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SYNAPCITY-DT: AI-DRIVEN URBAN ENERGY INTELLIGENCE FOR SMART CITIES

A DECISION-ORIENTED DIGITAL TWIN FRAMEWORK FOR UNCERTAINTY-AWARE RENEWABLE URBAN ENERGY MANAGEMENT

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ABSTRACT
This study presents SYNAPCITY-DT, an AI-driven urban energy digital twin framework for adaptive renewable energy operation under uncertainty. The framework integrates probabilistic photovoltaic forecasting, risk-aware battery energy storage optimization, and operational intelligence within a unified digital twin environment. Using real operational data from a utility-scale PV–BESS system in Finland, the framework evaluates uncertainty propagation across forecasting, planning, and operational decision-making. Results show that adaptive risk-aware control improves operational resilience, flexibility utilization, and decision robustness under varying forecast horizons. The study demonstrates the potential of AI-enabled digital twins as scalable urban energy intelligence systems supporting resilient and sustainable smart cities.

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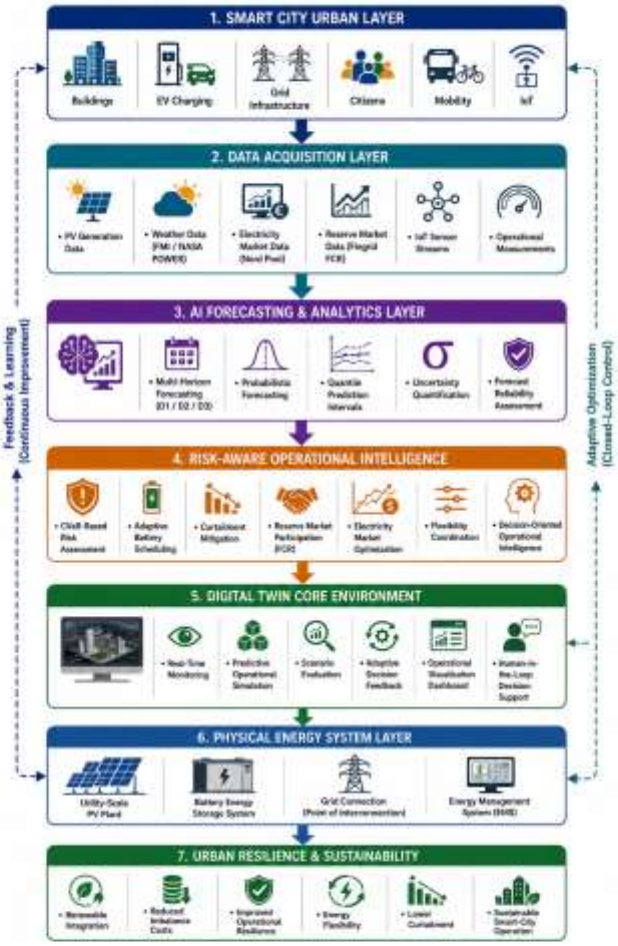
1. Introduction and Related Work

Cities are rapidly transitioning toward renewable-intensive and data-driven energy infrastructures as part of global decarbonization and smart-city transformation initiatives. Increasing electrification, distributed renewable generation, energy storage integration, electric mobility, and intelligent urban services are fundamentally reshaping how modern cities generate, consume, and manage energy. The accelerating deployment of photovoltaic (PV) systems, battery energy storage systems (BESS), and hybrid renewable power plants introduces substantial operational complexity because renewable generation is inherently variable, weather-dependent, and uncertain (International Energy Agency, 2025). At the same time, urban energy systems are expected to maintain high reliability, resilience, affordability, and sustainability under increasingly dynamic operating conditions.

Recent advances in artificial intelligence (AI), probabilistic forecasting, and digital-twin technologies have created new opportunities for intelligent urban energy management. Deep learning approaches, including recurrent neural networks, Transformer architectures, and probabilistic forecasting frameworks, have demonstrated strong capability for renewable generation forecasting and uncertainty quantification (Al-Dahidi et al., 2024; Wang et al., 2026; Xiong et al., 2025). Similarly, energy storage systems are increasingly recognized as critical enablers for renewable integration, power smoothing, flexibility provision, and grid-support services (Amorim et al., 2024; Cao et al., 2022; Yang et al., 2024). In parallel, digital twins have emerged as promising cyber-physical platforms capable of enabling real-time monitoring, simulation, predictive analytics, and operational optimization in urban environments (Elnosh et al., 2026; Zhang et al., 2024).

Figure 1. Proposed SYNAPCITY-DT integrated urban energy intelligence architecture.



Source: Own elaboration, 2026.

Figure 1. presents the proposed SYNAPCITY-DT integrated urban energy intelligence architecture combining probabilistic forecasting, risk-aware operational intelligence, adaptive battery coordination, electricity-market interaction, and digital-twin-assisted decision support for resilient smart-city energy management.

Despite these advancements, existing research often treats forecasting, storage operation, optimization, and digital-twin functionalities as partially independent research domains. Forecasting studies frequently emphasize prediction accuracy metrics without fully analyzing their operational consequences on dispatch reliability, imbalance costs, reserve participation, or battery degradation (Lindberg et al., 2024; Sweeney et al., 2020). Similarly, many BESS optimization studies focus primarily on sizing or deterministic scheduling while simplifying uncertainty propagation and operational risk (Liu et al., 2023; Ruan et al., 2025). Although recent digital-twin frameworks support monitoring and visualization, many remain limited in integrating uncertainty-aware operational intelligence, probabilistic decision-making, and adaptive risk-aware control within a unified urban-energy framework (Elnosh et al., 2026).

The rapid evolution of utility-scale hybrid renewable power plants further amplifies these challenges. Recent reviews emphasize that future hybrid energy systems must simultaneously coordinate forecasting, market participation, storage flexibility, reserve provision, and reliability management under uncertain renewable conditions (Das et al., 2025; Zhu et al., 2025). At the urban level, these challenges become even more critical because smart cities require continuous interaction between renewable energy systems, IoT infrastructures, electricity markets, mobility networks, and digital public services. Consequently, intelligent urban energy systems increasingly require not only predictive capability, but also adaptive operational intelligence capable of evaluating uncertainty, risk, flexibility, and system confidence before executing operational decisions. Probabilistic forecasting has emerged as an important direction for managing renewable uncertainty in electricity markets and operational planning. Unlike deterministic forecasts, probabilistic forecasting provides prediction intervals and quantile distributions that better characterize uncertainty propagation and operational risk (Maciejowska et al., 2024; Visser et al., 2024). Recent studies demonstrate that probabilistic renewable forecasting can significantly improve bidding strategies, reserve scheduling, and market participation under uncertainty (Agakishiev et al., 2025; Wang et al., 2024). Risk-aware optimization frameworks using Conditional Value-at-Risk (CVaR) have also gained increasing attention for renewable energy trading and integrated energy-system planning (Jadidoleslam, 2025; Xuan et al., 2021). However, the integration of probabilistic forecasting, CVaR-based operational intelligence, and urban-scale digital twins remains insufficiently explored.

In addition, recent smart-city energy research highlights the growing importance of adaptive, explainable, and interoperable AI systems capable of supporting real-time urban decision-making. AI-enhanced digital twins combined with IoT infrastructures can support predictive control, scenario simulation, resilience analysis, and operational transparency across interconnected urban systems (Yang et al., 2025; Zhang et al., 2024). Nevertheless, many current implementations remain primarily monitoring-oriented rather than decision-oriented. As urban energy systems become increasingly autonomous and renewable-intensive, there is a growing need for digital twins capable of integrating uncertainty-aware forecasting, operational optimization, market interaction, and adaptive intelligence within a closed-loop framework.

To address these limitations, this paper proposes SYNAPCITY-DT, an AI-driven urban energy intelligence framework that integrates probabilistic renewable forecasting, risk-aware operational optimization, battery flexibility management, and digital-twin-assisted decision intelligence for smart cities. Unlike conventional digital twins that primarily focus on monitoring and visualization, the proposed framework introduces a decision-oriented architecture capable of combining uncertainty quantification, adaptive operational intelligence, and real-time energy management within an integrated urban-energy ecosystem.

The framework combines probabilistic multi-horizon forecasting, risk-aware scheduling using CVaR-based optimization, battery energy storage coordination, electricity-market interaction, and real-time digital-twin feedback loops. The proposed architecture is validated using a Finnish utility-scale PV case study integrating real renewable-generation data, weather observations, electricity-market prices, and reserve-market information. Through this approach, SYNAPCITY-DT aims to support more resilient, adaptive, and intelligent urban renewable-energy operation under uncertainty while contributing toward next-generation AI-driven smart-city infrastructures. Table 1 summarizes the research gap and addresses the gaps in the proposed system.

Table 1. Summary of Related Research and Identified Gaps

Research Area	Recent Advances	Main Limitations	Research Gap Addressed in SYNAPCITY-DT
Renewable Forecasting	Deep learning, probabilistic forecasting, Transformer models improve renewable prediction accuracy (Al-Dahidi et al., 2024; Wang et al., 2026)	Forecasting often evaluated only using numerical accuracy metrics	Links probabilistic forecasting directly with operational decision intelligence
Battery Energy Storage Systems	Advanced sizing and operational strategies improve renewable flexibility (Amorim et al., 2024; Ruan et al., 2025)	Many approaches simplify uncertainty and degradation impacts	Integrates uncertainty-aware adaptive BESS operation
Electricity Market Participation	Risk-aware bidding and probabilistic market strategies improve profitability (Agakishiev et al., 2025; Wang et al., 2024)	Limited integration with urban digital twins and real-time intelligence	Combines market participation with urban operational digital twins
Digital Twins for Energy Systems	Real-time monitoring and predictive analytics capabilities are expanding (Elnosh et al., 2026; Zhang et al., 2024)	Most digital twins remain monitoring-centric rather than decision-centric	Introduces decision-oriented digital twin intelligence
Hybrid Renewable Power Plants	Hybrid PV-BESS coordination improves flexibility and reliability (Das et al., 2025; Zhu et al., 2025)	Forecasting, optimization, and operation often remain weakly coupled	Creates integrated uncertainty-aware operational framework
Smart-City Energy Systems	AI and IoT increasingly support urban sustainability and resilience	Existing systems lack adaptive operational intelligence under uncertainty	Develops adaptive AI-driven urban energy intelligence architecture

Source: Own elaboration, 2026.

The major contributions of this paper are summarized as follows:

1. A novel AI-driven urban energy intelligence framework named SYNAPCITY-DT is proposed for uncertainty-aware smart-city energy management.
2. A probabilistic multi-horizon renewable forecasting framework is integrated with risk-aware operational optimization and digital-twin-assisted decision intelligence.
3. A CVaR-based operational architecture is developed to improve renewable-energy scheduling, flexibility management, and market participation under uncertainty.
4. A real-time digital-twin feedback framework is introduced to support adaptive monitoring, explainability, and operational resilience.

