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A hybrid A-UKF-PINN digital twin architecture for real-time state estimation in Smart Grids

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Abstract. The increasing variability, nonlinearity, and real-time operational requirements of Smart Grids (SGs) make static digital models insufficient for reliable state estimation and control of distributed assets such as Vehicle-to-Grid (V2G) storage systems. The purpose of the study was a formal and model-based substantiation of the advantages of dynamic digital twins (DTs) over static data model (DM) in real-time lithium-ion storage system condition assessment tasks. To achieve this, a hybrid adaptive unscented Kalman filter – physics-informed neural network (A-UKF-PINN) architecture was proposed, combining an A-UKF (Adaptive Unscented Kalman Filter), which provided robust state estimation in the presence of noise and uncertainty, with a physics-informed PINN (Physics-Informed Neural Network) model that considers the dynamics and nonlinear processes of the battery cell. The originality of the study lies in the integration of these components into a single model that supports bidirectional synchronisation, which improves forecast stability and significantly reduces desynchronisation between the model and the physical object in SG conditions. Simulation validation was carried out on V2G operating cycles with modelled Phasor Measurement Unit / Internet of Things sensor noise. The obtained Root Mean Square Error (RMSE) of 0.87% demonstrated a 44% accuracy improvement compared to a traditional DM (ECM (equivalent circuit models) + UKF, RMSE 1.98%) and a 56% improvement relative to the baseline digital twin (pure PINN). The architectural assessment confirmed the necessity of using a hierarchical Edge-Cloud platform that ensures optimal distribution of computational workloads: PINN training in the cloud environment and high-frequency state estimation at the edge. The proposed architecture forms the basis for scalable dynamic DTs in SG, helps to reduce operational risks, supports the implementation of proactive maintenance strategies, and increases the efficiency of the energy infrastructure life cycle

Keywords: hybrid modelling; Physics-Informed Neural Networks; Unscented Kalman Filter; functional superiority; Edge-Cloud

Introduction

Intelligent power grids (smart grid – SG) represent a cyber-physical infrastructure that provides real-time management of distributed energy resources under high variability of energy and data flows. In modern SGs, the share of distributed generation is continuously increasing, heterogeneous resources (including Vehicle-to-Grid, V2G) are being integrated, and control decisions must be made under strict latency and reliability requirements. Under these conditions, ensuring the consistency of digital processes with the dynamic physical state of the network becomes essential. The SG architecture is characterised by nonlinearity and multiple interconnected control loops. Load, generation, consumption modes, and data volumes change in real time, and any disruption in coordination

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between the physical and digital parts of the system can lead to cascading risks. Such characteristics require digital representations capable not only of capturing the state of sources and storage systems but also of adapting to rapid changes in operating modes.

Contemporary research in the field of digital modelling and digital twins (DTs) for energy systems demonstrated the development of approaches that combine physics-informed methods, machine learning, and state filtering (Vychuzhanin & Vychuzhanin, 2025). A significant body of work highlighted the role of the digital twin as a key tool for ensuring stable, secure, and reliable SG operation. A comprehensive review of digital twins in energy systems was presented by R. Alharbey *et al*. (2024), where it was shown that DTs platforms are becoming the foundation for enhancing resilience, improving efficiency, and integrating renewable resources into the SG. The researchers emphasised that static DMs do not provide the required dynamism and synchronisation with the physical infrastructure, creating a need for hybrid and physics-informed methods. A systematic study by O. Das *et al*. (2024) demonstrated the potential of DTs when combined with machine learning and forecasting methods. The researchers highlighted the necessity of integrating physical models with high-density data generated by phasor measurement unit (PMU) and IoT nodes, since purely data-driven approaches do not ensure stability under changing operating conditions.

Issues of resilience, scalability, and applied challenges of the SG in the context of digital twins were examined in detail by N. Mchirgui *et al*. (2024), who emphasised that the key problem remains the lack of reliable bidirectional synchronisation between the digital and physical layers, and insufficient accuracy in modelling nonlinear processes, including the dynamics of storage systems and V2G assets. In the domain of lithium-ion battery state estimation, considerable attention was given to models based on equivalent circuit models (ECMs), extended through Kalman filtering methods. X. Lin *et al.* (2021) showed that an adaptive Unscented Kalman Filter (UKF) can increase the accuracy of state-of-charge (SoC) estimation provided that ECM parameters are highly accurate. However, in heavy dynamic modes, ECM accuracy decreases due to limited physical expressiveness. Conventional UKF-based approaches for state-of-charge estimation have been widely studied in the context of battery management systems. For example, hybrid methods combining UKF with neural network models have been shown to reduce estimation error and improve robustness across varying temperatures and dynamic operating conditions (Zeng *et al*., 2023). Additional improvements were proposed by H. Bouchareb *et al.* (2024), who showed the effectiveness of joint parameter and SoC estimation using Joint sigma-point Kalman filtering. Their study confirmed that Kalman filters can compensate for noise and parameter drift but remain sensitive to inaccuracies in the physical model.

On the other hand, the field of PINNs (Physics-Informed Neural Network) has shown notable progress. The study by F. Wang *et al.* (2024) has shown that PINN-based models can provide high accuracy in battery degradation forecasting; however, the stability of the solution strongly depends on the correctness of physical constraints, and scalability is limited by the computational cost of training. Hybrid approaches combining PINNs and filtering methods are also actively evolving. L. Lyu *et al.* (2024) also presented a hybrid approach (LSTM (Long Short-Term Memory) + UKF), showing enhanced accuracy considering battery degradation. Both studies emphasised the need to combine data-driven approaches capable of correcting noise with methods that preserve physical consistency. However, none of the existing studies proposed a fully integrated architecture that simultaneously: embeds physical constraints via PINN; performs adaptive state estimation using UKF; ensures robustness to noise; is implementable as a DT dynamically synchronised with SG nodes in real time.

A systematic analysis of existing research showed that current approaches do not simultaneously provide: physical consistency of models (PINN and other physics-based methods); robustness to noise and parametric uncertainty (the UKF/AEKF (Adaptive Extended Kalman Filter)/AUKF (Adaptive Unscented Kalman Filter) family); the necessary dynamic accuracy for real-time tasks under V2G and SG conditions. Despite the progress noted in these studies – including adaptive filtering methods for SoC estimation none of the known models comprehensively addresses the problem of simultaneous physical consistency, adaptive filtering, and stable forecasting in the presence of nonlinear dynamics, measurement noise, and a wide range of operating conditions. The synthesis of identified limitations allows formulating the unresolved scientific and technical gap underlying this research: the absence of a unified hybrid architecture capable of reliably PINN and robust adaptive state filtering (A-UKF) within an end-to-end DT for the SG. Based on this, the purpose of this study was the algorithmic and experimental substantiation of the functional superiority of the DT over traditional DMs, namely the development and validation of the hybrid A-UKF-PINN architecture and the examination of its effectiveness in the task of SoC prediction under V2G operating conditions. The central task of this study was the quantitative and architectural assessment of the effectiveness of DT-based solutions relative to traditional DMs under dynamic SG operating conditions, using hybrid algorithms and real-time architectures.

