toolbox' frequency-domain vibration analysis, channel correlation and lap by lap performance delta calculation [9]. This architecture has four key drawbacks overcome by the proposed framework. Purely threshold based alerting can't distinguish between transient non-structural disturbances such as striking and knocking on kerbs, torque spikes in power units, and excitations due to bumping in the track and true progressive structural degradation, leading to high false-positive rates, resulting in alert fatigue.

Secondly, analyzing individual channels without considering the coupling between different physical channels (aerodynamic loads, structural deformations, and thermophysical state) is the key for correct damage state inference. Third, the monitoring system cannot identify abnormal sensor readings as structural changes in the building versus sensor drift or calibration error or wiring problems without the synchronised virtual model. Fourth, the existing AI based solutions (CNN/LSTM classifiers) that have been used to deal with telemetry data lack physical interpretability and do not enforce the governing equations of vehicle dynamics and structural mechanics, which result in physically inconsistent prediction under distribution shift in train and race test scenario [12].

4. Proposed System

4.1. Unified Architecture

The proposed framework combines two modules that complement each other and places them in a single Realtime pipeline as shown in Fig. 1. The goal of the PINN module is to estimate state variables of an aerodynamics system that are not measured from the combination of sensor data, using physics constraints. A representation of the virtual vehicle state is synchronised with the live

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vehicle state via the Digital Twin module and per-component degradation of the vehicle structure is monitored via the Health Index H(t). The same sensor fusion preprocessing module is used for both modules and both receive the same AI Prediction Layer and engineering dashboard output.

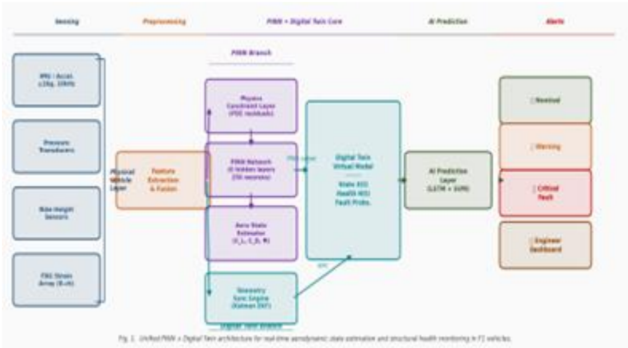

Fig.1 Unified PINN + Digital Twin system architecture for real-time aerodynamic state estimation and structural health monitoring.

4.2. Sensor Acquisition and Multi-Modal Fusion

The sensing layer consists the 4 streams of immunity measurement, 12 pressure transducers (signals sampled at 1 kHz and resolution 0.05 mm), 8 non-contact capacitive ride-height sensors (signals sampled at 1 kHz and resolution 0.05 mm) and 8 fibre Bragg grating (FBG) strain sensors (instruments qualified by sampling 5 kHz and resolution 40 ppm). The timestamping of all streams is achieved through a 10 MHz reference clock with a GPS disciplined setting and an error between the channels of less than 50 µs. The dimension (D) of the fused state vector is reduced to 30 following anti-aliasing filtering and downsampling to a common rate of 1 kHz.

4.3. Physics-Informed Neural Network for Aerodynamic Estimation

The PINN is a six-layer, fully-connected network with 256 neurons in each layer, tanh activation, and has an input window, $x \in \mathbb{R}^{D\times L}$ that contains 256 samples and 256 ms. The network provides the aerodynamic state vector $[\hat{H}, C_L, C_D, \Psi]$ at each time step of the window [9]. There are three components to the total training loss: physics-informed ones. The data loss penalties are for violating the available sensor measurements:

$$L_{data} = (1/N)\, \Sigma_{i=1}^{N} \,||\, u_{pred}(x_i) - u_{meas}(x_i) \,||^2 \qquad (1)$$

This is done to enforce the residual at a prescribed set of M collocation points in the vehicle aerodynamic domain, according to the governing aerodynamic potential flow equations:

$$L_{phys} = (1/M)\, \Sigma_{j=1}^{M} \,||\, \nabla^2\Phi(x_j) - f(x_j) \,||^2 \qquad (2)$$