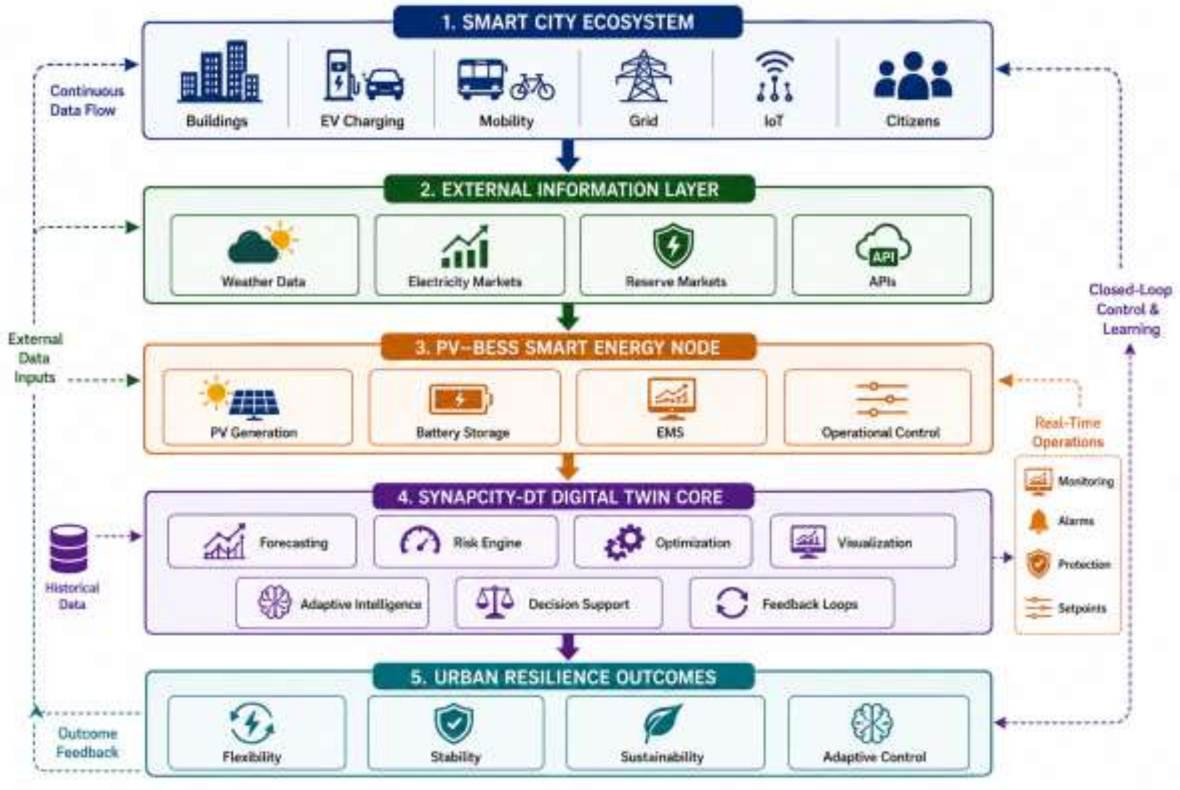
5. The proposed framework is validated using a real Finnish utility-scale PV case study integrating renewable generation, meteorological observations, electricity-market data, and reserve-market information.

2. Urban Energy System and Digital Twin Framework

2.1. Urban Energy Node Concept

The increasing penetration of renewable energy sources, distributed flexibility resources, and digital infrastructures is transforming conventional power systems into interconnected urban-energy ecosystems. In future smart cities, renewable-energy assets are expected to operate not only as electricity-generation units but also as intelligent and adaptive energy nodes capable of interacting dynamically with electricity markets, grid-support services, storage systems, mobility infrastructures, and urban digital platforms (Das et al., 2025; Hofbauer et al., 2022). In this context, photovoltaic (PV) systems integrated with battery energy storage systems (BESS) are becoming critical components for enabling flexibility-oriented and resilient urban-energy operation (Baccino & Santarelli, 2023; Čović et al., 2024). Figure 2 shows the conceptual representation of the SYNAPCITY-DT urban-energy-node ecosystem integrating renewable generation, battery storage, electricity-market interaction, adaptive operational intelligence, and digital-twin-assisted urban energy management.

Figure 2. Urban Energy Node Ecosystem.



Source: Own elaboration, 2026.

However, the large-scale integration of renewable energy introduces significant operational uncertainty due to intermittency, meteorological variability, fluctuating electricity prices, and balancing-market dynamics (Ejuh Che et al., 2025; Pavlík et al., 2025). Traditional renewable-energy management approaches frequently rely on deterministic forecasting and static scheduling strategies, which often limit operational adaptability under uncertain operating conditions (Sweeney et al., 2020). These limitations become increasingly critical in smart-city environments where urban infrastructures require continuous coordination between renewable generation, storage flexibility, market participation, and real-time operational intelligence.

Within the proposed framework, the PV–BESS system is modeled as an intelligent urban-energy node operating inside a cyber-physical urban-energy ecosystem. The proposed node continuously exchanges information with weather services, electricity markets, reserve-market platforms, operational sensors, and digital-twin environments. Rather than functioning solely as a renewable-generation facility, the system operates as an adaptive operational intelligence platform capable of uncertainty-aware forecasting, risk-aware scheduling, battery flexibility coordination, and resilient energy management.

The proposed urban-energy-node concept integrates multiple operational functionalities, including probabilistic forecasting, adaptive battery dispatch, reserve-market participation, imbalance-risk mitigation, curtailment reduction, and digital-twin-assisted operational supervision. This integration enables continuous synchronization between physical infrastructure and intelligent decision-support layers, allowing the operational framework to evolve from conventional reactive scheduling toward adaptive and predictive urban-energy intelligence.

2.2. SYNAPCITY-DT Multi-Layer Architecture

The proposed SYNAPCITY-DT framework is designed as a hierarchical multi-layer urban-energy intelligence architecture integrating heterogeneous data acquisition, probabilistic forecasting, operational optimization, and digital-twin-assisted adaptive control. The architecture combines both cyber and physical system components within a unified operational-intelligence environment.

The first layer corresponds to the data-acquisition and integration layer, which continuously collects operational measurements, weather observations, electricity-market prices, reserve-market information, and IoT-based monitoring signals. In this study, the framework integrates meteorological observations from the Finnish Meteorological Institute (FMI), solar-radiation data from NASA POWER, day-ahead electricity-market prices from Nord Pool, and reserve-market information from Fingrid (Finnish Meteorological Institute, 2025; NASA POWER, 2025; Nord Pool, 2025; Fingrid, 2025). The collected datasets provide the basis for forecasting, uncertainty quantification, operational scheduling, and digital-twin synchronization. Figure 3. Presents the Multi-layer architecture of the proposed SYNAPCITY-DT framework integrating probabilistic forecasting, risk-aware optimization, digital-twin analytics, and urban-energy resilience objectives.

Figure 3. Multi-Layer SYNAPCITY-DT Architecture.

Source: Own elaboration, 2026.

The second layer consists of the AI-based forecasting and uncertainty-analysis engine. This layer performs multi-horizon probabilistic forecasting using quantile-based prediction methods capable of estimating renewable-generation uncertainty distributions rather than single deterministic outputs. Recent studies have demonstrated that probabilistic forecasting provides superior operational value for renewable-energy trading, reserve scheduling, and adaptive operational planning compared with deterministic forecasting approaches (Maciejowska et al., 2024; Visser et al., 2024). In the proposed framework, probabilistic forecasting enables uncertainty propagation across downstream operational-decision layers.

The third layer corresponds to the operational-intelligence and optimization engine. This layer integrates battery scheduling, adaptive dispatch, reserve allocation, curtailment mitigation, and electricity-market participation under uncertain renewable conditions. Operational adaptation is performed using risk-aware optimization principles capable of balancing expected profitability and operational robustness. In addition, battery operation considers state-of-charge (SOC) constraints, charging and discharging efficiencies, reserve commitments, and flexibility availability under uncertainty-aware operational conditions (Karrari et al., 2022; Rezaeimozafar et al., 2024).

The fourth layer represents the digital-twin operational environment. This layer continuously synchronizes virtual operational states with real physical-system measurements to support predictive monitoring, adaptive analytics, operational visualization, and scenario simulation. Unlike conventional monitoring-oriented digital twins, the proposed framework integrates uncertainty-aware operational intelligence and adaptive decision support within the digital-twin environment (Elnosh et al., 2026; Zhang et al., 2024).

Finally, the urban-resilience and decision-support layer translates operational outputs into higher-level urban-energy objectives, including flexibility enhancement, renewable integration, operational resilience, and sustainable smart-city energy management. Through this hierarchical structure, SYNAPCITY-DT enables coordinated interaction between forecasting intelligence, adaptive optimization, and urban-energy-system operation.

2.3. Probabilistic Operational Intelligence

A major limitation in many existing renewable-energy management systems is the weak coupling between forecasting outputs and operational decision-making. Forecasting models are frequently evaluated using statistical accuracy metrics such as MAE or RMSE, while the operational implications of uncertainty on dispatch reliability, imbalance exposure, reserve participation, and battery degradation receive comparatively less attention (Lindberg et al., 2024; Wang et al., 2024). In renewable-rich urban systems, however, uncertainty directly affects operational flexibility, market performance, and system resilience.

To address this limitation, SYNAPCITY-DT introduces a probabilistic operational-intelligence framework that explicitly propagates uncertainty across forecasting, optimization, and operational-control layers. Instead of relying on deterministic predictions, the framework utilizes probabilistic quantile forecasting to characterize multiple renewable-generation scenarios across different forecast horizons. These probabilistic outputs are then incorporated into adaptive battery scheduling, reserve participation, and market-dispatch optimization.

The operational-intelligence engine evaluates forecast uncertainty together with electricity-market conditions, reserve-market opportunities, battery flexibility, and operational constraints to determine adaptive control actions. Consequently, charging, discharging, export scheduling, and reserve commitments are continuously adjusted according to operational confidence and uncertainty severity levels.

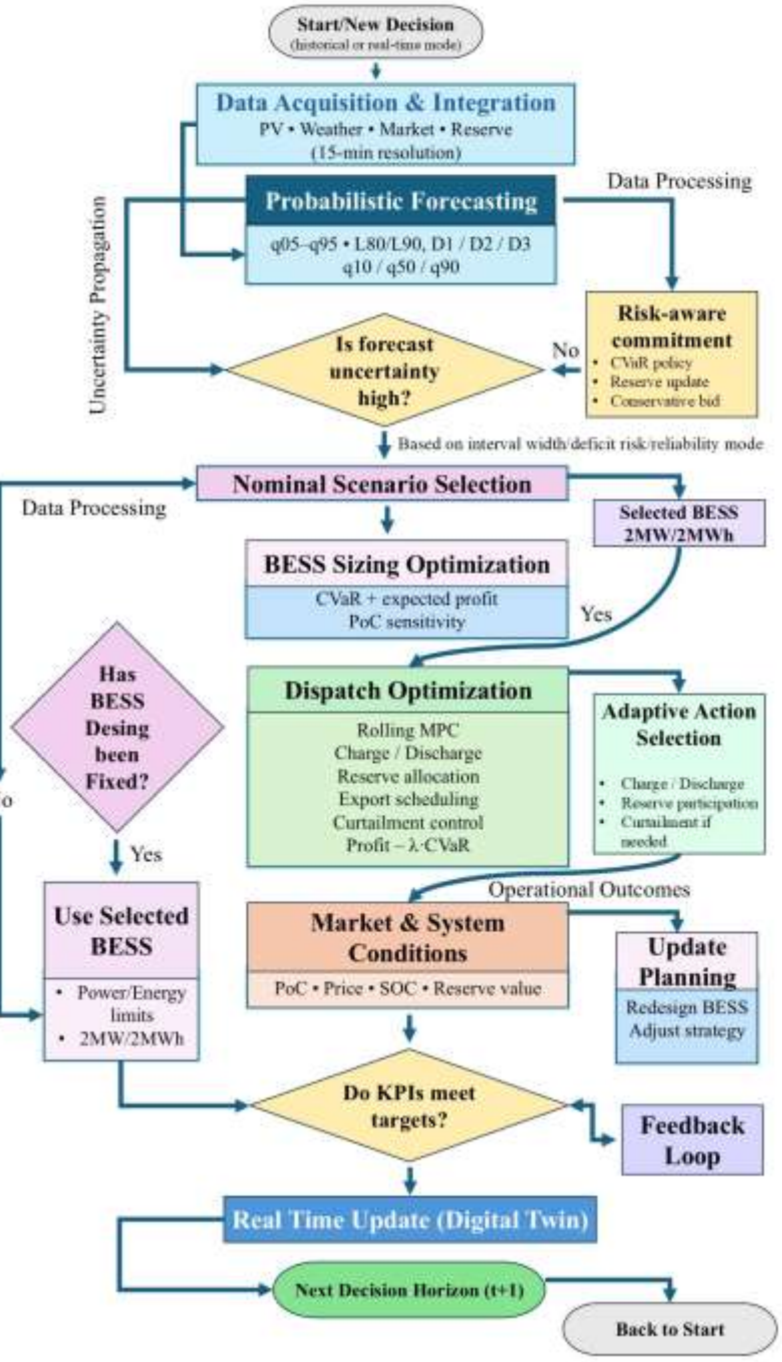
Risk-aware operational adaptation is implemented using a Conditional Value-at-Risk (CVaR)-based optimization framework widely adopted in stochastic energy-system optimization and electricity-market decision-making (Conejo et al., 2010; Shapiro et al., 2021). The operational objective is formulated as:

$$\max \ \mathbb{E}[Profit] - \lambda \cdot CVaR_{\beta}$$

Where $\mathbb{E}[Profit]$represents the expected operational profit, λdenotes the risk-aversion parameter, and $CVaR_{\beta}$quantifies the expected losses beyond a selected confidence level β. This formulation enables the framework to balance economic profitability against exposure to extreme operational losses and imbalance penalties under uncertain renewable conditions (Wipplinger, 2007; Xuan et al., 2021).