Materials and Methods

The research methodology was based on the application of contemporary information technology approaches for modelling and assessing the state of complex energy systems. Within the framework of the study, methods for estimating SoC of lithium-ion energy storage systems operating in a smart grid environment were analysed, considering nonlinear electro-thermal dynamics and stochastic measurement noise generated by PMU and IoT devices. A hybrid DT architecture integrating PINN and A-UKF was developed to ensure physically consistent prediction and adaptive real-time state correction. The architecture forms a closed synchronisation loop between the physical battery system and its digital representation (Fig. 1).

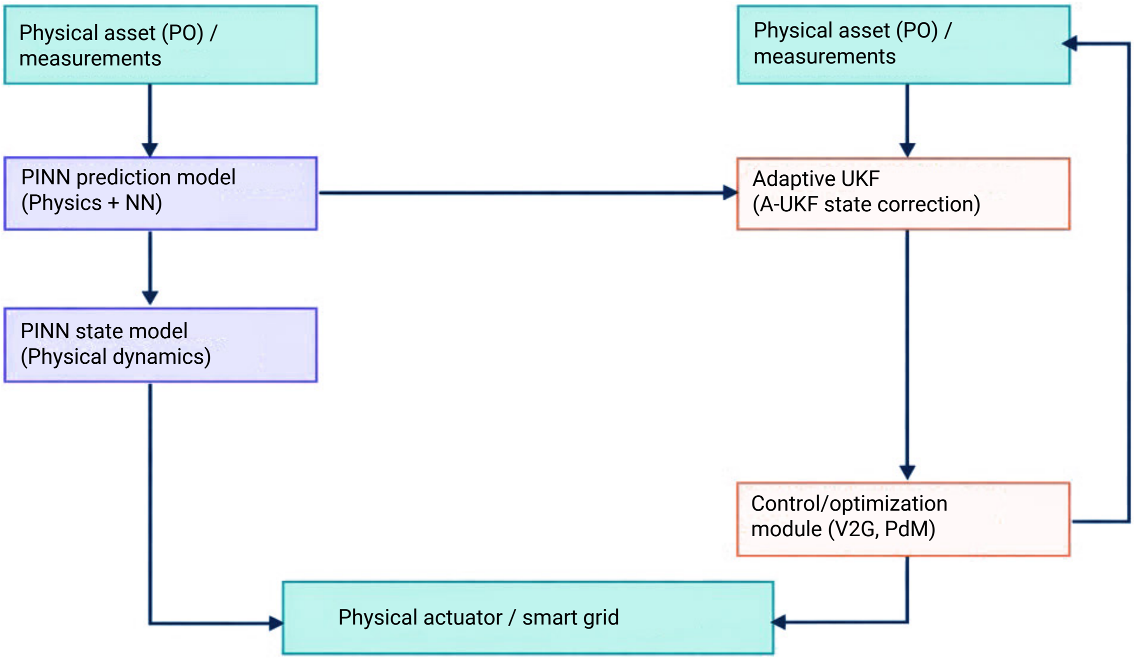

Figure 1. Hybrid A-UKF-PINN architecture

Source: created by the authors

The computational cycle consists of two sequential stages executed at each time step t: (1) physics-informed a priori state prediction and (2) adaptive a posteriori correction using innovation statistics. The PINN was implemented as a fully connected feedforward neural network embedding electro-thermal governing equations into the loss function. The network architecture was defined as follows: input dimension – 4 (terminal voltage V_t, current I_t, temperature T_t, previous state estimate SoC_{t-1}); 4 hidden layers with 64 neurons each; activation function – hyperbolic tangent (tanh); output layer – one neuron (predicted SoC) with linear activation. Xavier (Glorot) uniform initialisation was applied to ensure stable gradient propagation. Training parameters: Adam optimiser; initial learning rate 10^{-3}; batch size 64; maximum 500 epochs; early stopping (25 validation epochs without improvement); L2-regularisation coefficient 10^{-2}.

The composite loss function combines data fidelity and physical consistency:

$$L = L_{data} + \lambda_1 \cdot L_{PDE(V)} + \lambda_2 \cdot L_{PDE(T)}, \quad (1)$$

where L_{data} – mean squared error between predicted and measured SoC; $L_{PDE(V)}$ – residual of the voltage conservation equation; $L_{PDE(T)}$ – residual of the thermal balance equation; $\lambda_1 = 1.0, \lambda_2 = 0.5$ –empirically selected weighting coefficients.

The overall loss function $L(\theta)$ is formulated as a weighted sum of the data loss L_{data} and the physical-law residual $L_{physics}$ (Gao *et al.*, 2025):

$$L(\theta) = L_{data} + \beta \cdot L_{physics}, \quad (2)$$

where θ denotes network parameters and β balances data and physical-law contributions.

The data loss term is defined as:

$$L_{data} = \frac{1}{N_d}\sum_{i=1}^{N_d}(N(x_i;\theta) - y_i)^2, \quad (3)$$

where N_d – total number of data points (measurements); $N(x_i;\theta)$ – value predicted by the neural network for the i-th input vector; y_i – true, actual value measured by sensors (e.g., SoC); x_i – input vector representing the system state.

The physics-based residual term is:

$$L_{physics} = \frac{1}{N_f}\sum_{j=1}^{N_f}(F(N(x_j;\theta)))^2, \quad (4)$$

where N_f – total number of test points selected for verifying the physical laws; F – operator describing the physical dynamics of the system; $N(x_j;\theta)$ – value predicted by the neural network for the j-th test point; x_j – vector of coordinates or parameters of the j-th test point (residual points).