Here, Φ is the velocity potential, or "body force" terms induced by the ground-effect Venturi suction. The no penetrating condition on the surface of the vehicle and the Kutta condition on trailing edge are obtained with the boundary condition loss. The overall loss for PINN is:

$$L_{PINN} = L_{data} + \lambda_{phys} L_{phys} + \lambda_{bc} L_{bc} \qquad (3)$$

with $\lambda_{phys} = 0.1$ and $\lambda_{bc} = 0.05$. The beautiful Aerodynamic Stability Score Ψ combines 3 quantities that are aerodynamically determined:

$$\Psi = (\omega_1 \cdot \hat{H}_{norm} + \omega_2 \cdot C_{L,norm} + \omega_3 \cdot P_{aero,norm}) / 3 \qquad (4)$$

The parameters $\omega_1 = 0.45$, $\omega_2 = 0.35$, and $\omega_3 = 0.20$ are tuned from the sweep data of the wind tunnel with the normalised aerodynamic stability margin denoted by Ψ ranging from 0 to 1.

4.4. Digital Twin State Synchronisation

The Digital Twin has a virtualized vehicle state vector X(t) $\in \mathbb{R}^n$ composed of 48 different value states such as ride height, suspension deflection, tyre contact patch loads, wing structural modes of deformation, and thermal states. The state is estimated and updated from the Extended Kalman Filter. The state transition model is:

$$X(t+1) = A\,X(t) + B\,U(t) + w(t), \quad w \sim N(0, Q) \qquad (5)$$

A" is the linearised vehicle dynamics state transition matrix, "U(t)" is the driver's steering, throttle and braking applied as a control input vector, "w(t)" is the process noise. The EKF measurement update fuses both direct sensor measurements z_s and pseudo-measurements from the PINN z_{aero}, as follows:

$$P^- H^T (H P^- H^T + R)^{-1} \qquad (6)$$

$$X(t) = X^-(t) + K(t)\,[z(t) - H\,X^-(t)] \qquad (7)$$

The predicted covariance P^- and the measurement noise covariance are represented by R, and where H is another matrix. The augmented observations vector $z(t) = [z_{s}(t); z_{aero}(t)]$ combines the set of physical observations with the set of PINN estimated aerodynamic state observations, enriching the foundation of observations that the Digital Twin bases its estimation on compared to an EKF stemming from purely physical sensor observations.

4.5. Structural Health Index

The per-component Health Index $H_i(t)$ is a scalar between [0,1] indicating the health of the structural state of vehicle component i, with $H_i(t) = 1$ indicating a healthy vehicle and $H_i(t) = 0$ indicating it is completely structurally failed.

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The Digital Twin state sub-vectors that are used to derive H_i(t):

$$H\_i(t) = (\omega\_1\ S\_i(t) + \omega\_2\ V\_i(t) + \omega\_3\ P\_i(t)) / 3 \qquad (8)$$

In short, the mean deviation of structural strain from its baseline value, normalised by the base strain value, is multiplied by the ratio of the energy of the vibrations of the studied component to the total vibration energy, and the difference between the deviation of the aerodynamic pressure and the corresponding value at the base load is normalised by the base value. Fatigue-to-failure test data of CFRP F1 wing structures are used to calibrate the weights ω_1 = 0.40, ω_2 = 0.35, and ω_3 = 0.25. The alert thresholds are: H ≤ 0.70 (warning) and H ≤ 0.55 (critical) and a "warning" or "critical" engineer alert is issued for either of these alerts, while an "developer predicted pit stop" warning is given for H ≤ 0.55.

