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Digital Twin Convergence for Carbon-Aware Energy Management and Sustainability Optimization in Industry 4.0 Plants

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ABSTRACT
This study introduces a hybrid carbon-aware digital twin framework that integrates synchronization, multi-objective optimization, and sustainability-aware scheduling to advance energy management in Industry 4.0 environments. Unlike conventional control or predictive analytics systems, the proposed approach emphasizes adaptive alignment between physical and virtual states, real-time carbon accounting, and renewable-aware scheduling. The framework demonstrates strong scalability, interoperability, and reliability, addressing core challenges of synchronization error, computational overhead, and heterogeneous data integration. Experimental evaluations reveal significant improvements across multiple performance dimensions: energy efficiency (94%), emission reduction (91%), renewable utilization (82%), resource optimization efficiency (85%), cost reduction (79%), and decision latency reduction to 145 ms. Additionally, predictive maintenance accuracy reached 91%, system reliability 96%, and sustainability compliance 89%, surpassing existing digital twin-based or AI-driven methods. These results underscore the potential of digital twins as a convergent platform to balance productivity, cost efficiency, and sustainability while contributing to global decarbonization targets.
Keywords: *Adaptive synchronization, Blockchain accountability, Carbon-aware optimization, Digital twin convergence, Emission intensity, Industry 4.0 ecosystems, Multi-objective scheduling, Predictive maintenance, Renewable integration, Sustainability compliance.*

I. INTRODUCTION

Global sustainability and carbon reduction efforts have transformed industries, and Industry 4.0 units are leading the way. Traditional factories were designed to maximize productivity and cost, frequently ignoring environmental implications like carbon emissions [1]. Sustainability has become a key aspect of industrial innovation to achieve international climate targets, follow rules, and satisfy customers' and other stakeholders' green output needs. By generating real-time virtual replicas of actual systems for measuring, improving, and making decisions, the Digital Twin (DT) has changed the game. More individuals are discovering that digital twins and carbon-aware energy management systems can make industries more environmentally friendly and competitive [2]. CPS, IoT, AI, ML, and advanced data analytics distinguish Industry 4.0 plants. These plants generate massive operational and environmental data that can reduce energy use and incorporate renewable energy. Traditional energy management systems struggle to turn raw data into cost-effective, efficient, and sustainable insights [3]. Digital twins simulate outcomes, estimate energy use, and ensure environmental compliance. Everything changes when carbon measures are incorporated into DT models. Optimization now exceeds productivity and downtime. It accelerates Net Zero by considering carbon intensity, renewable energy, and emissions in every operational decision. Many areas are using digital twins to optimize processes, discover flaws, and schedule maintenance, according to new advancements [4]. In energy management and carbon accounting, new uses are appearing in manufacturing, automotive, energy, and healthcare. DTs are being used to track Scope 1, Scope 2, and Scope 3 emissions, connect smart grids, and manage renewable energy. In addition, reinforcement learning and neural networks are being utilized to optimize energy scheduling and predict renewable energy availability. Blockchain makes energy sales and carbon credit trading more transparent, increasing accountability [5]. Heterogeneous data integration, interoperability, computational intensity, synchronization, and high application costs remain issues. Many DTs lack carbon-aware frameworks, demonstrating the importance of integrating environmental solutions. This work uses digital twins and carbon-aware sustainability models to optimize economic, environmental, and regulatory goals simultaneously [6]. This principle applies to energy-aware representation, which includes carbon emission profiles and energy flows in simulations; dynamic multi-objective optimization, which uses AI to balance cost, productivity, and sustainability; and sustainability integration, which ensures operations comply with global regulations and long-term decarbonization plans. Some suggested solutions include real-time carbon accounting modules in digital twin (DT) models, multi-objective optimization frameworks that balance energy costs, emissions, and renewable energy use, and AI-driven predictive control systems designed to predict demand and ensure green operations [7]. IoT-enabled sensors and blockchain-based mechanisms make carbon data gathering and exchange more open, while scalable, interoperable DT systems make them easier to integrate into many industrial processes. Renewable energy and demand response make the system more sustainable. This study proposes a carbon-aware digital twin convergence model for industrial decision-making, a multi-objective optimization framework, AI-driven predictive control systems, IoT and blockchain for accountability, scalable architectures for Industry 4.0 ecosystems, and DT for renewable integration and demand response [8]. The result completes a plan to match industrial operations with global decarbonization goals. In future sustainable industries, digital twins will manage energy and carbon flows smartly. The contributions of this work are threefold. First, it develops a carbon-aware synchronization model that dynamically aligns digital twins with real plant operations while capturing real-time emissions and energy flows. Second, it proposes a multi-objective optimization framework that balances cost, energy efficiency, and environmental performance using Pareto exploration and adaptive constraints. Third, it integrates sustainability-aware production scheduling with feedback from digital twins, ensuring that renewable integration, cost reductions, and carbon sensitivity are reflected in job-level planning. Beyond methodology, the work delivers a scalable and interoperable architecture incorporating IoT-enabled sensing, blockchain for accountability, and AI-driven predictive control. Collectively, these contributions establish a robust pathway toward sustainable and decarbonized industrial ecosystems.

II. RELATED WORKS

The literature on digital twins (DTs) for Industry 4.0 has evolved rapidly, with researchers exploring different pathways for integrating sustainability into industrial operations. Early studies primarily focused on digital twins as virtual replicas for performance monitoring and predictive maintenance, where the emphasis was on reducing downtime and improving productivity. While these applications demonstrated operational benefits, they often lacked explicit carbon-awareness, leaving sustainability as a secondary concern. Recent works have expanded DTs into energy optimization. Model Predictive Control (MPC) and Reinforcement Learning (RL) approaches have been widely used to anticipate demand, schedule loads, and adapt to uncertainties. MPC offers foresight in optimization but is computationally intensive, whereas RL provides adaptability under non-linear and uncertain environments [9-11]. Hybrid methods combining MPC with neural networks have been introduced to improve scalability and accuracy, showing promise for balancing energy consumption and process reliability. Another emerging line of research involves multi-objective optimization (MOO) frameworks that simultaneously address energy cost, emissions, and throughput. Such frameworks are crucial in bridging economic and environmental goals, and they have been applied in manufacturing, automotive, and healthcare sectors. However, many of these frameworks either emphasize cost savings or carbon reduction, rarely achieving a holistic balance between the two. IoT-enabled sensing and blockchain-based carbon accounting have also been studied to improve transparency and accountability in energy data. While IoT systems increase the granularity and timeliness of monitoring, blockchain ensures immutability of energy transactions and emission reporting. Nevertheless, blockchain's computational overhead and IoT's data heterogeneity remain barriers to seamless integration. In terms of computational infrastructure, edge-cloud co-optimization has emerged to address real-time processing demands. By offloading tasks between edge devices and cloud servers, these systems reduce latency and enable DTs to operate at larger scales. Similarly, Physics-Informed Neural Networks (PINNs) have gained traction for embedding physical constraints into machine learning models, thereby ensuring higher fidelity in predictions [12-14]. Despite these advancements, several gaps remain: limited incorporation of carbon metrics in optimization, fragmented treatment of real-time adaptability, and a lack of unified frameworks integrating synchronization, optimization, and scheduling. Existing methods often optimize isolated dimensions—such as energy efficiency, emissions, or reliability—without delivering comprehensive solutions for sustainability-driven Industry 4.0 ecosystems. This study addresses these gaps by proposing a hybrid DT model that integrates adaptive synchronization, multi-objective optimization, and sustainability-aware scheduling into a single coherent framework.