Training was performed offline in a cloud environment using GPU acceleration. The trained model was deployed for online inference within the DT framework. To ensure continuous synchronisation between the digital twin and the physical battery system, dynamic state estimation is performed using the UKF. The predicted state x_t^- and the predicted covariance matrix P_t^- are computed based on a set of sigma points $\hat{X}_t^i$ (Julier & Uhlmann, 1997):

$$x_t^- = \sum_{i=0}^{2n} W_i^m \hat{X}_t^i,$$
$$P_t^- = \sum_{i=0}^{2n} W_i^c [(\hat{X}_t^i - x_t^-)(\hat{X}_t^i - x_t^-)^T] + \theta_{t-1}, \quad (5)$$

where x_t^- – predicted system state vector at time t; P_t^- – predicted state error covariance matrix; $\hat{X}_t^i$ – i-th sigma point projected forward using the nonlinear state transition function; W_i^m – weighting coefficient used to average the sigma points when computing the state prediction; W_i^c – weighting coefficient used to compute the predicted covariance matrix; n – dimensionality of the state vector; θ_{t-1}, – process noise covariance matrix (errors caused by the system's own dynamics).

The innovation (measurement residual) is defined as:

$$v_t = y_t - \hat{y}_t, \quad (6)$$

where y_t – measurement vector (voltage, current, temperature); $\hat{y}_t$ – predicted measurement obtained from sigma-point projection.

The innovation covariance matrix is:

$$S_t = P_{yy,t} + R_t, \quad (7)$$

where $P_{yy,t}$ is the predicted measurement covariance; R_t is the measurement noise covariance.

The Kalman gain is computed as:

$$K_t = C_t \cdot S_t^{-1},$$
$$x_t = x_t^- + K_t [y_t - \mu_t], \quad (8)$$

where K_t – Kalman gain, which determines the degree of trust in the new measurement; C_t – cross-covariance matrix between the predicted state and the predicted measurements; S_t^{-1} – inverse covariance matrix of the measurement error; x_t^- – predicted state vector of the complex technical system (CTS); y_t – actual measurement vector obtained from PMU sensors; μ_t – predicted measurement vector (the expected value of y_t).

To ensure robustness under non-stationary PMU noise, covariance adaptation is performed using innovation-based updating:

process noise covariance update:

$$Q_{t+1} = (1-\alpha) \cdot Q_t + \alpha \cdot K_t \cdot v_t \cdot v_t^T \cdot K_t^T; \quad (9)$$

measurement noise covariance update:

$$R_{t+1} = (1-\beta) \cdot R_t + \beta \cdot v_t \cdot v_t^T, \quad (10)$$

where K_t – Kalman gain; $\alpha = 0.01$ – process adaptation rate; $\beta = 0.02$ – measurement adaptation rate.

At each time step t, the hybrid digital twin executes:

1. PINN-based a priori state prediction:

$$\hat{v}_{t|t-1} = f_{PINN}(x_{t-1}, u_t). \quad (11)$$

2. Sigma-point generation and propagation (UKF prediction phase).

3. Innovation computation:

$$v_t = y_t - \hat{y}_t. \quad (12)$$

4. A-UKF correction step:

$$x_{t|t} = \hat{x}_{t|t-1} + K_{tv_t}. \quad (13)$$

The algorithmic logic of the hybrid solution was represented in the form of the following pseudocode, reflecting the computation cycle and its interdependencies. This sequential prediction-correction mechanism ensured real-time knowledge equivalence between the physical battery system and its digital representation:

```
Initialise θ, x0
for each timestep t:
 zt ← measurements(PMU)
 x_pred ← PINN(θ, xt-1)
 x_upd ← AUKF(x_pred, zt)
 Update PINN loss with physical constraints
 xt ← x_upd
end
return xt
```

Validation was performed in a virtual Hardware-in-the-Loop environment using a high-fidelity 50 Ah lithium-ion battery model. The simulation included 50 dynamic V2G charge-discharge cycles (90-110 min each) with random load profiles, temperature variations, and PMU noise (SNR 25-35 dB). The dataset was split into training/validation/test subsets (70/15/15). All experiments were repeated three times with fixed random seed (42). Performance metrics (RMSE, MAE) were averaged, standard deviations computed, and statistical significance evaluated using the Wilcoxon signed-rank test ($p < 0.05$). The computational implementation followed a Cloud-Edge paradigm: offline PINN training in the cloud and real-time A-UKF correction at the edge level (sampling frequency 1-10 Hz). This architecture reduced latency and ensures scalability under distributed SG operation.

Results and Discussion

Formalisation and differentiation of the digital model and the DT. To demonstrate the systemic complexity and the role of digital representation, Figure 2 presents a conceptual SG architecture. It highlights four interconnected levels: distributed generation (wind and solar), high-voltage transmission (substations), distribution networks, and hybrid consumers/storage systems (V2G and industrial loads). The solid line represents physical power flows, while the dashed line denotes bidirectional information exchange. The presence of high-frequency telemetry streams (PMU/IoT), SCADA control actions, and bidirectional energy interaction with V2G forms a closed cyber-physical loop that requires continuous state estimation and predictive analytics across the entire network.