In addition, the operational-intelligence layer incorporates adaptive battery-flexibility coordination by considering charging and discharging efficiencies, SOC constraints, reserve headroom availability, curtailment conditions, and market-price dynamics. This enables the framework to dynamically adjust operational behavior according to uncertainty evolution and system-operating conditions. Figure 4. Shows the decision-oriented uncertainty propagation workflow implemented within the SYNAPCITY-DT framework.

Figure 4. Uncertainty-to-Decision Operational Workflow.



Source: Own elaboration, 2026.

2.4. Digital Twin Operational Intelligence

The digital-twin environment constitutes the central coordination layer of the proposed SYNAPCITY-DT framework. Unlike conventional monitoring-oriented digital twins, the proposed framework integrates predictive operational intelligence, uncertainty-aware analytics, adaptive monitoring, and real-time decision support within a continuously synchronized cyber-physical environment.

The digital twin continuously receives operational measurements, market information, probabilistic forecast updates, and optimization outputs from the physical PV–BESS system. These inputs are used to generate dynamic operational representations capable of evaluating system behavior under changing renewable-generation and market conditions.

Through continuous synchronization between physical and virtual operational states, the digital twin supports predictive monitoring, adaptive diagnostics, scenario evaluation, and operational explainability.

One of the major functionalities of the proposed framework is the integration of uncertainty visualization and operational transparency. Forecast uncertainty intervals, battery flexibility margins, reserve-allocation status, market conditions, and operational-risk indicators are continuously monitored and visualized through the digital-twin environment. This capability enables both automated decision-making and human-in-the-loop operational supervision.

Furthermore, the digital twin supports adaptive operational learning by continuously evaluating the effectiveness of previous operational actions under varying uncertainty conditions. This allows the framework to transition from static scheduling approaches toward adaptive and context-aware urban-energy intelligence.

The integration of probabilistic forecasting, risk-aware optimization, battery-flexibility coordination, and digital-twin-assisted adaptive control enables SYNAPCITY-DT to operate as a scalable urban-energy intelligence framework capable of supporting resilient and renewable-intensive smart-city infrastructures.

3. Methodology and Case Study

3.1. Study Case and System Description

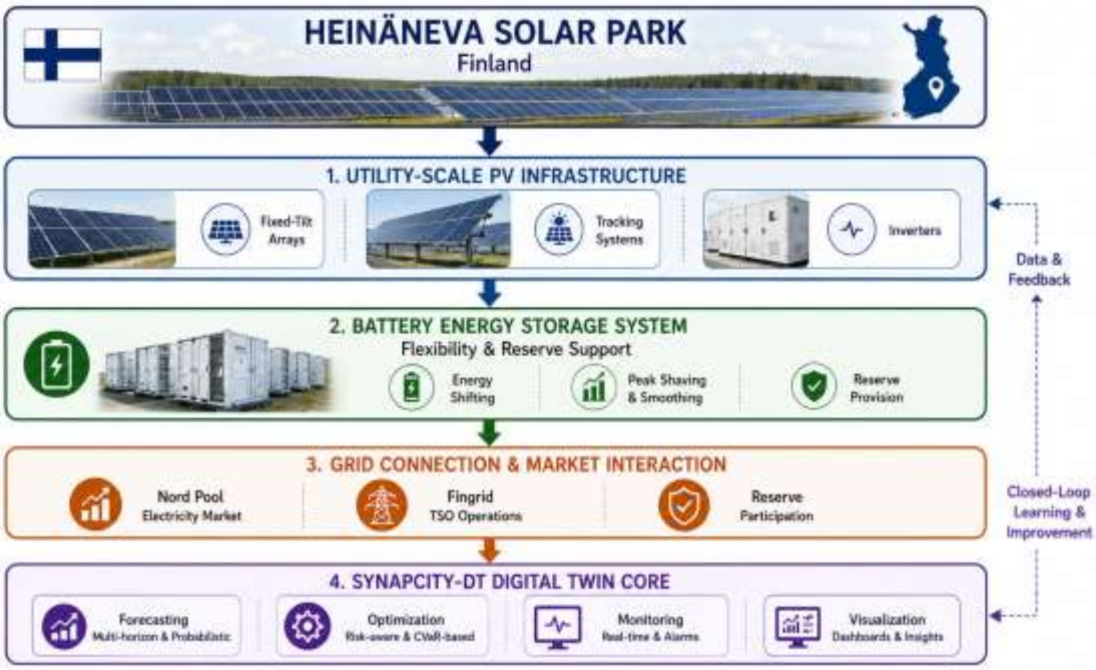
The proposed SYNAPCITY-DT framework was validated using real operational data from the Heinäneva Solar Park located in Finland. The case study represents a utility-scale grid-connected photovoltaic (PV) system operating under Nordic climatic conditions characterized by strong seasonal variability, rapid irradiance fluctuations, and highly dynamic renewable-generation patterns. These characteristics make the Finnish environment particularly suitable for evaluating uncertainty-aware operational intelligence and adaptive renewable-energy management.

The Heinäneva Solar Park operates as a large-scale renewable-generation asset connected to the electricity grid through a constrained point-of-connection (PoC) interface. The plant consists of approximately 80 MW of installed PV capacity with annual renewable-energy production on the order of 80 GWh. The system includes multiple PV blocks integrating both fixed-tilt and tracking-based configurations to improve renewable-energy harvesting under varying solar conditions. In addition, the operational framework incorporates a battery energy storage system (BESS) used for flexibility coordination, reserve participation, uncertainty mitigation, and adaptive dispatch support.

The operational environment considered in this study combines renewable generation, electricity-market participation, reserve-market interaction, and adaptive storage coordination under uncertain renewable conditions. Unlike conventional deterministic renewable-energy operation, the proposed framework continuously adapts operational decisions according to forecast uncertainty, market conditions, reserve opportunities, and system flexibility status.

The case study utilizes operational measurements with 15-minute temporal resolution covering approximately 4.5 months of real plant operation. The dataset integrates PV generation measurements, meteorological observations, electricity-market prices, reserve-market information, and operational system variables within a unified urban-energy intelligence framework. Through this real-world deployment environment, the proposed framework evaluates the interaction between probabilistic forecasting, adaptive operational optimization, and digital-twin-assisted decision intelligence under practical operating conditions. Figure 5. Presents the overview of the Finnish utility-scale PV–BESS smart-energy-node case study integrated within the proposed SYNAPCITY-DT framework.

Figure 5. Finnish Utility-Scale PV–BESS Smart Energy Node.



Source: Own elaboration, 2026.

3.2. Data Acquisition and Integration

The SYNAPCITY-DT framework integrates heterogeneous operational, meteorological, and market datasets within a unified decision-oriented digital-twin environment. The objective of the data-integration layer is to continuously synchronize real-world measurements with forecasting, optimization, and adaptive operational-control processes.

Operational PV measurements were obtained directly from the utility-scale renewable-generation system and include variables associated with PV output power, export levels, curtailment conditions, inverter operation, and system state measurements. Meteorological observations were acquired from the Finnish Meteorological Institute (FMI) and supplemented using NASA POWER solar-radiation datasets. Electricity-market prices were obtained from the Nord Pool day-ahead market, while reserve-market information was acquired from Fingrid Frequency Containment Reserve (FCR) datasets.

All datasets were synchronized to a unified 15-minute temporal resolution to ensure compatibility across forecasting, optimization, and operational-control layers. Data preprocessing included temporal alignment, interpolation of missing observations, normalization, outlier inspection, and feature harmonization across heterogeneous data sources. The integrated dataset contained approximately 12,700 operational observations and multiple renewable-energy, market, and environmental variables used throughout the forecasting and operational-intelligence framework.

The integration of multiple heterogeneous datasets enables the proposed framework to capture interactions between renewable variability, market dynamics, operational flexibility, and reserve opportunities under real operating conditions. This multi-domain integration is essential for supporting uncertainty-aware urban-energy intelligence and adaptive digital-twin operation.

Table 2. Summary of Integrated Datasets

Dataset Category	Source	Resolution	Main Variables
PV Operational Data	Utility-scale PV plant	15 min	PV output, export, curtailment

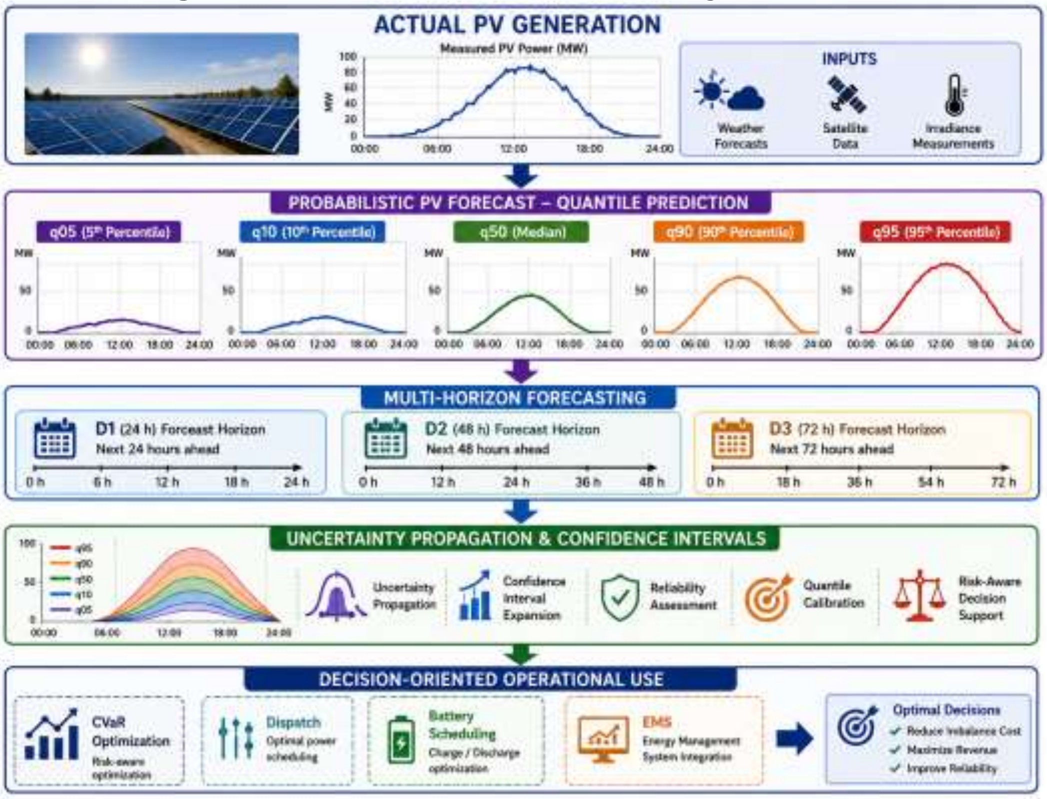
Weather Data	FMI	15 min	Temperature, irradiance, wind speed
Solar Radiation Data	NASA POWER	15 min	Solar irradiance indicators
Electricity Market Data	Nord Pool	Hourly	Day-ahead electricity prices
Reserve Market Data	Fingrid	Hourly	FCR prices and reserve values

Source: Own elaboration, 2026.

3.3. Probabilistic Forecasting Framework

The forecasting layer of SYNAPCITY-DT is designed to characterize renewable-generation uncertainty using probabilistic multi-horizon forecasting rather than deterministic point estimation. In renewable-rich urban-energy systems, operational uncertainty directly affects dispatch scheduling, reserve allocation, storage utilization, and electricity-market participation. Consequently, uncertainty-aware forecasting becomes essential for adaptive operational decision-making. Figure 6 shows the multi-horizon probabilistic forecasting structure used within the SYNAPCITY-DT framework for uncertainty-aware renewable-energy operation.

Figure 6. Multi-Horizon Probabilistic Forecasting Framework



Source: Own elaboration, 2026.

The proposed forecasting framework generates probabilistic quantile forecasts across multiple operational horizons denoted as D1, D2, and D3, corresponding respectively to 24-hour, 48-hour, and 72-hour forecasting windows. Quantile intervals ranging from q05 to q95 are used to characterize uncertainty distributions and operational confidence intervals. Prediction intervals enable the operational-intelligence layer to evaluate uncertainty severity and adapt operational behavior accordingly.

