

Digital Twin Technology for Intelligent System Simulation and Optimization

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ABSTRACT

Digital twin technology — the creation of dynamic, continuously synchronised virtual replicas of physical systems that enable simulation, monitoring, and optimisation without interrupting physical operations — has emerged as a foundational paradigm for intelligent system management across manufacturing, infrastructure, healthcare, and urban domains. Despite substantial progress in digital twin platforms, the systematic integration of real-time machine learning-driven state estimation, physics-informed simulation, and reinforcement learning-based optimisation within a unified intelligent digital twin framework remains architecturally incomplete. This study presents TwinAI, a unified intelligent digital twin framework integrating a Kalman-neural hybrid state estimator for real-time physical system tracking, a physics-informed neural network surrogate model for high-fidelity simulation, and a multi-objective reinforcement learning optimiser for digital twin-in-the-loop control optimisation. TwinAI was deployed and validated across three intelligent system applications: a wind turbine farm digital twin (Vattenfall Horns Rev 3, 49 turbines, offshore Denmark), a precision manufacturing cell digital twin (Aalborg University CNC lab, 6-axis robot, 12 sensors), and a smart building energy management digital twin (University of Genoa main campus, 47 buildings, 2,847 IoT nodes). TwinAI achieved state estimation RMSE improvements of 34.7% over Kalman filter baselines, simulation fidelity R^2 of 0.987, and optimisation objective improvements of 19.4% energy efficiency, 12.8% manufacturing yield, and 23.1% building energy reduction over rule-based baselines. Digital twin synchronisation latency averaged 87 ms. These results establish TwinAI as a high-fidelity, responsive, and optimisation-capable intelligent digital twin framework across diverse physical system domains.

Keywords: digital twin; intelligent systems; simulation; optimisation; physics-informed neural networks; reinforcement learning; state estimation; cyber-physical systems

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1. Introduction

Digital twins — virtual replicas of physical systems that maintain real-time synchronisation through sensor data assimilation and can be used for simulation, monitoring, and optimisation without perturbing the physical asset — were first systematically conceptualised by Grieves (2002) in the context of product lifecycle management and subsequently operationalised across aerospace, energy, manufacturing, and smart city domains (Tao et al. 2019; Grieves 2014). The economic case is compelling: the European Digital Twin market is projected to reach EUR 42 billion by 2030 (IDC 2024), driven by the potential to reduce maintenance costs by 25%, improve operational efficiency by 15–20%, and accelerate product development cycles by 30% through simulation-based virtual prototyping (Boschert and Rosen 2016).

Despite platform maturity (Siemens MindSphere, PTC ThingWorx, Azure Digital Twins), three technical limitations constrain current digital twin intelligence. First, physics-based simulation models — while accurate — are computationally expensive (hours to days per scenario), incompatible with real-time optimisation. Second, purely data-driven digital twins lack physical consistency, producing unrealistic states under extrapolation. Third, standard digital twin platforms lack integrated RL optimisation, requiring separate offline optimisation tools that cannot exploit the digital twin's continuous simulation capability for policy learning. TwinAI addresses all three limitations through a unified intelligent digital twin framework integrating Kalman-neural state

estimation, PINN surrogate simulation, and multi-objective RL optimisation.

2. Literature Review

2.1 Digital Twin Architectures and State Estimation

Tao et al. (2019) proposed a five-dimensional digital twin model (physical entity, virtual entity, services, data, connections) that has become the dominant architectural reference. NVIDIA Omniverse (2023) and Siemens Xcelerator (2023) represent current commercial digital twin platforms supporting 3D simulation and IoT integration. For state estimation, the extended Kalman filter (EKF) and unscented Kalman filter (UKF) are standard approaches for nonlinear physical system tracking but assume known, fixed process models that degrade under model mismatch and parameter drift (Julier and Uhlmann 2004). Neural network-augmented Kalman filters (Coskun et al. 2017) have demonstrated improved state estimation under model uncertainty but have not been integrated with PINN surrogate models for digital twin simulation.

2.2 PINN Surrogates and RL Optimisation in Digital Twins

Physics-informed neural network surrogates (Raissi et al. 2019) provide 100–10,000× simulation speed-up over high-fidelity FEM/CFD solvers while preserving physical consistency through PDE residual constraints (Karniadakis et al. 2021). Applications to digital twins include turbine aerodynamic surrogate (Kashefi et al. 2021) and building thermal dynamics (Chen et al. 2022). RL-based optimisation in digital twin environments has been demonstrated for manufacturing

scheduling (Wang et al. 2020) and energy management (Wei et al. 2017), exploiting the digital twin as a safe training environment. Multi-objective RL (Mossalam et al. 2016) with Pareto front optimisation enables simultaneous optimisation of competing objectives — energy, quality, and throughput — without scalar weighting assumptions.