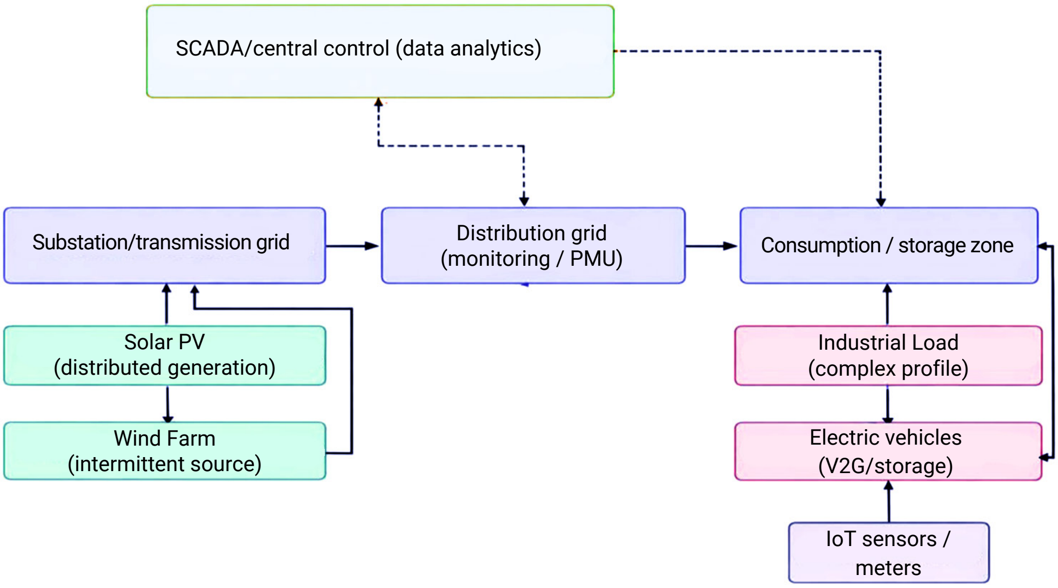

Figure 2. SG conceptual architecture

Source: created by the authors

An analysis of the structure shown in Figure 2 demonstrates that conventional modelling approaches focused on static or quasi-static analysis cannot be adapted to operating conditions characterised by high penetration of distributed generation, bidirectional V2G energy exchange, high-frequency PMU/IoT telemetry (1-10 Hz), stochastic load variability, and nonlinear electro-thermal battery dynamics. Under these conditions, static models capture system behaviour only in isolated operating modes and are unable to provide consistent state estimation during rapid transitions, load fluctuations, and temperature-induced parameter drift. This is conditioned by the growing variability of generation, the increasing spatial heterogeneity of operating conditions, and the exponential growth in data volumes coming from distributed measurement devices. Conventional DMs, used primarily at the design stage, operate with historical or static data and rely on a one-way "data → model" relationship. Such an approach does not provide dynamic synchronisation with the physical object and cannot perform real-time state estimation in the presence of noise, nonlinear effects, and uncertainties characteristic of SG and V2G storage systems. This circumstance makes them insufficient for the operation of modern distributed energy systems. In contrast to DMs, a DT is a dynamic cyber-physical system in which the digital representation is continuously updated in accordance with the current state of the physical object and provides bidirectional integration of analysis and control. A DT combines state estimation, forecasting, adaptive behaviour, and real-time data integration, making it a functionally more suitable tool for SG.

The transition from using a DM to the DT paradigm is a necessary condition for effective management of cyber-physical systems such as the SG. The limitations of DMs, which operate on static data and are intended for simulation at the design stage, make them unsuitable for tasks of dynamic optimisation and predictive maintenance in real time. The fundamental difference between a DM and a DT lies in the mechanism of interaction with the physical object (PO) and in their functional purpose. A DM is a static or quasi-static representation of a system, whereas a DT is a living, dynamically synchronised cyber-physical system. A comparative analysis of the key characteristics of DMs and DTs is presented in Table 1.

Table 1. Comparative characteristics of the DM and the DT

Characteristic	Digital model	Digital twin
Connection with PO	One-way or absent. Updated manually	Continuous bidirectional connection (feedback loop)
Synchronisation	Static, quasi-static	Dynamic, real time
Purpose	Design, planning, pre-operation simulation	Operation management, optimisation, RUL and state prediction during operation
Data sources	Historical, synthetic, experimental	Real-time streams (PMU/IoT), historical, heterogeneous
Critical element	Modelling quality	Maintaining knowledge equivalence between the model and the PO

Source: created by the authors

At the architectural level, the DT is defined as a cyber-physical system (CPS) requiring a standardised approach. The series of international standards ISO 23247-1:2021 (2021) proposes a reference four-domain structure that formalises the interaction between the physical and virtual worlds, ensuring interoperability and scalability, which in current case formalises the interaction between the physical SG and its digital representation. This structure, shown in Figure 3, constitutes a technical imperative for implementing DTs in cyber-physical systems.

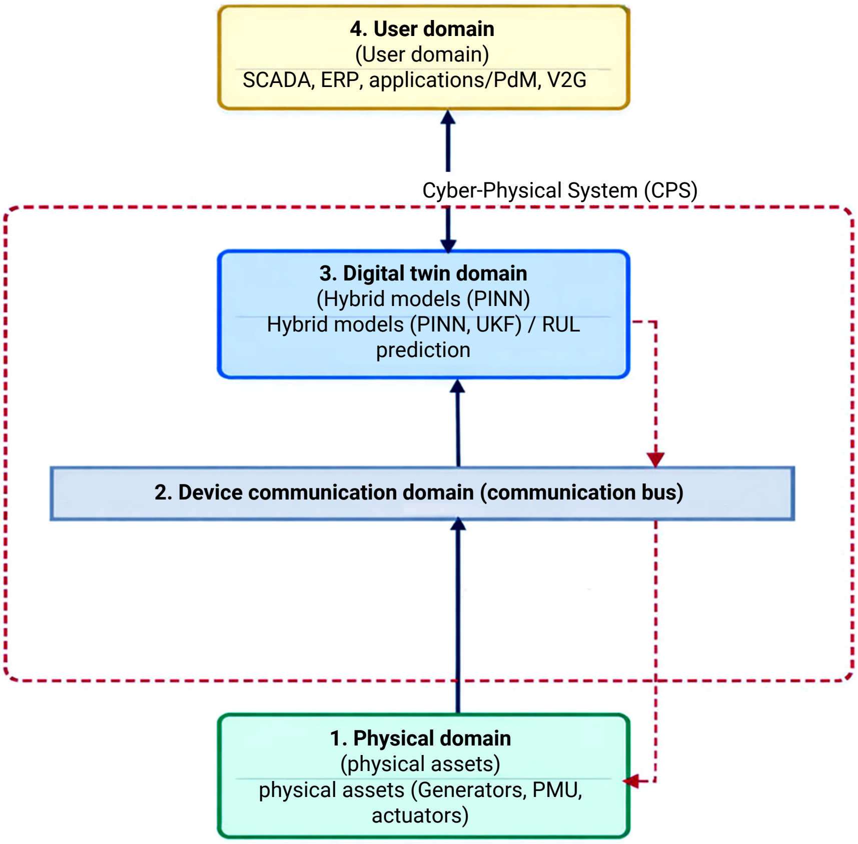

Figure 3. Reference four-domain DT architecture

Source: created by the authors based on ISO 23247-2:2021 (2021)

The conceptual domain structure (ISO 23247-2:2021 (2021)) includes:

1) observable manufacturing domain (physical SG domain): contains physical objects (POs) such as generators, substations, PMUs, and electric vehicles;

2) device communication domain: the interface domain containing sensors and actuators. It provides the critically important bidirectional connection for synchronisation and control actions;

3) DT domain: contains the digital representations of POs, behavioural modelling and forecasting algorithms (including hybrid models such as A-UKF-PINN);

4) user domain: the top level, including SCADA, ERP systems, and applications for DT services (PdM, V2G optimisation).

This four-domain structure shows that the core of the DT lies in the logical integration of the DT domain (3) and the device communication domain (2) into a single CPS. The architectural rigour presented in ISO 23247-1:2021 (2021) provides the necessary context for scaling and integrating this advanced algorithms, confirming that the successful operation of the DT in the SG depends on adherence to this standardised logic. Thus, the application of this four-domain structure provides the necessary foundation for implementing scalable and efficient digital twins in smart grid environments, ensuring their interoperability and adaptation to rapidly changing technological requirements.