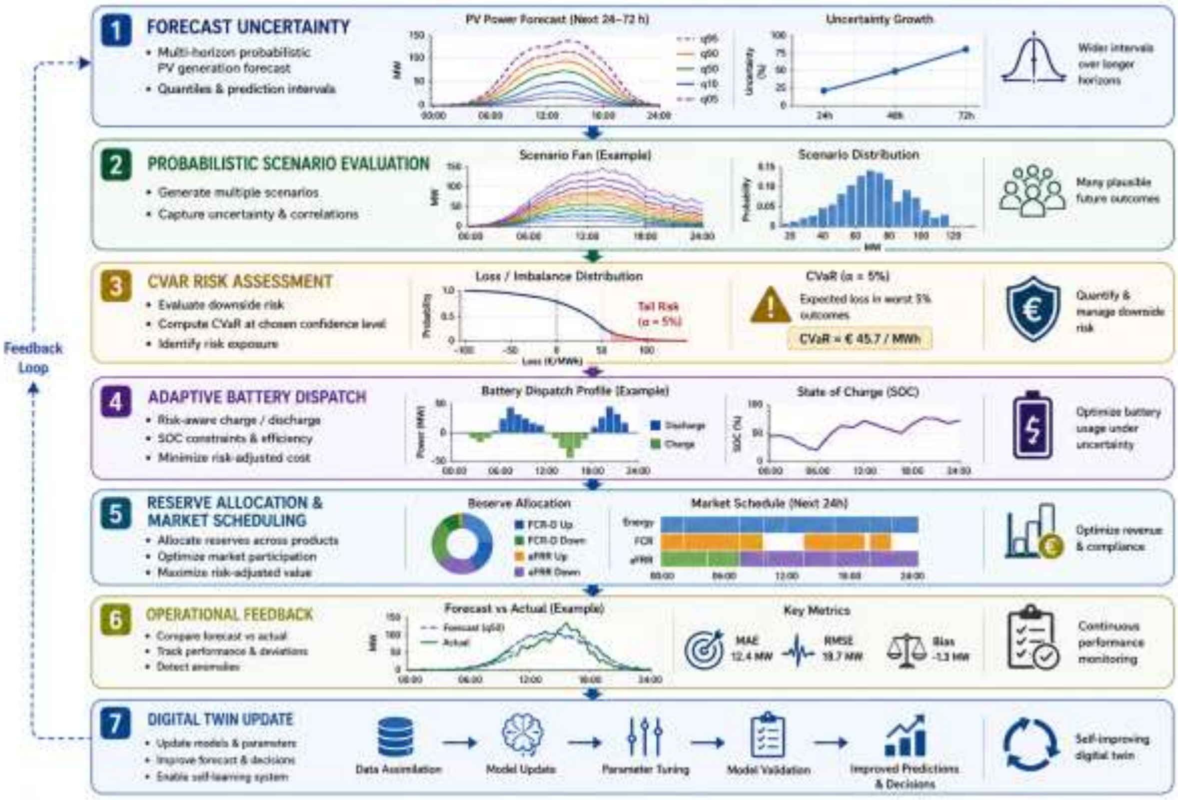
Unlike deterministic forecasting approaches that provide a single expected generation value, the probabilistic framework explicitly captures variability and uncertainty propagation under changing meteorological conditions. The forecasting layer therefore enables the operational system to evaluate not only expected renewable generation but also confidence bounds, risk exposure, and operational flexibility requirements.

The probabilistic forecasting framework is integrated directly with downstream operational-intelligence layers, allowing uncertainty information to influence reserve scheduling, battery dispatch, curtailment mitigation, and electricity-market decisions. This integration enables operational adaptation according to uncertainty severity and forecast confidence.

3.4. Risk-Aware Operational Optimization

The operational-intelligence layer of SYNAPCITY-DT performs adaptive renewable-energy scheduling under uncertain renewable-generation and electricity-market conditions. The optimization framework simultaneously coordinates battery dispatch, reserve participation, export scheduling, curtailment mitigation, and market interaction while accounting for operational flexibility and uncertainty propagation. Figure 7 presents a risk-aware operational-intelligence workflow integrating probabilistic forecasting, adaptive battery coordination, reserve scheduling, and digital-twin-assisted operational adaptation.

Figure 7. Risk-Aware Operational Intelligence Workflow



Source: Own elaboration, 2026.

Risk-aware operational adaptation is implemented through a Conditional Value-at-Risk (CVaR)-based stochastic optimization framework introduced in the previous section. The optimization objective balances expected operational profitability against exposure to adverse operational outcomes and imbalance risks under uncertain renewable conditions. By incorporating uncertainty-aware decision logic, the framework enables adaptive operational behavior according to forecast confidence levels and market dynamics.

The operational-intelligence engine continuously evaluates probabilistic forecast distributions, electricity-market prices, reserve-market opportunities, battery state-of-charge (SOC) conditions, charging and discharging efficiencies, export limitations, and reserve-allocation requirements simultaneously. Battery operation is dynamically adjusted according to uncertainty severity and operational confidence conditions. Under elevated uncertainty levels, the framework adopts more conservative scheduling strategies, including reduced reserve commitments, adaptive dispatch constraints, and increased operational flexibility margins to mitigate imbalance exposure and operational instability.

To improve operational adaptability, the optimization framework operates using a rolling-horizon structure in which forecasts, operational measurements, and market conditions are continuously updated within the digital-twin environment. At each operational interval, the framework re-evaluates forecast uncertainty, market conditions, and system flexibility before updating operational decisions for subsequent scheduling horizons. This adaptive structure enables continuous operational learning and uncertainty-aware decision refinement under changing renewable and market conditions.

The operational optimization layer therefore functions not only as a scheduling mechanism but also as an adaptive operational-intelligence engine capable of dynamically coordinating renewable generation, storage flexibility, and market participation within the broader SYNAPCITY-DT urban-energy ecosystem.

3.5. Digital Twin Operational Environment

The proposed SYNAPCITY-DT framework integrates a continuously synchronized digital-twin environment for real-time monitoring, operational visualization, predictive analytics, and adaptive operational supervision. The digital twin functions as the cyber-physical coordination layer connecting forecasting intelligence, operational optimization, and physical renewable-energy infrastructure.

The digital twin continuously receives operational measurements, market updates, probabilistic forecasts, optimization outputs, and reserve information from the physical PV–BESS system. These inputs are integrated within a unified visualization and operational-intelligence environment capable of evaluating system behavior under varying renewable and market conditions.

A major functionality of the digital twin is uncertainty-aware operational visualization. Forecast confidence intervals, reserve commitments, state-of-charge trajectories, export schedules, and operational-risk indicators are continuously monitored and visualized in real time. This enables both automated operational adaptation and human-in-the-loop supervisory decision-making.

In addition, the digital twin supports predictive operational analytics and scenario evaluation by continuously comparing operational outcomes against expected forecast conditions and optimization targets. Through adaptive feedback loops, the framework enables continuous operational refinement under changing uncertainty conditions.

The integration of probabilistic forecasting, adaptive optimization, and real-time digital-twin synchronization enables SYNAPCITY-DT to operate as a scalable urban-energy intelligence platform suitable for future renewable-intensive smart-city infrastructures.

4. Forecasting Reliability and Uncertainty Evolution

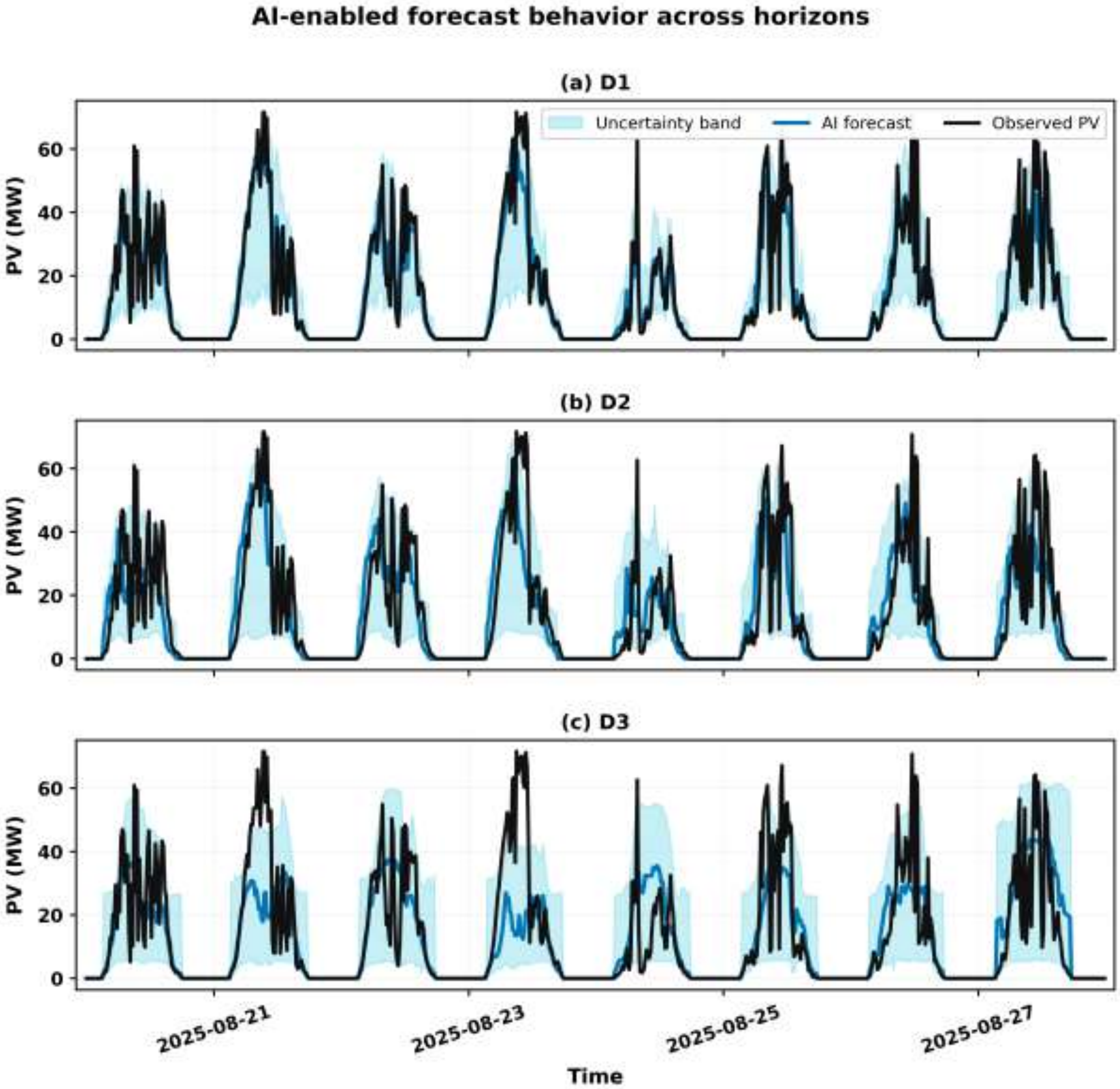
4.1. Digital Twin Operational Environment

Accurate characterization of renewable-generation uncertainty is essential for adaptive operational coordination in renewable-intensive smart-energy environments. Within the proposed SYNAPCITY-DT framework, probabilistic forecasting is used not only for renewable-generation prediction but also as a direct operational-intelligence mechanism supporting adaptive scheduling, reserve coordination, and uncertainty-aware decision-making. Figure 8 presents the multi-horizon forecasting behavior of the proposed AI-enabled probabilistic forecasting framework across D1, D2, and D3 operational horizons.

The forecasting results demonstrate a clear evolution of uncertainty propagation as the prediction horizon increases. The D1 forecasting horizon exhibits relatively narrow uncertainty intervals and strong alignment between predicted and observed PV generation profiles. In contrast, the D2 horizon introduces moderate uncertainty widening, particularly during rapidly changing irradiance conditions and peak-generation periods. The D3 horizon shows substantially larger prediction intervals and reduced operational confidence due to the increasing accumulation of meteorological uncertainty over longer forecasting horizons.

The widening uncertainty bands observed in Figure 8 highlight the operational importance of probabilistic forecasting in renewable-energy coordination. Rather than relying on deterministic point forecasts, the proposed framework continuously evaluates forecast confidence levels and interval evolution to support adaptive operational behavior. Under high-uncertainty conditions, the operational-intelligence layer dynamically modifies scheduling behavior, reserve commitments, and dispatch flexibility to reduce imbalance exposure and operational instability.