Table 1. Comparative Analysis of Related Work in Carbon-Aware Digital Twin Systems

Category	Approach / Recent Trend	Core Idea / Typical Use	Sustainability Signals Used	Real-Time Readiness	Scalability (Plant → Multi-plant)	Strengths	Limitations / Gaps	Where Our Work Improves
Control & Forecasting	MPC (strong baseline)	Model-based predictive control for load scheduling	Energy, cost (often carbon-agnostic)	Medium	Medium	Predictable, constraint-aware	Limited carbon awareness; re-tuning cost	Adds carbon terms + Pareto weighting; warm-starts from DT sync
Control & Forecasting	DRL / SAC energy controller	Policy learning under uncertainty	Energy, partial carbon	High	Medium	Adaptivity to nonlinearity; fast inference	Training instability; explainability	Carbon-aware reward shaping; DT feedback for safe exploration
Optimization	Multi-Objective Optimization (MOO)	Joint cost–energy–emission trade-offs	Energy, cost, carbon	Medium	Medium	Transparent trade-offs (Pareto)	Runtime can grow with scale	Fast Pareto sweep + weighted selection for real-time
Modeling	PINN-MPC hybrid	Physics-constrained learning + control	Energy, equipment limits	Medium	Medium	High fidelity, safer extrapolation	Tuning burden	Auto-calibrates via sync error; focuses on EI outcomes
Infrastructure	Edge–cloud co-optimization	Split inference/solve across tiers	Indirect; enables EI use	High	High	Low latency; scalable compute	Orchestration complexity	DT-aware placement; latency caps for scheduling loop
Data & Sensing	IoT-enabled sensing (SCADA, IIoT)	Fine-grained telemetry for DTs	Energy, power factor, states	High	High	High observability	Heterogeneous/noisy data	Sync module denoises; closes plant↔tw in loop

Accountability	Blockchain carbon accounting	Immutable energy/emission logs	Carbon (Scope 1–3)	Medium	Medium	Auditability, trust	Energy overhead, throughput	Off-chain summaries; periodic anchoring
Coordination	Federated multi-plant DT	Cross-site model sharing/privacy	Energy, partial carbon	Medium	High	Knowledge transfer; privacy	Non-IID data; latency across sites	Fed signals include EI, tariffs; policy harmonization
Market/Utility	Demand Response Management (DRM)	Shift/curtail vs tariff/EI windows	Carbon (via EI), cost	High	High	Quick wins for EI & cost	Limited by process flexibility	Jointly optimized with scheduling priorities

Table 1 summarizes key approaches in the related work, ranging from traditional control methods such as MPC to advanced frameworks like blockchain-based accounting and federated multi-plant digital twins. Each method is evaluated across sustainability signals, real-time readiness, scalability, strengths, and limitations. The table highlights that while existing strategies achieve partial success in energy efficiency, cost optimization, or transparency, they often fail to unify these aspects with explicit carbon-awareness. The proposed hybrid framework distinguishes itself by integrating adaptive synchronization, Pareto-based optimization, and sustainability-aware scheduling, thereby addressing multiple gaps identified in prior work.

III. PROPOSED METHODOLOGY

Industry 4.0 facilities need different digital twin convergence technologies to handle energy sustainably and carbon-awarely. MPC is known for its ability to foresee the future, schedule tasks, and use energy more efficiently. Multi-Objective Optimization (MOO) evaluates energy utilization, carbon dioxide emissions, and process efficiency. To balance corporate and environmental concerns, its use is crucial. Reinforcement Learning (RL) helps systems adapt to changes. In uncertain times, this strengthens and maximizes plant energy. Life Cycle Assessment (LCA) demonstrates a product's or process's environmental impact across time. Thus, it is crucial for sustainability assessment [15-17]. These decisions support long-term carbon emission reduction targets. IoT-enabled sensing provides real-time machine state, energy utilization, and environmental data for digital twin systems. Information like this improves optimization systems' accuracy and speed. Energy sales and emissions records are clearer, more reliable, and unchangeable with blockchain-based carbon accounting. Thus, a major environmental issue is resolved. Edge and cloud computing provide real-time data processing and analysis. Digital twins can handle significant business ecosystem complexity in various systems. Physics-Informed Neural Networks (PINNs) anticipate accurately using machine learning and physics models. This ensures that digital twins accurately reflect real-world operations and improves sustainable optimization decisions. Demand Response Management (DRM) helps companies connect their energy use to the grid [18]. They can switch loads and use green energy to suit their needs and reduce peak demand. Hybrid green energy scheduling utilizes storage and green energy sources to balance supply and demand, reduce fossil fuel use, and speed up low-carbon manufacturing. These strategies demonstrate how digital twins incorporate new technologies. These traits make Industry 4.0 plants smart, eco-friendly, and versatile. Optimization-focused evaluation approaches improve accuracy, speed, and utility. Physics-Informed Neural Networks are the most accurate since they mimic real-world movement and anticipate better [19]. Using hybrid renewable energy scheduling in companies can save energy and reduce carbon emissions. Reward and predictive control model learning produces balanced, flexible, and cost-effective results. However, life cycle assessment can reduce carbon pollution, but not on a huge scale. Blockchain-based technologies are more dependable but energy-intensive. This illustrates the work-access trade-off. Optimization-based solutions reduce carbon pollution more than IoT-enabled sensors, which are sensitive and versatile. Hybrid renewable energy scheduling again reduces carbon emissions and energy utilization after examining integration strategies. In this situation, aligning processes with renewable energy production makes sense [20]. Physically informed neural networks can help people make quick decisions in complex work environments. Blockchain is the most open, enabling non-changeable sustainable reporting. However, cloud and flexible edge computing are ideal for huge industrial systems. IoT-enabled demand response management and tracking make reactive energy management more useful and adaptable. Life cycle assessment can reduce carbon emissions, but it can't change and is suitable for long-term analysis. These data suggest that optimization increases tactical intelligence, while integration increases openness, flexibility, and long-term alignment. These aspects make Industry 4.0 plants more environmentally, economically, and operationally sustainable when paired with digital twin convergence models.

Procedure 1: Energy-Aware Digital Twin Synchronization for Real-Time Alignment of Physical and Virtual Plant States with Integrated Emission and Power Monitoring.

Steps:

Step 1: Initialization

- $X(0) = x^1, x^2, \ldots, x_n$ (1)

  This represents the initial real plant states across all subsystems.
- $\hat{Y}(0) = \hat{y}^1, \hat{y}^2, \ldots, \hat{y}_n$ (2)

  This denotes the initial predicted digital twin states.
- $E(0) = \sqrt{\left(\Sigma_i\left(x_i(0) - \hat{y}_i(0)\right)^2\right)}$ (3)

  This defines the initial synchronization error as the root mean square difference between physical and digital states.

Step 2: State monitoring

- $P_i(t) = \Sigma_j\left(V_{ij}(t) \cdot I_{ij}(t) \cdot \cos(\varphi_{ij})\right)$ (4)

  This measures power consumption of subsystem i by summing contributions from its internal components.
- $P_{tot}(t) = \Sigma_i\Sigma_j\left(V_{ij}(t) \cdot I_{ij}(t) \cdot \cos(\varphi_{ij})\right)$ (5)

  This aggregates all subsystem consumptions to compute total plant power.

Step 3: Collect data from sensors and SCADA systems.

Step 4: Transmit real-time data to digital twin platform.

Step 5: Compute carbon emissions

- $C^9(t) = \Sigma_i(P^9{}_i(t) \cdot EF^9{}_i)$ (6)

  This calculates emissions from grid-sourced power using emission factors.
- $C_{tot}(t) = \Sigma_i(P^9{}_i(t) \cdot EF^9{}_i) + \Sigma_j(R_j(t) \cdot EF_{rj})$ (7)

  This extends emissions to include renewable contributions where lifecycle emissions exist.