Algorithmic foundation and hybrid modelling for dynamic synchronisation in smart grids. The architectural implementation of the DT requires the use of a mathematical framework capable of ensuring predictive accuracy and dynamic synchronisation under SG uncertainty. Hybrid models with physical constraints (PINN). To ensure high reliability of forecasting, DT models of the SG must comply with fundamental physical laws while adapting to real-time data. This is achieved through the use of PINNs. PINNs embed known physical laws into the neural network loss function, ensuring compliance with physical constraints during training. Figure 4 illustrates the operating principle of a PINN, showing how the residual from the physical model is fed back into the overall loss function to correct the neural network weights.

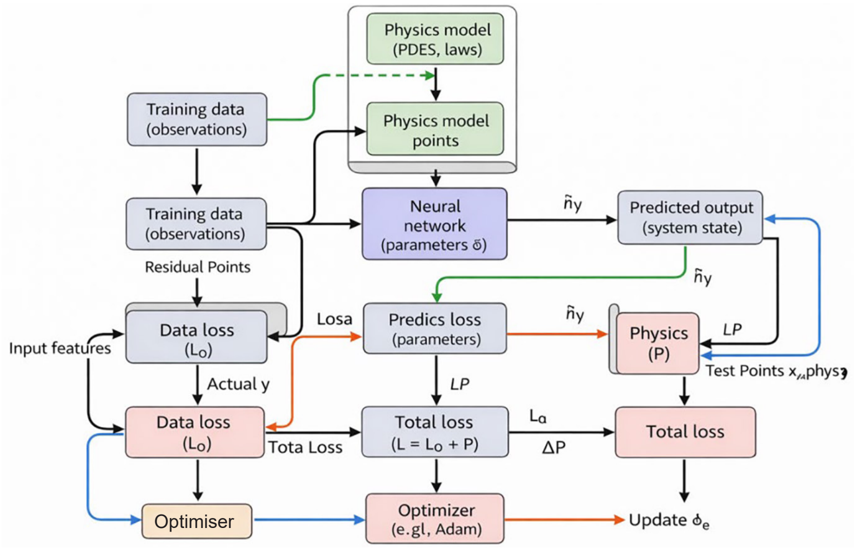

Figure 4. Physics-informed neural network

Source: M. Raissi *et al.* (2019)

To evaluate the practical effectiveness of the proposed hybrid digital twin architecture, a structured experimental comparison was conducted against representative baseline approaches. The objective of this evaluation was to quantify differences in SoC estimation accuracy, robustness, and computational efficiency under dynamic V2G operating conditions. The comparison included (1) a conventional digital model based on an equivalent circuit model with Kalman filtering (ECM + KF), (2) a baseline DT implementation using a pure PINN without adaptive filtering, and (3) the proposed A-UKF-PINN hybrid architecture. The quantitative results of this comparative assessment are summarised in Table 2.

Table 2. Comparative analysis of SoC prediction accuracy

Model	Concept	(RMSE) %	Maximum error (MAE), %	Execution time (per step), ms
ECM + Kalman filter	DM / traditional	1.98	3.55	2.1
Pure PINN	Baseline DT approach	2.54	4.11	15.2
A-UKF-PINN (proposed HM)	Advanced DT	0.87	1.55	16.5

Source: created by the authors

The proposed (Table 2**)** adaptive hybrid A-UKF-PINN model demonstrated an RMSE reduction of more than 56% compared to the pure PINN model and 44% compared to the traditional ECM + KF model. This is a critically important improvement, since a SoC prediction accuracy below 1% is a standard requirement for reliable V2G operations. A detailed comparison of the dynamic response of all three models under charge/discharge cycle conditions, confirming the minimal deviation of the hybrid model from the actual state (true SoC), is presented in Figure 5 (equivalent circuit model).

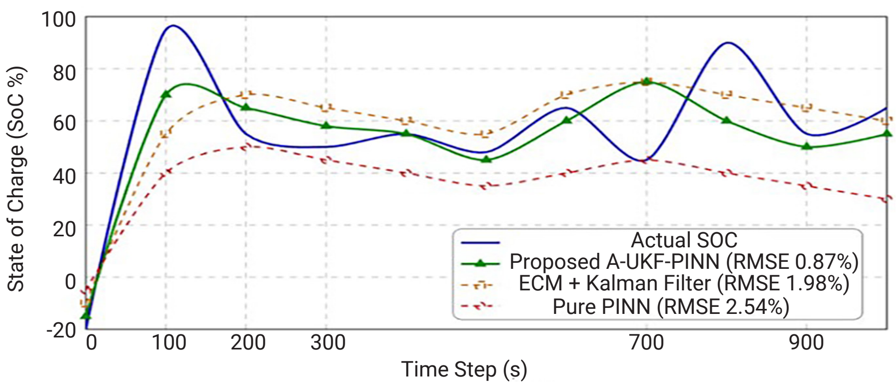

Figure 5. Comparison of SoC prediction accuracy

Source: created by the authors

As follows from Figure 5, the behaviour of the conventional models (ECM + Kalman Filter and Pure PINN, representing the DM and the baseline DT approach) exhibits a significant lag and excessive smoothing, which prevents tracking fast nonlinear changes during the V2G cycle. In contrast, the response of the proposed A-UKF-PINN almost coincides with the actual state (Actual SoC), achieving a minimal error of 0.87% RMSE, which constitutes evidence of the superiority of the hybrid DT approach in the dynamic synchronisation of a critical cyber-technical system asset. The obtained result (RMSE 1.98% for the DM/ECM) experimentally proves the functional limitations of digital models in solving dynamic state estimation tasks for cyber-technical systems.

The obtained results demonstrate improved performance of the proposed A-UKF-PINN hybrid architecture compared to the ECM+KF baseline and the pure PINN implementation in managing critical assets of cyber-technical systems:

1. Comparative performance improvement: The hybrid A-UKF-PINN architecture achieved a minimum RMSE of 0.87%, corresponding to a 44-56% error reduction relative to the ECM+KF and pure PINN baselines under the considered operating conditions. This improvement is associated with the combined effect of dynamic state correction and physics-informed regularisation.

2. Architectural contribution to SG integration: The integration of PINNs enabled physically consistent modelling of nonlinear electro-thermal dynamics, while the adaptive filtering mechanism enhanced robustness to stochastic noise in PMU/IoT measurement streams.