Figure 8. AI-Enabled Forecast Behavior Across Operational Horizons

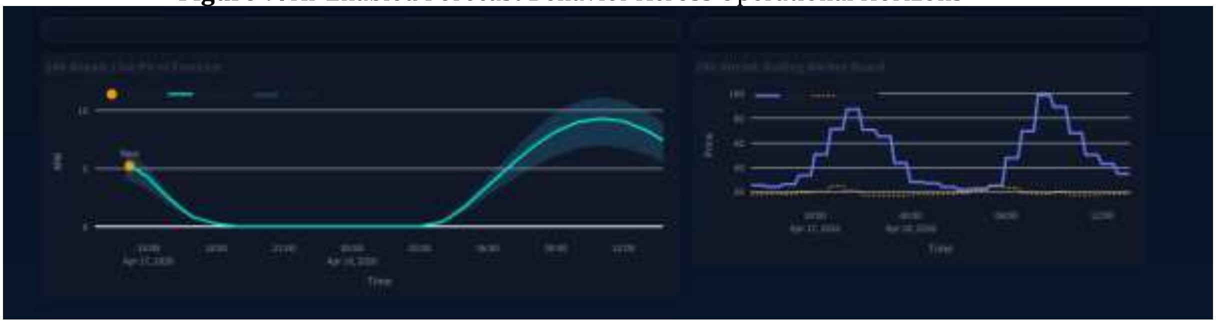


Source: Own elaboration, 2026.

The forecasting behavior additionally reveals the increasing operational complexity associated with long-horizon renewable-energy coordination. While short-horizon forecasts preserve strong temporal agreement with observed generation behavior, longer forecasting horizons exhibit larger uncertainty ranges and reduced confidence stability, particularly during highly variable renewable-generation intervals. These results demonstrate the necessity of integrating uncertainty-aware operational intelligence directly into renewable-energy management systems operating within future smart-city infrastructures.

To operationalize forecasting intelligence within real-time system coordination, the SYNAPCITY-DT framework integrates probabilistic forecasting outputs directly into the digital-twin operational environment. Figure 9 illustrates the real-time forecast–market operational analytics environment implemented within the proposed digital twin framework. The operational dashboard continuously synchronizes probabilistic forecast intervals, rolling market conditions, and operational indicators within a unified operational-intelligence environment

Figure 9. AI-Enabled Forecast Behavior Across Operational Horizons

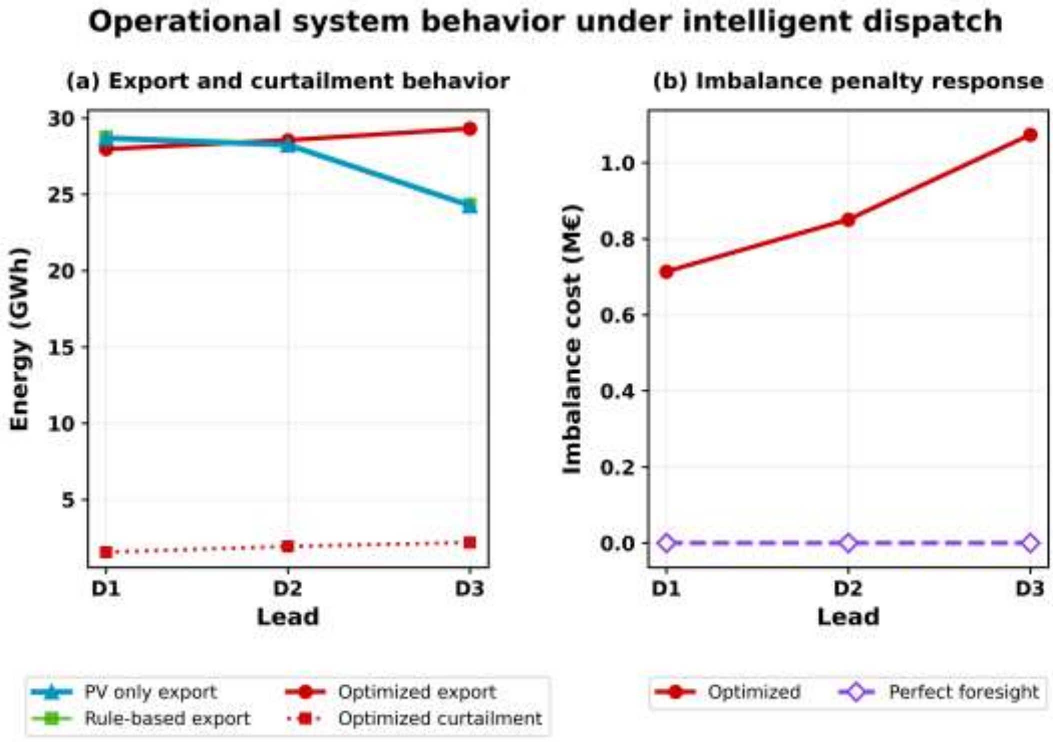


Source: Own elaboration, 2026.

4.2. Operational Risk and Economic Performance

The operational-performance behavior of the proposed SYNAPCITY-DT framework was evaluated under uncertainty-aware dispatch coordination across D1, D2, and D3 forecasting horizons. The analysis focuses on export optimization, curtailment management, and imbalance-cost mitigation under increasing forecast uncertainty and changing operational conditions. Figure 10 presents the operational system behavior under intelligent dispatch coordination.

Figure 10. Operational System Behavior Under Intelligent Dispatch



Source: Own elaboration, 2026.

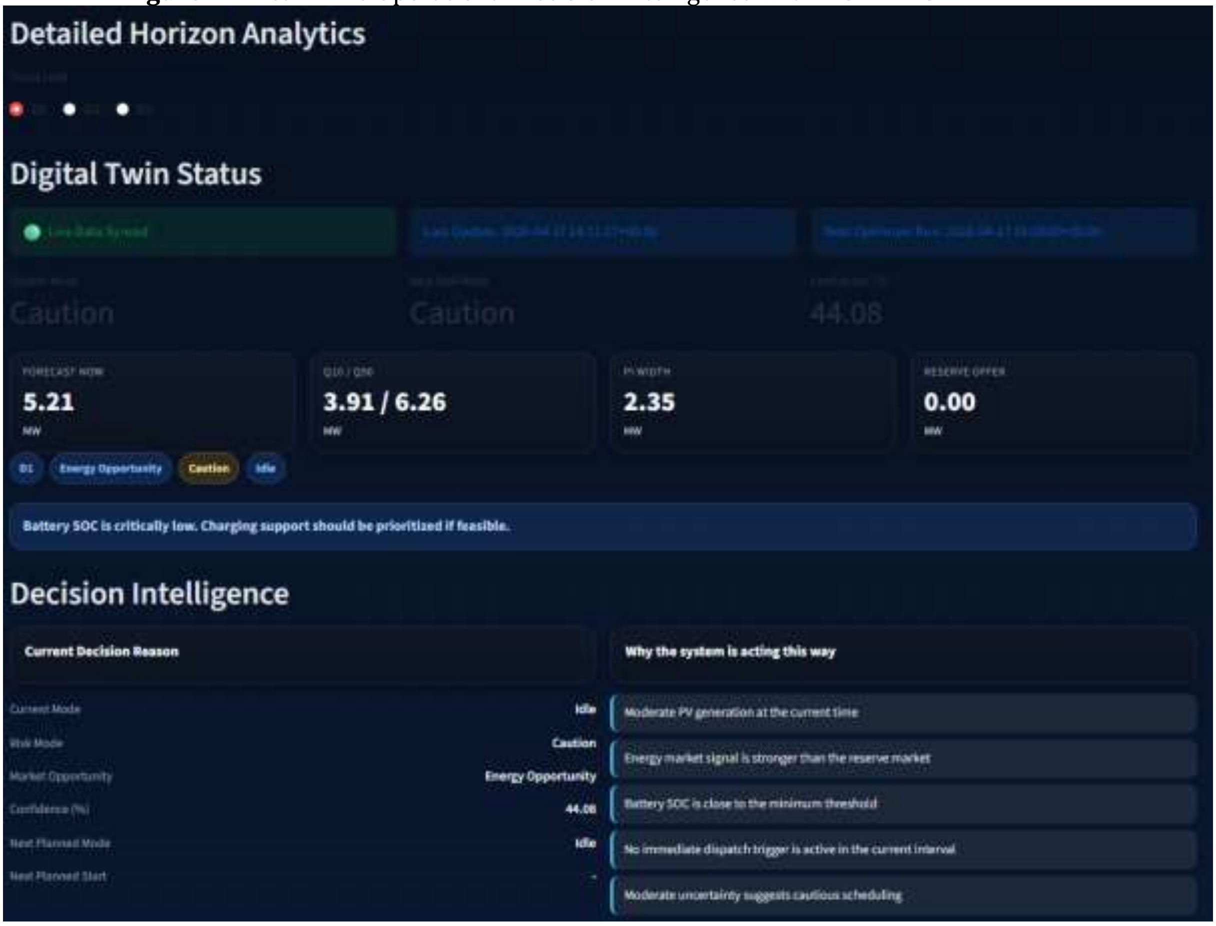
The results demonstrate that the optimized operational strategy consistently preserves higher export performance compared with conventional PV-only and rule-based dispatch approaches. While the PV-only and rule-based strategies experience substantial export degradation under increasing uncertainty, the proposed optimization framework maintains relatively stable export performance across all forecasting horizons through adaptive scheduling and uncertainty-aware operational coordination.

The operational behavior additionally reveals the increasing importance of intelligent curtailment coordination under long-horizon uncertainty conditions. Although optimized curtailment increases moderately from D1 to D3, the adaptive dispatch framework successfully preserves higher operational export stability while mitigating excessive imbalance exposure. This demonstrates that limited strategic curtailment can improve overall operational robustness when coordinated through uncertainty-aware optimization mechanisms.

Figure 10(b) further illustrates the imbalance-cost evolution under increasing forecast uncertainty. The imbalance penalties gradually increase from D1 to D3 due to the widening forecast uncertainty intervals observed in Section 4.1. However, the operational optimization framework maintains controlled imbalance growth despite increasingly uncertain renewable-generation conditions. In contrast, the perfect-foresight benchmark theoretically eliminates imbalance penalties but represents an idealized operational scenario not achievable in practical real-world deployments.

The operational results therefore demonstrate the effectiveness of integrating probabilistic forecasting and CVaR-based adaptive dispatch within a unified operational-intelligence framework. Rather than maximizing export aggressively under uncertain conditions, the proposed framework dynamically balances profitability, operational stability, and risk exposure through adaptive decision coordination.

Figure 11. Real-Time Operational Decision Intelligence Within SYNAPCITY-DT



Source: Own elaboration, 2026.

To operationalize these adaptive decisions within the real-time digital-twin environment, the SYNAPCITY-DT platform continuously evaluates operational confidence levels, battery state conditions, uncertainty propagation, and market opportunities. Figure 11 presents the operational decision-intelligence environment integrated within the digital twin framework

The digital-twin operational environment continuously evaluates uncertainty-aware operational indicators such as forecast confidence, prediction-interval width, reserve opportunities, battery state-of-charge (SOC), and adaptive operational readiness. The platform dynamically categorizes operational conditions into adaptive operational modes based on evolving uncertainty and system-state behavior.

As shown in Figure 11, the operational environment identifies elevated uncertainty conditions through the combined interpretation of forecast intervals, confidence metrics, and battery operational status. The decision-intelligence module subsequently generates operational reasoning explanations that support explainable operational supervision and adaptive control transparency. Rather than functioning as a static optimization platform, the framework continuously adapts dispatch coordination according to evolving renewable-generation and market conditions.