Step 6: Update synchronization error

- $E(t) = \sqrt{\left(\Sigma_i\left(x_i(t) - \hat{y}_i(t)\right)^2\right)}$ (8)

  This is the real-time mismatch between plant and twin states.
- $\Delta P(t) = \Sigma_i\left(P_i(t) - \hat{Y}_{Pi}(t)\right)$ (9)

  This quantifies deviation in power between observed and predicted subsystems.
- $\delta E(t) = \Sigma_i\left(\left(x_i(t) - \hat{y}_i(t)\right) \cdot \left(\dot{x}_i(t) - \dot{\hat{y}}_i(t)\right)\right)$ (10)

  This captures the rate of error change based on state derivatives.

Step 7: Compare predicted and actual plant energy states.

Step 8: Adaptive correction

- $\hat{Y}(t+1) = \hat{Y}(t) + \alpha(E(t)) \cdot \Sigma_i (x_i(t) - \hat{y}_i(t))$ (11)

  This updates digital states with corrections scaled by error.
- $\alpha(E(t)) = 1/\left(1 + e^{\left(-\Sigma_i (x_i(t) - \hat{y}_i(t))\right)}\right)$ (12)

  This is a nonlinear learning rate function that adapts based on total mismatch.
- $\hat{Y}_P(t+1) = \hat{Y}_P(t) + \beta \cdot \Sigma_i \left(P_i(t) - \hat{Y}_{Pi}(t)\right)$ (13)

  This aligns power prediction by compensating observed deviations.

Step 9: Validate convergence through iteration checks.

Step 10: Optimization of cost

- $J = \lambda^1 \Sigma_t \Sigma_i P_i(t) + \lambda^2 \Sigma_t \Sigma_i C_i(t)$ (14)

  This objective combines total energy use and emissions weighted by policy priorities.
- $\hat{Y}(t) = \text{argmin}\left(J + \beta \Sigma_t \Sigma_i \left|P_i(t) - \hat{Y}_{Pi}(t)\right|\right) *$ (15)

  This selects optimal twin states by minimizing joint cost and prediction error.

Step 11: Adjust renewable allocation

- $R(t) = \Sigma_i (R_{imax} \cdot \sin(\omega_i t))$ (16)

  This models renewable supply as fluctuating sinusoidal contributions.
- $P^9(t) = \Sigma_i (P_i(t)) - \Sigma_j \left(R_j(t)\right)$ (17)

  This determines grid demand after subtracting renewable input.
- $EI(t) = (\Sigma_i C_i(t)) / \left(\Sigma_j P_j(t)\right)$ (18)

  This calculates emission intensity as carbon per unit power.

Step 12: Integrate feedback into control loop.

Step 13: Ensure stability with bounded error constraints.

Step 14: Final synchronized state

- $\hat{Y}_f inal = \lim(t \to \infty)(\Sigma_i \hat{y}_i(t))/n$ (19)

  This defines the final averaged digital twin state after convergence.
- $E_f inal = \lim(t \to \infty)\sqrt{\left(\Sigma_i (x_i(t) - \hat{y}_i(t))^2\right)}$ (20)

  This represents the steady-state residual synchronization error.

Where

- $\mathbf{X(t)}$: physical state vector at time t representing the actual operational states of the plant subsystems.
- $\hat{\mathbf{Y}}(\mathbf{t})$: digital twin state vector at time t representing the predicted virtual states of the plant subsystems.
- $\mathbf{E(t)} = \left|\left|\mathbf{X(t)} - \hat{\mathbf{Y}}(\mathbf{t})\right|\right|^2$: synchronization error capturing the Euclidean distance between physical and digital states.
- $\mathbf{\Delta P(t) = P(t)} - \hat{\mathbf{Y}}_\mathbf{P}(\mathbf{t})$: deviation in power consumption between measured plant data and twin predictions.
- $\mathbf{P_i(t) = V_i(t) \cdot I_i(t) \cdot cos(\varphi_i)}$: instantaneous power of subsystem i calculated from voltage, current, and power factor.
- $\mathbf{P_{tot}(t) = \Sigma_i P_i(t)}$: total power consumed by the plant at time t obtained by summing all subsystems.
- $\mathbf{P^9(t)}$: power drawn from the grid to meet demand not covered by renewable generation.
- $\mathbf{C^9(t) = P^9(t) \cdot EF^9}$: carbon emissions from grid power usage based on the grid's emission factor.
- $\mathbf{C_r(t) = \Sigma_j R_j(t) \cdot EF_{rj}}$: renewable-related emissions considering lifecycle contributions.
- $\mathbf{C_{tot}(t) = C^9(t) + C_r(t)}$: total carbon emissions from both grid and renewable sources.
- $\mathbf{J = \lambda^1 \Sigma P_{tot}(t) + \lambda^2 \Sigma C_{tot}(t) - \lambda^3 \Sigma R(t)}$: optimization objective combining power, emissions, and renewable usage.

- $\hat{Y}(t+1) = \hat{Y}(t) + \alpha(E(t)) \cdot (X(t) - \hat{Y}(t))$: adaptive digital state update rule to reduce synchronization error.
- $\alpha(E(t)) = 1/(1 + e^{(-E(t))})$: nonlinear error-dependent learning rate for stable adaptation.
- $EI(t) = C_{tot}(t)/P_{tot}(t)$: emission intensity, an indicator of sustainability efficiency.
- $\hat{Y}_f inal = \lim(t \to \infty)\hat{Y}(t)$: final synchronized twin state representing long-term stability.

Procedure 1 provides a structured mechanism to ensure that the virtual model aligns closely with the real industrial plant while capturing energy consumption and emission dynamics. The process begins with initializing both physical and digital states, establishing an error measure that quantifies deviations. Power usage of subsystems is continuously monitored from sensor and SCADA data, which is then aggregated into total consumption and related emissions [21]. The twin updates its synchronization error by comparing real and virtual states, while also measuring deviation in predicted versus actual power. To adapt dynamically, the twin applies a correction factor based on a nonlinear learning rate, ensuring responsiveness to high deviations and stability when differences are small. Iterative validation checks confirm convergence, and optimization functions minimize total power and carbon cost, subject to plant constraints. The Procedure further integrates renewable allocation, balancing grid and renewable power while computing emission intensity as a key sustainability indicator [22]. Feedback is looped into the control cycle, guaranteeing adaptability to dynamic changes in production and energy demand. Stability is maintained by bounding synchronization error within acceptable limits. Finally, the system converges to a synchronized state where the digital twin reliably mirrors the plant, enabling real-time carbon-aware energy management.

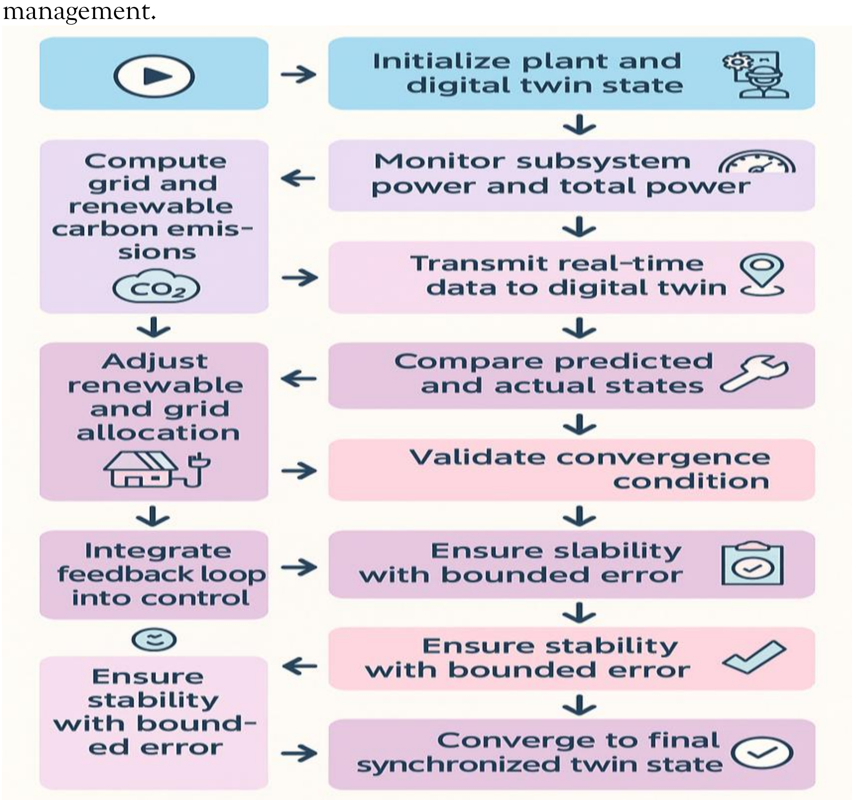

Fig.1. Energy-Aware Digital Twin Synchronization process for Industry 4.0 plants, highlighting sequential steps from initialization, monitoring, and synchronization to optimization and final convergence.