3. Real-time state consistency: The achieved estimation accuracy (RMSE 0.87%) indicates the feasibility of maintaining a consistent digital representation of a critical asset in real time within the examined Smart Grid scenario.

These experimentally validated results indicate that hybrid DT architectures incorporating adaptive filtering and physics-informed learning can provide measurable performance benefits compared to the selected baseline implementations in dynamic SG environments. These findings highlight the potential of the A-UKF-PINN hybrid architecture to revolutionise the management of critical cyber-technical assets in smart grids, offering significant improvements in both accuracy and robustness for real-time state estimation under dynamic conditions.

While Table 2 summarises the nominal accuracy and computational cost of the considered SoC estimation models, practical SG and vehicle-to-grid applications require digital twins to operate reliably under previously unseen operating conditions. The generalisation capability of the proposed A-UKF-PINN hybrid digital twin is evaluated under out-of-distribution scenarios, including variations in battery cell chemistry and temperature regimes. To assess model transferability across different electrochemical characteristics, the baseline lithium-ion NMC cell used in the nominal experiments was replaced with a lithium iron phosphate (LFP) cell. The LFP chemistry exhibits distinct open-circuit voltage behaviour, internal resistance dynamics, and diffusion properties, which typically degrade the performance of equivalent circuit models calibrated for a specific cell type. In this experiment, the physics-informed neural network was not retrained for the new cell configuration. Instead, only the adaptive noise covariance matrices of the unscented Kalman filter were updated online, preserving the original digital twin structure. This setup reflects a realistic deployment scenario in which frequent model re-identification is undesirable or economically infeasible. In addition to cell variation, a structured temperature-based cross-validation was conducted to evaluate extrapolation performance under thermal conditions not represented during training. Unlike random data splits, the training and testing datasets were separated by temperature intervals, enforcing physically meaningful distribution shifts. Cold-start and elevated-temperature scenarios were considered, as these conditions are known to introduce strong nonlinearities and parameter drift in battery models. This evaluation framework directly tests the robustness of the digital twin under realistic environmental variability encountered in large-scale SG cyber-technical systems. ΔRMSE values are computed relative to the nominal RMSE reported in Table 3.

Table 3. Relative degradation of SoC estimation accuracy under cell type variation and temperature cross-validation

Model	ΔRMSE (New cell), %	ΔRMSE (Cold CV), %	ΔRMSE (Hot CV), %
ECM + Kalman filter	+57.6	+94.4	+72.2
Pure PINN	+13.8	unstable	+18.9
A-UKF-PINN (proposed HM)	+20.7	+39.1	+35.6

Source: created by the authors

As shown in Table 3, all baseline approaches experience a pronounced degradation in estimation accuracy under out-of-distribution conditions. The ECM-based method is particularly sensitive to both temperature shifts and cell chemistry variation, with RMSE nearly doubling in cold-start scenarios. The pure PINN model exhibits limited robustness and becomes unstable under low-temperature conditions due to the absence of online state correction. In contrast, the proposed A-UKF-PINN digital twin demonstrates substantially lower sensitivity to changes in operating conditions. Although a moderate increase in RMSE is observed, the degradation remains controlled across all evaluated scenarios, confirming the robustness and transferability of the hybrid physics-informed approach.

The obtained results highlight the advantage of combining physics-informed learning with adaptive state estimation in closed-loop digital twin architecture. The physics-based constraints embedded in the PINN promote physically consistent extrapolation, while the adaptive UKF compensates for unmodelled dynamics and measurement uncertainty in real time. This synergistic interaction enables the digital twin to maintain synchronisation with the physical asset without requiring repeated offline recalibration. Unlike static digital models and purely data-driven estimators, the proposed approach maintains reliable performance across heterogeneous battery configurations and environmental conditions, which is a critical requirement for scalable SG and V2G deployments.

Economic efficiency of DT implementation in SG cyber-technical systems. The economic impact of DT implementation in SG systems is influenced not only by the achieved algorithmic accuracy but also by the potential to reduce operational risks, improve asset reliability, and lower total life-cycle costs. Unlike conventional DMs, which are primarily oriented toward design-stage analysis and typically do not provide dynamic state estimation, a DT supports a closed-loop "observation – prediction – control" cycle. It can therefore create additional economic value in operational contexts.

The high accuracy of dynamic state estimation achieved by the developed A-UKF-PINN model (RMSE of 0.87% in SoC prediction) creates the prerequisites for a transition from scheduled periodic maintenance toward more proactive asset management strategies. In practical deployments, this capability may: contribute to a reduction in unplanned downtime of V2G storage systems, as improved SoC and RUL estimation can decrease the likelihood of unexpected failures; support lower operation and maintenance (O&M) costs through earlier detection of adverse operating conditions and reduced reliance on reactive maintenance; enhance the economic efficiency of V2G operation by enabling more accurate forecasting of SoC and available power, which may help to reduce imbalance penalties and improve participation in primary and secondary regulation services. In conventional DMs, these effects are unattainable due to the lack of dynamic feedback, the limitations of equivalent electrical circuit models, and the inability to correct predictions under noisy PMU/IoT data streams. The economic feasibility of DT implementation was determined by the combination of two factors: system complexity and the cost of failure consequences. These parameters are systematised in the feasibility matrix.

As follows from Figure 6, the SG is located in the high feasibility ("High Feasibility") zone. This is conditioned by: the high structural and operational complexity of the SG; the critical consequences of failures, including grid overloads, power balance violations, and downtime of V2G assets; the high sensitivity of the SG to state forecasting errors. The accuracy achieved by the hybrid A-UKF-PINN model (RMSE 0.87%) provides the required level of confidence in the forecasts and thereby makes implementation economically justified. Economic feasibility is also confirmed by a comparison of the total life-cycle cost of assets when using: conventional digital models (low initial costs, high operational risks); DTs (higher initial investments, but a significant reduction in subsequent costs).