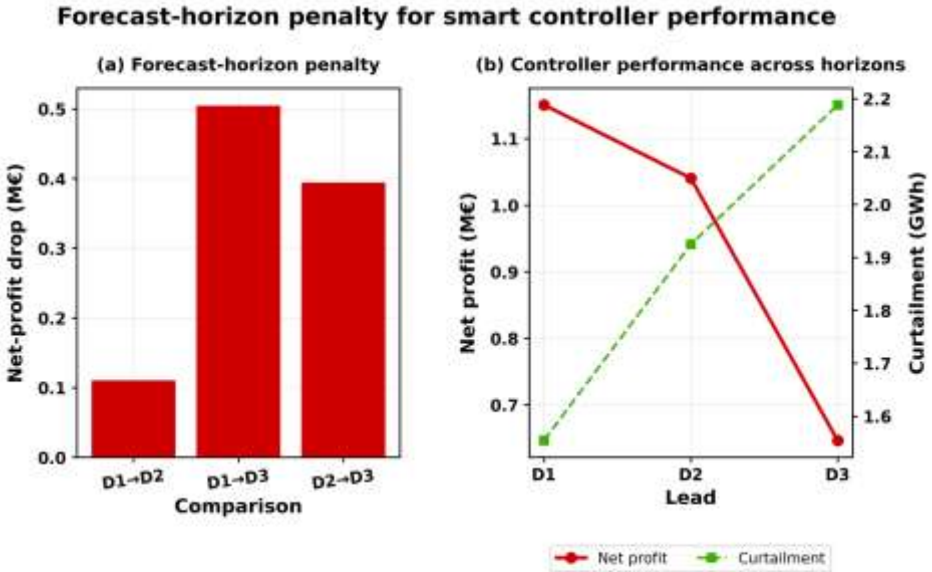
The operational coupling between uncertainty-awareness and decision explainability is particularly important for future smart-city energy infrastructures where renewable variability, electricity-market volatility, and operational complexity continuously interact. Through real-time digital-twin synchronization and adaptive operational reasoning, the proposed framework improves both automated operational intelligence and human-supervised situational awareness.

Overall, the results demonstrate that the SYNAPCITY-DT framework successfully combines probabilistic forecasting, risk-aware optimization, adaptive operational coordination, and explainable digital-twin intelligence into a unified renewable-energy operational environment capable of supporting resilient and uncertainty-aware smart-city energy management

4.3. Adaptive Battery Coordination and Operational Flexibility

Adaptive battery coordination is essential for renewable-rich smart-energy systems operating under uncertain generation and electricity-market conditions. Within the SYNAPCITY-DT framework, the battery energy storage system (BESS) functions not only as an energy-balancing asset but also as an adaptive operational-flexibility mechanism capable of coordinating reserve participation, uncertainty mitigation, export stabilization, and risk-aware dispatch adaptation. Figure 12 presents the operational flexibility behavior of the proposed intelligent control framework across different forecasting horizons.

Figure 12. Forecast-Horizon Penalty and Smart Controller Performance



Source: Own elaboration, 2026.

The results demonstrate a clear operational relationship between forecasting uncertainty and adaptive battery coordination behavior. As forecasting horizons increase from D1 to D3, the operational framework experiences progressive reductions in net operational profit accompanied by increasing curtailment behavior. This performance degradation is primarily associated with the widening uncertainty intervals discussed in Section 4.1, which force the operational controller to adopt increasingly conservative scheduling strategies to reduce imbalance exposure and operational instability.

Despite increasing uncertainty, the intelligent control framework preserves operational stability through adaptive flexibility coordination. Rather than aggressively maximizing export under uncertain conditions, the controller dynamically reallocates battery flexibility toward operational stabilization and reserve-support behavior. This demonstrates the importance of uncertainty-aware battery scheduling within renewable-intensive energy-management environments.

Figure 12(a) further illustrates the forecast-horizon penalty associated with increasing uncertainty propagation. The largest operational penalty occurs between D1 and D3 forecasting horizons, highlighting the significant operational value of short-horizon probabilistic forecasting for adaptive renewable-energy coordination. These results confirm that operational profitability is strongly coupled with forecasting reliability and adaptive flexibility management.

To support real-time operational adaptation, the SYNAPCITY-DT framework continuously evaluates operational transitions, dispatch smoothness, and switching behavior through integrated digital-twin supervision. Figure 13 presents the operational switching-behavior analytics environment implemented within the proposed framework.

Figure 13. Operational Switching Behavior and Flexibility Coordination Analytics

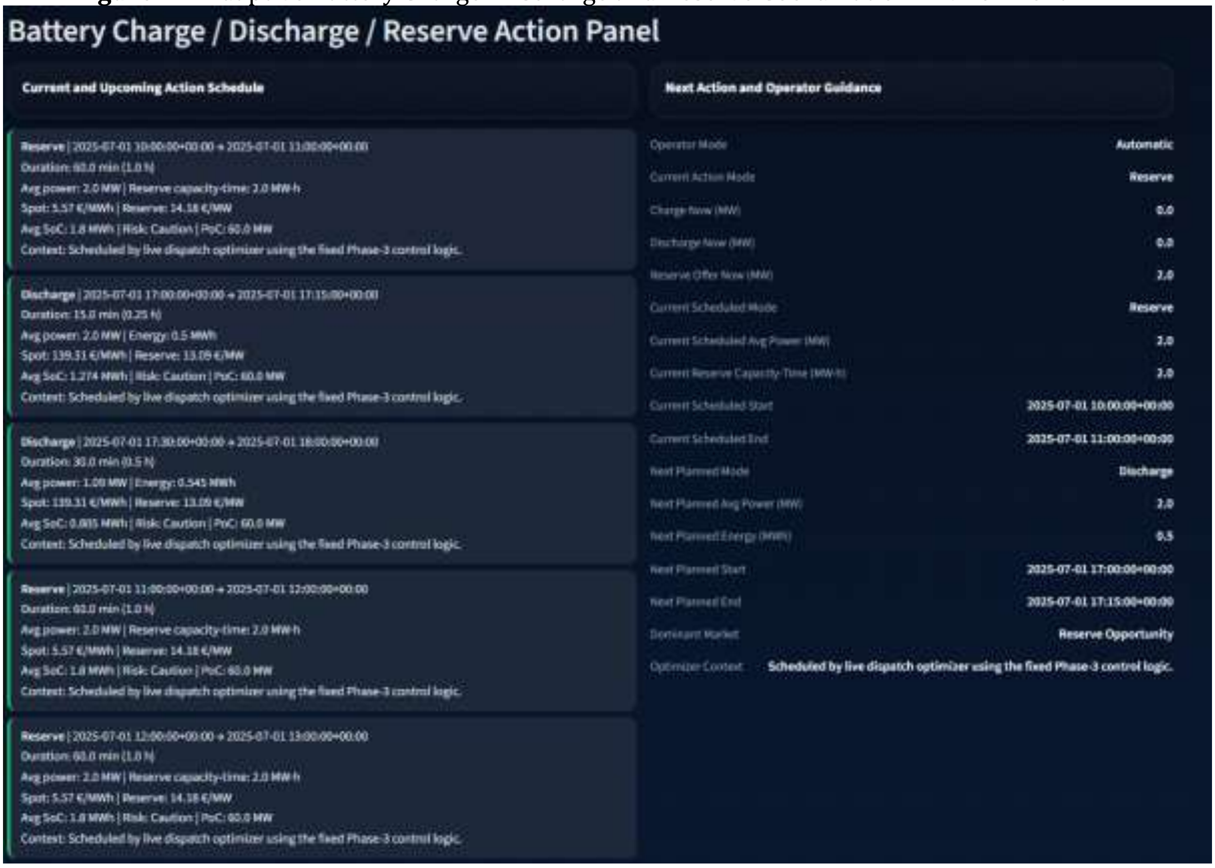
Source: Own elaboration, 2026.

The operational analytics reveal that dispatch-transition frequency increases under longer forecasting horizons due to increasing uncertainty-driven operational adaptation. The D1 operational horizon exhibits relatively stable dispatch behavior with minimal switching activity, whereas D2 and D3 horizons require progressively more adaptive operational transitions between charging, discharging, and reserve-support modes.

Importantly, the operational framework maintains controlled switching behavior despite increasing uncertainty conditions. Excessive dispatch switching can accelerate battery degradation, reduce operational stability, and increase system stress. The proposed framework therefore incorporates adaptive operational coordination mechanisms that balance flexibility responsiveness with dispatch smoothness and operational continuity.

In addition to operational-transition monitoring, the digital-twin environment continuously supervises battery state-of-charge (SOC), reserve opportunities, operational readiness, and market conditions. Figure 14 presents the adaptive battery action and reserve-coordination environment integrated within the operational digital twin

Figure 14. Adaptive Battery Charge–Discharge and Reserve Coordination Environment



Source: Own elaboration, 2026.

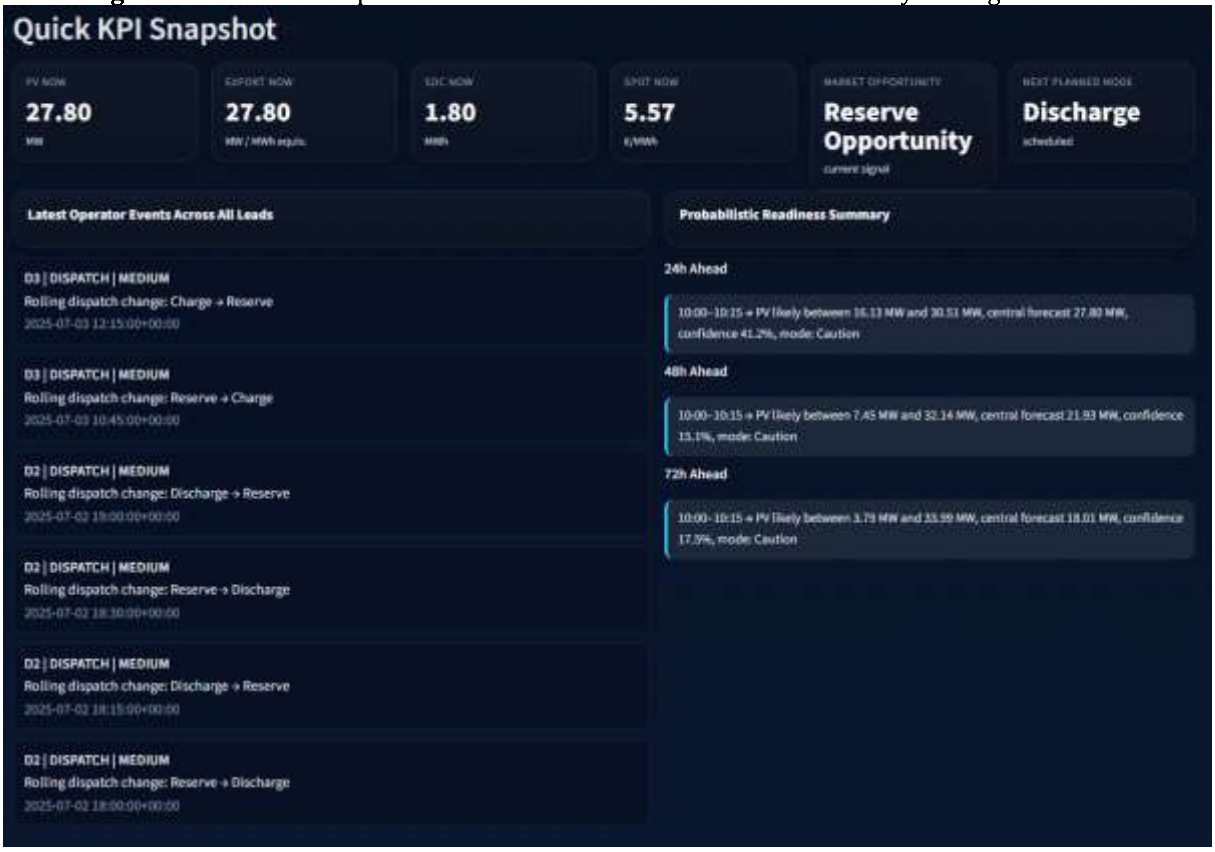
The operational environment dynamically coordinates charging, discharging, and reserve allocation according to forecast uncertainty, electricity-market conditions, battery SOC constraints, and operational risk levels. As shown in Figure 14, the framework continuously evaluates operational opportunities while preserving operational-security constraints and uncertainty-aware reserve margins.

The operational scheduling results further demonstrate the integration of explainable operational intelligence within the proposed framework. The digital-twin environment provides continuous visibility into scheduled operational actions, operational context, reserve capacity allocation, and adaptive operational recommendations. This improves both automated operational coordination and human-supervised situational awareness within renewable-rich smart-energy environments. The integrated KPI environment continuously synchronizes operational events, forecast confidence conditions, reserve opportunities, and operational flexibility indicators across multiple operational horizons. This enables the operational framework to maintain adaptive coordination under dynamically evolving renewable-generation and electricity-market conditions.

Overall, the results demonstrate that the proposed SYNAPCITY-DT framework successfully integrates uncertainty-aware battery coordination, adaptive operational flexibility, reserve-support intelligence, and explainable digital-twin supervision into a unified operational environment capable of supporting resilient renewable-energy management within future smart-city infrastructures

Figure 15 further presents the integrated operational-readiness and probabilistic flexibility environment within the proposed digital twin framework.