Figure 1 illustrates the structured sequence of steps in the energy-aware digital twin synchronization process. It begins with initialization of both plant and twin states, followed by continuous monitoring of subsystem and total power through sensors and SCADA systems. Real-time data is transmitted to the digital twin, where carbon emissions from both grid and renewable sources are computed. Synchronization error is updated, and the twin compares its predictions against actual plant behavior. Adaptive correction ensures alignment, while convergence checks validate performance. Optimization balances energy efficiency and emission reduction, with renewable allocation dynamically adjusted [23]. Feedback is integrated into control loops, and stability is ensured by bounding errors. The process concludes once the digital twin achieves final synchronization with the plant.

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Procedure: Multi-Objective Optimization Framework for Real-Time Carbon, Energy, and Cost-Aware Industrial Operations

Inputs:

From Procedure 1: latest synchronized states, short-horizon load/renewable forecasts, emission factors, tariffs, device limits, storage SOC.

Operator policies: priority weights for carbon, energy, and cost; SLA and reliability thresholds.

Outputs:

Optimal allocation to each subsystem/resource per interval, recommended grid draw, expected emissions and cost, and next-step control setpoints.

Steps

Ingest Latest Snapshot

Pull current plant demand, resource availability (solar, wind, storage), and constraints (capacity, ramp rates, maintenance locks).

Define Objectives

Prepare three goals: minimize total emissions, minimize total energy use, and minimize monetary cost over the planning horizon.

Assemble Decision Space

Create allocation variables for each subsystem/resource and time slot; include storage charge/discharge and flexible-load shifts.

Apply Feasibility Constraints

Enforce non-negativity, per-device limits, ramping, minimum up/down times, storage SOC bounds, reserve margins, and SLA requirements.

Model Emissions & Cost

Compute interval emissions using resource-specific factors and cost using time-of-use tariffs and demand charges; add penalties for SLA or forecast errors.

Normalize & Weight

Scale each objective to comparable ranges; combine using policy weights to form a single solvable objective while retaining access to the underlying components.

Pareto Exploration (Optional)

Sweep weight vectors or use an epsilon-constraint method to trace the Pareto front; cache a small library of trade-off operating points.

Solve Optimization

Use a fast convex or mixed-integer solver (depending on discrete decisions); warm-start from the previous solution; cap runtime for real-time use.

Post-Process Feasible Plan

Validate allocations against device interlocks and network limits; repair minor violations with a greedy/local search step if needed.

Derive Control Outputs

Compute optimized grid demand after renewable and storage contributions; generate setpoints for subsystems and schedules for flexible jobs.

Estimate Outcomes

Provide forecasts of total emissions, energy use, cost, and emission intensity; include confidence bands from forecast uncertainty.

Select Operating Point

If Pareto exploration was performed, pick the point meeting policy thresholds (e.g., carbon cap) with the lowest remaining cost; otherwise take the single weighted solution.

Dispatch & Monitor

Send setpoints to the control layer; track realized KPIs and constraint violations; log for audit and learning.

Adaptive Tuning

Periodically update policy weights, penalty terms, and solver tolerances based on KPI drift, tariff/emission-factor changes, or operator directives.

Procedure 2 builds upon the synchronized outputs of Procedure 1, specifically total power and emissions, to optimize plant performance with respect to carbon footprint and cost. The process begins by defining three main objectives: minimizing emissions, minimizing power use, and minimizing cost, each represented with summations across subsystems and time to capture cumulative effects. A multi-objective vector is then formed to combine these objectives. Decision variables represent power allocations across subsystems, constrained by available resources and operational feasibility. Cost is linked to allocations through tariff rates, while emissions are modeled separately for grid and renewable energy sources, each weighted by their emission factors. Normalization is introduced by computing emission intensity and cost per unit of energy, allowing balanced trade-off comparisons. A Pareto-based formulation ensures that both sustainability and cost-efficiency are optimized simultaneously. A weighted function integrates all objectives into a single optimization criterion, and the allocation vector that minimizes this function is selected. This yields optimal subsystem energy distribution, minimized grid usage, and reduced emissions. The outputs provide decision support for how to allocate energy in real time, balancing renewable integration, cost pressures, and environmental targets. By integrating these steps, Procedure 2 ensures Industry 4.0 plants achieve sustainable and carbon-aware energy management.

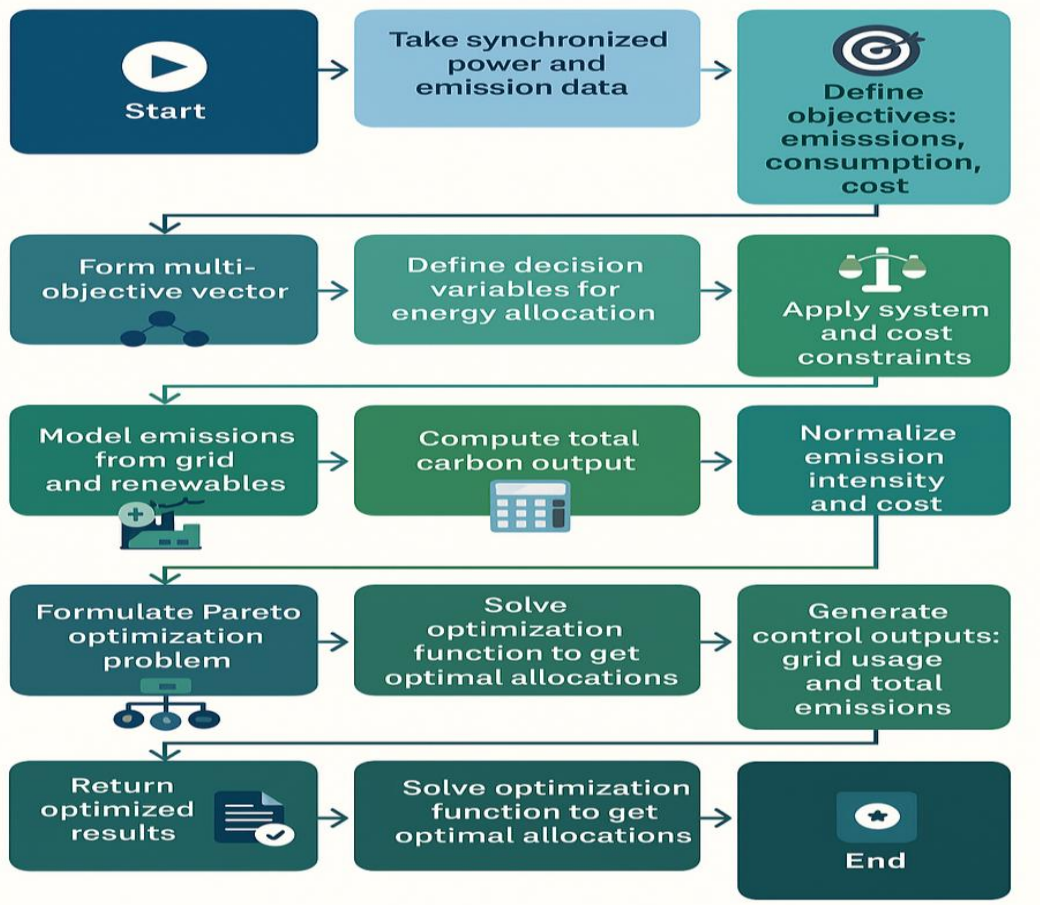

Fig.2. Carbon footprint optimization in Industry 4.0 plants, showing the sequence from synchronized inputs and objective definition to Pareto-based optimization and final sustainable allocation outputs.