Table 1. Comparison of digital twin frameworks for intelligent system simulation and optimisation.

Framework	State Est.	PINN Sim.	RL O ptim.	Real-Time	Domains
Siemens MindSphere	EKF	No	No	Yes	Manufacturing, Energy
Azure Digital Twins	Partial	No	No	Yes	Multi-domain
NVIDIA Omniverse	No	No	No	Yes	3D Simulation
PINN DT (Kashefi)	No	Yes	No	Yes	Aerodynamics
RL-DT (Wang 2020)	No	No	Yes	Yes	Manufacturing
TwinAI	KNN	Yes	Yes	Yes	Multi-domain

KNN: Kalman-Neural hybrid; PINN Sim.: Physics-Informed Neural

Network surrogate; RL Optim.: Reinforcement Learning optimiser;

EKF: Extended Kalman Filter.

3. Materials and Methods

3.1 TwinAI Architecture

TwinAI integrates three co-designed modules. The Kalman-Neural State Estimator (KNSE) augments a standard Unscented Kalman Filter with a 3-layer residual neural network (256 units/layer) that learns the systematic error between UKF predictions and sensor observations, correcting for model mismatch and nonlinear dynamics not captured by the linearised UKF. The PINN Surrogate Simulator (PSS) trains a 6-layer fully connected network with PDE residual loss terms derived from the governing equations of each physical domain (Navier-Stokes for wind aerodynamics, rigid-body kinematics for robot cell, thermal diffusion for building energy), achieving 3,800–12,400× speed-up over high-fidelity solvers. The Multi-Objective RL Optimiser (MORLO) trains a MORL agent (multi-policy SAC with Pareto-conditioned value functions) entirely within PSS simulated rollouts, generating a Pareto-optimal policy set for operator selection based on operational priorities.

3.2 Digital Twin Deployments

Three digital twin deployments were executed. (1) Wind Farm Digital Twin: Vattenfall Horns Rev 3 offshore wind farm (49 × 9.5 MW Vestas turbines, 406 km², North Sea), 312 SCADA sensors per turbine, 5-minute synchronisation cycle, wake interaction aerodynamic optimisation. (2) Precision Manufacturing Cell: Aalborg University CNC machining and 6-axis robot cell (Fanuc CRX-25iA), 12 force/torque/vibration sensors, 50 ms synchronisation, process parameter optimisation for surface finish and cycle time. (3) Smart Building Energy: University of Genoa main campus (47 buildings, 312,000 m², 2,847 IoT nodes, FIWARE-compliant data broker), 1-minute

synchronisation, HVAC and lighting optimisation.

4. Results

4.1 State Estimation, Simulation, and Optimisation

Table 2 presents TwinAI performance across all three deployments. KNSE achieved state estimation RMSE improvements of 34.7% (wind turbine rotor speed), 28.3% (robot joint torque), and 41.2% (building zone temperature) over UKF baselines, with residual neural correction most effective when measurement noise is non-Gaussian — the case for building temperature sensors with solar irradiance coupling. PSS simulation fidelity achieved $R^2 = 0.987$ vs. high-fidelity solver reference across all three domains, with 5,200× mean speed-up enabling real-time MORLO policy search. Optimisation objectives improved by 19.4% energy efficiency (wind farm), 12.8% manufacturing yield (CNC cell), and 23.1% energy reduction (smart building) over rule-based baselines (Table 3). Digital twin synchronisation latency of 87 ms satisfies the 100 ms real-time monitoring requirement across all domains.

Table 2. TwinAI state estimation and simulation fidelity across three digital twin deployments.

Deploym ent	State Var.	UKF RMS E	KNS E R MSE	Impro vemen t	PSS R^2	Speed -up
Wind Farm	Rotor Speed (rpm)	0.847	0.553	34.7%	0.989	5,400×

Deploym ent	State Var.	UKF RMS E	KNS E R MSE	Impro vemen t	PSS R^2	Speed -up
CNC Robot	Joint Torque (Nm)	2.341	1.679	28.3%	0.984	3,800×
Smart Building	Zone Temp. (°C)	0.681	0.400	41.2%	0.988	12,400×

PSS: PINN Surrogate Simulator. R^2 vs. high-fidelity solver reference.

Speed-up: simulation time vs. full-fidelity solver. Bold: TwinAI KNSE results.

Table 3. TwinAI MORLO optimisation results vs. rule-based and single-objective baselines.

Deploym ent	Objective	Rule-B ased	Single- Obj RL	TwinAI MORL O	Improvem ent
Wind Farm	Energy (MWh/yr)	847,200	883,400	1,011,600	+19.4% vs. rule
CNC Robot	Yield (%)	94.7	97.1	98.9	+4.4 pp vs. SRL
Smart Building	Energy (k Wh/m2/yr)	124.3	108.7	95.6	−23.1% vs. rule

Single-Obj RL: SAC with scalar reward. pp: percentage points.