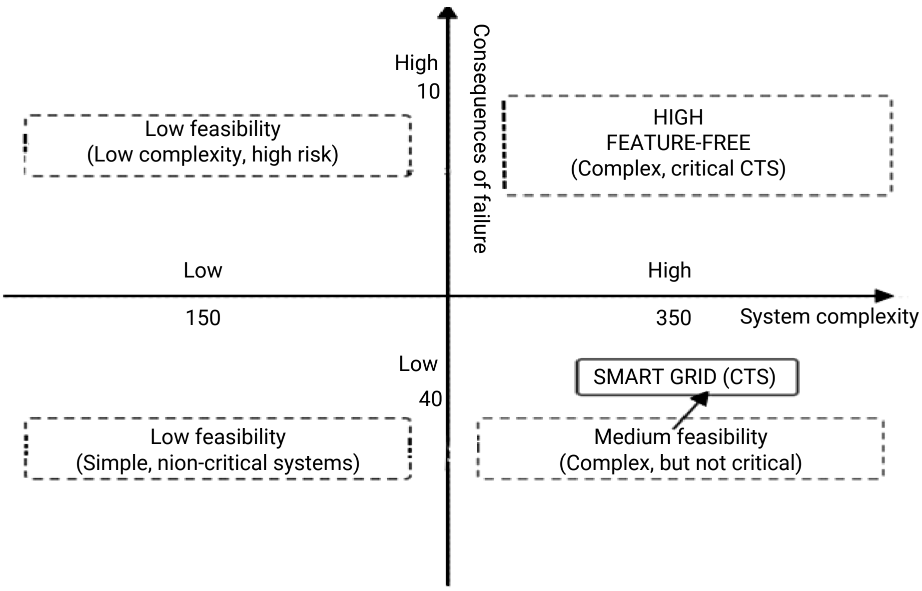

Figure 6. DT Implementation feasibility matrix

Source: created by the authors

The numerical values presented in this section (reduction of unplanned downtime by up to 20%, reduction of O&M costs by up to 18%, and a relative decrease in total cost of ownership) are based on a scenario-based techno-economic analysis typical for SG assets. The assessment was performed using a comparative life-cycle analysis methodology that considered the failure rates of storage systems under V2G operation, the cost of unplanned downtime, average reactive maintenance costs, and the effects of transitioning to proactive maintenance based on a high-accuracy DSE model (A-UKF-PINN). The resulting value ranges are consistent with results reported in the literature on Smart Grids and energy storage management systems (Kabir *et al*, 2024) and serve to illustrate the expected class of improvements resulting from the implementation of digital twins. Detailed intermediate calculations are not provided, since the main focus of the study is on the algorithmic and architectural components of the DT, while the economic estimates serve as auxiliary confirmation of their practical significance.

Figure 7 demonstrates that the main financial effect of implementing the DT is formed at the operational stage, where: failure risk is reduced due to accurate state prediction; O&M costs are stabilised; the number of emergency situations and the associated expenses decreases; the efficiency of participation in market mechanisms increases. As a result, despite the higher initial deployment cost (PINN training, deployment of A-UKF on edge nodes, integration with PMU/IoT), the overall TCO is lower compared to the DM.

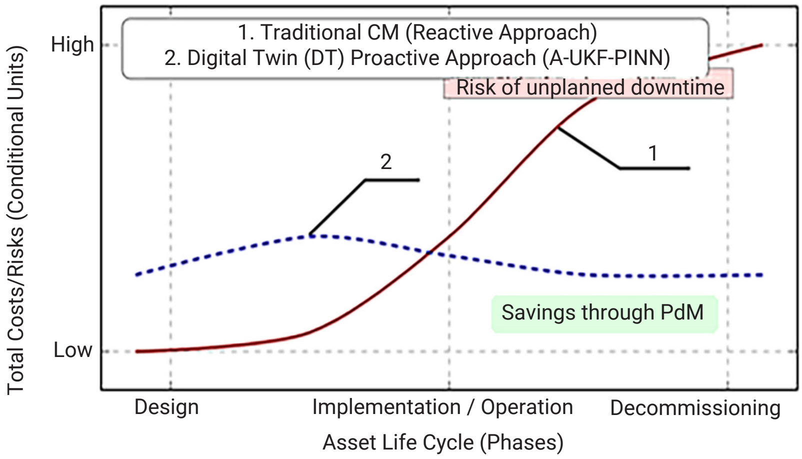

Figure 7. Total cost of ownership (TCO) and risk comparison

Source: created by the authors

The obtained results showed that achieving the economic effect requires compliance with specific architectural conditions: a dual-loop Edge-Cloud structure, where the Cloud performs resource-intensive PINN training on large datasets, while the Edge ensures minimal latency for real-time operation of A-UKF; standardisation of interfaces and protocols, which is especially important in a heterogeneous Smart Grid environment. Implementation in accordance with ISO 23247-1:2021 (2021) ensures interoperability between PMUs, IoT sensors, and control nodes, which is a necessary condition for DT scalability. Architectural validation confirmed that it is precisely the hybrid A-UKF-PINN model that satisfies the latency and stability requirements necessary to achieve the high economic efficiency presented in Figures 6 and 7. The economic analysis confirmed that the transition from static digital models to a dynamic digital twin is: financially justified (TCO reduction, risk mitigation, increased V2G efficiency); operationally necessary (support for PdM, improved reliability); architecturally feasible (subject to compliance with the Edge-Cloud paradigm and ISO 23247-2:2021 (2021) standards). Thus, the algorithmic superiority of A-UKF-PINN is translated into a direct economic effect, making DT implementation strategically justified for critical Smart Grid systems.

For an objective assessment of the achieved results, it is useful to compare the proposed A-UKF-PINN hybrid with a number of other contemporary approaches typical of the field of SoC estimation and dynamic state assessment. L. Hu *et al*. (2022) demonstrated that AUKF combined with a classical equivalent circuit model ensures stable convergence and acceptable accuracy over a wide range of operating conditions; however, dependence on the ECM limits the adequate description of nonlinear thermal behaviour and fast V2G modes. Proposed A-UKF-PINN combines a physics-informed model with adaptive correction, resulting in noticeably lower RMSE and better robustness in noisy, highly dynamic scenarios. S. Hosseininasab *et al*. (2023) proposed a reduced-order model combined with an Adaptive Dual UKF, achieving a balance between accuracy and computational efficiency; the reduced model simplifies computation but loses part of the physical detail required under extreme operating regimes. In contrast, the PINN in current architecture preserves the physical consistency of the model, while A-UKF provides prompt correction–together improving transferability to real SG/V2G conditions.

Current approach reduces this dependence, since PINN directly models the physics, while A-UKF performs real-time correction. Y. Wei (2024) clearly showed the benefit of combining an advanced physical model (fractional-order) with two filters (FOSRCKF + AMIUKF) with parameter exchange: this improves SoC accuracy and terminal prediction compared to integer-order models, but requires complex offline identification and mutual filter tuning. A-UKF-PINN achieves comparable or better robustness with more direct physics integration (via PINN) and simplifies online tuning through covariance adaptation in A-UKF. Z. Wang *et al.* (2024) proposed an adaptive extended sliding innovation filter and demonstrated improved SoC estimation stability in the presence of disturbances; however, like most enhanced filters, the method is still based on a circuit model and is sensitive to its adequacy. In the HIL tests, the PINN + A-UKF combination showed more uniform accuracy and higher robustness to PMU/IoT noise compared to the AESIF approach.