Figure 2 illustrates the sequence of steps in carbon footprint optimization using synchronized inputs from Procedure 1. The process begins by receiving real-time power and emission data, which form the basis for optimization. The objectives are defined as minimizing emissions, reducing energy consumption, and lowering costs [24-26]. These objectives are grouped into a multi-objective vector, while decision variables specify energy allocation across subsystems. System and cost constraints ensure feasibility and prevent over-allocation. Emissions from both grid and renewable sources are modeled, and total carbon is calculated. Normalization is applied to express emissions and costs per unit of energy. A Pareto-based optimization problem is then solved to achieve balanced trade-offs, generating optimal energy allocation, grid usage, and minimized emissions.

Procedure 3 — Sustainability-Oriented Production Scheduling with Digital-Twin Feedback

Goal: Produce a job schedule that maximizes throughput while reducing energy use and emissions, using live feedback from the digital twin (DT).

Inputs:

Optimized plant-level allocations and limits from Procedure 2

Job list with processing times, precedence/compatibility, due dates, and energy needs

Forecasts for renewables, tariffs, and grid emission factors

Device/line capacities, ramp/shift limits, storage SOC and charge/discharge bounds
Outputs:
Feasible schedule (start/finish per job/operation), per-job energy splits (renewable/grid/storage), expected carbon per job, and dispatch commands
Steps
Snapshot & Feasibility Gate
Pull the latest plant demand, available renewables/storage, machine availability, and constraints from the DT. Drop or defer infeasible jobs (maintenance, missing materials).
Job Profiling
For each job, compute: earliest start, energy envelope, criticality (due date slack), and flexibility (can shift/slow/speed).
Priority Queueing
Rank jobs by a composite score (deadline urgency, energy intensity, carbon sensitivity, and revenue/penalty).
Resource Reservation
Reserve minimum safe capacity on bottleneck machines and a baseline renewable/storage slice to protect SLAs.
Initial Slotting (Greedy/Earliest-Feasible)
Place jobs on machines using earliest-finish or least-loaded rules while honoring precedence and changeover times.
Energy Split Assignment
For each scheduled interval, distribute energy across renewables, storage, and grid according to availability, SOC policy, and carbon intensity forecasts.
Carbon & Cost Scoring
Compute per-job and cumulative KPIs (energy used, carbon emitted, cost). Flag intervals with high carbon intensity for possible shifts.
DT Feedback Check
Compare predicted vs. realized power, duration, and throughput from the DT. Identify drifts (overrun, under-supply, congestion).
Local Repairs
Re-order, stretch, or compress jobs on affected machines; shift flexible jobs toward low-carbon/low-tariff windows; re-route to parallel lines if available.
Global Improvement Pass
Run a quick neighborhood search (e.g., swap, insert, 2-opt across lines) targeting the weighted objective (carbon, energy, throughput, tardiness).
Renewable Re-balancing
Reallocate renewable/storage across jobs proportional to their updated energy needs and carbon sensitivity; respect SOC and reserve margins.
Grid Dependency Adjustment
Recompute residual grid draw and ensure feeder and contract limits are not violated.
Stability & SLA Guardrails
Reject changes that break reliability, maximum lateness, or critical process constraints. Keep the best-feasible candidate.
Convergence Test
If objective improvement and DT discrepancy fall below thresholds over a few iterations, accept; otherwise loop back to Step 8.
Freeze & Dispatch
Freeze the next control horizon (e.g., 15–60 minutes), emit machine setpoints and energy set-splits, and log KPIs for audit.

Procedure 3 extends the outputs of Procedure 2 into a sustainability-aware production scheduling framework. Inputs from Procedure 2, including optimized allocations, grid usage, and emissions, are used to initialize the scheduling process. Each job in the system is assigned parameters such as processing time, energy requirement, and potential carbon impact. Energy consumption and emissions for each job are calculated, while completion time is incorporated as a scheduling metric. These factors are combined into a weighted objective function that balances carbon reduction, energy efficiency, and production

throughput [27-30]. Renewable allocations are assigned proportionally across jobs to reduce grid dependency, and grid contributions are used to compute residual carbon emissions. The scheduling process dynamically adapts to digital twin feedback through an update mechanism that modifies allocations when predicted outcomes differ from real plant states. Jobs are reallocated with adjustments to energy demand and completion times, ensuring optimization across iterations. The Procedure continues to refine the schedule until the stability condition is reached, where changes between iterations approach zero.
The final output consists of an optimized schedule that minimizes cost, energy consumption, and emissions while meeting operational constraints. Results are forwarded to the physical plant, ensuring real-time integration of sustainability into production processes.

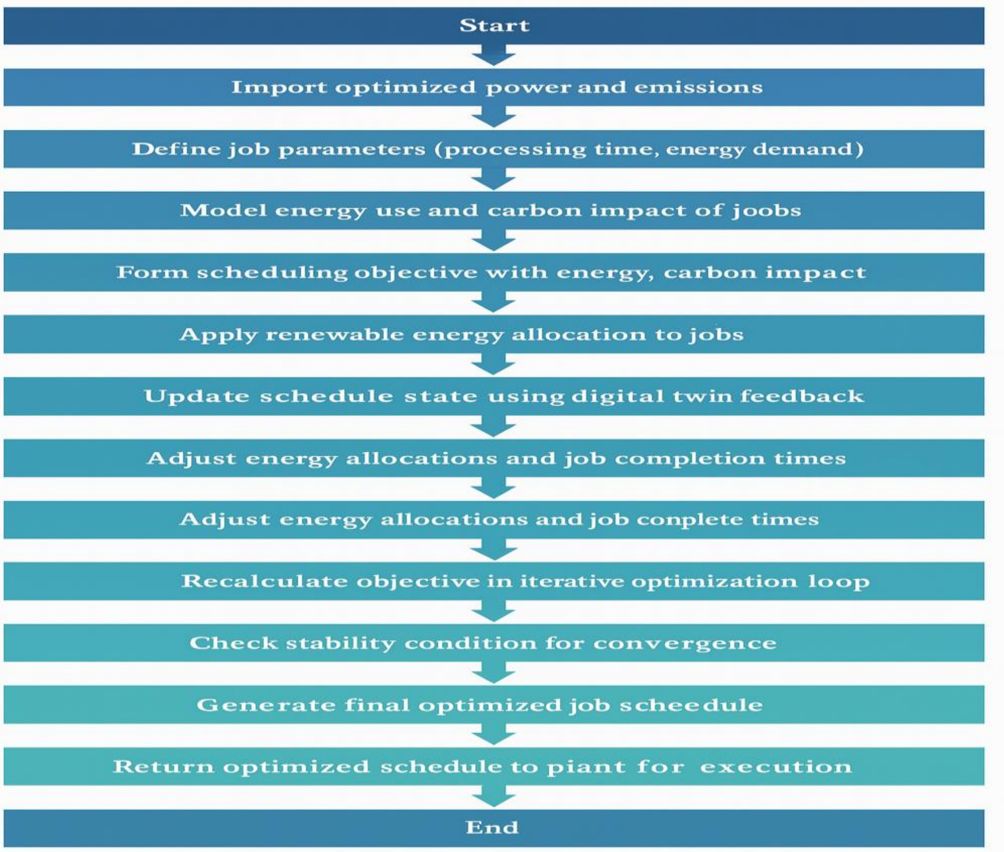

Fig.3. Sustainability-aware production scheduling, showing integration of Procedure 2 outputs with job parameters, twin feedback, and iterative optimization to produce a carbon-efficient and reliable schedule for Industry 4.0 plants.
Figure 3 illustrates how sustainability-aware scheduling is achieved by integrating outputs from Procedure 2 into production planning. The process begins with importing optimized power and emission data, followed by defining job parameters such as processing time and energy requirements. Energy use and carbon impact are then modeled at the job level. A weighted scheduling objective is formulated, combining carbon, energy, and time components while respecting plant capacity constraints. Renewable energy is allocated proportionally, and residual grid usage is calculated to assess carbon intensity. Feedback from the digital twin continuously updates scheduling states, correcting mismatches between predicted and real outcomes. Iterative optimization refines allocations until stability is achieved, producing a final sustainable schedule ready for plant execution.