Figure 15. Real-Time Operational Readiness and Probabilistic Flexibility Intelligence



Source: Own elaboration, 2026.

4.4. Integrated Digital Twin Operational Intelligence Environment

The SYNAPCITY-DT framework was further evaluated through an integrated digital-twin operational environment capable of combining probabilistic forecasting, adaptive dispatch optimization, reserve coordination, operator intelligence, and real-time decision monitoring within a unified operational interface. Unlike conventional supervisory-control dashboards that mainly provide passive visualization, the proposed framework performs active operational reasoning by continuously synchronizing forecasting uncertainty, market signals, battery conditions, and operational constraints into an adaptive intelligence layer.

Figure 16 presents the overall operational dashboard of the proposed SYNAPCITY-DT environment. The integrated platform combines multi-horizon operational monitoring (D1, D2, and D3), probabilistic readiness evaluation, dispatch coordination, risk-state interpretation, reserve scheduling, and operational alerts within a single intelligent-control environment. The framework continuously updates forecast confidence intervals, battery state-of-charge conditions, reserve opportunities, export behavior, and risk-awareness indicators under rolling operational horizons. This enables dynamic coordination between forecasting intelligence and operational control decisions.

The digital-twin environment additionally incorporates decision-intelligence explainability functions. Instead of only displaying operational outputs, the framework provides interpretable explanations regarding why specific actions are selected under changing operational conditions. As shown in Figure 16, the operational interface identifies reserve opportunities, uncertainty levels, battery constraints, and market conditions simultaneously while generating adaptive operational recommendations. Such explainable operational behavior becomes increasingly important in future AI-enabled smart-grid environments where operators require transparent understanding of autonomous system decisions.

The operational dashboard also demonstrates multi-layer flexibility coordination across forecasting horizons. The D1 horizon generally exhibits higher forecast confidence and lower uncertainty exposure, while D2 and D3 increasingly activate caution-oriented operational modes due to wider uncertainty intervals and increased operational risk. Consequently, the framework adaptively modifies reserve participation, charge/discharge behavior, and dispatch aggressiveness according to uncertainty propagation across forecasting horizons.

Figure 16 presents the integrated SYNAPCITY-DT operational intelligence environment developed for real-time renewable-energy coordination and adaptive operational supervision.

Figure 16. Integrated SYNAPCITY-DT Operational Intelligence Environment

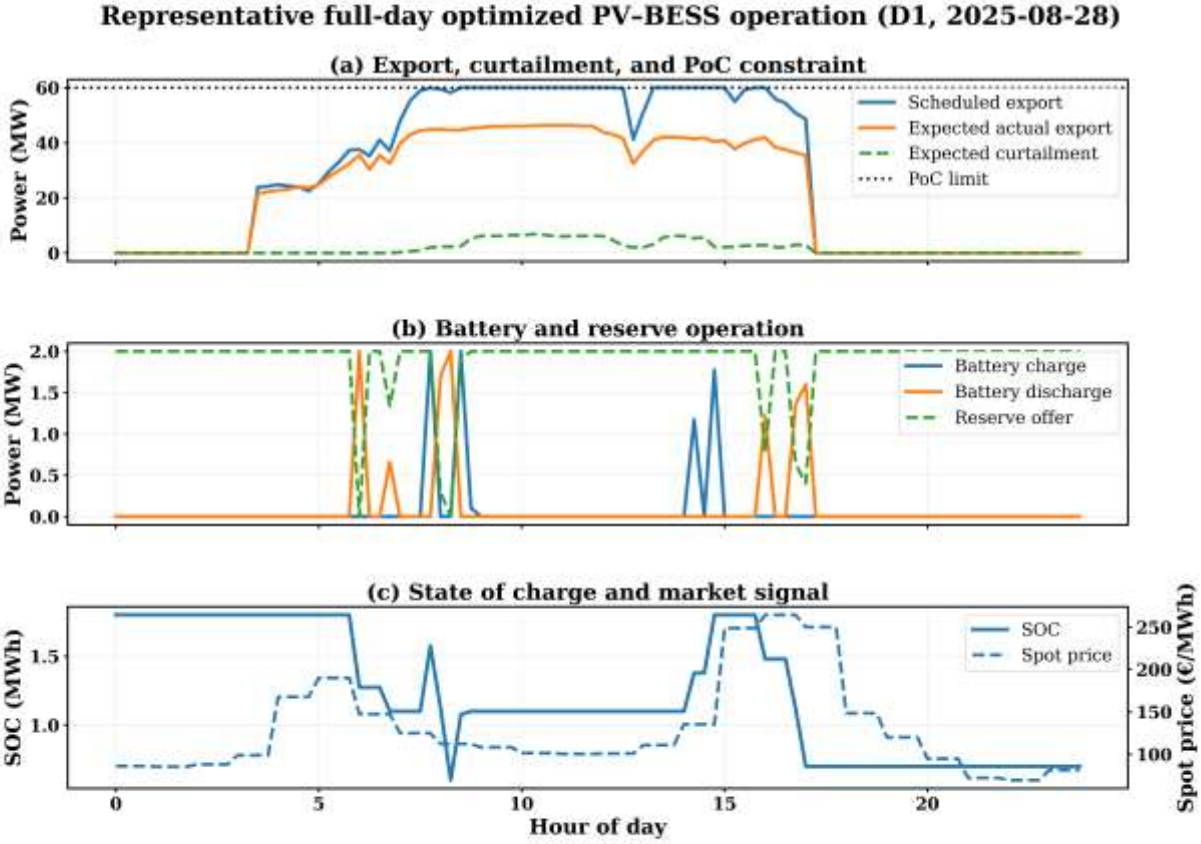
Source: Own elaboration, 2026.

Figure 17 illustrates a representative full-day operation of the optimized PV–BESS dispatch framework under the D1 operational horizon. The figure demonstrates the coordinated interaction between scheduled export, expected renewable generation, curtailment mitigation, reserve participation, and battery operation under the imposed point-of-connection (PoC) limitation. During high-generation periods, the optimization framework dynamically adjusts export scheduling while coordinating battery charging and reserve allocation to maintain operational feasibility and reduce imbalance exposure.

The lower operational layers shown in Figure 17 further demonstrate the adaptive interaction between battery charging/discharging behavior, reserve activation, state-of-charge evolution, and electricity-market signals throughout the operational horizon. The optimization framework preserves operational flexibility by strategically maintaining battery energy availability during uncertain periods while exploiting favorable market conditions under higher operational confidence levels. This coordinated adaptive behavior illustrates how the proposed digital-twin environment performs continuous operational synchronization between uncertainty-aware forecasting, market participation, and battery flexibility management.

Overall, the results demonstrate that SYNAPCITY-DT operates not merely as a visualization platform but as an integrated operational-intelligence framework capable of combining probabilistic forecasting, adaptive optimization, explainable decision support, and real-time operational coordination within a unified smart-city energy-management environment. The framework therefore represents a transition from conventional passive monitoring architectures toward intelligent cyber-physical urban-energy coordination systems capable of supporting future renewable-dominated smart-grid infrastructures.

Figure 17. Representative full-day operational behavior of the optimized PV–BESS dispatch framework



Source: Own elaboration, 2026.

4.5. System-Level Smart-City Implications and Urban Energy Intelligence

Figure 18 presents the integrated benchmark summary of the optimized operational strategy across the D1, D2, and D3 forecasting horizons. The results demonstrate how forecast-horizon uncertainty influences long-term economic performance, renewable-utilization efficiency, battery utilization behavior, and operational sustainability indicators within the proposed SYNAPCITY-DT framework.

The annual net-profit results indicate that the D1 operational horizon achieved the highest economic performance, reaching approximately €3.18 million annually, followed by D2 with approximately €2.88 million and D3 with approximately €1.79 million. A similar trend is observed for the net-present-value (NPV) analysis, where D1 achieved the highest long-term investment value exceeding €26 million, while D3 produced the lowest NPV at approximately €14.5 million. These results demonstrate that shorter operational horizons with lower uncertainty exposure enable more economically efficient scheduling and improved renewable-energy value capture.

The annual battery-cycling behavior remained relatively stable across operational horizons, with approximately 79 cycles for D1, 70 cycles for D2, and 71 cycles for D3. This indicates that the proposed optimization framework maintains balanced storage utilization without excessively increasing battery degradation exposure despite changing operational uncertainty conditions. The results therefore suggest that the framework successfully coordinates operational flexibility and degradation-aware scheduling simultaneously.

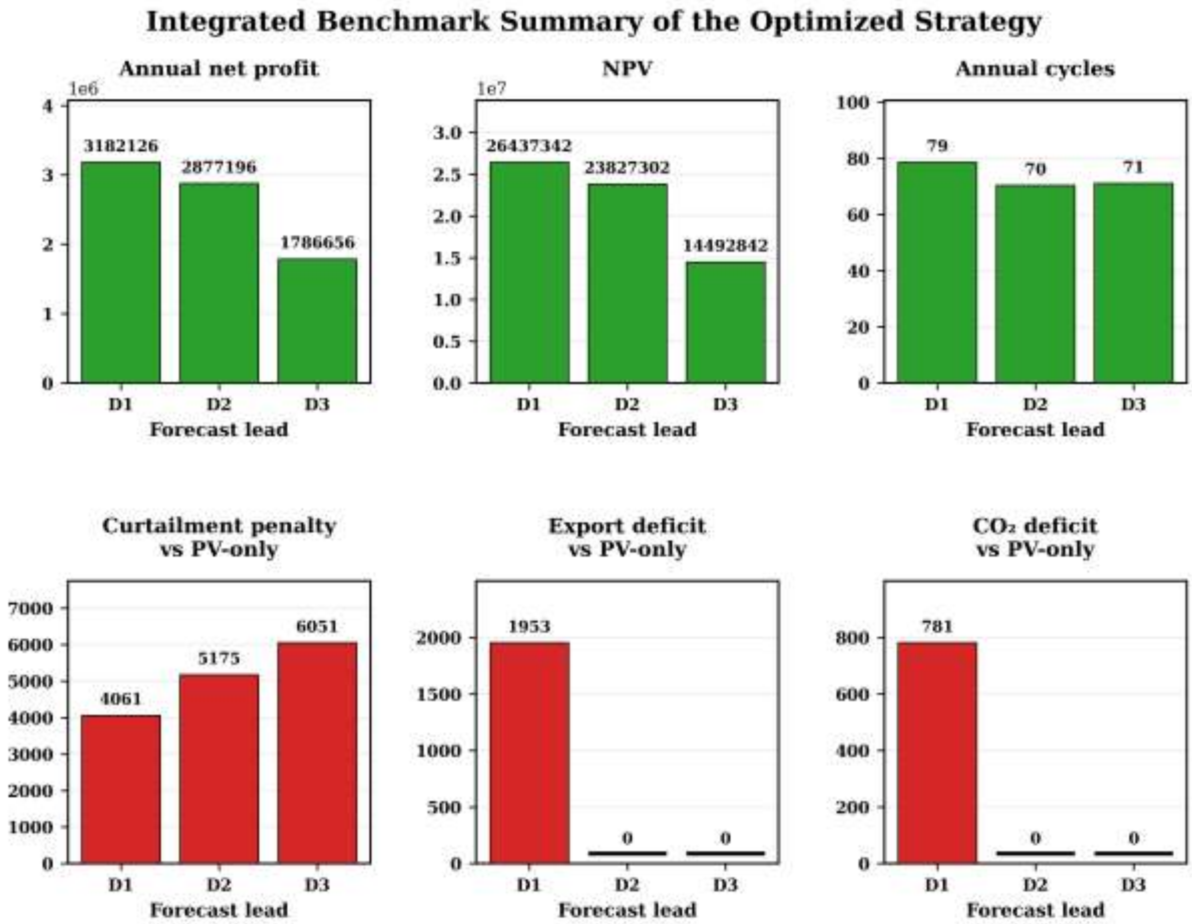
The curtailment-related analysis further demonstrates the influence of forecast uncertainty on renewable-energy utilization efficiency. As shown in Figure 18, curtailment penalties progressively increased from D1 toward D3, indicating that wider uncertainty intervals force increasingly conservative export scheduling and flexibility reservation.

Consequently, longer forecasting horizons reduce renewable-energy utilization efficiency due to increased operational uncertainty and precautionary control behavior.