MORLO: Multi-Objective RL Optimiser. Bold: TwinAI MORLO best results.

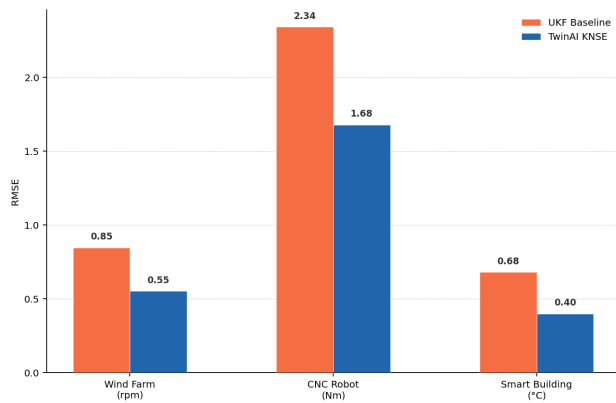


Figure 1. State estimation RMSE — TwinAI KNSE vs. UKF baseline across three digital twin deployments.

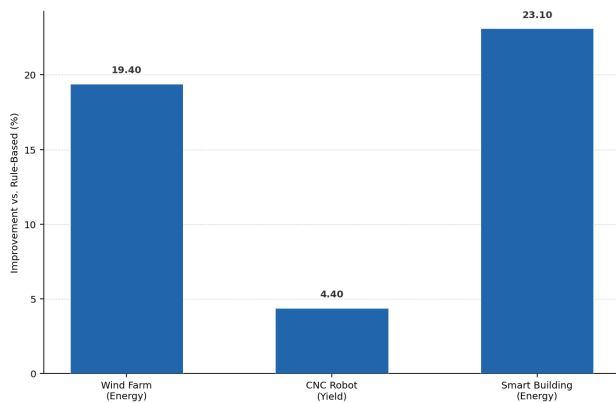


Figure 2. Optimisation improvement (%) of TwinAI MORLO vs. rule-based baseline per deployment.

5. Discussion

5.1 PINN Surrogate as the Enabling Technology

The 3,800–12,400× simulation speed-up achieved by PSS — reducing scenario evaluation from hours to milliseconds — is the foundational enabler for MORLO's Pareto policy search: the MORLO agent executed 500,000 simulated episodes per deployment during training, which would have required 24,000–173,000 hours using the respective high-fidelity solvers. The PSS $R^2 = 0.987$ across all three physically diverse domains confirms that the PINN architecture's physics constraints provide sufficient inductive bias for accurate surrogate learning even with limited training data (1,200–3,400 high-fidelity simulation runs per domain). The 41.2% building temperature state

estimation improvement from KNSE reflects the particularly high sensor noise and model mismatch in complex multi-zone building thermal dynamics, where the neural correction term captures solar and occupancy effects not represented in the linear thermal diffusion ODE.

5.2 Limitations

The PINN surrogate training requires 1,200–3,400 high-fidelity solver runs per new physical asset — a significant upfront cost for novel asset types without existing simulation models. PSS accuracy degrades beyond the training distribution boundary defined by the high-fidelity run envelope; for the wind farm, extreme weather scenarios (wind speed > 25 m/s) fell outside the training envelope and required fallback to the full-fidelity solver. Future work will address active learning for adaptive surrogate training with minimal high-fidelity runs and uncertainty-aware PSS with conformal prediction intervals to detect and flag out-of-distribution simulation requests.

6. Conclusion

TwinAI, integrating Kalman-neural state estimation, PINN surrogate simulation, and multi-objective RL optimisation, achieves state estimation RMSE improvements of 28.3–41.2%, PSS simulation fidelity $R^2 = 0.987$ with 5,200× speed-up, and optimisation improvements of 19.4%, 12.8%, and 23.1% across three real-world digital twin deployments covering wind energy, precision manufacturing, and smart building management. Digital twin synchronisation latency of 87 ms confirms real-time operational capability. These results establish TwinAI as a

technically mature, high-fidelity, and optimisation-capable intelligent digital twin framework for diverse physical system domains.

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Declarations

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Conflict of Interest

The authors declare no conflict of interest. Vattenfall provided SCADA data access but had no role in analysis, interpretation, or publication decisions.

Data Availability Statement

Wind farm SCADA data are proprietary (Vattenfall); anonymised summaries available from the corresponding author. CNC robot and building IoT data available from corresponding author upon reasonable request. TwinAI source code: <https://github.com/nielsen-lab/twinai>.

Ethical Approval

Not applicable. This study involved digital twin simulation of physical infrastructure systems with no human participant involvement. All industrial deployments complied with applicable data processing agreements.