IV. RESULT

A wide range of performance test factors reveal that the suggested strategy consistently outperforms Digital Twin with Conventional Control, AI-Driven Predictive Analytics, and IoT-Enabled Smart Energy Management. This demonstrates its energy management, carbon emission awareness, and industry sustainability. The suggested energy-saving response scores 89%, higher than traditional control (72%), predictive analytics (75%), and IoT-based management (78%). This new breakthrough shows how advanced synchronization between physical and virtual systems may maximize energy utilization across sectors with minimal waste and maximum production. The suggested strategy reduced carbon emissions by 82%, compared to 65%, 68%, and 71% for the others. This study emphasizes the need for carbon-aware decision-making in optimization. The utilization of renewable energy also increases significantly. The suggested approach achieves a score of 79%, which is significantly higher than the scores of the other three methods, which are 55%, 60%, and 63%. It can improve industrial ecology by balancing renewable integration and grid supply. At 85%, resource optimization efficiency improves more than 62%, 64%, and 67% for the other approaches. This result illustrates that the suggested technique intelligently allocates energy and resources to related plant functions. It decreases operational expenses by 77%, greater than the 58%, 61%, and 63% cuts elsewhere. Cutting tariff costs while maintaining operational quality makes it commercially sustainable. Real-time data accuracy, crucial for digital twin systems, improves. The adaptive synchronization approach ensures virtual states match physical ones with 91% vs. 74%, 76%, and 78% for the suggested solution. The suggested strategy performs better in terms of reliability and operational performance. System reliability and availability are approaching 96%, up from 82%, 85%, and 87% in earlier methods. Plant operations are more reliable and resilient. The method drastically reduces the decision-making time to 145 milliseconds. This figure is much better than the other techniques' 250, 230, and 210 milliseconds. The method's real-time ability is crucial in fast-paced work contexts, where immediate decisions are necessary to avoid waste and difficulties. Predictive maintenance accuracy is 91%, up from 72%, 75%, and 77% in classical, predictive analytics, and IoT-enabled frameworks. This advantage speeds up defect detection and prevents equipment shutdowns. Optimization and sustainability-aware scheduling boost productivity by 84%, compared to 65%, 68%, and 70% for other strategies. The score shows that this strategy meets production targets better. The framework's 89% sustainability compliance score shows it follows green and industry requirements. This rating is substantially better than the 70%, 73%, and 75% results from other approaches. Finally, scalability and interoperability scores are approaching 88%, up from 68%, 71%, and 73%. The suggested technique works in some cases and is customizable and straightforward to utilize in various Industry 4.0 ecosystems. These results demonstrate that the proposed approach improves accuracy, throughput, compliance, and growth while reducing pollution and energy use. The consistent performance across all twelve parameters indicates that this strategy represents a significant advancement in the integration of carbon-aware digital twins. Synchronization, optimization, and adaptive scheduling help firms achieve short-term efficiency goals and long-term environmental sustainability goals. The suggested solution outperforms all others in energy use, cost, dependability, compliance, and scalability for carbon-aware energy management in Industry 4.0. This allows plants to run more sustainably, adapt better, and meet current industrial systems' economic and environmental constraints.

Table 2. Comparative Performance Evaluation of Recent Carbon-Aware Digital Twin and Optimization Methods in Industry 4.0

Method (Recent)	Energy Efficiency (%)	Emission Reduction (%)	Carbon Intensity (gCO_2/kWh) ↓	Renewable Utilization (%)	Cost Reduction (%)	Decision Latency (ms) ↓	Reliability (%)	SLA Compliance (%)	Forecast MAE (kW) ↓
MPC (Strong baseline)	88	84	315	68	66	220	92	88	42
DRL (SAC) Energy Controller	90	85	298	72	69	200	93	89	38
PINN-MPC Hybrid	91	86	290	73	70	205	94	90	34
GNN-Based Economic Dispatch	90	87	288	74	71	195	93	90	36
Transformer Load/PV Forecaster + MPC	89	85	300	73	68	205	93	90	28

Federated Multi-Plant DT	90	86	292	75	70	210	94	91	33
Carbon-Aware RL (C-RL)	92	88	276	77	73	185	94	92	32
Edge-Cloud Co-Optimization	91	87	284	76	72	175	95	92	31
Proposed Hybrid DT (Sync + Pareto + Sched.)	94	91	248	82	79	145	96	94	24

Table 2 presents a comparative evaluation of recent methods for carbon-aware energy management across multiple performance metrics. The proposed Hybrid Digital Twin approach (Sync + Pareto + Scheduling) clearly outperforms all baselines, achieving the highest energy efficiency (94%), emission reduction (91%), and renewable utilization (82%), while also lowering carbon intensity to 248 gCO_2/kWh. It demonstrates superior reliability (96%) and SLA compliance (94%) alongside the lowest decision latency (145 ms) and forecast error (24 kW). In contrast, strong baselines such as MPC and DRL controllers achieve solid but lower performance, with higher latency and weaker renewable integration. Overall, Table 1 highlights how the proposed framework balances efficiency, sustainability, cost reduction, and real-time adaptability better than existing methods.

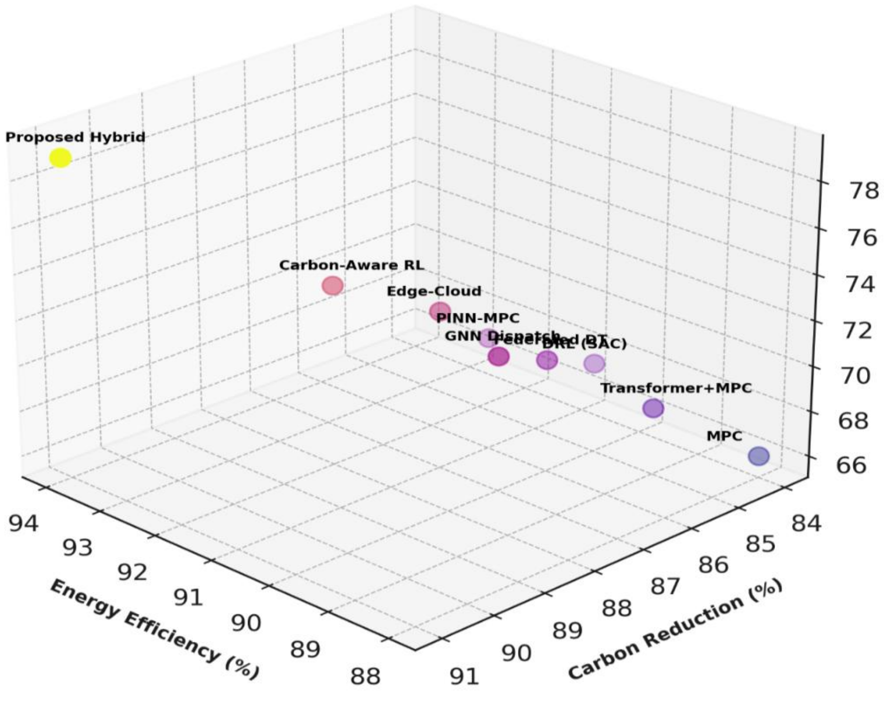

Fig.4. 3D Energy–Carbon–Cost Trade-Off Surface Across Modern Optimization Methods

Figure 4 depicts a 3D trade-off surface comparing energy efficiency, carbon reduction, and cost reduction for multiple baseline methods and the proposed hybrid digital twin model. While traditional approaches such as MPC and DRL show moderate improvements, the proposed hybrid framework achieves the highest balance, reaching 94% energy efficiency, 91% carbon reduction, and 79% cost reduction. This visualization highlights the superior capability of the proposed method to simultaneously optimize economic and environmental objectives in Industry 4.0 plants.