Interestingly, the export-deficit and CO_2-related indicators reveal different operational characteristics across horizons. The D1 horizon exhibited measurable export and CO_2 deficits relative to PV-only operation, whereas D2 and D3 showed near-zero deficit behavior. This indicates that the shorter-horizon strategy prioritizes aggressive market participation and renewable-energy utilization to maximize profitability, occasionally introducing limited export deficits and associated operational trade-offs. In contrast, the more conservative D2 and D3 strategies reduce operational exposure and deficit risks by adopting stricter uncertainty-aware scheduling policies.

Overall, the system-level results demonstrate that the proposed SYNAPCITY-DT framework enables adaptive trade-offs between profitability, renewable-energy utilization, operational robustness, and uncertainty management across forecasting horizons. The framework therefore provides not only localized dispatch optimization but also broader urban-energy operational intelligence capable of supporting future renewable-dominated smart-city infrastructures through coordinated forecasting, adaptive flexibility management, and uncertainty-aware operational decision-making.

Figure 18. Integrated benchmark summary of the optimized operational strategy



Source: Own elaboration, 2026.

5. Discussion

5.1. Operational Intelligence and Forecast-Driven Energy Coordination

The results demonstrate that renewable-energy operational performance is strongly dependent on forecast uncertainty and its propagation into downstream operational decision-making. The proposed SYNAPCITY-DT framework addresses this challenge by tightly integrating probabilistic forecasting, adaptive operational optimization, and digital-twin coordination within a unified operational-intelligence environment. Unlike conventional renewable-energy scheduling approaches where forecasting and dispatch are frequently treated as isolated tasks, the proposed framework continuously incorporates uncertainty-awareness into operational coordination and adaptive flexibility management.

The comparative operational results shown in Figures 9, 11, 13, and 18 indicate that shorter forecasting horizons provide substantially improved operational performance and economic efficiency. The D1 horizon consistently achieved the highest profitability, strongest renewable-energy utilization, and lowest curtailment exposure due to narrower uncertainty intervals and improved dispatch confidence. In contrast, the D3 horizon exhibited increasingly conservative operational behavior resulting from wider uncertainty propagation and elevated operational risk exposure.

These findings demonstrate that operational forecasting performance should not be evaluated solely through statistical accuracy metrics such as RMSE or MAE. Instead, the operational value of forecasting should be assessed according to its influence on downstream decision-making, reserve coordination, flexibility allocation, imbalance mitigation, and operational resilience. Within the proposed framework, probabilistic forecasting functions as an operational-intelligence mechanism directly influencing adaptive dispatch coordination and uncertainty-aware energy management.

The operational results additionally highlight the importance of rolling operational adaptation within renewable-rich smart-energy systems. By continuously synchronizing forecasts, operational measurements, reserve opportunities, and electricity-market signals, the framework dynamically updates operational behavior according to evolving renewable and market conditions. Such adaptive operational coordination becomes increasingly important for future smart-city infrastructures where renewable variability and operational uncertainty are expected to intensify significantly

5.2. Digital Twin Intelligence and Explainable Smart-Grid Operation

A major contribution of this study is the integration of explainable operational intelligence within a real-time digital-twin environment. Existing renewable-energy digital twins frequently focus on visualization, monitoring, predictive maintenance, or cyber-physical system representation. In contrast, the proposed SYNAPCITY-DT framework enables active operational reasoning and adaptive operational supervision under uncertain renewable-generation conditions.

As illustrated in Figures 16 and 17, the digital-twin environment continuously synchronizes probabilistic forecasts, operational constraints, battery flexibility conditions, reserve opportunities, dispatch schedules, and market conditions within a unified operational-intelligence architecture. The framework therefore acts not only as a visualization platform but also as an adaptive operational-coordination layer capable of supporting uncertainty-aware renewable-energy management.

An important characteristic of the proposed framework is its explainable operational decision capability. Rather than generating opaque optimization outputs, the operational dashboard continuously communicates why specific operational decisions are selected under changing operational conditions. Forecast uncertainty levels, reserve opportunities, battery SOC conditions, operational readiness indicators, and market-awareness signals are integrated into interpretable operational recommendations visible to system operators.

This explainability layer is particularly important for future AI-enabled smart-grid infrastructures where autonomous operational systems must remain transparent, interpretable, and operationally trustworthy. Human operators supervising renewable-intensive urban-energy systems require continuous situational awareness and operational reasoning visibility to maintain confidence in adaptive AI-driven operational behavior.

The integrated multi-horizon coordination environment additionally strengthens operational resilience by enabling simultaneous supervision of D1, D2, and D3 operational conditions. Instead of relying on a single operational forecast, the framework continuously evaluates uncertainty propagation and operational flexibility conditions across multiple horizons simultaneously. This enables proactive identification of reserve shortages, flexibility limitations, and elevated operational-risk conditions before critical instability emerges.

The results therefore suggest that future smart-city digital twins should evolve from passive cyber-physical representations toward adaptive operational-intelligence systems capable of uncertainty-aware coordination, explainable decision support, and real-time operational synchronization.

5.3. Smart-City and Urban-Energy Implications

The increasing penetration of renewable-energy resources within urban-energy infrastructures introduces substantial operational variability, flexibility requirements, and coordination complexity. The proposed SYNAPCITY-DT framework addresses these challenges by integrating uncertainty-aware forecasting, adaptive flexibility management, operational intelligence, and digital-twin coordination into a unified renewable-energy management architecture.

The results demonstrate that intelligent operational coordination can substantially improve renewable-energy utilization efficiency, operational robustness, and adaptive flexibility management under uncertain renewable-generation conditions. These capabilities are particularly relevant for future smart-city environments where distributed renewable generation, battery storage systems, electric vehicles, intelligent buildings, and demand-side flexibility mechanisms must operate within increasingly dynamic cyber-physical energy ecosystems.

The operational dashboard environment shown in Figure 16 additionally highlights the importance of human-centric operational intelligence within future smart-grid infrastructures. Although operational optimization is becoming increasingly automated, future urban-energy systems will still require interpretable operational supervision, operational transparency, and operator situational awareness to ensure trustworthy AI-enabled coordination. The explainable operational-intelligence layer therefore contributes not only to operational efficiency but also to human-supervised smart-city resilience and adaptive governance.

The proposed framework further supports the broader transition toward autonomous urban-energy coordination systems. Through continuous synchronization of forecasting intelligence, market-awareness, reserve coordination, and operational flexibility, the framework enables adaptive cyber-physical energy management capable of responding dynamically to changing renewable and market conditions.

From a sustainability perspective, the framework contributes toward improving renewable-energy utilization efficiency while reducing curtailment exposure and imbalance-related operational losses. Such improvements may strengthen the integration of renewable resources within future carbon-neutral urban-energy systems while supporting resilient and adaptive smart-city infrastructure development.

5.4. Research Contributions and Novelty

This study contributes to the renewable-energy and smart-city research domains through several methodological and operational innovations. First, the proposed SYNAPCITY-DT framework integrates probabilistic forecasting, risk-aware optimization, adaptive battery coordination, reserve participation, operational explainability, and digital-twin synchronization within a unified operational-intelligence environment. Existing studies frequently investigate these components independently, whereas the proposed framework performs coordinated operational integration across forecasting, optimization, and execution layers.

Second, the study introduces an uncertainty-aware operational-intelligence architecture capable of dynamically adapting operational behavior according to forecast-confidence conditions and operational-risk propagation. The proposed multi-horizon coordination structure enables continuous adaptive operational supervision under changing renewable-generation and electricity-market conditions.

Third, the framework contributes an explainable operational-intelligence environment for renewable-energy digital twins. Unlike conventional operational dashboards focused primarily on visualization, the proposed environment continuously explains operational reasoning associated with uncertainty conditions, reserve opportunities, operational risks, and battery operational constraints.

Fourth, the study contributes an operational evaluation perspective where forecasting performance is assessed according to downstream operational impact rather than purely statistical forecasting accuracy. This enables more realistic assessment of forecasting systems operating within renewable-rich operational smart-grid environments.

Finally, the proposed framework demonstrates how integrated operational intelligence may support future smart-city energy infrastructures through adaptive flexibility management, cyber-physical synchronization, and uncertainty-aware renewable-energy coordination.

5.5. Operational Intelligence and Forecast-Driven Energy Coordination

Despite the promising results obtained in this study, several limitations should be acknowledged. First, the proposed framework was evaluated using a single utility-scale PV–BESS case study located in Finland. Although the selected operational environment provides realistic renewable-generation variability and electricity-market interaction behavior, additional validation across different climatic regions and urban-energy infrastructures would strengthen the generalizability of the framework.

Second, the operational analysis utilized a limited historical dataset covering approximately 4.5 months of operational measurements. While the dataset captures realistic operational uncertainty and renewable variability conditions, longer-term multi-seasonal datasets would enable more comprehensive analysis of long-term operational robustness and seasonal uncertainty propagation.

Third, battery degradation behavior was represented using simplified operational assumptions rather than detailed electrochemical degradation modeling. Future research could integrate physics-informed battery-aging models and lifecycle-aware operational optimization to improve long-term storage sustainability analysis.

Fourth, the present framework primarily focuses on operational-level coordination and does not explicitly incorporate detailed AC power-flow constraints or urban-distribution-network interaction modeling. Future studies may integrate network-aware operational constraints, voltage stability coordination, and distributed urban-energy interaction analysis within the digital-twin environment.

Potential future research directions include:

- multi-agent urban-energy coordination,
- federated digital twins,
- edge-AI-enabled operational control,
- electric-vehicle and vehicle-to-grid integration,
- hydrogen-energy coordination,
- reinforcement-learning-based adaptive dispatch,
- distributed flexibility trading,
- and city-scale renewable-energy orchestration.

The integration of these technologies may further strengthen the capability of digital-twin-based urban-energy intelligence systems to support future renewable-dominated autonomous smart-city infrastructures.

6. Conclusion

This study presented SYNAPCITY-DT, an AI-driven urban-energy digital twin framework for uncertainty-aware renewable-energy coordination within future smart-city infrastructures. The proposed framework integrates probabilistic photovoltaic forecasting, risk-aware operational optimization, adaptive battery flexibility coordination, reserve participation, and explainable digital-twin intelligence within a unified operational environment capable of supporting renewable-rich cyber-physical energy systems.

The results demonstrated that forecast uncertainty significantly influences downstream operational behavior, renewable-energy utilization efficiency, reserve coordination, and operational profitability. The comparative analysis across D1, D2, and D3 operational horizons revealed that shorter forecasting horizons provide improved operational confidence, reduced curtailment exposure, and higher long-term economic performance. At the same time, longer operational horizons require increasingly conservative operational strategies due to uncertainty propagation and elevated operational-risk exposure.

The proposed framework additionally demonstrated the importance of integrating probabilistic forecasting directly into operational decision-making processes. Rather than treating forecasting and operational control as isolated functions, SYNAPCITY-DT continuously synchronizes uncertainty-aware forecasting, operational flexibility management, reserve coordination, and electricity-market interaction within a rolling operational-intelligence environment. This integrated coordination structure improved operational robustness while enabling adaptive renewable-energy management under dynamically changing operational conditions.

A major contribution of the study is the integration of explainable operational intelligence within a real-time digital-twin environment. The proposed dashboard framework not only visualizes operational conditions but also provides interpretable operational reasoning associated with uncertainty levels, reserve opportunities, battery constraints, and adaptive dispatch coordination. This explainability layer strengthens operator situational awareness and contributes toward trustworthy AI-enabled smart-grid operation within future urban-energy infrastructures.

The study further demonstrated that digital twins for renewable-energy systems should evolve beyond passive visualization and monitoring platforms toward intelligent cyber-physical operational-coordination environments capable of adaptive reasoning, uncertainty-aware synchronization, and real-time operational supervision. The proposed framework therefore contributes toward the broader development of resilient, renewable-dominated, and AI-enabled smart-city energy systems.

Although the framework was evaluated using a utility-scale PV–BESS case study under Nordic operating conditions, the proposed operational-intelligence architecture remains scalable to broader urban-energy applications involving distributed renewable resources, intelligent microgrids, urban flexibility coordination, and future autonomous energy ecosystems.

Future research may extend the framework toward multi-agent operational coordination, federated digital twins, reinforcement-learning-based dispatch intelligence, electric-vehicle integration, hydrogen-energy coordination, and city-scale renewable-energy orchestration. The integration of these technologies may further strengthen the capability of AI-driven digital twins to support future resilient, adaptive, and sustainable smart-city energy infrastructures.

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