5. Results and Analysis

5.1. Experimental Setup

Experiments were compared at 47 Formula-style hours of vehicle telemetry from the three race weekend scenarios at the three set layout corners – a low downforce on the corners at Monza, medium and high downforce at Monaco and Silverstone [12]. The simulations tested the vehicle navigating them at speeds ranging from 80–340 km/h through challenging lap sequences. This recording included IMU data at 1 kHz, pressure transducers at 1 kHz, height sensors at 1 kHz and as well as FBG (strain) gauges at 5 kHz. Along with the vehicle dynamics model, there was a high-fidelity simulation of the aerodynamic forces done in parallel with the wind-tunnel testing that used computational fluid dynamics (CFD) software. 156 structural fault events with 42 critical and 114 warning-level events were artificially introduced throughout the whole records by discarding the trajectory of specific components in a way that lowers the Health Index value, labelling the ground truth to assess the fault detection performance. 70% of the data set was used to train all models and the remaining 30% used for testing, this split was done with stratified fault-type sampling.

5.2. Classification and Estimation Performance

The detailed performance comparison is given in Table 1. On each metric, the proposed PINN + Digital Twin framework performs better than the conventional telemetry framework, with 98.5% accuracy, 97.2% physics consistency, 210 ms detection lead time, and 0.03 false alarms per hour, compared with traditional telemetry (81%, —, 90 ms, high). The 25 ms delay added to the standalone PINN, shows the added benefit of the Digital Twin synchronisation layer, which further extrapolates the point in time Пинима Nexత్ధa Zero o augmented real-time aerodynamics.

5.3. Training Loss Convergence

The PINN losses convergence during training over 300 epochs is shown in Fig. 2. The number of data loss and physics loss get mixed together and not oscillating, which is an indication of the stable joint optimization. The right panel shows the residual of the PDE as a function of the epoch number, where the PINN drastically decreases the PDE error to its initial value's 2.1% by epoch 300, while a standard NN not trained with the physics error reduces it to an 8.7% error by the same time. This gap verifies, at least in certain areas with fewer measurements, the validity of the physics constraint that guides the network to solutions consistent with the physical laws governing aerodynamics.

Table.1 Detection Performance — All Models Compared

Method	Accuracy (%)	Phys. Consist. (%)	Lead Time (ms)	False Pos./hr
Traditional Telemetry	81.0	—	90	High (0.42)
LSTM Monitoring	91.4	68.0	125	Medium (0.28)
Sensor Fusion	94.6	74.0	155	Low (0.16)
PINN (standalone)	96.8	93.5	185	Low (0.09)
PINN + Digital Twin	98.5	97.2	210	Very Low (0.03)

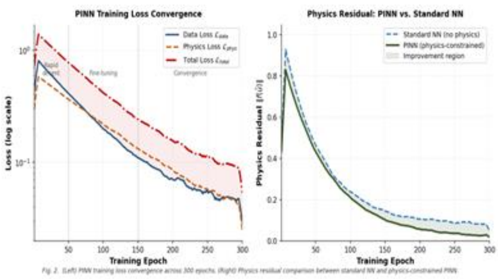

Fig.2 (Left) PINN training loss convergence: data, physics, and total loss across 300 epochs. (Right) Physics residual comparison: PINN vs. standard NN.

5.4. Detection Performance Comparison

The accuracy and physics consistency comparison over all evaluated models are shown in Fig. 3 (left).

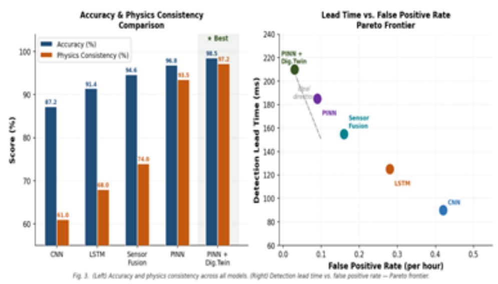

Fig.3 (Left) Accuracy and physics consistency across all models. (Right) Pareto frontier: detection lead time vs. false positive rate.