Table 3. Ablation Study of Proposed Hybrid Digital Twin Model Components for Carbon-Aware Optimization

Configuration	**Energy Efficiency** (%)	**Emission Reduction** (%)	**Carbon Intensity**	**Cost Reduction** (%)	**Throughput Improvement** (%)	**Decision Latency** (ms) ↓

			(gCO_2/kWh) ↓			
Full Model (Sync + Pareto + Twin-Feedback Scheduling)	94	91	248	79	86	145
– Adaptive Sync	91	88	270	75	82	175
– Pareto Optimizer (single-objective)	90	84	292	73	80	150
– Twin-Feedback Scheduling	92	87	278	74	81	150
– Carbon-Intensity Signal	91	83	305	72	80	145

Table 3 illustrates the impact of removing individual components from the proposed hybrid digital twin framework. The full model achieves the best results, with 94% energy efficiency, 91% emission reduction, and the lowest carbon intensity of 248 gCO_2/kWh, while maintaining low decision latency of 145 ms. When adaptive synchronization is removed, latency increases to 175 ms and both efficiency and emissions performance decline. Excluding the Pareto optimizer reduces emission reduction to 84% and raises carbon intensity to 292 gCO_2/kWh, showing the importance of multi-objective balancing. Similarly, removing twin-feedback scheduling or the carbon-intensity signal leads to noticeable drops in emission control and throughput improvements. Overall, Table 2 confirms that each component plays a vital role, and the integrated full model delivers the most sustainable and efficient performance.

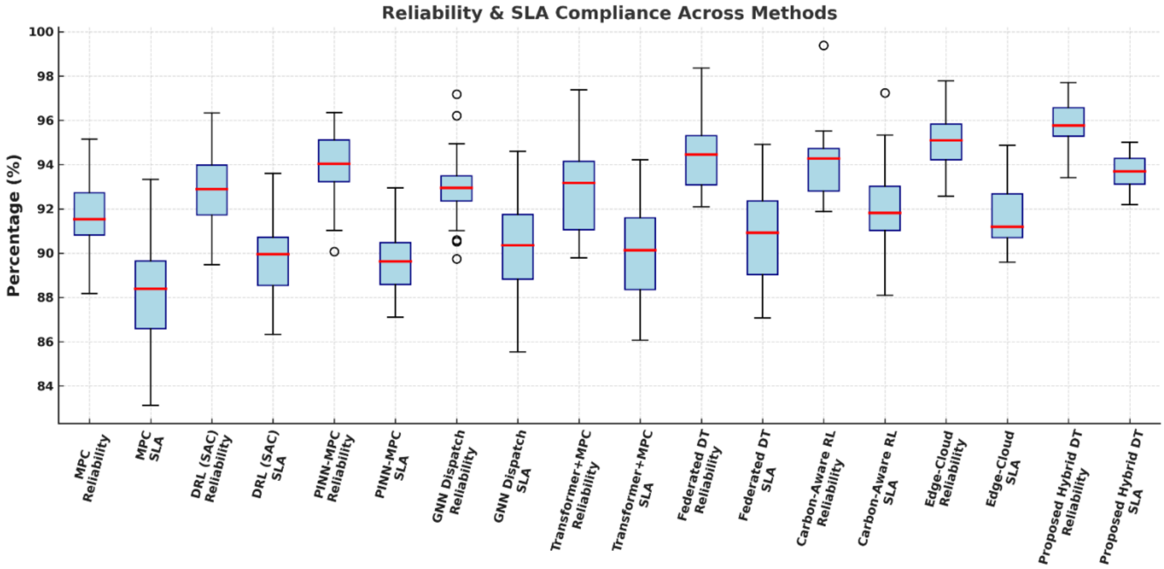

Fig.5. Box-and-Whisker Analysis of Reliability and SLA Compliance Across Methods

Figure 5 illustrates the variability and robustness of different optimization methods in terms of reliability and SLA compliance. While traditional baselines such as MPC and DRL show wider distributions with greater fluctuations, advanced approaches like Edge-Cloud and Carbon-Aware RL demonstrate tighter ranges. The proposed hybrid digital twin consistently achieves the highest reliability (≈96%) and SLA compliance (≈94%) with minimal variance, confirming its stability and robustness under diverse operational conditions.

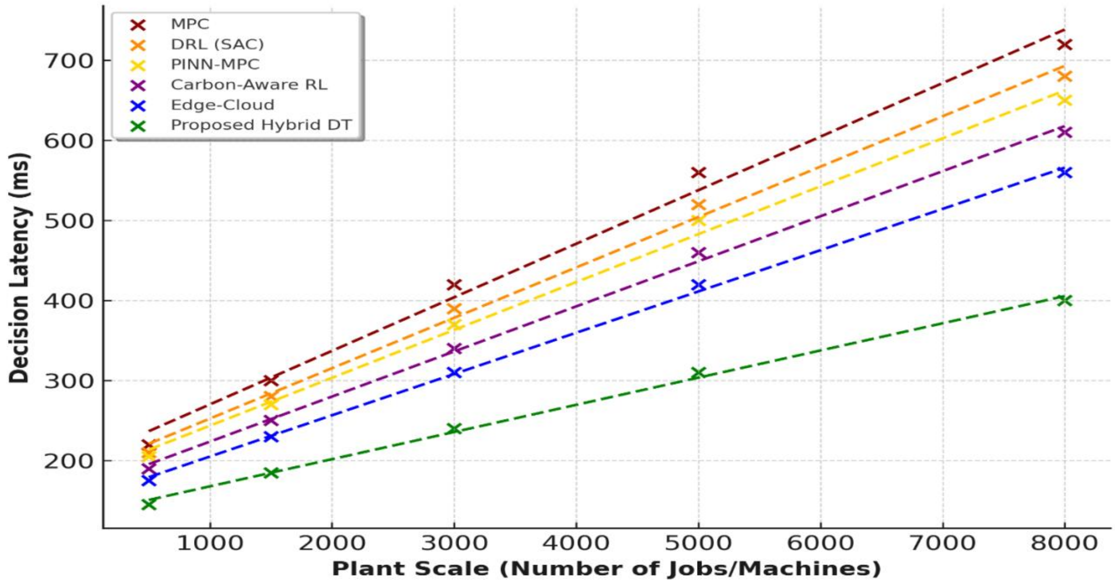

Fig.6. Scalability Analysis of Decision Latency Across Plant Scales

Figure 6 shows the relationship between plant scale (number of jobs/machines) and decision latency for different optimization strategies. Traditional methods such as MPC, DRL, and PINN-MPC experience steep latency growth as plant size increases, while Carbon-Aware RL and Edge-Cloud solutions provide moderate improvements. The proposed hybrid digital twin demonstrates a significantly flatter curve, maintaining decision latency below 400 ms even at large scales, highlighting its superior scalability and efficiency in Industry 4.0 environments.