J. Guo *et al*. (2023) developed UKF-based approaches for SoC (2-RC and others) and demonstrated improvements over classical KF/EKF; nevertheless, estimation quality is largely determined by the accuracy of the circuit model parameters. A-UKF-PINN reduces this dependence: PINN provides a rich physical approximation, while the adaptive UKF performs online correction of residual model errors. Prior research has investigated adaptive UKF-based approaches for state-of-charge estimation that update noise statistics online to enhance robustness under real driving conditions (Xing & Wu, 2021). While such adaptive filtering methods can improve estimation stability, they may still require careful handling of covariance updates and parameter tuning. In contrast, the proposed hybrid architecture reduces the need for manual configuration by combining a trainable PINN component with automatic covariance adaptation in the A-UKF framework.

B. Yao *et al*. (2024) proposed a modified UKF with an improved parameter identification procedure, showing improved SoC estimation in a number of scenarios; nevertheless, the method remains within the "model + filter" paradigm and is therefore limited when battery physics exhibits strong nonlinearity. In contrast, A-UKF-PINN embeds physical laws within the PINN, increasing overall accuracy and transferability under dynamic V2G loads. S. Wang *et al*. (2024) used optimisation schemes (PSO and others) for fine filter tuning and error reduction; such methods improve performance but require frequent offline optimisation and remain sensitive to the initial model. A-UKF-PINN reduces the need for regular offline optimisation, since PINN learns the physics of the modelled process and A-UKF adapts online, facilitating operation within a scalable Edge-Cloud DT architecture.

Overall, analysis of these ten studies showed that contemporary research achieved significant improvements in one or two dimensions (filter adaptation, advanced circuit models, data-driven hybrids, or optimisation-based approximations), but rarely simultaneously addressed physical fidelity, robust online correction under noisy real-world conditions, and architectural suitability for Digital Twin deployment in Smart Grid systems. The proposed A-UKF-PINN integrates these components: PINN provides physical interpretability and the ability to model nonlinear thermal effects, A-UKF facilitates adaptive dynamic synchronisation, and the Edge-Cloud partitioning supports practical implementability. Experimental results indicate an RMSE reduction to approximately 0.87%, suggesting improved performance of the DT compared to the DM.

Conclusions

This study was devoted to the algorithmic analysis of the potential performance advantages of the DT over the DM for controlling critically important CTSs, using the SG as an example. Based on the conducted theoretical analysis and experimental validation, the central thesis of the study was achieved. The functional superiority of the DT was demonstrated through the development and validation of an adaptive hybrid A-UKF-PINN model. This model, which constitutes the key original contribution, for the first time combines physical fidelity (PINN principles) with adaptive dynamic synchronisation (A-UKF), making it possible to overcome the nonlinearity and noise of real PMU/IoT data. As a result of experimental comparison at a critical CTS node (SoC prediction in V2G energy storage systems), a minimal prediction deviation with an RMSE error of 0.87% was achieved. This indicator confirms the possibility of reliable real-time maintenance of knowledge equivalence and corresponds to a 44% error reduction compared to the conventional digital model (ECM + Kalman Filter) and a 56% reduction compared to the baseline DT approach (pure PINN). Thus, the achieved numerical results serve as direct evidence of the superiority of the DT integrated with advanced hybrid algorithms. Based on the obtained results, key engineering and economic conclusions were formulated. It is proven that the transition to DT is an economic imperative for SGs. Architectural validation showed that achieving high accuracy (RMSE 0.87%) and scalability of the DT solution at the scale of the entire CTS is possible only through the use of a hierarchical Edge-Cloud computing architecture and compliance with reference architectural standards. This confirms that an effective DT is formed by the logical integration of the DT domain and the communication domain into a unified cyber-physical system. Further research should focus on the development of decentralised learning mechanisms to protect data privacy when scaling distributed DTs in SGs, and on the creation of self-managing DTs capable of autonomously adapting their hybrid models to long-term asset ageing.

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Conflict of Interest

None.

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Гібридна цифрова двійникова архітектура A-UKF–PINN для оцінювання стану в реальному часі в інтелектуальних електромережах (Smart Grid)

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Анотація. Зростаюча мінливість, нелінійність та вимоги до роботи в режимі реального часу розумних енергомереж роблять статичні цифрові моделі недостатніми для надійної оцінки стану та контролю розподілених активів, таких як системи зберігання Vehicle-to-Grid (V2G). Метою дослідження було формальне та імітаційне обґрунтування переваг динамічних цифрових двійників (DTs) порівняно зі статичними data model (DM) у задачах оцінювання стану літій-іонних накопичувачів у реальному часі. Для цього запропоновано гібридну архітектуру A-UKF–PINN, що поєднує адаптивний несцентований фільтр Калмана (A-UKF), який забезпечує стійке оцінювання стану за наявності шумів і невизначеностей, із фізично інформованою моделлю PINN (Physics-Informed Neural Network), яка враховує динаміку та нелінійні процеси акумуляторного елемента. Новизна роботи полягає в інтеграції цих компонентів в єдину модель із двобічною синхронізацією, що підвищує стабільність прогнозування та істотно зменшує десинхронізацію між моделлю й фізичним об'єктом в умовах Smart Grid. Імітаційну валідацію проведено на робочих циклах V2G з урахуванням змодельованих шумів датчиків PMU/IoT (Phasor Measurement Unit / Internet of Things). Отримане значення Root Mean Square Error (RMSE) 0,87 % продемонструвало підвищення точності на 44 % порівняно з традиційною DM (ECM (equivalent circuit models) + UKF, RMSE 1,98 %) та на 56 % відносно базового цифрового двійника (чистий PINN). Архітектурна оцінка підтвердила необхідність використання ієрархічної платформи Edge-Cloud, що забезпечує оптимальний розподіл обчислювальних навантажень: навчання PINN у хмарному середовищі та високочастотне оцінювання стану на периферії. Запропонована архітектура формує основу для масштабованих динамічних DT у Smart Grid, сприяє зниженню операційних ризиків, підтримує впровадження стратегій проактивного технічного обслуговування та підвищує ефективність життєвого циклу енергетичної інфраструктури

Ключові слова: гібридне моделювання; фізично інформовані нейронні мережі; несцентований фільтр Калмана; функціональна перевага; Edge-Cloud