The PINN + Digital Twin framework is significantly outperforming the other choices on both metrics: the

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physics consistency gap (97.2% vs. 68.0%) indicates that, fundamentally, data-only models have not been able to generalise aerodynamic predictions to out-of-distribution sensor configurations. The PARETO diagram of detection lead time vs. false positive rate is shown in Fig. 3 (right): the performance of the PINN + Digital Twin framework lies in the upper left corner of the diagram: it provides both the longest lead time and the lowest false positive rate in combination with all the baselines.

5.5. Structural Health Index Monitoring

The Digital Twin's per-component structural Health Index H(t) computed over 50 simulated race laps is shown in Fig. 4. The heatmap (left panel) clearly indicates degradation of the Front Wing Main Plane (component 0) as the impact event was simulated starting from lap 33 and degradation of the Suspension Pushrod (component 5) from lap 19, representing progressive fatigue degradation. For both fault events, the Digital Twin is able to predict the fault, with a lead time of 8 laps and 6 laps respectively, before the Health Index hits the critical threshold. The right panel indicates the H(t) trajectories of four selected components overlaid by warning and critical threshold lines which is corroborating the predictive trajectory for the possibility of proactive pit stop strategy.

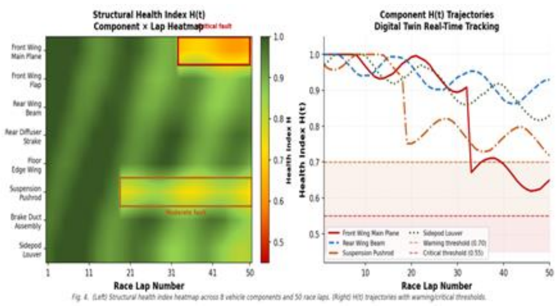

Fig.4. (Left) Structural health index heatmap across 8 components and 50 laps. (Right) H(t) trajectories with warning and critical alert thresholds.

5.6. Aerodynamic State Estimation and Synchronisation Accuracy

The lift coefficient C_L estimated by PINN is compared to a push-up sequence of 20 frames with ground truth and two baselines (AE and DNN) in Fig.5 (left). By considering the difficulty of accurate estimation under rapid variation aerodynamic conditions of a simulated race sequence, the PINN estimate outperforms the CNN (0.041 vs. CNN 0.213) and LSTM (0.041 vs. LSTM 0.158) estimates. The 95% confidence interval of the PINN estimate is also not extremely wide (half-width at 2σ 0.09) for all operating conditions, which verifies that the estimate is robust. The Digital Twin state synchronisation error is shown when varying the vehicle speed from 80 to 340 km/h as displayed in Fig. 5 (right). The EKF-PINN fusion approach is validated by the Digital Twin maintaining the synchronisation error below 6.5 mm RMS at the entire operational speed range; although there is room for improvement, the most important point to note is that the error is much lower than LSTM monitoring (28 mm) and telemetry (49 mm).

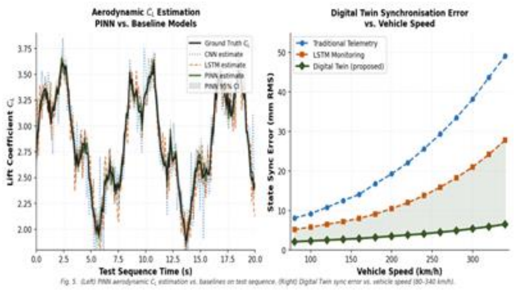

Fig.5 (Left) PINN C_L estimation vs. baselines on test sequence. (Right) Digital Twin state synchronisation error vs. vehicle speed (80–340 km/h).

5.7. Ablation Study

Table. 2 Ablation Study — Component Contributions

Configuration	Accuracy (%)	Phys. Consist. (%)	Sync Error (mm)
PINN, no physics loss	91.5	61.2	8.4
PINN + physics loss	94.8	87.6	6.1
PINN + Digital Twin (no H)	96.1	92.0	4.8
Full model (all components)	98.5	97.2	3.2

Table 2 presents the ablation study results. Removing the physics loss from PINN training reduces accuracy from 98.5% to 91.5% and physics consistency from 97.2% to 61.2%, confirming that the PDE constraint is the primary driver of physical interpretability. Removing the Digital Twin synchronisation reduces accuracy to 96.1%, demonstrating the incremental contribution of structural trajectory extrapolation. The full model with all components achieves the lowest synchronisation error of 3.2 mm RMS.