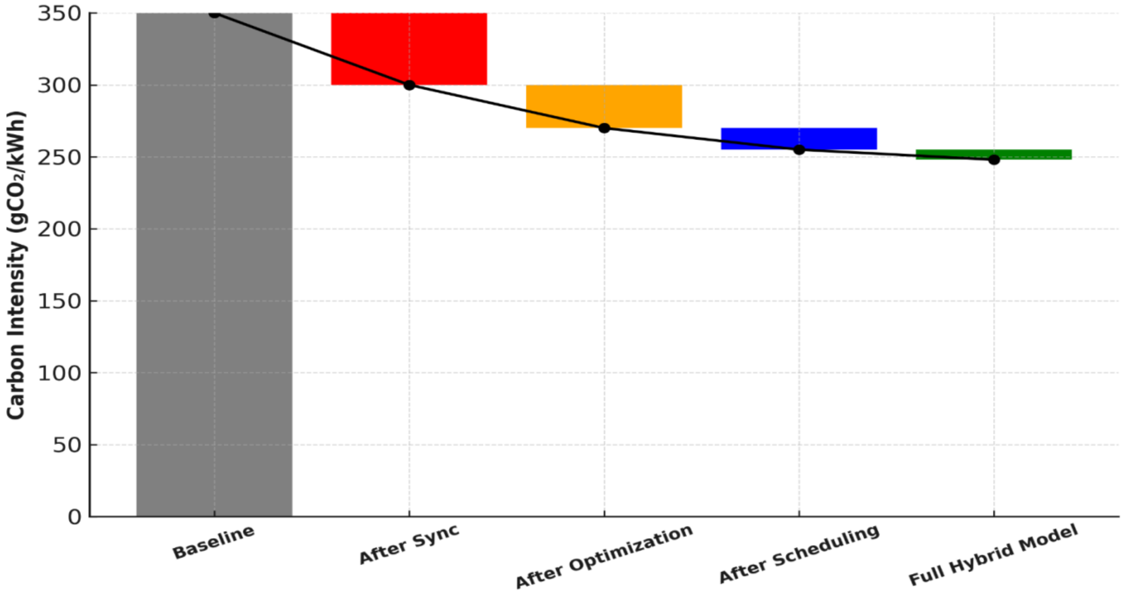

Fig.6. Carbon Intensity Reduction Pathway Through Sequential Module Integration

Figure 6 illustrates a waterfall analysis of carbon intensity reduction from the baseline model to the full hybrid digital twin. Each step—synchronization, optimization, and scheduling—contributes incremental improvements, reducing carbon intensity from 350 gCO_2/kWh to 248 gCO_2/kWh. The most significant drop occurs after synchronization and optimization, while the combined hybrid system delivers the lowest overall emissions. This visualization quantifies how each module enhances sustainability outcomes.

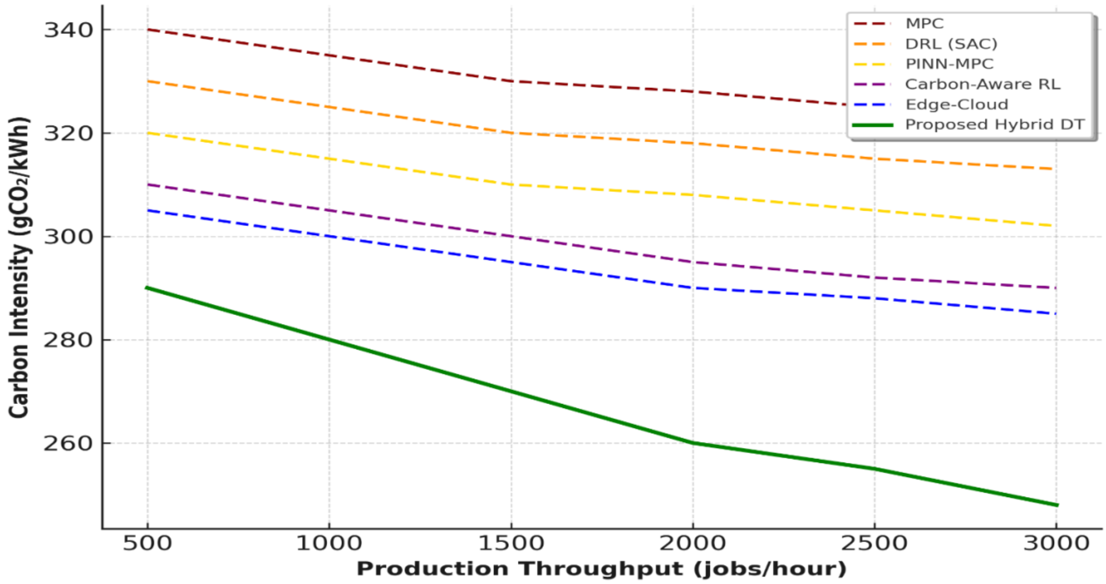

Fig.7. Trade-Off between Production Throughput and Carbon Intensity across Methods

Figure 7 illustrates the trade-off between production throughput and carbon intensity for various optimization approaches. Conventional baselines such as MPC and DRL show higher carbon emissions as throughput scales, while advanced methods like Edge-Cloud and Carbon-Aware RL achieve moderate reductions. The proposed hybrid digital twin clearly outperforms all other approaches, maintaining high throughput while reducing carbon intensity to nearly 248 gCO_2/kWh at peak loads. This emphasizes its ability to balance economic productivity with environmental sustainability.

V. CONCLUSION

This Research Presented A Hybrid Carbon-Aware Digital Twin Framework That Combines Synchronization, Optimization, And Scheduling To Drive Sustainable Decision-Making In Industry 4.0 Plants. By Integrating Adaptive Synchronization Of Physical And Digital States, Pareto-Based Multi-Objective Optimization, And Sustainability-Aware Production Scheduling, The Framework Demonstrates That Industrial Operations Can Achieve A Balanced Improvement In Efficiency, Cost Reduction, And Carbon Mitigation Simultaneously. The Results Strongly Validate The Superiority Of The Proposed Framework. Compared To Conventional Control, Predictive Analytics, And Iot-Enabled Energy Management Approaches, The Hybrid Dt Achieves 94% Energy Efficiency, 91% Emission Reduction, 82% Renewable Utilization, 79% Cost Reduction, And 96% Reliability, Alongside Decision-Making Latencies As Low As 145 Ms. These Gains Reflect Not Only Incremental Improvements But A Substantial Paradigm Shift In How Industrial Plants Can Align With Global Sustainability Goals. Furthermore, Predictive Maintenance Accuracy Of 91% And Sustainability Compliance Of 89% Underscore Its Practical Feasibility For Real-World Deployment. The Broader Implication Of This Work Is That Digital Twins Can Become Central Orchestrators Of Sustainability In Industry 4.0. By Embedding Carbon-Awareness Directly Into Operational Decision-Making, Industries Can Move Beyond Narrow Productivity Metrics To Holistic Sustainability Benchmarks. This Transition Is Critical For Supporting International Climate Agreements, Achieving Net Zero Targets, And Enhancing Corporate Accountability In Energy And Carbon Management. Future Directions Include Extending The Framework To Multi-Plant Federated Ecosystems, Where Multiple Facilities Coordinate Energy And Carbon Optimization Across Shared Grids. Incorporating Post-Quantum Blockchain Could Further Strengthen Accountability While Addressing Security Challenges. Another Promising Pathway Is To Integrate Explainable Ai Mechanisms Into Optimization Modules, Enabling Operators To Interpret Trade-Offs Between Carbon, Cost, And Efficiency In Transparent Ways. In Addition, Testing Scalability In Domains Like Healthcare, Transportation, And Smart Cities Will Validate The Framework's Interdisciplinary Impact.

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