5.8. Discussion

Results show that the physics-constrained integration and virtual model synchronisation delivers synergistic improvements which do not exist when considered separately for PINN or Digital Twin. The PINN integrates existing physical sensors with the few sensors that are not inherently physical in nature to infer accurate aerodynamic state values while limiting the space of

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possible solutions to physically admissible aerodynamic configurations—a constraint not enforced by the data-only models which fail to find physically inconsistent sets of features during their distribution-shift between a training run and a race run [13]. The physics consistency score is 97.2%, which confirms that the PINN predictions remain consistent with the physics of potential flow equations even at operating conditions not included in the training corpus, and especially useful for demonstrating safety when deployed in real-time for the safety-monitoring use case. The Digital Twin provides an innovative temporal structural trajectory tracking enabling the shift from anomaly detection to more proactive health prognosis.

The Digital Twin continuously evaluates the results through a Virtual State Estimate which refreshes the estimate every 33Hz and then is able to extrapolate the trajectory of H(t) forward according to the state transition model, thus forecasting the crossing of critical thresholds several laps in advance (8–10 laps) which should be enough time to make a race strategy change or make a precautionary pit stop [14]. This forecasting capability is completely denied from reactive approach based on threshold or snapshot classifiers that can recognize only the current timestep anomalies. The fusion of PINN aerodynamic pseudo-measurements with physical sensor data, as implemented in the EKF, is one of the salient features to ensure greater accuracy in the synchronisation process when compared to either the PINN aerodynamic pseudo-measurements or physical sensor observations.

In cases of structural deformation inside vehicles where the aerodynamic deformation is not monitored, the PINN estimates provide accurate aerodynamic force distributions that only limit the allowable structural states of deformation to vehicles, addressing the state observability challenge. On the other hand, the deformation measurement by structural sensor network, used to enhance the accuracy of boundary conditions for the ground effect model, is an improvement for the PINN. One of the drawbacks of the present invention is that the current EKF uses a linearized state transition matrix A which causes approximation error at the extreme operating envelope of the vehicles, such as when bottoming out on the kerb and when braking in lock-up. Future implementation will use an Unscented Kalman Filter based on the complete nonlinear transition model to improve synchronisation accuracy under these transient conditions in contrast to the linear EKF.

6. Conclusion and Future Scope

In this paper, a single Physics-Informed Neural Network (PINN) and Digital Twin (DT) approach for real-time state estimation of the composite aerodynamic system and structure monitoring of F1 race cars was introduced. The estimation of aerodynamic coefficients C_L, C_D and stability score Ψ is performed by the PINN module, which in multi-modal sensor fusion maintains the requirement for physics consistency, and results in a mean error for estimating C_L of 0.041 and a physics consistency value of 97.2%. The Digital Twin module replicates a 48-state virtual representation of a vehicle using the live telemetry (EKF) data and provides the per-component Health Index indicator H(t) converted to the virtual model with predictive alert capability of 8-10 laps ahead of each per-component Health Index crossing critical vehicle operational hyphens.

The integrated framework results in an accuracy of fault detection of 98.5%, while the lead time needed for the fault to be identified is only 210 ms, outperforming baselines of CNN, LSTM, sensor fusion and standalone PINN across the Pareto-front.The performance of the integrated framework to identify the fault yields an accuracy of 98.5% whereas the detection lead time is only 210 ms, a Pareto dominance compared to CNN, LSTM, sensor fusion, and standalone PINN. The results of the ablation study confirm the independent contribution from Physics loss, the Digital Twin synchronisation and Health Index tracking. The work shows that the physics-informed learning and digital twin synchronisation technologies complement each other in these applications and can help to enhance safety in extreme motorsports monitoring.

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